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The Perception of Movement through Musical Sound: Towards a Dynamical Systems Theory of Music Performance

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Performers' ancillary body movements, which are generally thought to support sound-production, appear to be related to musical structure and musical expression. Uncovering systematic relationships has, however, been difficult. Researchers have used the framework of embodied gestures, adapted from language research, to categorize and analyze performer's movements. I have taken a different approach, conceptualizing ancillary movements as continuous actions in space-time within a dynamical systems framework. The framework predicts that the movements of the performer will be complexly, but systematically, related to the musical movement and that listeners will be able to hear both the metaphorical motion implied by the musical structure and the real movements of the performer. In three experiments, I adapted a set of statistical, time-series, and dynamical systems tools to music performance research to examine these predictions. In Experiment 1, I used force plate measurements to examine the postural sway of two trombonists playing two solo pieces with different musical structures in different expressive styles (normal, expressive, non-expressive). In Experiment 2, I recorded the postural sway of listeners as they listened to the performances recorded in Experiment 1 while "conducting" them. In Experiment 3, I asked the same two performers to mirror the expression of their own and the other musician's performances while their postural sway was recorded. Experiment 1 showed that performers changed their patterns of movement to reflect musical boundaries (places of change in musical structure), but did so differently depending the larger musical context, showing a complex, but systematic relationship between the musical structure, expression, and movement. Further, Experiment 1 showed that ancillary movements are not ancillary, but an intimate part of the creative process which produces musical performance. Experiment 2 and 3 showed that listeners and performers, when asked to mirror the expression of the recorded performance, mirrored both the real movements of performers as well as the metaphorical motion implied by the musical structure. This dissertation provides a new framework for the study of musical performance that treats the body as an important factor in the both the creation and experience of listening to music.

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Towards a Dynamical Systems Theory of Music Performance

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The Perception of Movement through Musical Sound:

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Dedication

This work is dedicated to those individuals who have changed the course of my life and put me on this path (in chronological order): Ellen & Ed Zacko, Janet Smithers, Rita Aiello, and Roger Chaffin.

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First and foremost the person who has made this work possible is Dr. Roger Chaffin. Dr. Chaffin has been mentor, advisor, collaborator, and cheerleader. This work is the culmination of our many long and fruitful discussions and debates on psychology, music, and music performance. Further, Dr. Chaffin allowed me the flexibility to question everything and the time to seek the answers under his kind and careful guidance. This work is as much a product of him as it is of me.

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Finally, I am gratefully indebted to all the people who helped make this work possible. Their sacrifice of time and effort is a gift I plan to pass on to others as thoughtfully, respectfully and patiently as was shown to me during my studies. I hope the pages below are worthy of their efforts.

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Chapter 1: Introduction

Overview

Music and movement are inseparable. Music production is always the result of movement: violinists moving their fingers and wrists or trombonists moving their lips and arms. The intrinsic relationship between the movement of the body and a musical performance has led researchers across domains such as philosophy, music theory, musicology, and psychology, to examine the relationship between movement and music (Shove & Repp, 1995). Music often causes listeners to move their bodies in response to what they are hearing both spontaneously (Clayton, 2007; Demos, Chaffin, Begosh, Daniels, & Marsh, 2011) and intentionally (for a review see Repp & Su 2013). How might those movements be related to the music and the performer's movements?

Ancillary body movements, which occur spontaneously in performance, range from postural sway, flourishes of the hands, head movements, and other movements not necessary to produce the sound (Jensenius et al., 2010). Ancillary movements are not just meaningless random movements, but are linked to musical expression (Dahl & Friberg, 2007; Davidson, 2007; Nusseck & Wanderley, 2009), musical skill (Rodger, 2010; Rodger, O'Modhrain, & Craig, 2013), and more directly to the actual production of the sound (Davidson & Dawson, 1995; Wanderley et al., 2005). Further, body movements are important to understanding the fundamental act of human communication (McNeill, 2005).

Ancillary body movements in performance are important to help heighten the musical experience of the audience. Music theorist, teacher, and pianist Alexandra Pierce has described ways in which performers can deliberately use their body movements to convey musical structure and expression. She writes, "movement refines [the performer's] listening, which in turn alters the quality of movement so that it becomes like music, having fluency, coherence, and shape" (Pierce, 2007, p.1). On this view, performers use the ancillary movements of their body to shape the ongoing performance.

Music Performance

A music performance is a complex physical and mental process that evolves in in real-time, as the performer constantly adapts her goals for the upcoming passage to what she just played. While the musician performs, she must manipulate, though not always consciously, her moment-to-moment movements in order to execute nuances in articulation, tempo, timbre, and dynamics (Repp, 1996; Palmer, 1997). These nuances convey to other musicians and to listeners, the performer's interpretation, or understanding of the music (Kendall & Carterette, 1990). For a performer to create an interpretation, she must first interpret the musical structure provided by the composer, and then integrate that conceptualization of the structure with her expressive intentions (Juslin, 2009). Performances in the Western art music tradition are usually highly practiced and polished and performers use the same nuances of tempo and dynamics to convey the same emotional message from one performance to the next with remarkable precision (Chaffin, Lemieux, & Chen, 2007; Clarke, 1995; Repp, 1995). However, performances are not identical. The performer is not a compact disk. Instead, performance is an interactive process, which integrates and adapts to the environment, to members of the ensemble, and to errors (Davidson, 2005, 2009; Hargreaves, MacDonald, & Miell, 2005).

Hargreaves et al., (2005) proposes the reciprocal feedback model of musical performance that takes into account the elements that work together to create a performance. As shown in

Figure 1, the performer and the composer are only two components of the model. Performers bring to each performance their performance skill, personal experience, current internal state (such as arousal, anxiety level), and expressive intentions. Performers interpret what the composer has given them which is a product of the composer's own expressive intentions, internal states, and reasons for composing the work, things which would rarely be known by performers. In Chapter 2, I will examine the role of body movements in the performer's interpretive process.

In addition, the performance occurs in a particular physical and social context, which affects how performers control the acoustic parameters to reflect their expressive intentions. The sound created by a performance is affected dramatically by how performers control the acoustic parameters to reflect their expressive intentions and by the physical environment. The same performance sounds very different played in a Cathedral versus a living room. Similarly, different social situations have different social norms and expectations. For example, a funeral in New Orleans is accompanied by happy music whereas in New England sad music is played. The term "music" is often used colloquially to refer to either the composition or its performance; however, it is better understood as a combination of all the elements involved. Composition, performance, social context, and style all come together to create music. In addition, the musician performs with the genre or style of the piece in mind so that the performance tradition also shapes the performance of the work. It is important to keep in mind that the musical score is no more "music", than a written script is a movie.

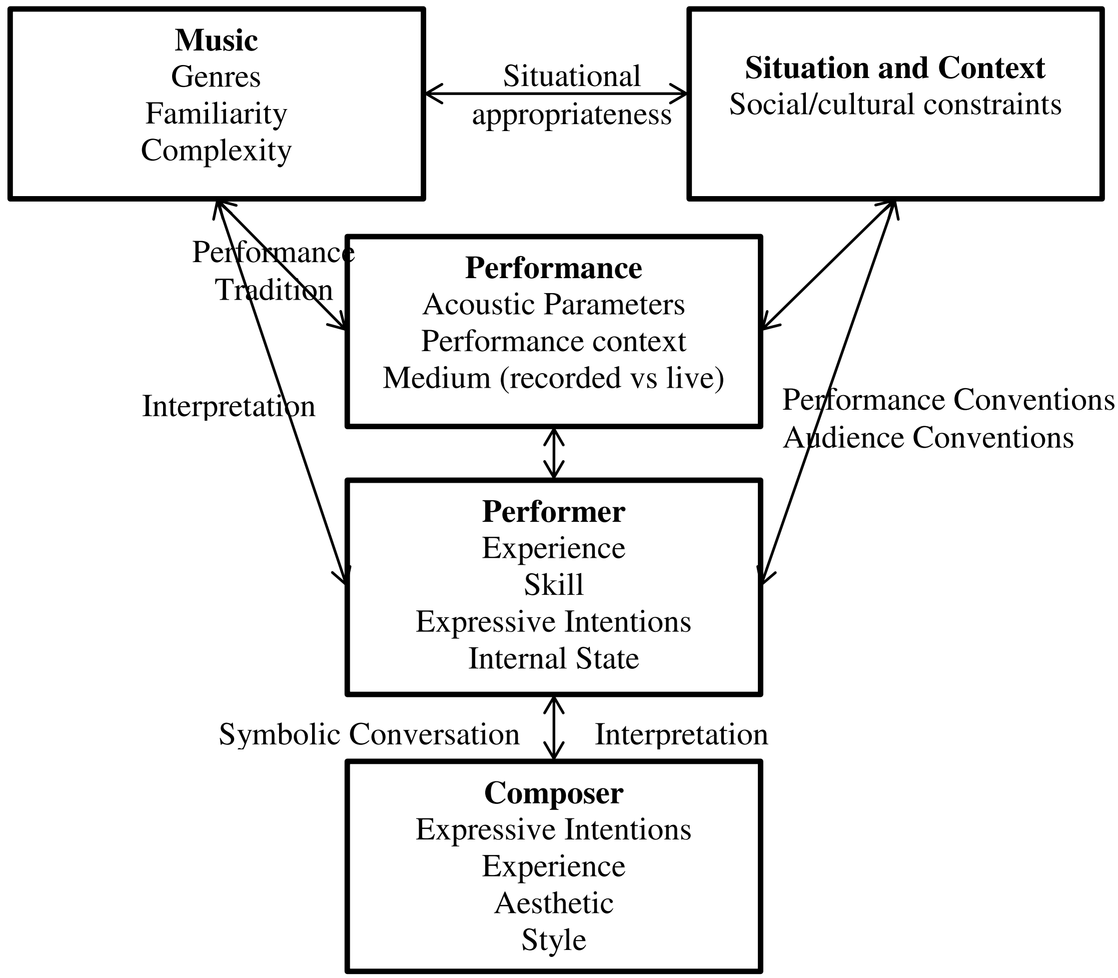


Figure 1. Model of Music Performance adapted from Figure 1.2 Hargreaves et al., (2005. p. 15).

The listener's perspective is represented by Hargreaves et al. (2005) in the model that is shown Figure 2. This model complements the music performance model, showing the situation from the listener's perspective. In this model, listeners bring with them their knowledge of music, their musical training, past experience, musical identity (how they identify themselves with respect to music), and individual variables (such as their gender and personality). In this model, music and situational contexts remain relatively the same. However, the listener's responses to musical performance depend on psychological factors (perception and cognition) related to what they are hearing. The two models proposed by Hargreaves et al., (2005) provide a framework in which to consider playing and listening to music, as we examine the contribution of a performer's ancillary body movements to the music and to the listener's experience of it.

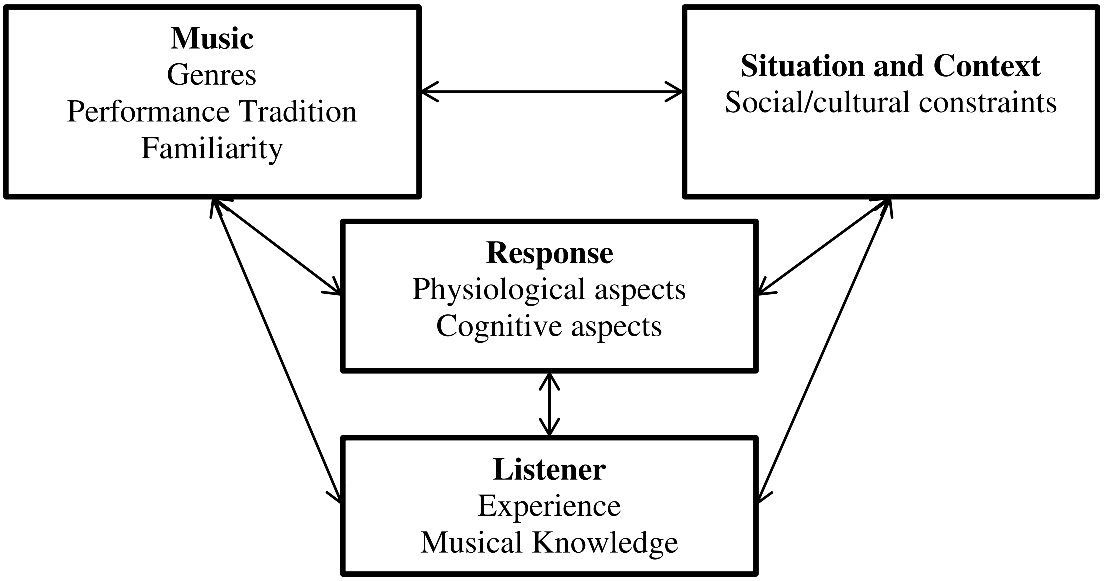


Figure 2. Model of Music Response Adapted from Figure 1.1 Hargreaves et al., (2005) p. 8.

In Chapter 4, I will explore the existing classical approaches (cognitive and ecological) and more recent approaches (embodiment) to musical communication. In addition, I will explore an alternative to these frameworks based on dynamical and complex systems. This framework can subsume Hargreaves et al.'s (2005) performance and response model, thereby providing a bridge between the psychological and musicological approaches to music performance, while also handling the role of the body.

Body Movements in Performance

The movements of the body serve an important function in acts of communication, besides producing sounds that express a message. The movement of lips, for example, can override the sounds of speech, as seen in the McGurk Effect (McGurk & MacDonald, 1976).

Further, sound carries information about the body that created it. For example, people can hear the gender of a walker (Xiaofeng, Logan, & Pastore, 1991). Listeners mirror the postural sway of speakers based on sound alone (Shockley, Santana, & Fowler, 2003). In music performance, seeing is as good as hearing when it comes to extracting the expressive intentions of the performer (Davidson, 1993) and it generally does not matter what part of the body the perceiver sees (Dahl & Friberg, 2007). When listening to music, listeners move their arms in similar patterns to those of the performer even when they do not know the instrument (Leman, Desmet, & Styns, 2008), demonstrating that the sound-producing movements of the performer are relayed by the sound.

Researchers who have studied body movements in music performance have mostly taken a traditional cognitive perspective and focused on understanding which part of the body movements provides the *signal*, i.e., the meaningful movements called *gestures*, and which movements have no meaning and thus are *noise*. The general model for this approach has come from the study of gestures in language and speech (Kendon, 1993; McNeill, 1992, 2005). Gestures that accompany speech communicate information to the perceiver (Beattie & Shovelton, 1999). Additionally, gestures may *ground cognition*[1] in action (Beilock & Goldin-Meadow, 2010) and aid in memory retrieval (Cook, Yip, & Goldin-Meadow, 2010). Gestures do not always match the intended meaning of the speech act, but sometimes can signify contradictory messages. In such cases, gestures may be more revealing than speech of the actual intentions of the speaker (Goldin-Meadow, 2003).

[1] Grounded cognition is the idea that mental representation are not stored in memory as amodal symbols, but are stored as modal symbols and are part of the perceptual system that took in the information (Barsalou, 2008). See Chapter 4.

Since the study of gestures in music performance has evolved from the study of gestures in speech and language, there are some difficulties in using the concept of gestures in music. I will explore those problems in Chapter 5. Here, I will review how gestures are categorized in music performance. In music performance research, different researchers have made different distinctions and used different terminology in describing the movements involved in music production. In this dissertation, I will use the terminology and definitions of Jensenius, Wanderley, Godøy, and Leman (2010). They distinguish four major types of body movements: sound-producing, ancillary/sound-accompanying, communicative, and sound facilitating gestures. Sound-producing gestures are those necessary to make the sound. Sound-accompanying gestures are not necessary to make sound but may follow the music or mimic the sound-producing gestures. Communicative gestures refer to the McNeill (1992) definition of gesture. In music these are either performer-to-performer or performer-to-listener directed gestures and are used to communicate some musical idea or necessary joint-action. Sound facilitating gestures are preparatory movements of other parts of the body that facilitate the actions necessary to produce the music, for example, a violinist moving his thumb up the fingerboard in anticipation of moving his whole wrist to prepare for a shift. Depending on the instrument, sound facilitating gestures may be audible (Wanderley, 1999). For example, when a violinist shifts it affects the pitch of the off-set of the preceding note and the onset of the succeeding note (Fyk, 1995).

In music, body gestures are instrumental in conveying of emotion to the audience (Dahl & Friberg, 2007), the conductor's intentions to the orchestra (Luck, 2000), and coordination cues between performers (Goebl & Palmer, 2009). Research has focused on the communication between the performer and the audience, but music performance is not a series of one-way communications between performers or between the performer and the listener. Instead, music performance is a social activity in which performers and listeners are in a relationship involving constant, bidirectional information sharing (Swayer, 2005). Music performance is not just an intellectual activity; music is a way for members of a group to bond with each other by sharing a common experience (Gioia, 2006), to coordinate social actions (Blacking, 1995), and to express emotion (Juslin, 2005). Any theory of musical communication must take into account these social and collaborative functions of music performance (Swayer, 2005). Therefore, while the word "performance" is often used to refer the actions of the musicians to produce the sound, it can thought of as synonymous with the word "communication", as performance is the act of communicating musical ideas.

Research Questions and Goals

Researchers examining sound-accompanying movements have generally assumed a one-to-one correspondence between a particular body gesture and a specific musical gesture (for example, a cadence). The challenge in the examination of sound-accompanying gestures is that unlike the consistency that can be observed in the sound-producing gestures, sound-accompanying movements look different in each performance (Davidson, 2007). However, sound-accompanying movements have been observed to relate to some aspects of the musical structure (Davidson, 2009; Ginsborg, 2009; MacRitchie, Buck & Bailey, 2013; Palmer, Koopmans, Carter, Loehr, & Wanderley, 2009; Wanderley, 2002; Wanderley, Vine, Middleton, McKay, & Hatch, 2005) as well as expression (Dahl & Friberg, 2007; Nusseck, & Wanderley, 2009).

The sounds generated by the performer must be systematically related to the musical structure and musical expression. However, uncovering of the nature of the relationship has been hampered by methodological difficulties, primarily because the movements are generated by a non-linear process (Davidson, 2009; Leman, et al., 2009). Further, the movements may serve multiple purposes (Davidson, 2009). I will create a musical communication framework based on complex systems that does not make the same assumptions as the classical approaches and uses tools better suited to non-linear data. I expect nonlinear dynamical system tools to provide new insight into the relationship between ancillary body movements and musical structure and expression. Therefore, the first experiment will examine multiple performances of the same song using both traditional tools and non-linear dynamical systems tools.

Since musical expression and musical structure are inseparable in natural performance, comparison between performances, even by the same musician, is problematic. Clarke (1989) rejects the traditional notion that musical structure is fixed, and proposes instead that as the performer changes his or her expressive intentions, so will their perception of the musical structure change. My third experiment will control for the expressive intentions of performers, by asking them to listen to music while mirroring performances by themselves or by another musician. This will allow for the control of expression in order to distinguish the effects of musical structure from those of expression. The success of Experiment 3 depends on the success of Experiment 1 in finding a systematic relationship between ancillary body movements and the music.

Understanding the systematic relationship between the movements and musical structure and expression only provides half of the picture for understanding musical communication. The expressive intentions of the performer can be decoded just by watching their body movements (Dahl & Friberg, 2007; Davidson, 1993, 1994; Nusseck, & Wanderley, 2009). This suggests that there is an intrinsic link between the ancillary movements of performer and the sound they produce. For music to serve as a medium for social bonding and joint action, the music must be used to align the movements of the listeners. There are several possibilities for how listeners might align their bodies to music they hear and each musical communication framework makes different prediction about this. The complex systems framework I am proposing predicts that the listeners will align their bodies with that of the performing musician.

Chapter 2: Musical Structure and Expression

Overview

Musical structure and expression are among the oldest areas of discussion in music. Theories about the construction of Western music date back to Pythagoras's (5th century B.C.E) ideas about musical ratios and harmony. Modern conceptions of harmony were developed during the 18th century by Rameau among others (Randel, 2003). The idea that the structure of the music and the expression are connected is equally old, however modern research on the topic only began about a century ago (Gabrielsson, 2009). I will first review the modern conceptions of musical structure and expression and then move on to some of the important elements that make up musical structure.

Musical Form

The term "musical structure" is used synonymously with the term "musical form" which is defined as, "the shape of a composition as defined by all its pitches, rhythms, dynamics, and timbres" (Randel, 2003, p. 329). At the largest scale, compositions are classified as containing either simple/single forms or compound forms. The latter contain multiple single forms (such as sonata-allegro form). Forms are generally classified based on tonality and repetition patterns. Within a single form, the internal structure is typically organized hierarchically and temporally (McMullen & Saffran, 2004). The hierarchical nature of music can be described as strings of notes that make up a theme to create phrases, which lead to larger units. Western listeners have a hierarchical internal representation of the relevant structures and prefer that the piece end on the tonic. They rarely prefer that the piece end with notes outside of the diatonic context (Krumhansl, 1996).

Listeners segment the music into coherent units by way of musical boundaries, which are often at, but do not require, harmonic cadences (Krumhansl, 1996; Lerdahl & Jackendoff, 1983; Tan, Aiello, & Bever, 1981). Harmonic cadences come in different forms, but can differ in salience of closure depending on the type of cadence and the musical context leading to the cadence. Musical context is in part created by the amount of tension that is produced by the music building to the harmonic resolution, which is one type of musical boundary (Krumhansl, 1996). The most salient harmonic musical boundaries, regardless of context, are considered perfect authentic cadences (PAC). These are triads, built on the root position of a V chord leading to I or tonic chord. Whereas PACs are used often to end a large section or the whole piece, authentic cadences [V-I not in the root position] are often used to close phrases within sections.

Additional types of cadences are the plagal (IV–I), imperfect (I or V or ii, IV going to a V), or deceptive cadences (V to something other than I), which are all different ways of creating meaningful units in the music. It is important to note that these cadences are generally only relevant in roughly the common practice period (17^{th} to early 20^{th} century) and can only be considered basic guidelines (Piston & Devoto, 1978). Harmonic cadences are not the only type of musical boundary that allows listeners to segment the music. Segmentation of the music can occur at places of textural changes, periods of rest, and changes in the melody (Krumhansl, 1996). Krumhansl finds these segments occur at changes in the musical ideas; however, there are sometimes more musical ideas than segments. This suggests that these elements do not act on their own but in concert to produce psychologically real places of segmentation.

Psychological studies of musical form have focused on harmonic musical boundaries. These studies typically involve pressing a button when the listener feels a musical boundary has occurred in common practice period music. Segmentation judgments of both musicians and non-musicians are generally in agreement with the formal analyses of the music provided by music theorists (Clarke & Krumhansl, 1990; Deliege & El Ahmadi, 1990). Listeners, both musicians and non-musicians, are able to detect boundaries in the musical structure even when they are unfamiliar with the music (Frankland & Cohen, 2004). Listeners, both musicians and non-musicians, are even aware of the macro structure in non-tonal music (Addessi & Caterina, 2005). Furthermore, responses to musical boundaries often reflect the hierarchically organization of musical boundaries (Aiello, Aaronson, & Demos, 2004).

Musical Expression

Choosing one particular way to segment the music is perhaps the performer's most important task. The performer must *interpret* the musical structure to highlight the musical structure and help the listener understand what they believe is the meaning of the music (Clarke. 1987). The performer *expresses* his interpretation by controlling tempo, dynamics, timbre, and articulation (Palmer, 1997). Musical expression is, therefore, not written into the composition but is something the performer creates and cannot be separated from the underlying musical structure.

The effect of a particular part of the musical structure on how listener perceives the expression at a particular point in the music may change depending on the particular musical context (other musical elements) and the listener's own experience (Huron, 2006). For example, minor mode music in the western classical tradition is often perceived as sad, but the seventh movement from J.S. Bach's B minor orchestral suite is often viewed as happy. Aside from being minor, it is also fast in tempo and sharp in timbre (Gabrielsson, 2009). Considerable research has been done examining how specific musical elements, both individually and in context of others, are perceived by Western listeners (for a review see Gabrielsson & Lindstrom, 2001).

Research on expression has focused primarily on two possibilities when examining how the music affects the listener. First, the listener may perceive the emotional content the performer is attempting to convey through the musical sound. Second, the listener may experience an emotion as induced by the music. The induction of emotions is typically measured via physiological measurements or brain scans, while the perceived emotion is usually measured via self-report by the listener (Gabrielsson & Lindstrom, 2001). Both the induction and perception of emotion from music depends on a multitude of factors, such as the musical structure, individual experience (such as musical training or culture), and situational factors (such as social context, performance location and condition) (Gabrielsson, 2009). For the purposes of this dissertation, I will focus on the valence of expression (i.e., more or less expressive), and not on any particular emotion, and I will review elements of performance and music structure as they relate to the communication of expression.

Timing & Intensity Cues

The temporal production of a performance can be described by three parameters: articulation, tempo and expressive timing (Juslin, 2009). Articulation is the time between onset and offset of sound, in other words, the silence that occurs between notes. Tempo is understood as the average speed it takes to play musical beats. Expressive timing is the variation in the time taken to play the noted values provided by the composer.

Intensity refers to the aspects of the sound production not related to timbre or pitch. The performer can vary the loudness (i.e., dynamics) and attack (i.e., rate of change in loudness of individual notes) (Juslin, 2009). This dissertation will be limited to tempo, expressive timing, and loudness as they are larger scale reflections of expressive performance. Articulation and attack reflected micro changes in performance that are no less important than macro features. However, because this dissertation focuses on postural sway, which involves slow changing movements, small, short-term variations in tempo and dynamics will be ignored.

Tempo and dynamics are the two main ways a performer can convey to the audience their expressive intentions (Palmer, 1997). Tempo is a complex percept that listeners derive from the way a performer controls the timing of moment-to-moment changes in beat-to-beat transitions (Palmer, 1997). Overall, tempos generally have different expressive connotations. For example, faster tempos are generally perceived as expressing happiness, joy, or anger; slower tempos usually elicit feelings of calmness, peace or sadness (Gabrielsson & Lindstrom, 2001). Tempo changes within performances can be intentional or unintentional (Palmer, 1997) and show long-range correlations, reflecting 1/f noise (Rankin, Large, & Fink, 2009). The fluctuations in tempo are not random but are related to the musical structure, highlighting phrase boundaries and higher levels boundaries in the structure (Clarke, 1998; Shaffer & Todd, 1987; Sloboda, 1985; Todd, 1985). As tempo is, in part, a product of expressive timing, Repp (1992) examined the expressive timing of 28 different performances of Schumann's Traumerei and showed regularities in the timing functions as they related to the ritardandi (slowing down) approaching structural boundaries. Gabrielsson (1987) and Palmer (1989) have both examined timing, as well as other musical features, across several pianists playing the same musical selection. These investigations have generally found that the beginnings and ends of sections are generally slower, while middles of sections are generally faster. This pattern has been described as tempo *arches* and they can be described mathematically using polynomials (Shaffer & Todd, 1987; Todd, 1992).

Tempo and dynamics are often highly related, if not coupled, in performance. Within certain musical contexts, the modern Western convention is to get faster/louder at the points of high musical tension and slower/softer at the ends of phrases. Different levels of loudness produced by the performer can result in the perception by the listener of different expressive intentions from tension and anger to joy. Large variations in loudness often suggest fear, while rapid changes can indicate playfulness or pleading, while no changes can indicate sadness or peace (Gabrielsson & Lindstrom, 2001). The amount of change in loudness is reliably reflected in the perceptual valence scores of listeners (Juslin, 2009). Loudness, like tempo, is also used to highlight musical boundaries. Musical boundaries are the psychological reality of the musical form (Palmer, 1997).

Chapter 3: Body Movement in Music Performance

Overview

Study of the connection between the body and music performance has focused on ancillary movements, notably the sway of the upper body, which generally occurs in any kind of music performance, irrespective of the instrument. Ancillary movements have been studied from two perspectives: perceptual studies have examined how individuals perceive the movements of performers and production studies have examined how the body moves in performance. Studies of the production of the ancillary movements in performance are often accompanied by study of the perception of those movements as well. First, I will review production and joint production/perception studies, and then I will review perception-only studies. I will then briefly describe the small number of studies that have examined the coordination of movements between different performers during musical performance.

Production/Perception Studies

From Structure to Movement

Groundwork. In one of the first studies on the topic Davidson (1993), using point light displays, examined the expressive components of musical gestures and, at a descriptive level, the periodicity of those movements. Davidson asked violinists to perform the same piece with three different general expressive intentions (deadpan, normal, and projected/exaggerated). Participants were shown the point light displays of performances with no sound and were asked to judge their expressiveness. Based on sight alone, participants could identify the expressive intention of the performer as accurately as participants that could hear the performances. Over the course of two decades of research on the topic of the movements of performers, Davidson

(2009) has shown that performers sway their bodies rhythmically centered on their balance point. For standing performers, this means changes in center of gravity (which can be measured by center or pressure). For sitting performers this meant changes around the waist. In each case, the amplitude of the movement increases with the amount of expression the performer intends to convey.

To better understand which parts of the body relayed the expressive information Davidson (1994) examined the movements of a male professional pianist playing Beethoven's Bagatelle No. 11, in both the medio-lateral (ML) and anterior-posterior (AP) directions. As in Davidson (1993), the pianist played with three different levels of expression. Again, this study showed that the amplitude of movements increased with the level of expression. Judges were asked to rate the performance expressiveness based on seeing different parts of the body (head, torso, hands, etc.). Ratings of the expressive intentions of the performer were conveyed most clearly by the upper torso and head.

Wanderley (2002) examined the clarinet bell movements of clarinetists who were given the similar instructions to those used by Davidson (1993). Overall, exaggerated performance showed greater amplitude of movements, but mirrored the contour of normal performance, while non-expressive movements, were lower in amplitude to normal performances and, as well, were different in contour and noisier. By comparing performances (both within and between performers and performances), Wanderley showed, through the use of correlation, that the same performer produced similar patterns of movement at particular locations in the musical score across multiple performances. Further, he showed that across performers, movements were more similar at structurally important locations. The important conclusion was that the ancillary movements were part of the performance, and not just random movements.

Palmer, Koopmans, Carter, Loehr, and Wanderley (2009) examined the movements of clarinetists playing in three different expressive styles: normal, exaggerated, and inexpressive. As in previous studies with clarinetists, they measured the movement of the bell and acoustical features of the performance. By accounting for the acoustical features, they were able to show that the amplitude of movements of the bell was related to the expressive timing of the performance. Therefore, the authors conclude that ancillary movements serve to highlight the phrasal structure of the music.

MacRitchie, Buck and Bailey (2013) examined the relationship of pianists' overall body motion to the phrasal structure of the music. Using autocorrelation, they concluded that the periodicity seen in the body movements reflected the periodicity of the phrasal structure. They made no direct comparison between the movement and musical structure. Instead, they compared tempo and dynamics to body movement within phrases. Using ANOVA, they found a relationship between these expressive parameters and the movements of the body. Their results demonstrate that there is a relationship between the motion patterns and the phrasing of the music but they do not clearly identify the nature of this relationship.

Gestural Approaches. The primary way in which researchers have attempted to categorize the "meaningful" ancillary movements of performers has been to relate the frequency of different types of gestures to properties of the music and to performers' expressive intentions. Wanderley, Vine, Middleton, McKay, and Hatch (2005) examined the movements of clarinetists playing three different pieces. The movements of the performers were categorized by coders.

The majority of movements (57.5%) were classified as up and down movements of the clarinet bell, the head, and the shoulders. The second largest grouping (19%) involve the bending movements of either the waist or the knees. The rest of the movements (23.5%) were made up of arm flapping, foot stepping, and weight shifting. Based on visual inspection of the movements, the authors concluded that the movements related either to the phrasal structure of the music or the metrical patterns. Further, the movements seemed to exhibit co-articulation, meaning that the movements from one section blended into the next. Coarticulation of movements has also been observed in speech (Mann & Repp, 1981), in the movements of pianists' fingers (Jerde, Santello, Flanders, & Soechting, 2006), and in violinists' fingers and bow arm-movements (Wiesendanger, Baader, & Kazennikov, 2006).

Davidson (2007) examined the expressive gestures a pianist used during performance of one of Beethoven's bagatelles. Based on qualitative coding, Davidson showed that the movements of the body could not be characterized as either intention specific (expressive or non-expressive) or related to any aspect of the musical structure. The pianists did make gestures at the same locations in the musical score across multiple performances, but the exact gesture was not the same. Therefore, particular aspects of the musical structure did not seem to result in particular gestures. Both the findings of Davidson (2007) and Wanderley et al. (2005) suggest that particular places in the music are related to the presence of some kind of expressive gesture, but that the exact gesture is not consistent.

Movement's Effect on Sound Production

Davidson and Dawson (1995) created music for pianists using only keys that were centered in front of the body so that the performer would not be required to make any movement of the torso. Although the music did not require movement of the torso, the performers moved expressively, both swaying and making gestures. When some participants were asked to learn the music while restrained, preventing them from making any expressive movements, their performances were rated as less expressive by judges, even though they were not asked to perform the music any differently. This suggests that changes to body movements affect sound production, in particular the expressiveness of the music produced.

Wanderley et al. (2005) found that the timing of phrases was changed when performers were given instructions on how to move. When performers were instructed not to move as they performed, they played faster and had less expressive timing at the ends of phrases. Movement does not just affect the expressive timing of a performance; it also affected the amplitude and phase of the sound as recorded by a microphone (Wanderley & Depalle, 2004). As the performer moves, there is an effect on the amplitude and phase because of the changes in the reflections of the sound from the ground, or other objects in the room.

In summary, these studies show that there is a relationship between ancillary movements and the composition (Davidson, 2007; MacRitchie, et al., 2013; Wanderley, 2002; Wadneraly, et al., 2005). Further, there is a bi-directional relationship between performers' movements and expressive quality of performance (Davidson & Dawson, 1995; Palmer, et al., 2009; Wanderley et al., 2005). These findings suggest that the distinction between ancillary and sound producing movements may be misleading. Ancillary movements may be more intimately involved in the creation of musical sound than their name suggests.

Perception Studies

Davidson (2002) asked whether the information gained from watching a performance comes from specific places in the piece or from the variability of movements in performance. Musician judges watched two-second excerpts of each performance style from the same recording made by Davidson (1994). These excerpts selected locations that were either high (4th quartile) or low (1st quartile) in variability of movement, measured separately for the hands and torso. Judges were able to distinguish between the three performance styles and rated the more variable clips as more expressive overall. The only exception was the case of the hands only (sound-producing movement) with low variability movements, which was less informative than the torso (ancillary movement) which were more helpful in allowing perceivers to distinguish the expressive intentions of the performer. A second set of judges was asked to decide for each excerpt whether the performer was trying to be expressive. There was a high level of agreement (87%) between the judges and there was high agreement between judgments made while watching the hands and the torso. Almost all (97%) of the high variability movement clips were thought to contain an expressive intention, as compared to 24% of low variability movements. Almost every musical bar was said to contain an expressive location and they were related to many different aspects of the musical structure (such as cadences, phrase peaks, rests, harmonic modulations). These locations were not picked based on the change in amplitude of the movements; some places with large changes were ignored by judges and some places with small changes were universally selected. Therefore, while there is a relationship between movements and musical structure it is not a simple one-to one-correspondence between action and perception.

Dahl and Friberg (2007) asked a xylophonist to improvise different musical selections to express four different emotions: happiness, sadness, anger and fear. Participants were asked to rate each performance as to the expressive intentions of the performer and musical cues (sound level, tempo, articulation, and tempo variability) while looking at different parts of the performer's body: head only, torso only, no hands, full body. Participants were accurate in the identification of the expressive intentions for all the emotions except fear. In addition, it generally did not make a difference as to which part of the body they viewed.

Nusseck and Wanderley (2008) created kinematic displays, similar to point light displays, of four different clarinetists playing the first phrase (8 bars or 24 beats) of the first movement of Brahms' First Clarinet Sonata. Music school students rated the performers' movements on four dimensions: musical tension, intensity, fluency of movement, and the professionalism of the performer. To test the validity of the kinematic displays, raters watched either a video, or the point light displays from either side view or front view. In general, the video and point-light displays were rated in the same way. The point light displays were then modified to select out different parts of the body. Participants saw either the original movements, movements where the arms or torso was frozen, or a backwards motion of the body. There were no differences between the conditions. The authors concluded that the ratings were independent of which body part was in motion, or even if the movement of the body was reversed. In a second experiment, the movements of the body were manipulated, either reduced (20%) in amplitude or exaggerated, up to 150%. Ratings of expressive intensity were most strongly affected by the changes of amplitude, with higher amplitude movements being rated as more intense. These results are in line with the observations of Davidson (2009) and Wanderley et al. (2005), showing that the amount of ancillary movement increases with the degree of expression intended by the performer. Nusseck and Wanderley's work shows that observers are able to perceive differences in intensity.

To examine the relationship between sound-producing gestures and movement, Leman, Desmet, and Styns (2008) asked participants to listen to the Chinese Guqin (an instrument like a zither) and move their arms/hands with the music in the same way that they imagined that the performer would have done. Participants were not familiar with the instrument. Participants' arm movements were similar to the velocity patterns of the player's shoulder and these similarities became stronger over the course of the experiment. Listeners also moved their bodies rhythmically relative to the meter of the music, corresponding in simple integer ratios (Toiviainen, Luck, & Thompson, 2009; Toiviainen, Luck, & Thompson, 2010). The listeners seemed to only embody one ratio at a time per body part, but they changed to different ratios as they listened. Further, different body parts oscillated at different ratios concurrently.

In summary, perception studies show that the movements of the performers inform the watcher as to their expressive intentions and those intentions can be perceived from seeing any body part (Dahl & Friberg, 2007; Davidson, 1993, 2002; Nusseck & Wanderley, 2008).

Coordination Studies

Coordination studies have focused on synchronization through timing and rhythm (for reviews see Repp, 2005; Repp & Su, 2013). Synchronization is can be understood as the temporal phase alignment or frequency entrainment between two oscillators, linear or chaotic (Pikovsky, Rosenblum & Kurths, 2001). Synchronization often occurs spontaneously between individuals engaged in rhythmic tasks. Spontaneous synchronization often occurs intermittently, where there is recurrent, but not stable, phase-locking between individuals.

Spontaneous synchronization can occur through visual channels (Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; Richardson, Marsh, & Schmidt, 2005), auditory channels or both (Demos et al., 2011; Néda, Ravasz, Brechet, Vicsek, & Barabási, 2000). In music performance, synchronization between sound-producing gestures of performers is very strongly coupled (Loehr & Palmer, 2009; Palmer & Loehr, 2011; for a review see Palmer, in press).

Keller, Knoblich, and Repp (2007) asked pianists to record the melody and accompaniment of a work separately. Pianists were then asked to duet either with themselves or with another person. Pianists were better able to recognize their own performances, duet with themselves, and detect their own style (i.e., expressive timing nuances). Goebl and Palmer (2009) examined pianist duos while controlling for the type of auditory feedback and the leader follower role. As the amount of auditory feedback between the performers decreased, there was an increased reliance upon the visual movements of the other performer to guide coordination. In addition, performers adjusted their movements based on the lack of auditory feedback. Leaders raised their fingers higher, presumably for the partner to see better, and the coordination of the pianists' head movements increased.

In summary, musicians use the movements of other performers to coordinate performance (Goebl & Palmer, 2009) and can recognize and coordinate better with their own performances (Keller, et al., 2007).

Conclusion

These findings suggest that musician's ancillary movements during performance provide information that can be used for a variety of different purposes: communicating with the audience, coordinating with other musicians, and enhancing the musical sound. The evidence that musicians' ancillary movements provide information about the music appears, at first glance, inconsistent with the evidence that movements are different in each performance of the same work and different from one performer to the next (Davidson, 2009). How can there be so much information contained in body movements, yet little reliability between the performers? A systematic relationship must exist, but has yet to be uncovered. One possible explanation is that the theoretical approach to musical communication that researchers have taken has limited the field of study to looking for specific relationships between music and performer movements. The next chapter will examine this idea further.

Chapter 4: Current Musical Communication Frameworks

Overview

How researchers approach the study of communication in music depends on the theoretical frameworks they adopt for understanding the function of music, as well as their perspective on cognition more broadly. I will start by with an overview of ideas about the function of music, and then review four major perspectives on perception and cognition: Cognitive, Embodied, Ecological, and Complex System (Dynamical systems).

Musical Function

Music existed long before the Western concert practice of audiences sitting in darkened theaters or walking around listening to digital recorders using headphones (Swayer, 2005). Music has served important cultural and social functions for many millennia, and those functions provide an important clue as to the relationship of music and movement (Blacking, 1995; Cross, 2005). So what is the social function of music? As mentioned in Chapter 1, music can align a group's shared sense of action and create a feeling of group affiliation (Blacking, 1995; Gioia, 2006). Music is also used to coordinate joint action. Joint action is a social interaction where individuals coordinate their movements, for example hauling in fishing nets, raising a roof, or planting a field (Sebanz, Bekkering, & Knoblich, 2006). Demos et al. (2011) showed that individuals coordinate with either music or with the sound of another person's movement and, most importantly, that coordinating with music increased the feeling of connection with the other person.

Alignment and coordination appears to act as a cue that the listener understands and is ready to engage in joint action. LaFrance (1982) showed that when people converse, the listener mirrors the speaker's postures. Further, Fowler, Richardson, Marsh, and Shockley (2008) have shown that interlocutors align their postural sway. The mirroring of posture and the coupling of movements not only increase the likability of the partner, but also increases cooperative action (Wiltermith & Heath, 2009). Movement appears to act as a cue that the other person understands and is ready to engage in joint action. Additionally, the alignment of the conversers' speech properties may signal that the interlocutors are achieving common ground (Clark, 1996).

For music performance, we need a framework that can encompass the challenge of understanding musical meaning and also explain how music serves these social functions. In the following sections, I will review the frameworks that are currently used to understand perception, cognition, and joint action. The most widespread and oldest is the cognitive perspective.

Cognitive Perspective

The standard cognitive perspective is that information is taken in through auditory or visual channels, where the signal is separated from the noise via computational extraction (Shannon &Weaver, 1949). The information, now in the form of mental representations, is believed to be amodal, meaning that it is independent of the perceptual system that encoded the information from the external environment (Barsalou, 1999). This perspective divorces the mind from the body and would predict that the role of body in expressive performance is simply one of execution. Further, perception becomes divorced from the perceptual channels that take in the information into the amodal symbol. The mind, from this perspective, is a symbol manipulating and processing machine. The job of the cognitive psychologist is to understand how information enters the mind/brain, is stored, manipulated, and acted upon (Varela, Thompson, & Rosch, 1991). From this perspective, the sender conveys a noisy signal, which must be decoded by the listener. This view of cognitive systems has influenced not only cognitive psychology, but also musicologists seeking to explain the communication of musical meaning and it has been important in shaping views on musical motion.

Cognitive Perspective on Musical Motion

The cognitive perspective has led to the idea that the musical structure itself implies a particular motion. Shepard (1984) suggested that the perceived motion from musical sounds is equivalent to 'apparent motion' in vision, just a perceptual illusion. Shove and Repp (1995) list categories into which musical motion can be classified: rhythmic, melodic, and harmonic motion. Rhythmic motion can arise from tension created from meter or rhythmic dissonances. Harmonic tension can also arise from harmonic dissonance. Melodic motion arises from the melodic contour, the movement from pitch to pitch. Todd (1999) has suggested that the illusion of movement in music arises from how the music affects the neurobiological mechanisms of audition and in particular the vestibular system.

To give a musical example, Schubert wrote a *referentialist* song for soprano and piano called, "Gretchen at the Spinning Wheel" (1814, Op.2, D 118). While Gretchen sings, she works at the spinning wheel, represented by the piano. The pianist is required to use her right hand to play an up-and-down, close-in-pitch melodic contour, which represents the spinning motion of the wheel. This music conveys *metaphorical motion* (Clarke, 2001). Is metaphorical movement all that music can convey?

If music only conveys metaphorical motion, it leads us to certain expectations as to the perceptions of the listener. Assuming listeners can decode the metaphor, then they should perceive roughly the same motion. If listeners decode the metaphors in different ways, their perceptions of the movement will differ. For some compositions, such as in the case of Gretchen and the Spinning Wheel or Smetana's The Moldau (flowing of a river), the metaphor is obvious. What about in cases not where the composer is not trying to reference a particular motion? Do listeners just not hear motion, such as in a Straus Waltz? The feelings of movement in a waltz often comes from rhythmic motion, also a type of metaphorical motion, though here the meaning is open to more interpretation by the listener. Finding reliability between metaphorical motion perceived by listeners might be more difficult if the music is not dance music or has no specific referentialist meaning, J.S Bach's Art of Fugue for example. These are questions that do not yet have empirical answers, but we can surmise the more abstract the music the more abstract the metaphor, which would result in different movement interpretations by listeners.

The traditional cognitive psychology approach has provided an important insight into how music motion could be perceived by the listeners. However, it has not been as successful in accounting for how the performer's own body might be important in generating and transmitting metaphorical motion. Further, we know that the body does not play a passive role in performance, but that changes to the body of the performer can change the way a performer creates the music (Davidson & Dawson, 1995; Palmer, et al, 2008; Wanderley et al., 2005). An advanced cognitive perspective, the embodied perspective, has been proposed to deal with the difficulties in accounting for the role of the body.

Embodied Perspective

The information processing cognitive perspective creates several problems. The first is the symbol *grounding* problem (Wilson, 2002), which refers to the fact that in an information processing perspective, the information must be decoupled from its source, pass through stages of computation (Marr, 1982), and then be reconnected to its meaning. Decoupling information from its source also causes the percept to become separated from environment: this is called the *embedding* problem.

How does the mind separate a percept from its meaning only to later put the post-processed information back together with its meaning? In auditory perception, this is called the *binding* problem. On this view, when you hear a piano key struck, you first filter out the background from the signal (the musical note), separate qualities of the sound into pitch, timbre, and loudness, and finally pass that information on for further processing to link the sound to memories and to extract the meaning from the experience.

As a workaround to the difficulties of the standard cognitive model, psychologists have proposed the embedded-embodied approach to cognition (Barsalou, 1999; Wilson, 2002). There are several different versions of embodiment theory. Each generally views the information being relayed to an individual as *situated* in the context of the environment and *grounded* in the mechanisms of motor control and sensory processing. It attempts to integrate the mind and body within the traditional information-processing framework. Unlike traditional cognitive theories, however, the mind is not considered to be an amodal symbol-processing device. Instead, symbols are grounded in perceptual systems and situated in the environment (Wilson, 2002).

Embodied cognitive theories have been extended to joint action. The most prominent extension has been with the action-simulation approach (Sebanz, Bekkering, & Knoblich, 2006; Keller, Knoblich, & Repp, 2007), which proposes that the brain simulates perceived human movements, possibly using the mirror neuron system (Rizzolatti, Fadiga, Gallese, & Fogassi, 1996). The mirror neuron system is proposed to be in the premotor cortex and to become active when perceiving one's own actions or those of another, as well as when actually producing actions (di Pellegrino, Fadiga, Fogassi, Gallese, & Rizzolatti, 1992). This system may be what allows both joint action (Wilson & Knoblich, 2005), and also the perception of gestures (Hostetter & Alibali, 2008). An action-simulation is the anticipation of action and its effects, via imagination, which occurs automatically, via mirror neurons, when seeing an action (Dokic & Proust, 2002). One prediction of this hypothesis is that the system can better perceive its own actions than the actions of another person (Knoblich & Flach, 2001). This prediction was supported in the domain of piano performance by showing that pianists are better able to recognize and play with their own performances and those of another pianist (Keller, Knoblich, & Repp, 2005; Repp & Knoblich, 2004).

One of the challenges for this approach is to make clear what is 'imagined' and how the actions of another person are 'anticipated'. What part of the action does the mirror neuron system 'mirror'? For example, how are temporal and spatial parameters mirrored? Action-simulation relies on the idea of a motor-program. A motor program is an abstract memory structure that regulates the movement of the body and specifies the order, phase, and force with which muscles are invoked (Schmidt, 1976, 1982). This top-down approach requires an executive controller to provide the appropriate motor-program for the situation and makes a distinction between the planning and execution of an action.

The strength of this framework is that it can account for the motion implied by the musical structure. Further, the embodied approach can account for the connection between the body and the performance by grounding and situating cognition in the perceptual systems. However, as with the traditional cognitive approach, it places the meaning of the music fully within the listener's mind. From this perspective, we would ask the question: what information is being transmitted from the performer to the listener in order for them to decode the meaning of the music? However, the Hargreaves et al. (2005) model of music performance, described in Chapter 1, rules out any approach that relies on the idea of information transmission.

An alternative that does not rely on the transmission approach to information sharing is the ecological perspective. In addition, the ecological perspective has gained popularity among musicologists because it treats meaning in an entirely different way (Clarke, 2001, 2005; Windsor, 2012).

Ecological Perspective

The ecological approach does not accept the dualism of mind and body or of organism and environment that is implicit in the cognitive approach (Gibson, 1966; 1979). Instead, the organism and environment "make an inseparable pair" (Gibson, 1979, p.8). The environment is suited to the animal and animal is suited to its environment. From this perspective, meaning does not need to be constructed in the mind of the perceiver, instead the meaning already exists in the environment, to which the perceiver must become *attuned* (through learning). Information is directly perceived in *event*s. An event is any change that is relevant for the perceiver. Events are hierarchically nested. For example, a person may perceive changes in notes, which are nested in beats, which are nested in musical phrases, and which are nested in movements. The musical beat can be thought of as an event, which is stable from one performance to the next (London, 2004). In other words, the number and order of beats remains the same within and between performances, however the amount of Newtonian time it takes to complete a beat is never the same.

Animals learn to perceive *affordances* of objects. These are action possibilities created by the relationship between the organism and the environment. Affordances are scaled relative to the individual, and the individual becomes attuned to those affordances through experience. The concept of affordances moves the meaning of the object into the environment and outside of the head of the perceiver. The perceiver becomes attuned to the meaning of an object such as music through experience and of the affordances that music provides (Godøy, 2010; Windsor & & De Bezenac, 2012). For example, the music may provide the listener with affordances such as dancing, worship, interpersonal coordination, persuasion, emotional catharsis, and marching (Clarke, 2005). In addition, Clarke (2001) suggests that music may afford three different types of motion.

Ecological Approach to Musical Motion

Clarke (2001) extended the ecological approach to account for musical motion by incorporating the elements of musical motion from the cognitive approach. Clarke (2001) contends that the motion experienced when listening to music comes from three sources: *real, metaphorical*, and *fictional*. First, listeners hear the actions of the instrument and the movements of the musical performers in the same way that they hear the articulation gestures of speakers

(Fowler, 1986); this is the perception of *real* motion. Second, listeners hear the movements implied by the musical structure; this is *metaphorical* motion. Third, listeners interpret what they hear and, through use of their imagination, comprehend the meaning of the music; this is *fictional* motion. Walt Disney provided an excellent example of fictional motion in his movie Fantasia (1940), in which dancing creatures and objects provide compelling visual interpretations of the fictional motion suggested by the sound.

I will adopt Clarke's analysis and assume these are the three ways in which music and motion are related. Among the affordances provided by music may be the coordination between individuals described in Chapter 1. Social affordances have been explored as a way to understand how individuals coordinate actions.

