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Fractal Dynamics in Dexterous Tool Use: The Case of Hammering Behavior of Bead Craftsmen

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Dexterous behavior exhibits exquisite context sensitivity, implying the efficacy of exploration to detect the task-relevant information. Inspired by the recent finding that fractal scaling of exploratory movements predicts how well the movements sample available perceptual information, we investigate the possibility that dexterity of craftsmen would be characterized by fractal (long-range) temporal correlation properties of fluctuations in their movement wielding a tool. A reanalysis of hammering behavior involved in stone beads production in India (Nonaka & Bril, 2012) revealed the presence of long-range, power–law correlations, as part of multiplicative cascades operating over a wide range of time scales. In the unfamiliar condition using unusual material, the wielding behavior of highly skilled experts displayed a significant increase of long-range temporal correlations, whereas that of less experts exhibited a significant loss of long-range correlations and reduced heterogeneity of scaling properties over time, which robustly discriminated the groups with different skill levels. Alterations in long-range correlation properties of movement fluctuations are apparently associated with changes in the situation differently depending on the level of expertise.

Keywords: dexterity, expertise, context sensitivity, affordances, tool use

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What is “dexterity”? In the book so-entitled, Russian movement scientist Bernstein wrote as follows: “Good coordination and dexterity are obviously different. Perfect general coordination, ‘harmony in movements,’ is necessary for a sprinter, for a long-distance swimmer . . . But the word dexterity does not fit these movements” (Bernstein, 1996, p. 20). Bernstein (1996) metaphorically described dexterity as “the ability to create a perfect key for any emerging lock” (p. 215). Simply put, one cannot move dexterously, but one can only solve a motor problem dexterously (Reed & Bril, 1996). Dexterity is a fundamentally context-dependent property of behavior which involves not merely the ability to produce motor output, but the ability to tailor one’s behavior in such a way to resonate to the task-relevant aspects of the environment. Consequently, dexterous behavior exhibits bewildering repertoire of patterns to adapt to the exigencies and unpredictable changes in the environment (Stergiou & Decker, 2011). Understanding the nature of dexterity and how it may be acquired has been among the key issues in psychology of human performance (Bernstein, 1996; Kay, Turvey, & Meijer, 2003; Newell, 1985; Vereijken, van Emmerik, Whiting, & Newell, 1992; Newell, Broderick, Deutsch, & Slifkin, 2003; Beek & Turvey, 1992; Ericsson & Lehmann, 1996; Winold, Thelen, & Ulrich, 1994; Bril, Roux, & Dietrich, 2000, 2005; Bril, Rein, Nonaka, Wenban-Smith, & Dietrich, 2010; Biryukova & Bril, 2008; Nonaka & Bril, 2012; Nonaka, 2013). However, its inherent context dependency and the volatile variability of observed behavior present a major challenge to scientists who seek to identify invariant characteristics and to propose general laws that describe dexterity.

In most real-life situations, those contexts to which expedient behavior of organisms adapts cannot be cut up into to momentary, discrete inputs (Gibson, 1979). For example, consider a baseball

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player catching a ball dexterously. Coordination of bodily movements involved in the act would vary infinitely depending on the ball's trajectory, the player's initial position, and a number of other factors. The behavior would not be dexterous without the player's ability to orient oneself to gravity, the playing field, and the course of play, to the opposing hitters and the ball's motion to which they give rise, and the ability to change one's orientation so as to meet the ball with one's glove (Reed, 1988). The player perceives and acts to satisfy fluid constraints of embedding contexts and unfolding situations in the environment (Van Orden, Kello, & Holden, 2010). Typically, such meaningful aspects or events of the environment are hierarchically nested and each of them has its own temporal or spatial scale (Reed, 1988; Chater & Brown, 1999). Accordingly, if one is to act dexterously, one's movements and postures must be sensitive to those fluctuations in functional relationships to the nested structures of the environment spanning different spatial and temporal scales (Nonaka & Bril, 2012; Riley, Shockley, & Van Orden, 2012).

Roux, Bril, and colleagues documented such nested context dependencies of dexterous behavior in a series of studies on stone bead craftsmen in Khambat, India (Roux & Pelegrin, 1989; Roux, Bril, & Dietrich, 1995; Roux, 2000; Bril, Roux, & Dietrich, 2000, 2005; Biryukova & Bril, 2008; Nonaka & Bril, 2012). Stone bead making relies on a specific fracture mechanics called conchoïdal fracture exhibited by particular types of stone, which allows craftsmen to fracture the material in a controlled manner (Bril et al., 2005; Nonaka, Bril, & Rein, 2010). In the stone bead making task, craftsmen use the two following tools jointly (Figure 1A): (1) a sharp-pointed iron bar about 50 cm long and 2 cm thick, stuck obliquely into the ground in front of the craftsman, and (2) a buffalo-horn hammer mounted on a thin wooden stick. The craftsman positions a piece of stone held between his fingers of one

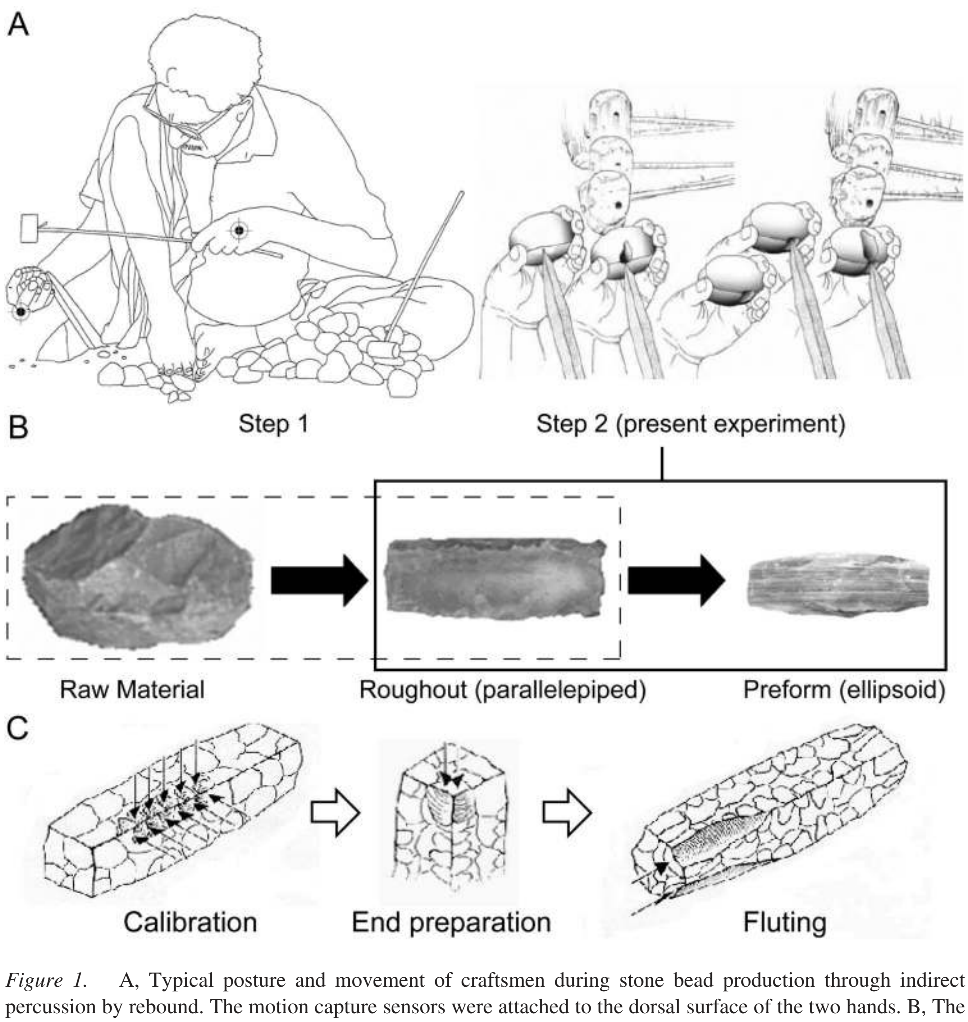

Figure 1. A, Typical posture and movement of craftsmen during stone bead production through indirect percussion by rebound. The motion capture sensors were attached to the dorsal surface of the two hands. B, The two steps of the fabrication of an ellipsoidal bead, (1) from raw material to a parallelepiped-shaped roughout, and (2) from a roughout to an ellipsoidal preform. Only the second step is considered in the present study. C, Three subprocesses of an ellipsoidal bead production: calibration, end preparation, and fluting. Black arrows represent the direction of the hammer blows. Only calibration was considered in the present study. Adapted from "Nesting of Asymmetric Functions in Skilled Bimanual Action: Dynamics of Hammering Behavior of Bead Craftsmen," by T. Nonaka and B. Bril, 2012, *Human Movement Science, 31*, pp. 58–59. Copyright 2012 by Elsevier Ltd.

hand against the pointed tip of an iron bar, and strikes the piece with the hammer held in the other hand so that a stone flake is fractured from the point of contact with the iron bar. By detaching flakes of different profiles by a series of hammer strikes, craftsmen shape the stone into a specific form. This process consists of the following two stages (Figure 1B): (1) shaping of what is called a "roughout," which displays gross geometric characteristics of the product (in the case of ellipsoidal beads, roughouts are roughly parallelepiped-shaped), and (2) shaping of the final product called a "preform," which will then be ground, drilled, polished, and glossed (Roux et al., 1995).

