Physica A 387 (2008) 5271–5278

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Strong anticipation: Sensitivity to long-range correlations in synchronization behavior

Damian G. Stephen [a,b,*], Nigel Stepp [a,b,c], James A. Dixon [a,b,c], M.T. Turvey [a,b,c]

[a] *Center for the Ecological Study of Perception and Action, University of Connecticut, United States*

[b] *Department of Psychology, University of Connecticut, United States*

[c] *Haskins Laboratories, United States*

ARTICLE INFO

Article history:
Received 12 November 2007
Received in revised form 30 April 2008
Available online 17 May 2008

Keywords:
Strong anticipation
Synchronization
Tapping
Detrended fluctuation analysis

ABSTRACT

Strong anticipation has emerged as a new framework for studying prospective control. According to earlier theories of prediction, anticipatory behavior rests on temporally local predictions from internal models. Strong anticipation eschews internal models and draws on the embedding of an organism in its environment. In this formulation, behavior is sensitive to the non-local temporal structure of the environment. We present initial evidence for strong anticipation in a synchronization task with tapping as the behavior. Participants were instructed to synchronize, to the best of their abilities, with a (unpredictable) chaotic signal. Our data suggest a close relationship between the long-range correlations of the chaotic signal and the long-range correlations of the synchronization behavior.

Published by Elsevier B.V.

1. Introduction

Explanations of anticipation in cognitive science and neuroscience typically attribute internal predictive models to organisms. Dubois [1] labels anticipation of a model-dependent kind as *weak* and contrasts it with *strong* anticipation that arises from lawful regularities embedded in the ordinary mode of functioning of a system and its environment. A prominent example of model-independent strong anticipation is *anticipating synchronization* [2,3], a temporal relation that emerges from time delays in appropriately coupled "master" and "slave" dynamical systems. The slave system anticipates the master system by synchronizing with a state that lies in the future of the master system. Anticipating synchronization may be very general. It can be demonstrated empirically in both physical, e.g., Ref. [4], and biological, e.g., Ref. [5], systems and has been shown through modeling to accommodate defining characteristics of proactive regulation in physiological and neural systems [6,7]. Importantly, the *fact* of anticipating synchronization renders the notion of strong anticipation as neither impossible nor mysterious.

Most broadly construed, strong anticipation is an assertion of non-local dependence of an organism's current behavior on the global temporal structure within its environment. An organism and its environment together make up a single system with temporal structure that extends far beyond the short range. On the one hand, current states of the organism-environment system depend on initial conditions. On the other hand, they depend on the possibilities for future events. In anticipation, the organism acts at once on its past history and on the potential outcomes afforded by its fit with the environment. (For a discussion of perceiving possibilities for action, and ontological hypotheses for prospective control of behavior, see Ref. [8].) The broad construal of strong anticipation is elaborated in Section 3. It is prefaced by a synopsis of an

* Corresponding address: Department of Psychology, University of Connecticut, 406 Babbidge Road, Unit 1020, Storrs, CT 06269-1020, United States. Tel.: +1 860 486 6880.
E-mail address: damian.stephen@uconn.edu (D.G. Stephen).

0378-4371/$ – see front matter Published by Elsevier B.V.
doi:10.1016/j.physa.2008.05.015

