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RESEARCH ARTICLE

Complexity of human postural control in young and older adults during prolonged standing

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Abstract Aging is known to have a degrading influence on many structures and functions of the human sensorimotor system. The present work assessed aging-related changes in postural sway using fractal and complexity measures of the center of pressure (COP) dynamics with the hypothesis that complexity and fractality decreases in the older individuals. Older subjects (68 ± 4 years) and young adult subjects (28 ± 7 years) performed a quiet stance task (60 s) and a prolonged standing task (30 min) where subjects were allowed to move freely. Long-range correlations (fractality) of the data were estimated by the detrended fluctuation analysis (DFA); changes in entropy were estimated by the multi-scale entropy (MSE) measure. The DFA results showed that the fractal dimension was lower for the older subjects in comparison to the young adults but the fractal dimensions of both groups were not different from a 1/*f* noise, for time intervals between 10 and 600 s. The MSE analysis performed with the typically applied adjustment to the criterion distance showed a higher degree of complexity in the older subjects, which is inconsistent with the hypothesis that complexity in the human physiological system decreases with aging. The same MSE analysis performed without adjustment showed no differences between the groups. Taken all results together, the decrease in total postural sway and long-range correlations in older individuals are signs of an adaptation process reflecting the diminishing ability to generate adequate responses on a longer time scale.

Keywords Equilibrium · Nonlinear dynamics · Fractals · Entropy · Time scales

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Introduction

One of the factors that has profoundly affected human evolution is the adoption of bipedal stance. Ever since humans have begun to stand upright, they have been facing the challenge to balance the body over a relatively small area of support. This challenge is apparent in the body sway that is always present, even when a healthy person tries to stand as still as possible. Maintaining balance is a complex control task for the central nervous system and it is achieved by the integration of different types of sensory information, predominantly visual, vestibular, and proprioceptive, together with the reliance on the passive properties of the musculoskeletal system.

Aging is an important factor that can affect the ability to maintain postural balance. The effects of aging have been intensely investigated but, thus far, neither are the basic mechanisms of postural stability sufficiently understood, nor is it known how to prevent loss of stability in older individuals. Lipsitz et al. have provided support that a key signature of aging is the decrease in complexity in the human system (Lipsitz and Goldberger 1992; Goldberger et al. 2002b; Lipsitz 2002, 2004). For example, the authors have shown that the structure of fluctuations of the cardiac signals, i.e., their complexity, is significantly different in young and older adults (Costa et al. 2002; Lipsitz 2002). In a series of studies Newell et al. have examined isometric force production and identified differences in complexity in

older people when producing constant finger forces (Vaillancourt et al. 2004).

Structural and dynamical complexity in measured signals arises from the many spatiotemporal scales in a biological system. It is ubiquitous and is generally viewed as the source of the system's capacity to adapt to a constantly changing environment (Goldberger et al. 2002b; Lipsitz 2002). However, despite its ubiquity and importance for understanding human behavior, complexity remains an elusive concept and no single definition has yet been agreed upon (Gell-Mann 1995; Costa et al. 2002). Complexity is not equivalent to variability and it is not measurable by standard statistical tools like variance. A more variable system can easily be less complex and vice versa. It is often associated with a time evolution that has a rich structure on multiple time scales. With this understanding, the sinusoidal time course of a simple harmonic oscillator is not complex since its structure has only one time scale and it is fully predictable. A completely random evolution, on the other hand, like that of a sequence of coin tosses, is also not complex. Even though the sequence of events is not predictable, it neither involves multiple time scales nor does it display the adaptive nature that is typical of a complex system (Goldberger et al. 2002b; Lipsitz 2002; Vaillancourt and Newell 2002).

The notion of complexity has close kinship with that of information content in information theory. Information content is quantifiable by means of entropy which is a well-defined concept and a number of measures have been developed. Relating complexity to these ideas have led to the interpretation that the higher the information entropy in a time series, the more complex it is. Various algorithms have been proposed to estimate information entropy, i.e., complexity (Pincus 1991; Richman and Moorman 2000; Costa et al. 2002). Costa et al. (2002) developed a multiscale entropy (MSE) analysis building upon the definition of the so called sample entropy (SE) proposed by Richman and Moorman (2000). Costa et al. demonstrated that the MSE curves identified diseased hearts to have a significant decrease in the sample entropy SE on multiple time scales, indicating a lower degree of complexity. Motivated by these advances, the focus of the present study was to examine the complexity in the time evolution of postural control and effects of aging on the sway dynamics.

For research and clinical purposes, the ability of the central nervous system to maintain balance can be assessed by investigating the sway of a person's body during standing. The majority of the previous studies on postural sway that did not apply external perturbations have focused on quiet stance where subjects are instructed to "stand as still as possible". The objective of this instruction is to examine the postural system at its limit such that the remaining sway reveals features of the control system. These studies are naturally confined to a relatively short time of recording due to fatigue (a few minutes maximum).

Standing in daily life often occurs over a prolonged period (longer than a few minutes), for example when waiting in a line or while talking with somebody. This kind of standing is less constrained and is typically interspersed with recurrent, self-induced changes in the body configuration. These changes are performed almost unconsciously and cannot be generally associated with any external stimulus. Such natural prolonged standing is not as fatiguing as standing still and can also easily be reproduced in the laboratory. By looking at the COP displacements during prolonged standing over 30 min, Duarte and Zatsiorsky (1999) associated the postural changes to three types of change in the COP data: (1) *shifting*—a fast displacement of the average position of the COP from one region to another (step-like); (2) *fidgeting*—a fast and relatively large displacement followed by a return of the COP to approximately the same position (pulse-like); (3) *drifting*—a slow continuous displacement of the average position of the COP (ramp-like). Applying other nonlinear measures to these long-time series of COP displacement in healthy adults such as the Hurst exponent, detrended fluctuations, and power spectral analyses. Duarte and Zatsiorsky (2000, 2001) revealed slow and fast frequencies with different amplitudes suggesting fractal properties and long-range correlations. This fractal property revealed structural characteristics of the COP data which have important implications for the control of human balance (Duarte and Zatsiorsky 2000).

