Origins of Timing Errors in Human Sensorimotor Coordination

Yanqing Chen
Mingzhou Ding
J. A. Scott Kelso
Center for Complex Systems and Brain Sciences
Florida Atlantic University

ABSTRACT. The authors analyzed fluctuations in timing errors when 8 human participants attempted to coordinate movement with external rhythmic signals. The temporal dynamics of the errors is usually described in terms of simple, self-correcting models. Here the authors demonstrate that timing errors are characterized by a $1/f^\alpha$ type of long memory process. The value of the exponent α differentiates different types of coordination states: synchronization and syncopation. More interesting, evidence was found that α can be changed when participants use different coordination strategies. Together with the authors' understanding of the generation mechanism for long memory processes, these results suggest that $1/f^\alpha$ type of long-range correlated timing errors are of higher cortical origin and are likely the outcome of distributed neural processes acting on multiple time scales.

Key words: finger movement, human timing, long memory process, motor coordination, multiple time scales, $1/f$ noise, synchronization, syncopation

In many human activities, such as music and dance, the motor system is required to act in a specific timing relationship with certain external events. For over a century, experimental psychologists and others have sought to understand the underlying timing mechanism (Bartlett & Bartlett, 1959; Dunlap, 1910; Woodrow, 1932). A basic experimental method for studying the timing mechanism is to require the participant to tap in synchrony (on the beat) or in syncopation (off the beat) with an external rhythmic stimulus (Kelso, DelColle, & Schöner, 1990). Inevitable timing errors occur with respect to the stimulus, a thorough analysis of which is an essential step toward unraveling the underlying control mechanism. In early work, Dunlap (1910), Woodrow (1932), and Bartlett and Bartlett (1959) focused on the mean and variance of the timing errors, but they did not study the possible sequential aspects of the cycle-to-cycle fluctuations. In subsequent work, researchers attempted to relate correlations among timing errors to the performance strategy (Hary & Moore, 1987; Mates, 1994; Vorberg & Wing, 1996). The prevailing hypothesis is that the participant perceives the timing error and makes locally correlated corrective adjustments, resulting in short-range correlated timing errors (Pressing, 1999; Pressing & Jolley-Rogers, 1997; Vorberg & Wing, 1996). To test that hypothesis, we carried out finger-tapping experiments in which participants produced long stationary fluctuating time series while they performed the tasks of synchronization and syncopation to a regular sequence of sounds (Kelso et al., 1990). Our examination of the overall correlation structure of the error time series uncovered a very different pattern, namely, a $1/f^\alpha$ type of long memory process. In a further experiment, participants were required to produce syncopation by using different strategies. Evidence was presented that suggests that cognitive strategies may influence the long-term statistics of timing errors, a result that one cannot predict by using local error-correction models.

Method

Task

Eight right-handed men took part in each experiment. Each participant signed the informed consent form, which had been approved by the local Institutional Review Board. Participants were seated in front of a computer placed inside a sound-attenuated experimental chamber and were instructed to rhythmically press their right index finger on a computer key in a specific phase relationship with periodic

auditory beeps (duration = 50 ms), delivered through the computer. The frequency of the metronome was 1 Hz. In the first experiment, all 8 participants performed the first two conditions: synchronization and syncopation. In the synchronization task, the participant was required to tap in synchrony with the metronome. In the syncopation condition, the participant had to press the computer key in between adjacent stimuli. Each participant performed two trials in each condition; a total of 32 time series were collected in the first experiment. The second experiment was designed so that participants would produce syncopation by using different coordination strategies. For the 2:1 strategy, participants ($n = 4$) made two flexion movements during every 1-s stimulus interval, one flexion movement synchronized with the stimuli (no key depression), and a second flexion movement (with key depression) in the middle of the cycle, thus syncopating with the 1-Hz stimuli. In a way, that procedure is like playing a drum twice as fast as the basic musical rhythm. The second coordination strategy required participants ($n = 4$) to intentionally control an extension movement (key release) with the stimulus instead of a downward flexion key press, so that when the finger relaxed back to the lowest position, the (computer-registered) key press was in the middle of the cycle (syncopation). At 1 Hz, all those modes of coordination could be maintained, thus giving us a unique opportunity to investigate changes in the coordination dynamics even though the environmental conditions remained the same. A total of 16 time series were collected in the second experiment.

