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Time intervals production in tapping and oscillatory motion

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Abstract

We applied spectral analysis on series of time intervals produced in a synchronization-continuation experiment. In the first condition intervals were produced by finger tapping, and in the second by an oscillatory motion of the hand. Results obtained in tapping were consistent with a discrete, event-based timing model. In the oscillatory condition, the spectra suggested a continuous, dynamic timing mechanism, based on the regulation of effector stiffness. It is concluded that the oscillatory character of movement can offer an important resource for timing control. The use of an event-based timing control such as postulated in the Wing–Kristoffersson model could be restricted to a quite limited class of rhythmic tasks, characterized by the concatenation of discrete events.

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1. Introduction

The production of rhythmical movements is a central theme of research for the psychology of motor control. Among a number of complementary lines of research,

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tapping performance has received a persistent attention over more than a century (Nicholson, 1925; Stevens, 1886; Woodrow, 1932). In tapping experiments, participants attempt to tap continuously at a specified tempo. The simplest experimental tapping design is the synchronization–continuation paradigm: in this kind of experiment, subjects have in a first phase to synchronize their taps with the periodic signals given by a metronome, then the metronome is removed and subjects try to continue to tap regularly following the prescribed tempo. The variable of interest is the series of inter-tap intervals (I) produced during the continuation phase of the experiment.

Wing and Kristofferson (1973) proposed a very simple model for accounting for I variability in synchronization–continuation experiments. This model includes two components: an internal clock, which provides a series of temporal intervals C_i, and a motor component, responsible for the execution of the tap $_i$ at the expiration of the interval C_i. This motor component does not operate instantaneously, and all taps have an assigned motor delay M_i. In terms of these two components, the observed I_i interval is written as

$$I_i = C_i + M_i - M_{i-1}. \tag{1}$$

The difference in motor delays arises from the particular boundary condition typically used in tapping experiments: The ending of the ($i-1$)st interval is also the beginning of the ith interval. In the original model, the internal clock and the motor component are regarded as independent random white noise sources. In other words, both C_i and M_i are considered as uncorrelated in time. Some experimental predictions can be derived from this model. The first one is a significant, and negative lag-one autocorrelation in I_i series. This negative dependency between successive intervals arises from the presence of equal terms of motor delay, but of opposite signs. The model suggests in contrast an extinction of autocorrelation for lags higher than one. These two predictions were successfully tested in a series of experiments (Vorberg & Wing, 1996; Wing & Kristofferson, 1973).

This model also suggests the possibility to distinguish between variance due to timekeeping process and variance in motor response delay. Conceptually, one could suppose that motor error has a constant variance, independent of the mean inter-tap interval. Conversely, the internal clock could be suspected to be Weberian: its specific variance should be linearly related to mean interval duration. The Wing–Kristofferson model allows a very simple empirical determination of the variability of each component, according to the following equations:

$$\sigma_M^2 = -\gamma_I(1), \tag{2}$$

$$\sigma_C^2 = \gamma_I(0) + 2\gamma_I(1), \tag{3}$$

where σ_M^2 and σ_C^2 represent the respective variances of M and C, and $\gamma_I(k)$ the lag-k autocovariance of I. This hypothesis of a differential effect of interval duration on clock and motor variances was demonstrated in several experiments (Vorberg & Wing, 1996; Wing & Kristofferson, 1973; Wing, 1980). Ivry and Keele (1989) showed that certain pathologies (like cerebellar lesions) affected clock, but not motor error variance, and thus provided evidence for neuroanatomical localization of the processes underlying the clock component.

The experiments testing the assumptions derived from the Wing–Kristofferson model generally used a quite short continuation phase (i.e., from 20 to 50 successive taps). Within this range, time series generally appear stationary, allowing a valid estimate of mean, standard deviation, or autocovariance. The use of a longer continuation phase (more than 1000 taps) revealed the presence of drifts in the series of intervals (Ogden & Collier, 1999): tempo tends to drift towards certain preferred frequencies, referred to as "attractor tempos". Some experiments showed that drift phenomena could also be discernible in classical short continuation phases (Collyer, Broadbent, & Church, 1992, 1994; Madison, 2001).

Drifts, nevertheless, are not only present in the very first part of the inter-tap intervals series, but seem to occur continuously, and following different and intricate time scales. In its pioneering work, Stevens (1886) observed that the variability of his series comprised both short-term fluctuations, described as a "constant zig–zag", and longer-term drifts, characterized as "larger and more primary waves". Such observations are reminiscent of 1/*f* fluctuations, a ubiquitous feature in biological systems (West & Shlesinger, 1989, 1990), and recently evidenced in a number of psychological time series (Gilden, 2001; Van Orden, Holden, & Turvey, 2003). Gilden, Thomton, and Mallon (1995) tested this hypothesis in a synchronization–continuation experiment, with initially prescribed intervals from 0.3 to 10 s. They performed spectral analyses on series of 1000 intervals, and the double-logarithmic plot of average power spectra revealed linear negative slopes (ranging from -0.94 to -1.1) in the low-frequency region, typical of 1/*f* noise. In the high-frequency region, a linear positive slope was obtained, indicative of the presence of differenced white noise in the series. Similar results were obtained in a number of experiments on continuation tapping (Chen, Repp, & Patel, 2002; Musha, Katsurai, & Teramachi, 1985; Yamada, 1996; Yamada & Yonera, 2001; Yamada, 1995).