Freitas et al. (2005) were the first to investigate older individuals standing for a prolonged period to get insight into the fluctuations on longer spatiotemporal scales. The authors reported that older individuals swayed approximately 50% less than young adults and showed a significant reduction in the amplitude of shifts, but with no changes in the fidget and drift patterns. Interestingly, this decrease in sway is in contrast to what was observed during short quiet standing (60 s) where older individuals showed approximately 30% more sway, in agreement with what has been reported before (Horak et al. 1989). In line with the argument in the literature that aging is characterized by a decrease in complexity, it can be speculated that this expresses the general decrease in mobility but it can also express a change in the complexity of the aging postural control system. More specifically, it has been hypothesized that complexity is decreased in older people, supported by findings such as decreased entropy in the heart rate and blood pressure dynamics from healthy elderly subjects in the literature (Costa et al. 2002; Lipsitz 2002).

With the aim to assess the effects of aging on the complexity and fractality of the postural control system, the present study analyzed postural sway during prolonged standing for two groups of subjects, one with older and one

with younger healthy adults. The study applied measures of complexity and fractality using tools from nonlinear time series analysis. The hypothesis is that both complexity, quantified by multiscale entropy analysis, and fractality, quantified by detrended fluctuation analysis, of the postural sway time-series are decreased in the older subjects. Our hypothesis is that these nonlinear time series analyses will provide useful information about whether the observed age-related differences in prolonged standing reflect structural non-local changes of the postural control mechanism.

Methods

Participants

Fourteen older individuals at the age of 68 ± 4 years (mean ± SD, range 61–76 years), height of 1.58 ± 0.08 m and mass of 64 ± 12 kg participated in the older group. Fourteen healthy adults with an age of 28 ± 7 years (range 19–40 years), height 1.65 ± 0.11 m, and mass 63 ± 10 kg were members of the young control group. All older subjects were enrolled in a physical activity program in the University of Sao Paolo for at least 1 year, which consisted of moderate physical activities twice a week. These activities included brisk walking, local muscular endurance training with light loads, and flexibility exercises. The intensity of these 30-min exercise programs was qualitatively monitored such that they did not cause any excessive sweating or large increase in heart rate. All participants reported to have normal or corrected to normal vision. None of them in the adult group had any known history of postural or skeletal disorders, but in the older group there were three subjects with arthritis of the knee and two subjects who reported to have labyrinthitis. Despite these self-reports, none of them reported any particular problems in balance control nor had a history of falling. To test for interferences in their data, specific comparisons were conducted on the dependent measures of these three subjects. Results verified that these subjects were not statistically different from the other older subjects. All participants had given prior consent to the experimental procedures in agreement with the Helsinki protocol.

Design and procedure

All participants performed one trial of prolonged standing for 30 min. Immediately before this long recording, they also stood in quiet stance for 60 s. In all trials, the participants stood barefoot on a force plate (50.8 cm × 46.4 cm, AMTI, OR6-WP). In the short quiet-standing trial, participants were asked to select a comfortable position with their feet approximately at shoulder width and to stay as still as possible looking straight ahead to a point at eye height. In the prolonged standing task, participants were allowed to change their posture freely at any time without specific instructions about how to stand, except the requirement not to step off the force plate. This instruction aimed to mimic prolonged standing in regular daily activities where standing is typically a secondary task while something else is done. To reproduce the latter aspect in the laboratory setting, all participants watched a television program (the same program for all the participants) on a TV set that was located 2 m in front of the participant.

Data acquisition and analysis

The forces and their moments were recorded by the force plate at a 20 Hz sampling frequency and the positions of the center of pressure (COP) in the anterior–posterior (AP) and medio-lateral (ML) directions were calculated. The first typical measure that expresses the total amount of sway for each participant is the standard deviation (SD) of the COP displacement in both AP and ML directions. These results were calculated for each participant for both short and prolonged standing and were already reported in Freitas et al. (2005). To study the underlying dynamical properties of the COP time series, this study used two different methods to assess the temporal structure of the fluctuations: the detrended fluctuation analysis (DFA) (Peng et al. 1995) and the multi-scale entropy (MSE) method (Costa et al. 2002). The latter measure was only calculated for the prolonged standing data (36,000 data points) as long time series are required. It is important to point out that increasing the sampling frequency only to increase the number of data points is not a viable solution to generate the long time series that are necessary for such analyses. The typical time-length scale in the COP signal is in the range of tenths of a second to few seconds (95% of the power of the COP signal during quiet standing is below 1 Hz, Maurer and Peterka 2005). Increasing the sampling frequency would only artificially increase the number of data points without adding information.

Detrended fluctuation analysis

The detrended fluctuation analysis (DFA) is a modification of the root-mean square analysis of a random walk (Feder 1988) but is less sensitive to non-stationarities and noise in the data (Peng et al. 1995). The DFA exponent was originally proposed to estimate the fractal dimension of a time series by measuring the statistical properties of the fluctuations in the time series. The sampled time series $u(i)$ is first cumulatively summed to obtain an integrated time

series $y(k) = \sum_{i=1}^{k} u(i)$, $k = 1, 2, \ldots, N$. This integrated time series $y(k)$ of total length N is then parsed into non-overlapping windows of equal width w, such that there are a total of N/w windows. Inside each window, the time series $y(k)$ is detrended by a linear least square fit, denoted by $\hat{y}(k)$. The root mean square value of the deviations of the time series $y(k)$ around the time series $\hat{y}(k)$ is computed:

$$F(w) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - \hat{y}(k)]^2}$$

where $F(w)$ is the so-called detrended fluctuation parameter. Note that F is a function of the window width w since the time series $\hat{y}(k)$ depends on the chosen window size. In a typical time series obtained from a complex biological system, $F(w)$ obeys a power-law function, i.e., $F(w) \propto w^{\alpha}$. The scaling exponent α, obtained from the slope of the linear regression of $F(w)$ over w on a log–log scale quantifies the long-range correlations in the time series. For white noise, the exponent α is known to be 0.5; for $1/f$ noise it is 1.0; and for Brownian noise α is 1.5. In the ideal case of a stationary time series of infinite length, α is mathematically related to the more familiar power spectral exponent β as follows: $\alpha = (1 + \beta)/2$ (Havlin et al. 1988). Therefore, DFA may be seen as a method in the time domain that is analogous to power spectral analysis performed in the frequency domain. The fact that a process presents similar characteristics over different scales is known as self-similarity. It can be expressed by a power-law scaling which is also a sign of complexity. Therefore, the fractal dimension has also been used to describe the complexity of a process (Lipsitz and Goldberger 1992; Goldberger et al. 2002a). However, the DFA exponent itself does not have a direct relation with complexity: a $1/f$ noise process is considered maximally complex ($\alpha = 1.0$), whereas white ($\alpha = 0.5$) and Brownian ($\alpha = 1.5$) noise have lower or no complexity (Lipsitz 2002).