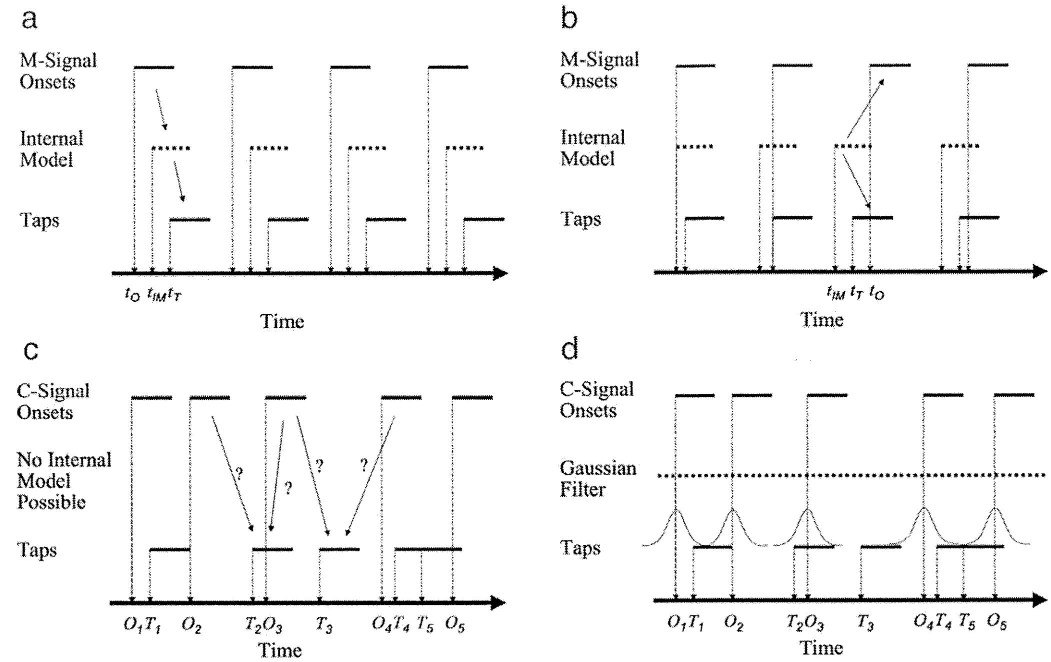

Fig. 1. (a) During an initial learning phase, each onset of a metronome signal ("M-Signal") occurs first (the solid lines at the top) and later produces a sensory trace that contributes to the internal model (the dashed lines in the middle). The sensory traces signal the participant to tap (the solid lines on the third row). In this learning phase, the onset will precede the sensory trace in the internal model (i.e., $t_{IM} > t_O$), and the sensory trace precedes the tap (i.e., $t_T > t_{IM}$). Thus, the onset precedes the tap (i.e., $t_T > t_O$). (b) As sensory traces accumulate in the internal model, anticipation of the metronome signal becomes possible. Using the internal model, the participant is able to predict each next onset and then to produce the tap so that the tap actually precedes its corresponding onset (i.e., $t_O > t_T > t_{IM}$). (c) Because the chaotic signal ("C-Signal") is unpredictable, some taps are early (T_5 early for O_5), some are late (T_1 late for O_1 and T_4 late for O_4), and other taps could be very difficult to match to onsets (T_2 and T_3). (d) In the "Gaussian tap" hypothesis, the taps are normally distributed around the onsets of the chaotic signal.

anticipatory phenomenon in a widely used and simple experimental procedure. The phenomenon and procedure are points of departure for the experiment reported in the present article.

2. Negative mean asynchrony

The notion of anticipation is prominent in studies of person-to-metronome synchronization. Radil, Mates, Ilmberger, and Pöppel [9], for example, reported a mean asynchrony, an "anticipation tendency" [10, p. 973], of −30 ms between taps and onsets of metronome beats. However, there are questions about the usefulness of negative mean asynchrony (NMA) as a marker of anticipation in general [10]. Participants in synchronization experiments exhibit strong individual differences in NMA [11,12]. Musicians exhibit smaller NMA (i.e., they tap closer to synchrony) than non-musicians [13]. NMA is also context dependent. NMA is diminished either when taps are accompanied with auditory feedback [11,14] or when the inter-onset interval is reduced [15–17]. NMA increases when the tapping finger is anesthetized [18]. NMA is a complex phenomenon that has justifiably motivated a wealth of research, but it may not be sufficiently general to account for the prospective control underlying adaptive function.

NMA is typically treated as a weak form of anticipation. In the initial stages of synchronizing tapping to a metronome, the synchronization is marked by a period of positive asynchronies as the internal model is formed (see Fig. 1(a)). Once formed, the internal model permits predictions of individual onsets and, thus, negative asynchronies (see Fig. 1(b)). Each negative asynchrony reflects anticipation on a very local time scale—that is, anticipation for a single event. A tap is either "early" or "late" for synchronization with an onset, and following each tap, the participant begins anew with prediction of the next onset. Certainly, the regular metronome signal lends itself to prediction. If every inter-onset interval is equal, an internal model should have no difficulty predicting on the local time scale. The present study substitutes unpredictable chaotic signals for predictable metronomic signals. Under this substitution an internal model of the kind depicted in Fig. 1, and perhaps more generally, is no longer viable.

3. A role for long-range correlations in strong anticipation

The case of synchrony with a chaotic signal brings synchronization research beyond its familiar frontiers. It is a research problem not unlike beat perception in music psychology [19]. Music is not limited to metronomic regularity. The baseline for simplicity would be a single tone repeated at regular intervals. Music can vary both in ordinal complexity and temporal complexity [20]. Ordinal complexity involves a variety of notes along the octave. Temporal complexity involves an irregularity of inter-tone intervals. A temporally complex musical score will have no local cues for beat, and yet people are able to perceive a beat on the non-local scale. Dancing to temporally complex music involves coordination with the global temporal structure of the score [19]. Synchronization with a chaotic signal cannot rely on local cues for prediction; it may rely instead on coordination with global temporal structure. We seek to integrate strong anticipation with this notion of global coordination.