Gilden et al. (1995) interpreted their results on the basis on the Wing–Kristofferson model, which contains a differenced white noise (see Eq. (1)). Their results suggest, nevertheless, that the internal clock should be considered as a source of 1/*f* noise, and not as a white noise process. On the basis on numerical simulations, they showed that a model adding a 1/*f* noise and a differenced white noise was able to reproduce the experimental spectra. The discovery of 1/*f* noise in psychological series was questioned by several authors (Pressing & Jolley-Rogers, 1997; Wagenmakers, Farrell, & Ratcliff, in press). Pressing and Jolley-Rogers (1997) suggested that the 1/*f* shape of the spectra could be due to the nonstationarity of the series. 1/*f* noise was discovered, nevertheless, in a number of other experiments on psychological series, suggesting the ubiquity of the phenomenon (Delignières, Fortes, & Ninot, 2004; Gilden, 1997, 2001; Van Orden et al., 2003). This result was generally interpreted as the characteristic signature of complexity in human cognition: cognitive processes are conceived as behaving as a complex dynamical system, evolving far from equilibrium at the borderline between stability and chaos (Gilden, 2001; Marks-Tarlow, 1999, 2002; Van Orden et al., 2003).

The discovery of a possible differenced white noise process, revealed by the positive slope of the log–log spectrum in the high-frequency region, is less controversial. This result comforts the Wing–Kristofferson model, and especially the idea that tapping performance is governed by an event-based timing process (Schöner, 2002): each tap is triggered by a discrete cognitive event, and then each inter-tap interval is determined by two boundary events and their associated motor delays. Gilden (1997) and Van Orden et al. (2003) did not found this characteristic shape of the spectrum at high frequencies in a serial reaction time experiments, despite a similar $1/f$ behavior in the low frequency region. One could suppose that in these cases, the motor component is expressed in a single term because the interval begins not with a key press but with the presentation of the stimulus (Gilden, 1997).

Nevertheless, the event-based model is not the only conceivable hypothesis for the timing of motor acts (Schöner, 2002). An alternative model could be to consider the effector as a self-sustained oscillator, obeying a limit cycle dynamics. Such a hypothesis was proposed by Yamada (1995) and Chen, Ding, and Kelso (1997) in tapping experiments. Kay, Saltzman, Kelso, and Schöner (1987) showed that the oscillatory behavior of human limbs could be adequately modeled by a so-called "hybrid" model obeying the following equation:

$$\ddot{x} + \alpha\dot{x} + \beta\dot{x}^3 + \gamma x^2\dot{x} + \omega^2 x = 0, \tag{4}$$

where the dot notation represents differentiation with respect to time. In this model $\alpha\dot{x}$ is a linear damping term, $\beta\dot{x}^3$ and $\gamma x^2\dot{x}$ are nonlinear dissipative terms, and $\omega^2 x$ represents linear stiffness. For $\beta, \gamma > 0$ and $\alpha < 0$, this model presents a limit cycle dynamics. For $|\alpha| \ll \omega$, the oscillation frequency of such model is determined by the stiffness coefficient ω. Within this limit cycle particular "anchoring" events (such as movement reversals) can be used to delimit time intervals. This kind of "dynamic timing model" (Schöner, 2002) represents an alternative way for conceiving the production of rhythmical activities.

The duration of the time intervals produced by this model depends on a single control parameter, the linear stiffness. One can suppose that for accounting for the inherent variability of biological systems, a Gaussian white noise should be added to the model, leading to random, uncorrelated fluctuations in the series of produced time intervals. In this case the error term affects directly the time interval, and not the successive events that delimit the interval, as in the Wing–Kristofferson model. The simplest formulation of such dynamical model should read as follow:

$$I_i = C_i + \xi_i, \tag{5}$$

where C_i represents the duration determined by Eq. (4) and ξ_i a Gaussian white noise term. As a consequence, the characteristic positive slope observed at high frequencies in the log–log plot of the power spectrum, indicative of the presence of a differenced noise in the series, should not be present when a dynamical timer produces time intervals. A flattening of the slope in the high-frequency region should reveal the presence of the single white noise term, but a positive slope is clearly unexpected.