Social Affordances

A social affordance is information picked up during a social interaction that tells the perceiver something useful about the other person (McArthur & Baron, 1983). For example, thieves can judge which women are more 'muggable' based on how the women walk (Gunns, Johnson, & Hudson, 2002). Music may provide a medium for social affordances to occur or as a way to constrain social affordances. Clayton argues that "musical behavior is deployed in the management of relations between self and other and that it can and does perform this function at multiple levels simultaneously" (Clayton, 2009, p.43). For example, at a dance club, the type of music may afford the dancers different acceptable levels of touching, such as body grinding during techno music or hand holding during ballads. The music affords different social actions. Musical affordances will also depend on cultural and social context (Clayton, 2007). Music, therefore, provides a medium for people to engage in a shared experience that unites them in a common goal.

Joint action can be achieved by social affordances (Marsh, Richardson, Baron, & Schmidt, 2006; Richardson, Marsh & Baron, 2007). For example, two individuals will use the size of an object, as compared to their own body size, in judging whether they can move an object on their own or require the help of another person (Richardson, Marsh & Baron, 2007). How might music be used to coordinate the action of individuals? One possibility is that the music itself may afford a particular action. For example, a particular rhythmic stimulus indicates when a person should tap their toes (Clarke, 2005). Thus if individuals perceive the same metaphorical motion, they will be coordinated as a byproduct of responding to the music. In addition, music may afford joint action because the listeners perceive the movements of the performer or the instrument (Clarke, 2001). If the listeners move in the same way as the performer, they would coordinate with each other by using the performer as their leader.

From the ecological perceptive Clarke (2001) has provided three possible sources for the motion in music. The three sources are not purely ecological, but a merger between ecological and cognitive perspectives. For the ecological perspective, the movements of the performer need to be considered as a meaningful source of information. From the cognitive perspective, the imagination of the listeners in understanding the musical meaning needs to be considered. Finally, both perspectives take into account the metaphorical motion implied by the musical structure. Ecological and cognitive perspectives are near polar opposites, but both provide useful ways of understanding musical motion. In addition, both perspectives claim to account for joint action, but have not provided a mechanism to explain how movement and music are connected.

Recently, both cognitive and ecological psychologists have proposed using a complex systems/dynamical systems approach that might fill this gap (such as Dahl & Friberg, 2004; Large, 2000; Kelso, 1995; Loehr, Large, & Palmer, 2011; Marsh, 2011; Richardson et al., 2005; Thelen & Smith, 1994; Vallacher & Nowak, 1994).

Dynamical Systems Perspective

A complex, or dynamical system is one where the outcomes are emergent and can differ based on the constraints placed on the system, which cause the system to organize in different ways. Dynamical systems are generally not decomposable into linear elements as they are created through non-linear interactions (Strogatz, 1995). An important feature of dynamical systems is that they organize themselves without a central controller forcing order upon the system. A dynamical systems approach to cognition assumes that the cognitive system follows dynamical principles with the various parts of the system interacting and changing over time as a result of these interactions (Van Gelder, 1995, 1998).

Dynamical systems are frequently used to explain the behavior of complex systems and most recently been used explain periodic behavior like musical timing. Large (2000) proposed that musical timing and tempo may be the result of neural oscillations that exhibit limit-cycle behavior (e.g., Loehr, Large, & Palmer, 2011). A limit cycle is a periodic, or complexly periodic behavior that is self-sustaining and can be affected by perturbations, i.e., energy inflicted upon the system from outside (Strogatz, 1994). Depending on the amount of energy input into the system, the system may change its behavior but will eventually return to its periodic behavior (Warren, 2006). For example, when individuals are tracking a particular tempo, if they are disrupted, they eventually phase correct and realign themselves with the beat (Repp, 2005).

The body movements of performers have been described as exhibiting periodic components and do seem related to musical timing, but they also relate to musical structure and expression. This interaction between timing, structure, and expression may result in behavior that is more complex and less predictable than limit cycles. Such behavior is *chaotic*. Chaos is "when a deterministic system exhibits aperiodic behavior that depends selectively on the initial conditions, which makes long-term predictions impossible", (Strogatz, 1994, p.3). A chaotic system is a deterministic system. Its behavior is predictable to some degree, but is highly sensitive to the conditions and constraints placed on it. Its behavior may differ from one execution to the next even through the conditions appear to be very similar.

The dynamical systems framework has been extended to include the body from both the cognitive (de Bruin & Kastner, 2011) and ecological perspectives (Kelso, 1995; Warren, 2006). Further, this work from ecological perspective has included social phenomena (Marsh, 2010). Both approaches do not require computation in the traditional sense, i.e., the manipulation of symbols. Instead, information is transformed through interactions within the system according to dynamical laws (Warren, 2006). The body and the neurological systems interact and the information flows between them in a way that affects both of them.

Synergy theory is a dynamical approach to the motor control proposed by Latash (2008) based on Bernstein's (1967) approach to motor coordination. Synergies are temporarily assembled elements that reduce the number of separate elements that need control (Bernstein, 1967; Latash, 2008). On this view, there is no 1:1 correspondence between the neural activation and the resulting activity of body parts (Thelen, 1995). Instead, it is through the complex interactions of the parts of the system, i.e. muscles, limbs, spine, and brain that order emerges. A synergy cannot be explained in terms of the simple addition of the activity of joints and muscles. Instead, the resultant activity is different from the sum of its parts (Latash, 2008). The interactive qualities of the system often make these systems non-linear in nature. Non-linear approaches can handle holistic systems in a robust manner as compared to linear systems that serve as mere approximations (Strogatz, 1994).

Synergy theory (Latash, 2008) has three main mechanisms: pattern sharing, task-dependence, and flexibility/stability. Pattern sharing refers to the idea that the work required to accomplish a particular goal is distributed across units (e.g., neurons, muscles, or people). Task-dependence refers to the idea that a particular unit that has formed a synergy can be reused to accomplish a different task (e.g., using your hand to turn a knob or turn a screwdriver). Most important for predictive purposes is the idea that there is a trade-off between flexibility and stability in accomplishing an action. To accomplish a task, the components of most complex systems can be configured any of an infinite number of ways; this is known as the degrees of freedom problem. The synergy provides a way to limit the degrees of freedom (i.e., reduce the variability) and provide stability to the system. Stability (order in the system) arises as constraints (limits on the degrees of freedom) are placed on the system. From this, it follows that, as one part of the system becomes more stable, another part of the system must become more flexible, i.e., variable.

Winold, Thelen, and Ulrich (1994) have examined synergies in the context of cellists bowing repeated passages. They have shown that when playing a repeated note rapidly, cellists have more variability in their elbows and less in their wrists. When playing slowly, the relationship is reversed. Therefore, speed is the constraint on the system, which changes the stability and flexibility of the wrist and elbow with the result that the cellist uses proper bowing technique to produce the sound. Measuring the variability of a system cannot always be done on a single dimension of the system. For example, a cellist bowing is a complex multi-dimensional system that involves fingers, wrist, elbow, and shoulder. These dimensions would correlate with other, but may not actually provide orthogonal components that would be most useful for analysis.

One way to identify the orthogonal components of the system is to examine the system in phase-space. Phase-space is an abstract mathematical space that represents the states of a system (Abarbanel, 1995). One-dimensional data from a multidimensional *nonlinear* system can be transformed into a higher dimensional representation of the complete original system, but only when the degrees of freedom of the dynamics are coupled (Abarbanel, 1995, p.21). A *nonlinear* system measured in one dimension contains the information needed to reconstruct the other dimensions, because the missing dimensions were created in an interactive process. Takens (1981) was able to provide a method to reconstruct those hidden dimensions of the system, making it possible to reconstruct phase-space using orthogonal time-lags of the original measurement of the system. The reconstructed phase space has the same topology as the original dynamical system in that it preserves the invariant aspects of the sequence of the points, but may not match the integer dimension of the original space (Abarbanel, 1995, p. 17). This mathematical space provides a God's eye view of the components of the system. Once the phase-space has been reconstructed, the system can be analyzed by techniques such as recurrence quantification analysis (RQA) for a single system and cross-recurrence quantification analysis (CRQA) for comparing two systems (see Chapter 6 for further details).

In Chapter 6, I will describe how phase-space reconstruction can be used to represent the movements of a musician in an abstract, multi-dimensional phase-space which will represent the interacting components of the motor system that produce both ancillary and sound producing movements. Once the movements are converted to phase-space, RQA and CRQA can be used to measure how the system evolves over times and relates to musical structure.

For the past 20 years and more researchers studying music and movement have sought to demonstrate the fact, evident to anyone who has attended a performance, that there is a close and systematic relationship between music and movement both for performers and listeners. As we saw in Chapter 3, these efforts have been hampered by the apparent inconsistency of the movements. Analysis of the movements using dynamical systems methods solve part of this puzzle by showing that the movements actually represent a complex system that cannot be measured by traditional means.

Chapter 5: Towards a Dynamical Theory of Music Performance

Overview

In this chapter, I will outline a dynamical systems theory of music performance based on the concepts of complex systems and synergies and outline three experiments designed to explore and test its potential. As I have described in previous chapters, the current frameworks for studying cognition and perception have been insufficient to capture the scope and complexity of music performance, particularly to solve the problem of understanding the role of the human body in performing and perceiving music. There is, however, good reason to expect that a complex systems approach will be more productive. Considering music performance as complex self-organizing system does require, however, some modification to traditional approaches, particularly to the concept of gestures.

Dynamical Gestures in Music Performance

Whether one takes an ecological or the cognitive approach to understanding cognition, the dynamical systems framework provides a new way to conceptualize the role of gesture in communication. The dynamical system toolkit makes it possible to examine gestures as part of a time evolving system that places constraints and conditions on when and how the gesture occurs. The cognitive approach assumes that a gesture is a discrete action controlled by a motor program. The program is invoked by a central controller whenever the meaning represented by the gesture must be conveyed. Under the dynamical systems framework, this concept of a gesture changes. Gestures are no longer discrete actions; instead, gestures are continuous actions that evolve over time and are constrained by the context in which they occur, both physical and social. Instead of a 1:1 correspondence between discrete gestures and discrete meanings, the meaning of a particular gesture depends on the musical and social context.

The empirical study of the role of gestures in communication has been developed primarily with respect to language rather than music. The translation of the idea from language to music performance research may be more problematic than helpful. Parallels between music and language end at the superficial structural level. There are important differences in their syntax and semantics (Sawyer, 2005). For my purposes, the most important differences are in the semantics. Language has discrete units that have discreet meanings, for example morphemes and words. Language gestures often consist of specific speech acts that express specific ideas, e.g., pointing. The meaning of such gestures is generally bound closely in time with the act of gesturing (McNeil, 2006). In music, in contrast, both meanings and gestures are more continuous, less clearly demarcated, and more fluid.

The problem of the meaning is complicated in music, at least in the Western musical tradition, by the presence of an additional layer in communication process – the composer. Performers do not simply express their own musical meanings; they interpret those of the composer. Glenn Gould's two recordings of the Bach's Goldberg Variations (in 1955 & 1981) provide an example of the difficulty this creates. In the later recording, the first movement lasts nearly twice as long in the earlier recording. The change in the performance time was the product of more than a simple change in tempo. Gould explained that, in the second recording, he changed his focus to highlight more the contrapuntal and rhythmic aspects of the music (Gould & Page, 1982). To hear the two recording is like hearing two entirely different compositions. While language also allows ambiguity, fluidity of meaning appears to be much greater in music.

The main challenge for researchers studying musical gestures has been to identify units of meaning in music that can be mapped on to the movements of the body. The result has been a proliferation of distinctions and terminology for describing the movements involved in music production. In Chapter 1, I adopted the classification of these movements proposed by Jensenius, et al. (2010): sound-producing, ancillary/sound-accompanying, communicative, and sound facilitating gestures. There are at least three problems with classifying the movements of the body during performance in this way, using this system or any other. First, decisions as to which movements fall into which category are based on subjective judgment. Second, classification requires the arbitrary segmentation of continuous body movements. Third, it ignores that fact the movements of the body in performance often serve multiple purposes (Davidson, 2009).

Instead, I propose to study movement during performance using tools developed to describe dynamical systems, in particular RQA and CRQA. These tools do not require a priori segmentation of the performance into meaningful units. Instead, movements can be compared concurrently across an entire performance.

Synergies in Music Performance

Moving to a framework of complex self-organizing system means the loss of the concept of the central executive controlling and commanding the motor system (i.e., motor programs). This means we need a new way to understand how order is achieved in the motor system. Synergy theory, described in Chapter 4, provides the necessary framework for understanding how constraints and interactions within the motor system provide both stability and flexibility.

Any self-organized system is governed by the constraints placed on the system, and it is those constraints that cause the system to form order. Rather than searching for a set of functions that govern the production of music, as cognitive theorists have done (Shaffer & Todd, 1987; Todd, 1992), a synergistic approach focuses on the dynamic interaction of the various systems that contribute to a musical performance: score, instrument, performer, location, audience, etc. By examining the interaction of all these various elements, we will be in a position to understand how they combine to create a music performance. A synergistic approach provides the tools needed to pursue the model proposed by Hargreaves et al., (2005), described in Chapter 1. This approach predicts that from the interactions of the various components we should find emergent properties which cannot be predicted based on the individual components alone. For example, this approach might explain how the same degree of loudness can have different meanings depending on the tempo of the performance (see Chapter 3 for more detail).

Synergies can occur within each level and between different levels of a system, as well as between different systems. There are synergies between components of the motor system (e.g., brain, neurons, muscles), between the motor system and cognitive system, and between different musicians coordinating their playing to create an ensemble performance (Latash, 2008). Each level will be needed to understand the relationship between the movements of musicians in performance and the music that they create.

Under the synergistic view of the motor system, the distinction between ancillary and sound-producing movements is arbitrary. All of the components that make up the motor system are inter-connected so that changes in one part of the system ripple across the whole system. Changes in sound-producing movements should be reflected in every movement of the whole body. Of course, some parts of the system will be more affected on others. Movements that are more directly connected to sound production will be more affected than those connected less directly. The nature of the sound producing movements and the changes they induce are different for each instrument.

Musicians' movements during performance have been studied for a variety of instruments including voice (Davidson, 2001, 2006), clarinet (Palmer et al., 2009; Wanderley, 2002; Wanderley et al., 2005), piano (Clarke & Davidson, 1998; Davidson, 1994, 2002, 2007; MacRitchie et al., 2013), violin (Davidson, 1993), and cello (Winold et al., 1994). In this dissertation, I will use the trombone and will measure the postural sway of the entire body. Unlike singers and pianists, the trombone has the important advantage that both hands are engaged in holding the instrument, and so are not available for gesturing, making it likely that postural sway will provide a more direct reflection of any musical gestures they might make. In this respect, the trombone is similar to most other wind instruments and to string instruments. String instruments have the disadvantage that the two hands make different kinds of movements and that the direction of bowing movements is usually diagonal to the main front-to-back orientation of the body. Of the wind instruments, the clarinet has been used effectively to study ancillary movement during music performance (Palmer et al., 2009; Wanderely, 2002; Wanderely et al., 2005). The clarinet, however, along with most other wind instrument, has the disadvantage that it provides no easy way to separate out the contribution of sound producing movements. The postural sway of trombone appears to provide a unique opportunity, out of all the various types of musical instruments, for separating ancillary movements more and less connected to sound producing movements.

Postural sway takes place in two orthogonal spatial dimensions. These are usually captured by measuring anterior-posterior (AP) and medio-lateral (ML) movements. For trombonists, postural sway on the AP axis is more directly affected by sound-producing movements than sway on the ML axis. Pitch changes on the trombone are achieved, partially, by the in/out movements of the trombone slide. With every move of the slide, the trombonist has to adjust his center of gravity by adjusting AP sway. (While trombonists can and do turn their instruments from side to side, this is a communicative gesture that occurs rarely, if at all, in the Western European musical tradition. Most of the time, trombonists and their instruments face directly forward). As a result, AP sway is more affected by the sound-producing movements of the slide than ML sway.

The synergy approach cautions us that movements in the two dimensions are unlikely to be independent. There is evidence that AP and ML sway are controlled separately under some conditions (Winter, Prince, Frank, Powell, & Zabjek, 1996), and are coupled when the task demands it (Balasubramaniam, Riley, & Turvey, 2000; Mochizuki, Duarte, Amadio, Zatsiorsky, & Latash, 2006). For present purposes, all that is required is that AP sway be more closely tied to the sound-producing movements of the slide, and that ML sway be more loosely coupled. In this case, ML sway will provide a purer measure of the ancillary movements of the rest of the body. To the extent that ancillary movements reflect properties of the music and the musician's expressive and stylistic intentions, we can expect these effects to appear more strongly in ML and more weakly, or not at all, in AP sway.

A synergy is not a unidirectional but a bidirectional coupling between parts of a system that interact with and affect each other. For this reasons, self-organizing systems typically do not involve causal chains of action. Instead, they have emergent properties that evolve from the interaction of the parts. In the case of body sway, ancillary ML movements (possibly reflecting musical expression) are connected to sound-producing AP movements, and each affects the other. This is different than the prevailing cognitive understanding in which the musical score drives the sound-producing movements, which are supported by ancillary movements. It is also different from the embodied cognitive view according to which ancillary movements reflect the off-loading to the body of cognitive process. Within the framework of synergies and dynamical systems theory, the role of ancillary movements (i.e., those not directly involved in making musical sounds) is more than simply assisting the musician in performance. On this view, so called "ancillary movements" are a joint, if unequal, partner along with the sound producing movements in the creation of the musical sounds of the performance.

I propose to retain the distinction between ancillary and sound producing movements. I will use the distinction in describing and interpreting the results for AP and ML sway. I will, however, be using these terms within a different conceptual framework than the cognitive framework of their originators (Jensenius et al., 2010).

Support for this idea of a bidirectional relationship between ancillary movements and sound-production has already come from Davidson and Dawson (1995) and Wanderley et al. (2005). Interfering with a performer's ancillary movements changes their sound-production in terms of expressiveness (timing and loudness). The relationship also works in the other direction, as predicted by the notion of a bidirectional synergy: ancillary movements contain information about sound-producing movements. This explains why watching a musician is enough to identify the expression intentions of the performer (Davidson, 1993, 1994, 2007; Nusseck, &

Wanderley, 2009) and why it makes little difference as to which body part the watcher sees (Dahl & Friberg, 2007): because sound producing and ancillary movements are both part of the same dynamical system, and the performer's expressive intentions are reflected in both. This also explains how the ancillary movements can contain a representation of the *metaphorical* motion implied by the music. The body is simply reflecting the expressive intentions of the performer. This cognitive state reverberates through every part of the interconnected component systems with every piece containing information about every other component.

Finally, viewing music performance as the product of an interconnected dynamical system also makes the same surprising prediction as Clarke (2001): musical sounds convey to the listener concrete information about the physical (real) movements that produced them. Specifically, I propose that in my experiments listeners will be able to *hear* the postural sway of the performers. This may sound strange on first reading. Some examples may help. Imagine being in a marching band in front of a trombone player. If the player behind you sways his body in the wrong direction, you will be instantly alerted to the change in direction by the sound hitting the back of your head. Instead of hearing it more loudly in the ear you expect, it will be louder in the other ear. This is one example of *hearing* the movement of a performer. A more familiar example may be hearing the change in direction of a string player's bow, something that is clearly audible to any listener. Another example that comes from my own experience as a violinist and may only be audible to an experienced string player. I can hear when a performer shifts their left hand up or down the fingerboard. There are subtle but measurable changes in offset of the pitch before and the onset of the pitch after the slide due to the coarticulation of the fingers (Fyk, 1995).

In these experiments, I am using trombonists who move a slide to change pitch. Although it remains to be objectively demonstrated that people can hear the movement of a trombone slide as it changes position, there can be little doubt about the question. The characteristic sound of a trombone "slide" conveys information about the movement that produced it more clearly than most musical sounds.

In these experiments, I am also measuring postural way. There is evidence that listeners can hear the sway of the musician in recorded music, recovering the movements of the instrument from the changing phase and amplitude of the sounds that reached the microphone (Wanderley & Depalle, 2004). I will show below that the swaying of trombonists is likewise audible in recordings of their playing. Postural sway is audible not only to the original performer and to another trombonist (Experiments 1 & 3), but also to non-trombonist musicians and to non-musicians (Experiment 2).

We have already seen in Chapter 1 that listeners hearing rhythmic sounds spontaneously coordinate their own movements with the sound (Demos et al., 2011). A similar kind of spontaneous coordination occurs when interlocutors align their postural sway as they engage each other in conversation (Fowler et al., 2008). In the experiments reported below, I will look for evidence that when listening to recorded trombone performances, listeners spontaneously coordinate their postural sway with that of the performer, both when simply listening (Experiment 2) and when playing along with the recording (Experiment 3).

Experimental Overview

I will be examining postural sway of musicians in performance and listener's movements in response to hearing the performances. Given the dynamical systems framework I have outlined, I expect that postural sway will contain some information about the sound producing movements of the performance. As described above, postural sway is measured in two directions AP and MP. I will examine sway in each direction in three different ways. First, I will examine the *position*, which is the spatial location of the performer's center of mass. Second, I will examine the change of position. This metric is created by taking the difference scores of the position. In physics, this measure is typically called *velocity;* I will call it *change in position*. I will analyze both position and change in position using traditional signal processing techniques i.e., cross-correlation and time-frequency transformation. The third way of examining sway will use measures derived by dynamical systems analysis: RQA, CRQA, and Hurst exponent analysis via detrended fluctuation analysis. The five measures that I will use are described more fully below, in Chapter 6, but I give a brief account of them here.

RQA is designed to understand how the system evolves in time and is self-referential: how the system repeats (Abarbanel, 1995; Eckmann et al., 1987). CRQA compares two systems by showing when they overlap with each other in phase-space (Marwan, Carmen Romano, Thiel, & Kurths 2007). RQA and CRQA allow measurement of the recurrence of a system, i.e., the frequency and duration with which the system is in the same state at different points in time. In other words, they track state-sameness across all possible time-lags. These techniques also provide measures of three additional properties of the system's recurrence: its orderliness (entropy), predictability (determinism), and stability (mean line). Each measure provides a different and largely independent view into how the system changes over the course of time. When applied to the body sway of a musician during a musical performance, they show the swaying of the performer evolves over the course of the performance.

I do not see dynamical systems tools as replacing traditional techniques of signal analysis; instead, I see them providing additional ways of examining complex systems. Each set of tools allows different hypotheses to be tested. Examining all of the various measures together, both linear and non-linear, may provide insights that cannot be achieved by examination of each measure alone. The following sections outline specific predictions and goals for each experiment.

Experiment 1: Musical Structure, Expression and Postural Sway

Purpose. Both traditional and dynamical systems analyses were to used examine the postural sway of trombonists in performance. Trombonists played two different pieces of music (*songs*) in each of three different *performance styles*: normal, expressive, non-expressive (replicating the instructions of Davidson, 1993). The two songs differed in the number of musical boundaries (i.e., sections and subsections called for by the musical form). I will refer to them as the *more structured* and *less structured song*. Varying the performance style is a way to change the expressive intentions of the performer. Varying the song is a way to change the constraints acting to organize the system. One possible explanation for differences between songs will be to attribute them to differences in the metaphorical motion implied by the different compositions (Clarke, 2001), and the relationship between expression intentions, and musical structure on the movements of the body.

To examine the relationship between musical structure, expression, and postural sway, I compared the musician's postural sway in two performances of the same song and I compared these a comparable performance of the same song by the other musician. I measured sway in two dimensions and analyzed each separately: Forward/back or anterior/posterior (AP) and left/right or medio/lateral (ML). I expected AP sway to be more strongly affected by sound producing movements of the slide than ML sway. The expressive elements (tempo and loudness) were also compared. The similarities within and between musicians' postural sway patterns provide a measure of how much the musical score is reflected in the movements. The main goal of Experiment 1 was to demonstrate this relationship since Experiments 2 and 3 assume the existence of such a relationship.

Expressive and non-expressive performances have been used as ways of heightening and dampening expression, while leaving the musical structure intact (Wanderley et al., 2005). Comparison of the three different performance styles (normal, expressive, and non-expressive) allowed assessment of the relationship of musical expression to the body movements evoked by the musical structure.

Predictions. If the performances are dissimilar, this could mean that the movements are randomly generated, but this should not be the case given the finding of MacRitchie et al. (2011), Palmer et al. (2008), and Wanderely et al. (2005). The performance style manipulation depends on the idea that musical expression is something that can be added in greater or lesser amounts by the performer on top of the musical structure. If this assumption holds true, then the musicians will parse the score into the same number of phrases regardless of the performance style. If however, the musical structure and the expressive intentions of the performer are linked (Clarke, 1998), then the musicians may parse the score differently depending on the style they are playing in. This result would contradict the conventional view that musical form is an inherent, fixed property of the musical score.

If the parsing of the musical form does change with the performance style, it is possible that the change will interact with the musical form. The more structured song will contain more options for the performer to parse the music in different ways than the less structured song. At the same time, the more structured song will constrain the performer more strongly to select those locations that the composer has dictated as available options. If the way the musicians parse the music is related to their postural sway, then the more different their parsing of the score, the less overlap there will be between their playing of song. If the two songs differ in this way, it will suggest not only that body sway is affected by the metaphorical motion implied by the composition, but also that the metaphorical motion implied can change depending on the interpretive choices of the performer.

Metaphorical motion is often believed to derive from the individual pattern of notes that create the rhythm and melodic contour of the composition (Repp & Shove, 1995). Performers move rhythmically as they play and that has already been shown to be related to sway movements in clarinetists and pianists. Therefore, I also expect trombonists to do the same, but I will use Short-Time Fourier transforms (STFT) to quantify the observations of Davidson (2009), Wanderley (2002), and Wanderley et al. (2005).

I will examine the effect of structure on body sway by quantifying the overlap between performers using three different dependent measures: position, change in position, and cross-recurrence. The relationships between the movements maybe weak, but the question is whether they are in phase at above chance levels. These studies will be the first to use surrogate methods to evaluate the reliability of effects. They are also the first to use the full range of linear and non-linear methods to compare the phase-relationship of movement between and within performers, and the first to fully exploit the use of mixed effects modeling for this purpose.

If performers overlap significantly in *position*, it would suggest that the musical score is telling them when and how they should be swaying their bodies. This would suggest that the score contains *spatial information* that is interpreted similarly by the motor systems of both performers. Alternately, performers could exhibit significant overlap in *change of position*. This would mean that performers move at the same time relative to music, but not in the same physical directions. In other words, the music tells them when to move, but not how to move. This would suggest that the score contains *action information.* Finally, if the performers overlap significantly in phase-space using cross-recurrence, it means that the performers move in similar complex patterns, but not necessarily in the same spatial way. In other words, this would mean that multiple aspects of musical composition are interacting with the musician's body to create reliable *patterns* of movements. I will call this *patterning information*. The three metrics are relatively independent and any one or all of them can be significant concurrently.

Given the observations of previous researchers, I predict that there will be little between-performer overlap in performers' ML sway in position. There could be overlap in the change of position, because performers have been observed making particular actions at particular points in the music, but rarely the same ones. These actions are more common at musical boundaries, so the more structured music will have higher overlap than the less structured music. The overlap of the two musicians should be higher for AP sway because this is more directly related to movements of the trombone slide, which should be the same for both.

The prediction for cross-recurrence depends on whether the musical composition is driving the patterns of body movement. The intuitive prediction by researchers and musicians alike is that there is high overlap, but researchers have yet to find a way to measure the similarity. Cross-recurrence may provide that answer. Alternatively, movement patterns may be idiosyncratic and different for each performer. In this case, there will be little overlap in recurrence even if each musician's postural is regularly related to the musical structure. In this case, it will be necessary to use RQA to examine of each performance independently.

RQA provides not just an understanding of the similarities between performances, but can also show effects of musical structure. If the musical form is acting to constrain the system, there are three ways in which recurrence might be affected at musical boundaries. One possibility is that recurrence at boundaries will be higher. This would denote that a performer moves in the same pattern relative to phrasal boundaries. Alternatively, recurrence at these places may be lower, meaning that the performer does something novel each time they approach a boundary. A third possibility is that these effects will differ for the two songs.

Previous studies have shown that movement is affected by performance style: the musician's intention to play more or less expressively (Davidson, 2009; Wanderley, 2002). If this effect is replicated, the RQA measures should also be affected. I expect that non-expressive performances will be less deterministic, as this condition removes an important constraint on their movements, i.e., expression. By the same token, when the musicians play more expressively, the system will have more constraints placed upon it causing it to be more predictable. At the same time, previous research has shown that the amplitude of movements increases which can be expected to decrease recurrence.

Experiment 2: Listeners Mirroring of Expression

Purpose. Experiment 2 examines the sway of non-musician and musician listeners as they listen to the recordings of the performances examined in Experiment 1. I asked listeners to "conduct" the expression of the performance. Experiment 2 will allow us to see to what extend the listeners movements align with those of the performer.

Prediction. We know that people synchronize both intentionally and spontaneously with rhythmic sounds (Demos et al., 2011). We can expect, therefore, that listeners' sway in Experiment 2 will reflect the rhythmic and/or tempo of the music. We also expect that performers' postural sway will be complex and will reflect other characteristics of the performance, in addition to rhythm. So, we expect the listeners' movements to be affected by these additional characteristics, including the performance style and the musical properties of the song, such as its structure and melodic line.

Listeners in Experiment 2 were not playing the trombone, so their body movements were not constrained by the instrument. Their AP sway was not affected by the rebalancing needed to control changes in their center of gravity. This may mean that AP and ML sway could be similar than in Experiment 1. Alternatively, if listeners hear the sound-producing movements of the performer, as suggested by Clarke (2001), then the coordination of their movements will be stronger for AP than for ML sway, because AP sway is more tightly linked to sound production. This would be a surprising result because it would suggest that listeners' movements were driven directly by the sound producing movements of the musician rather than by their perception of the musical structure or expressive intentions of the musician.

Experiment 3: Performer's Mirroring of Expression

Purpose. Previous research suggests that performers never play music the same way twice. While they can be highly reliable in the control of their acoustic parameters, they are never quite the same. One possible source of these differences is that the performer's expressive interpretation of the music may change. The goal of Experiment 3 was to control for music expression by having two performers mirror each other's and their own timing and dynamics. They mirrored themselves three times and the other musician three times while listening to the performances and playing each of the two songs that they recorded in Experiment 1with each of the three performance styles (normal, expressive, and non-expressive).

Figure 3 shows the four comparisons to be made for each of the measures of similarity between the performers used in Experiment 1(Position, Change in Position, and Cross-recurrence) for each direction of movement (AP and ML). I will distinguish between *overlap* and *mirroring*. Mirroring refers to similarity between the movements (postural sway) of two performances when the musician intentionally tries to replicate the expressive qualities of the other performance. Overlap refers to similarity that occurs incidentally when the musician is not trying to match the other performance.

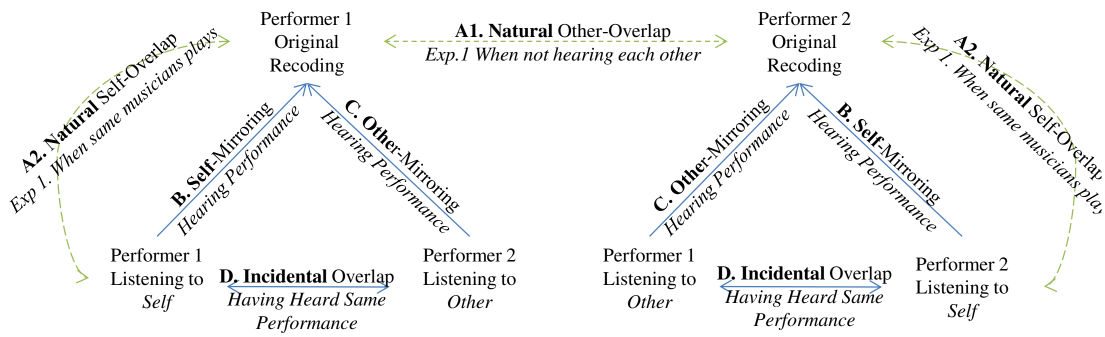


Figure 3. Four Types of Overlap and Mirroring for Two Musicians Performing the Same Song when Not Hearing (Experiment 1) or Hearing (Experiment 2) another Performance by Themselves (Self) or by the Other Musician (Other).

The comparisons involving overlap (labeled A1, A2 and D in Figure 3) involve performances in which each musician plays without hearing the sound of another performance at the same time. The comparisons involving mirroring (Labeled B and C in Figure 3) involve performances in which each musician is asked to play along with another performance of the same song, mirroring it as closely as possible. *Natural Other-Overlap* (A1) involves the comparison of two musicians playing the same music when neither can hear the other. *Natural Self-Overlap* (A2) is the comparison between two performances of the same piece by the same musician. The two types of overlap are examined in detail in Experiment 1. They are re-presented here as a basis for comparison with the *mirroring* trials which were the focus of Experiment 2.

The third comparison is between the recorded original movements of the performer and the movements of the performer as he is trying to mirror his own expression from that original recording. I will call this comparison *Self-Mirroring* (Labeled B). This will be compared to A2. The fourth comparison is just like the second, but involves cross-performer mirroring. I will call this comparison *Other-Mirroring* (Labeled C). This will be compared to A1. Finally, the fourth comparison is between trials when both performers mirrored the expression from the same performance. I will call this comparison *Incidental Overlap* (Labeled D).

Predictions. I expect performers to mirror each other's postural patterns as they mirror the expressive intentions of the performer. I expect this to occur for the same reason that participants in a conversation mirror the postural patterns of the other speaker (Fowler et al., 2008). I expect that performers will mirror their own movements more closely than the movements of another performer, just as they are better at recognizing their own performances and can duet better with themselves than with another musician (as in Keller et al., 2007). The patterns of similarity for mirroring and overlap will indicate what kind of information about movement is contained in the sound of a performance. As described above in the predictions for Experiment 1, I will examine three types of movement information: *spatial information* (position), *action information* (Δ position), *and patterning information* (cross-recurrence).

All dependent variables will be tested against the phase-null hypothesis. The Natural Overlap comparisons (A1 & A2 in Figure 3) will be examined in Experiment 1. For simplicity, I will assume here that there is no significant natural overlap between performers. However, if there is natural overlap, then the result of interest will be whether the other comparisons are stronger or weaker. Other-mirroring (C) will give insight as to which types of information about real movement the sound contains. Incidental overlap (D) will give an insight into the metaphorical motion contained in the sound.

For position, if other-mirroring is significant, it means that expression is guiding both *where and how* a performer sways. If incidental overlap is significant, and if A1, B, C are not, it means that the performance carries spatial information that is not related to the composition or to the real movements of the performer. This would indicate that the metaphorical motion in score tells both performers how to move. This would mean that Western art music is like the "hokey-pokey", a rather unlikely outcome. Finally, it is possible that B, C and D would all be significant, in which case D would simply be incidental (i.e., an artifact) because of B and C. This applies to all dependent measures.

For change in position, if other-mirroring is significant, it means that expression is guiding *when* a performer sways but not *how* they sway. If incidental overlap is significant, and A1, B, C are not, it means that the performance carries action information not related to the composition or to the real movements of the performer.

For recurrence, if other-postural mirroring is significant, it means that expression is guiding the *patterns* a performer makes with his sway. If incidental overlap is significant, and A1, B, C are not, it means that the performance carries patterning information unrelated to the real movements of the performer. Think of a dance club filled with blind dancers. They may all move in similar patterns, as dictated by the music, but they cannot synchronize exactly with the movements of the other dancers.

The purpose of having performers listen to the various expressive styles is to gain additional understanding of how more or less expression impacts the type of information conveyed to the listener. One possibility is that swaying movements are driven by the musical structure. In this case, removal of expression from the performance will allow the influence of the musical structure to emerge more clearly resulting in an increase in coordination. Alternatively, if swaying movements are driven by expression and not structure, then coordination will be higher for expressive performances. This of course assumes that there is no other change in the system that occurs due to modifications of expressive intention.

As for Experiment 1, I expect that reducing expression will remove a constraint on the system making movements less predictable, and that increasing expression will increase predictability, while also reducing recurrence, making the system less orderly. If this happens, and expression increases chaos, then it is unlikely that listeners in Experiment 3 will synchronize their movements with those of the performer in either the expressive or the non-expressive performances.

Chapter 6: Method

Experimental Method

Participants

Participants in Experiments 1 and 2 were two male professional tenor trombone players each with over 25 years of experience. Both musicians perform and teach on multiple brass instruments. Both performers had taught both pieces of music that they were asked to play. Participants in Experiment 2 were 1 graduate student and 28 undergraduate students (Females, n = 20, mean age = 19.04, SD age = 0.73) at the University of Connecticut. Undergraduates received class credit for their participation. Sixteen of the participants (51.61%) were musicians (Mean years = 8.56, SD =4.05) and played a range of instruments or identified as singers. Participants had to have more than 4 years of training to be considered a ‘musician’. Six participants (19.35%) had experience dancing (Mean years = 10.17, SD =4.26). The rest of the participants had little to no musical experience (Mean years = 0.79, SD =1.19).

Materials

Body movements. Center of Pressure (COP) measurements were taken with a Wii Nintendo BalanceBoard (Nintendo, Kyoto, Japan). The Wii BalanceBoard has been shown to be a reliable tool and low cost replacement for the force plate as a way to measure postural sway (Clark, Bryant, Pua, McCrory, Dennell, & Hunt, 2010).   The Wii BalanceBoard was connected via Bluetooth to a Dell Inspiron E1505 computer with Windows 7 and Matlab 2011b. Matlab interfaced with the Wii BalanceBoard using WiiLab toolbox (Ahmed, 2012). Data was collected using the Psychophysics toolbox version 3.0 (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007).

The noise of the movement collection apparatus was examined in a single 4 minute session with the equipment sitting stationary while recording at 34 Hz (SD = .085). Data was linearly interpolated to 34 Hz to correct for the timing variances and low-pass filtered (Butterworth filter) at 16 Hz. The Wii BalanceBoard was tested with 60 pounds of weight. COP measurements were taken in centimeters for the medio-lateral (COP: ML), i.e., left-to-right, sway and the anterio-posterior, (COP: AP), i.e., forward-to-back sway. Root mean square (RMS) of the noise of COP: ML was .048 CM and COP: AP was .032 CM. Detrended fluctuation analysis (DFA) was used to assess the type of noise generated by the Wii Balance board and it was shown to generate white noise (COP:ML Hurst = . 502; COP:AP Hurst = . 505).

Sound. An external USB sound mixer (M-Audio) and Shure microphone were used to collect the performances in Experiments 1 and 2. The microphone was placed on a microphone stand approximately 4 feet above the ground approximately 4 feet back from the performer and 1 foot left of center. The microphone distance from each performer remained unchanged as did the location of each performer. For the playback of the performances, Experiment 2 used over-the-ear studio reference headphones. Experiment 3 used 2 desktop computer speakers.

Sound was manipulated using Soundforge 9.0. Sound level measures were taken as non-overlapping RMS measurements at a sampling rate of 34 Hz. Experiments 2 and 3 were de-noised using 12 dB to remove some of the background recording noises. The performances were not normalized and therefore loudness differences between performances were kept as they were naturally performed.

Music Stimuli

All three experiments used the same musical stimuli. In Experiment 1, performers performed two pieces written by Marco Bordogni (1789-1856) and transcribed by Joannes Rochut (Rochut, 1928). The two pieces were selected because they share similar musical properties, but differ in musical structure.

Rochut number 4 has 154 beats and 238 notes, is in the key of F major, and follows a standard ABA form, with a nested question and answer structure within each section. The first Section A starts at note 1. Section B starts at note 120. Section A returns at note 164 and the Coda begins at note 207. The first section A can be divided into three subsections, each consisting of a 12-beat question followed by a 12-beat answer. The B section contains one subsection consisting of a question and answer followed by a 13-beat coda. The second A section follows the same structure as the B section. The piece ends with a final coda.

To help visualize this musical structure, Figure 4 represents the melodic contour in quarter beats, extracted using Matlab Miditoolbox (Eerola & Toiviainen, 2004). Figure 5 shows the autocorrelation (i.e., a signal correlated with itself at all possible time-lags) of the melodic contour. As shown, the musical pattern repeats often and in a regular way, as would be expected of this highly nested musical form. As seen in Figure 6, the most frequent intervals in Rochut no. 4 are major seconds and perfect fourths, intervals that are characteristic of its major modality.

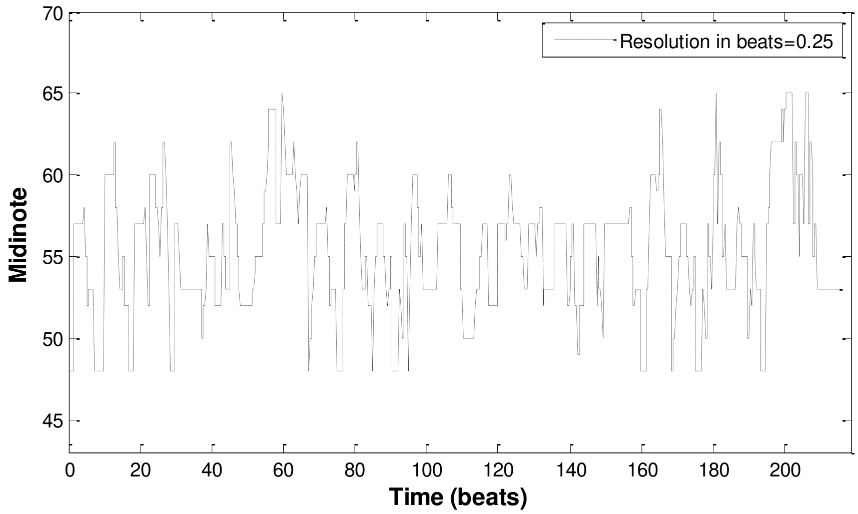


Figure 4. Melodic Contour for Rochut 4.

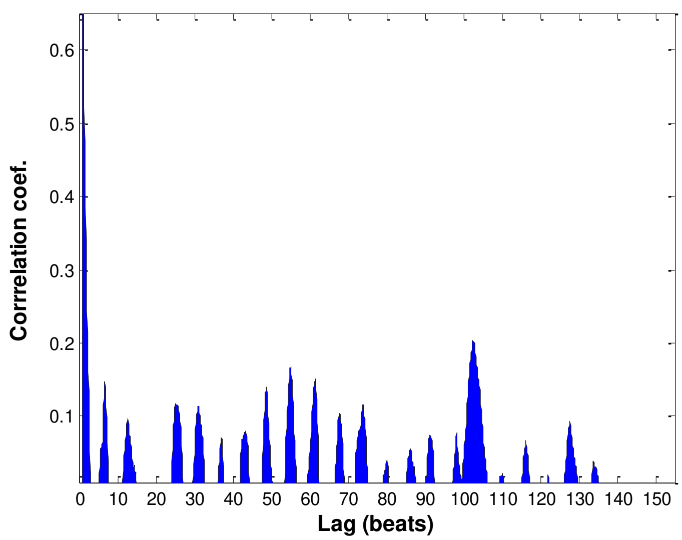


Figure 5. Autocorrelation of Melodic Contour for Rochut 4.

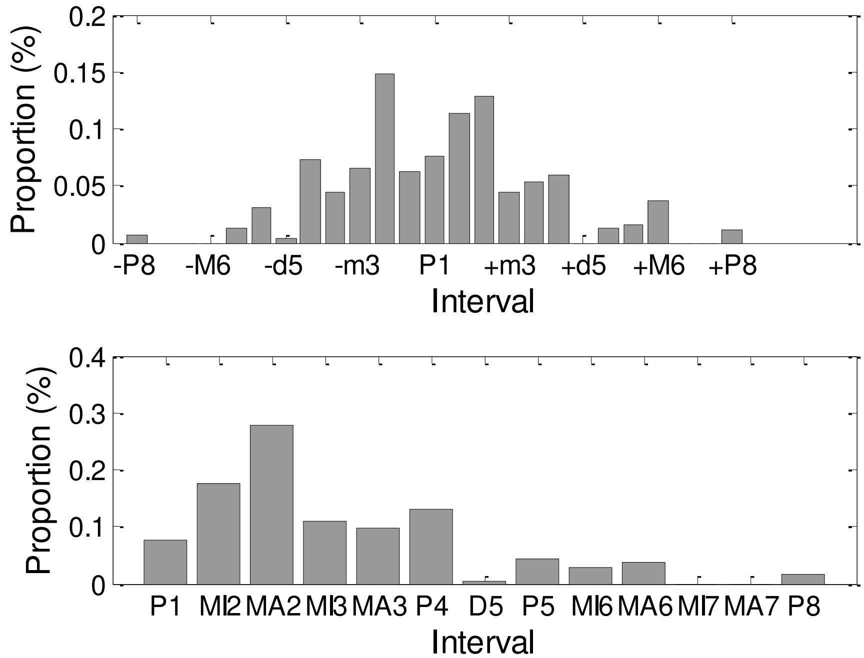


Figure 6. Interval type and direction for Rochut 4.

Rochut number 13 has 170 beats and 245 notes, is in the key of E-flat major, and follows a through-composed format (i.e., does not contain repetitions), with four major sections. The first section starts at note 1, section two at note 67, section three at note 138, and finally section four (the coda) at note 196. Figure 7 shows the melodic contour, which at first glance does not differ from the contour of Rochut No. 4. However, the difference is evident in the autocorrelation of the melodic contour (Figure 8). There are far fewer repetitions, with less equal spacing between similar melodic patterns than in Rochut No. 4. The interval distribution, shown in Figure 9 is similar to Rochut No. 4, as indicated by the high Cronbach's Alpha of .932 between the two distributions.

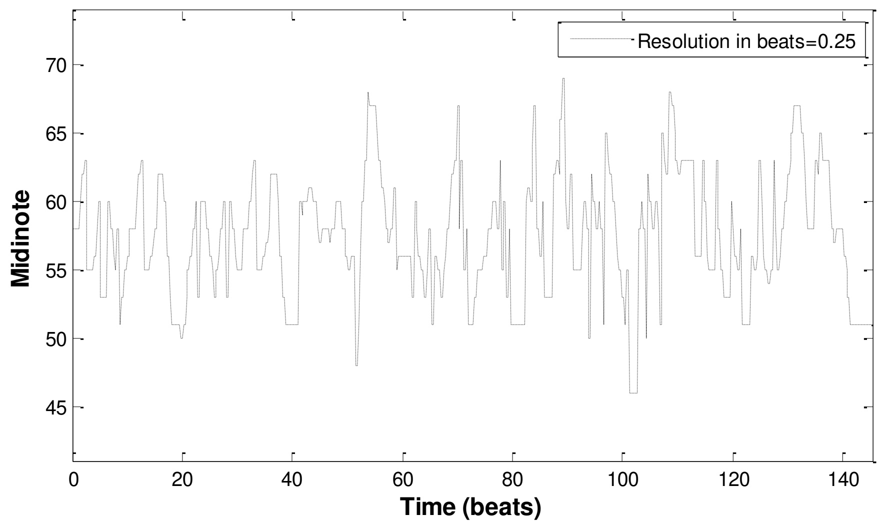


Figure 7. Melodic Contour for Rochut 13.

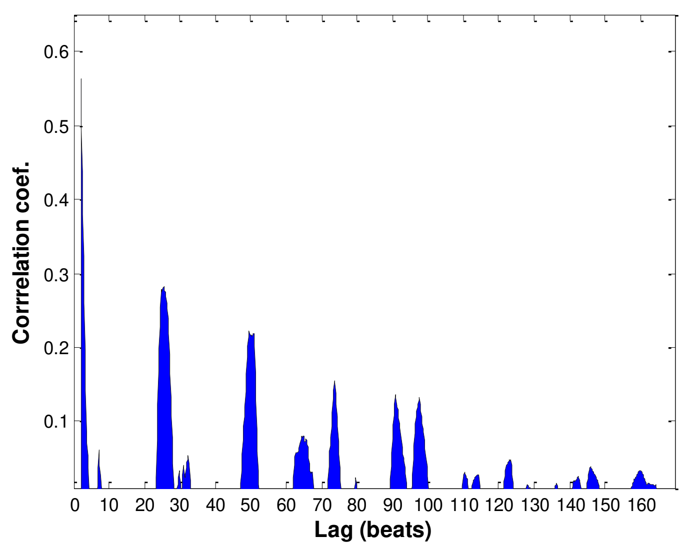


Figure 8. Autocorrelation of Melodic Contour for Rochut 13.

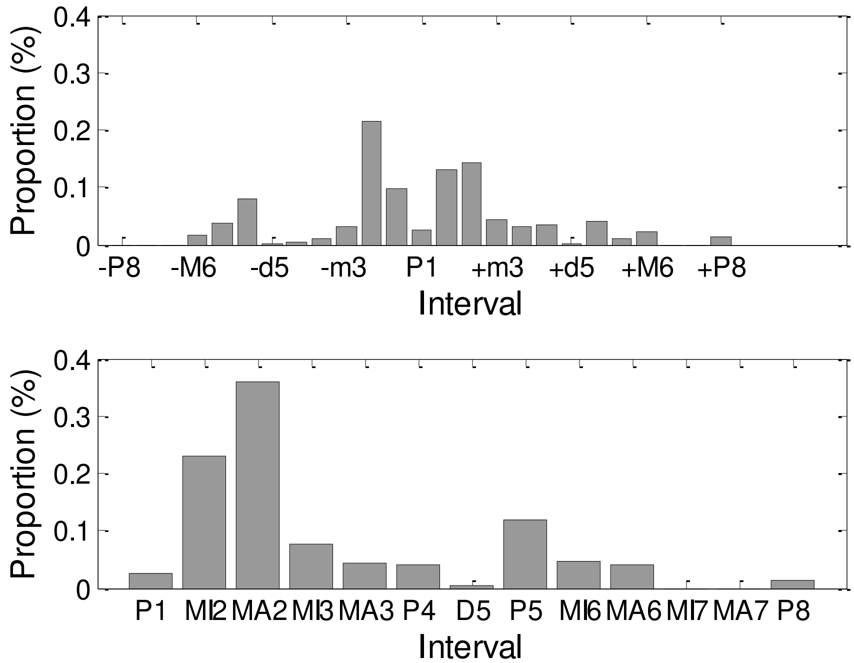


Figure 9. Interval type and direction for Rochut no. 13.

Procedure

Experiment 1. The two performers were told that their body movements would be recorded while they performed the two pieces, which they were asked to practice before the recording session. On arrival at the recording room, the performers were asked to take a few minutes to warm up while standing on the Wii Balance Board. They were asked not to move their feet while performing, but to otherwise move their bodies in any way they needed to make the music. They were asked to play each piece six three times, twice in each of three different musical styles: Normal, Expressive, and Non-expressive. For the Normal style, they were asked to play in a way that they considered natural. For the Expressive style, they were asked to play in an overly expressive way. Both performers understood this as a direction to exaggerate both dynamics and tempo to an extent that they considered the resulting performances to be unmusical. For the non-expressive style, they were asked to play without variation in tempo and with reduced dynamic variation, “like a MIDI performance”. Each style was played twice, back-to-back. Each piece was recorded on separate days, and the order of pieces was reversed between performers. For both performers and both pieces, normal performances were always done first. This was done because natural performances were the baseline on which the other performance styles were based. Further, these other styles (expressive and non-expressive) are somewhat un-natural for performers, so that playing them before the normal performance could have influenced the normal style. Therefore, only the order of the Expressive and Non-expressive performances was counterbalanced across pieces and performers. Each recording session lasted approximately one hour and the whole experiment took two hours per participant. After each performance, performers were asked to indicate how they had phrased the music by marking their phrasing on the score. This procedure followed the protocols developed by Chaffin, Imreh, and Crawford (2002).