Every single trial contained 550 responses. We used a computer program to register the response time with 1-ms resolution. We analyzed the error time series, defined as the time between the computer-recorded response time and the metronome onset time, indexed by the number of taps. All data were based on participants' successful completion of the requirement, that is, synchronization or syncopation without interruption, without missing stimuli or making extra responses.
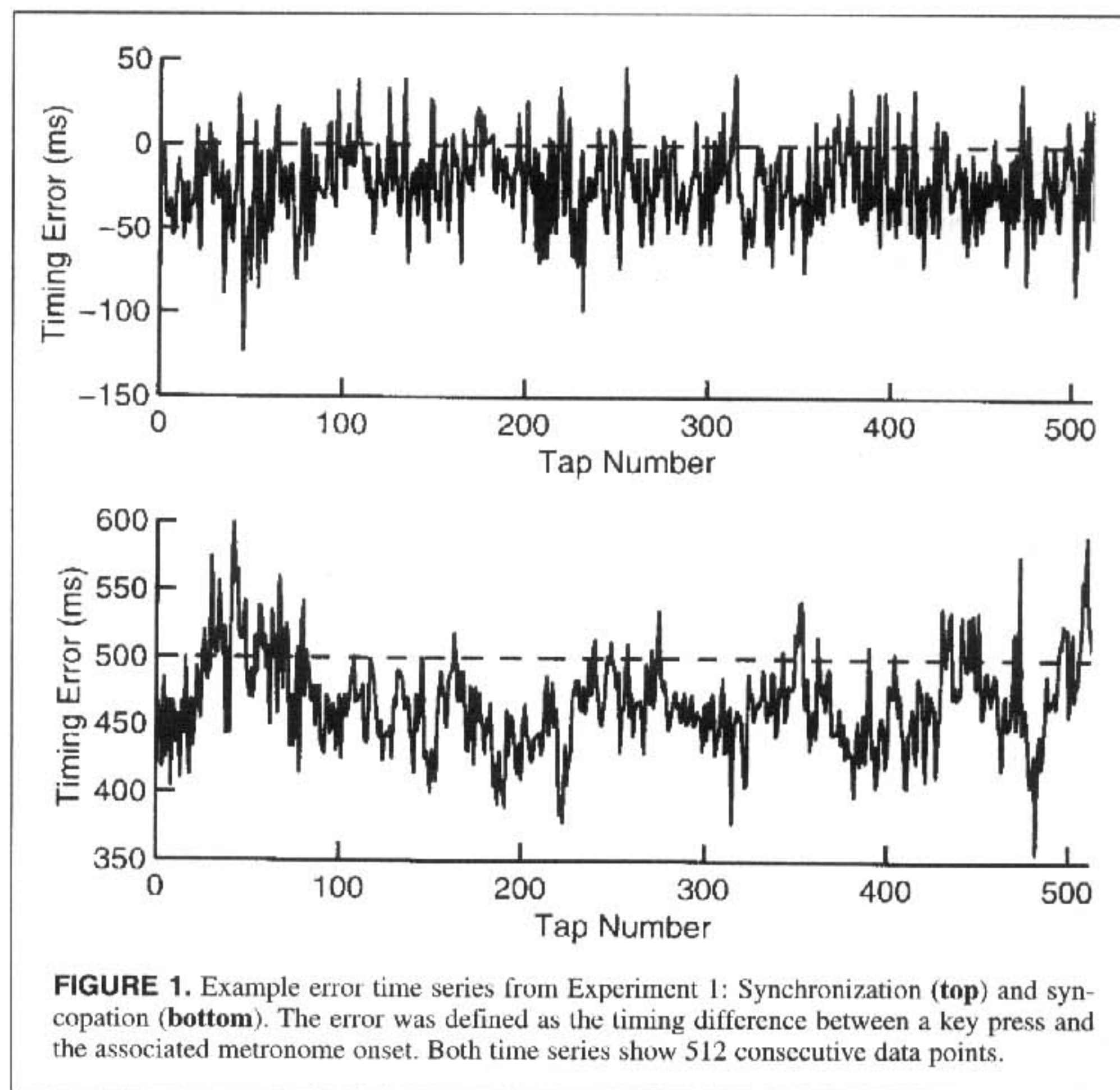
Data Analyses