There is an incompatibility between Dubois's [1] notion of strong anticipation and the conventional asynchrony analysis of synchronization research. The analysis of asynchronies treats anticipation as being local to each signal's onset (Fig. 1(b)). However, strong anticipation, the kind hypothesized for chaotic signals, is not restricted to local discrepancies of this sort.

To define a formalism for the description of anticipatory systems, Dubois extends the notion of recursion. Where the typical recursive equation defines a function $x(n)$as minimally $x(n) = f(x(n-1))$,[1] incursive and hyperincursive equations include dependence on states $x(n+i)$, $i \geq 0$. That is to say they may be dependent on both past *and* future states. Hyperincursion, specifically, is a generalization of incursion wherein a decision function chooses between multiple possible future states [21]. Given the myriad ways to define the function f, an anticipatory system need never be explicitly "early" or "late" for an individual event in its environment. The system is anticipatory because of its dependence on future states, not because of its particular state at any particular instant.

Hyperincursion brings another definition of anticipation. Instead of prediction on a local time scale, there is global coordination on a non-local time scale. Long-range correlations as observed in fractality may be relevant to such global coordination. Indeed, Dubois [22–24] has drawn a parallel between hyperincursion and fractality. Ideally, the long-range correlations in the behavior of an organism should match the long-range correlations in its environment [25,26].

Because of its role in assessing long-range correlations, detrended fluctuation analysis (DFA) [27–29] may be a helpful tool for investigating strong anticipation. DFA computes the root mean squared (RMS) error of linear fits over progressively larger bins of the integrated time series. The relationship between RMS error and bin size is called the fluctuation function. When the fluctuation function follows a linear trend in double-log plots, the slope of this linear trend is a scaling parameter α that provides a measure of the long-range correlation. We expect that strong anticipation would be the dependence of an organism's long-range correlations on its environment's long-range correlations. So, a relationship between the scaling parameter α of the organism's behavior and the scaling parameter α of the environment might serve as preliminary evidence of strong anticipation.

4. Chaos and anticipation

There is an extensive literature in cognitive science on the human ability to anticipate chaotic signals. In a vigilance task [30], a target moved along a horizontal line in a trajectory defined by the chaotic regime of the logistic map. Participants were instructed, at each time point, to anticipate the next location of a target on the screen. Error decreased as participants continued, and their responses converged on a parabolic lag 1 autocorrelation, characteristic of the logistic map. Later studies tested the ability to make short-term forecasts of trajectories from the Hénon [31] attractor. The latter ability showed significant improvement above and beyond forecasts of random and surrogate series [32,33]. These investigations of anticipating chaotic signals have tended toward weak explanation [34].

The non-linear determinism of chaos may provide a rich foundation for sensitivity to temporal structure independent of cognitive internal models [35]. In the case of unidirectional coupling of two Ikeda [36,37] map oscillators, anticipatory synchronization in the slave oscillator has been shown to be equal to the lag in the master oscillator. The Ikeda equations used were as follows:

$$\dot{x} = -\alpha x - \beta \sin x_\tau \tag{1}$$

$$\dot{y} = -\alpha y - \beta \sin x \tag{2}$$

with $\alpha = 1$ and $\beta = 20$. This lag, represented by the parameter τ defines the delay of the chaotic map. τ defines the depth of temporal structure in a chaotic map or, alternatively, the memory of the chaotic map for its previous values.

We employed Eq. (1) to build chaotic signals and asked participants to synchronize with the signals to the best of their abilities. Eq. (1) defined a master oscillator with a lag. Whereas Voss [35] treated Eq. (2) as a slave oscillator with no lag, our study placed the participant in the position of a slave oscillator with a lag we did not manipulate. The primary hypothesis was that tapping behavior would reflect anticipation proportional to the parameter τ of each chaotic signal. In Voss's examples, anticipation is equivalent to NMA but, as previewed above, the intent here is to interpret anticipation in the "strong" sense of Dubois [1]. Accordingly, analysis was directed at long-range correlations in the tapping behavior as quantified by DFA.[2]

[1] More generally, $x(n) = f(\{x(n-i) | i \in P\})$.

[2] Previous research has examined long-range correlations to evaluate the fractal nature of tapping behavior. A participant tapping in the absence of a metronome will produce an inter-tap interval time series with fractal scaling, $\alpha = 1$ [38,39]. However, when instructed to synchronize with a regular metronome, participants produce inter-tap interval time series with $\alpha = 0.5$ [40–42]. To our knowledge, the current study is the first study examining fractal properties of synchronization with a chaotic signal.

Specifically, we predicted that, in each case of synchronization to a chaotic signal, the long-range correlation (i.e., the scaling parameter α) of tapping behavior would be directly related to the parameter τ used to construct the signal.