There were a few deviations from the procedures for Performer 2, who insisted on re-recording three the performances because he was dissatisfied with his playing. He recorded Rochut No.4 in the normal style four times and both songs in the expressive condition three times. The re-recordings were done back-to-back during the performance of each style. He then indicated which recording he felt was his best, and insisted that these be analyzed and that the ones that he felt were not up to his standards should not be. For the normal performance of Rochut No. 4, he selected the third and fourth recording. For both songs, he chose the first and third expressive performance.

Experiment 2. Participants were asked to stand on the Wii BalanceBoard while listening to the normal, expressive and non-expressive performances. They were told that their movements would be recorded as they listened to the music and were instructed to move with the music in any way necessary to allow their body to reflect the musical expression they were hearing, acting like a musical conductor in front of an orchestra. They were given a baton to hold in their dominant hand and told not to “count time” but instead to move their arms as if to draw out the emotion from the performer.

While the real interest of this experiment was in the postural sway, pilot testing with participants revealed that they felt uncomfortable just standing on the board listening. As a result, their swaying movements were constricted and intermittent. Giving them the baton to wave gave them to do something with their hands, and made the task feel more natural. Further, participants seemed less conscious of their overall body sway when they thought that the most important measurement was taken from the movement of their hands. This made them more comfortable and less self-conscious, allowing them to freely and continuously move their whole body.

This was a self-guided experiment using the Matlab psychophysics toolbox. During the task the experimenter left the room so the participants would not feel uncomfortable having someone watch their body movements. They were told they were not being watched and there were no cameras in the room. Participants heard the performances through desktop speakers with the volume at a moderate level that was constant across participants. The performances they heard were the same stimuli used in Experiment 2. Each participant heard only one of the songs.

The order of the performances followed a partial Latin square design. The order for the second song was a mirror image of the order of the first song.

After each performance, participants were asked to respond to three statements on the computer screen using a five-point scale with 1 (disagree strongly) to five (agree strongly). Participants were asked, “I felt the performance had a strong clear beat” and “ I found the music pleasant.” Finally, participants were asked the same question that was asked to the performers in Experiment 3, “How expressive was the performance you just heard?” with 1 (not at all expressive) to 5 (extremely expressive). At the end of the experiment, the participant’s familiarity with the music they had heard was assessed as was their musical training background and basic demographic information.

Experiment 3. Six months after Experiment 1, the same two musicians returned to the lab for two more sessions in which they performed while listening to the earlier performances. They were instructed to play along with the recording as closely they could while listening to the performance through a headphone in one ear of their choice. As in Experiment 1, each session was devoted to one of the two pieces with the order of the pieces counterbalanced across musicians. In each session, the musicians heard one performance of each style from each performer, for a total of six performances: two normal, two expressive, and two non-expressive performances, one of each pair by themselves, the other by the other musician. The order of the six performances was randomized separately for each performer. Performers were not informed which performer or which style they were hearing. The selection of recordings within each song was counterbalanced between performers: Performer 1’s normal recording one and Performer 2’s normal recording two were selected.

Performers were asked to first listen to each recording before attempting to play it back in order to allow them to better follow the expressive variation in the performance. After listening to each performance and before playing, performers were asked to rate what they had just heard. They were first asked, “how expressive was the performance you just heard?” Performers were then asked to rate the performance from 1 (not at all expressive) to 5 (extremely expressive) (Bhatara, Tirovolas, Duan, Levy, & Levitin, 2011). The performers were then asked to guess whether they or the other performer was playing, and which of the three styles they had just heard (Keller, Knoblich, & Repp, 2007). After performing the music, they were asked these questions again and then in addition, “how easy was it for you to play?” on a 1 (not easy at all) to 5 (very easy) scale. The total time for each session was approximately one hour.

Time Series Methods

Time-Warping

The timing of any two performances of the same piece is different. This makes traditional methods of analysis, such as cross-correlation, difficult to do because the performances are not time locked. One way to time lock different performances is to time-warp them so as to equalize note durations in Newtonian time.

The location of each note in each performance was located initially by listening, and then more precisely by finding the local minima in the acoustic wave of each performance to determine onset and offset times. This process was repeated twice to increase the reliability of note location. All the performances, across all styles and musicians, were compared for each piece in order to identify the shortest the duration of each note across performances. The duration of each note was then set equal to the shortest duration for that note across performances. The reason for the selection of the shortest note was so to avoid adding data points to the time-series (up-sampling). Instead, data were down-sampled and linearly interpolated. For example, if it took 38 time samples to play a particular note in Performance 1, and 33 samples to play the same note in Performance 2, then the note in Performance 1 was down-sampled to 33 samples, thereby making the two performances equal in Newtonian time. Linear interpolation was used because more complex interpolation methods did not provide any better fit. Had larger units such as beats been used to time-lock the performances, linear interpolation would not have been appropriate.

Linear Methods

Root mean square (RMS) is the common way to measure the variability of a time-series. This method requires that data-points be squared, summed, divided by the number of samples, and finally square-rooted. When the mean of a time-series is zero, RMS is equal to its standard deviation. When the mean of the time-series is not zero, the RMS is a measure of the magnitude of the time-series. I used RMS to measure the magnitude of postural sway and the loudness of the music played. Time-series can be windowed and the RMS can be taken within each window. In Experiment 1, I took the RMS for each musical beat for both postural sway and loudness.

Cross-correlational methods are commonly used to detect similarities between signals. Like Pearson correlations, cross-correlation provides a normalized value ranging between -1 and 1, with perfect correspondence between the signals resulting in a value of 1. Cross-correlation provides a high value when the two signals are mode- and phase-locked. The phase relationship (in-phase or anti-phase) does not matter, only the phase-locking. Cross-correlation is not a time-frequency signal processing method. This means that it provides a single value for the degree of overlap across the time-window of interest. Cross-correlation can be converted to a time-frequency method by windowing the time-series (as in Demos et al., 2011). However, that requires the time to be absolute (Newtonian), which is not the case for musical time, as noted above. Alternative methods that use time-frequency transformation either require stationary or single frequency systems, such as Hilbert transformation. Methods that examine multi-frequency stationary data (such as wavelet coherence analyses) often do not allow straightforward interpretation due to the complex nature of the comparisons involved or the very large number of parameters that need to be set. Finally, time-frequency methods only compare the signal at the same points in time. One method that examined the signal at all-time points at the same time is the Short-Time Fourier transform described in the next section.

Periodicity and Metrical Pattern of Movements

Time-frequency methods are useful in uncovering the periodicity of a time-series and examining the multi-frequency spectrum as it changes over time. One such method is Short-Time Fourier transform (STFT). This primarily allows visualization of the simple periodicity. Figure 10, both panels, shows an example of STFT with a sine-wave that contains two frequencies, .25 and .50 Hz, over two minutes. As can be seen, the strongest two bands occur at the expected frequencies. The main purpose of this analysis is to assess the fundamental or strongest frequency of the movements of the body. The strongest frequency can be extracted and averaged at the measure level for comparison to properties of the composition, such as meter.

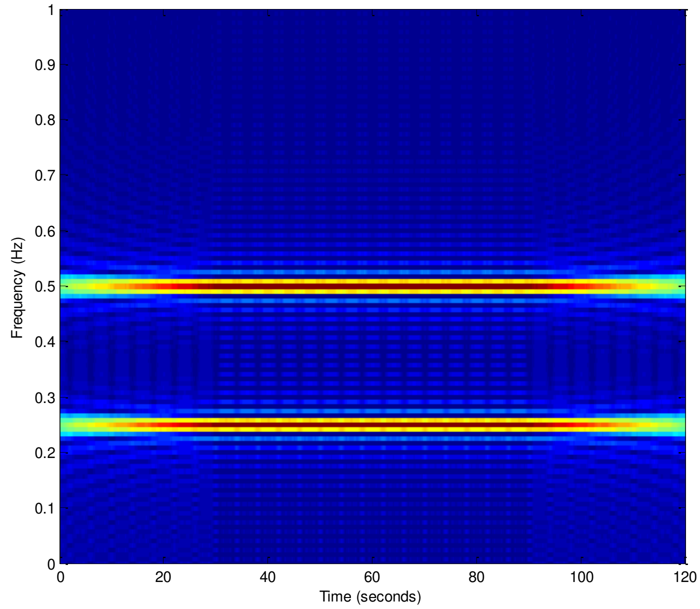


Figure 10. STFT on a sine-wave with frequencies of .25 and .5 Hz.

The average frequency per measure can be then be divided by the average tempo for that measure (in Hz) to provide a measure of the rhythmicity of the movements. If the ratio is 1, it means that the postural sway is moving at the same frequency as the music. This will probably never be the case, as it would require the person to sway rather quickly. Most likely the postural sway will be in a simple ratio to the musical beat. London (2004) enumerates the possibilities, which I summarize in Figure 11 below. At the first level in this metrical hierarchy, “B” (the tempo in beats per minute) is multiplied by either two or three, indicating the duration of each sway in beats depending on whether the musician sways in either a duple or triple meter. At the second level, possible meters for still slower sways. The third level, in turn, shows possible durations of still slower sways.

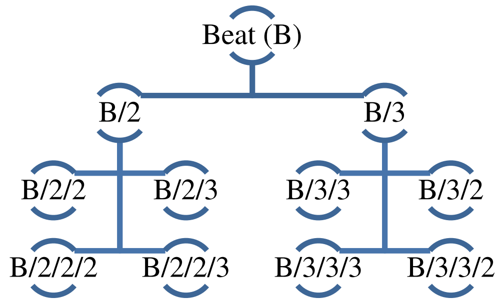


Figure 11. Metric Periodicities based on London, 2004, p. 39.

Phase Space Reconstruction & Recurrence Quantification Analysis

As described in Chapter 5, this method is a way of measuring how a system repeats (recurrence) in phase-space. Phase-space reconstruction (PSR) from a one-dimensional time-series requires the selection of two parameters and RQA requires three (see Abarbanel, 1995, Marwan, 2003, and Marwan, Carmen Romano, Thiel, & Kurths, 2007, for a detailed account). Here, I describe the issues involved in their selection.

Time-lag for PSR. Choosing a time delay that is too long cuts out too much data while selecting a time delay that is too short may not accurately represent the system (Abarbanel, 1995). Additionally, choosing an inappropriate time delay may result in losing any connection between the measurement and the underlying system, making the system look completely random. By using Shannon's concept of mutual information, we can investigate the system using probability to see when the two measurements (the original time series and the time lagged time series) look independent. This analysis produces a statistic called the Average Mutual Information index (AMI) that is like a non-linear correlation. Choosing a delay that minimizes AMI ensures that the components will be nearly orthogonal.

Embedding Dimension for PSR. A ‘sufficient’ number of embedding dimensions must be selected. To find the sufficient number the system must be systematically unfolded into higher dimensions until the data points do not overlap spuriously. If we add another dimension and the data points stay as 'neighbors', then we know they were not false neighbors (i.e., spurious recurrent points). False neighbors are projections from higher dimensions because the system has not been fully unfolded. This is called a false neighbors-nearest-neighbor-analysis (Abarbanel, 1995).

Theiler Window for RQA. When unwrapping the system, the data points close in time must eliminated so that they do not provide spurious recurrent points. The reason for this is that data points close in time are typically similar due to proximity in time, and not for any other reason and therefore they are not considered to be true neighbors. To avoid this problem we set a Theiler window that determines which recurrent points will be ignored. This value can be set theoretically or through the use of autocorrelation. When needed, I will set this value theoretically, based on the mean time it takes to play one eighth note (9 samples).

Radius Window & Size for RQA. By creating a recurrence plot from the PSR, we can begin to examine how the system 'nearly' recurs over time. Researchers must decide how close they are willing to allow two points in phase space to be to count as recurrent. There are several different methods to finding these nearly overlapping points (see Marwan, 2003 & Marwan, et al., 2007 for a review). One approach is to not set a neighborhood size and instead create a recurrence plot based on distance. While useful for visualization purposes, this method does not help in later data analysis as it provides a vector and not a single measure for a pre-assigned window size within the recurrence plot. The alternative method is to assign a threshold for the neighborhood size. This involves the researcher setting a parameter for the threshold radius and selecting a method of normalization (such as maximum norming). Marwan et al. (2007) suggest

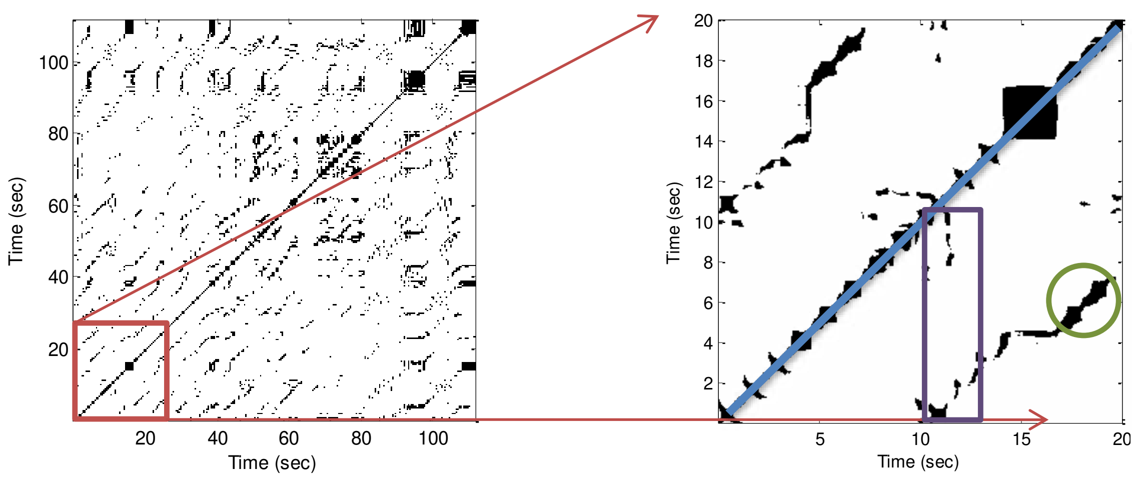
Maximum norming (vs. Euclidian norming) as it is more robust against changes in the number of embedding dimensions.

Finally, the radius size must be selected. One method is to make the radius size five standard deviations larger than the estimated amount of noise in the system. An alternative method sets it as a percentage of the maximum size (not to exceed 10%) of the PSR. Alternatively, the researcher can choose a fixed percentage of the recurrence that they are interested in seeing. Regardless of the method, the amount of recurrence should be limited because too much recurrence in the plot will hide the underlying system. I tried to maintain a radius of around 10% of phrase space and about 10% total recurrence as this has been the method of choice for most researchers using these tools.

RQA measures. Once a recurrence plot is created, there are a variety of quantitative measures that can be extracted (Marwan et al. (2007). I will focus on four: recurrence, mean line, entropy, and determinism. Each measure can be taken across different size windows in the recurrence plot, allowing the researcher to see how the various RQA measures change over time. I will use the window size of musical beats.

Within a window, percentage *recurrence* (%R) measures the number of times the system recurs. Recurrent points appear as diagonal lines in the plot and can be measured by taking the *mean line* length, which gives us a measure of system stability. The larger the mean line value, the longer the system stays recurrent. To measure system order, the entropy of the distribution of the recurrent line length is taken. The higher the number, the more ordered the diagonal lines. This is a measure of complexity. I have normalized the traditional value by taking the log of the number of total lines in a window to better compare across different window sizes. *Entropy* ranges from 0 to 100. Higher entropy indicates a less complex system. Finally, to measure the predictability/determinism of the system, a ratio of the number of recurrent points in a line to the total number of recurrent points is calculated. Higher percentage *determinism* (0-100%) means the system is more predictable, i.e., there are a higher proportion of recurrent lines to random, lone recurrent dots.

Figure 12 displays the recurrence quantification plot of Performer 2's first expressive performance of Rochut 4 along with an enlarged plot of the first 20 seconds. The diagonal, known as the *line of synchronization*, represents a lag of zero (lag-0). Lag between the two systems increases with distance from the diagonal. Points of recurrence are shown as black dots. *mean line* length reflects the degree to which these points form diagonal lines. Regions of high determinism and high entropy are circled in the enlarged plot.



Blue line = Line of Synchronization
Black Dots = *Recurrence*
Black Diagonal lines = *Mean Line*
Green Circle = Region of High *Determinism*
Purple Rectangle = Region of High *Entropy*

Figure 12. Left panel displays the Recurrence Quantification Plot of Performer 2's first expressive performance of Rochut 4. The right panel displays the RQA measures for the first 20 seconds of the left panel.

Cross Recurrence Quantification Analysis

When RQA is extended from one time-series to two, it is called cross recurrence quantification analysis (CRQA). Both are available in the Matlab CRP Toolbox (Marwan & Kurths, 2002). CRQA can be considered a generalized form of the cross-correlation method (Marwan et al., 2007). When the two time-series are examined in phase-space, we look for locations where the two signals come to the same state. These locations are where the two systems are in alignment with each other (i.e., coordinated in phase-space). As with RQA, these locations can be considered at all possible time lags or only at lag-0, called the line of synchronization (Marwan et al., 2007).

CRQA requires that both performances undergo PSR, but this presents a challenge. What if the embedding dimensions or the time lag differs between the two performances? In the case of embedding dimensions, you can simply take the larger one. Overestimating is better than underestimating and, further, using a maximum norming helps make the process more robust. The big difference between RQA and CRQA is that CRQA does not require a Theiler window because these are two different time series being compared (Marwan et al., 2007).

Parameter selection for RQA and CRQA

To choose a time lag for RQA, AMI (Average Mutual Information) indices were computed across all performances of each piece by each musician. Figure 13 and Figure 14 shows the AMI values at different time lags separately for each musician, for Rochut 4 and 13 respectively. For each chart, the first minimum of the AMI function was selected and the median value was taken to give a time lag from all performances, which resulted in a value of 42 samples for ML sway and 38 samples for AP sway. This process was repeated for Rochut 13 and the median for ML and AP was 40. Because the values were so close and because the system oscillated with a very low frequency (between .15 Hz & .3 Hz) both ML and AP was set to 42 for both songs. The larger number was selected so as not to underestimate the value for ML sway in Rochut 4.

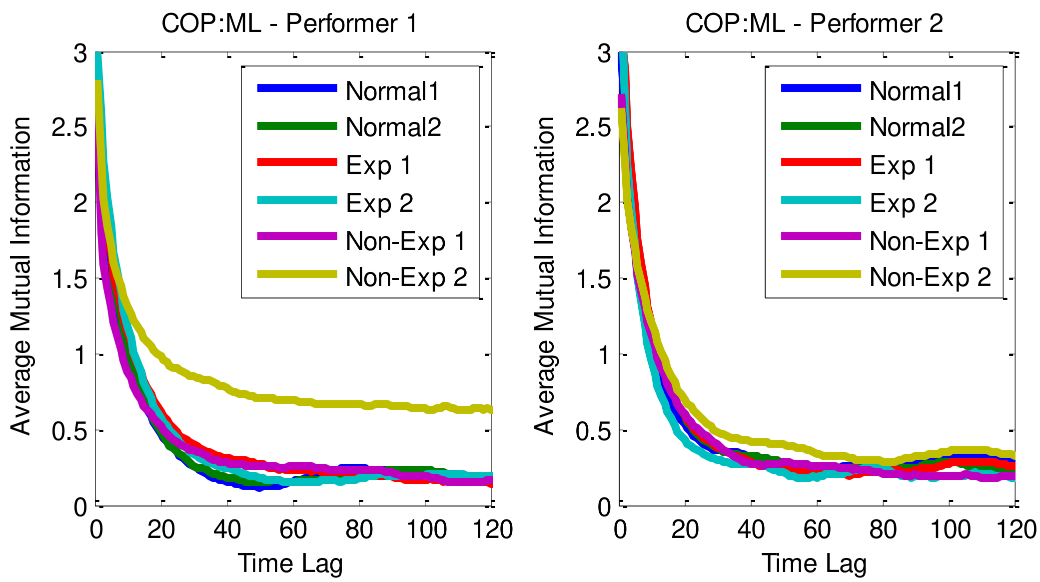


Figure 13. Rochut 4 Average Mutual Information of COP: ML for all Performances

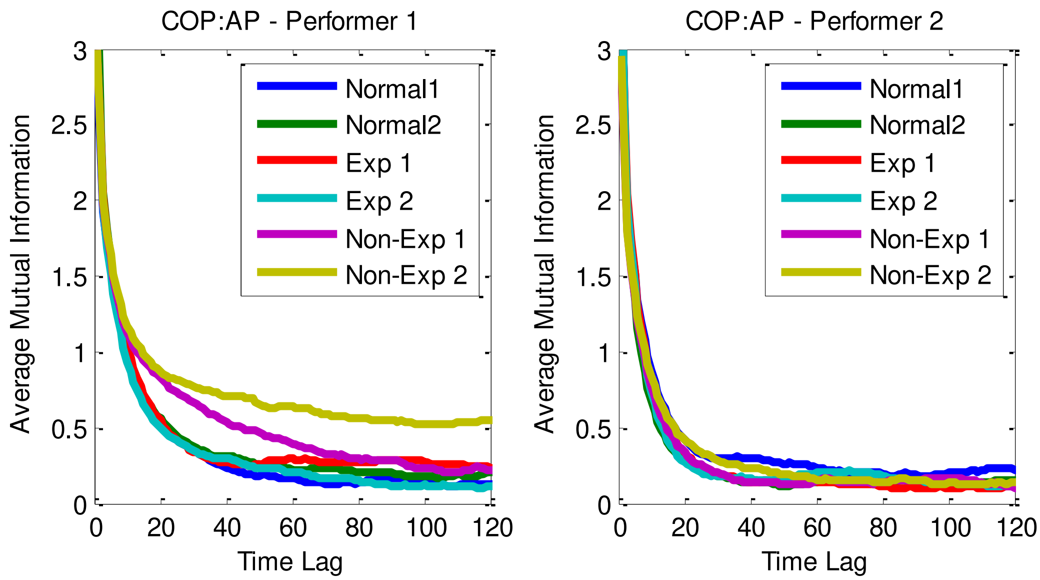


Figure 14. Rochut 13 Average Mutual Information of COP: AP for all Performances.

Figure 15 shows the effect of increasing radius size for Rochut 4. A radius size was selected that gave about 10% recurrent points and was near or below 10% of phase space. This value was selected to work for both Rochut 4 and 13. For ML sway, that resulted in 4% of phase space. For AP, the value needed to be higher, comprising 13.5 % of phase space. The reason for the high value was that in the non-expressive condition the movements were very small. So, to ensure recurrent points were found, the value had to be increased. However, as can be seen in Figure 15, the change in radius size had a linear effect on the percentage of recurrent points. Therefore, the selection of a particular radius size will likely not change the pattern of results; it will only affect the percent recurrence reported.

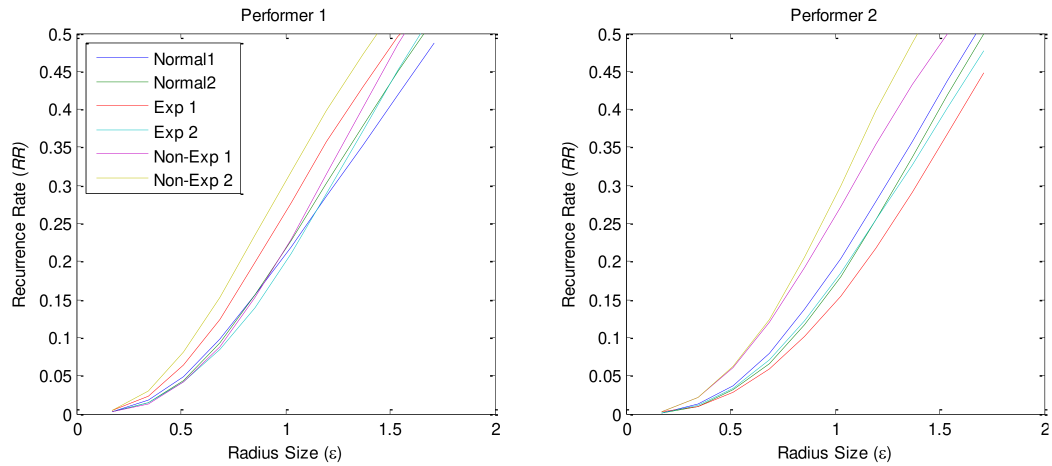


Figure 15. Radius Size and Recurrence Rate for Rochut 4.

Selection of Time-Window for RQA measures. RQA measures are usually taken at equal windows of time with a 50% overlap. However, musical time does not pass at regular intervals in absolute time because of expressive variation. Therefore, time was converted to an event based time series in a musically relevant time metric of musical beats. The number of data samples within each musical beat differed depending on the amount of absolute time that passed. This depended on the expressive timing. For Rochut 4 there were an average of 25.84 (SD = 4.41) data samples per beat and for Rochut 13, 22.52 (SD = 3.89) samples per beat. In addition, the windows of analysis in which RQA measures were chosen so each beat could be compared to all other beats in the performance.

Long Range Correlations

Detrended fluctuation analysis, introduced by Peng, Bukdrebm Havlin, Simons, Stanlet, and Goldberger (1994), is a technique to examine the quality of the noise of a system by revealing the Hurst exponent which estimates the long-range correlation in a nonlinear or chaotic time-series. The Hurst exponent gives insight into the way a system behave over time as described in Table 1.

Table 1.

Hurst Exponent Values and Their Meaning.

Hurst Exponent	**Noise Quality**	**Meaning**
0 to about .49	Anti-correlated noise	Anti-persistent system
About .5	White noise	Random Fluctuations
.6 to .9	Correlated noise	Correlation between successive time-steps
1.0	Pink noise (1/f)	Long range Correlations
1.1 to 1.4	Unbounded noise	Non stationary or unbounded noise
1.5	Brown noise	Random Walk

Postural sway in these experiments exhibited very high noise (alpha >1.5) and so the derivative was analyzed (Ihlen, 2012). Further, since postural sway is often periodic, polynomial de-trending may be inappropriate, so continuous wavelets were used to de-trend (Ihlen, 2012). Multi-fractal continuous wavelet transform analysis [MFCWT] was used. MFCWT measures the self-similarity (i.e., fractality) of the system and provides a measure of the Hurst exponent at different time scales (see Ihlen, 2012 for a complete description of this technique). A range of time scales can be examined and are usually measured from small (e.g., small groups in time close together) to large-scale (e.g., long vectors of concurrent time points). The small time scale can provide information as to the self-similarity of the time-series at a micro level, for example millisecond level variations. I have chosen to examine the large scale (q=2) fluctuations (several seconds) as I was primarily interested in large-scale swaying movements. I was not interested in the trembling type motion that also occurs as the body maintains an upright and in-balance posture.

Statistical Methods

Surrogate Methods

Unlike traditional experimental methods in psychology, where large samples are typically collected, music performance research generally precludes the collection of data from large numbers of performers and performances. Further, each time-series may depend on factors that cannot be replicated, for example, the first performance on stage. Therefore distributions of parameters of the time-series cannot be generated. The solution to this problem is to create data surrogates to test particular null hypotheses about time-series parameters or statistical tests. The most common null hypothesis is the white-noise null hypothesis. In non-time-series data, this method is accomplished by resampling techniques such as bootstrapping to build distributions (Efron & Tibrshirani, 1993). Once the distribution is created, the actual measurement is tested against the distribution to see if it is in critical region. Often a non-parametric bootstrap is applied where the critical region is defined by the percentile method; in this case the actual measurement must be outside of 95% of the scores in the distribution.

The same logic can be extended to music performance. Since music performance data are a time-series, the surrogates are created by randomly shuffling the time-series and then computing the selected statistic. The process is repeated a predetermined number of times (typically 500 or more) until a distribution of the statistic is built. The actual value is then tested against that distribution using the percentile method. For example, in evaluating cross-correlation between two signals, one signal is shuffled while the other remains untouched and the cross-correlation computed. The process is repeated many times (usually about 500). If the actual value is different from the bulk of the surrogate cross-correlation values (95%), the actual value is shown to be different from the null hypothesis. The conclusion is that the two signals are related and are different from white noise. The shuffling method can only test whether the data are generated by a random process. More complex hypotheses cannot be tested because random shuffling destroys the autoregressive structure of the original data.

Thiel, Eubank, Longtin, Galdrikian, and Farmer (1992), suggested an alternative method called phase-shuffling, that tests the non-linear structure of the data. This method converts the time-series into its Fourier components and shuffles the phase and then reassembles the time-series. After this point the processes is identical to the random shuffling surrogate method. This method preserves the autoregressive structure of the data, but does not handle the low and high frequency parts of the time-series spectrum, creating a biased empirical distribution. To correct this problem Schreiber and Schmitz (1996), developed Iterative Amplitude Adapted Fourier Transform (IAAFT). This not only preserves the autoregressive structure, but also helps to preserve the distribution of the original time series. Therefore, when a particular statistic is different from IAAFT surrogates, it suggests that the time-series have more in common than just the same autoregressive parameters. The exact meaning will depend on which statistical test is used. I will use both methods and will refer to random shuffled surrogate testing as the *white-noise null hypothesis* and IAAFT surrogate testing as the *phase-shuffled null hypothesis*.

IAFFT surrogates do have a significant drawback if the time series represents an oscillator with a fixed cycle rate. If the frequency is stable, this method will not reveal any difference between the surrogates and the original time series. This method requires the oscillator to have a varying frequency or to be non-linear. To determine whether the postural sway measures were non-linear, I conducted a series of simulations where each performance COP (AP and ML) correlated with time-lagged copies of all performances from Experiment 1. The degree of overlap was assessed with cross-correlation and cross-recurrence both using IAAFT surrogates to assess significance (alpha = .05). This method revealed a significant overlap, for both cross-correlation and cross-recurrence metrics, between the time-lagged and original signal at lag-0 with up to 880ms delay. This same method failed if any time lag was introduced into a linear oscillator system (simple sine waves). The test showed that the postural sway was the product of a non-linear system.

Both the random shuffled data and IAAFT methods were used as necessary. For cross-correlations and cross-recurrence, a significant white-noise null hypothesis test suggested that the two time-series under investigation had similar time-dependent structures. A significant phase-shuffled hypothesis test for cross-correlation and cross-recurrence suggested the signals exhibited some significant degree of phase-locking. Phase-locking is when the phase of both time-series change together in the same way. For example, in a simple oscillator, this would mean they cycle from 0° to 180° together and any unexpected changes in the phase is directly mirrored by the other signal.

Mixed Effects Methods

Mixed effects models were designed for longitudinal data where the researcher is interested in the change that occurs over time either due to time itself or some other variable (Singer & Willett, 2003). This technique will be applied to RMS and RQA measures after the time-series has been reduced down to the level of musical beats. These models allow for the use of both fixed and random effects, and for different size phrases. They also control for the autoregressive properties of the time-series, and allow for time-invariant and time-variant predictors. Finally, they permit the inclusion of linear and non-linear effects in the same model. The LME4 package in R was used for these analyses (Bates, Maechler, & Bolker, 2012). When possible, I included all within-subject variables as random effects. Interactions between the within-subject variables were not included as predictors as they did not improve model fit. Because the random effects will be allowed to correlate, this precludes the use of boot-strapping techniques to test for the significance of the individual predictors. In these cases, t-values were assessed as if they were Z-values (as in Barr, Levy, Scheppers, & Tily, 2013)

The between-subject variables in Experiments 2 & 3 were treated as fixed but not as random variables. All mixed effect models in Experiment 1 used the exact same random structure to facilitate comparison. When necessary, a forward modeling technique was employed to test whether additional predictors or additional interactions between predictions improved the model fit (using a deviance test chi-square distribution).

Chapter 7: Results & Discussion for Experiment 1: Movements, Musical Structure, and Expression

Overview

The results of Experiment 1 are described in two chapters. This chapter examines in detail the movements of the performers relative to the musical structure and expression. Specifically, I will show how performance style, musical phrasing, expressive features (Tempo, Loudness), song selection (less vs more structured), and the changes in direction of melodic contour were related to postural sway at the musical beat level using mixed effect models. The next chapter examines the reliability of the movements of the performers both with respect to themselves and the other performer.

Dependent Measures

To examine postural sway at the beat level the movements need to be summarized per beat. As described in the methods, there are two approaches, the linear (RMS) and the non-linear (RQA). I have used both as they examine different properties of the system. To review, RMS measures the amount of movement in one-dimension. RQA measures the recurrence of the system in phase-space, as well as its predictability, orderliness, and stability. Each dependent measure was extracted from each performance separately for ML and AP sway.

Model Fitting Procedures

RQA analyses were conducted in the manner outlined in the methods section. Each dependent measure was analyzed using mixed effect models. A forward modeling technique was used to test whether or not additional predictors, such as interactions and expressive features, would help to explain postural sway. Each model for each dependent measure was constructed in an identical manner. All models used the same random effects, which included the phrasal structure of the performance as supplied by the performer, the performance style, the serial position within the phrase (linear and quadratic), the song, and finally the performer. The first model included fixed effects that were the same predictors as the random effects, except for performer, which was included only as a random effect. The second model added the interactions between performance style, song, and phrasal structure. The third model added the expressive features (tempo and loudness) and change in the melodic contour. The fourth model added the interactions between the expressive features. Deviance tests were used to examine whether the more complex models improved the model fit.

Expressive features were transformed to z-scores to facilitate comparisons between the features and between models – the interpretation of the model parameters is the same for models with and without expressive features. The Z-score transformation was done across all performances and performers, thus maintaining the relative magnitude of differences within and between performances.

Reading Tables and Figures

Mixed effect tables can be read in a similar way to linear regression. The intercept term represents the intercept (mean) for the normal performance of the less structured music. Means for the other effects are obtained by adding them to the intercept – this is a result of the use of dummy coding (0/1). Serial position effects for beats within phrases are displayed in figures following each table and were generated by multiplying the fixed effect value with the serial position of the beats within the bar and adding the intercept and the main effect for the performance style. Both linear and quadratic slopes were tested. When only the linear slope was significant then the direction (positive or negative) can be interpreted as in a traditional regression. However, when both linear and quadratic effects are significant, then the slope must be interpreted in terms of both the magnitude and direction of the effects. Two basic outcomes are possible: The sign of the linear and quadratic effects may be the same or opposite. Same signs will result in an exponential type function. Opposite signs will create either an *arch* function (positive linear and negative quadratic effects) or inverse arches also called *U-shaped* functions (negative linear and positive quadratic effects). Even if the linear term is not significant, the quadratic term must be examined relative to the linear term.

Linear Analysis

RMS of ML Postural Sway

Overview. I begin with the linear approach to analysis, describing the results first for ML postural sway and then for AP sway. Table 2 shows the results of hierarchically nested models for the root mean square (RMS) of ML postural way. Figure 16 shows the effect of serial position within a phrase as a function of performance style, separately for each song.

Performance style. In all models, there was a main effect for the performance style. There was the most ML sway for expressive performances and the least for non-expressive movements. The effect size became stronger as additional variability was explained in the more complex models.

Song selection. There was no main effect for song selection. On average, the amount of ML sway was the same in the two songs.

Performance style x Song selection. There was significant improvement of Model.X2 over Model.X1. The improvement was due, in part, to the significant interaction between the song and the performance style. Figure 16 shows that the effect of performance style was much larger for the less structured than for the more structured song.

Serial position within phrases. There was no main effect for serial position within a phrase. However, the improvement of Model.X2 over Model.X1 was also due to the significant three-way interaction between song, serial position within phrase, and performance style seen in Figure 16. Figure 16 shows that for the less structured song the amount of movement increased from beginning to end of the phrase for the normal and the expressive performances, while for the non-expressive performances there was almost no movement throughout the phrase. For the more structured song, the effects of serial position were almost the opposite. For the expressive performances, movement increased across the phrase; for non-expressive performances, movement decreased across the phrase; for normal performances, amount of movement was relatively constant across the phrase.

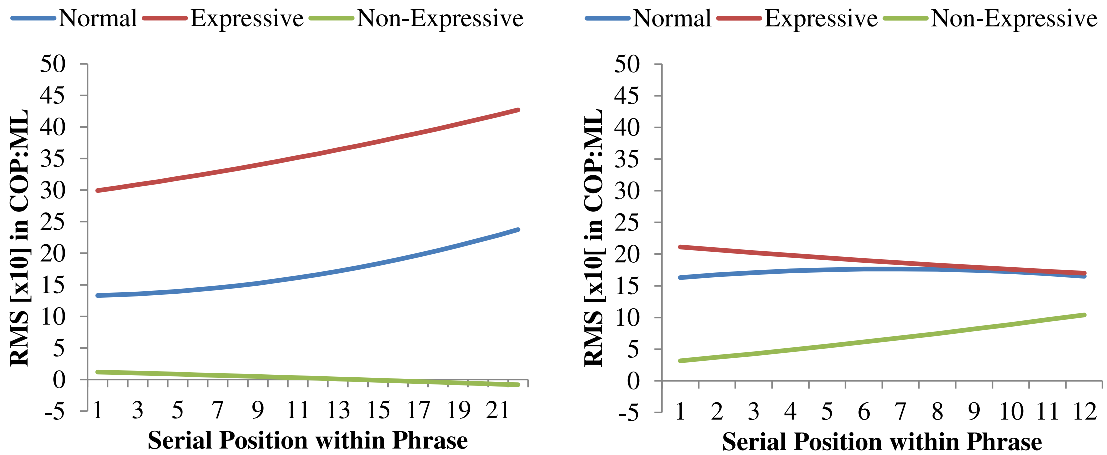
Expressive features. Adding in the expressive features, loudness, tempo, and change in the melodic contour alone, did not improve the model fit of Model.X3. However, the interaction between these features did improve the fit in Model.X4. Therefore, changes in the melodic contour that were also accompanied by changes in tempo and loudness were marked by decreased ML movement.

Table 2**.**

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position of Beats within Phrases, and Expressive Features: RMS of COP: ML.

RMS COP: ML [x10]	**Model.X1**		**Model.X2**		**Model.X3**		**Model.X4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	18.91***	(2.22)	13.37***	(2.57)	13.33***	(2.55)	13.26***	(2.58)
Expressive Style	8.09**	(2.75)	16.03***	(3.01)	16.20***	(3.00)	16.25***	(3.01)
Non-Expressive Style	-12.98***	(1.32)	-11.97***	(1.74)	-11.92***	(1.73)	-11.97***	(1.73)
Serial Position within Phrase	-0.13	(0.24)	0.01	(0.30)	0.04	(0.30)	0.04	(0.30)
Serial Position^2 within Phrase	0.02**	(0.01)	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)
Song [Structured]	-3.95	(2.04)	2.36	(2.69)	2.41	(2.69)	2.53	(2.69)
Expressive x SP w/ Phrase	-0.24	(0.22)	0.42	(0.32)	0.4	(0.32)	0.38	(0.32)
Non-Expressive x SP w/ Phrase	0.39	(0.22)	-0.09	(0.27)	-0.12	(0.27)	-0.13	(0.27)
Expressive x SP^2 w/ Phrase	0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Non-Expressive x SP^2 w/ Phrase	-0.03**	(0.01)	-0.02*	(0.01)	-0.02*	(0.01)	-0.02*	(0.01)
Song x SP w/ Phrase			0.54	(0.35)	0.54	(0.35)	0.51	(0.35)
Song x SP^2 w/ Phrase			-0.06***	(0.02)	-0.06***	(0.02)	-0.06***	(0.02)
Expressive x Song			-10.32***	(2.27)	-10.43***	(2.27)	-10.45***	(2.27)
Non-Expressive x Song			-0.96	(2.31)	-1.26	(2.31)	-1.18	(2.31)
Expressive x SP w/ Phrase x Song			-1.46**	(0.46)	-1.45**	(0.46)	-1.42**	(0.46)
Non-Expressive x SP w/ Phrase x Song			0.04	(0.48)	0.07	(0.48)	0.09	(0.48)
Expressive x SP^2 w/ Phrase x Song			0.06***	(0.02)	0.06***	(0.02)	0.06**	(0.02)
Non-Expressive x SP^2 w/ Phrase x Song			0.07***	(0.02)	0.07***	(0.02)	0.07***	(0.02)
Expressive Features								
Loudness of Performance [RMS Zscore]					-0.42	(0.23)	-0.32	(0.23)
Tempo [Zscore]					0.19	(0.24)	0.20	(0.24)
Melodic Contour [Zscore]					-0.12	(0.19)	-0.09	(0.19)
Loudness x Tempo							0.41*	(0.20)
Loudness X Melody							-0.18	(0.19)
Tempo x Melody							0.26	(0.19)
Loudness x Tempo x Melody							-0.57**	(0.18)
Goodness of Fit								
Deviance	27901.69		27289.3		27285.02		27272.04	
AIC	27979.69		27383.3		27385.02		27380.04	
BIC	28220.4		27673.38		27693.61		27713.32	
Chi-square (df)	- (39)		612.39*** (47)		4.23 (50)		12.97* (54)	

***$p < .001$, **$p < .01$, & * $p < .05$



Rochut 13. Less Structured Rochut 4. More Structured

Figure 16. Model.X4 Mixed Model of Root Mean Square [x10] within Musical Phrases Both Songs for ML postural sway.

RMS of AP Postural Sway

Overview. Table 3 shows the result of hierarchically nested models for the root mean squared (RMS) of AP postural way. Figure 17 shows the effect of serial position within a phrase as a function of performance style, separately for each song.

Performance style. In all but the first model, AP swaying movements were smaller for expressive than for normal performances.

Song selection. There was a main effect for song selection, but that effect disappeared in later models that included interactions of song with other variables. On average, the amount of AP sway was the same in the two songs.

Performance style x song selection. There was significant improvement of Model.Y2 over Model.Y1. The improvement was in part due to a significant interaction between song and performance style. In expressive performances there was more AP postural sway for the more structured than for the less structured song. This difference did not occur for normal or for non-expressive performances.

Serial position within phrases. There was no main effect for serial position within a phrase. However, the improvement of Model.X2 over Model.X1 was also due, in part, to a significant effect three-way interaction between song, serial position within a phrase, and performance style. Figure 17 shows that for the less structured song the amount of movement increased from beginning to end of the phrase for the expressive and the non-expressive performances, while for the normal performances the amount of movement decreased across the phrase. For the more structured song, the serial position functions for all three performance styles were essentially flat, exhibiting only a very slight arches.

Expressive Features. The addition of expressive features in Model.Y3 significantly improved the model fit from Model.Y2. This improvement was due to tempo. The faster the performers played the more their AP sway increased. The addition of the interactions between expressive features in Model.Y4 decreased the model fit, possibly because these interactions shared the same variability as serial position effects within phrases.

Table 3.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: RMS of COP: AP.

RMS COP: AP [x10]	Model.Y1		Model.Y2		Model.Y3		Model.Y4	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	7.68***	(1.40)	9.05***	(1.43)	8.79***	(1.43)	8.85***	(1.43)
Expressive Performance	-1.18	(1.38)	-4.12**	(1.43)	-4.00**	(1.42)	-3.56*	(1.45)
Non-Expressive Performance	0.88	(0.94)	1.04	(1.00)	1.04	(1.00)	1.06	(1.00)
Serial Position within Phrase	-0.09**	(0.04)	-0.07	(0.06)	-0.06	(0.06)	0.04	(0.04)
Serial Position^2 within Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	-0.00	(0.00)
Song [Structured]	2.12**	(0.73)	-0.86	(0.97)	-0.57	(0.97)	-0.09	(0.96)
Expressive x SP w/ Phrase	0.18***	(0.04)	0.18**	(0.07)	0.19**	(0.06)	-0.04	(0.06)
Non-Expressive x SP w/ Phrase	0.12	(0.07)	0.13	(0.09)	0.12	(0.09)	0.06	(0.08)
Expressive x SP^2 w/ Phrase	0.01***	(0.00)	0	(0.00)	0	(0.00)	0.01***	(0.00)
Non-Expressive x SP^2 w/ Phrase	0	(0.00)	0	(0.00)	0	(0.00)	0	(0.00)
Song x SP w/ Phrase			0.22*	(0.11)	0.22*	(0.11)	0.01	(0.11)
Song x SP^2 w/ Phrase			-0.02***	(0.00)	-0.02***	(0.00)	0	(0.00)
Expressive x Song			5.62***	(0.77)	5.58***	(0.77)	4.66***	(0.74)
Non-Expressive x Song			1.62	(0.86)	1.67	(0.86)	1.34	(0.84)
Expressive x SP w/ Phrase x Song			-0.16	(0.14)	-0.17	(0.14)	0.1	(0.14)
Non-Expressive x SP w/ Phrase x Song			-0.46**	(0.17)	-0.46**	(0.17)	-0.38*	(0.17)
Expressive x SP^2 w/ Phrase x Song			0.01**	(0.01)	0.01**	(0.01)	0	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			0.02**	(0.01)	0.02**	(0.01)	0.02*	(0.01)
Expressive Features								
Loudness of Performance [RMS Zscore]					0.08	(0.08)	0.07	(0.08)
Tempo [Zscore]					0.26**	(0.09)	0.25**	(0.09)
Melodic Contour [Zscore]					0	(0.07)	0.01	(0.07)
Loudness x Tempo							0.01	(0.07)
Loudness X Melody							0	(0.07)
Tempo x Melody							-0.03	(0.07)
Loudness x Tempo x Melody							-0.01	(0.07)
Goodness of Fit								
Deviance	20423.33		20149.51		20139.45		20148.27	
AIC	20501.33		20243.51		20239.45		20256.27	
BIC	20742.03		20533.59		20548.04		20589.55	
Chi-square (df)	- (39)		273.82*** (47)		10.07* (50)		0.00 (54)	

***p < .001, **p < .01, & * p < .05

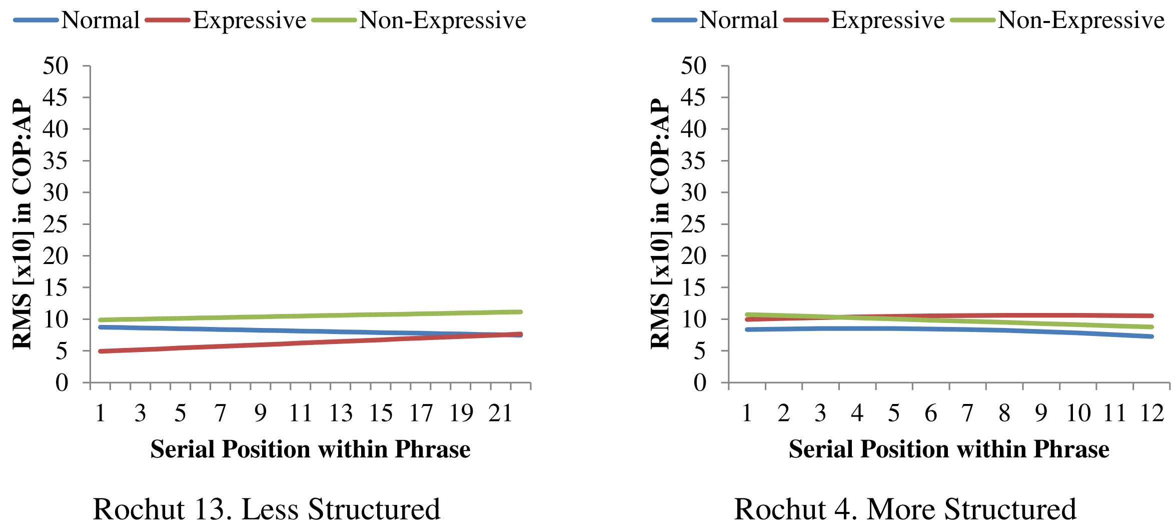


Figure 17. Model.Y3 Mixed Model of Root Mean Square [x10] within Musical Phrases Both Songs for AP postural sway.

Dynamical Systems Analysis

Overview. I turn now to the four dynamical systems measures: recurrence, determinism mean line, and entropy. For each measure, I describe the results for ML and AP sway in turn**.** Each measure captures a different property of a complex system. As reviewed in Chapter 6, percentage of *recurrence* measures the number of times the system recurs. To measure of the predictability of the system, a ratio of the number of recurrent points in a line to the total number of recurrent points is calculated. Higher percentage *determinism* means the system is more predictable, i.e., more recurrent lines to random, lone recurrent dots. Recurrent points that form diagonal lines can be measured by taking the *mean line* length, which gives us a measure of system stability. The larger the mean line is more stable the system. *Entropy* measures system order by the variability of the distribution of the recurrent line lengths. Higher entropy indicates a more complex system.

Recurrence Rate of ML Postural Sway

Overview. Table 4 shows the result of hierarchically nested models for the percentage of recurrence (%R) of ML postural way. Figure 18 shows the effect of serial position within a phrase as a function of performance style, separately for each song. Recurrence reflects how much the system repeats itself over time.

Performance style. In all but the first model, there was a main effect for performance style. There was less recurrence in ML sway for expressive performances and more recurrence in non-expressive performances. The effect size for the expressive performances increased when the interactions with song selection were added in Model.Rx2, suggesting that there was a difference between the expressive performances of the two songs.

Song selection. There was a main effect for song selection. On average, the amount of recurrence in ML sway was lower in the more structured than in the less structured song. The effect size increased in the models that contained the interactions with the song selection.

Performance style x song selection. There was significant improvement of Model.Rx2 over Model.Rx1. For the expressive style, more structured music had a higher intercept (more recurrence) than the less structured music. This interaction was not present for the non-expressive performances.

Serial position within phrases. There was no main effect for serial position within a phrase in Model. Rx1, but a main effect did appear in Model.Rx2, due to a three-way interaction of serial position with song, and performance style, as shown in Figure 18. This resulted in a significant improvement of Model Rx2 over Model.Rx1. For the less structured song, Figure 18 shows U-shaped serial position functions for all three performance styles, indicating more recurrence at beginnings and ends of phrases. The U-shape was most pronounced for non-expressive performances and least pronounced for expressive performance, with normal performance in-between the two. For the more structured song, there were significant arch-shaped serial position functions for both the normal and the non-expressive performances, indicating less recurrence at the beginnings and ends of phrases. (The functions appear almost linear in the figure because the phrase length is short, but quadratic effects were significant). For expressive performances, in contrast, the serial position function was flat.