In all time series, we eliminated the first 10 data points to remove initial transients. The subsequent 512 points were used for further analysis. (The remaining data points were discarded.) Spectral analysis (Beran, 1995) was based on standard methods. We calculated each individual spectrum after removing the mean and normalizing by the standard deviation for the individual time series. To calculate the spectral exponents of each individual time series, we used the frequency domain maximal likelihood estimation (MLE; Beran, 1995), which, based on a fractional Gaussian noise model, estimates the long memory in a time series from its power spectrum. The details of the method and the mathematical background can be found in Beran (1995, chap. 6). The second method we used is called rescaled range analysis (Bassingthwaighte, Liebovitch, & West, 1994), in which one constructs a random walk from each time series by

using partial sums (Rangarajan & Ding, 2000) and estimates the power law increases in the mean range of the random walk as a function of the number of data points. The exponent of this power law is defined as the Hurst exponent (H). Both MLE and rescaled range analysis give an estimate of the Hurst exponent, which relates to the power spectrum slope α through the relation: $\alpha = 2H - 1$. MLE is believed to be the most accurate statistical estimator available, with minimal standard deviation of the estimation limited only by data length (0.07 for 512 data points).

Results

Two sample time series of the timing errors from synchronize (top) and syncopate (bottom) of the first experiment are shown in Figure 1, indicating the presence of highly variable random processes. In Figure 2, we show the averaged power spectra for the two conditions on a log-log scale. Excellent straight-line fits mean that the power $S(f)$ scales with the frequency f as a power law $S(f) \sim 1/f^\alpha$. By virtue of the Fourier transform, the autocorrelation function $C(k)$ also scales with the time lag k as a power law $C(k) \sim k^{-\beta}$, where $\beta = 1 - \alpha$. This slow decrease of the correlation between errors separated by the time interval k is in contrast with the rapid exponential decay predicted by theories that posit local correlation. In fact, for α between 0 and 1, as was the case in the present experiment, the $C(k)$ function decays so slowly with k that the underlying statistical process is said to have long memory (Beran, 1995). Thus, the value of one synchronization or syncopation error is related to and affects the errors into the distant future. Remarkably, the scaling exponent allowed us to distinguish clearly the two basic modes of coordination. Comparison of the numerical values of $\alpha = 0.77$ for syncopation (bottom curve in Figure 2) and $\alpha = 0.54$ for synchronization (top curve in Figure 2) further revealed that the correlation between syncopation errors decayed much more slowly than that of synchronization. The longer the separation between timing errors, the more pronounced was the difference in the strength of the correlation between the syncopation and synchronization errors.

In Figure 2, we have used the averaged spectra to summarize the results from synchronization and syncopation. To evaluate the statistical significance of the difference between the two conditions, we applied the frequency domain maximal likelihood estimator (MLE; Beran, 1995) to each of the 32 time series (16 from synchronization and 16 from syncopation) to calculate the individual exponent α. The overall α value for synchronization was 0.45 ± 0.16, whereas for syncopation, $\alpha = 0.73 \pm 0.17$. We found the two exponents to be significantly different by using a two-tailed t test ($p < .025$). As a verification step, we applied rescaled range analysis (Bassingthwaighte et al., 1994) to each of the 32 time series. The estimated α values were again different between the two conditions ($\alpha = 0.45 \pm 0.16$ for synchronization, and $\alpha = 0.61 \pm 0.12$ for syncopation), despite the fact that the rescaled range analysis has the tendency to

FIGURE 1. Example error time series from Experiment 1: Synchronization (**top**) and syncopation (**bottom**). The error was defined as the timing difference between a key press and the associated metronome onset. Both time series show 512 consecutive data points.

underestimate α when $\alpha > 0.75$ (Schepers, van Beek, & Bassingthwaighte, 1992). The convergence between the two different methods, one in the spectral domain and the other in the time domain, is important because it is known that each method alone is susceptible to producing false conclusions. Together, however, they form a robust integrated approach (Rangarajan & Ding, 2000).

Synchronization is a relatively simple task for humans to perform. Syncopation, however, is more demanding, requiring longer training and a higher level of concentration to ensure quality performance. Moreover, it is known that syncopation is a less stable form of coordination and that spontaneous switching to synchronization can occur at both behavioral (Kelso et al., 1990) and neural levels (Kelso et al., 1992). The difference between the α values for the two conditions suggests that the scaling exponent is a correlate of task difficulty. It is known that syncopation (e.g., flexion movements off the beat) can be performed at high movement rates if the participant consciously decides to place extension movements on the beat (Kelso et al., 1990). Might investigators then be able to shift the values of the scaling exponents by altering cognitive strategy? Were that so, long-range correlation in timing behavior may be said to originate in the higher level functioning of the human brain.