As previously indicated, such positive slope in the high-frequency region was evidenced in a number of tapping experiments, suggesting the relevancy of the

Wing–Kristofferson model in such experimental protocols. Tapping can be considered as the concatenation of discrete motor events, and the oscillatory (continuous) models postulated by Yamada (1995) or Chen et al. (1997) appear inadequate in this particular case. Nevertheless, a number of rhythmical activities (e.g., dance, applause, locomotion) are evidently governed by limit cycle dynamics (Clark, Truly, & Phillips, 1993; Schot & Decker, 1998), and such dynamical models were successfully applied to oscillatory motions of the hands or the fingers, quite similar to those involved in tapping experiments (Haken, Kelso, & Bunz, 1985; Kay et al., 1987; Kelso, 1995).

The aim of the present experiment was then to show that the processes controlling the motor production of time intervals could depend on the nature of the required movements. We compared the spectral properties of time interval series produced by finger tapping or by an oscillatory motion of the hand. We excepted to reproduce in finger tapping the results obtained by Gilden et al. (1995), reinforcing the event-based timing model proposed by Wing and Kristofferson (1973). Assuming that the oscillatory motion of the hand is sustained by a limit cycle dynamics, we conversely expected in the second condition power spectra supporting the hypothesis of a continuous, dynamical timing control.

2. Method

2.1. Participants

Twenty participants (10 men and 10 women, mean age 28.5 ± 7.4) were involved in the experiment. All were right handed, and none of them had particular expertise or extensive practice in music. They signed an informed consent form, and were not paid for their participation.

2.2. Procedure

The participants were randomly assigned to two experimental groups. The first group performed a synchronization–continuation tapping task, with the right hand. During the first stage participants were requested to synchronize their taps with the signals emitted by a metronome following a frequency of 1.25 Hz. After 10 signals the metronome was removed, and participants tried to continue to tap regularly, following the initial tempo. The second group performed a similar synchronization–continuation task, but time intervals were produced through the oscillations of a joystick, which could only be moved in the frontal plane. The joystick was manipulated with the right hand. During the first stage participants were requested to synchronize the left reversal point of the oscillation (maximal pronation) with the signal of the metronome. After 10 signals the metronome was removed, and participants tried to continue to oscillate regularly, following the initial tempo. In the two situations, the continuation phase was pursued up to the recording of 700 successive time intervals.

2.3. Experimental device

The experiment was individually performed in a quiet room. The auditory signals were generated by a specific software installed on a PC (Amstrad CPC464). In the tapping task participants had to tap on a rectangular (2 cm × 4 cm) plate with their right index finger. A switch was set up on the back of the plate and allowed the detection of the occurrence of each tap. For the oscillatory task, we used a 15 cm wooden joystick. Participants were asked to perform regular oscillations, with amplitude of about 45° on each side of the central (vertical) position. The angular movements were recorded with a potentiometer located at the axis of the joystick. In the two experimental conditions, data were recorded via an A/D converter towards a 486 processor with a sampling frequency of 100 Hz.

2.4. Data processing

In order to avoid the initial drift that classically occurs in continuation experiments, the first 100 data points of each series were eliminated, and the subsequent 512 points were used for further analyses (Chen, Ding, & Kelso, 2001; Yamada, 1996). In order to analyze the spectral properties of the series, we applied the method proposed by Fougere (1985), and modified by Eke et al. (2000). This method used a combination of preprocessing operations: first the mean of the series was subtracted of each value, and then a parabolic window was applied: each value in the series was multiplied by the following function:

$$W(j) = 1 - \left(\frac{2j}{N+1} - 1\right)^2 \quad \text{for } j = 1, 2, \ldots, N. \tag{6}$$

This transformation induces a tapering of the series and is supposed to reduce of the leakage in the periodogram. Finally the series was linearly detrended. Eke et al. (2000) recommended to perform these preprocessing operations in this order. This method was proven to significantly improve the relevancy of slope estimates, as compared with standard periodogram method (Delignières et al., submitted for publication; Eke et al., 2000, 2002; Fougere, 1985). The Fast Fourier Transform algorithm was then applied on the obtained series, and the resulting frequency and power data were converted in $\log_{10}$ for further analyses.

The slope of the power spectrum, in log–log coordinates, was separately estimated in the low-frequency and the high-frequency regions. The frequency interval in which the inflexion of the spectra occurred was graphically estimated. This interval was then excluded from the calculations, and delimited the low-frequency and high-frequency regions. The point of inflexion was defined as the intersecting point of the regression lines of the low-and the high-frequency regions.

2.5. Simulation experiment

Finally, a simulation experiment was conducted in order to check whether it was possible to reproduce the experimental results on the basis of Eqs. (1) and (5). The details of this procedure will be described in the following part.

3. Results

The mean interval duration was 0.73 s (SD = 0.15 s) for the tapping task, and 0.76 s (SD = 0.08 s) for the oscillatory task. There was no statistical difference between these two means ($F(1, 18) = 0.311$; $p > 0.05$). Note that mean interval durations ranged from 0.43 to 0.99 s in the tapping task, and from 0.65 to 0.93 s in the oscillatory task. The mean standard deviation was statistically similar for the two tasks (0.04 s, $F(1, 18) = 0.162$; $p > 0.05$).