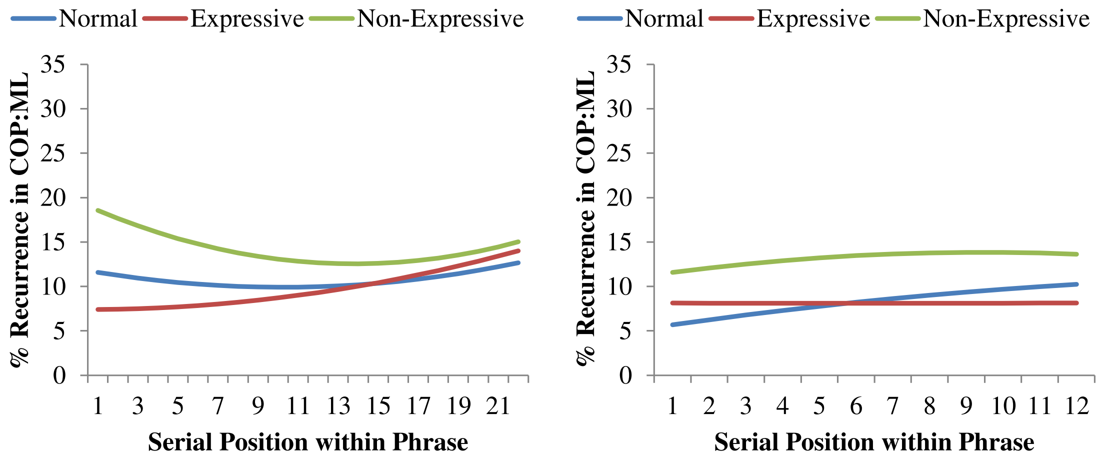
Expressive features. The addition of the expressive features in Model.Rx3 significantly improved the model fit, as did the interactions between them in Model.Rx4. Increases in loudness and increased change in the melodic contour each resulted in more recurrent patterns. The main effect of tempo was not significant, but there was an interaction of tempo and melodic contour. Finally, there was a three-way interaction between the three expressive features resulting in an overall negative effect. As the performers got louder and faster and as the change in melodic contour increased, their movements became less recurrent.

Table 4.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Recurrence Rate of COP: ML.

%R COP: ML	**Model.Rx1**		**Model.Rx2**		**Model.Rx3**		**Model.Rx4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	8.88***	(1.02)	12.15***	(1.09)	11.99***	(1.09)	11.98***	(1.09)
Expressive Performance	0.11	(0.98)	-4.32***	(1.23)	-5.11***	(1.20)	-4.58***	(1.23)
Non-Expressive Performance	6.58***	(1.03)	7.82***	(1.31)	7.63***	(1.28)	7.56***	(1.30)
Serial Position within Phrase	0.26	(0.18)	-0.38*	(0.18)	-0.37*	(0.16)	-0.41*	(0.19)
Serial Position^2 within Phrase	0.00	(0.01)	0.02*	(0.01)	0.01**	(0.01)	0.02*	(0.01)
Song [Structured]	-1.93*	(0.77)	-7.56***	(1.35)	-7.41***	(1.35)	-6.90***	(1.37)
Expressive x SP w/ Phrase	-0.28	(0.17)	0.41	(0.21)	0.58**	(0.19)	0.4	(0.21)
Non-Expressive x SP w/ Phrase	-0.54***	(0.15)	-0.61**	(0.19)	-0.53**	(0.19)	-0.61**	(0.19)
Expressive x SP^2 w/ Phrase	0.01	(0.01)	-0.01	(0.01)	-0.01*	(0.01)	-0.01	(0.01)
Non-Expressive x SP^2 w/ Phrase	0.01*	(0.01)	0.02**	(0.01)	0.01*	(0.01)	0.02**	(0.01)
Song x SP w/ Phrase			1.11***	(0.25)	1.11***	(0.24)	1.02***	(0.25)
Song x SP^2 w/ Phrase			-0.04***	(0.01)	-0.04***	(0.01)	-0.04**	(0.01)
Expressive x Song			7.77***	(1.59)	8.29***	(1.56)	7.65***	(1.58)
Non-Expressive x Song			-2.05	(1.68)	-1.55	(1.68)	-1.62	(1.67)
Expressive x SP w/ Phrase x Song			-1.11***	(0.32)	-1.25***	(0.30)	-1.03**	(0.32)
Non-Expressive x SP w/ Phrase x Song			0.57	(0.34)	0.53	(0.34)	0.59	(0.34)
Expressive x SP^2 w/ Phrase x Song			0.03*	(0.01)	0.03**	(0.01)	0.02	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			-0.03*	(0.01)	-0.03*	(0.01)	-0.03*	(0.01)
Expressive Features								
Loudness of Performance [RMS Zscore]					0.61***	(0.16)	0.70***	(0.16)
Tempo [Zscore]					0.11	(0.17)	0.12	(0.16)
Melodic Contour [Zscore]					0.51***	(0.14)	0.56***	(0.14)
Loudness x Tempo							0.25	(0.14)
Loudness X Melody							-0.28*	(0.13)
Tempo x Melody							0.35*	(0.14)
Loudness x Tempo x Melody							-0.44***	(0.13)
Goodness of Fit								
Deviance	24844.23		24766.48		24748.06		24717.85	
AIC	24922.23		24860.48		24848.06		24825.85	
BIC	25162.93		25150.56		25156.66		25159.13	
Chi-square (df)	- (39)		77.75*** (47)		18.42*** (50)		30.22*** (54)	

***p < .001, **p < .01, & * p < .05



Rochut 13. Less Structured Rochut 4. More Structured

Figure 18. Model.Rx4 Fixed Effects of % Recurrence within Musical Phrases Both Songs.

Recurrence Rate of AP Postural Sway

Overview. Table 5 shows the result of hierarchically nested models for the percentage of recurrence (%R) of AP postural way. Figure 19 shows the effect of serial position within a phrase as a function of performance style, separately for each song.

Performance style. In all models non-expressive style performance showed significantly more recurrence. Expressive performance showed a weak negative effect, which was significant in the first model. The interaction between performance style reduced the effect for expressive performance, but doubled the effect size for non-expressive performance.

Song selection. There was a main effect for song selection. On average, the amount of recurrence in AP sway was lower in the more structured than the less structured song.

Performance style x song selection. While there was significant improvement of Model.Ry2 over Model.Ry1, there was no significant interaction between song selection and performance style. The improvement was due to the interactions with serial position within a phrase.

Serial position within phrases. There was no main effect of serial position within a phrase in any of the models, and no interactions of serial position with performance style. There were, however, significant interaction between serial position and song selection, and significant three-way interactions between serial position with song and performance style, in Model.Ry2-4, as seen in Figure 19. Figure 19 shows that for the less structured song the serial position functions were essentially flat for both normal and expressive performance while the slope for the non-expressive performances was negative, though not significantly so. For the more structured song, there was a weak, but significant arch for normal performances, and a flat serial position function for expressive and non-expressive performance.

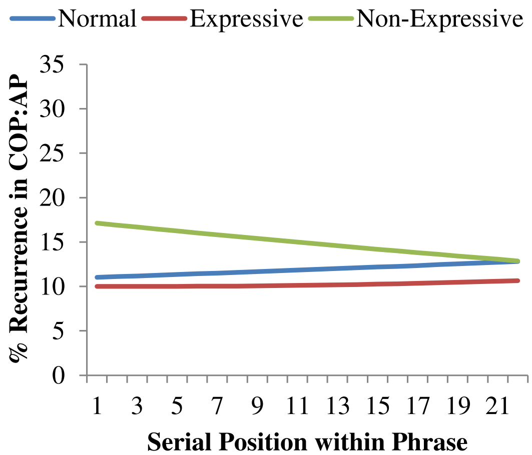
Expressive features. The addition of the expressive features in Model.Rx3 significantly improved the model fit, but the interactions between them in Model.Rx4 did not. The effect of tempo was significant, indicating more recurrence at faster tempi.

Table 5.

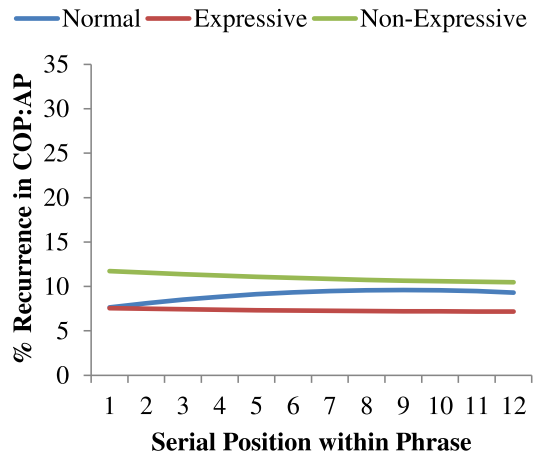
Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Recurrence Rate of COP: AP.

%R COP: AP	**Model.Ry1**		**Model.Ry2**		**Model.Ry3**		**Model.Ry4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	11.88***	(0.94)	11.22***	(1.01)	10.90***	(1.03)	10.95***	(1.03)
Expressive Performance	-1.59*	(0.67)	-1.1	(0.91)	-0.9	(0.92)	-0.92	(0.92)
Non-Expressive Performance	3.79***	(0.82)	6.46***	(1.14)	6.40***	(1.13)	6.40***	(1.13)
Serial Position within Phrase	0.00	(0.08)	0.07	(0.10)	0.08	(0.10)	0.08	(0.10)
Serial Position^2 within Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0	(0.00)
Song [Structured]	-3.53***	(0.83)	-4.20***	(1.24)	-3.77**	(1.25)	-3.82**	(1.25)
Expressive x SP w/ Phrase	0.01	(0.07)	-0.09	(0.11)	-0.09	(0.11)	-0.09	(0.11)
Non-Expressive x SP w/ Phrase	-0.09	(0.12)	-0.3	(0.16)	-0.31	(0.16)	-0.30	(0.16)
Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Non-Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Song x SP w/ Phrase			0.47*	(0.19)	0.47*	(0.19)	0.48*	(0.19)
Song x SP^2 w/ Phrase			-0.03***	(0.01)	-0.03***	(0.01)	-0.03***	(0.01)
Expressive x Song			1.41	(1.30)	1.37	(1.29)	1.40	(1.29)
Non-Expressive x Song			-1.72	(1.45)	-1.61	(1.45)	-1.62	(1.45)
Expressive x SP w/ Phrase x Song			-0.52*	(0.24)	-0.52*	(0.23)	-0.53*	(0.23)
Non-Expressive x SP w/ Phrase x Song			-0.45	(0.29)	-0.44	(0.29)	-0.45	(0.29)
Expressive x SP^2 w/ Phrase x Song			0.03***	(0.01)	0.03***	(0.01)	0.03***	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			0.04**	(0.01)	0.04**	(0.01)	0.04**	(0.01)
Expressive Features								
Loudness of Performance [RMS Zscore]					0.14	(0.14)	0.13	(0.14)
Tempo [Zscore]					0.40**	(0.15)	0.40**	(0.15)
Melodic Contour [Zscore]					0.08	(0.12)	0.1	(0.12)
Loudness x Tempo							-0.07	(0.12)
Loudness X Melody							-0.08	(0.12)
Tempo x Melody							-0.15	(0.12)
Loudness x Tempo x Melody							0.09	(0.11)
Goodness of Fit								
Deviance	23832.7		23793.43		23784.31		23781.42	
AIC	23910.7		23887.43		23884.31		23889.42	
BIC	24151.4		24177.51		24192.9		24222.7	
Chi-square (df)	- (39)		39.27*** (47)		9.12* (50)		2.89 (54)	

***p < .001, **p < .01, & * p < .05



Rochut 13. Less Structured



Rochut 4. More Structured

Figure 19. Model.Ry4 Fixed Effects of % Recurrence within Musical Phrases Both Songs.

Predictability: Determinism of ML Postural Sway

Overview. Table 6 shows the result of hierarchically nested models for the percentage of determinism (%DET) in the recurrence of ML postural sway. Figure 20 shows the effect of serial position within a phrase as a function of performance style, separately for each song. In order to control for the effects of recurrence and make it possible to draw conclusions about determinism that are independent of recurrence, the mixed effects models included recurrence as a predictor. Higher determinism levels reflect more predictable recurrent body movement patterns.

Performance style. There was more determinism in expressive performances, but the effect was not significant until interactions with song were added. There was significantly less determinism in non-expressive performances in all models; the effect size decreased progressively as interactions with song and with expressive features were added in the second and third models respectively.

Song selection. There was a main effect for song selection. On average, the amount of determinism was substantially higher in the more structured than in the less structured song.

Performance style x song selection. There was significant improvement of Model.Dx2 over Model.Dx1. For expressive performances, determinism was higher for the more structured than for the less structured song. For non-expressive performances, there was no difference between the two songs. Thus, the more structured song had the most predictable pattern of recurrent body movements, and the normal performance was the most predictable overall.

Serial position within phrases. There was no linear main effect for serial position within a phrase in any of the models. There were small but significant effects for the quadratic slopes after the first model, as seen in Figure 20. Figure 20 shows that for normal performances of the less structured song, determinism increased as the performer approached the end of the phrase. The other serial position functions were essentially flat, indicating no change in predictability across the phrase.

Expressive features. The addition of the expressive features in Model.Dy3 improved the model fit, but the addition of their interactions in Model.DY4 did not result in further improvement. The significant effects of tempo in both models indicate that tempo and determinism were related; the recurrence of faster performances was less predictable. I will not describe the three-way interaction of loudness, tempo and melody in the fourth model because it did not produce a significant improvement in model fit.

Table 6.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Determinism of COP: ML.

%DET COP: ML	**Model.Dx1**		**Model.Dx2**		**Model.Dx3**		**Model.Dx4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	69.51***	(2.93)	65.10***	(2.86)	66.96***	(2.97)	66.79***	(2.95)
% Recurrence	-0.44***	(0.03)	-0.44***	(0.03)	-0.44***	(0.03)	-0.44***	(0.03)
Expressive Performance	1.33	(1.55)	8.37***	(1.82)	6.81***	(1.79)	6.90***	(1.79)
Non-Expressive Performance	-6.60***	(1.38)	-4.26*	(1.93)	-3.75*	(1.85)	-3.75*	(1.86)
Serial Position within Phrase	0.11	(0.10)	0.17	(0.11)	0	(0.10)	0.01	(0.10)
Serial Position^2 within Phrase	0	(0.01)	0.01*	(0.01)	0.02**	(0.01)	0.02**	(0.01)
Song [Structured]	14.65***	(2.62)	20.13***	(3.05)	17.43***	(3.24)	17.60***	(3.22)
Expressive x SP w/ Phrase	-0.1	(0.15)	-0.2	(0.18)	-0.07	(0.17)	-0.08	(0.17)
Non-Expressive x SP w/ Phrase	0.18	(0.21)	-0.32	(0.28)	-0.16	(0.28)	-0.15	(0.28)
Expressive x SP^2 w/ Phrase	0.01	(0.01)	-0.01	(0.01)	-0.02*	(0.01)	-0.02*	(0.01)
Non-Expressive x SP^2 w/ Phrase	-0.01	(0.01)	0	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Song x SP w/ Phrase			0.27	(0.35)	0.29	(0.34)	0.29	(0.34)
Song x SP^2 w/ Phrase			-0.05**	(0.02)	-0.04**	(0.02)	-0.05**	(0.02)
Expressive x Song			-10.18***	(2.44)	-9.40***	(2.41)	-9.55***	(2.40)
Non-Expressive x Song			-4.99	(2.71)	-4.85	(2.68)	-4.97	(2.68)
Expressive x SP w/ Phrase x Song			-0.19	(0.44)	-0.26	(0.44)	-0.24	(0.44)
Non-Expressive x SP w/ Phrase x Song			1.02	(0.55)	0.91	(0.54)	0.92	(0.54)
Expressive x SP^2 w/ Phrase x Song			0.04*	(0.02)	0.05*	(0.02)	0.05*	(0.02)
Non-Expressive x SP^2 w/ Phrase x Song			-0.02	(0.02)	-0.02	(0.02)	-0.02	(0.02)
Expressive Features								
Loudness of Performance [RMS Zscore]					-0.02	(0.26)	0	(0.27)
Tempo [Zscore]					-2.54***	(0.27)	-2.61***	(0.27)
Melodic Contour [Zscore]					0.1	(0.23)	0.04	(0.23)
Loudness x Tempo							0.27	(0.23)
Loudness X Melody							0.32	(0.22)
Tempo x Melody							0.09	(0.23)
Loudness x Tempo x Melody							0.43*	(0.21)
Goodness of Fit								
Deviance	28488.81		28405.33		28324.29		28315.24	
AIC	28568.81		28501.33		28426.29		28425.24	
BIC	28815.68		28797.58		28741.06		28764.69	
Chi-square (df)	- (40)		83.48*** (48)		81.038***(51)		9.06 (55)	

****p* < .001, ***p* < .01, & * *p* < .05

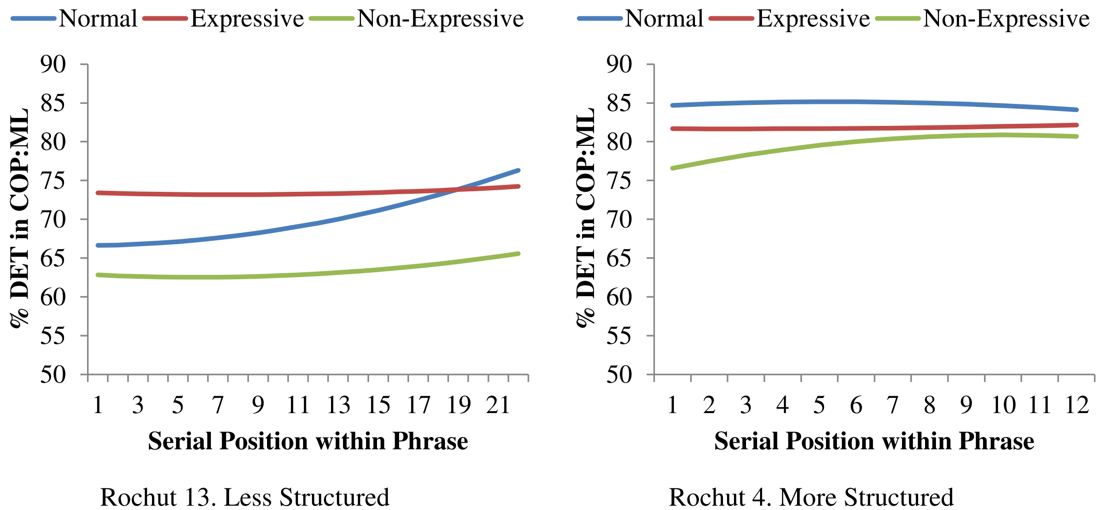


Figure 20. Model.Dx4 Fixed Effects of % Determinism within Musical Phrases Both Songs.

Predictability: Determinism of AP Postural Sway

Overview. Table 7 shows the result of hierarchically nested models for the percentage of determinism (%DET) in the recurrence of AP postural sway. Figure 21 shows the effect of serial position within a phrase as a function of performance style, separately for each song.

Performance style. There was significantly more determinism in expressive performances in all models. There was less determinism in non-expressive performances but not significantly so until interactions with song were added in the second model.

Song selection. There was no main effect for song selection.

Performance style x song selection. There was significant improvement of Model.Dy2 over Model.Dy1. The improvement was due the interaction of performance style and song selection. As seen in Figure 21, the intercepts of the three performance styles were different in the less structured song, but the same in the more structured song. In the less structured song, expressive performances were more predictable than normal and non-expressive performances.

Serial position within phrases. There were no main effects or interactions involving serial position within a phase. The serial position functions in Figure 21 were essentially flat.

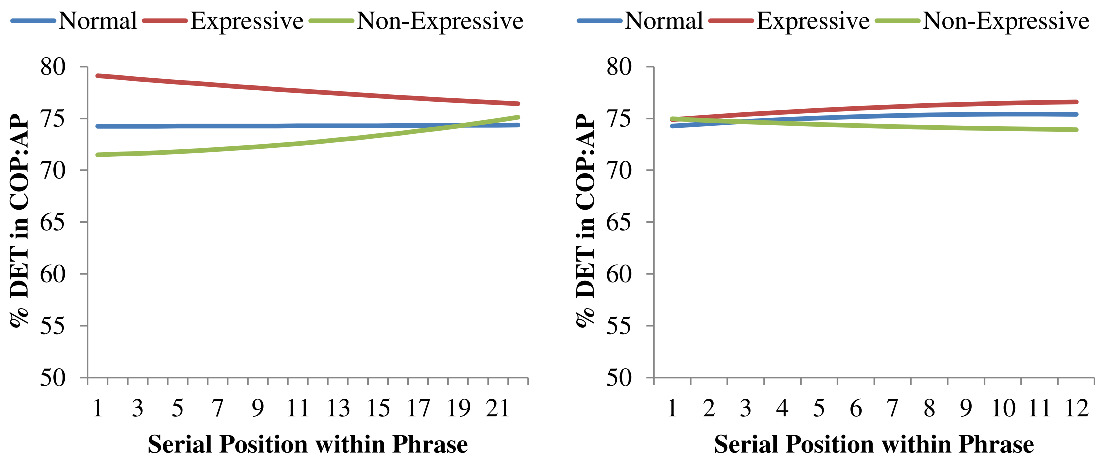
Expressive features. The addition of expressive features and their interactions in Model.Dy3 and Dy4 improved the model fit. Faster performance was related to less predictability in both models. However, when the performer also got faster and louder the AP movements become more predictable.

Table 7.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Determinism of COP: AP.

%DET COP: AP	**Model.Dy1**		**Model.Dy2**		**Model.Dy3**		**Model.Dy4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	74.34***	(0.83)	73.66***	(0.89)	74.63***	(0.87)	74.21***	(0.92)
% Recurrence	0.19***	(0.02)	0.20***	(0.02)	0.20***	(0.02)	0.20***	(0.02)
Expressive Performance	2.85***	(0.73)	5.44***	(0.94)	4.57***	(0.91)	5.04***	(0.97)
Non-Expressive Performance	-0.33	(0.92)	-2.84*	(1.23)	-3.11*	(1.23)	-2.79*	(1.27)
Serial Position within Phrase	0.04	(0.06)	0.02	(0.07)	-0.05	(0.06)	0.00	(0.08)
Serial Position^2 within Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Song [Structured]	0.56	(0.60)	0.61	(1.17)	-0.65	(1.15)	-0.24	(1.19)
Expressive x SP w/ Phrase	-0.05	(0.08)	-0.15	(0.10)	-0.09	(0.09)	-0.16	(0.11)
Non-Expressive x SP w/ Phrase	-0.22	(0.13)	-0.01	(0.17)	0.10	(0.16)	0.04	(0.17)
Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Non-Expressive x SP^2 w/ Phrase	0.01*	(0.00)	0.01	(0.01)	0.00	(0.01)	0.01	(0.01)
Song x SP w/ Phrase			0.31	(0.20)	0.34	(0.20)	0.27	(0.21)
Song x SP^2 w/ Phrase			-0.02	(0.01)	-0.02	(0.01)	-0.01	(0.01)
Expressive x Song			-4.31**	(1.43)	-4.00**	(1.40)	-4.44**	(1.44)
Non-Expressive x Song			4.07*	(1.61)	4.20**	(1.58)	3.90*	(1.61)
Expressive x SP w/ Phrase x Song			0.12	(0.26)	0.08	(0.25)	0.18	(0.26)
Non-Expressive x SP w/ Phrase x Song			-0.51	(0.32)	-0.56	(0.32)	-0.48	(0.32)
Expressive x SP^2 w/ Phrase x Song			0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			0.01	(0.01)	0.02	(0.01)	0.01	(0.01)
Expressive Features								
Loudness of Performance [RMS Zscore]					-0.04	(0.16)	-0.01	(0.16)
Tempo [Zscore]					-1.24***	(0.16)	-1.26***	(0.16)
Melodic Contour [Zscore]					0.07	(0.13)	0.03	(0.14)
Loudness x Tempo							0.30*	(0.14)
Loudness X Melody							0.2	(0.13)
Tempo x Melody							0.12	(0.13)
Loudness x Tempo x Melody							-0.1	(0.13)
Goodness of Fit								
Deviance	24698.07		24642.76		24592.5		24577.08	
AIC	24778.07		24738.76		24694.5		24687.08	
BIC	25024.95		25035.02		25009.27		25026.53	
Chi-square (df)	- (40)		55.31*** (48)		50.27***(51)		15.42** (55)	

***p < .001, **p < .01, & * p < .05



Rochut 13. Less Structured   Rochut 4. More Structured

Figure 21. Model.Dy4 Fixed Effects of % Determinism within Musical Phrases Both Songs.

Stability: Mean Line of ML Postural Sway

Overview. Table 8 shows the result of hierarchically nested models for the mean line (MeanL) of the recurrence of ML postural sway. Figure 22 shows the effect of serial position within a phrase as a function of performance style, separately for each song.

In order to control for the effects of recurrence and make it possible to draw conclusions about the mean line that are independent of recurrence, the mixed effects models included recurrence as a predictor. The table presents values that are multiplied by 10 because some of the effects were small. The figure is displayed with actual mean line values. These values represent the number of data points that form a line on average. They can, therefore, be understood as a measure of the mean time that the performers engaged in a particular stable pattern. Mean line values can be converted to time by dividing by the sampling rate (34 Hz) to give time in seconds. For example, a mean line of 4 represents an average recurrence lasting 118ms, the time required to play a single 8th note. In sum, higher mean line values reflect longer lasting, and thus more stable, recurrent body movement patterns.

Performance style. There was more stability in expressive performances in the first two models, but the effect became smaller and non-significant in later models that included the expressive features. The change suggests that stability is a product of playing expressively. This interpretation is consistent with the fact that there was significantly less stability in non-expressive performances. The size of the effect nearly doubled in the models that contained the interactions with the song selection, indicating that it was mainly due to one of the two songs.

Song selection. There was a main effect for song selection. On average, the more structured music was less stable.

Performance style x song selection. There was significant improvement of Model.Mx2 over Model.Mx1. The improvement was due the interaction of performance style and song selection. As seen in Figure 22, the normal and expressive performances were more stable than non-expressive performances and this difference was twice as large for the less structured than for the more structured song. In contrast, non-expressive performances were equally stable in both songs.

Serial position within phrases. There was no main effect of serial position within a phrase and the two-way interactions of serial position with song selection and performance style were also not significant. There was, however, a three-way interaction between these predictors. As Figure 22shows, the serial position function for the non-expressive performances of the less structured song was significantly arched; there was less stability at the starts and ends of phrases.

Expressive features. The addition of the expressive features in Model.Mx3 improved the model fit, but the addition of their interactions in Model.Mx4 did not result in further improvement. The significant effects of loudness and tempo in both models indicate that both of these expressive features were related to stability, as suggested above. Louder and faster performances were *less* stable in their patterns of recurrence than quieter and slower performances.   Since both tempo and loudness were entered in to the model as Z-scores, we can directly compare their effect sizes and we can see that tempo had a much more robust effect on stability than loudness.

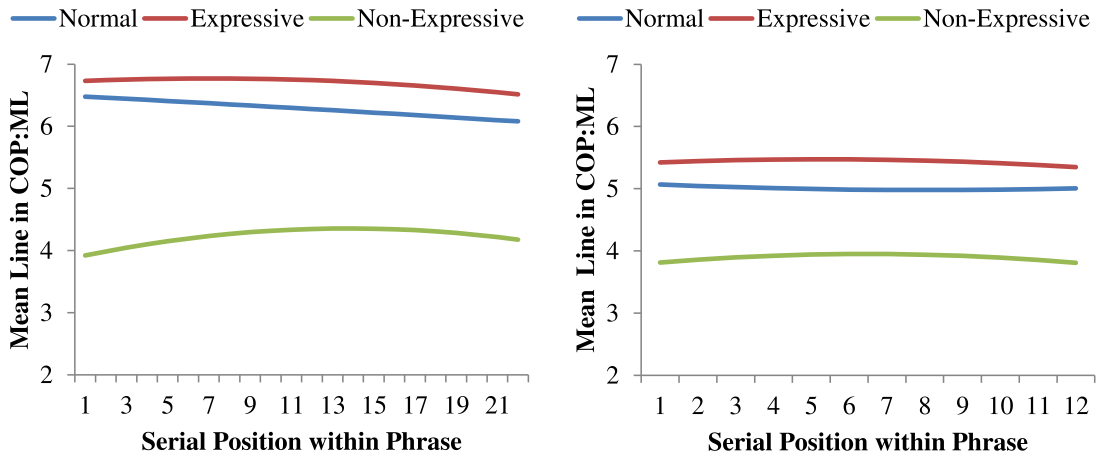
These effects reinforce the suggestion made five paragraphs earlier that stability is a product of expressive playing. Here we see the nature of the connection in more detail. Louder playing and faster tempi produced less stable patterns of ML movement; softer playing and slower tempi produced more stability. As noted above, adding loudness and tempo in the third and fourth models strongly diminished the effect of playing more expressively. This is the first time, in this entire series of analyses, that an expressive feature has had such an effect on another predictor. This unusual result means that the effect of playing more expressively, i.e., more stability, may be attributed, more precisely, to the fact that when playing more expressively the musicians played more softly and, most especially, more slowly.

Table 8.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Mean Line of COP: ML.

MeanL COP: ML [x10]	**Model.Mx1**		**Model.Mx2**		**Model.Mx3**		**Model.Mx4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	59.09***	(2.34)	59.72***	(2.68)	64.66***	(2.29)	64.45***	(2.17)
% Recurrence	1.53***	(0.03)	1.53***	(0.03)	1.55***	(0.03)	1.55***	(0.03)
Expressive Performance	5.72***	(1.66)	5.71**	(2.18)	2.06	(2.05)	2.19	(1.85)
Non-Expressive Performance	-16.20***	(2.53)	-27.78***	(3.14)	-26.29***	(2.70)	-25.96***	(2.67)
Serial Position within Phrase	0.17	(0.10)	0.12	(0.24)	-0.19	(0.26)	-0.15	(0.16)
Serial Position^2 within Phrase	0.00	(0.00)	-0.01	(0.01)	0.00	(0.01)	0.00	(0.00)
Song [Structured]	-5.58*	(2.45)	-6.74*	(3.25)	-13.89***	(2.66)	-13.27***	(2.59)
Expressive x SP w/ Phrase	0.08	(0.16)	0.13	(0.31)	0.31	(0.32)	0.25	(0.19)
Non-Expressive x SP w/ Phrase	-0.05	(0.23)	0.59	(0.32)	0.94**	(0.31)	0.90**	(0.30)
Expressive x SP^2 w/ Phrase	-0.01*	(0.01)	0.00	(0.01)	-0.01	(0.01)	-0.01**	(0.00)
Non-Expressive x SP^2 w/ Phrase	0.00	(0.01)	-0.01	(0.01)	-0.03**	(0.01)	-0.03**	(0.01)
Song x SP w/ Phrase			-0.21	(0.41)	-0.16	(0.40)	-0.4	(0.35)
Song x SP^2 w/ Phrase			0.02	(0.02)	0.02	(0.02)	0.03*	(0.01)
Expressive x Song			-0.44	(2.75)	0.6	(2.59)	1.03	(2.43)
Non-Expressive x Song			13.78***	(2.97)	12.60***	(2.76)	12.24***	(2.75)
Expressive x SP w/ Phrase x Song			0.44	(0.53)	0.35	(0.51)	0.25	(0.44)
Non-Expressive x SP w/ Phrase x Song			0.06	(0.60)	-0.05	(0.56)	0.00	(0.55)
Expressive x SP^2 w/ Phrase x Song			-0.04*	(0.02)	-0.04	(0.02)	-0.03*	(0.02)
Non-Expressive x SP^2 w/ Phrase x Song			-0.04	(0.02)	-0.03	(0.02)	-0.03	(0.02)
Expressive Features								
Loudness of Performance [RMS Zscore]					-0.86**	(0.26)	-0.86**	(0.27)
Tempo [Zscore]					-6.80***	(0.27)	-6.83***	(0.27)
Melodic Contour [Zscore]					0.39	(0.22)	0.33	(0.23)
Loudness x Tempo							0.37	(0.23)
Loudness X Melody							0.32	(0.22)
Tempo x Melody							-0.14	(0.23)
Loudness x Tempo x Melody							-0.01	(0.21)
Goodness of Fit								
Deviance	28983.84		28868.62		28293.42		28290.53	
AIC	29063.84		28964.62		28395.42		28400.53	
BIC	29310.72		29260.87		28710.19		28739.98	
Chi-square (df)	- (40)		11522*** (48)		575.20*** (51)		2.89 (55)	

***p < .001, **p < .01, & * p < .05



Rochut 13. Less Structured

Rochut 4. More Structured

Figure 22. Model.Mx4 Fixed Effects of Mean Line within Musical Phrases Both Songs.

Stability: Mean Line of AP Postural Sway

Overview. Table 9 shows the result of hierarchically nested models for the mean line (MeanL) of the recurrence of AP postural sway. Figure 23 shows the effect of serial position within a phrase as a function of performance style, separately for each song.

Performance style. There were no differences between the performance styles.

Song selection. There was a main effect for song selection. On average, the more structured song was less stable.

Performance style x song selection. There was no interaction between performance style and song selection.

Serial Position within phrases & Interactions with phrases. There was significant improvement of Model.My2 over Model.My1. Since there was no main effect of serial position within a phrase and two-way interactions of serial position with song selection and performance style were not significant, the improved fit can be attributed to the three-way interaction of these predictors. Figure 23 shows that for non-expressive performances of the more structured song, the serial position function was lower and had a more negative slope for the less structured than for the more structured song.

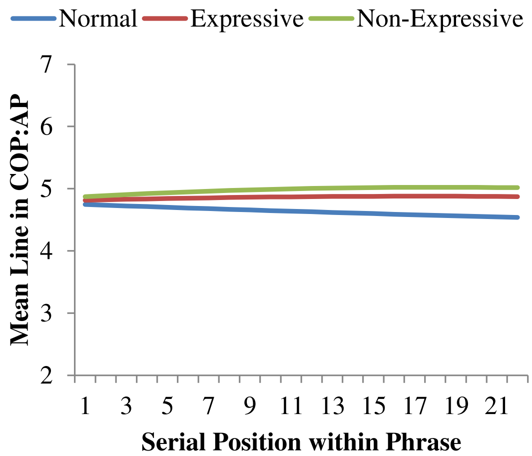
Expressive features. The addition of the expressive features in Model.My3 improved the model fit, but the addition of their interactions in Model.My4 did not result in further improvement. The significant effects of tempo in both models indicate that stability increased as tempo decreased, as was also the case for ML sway.

Table 9.

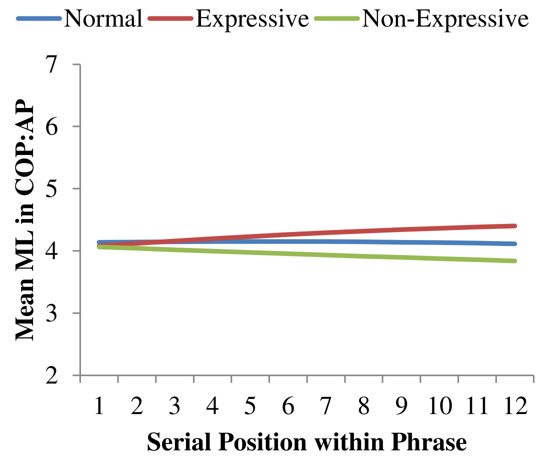
Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Mean Line of COP: AP.

MeanL COP: AP [x10]	**Model.My1**		**Model.My2**		**Model.My3**		**Model.My4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	47.60***	(1.04)	47.31***	(0.86)	47.53***	(1.06)	47.47***	(1.07)
% Recurrence	0.92***	(0.02)	0.90***	(0.02)	0.91***	(0.02)	0.91***	(0.02)
Expressive Performance	0.17	(0.95)	1.02	(1.08)	0.43	(1.15)	0.48	(1.15)
Non-Expressive Performance	-1.02	(1.39)	0.53	(1.57)	0.91	(1.66)	0.95	(1.66)
Serial Position within Phrase	-0.06	(0.08)	-0.13	(0.07)	-0.12	(0.10)	-0.12	(0.10)
Serial Position^2 within Phrase	0	(0.00)	0	(0.00)	0	(0.00)	0	(0.00)
Song [Structured]	-6.11***	(0.76)	-5.70***	(1.33)	-6.36***	(1.41)	-6.29***	(1.41)
Expressive x SP w/ Phrase	0.27**	(0.09)	0.16	(0.10)	0.21	(0.12)	0.20	(0.12)
Non-Expressive x SP w/ Phrase	0.12	(0.14)	0.29	(0.17)	0.31	(0.19)	0.30	(0.19)
Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Non-Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Song x SP w/ Phrase			0.3	(0.22)	0.21	(0.22)	0.2	(0.22)
Song x SP^2 w/ Phrase			-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Expressive x Song			-1.31	(1.51)	-1.4	(1.54)	-1.41	(1.54)
Non-Expressive x Song			-1.06	(1.72)	-1.33	(1.74)	-1.37	(1.74)
Expressive x SP w/ Phrase x Song			0.09	(0.27)	0.16	(0.28)	0.16	(0.28)
Non-Expressive x SP w/ Phrase x Song			-0.70*	(0.34)	-0.63	(0.35)	-0.63	(0.35)
Expressive x SP^2 w/ Phrase x Song			0	(0.01)	0	(0.01)	0	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			0.02	(0.01)	0.02	(0.01)	0.02	(0.01)
Expressive Features								
Loudness of Performance [RMS Zscore]					0.03	(0.17)	0.04	(0.17)
Tempo [Zscore]					-1.16***	(0.17)	-1.15***	(0.17)
Melodic Contour [Zscore]					0.14	(0.14)	0.13	(0.14)
Loudness x Tempo							0.11	(0.14)
Loudness X Melody							0.07	(0.14)
Tempo x Melody							-0.11	(0.14)
Loudness x Tempo x Melody							-0.11	(0.13)
Goodness of Fit								
Deviance	25149.53		25119.18		25049.27		25046.9	
AIC	25229.53		25215.18		25151.27		25156.9	
BIC	25476.4		25511.44		25466.04		25496.35	
Chi-square (df)	- (40)		30.34*** (48)		69.9*** (51)		2.37 (55)	

***p < .001, **p < .01, & * p < .05



Rochut 13. Less Structured



Rochut 4. More Structured

Figure 23. Model.My4 Fixed Effects of Mean Line within Musical Phrases Both Songs.

Orderliness: Entropy of ML Postural Sway

Overview. Table 10 shows the result of hierarchically nested models for the percentage of entropy (%ENT) in the recurrence of ML postural sway. Figure 24 shows the effect of serial position within a phrase as a function of performance style, separately for each song. In order to control for the effects of recurrence and make it possible to draw conclusions that are independent of recurrence, the mixed effects models that follow in this chapter all include recurrence as a predictor, ensuring that any effects, in this case for entropy, are independent of those for recurrence. Higher entropy levels reflect a more complex system.

Performance style. There was more entropy in expressive performances, but the effect was not significant until the addition of the expressive features and their interactions in Model.Ex3-Ex4. There was less significantly less entropy in non-expressive performances and the effect size doubled in the models that contained the interactions with the song selection.

Song selection. There was a main effect for song selection. On average, entropy was lower in the more structured than in the less structured song.

Performance style x song selection. There was significant improvement of Model.Rx2 over Model.Rx1 due to the interaction of song selection and performance style. For non-expressive performances, entropy was higher for the more structured than for the less structured song. For expressive performances, there was no difference between the two songs.

Serial position within phrases. There was no main effect for serial position within a phrase. However, the improvement of Model.Ex2 over Model.Ex1 was also due to the significant three-way interaction of serial position with song and performance style, as seen in Figure 24. For the less structured song, the serial position function for expressive performances was U-shaped, indicating more entropy at the beginnings and ends of phrases. For normal and non-expressive performances, there was a positive linear effect. For the more structured song, there was a positive linear slope for expressive performances, a flat line for normal performances, and an arch shaped function for non-expressive performances.

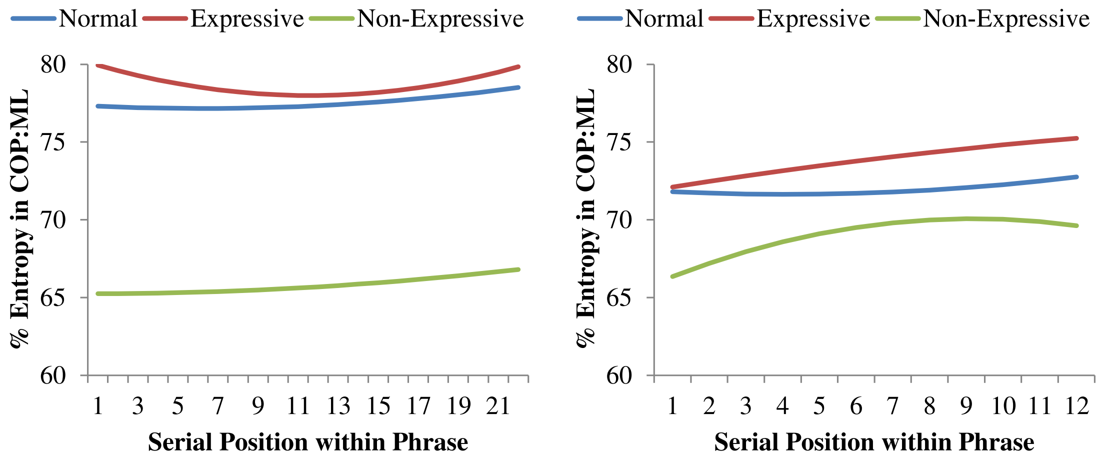
Expressive features. The addition of the expressive features in Model.Ex3 and Model.Ex4 did not improve the model fit. While there was a significant effect for melodic contour, it did not improve the fit. Therefore, the conservative approach to mixed effect modeling suggests discounting the effect as a reliable predictor of entropy.

Table 10.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Entropy of COP: ML.

%ENT COP: ML	**Model.Ex1**		**Model.Ex2**		**Model.Ex3**		**Model.Ex4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	75.93***	(0.89)	77.41***	(1.05)	77.27***	(1.06)	77.26***	(1.03)
% Recurrence	0.72***	(0.02)	0.72***	(0.02)	0.72***	(0.02)	0.72***	(0.02)
Expressive Performance	1.62	(1.24)	2.66	(1.45)	2.92*	(1.46)	2.96*	(1.44)
Non-Expressive Performance	-6.04***	(1.31)	-12.22***	(1.71)	-12.23***	(1.72)	-12.12***	(1.71)
Serial Position within Phrase	0.09	(0.21)	-0.06	(0.23)	-0.06	(0.22)	-0.07	(0.22)
Serial Position^2 within Phrase	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.01	(0.01)
Song [Structured]	-3.89***	(0.89)	-5.82***	(1.61)	-5.40***	(1.64)	-5.42***	(1.63)
Expressive x SP w/ Phrase	-0.1	(0.19)	-0.32	(0.24)	-0.34	(0.24)	-0.33	(0.23)
Non-Expressive x SP w/ Phrase	0.06	(0.16)	0.10	(0.21)	0.07	(0.21)	0.06	(0.21)
Expressive x SP^2 w/ Phrase	0.00	(0.01)	0.01	(0.01)	0.01	(0.01)	0.01	(0.01)
Non-Expressive x SP^2 w/ Phrase	-0.01	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)
Song x SP w/ Phrase			-0.05	(0.28)	-0.09	(0.28)	-0.08	(0.28)
Song x SP^2 w/ Phrase			0.01	(0.01)	0.01	(0.01)	0.01	(0.01)
Expressive x Song			-2.9	(1.77)	-3.11	(1.76)	-3.17	(1.75)
Non-Expressive x Song			5.78**	(1.87)	5.64**	(1.87)	5.56**	(1.87)
Expressive x SP w/ Phrase x Song			0.81*	(0.36)	0.86*	(0.36)	0.87*	(0.35)
Non-Expressive x SP w/ Phrase x Song			1.05**	(0.38)	1.10**	(0.38)	1.11**	(0.38)
Expressive x SP^2 w/ Phrase x Song			-0.04*	(0.01)	-0.04*	(0.01)	-0.04*	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			-0.07***	(0.02)	-0.07***	(0.02)	-0.07***	(0.02)
Expressive Features								
Loudness of Performance [RMS Zscore]					-0.05	(0.18)	-0.07	(0.18)
Tempo [Zscore]					0.29	(0.18)	0.29	(0.19)
Melodic Contour [Zscore]					0.36*	(0.15)	0.33*	(0.15)
Loudness x Tempo							0.04	(0.15)
Loudness X Melody							0.17	(0.15)
Tempo x Melody							-0.1	(0.15)
Loudness x Tempo x Melody							0.02	(0.14)
Goodness of Fit								
Deviance	25675.18		25530.42		25522.98		25521.61	
AIC	25755.18		25626.42		25624.98		25631.61	
BIC	26002.06		25922.67		25939.75		25971.06	
Chi-square (df)	- (40)		144.76*** (48)		7.44 (51)		1.37 (55)	

***p < .001, **p < .01, & * p < .05



Rochut 13. Less Structured   Rochut 4. More Structured

Figure 24. Model.Ex4 Fixed Effects of % Entropy within Musical Phrases Both Songs.

Orderliness: Entropy of AP Postural Sway

Overview. Table 11 shows the result of hierarchically nested models for the percentage of entropy (%ENT) in the recurrence of AP postural sway. Figure 25 shows the effect of serial position within a phrase as a function of performance style, separately for each song. In order to control for the effects of recurrence, the mixed effects models include recurrence as a predictor, ensuring that any effects for entropy are independent of those for recurrence. Higher entropy levels reflect a more complex system.

Performance style. There was less entropy in expressive than in normal performances in all models. The same was true for non-expressive performances, after interactions with song selection were added in Model.Ey2.

Song selection. There was a main effect for song selection. On average, the amount of entropy was lower in the more structured than the less structured song.

Performance style x song selection. There was significant improvement of Model.Ey2 over Model.Ey1. For non-expressive performances, entropy was higher for the more structured than for the less structured song. For expressive performances, there was no difference between the two songs.

Serial position within phrases. There was no main effect for serial position within phrase in Model. Ey1 or Ey2. However, the improvement between Model.Ex2 over Model.Ex1 was also due to the significant effect three-way interaction of serial position with song and performance style, as seen in Figure 25. The slopes of the serial position functions were different for the two songs, significantly so for non-expressive performances. For non-expressive performances, complexity decreased over the course of the phrase in the more structured song but not in the less structured song.

Expressive features. The addition of the expressive features in Model.Ey3 improved the model fit, but the addition of their interactions in Model.EY4 did not result in further improvement. The significant effects of tempo in both models indicate that tempo and entropy were related; faster performances were more complex in their recurrence.

Table 11.

Forward Fitted Mixed Effects Models for Performance Style, Song Selection, Serial Position, and Expressive Features: Entropy of COP: AP.

%ENT COP: AP	**Model.Ey1**		**Model.Ey2**		**Model.Ey3**		**Model.Ey4**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	73.49***	(0.60)	73.96***	(0.70)	73.75***	(0.71)	73.91***	(0.59)
% Recurrence	0.66***	(0.02)	0.66***	(0.02)	0.66***	(0.02)	0.66***	(0.02)
Expressive Performance	-2.51***	(0.69)	-2.35**	(0.89)	-2.19*	(0.89)	-2.11*	(0.84)
Non-Expressive Performance	-0.06	(0.92)	-2.84*	(1.20)	-2.97*	(1.17)	-2.81*	(1.14)
Serial Position within Phrase	-0.06	(0.06)	-0.08	(0.08)	-0.08	(0.08)	-0.09	(0.06)
Serial Position^2 within Phrase	0	(0.00)	0	(0.00)	0	(0.00)	0	(0.00)
Song [Structured]	-4.03***	(0.70)	-5.89***	(1.19)	-5.44***	(1.19)	-5.52***	(1.16)
Expressive x SP w/ Phrase	0.18*	(0.07)	0.11	(0.10)	0.12	(0.10)	0.08	(0.08)
Non-Expressive x SP w/ Phrase	-0.11	(0.12)	0.20	(0.16)	0.18	(0.16)	0.14	(0.15)
Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Non-Expressive x SP^2 w/ Phrase	0.00	(0.00)	0.00	(0.01)	0.00	(0.01)	0.00	(0.00)
Song x SP w/ Phrase			0.3	(0.19)	0.29	(0.19)	0.32	(0.18)
Song x SP^2 w/ Phrase			-0.01	(0.01)	-0.01	(0.01)	-0.02	(0.01)
Expressive x Song			0.16	(1.33)	0.18	(1.33)	0.19	(1.30)
Non-Expressive x Song			5.58***	(1.49)	5.57***	(1.49)	5.33***	(1.46)
Expressive x SP w/ Phrase x Song			0	(0.24)	-0.01	(0.24)	-0.02	(0.24)
Non-Expressive x SP w/ Phrase x Song			-0.86**	(0.30)	-0.85**	(0.30)	-0.81**	(0.29)
Expressive x SP^2 w/ Phrase x Song			0.01	(0.01)	0.01	(0.01)	0.01	(0.01)
Non-Expressive x SP^2 w/ Phrase x Song			0.03*	(0.01)	0.03*	(0.01)	0.03*	(0.01)
Expressive Features								
Loudness of Performance [RMS Zscore]					0.03	(0.14)	0.02	(0.14)
Tempo [Zscore]					0.56***	(0.15)	0.55***	(0.15)
Melodic Contour [Zscore]					0.2	(0.12)	0.18	(0.13)
Loudness x Tempo							0.03	(0.12)
Loudness X Melody							0.06	(0.12)
Tempo x Melody							0.06	(0.12)
Loudness x Tempo x Melody							-0.07	(0.12)
Goodness of Fit								
Deviance	24031.46		24010.73		23994.94		24003.15	
AIC	24111.46		24106.73		24096.94		24113.15	
BIC	24358.34		24402.98		24411.71		24452.61	
Chi-square (df)	- (40)		20.73** (48)		15.79** (51)		0 (55)	

***p < .001, **p < .01, & * p < .05

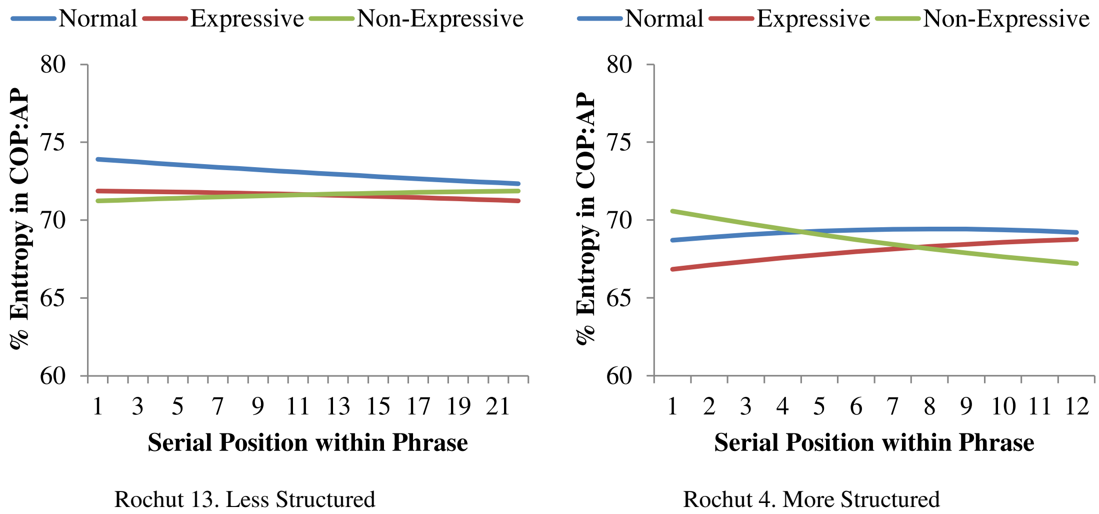


Figure 25. Model.Ey4 Fixed Effects of % Entropy within Musical Phrases Both Songs.