We also expected a relationship between the long-range correlation of the inter-tap interval time series and the long-range correlation of the corresponding chaotic signals. Interestingly, in the vein of forecasting research described above, Smithson [43] tested forecasting of persistent, anti-persistent, and random time series. In each persistence condition, the average Hurst exponent of the participants' forecast time series appeared similar to the average Hurst exponent of the corresponding chaotic time series. Specifically, Smithson reported an ANOVA indicating (1) that the average Hurst exponent of participants' forecast time series was significantly higher for persistent time series than for random time series, and (2) that the average Hurst exponent of participants' forecast time series was significantly higher for random time series than for anti-persistent time series. That is, the average Hurst exponents of forecast time series for anti-persistent, random, and persistent time series ordered similarly to the average Hurst exponents of the anti-persistent, random, and persistent time series themselves.

Whereas Smithson [43] reported a broad relationship of averages across three persistence conditions, we sought a more fine-grained, continuous relationship between long-range correlations in the chaotic signals and participants' response time series. We hypothesized that the signal-forecast similarity found in Smithson's data would emerge in our synchronization data as a correlation between the scaling parameter α of inter-tap interval time series and the scaling parameter α of the corresponding chaotic signals.

5. Method

The chaotic signals were produced by a C program using Eq. (1) and parameters $\alpha = 1$ and $\beta = 20$ [44]. For each Ikeda [36,37] metronome signal, the map began at randomly selected initial conditions and continued with one of three settings of delay: $\tau = 2, 5$, or 10. The values of the resulting Ikeda map were normalized to range from 1 to 1.5, and these values became the inter-onset intervals (in seconds) of the chaotic signal. Each chaotic signal consisted of 1000 onsets. With each new onset, the program made a visual presentation on the computer screen. Each participant was instructed to tap any key on the keyboard in synchrony with each new onset, to the best of his or her ability. This program also recorded the inter-tap intervals. Each of six participants (25–65 years of age) completed 1–2 trials (1000 onsets per trial) for each of the three values of τ. In total, 21 trials (6 for $\tau = 2$, 6 for $\tau = 5$, and 9 for $\tau = 10$) were completed. All gave their consent in accordance with the University of Connecticut's internal review board's regulations for studies with human participants. None were compensated for their participation.

6. Results

A key premise of this experiment is that the chaotic signal presented to participants is unpredictable by linear standards. The linear redundancy of the Ikeda signals may be used to evaluate the signals' linear predictability. Linear redundancy is an information-theoretic statistic indexing the linear dependence across time, varying inversely with entropy [45–48]. For any observable $y(t)$, the linear redundancy is computed over a set of n lagged copies $y(t+i)$, $i = 1, \dots n$. Over n time steps, linear redundancy is equal to:

$$L(y(t); \dots; y(t+n)) = \frac{1}{2}\sum_{i=1}^{n}\log(c_{ii}) - \frac{1}{2}\sum_{i=1}^{n}\log(\sigma_i), \tag{3}$$

where c_{ii} are the diagonal elements and σ_i are the eigenvalues of the $n \times n$ covariance matrix.

We compared the linear redundancy of five signals from each τ condition to the linear redundancy of a sine wave with comparable amplitude. Over the first 200 time steps, there was a significant difference among integrals of linear redundancy for the four kinds of signal, $F(3, 12) = 15.98$, $p < .001$. The integral of linear redundancy for the Ikeda signals at $\tau = 2$ ($M = 2.24$, $SE = 0.07$), at $\tau = 5$ ($M = 2.22$, $SE = 0.23$), and at $\tau = 10$ ($M = 3.33$, $SE = 0.35$) is significantly less than the integral of linear redundancy for the sine wave (86.18). In other words, the Ikeda signals exhibit extremely minimal predictability.

Participants attempted to tap in time with chaotic signals that were separated by an interval (1.0–1.5 s) in excess of the typical simple reaction time (see Fig. 2). Given these conditions, three simple scenarios can be imagined: (1) pure reaction, in which each tap follows each signal onset by some average reaction latency, (2) pure proaction, in which each tap precedes each signal onset by some average proaction latency, and (3) pure synchrony, in which each tap coincides with each signal onset. For each scenario, equivalent α values would characterize the chaotic and tapping time series. The tapping signals of the participants resembled none of these scenarios. The behavioral inconsistency meant that taps were hard to match to signal onsets and that the mean (M) number of taps, 1010.60, with a standard error (SE) of 5.72, did not match the number (1000) of onsets in the signal (one-tailed $t(19) = 1.86$, $p < .05$). A necessary condition for any of the three scenarios listed above is that the number of taps matches the number of onsets exactly. That number of the taps significantly exceeded the number of onsets indicates that participants' behavior could not have been purely reactive, purely proactive or purely synchronous. Instead, they exhibited a mix of reaction, proaction, and synchrony as schematized in Fig. 1(c).