The averaged power spectra are displayed in Fig. 1. The visual examination of individual spectra revealed that in both conditions, the points of inflexion of all spectra roughly fell within the interval [−1.056; −0.840], corresponding in natural scale to frequencies of about 0.088 and 0.145 Hz, respectively. This interval was excluded from further analyses and was used to delimit the low- and high-frequency regions. In the low-frequency region, the mean slope was −0.95 (SD = 0.37) for the tapping task, and −1.19 (SD = 0.24) for the oscillatory task. There was no statistical difference between the two groups ($F(1, 18) = 3.41$; $p > 0.05$). The individual slopes ranged from −0.61 to −1.68 for the tapping task, and from −0.94 to −1.63 for the oscillatory task. In the high-frequency region, the mean slope was 0.30 (SD = 0.41) for the tapping task, and −0.23 (SD = 0.31) for the oscillatory task. There was a significant difference between the two groups ($F(1, 18) = 18.86$; $p < 0.05$). The individual slopes in the high-frequency region were positive in all cases for the tapping task, and negative in most cases for the oscillatory task (except for one participant who presented a positive slope of about 0.11). The averaged spectra represented in Fig. 1 can be considered as qualitatively representative of the individual spectra obtained in each condition.

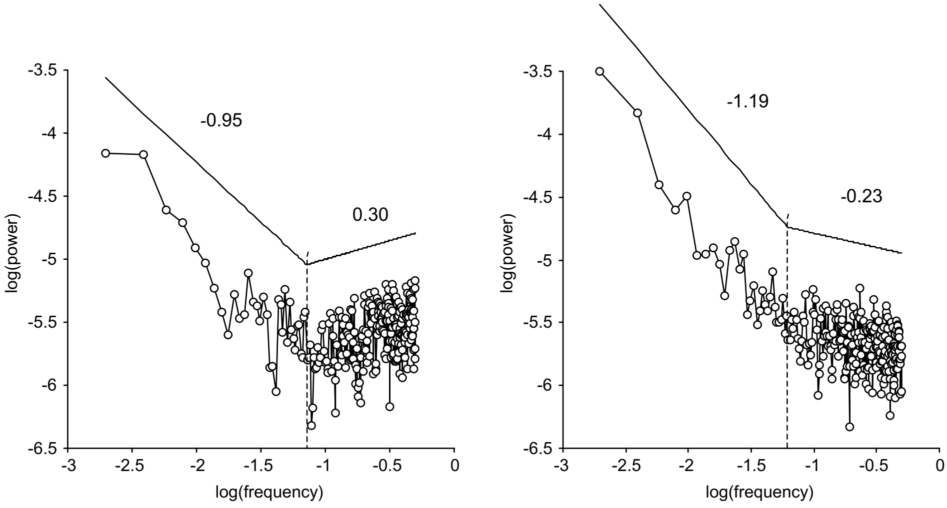

Fig. 1. Averaged power spectra (in log–log coordinates), for the tapping task (left) and the oscillatory task (right).

On the basis of the linear equations obtained for the two regions of the spectrum, we computed the coordinate of the point of inflexion. The inflexion occurred on average for a frequency of 0.072 Hz (SD = 0.043) for the tapping task, and for a frequency of 0.061 Hz (SD = 0.050) for the oscillatory task. There was no statistical difference between the two groups ($F(1, 18) = 1.25$; $p > 0.05$).

For the simulation experiment, the first requirement was to obtain fractal series, in order to simulate the C components of Eqs. (1) and (5). We used the algorithm designed by Davies and Harte (1987) (for a detailed presentation see Cannon, Percival, Caccia, Raymond, & Bassingthwaighte (1997)). This algorithm allows generating "exact" fractional Gaussian noise series of known Hurst exponent (H). The distinction between fractional Gaussian noises (fGn) and fractional Brownian motions (fBm) was introduced by Eke et al. (2000). These two families of processes possess fundamentally different properties: fBm are non-stationary with time-dependent variance, while fGn are stationary with a constant expected mean value and constant variance over time. These two processes are conceived as mathematically related: a fGn is defined as the series of successive increments in a fBm. Conversely, when a fGn is cumulatively summed, the resultant series constitutes an fBm. Each fBm is then related to a specific fGn, and both are characterized by the same H exponent, ranging from 0 to 1 in both cases. Spectral analysis can be used to classify signals as fGn or fBm (Eke et al., 2000): the characteristic slopes obtained for fGn range between +1 and -1, and the slopes for fBm series between -1 and -3. Note that $1/f$ noise constitutes the boundary between these two families, with a characteristic slope of about -1.