Roux et al. (1995) hypothesized that the capacity of craftsmen to adapt to a new raw material would index the level of dexterity. The new raw material chosen was glass, which is much more fragile than stone but still has the property of conchoïdal fracture. Two groups of craftsmen from high-quality workshops (HQ) and lower-quality workshops (LQ) shaped an ellipsoidal-shaped preform out of a roughout made of glass. The outcome was compared through the filming of the beads from eight different angles and the computation of parameters indexing the overall shape, the symmetries along the longitudinal and transversal axis, and the contour of the bead in terms of regularity and smoothness (for details, see Roux et al., 1995; Bril et al., 2000, 2005). All these criteria clearly distinguished the products of the two groups of craftsmen, in which expert craftsmen had systematically produced more spherical and symmetrical beads with smoother contour (Figure 2B). Subsequent studies found that underlying such superior quality of products of experts was nested hierarchy of attunements to the environmental constraints (Bril et al., 2005; Biryukova & Bril, 2008; Nonaka & Bril, 2012). The hammer-arm system has its own resonant frequency depending on its mass distribution, the position held, and its axis of rotation. At one level, both groups of craftsmen decreased the amplitude of the oscillation of the hand wielding a hammer when relatively fragile glass was used. At another level, the hammering movement and the hand holding the stone appeared to be adjusted to the movement of each other, where large interstroke variability of the hammerhead direction accompanied by the regularity of coupling dynamics in bimanual coordination was characteristic of highly skilled experts (Nonaka & Bril, 2012). Yet at another level, cross recurrence quantification analysis (Zbilut, Giuliani, & Webber, 1998; Shockley, Butwill, Zbilut, & Webber, 2002) revealed that the bimanual movement coordination of experts was modulated according to the requirements of different subgoals, where the dynamics of bimanual coupling was found to be more stable and less noisy during the most critical phase of the task—the removal of large crests. Furthermore, such modulation of dynamics got exaggerated in the situation using unfamiliar glass that presumably requires the greater degree of stabilization. What these results implied was that there is a hierarchy of streams of regulatory activities which maintain or alter the task-relevant relationships to the environment, and that dexterous behavior requires these streams of activities to be organized into a coherent whole in such a way not to be dysfunctional to the ongoing function of one another (Nonaka & Bril, 2012).

Perception depends on the perceiver's active exploration for the nested structure of the environment (Gibson, 1966). A growing body of research suggest that the fluctuations in exploratory behaviors exhibit a temporally nested structure termed "fractal" in which fluctuations grow as a power–law of time scale according to potentially noninteger exponents (Stephen, Arzamarski, & Michaels, 2010; Stephen & Hajnal, 2011; Stephen & Anastas, 2011; Stephen, Hsu, Young, Saltzman, Holt, Newman, Weinberg, Wood, Nagpal, & Goldfield, 2012). In general, exploration requires fluctuations, and fluctuations increase in time. The Hurst exponent H expresses how fast fluctuations grow. For uncorrelated white noise, fluctuations grow at the square root of time with a Hurst exponent $H = 1/2$. When fluctuations are temporally long-range correlated with systematically larger fluctuations at longer time scales and smaller fluctuations at shorter time scales, the value of Hurst exponent approaches 1. In one of the series of studies on the fractal temporal correlations of perceptual exploration, Stephen et al. (2010) tested whether the Hurst exponent of fluctuations in exploration would predict the efficiency of exploration. They used the paradigm of dynamic touch, in which participants judged the length of a rectangular object by manipulating it without visual information. Followed by the pretest phase, participants were given visual feedback about the actual length of the block, which

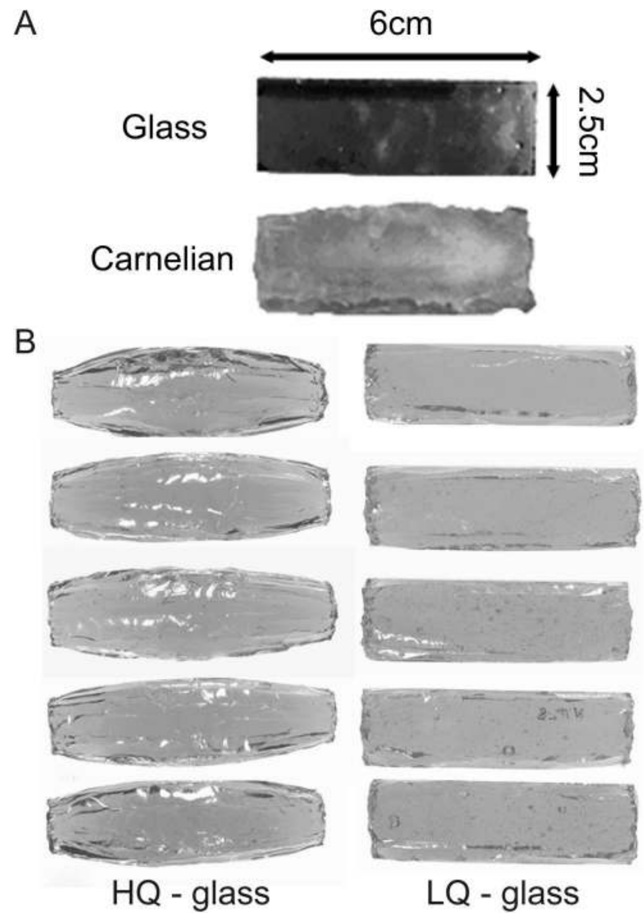

Figure 2. A, Two kinds of roughout made of different raw materials used in the experiment (glass and carnelian stone). B, Examples of glass preforms produced by an HQ and an LQ craftsman. Adapted from "Nesting of Asymmetric Functions in Skilled Bimanual Action: Dynamics of Hammering Behavior of Bead Craftsmen," by T. Nonaka and B. Bril, 2012, *Human Movement Science, 31*, pp. 59–61. Copyright 2012 by Elsevier Ltd.

induced changes in perceptual judgments in the posttest phase, usually in such a way to make the judgments more accurate. During the trials, the exploratory wielding movements of the hands of the participants were recorded by 3D motion capture system. Using detrended fluctuation analysis (DFA; Peng, Buldyrev, Havlin, Simons, Stanley, & Goldberger, 1994; Peng, Havlin, Stanley, & Goldberger, 1995), they found that the Hurst exponent of hand displacements between successive samples during wielding was in fact related to the changes in the perceptual responses that follow, in such a way that fractal hand wielding (i.e., the Hurst exponent close to 1) promoted improved accuracy. Not only in the experimental paradigm of dynamic touch, but in a variety of perceptual paradigms, evidence has been found that long-range correlation properties of exploratory movements index how well the exploratory movements sample available perceptual information (e.g., Stephen & Anastas, 2011).