Multi-scale entropy

The multi-scale entropy (MSE) method aims to measure the information content of a complex time series on multiple time scales. In a previously suggested method Richman and Moorman (2000) defined the so-called sample entropy (SE) which is well-suited for physiological data. The basic idea in the definition of SE is to provide a measure of an "orderly structure" in a time series by testing if there are any repeated patterns of various lengths, including those that may not be repeated at regular intervals. To achieve this in a time series with N data points, a sequence of m successive points is selected from all possible m-point sequences, i.e., a total of $N - m + 1$. As a next step, all m-point sequences that are similar to the selected one are counted, excluding the selected one itself. This number is denoted by $n_i^{r,m}$ where the index i denotes the sequence number and r the similarity radius. The ratio $n_i^{r,m}/(N - m + 1)$ gives the probability of finding an m-point sequence similar to the selected one. The mean of all of such probabilities, each computed for every possible different m-point sequence in the time series, gives the probability that two randomly selected m-point sequences are similar to each other.

The similarity between two m-point sequences is evaluated by calculating the maximum of the component-wise differences between two arbitrary sequences of length m $[u(k), u(k + 1), u(k + 2), \ldots, u(k + m)]$ and $[u(l), u(l + 1), u(l + 2), \ldots, u(l + m)]$ as

$$d = |\max\{[u(k) - u(l)], [u(k + 1) - u(l + 1)], \ldots, [u(k + m) - u(l + m)]\}|.$$

The two sequences are defined to be similar if d is smaller than some criterion distance. To facilitate comparison across different time series with different variability, this criterion distance is not a fixed quantity but is normalized for every time series. Costa et al. recommended the criterion distance to be between 10 and 20% of the standard deviations of the respective time series. The gain parameter, 0.10 or 0.20 in this case, is referred to as similarity radius r. Note that the resultant probabilities strongly depend on this criterion distance and larger values of r will yield a larger number of similar sequences for any given sequence length m (Costa et al. 2005).

Now consider two m-point sequences that are similar to each other. If one more point from the time series is added to each of them, the two resulting $(m + 1)$-point sequences may or may not be similar any longer. The average conditional probability C^r that they are indeed similar can be written as:

$$C^r = \frac{\frac{1}{(N-m+1)}\sum_{i=1}^{N-m+1} n_i^{r,m}}{\frac{1}{(N-m)}\sum_{i=1}^{N-m} n_i^{r,m+1}} \approx \frac{\sum_{i=1}^{N-m+1} n_i^{r,m}}{\sum_{i=1}^{N-m} n_i^{r,m+1}}.$$

The natural logarithm of C^r is defined as the sample entropy SE. It is a real number that depends on three parameters: the number of points in the sequences, m, the similarity radius r, and the total number of data points in the time series N. To test the robustness of the MSE results, the same analyses were also performed for r = 0.10, 0.15, 0.25, and 0.30. However, while the overall MSE values showed the expected increase with increasing r, the relative results for young and older adults did not change. We also varied the parameter m from 1 to 5 and the relative results for young and older adults did not change either. We report the MSE values with r set to 0.20 (with the criterion distance to be 0.20 times SD) and m set to 2. The number of data points N for the prolonged standing trials was 36,000.

This definition of sample entropy was extended by Costa et al. (2002) to define the multi-scale entropy (MSE) as a result of successive smoothing of the time series. The smoothing was done by averaging the data points in given non-overlapping windows; τ is the number of data points that defines the window, called the time-scale factor. Thus, the time series becomes more coarse-grained with increasing τ, i.e., decreasing the length of the time series to N/τ. For every smoothing, one value is obtained for the sample entropy SE. The graph of SE as a function of τ is referred to as the MSE curve, which can be interpreted as a measure of information content on multiple time scales of the signal. For $1/f$ noise MSE is known to saturate with increasing τ to a constant value that is approximately 1.8. For white noise it shows an exponential decrease starting from a value of approximately 2.5. For Brownian noise it also shows an exponential decrease but starts from a value of approximately 1.7.

The MSE measure is known to be sensitive to data that have fluctuations with amplitudes that are orders of magnitude higher than the rest of the time series because such "outliers" change the standard deviations of the time series and consequently, the value of the criterion distance ($r \times$ SD). In their study of cardiac rhythm in individuals with congestive heart failure, Costa et al. (2005) have observed and studied this effect when statistical outliers were present. This caveat needs to be kept in mind because in prolonged standing there are significant postural changes—fidgets, shifts and drifts—that will produce a similar effect. It should be noted, however, that these changes are not outliers, resulting for example from measurement noise, but rather changes that have important physiological meaning.

To evaluate the effect of these postural changes on the MSE results, we calculated the MSE measure not only of the raw time series but also of the time series that eliminated or normalized for these features. We implemented these calculations in two different ways, following the discussion of the sensitivity of the MSE measure to outliers by Costa et al. (2005). In the first procedure, we did not normalize the criterion distance by the standard deviations as initially performed. Rather, we adopted an absolute criterion distance for all time series, $r = 0.2$ (which for our data means a value of 0.2 cm). In the second procedure, the COP time series were "corrected for outliers" by removing the three types of postural changes, shifts, fidgets, and drifts. The shifts and fidgets were identified by previously developed algorithms and then removed from the entire time series. The algorithms are based on a moving window analysis using threshold criteria for amplitude and width of the patterns (a complete description of these algorithms can be found in Duarte and Zatsiorsky 1999; Duarte et al. 2000). To eliminate drifts the COP time series were high-pass filtered using a high-pass Butterworth filter with a cutoff frequency ten times the lowest possible frequency in the time series: $10/1{,}800 = 0.0056$ Hz. Finally, the data with values higher than three standard deviations were removed to eliminate any possible remaining outlier.

The MSE analyses and the additional normalization procedures were only performed on the prolonged standing data, as the trials from quiet standing did not have enough data points. The time-scale factor τ was varied from 1 to 50 data points, equivalent to 50–2,500 ms. The DFA analysis was applied to both short and prolonged standing trials. For the short standing data (60 s), the window sizes w ranged between 1 and 10 s, increasing in increments of 50 ms. For the prolonged standing data (30 min), the range of window sizes w was chosen to be between 1 and 10 s and between 10 and 600 s, again in increments of 50 ms. The reason for conducting the DFA analysis of the long time series with two time scales, 1–10 s and 10–600 s, was to compare the DFA results of the shorter time scale with the DFA results of the short standing data. Further, the two time scales when applied to the long time series were non-overlapping and thereby permitted an additional within-subject comparison between time scales. For the DFA analysis, it was not necessary to also analyze the normalized and filtered COP time series as the DFA exponent is not affected by the time-series' standard deviations.