The first problem was to determine the fractal properties of the series to be included in the simulation. In the tapping condition, the mean slope in the low-frequency region was -0.95. Because the power in a differenced white noise series is concentrated in the high-frequency region, the addition of such a series to a fractal series is not expected to significantly affect the slope of the total power spectrum in the low-frequency region. Then the underlying fractal series could be considered as a fGn, located at the upper limit of the fGn family, close to $1/f$ noise. For fGn, the relationship between H and the slope of the power spectra is given by (Eke et al., 2000):

$$H = (1 - \text{slope})/2. \tag{7}$$

Then for the simulation of tapping data, we generated 40 fGn series of 2048 data points by setting the H exponent to 0.98. The obtained series were submitted to spectral analyses (${}^{\text{low}}\text{PSD}_{\text{we}}$ method, Eke et al., 2000), and presented a mean slope in log–log coordinates of about -0.97 (SD = 0.13).

On the contrary, the addition of white noise is known to significantly flatten the slope of the power spectrum (Cannon, Percival, Caccia, et al., 1997; Rangarajan & Ding, 2000). On the basis of previous simulation experiments on the effect of noise on fractal analyses (Delignières et al., submitted for publication), we estimated to -1.26 the mean slope to be used in the simulation, in order to roughly reproduce the observed slope of -1.19 after the addition of white noise. This slopes are typical of fBm series. For this kind of series, the relationship between H and the slope of the power spectra is given by (Eke et al., 2000):

$$H = (-1 - \text{slope})/2. \tag{8}$$

We generated 40 fGn series by setting the H exponent to 0.13, and we integrated these fGn series for obtaining the corresponding fBm series. The obtained series were checked by spectral analysis, and presented a mean slope in log–log coordinates of about -1.26 (SD = 0.14). All series were then normalized to zero mean and unit variance.

We also generated 40 white noise series, with zero mean and unit variance. Each of the 40 fGn series were then combined with a differenced white noise (Eq. (1)), and

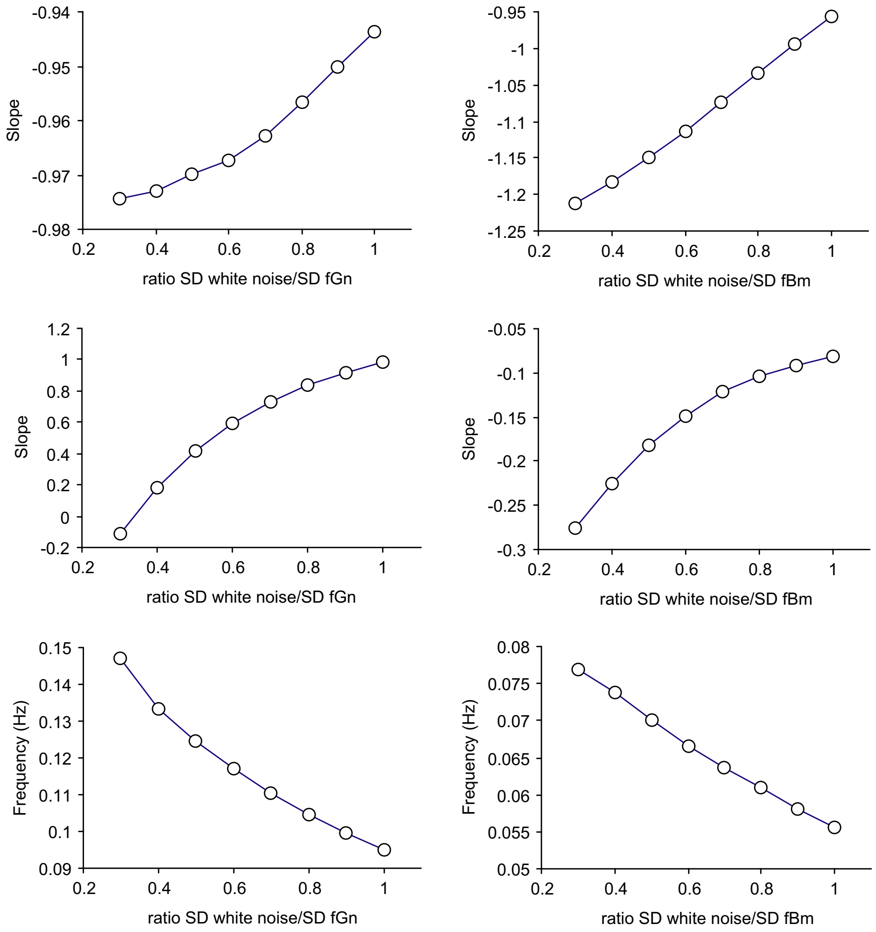

Fig. 2. Evolution of the low-frequency region slope (top), the high-frequency region slope (middle), and the frequency corresponding to the point of inflexion (bottom), against the SD ratio. The results for fGn + differenced white noise are displayed in the left column, and those for fBm + white noise series in the right column.