Summary of Results

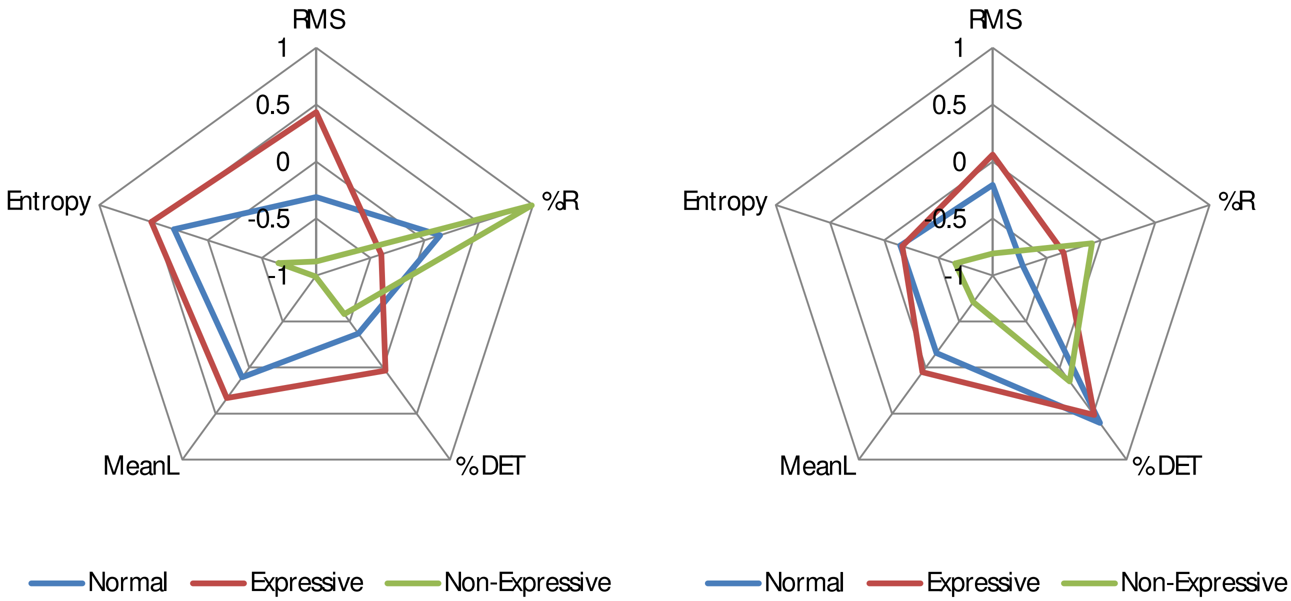
Overview

I will summarize the results of the mixed effect analyses by organizing them into three groupings: First the *intercepts* of the effect of performance style for each song selection; second, the *slopes* for the serial position effects within the phrase for each performance style, for each song selection; third, the effects of the *expressive features.* I will present the three summaries first, and then discuss each in turn.

Intercepts

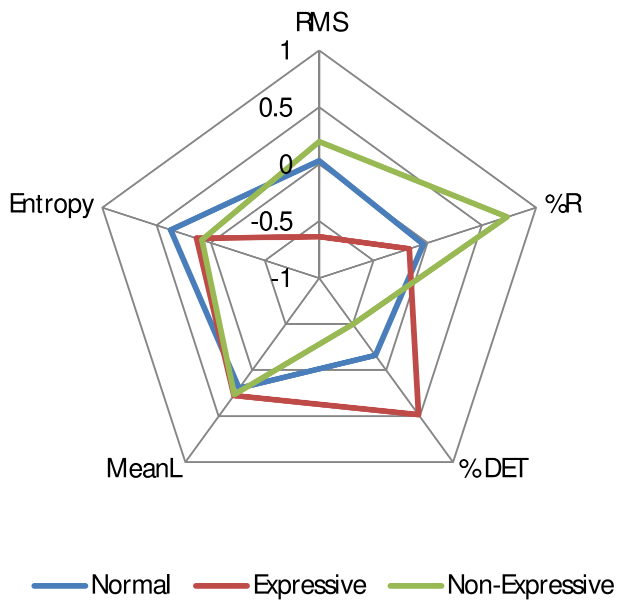
Each of the dependent measures (RMS, %R, %DET, %ENT, MeanL) was scaled differently, making it difficult to compare them directly. To provide a simple visual summary that allows comparison of different measures, I have taken each of the intercepts generated by the second mixed effect model of each measure and converted them to Z-scores. Figure 26 for ML postural sway and Figure 27 for AP postural sway display these Z-score means in a five-dimensional radial plot that include all five measures: RMS, %R, %DET, %ENT, and MeanL.

These visualizations do not provide any new statistical information. Their purpose is to provide a way to visually examine all the dependent measures at the same time.

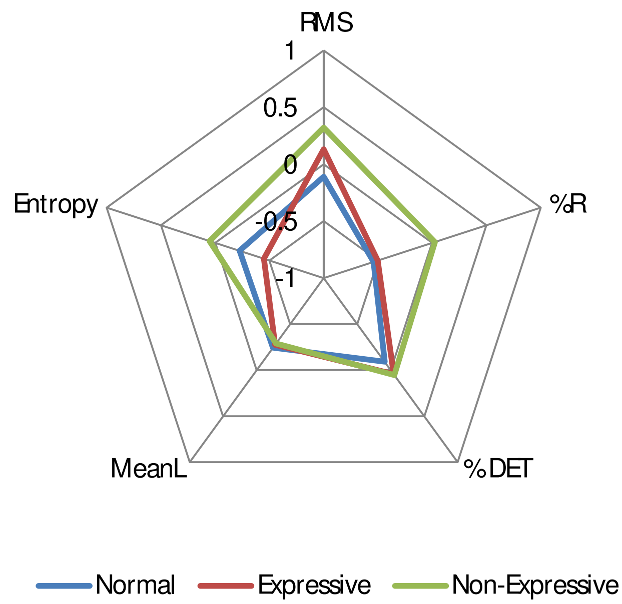


Rochut 13. Less Structured   Rochut 4. More Structured

Figure 26. Mean Z-score values of linear (RMS) and RQA (%R, %DET, %ENT, MeanL) analyses for each performance style, separately for each song: *ML Postural Sway*



Rochut 13. Less Structured



Rochut 4. More Structured

Figure 27. Mean Z-score values of linear (RMS) and RQA (%R, %DET, %ENT, MeanL) analyses for each performance style, separately for each song: *AP Postural Sway*

Slopes

Table 12 summarizes the slopes for each of the five dependent variables (RMS, %R, %DET, %ENT, MeanL) for the second mixed effects model in each analysis for ML and AP postural sway. Each table displays only the significant slopes which are shown separately for each performance styles for each song. Each slope is categorized as one of four types, each represented by a symbol: Positive slope (∕), Negative slope (\ ), Arch (∩), and Inverse arch (∪).

Table 12.

Summary of significant slopes from the 2nd mixed effect models of linear (RMS) and RQA (%R, %DET, %ENT, MeanL) analyses, separately for each song and for each performance style, and for both directions of postural sway (ML & AP)

Slopes within phrases		**Rochut 13. Less Structured**					**Rochut 4.More Structured**				
		RMS	RR	Ent	DET	MeanL	RMS	RR	Ent	DET	MeanL
COP: ML	Normal Perf		∪					∩			
	Exp Perf		/				\		∩		
	Non-Exp Perf		∪				/	∩	∩		
COP: AP	Normal Perf	∩									
	Exp Perf	\						\			
	Non-Exp Perf								∪		\

Expressive Features

Table 13 provides a summary of the significant effects of the expressive features: tempo, loudness, and changes in melodic contour. A positive effect, represented as (+), means that increases in the expressive feature were positively related to the dependent measure, each of which is shown separately for each direction of postural sway (RMS, %R, %DET, %ENT, MeanL). A negative effect, represented as (-), means the opposite. The significant effects shown in the table were extracted from the fourth model in each analysis.

Table 13.

Summary of significant effects of Expressive Features from the 4th mixed effect model of linear (RMS) and RQA (%R, %DET, %ENT, MeanL) separately for each song and for each performance style, and for both directions of postural sway (ML & AP)

	ML Postural Sway					**AP Postural Sway**				
Expressive Features	RMS	RR	Ent	DET	ML	RMS	RR	Ent	DET	ML
Loudness		+			–					
Tempo				–	–	+	+	+	–	–
Melodic Contour		+	+							
Loudness x Tempo	+								–	
Loudness X Melody		–								
Tempo x Melody		+								
Loudness x Tempo x Melody	–	–		+						

Discussion

These results provide the most complete and conclusive demonstration yet of the widely held belief that musicians' movements while playing are related to the musical structure that they play (Davidson, 2009; MacRitchie et al., 2013; Palmer et al., 2009; Wanderley, 2002; Wanderley et al., 2005). The most important feature of the present results was the relationship between the recurrence and the serial position in the phrase as well as the differences between the songs for this pattern. The orderly nature of these complex effects strongly suggests that musicians' movement is the product of a dynamical system and that changes in the musical context change the relationship to the musical structure. Further, the results demonstrate that movements are systematically related to the musician's stylistic intentions (performance style), the nature of the music played (song selection), musical properties such as formal structure (serial position within a phrase) and melodic contour, and that the effects of all of these interact and have different effects depending on the direction of the movement.

Not surprisingly, the results are complex. The main point, however, is not any specific relationship but the demonstration of the kind of complex web of relationships expected of a complex system. The existence of these relationships provides the necessary foundation for Experiments 2 and 3 in which I examine the effect of musicians' movements on listeners. It is, of course, encouraging that many of the relationships make intuitive sense, and in the following sections I provide a brief overview of some of the most interesting results.

Linear Analysis

The root mean square has been one of the primary methods used in examining the movements of musicians in performance (e.g., Thompson & Luck, 2011; Wanderley et al., 2005). While AP movements reflect a very uninteresting pattern, this method showed that the most interesting changes in the ML movements. As has been documented before (Davidson 2009; Wanderley et al., 2005), in the non-expressive performance musicians moved less. Musicians did not always move more in the expressive performances; the amount of it depended on the song selection.

While this analysis does not give any information as to the actual patterns of body sway that occurred, it does suggest that the performer must adopt different strategies of movement relative to different musical selections. This investigation is possible specifically because of the flexibility mixed effect models. These models allow each phrase to have a different length, something impossible in traditional regression. Further, it does not require we look for statistical differences in the mean RMS measure by measure (as in Thompson & Luck, 2011), inflating the type I error rate. Instead, we can examine reliable differences in non-linear slopes and intercepts concurrently between performances, musicians, and songs.

RMS only provides a limited view of body movements in performance as it only looks at whether the movements changed to be more or less in amplitude. This method cannot be used to examine the patterns and stability of those patterns over time; this is what the RQA analyses provide.

Dynamical Systems Measures

Recurrence quantification analysis provides a new way to examine how patterns of body movement are self-similar and change overtime. This method does not require the researcher to define a priori what constitutes a pattern or all the possible patterns. Instead, the movements are examined for self-similarities at all size scales simultaneously. I have applied this analysis to postural sway, but any movement of the body can be examined in the same way. In addition to recurrent patterns, this analysis simultaneously provides information about the stability, predictability, and orderliness of the system under investigation. This analysis provided some new insights into how the performer's sway was reliably related to musical structure and expressive features of the performance.

Regardless of the song, the ML movements for the expressive performance tended to be the most variable (RMS), most complex (Entropy), yet also most stable (MeanL) and most predictable (%DET), but least recurrent (%R). Non-expressive performance was the complete opposite of expressive performance on each measurement: less variable, less complex, less sable, less predictable, and more recurrent. However, there seems to be a balancing act occurring between ML and AP, in terms of both variability (RMS) and entropy. When the performer sways more in the ML direction, their AP sway is more suppressed and less complex. Further, when a performer suppresses their ML sway, their AP sway becomes more variable and more complex. This balancing act is characteristic of the kind of trading off between stability and flexibility that is the defining feature of a synergy. As the performer suppresses one type of sway, the other becomes more variable. This the same type of behavior seen in the sound-producing gestures of cellists (Winold et al., 1994). For cellists, the constraint on their bow arm movements was speed. In this case, the two directions of postural sway for the standing performer are constrained by the performer's expressive intentions. The expressive intentions of the performer also affected the way they swayed relative to the musical form.

The difference in the musical structure resulted in differences in the recurrence of sway patterns. Normal performances of more structured music showed an arch pattern, while the less structured music showed an inverted arch. In other words, in more structured music, there was a greater likelihood for the performers ML movements to be less similar at the starts and ends of phrases. While in less structured music, there was more ML similar at the starts and end of phrases. Why the differences between the two types of music?

Possibly, when phrases are closer together (more structured music) musicians use novel movements to denote the new phrases in order to draw attention to them. As phrases occur more often, it might be artistically ugly and boring for the audience if the musicians repeatedly used the same movement patterns so often and so close together in time. Highly repetitive movements are the hallmark of certain types of disorder. On the other hand, when the time to complete a phrase was longer, the musicians adopted a different strategy and repeated their movements more at the starts and ends of phrases. This strategy may optimize the chances that audience will be able use the musician's body movements to parse the music they are hearing by seeing the performers actions. Therefore, the musical form is related to the movements of the body, but there is no 1:1 correspondence between them. The relationship between the patterns of body movements and the musical form are systematic, but are dependent on the musical context. This suggests that one of the main parameters governing the recurrence of movement patterns is the length of the musical phrase.

Change in the expressive intentions of the performer was another parameter that governed the performers' sway patterns relative to the musical form. Removing expression helped make clearer the pattern seen in the normal performance style, while adding extra expression changed the pattern so that there was little difference as the phrase unfolded. However, changing the expression—either less or more—changed the complexity of the body movements. At the starts and ends of phrases, the performers' movements become less complex than in the middle of phrases. So, for non-expressive performance, where they do not move much, they do repeat patterns, but less complex ones. In expressive performance, the musicians do not repeat patterns, but do change their movements to make them less complex. The reduction in complexity may be a way to signal to the audience, i.e., to use changes in their sway patterns to highlight the musical structure. Finally, these effects are independent of movement variability, as the performer gets more variable towards the ends of phrase in non-expressive performance, but less variable in expressive ones. The AP sway patterns do not really change relative to musical form as did the ML sway patterns.

AP sway is most strongly related to the speed of the performer. When the performers play faster, they become more variable, yet more recurrent, more complex, but less predictable and stable. Tempo also was related to ML sway in that faster playing resulted in less predictable and stable movements. In terms of loudness, for ML sway, the performer became more recurrence but less predictable. Why is faster speed and louder playing related to increases in recurrent body patterns while also being less predictable? One possibility is that tempo and loudness reflect changes in the expressive intentions of the performer. When the music gets more exciting, the movements of the body become less predictable but more similar. It is like watching an excited Greek or Italian person engage in a conversation. As they get more excited they use more hand gestures and repeat them more often, but they become harder to predict because the person becomes more chaotic, switching between gestures more often.

Tempo and loudness are created by the performer, but the melodic contour comes from the composer. Change in melodic contour increased both recurrence and complexity, but the amount of recurrence was also affected by how changes in melodic contour related to tempo and loudness. When all three interacted, it resulted in lower recurrence but higher predictability. This likely occurred because melodic changes that co-occur with changes in loudness and tempo occur at musically important locations, like phrase endings and musical climaxes. At these places, the musician is likely to do something novel but predictable in ML sway.

Chapter 8: Results & Discussion for Experiment 1: Reliability and Measurements of the Movement System

Overview

This chapter examines the reliability of the movements of the performers with respect to both themselves and the other performer. In addition, I introduce techniques for describing movement that are new in the field, such as periodicity, rhythmicity, and long- both term correlations.

Phrasing of the Performance

Review of methods, measures & analyses. To evaluate how the performers chose to parse the musical form in each performance style, I examined the number of phrases they reported and whether the phrases occurred at musical form boundaries. This analysis was conducted separately for each performer and for each song. As described in Chapter 6, Rochut 4, the more structured song, had an ABA form and three levels of boundaries (L1-L3, highest to lowest respectably). Rochut 13, the less structured song, was through composed (less repetitive structure) and had two levels of boundaries. Below, I describe the results for each song in turn.

Rochut 4. Table 14 shows the number of phrases into which the performers parsed the musical score for Rochut 4. Table 14 shows that Performer 1 parsed the scores into more phrases than Performer 2 overall, $t(10) = 3.79$, $p < .05$. However, Performer 2 was more likely to start his phrases at one of the 12 musical boundaries present in the musical form, $t(10) = 2.43$, $p < .05$. Performer 1, on the other hand, marked so many phrase starts in each performance he was more likely to further segment the L3 form into smaller units.

Table 14.

Number of Phrase Boundaries and Percentage Phrase Boundaries Co-occurring with Musical Form (L1, L2, & L3) in Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances by Two Performers: Rochut 4.

		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*
Number of Phrases	Performer 1	12	13	17	16	23	24
	Performer 2	8	8	14	5	8	8
% of Phrase Starts at Musical Form (L1-L3)	Performer 1	100.00%	92.31%	70.59%	75.00%	47.83%	50.00%
	Performer 2	100.00%	100.00%	78.57%	100.00%	100.00%	100.00%

Table 15 shows what percentage of each of the levels of musical form were marked as phrase starts by each of the performers. As can be seen in Table 15, both performers started phrases at nearly all of the L1 and L2 boundaries. However, Performer 2 was more likely to not start a phrase at a L3 boundary. The reason for this was that Performer 2 only used 8.5 phrases per performance on average and there were seven L1 and L2 boundaries. Performer 1 on the other hand, marked all of the L3 boundaries.

Table 15.

Percentage of Phrases Starting at Three Levels of Musical Form (L1, L2, & L3) in Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances by Two Performers: Rochut 4.

		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*
% L1 Form Marked as Phrase start	Performer 1	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	Performer 2	100.00%	100.00%	100.00%	60.00%	100.00%	100.00%
% L2 Form Marked as Phrase start	Performer 1	100.00%	100.00%	100.00%	100.00%	50.00%	100.00%
	Performer 2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% L3 Form Marked as Phrase start	Performer 1	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	Performer 2	20.00%	20.00%	80.00%	0.00%	20.00%	20.00%

Table 16 shows the mean length of phrases in beats. As we would have expected given the number of boundaries marked by Performer 1, he opted for shorter phrases than Performer 2, $t(10) = 4.03$, $p < .01$. The difference occurred, however, mainly for the Expressive and Non-

Expressive styles for which Performer 1 divided each L3 unit into smaller units, reflecting their division into a question and answer, while Performer 2 did not subdivide these L3 units. For the normal performance style, there was very little difference between the two musicians.

Table 16.

Mean Beat Length of Performers' Phrases in Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances by Two Performers: Rochut 4.

		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*
Performer 1	Mean	12.00	11.00	8.94	9.53	6.50	6.22
	SD	1.55	2.76	3.64	3.64	2.37	2.00
Performer 2	Mean	18.86	18.86	10.15	27.50	18.86	18.86
	SD	7.54	7.54	4.36	6.24	6.74	6.74

Rochut 13. Table 17 shows the number of phrases into which each performer divided the music, for Rochut 13. As seen in Table 17, Performers 1 and 2 did not parse the scores differently overall, $t(10) = 1.67$, $p = .12$. However, Performer 2 was more likely to start his phrases at one of the 14 musical boundaries related to the musical form, $t(10) = 2.75$, $p < .05$.

Table 17.

Number of Phrase Boundaries and Percentage Phrase Boundaries Co-occurring with Musical Form (L1, L2, & L3) in Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances by Two Performers: Rochut 13.

		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*
Number of Phrases	Performer 1	12	12	19	18	9	9
	Performer 2	12	12	9	9	9	9
% of Phrase Starts at Musical Form (L1-L2)	Performer 1	83.33%	83.33%	55.56%	58.82%	88.89%	88.89%
	Performer 2	100.00%	100.00%	100.00%	77.78%	100.00%	100.00%

Table 18 shows what percentage of each of the levels of musical form were marked as phrase starts by each of the performers. As can be seen in Table 18, both performers started phrases at all of the L1 boundaries. In contrast, far fewer of the L2 boundaries were used as locations of phrase starts (40-80%), and this was true of both musicians. This is far lower than seen in L2 boundaries for the more structured song, which was nearly 100%. The parsing of the lower level music structure was less consistent for the more free form, through-composed Rochut 13 than for the more repetitive, structured Rochut 4.

Table 18.

Percentage of Phrases Starting at Two Levels of Musical Form (L1, L2, & L3) in Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances by Two Performers: Rochut 13.

		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*
% L1 Form Marked as Phrase start	Performer 1	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	Performer 2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
% L2 Form Marked as Phrase start	Performer 1	70.00%	70.00%	70.00%	70.00%	50.00%	50.00%
	Performer 2	80.00%	80.00%	50.00%	40.00%	50.00%	50.00%

Table 19 shows the mean length of phrases in beats. As we would have expected given that the number of phrases by performers was similar, there was no difference in the mean length of phrases 1, $t(10)$ =.94, p = .37.

Table 19.

Mean Beat Length of Performers' Phrases in Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances by Two Performers: Rochut 13.

		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*
Performer 1	Mean	13.00	13.00	9.35	9.94	17.88	17.88
	SD	4.31	4.31	3.64	3.57	6.36	6.36
Performer 2	Mean	12.00	12.00	16.50	17.88	16.50	16.50
	SD	6.59	6.59	6.55	5.82	6.09	6.09

Discussion

The performers changed their interpretation of the musical structure when they changed their expressive style. It appears that in order to play more or less expressively, the musicians found it necessary to highlight different aspects of the music form. Both musicians adhered the highest-level musical boundaries, but the musicians were less consistent in their parsing the music at lower level boundaries. This is consistent with the findings of Aiello et al. (2004), who found that expert musician listeners segmented the music more similarly at the more important musical boundaries. The new results suggest that the same is true of performers. More important boundaries were always highlighted, while less important boundaries were respected or disregarded, depending on the performer's expressive intentions. This suggests that it may be a mistake to regard musical form as fixed when looking for a relationship between form and movement. Instead, it may be necessary to ask musicians to provide their individual interpretation of the musical structure after each performance. It is possible that the inconsistency of the relationship between form and movement observed in previous studies may be attributable, at least in part, to changes in the interpretation of musical form.

The range of possible interpretations of musical form may also depend on the musical selection. As expected, the more structured song was interpreted more differently by the musicians than the less structured song. The more structured Rochut 4 was more repetitive than the less structured, through-composed Rochut 13, allowing for more possibilities in selecting the level boundary the performer wished to highlight. At the same time, the musicians also respected all three levels of the musical structure more consistently for the more highly structure Rochut 4 than for the less structured Rochut 13. Rochut 4 apparently allowed them more freedom in deciding how deep to parse, but less freedom about where to parse. We will look for effects of these different kinds of interpretive freedom on the body movements of the performers when playing.

Comparison of ML and AP Sway and Loudness for each Performance

Review of methods, measures & analyses. The next four tables show the cross-correlation (lag-0) of ML sway, AP sway, and loudness separately for each piece and each performer. Table 20 and Table 21 show the cross-correlations for Performers 1 and 2 respectively, each playing Rochut 4. Table 22 and Table 23 show the same for Rochut 13. The tables show cross-correlations for both absolute values (*position*) and for differences (derivative or *Δ Position*) for each dependent variable.

Tempo was not included in these analyses because it is on a different time scale (beats) from sway and loudness. The latter were recorded at 34 Hz in continuous (Newtonian) time, while tempo was measured discretely as inter-beat intervals.

Loudness and postural sway probability values were generated using both the random-shuffled (white noise-null) and phase-shuffled (phase-null) surrogate methods in combination with the percentile method (alpha = .05). As described in the Method section, significant effects compared to the white noise-null hypothesis suggest that the two performances share a similar time-dependent structure. A significant effect compared to the phase-null hypothesis suggests the two time-series are phase-locked, at least intermittently, to a greater extent than expected by chance.

Rochut 4. Table 20 and Table 21 show the cross-correlations for Rochut 4 for Performers 1 and 2 respectively. For both performers, sway in the ML and AP directions was significantly related when tested against the white noise null hypotheses. This suggests that ML and AP sway had similar time-depended structures (probably autoregressive). When tested against the phase-null hypothesis, Performer 1 showed only one significant effect (Normal Performance 1). For this performer, ML and AP sway were mostly not phase-locked. Performer 2, on the other hand, showed phase-locking in position, but not in change in position in both the normal and expressive performances. *Where* he moved in ML and AP direction was not independent, but *when* he moved was independent. For example, when he swayed right, he was more likely to move forward. The explanation could be as simple as the positioning his feet. If one foot were slightly behind the other it would cause his ML and AP to be more correlated.

The relationship between loudness and ML sway suggested that both performers' swaying had a similar time-dependent structure. The phase-null testing suggested that there was some form of phase relationship between ML sway and loudness for some, but not all performances. In contrast, AP sway and loudness were generally more strongly related but only in position. This suggests that there was some complex phase coupling in position, but that changes in loudness and change in position were independent and had different time-depended structures (possibly different autoregressive properties). This suggests that, when trombonists play louder, they move their bodies back and to the side, but *when* they do this is less tightly coupled with when they play louder. As I watched them perform, it appeared that this occurred because when they want to play louder they tilted their horns up and, to balance their bodies, shifted their mass to the left. They had already moved on to softer passages before their posture reset to a more normal position, hence the non-significant effect for the change of position/loudness comparison. When they played softer passages, they moved their horns down towards the floor, causing their center of balance to shift forward.

Table 20.

Cross-Correlations Analyses of Comparisons of Center of Pressure Measures (ML & AP Postural sway) and Loudness in the Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances: Rochut 4, Performer 1.

Correlation	dx/dt	N1	N2	E1	E2	NE1	NE2
COP: ML vs COP: AP	Position	-0.46*†	-0.20*	-0.08*	0.17*	-0.03	-0.36*
	Δ Position	0.15*	0.09*	0.14*	0.21*	0.16*	0.15*
COP: ML vs Loudness	Position	-0.39*†	-0.11*	0.03*	-0.12*†	-0.29*†	-0.30*†
	Δ Position	0.04*	0.01	0.03*	0.04*	-0.04*	0.10*†
COP: AP vs Loudness	Position	-0.37*†	-0.20*†	-0.13*†	-0.27*†	-0.23*†	-0.19*†
	Δ Position	-0.03	-0.03	0.02	-0.04*	-0.04	0.05*

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates

Table 21.

Cross-Correlations Analyses of Comparisons of Center of Pressure Measures (ML & AP Postural sway) and Loudness in the Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances: Rochut 4, Performer 2.

Correlation	dx/dt	N1	N2	E1	E2	NE1	NE2
COP: ML vs COP: AP	Position	-0.34*†	-0.65*†	-0.37*†	-0.42*†	-0.24*	-0.29*
	Δ Position	0.14*	0.17*	0.15*	0.15*	0.03	0.03
COP: ML vs Loudness	Position	-0.27*†	-0.34*†	-0.32*†	-0.43*†	-0.20*†	-0.04*
	Δ Position	-0.02	0.01	0.03*	0.02*	-0.03*	-0.01
COP: AP vs Loudness	Position	0.09*†	-0.13*†	-0.17*†	-0.25*†	-0.18*†	0.04*
	Δ Position	-0.04	0.02	0.01	0.01	0.05*†	0.03

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates.

Rochut 13. Table 22 and Table 23 for Rochut 13 showed a slightly different pattern of results from Rochut 4. The relationship between the ML and AP sway was roughly the same as Rochut 4, as was AP sway and loudness. What was most different was the relationship between

ML sway and loudness for Performer 2. In Rochut 4, ML sway and loudness were phase-locked, but for this song they were not. I surmise that the performer's feet were planted differently on the Wii Balanceboard. I would guess the left foot was planted somewhat behind right foot which would cause the performer to need to shift his weight less when he tilted his horn up to play louder.

Table 22.

Cross-Correlations Analyses of Comparisons of Center of Pressure Measures (ML & AP Postural sway) and Loudness in the Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances: Rochut 13, Performer 1.

Correlation	dx/dt	N1	N2	E1	E2	NE1	NE2
COP: ML vs COP: AP	Position	-0.19*	-0.11*	-0.06*	-0.07*	0.20*	-0.15*
	Δ Position	0.08*	0.19*	0.17*	0.13*	0.00	0.1*
COP: ML vs Loudness	Position	-0.06*	0.03*	-0.06*	-0.03*	-0.17*†	-0.14*†
	Δ Position	0.01	0.05*	0.04*	0.02*	0.01	-0.03*
COP: AP vs Loudness	Position	-0.17*†	-0.06*†	-0.03	-0.15*†	-0.1*†	-0.08*†
	Δ Position	-0.02	0.02	-0.01	-0.03	0.03	-0.02

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates

Table 23.

Cross-Correlations Analyses of Comparisons of Center of Pressure Measures (ML & AP Postural sway) and Loudness in the Two Normal (N), Expressive (E) and Non-Expressive (NE) Performances: Rochut 13, Performer 2.

Correlation	dx/dt	N1	N2	E1	E2	NE1	NE2
COP: ML vs COP: AP	Position	0.15*	0.51*†	0.47*†	0.29*	0.06*	0.31*
	Δ Position	0.11*	0.12*	-0.17*	0.08*	0.03	0.01
COP: ML vs Loudness	Position	0.02*	0.07*	0.05*	0.05*	-0.03*	0.09*
	Δ Position	0.02*	-0.01	-0.03*	-0.02*	0.01	0.02*
COP: AP vs Loudness	Position	0.10*†	0.11*†	0.09*†	0.10*†	-0.05*	0.06*†
	Δ Position	0.03	-0.03	0.03	0.02	-0.02	-0.01

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates

Discussion

The most important result in this analysis was that ML and AP sway did not exhibit significant phase-locking in change of position. This means that AP and ML sway are independent ways of measuring expressive body movements in performance for trombone players. Since the two movements are roughly independent, I am justified in examining both movements in looking for a relationship between structure, expression, and movement.

Postural sway, both ML and AP, were related to the sound-producing gesture of making the music louder (or softer) which influenced the position of the performer's body. These are the types of movements referred to by Jensenius et al. (2010) as sound-facilitating gestures; movements that assist in sound-production. Was this the only goal of performer when they shifted their weight to allow them to tilt the horn up to create a louder sound? Could this movement also be an ancillary movement that conveyed expression? Tilting the horn up to make the sound louder, is one of several ways to increase sound level. In a concert hall, raising the horn allows the sound to better fill the concert hall. My performers, however, were playing in the lab, not in a concert hall, but they raised their horns anyway. We cannot know the reason for this and cannot, therefore, make the distinctions between the types of body movement suggested by Jensenius, et al. (2010). It seems likely that this particular movement served a dual function, both conveying expression and increasing loudness.

The relationship between the sound-producing gesture and the postural sway may serve a social purpose as well. Public speakers are taught to stand up straight, head held high, and direct their speech up and out across the room. When speakers are nervous, they tend to drop their heads and speak to the floor using a quite tone. Addressing the room in a confident manner both commands attention and ensures that the message is heard. So too, the musicians in my study followed this same, natural way of addressing the room even though no audience was physically present.

Finally a note of caution for future experiments. I was hesitant to insist that the performers place their feet on the force plate in a predefined manor. Although this freedom made the task more natural for the performer, it may have introduced noise into the data collection and affected the amount of coupling between postural sway and sound-producing gestures.

Comparison of Performance Styles separately for each Musician and each Song

Review of methods, measures & analyses. Table 24 and Table 25 show the cross-correlation between repeated performances of the same piece by the same musician, separately for each performance style. Results for Rochut 4 and 13 are shown separately in Table 24 and Table 25 respectively. The tables show inter-performance lag-0 cross-correlations for tempo, loudness, and ML, and AP sway, and for the difference (derivative) of each dependent variable. Additionally, for ML and AP sway, the tables also show lag-0 cross-recurrence values.

As described in the method section, tempo was measured in musical beats, while loudness and postural sway were measured at 34Hz. To facilitate comparison between these different measures, for this analysis, loudness and postural sway were time-warped to align the musical material in time. Probability values for tempo were generated by traditional bootstrapping procedures using the percentile method (alpha = .05) as they could not be phase-shuffled. For tempo, a significant cross-correlation can be understood in the same way as a Pearson correlation. Loudness and postural sway probability values were generated using both the random-shuffled (white noise-null) and phase-shuffled (phase-null) surrogate methods in conjunction with the percentile method (alpha = .05). As described in the method section, significant effects using the white noise-null hypothesis suggest the presence of similar time-dependent structures in the two performances. Significant effects using the phase-null method suggest that the two time-series are phase-locked, at least intermittently, more than expected by chance.

Table 24 and Table 25 show only comparisons between repeated performances in the same performance style. Appendix B provides an expanded analysis showing all possible comparisons of each individual performance in each performance style.

Expressive Features. As can be seen in Table 24 and Table 25, cross-correlations were quite high for tempo and change in tempo regardless of the performance style. Values were slightly but consistently lower for Performer 2 than for Performer 1. Loudness and change in loudness for the two performances were phase-locked, at least intermittently when the time-series were time-warped. Regardless of song, performers were highly reliable with themselves when they are performing with the same expressive intention.

ML Postural Sway. As seen in Table 24 and Table 25, ML postural sway showed overall much lower cross-correlation between performances of the same style as compared to the tempo or loudness. For position in both songs, normal performance style exhibited phase-lock, and generally, normal performances showed higher reliability than expressive and non-expressive performances, which did not always show phase-lock. The differences were more pronounced in the less-structured music; where expressive and non-expressive performances resulted in cross-correlations nearly 1/3 to 1/2 lower than normal performances. This suggests that performers tended to sway in the same direction more in the normal style. Change in position, on the other hand, showed more similar cross-correlation values between the styles only for Rochut 4. This suggests that the performers tended to move at the same times, but not necessarily in the same direction, and did so more for the more structured than the less structured song.

The cross-recurrence metric nearly mirrored the significance pattern of position, but with one exception, the expressive performance of Performer 2. However, the magnitude of overlap clearly trended in the same direction for both songs unlike the cross-correlation pattern. Normal performances always showed stronger overlap in phase-space than expressive performances, which in turn were always stronger than non-expressive performances. The significant phase-locking in phase-space suggests that the components that made up ML postural sway changed at the same times in different performances by the same musician playing in the same style.

AP Postural Sway. As seen in Table 24 and Table 25, AP postural sway showed overall much lower cross-correlation between performances of the same style as compared to tempo, loudness, or ML sway. For position in both songs, normal performance style exhibited phase-locking except for Performer 1 in Rochut 13, and generally, normal performances showed higher reliability than expressive and non-expressive performances, which did not always show phase-locking. Performer 2 was much more consistent in AP movements, but only for the more structured song. Change in position was more likely to show significant phase-locking than position. This suggests that *when* the performers moved in the AP direction was more similar across performances in the same style than *how* they moved.

Cross- recurrence showed a different pattern from the position or change in position cross-correlation. For the more structured song, both performers showed significant phase-locking for normal and expressive performances, but not for non-expressive performances. This pattern was not replicated for the less structured song, Performer 2 did not show any significant phase-locking, but did show significant cross-correlation for position and change of position cross-correlations. In general, the magnitude of overlap clearly trended in the same direction for both songs just as was evidenced in the ML cross-recurrence analysis.

Table 24.

Summary of Cross-Correlations and Cross-Recurrence for Within Musician Comparisons of the Same Performance Style: Rochut 4.

Rochut 4.	Performer 1			Performer 2		
Inter-Performance	Normal	Exp	Non-Exp	Normal	Exp	Non-Exp
Expressive Features						
Tempo *Xcorr*	0.84*	0.84*	0.84*	0.82*	0.78*	0.67*
Δ Tempo *Xcorr*	0.84*	0.83*	0.87*	0.80*	0.79*	0.71*
Loudness *Xcorr*	0.84*†	0.85*†	0.89*†	0.85*†	0.87*†	0.82*†
Δ Loudness *Xcorr*	0.61*†	0.68*†	0.74*†	0.72*†	0.71*†	0.72*†
COP:ML						
Position *Xcorr*	0.54*†	0.45*†	0.25*	0.53*†	0.61*†	0.49*†
Δ Position *Xcorr*	0.39*†	0.37*†	0.40*†	0.61*†	0.61*†	0.51*†
% Cross-Recurrence	33.45*†	16.47*†	9.24*	46.51*†	30.94*†	24.23*†
COP:AP						
Position *Xcorr*	0.35*†	0.28*	0.28*	0.42*†	0.40*†	0.31*†
Δ Position *Xcorr*	0.18*†	0.29*†	0.45*†	0.37*†	0.36*†	0.32*†
% Cross-Recurrence	17.12*†	10.49*†	9.63*	12.69*†	10.39*†	8.9*

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on IAFFT surrogates.

Table 25.

Summary of Cross-Correlations and Cross-Recurrence for Within Musician Comparisons of the Same Performance Style: Rochut 13.

Rochut 13.	Performer 1			Performer 2		
Inter-Performance	Normal	Exp	Non-Exp	Normal	Exp	Non-Exp
Expressive Features						
Tempo *Xcorr*	0.85*	0.72*	0.75*	0.78*	0.75*	0.76*
Δ Tempo *Xcorr*	0.83*	0.73*	0.81*	0.78*	0.68*	0.80*
Loudness *Xcorr*	0.81*†	0.78*†	0.82*†	0.73*†	0.73*†	0.76*†
Δ Loudness *Xcorr*	0.66*†	0.66*†	0.69*†	0.63*†	0.62*†	0.65*†
COP:ML						
Position *Xcorr*	0.43*†	0.37*†	0.19*	0.44*†	0.29*	0.22*
Δ Position *Xcorr*	0.38*†	0.31*†	0.20*†	0.37*†	0.24*†	0.17*
% Cross-Recurrence	30.22*†	22.47*†	14.08*	38.43*†	24.16*†	17.12*
COP:AP						
Position *Xcorr*	0.42*	0.43*†	0.19*	0.30*†	0.18*	0.09*
Δ Position *Xcorr*	0.26*†	0.27*†	0.37*†	0.11*†	0.13*†	0.23*†
% Cross-Recurrence	14.46*†	10.18*†	8.63*	10.71*	8.45*	10.50*

*p <.05 based on 500 shuffled surrogates. † p <.05 based on IAFFT surrogates.

Discussion

In cross-recurrence analysis, the two signals are examined for overlap in a phase-space allowing components of the system that are nearly orthogonal to be compared concurrently. In other words, once a system is unwrapped in phase-space, if just one orthogonal component is different from the other, there will be no-overlap between the systems regardless of the cross-correlation. Cross-recurrence thus provides a more sensitive analysis of the overlap between two signals than cross-correlation, particularly for more complex systems, i.e., systems with more dimensions (components) and more non-linearity. Here, the results for cross-recurrence and cross-correlation were identical and differences of interest were much clearer for cross-recurrence.

The most important result was that values were higher for normal than for expressive or non-expressive performances, for both ML and AP sway. Swaying movements were more consistent from one performance to another for normal performances, i.e., were less chaotic and more similar. Attempting to add extra expression and to remove expression both decreased stability, resulting in movements that were less similar from one performance to the next, i.e., were more chaotic and more different from one performance to the next.

Non-expressive performances were noisier. We see in these results that removing expression from performance seems to remove a key constraint governing the movements of the body. This finding is understandable within the dynamical systems frame work as well as being consistent with the observations made by Wanderley (2002). If the performers were encoding the movements of their body with musical structure only, we would have expected body movements to be the same in the non-expressive performances as in the normal and expressive performance. This assumes, however, that musical structure and expression are independent. If the musical structure depends on the performer's expressive intentions, as Clarke (1998) suggests, then we might expect non-expressive performances to result in the performers changing their conception of the musical form and their movements. This is the kind of complex interrelationship expected of dynamical system.

Removing a constraint that governs the system opens up the degrees of freedom, and thereby de-stabilizes the body movements. In this case, the constraint that was removed was normal expression. Adding extra expression is not the remedy to stabilize body movements either, as we saw. Adding extra expression can be thought of as adding too much energy into the system. The result may be a reduction in the degrees of freedom for interpretation of musical structure, resulting in increased stability, but that stability is lost because the system becomes overwhelmed by expression. In a self-organizing system, balance must be achieved by regulating the flow of energy into and out of the system (Latash, 2008). Too much energy exchange and the system moves towards chaos. This is why normal performances showed the highest overlap. The performer did not need to constantly pump energy into the system to make it overly expressive, and so was able to maintain a more natural interpretation of the musical structure.

Comparison of Musicians separately for each Performance Style

Review of methods, measures & analyses. Table 26 and Table 27 show separately for each song the inter-performer lag-0 cross-correlations for tempo, loudness, ML, and AP sway between performances of the same style per performer. Further, the table shows the results for the difference (derivative) of each dependent variable. ML and AP sway were also analyzed using lag-0 cross-recurrence.

Analyses for Table 26 and Table 27 parallel Table 24 and Table 25 in the previous section, except that this analysis compares between performers for each performance style. Since each performer played each style two times it made for *four* possible comparisons between performers for each style. The cross-correlation and cross recurrence values in the table represent the mean value for the four comparisons. For these analyses, loudness and postural sway were time-warped to facilitate comparison. Probability values for tempo were generated via traditional bootstrapping procedures using the percentile method (alpha = .05) as they could not be phase-shuffled. Loudness and postural sway probability values were generated using both the random-shuffled (white noise-null) and phase-shuffled (phase-null) surrogates and applying the percentile method (alpha = .05). The superscript number in each table represents the number of comparisons that were significant for each null-hypothesis test. Appendices B and C show the expanded analysis in which all possible comparisons of each individual performance were undertaken, for each dependent variable.

Expressive Features. As be seen in Table 26 and Table 27, the tempo and change in tempo, regardless of style of performance, were not as high as for the within musician comparisons. Musicians differed more for the more structured song than the less structured song, as evidenced by the lower mean cross-correlation tempo values in Rochut 4. Further, in the less structured song, performers were more consistent between the different performance styles than in the more structured song.

Loudness and change in loudness displayed a different pattern from tempo. The overlap between performers for both songs was high and always significant, but not as high as in the within performer analyses. Further, the similarities between performers' loudness was highest in the non-expressive performances. This may have been due the decrease in dynamic variability of the sound production. Unlike tempo, the more structured song showed higher reliability between performers than the less structured song. However, the most structured song had more periods of rest, which may have inflated the cross-correlation values thereby making them difficult to directly compare.

ML Postural Sway. As seen in Table 26 and Table 27, ML postural sway showed overall much lower cross-correlation between performances of the same style than tempo or loudness. The pattern of results were very difference for the more and less structured songs. The more structured song did not always show the same time-dependent structure (white null hypothesis). In fact, for position only 2 of 4 and 3 of 4 comparisons, in the normal and expressive/non-expressive performance styles, respectively, showed the same time-dependent structure. In no case was there any phase-locking between performers for position. However, for normal and expressive performance styles, performers where significantly phase-locked in change of position, but only for the more structured song. The less structure song never showed any phase-locking. This result gives a mixed picture. Regardless of the song, the performers' ML movements were idiosyncratic in *how* they swayed. However, for the more structured song, *when* performers swayed was similar, except in non-expressive performances.

Cross-recurrence analysis showed the highest mean recurrence (overlap in phase-space) for non-expressive performance, but none showed significant phase-locking for both songs. Normal performances were sometimes more similar in phase-space in both time-dependent structures and phase-locking. The cross-correlation and cross-recurrence analysis yielded different patterns of results suggesting they were measuring different aspects of the system, as we saw in the within musicians comparisons. The lack of consistency suggests that performers something showed similar behavior and sometimes made more idiosyncratic movements.

AP Postural Sway. For the more structured music, cross-correlation values between performers was similar to ML sway values. In general, all performances of the same style had the same time-depended structure, again probably autoregressive, but occasionally overlapped in phase for either position or change in position. For the less structured song, they never were related in phase as we saw in ML sway.

The cross-recurrence analysis revealed that the movements did not always have the same time-dependent structure and were never phase-related. This suggests that the AP movements were even more idiosyncratic than ML movements.

Table 26.

Summary of Mean Cross-Correlations and Mean Cross-Recurrence Analyses for Between—Musician Comparisons of the Same Performance Style: Rochut 4.

Rochut 4.	Performer 1 vs Performer 2		
Inter-Performer	Normal	Exp	Non-Exp
Expressive Features			
Tempo *Mean Xcorr*	0.47*$^{(4)}$	0.37*$^{(4)}$	0.16*$^{(3)}$
Δ Tempo *Mean Xcorr*	0.39*$^{(4)}$	0.22*$^{(4)}$	0.09*$^{(1)}$
Loudness *Mean Xcorr*	0.67*$^{(4)}$†$^{(4)}$	0.68*$^{(4)}$†$^{(4)}$	0.72*$^{(4)}$†$^{(4)}$
Δ Loudness *Mean Xcorr*	0.53*$^{(4)}$†$^{(4)}$	0.50*$^{(4)}$†$^{(4)}$	0.60*$^{(4)}$†$^{(4)}$
COP:ML			
Position *Mean Xcorr*	0.07*$^{(2)}$	0.07*$^{(3)}$	0.15*$^{(3)}$
Δ Position *Mean Xcorr*	0.15*$^{(4)}$†$^{(4)}$	0.13*$^{(4)}$†$^{(4)}$	0.05*$^{(3)}$†$^{(1)}$
Mean Cross-Recurrence	12.04*$^{(3)}$†$^{(2)}$	9.07*$^{(4)}$†$^{(1)}$	12.73*$^{(4)}$
COP:AP			
Position *Mean Xcorr*	0.01*$^{(4)}$†$^{(1)}$	-0.15*$^{(4)}$†$^{(2)}$	-0.04*$^{(2)}$
Δ Position *Mean Xcorr*	0.01*$^{(3)}$†$^{(2)}$	-0.07*$^{(4)}$†$^{(2)}$	0.06*$^{(3)}$†$^{(2)}$
Mean Cross-Recurrence	5.59*$^{(1)}$	5.29*$^{(1)}$	7.67*$^{(3)}$

*p <.05 based on 500 shuffled surrogates. † p <.05 based on 500 IAFFT surrogates

*Note: Numbers in () next to each *or † represent the number of comparisons that were significant. The highest possible value is 4.*

Table 27.

Summary of Mean Cross-Correlations and Mean Cross-Recurrence Analyses for Between—Musician Comparisons of the Same Performance Style: Rochut 13.

Rochut 13.	Performer 1 vs Performer 2		
Inter-Performer	Normal	Exp	Non-Exp
Expressive Features			
Tempo *Mean Xcorr*	0.54*(4)	0.58*(4)	0.49*(4)
Δ Tempo *Mean Xcorr*	0.54*(4)	0.46*(4)	0.63*(4)
Loudness *Mean Xcorr*	0.64*(4)† (4)	0.47*(4)† (4)	0.61*(4)† (4)
Δ Loudness *Mean Xcorr*	0.55*(4)† (4)	0.50*(4)† (4)	0.55*(4)† (4)
COP:ML			
Position *Mean Xcorr*	0.07*(2)	0.02*(4)	0.05*(4)
Δ Position *Mean Xcorr*	0.04*(4)	0.06*(4)	0.04*(3)
Mean Cross-Recurrence	8.66*(4)† (1)	8.33*(3)† (1)	13.3*(2)
COP:AP			
Position *Mean Xcorr*	0.05*(4)	0.03*(4)	-0.05*(4)
Δ Position *Mean Xcorr*	-0.01*(3)	0.01*(3)	0.06*(4)† (1)
Mean Cross-Recurrence	9.11*(2)	7.55	8.70*(2)

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates
*Note: Numbers in () next to each *or † represent the number of comparisons that were significant. The highest possible value is 4.*

Discussion

The between-musicians comparisons reveal a very different pattern than the within musician comparisons. When musicians played in the same style, they were likely to perform the expressive features of the music in similar ways, as expected. However, their body movements were very different. Whether the performer swayed left/right or back/forth was relatively idiosyncratic. However, for the more structured song, they tended to move at the same time. Why for the more structured song and not the less structured song? One possibility is how the musicians understand the musical form. It was the more structured music that showed the greatest differences overall in the number of ways they parsed, the score, but not necessarily, in where they marked those boundaries. In the less structured music, the number of parses was not different, but where they parsed the score was more idiosyncratic. Is a difference in their conception of the music form enough to account for the differences in movement?

For ML sway to have overlapped in change of position suggests that overlap was occurring at a much faster-time scale than large-scale musical form. The two pieces also differed in rhythm. Rochut 13 was nearly all 16th notes, while Rochut 4 had a long-short-long rhythmic pattern. This long-short-long pattern may have been reflected in the change patterns of ML sway. The less structured music with the smoother 16th note pattern provided less rhythm variation that could be reflected in the body movements. Body movements may reflect the metaphorical motion that Clarke (2001) suggested are contained in the movements of musicians. Further, for trombonists this motion is contained in the ML sway, not AP sway. The metaphorical motion suggested by the rhythm of the music may be the source of the similarities between the movement patterns of the performers. We will examine this possibility more closely in Experiment 3.

AP sway was very much idiosyncratic to the performer. Where within performer analyses often showed AP movements were often phase-locked, between performer analyses suggest very different time-series structures. The AP direction is the direction more directly related to the movement of the trombone slide. As the performers moved the trombone slide back and forth in the same way to play the same music, we might have expected the performers to move in a more similar pattern for AP than for ML sway. As this was not the case, it suggests that AP movements may play a role in conveying expression in addition to their role in adjusting to the movements of the slide. As the intra-performer analysis showed, performers used their AP sway to convey expressive variation in loudness.

Both cross-recurrence and cross-correlations arrived at the same conclusion, the movements of performers were generally idiosyncratic, but some aspects of metaphorical motion given by the structure of the music may be seen in movements of the body. This supports the conclusions of Davison (2009) and Wanderely et al. (2002). However, the idiosyncratic nature of the body movements does not rule out the possibility that movements are systematically related to the musical structure. Instead performers could be embodying different aspects of the music structure, such musical form and metrical structure. By embodying different aspects of the structure, their movement would be different from each other. The rest of the results for Experiment 1 are devoted to understanding which aspects of the musical structure might be embodied by the performer.

Periodicity of Performers Postural Sway Movements

Review of methods, measures & analyses. Figure 28 shows a Short-Time Fourier Transform (STFT) for Performer 1 playing the first normal performance, where the X-axis represents time and the Y-axis represents the frequency, in Hz, of the oscillation of ML postural sway. As the performer could have exhibited multiple periodicities of movement of postural sway, the colors in the figure represented the strongest periodicity (in red) to no periodicity (in dark blue). This analysis only reflects simple periodic movement (sine wave-like movements). For this particular performance, the musician moved his body at just below .2 Hz for the first 20 seconds and then changed his body movements to be either non-periodic or complexly periodic/chaotic. At 60 seconds, the analysis revels his ML postural sway exhibited two distinct periodicities (about .11 Hz and .22 Hz), which are simple harmonics (ratio of 2:1).