We designed the second experiment to probe that idea, and we required participants to use different sensorimotor coordi-

nation strategies while producing movement responses between stimuli, thus giving rise to variable timing errors mimicking the syncopation task. The averaged power spectra for the 2:1 strategy (top) and for the extension-on-the-beep strategy (bottom) are shown in Figure 3. Using MLE, we found the scaling exponent from the 2:1 strategy to be $\alpha = 0.48 \pm 0.19$, which is nearly the same as that of the original synchronization. For the participants who took part in the extension-on-the-beep strategy, the result was not as clear. From the averaged spectrum, the scaling exponent was found to be 0.83 ± 0.07, which is in fact closer to the syncopation exponent. However, closer inspection of each participant's response indicated that, for 1 participant who performed the task particularly well, the exponent was about 0.45 (Figure 4), close to that of the synchronization task. These results offer evidence that the cognitive strategy may influence the value of the scaling exponent α, lending support to the notion that the source of long-range correlations in timing lies in the central nervous system.

Discussion and Conclusion

Dunlap (1910) was the first to observe cycling behavior in the timing error series. He noted that the errors tend to grow larger and larger in a given direction (too early or too late) until a correction causes a change in direction where the same pattern repeats. Dunlap called this the drifting
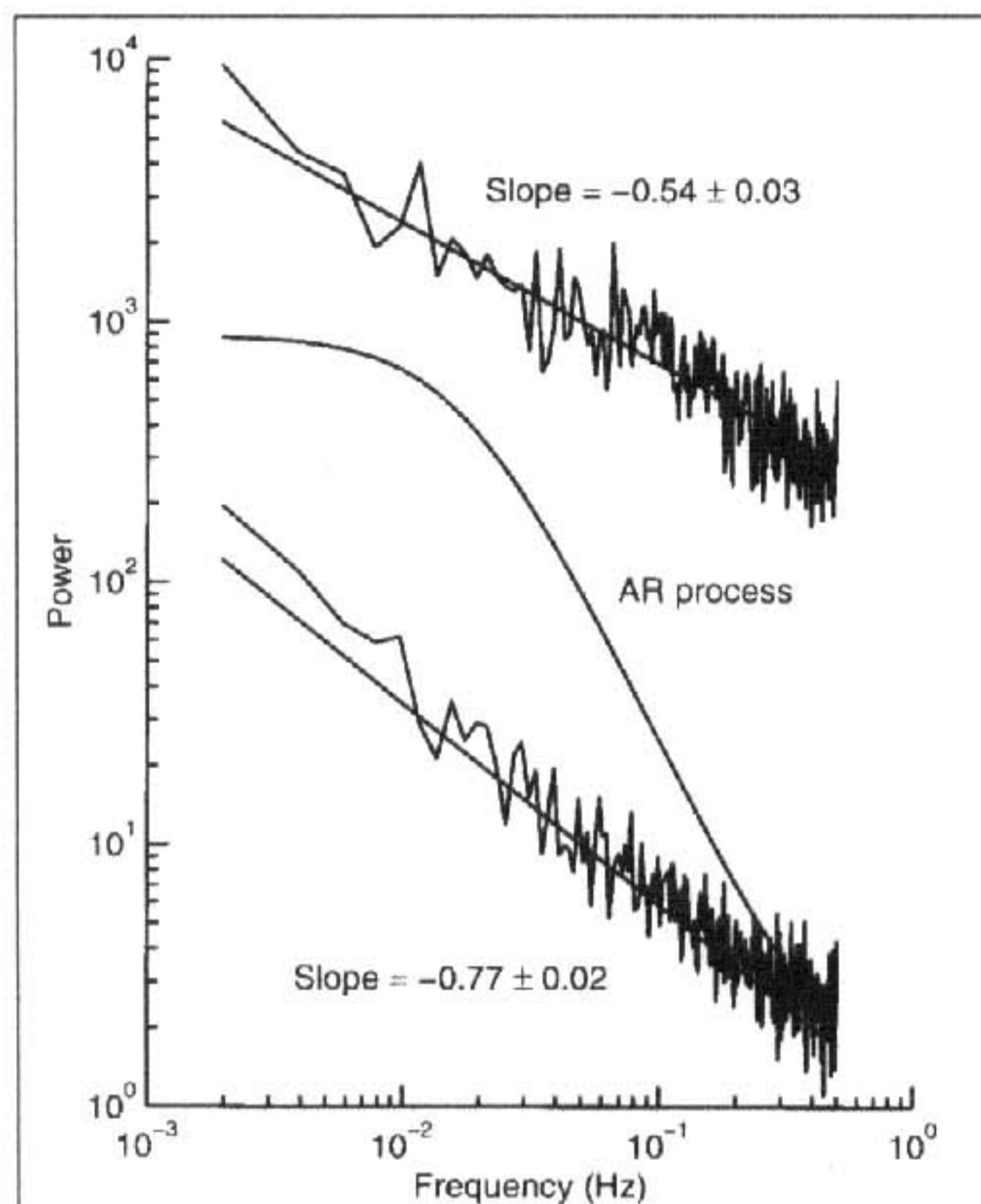
FIGURE 2. Averaged spectral density of the error time series for synchronization (**top**) and syncopation (**bottom**) from the first experiment. We have converted the unit of frequency from 1/beat to Hertz as follows. Because the interval between two data points in the error time series is the stimulus period T (1.0 s in this case), the frequency f was defined as $f_k = (k - 1)/(mT)$, for $k = 1, 2, \ldots, m/2 - 1$, where m (= 512) is the total length of the time series. The power spectrum of a first-order autoregressive (AR) process is also plotted in the middle as a comparison. Notice that in the low-frequency portion the autoregressive process shows a flattened (whitened) spectrum.