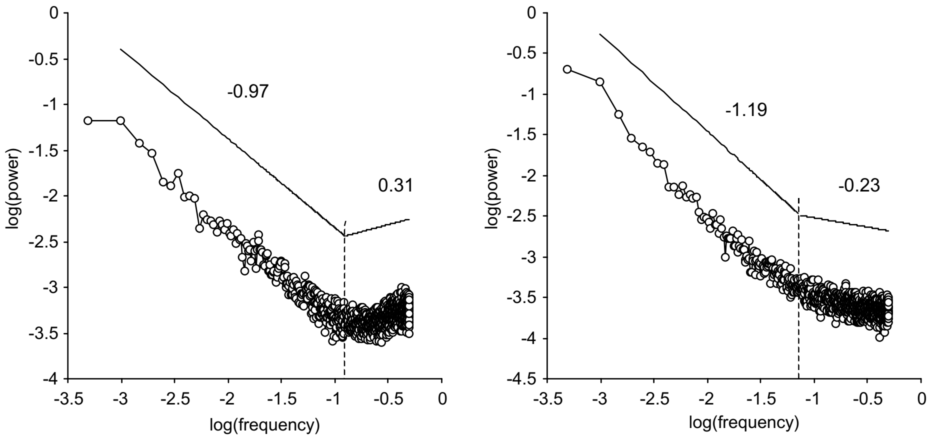

Fig. 3. Averaged power spectra (in log–log coordinates), for the fGn + differenced white noise series (left panel, SD ratio = 0.45, and for the fBm + white noise series (right panel, SD ratio = 0.39).

each of the 40 fBm series with a white noise (Eq. (5)). The ratio of the white noise standard deviation to the fGn (or fBm) standard deviation was varied for each original fGn or fBm series from 1.0 to 0.3 by steps of 0.1.

For each obtained series, we calculated the slopes of the power spectrum in the low-frequency and the high-frequency regions, and the frequency corresponding to the point of inflexion, according to the procedures previously described. The evolutions of these three variables over the range of studied SD ratios are displayed in Fig. 2. As expected, the slope of the power spectra in the high-frequency region was positive for the fGn + differenced white noise series, and negative for the fBm + white noise series. In each case the slope tended to increase with SD ratio. Finally the frequency corresponding to the point of inflexion tended to decrease as SD ratio increased. Considering the slope in the high frequency region as the main feature of our experimental average spectra, we estimated the SD ratio required for producing the empirical slopes. This ratio was about 0.45 for the fGn + differenced white noise series, and 0.39 for the fBm + white noise series. The average power spectra obtained with these two SD ratio values are displayed in Fig. 3. Under these parameter settings, the slopes in the high-frequency region were adequately simulated (fGn + differenced white noise: 0.31 vs 0.30; fBm + white noise: −0.23 vs −0.23), as well as the slopes in the low-frequency region (fGn + differenced white noise: −0.97 vs −0.95; fBm + white noise: −1.19 vs −1.19). The frequency of inflexion was correctly reproduced fBm + white noise series (0.074 Hz vs 0.072 Hz), but appeared at a quite higher frequency for the fGn + differenced white noise series (0.124 vs 0.061 Hz).

4. Discussion

The results obtained for the tapping task were consistent with those previously reported in the literature. The slope of the average power spectra in the low-frequency region was close to -1, and confirmed the hypothesis of Gilden et al. (1995) concerning the presence of $1/f$ noise in the series of intervals produced by the internal clock. Pressing and Jolley-Rogers (1997) suggested that this result could be simply due to the nonstationarity of the series (related to the drift phenomenon), and that this $1/f$-like behavior should disappear after a detrending of the series. The present result was obtained despite the discarding of the first part of the series (which was supposed to contain the drift, see Chen et al., 2001, or Ogden & Collier, 1999), and a linear detrending of the remaining points. We also obtained positive slopes in the high-frequency region, a result previously described by Chen et al. (2002), Yamada (1995), Yamada (1996) and Yamada and Yonera (2001). These positive slopes confirmed the presence of a differenced noise in the series, as postulated by the Wing–Kristofferson model.

The use of spectral analysis with such short series could be questioned. We are aware to be, with only 512 data points, at the lower limit of the acceptable lengths for a valid application of these analyses (Eke et al., 2000). With spectral analysis and other fractal analysis methods (such as *detrended fluctuation analysis*, *rescaled range analysis*, etc.), the length of the series determines directly the accuracy of the results (Caccia, Percival, Cannon, Raymond, & Bassingthwaigthe, 1997; Cannon, Percival, Caccia, et al., 1997; Eke et al., 2000; Eke, Hermann, Kocsis, & Kozak, 2002). As such, the values of the individual slopes should be considered with caution, only as rough estimates of the true underlying processes. The application of time series analyses, nevertheless, supposes that the system under study remains unchanged during the whole window of observation. In psychological experiments, the lengthening of the task raises evident problems of fatigue or lack of concentration (Madison, 2001). The use of series of 2^9 or 2^{10} data points appears as an acceptable compromise between the requirements of time series analyses and the limitations of psychological experiments.