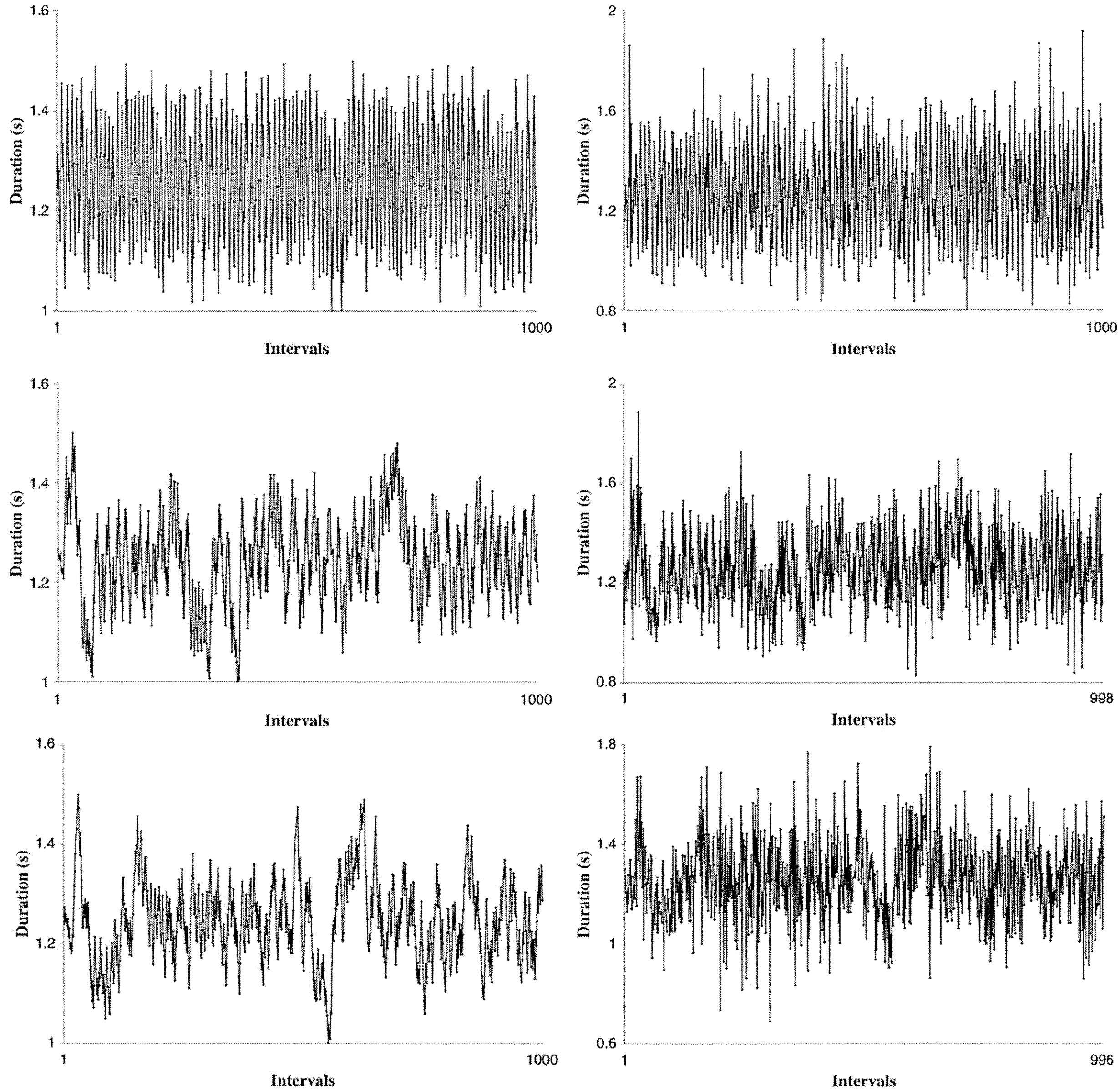

Fig. 2. Examples of the inter-onset and inter-tap interval time series. The left panels show the time series for the chaotic signal; the right panels show the time series for a participant's responses. The top, middle, and bottom rows depict examples from conditions $\tau = 2, 5$, and 10, respectively.