What remains to be explained is how those fractal fluctuations in exploratory movements may arise (Stephen & Dixon, 2011; Ihlen & Vereijken, 2010; Kello, Beltz, Holden, & Van Orden, 2007). How could fluctuations of organismic behavior be tailored in such a way to attune to the sought-after ecological information about the task-relevant aspects of the environment? Several scientists sought to explain such tailoring of fluctuations as multiscale self-organizing structures analogous to turbulent fluid flow. In an attempt to understand fluid turbulence, Mandelbrot (1972, 1974) modeled intermittency and self-similar hierarchies as autonomous phenomena—the multiplicative resultant of many functions, each corresponding to a different range of eddy wavelengths. These models were termed *multiplicative cascading processes* and have been shown to capture intermittent structures in very diverse phenomena (Mandelbrot, 2001; Ihlen & Vereijken, 2010; Stanley & Meakin, 1988). In such models, the intermittent structure in time or space is defined by multiplicative interactions that transport energy and information across spatiotemporal scales (Ihlen & Vereijken, 2010; see Figure 3). Heterogeneity across time makes multiplicative cascading processes an ideal formalism for discussing the development of a new fractal scaling (Stephen & Dixon, 2011). Stephen and colleagues investigated the behavior of participants who attempted synchronize finger taps to an unpredictable, chaotic metronome, and found that the Hurst exponents of intertap intervals correlated with the Hurst exponents of interonset intervals of the metronome (Stephen, Stepp, Dixon, & Turvey, 2008). In other words, fluctuations in participants' behavior were found to be strongly attuned to the long-range fluctuations in an unpredictable environment (i.e., metronome). The subsequent analysis revealed that changes in the long-range, multiscale fluctuations of synchronization behavior are indeed the result of interaction between the fluctuations of many different sizes (Stephen & Dixon, 2011). This was indicated by the difference in distribution of fractal exponents described in terms of *singularity spectrum*—a spectrum expressing heterogeneity in terms of different local exponents that define scale-invariant relationships—between the original time series and the surrogate time series whose temporal sequence was destroyed while preserving the same power spectrum and distribution as the original time series (Schreiber & Schmitz, 1996).

In what follows, we seek to analyze the dynamics of dexterous behavior of expert bead craftsmen by means of a quantitative framework of fractal analysis. In doing so, the emphasis was placed on the ecology of the task, following the tradition of the previous studies on the same skill (Roux et al., 1995; Bril et al., 2005; Biryukova & Bril, 2008). Recent carefully controlled laboratory experiments suggest that human performance is inextricably entangled with laboratory contexts to the greater degree than has been presumed (Van Orden, Holden, Podgornik, & Aitchison, 1999; Holden, Choi, Amazeen, & Van Orden, 2011; Kello et al., 2007; Van Orden et al., 2010). For example, Holden et al. (2011) showed that, in a simple reaction time task, unsystematic changes in task context—the increase of the amplitude of white noise injected into the temporal interval between a "ready" signal and a signal to respond or that between each trial response and the next ready signal—change the fractal patterns in trial-series of response times in the direction of random noise. Small changes in the laboratory context or other relevant circumstances may change the fundamental structure of variation and thereby observed behavior itself. A growing body of evidence suggests that the assumption that the causal basis of behavior is somehow separate from the context in which behavior is observed is unwarranted (Van Orden et al., 1999, 2010; Holden et al., 2011; Kello et al., 2007). Rather, the contexts of the experimental task are constitutive of the observed task performances (Van Orden et al., 2010). This may be especially true in the case of dexterity, the hallmark of which is the context sensitivity itself (Stergiou & Decker, 2011). It follows that we need to study dexterous action in the settings in which it is actually found, to establish how it is organized and reorganized to meet the needs of embedding contexts and unfolding situations (Reed, 1993).

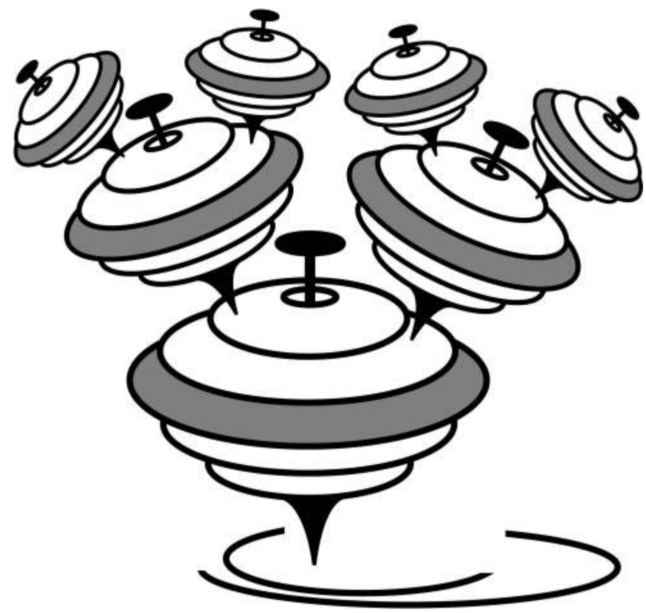

Figure 3. An example of multiplicative cascading processes—"the Scaling Gyroscopes Cascade" (Schertzer, Lovejoy, Schmitt, Chigirinskaya, & Marsan, 1997) with big tops have little tops that feed on their momentum and little tops have smaller tops. Adapted from "Multifractal Cascade Dynamics and Turbulent Intermittency," by D. Schertzer, S. Lovejoy, F. Schmitt, Y. Chigirinskaya, and D. Marsan, 1997, *Fractals, 5*, p. 431. Copyright 1997 by World Scientific Publishing Company.

Taking this point seriously, the present work reanalyzed the data from a field experiment conducted in a rural Indian village

(Nonaka & Bril, 2012), in which the data were collected in a context as close as possible to the craftsmen's everyday activity (cf., Roux et al., 1995). In the experiment, two groups of craftsmen (from high quality workshops and lower quality workshops) shaped the beads made of two different materials (carnelian stone—familiar material and glass—unfamiliar material) in the workshops they normally work. Nonaka and Bril (2012) were primarily interested in the aspect of asymmetric bimanual coordination in hammering behavior. In contrast, the present study focused on the fractal dynamics of the movement of the hand wielding a hammer during the exploratory phase of the task (i.e., calibration, Figure 1C). In particular, we explored the possibility that dexterity of craftsmen is characterized by the long-range correlation properties of the movement wielding a tool. Because this is an exploratory study, we focused on a set of general questions such as the following: Will the fluctuations in hammering movements during bead making (i.e., tapping the bead repeatedly to standardize the surface of the bead) be long-range correlated (i.e., will exhibit the Hurst exponent close to 1)? Underlying such fluctuations, will there be multiplicative contingencies across time scales (i.e., will the heterogeneity over time of scaling exponents characterizing the original time series differ from that of surrogate time series devoid of such contingencies)? Will such fractal organization index the dexterity of expert craftsmen, who have been shown to exhibit considerable adaptability to cope with unfamiliar situations (Roux et al., 1995; Bril et al., 2005)?

Method

Participants

In Khambat, the workshops that produce superior quality beads and the workshops that produce lower quality beads are clearly distinguished, and the craftsmen are given different socioeconomic status according to the workshops they belong to (Roux et al., 1995). Participants were recruited from these two classes of workshops. HQ consisted of six expert craftsmen from the higher quality workshops. LQ consisted of six craftsmen from the lower quality workshops. Craftsmen from both groups manufacture beads for their living. In total, 12 professional stone bead craftsmen took part in the experiment. Among participants from high quality workshops, HQ1 is acknowledged as the "best" craftsman in Khambat not only by the salesmen, but also by the Indian government who gave him grants to run a training center. All the craftsmen in the study volunteered, and for their participation they were paid the highest rate for one day's work. They gave their verbal agreement to participate in the study to the owner of the workshop, who hosted the experiment.

Equipment and Setup

Following Roux et al. (1995), in addition to carnelian stone typically used in bead production, glass was included as raw material. Parallelepiped-shaped pieces of glass ($6 \times 2.5 \times 2.5$ cm) and pieces of carnelian stone with approximately the same size were used as the roughouts (Figure 2A). The hammer used in the experiment had the following properties: weight of hammerhead = 22 g, handle length = 35 cm, handle weight = 7 g. A Spatial Tracking System (STS-Polhemus) was used to record the movements of the two hands. This system uses an electromagnetic field to determine the three-dimensional positions and orientations of the sensors relative to the stationary system. The static accuracy of the STS system was .08 cm RMS for the sensor positions. Calibration measurements showed that the system was accurate within 0.7 m of the origin of the stationary system. The two sensors of the STS were firmly attached with adhesive tape to the dorsal surface of the two hands of each participant (Figure 1A). Movement data were recorded at 60 Hz. Both sensors were within a 0.7-m sphere of the stationary system to ensure acceptable accuracy of the STS. The craftsmen reported that the sensors were not a hindrance. The present study analyzed only the position data from the sensor attached to the hand wielding the hammer.