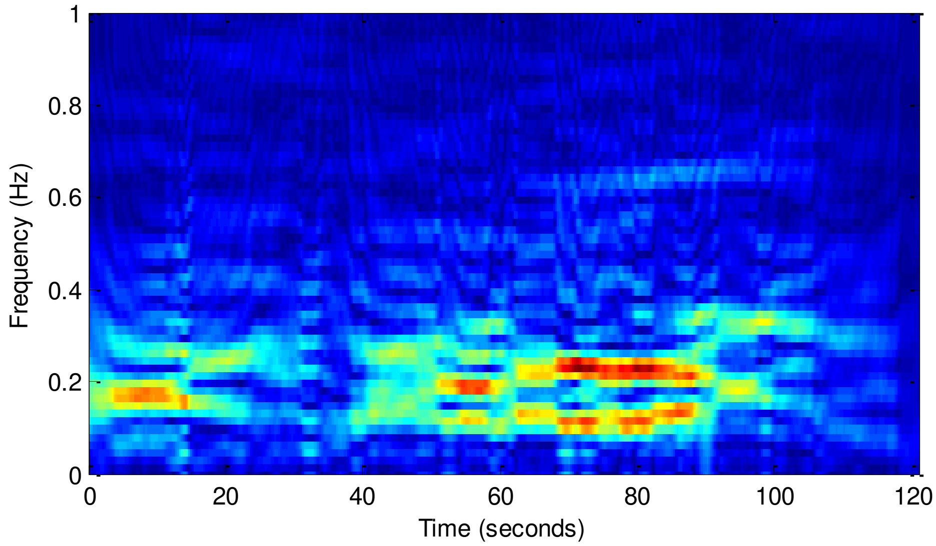


Figure 28. STFT of the Performer 1 First Normal Performance of ML Postural Sway Rochut 4.

Figure 29, for the first non-expressive performance by Performer 1, showed a very different picture. Often he did not move in a simple periodic manner.

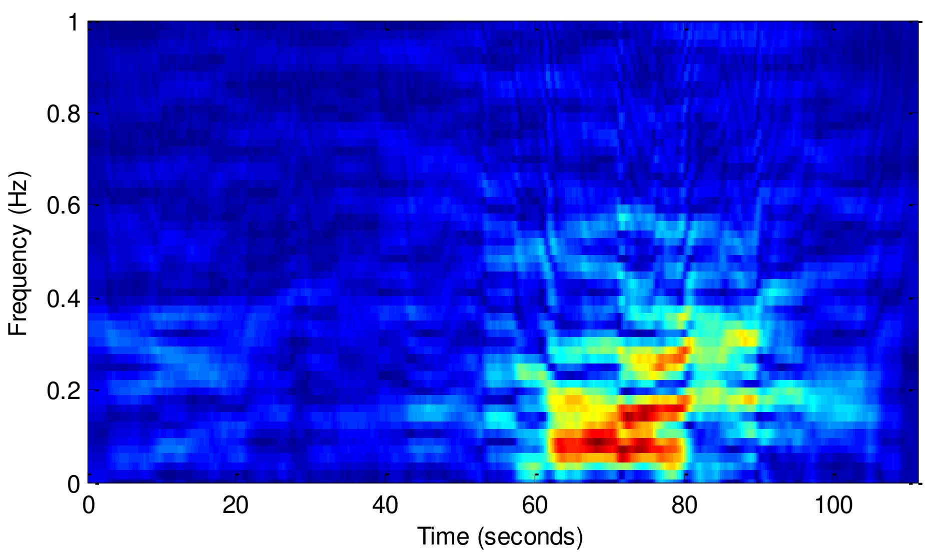


Figure 29. STFT of the Performer 1 Second Non-Expressive Performance of Rochut 4.

The two figures just examined, provide a typical example of the kind of periodic the postural sway of the two performers. It is important to note the ML postural sway was very slowly oscillating and that postural sway may contain multiple concurrent frequencies. The multiple frequency issue will not be explored further in this dissertation.

Exploring these individual performances in this manner, while informative, makes it difficult to quantify the periodicity of the movements. To summarize the STFT results for each performance, the strongest frequency was extracted and averaged within each musical measure. The result was a vector, as long as the number of measures of each song, for each individual performance. The vector represented the peak frequency of sway for each measure. The number of measures in the vector that represented a non-zero period was divided by total number of measures to obtain a percentage of measures where the performer was moving periodically. These values were then analyzed using mixed models to determine the effects of performance style and song on the amount of periodic sway.

Summary of STFT. Table 28 shows a mixed model analysis separately for ML postural sway (COP:ML) and AP postural sway (COP:AP) to examine the results of the mean percentage of periodicity. The model contained the performance style and song selection as both fixed and random factor to give a conservative approach. Figure 30 for COP: ML and Figure 31 for COP:AP represent the averages for each condition, averaged over performer, with standard error bars (errors bars do not reflect mixed effect model fits).

Table 28.

Proportion of Measures of Performers' Postural Sway that Exhibit Periodic Movements in the ML and AP Directions.

	COP:ML		COP:AP	
Fixed Effects	Estimate	SE	Estimate	SE
(Intercept)	0.92***	(0.05)	0.03	(0.02)
Expressive Performance	-0.30	(0.16)	-0.03	(0.02)
Non-Expressive Performance	-0.53***	(0.16)	0.13	(0.08)
Song [Structured]	-0.04	(0.17)	0.27*	(0.12)
Expressive x Song	0.06	(0.24)	0.05	(0.17)
Non-Expressive x Song	-0.15	(0.24)	-0.33*	(0.17)
Goodness of Fit				
Deviance	-6.31		-90.36	
AIC	27.69		-.56.36	
BIC	47.72		-36.33	

ML Postural Sway. Figure 30 shows that performers tended to move periodically for most of the normal performances. They were less periodic in expressive performances and significantly less periodic in the non-expressive performance in contrast with the normal performance.

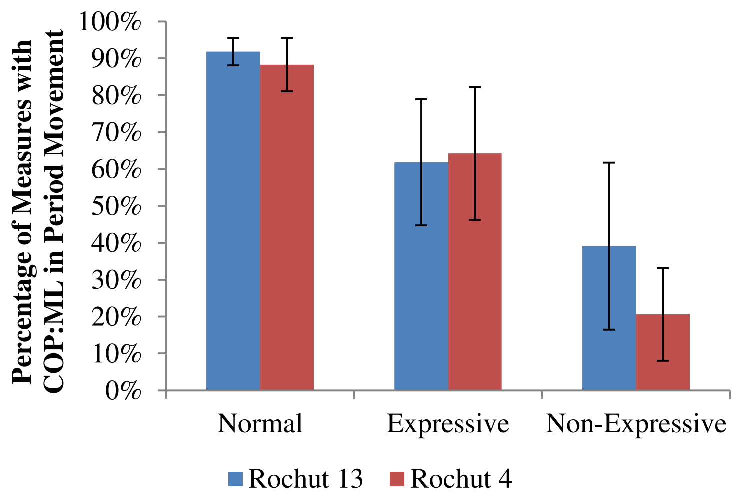


Figure 30. Percentage of Measures with COP:ML Performer Movements that are Periodic.

AP Postural Sway. Figure 31 for AP sway shows that the performers did not move periodically as they did for ML sway. Overall, the amount of periodicity was not different from zero. However, the more structured song did show periodic behavior significantly greater than zero, except in the less structured song for non-expressive performance.

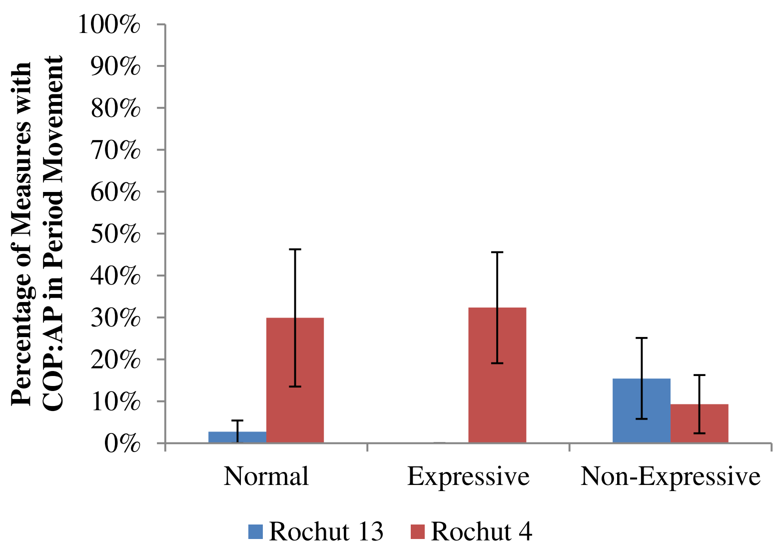


Figure 31. Percentage of Measures with COP:AP Performer Movements that are Periodic.

Overview of Metricality. The movements of the performers for ML postural sway were periodic, but were they related to the musical meter? The vector generated for periodicity analysis was taken and divided by the tempo for each measure. Then those ratios were compared to the expected metrical ratios (London, 2004) shown in Figure 11 in the method section. The number of measures that were 'near' metrical ratios (± .0069) were counted and divided by the total number of measures. The value of .0069 was selected as it was half of the smallest distance between the metrical ratios.

Table 29 shows a mixed model analysis separately for ML postural sway (COP:ML) and AP postural sway (COP: AP) to examine the results of the mean percentage of rhythmicity. The model contained the performance style and song selection as both fixed and random factor to give a conservative approach. Figure 32 for COP: ML and Figure 33 for COP:AP represent the averages for each condition, averaged over performer, with standard error bars (errors bars do not reflect mixed effect model fits).

Table 29.

Proportion of Measures of Performers' Postural Sway that Exhibit an Expected Relationship with the Meter of the Music.

	COP:ML		**COP:AP**	
Fixed Effects	Estimate	SE	Estimate	SE
(Intercept)	0.45***	(0.08)	0.01	(0.00)
Expressive Performance	-0.15	(0.10)	-0.01	(0.00)
Non-Expressive Performance	-0.24*	(0.10)	0.08	(0.09)
Song [Structured]	-0.04	(0.09)	0.11	(0.07)
Expressive x Song	0.07	(0.13)	0.01	(0.09)
Non-Expressive x Song	-0.09	(0.13)	-0.16	(0.09)
Goodness of Fit				
Deviance	-29.71		-123.26	
AIC	-4.29		-89.26	
BIC	24.32		-69.23	

ML Postural Sway. Figure 32 shows that performers tended to move rhythmically the most in normal performances. They moved significantly less rhythmically in the non-expressive performance in contrast with the normal performance.

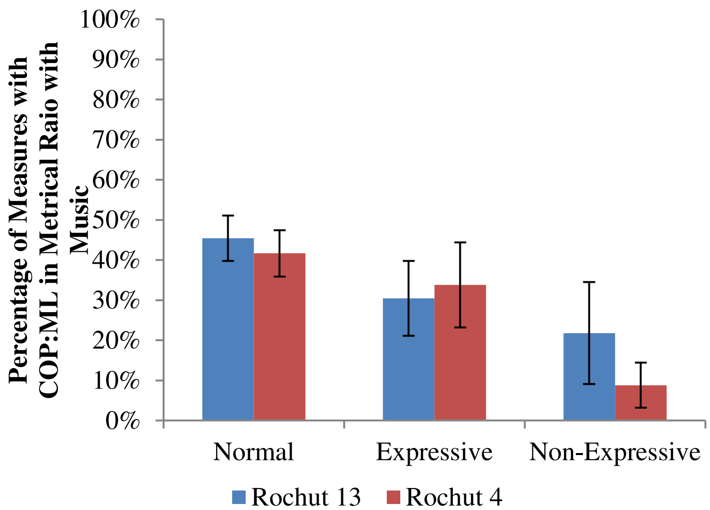


Figure 32. Percentage of Measures with Performers' COP:ML Movements that were Metrically Related to Music.

AP Postural Sway.

Figure *33* shows that performers tended to not move rhythmically in any of the conditions or songs. The amount of rhythmical movement never was significantly different from zero.

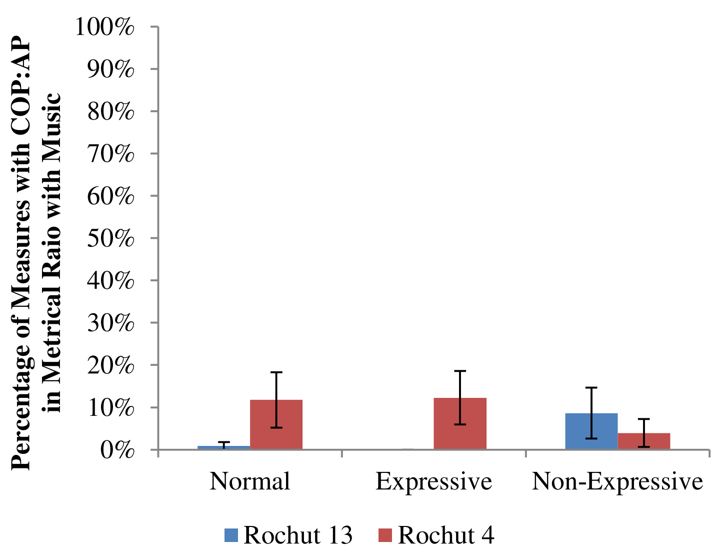


Figure 33. Percentage of Measures with Performers' COP:AP Movements that were Metrically Related to Music.

Discussion

Previous studies showed that the movements of performers (pianists, singers, and clarinetists) are periodic and so were the trombonists in the present study, but only in the ML plane (Clarke & Davidson, 1998; Davidson, 2009; MacRitchie et al., 2013; Wanderley 2002). These periodic movements are one type of metaphorical motion predicted by Clarke (2001). The previous studies that have reported the periodicity of the movements based on visual observations of the performer in action. They did not supply a quantitative method to examine the relationship between the musical meter and tempo to the movements of the body (Clarke & Davidson, 1998; Davidson, 2009; MacRitchie et al., 2013; Wanderley 2002). While the methods used here are designed for linear systems, they do provide a quantitative method to examine the periodicity of the movements. Further, they can be expanded to measure simultaneous multiple periodicity.

Non-expressive performances were less periodic, as in previous studies (Wanderley, 2002). Further, these movements were also unrelated to the tempo and meter of music. Performers are not always moving in the metrical ratios that London (2004) suggested, but they do so much of the time and less so in expressive or non-expressive performance, but only in ML sway. ML sway is a type of movement that is not necessary to play the trombone, and therefore less constrained. AP sway showed no simple periodicity and so I will continue to examine it independently from ML sway.

It remains to be seen if listeners' body movements will also reflect the same type of metaphorical motion seen in the ML sway of the performer. This question will be more fully explored in Experiment 3. STFT provides a useful way to examine the ML body movements, but they do not give a full accounting of quality and self-similarity of the body movements. If AP movements are not periodic, what are they? To examine this question I used an alternative method, developed for examining non-linear systems: detrended fluctuation analysis.

Long Range Correlations

Review of methods, measures & analyses. As described in the method section, multi-fractal continuous wavelet transform analysis (MFCWT) was used to examine the large-scale body fluctuations of each individual performance. Loudness was also included to provide a comparison between postural sway and one of the two dimensions of musical performance that reflect musical expression. Difference scores were taken for ML and AP sway (i.e., change in position), but not for loudness.

The reasons for using difference scores for ML and AP sway can be best explained in the context of the rational for not taking differences scores on loudness. When a musician plays, they are constantly adjusting their loudness or actively maintaining a particular volume. Therefore, the loudness level at all times is reflective of the performer's expressive intentions, as they constantly need to regulate the amount of energy they pour into the instrument. The postural sway is not always reflective of their expressive intentions in the same way as loudness. For example, a performer can sway to the left and stay there for some period without exerting extra energy to maintain that position. As they stand shifted to the left, there will be jitter in those movements as they maintain balance. I am not interested in balance; I am interested in when the performer must pump energy into the system to show their expressive intention. Therefore, expressive intentions are that are directly captured by loudness are better captured by change in position than position than by position. Tempo was not analyzed in the same way because it did not provide enough data for MFCWT, which requires several thousand data points per performance; tempo (measured in beats) only provided a few hundred.

Table 30 shows the results of the MFCWT were analyzed for reliability in separate mixed effects models for each dependent variable (ML, AP, loudness). Performance style and song were only analyzed as fixed effects because treating them as random effects caused boundary condition violations (see Singer & Willet, 2003). Figures for each dependent variable were generated from the table. Each figure shows the Hurst exponents by the performance style and song.

Table 30.

Mixed effects model of MFCWT analysis for large scale ML and AP movements as well as Loudness of each performance.

Ratings	**COP:ML**		**COP:AP**		**Loudness**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	1.00***	(0.08)	0.59***	(0.02)	1.04***	(0.02)
Expressive Performance	-0.05	(0.08)	0.01	(0.03)	-0.01	(0.03)
Non-Expressive Performance	-0.21*	(0.08)	-0.06*	(0.03)	-0.11***	(0.03)
Song [Structured]	-0.17***	(0.08)	-0.06*	(0.03)	0.03	(0.03)
Expressive x Song	0.06	(0.11)	-0.02	(0.04)	0.02	(0.04)
Non-Expressive x Song	0.04	(0.11)	-0.03	(0.04)	-0.02	(0.04)
Goodness of Fit						
Deviance	28.45		82.34		82.99	
AIC	12.45		66.34		66.99	
BIC	3.03		56.91		57.56	

ML postural sway. Figure 34 shows that ML sway during normal performances of the less structured song exhibited 1/f pink noise[2], (Hurst =1), reflecting the presence of long-range correlations within the time series. There was no difference between expressive performance

[2] Table 1 in the method section provides a complete review of the meaning of the alpha value (Hurst exponent) generated in this analysis.

and normal performance. However, non-expressive performance was whiter than normal performance (alpha = .79), indicating that movements in the ML plane were more auto-correlated for non-expressive performances than normal perfomances. In addition, there was a significant difference between the songs. The more structured song (Rochut 4) was whiter than the less structured song (Rochut 13). The whitening of the signal moves the more structured music further into the correlated noise region. This suggests that the ML sway of the two songs had different long-range structures.

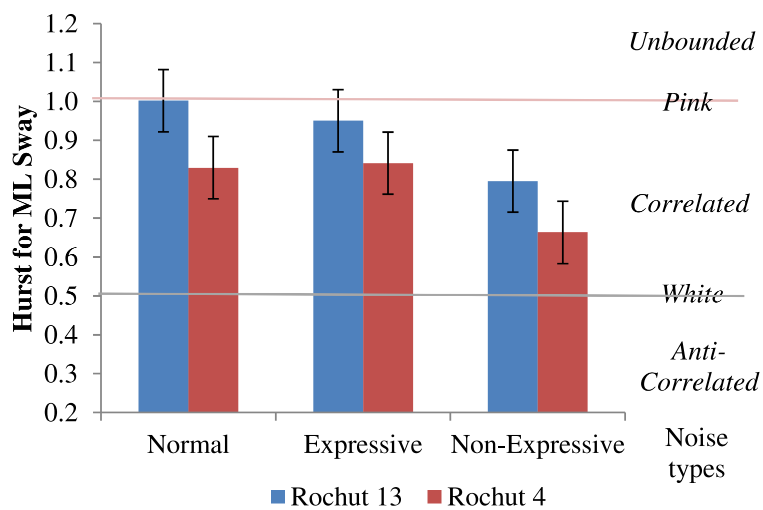


Figure 34. Hurst exponents by the performance style and song: ML Sway.

AP postural sway. Figure 35 shows that AP sway did not exhibit the same long-range correlation as ML sway. AP sway was generally closer to white noise (Hurst = .5). However, AP sway exhibited the same pattern of effects of playing style and song as ML sway. Movement was whiter for non-expressive performances than for normal and expressive performances, and whiter for the more structured than for the less structured song.

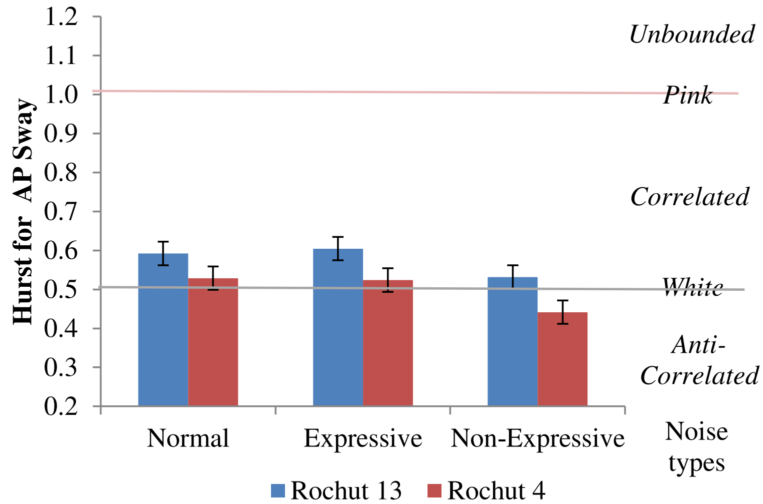


Figure 35. Hurst exponents by the performance style and song: AP Sway.

Loudness. Figure 36 shows that overall, loudness exhibited a pink noise structure, indicating the presence of long range correlations. There was no difference between the two songs. Non-expressive performance produced a whiter signal, as we saw with both ML and AP sway, thereby showing that the non-expressive loudness reflects an auto-correlated process (Hurst = .93).

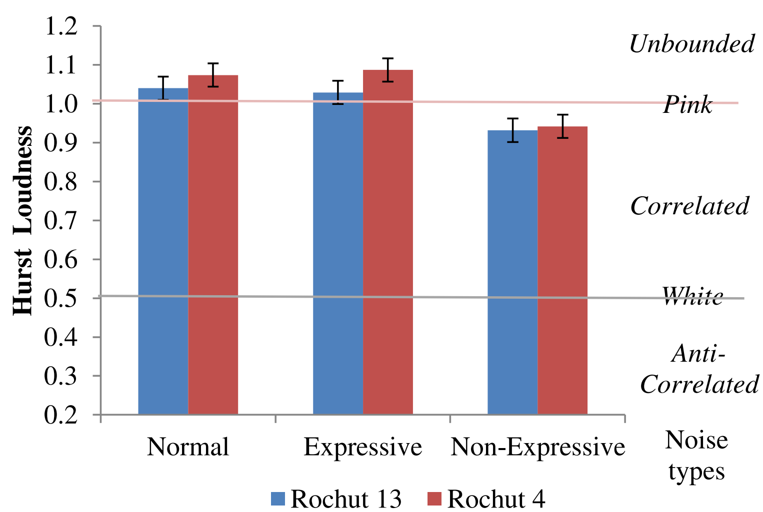


Figure 36. Hurst exponents by the performance style and song: Loudness.

Discussion

ML sway and loudness had a pink (1/f) noise structure, while AP sway was closer to the structure of white noise. The tempo of music performance is also pink, like ML sway and loudness (Rankin, Large, & Fink, 2009). There are two possible explanations for this pattern of results. First, the pattern may simply be coincidental. Biological systems often generate 1/f structures (West & Shlesinger, 1989, 1990). AP sway may have simply failed to exhibit pinkness in our data by chance. The more interesting possibility is that the type of noise reflects something important about the functioning of the system. On this view, ML sway, loudness, and tempo are each products of the performance system operating under similar conditions, while AP sway may be have additional constraints placed on it (i.e., the balancing the instrument). In other words, ML sway is a product of the same perceptual-motor process responsible for expressive variation in loudness and tempo. On this view, ML sway is not a kind of "ancillary" movement but is an integral part of natural, expressive performance.

In support of the idea that body movement and expressive features are part of the same system, the results showed that loudness and ML sway shifted together towards white as expression was reduced. Why would the more structured music have resulted in a whitening of the postural sway and not the loudness? I postulate that the difference occurred because changes in loudness are an invariant way to let the listener know about changes in the musical structure. At phrasal boundaries, the performer always gets softer, no matter the music. In contrast, the use of postural sway to indicate phrasal boundaries depends more on the nature of the music. The question of how the performers used their bodies to indicate phrase boundaries will be explored more fully in the next chapter. For now, the results of the MFCWT analysis suggest that the performers highlighted the musical structure with their body differently in the two songs.

Why did AP sway reflect a different aspect of the performance than ML sway? ML sway was connected to the metaphorical motion in the music, while AP sway was not. A likely explanation is that AP sway was needed to keep the performers upright as their center of mass changed with the back and forth movement of the trombone slide. Therefore, ML sway is more free to be expressive while AP sway is more constrained by the actions needed to perform on the instrument.

Chapter 9: Results & Discussion for Experiment 2: Listener's Mirroring of Expression

Listener's Ratings

Review of methods, measures & analyses. Table 31 shows the results of listener's ratings of the recordings collected in Experiment 1. Listeners rated a) how expressive they found the performances they were trying to mirror, b) how clear the beat was of the performance, and c) how pleasant the performance was. Each rating was analyzed separately in mixed effects models using the performance style, song selection, and who was performing (self or the other musicians) as predictors of the ratings. The performance style predictor was rotated[3] to assess the difference between Normal style and the other two styles. Figures were created from the modeling results.

Table 31.

Mixed Effects Models of Listeners Ratings of Expressiveness, Beat Clarity, and Pleasantness of Recordings

Ratings	**Expressive**		**Beat Clarity**		**Pleasantness**	
Fixed Effects	Estimate	SE	Estimate	SE	Estimate	SE
(Intercept)	3.03***	(0.19)	3.71***	(0.21)	3.50***	(0.19)
Expressive Performance	0.40*	(0.17)	0.00	(0.20)	0.03	(0.18)
Non-Expressive Performance	-0.55**	(0.17)	-0.52**	(0.20)	-0.47**	(0.18)
Performer	0.09	(0.14)	0.17	(0.16)	0.24	(0.14)
Song [Structured]	0.02	(0.19)	-0.23	(0.21)	0.07	(0.19)
Goodness of Fit						
Deviance	485.35		530.07		489.35	
AIC	499.35		544.07		503.35	
BIC	521.46		566.18		525.46	

***$p < .001$, **$p < .01$, & * $p < .05$

[3] See Method section on Mixed Effect Models for an explanation of the rotation of predictors.

Expressiveness. Figure 37 shows the model results for expressiveness. Participants could distinguish between the performers' expressive intentions. Each of the performance styles were different from the others, in the expected directions, and there were no effects of song or performer.

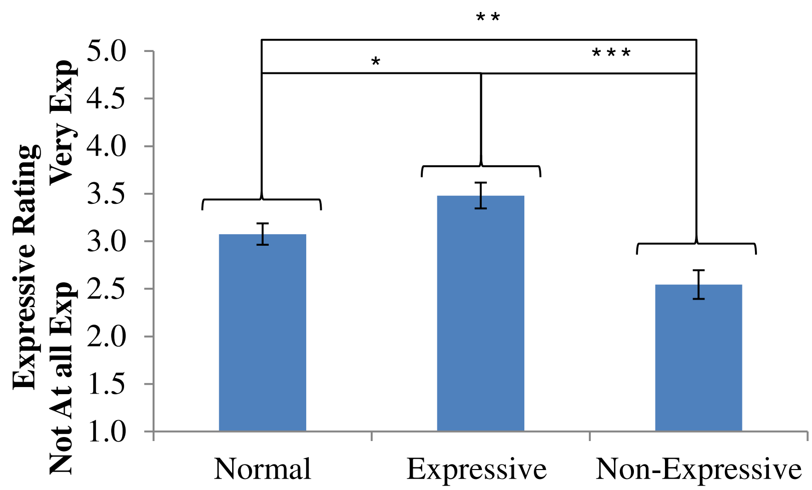


Figure 37. Expressive Ratings by Listeners for Each Expressive Style they heard.

Beat Clarity. Figure 38 shows the model results for beat clarity. Participants found the beats clearer in the Normal and Expressive performance styles than the non-expressive styles. There were no effects of song or performer.

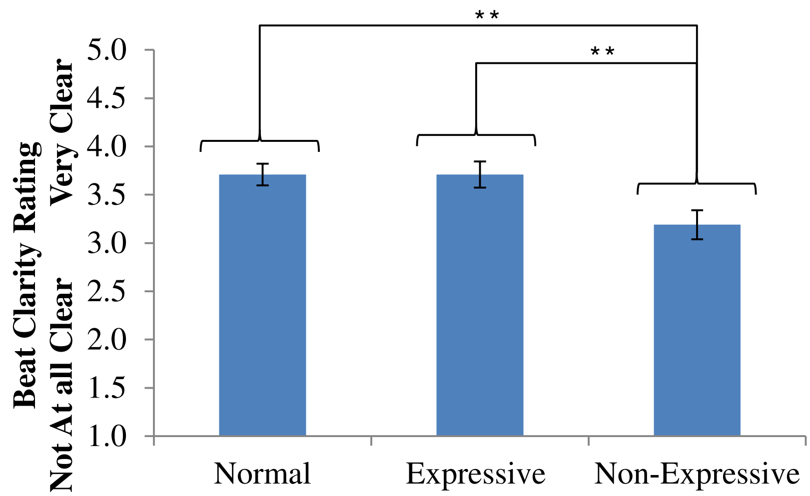


Figure 38. Beat Clarity Ratings by Listeners for Each Expressive Style they heard.

Pleasantness. Figure 39 shows the model results for pleasantness. Participants found the Normal and Expressive performances styles more pleasant than the non-expressive styles. There were no effects of song or performer.

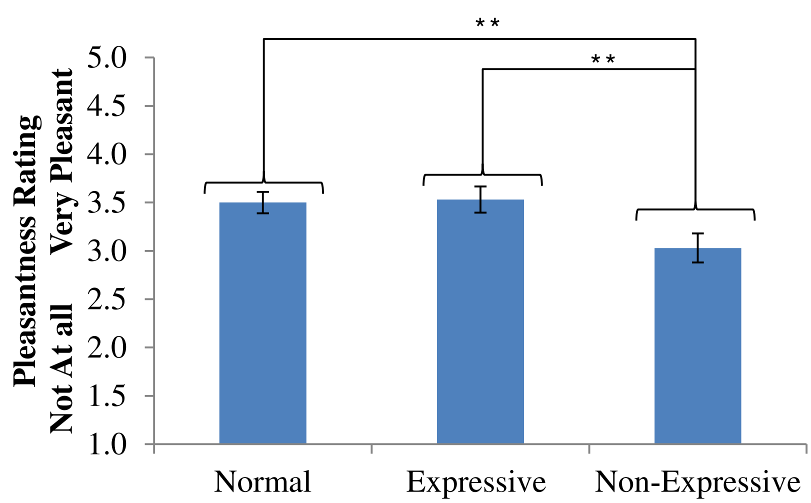


Figure 39. Pleasantness Ratings by Listeners for Each Expressive Style they heard.

Discussion

Listeners clearly could distinguish the expressive intentions of the performers as was expected. They however, did not find the more expressive performances less pleasant as seen by Bhatara et al. (2011). The difference may be because Bhatara et al. (2011) digitally altered performances to be more expressive, whereas here the performers exaggerated their performances naturally. Performers may exaggerate their performance in a way that makes the performances still "musical", something apparently not achieved by the digital manipulation of timing and dynamics in Bhatara et al.'s study. Now that listeners have been shown to perceive the expressive intentions in these particular performances in the acoustic signal, we can ask whether the listeners swayed their bodies with the performers.

Listener Postural Mirroring with the Performer's Movements

Review of methods, measures & analyses. The postural sway movements of the listener were compared to the movements of the performer. Overlap was measured by cross-correlation and cross-recurrence analysis (as in Experiment 1). Postural sway probability values were generated using the phase-shuffled (phase-null) surrogates and applying the percentile method (alpha = .05). The white noise hypothesis was not evaluated, as the main interest is whether listeners would mirror, i.e., phase-synchronize, with the movements of the performer.

The ML and AP sway movements of the listener were cross-correlated (position and Δ position) and cross-recurred[4] with the ML and AP sway movements of the performer. Two different time lags were used in this analysis. The first, time-*locked,* allowed 7 samples, or about one 8th note, as the time window in which overlap was examined. This is the same as the time lag use in Experiment 3. The time-lagged analysis allowed two musical beats, 54 samples. The

[4] Parameters for the cross-recurrence analysis were identical to Experiment 1.

significant values (coded as 1) indicated intermittent synchrony, which occurred when movements were perfectly in-phase or out-of-phase[5] (0° or 180°) with each other. Intermittent synchrony is characteristic of spontaneous auditory synchrony. A significant effect compared to the phase-null hypothesis suggests the two time-series were phase-locked, at least intermittently, to a greater extent than expected by chance.

Lastly, if listeners were significant in the time-*locked* analysis, they would have also been significant time-*lagged* time analysis. To make the analyses orthogonal, any time a listener's trial was time-locked, the time-lagged results were converted to a zero (non-significant). Therefore, in all the figures below, time-locked and time-lagged percentages of trials can be added together to provide a total percentage of intermittent synchrony.

Position cross-correlation. Figure 40 shows the percentage of trials with significant mirroring of position by the listener for the performer's ML and AP sway movements, for both songs and for both time-lags. There are virtually no significant overlaps in position between the listener and the performer.

[5] In-phase movements were considered as either 0° or 180°. 180° is normally considered anti-phase (syncopated movements), but here for postural sway it would mean the one-person moves left and the other right. Therefore, each analysis presented was analyzed twice looking for predominately 0° or 180° degree phase movements. To test for 180° phase, one of the time-series was multiplied by -1 and the analysis was repeated. Significant anti-phase recurrences are considered the same as in-phase recurrences.

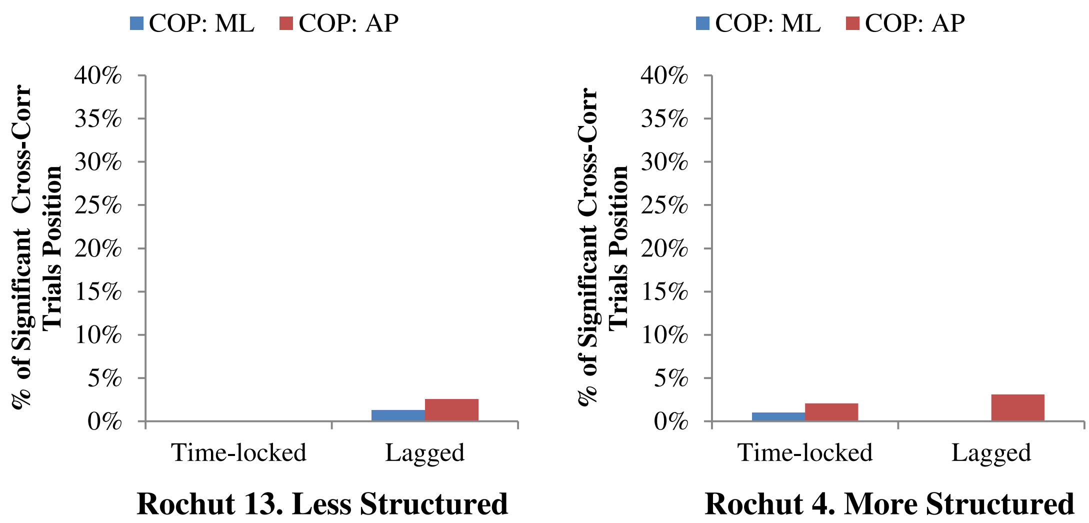


Figure 40. Percentage of trials exhibiting significant phase-lock in position (cross-correlation) with the movements of the performer.

Δ Position cross-correlation. Figure 41 shows the percentage of trials with significant mirroring of change in position by the listener for the performer's ML and AP sway movements, for both songs and for both time-lags. There was significant intermittent synchrony in both the ML and AP directions. However, using a Fisher's exact test, there was no difference between the ML and AP direction within each song (Rochut 4, p =.24, two-tailed; Rochut 13, p = .99, two-tailed). However, there was a significant effect between the AP and ML directions for short and long lag durations when the two songs were merged together ($p < .01$, two-tailed). There was no difference between performance styles (p = .99, two tailed). Further, the likelihood of synchronizing in the ML direction was unrelated to the likelihood synchronizing in the AP direction, $r(27) = -.003$, p = .99. Those participants that exhibited intermittent synchrony with the performer were more likely (68.25% vs 31.74) to have had musical or dance training ($p <$ .01, sign test).

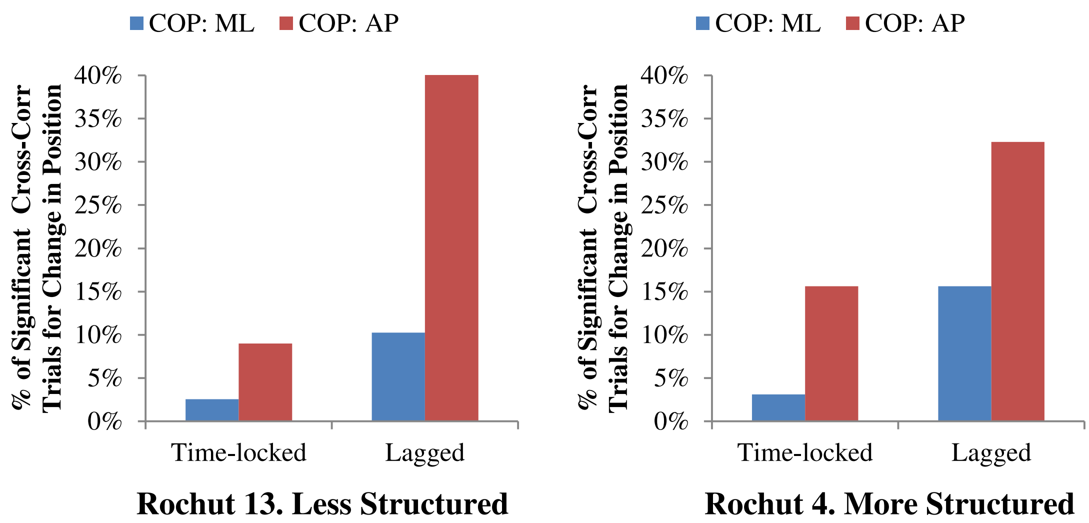


Figure 41. Percentage of trials exhibiting significant phase-lock in change of position (cross-correlation) with the movements of the performer.

Cross-recurrence. Figure 42 shows the percentage of trials with significant mirroring for cross-recurrence between the performer and listener‘s ML and AP sway movements, for both songs and for both time-lags. There was significant intermittent synchrony in phase-space in both the ML and AP directions.

For time-locked analyses, ML sway was stronger than AP sway, and the reverse was true in the time lagged analysis (Rochut 4, p <.05, two-tailed; Rochut 13, p = .09, two-tailed). In addition, if a listener synchronized in the ML direction they were less likely to time-lock synchronize in the AP direction, $r(27) = -.43$, p <.05, but more likely to time-lag synchronize, $r(27) = .44$, p <.05.

Merging the two songs, again there was no performance style effect (p = .25, two-tailed). Participants with music or dance training were more likely to time-lock synchronize in both the ML direction (64.71% vs 35.29%; p =.06, sign test) and the AP direction (73.33% vs 26.67%; p

=.06, sign test). This was also true for time-lagged synchronization in the ML direction (67.69% vs 32.31%; p <.01, sign test) and the AP direction (65.28% vs 34.72%; p <.05, sign test).

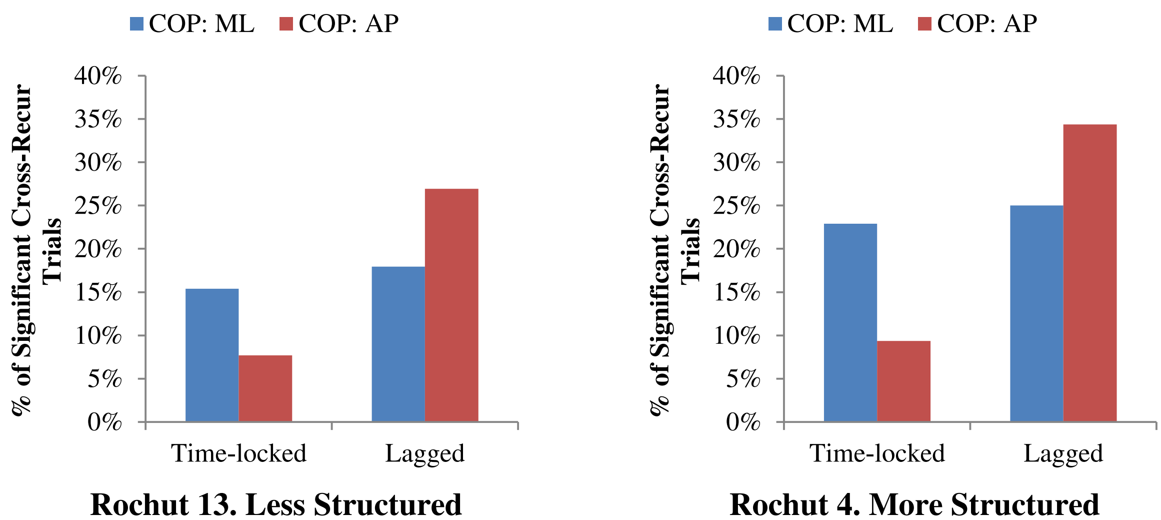


Figure 42. Percentage of trials exhibiting significant phase-lock in cross-recurrence with the movements of the performer.

Discussion

When listeners were asked to mirror expression, they intermittently synchronized with the movements of the performer. In other words, listeners heard the *real* movements of performers. Listeners have been shown previously to move relative to sound-producing movements (Leman, Desmet, & Styns, 2008), but here they moved with the ancillary movements as well. This supports the claim that sound-producing and ancillary movements are interconnected in the same system. Further, listeners mirrored the idiosyncratic movements of the performer, showing that information about these movements was in the sound generated by the performer. In Experiment 1, the AP movements of the performers were mostly idiosyncratic, not periodic. They were unrelated to musical meter and were very close to white-noise. Despite of this, listeners in Experiment 2 were able to mirror their movements.

Leman et al. (2008) asked people to move with the instrument while I did not. Instead, I asked them to let their movement reflect expression. This suggests that the expressive intentions of the performer were enacted through their movements and heard by listeners. Finally, listeners with musical training were better at mirroring then those without, but even those without musical training were able to hear the real movements. The question remains of what movements listeners heard.

In the case of AP movement, it appears listeners head *action information*. The AP movements of the performer were directly related to the sound-producing movements of the instrument, i.e., to movements of the trombone slide. This is why ML sway was more clearly related to the musical structure than AP sway in Experiment 1. If listeners were using the musical structure to align with the performer, then their ML sway would have aligned more than their AP sway. Instead, alignment was stronger for AP sway. Also, if structure had provided the landmarks used for alignment, there would have been more alignment in the more structured song, but this was not the case, at least for the linear analysis. There was, however, a difference between the two songs in the cross-recurrence analysis.

Cross-recurrence analysis indicated synchronization on a larger percentage of trials than the analysis for change of position. This suggests that listeners were moving in similar patterns and aligning in phase-space with the performer. Therefore, it was the complex movements of the performer that were inherent in the sound. In Experiment 1, the most structured music had higher cross-recurrence between performers (Chapter 8) and between the performer and listener.

As well for ML sway, could it be that listeners are hearing the structure encoded into the recurrent patterns of their own sway? Listeners were more likely to mirror the more structured music in cross-recurrence. This suggests that the musical structure is complexly encoded into the body movements, as seen in Experiment 1, and that traditional methods cannot be used to examine them. Further, alignment in phase-space when there was no alignment in position suggests that these movements were not aligned spuriously because the listener was simply moving with the same periodicity as the performer. In the next section, I will provide further evidence on this point.

Additional analyses would be needed to see when in the signal there was significant cross-recurrence. Here, I have restricted the analyses to the whole trial for two reasons. First, more fine-grained analysis requires multiple comparisons which can inflate type-I error. Second, traditional type-I error corrections would require many surrogates to test more stringent alphas, which would require more computational power or multiple weeks of computational time. Alternative methods, such as False Discovery Rate (Benjamini & Hochberg, 1995) are possible, but have never been implemented with phase-surrogates. Simulation experiments are needed to test their efficacy. Computational power is also the reason that I did not compare the movements of listeners to each other to understand what participants are doing in trials where did not synchronize.

Periodicity of Listeners Postural Sway Movements

Review of methods, measures & analyses. As in Experiment 1, Short-Time Fourier Transform (STFT) analyses were used to identify listener's periodic and rhythmic movements. Table 32 shows mixed model analyses of the mean percentage of periodicity, separately for ML postural sway (COP:ML) and AP postural sway (COP: AP). The models included performance style and song selection as both fixed and random factors to give a conservative approach.   Figure 43 for COP: ML and Figure 44 for COP:ML show the averages for each condition, across performers, with standard error bars.

Table 32.

Proportion of Measures of Listeners' Postural Sway that Exhibit Periodic Movements in the ML and AP Directions.

Periodicity	**COP:ML**		**COP:AP**	
Fixed Effects	Estimate	SE	Estimate	SE
(Intercept)	0.86***	(0.04)	0.76***	(0.04)
Expressive Performance	-0.05	(0.04)	0.02	(0.04)
Non-Expressive Performance	-0.00	(0.04)	-0.05	(0.04)
Song [Structured]	0.00	(0.05)	-0.02	(0.05)
Expressive x Song	0.10	(0.05)	0.06	(0.06)
Non-Expressive x Song	-0.01	(0.05)	0.08	(0.06)
Goodness of Fit				
Deviance	-136.63		-131.76	
AIC	-120.63		-115.76	
BIC	-95.36		-90.49	

ML Postural Sway. Figure 43 shows that performers tend to move periodically for all performance styles. The mixed effect model did not find any differences between the performance styles.

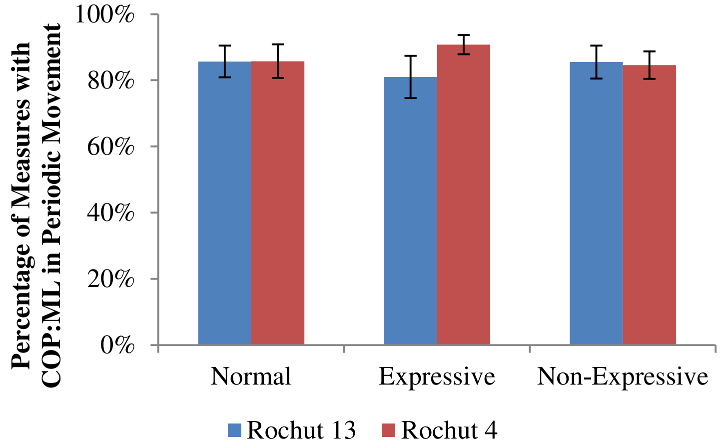


Figure 43. Percentage of Measures with COP:ML Listeners' Movements that are Periodic.

AP Postural Sway. Figure 44 shows that performers tend to move periodically for all performances styles. The mixed effect model did not find any differences between the performance styles.

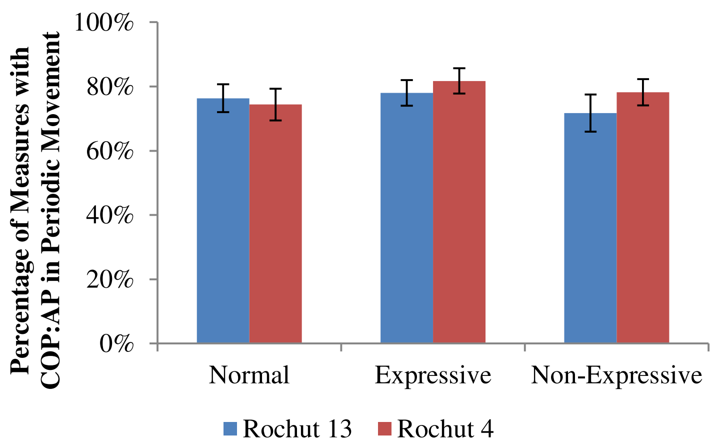


Figure 44. Percentage of Measures with COP:AP Listener Movements that are Periodic.

Metricality of Listeners' Postural Sway Movements

Overview of Metricality. The movements of the listeners for ML postural sway were periodic, but were they related to the musical meter? The vector generated for periodicity analysis was taken and divided by the tempo for each measure. Then those ratios were compared to the expected metrical ratios (London, 2004) shown in Figure 11 in the method section. The number of measures that were 'near' metrical ratios (± .0069) were counted and divided by the total number of measures. The value of .0069 was selected as it was half of the smallest distance between the metrical ratios (same parameters as Experiment 1).

Table 33 shows mixed model analyses separately for ML postural sway (COP:ML) and AP postural sway (COP: AP) that examine the results of the mean percentage of rhythmicity. The model contained the performance style and song selection as both fixed and random factors to give a conservative approach. Those listeners that intermittently synchronized in change in position and cross-recurrence were also included as fixed predictors in the models. These additional predictors were included to ensure that intermittent synchrony reported in the last section was not due to higher levels of rhythmicity. If this were the case, we would expect that those participants who either showed significant phase-locking or lagged-phase relationships would show higher levels of metrical-related movements. Figure 45 for COP: ML and Figure 46 for COP:AP show the averages for each condition, across performers, with standard error bars.

Table 33.

Proportion of Measures of Listeners' Postural Sway that Exhibit an Expected Relationship with the Meter of the Music.

	COP:ML		COP:AP	
Fixed Effects	Estimate	SE	Estimate	SE
(Intercept)	0.31***	(0.03)	0.31***	(0.03)
Expressive Performance	-0.06*	(0.03)	0.03	(0.03)
Non-Expressive Performance	-0.05	(0.03)	-0.07*	(0.03)
Song [Structured]	-0.07	(0.05)	-0.02	(0.04)
Expressive x Song	0.06	(0.04)	0.02	(0.04)
Non-Expressive x Song	0.06	(0.04)	0.10*	(0.04)
Intermittent Sync Δ Position (Time-locked)	-0.04	(0.06)	-0.05	(0.03)
Intermittent Sync Δ Position (Lagged)	0.01	(0.03)	0.05*	(0.02)
Intermittent Sync Cross-Rec (Time-locked)	0.01	(0.03)	0.03	(0.04)
Intermittent Sync Cross-Rec (Lagged)	0.00	(0.02)	-0.04*	(0.02)
Goodness of Fit				
Deviance	-235.8		-222.53	
AIC	-211.8		-198.53	
BIC	-173.89		-160.62	

ML Postural Sway. Figure 45 shows that performers tended to move rhythmically the most in normal performances. Table 33 showed that they moved significantly less rhythmically in the expressive performance in contrast with the normal performance. Those who intermittently synchronized were not more likely to show rhythmic behavior.