Like Smithson [43], we wished to compare long-range correlations of anticipatory behavior with long-range correlations of chaotic signals. DFA was performed on all of the inter-onset and inter-tap interval time series. The fitting region used was from 7 inter-tap or inter-onset intervals to 250 inter-tap or inter-onset intervals (see Fig. 3). Analysis of variance revealed a significant main effect for the parameter τ on α, $F(2, 18) = 10.75, p < .001$ (see Fig. 4). α was greatest for $\tau = 10$ ($M = 0.77, SE = 0.03$), less for $\tau = 5$ ($M = .65, SE = .04$), and least for $\tau = 2$ ($M = 0.33, SE = 0.04$). DFA was similarly performed on all of the inter-onset intervals of the chaotic time series. The scaling parameter α of the chaotic inter-onset intervals strongly predicted the scaling parameter α of the inter-tap intervals, $r(19) = 0.96, p < .0001$ (see Fig. 5).[3]

[3] We chose the maximum bin size $n_{\max}$, using the convention, $n_{\max} = N/4$, where N is the length of the time series [49]. However, we also conducted the analyses using a more conservative fitting region, with $n_{\max} = N/10$, as recommended in Ref. [50]. The scaling parameters of the chaotic signals and of the tapping signals resulting from this more conservative fitting region were very similar to those obtained using the more conventional fitting region, correlating at $r(19) = .95, p < .0001$ for chaotic signals and at $r(19) = .94, p < .0001$ for tapping signals. Furthermore, using the more conservative fitting region did not change the correlation between scaling parameters of chaotic signals and of matching tapping signals, $r(19) = .96, p < .0001$. The analyses reported in the text are based on the conventional fitting region, $n_{\max} = N/4$.

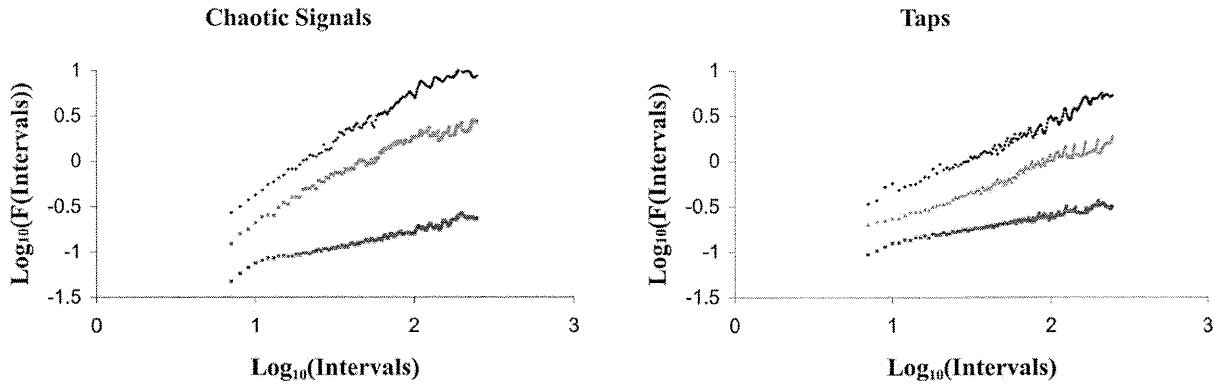

Fig. 3. Fluctuation functions for chaotic signals and for participants' responses plotted on double-log axes. The curves have been shifted by a constant factor for the sake of clarity. The left panel shows fluctuation functions for chaotic signals; the right panel shows fluctuation functions for participants' responses. In both panels, the top, middle, and bottom fluctuation functions show data from conditions $\tau = 10, 5$, and 2, respectively. In the left panel, slopes (in the same order) are 0.96, 0.71, and 0.40. In the right panel, slopes (in the same order) are 0.81, 0.61, and 0.31.

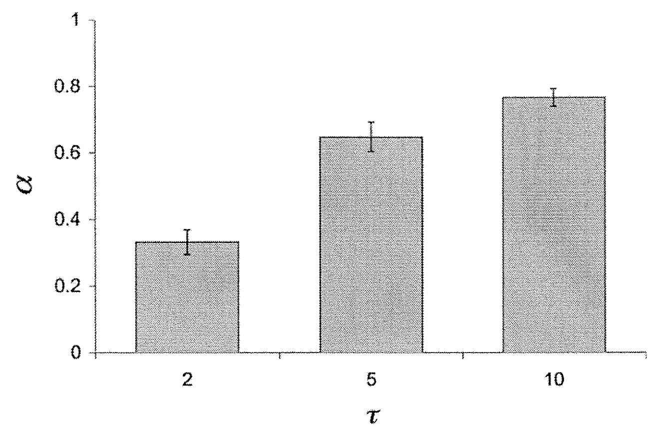

Fig. 4. DFA slope α of participants' responses in each τ condition.