Design and Procedure

The craftsmen were in a situation as close as possible to their everyday activity. Participants sat on a rug in their preferred sitting posture. All of them used the posture illustrated in Figure 1A. The task consisted of shaping an approximately 6 cm $\times$ 2.5 cm $\times$ 2.5 cm parallelepiped-shaped roughout into an ellipsoidal preform (Figure 1B). In the present study, the hammering behavior in the preparatory phase (referred to as "calibration" in Roux et al., 1995) was studied. In this part of the bead making process, craftsmen standardize the surface by removing tiny flakes to prepare for the subsequent detachment of large crests (Figure 1C). A session consisted of producing a series of five samples of beads of each of the two raw materials. The craftsmen were instructed to produce an ellipsoidal bead and to take their time to manufacture a bead of high quality.

Data Reduction

By labeling the video recording with Actogram software (Octares Editions, Toulouse), the first 30-s sequences of calibration (standardization of surfaces to prepare for the removal of crests) were extracted from each trial. The reasons for selecting the first 30 seconds of a performance for the analyses were that the entire process of shaping preforms (i.e., calibration, end preparation, and fluting, see Figure 1C) lasted no longer than about two minutes and it was often not possible to extract a part longer than 30 s or to select other parts of a subgoal sequence within the same trial. Therefore, the choice of 30-s duration was not arbitrary, but based on the durations of the measured data. Sometimes, the duration of calibration sequence was shorter than 30 seconds, and in such cases the trial was reported as missing. In total, 108 time series (30 seconds, 1800 points) from the marker of the STS system during calibration sequences contributed to the analysis.[1]

Data Analysis

During the bead making task, the hammering hands of the craftsmen were almost constantly oscillating. The top three panels in Figure 4 show three dimensions of the position time series for one participant from the HQ group during calibration in one trial. We computed a time series of the displacement (i.e., euclidean distances) between successive samples in the position time series.

[1] For a full description of the methods, see Nonaka and Bril (2012).

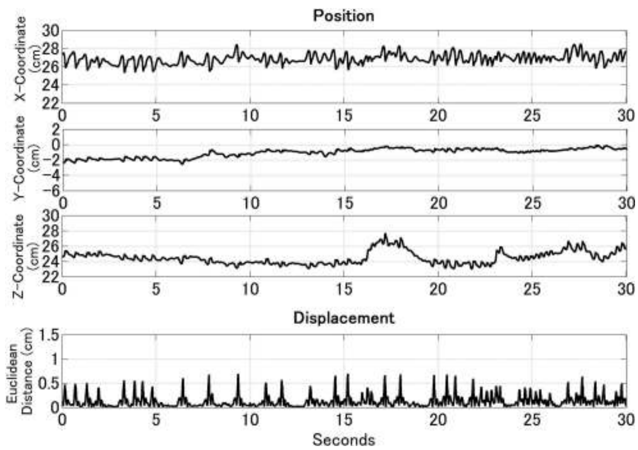

Figure 4. Sample time series from a single trial by a single participant HQ1 (expert). The top three panels show each of the three Euclidean coordinates composing the position time series. The bottom panel shows the time series of Euclidean displacements derived from the position time series.

The bottom panel in Figure 4 shows the displacement time series for the position time series in the top panel. Each of these 1800 displacement time series (30 seconds) was used for further analyses.

Detrended fluctuation analysis (DFA). To detect and quantify the scaling and correlation properties of the displacement time series, we have used a modified root-mean-square analysis of a random walk called detrended fluctuation analysis (DFA; Peng et al., 1994, 1995). In DFA method, first, the original time series $x(t)$ (with N samples) is shifted by the mean $\overline{x(t)}$ and integrated (cumulatively summed) to produce the new time series $y(t)$:

$$y(t) = \sum_{i=1}^{N} [x(i) - \overline{x(t)}]. \tag{1}$$

Next, the integrated time series is divided into windows of equal length, n. For each window of length n, a least squares line (representing the *trend* in that window) is fit to the data. The y coordinate of the straight line segments is denoted by $y_n(t)$. For a given window size n, the characteristic size of the fluctuations, denoted by $F(n)$, is then calculated as the root-mean-square deviation between $y(t)$ and its trend $y_n(t)$ in each box:

$$F(n) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \left[y(t) - y_n(t)\right]^2}. \tag{2}$$

This computation is repeated over all time scales (window sizes). Typically, $F(n)$ will increase with window size n. A linear relationship on a log-log graph indicates the presence of scaling (self-similarity), such that fluctuations in small windows are related to the fluctuations in larger windows in a power–law fashion. The slope of the line relating log $F(n)$ to log n determines the fractal scaling exponent, H:

$$F(n) \sim n^{H}. \tag{3}$$

If $H = .5$, there is no correlation and the time series is uncorrelated white noise. If $H > .5$, the time series is correlated, and the closer the value of H to 1, the stronger the fractal temporal correlations in the time series. We will be using a first-order differentiation of wielding trajectories as a data $x(t)$, which can be classified as fractional Gaussian noise (Eke, Herman, Kocsis, & Kozak, 2002), and the scaling exponent will be hereafter denoted as H_{fGn} following Eke et al. (2002).[2] Considering the nature of the present data that are not well-defined mathematically, we adopted a conservative range of sampling window sizes $10 < n < N/10$, following the suggestion made by Hu, Ivanov, Chen, Carpena, and Stanley (2001).

To validate that the obtained H_{fGn} is associated with long-range correlations in the fluctuations of the measured time series, we performed DFA on randomly shuffled versions of each of the original 108 displacement time series, as well as on the original time series. Shuffling was meant to destroy the original temporal sequence while preserving the mean and variance of each time series. Hence, a truly fractal signal will bear a scaling exponent $H_{fGn} > .5$ in its original sequence but not in a shuffled sequence (Peng et al., 1994; 1995).

Direct determination of a singularity spectrum. Next, we tested the possibility that the displacement time series generated by wielding behavior may require many local fractal exponents to characterize their scaling properties fully. Given this possibility, we looked into the distribution of local fractal exponents—a *singularity spectrum*, which summarizes the temporal change in patchiness in the time series. We adopted the algorithm developed by Chhabra and Jensen (1989) to directly compute the singularity spectrum, which is given as follows (cf., Kelty-Stephen, Palatinus, Saltzman, & Dixon, 2013). Cover the measure time series with N_n nonoverlapping sampling windows with n samples and calculate the probability in each of these sampling windows. Define the proportion in the ith sampling window P_i as the local sum of the series within the ith sampling window divided by the grand sum of the time series:

$$P_i(n) = \frac{\sum_{k=1+n(i-1)}^{in} x(k)}{\sum x(t)} \sim n^{\alpha_i}. \tag{4}$$

The exponent α_i is called *singularity strength*, which reflects the single, scale-invariant form of the relationship between proportion and window lengths. Next, we construct a one-parameter family of normalized measures $\mu(q)$ where the probabilities in the sampling windows with n samples are

$$\mu_i(q, n) = \frac{[P_i(n)]^q}{\sum_{i=1}^{N_n} [P_i(n)]^q}. \tag{5}$$

[2] To test whether the displacement time series are stationary, a 127-frequency window-averaged spectral analysis was conducted on the normalized (z scored), first 2^{10} points of the original time series (see Holden, 2005 for the details of the method). The mean spectral slope found for the lowest 25% frequencies in log-log coordinates was $-.63$ ($SE = .02$), consistent with stationary fractional Gaussian noise description (Eke et al., 2002). Recurrence quantification analysis further confirmed system stationarity yielding the mean *TREND* value of $-.10$ ($SE = .03$; see Nonaka & Bril, 2012 for the input parameters used), which were within the stationarity boundary of $\pm$ 5 (cf., Webber & Zbilut, 2005).

where q is a statistical moment that provides the microscope for exploring different regions of the singular measure. For $q > 1$, $\mu(q)$ amplifies the more singular regions of P, whereas for $q < 1$, it accentuates the less singular regions, and $q = 1$ the measure $\mu(1)$ replicates the original measure. Then the Hausdorff dimension $f(q)$ of partition function $\mu(q)$ is derived as the scaling relationship of the Shannon entropy of $\mu_i(q,n)$ with scale n.

$$f(q) = -\lim_{N\to\infty} \frac{1}{\log N_n} \sum_{i=1}^{N_n} \mu_i(q,n)\log[\mu_i(q,n)] = \lim_{n\to 0} \frac{\sum_{i=1}^{N_n} \mu_i(q,n)\log[\mu_i(q,n)]}{\log n} \tag{6}$$

In addition, we can compute the average value of the singularity strength $\alpha_i = \dfrac{\log(P_i)}{\log n}$ with respect to $\mu(q)$ by evaluating

$$\alpha(q) = -\lim_{N\to\infty} \frac{1}{\log N_n} \sum_{i=1}^{N_n} \mu_i(q,n)\log[P_i(n)] = \lim_{n\to 0} \frac{\sum_{i=1}^{N_n} \mu_i(q,n)\log[P_i(n)]}{\log n} \tag{7}$$

Equations (6) and (7) provide a relationship between a Hausdorff dimension f and an average singularity strength α as implicit functions of the parameter q. Then, based on Equations (6) and (7), the $f(\alpha)$ singularity spectrum is computed directly from experimental data. It has been suggested that the accuracy of the estimation of singularity spectrum by the above method of Chhabra and Jensen (1989) depends strongly on the degree of approximation involved in the calculation of the slopes on which values $f(q)$ and $\alpha(q)$ are based (Zamir, 2003). For the current study, we included only those values of q ($-1.4 \le q \le 3$) for which the scaling relationships of $f(q)$ and $\alpha(q)$ in Equations (6) and (7) for all the time series reflected correlation at $r^2 \ge .90$. Figure 5 depicts examples of regression-based estimation of $f(q)$ and $\alpha(q)$, respectively. The same range of sampling window sizes as DFA was used for the calculation of singularity spectra.