Two surrogate analyses were conducted to test the properties of the COP data and the statistical difference with the MSE and DFA results were determined. For a first surrogate data set, the original time series were randomly shuffled to create a new set of data with the same mean and variance as the original ones, but with an independent and identical distribution. This surrogate analysis specifically tests the null hypothesis that the process is generated by uncorrelated noise. For white noise the DFA exponent α should equal to 0.5 and the MSE curve should show an exponential decrease. For a second surrogate data set, a phase-randomized surrogate analysis (Theiler et al. 1992) was conducted and the statistical difference with the MSE and DFA results determined. This surrogate analysis specifically tests the null hypothesis that the process is generated by a linearly correlated noise with Gaussian innovations (linear process). To this end, we computed the fast Fourier transform (FFT) of the data, added a random number between 0 and 2π to the phase of the FFT data, and then calculated the inverse FFT to obtain the surrogate data. This new set of data has the same mean, variance, and autocorrelation function as the original ones. Rejection of the null hypothesis for the phase-randomized surrogate analysis implies that the data exhibits nonlinear correlations. To determine differences in the DFA and MSE measures, for the surrogate analyses dependent t tests were used and for the age comparison independent t-tests were

used, all with a significance level of 0.05. Statistical comparisons of the MSE results for the adult and elderly were conducted by comparing the area under each MSE curve (Costa et al. 2007): $\text{MSE area} = \sum_{i=1}^{50} \text{SE}(i)$. Additional statistical comparisons of the sample entropy values for the adult and elderly were conducted at three selected τ parameters, $\tau = 1$, 10, and 40. To accommodate for these multiple comparisons, we employed Bonferroni adjustments on the obtained P values.

Results

In Fig. 1, panels a and b show exemplary COP time series of prolonged standing for the AP and ML directions of one young adult participant; panel c shows the corresponding two-dimensional trace on the force platform. Panels d–f present the corresponding plots for one member of the older group. The differences in structure and amplitude of fluctuations between the young adult and the older participant are evident. The large jerks visible in the time series of the young participant correspond to gross postural changes leading to clustered structures in the 2D depiction. The older participant shows a tight cluster of fluctuations in the 2D plot without any such large changes. This difference in behavior between young and older individuals is representative for all participants and is visible in the group averages.

Figure 2 displays the results from the DFA analysis for all 14 young adults and 14 older participants. The six panels show the detrended fluctuation parameter F plotted as a function of window width w in a log–log plot. In each panel, the data plotted with hollow circles show the F values for a representative participant from the respective group. The solid lines represent the linear least-square fits to the F values of each participant's trial. The slopes of these lines are the DFA exponents α obtained for each trial of each of the 14 participants. Panels a and b show the results for quiet standing for a range of w from 1 to 10 s; panels c and d show the data for prolonged postural sway calculated for the same window sizes as used in the quiet standing; panels e and f illustrate the results for prolonged standing but calculated for window sizes between 10 and 600 s. For a better comparison of the slopes of the regressions, all lines were shifted vertically to one common y-intercept, which was taken from one representative participant. All these results are for the AP direction; the results for the ML direction were very similar and are not shown.

For a better evaluation of the results the same DFA calculations were also applied to simulated Brownian noise and white noise data. The results are shown by the two dashed lines in each graph. As can be seen, all of the actual data lie between Brownian noise for which $\alpha = 1.5$ and white noise for which $\alpha = 0.5$. The fact that all measured slopes are around 1 gives evidence for the fractal nature of these data. The inter-individual differences for the small window sizes are larger for the quiet standing condition compared to prolonged standing (seen by the spreading of the lines in Fig. 2a, b compared to c, d). Larger inter-individual differences are observed again for the larger window sizes in the prolonged standing condition (seen by the spreading of the lines in Fig. 2e, f compared to c, d).

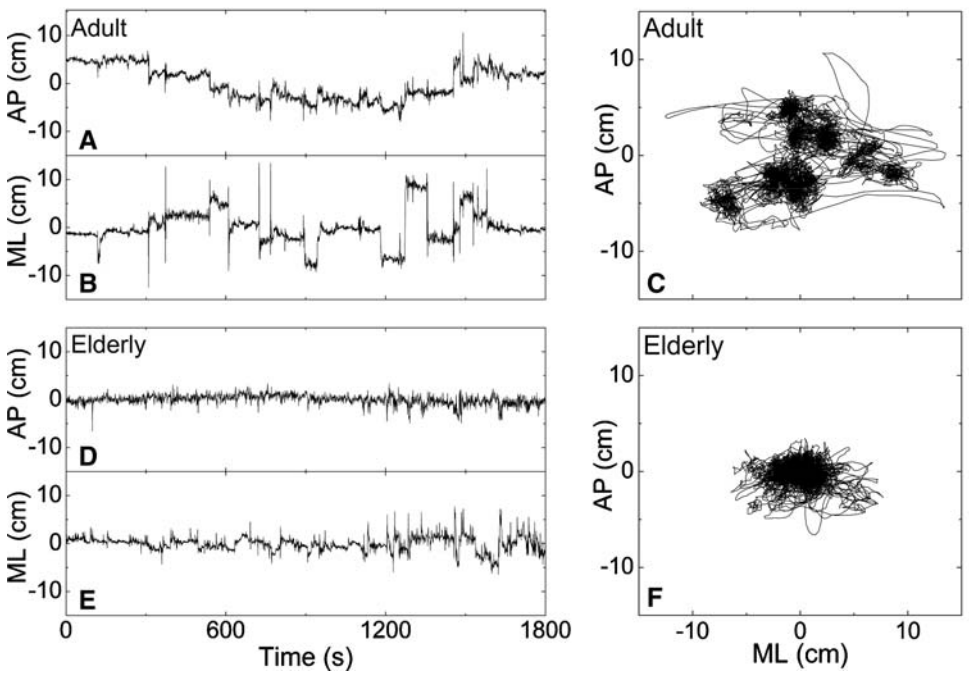

Fig. 1 **a**, **b** Exemplary COP time series for the anterior–posterior (AP) and medio-lateral (ML) directions, respectively, for a young adult performing a prolonged standing for 30 min. **c** The corresponding path that the COP traced on the force platform. **d**–**f** Similar plots for an older subject