The most important, in our results, is the inter-individual consistency of the global shape of the power spectra, with a linear negative slope in the low-frequency region, and a positive slope in the high-frequency region. Several interpretations have been proposed for explaining the presence of an inflexion point in the power spectra of tapping series. Musha et al. (1985) located this critical point at a frequency of about 0.1 Hz, and concluded that errors in tapping were undetectable or corrigible within 10 s. Using various initial tempos in a synchronization–continuation experiment, Yamada (1996) showed that the critical point appeared at different frequencies for different tempos, but occurred consistently at about 10 cycles for 200 taps. The author concluded that the capacity of memory that governs tapping should be expressed in number of events (20 taps), but not in terms of time. In support of this claim, he showed that an autoregressive model including about 20 terms gave a good account for the observed fluctuations in tapping series (see also Yamada & Yonera, 2001). Gilden et al. (1995) proposed a simpler explanation, on the basis of the Wing–Kristofferson model, considering the internal clock as a source of $1/f$ noise. They showed, on the basis of numerical simulations, that the aggregation of a $1/f$ noise and a differenced white noise reproduced the experimental data set, and that the appearance of the positive slope at high frequencies was determined by the ratio between the respective variabilities of the internal clock and the motor component. More specifically, their simulations reproduced the experimental localization of the point of inflexion of the spectrum. Note that we failed, in the present simulation, to exactly reproduce this localization: the point of inflexion occurred at a higher frequency with simulated data than with our experimental series. This discrepancy is difficult to explain and remains an open question for future research. Our simulations, nevertheless, reinforce the idea that the localization of the inflexion is determined by the ratio of the variances of the two added processes (see Fig. 2).

Our main hypothesis was supported by the negative slopes obtained for the high-frequency region in the oscillatory task, suggesting the presence of a single white noise error term in the series. This result clearly invalidates the Wing–Kristofferson model in this kind of task. Time intervals are not controlled, as in tapping experiments, by the periodic occurrence of discrete events, but by the setting of a parameter that directly determines interval duration. In this perspective, the limit cycle model, allowing the control of the period of oscillation by the setting of linear stiffness, constitutes a good candidate. Such dynamical model presents a number of advantages, and particularly an inherent property of stability: Whenever an oscillator cycle is lengthened or shortened by some perturbation, the oscillator returns to the stable limit cycle time over the next (or the next few) cycle.

As pointed out by Schöner (2002), there is a strong theoretical opposition between event-based descriptions of rhythms or temporal order, and continuous, trajectory-based descriptions. Event-based timers are conceived as central, and rather abstract entities, exclusively devoted to the generation of temporal order. On the opposite, dynamic timers represent "an integrated description of movement generation, so that the state of the dynamic timer corresponds directly to the state of the effector" (Schöner, 2002, p. 45). Dynamic timers appear effector-specific, and essentially peripheral.

The discovery of $1/f$ noise in the low-frequency region for the oscillatory task was not really expected. The behavior of oscillating limbs is generally modelled through limit cycle dynamics, which *per se* produces a pure periodic behavior. Obviously, actual rhythmic movements do not converge on a single trajectory in the phase plane, but produce a band of intersecting curves. This variability was generally interpreted as the simple addition of stochastic, uncorrelated noise, to limit cycle dynamics (see, for example, Kelso, 1995). Daffertshofer (1998) investigated the conditions under which a limit cycle oscillator subjected to noise could produce serial correlation between successive movement periods, and showed that such behaviors were obtained only with some very atypical and unrealistic parameter settings (e.g. extremely large stiffness coefficients). Clearly, the presence of (long-term) dependence in our series cannot be explained by an underlying limit cycle dynamics.

Chen et al. (1997) proposed a possible solution by showing that an enriched version of the limit cycle model could give raise to a $1/f$-like behavior. This modified model included a Gaussian white noise term, and a process of delayed feedback. However, the authors aimed at modelling, in this experiment, the error time series in a synchronization experiment. In this particular situation, the inclusion of a (delayed) feedback process seemed relevant, because the metronome gave a continuous reference for correctness. This was not the case in the present continuation paradigm, and the relevancy of such stochastic delay differential equation seems more difficult to support.

Another possible explanation can be found in a paper by Mitra, Riley, and Turvey (1997), who evidenced the chaotic nature of the oscillatory motion of the hand. This result suggests that limit cycle dynamics could not be sufficiently general for modeling limb movement dynamics. An advantage of chaotic motion over noisy limit cycle is the special blend of stability (trajectories are bounded) and variability (trajectories do not repeat) that is characteristic of dynamics on strange attractors.

It is important to point out that there is no direct relation between fractals and chaos. Fractals and deterministic chaos are mathematical tools, which are used to model different kinds of phenomena. Fractals are mainly defined by the property of self-similarity, and chaos by the sensitivity to initial conditions. Many fractals are in no way chaotic (e.g., the Koch snowflake curve), and conversely fractal structures can arise in nonchaotic dynamics (Grebogi, Ott, Pelikan, & Yorke, 1984). However often chaotic phenomena exhibit fractal properties, and Koleva and Covachev (2001) recently showed that chaotic dynamical systems and $1/f$ noise share a number of common features, and especially the $1/f$-like shape of the power spectrum at low frequencies. As such, the chaotic behavior of the oscillatory motion of the limb evidenced by Mitra et al. (1997) could be at the origin of the $1/f$ shape observed in our experimental spectra.