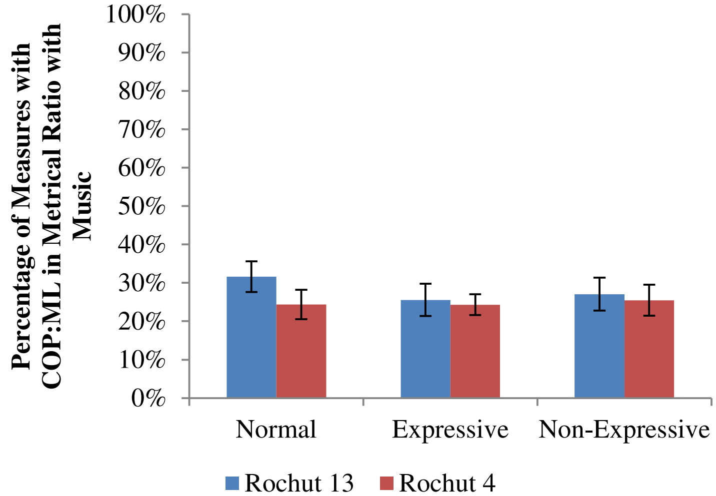


Figure 45. Percentage of Measures with Listeners' COP:ML Movements that were Metrically Related to Music.

AP Postural Sway. Figure 46 shows that performers moved rhythmically the most in normal performances. Table 33 showed that they moved significantly less rhythmically in the non-expressive than in the normal performance for Rochut 13, but not for Rochut 4. Those who time-locked intermittently synchronized in change in position were slightly more likely to show rhythmic behavior. However, those time-locked intermittently synchronized in cross-recurrence were less likely to show rhythmic behavior.

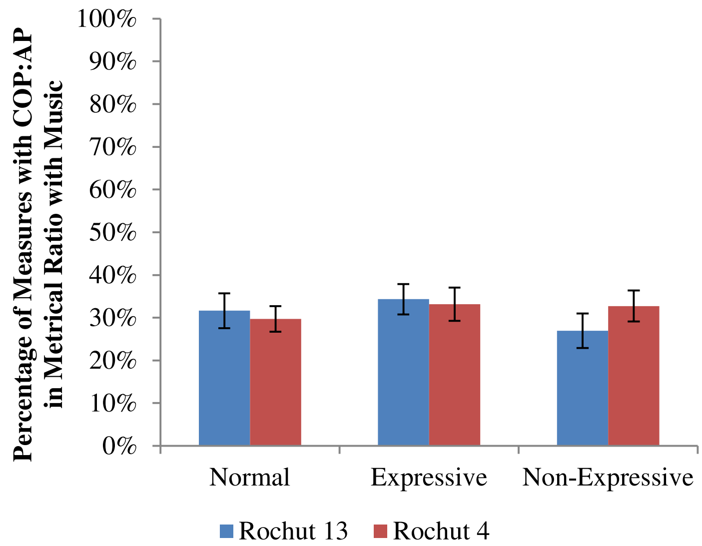


Figure 46. Percentage of Measures with Listeners' COP:AP Movements that were Metrically Related to Music.

Discussion

Listeners are clearly moving periodically to the performance regardless of style. In Experiment 1, there were clear differences in periodicity between the performance styles. In this experiment, listeners were moving rhythmically at levels not far below the performer. Therefore, listeners were hearing the *metaphorical* motion implied the composition. Further, those who moved more rhythmically or periodically were not any more likely to synchronize with the movements of the performer. Therefore, the perception of the *real* movements of the performer and of the *metaphorical* motion implied by the composition were both enacted when the listeners used their bodies to express their understanding of the musical expression.

Long Range Correlations

Review of methods, measures & analyses. As Experiment 1, multi-fractal continuous wavelet transform analysis (MFCWT) was used to examine the large-scale body fluctuations for each individual performance. Difference scores were taken for ML and AP sway (i.e., change in position).

Table 34 shows the results of the MFCWT analyzed for reliability in separate mixed effects models for ML and AP sway. Performance style and song were only analyzed as fixed effects because treating them as random effects caused boundary condition violations (see Singer & Willet, 2003). Figures for each dependent variable were generated from the table. Each figure shows the Hurst exponents as a function of performance style and song.

Whether or not listeners intermittently synchronized in change in position and cross-recurrence were also included as fixed predictors in the models. These additional predictors were included to see if participants who intermittently synchronized would also show different long-range correlations.

Table 34.

Mixed effects model of MFCWT analysis for large scale ML and AP movements as well as Loudness of each performance.

	COP:ML		**COP:AP**	
Fixed Effects	Estimate	SE	Estimate	SE
(Intercept)	0.66***	(0.06)	0.59***	(0.04)
Expressive Performance	0.00	(0.03)	0.02	(0.02)
Non-Expressive Performance	-0.07**	(0.03)	0.02	(0.02)
Song [Structured]	0.04	(0.09)	0.00	(0.06)
Expressive x Song	0.01	(0.04)	0.00	(0.03)
Non-Expressive x Song	0.07	(0.04)	0.03	(0.03)
Intermittent Sync Δ Position (Time-locked)	0.00	(0.03)	-0.01	(0.03)
Intermittent Sync Δ Position (Lagged)	-0.05*	(0.02)	0.00	(0.01)
Intermittent Sync Cross-Rec (Time-locked)	-0.06	(0.06)	0.01	(0.02)
Intermittent Sync Cross-Rec (Lagged)	-0.00	(0.03)	-0.03*	(0.02)
Goodness of Fit				
Deviance	-192.66		-299.30	
AIC	-168.66		-275.30	
BIC	-130.75		-237.39	

ML postural sway. Figure 47 shows that ML sway for normal performances exhibited correlated noise[6], reflecting the presence of auto-correlation within the time series. There was no difference between the songs. There was no difference between expressive and normal performances. However, non-expressive performances were whiter than normal performance. Finally, Table 34 shows that listeners who time-lagged synchronized in change of position were likely to have a little whiter signal.

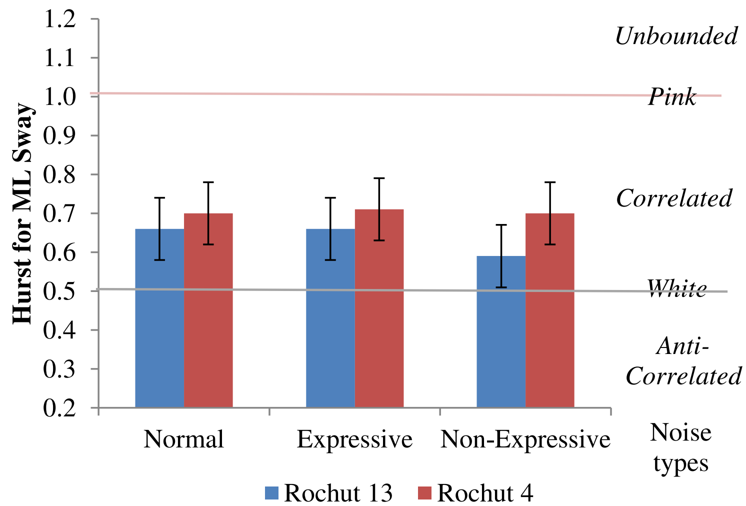


Figure 47. Hurst exponents by the performance style and song: ML Sway.

AP postural sway Figure 48 shows that AP sway for normal performances exhibited correlated noise, reflecting the presence of auto-correlation within the time series. There was no difference between the songs or between the performance styles. Finally, Table 34 shows that participant who were time-lagged synchronized in cross-recurrence were likely to have a little whiter signal.

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[6] Table 1 in the method section provides a complete review of the meaning of the alpha value (Hurst exponent) generated in this analysis.

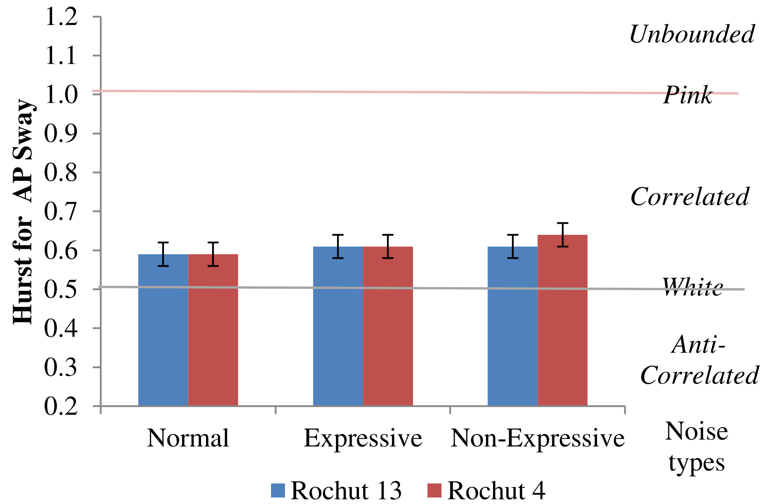

Figure 48. Hurst exponents by the performance style and song: AP Sway.

Discussion

These results highlight the differences between performer's movements (Experiment 1) and listener's movements. AP movements were similar overall, except that performer's movements were closer to being white. The big difference was in ML movements. Performers' movements were pink, but listener's movements were merely auto-correlated and not much different from AP sway. I expected the biggest difference to be in AP movements as these were the movements more strongly connected to the instrument. However, this was not the case. This and suggests that ML movements of performers are special in a way that listeners' ML and AP movements are not. This makes it clear that, while listeners may be hearing both the *real* movements of the performer and *metaphorical* motion of the composition, the listener is undergoing a different process.

It was not possible to determine whether listeners' alignment to the performer was the result of an interpersonal synergy (Riley, Richardson, Shockley, & Ramenzoni, 2011). Listeners could not actually form a synergy because listening in this experiment was a unidirectional process. The listener could not interact with the performer and the performer could not respond to changes in the listener. To test the idea this connection may be the result of interpersonal synergy, we would need to examine two people who can communicate in a joint task.

Chapter 10: Results & Discussion for Experiment 3: Expressive Mirroring Study

Performer Ratings of Trials

Review of methods, measures & analyses. The two trombonists from Experiment 1 performed the same two songs that they had played in Experiment 1 while playing along with (*mirroring*) recordings of the performances from Experiment 1 as closely as possible. I will refer to the trombonist who performed the piece in Experiment 1 as the *performer* and the trombonist who mirrored the performance in Experiment 3 as the *listening performer.* The study asked how the listening performer's ability to mirror the earlier performance was affected by whether he were hearing himself or the other trombonist, and examined the effects of performance style and song. As in Experiments 1 and 2, ML and AP postural sway movements were examined separately.

Performers' ratings of the performances. The musicians listened to each performance before playing and rated it for how *expressive* they found the performance. They were also asked to identify the performance style and the performer. After each performance, they made the same judgments and rating again, and rated how easy the performance had been to mirror. The two ratings were analyzed separately in mixed effects models using performance style, song selection, and who was performing (themselves or the other musicians) as predictors. The interaction between performance style and who was performing could not be assessed, as there were only two performers, which provided insufficient data to examine this effect.

Easiness Rating. Table 35 summarizes the results of the mixed effects model of the listening performers' ratings of *easiness* of performing and how *expressive* they found the performances they were mirroring.

Table 35.

Mixed Effects Models of Performers' Ratings of Easiness of Performance, and Expressive Rating of the Performance Heard.

Ratings	**Easiness**		**Expression**	
Fixed Effects	Estimate	SE	Estimate	SE
(Intercept)	3.88***	(0.26)	3.02***	(0.25)
Expressive Performance	-0.56	(0.30)	1.31***	(0.27)
Non-Expressive Performance	0.12	(0.30)	-1.50***	(0.27)
Hear Other Person	-0.79**	(0.25)	0.08	(0.22)
Song [Structured]	-0.21	(0.14)	-0.25	(0.22)
Goodness of Fit				
Deviance	30.14		38.61	
AIC	44.14		52.61	
BIC	52.36		60.86	

***$p < .001$, **$p < .01$, & * $p < .05$

Easiness Rating. Figure 49 shows the model results for the easiness ratings for each performance style and for whom they were hearing. The followers rated playing along with themselves as easier than playing along with the other person. They rated the non-expressive performances as easier to play along with than the expressive performances. The normal performances did not differ from the expressive and non-expressive performances.

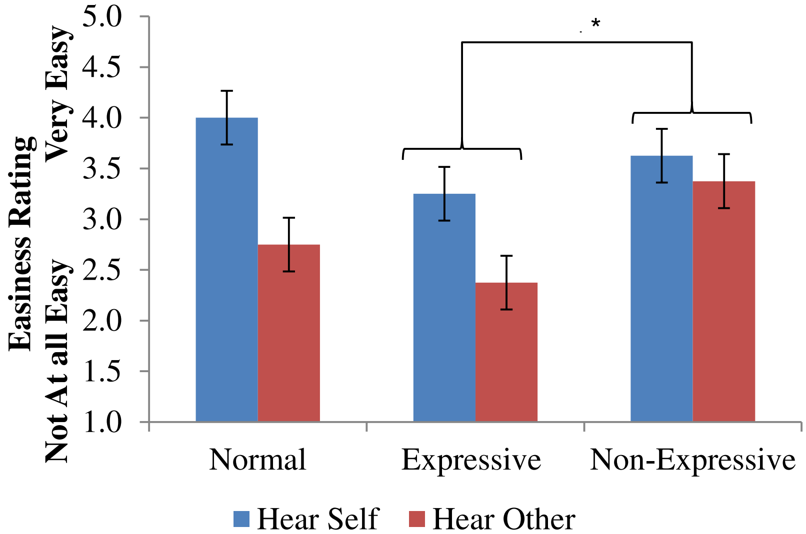

Figure 49. Performer Ratings of Easiness to Mirror each Performance Style and by who they were Hearing Perform.

Expressive Rating. Figure 50 shows the results for the expressive ratings. Followers accurately gauged the expressiveness of each performance they heard, regardless of whose performance they were hearing, and were able to guess which style they heard 100% of the time. However, Performer 1 incorrectly identified who was playing once, while Performer 2 misidentified the player twice.

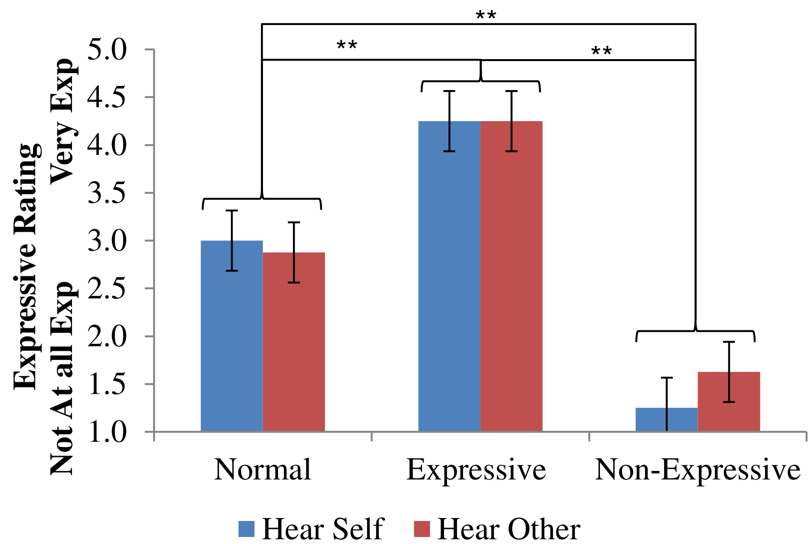

Figure 50. Performer Ratings of the Expressiveness of Each Performance of each Style and by who they were Hearing Perform.

Discussion

Keller et al. (2007) found that performers were better at dueting with themselves. So too, the trombonists in the present study found it easier to play along with their own performances. The musicians reported that following was difficult because it was hard to predict the timing, and their ratings showed that they found the expressive performances to be the most difficult. It was apparently easier for them to anticipate the expressive variations in timing of their own performances. Despite this, they were sometimes mistaken in their identification of the performer that they were following.

Expressive Mirroring Task and Postural Mirroring Behavior

Review of Methods, Measures & Analyses

Overview I compared the postural sway movements of the performers in the present study with those of the performances from Experiment 1 that they were mirroring. The ML and

AP sway movements (position and Δ position) of the two performances were cross-correlated and cross-recurred[7] (as in Experiments 1 and 2). A lag of seven data points (less than an 8th note), was allowed as the time window in which to examine similarities between the postural movements.

Postural sway probability values were generated using the phase-shuffled (phase-null) surrogate method, as in Experiment 2. Only phase-shuffled null hypothesis tests were performed because I was interested to see if performers synchronized their movements. As in Experiments 1 and 2, significant effects indicated intermittent synchrony. Effects for position indicated that musicians in the two performances were aligned in where they moved their bodies as they swayed back and forth during the performance. Effects for change of position indicated that the musicians in the two performances moved at the same times, i.e., at the same location in the music. Effects for recurrence rate indicated that there was complex coupling when the movements were projected into phase-space. In all three analyses, for both for cross-correlation and cross-recurrence, perfect synchronization would be indicated by a value of 1, which occurs when movements are perfectly in-phase or out-of-phase[8] (0° or 180°) with each other. Lower values that are significant indicate intermittent synchrony, a characteristic of spontaneous coordination.

Reading Figures. The mirroring of postural sway was summarized in diagrams like the one in Figure 51, in which the various possibilities for comparing the movements of performer and listening performer in Experiment 2 are identified by label.

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[7] Parameters for the cross-recurrence analysis were identical to those in Experiment 1 & 2.
[8] In-phase movements were considered as either 0° or 180°. Significant anti-phase recurrences is indicated on the figures.

As described in Chapter 5, there are four possible comparisons that must be considered when evaluating similarities between two musicians playing the same piece. I will use the term *natural overlap* to refer to the similarity between the two musicians who each plays the same song independently, without simultaneously hearing another performance, as in Experiment 1. There were two types of natural overlap present in Experiment 1: between the two musicians (labeled *A1. Natural Other- Overlap* in Figure 51) and between the two performances of each song by the same musician (labeled *B. Natural Self-Overlap* in Figure 51). These two natural overlap conditions provide baselines against which to assess the success of the performers' efforts in Experiment 3 to *mirror* another performance, either their own (labeled *B. Self-Mirroring* in Figure 51), or the other performer's (labeled *C. Other- Mirroring* in Figure 51). The final comparison present in Experiment 3 is between the two performers when both mirrored the same performance.   I will call this comparison *Incidental Overlap* (labeled D in Figure 51).

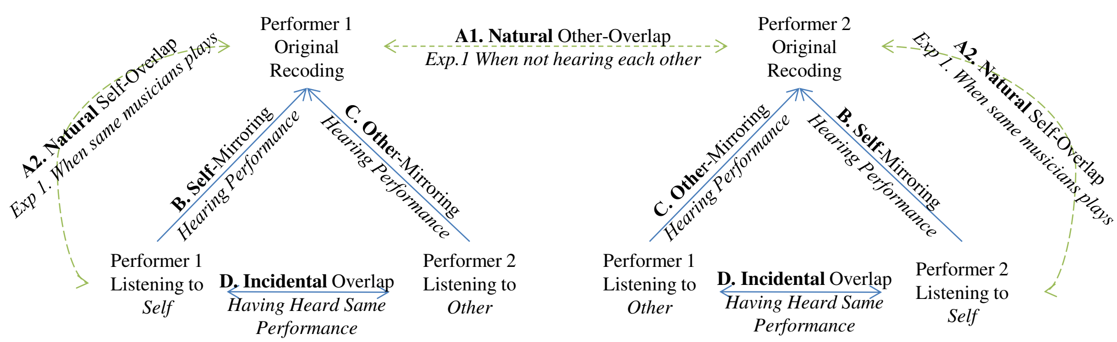

Figure 51. Four Types of Overlap and Mirroring for Two Musicians Performing the Same Song when Not Hearing (Experiment 1) or Hearing (Experiment 2) another Performance by Themselves (Self) or by the Other Musician (Other).

In the figures below, the results of the cross-correlation and cross-recurrence analyses are summarized in figures similar to Figure 51, except that each of the labeled overlap and mirroring relationships in Figure 51 is replaced with corresponding values from the appropriate analyses. Each label is replaced by three values representing the cross-correlation of three measures: position, change in position, and cross-recurrence. As explained earlier, each measure captures a different type of information about movement: Spatial (position), Action (Δ position), and Patterning (cross-recurrence).

Hypotheses. As described in Chapter 5, musical sound can convey information about two different types of motion: *real* and *metaphorical*. Real motion is the movement of the performer. Evidence of that listeners are sensitive to real motion would be provided by *Other-Mirroring*. Metaphorical movement is implied by the composition. Evidence of that listeners are sensitive to metaphorical motion would be provided by *Incidental Overlap*. In each case, evidence for mirroring or overlap would be provided by significant cross-correlation between movements of performer and listening performer. Real and metaphorical motion can both be conveyed by any or all of the different types of movement information: Spatial (position), Action (Δ position), and Patterning (cross-recurrence). A significant effect for any one of the three measures would be evidence of mirroring or overlap of that kind of information.

Evidence that real motion was conveyed by the sound would be provided by significant *Other-Mirroring* (C in Figure 51) and the absence of significant *Natural Other-Overlap* (A1 in Figure 51), for one or more of the dependent variables (position, Δ position, or cross-recurrence). In this case, I can conclude that the corresponding type of information was in the sound. However, if there was *Natural Other-Overlap* then this conclusion is not warranted. Significant

Natural Other-Overlap would suggest instead that the effect for *Other-Mirroring* was a spurious by-product of incidental, natural similarity between the two performers rather than of information conveyed by the musical sound.

Likewise, evidence that *metaphorical* motion was conveyed by the sound would be provided by a significant effect for *Incidental Overlap* (D in Figure 51) and no significant effect for *Natural Other-Overlap* (A1 in Figure 51). Again, significant *Natural Other-Overlap* would suggest that the effect for *Incidental Overlap* was spurious. Metaphorical motion also has to satisfy another condition. *Incidental Overlap* may also be spurious if both *Self-Mirroring* (B in Figure 51) and *Other-Mirroring* (C in Figure 51) are significant. In this case, *Other-Mirroring* could be a by-product of mirroring by both performers. So, I can conclude that metaphorical motion was conveyed if there is *Incidental Overlap* in the absence of *Natural Other-Overlap,* and of *Self-Mirroring* coupled with *Other-Mirroring*. Finally, if only *Other-Mirroring* and *Incidental Overlap* are significant, I can conclude that the musical sound conveys both real and metaphorical motion to the listening performer.

There is one final hypothesis: action-simulation (Sebanz, Bekkering, & Knoblich, 2006; Keller, Knoblich, & Repp, 2007). The action-simulation hypothesis predicts that *Self-Mirroring* (B in Figure 51) would be stronger than *Other-Mirroring* (C in Figure 51). Again, this result is not sufficient by itself. *Self-Mirroring* must also be stronger than *Natural Self-Overlap* (A2 in Figure 51). If the *Natural Self-Overlap* is significant, I cannot conclude that mirroring is a product of action simulation. Instead, the advantage of self-mirroring over other-mirroring may be the spurious by-product of incidental, natural similarity between repeated performances of the same song by the same musician rather than of information conveyed by the musical sound.

ML Postural Sway for the More Structured Song

Normal performance style. Figure 52 shows the results for ML postural sway for the more structured song in the normal performance style. Natural Other-Overlap was significant for position and change of position. Other-Mirroring for Performer 1 was significant for all three dependent variables, but not for Performer 2 who only showed overlap in change of position. This suggests that Performer 1, when mirroring the expression of the other performer, changed in postural sway to match sway of Performer 1, suggesting that he perceived spatial information.

The Natural Self-Overlap for both performers was significant in all three dependent variables. Self-Mirroring for Performer 1 overlapped in recurrence; however, Performer 2 did so in all three dependent variables. These values were lower than seen in Natural Self-Overlap; suggesting mirroring expression was disrupting the natural postural sway stemming from the composition. This is not consistent with the action-simulation hypothesis.

Incidental Overlap was significant for change in position and cross-recurrence, for both performers. This would be evidence that the performers perceived metaphorical motion present in the composition, except that both performers also showed significant Natural-Self Overlap on the same measures. The Incidental Overlap, therefore, provides no support for the conclusion that the performers perceived metaphorical motion conveyed by the composition.

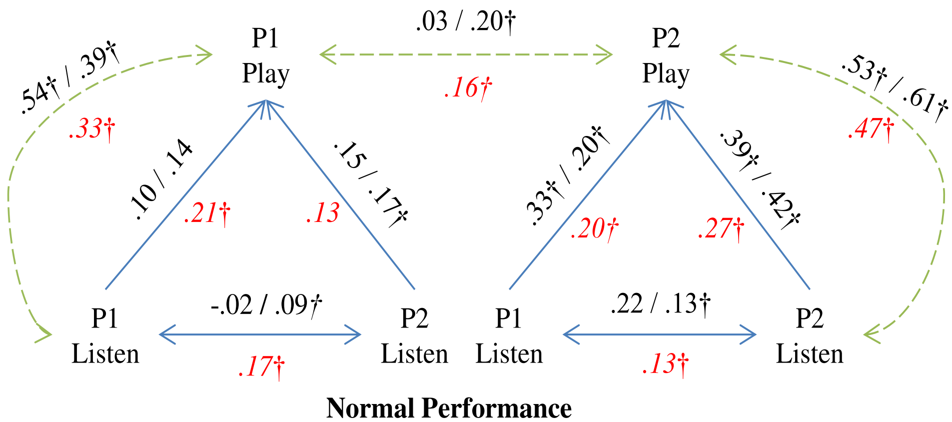

Figure 52. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † p <.05 based on IAFFT surrogates: Rochut 4 COP: ML Normal Performance

Expressive Performance Style. Figure 53 shows the results for ML postural sway for the more structured song in the expressive performance style. Natural Other-Overlap between the performers was significant in change of position only. Other-Mirroring was significant only for cross-recurrence for Performer 1, while Performer 2 showed no overlap. This suggests that when Performer 1 mirrored the other performer, he also changed his pattern of postural sway to Performer 2. Therefore, we can conclude that Performer 1 perceived *patterning* information about other performer's movements that was conveyed by the sound.

The Natural Self-Overlap for both performers was significant in all three dependent variables. Self-Mirroring for Performer 1 and Performer 2 significantly overlapped all three dependent variables as well. For both performers, all three values were equal or slightly lower than seen in Experiment 1, suggesting that mirroring expression was disrupting the natural postural sway stemming from the composition. This is not consistent with the action-simulation hypothesis.

The Incidental Overlap was not significant. I can conclude that the performance did not contain metaphorical motion.

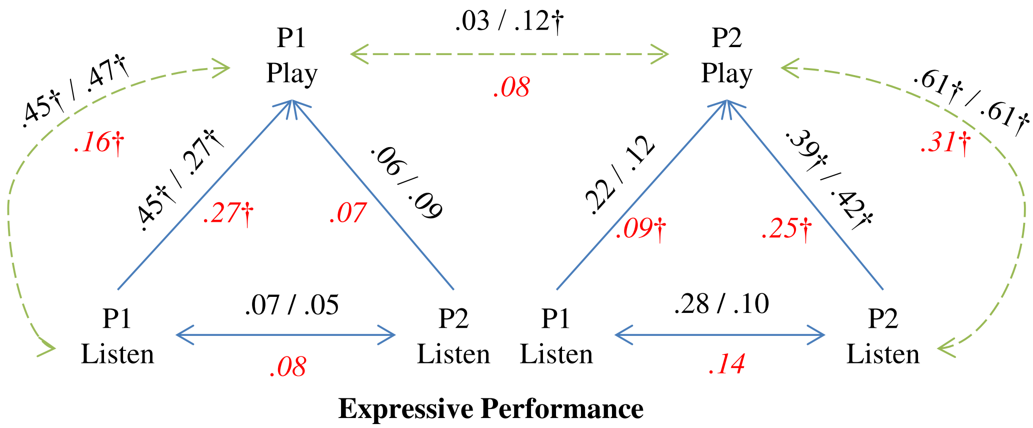

Figure 53. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † *p* <.05 based on IAFFT surrogates: Rochut 4 COP: ML Expressive Performance

Non-Expressive Performance Style. Figure 54 shows the results for ML postural sway for the more structured song in the non-expressive performance style. Natural Other-Overlap between the performers was not significant for all three dependent variables. Other-Mirroring for Performer 1 was significant for all three dependent variables, but Performer 2 showed significant overlap only in recurrence. This suggests that Performer 2 perceived patterning information and Performer 1 perceived spatial, action, and patterning information.

The Natural Self-Overlap for Performer 2 was significant for all three dependent variables and for change of position for Performer 1. Self-Mirroring was significant for Performer 1 for change of position, and for both position and change of position for Performer 2. For both performers, all three values were equal to or lower than those for Natural Self-Overlap in Experiment 1 and cross-recurrence. This is not consistent with the action-simulation hypothesis.

Incidental Overlap was significant for cross-recurrence and significant for change in position when performers were listening to Performer 2, suggesting that this overlap may be an incidental effect. This suggests that the listening performers perceived pattern metaphorical information coming from the composition in the playing of both performers.

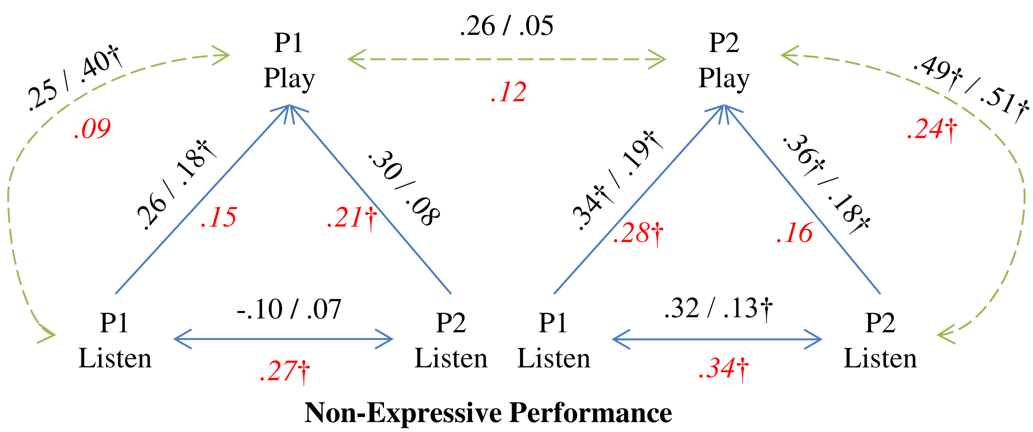

Figure 54. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † p <.05 based on IAFFT surrogates: Rochut 4 COP: ML Non-Expressive Performance

AP Postural Sway for the More Structured Song

Normal performance style. Figure 55 shows the results for AP postural sway for the more structured song in the normal performance style. Natural overlap between the performers was significant in change of position. Other-Mirroring for Performer 1 and 2 both showed no overlap in the three dependent variables. This suggests both performers perceived no real motion.

The Natural Self-Overlap for both performers was significant for all three dependent variables. Self-Mirroring for Performer 1 and 2 both showed significant overlap in change of position. For both performers, all three values were lower than seen in Experiment 1. This is not consistent with the action-simulation hypothesis.

The Incidental Overlap showed a similar pattern of results to the natural overlap pattern. This pattern of results suggests that the sound did not convey any metaphorical information.

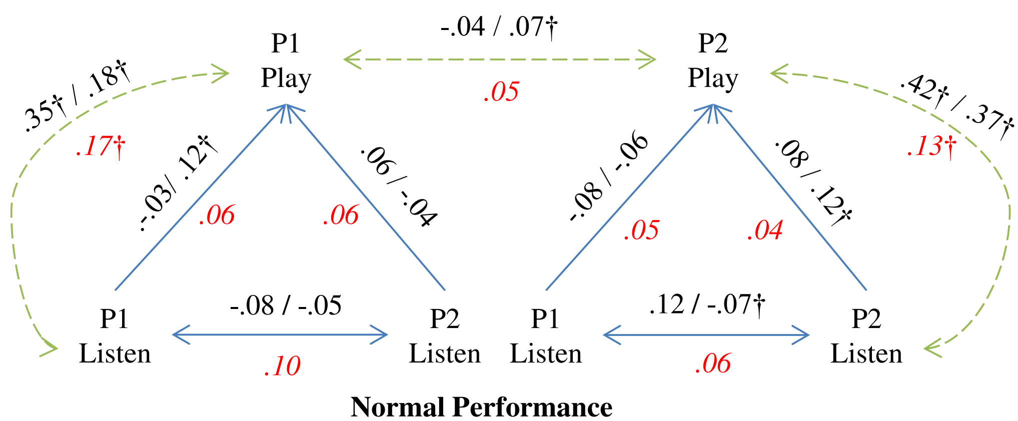

Figure 55. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † *p* <.05 based on IAFFT surrogates: Rochut 4 COP: AP Normal Performance

Expressive performance style. Figure 56 shows the results for AP postural sway for the more structured song in the expressive performance style. Natural Other-Overlap was significant for position. Other-Mirroring was significant for change of position and cross-recurrence for Performer 1, but not for Performer 2 who showed no overlap. This suggests that Performer 1 perceived action and patterning information, while Performer 2 did not.

The Natural Self-Overlap was significant for all three dependent variables for Performer 2 and for Performer 1 for change of position and cross recurrence. Performers 1 and 2 both showed significant Self-Mirroring for change of position. Self-Mirroring was also significant for cross-recurrence for Performer 2. These values were lower than the Natural Self-Mirroring in Experiment 1. This is not consistent with the action-simulation hypothesis.

Incidental Overlap was significant for change of position, when both performers listened to Performer 1. This suggests that they both perceived the metaphorical motion information coming from the composition, but only in the playing of Performer 1.

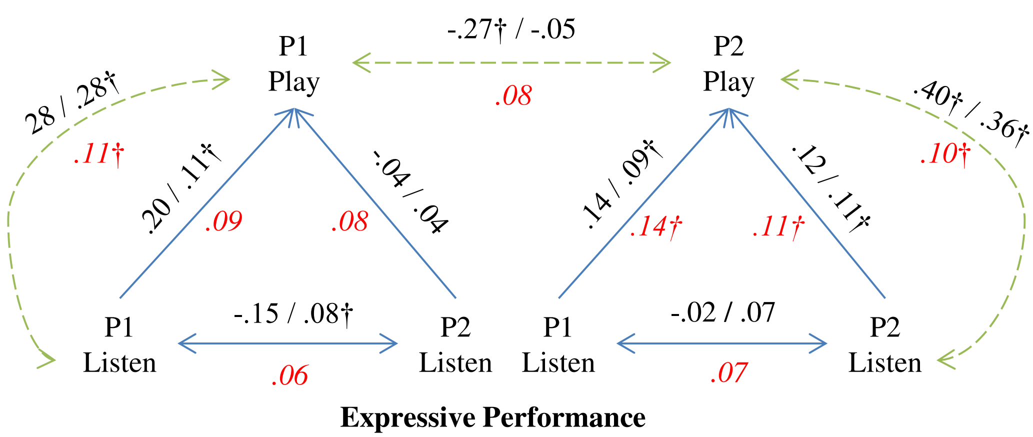

Figure 56. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † p <.05 based on IAFFT surrogates: Rochut 4 COP: AP Expressive Performance

Non-Expressive performance style. Figure 57 shows the results for AP postural sway for the more structured song in the non-expressive performance style. There was no significant Natural Other-Overlap. Other-Mirroring was significant for cross-recurrence for both Performer 1 and Performer 2 for all three dependent variables. This suggests that Performer 1 perceived patterning information, while Performer 2 perceived spatial, action, and patterning information.

The Natural Self-Overlap was significant for position and change of position for Performer 2 and for Performer 1 only for change of position. Self-Mirroring was significant for

Performers 1 and 2 for change of position. These values were lower than the Natural Self-Overlap seen in Experiment 1. This result is not consistent with the action-simulation hypothesis.

The Incidental Overlap was significant for change of position, when both performers listened to Performer 2. This suggests that they both perceived this type of metaphorical motion information coming from the composition, but only in the playing of Performer 2.

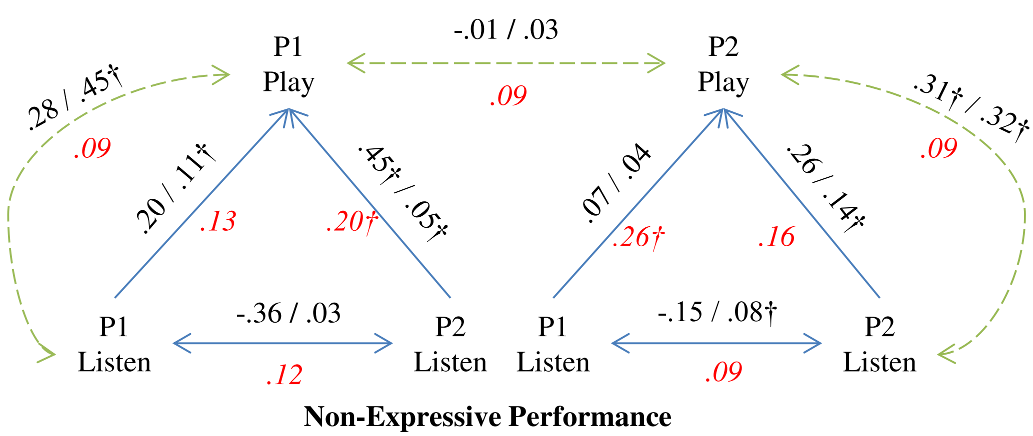

Figure 57. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † *p* <.05 based on IAFFT surrogates: Rochut 4 COP: AP Non-Expressive Performance

ML Postural Sway for the Less Structured Song

Normal performance style. Figure 58 shows the results for ML postural sway for the less structured song in the normal performance style. Natural Other-Overlap between the performers was significant for cross-recurrence. Other-Mirroring was not significant for any of the dependent variables. This suggests that both musicians did not perceive real movement in the performances.

For both performers, Natural Self-Overlap was significant for all three dependent variables, while Self-Mirroring was not significant for all three dependent variables. This result is not consistent with the action-simulation hypothesis.

Incidental Overlap was not significant for any of the dependent variables. This pattern of results suggests that the sound did not convey information about metaphorical motion.

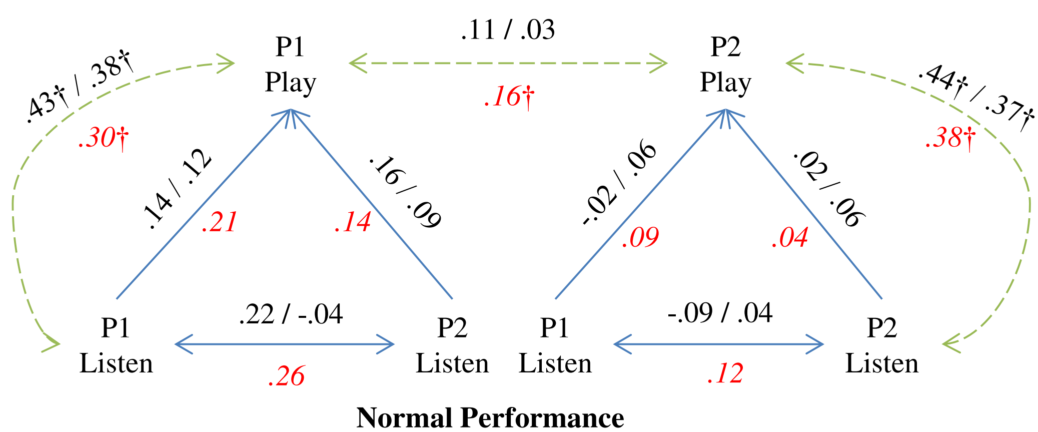

Figure 58. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † p <.05 based on IAFFT surrogates: Rochut 13 COP: ML Normal Performance

Expressive performance style. Figure 59 shows the results for ML postural sway for the less structured song in the expressive performance style. Neither Natural Other-Overlap nor Other-Mirroring were significant for any of the three dependent variables for either performer. This suggests that both musicians did not perceive any real movement in the performances.

For both performers, Natural Self-Overlap was significant for change of position and cross-recurrence. Self-Mirroring was also significant for both performers for change of position and for cross-recurrence for Performer 1. The values were, however, lower than those for Natural Self-Overlap Experiment 1, and so do not provide support for the action-simulation hypothesis.

Incidental Overlap was not significant for any of the dependent variables, suggesting that the sound did not convey any metaphorical motion.

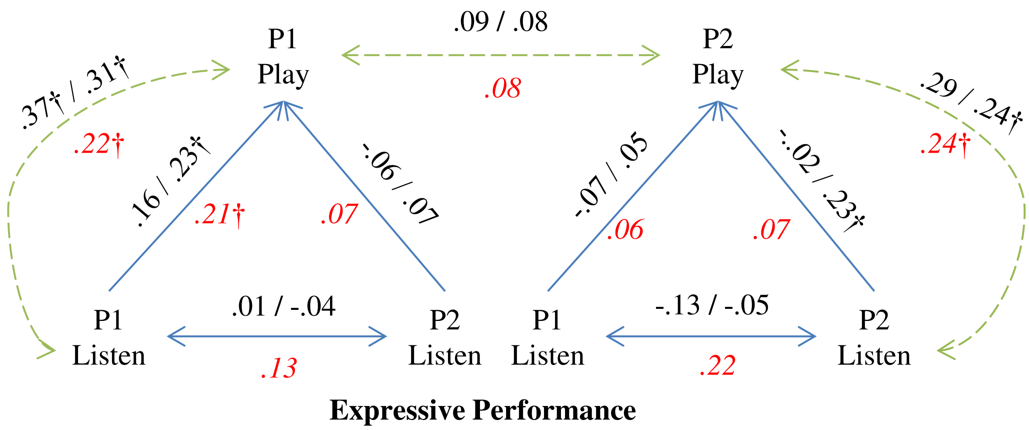

Figure 59. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † p <.05 based on IAFFT surrogates: Rochut 13 COP: ML Expressive Performance

Non-Expressive performance style. Figure 60 shows the results for ML postural sway for the less structured song in the expressive performance style. Neither Natural Other-Overlap nor Other-Mirroring were significant for any of the three dependent variables for either performer. This suggests that both musicians did not perceive any real movement the performances.

Natural Self-Overlap was significant in change of position and cross-recurrence, only for Performer 1. Self-Mirroring was significant for change of position for Performer 1, and for cross-recurrence for both performers. However, for Performer 2, the cross-recurrence was in anti-phase, meaning the pattern of movement in the two performances were mirror images of each other. The Self Mirroring values were higher than the Natural Self-Overlap seen in Experiment

1. This is evidence of action simulation and suggests that deliberate mirroring of their own performance increased the similarity of complex patterns in postural sway.

Incidental Overlap was not significant for any of the dependent variables, suggesting that the sound did not convey information about metaphorical motion.

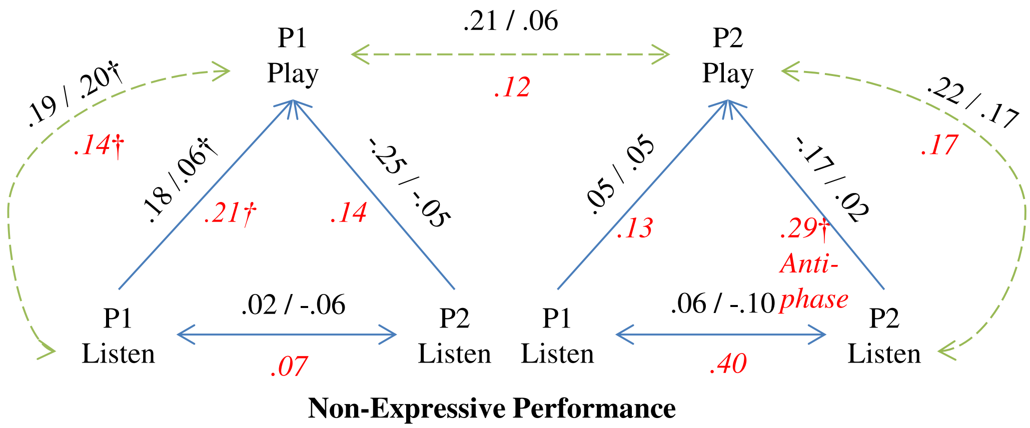

Figure 60. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † *p* <.05 based on IAFFT surrogates: Rochut 13 COP: ML Non-Expressive Performance

AP Postural Sway for the Less Structured Song

Normal performance style. Figure 61 shows the results for AP postural sway for the less structured song in the normal performance style. Natural Other-Overlap between the performers was not significant for any of the three dependent variables. Other-Mirroring was significant for cross-recurrence for Performer 1 but not for Performer 2 who showed no overlap for any of the dependent variables. This suggests that Performer 1 perceived patterning information.

Natural Self-Overlap was significant for all three dependent variables for Performer 2 and for change of position and cross-recurrence for Performer 1. Self-Mirroring was significant for change of position for Performer 1, but not for Performer 2, who showed no overlap in any of the dependent variables. The values were about the same as those in Experiment 1 for Performer 1, and lower for Performer 2. This result is not consistent with the action-simulation hypothesis.

Incidental Overlap was significant for position and cross-recurrence for both performers when listening to Performer 2. This pattern of results suggests that they both perceived metaphorical motion conveyed by the score that was reflected in the position and patterning of Performer 2's movements.

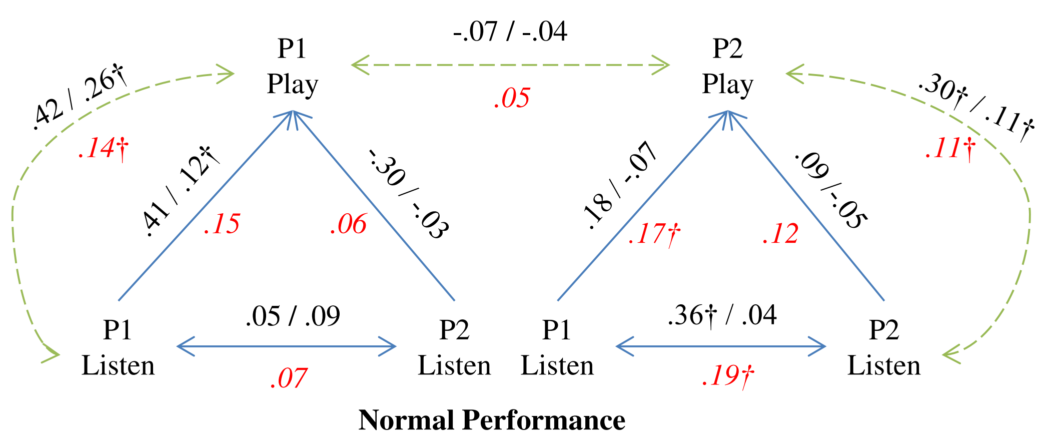

Figure 61. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † *p* <.05 based on IAFFT surrogates: Rochut 13 COP: AP Normal Performance

Expressive performance style. Figure 62 shows the results for AP postural sway for the less structured song in the expressive performance style. Natural Other-Overlap was not significant for any of the three dependent variables. There was also no significant effect of Other-Mirroring for either performer for any of the dependent variables. This suggests that neither musician perceived real movement in any of the performances.

The Natural Self-Overlap was significant for Performer 1 for all three dependent variables, and for Performer 2 only for change of position. Self-Mirroring was significant for change of position for both performers, and for position for Performer 2. Of these three effects for Self-Mirroring, only the mirroring of position by Performer 2 is evidence of action simulation.

Incidental Overlap was significant for all three dependent measures for both performers, but only when listening to Performer 2. Further, the effect for position was negative meaning they were opposite in position (anti-phase) as was cross-recurrence. Incidental Overlap was also significant when listening to Performer 1, for change of position. This pattern of results suggests that both musicians perceived metaphorical motion conveyed by the score that was reflected in the position and patterning of Performer 2's movements and in differences of position of Performer 1's movements.

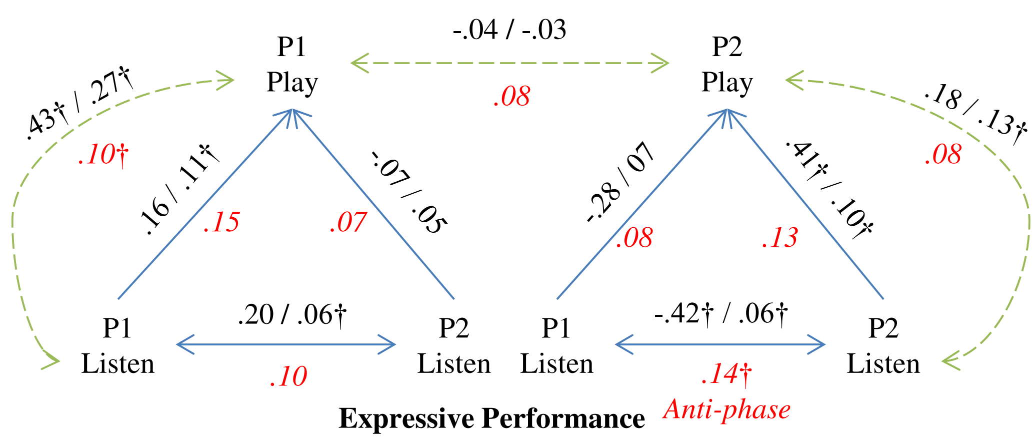

Figure 62. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † *p* <.05 based on IAFFT surrogates: Rochut 13 COP: AP Expressive Performance

Non-Expressive performance style. Figure 63 shows the results for AP postural sway for the less structured song in the non-expressive performance style. Natural Other-Overlap was not significant for any of the three dependent variables. Other-Mirroring was significant for change in position for Performer 1, while Performer 2 showed no overlap for any of the dependent variables. This suggests that only Performer 1 perceived action information.

Self-Mirroring was significant for change of position for both performers, and for also cross-recurrence (anti-phase) for Performer 2. The values for change of position were lower than those for Natural Self-Overlap seen in Experiment 1, and so do not provide support for the action-simulation hypothesis. However, the value for cross-recurrence value was higher, and thus provides support for the action-simulation hypothesis.

Incidental Overlap was not significant overlap for any of the three dependent measures, suggesting that the sound did not convey metaphorical motion.

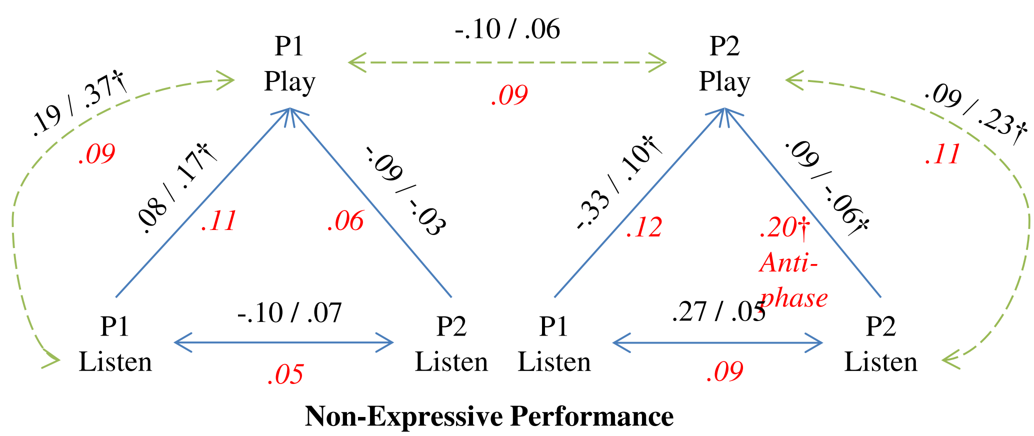

Figure 63. Cross-Correlation Values (Position / Change in position) in black and Cross-Recurrence Values in Red. † p <.05 based on IAFFT surrogates: Rochut 13 COP: AP Non-Expressive Performance

Summary of Results

Table 36 shows a summary of the significant pattern of results for each of the three types of mirroring: Real (R), Metaphorical (M), and Action-Simulation (AS). The type of information mirrored is indicated by subscript: Spatial (S), Action (A), Patterning (P). The summary takes the same conservative approach to mirroring that I described above. Cases of mirroring are included in the summary only when there was significant mirroring *and* the corresponding natural comparison was *not* significant. Significant effects of mirroring were not included if the corresponding natural comparison was also significant. In these cases the significant mirroring effect may have been spurious, a product of natural overlap rather than real mirroring. For example, the summary table does not include the significant mirroring of Performer 2 by Performer 1 for the Normal performances of Rochut 4 (Figure 52) in both change in position and cross-recurrence because the Natural Other-Overlap was also significant for these two cases. The summary includes only mirroring effects that cannot be attributed to natural overlap.