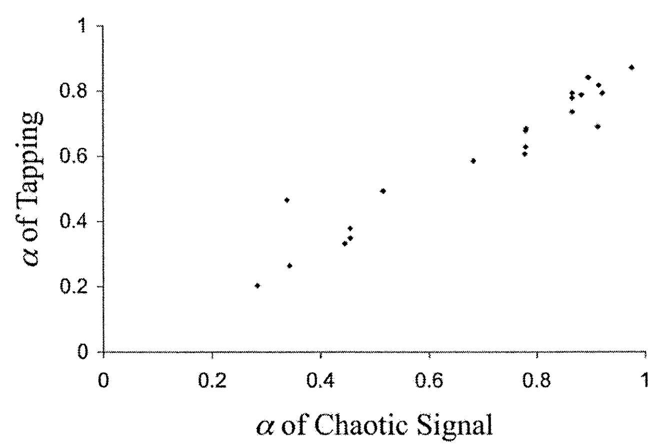

Fig. 5. DFA slope α for each inter-tap interval series plotted against DFA slope α for the corresponding chaotic signal.

The strong correlation between the α of inter-onset intervals and the α of inter-tap intervals could still reflect a trivial case of entrainment. The proposed mix of reaction, proaction, and synchrony in participants' response allows for a fourth possible scenario that would produce a trivial correlation. That is, the mimicking of the long-range correlations of inter-tap intervals with inter-onset intervals could have been the result of extremely close—if unexpected—entrainment to the chaotic signal. Responses might lead, lag, or coincide by turn, all within a Gaussian distribution and without any long-range

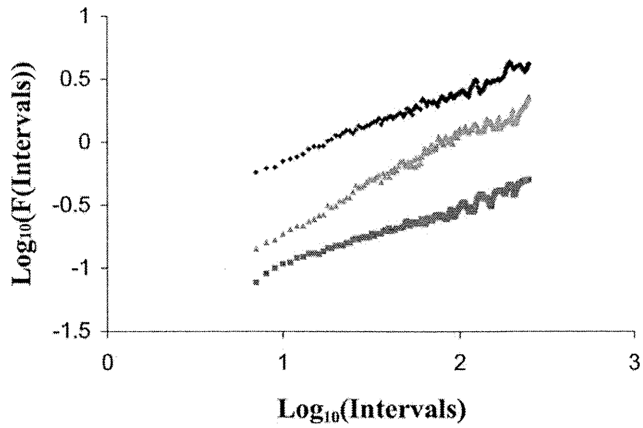

Fig. 6. Fluctuation functions for "Gaussian tap" simulations plotted on double-log axes. The curves have been shifted by a constant factor for the sake of clarity. The top, middle, and bottom fluctuation functions show data from conditions $\tau = 10, 5$, and 2, respectively. The slopes (in the same order) are 0.54, 0.70, and 0.48.

structure. If the latter were the case, then the inter-tap intervals might be modeled as the chaotic inter-onset intervals with a superposed Gaussian noise signal. This hypothesis does not require an internal model so much as it may a Gaussian filter, producing a response within a normally distributed time window encompassing the onset (see Fig. 1(d)).

To test this hypothesis, a "Gaussian tap" was simulated for each of the chaotic time series. Each inter-tap interval time series could potentially be decomposed as the sum of two sources of variability: the variability of the original chaotic signal and the variability of the participant's behavior. In the fourth scenario described in the last paragraph, the variability of the participant's behavior would be best described as a Gaussian distribution scaled to the difference between the standard deviation of the inter-tap interval time series and the standard deviation of the original chaotic signal. Essentially, the "Gaussian tap" simulations were created by adding a white noise signal of amplitude equal to participant variability. For a participant q who received a chaotic signal $CSig_q$ with variance $c^2$and who produced with an inter-tap interval time series with variance b^2, the resulting "Gaussian tap" $GTap_q$ was calculated as follows:

$$GTap_q = CSig_q + N(0, b^2 - c^2). \tag{4}$$

The effect of superposing white noise onto the original chaotic signal was to neutralize any long-range correlations in the original signal. DFA of a signal with superposed noise will differ from DFA of the original signal, depending on the original signal's long-range correlations and depending also on the amplitude of the superposed noise. This difference has been captured by the superposition rule [50,51]. By this rule, the fluctuation function for the composite signal $F(n)/n$ can be calculated as follows:

$$[F(n)/n]^2 = [F_\eta(n)/n]^2 + [F_{wn}(n)/n]^2, \tag{5}$$

where $F_\eta(n)/n$ is the fluctuation function for the original signal and $F_{wn}(n)/n$ is the fluctuation function for the white noise. We found that, for all τ conditions, the superposition rule held for all "Gaussian tap" simulations. The fluctuation function calculated from the superposition rule and the observed fluctuation function of the simulated "Gaussian tap" were correlated, on average, at $r(242) = 0.99$ for $\tau = 2$ ($SE = 0.004$), at $r(242) = 0.99$ for $\tau = 5$ ($SE = 0.002$), and at $r(242) = 0.99$ for $\tau = 10$ ($SE = 0.002$).