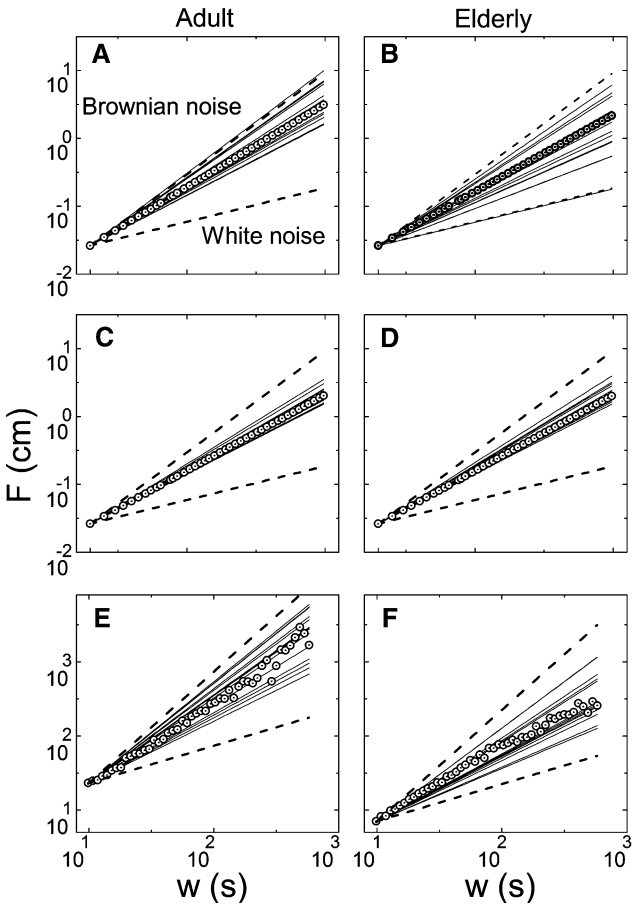

Fig. 2 Detrended fluctuation analysis (DFA) for the adult and older groups in the AP direction. *Thin solid lines* represent the linear fits of the data of the 14 participants of each group; the *dashed lines* indicate the linear fits of *white* and *Brown noise* for comparison. The slopes correspond to the DFA exponents. **a**, **b** Linear fits of the quiet standing trials, for window sizes between 1 and 10 s; **c**, **d** prolonged standing trials for lags from 1 to 10 s; **e**, **f** linear fits of the prolonged standing trials for window sizes from 10 to 600 s

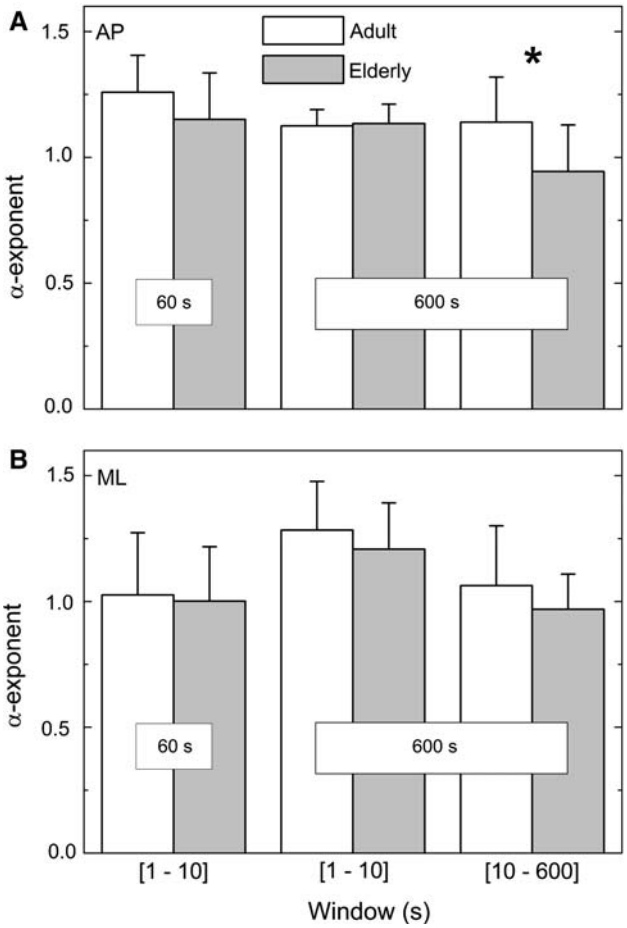

Fig. 3 **a** DFA exponents in the anterior–posterior (AP) direction for the short (60 s) and prolonged (30 min) standing time series of young adults (*white bars*) and older participants (*gray bars*); **b** similar results for the ML direction. Means and SD for each group ($N = 14$)

This difference in the distribution of the results is probably due to the fact that the calculation of the F value is based on more data for smaller window sizes than for larger window sizes in relation to the data length.

Figure 3 summarizes the statistical comparisons of the α-exponents for young adults and older subjects. Older participants tended to have slightly lower α-exponents than the young adults in both short and prolonged standing in both sway directions. However, only one difference between young and older individuals in the AP direction for the prolonged standing task was statistically significant, $t(26) = -2.92$, $P = 0.007$. The difference in the ML direction shows the same trend but do not reach significance. An additional comparison of all individual values with the value 1 indicating (the exponents of the $1/f$ noise) revealed no differences: $t(13) = -0.86$, $P = 0.41$ for the older group; $t(13) = 1.13$, $P = 0.28$ for the young adult group.

Figure 4 shows the results of the MSE analysis from the prolonged standing trials for both participant groups. Figure 4a and b present the means and the standard deviations of the 14 participants from analyses of the raw COP data, performed separately for the AP and ML directions. The black curves represent the young and the gray curves represent the older adults. In all four plots the curves begin at similar values for $\tau = 1$ and subsequently separate until they saturate with increasing τ. This illustrates that the calculations for different time-scale factors reveal information that is not contained in SE alone ($\tau = 1$) and differences appear only at longer time scales. The results shown in Fig. 4a, b were obtained with the parameter r set to 0.20.

Figure 5a shows the mean and standard deviations of the MSE area across the 14 participants for each age group and direction. The older group showed a significantly higher MSE area than the adult group for both AP ($t(26) = -2.93$, $P = 0.007$) and ML ($t(26) = -3.85$, $P = 0.001$) directions.