FIGURE 3. Averaged spectral density of the error time series for the 2:1 strategy (**top**) and the extension-on-the-beep strategy (**bottom**) from the second experiment.

phenomenon and attributed it to a frequency mismatch between stimulus and response. Spectral analysis here revealed a highly organized power law relationship between the amplitude of the cycle and its frequency. In models of self-correcting adjustments it is typically predicted that the autocorrelation function will decay exponentially, leading to a Lorentzian type of power spectrum, as shown by the middle curve in Figure 2 (Pressing, 1999; Pressing & Jolley-Rogers, 1997). Although data presented by Pressing and Jolley-Rogers (1997) supported that type of spectrum, the inconsistency between the middle curve in Figure 2 and the data in the same figure is quite apparent. It is possible that the higher levels of music skills possessed by the participants in Pressing and Jolley-Rogers' study (1997) were a contributing factor. Moreover, severe de-trending can also lead to whitening of the spectrum in the low-frequency end. Further investigations are needed to resolve these issues.

It is worth noting that power law relations in the spectral domain can appear quite naturally in systems with many
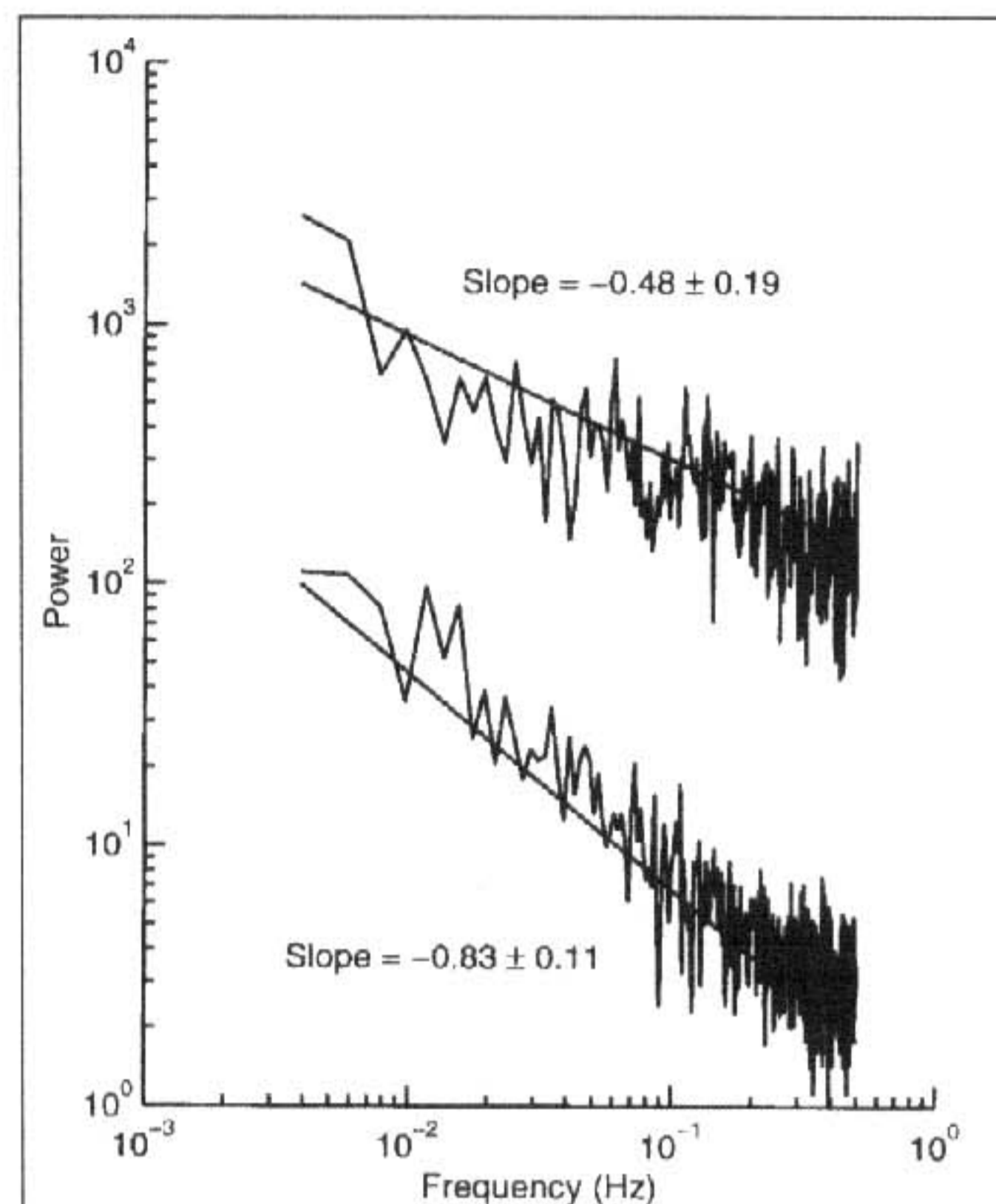