The magnitude of its distribution region of singularity spectrum $f(\alpha) \sim \alpha$ along α axis (i.e., the width $\alpha_{\max} - \alpha_{\min}$) defines the amplitude difference between the variability in the intermittent and in the laminar periods within the time series (Ihlen & Vereijken, 2010). As a result, the singularity-spectrum width $\alpha_{\max} - \alpha_{\min}$ quantifies the influence of the multiplicative interaction between the multiple time scales of the time series. Larger singularity-spectrum width is associated with stronger multifractal behaviors, whereas smaller singularity-spectrum width is associated with weaker multifractality that tends to be monofractal. To validate that the obtained singularity spectrum width originates from the multiplicative interactions between temporal scales, the width of the singularity spectrum resulting from analysis of the original displacement time series was compared with the singularity spectra for a distribution of surrogate time series generated by the iterative amplitude-adjusted Fourier-transformation (IAAFT; Schreiber & Schmitz, 1996) method, which randomly reshuffles the values of the original time series while preserving the same autocorrelations and the same probability distribution as the original time series (Schreiber & Schmitz, 1996). When the singularity spectrum of the original time series has significantly different width than the distribution of singularity spectra for the surrogate time series, the original time series can be said to exhibit multiplicative interactions between temporal scales. We compared the singularity-spectrum width for each original time series with the singularity-spectrum widths for 50 of its IAAFT surrogates to validate the influence of multiplicative interactions between temporal scales.

Statistical Analysis

A linear mixed-model ANOVA with group and raw material as fixed-effects and participant as a random effect was conducted for each dependent variable (i.e., H_{fGn} and $\alpha_{\max} - \alpha_{\min}$). To account for the correlation between trials made by the same participant, a participant factor was included as an additional random-effect (Boyle & Willms, 2001). Bonferroni-corrected post hoc analysis was used for multiple comparisons. Difference between each original time series and its surrogate time series was tested as a paired samples t test and a one-sample t test for H_{fGn} and the singularity-spectrum width, respectively. All the statistical tests were made using SPSS 16.0. The alpha value for a significant effect was set at .05 in all the statistical analyses.

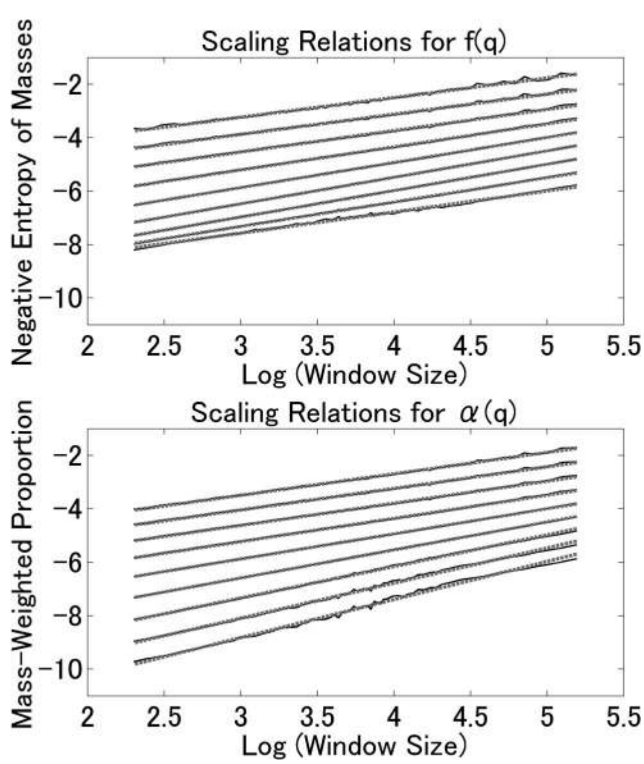

Figure 5. Examples of linear fits to the semilog plots used to calculate $f(q)$ (upper panel) and $\alpha(q)$ (lower panel) with $-1.4 \le q \le 3$. The value of q is incremented by .55 from the bottom curve ($q = -1.4$) to the top curve ($q = 3$). Curves are spaced by a constant factor to improve visibility. Dashed gray lines indicated the best least-squares fit whose slope is used as the estimate for $f(q)$ and $\alpha(q)$, all $r^2 \ge .90$.

Results

Fractal Temporal Correlations of Wielding Behaviors

The scaling exponents H_{fGn} estimated for the original displacement time series (M = .81, SE = .008) are consistent with fractal fluctuations.[3] They were higher than scaling exponents H_{fGn} for the shuffled version of the displacement time series (M = .51, SE = .003), paired-samples $t(107) = 34.08$, $p < .001$. Figure 6 depicts the fluctuation function of an original displacement time series (black line) and the fluctuation function of a shuffled version of the same displacement time series (gray line) on double-log scaled axes. The slope of the former is steeper than the latter.

Next, we looked into the difference in H_{fGn} across groups with different skill levels in the conditions using familiar and unfamiliar materials. In the linear mixed model ANOVA on mean H_{fGn} obtained from the DFA analysis of the original displacement time series, the only significant effect found was the interaction between group and material, $F(1, 96) = 28.27$, $p < .001$. A post hoc analysis revealed the divergence in the pattern of alteration of fractal dynamics between groups when craftsmen used the unfamiliar material (glass). For HQ, the long-range correlation in the movement of the hammering hand represented by the value of H_{fGn} significantly increased in this unfamiliar situation, $p < .001$ (stone: M = .81, SE = .03 glass: M = .86, SE = .03). Contrary to HQ, when LQ attempted to shape the novel material, there was a marked alteration of the dynamics of wielding behavior which accompanied the significant loss of long-range correlations represented by the value of H_{fGn}, $p < .001$ (stone: M = .84, SE = .03, glass: M = .76, SE = .03). The difference across skill levels in the long-range correlation properties of the hand movement was significant in the glass condition, $p = .019$, whereas when the familiar material (carnelian stone) was used, no significant difference across groups was found.

To doubly guard against the possible claim that changes in H_{fGn} derives from the difference in linear measures, we further ran mixed model ANOVA on the mean resultant velocity (i.e., displacement). The only significant effect was that of material, $F(1, 95) = 109.55$, $p < .001$, in which craftsmen from both groups moved their hammering hands with significantly smaller velocity on average when glass was used than when stone was used (stone: M = 11.20 cm/s, SE = .08 cm/s, glass: M = 8.41 cm/s, SE = .08 cm/s). The result was consistent with that of Bril et al. (2005) who found the decrease of hammerhead acceleration, and that of Nonaka and Bril (2012) who found that the decrease of amplitude of oscillation of the hammering hand (i.e., Euclidean distance between the peaks of the oscillations of the hammering hand) when relatively fragile glass was used.

Inspection of Figure 7 which presents the individual differences in H_{fGn} and mean resultant velocity suggests that HQ1, the most prominent expert, exhibited a pronounced increase in H_{fGn} when he was coping with the novel situation using glass. Also, the movement of HQ1 wielding a tool tended to involve consistently lower resultant velocities than the other craftsmen. Figure 7 further suggests that for most LQ craftsmen, there was a large drop in H_{fGn} when they were coping with the unfamiliar material.