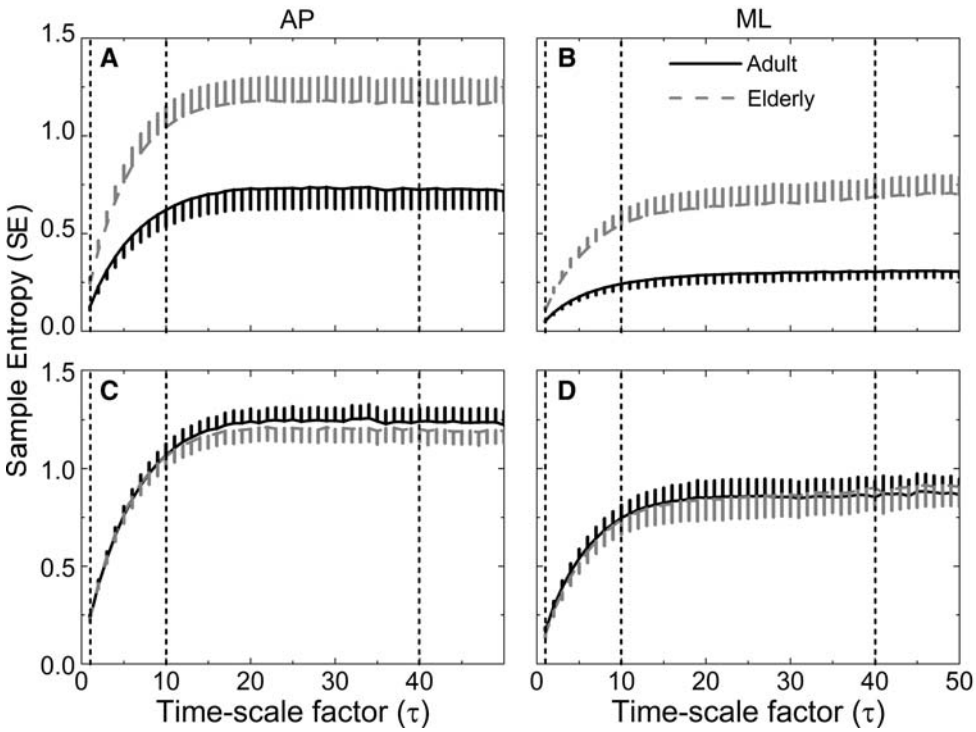

Fig. 4 **a**, **b** MSE curves (mean and SD) for postural sway time series of 14 adult and 14 older participants in the AP direction (*left column*) and ML direction (*right column*) for the regular analysis with $r = 0.20$; **c**, **d** similar plots for the COP time series after the r parameter was not adjusted

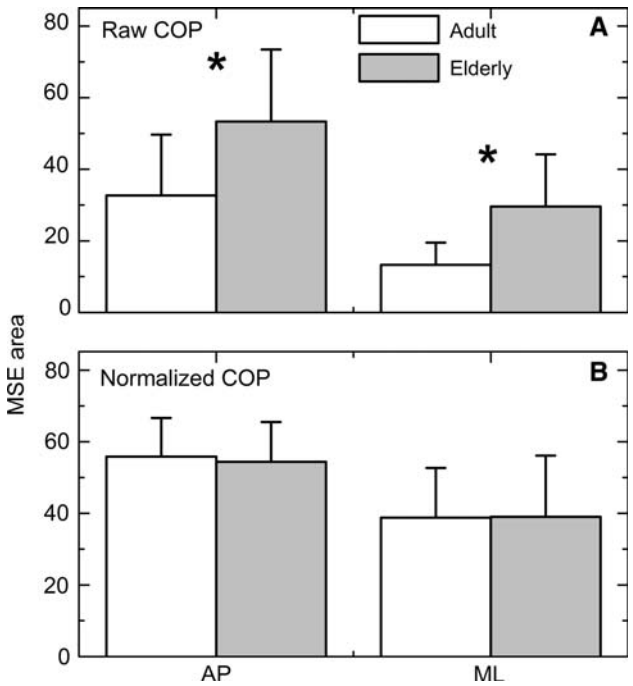

Fig. 5 Area under the MSE curve (mean and SD) for postural sway time series of 14 adult and 14 older participants in the AP and ML directions for the raw COP time series (**a**) and for the normalized COP time series after the similarity radius r was corrected (**b**)

Figure 4c, d show results from the MSE analyses when the criterion distance was not adjusted. Compared to the curves in Fig. 4a, b the MSE values for the young and older groups became very similar. The comparison of these MSE areas confirmed this impression and rendered no statistical differences between groups as significant for both AP ($t(26) = 0.35$, $P = 0.73$) and ML ($t(26) = -0.04$, $P = 0.97$) directions. The means and standard deviations of MSE area across participants for both groups are shown in Fig. 5b.

In addition, statistical comparisons of the sample entropy values for the adult and elderly were conducted at three selected τ parameters, 1, 10, and 40, shown by the vertical dashed lines in Fig. 4a, b. Figure 6a shows the mean and standard deviations of the sample entropy values for the three selected τ parameters. For all three values of τ the elderly group showed a significantly higher sample MSE values than the adult group, each $t(26) > 3.06$, $P < 0.01$. When the criterion distance was not adjusted, similar as for the results for the MSE area, the comparison of the MSE values at the three time-scale factors τ also failed to render significant statistical differences between groups, $t(26) < 0.86$, $P = 1$. The means and standard deviations of the MSE values in this case are shown in Fig. 6b.

Applying the second correction procedure, which removed the three types of postural changes, yielded similar results: the difference in MSE results disappeared leaving both groups with the same degree of complexity, MSE area: $t(26) = 1.19$, $P = 0.24$ and ML $t(26) = -0.55$, $P = 0.59$; MSE values at the three τ factors: $t(26) < 1.0$, $P = 1$. However, a caveat is in place: removal of the drifts by high-pass filtering removes the long-range correlations. This can

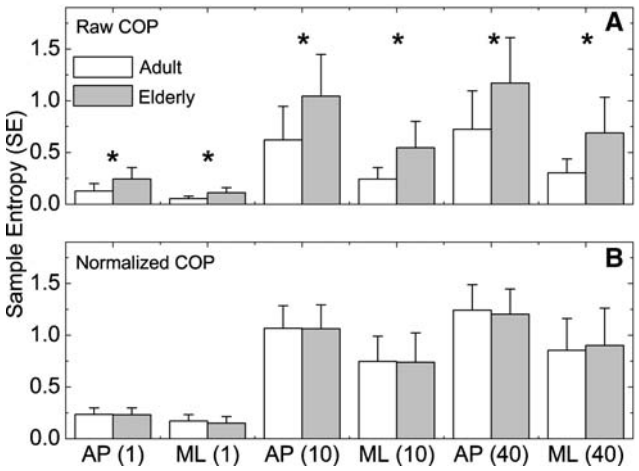

Fig. 6 Sample entropy values (mean and SD) at the time-scale factor 1, 10, and 40 for postural sway time series of 14 adult and 14 older participants in the AP and ML directions for the raw COP time series (**a**) and for the normalized COP time series after the similarity radius r was no longer adjusted (**b**)

be seen in Fig. 7 that shows the same time series as in Fig. 1 after the postural changes were removed. Evidently, the DFA analysis will be affected by such a procedure and produce lower values for the exponents. Therefore, these corrected data were only considered for the MSE analysis.