time scales (Granger, 1966). If we view the error variable measured in the present experiment as the final outcome of neural activities from many structures on multiple time scales (Bressler, Coppola, & Nakamura, 1993; Chen, Ding, & Kelso, 1999; Mandell & Kelso, 1991), then it seems that the $1/f$ framework is more appropriate than the simple self-correcting models for describing the temporal dynamics of the error series. A very similar revelation has taken place in the past few years in a related movement task called continuation; in that task, participants continue to reproduce a given time interval from memory after the metronome pacing signal has been turned off. In early work on that paradigm, researchers concentrated on the correlation between two adjacent intertap intervals (Wing & Kristofferson, 1973). In later experiments, intervals not directly abutting each other were also found to exhibit significant correlation (Wing, 1977). In more recent work using spectral techniques, Gilden, Thornton, and Mallon (1995) showed that, in fact, the interval can be described by a $1/f^\alpha$ process with $\alpha = 1$ and may take on important cognitive functions. Finally, we note that, despite the fact that $1/f^\alpha$ processes have been observed in many physical and biological systems (Chen et al., 1997; Kobayashi & Musha, 1982; Mandelbrot & Van Ness, 1968), the functions of such processes have remained obscure. In our experiments, we have established a functional role for those types of processes by showing
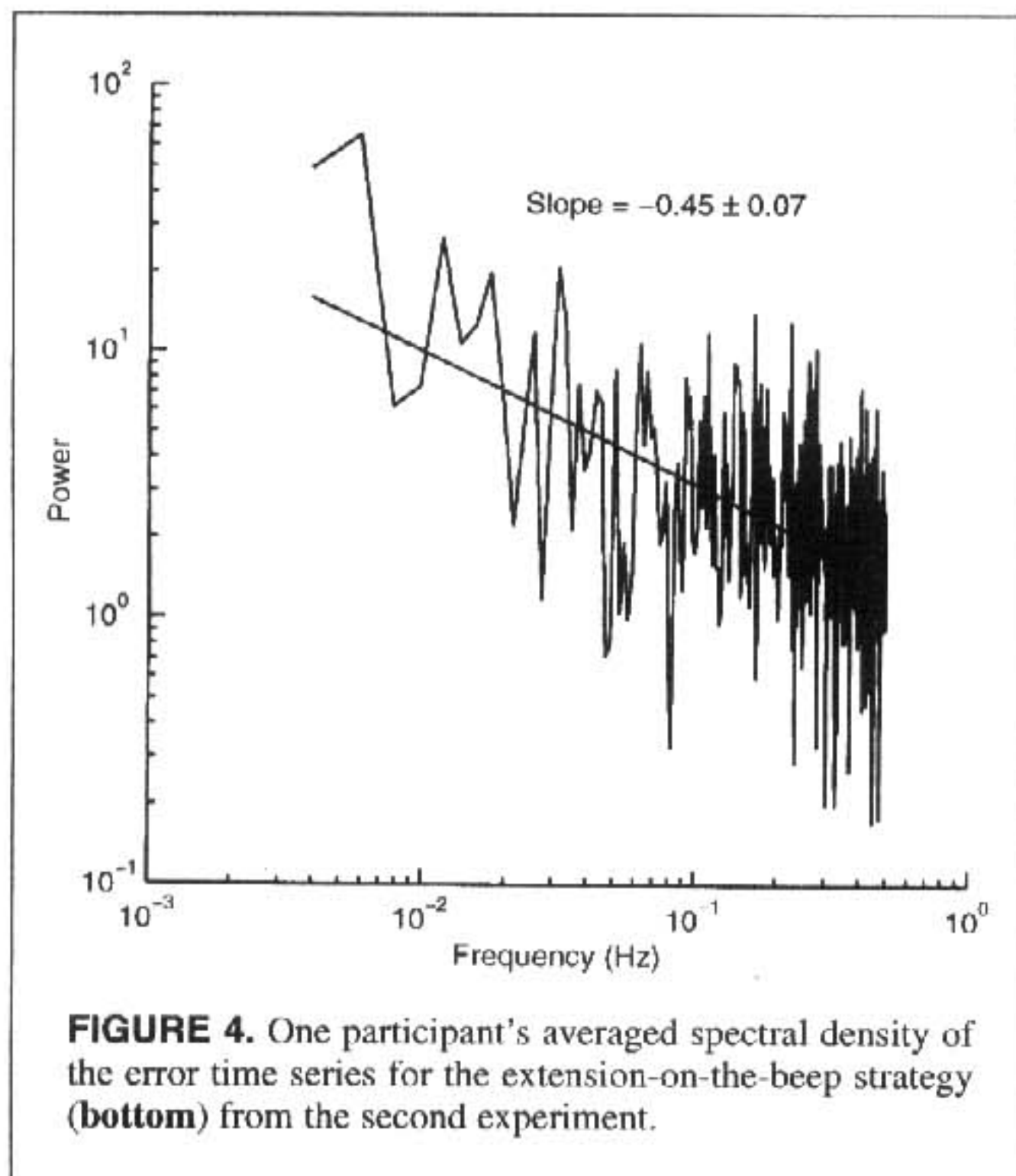
FIGURE 4. One participant's averaged spectral density of the error time series for the extension-on-the-beep strategy (**bottom**) from the second experiment.

that the scaling exponent differentiates basic modes of sensorimotor coordination and is altered by cognitive manipulations. That finding leads to one possible interpretation of $1/f^\alpha$ long memory in sensorimotor coordination. In local error-correction models, external timing information (stimulus period) is thought to be remembered and stored in the "central clock" component, but the output timing fluctuations can exhibit only short-term correlation (i.e., memory). The finding of $1/f^\alpha$ type of long memory shown in this study suggests that timing information in human sensorimotor coordination may not be stored or memorized directly in certain locations but evolves dynamically through activities at multiple time scales—a kind of dynamic memory.

In conclusion, we have established that the timing fluctuations in human sensorimotor coordination tasks are characterized by a $1/f^\alpha$ type of long memory process. The specific value of the exponent α was determined by task difficulty (synchronization or syncopation) and altered by coordination strategy. Taken together, our experiments suggest that the source of $1/f^\alpha$ fluctuations in human sensorimotor coordination lies in the multiple time scale activities of distributed neural areas in the human brain (Rao et al., 1997).

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