Multiplicative Cascading Processes

We estimated the singularity spectrum for each hand-displacement time series, and evaluated the difference between the width of singularity-spectrum (i.e., $\alpha_{max} - \alpha_{min}$) for 50 IAAFT surrogate signals and that of the corresponding original time series as one-sample, two-tailed Student's t statics. In all, there were 106 hand-displacement time series (i.e., 98.15% of all 108 hand-displacement time series) whose spectra had significantly different widths than those of their surrogates, $|ts|$ ranging from 2.15 to 411.55 (see Figure 8).[4] One hundred hand-displacement time series (i.e., 92.59% of all time series) had singularity spectra that were significantly wider than those of their surrogates. The result suggests, in general, the singularity spectra of the original time series were wider than the corresponding shuffled, surrogate signals which have the same autocorrelations and the same probability distribution as the original signals (Schreiber & Schmitz, 1996). The significant difference between the singularity-spectrum width of the original time series and the ensemble of surrogates indicated that a large portion of the displacement time series originated from intermittent dynamics that are induced by multiplicative interactions between temporal scales.

The difference across groups with different skill levels when using the two different materials were further evaluated. Figure 9 shows the singularity spectra computed for HQ (top) and LQ (bottom) in the carnelian stone condition (black circles) and the glass condition (gray circles). Inspection of Figure 9 suggests the decrease of the width of the singularity spectrum in the glass condition only for LQ. A mixed model on mean singularity-spectrum width found a significant main effect of material, $F(1, 95) = 29.11$, $p < .001$, and the interaction between group and material, $F(1, 95) = 8.95$, $p < .01$. Confirming the above impression, Bonferroni-corrected pairwise comparisons found that for LQ, the singularity-spectrum widths were narrower when glass was used compared to the normal stone-using condition (stone: M = .45, SE = .05, glass: M = .28, SE = .05), $p < .001$. However, no such difference was found for HQ craftsmen (stone: M = .49, SE = .05, glass: M = .45, SE = .05). The pairwise comparison further confirmed that HQ craftsmen exhibited a significantly wider singularity-spectrum widths compared to LQ craftsmen in the glass condition, $p < .05$ (see Figure 9). Looking further into individual differences (see Table 1), the movement of the best craftsman (HQ1) exhibited a pronounced increase in singularity-spectrum width when coping with the unfamiliar glass, which may be associated with degree of heterogeneity in fractal scaling.

[3] Alternate fractal analyses also indicated the presence of fractal fluctuations: Spectral analysis (see footnote 2) approximated H_{fGn} of .81 in agreement with the direct estimate of H_{fGn} from DFA (for conversion formulas, see Eke et al., 2002). All the 108 time series displayed larger spectral exponents (i.e., steeper spectral slopes) than those of a randomly shuffled version of the same time series. The average fractal dimension of the original time series, computed using the standardized dispersion static (see Holden, 2005 for the details of the method), was 1.22 (SE = .005) approximating H_{fGn} of .78, not far from H_{fGn} estimated by DFA. All the 108 series yielded smaller fractal dimensions than their shuffled surrogate counterparts.

[4] Bootstrap t test, which requires fewer distributional assumptions about the data (Efron & Tibshirani, 1993), found significant differences between the original spectrum width and 1000 bootstrapped samples of 50 surrogate spectrum widths for a comparable percentage (97.22%) of the data.

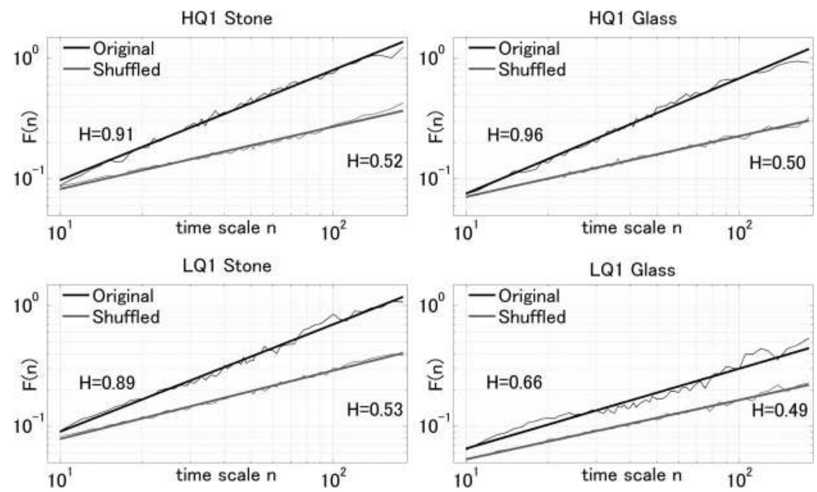

Figure 6. Fluctuation functions from detrended fluctuation analysis (DFA) on sample displacement time series in the two material conditions (left, stone; right, glass) by HQ1 (upper panels) and LQ1 (lower panels). The black lines correspond to the source time series, whose shuffled versions are represented by gray lines, whose slopes indicate scaling exponents. Lines are overlaid with regression lines, and axes are logarithmically scaled.

To visualize the difference of fractal dynamics between experts and nonexperts revealed in the glass condition, each trial was characterized by the scaling exponent H_{fGn} obtained from DFA and the width of the singularity spectra (see Figure 10). The plot shows that these two quantities, especially the singularity-spectrum width, discriminates the skill level of craftsmen in a fairly clear manner when they are faced with the unfamiliar context that requires adaptability.

Discussion

Building on the previous works by Roux, Bril, and colleagues on dexterous tool-using behavior (Roux & Pelegrin, 1989; Roux et al., 1995; Roux, 2000; Bril et al., 2000, 2005; Biryukova & Bril, 2008; Nonaka & Bril, 2012) and Stephen and colleagues on perceptual exploration (Stephen et al., 2010, 2012; Stephen & Hajnal, 2011), we explored an interesting possibility that dexterity of craftsmen would be characterized by the fractal temporal correlations of the movement wielding a tool. The data of experts from a "field experiment" (Bril et al., 2005) made possible the inquiry into dexterity in the setting where it actually "lives," which arguably has important implications that supplement the current knowledge of the context-dependent nature of dexterity. Summarily, the results are as follows:

i. The movement fluctuations of the hand wielding the hammer during bead knapping exhibited long-range temporal correlations.
ii. In the unfamiliar situation (condition using glass), the wielding behavior of HQ displayed a significant increase of long-range temporal correlations, whereas that of LQ exhibited a significant loss of long-range correlations.
iii. When the fragile material (glass) was used, mean resultant velocity (within a 30-s sequence) of the hammering movement significantly decreased for HQ and LQ alike.
iv. The dynamics of the hammering movement was influenced by multiplicative interactions between fluctuations in different temporal scales, as indicated by the significant difference between the singularity-spectrum widths of the original time series and those of the surrogate time series.
v. The influence of these interactions was shown to be dependent on the task constraints and the level of expertise, with the singularity-spectrum width significantly narrowed in the glass condition only for LQ. In the unfamiliar situation, multifractality of tool-wielding behavior clearly discriminated the groups with different skill levels.
vi. The most prominent expert (HQ1) exhibited a pronounced increase in both in the long-range temporal correlations and in the heterogeneity of scaling properties over time when coping with the unfamiliar material.

In what follows, we will discuss the implications of the above results for the understanding of the nature of dexterity roughly in the above order.

Fractal Scaling and Context Sensitivity

The first main result is that the movement of the hand wielding the hammer during the initial phase of bead knapping is long-range correlated (result *i*). The removal of flakes by means of hammer strikes is an irreversible process, in which each strike renews the condition for the subsequent strikes at the rate of around 3 Hz (Nonaka & Bril, 2012). As a consequence, successful bead making requires rich flexibility and exquisite context sensitivity for the behavior to be tailored according to fluctuations in the situation. The presence of long-range, power–law correlations in the wielding behavior of craftsmen may be adaptive from at least the following three perspectives: (1) the fractal temporal correlations in exploration allows for the attunement to the nested flows of environmental fluctuations spanning across different temporal scales (Stephen et al., 2010; Stephen & Hajnal, 2011); (2) long-range temporal correlations serve as a self-organizing mechanism for complex processes that generate fluctuations across a wide range of time scales, which allows for idiosyncratic local dynamics