To further test the null hypothesis of white noise, two surrogate analyses were conducted on the DFA and MSE measures. The DFA exponents from the random shuffled surrogate data in both postural tasks in AP and ML directions and for both window sizes were between 0.48 and 0.50, indicating white noise. Pairwise t tests confirmed that the α exponents of the surrogate data were significantly different from their corresponding unshuffled data (all comparisons yielded $t(26) > 10$, $P < 0.005$). The MSE curves from the surrogate data showed the same exponential decrease for both groups in the two sway directions, as expected for white noise. The DFA exponents from the phase-randomized surrogate data in both postural tasks in AP and ML directions and for both groups and window sizes were not different from their corresponding original data (all comparisons yielded $t(26) < 1$, $P > 0.05$). The MSE curves from the surrogate data showed a similar pattern but with a significantly greater area under the curve (higher complexity) for both groups and directions (all comparisons yielded $t(26) < -3.2$, $P < 0.004$), suggesting that the COP data of prolonged standing tasks are produced by a nonlinear process.

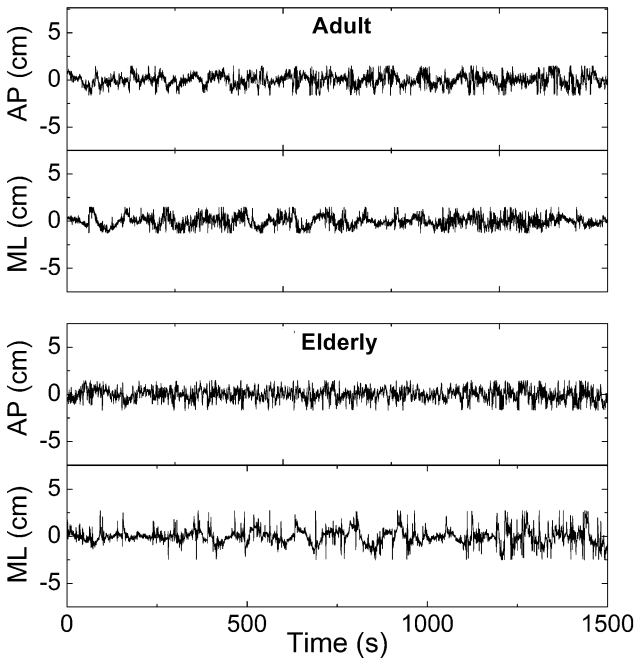

Fig. 7 The same COP time series for the AP and ML directions for a young adult (*top*) and an older subject (*bottom*) as shown in Fig. 1, but after the postural changes removal (see "Methods")

Discussion

The present study investigated the effects of aging on the complexity of postural sway dynamics during prolonged standing to test the hypothesis that aging is associated with a decrease in complexity. This hypothesis was extended from results in other physiological measures, such as cardiac signals where older people displayed lower complexity (Lipsitz 2002). Two nonlinear analytical tools were applied to the time series of the center of pressure during standing: the detrended fluctuation analysis (DFA) which quantifies the long-range correlations or fractal dimension of the data (which is also related to the complexity of the data) and the multi-scale entropy analysis (MSE) which is an information-theoretic measure that quantifies the entropy or complexity of the data. To be able to capture the structure on multiple time scales, importance was given to recording relatively long time series of half-an-hour in addition to the typical short ones of 1 min. This prolonged standing task mimics realistic situations where people stand comfortably with few constraints for a relatively long period.

Fractality

Differences between the two postural tasks were present in the DFA results. First of all, the α-exponents indicate a fractal-like nature of the sway dynamics for both tasks and groups—with older participants showing slightly smaller exponents than the young adults, especially for the prolonged standing. The values of the α-exponents for the adult group are in agreement with earlier results by

Duarte and Zatsiorsky (2000, 2001). This difference between age groups, however, is only significant for the COP data at the anterior–posterior direction during the prolonged standing task for the longer time scales, i.e., window sizes between 10 and 600 s (older 0.94 ± 0.19; young adults 1.14 ± 0.18). These values show that the two groups depart from 1/*f* noise in different directions: the older subjects towards white noise ($\alpha = 0.5$) which is a completely unpredictable process and the young adults towards Brownian noise ($\alpha = 1.5$) which is a 'smoother' process with only local correlations. However, a comparison of the group values revealed that the fractal dimensions of all groups were not different from the exponent of the 1/*f* noise.

Thurner et al. (2002) and Lipsitz (2002) conducted power spectral analyses in short quiet standing (20 and 30 s, respectively). Both studies reported higher power spectral exponents β in older persons compared to young adults and interpreted this result as evidence for a decrease in complexity in aging postural control. Note that β is the slope of the linear regression to the power spectrum on a log–log scale and is analytically related to the DFA exponent α as: $\beta = 2\alpha - 1$ (Havlin et al. 1988). The β values found by these authors at the short time scale were above the value for Brownian noise ($\beta = 2$ or $\alpha = 1.5$). Time series with such high exponents are more regular and consequently referred to as less complex. These results, however, reflect mostly the structure in the COP data at shorter time scales (below 1 s), where it is known that the COP data obeys a power law with a different (higher) exponent than in the long time scales (Collins and De Luca 1993; Duarte and Zatsiorsky 2001). It is not clear, however, why there would be an age-related difference only at a short time scale and not at a long time scale.

The smaller α-exponents observed for the older group at longer time scales during prolonged standing suggest more saturation in the power law relation, i.e., the unconstrained nature of the task was less explored. This interpretation is consistent with the decrease in the amplitudes of the postural changes in the older subjects as already reported by Freitas et al. (2005). As such, the smaller α-exponents may be indicative of a malfunction of the postural control system to generate adequate responses to perturbations on longer time scales. Conversely, postural changes may be interpreted as a mechanism that brings about the power-law relation in the body sway across different time scales.