Table 36.

Summary of Pattern of Significant Results for Real (R), Metaphorical (M), and Action-Simulation (AS) Mirroring of Three Types of Information[1]*: Spatial (S), Action (A), Patterning (P)*

	ML Postural Sway			AP Postural Sway		
	Normal	Expressive	Non-Exp.	Normal	Expressive	Non-Exp.
More Structured Song: Rochut 4	R_S	R_P	R_S, R_A, R_P M_P AS_P		R_A, R_P M_A	R_S, R_A, R_P M_A,
Less Structured Song: Rochut 13				R_P M_S, M_P	M_s,M_a,M_P AS_S	R_A, AS_p

[1] Type of information indicated by subscript

Discussion

The postural sway of the listening musician mirrored that of the performing musician. For the more structured song, listeners mirrored ML sway for all three performance styles and AP sway for expressive and non-expressive performances. For the less structured song, listeners mirrored AP sway but not ML sway. There was a similar difference between the two songs in Experiment 1, where the natural overlap between the performers was higher for the more structured than for the less structured song. Both results suggest that musical structure provided a constraint on the music performance system, decreasing the possible ways it could organize.

One effect of musical structure appears to have been to couple ancillary, ML postural sway with sound-producing, AP postural sway. In the present experiment, the listening musicians were able to mirror the sound-producing movements reflected in the AP sway of the performer for both songs, but were able to mirror ancillary ML swaying movements only for the more structured song. This suggests that the constraint that the musical structure provided was responsible for this coupling of the ML and AP movements. This would explain why the more structured song showed mirroring in ML sway, but the less structured did not. Further support for this hypothesis comes from an additional comparison with these results with those from Experiments 1. The performances that elicited the mirroring of real movement in Experiment 3 were the same performances for which with information ML sway, AP sway, and Loudness were all linked in Experiment 1 (see Tables 20-21 in Chapter 8), supporting my claim that sound-producing movements and ancillary movements are part of the same system .

The non-expressive performances were an exception. For these performances, ML sway AP sway, and Loudness were not linked in Experiment 1, although they did elicit mirroring of real movement in Experiment 3. Non-expressive performances were also differed from expressive and normal performances in Experiment 3; they elicited metaphorical motion and possibly show action simulation. Mirroring in non-expressive performances appears to have been achieved in a different way than mirroring in the expressive and normal performances. The musicians reported that they found the mirroring difficult because it was hard to anticipate expressive variations in timing. These variations may have been easier to anticipate in the more structured piece, resulting in better mirroring for non-expressive performances. In contrast, mirroring in expressive and normal performances may have been achieved primarily through mirroring the movements of the trombone slide resulting in greater mirroring for AP than for ML sway.

These results are similar to those of Experiment 2, where listeners mirrored the performer's postural sway when asked to conduct the same performances in a way that mirrored the performer's expression. In Experiment 2, we concluded that listeners were hearing *action* and *patterning* information about the performer's AP and ML movements. The same appears to have been true for the performers in Experiment 3: the musicians were hearing the movements of the other musician in the sound.

There is, however, an alternative explanation for the mirroring in Experiment 3. The mirroring of posture in Experiment 3 might simply have been due to the fact that mirroring expression controlled the timing and dynamics, making each performance more similar and thereby making the postural sway similar. When a musician controls the expressive timing and dynamics between himself and the other musician, he may also be decreasing the differences between the sound-producing movements making it easier for the ancillary gestures to be more similar. If so, then there should have been an increase in degree of similarity when the performer mirrored his own performance; this result would parallel the prediction of action simulation. However, in most cases the mirroring of expression disrupted the natural-self overlap a performer had with himself. Those cases where Self-Mirroring was strengthened could also support the action-simulation hypothesis or simply the alignment sound-producing gestures as I suggested above. This experiment cannot distinguish these possibilities. However, it is clear the both real and metaphorical motions were perceived by the listening performer.

Mirroring occurred for all three types of movement information: spatial, action, and patterning. When mirroring spatial information, the listening musician aligned with the position of the performing musician. When mirroring action information, the listener changed position at the same points in the piece as the performer. When mirroring patterns, the listener tracked the sway of the performer.

Lastly, this task was difficult. Musicians did not practice performing with each recording ahead of time. One listening is not enough to learn another musicians timing and dynamics well enough to perfectly reproduce all the nuances. I purposely did not allow time to practice and allowed 6 months between recording and listening trials to ensure performers simply did not remember how they moved when they played. If I were to do this experiment again, I would allow the performers time to practice to see if more mirroring occurs as the performers become better at anticipating the exact the timing and dynamics from each performance.

Chapter 11: General Discussion

Dynamical Systems Theory to Music Performance

Almost universally, musical performers make large-scale body movements as they play, swaying from side to side in ways that appear to be both musically expressive and unnecessary for the production of the musical sounds. The study of these large-scale movements has presented researchers with a challenge in that when musicians perform the same piece repeatedly, they produce very similar sounding music but move their bodies differently each time. This has led to the idea that these movements are ancillary, i.e., they accompany the sound, supporting other movements that actually produce it (Jensenius et al., 2010). However, experimental evidence suggests that the role of these large-scale body movements is not ancillary, i.e., supportive of sound-production. Instead ancillary movements have been linked to musical expression (Dahl & Friberg, 2007; Davidson, 2007; Nusseck & Wanderley, 2009), musical skill (Rodger, 2010; Rodger, O'Modhrain, & Craig, 2013), and directly to the production of the actual musical sound (Davidson & Dawson, 1995; Wanderley et al., 2005). In this dissertation, I have proposed a new framework, based on dynamical systems theory, which can explain how ancillary movements can differ in each performance but still provide listeners with information about the musical expression.

Body Movements of the Performer

The shift to a dynamical systems framework requires rethinking some of the assumptions of the standard cognitive approach to movement, in particular to the idea of gestures as discrete acts of communication. In Experiment 1, there was clear evidence that taking a different approach, and treating movements as continuous, time-evolving actions in space, provided a new and useful way of understanding the connections between movement, musical structure, and expression. Further, Experiment 1 provided evidence that the correspondence between the movements of the performer and the musical structure was complex, rather than a 1:1 correspondence between a particular musical idea and a body movement. Instead, the movement's relation to the musical structure differed between musical selections, depending on the distance between musical boundaries. This finding showed the value of the dynamical system approach. Ideas about trade-offs between flexibility and stability from synergy theory (Latash, 2008), and about constraint and organization from dynamical systems theory more generally, provided important insights into the relationship between movement, musical structure, and expression. For example, the musicians changed their movements in the ML and AP sway planes relative to each other and relative to their expressive intentions. As AP movements become more variable, ML movements become more stable. The expressive intention of the performer provided a constraint on the movements: Too much expression and the movements became chaotic; too little expression and they became almost random.

Pushing performers to extremes of expressiveness has been widely used as an experimental manipulation in the study of music performance. The effects of this manipulation in Experiment 1 suggest that it may not be the best approach. In psychology, we have generally thought of systems as linear and therefore wanted to push them to extremes to make sure we can see differences. This is not an appropriate strategy when dealing with a non-linear dynamical system. What we have done to performers can be thought of as similar to turning up the volume on a speaker too high so that the speaker distorts the sound and then turning it too low so that the speaker only ekes out a white-noise hiss. To gain an appreciation of how expression constrains the system to change body movement in music performance, we should try more subtle manipulations and then see how the system unfolds.

The change in the performers' expressive intentions did not just affect their movements, but also how they enacted the musical structure. In other words, the performers changed how they phrased the music in response to changes in their expressive goals, as proposed by Clarke (1989). Music performance research to this point has focused on effects of researcher-defined musical boundaries that are assumed to be fixed. Music performance is not, however, simply the implementation of a composition, but an interplay between the performer, his expressive intentions, the composition, the social context, and the performer's skill level. All of these are included in Hargreaves et al.'s (2005) model of music performance, which the authors suggest requires a dynamical framework. I see my dynamical systems framework as a first step toward the development of a full realization of this model of performance.

Listeners Hear Movement

The framework I have proposed makes predictions about what information should be available in musical sounds because of the way sound-producing movements are connected to body sway. There are three types of information that might be available to the listener: Spatial, action, and patterning information. Effects of spatial information would mean that the music informs listeners *where* to sway; action information tells them *when* to sway; patterning information, identified by cross-recurrence quantification, provides listeners with information about complex movement patterns. I expected that listeners would move like performers in terms of their actions and patterns. I expected listeners to mirror performers for two reasons. First, because my theory predicts that musical expression is linked to body movement. Therefore, when people hear musical expression, they hear body movement as well. Second, because music functions to bring people together as part of a social group (Blacking, 1995; Cross, 2005), and does so by enabling their engagement in joint action and sharing of the same experience (Gioia, 2006).

Real Movement. The results of Experiment 2 clearly showed that listeners intermittently phase-synchronized their movements to the movements of the performer they were hearing, either time-locked or lagged. The synchronization could not be explained as a by-product of the listeners moving to the meter of the music, as the performers did not sway with the musical meter in the AP direction. Therefore, listeners could hear the real movements of the performer in both AP and ML sway directions. For both AP and ML sway, listeners aligned with the action and patterning information in the performance, while the expressive intentions of the performer made no difference.

What were the listeners hearing in the sound? For movements in the AP direction, the obvious answer seems to be that they heard the movements of the trombone slide. What about the ML direction? One possibility is that ML sway causes changes in the phase and amplitude of the sound (Wanderley & Depalle, 2004) and that listeners were sensitive to these effects. Both of these suggestions are speculative. Regardless of what properties change in the sound as a function of body movement, my data show that musical sounds do contain information about movement. The nature of the information needs further examination. Essentially, listeners can be thought of as using their own perceptual-motor processes to hear the movements of the performer *through* the sound. The listener's ability to understand the expressive intentions of the performer may be through use of the listener's own motor system. This suggestion of a link between the motor and perceptual systems has parallels with the motor theory of speech perception (Liberman, Cooper, Shankweiler, & Studdert-Kennedy, 1967; Liberman & Mattingly, 1985), which has recently been revived with new fMRI evidence (Lotto, Hicktok, & Holt, 2009).

There is also evidence of motor system activation while listening to music (Zatorre et al., 2007), though it seems that listeners use their motor system more when they understand the mapping between pitch and the action required to produce it (Lahav et al., 2007). Similarly, my listeners who were trained as musicians were more likely to synchronize. It is important to note, however, that the non-musical listeners mirrored the performer as well.

Metaphorical movement. Clarke (2001) has theorized that music contains not just the real movements of listeners, but also metaphorical movement implied by the composition. While there are several possibilities as to what in the composition may imply motion (reviewed by Shove & Repp, 1995), the periodic nature of both meter and postural sway make them obvious candidates for comparison. Further, metrical movements can be quantified in a rather straightforward manner. Experiment 1 showed that the performers moved periodically and metrically, and did so less for expressive and non-expressive performance styles. This was not true for the listeners in Experiment 2, who moved periodically and somewhat metrically to the music regardless of what the performer did. This suggests that while the performer's expressive goals change the degree to which his body reflects the metrical metaphor of the music, the listener's response is not similarly affected. This means that when examining the movements implied by music performance, we must be aware of both the real motion of the performer and of metaphorical motion implied by the music. More research will be needed to determine which aspects of a composition imply metaphorical motion in ways that affects listeners' responses.

Performers Hear Movement

Just as Experiment 2 examined listeners' movements while conducting so as to evoke musical expression, so Experiment 3 examined the trombonists' movements as they played along, trying to mirror the expression (timing and dynamics) of the same performances. The results showed that, like the listeners in Experiment 2, the listening trombonists in Experiment 3 synchronized intermittently with the movements of performer. Synchrony in the follower was more likely to occur when the original performance showed strong coupling between ML and AP sway as well as between ML or AP sway and loudness. This supports my prediction that the interaction between ML/AP sway and the expressive intentions of the performer are bidirectional and related to sound-production.

An alternative to my dynamical systems explanation of mirroring is the idea of action simulation (Sebanz, et al., 2006; Keller, et al., 2007). There was little behavioral evidence in the results of Experiment 3 for the prediction of the action simulation account that mirroring of postural sway would be greater when the listening musicians played along with their own performances rather than those of the other musician. The performers did report that it was easier to mirror their own expression, as Keller et al. (2007) found. However, there was little behavioral evidence to support this. Although they did mirror their own movements more, the level of this mirroring was rarely above natural levels of overlap. There were two differences between this experiment and those by Keller et al. (2007). First, Keller et al. examined the alignment of sound-producing movements, whereas I measured the alignment of body sway.

Second, Keller et al.'s musicians performed as duos, which did not allow them to assess the amount of natural overlap with themselves in the way I did. It is possible that, like my trombonists, the reason that Keller et al.'s musicians mirrored themselves more than they mirrored the other musician was natural overlap rather than action simulation.

This suggests that chance measures need to be created to separate true cases of mirroring from cases of natural overlap between performers. In Experiment 1, performers made multiple recordings in the same style to provide a way to measure the reliability of body movements within the same musician. This provided a measure of the natural, chance level of body synchrony between two performances. It is obvious that performers would move with higher alignment when playing with their own recordings, but is this because they can better simulate their own actions or because using the same musician controls for individual differences? In Experiment 3, it was true that performers were more likely to mirror their own movements than the other musicians, but they also naturally 'mirrored' their own movements even when they could not hear their own performance. When self-mirroring trials were compared to this natural baseline measure of chance, the self-mirroring was weaker than natural overlap except for three cases. The development of proper chance measures is one of the methodological advances I have brought to the study of musicians' movements.

Methodological Advances

The introduction of dynamical systems techniques, surrogate testing methods, and mixed effects models, to understanding the movements of performers has yielded statistical support for many of the observations that have been made previously by researchers in the field without the benefit of suitable statistical tests. These methods provide the most powerful and most appropriate tools for examining body movement. To my knowledge this is the first time they have been used to examine body movements in performance.

Dynamical Systems Methods

In this dissertation, I used several different dynamical systems methods to examine the movements of performers. Recurrence quantitation analysis provided a way to examine the movements of performers in a data driven fashion that did not require making decisions as to what movements constituted a gesture. Essentially, the patterns of movement were examined at all-time points concurrently, which provided measures, not of just when the body repeated, but also how orderly, predictable, and stable those patterns were. These metrics provided new insights into how the body movements changed relative to the musical structure and the expressive aspects of the performance.

The extension of recurrence quantitation analysis to cross-recurrence quantitation analysis provided a more sensitive measure than cross-correlation as it provided a way to measure patterns of overlap that were impossible to examine with cross-correlation. I used cross-recurrence quantitation analysis to examine whole performances, but the method can be scaled down to musical beats as I did with recurrence quantitation analysis to ask more nuanced questions about where in the musical composition the two performers actually overlapped.

Surrogate Hypothesis Testing

One of the challenges of using to methods like cross-recurrence and cross-correlation is to quantify the degree to which the overlap between the two signals is beyond chance overlap. The hypothesis used by most researchers has been the white-noise hypothesis, mainly because this is how signal engineers developed the tools. The white-noise hypothesis is generally inappropriate for movement research as it only asks if the two signals are different from the expected overlap if one signal were white noise. However, body movement is more complex than white noise. Phase (IAAFT) surrogates provide a solution as they show overlap between the two signals in phase, a requirement to say the two signals are coupled, i.e., synchronized. As seen in Experiment 1, without the use of phase surrogates, the values of cross-correlation can be misleading. There, non-expressive performances had high cross-correlation values, but were not actually synchronized. Phase surrogates do come at a computational cost, as the time needed to run some of these analyses is very long on standard computers, making data exploration a long process. Regardless, this method provided a way to properly test for phase overlap in the performances and allowed me to conclude that mirroring had occurred.

Mixed Effect Models

Mixed effects models provide new and more powerful ways to examine performance. They allowed the comparison of multiple songs containing different phrase lengths. They also allow us to include predictors that are individualized for each performer and for each performance. With traditional methods, the questions that I asked in Experiment 1 would not have been answered. The results showed that, as others have noted, the performances were different every time. Not only were the two songs different from each other in terms of the number and length of phrases, but these changed with the performance style. Moreover, these changes were different for each performer. Mixed models were able to capture the complexity of these relationships. Further, unlike traditional methods, mixed effect models do not assume that data points are independent. Mixed models provide, therefore, an appropriate method for examining autoregressive data structures of the sort that are common in measures of movement and of performance more generally.

Conclusion

Performers' body movements were systematically related to the musical structure and to the performers' expressive intentions. This relationship was not, however, determined simply by the locations of musical boundaries; the effect of structural boundaries depended on the distance between them. Further, there was no 1:1 correspondence between the musical structure and musical gestures. The concept of gesture, at least in the form borrowed from language research, does not work for music performance. Musical gestures need to be conceptualized as continuous actions in space-time and be analyzed in a manner that reveals how they relate to the musical structure. This research showed that body sway movements that are normally considered ancillary, i.e., supporting sound-production, were actually not ancillary, but an intimate part of the process of creating the musical sound of the performance.

I have combined my findings with those of other researchers to create the beginnings of a dynamical system framework for music performance. Using this framework and the tools for analyzing dynamical systems, I have shown that listeners mirror both the real movements of performers as well as the metaphorical motion implied by the composition. This conclusion provides new insight into musical communication, and possibly into communication more generally. This new understanding of musical communication treats the body as an important factor in both the creation of music and in the experience of listening to music.

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Appendix A: Title of Appendix

Appendix B: List of Abbreviations

Appendix C: Expanded Experiment 1 Linear Analysis

Appendix D: Expanded Experiment 1 Dynamical Analysis

Appendix B: List of Abbreviations

AMI	Average Mutual Information index
AP	Anterior-Posterior
COP	Center of Pressure
CRQA	Cross Recurrence Quantitation Analysis
ML	Medio-Lateral
MFCWT	Multi-fractal continuous wavelet transform analysis
RMS	Root Mean Square
PSR	Phase-Space Reconstruction
RQA	Recurrence Quantitation Analysis
STFT	Short-Time Fourier Transform
Xcorr	Cross-Correlation

Appendix C: Expanded Experiment 1 Linear Analysis

Within Musician Performance Level Analyses

Overview. Table 37 and Table 38 each show the inter-performance lag 0 cross-correlations for tempo/loudness, as well as change of tempo/loudness within performances for the same performer. Tempo was measured by beat, while loudness was measured at the same sampling rate (34 hz) as the postural measures. Table 39 and Table 40 each show the inter-performance lag 0 cross-correlations for position and change of position of ML, AP postural sway within performances for the same performer for both songs. Loudness and postural sway were time-warped to facilitate comparison. Probability values were generated using both the shuffled and phase shuffled surrogates and applying the percentile method. Probability values for tempo were generated via traditional bootstrapping procedures using the percentile method.

Expressive Features. As be seen in Table 37 and Table 38, the tempo and change in tempo regardless of style of song is quite high. However, it is lowest for all comparisons involving non-expressive performances. For both songs, the strongest correlations are the same style comparisons, highlighted in grey. The same pattern of results can be seen in Table 37 and Table 38 for both loudness and change in loudness. Again, performers show nearly identical patterns with the strongest relationships occurring between normal and expressive performances. Again, the strongest relationships occur intra style, with non-expressive performances showing the weakest intra-style relationships.

Table 37.

Inter-performance Correlations for Tempo Rochut 4 for Performer 1 & 2.

Tempo		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Tempo	*N2*	0.84*					0.82*				
	E1	0.73*	0.70*				0.81*	0.81*			
	E2	0.79*	0.83*	0.84*			0.71*	0.79*	0.78*		
	NE1	0.72*	0.74*	0.62*	0.73*		0.72*	0.71*	0.70*	0.64*	
	NE2	0.69*	0.70*	0.63*	0.71*	0.84*	0.68*	0.66*	0.56*	0.52*	0.67*
Change in Tempo	*N2*	0.84*					0.80*				
	E1	0.72*	0.71*				0.82*	0.75*			
	E2	0.77*	0.83*	0.83*			0.76*	0.76*	0.79*		
	NE1	0.74*	0.79*	0.72*	0.80*		0.66*	0.68*	0.66*	0.61*	
	NE2	0.77*	0.78*	0.73*	0.82*	0.87*	0.61*	0.65*	0.55*	0.48*	0.71*

**p* <.05 based on 500 shuffled surrogates.

Table 38.

Inter-performance Correlations for Tempo Rochut 13 for Performer 1 & 2.

Tempo		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Tempo	*N2*	0.85*					0.78*				
	E1	0.73*	0.68*				0.70*	0.75*			
	E2	0.70*	0.69*	0.72*			0.79*	0.83*	0.75*		
	NE1	0.65*	0.73*	0.44*	0.39*		0.73*	0.76*	0.63*	0.70*	
	NE2	0.59*	0.65*	0.44*	0.40*	0.75*	0.67*	0.66*	0.55*	0.64*	0.76*
Change in Tempo	*N2*	0.83*					0.78*				
	E1	0.74*	0.69*				0.60*	0.66*			
	E2	0.74*	0.72*	0.73*			0.81*	0.82*	0.68*		
	NE1	0.75*	0.80*	0.62*	0.68*		0.73*	0.79*	0.60*	0.76*	
	NE2	0.75*	0.78*	0.61*	0.62*	0.81*	0.74*	0.72*	0.55*	0.75*	0.80*

**p* <.05 based on 500 shuffled surrogates.

Table 39.

Inter-performance Correlations for Loudness Rochut 4 for Performer 1 & 2.

Loudness		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Loudness	*N2*	0.84*†					0.85*†				
	E1	0.83*†	0.82*†				0.82*†	0.81*†			
	E2	0.83*†	0.85*†	0.85*†			0.78*†	0.83*†	0.87*†		
	NE1	0.78*†	0.74*†	0.73*†	0.78*†		0.81*†	0.76*†	0.75*†	0.71*†	
	NE2	0.78*†	0.75*†	0.73*†	0.76*†	0.89*†	0.75*†	0.74*†	0.64*†	0.64*†	0.82*†
Change in Loudness	*N2*	0.61*†					0.72*†				
	E1	0.60*†	0.63*†				0.67*†	0.69*†			
	E2	0.59*†	0.64*†	0.68*†			0.68*†	0.68*†	0.71*†		
	NE1	0.59*†	0.61*†	0.62*†	0.61*†		0.69*†	0.67*†	0.63*†	0.65*†	
	NE2	0.61*†	0.65*†	0.63*†	0.59*†	0.74*†	0.65*†	0.64*†	0.6*†	0.61*†	0.72*†

*p <.05 based on 500 shuffled surrogates. † p <.05 based on IAFFT surrogates.

Table 40.

Inter-performance Correlations for Loudness Rochut 13 for Performer 1 & 2.

Loudness		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Loudness	*N2*	0.81*†					0.73*†				
	E1	0.76*†	0.78*†				0.72*†	0.62*†			
	E2	0.74*†	0.75*†	0.78*†			0.7*†	0.63*†	0.73*†		
	NE1	0.76*†	0.78*†	0.71*†	0.67*†		0.72*†	0.62*†	0.56*†	0.52*†	
	NE2	0.79*†	0.81*†	0.74*†	0.74*†	0.82*†	0.74*†	0.62*†	0.64*†	0.59*†	0.76*†
Change in Loudness	*N2*	0.66*†					0.63*†				
	E1	0.66*†	0.65*†				0.62*†	0.61*†			
	E2	0.63*†	0.63*†	0.66*†			0.6*†	0.59*†	0.62*†		
	NE1	0.64*†	0.63*†	0.62*†	0.58*†		0.64*†	0.6*†	0.57*†	0.56*†	
	NE2	0.66*†	0.66*†	0.65*†	0.63*†	0.69*†	0.63*†	0.57*†	0.59*†	0.56*†	0.65*†

*p <.05 based on 500 shuffled surrogates. † p <.05 based on IAFFT surrogates.

ML Postural Sway. As seen in Table 41 and Table 42, ML postural sway shows overall much lower reliability between performances than tempo or loudness. However, for both songs the intra-style relationship again show stronger correlations then inter style comparison. Further, only in change of position is there a significant relationship (phase-surrogates) between non-expressive performances and some of the non-expressive and overly expressive performances.

For performer 2, all of the comparisons are significant using both null hypothesis tests, but the correlations between the non-expressive and other performances are lower than the correlations between normal and expressive styles. The overall correlations for performer 1 are generally much weaker than for performer 2. This suggests that performer 2 retains more of his individualistic style from one performance to the next in ML postural sway movements. However, this effect for Performer 2 weakens for Rochut 13. Further, for Rochut 13, we also see that the intra-performance position correlations for performer 1 are weakened and there are overall less significant correlations. However, change in position is more robust then raw position for the less structured music. Overall, these results for ML postural sway highlight differences in the way each performer retain their sway from one performance to the next. More structured music results in more similarities between performances seen in ML sway.

Table 41.

Inter-performance Correlations for COP: ML Rochut 4 for Performer 1 & 2.

COP: ML		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Position	*N2*	0.54*†					0.53*†				
	E1	0.39*†	0.36*†				0.61*†	0.62*†			
	E2	0.48*†	0.49*†	0.45*†			0.63*†	0.64*†	0.61*†		
	NE1	0.21*	0.23*	0.01	0.2*		0.54*†	0.53*†	0.46*†	0.61*†	
	NE2	-0.08*	0.16*	0.07*	0.14*	0.25*	0.39*†	0.40*†	0.33*†	0.37*†	0.49*†
Change	*N2*	0.39*†					0.61*†				
in	*E1*	0.27*†	0.33*†				0.63*†	0.58*†			
Position	*E2*	0.35*†	0.35*†	0.37*†			0.62*†	0.62*†	0.61*†		
	NE1	0.11*	0.04*	0.09*†	0.12*†		0.49*†	0.51*†	0.44*†	0.54*†	
	NE2	0.05*	0.05*	0.11*†	0.15*†	0.4*†	0.46*†	0.46*†	0.41*†	0.43*†	0.51*†

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates.

Table 42.

Inter-performance Correlations for COP: ML Rochut 13 for Performer 1 & 2.

COP: ML		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Position	*N2*	0.43*†					0.44*†				
	E1	0.15*	0.36*†				0.32*	0.45*†			
	E2	0.18*	0.30*	0.37*†			0.5*†	0.55*†	0.29*		
	NE1	-0.1*	0.10*	-0.13*	0.10*		0.27*	0.39*	0.19*	0.2*	
	NE2	0.35*†	0.22*	0.09*	0.32*†	0.19*	0.27*	0.49*†	0.17*	0.38*	0.22*
Change in Position	*N2*	0.38*†					0.37*†				
	E1	0.18*	0.25*†				0.28*†	0.3*†			
	E2	0.26*†	0.29*†	0.31*†			0.34*†	0.42*†	0.24*†		
	NE1	-0.02*	0.01	-0.04*	-0.03*		0.18*	0.24*†	0.22*†	0.15*†	
	NE2	0.16*	0.2*†	0.12*	0.11*	0.2*†	0.3*†	0.3*†	0.21*†	0.2*†	0.17*

*p <.05 based on 500 shuffled surrogates. † p <.05 based on IAFFT surrogates.

AP Postural Sway. Table 43 and Table 44 each shows AP sway between performances. For both performers, the significant effects on the shuffled surrogates for nearly all comparisons suggest that the time structure of the AP postural sway is similar. This is true for change in position as well. However, for Performer 1, AP postural sway exhibits few phase-shuffled surrogate results for position, but many for change in position. This suggests that Performer 1 matches the patterns of his movements, but not the position of his movements in AP sway. This is true for both songs. Performer 2 exhibits a different pattern from Performer 1 in Rochut 4, but not in Rochut 13. For Rochut 4, Performer 2 shows significant overlap in both position and change in position for most performances, except non-expressive performances. For non-expressive performances, he only generally overlaps in change of position. For Rochut 13 his pattern reflects a similar pattern to Performer 1, in that the significant phase overlap occurs in change in position as opposed to position.

Table 43.

Inter-performance Correlations for COP: AP Rochut 4 for Performer 1 & 2.

COP: AP		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Position	*N2*	0.35*†					0.42*†				
	E1	0.03	0.46*†				0.38*†	0.38*†			
	E2	0.37*†	0.30*	0.28*			0.29*†	0.40*†	0.40*†		
	NE1	-0.06*	0.03	0.16*	0.02		0.23*	0.23*	0.21*	0.19*	
	NE2	-0.08*	-0.11*	-0.15*	-0.02	0.28*	0.26*†	0.21*	0.20*	0.12*	0.31*†
Change in Position	*N2*	0.18*†					0.37*†				
	E1	0.12*†	0.2*†				0.35*†	0.35*†			
	E2	0.13*†	0.27*†	0.29*†			0.37*†	0.41*†	0.36*†		
	NE1	0.05*	0.21*†	0.18*†	0.2*†		0.21*†	0.27*†	0.20*†	0.24*†	
	NE2	0.06*	0.29*†	0.18*†	0.33*†	0.45*†	0.2*†	0.21*†	0.20*†	0.2*†	0.32*†

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on IAFFT surrogates.

Table 44.

Inter-performance Correlations for COP: AP Rochut 13 for Performer 1 & 2.

COP: AP		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
Position	*N2*	0.42*					0.30*†				
	E1	0.14*	0.33*†				0.17*	0.19*			
	E2	0.29*	0.34*†	0.43*†			0.12*	0.15*	0.18*		
	NE1	0.13*	0.16*	-0.10*	0.04		0.27*†	0.25*	0.15*	0.14*	
	NE2	-0.07*	0.14*	-0.18*	-0.17*	0.19*	-0.02	0.3*†	0.08*	0.27*	0.09*
Change in Position	*N2*	0.26*†					0.11*†				
	E1	0.18*†	0.2*†				0.12*†	0.2*†			
	E2	0.21*†	0.26*†	0.27*†			0.07*†	0.24*†	0.13*†		
	NE1	0.15*†	0.18*†	0.06*	0.11*†		0.19*†	0.22*†	0.06*	0.11*†	
	NE2	0.16*†	0.24*†	0.09*†	0.12*†	0.37*†	0.11*†	0.15*†	0.12*†	0.13*†	0.23*†

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on IAFFT surrogates.

Between Musician Performance Level Analyses

Overview. Table 45 and Table 46 each shows the inter-performer lag 0 cross-correlations for tempo/loudness, as well as change of tempo/loudness within performances for the same performer. Tempo was measured by beat, while loudness was measured at the same sampling rate as the body measures. Table 47 and Table 48 each shows the inter-performance lag 0 cross-correlations for position and change of position of ML, AP postural sway between performers for both songs. Loudness and postural sway were time-warped to facilitate comparison. Probability values were generated using both the shuffled and phase shuffled surrogates and tested using the percentile method. Probability values for tempo were generated via traditional bootstrapping procedures using the percentile method.

Expressive Features. Table 45 represents all the inter-performance correlations for tempo between the performers. These complete set comparisons generally show that both tempo and change of tempo between performers is reliably similar. This is truer for the less structured music, Rochut 13, than for Rochut 4. The reason for this is probably because the lengths and number of phrases between performers was more similar for Rochut 13. Since the phrases are more similar, speeding up and slowing down at phrase boundaries are more aligned. Overall, non-expressive performances were the most different from each other than all other performances. Normal performances were the most similar and expressive performances were in between normal and non-expressive, but closer to normal.

Table 46 for loudness reflects values that are higher than tempo. However, loudness was measured at 34Hz resulting in more data points and thus making it difficult to directly compare to tempo. There is little variation between the performances, and all the values are extremely high. The purpose of these comparisons is to show that expressive features of performance are very strongly related.

Table 45.

Inter-Performer Correlations for Tempo Rochut 4 for Performer 1 & 2.

Tempo		Rochut 4		**P2**				Rochut 13		**P2**			
		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*	*N1*	*N2*	*E1*	*E2*	*NE1*	*NE2*
Tempo	*N1*	0.44*	0.46*	0.40*	0.41*	0.43*	0.27*	0.59*	0.50*	0.52*	0.55*	0.49*	0.60*
	N2	0.47*	0.52*	0.44*	0.41*	0.41*	0.34*	0.56*	0.49*	0.50*	0.50*	0.51*	0.59*
P1	*E1*	0.32*	0.37*	0.36*	0.34*	0.31*	0.18*	0.57*	0.60*	0.53*	0.58*	0.43*	0.44*
	E2	0.38*	0.45*	0.37*	0.39*	0.39*	0.29*	0.60*	0.62*	0.58*	0.62*	0.50*	0.52*
	NE1	0.21*	0.32*	0.25*	0.27*	0.20*	0.16*	0.39*	0.31*	0.32*	0.24*	0.39*	0.50*
	NE2	0.21*	0.28*	0.21*	0.23*	0.16*	0.12	0.43*	0.39*	0.42*	0.33*	0.47*	0.58*
Change in Tempo	*N1*	0.33*	0.35*	0.31*	0.35*	0.35*	0.18*	0.58*	0.49*	0.54*	0.54*	0.51*	0.69*
	N2	0.39*	0.47*	0.41*	0.40*	0.34*	0.25*	0.55*	0.55*	0.54*	0.54*	0.58*	0.66*
	E1	0.18*	0.19*	0.17*	0.18*	0.14	0.07	0.43*	0.44*	0.42*	0.40*	0.38*	0.46*
P1	*E2*	0.25*	0.33*	0.24*	0.28*	0.29*	0.19*	0.52*	0.51*	0.50*	0.46*	0.45*	0.60*
	NE1	0.20*	0.28*	0.22*	0.22*	0.15	0.07	0.54*	0.56*	0.45*	0.50*	0.57*	0.63*
	NE2	0.24*	0.28*	0.23*	0.25*	0.17*	0.04	0.56*	0.58*	0.55*	0.59*	0.62*	0.68*

*p <.05 based on 500 shuffled surrogates.

Table 46.

Inter-performance Correlations for Loudness for Performer 1 & 2.

		Rochut 4		**P2**				Rochut 13		**P2**			
		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*	*N1*	*N2*	*E1*	*E2*	*NE1*	*NE2*
Loudness	*N1*	0.66*†	0.70*†	0.68*†	0.70*†	0.67*†	0.60*†	0.64*†	0.61*†	0.57*†	0.56*†	0.57*†	0.61*†
	N2	0.65*†	0.67*†	0.67*†	0.67*†	0.70*†	0.59*†	0.64*†	0.65*†	0.53*†	0.52*†	0.59*†	0.62*†
	E1	0.64*†	0.67*†	0.67*†	0.67*†	0.62*†	0.53*†	0.52*†	0.58*†	0.46*†	0.44*†	0.50*†	0.51*†
P1	*E2*	0.65*†	0.68*†	0.68*†	0.68*†	0.66*†	0.58*†	0.55*†	0.56*†	0.49*†	0.47*†	0.50*†	0.54*†
	NE1	0.68*†	0.69*†	0.66*†	0.66*†	0.70*†	0.71*†	0.56*†	0.57*†	0.46*†	0.45*†	0.58*†	0.56*†
	NE2	0.68*†	0.7*†	0.65*†	0.64*†	0.74*†	0.74*†	0.64*†	0.6*†	0.54*†	0.55*†	0.64*†	0.65*†
Change in Loudness	*N1*	0.53*†	0.54*†	0.52*†	0.51*†	0.53*†	0.53*†	0.55*†	0.53*†	0.5*†	0.50*†	0.53*†	0.54*†
	N2	0.53*†	0.53*†	0.53*†	0.51*†	0.53*†	0.51*†	0.56*†	0.54*†	0.53*†	0.52*†	0.52*†	0.58*†
	E1	0.48*†	0.53*†	0.55*†	0.49*†	0.47*†	0.49*†	0.53*†	0.54*†	0.52*†	0.51*†	0.54*†	0.54*†
P1	*E2*	0.48*†	0.52*†	0.50*†	0.47*†	0.48*†	0.47*†	0.52*†	0.53*†	0.5*†	0.48*†	0.52*†	0.52*†
	NE1	0.60*†	0.60*†	0.60*†	0.58*†	0.58*†	0.62*†	0.55*†	0.53*†	0.47*†	0.48*†	0.54*†	0.53*†
	NE2	0.59*†	0.61*†	0.57*†	0.57*†	0.6*†	0.61*†	0.59*†	0.55*†	0.51*†	0.53*†	0.57*†	0.56*†

*p <.05 based on 500 shuffled surrogates. † p <.05 based on 500 IAFFT surrogates

ML Postural Sway. Unlike in tempo and loudness, Table 47 shows that ML postural sway has little reliability between position of sway even after performances were time warped to make them comparable. There is not one performance that is phase locked between the performers. This matches the findings of Davison (2007, 2009): each performer has their own style and they never quite move the same way as each other. The one exception is non-expressive performances. For both songs and both performers non-expressive performances had stronger correlations than normal or expressive performances, but they were still not phase-coupled. However, all of the changes in position were significantly phase-coupled. This suggests that the performers are likely to move at the same times, just not in the same way. It is also important to note that the strength of the correlations for change in position are weak and are well below the levels seen in either loudness or tempo. For the less structured music, Rochut 13, there was no significant phase coupling between the performers for either position or change in position.

Table 47.

Inter-performance Correlations for COP: ML.

		Rochut 4		**P2**				Rochut 13		**P2**			
		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*	*N1*	*N2*	*E1*	*E2*	*NE1*	*NE2*
Position	*N1*	0.03	0.03	0.09*	-0.04*	-0.04*	0.08*	0.14*	0.11*	0.13*	0.08*	0.28*	0.07*
	N2	0.13*	0.09*	0.1*	0.05*	0.16*	0.15*	0.02	0.01	0.13*	-0.08*	-0.05*	-0.04*
	E1	0.04*	0.08*	0.05*	0.06*	0.02	-0.07*	-0.13*	0.01	-0.09*	-0.08*	-0.06*	0.02
P1	*E2*	0.16*	0.07*	0.03	0.14*	0.02	0.03*	-0.03	0.01	0.16*	0.09*	-0.15*	0.07*
	NE1	0.25*	0.19*	0.3*	0.22*	0.23*	0.26*	-0.07*	-0.24*	-0.12*	-0.2*	-0.16*	-0.11*
	NE2	0.09*	0.08*	0.17*	0.11*	0.11*	0.01	0.11*	0.25*	0.11*	0.12*	0.21*	0.25*
Change	*N1*	0.16*†	0.20*†	0.16*†	0.17*†	0.14*†	0.15*†	0.06*	0.03*	0.05*	0.03*	0.09*	0.09*
in	*N2*	0.14*†	0.11*†	0.15*†	0.09*	0.16*†	0.16*†	0.05*	0.03*	0.12*	0.03*	-0.02*	0.02*
Position	*E1*	0.1*†	0.11*†	0.12*†	0.10*†	0.07*	0.1*†	0.03*	0.02*	0.06*	0.03*	0.01	0.06*
P1	*E2*	0.15*†	0.13*†	0.12*†	0.16*†	0.06*	0.09*	0.02*	0.07*	0.08*	0.08*	-0.05*	0.09*
	NE1	0.09*†	0.07*†	0.07*†	0.07*†	0.08*†	0.05*	-0.01	0.01	-0.01	-0.05*	0.04*	0.01
	NE2	0.05*	0.06*†	0.07*†	0.03*	0.05*	0.01	-0.01	0.07*	0.06*	0.06*	0.06*	0.05*

$^*p$ <.05 based on 500 shuffled surrogates. † p <.05 based on 500 IAFFT surrogates

AP Postural Sway. As seen in Table 48, AP postural sway shows very weak relationships between performers in terms of position, except in a few cases for Rochut 4. There were a few phase-coupled performances between performers, such as some of the normal and expressive performances. This pattern is not mirrored in Rochut 13, and otherwise the effect on position is equally unrelated between performers as is ML postural sway. As for change in position, there are not as many phase locked performances as we saw for change in position for ML postural sway in Rochut 4. Further, for Rochut 13 there are also a few significant phase couplings. Most notably with the 1st non-expressive performances of performer 2 with nearly all of the performances of performer 1. Overall, the phase coupling between performers, even when significant, is weak.

Table 48.

Inter-performance Correlations for COP:AP.

		Rochut 4		**P2**				Rochut 13		**P2**			
		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*	*N1*	*N2*	*E1*	*E2*	*NE1*	*NE2*
Position	*N1*	0.20*†	-0.04*	0.13*	0.14*	-0.01	0.17*	0.1*	-0.07*	-0.08*	-0.08*	0.03	0.09*
	N2	-0.07*	-0.06*	-0.19*†	-0.08*	0.05*	0.26*†	0.08*	0.08*	0.14*	0.01	0.06*	0.11*
	E1	-0.07*	-0.07*	-0.27*†	-0.28*†	-0.01	0.16*	-0.06*	-0.03	0.2*	-0.04*	0.14*	0.03
P1	*E2*	-0.05*	-0.16*	-0.08*	-0.12*	-0.08*	-0.04*	-0.03	-0.21*	0.01	-0.04*	0.16*	-0.12*
	NE1	-0.05*	-0.14*	-0.11*	-0.21*	-0.01	-0.01	-0.11*	0.03	-0.25*	-0.14*	0.11*	-0.15*
	NE2	0.13*	-0.07*	-0.12*	-0.02	-0.11*	-0.06*	0.03	-0.06*	-0.1*	0.13*	-0.10*	-0.06*
Change	*N1*	0.05*	0.07*†	-0.02	0.05*	0.06*†	0.06*	0.04*	-0.04*	-0.08*†	-0.04*	0.13*†	0.01
in	*N2*	-0.07*†	-0.02	-0.07*†	-0.06*†	0.02	0.04*	-0.05*	0.02	-0.03*	0.07*	0.13*†	0.05*
Position	*E1*	-0.05*	-0.05*	-0.05*	-0.05*	0.05*	0.05*†	-0.07*	0.01	0.05*	-0.02	0.12*†	0.03*
P1	*E2*	-0.06*†	0.03*	-0.11*†	-0.07*†	0.09*†	0.05*	-0.04*	0.03*	0.04*	-0.03*	0.12*†	-0.03*
	NE1	-0.04*	-0.03*	-0.03	-0.03	0.06*†	0.03	-0.09*†	-0.03*	0.03*	-0.03*	0.09*†	0.04*
	NE2	-0.06*†	0.02	-0.05*†	-0.08*†	0.06*†	0.07*†	0.04*	-0.05*	-0.05*	0.04*	0.06*	0.05*

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates

Appendix D: Expanded Experiment 1 Dynamical Analysis

Cross-Recurrence of Postural Sway Within Performer

Overview. Table 49 and Table 50 each show the inter-performer lag 0 cross-recurrence for ML and AP postural sway between performances for the same performer for both songs. A high recurrence rate means that that the signals overlap in phase space. Overlap in phase space lag 0 means that the two signals are complexly coupled to some degree. Therefore, the results of the cross-correlations and cross-recurrence do not have to agree as they measure different types of relationships between the signals. However, the most direct comparison will be with position in the cross-correlation. Generally, if there is a significant phase relationship in cross-correlation, the recurrence analysis will likely capture it as well. However, this analysis is more sensitive than a cross-correlation analysis in that the amplitude differences between the performances do matter. In a cross-correlation, the amount of movement is not relevant. What is important for this analysis is the direction of movement. Therefore, if two signals exhibit very different amplitudes, cross recurrence may not necessarily find overlapping places between the signal because one signal does not actually cross the phase space of the other. Cross recurrence analysis, therefore, sets a higher bar for showing that 2 signals significantly overlap. In addition, a significant phase-relationship in recurrent space might not be seen in the cross-correlation as overlap may be occurring in the higher dimensions.

Rochut 4. Table 49 shows that for performer 1, there is one additional phase-coupled relationship not seen in the cross-correlation: the 1st normal performance and the 1st non-expressive performance. The cross-correlation analysis has shown a significant relationship for performer 2 in the expressive and non-expressive performances. However, the cross-recurrence analysis does not show this effect. This is because non-expressive performances exhibit very little change in amplitude. Therefore, the systems do not cross in phase space given the radius size set. A similar set of results are shown for the AP postural sway in cross recurrence.

Rochut 13. Table 50shows that for ML postural sway there is significant overlap between the performances. This was not evident in the cross-correlation analysis, which only showed 5 significant phase coupled performances. However, the cross recurrence analysis shows significantly coupled performances. In fact, all of the normal and expressive comparisons are significant for both performers. Unlike Rochut 4, which seems to have a more linear oscillation, Rochut 13 may have a more complex oscillatory pattern for ML postural sway and therefore is missed by the cross-correlation analysis. For AP postural sway there are a few additional significant effects not seen in the cross-correlation analysis, and several effects not carried over from the cross-correlation analysis of position. The pattern of results between Rochut 4 and Rochut 13 for AP postural sway does not exactly pattern the same, However, ML postural sway overlap pattern between the two songs does.

Table 49.

Inter-performance Cross-Recurrence Rate for Rochut 4 for Performer 1 & 2.

Postural sway % Recurrence		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
COP:ML	*N2*	33.45*†					46.51*†				
	E1	24.21*†	15.91*†				20.48*†	29.57*†			
	E2	27.11*†	22.93*†	16.47*†			37.29*†	35.94*†	30.94*†		
	NE1	13.04*†	9.98*	7.37	7.82		30.96*†	16.96*†	11.54*	15.12*†	
	NE2	8.27*	14.22*	11.4*	7.3	9.24*	19.75*†	23.98*†	15.22*	15.54*	24.23*†
COP:AP	*N2*	17.12*†					12.69*†				
	E1	13.14*†	13.08*†				12.9*†	12.86*†			
	E2	9.3*	9.86*†	10.49*†			10.38*†	11.24*†	10.39*†		
	NE1	12.1*†	6.64	10.98*	9.73*		11.27*†	8.3*	9.35*†	7.02*	
	NE2	6.81	7.72	4.8	12.51*	9.63*	10.65*†	6.64	6.47	5.07	8.9*

*p <.05 based on 500 shuffled surrogates. † p <.05 based on 500 IAFFT surrogates.

Table 50.

Inter-performance Cross-Recurrence Rate for Rochut 13 for Performer 1 & 2.

Postural sway % Recurrence		Performer 1					Performer 2				
		N1	*N2*	*E1*	*E2*	*NE1*	*N1*	*N2*	*E1*	*E2*	*NE1*
COP:ML	*N2*	30.22*†					38.43*†				
	E1	17.82*†	23.62*†				27.97*†	27.73*†			
	E2	12.84*†	17.02*†	22.47*†			37.24*†	41.39*†	24.16*†		
	NE1	8.42	14.09*†	5.71	8.59*		9.65*	15.32*	13.98*	27.3*†	
	NE2	24.53*†	23.35*†	9.65	16.27*†	14.08*	13.86*	24.45*	14.65*	23.92*†	17.12*
COP:AP	*N2*	14.46*†					10.71*				
	E1	12.11*	14.22*†				10.46*	9.54*			
	E2	18.42*†	13.83*	10.18*			10.6*	10.39*	8.45*		
	NE1	10.11*	11.06*	6.06	7.71		9.48*	10.42*	7.89*	7.19	
	NE2	12.67*	13.84*†	10.99*	14.76*†	8.63*	9.09*	11.69*	9.16*	11.59*	10.5*

*p <.05 based on 500 shuffled surrogates. † p <.05 based on 500 IAFFT surrogates.

Cross-Recurrence of Postural Sway Between Performer

Table 51 examines the intra-performer lag 0 cross-recurrence for ML and AP Postural sway within the same song. The cross-correlation analysis for ML postural sway showed no significant phase overlap between the performers for the same song for any particular performance. However, the cross-correlation analysis did show that time structure of the ML movements between select performance were similar, as evidenced by the significantly shuffled surrogates. The cross recurrence analysis, on the other hand, showed nine performances for Rochut 4 and six performances for Rochut 13with similar phase relationships between the performers. Where the cross-correlation analysis showed no phase relationships, the cross recurrence analysis does. This again suggests that while the natural phase relationships between the performances are different, performers do sometimes align. For AP postural sway, there was only one performance that exhibited phase overlap between performers. In the cross-correlation analysis, there were some significant phase overlaps in both position and change in position.

Table 51.

Inter-performance Cross-Recurrence Rates for Performer 1 & 2.

Postural sway % Recurrence		Rochut 4		**P2**				Rochut 13		**P2**			
		N1	*N2*	*E1*	*E2*	*NE1*	*NE2*	*N1*	*N2*	*E1*	*E2*	*NE1*	*NE2*
ML	*N1*	11.83*	7.75	7.82*	13.59*†	15.08*	12.28*	8.74*	10.74*†	10.14*	3.76	16.39*	10.39*
	N2	15.57*†	13.14*†	8.02*	7.99*	11.8*	14.46*	8.46*	6.74*	15.58*†	12.07*†	5.05	7.69
P1	*E1*	13.8*†	12.18*	7.82*	9.96*	14.22*	12.63*	8.11*	3.62	8.28*	4.42	6.70	5.12
	E2	8.68*	8.54*	7.51*	11.03*†	10.97*	10.07*	4.14	5.58	9.20*	11.41*†	4.14	8.32*
	NE1	14.87*†	8.65*	12.69*†	10.17*	10.27*	10.82*	6.74*	4.00	9.65*	6.18	5.72	6.28
	NE2	14.56*	7.4	9.75*	12.97*†	17.54*	12.42*	6.14	13.72*†	4.74	19.82*†	24.36*	16.95*
AP	*N1*	8.06*	4.39	7.4*	8.06*	4.91	8.54*	11.3*	7.58	6.49	10*	10.6*	7.02
	N2	5.74	4.15	3.32	5.36	7.71*	10.03*	10.88*	6.74	5.37	9.12*	12.43*	11.12*
	E1	8.41*	4.01	5.12	3.67	7.13*	6.71*	5.9	2.91	7.20	6.77	6.74	9.34*
P1	*E2*	3.56	5.57	6.4*	5.98	10.27*†	6.09	9.06*	8.56	7.58	8.63	12.18*	5.65
	NE1	8.44*	6.16	7.23*	4.77	7.02*	6.47	6.04	5.69	3.12	3.76	6.11	6.98
	NE2	6.5	8.16*	4.64	5.57	7.19*	10.07*	9.37*	12.25*	6.28	12.71*	13.09*	8.7*

**p* <.05 based on 500 shuffled surrogates. † *p* <.05 based on 500 IAFFT surrogates.