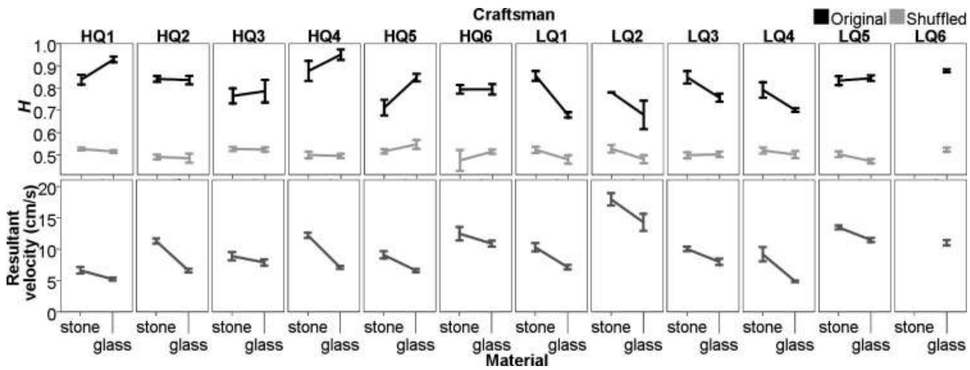

Figure 7. Upper panels: Means of the scaling exponents H_{fGn} estimated for the original displacement time series as a function of participant and raw materials. Error bars represent standard errors of the means. Lower panels: Means of the three-dimensional Euclidean displacement per second (i.e., resultant velocity) of the hammering hand as a function of participant and raw materials. Error bars represent standard errors of the means. The Participant LQ6 had no trial of stone condition that had a duration more than 30 seconds.

to be reflected in the global goal-directed dynamics, and vice versa (Goldberger, Amaral, Hausdorff, Ivanov, Peng, & Stanley, 2002; Stergiou & Decker, 2011; Riley et al., 2012); and relatedly, (3) the absence of a characteristic scale inhibits the emergence of overly regular patterns, which would greatly narrow functional responsiveness to the changing situations (Goldberger et al., 2002; Stergiou & Decker, 2011; Riley et al., 2012).

As mentioned before, the previous study reported that when the unfamiliar glass was used, LQ could not shape the ellipsoid at all (Roux et al., 1995; Bril et al., 2005). In contrast, HQ managed to shape the designated shape despite the radically different constraints of the material. At a superficial level, the present study showed that the hammering movements were adapted to the fragility of glass, whose mean velocity exhibited a significant decrease for both HQ and LQ alike (result *iii*). In other words, both groups of craftsmen have adapted their movement to the properties of the raw material, which indicates that both groups have knowledge of the gross mechanical properties of the raw material. Yet, although the mean velocity at a single time scale did not distinguish the behaviors of the two groups, long-range correlation properties across multiple time scales in the fluctuations of movement wielding a tool did distinguish them. When LQ craftsmen attempted to shape the unusual material (glass), there was a marked alteration of the dynamics of wielding behavior accompanied by a significant loss of long-range temporal correlations, which Lipsitz and Goldberger (1992) might refer to as a "loss of complexity." Contrary to LQ, HQ exhibited a "gain of complexity" in which even the greater degree of long-range correlations were observed in their movement when they faced this unfamiliar situation (result *ii*).

Changes in power–law relationships have been investigated by a considerable body of work spanning various disciplines (Dixon, Holden, Mirman, & Stephen, 2012). For instance, the degree to which one stride interval is correlated with previous and subsequent intervals over different time scales will be reduced with age and with the development of neurological disorders such as Hun-

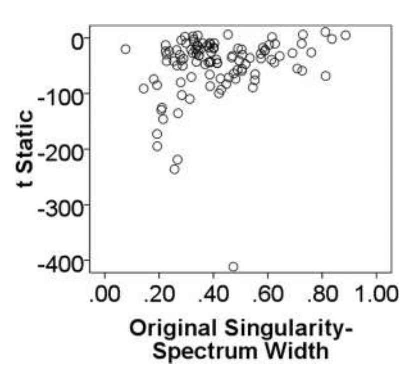

Figure 8. *t* statics for singularity-spectrum widths for the distribution of singularity-spectrum widths for IAAFT surrogates when compared against each original hand-displacement time series (all conditions pooled).

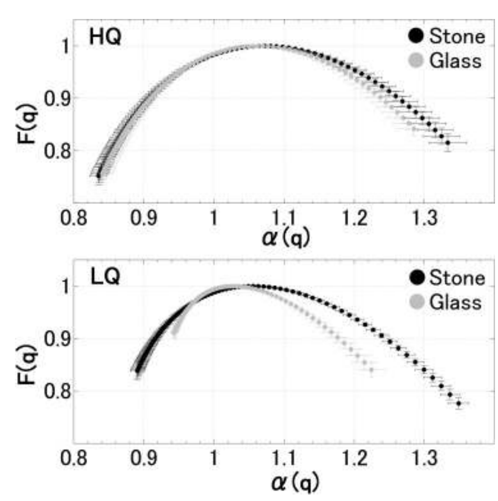

Figure 9. Singularity spectrum $f(\alpha(q))$ $(-1.4 \leq q \leq 3)$ estimated for HQ (upper panel) and LQ (lower panel) in the conditions using carnelian stone (black spheres) and glass (gray spheres) as raw materials. The vertical and horizontal bars are standard errors of the means for $f(q)$ and $\alpha(q)$, respectively, of multiple realizations of each condition (HQ stone, 24 trials; HQ glass, 30 trials; LQ stone, 26 trials; and LQ glass, 28 trials).

Table 1
Means and Standard Deviations of Resultant Velocity, H_{fGn}, and Singularity-Spectrum Width for the Twelve Craftsmen of the Two Groups (HQ and LQ)

Craftsman	Material	Resultant velocity (*cm/s*) *M*	*SD*	H_{fGn} *M*	*SD*	Singularity-spectrum width *M*	*SD*
HQ1	Stone	6.62	1.17	0.84	0.05	0.65	0.07
	Glass	5.21	0.52	0.93	0.03	0.78	0.10
HQ2	Stone	11.29	0.91	0.84	0.03	0.63	0.10
	Glass	6.59	0.65	0.84	0.04	0.34	0.08
HQ3	Stone	8.90	1.45	0.76	0.08	0.33	0.05
	Glass	7.88	1.12	0.79	0.11	0.28	0.09
HQ4	Stone	12.21	0.73	0.88	0.08	0.41	0.08
	Glass	7.09	0.50	0.95	0.05	0.36	0.06
HQ5	Stone	9.09	1.00	0.71	0.06	0.28	0.00
	Glass	6.60	0.61	0.85	0.04	0.34	0.03
HQ6	Stone	12.46	1.86	0.79	0.03	0.62	0.12
	Glass	10.88	1.03	0.79	0.05	0.57	0.14
LQ1	Stone	10.30	1.46	0.86	0.05	0.40	0.03
	Glass	7.14	0.76	0.68	0.03	0.25	0.05
LQ2	Stone	17.95	1.40	0.78	0.00	0.28	0.02
	Glass	14.29	2.70	0.68	0.13	0.26	0.15
LQ3	Stone	10.04	0.91	0.85	0.07	0.48	0.06
	Glass	7.98	1.15	0.76	0.04	0.34	0.11
LQ4	Stone	9.19	2.52	0.79	0.08	0.47	0.10
	Glass	4.88	0.28	0.70	0.02	0.20	0.02
LQ5	Stone	13.48	0.84	0.83	0.06	0.52	0.07
	Glass	11.46	0.68	0.84	0.02	0.37	0.02
LQ6	Stone	—	—	—	—	—	—
	Glass	11.05	0.97	0.88	0.02	0.29	0.06

Note. The participant LQ6 had no trial from stone condition that had a duration more than 30 seconds.

tington's disorder (e.g., Hausdorff, Mitchell, Firtion, Peng, Merit, Cudkowicz, Wei, & Goldberger, 1997; Van Orden, Kloos, & Wallot, 2009). The scaling properties of cardiac interbeat interval time series are altered with ageing: Over short time scales, fluctuations resemble a random walk process, whereas over the longer range, they resemble random white noise. Both short-range and long-range exponents are significantly different in the elderly subjects compared with young adults (Iyengar, Peng, Morin, Goldberger, & Lipsitz, 1996). Such degradation of correlated, multiscale dynamics may reflect weakened integrity across the streams of adjustments to the task-related aspects of the environment at different temporal scales (Goldberger et al., 2002).