Entropy of sway

The MSE results also rendered different effects for older and healthy young adults: the first analysis of the raw data indicated that older individuals showed a higher degree of complexity, especially when the data became more coarse-grained by larger time scale factors. This result runs counter to the hypothesized lower degree of complexity in older people (Lipsitz and Goldberger 1992; Goldberger et al. 2002b; Lipsitz 2004). Does this contradictory result have any meaning or is it an artifact of the algorithm? Returning to the details of the MSE algorithm, it was emphasized that the criterion distance for similarity of two sequences is partly determined by the standard deviations of the time series. Hence, the more variable the time series, the larger is the criterion distance and the more easily two sequences are counted as similar. Consequently, the SE and MSE values tend to be lower. In the present data, the standard deviations of the mean COP time series for the young adult group were about 85% higher than for the older group in the AP direction, and 125% higher in the ML direction. While this choice of the criterion distance is deliberate to achieve comparability of signals with different magnitudes in their fluctuations, it also normalizes the data for non-random meaningful differences, such as the postural changes in prolonged standing in older and young adults. Hence, this parameterization of the MSE analysis runs danger to "normalize out" the structure that we are interested in.

Given that the results obtained for the raw COP time series were consistent with this potential confound—young adults with larger postural changes showed lower MSE values due to the larger criterion distance—we conducted one more test where we eliminated this normalization via the similarity radius *r*: the criterion distance was identical for all data. The results of MSE values then showed that the previously observed difference in the MSE measure between the adult and older groups disappeared. However, the degree of complexity in adults was now only similar to older people, not higher; hence, the result was still not consistent with the hypothesis that older people show decreased complexity. This result was confirmed once more by a third test that removed postural changes. This third test was partly motivated by the study of the sensitivity of the MSE measure to outliers by Costa et al. (2005). Yet, it should be kept in mind that, different from Costa's study where the data contained real outliers, the large and irregular postural changes are an inherent part of the observed data with physiological meaning.

Recently, Costa et al. (2007) applied the MSE measurement to understand the effect of a stochastic-resonance-based therapy (subthreshold mechanical vibrations applied to the feet) on postural sway during quiet standing of young and older adults. They observed an increase in complexity after the therapy, a decrease in complexity in older fallers, but no difference in complexity between healthy young and older adults. Although they studied a different time scale

(shorter than 1 s), the observed absence of age-related effects on the complexity of postural sway is consistent with our findings. In another study on postural sway during short quiet standing of older individuals with and without stroke, using sample entropy as a measure of complexity Roerdink et al. (2006) found that stroke patients showed higher complexity in the medio-lateral direction compared to healthy controls but lower values in the anterior-posterior direction. All these somewhat contradictory results of power spectral, DFA, SE, and MSE analyses suggest that the effects of aging and disease on the complexity of postural sway require further investigation.

One explanation for our seemingly conflicting results is that natural prolonged standing is a relatively complex whole-body task where postural movements such as shifting weight from one foot to another are sensitively intertwined with the overall task of maintaining equilibrium. Given that humans seem to be unable to remain completely motionless for a prolonged period postural changes seems to be the solutions for this task 'found' by the nervous system (Bridger 1991; Whistance et al. 1995; Duarte and Zatsiorsky 1999). Therefore, the postural control system continuously deals with weight transfer and reconfiguration of the body that relocates the center of pressure and yet balances the body without falling. In this light, prolonged standing seems to be more challenging than short quiet standing. Older individuals seem to respond less to these task demands than young adults, as evidenced by fewer postural changes of large amplitude during prolonged standing (Freitas et al. 2005). The DFA measures are consistent with this observation such that older individuals exhibit lower DFA exponents suggesting that the unconstrained nature of the task was less explored. The absence of the hypothesized decrease in complexity in the MSE measure may therefore be ascribed to an adaptation process; older people reduced their postural sway as a sign of their inability to deal with the complex challenges of maintenance of equilibrium. The effect of this reduced mobility is that the structure at longer time scales of the signal was less pronounced.

Another explanation for our results may be found in a proposition by Vaillancourt et al. (2002, 2004). Contrary to the hypothesis of a general decrease in complexity with aging, Vaillancourt et al. (2002, 2004) argue that complexity may both increase and decrease with aging, depending on the task. The researchers showed that for a task where subjects maintained a constant level of isometric force, aided by visual feedback, complexity as measured by MSE indeed decreased with aging (Vaillancourt et al. 2004). In contrast, when the same subject tracked a sinusoidal wave by varying isometric force the complexity measure increased with aging. Vaillancourt et al.'s hypothesis is that aging physiological systems are specifically deficient in adapting to varying environmental demands. More specifically, their bidirectional complexity hypothesis postulates that tasks with a stable equilibrium point show a decrease in complexity with age, in contrast to tasks with limit cycle stability that show an increase. Hence, the complexity of selected measures depends on the nature of the task and the dynamics of the specific physiological system.

From this viewpoint, the postural task may be interpreted as the tracking of a moving equilibrium point, an interpretation that has in fact been proposed as a basic underlying mechanism of postural control (Zatsiorsky and Duarte 1999; Dijkstra 2000; Cabrera and Milton 2004). While probably relevant for all postural tasks, this interpretation was particularly motivated by the sway trajectories in prolonged standing, which intermittently tend to fluctuate around an equilibrium point. However, it needs to be kept in mind that the tracking of an externally presented pattern as in Vaillancourt's task is not the same as the tracking of a self-generated equilibrium point. In fact, the presence of such an equilibrium-point is the product of a complex interactive process.

One last aspect need to be kept in mind for the understanding of our results. The older participants in our study were active individuals who have regularly attended fitness classes for 1 year. None of them had a history of falls indicating balance problems. This activity may have contributed to a slowing of the general aging process such that their data show less symptoms of age than those of their more sedentary age-peers. Therefore, it may also be interesting to examine older individuals who do not follow a regular exercise regime or also those who are more frail in comparison to the average individual.

In conclusion, the results of our analysis of complexity in postural sway of older people are inconsistent with the generally acknowledged hypothesis that complexity in the human physiological system decreases with aging (Lipsitz and Goldberger 1992; Goldberger et al. 2002b; Lipsitz 2004). Given that older people show significantly decreased amplitudes in postural sway, we interpreted this finding as the consequences of adaptation processes suggesting a failure of the postural control system to generate adequate responses on longer time scales. Such adaptation seems to become visible only in the prolonged standing task as no such indication was seen in short quiet standing.

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