The fact that we used fGn series to simulate the tapping spectra and fBm series for the oscillation spectra cannot really be considered, in our opinion, as an argument in favor of a formal distinction between the mathematical properties of the underlying processes. As could be seen, there was no statistical difference between the low-frequency slopes observed in the two conditions, and the simulated fGn and fBm series were rather close one to the other, on both sides of the $1/f$ boundary. The only conclusion that can be drawn from our results is that both event-based and dynamic timers seem to exhibit similar fractal properties, suggesting their inherent complexity.

$1/f$ fluctuations appear to be a rather ubiquitous phenomenon in most natural and biological systems, and were evidenced, for example, in heart rate variability (Peng et al., 1993), in the duration of successive steps in locomotion (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995), in the trajectory of the center of pressure during upright stance (Collins & De Luca, 1993; Delignières, Deschamps, Legros, & Caillou, 2003), in series of relative phases during a cyclical bimanual coordination task (Schmidt, Beek, Treffner, & Turvey, 1991), or in the evolution in time of self-esteem (Delignières et al., 2004). $1/f$ behavior is conceived as the best compromise between order (predictability) and chaos (unpredictability), and systems exhibiting such fluctuations are thought to possess inherent properties of stability, allowing simultaneously self-maintenance, but also creativity and adaptability (West & Shlesinger, 1990). Peng et al. (1993) showed that $1/f$ fluctuations represent the typical signature of heart rate variability in young and healthy adults, and that aging or heart disease leads to specific alterations in heart beat fractality.

The emergence of such long-term correlation remains, however, an intriguing and unexplained phenomenon. One of the most appealing hypotheses conceives $1/f$ fluctuations as the typical signature of self-organized critical states in complex systems

(Bak & Chen, 1991; Davidsen & Schuster, 2000; De Los Rios & Zhang, 1999). This hypothesis is in line with the contemporary approaches in the domains of motor control, cognition sciences, or psychology, which are widely influenced by the theoretical background of nonlinear dynamical systems (Kelso, 1995; Van Gelder, 1998).

Several alternative hypotheses have been proposed, and in fact, a number of different mechanisms appear capable to generate 1/*f*-like behavior (Wagenmakers et al., in press). Granger (1980) showed that the aggregation of short-range processes (such as autoregressive processes) led to the emergence of such long-term structured variability (see also Chong & Wong, 2001; Wagenmakers et al., in press). Pressing (1999) suggested that a similar aggregation of moving-average short-term processes could lead to similar results. Hausdorf and Peng (1996) showed that multi-scaled randomness would give rise to such behavior under some conditions. Recently, Kaulakys developed a very simple analytically solvable model exhibiting 1/*f* spectrum over a wide range of frequency (Kaulakys, 1999, 2000; Kaulakys & Meškauskas, 1998, 2000). This model suggest that the appearance of 1/*f* noise in a series of pulses could be due to the fact that the successive recurrence times obey an autoregressive process with very small damping. However, this model presents a quite limited interest in the present study, since we precisely found 1/*f* properties in series of recurrence times.

As can be seen, the origin of 1/*f* fluctuations remains an open question. A number of simple formal models seem able to mimic their spectral properties, but one can doubt that a single model could take into account the diversity of systems that exhibits such fluctuations. Further research are necessary to improve the estimation methods and to elaborate psychologically interpretable models (Wagenmakers et al., in press).

5. Conclusion

On the basis of an analysis of power spectra, we showed in the present experiment that the production of time intervals in two synchronization–continuation tasks, performed either in a tapping mode or in an oscillation mode, was underlain by two different kinds of timing control. In the first case the timer delivers a series of events that delimitate the intervals, and in the second case the timer directly determines the duration of each interval. These properties are consistent with the distinction proposed by Schöner (2002) between event-based, discrete timers, and dynamic, continuous timers. Moreover, we showed that these two timers produce time intervals series that possess 1/*f* properties, suggesting that both are complex systems, composed of multiple interconnected elements.

The event-based Wing–Kristofferson model was for a long-time considered as a generic process, involved in the control of all kinds of rhythmic activities. Our present results suggest that the nature of the requested activity (and especially its oscillatory character) could induce another mode of timing control. In the tapping task, all participants produced interval series supporting the hypothesis of an event-based timing control. On the opposite, in the oscillatory task all participants but one appeared using a dynamic timer. The oscillatory character of the movement seemed to offer an alternative resource for timing control, spontaneously used by most participants. Considering the ubiquity of oscillatory motion in most human activities, such as dance, locomotion, sport, etc., one could suppose that such dynamic timers should represent the most common mode of timing control. The relevancy of event-based timing models could then be limited to a set of discrete/repetitive tasks, such as tapping.

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