In the case of bead making, the use of the novel material must require the exploration of the affordances of the material for shaping by means of flaking. In such a case, the finer the exploration for the task-relevant properties of the material, the better the probable outcome of the activities that follow. How exactly this divergence in the pattern of alteration of fractal dynamics between groups corresponds to the divergence in the quality of products is unclear. Yet, this result does clearly support the first of the three conjectures listed above, which is based on Stephen and colleagues' findings in laboratory settings that the long-range correlation properties of exploratory movement predicts how well the available energy distributions for perceptual information are used (Stephen et al., 2010; Stephen & Anastas, 2011; Stephen & Hajnal, 2011). The acute sensitivity of highly skilled experts to the properties of different materials, as is apparent in the quality of the products, is indeed accompanied by the fractal dynamics of exploratory movement. What the present data contribute that has been missing before is the evidence from a dexterous skill in the out-of-laboratory context that fractal temporal correlations of exploratory behavior indexes the dexterity of skills coping with the situation that requires the acute detection of task-relevant information.

On the Role of Multiplicative Cascading Processes

The DFA algorithm measures only one exponent characterizing a given time series. Yet, further possibility is present that the dynamics of wielding behavior may require a larger number of exponents to characterize their scaling properties, which may arise from multiplicative interactions between fluctuations at different temporal scales (Ivanov et al., 1999; Ihlen & Vereijken, 2010; Stephen & Dixon, 2011). The subsequent analysis of the present data indeed revealed the heterogeneity of fractal scaling over time (i.e., multifractality) in the dynamics of the hammering behavior of craftsmen. To validate whether multifractality of the measured time series originated from multiplicative interactions between fluctuations at different temporal scales, the original time series was compared with the surrogate time series in which temporal sequence was destroyed while its original autocorrelations and probability distribution were preserved (Schreiber & Schmitz, 1996). The significant differences between the singularity spectrum widths of the original time series and those of the corresponding surrogates indicate that a large portion of the time series was influenced by intermittent dynamics that are induced by multiplicative interactions across time scales (result *iv*). Such multiplicative streams coordinating multiple time scales have been documented in perceptual-motor fluctuations in a variety of laboratory cognitive and motor tasks (Stephen, Anastas, & Dixon, 2012; Stephen et al., 2012; Scafetta, Griffin, & West, 2003; Ihlen & Vereijken, 2010; Ihlen, Skjæretb, & Vereijken, 2012). Yet, it is just beginning to be understood what practical role such cascade dynamics might have for behavior. For example, in one of the pioneering studies that clearly addressed the practical role played

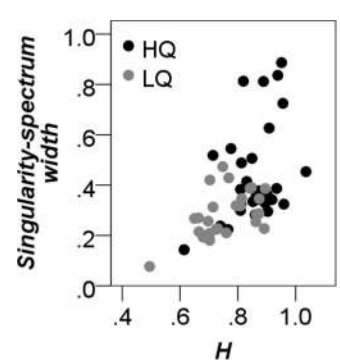

Figure 10. Each trial from the glass condition (58 trials in total) is characterized by two quantities for HQ (black spheres) and LQ (gray spheres) craftsmen. The first quantity (y axis) is the degree of multifractality, which is represented by the difference between the maximum and minimum values of singularity strength for each trial. The second quantity (x axis) is the scaling exponent H_{fGn} obtained from DFA.

by multiplicative cascading processes, Stephen and Dixon (2011) provided the evidence that such a flexible fractal scaling dynamics underlies the development of a new fractal scaling resonating to the fluctuations in the environment.

Regarding the practical role such multiplicative cascade dynamics might play in the task under study, we found it useful to juxtapose the results of the previous studies on the same skill in grounding the present results. Biryukova and Bril (2008) analyzed the subsequent phase of bead making called "fluting"—the removal of large crests by hard strikes—of the same HQ craftsmen as the ones participated in the present study. They reported that the best craftsman (HQ1) exhibited the most fluid combination of multiple joint degrees of freedom of the hammering arm. Contrary to the others whose movement was largely dominated by a couple of particular joint degrees of freedom, all the degrees of freedom in the wrist, the elbow, and the shoulder were involved in the hammering movement of the best craftsman. In addition, the highly skilled craftsman exhibited the largest interstroke variability in the coordination of movement as well as in the hammer-head trajectory. The subsequent study showed that underlying the large variability of the hammerhead trajectory was a rather stable coupling dynamics between the hammering hand and the postural hand which orients the stone (Nonaka & Bril, 2012). Such fluid interactions among the movements with different ranges and different intrinsic cycles giving rise to the volatile variability in the overall pattern of tool-environment relationship is likely to be adaptive, which potentially provides the basis for flexibility to cope with different materials, as well as to possible internal and external perturbations. This conjecture is supported by the finding from the present analysis, where the influence of multiplicative interactions between the fluctuations at different temporal scales was significantly reduced in the glass condition for LQ who were not able to cope with this unfamiliar material (result *v*).

Moreover, when we looked into individual differences, the most prominent expert (HQ1), who managed to shape the material into the almost ideal ellipsoidal shape, exhibited the increase in the degree of heterogeneity in fractal scaling (indexed by singularity-spectrum width) when coping with the unfamiliar glass (result *vi*). Combined with the results from the previous studies, the results of the present experiments indicate that the dexterous behavior of experts craftsmen flexibly dealing with unfamiliar situations may emerge from the sensitivity of motor coordination to the fluctuations in the environment, ranging possibly from such microscale fluctuations as the subtle change of position and angle of the stone held in the other hand (cf., Nonaka & Bril, 2012) or the change of the resonant frequency of the hammer-arm system which depends on the joints involved in the movement, to such macroscale fluctuations as different constraints of different materials used. In any case, if we are to ask whether the attunement to the novel task constraints exhibited by highly skilled experts arose from the activity of insular components or from the multiplicative interaction among many nested structures (Dixon et al., 2012), the results of the present experiment provide support for the latter answer.

Studying the dexterous hammering behavior during correct striking with a chisel, Bernstein (1967) showed that it is impossible to alter selectively any one given detail in the bodily movement without affecting others. "Movements react to changes in one single detail with changes in a whole series of others which are sometimes very far removed from the former both in space and in time, . . . they are structurally whole, simultaneously exhibiting a high degree of differentiation of elements and differing in the particular forms of the relationships these elements" (Bernstein, 1967, p. 69). What Bernstein implied was that the problem of explaining dexterous skills is related to the issue of how the various streams of subsidiary activity are coordinated into unified acts. In general, at any given time, a skilful actor will be engaged in maintaining and altering a variety of functional relationships to the environment (Reed, 1988). Perhaps at the most fundamental level, an actor needs to maintain an upright posture while breathing, which changes the shape of the chest and disbalances the trunk above the hips and the head above the trunk (Gurfinkel, Kots, Palstev, & Feldman, 1971). Although the movements of various parts of the body fluctuates in different ways, and although these fluctuations are not inconsiderable, these oscillations need to be constrained and coordinated in such a way not to be dysfunctional to the ongoing functions performed in the environment (Reed, 1988; Zhang, Scholz, Zatsiorsky, & Latash, 2008; Riley et al., 2012; Nonaka & Bril, 2012; Nonaka, 2013; Gelfand & Latash, 1998). Even a simple everyday skill is composed of a number of components cycling at different temporal scales, facilitating a variety of subsidiary functions, and constrained together by perception to serve the overall function at hand (Reed, 1988; Nonaka & Bril, 2012; Nonaka, 2013). To paraphrase Reed (1988), a healthy adult is almost always orienting, breathing, exploring perceptual information, manipulating, locomoting, and using a tool which alters the intrinsic dynamics of the body. These separate streams of activity continually overlap. We do not stop exploring perceptual information when we adjust our postures, nor do we stop breathing when we hit a stone with a hammer. Each stream of activity has its own characteristic temporal cycles, according to the aspects of the environment to which each activity is linked, as well as to the intrinsic dynamics of the bodily movements involved. The crucial issue here is how these various streams of relationships with different temporal and spatial scales are kept separately nested into a coherent whole in such a way not to be dysfunctional to one another, cycling in parallel, depending on a hierarchy of task-relevant relationships to the environment to be established (Reed, 1988; Zhang et al., 2008; Riley et al., 2012; Nonaka & Bril, 2012; Nonaka, 2013). In the case of dexterous behavior which exhibits exquisite context sensitivity to create a perfect key for any emerging lock (Bernstein, 1996), the coordination of subsidiary streams of activities to regulate the hierarchy of functional relationships to the environment should require even greater adaptability. From this point of view, it does not seem improbable that the presence of interactions among fluctuations across multiple temporal scales giving rise to the heterogeneity in the fractal dynamics as was found in the present study may be the hallmark of dexterous behavior in general, which provides the room for flexibility to deal with unpredictable situations as well as to possible perturbations. Further research may address the generality of the present argument.

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