These "Gaussian tap" simulations modeled the likely tapping behavior in the case that tapping behavior was locally sensitive to the timing of each individual onset. Ten samples of "Gaussian taps" were simulated. DFA was computed for each simulated signal. The fitting region used was from 7 inter-tap or inter-onset intervals to 250 inter-tap or inter-onset intervals (see Fig. 6). The average correlation of scaling parameter α of these "Gaussian taps" with the scaling parameter α of the chaotic signals was significantly less ($M = 0.71$, $SE = 0.02$) than the correlation between tapping α chaotic intervals α, $t(9) = 12.50$, $p < .0001$.

7. Conclusion

In this paper, we have presented a finding consonant with the hypothesis, advanced by Anderson and Schooler [25, 26], that learning and memory reflect near-optimal statistical inference about the patterning of environmental events. In their view, adaptation of behavior to the environment's statistical structure requires neither explicit statistical inference nor explicit prediction. Using Dubois's [1] terminology, the adaptation is a necessary consequence of a strongly anticipatory system.

As we noted in the introduction, the prime contemporary example of a strongly anticipatory system is one that exhibits anticipating synchronization—a "master" (e.g., environment) and "slave" (e.g., organism) so related through time-delayed feedback as to manifest moment-to-moment negative phase relationships (i.e., pure proaction) [2–7]. By virtue of the coupling, the slave adapts to the states of the master and, by the same token, to the master's statistical structure. In the variant of a strongly anticipatory system promoted in the present experiment, the slave is not adapted to the states of the master but is adapted to their statistical structure. Simply put, the relation of slave and master in the two cases is not of like kind. A progression is implied, from the kind of relation that defines strongly anticipatory systems that exhibit anticipation of both states and statistical structure, to the kind of relation that defines strongly anticipatory systems that exhibit only anticipation of statistical structure. Ideally, future mathematical and empirical studies will make the progression evident.

Acknowledgement

Partial support was provided by NSF grant BCS-0643271.

References

[1] D.M. Dubois, in: M.V. Butz, S. Olivier, G. Pierre (Eds.), Anticipatory Behavior in Adaptive Learning Systems, in: LNAI, vol. 2684, Springer-Verlag, Berlin, 2003, pp. 110–132.
[2] H.U. Voss, Phys. Rev. Lett. 87 (2001) 014102.
[3] H.U. Voss, Internat. J. Bifur. Chaos 12 (2002) 1619.
[4] S. Sivaprakasam, E.M. Shahverdiev, P.S. Spencer, K.A. Shore, Phys. Rev. Lett. 87 (2001) 154101.
[5] R. Toral, C. Masoller, C.R. Mirasso, M. Ciszak, O. Calvo, Physica A 325 (2003) 192.
[6] N. Stepp, M.T. Turvey, in: M. Sasaki, N. Furuyama, H. Mishima (Eds.), Proc. 14th Intl. Conf. Perc. and Action, Yokohama, Japan, 2007.
[7] N. Stepp, M.T. Turvey, Behav. Brain Sci. 31 (2008) 216.
[8] M.T. Turvey, Eco. Psyc. 4 (1992) 173.
[9] T. Radil, J. Mates, J. Ilmberger, E. Pöppel, Experientia 46 (1990) 762.
[10] B.H. Repp, Psychon. B. Rev. 12 (2005) 969.
[11] G. Aschersleben, W. Prinz, Percept. Psychophys. 57 (1995) 305.
[12] B.H. Repp, A. Penel, J. Exp. Psychol. Human Percept. Perform. 28 (2002) 1085.
[13] G. Aschersleben, Brain Cognition 48 (2002) 66.
[14] G. Aschersleben, W. Prinz, J. Motor. Behav. 29 (1997) 35.
[15] J. Mates, T. Radil, U. Müller, E. Pöppel, J. Cognitive. Neurosci. 6 (1994) 332.
[16] M. Peters, Psychiat. Res. 51 (1989) 38.
[17] B.H. Repp, J. Motor. Behav. 35 (2003) 355.
[18] G. Aschersleben, J. Gehrke, W. Prinz, Exp. Brain Res. 136 (2001) 331.
[19] E.W. Large, J. New Music Res. 22 (2001) 173.
[20] P. Janata, S.T. Grafton, Nat. Neurosci. 6 (2003) 682.
[21] D.M. Dubois, in: D.M. Dubois (Ed.), Computing Anticipatory Systems: CASYS, First Intl. Conf., AIP Conf. Proc. 437, Woodbury, New York, 1998, pp. 3–29.
[22] D.M. Dubois, The Fractal Machine, Liège University Press, Liège, 1992.
[23] D.M. Dubois, Comm. Cog. Art. Intel. 9 (1992) 335.
[24] D.M. Dubois, D.M. Dubois (Ed.), Computing Anticipatory Systems: CASYS, Fourth Intl. Conf., AIP Conf. Proc. 573, Woodbury, New York, 2001, pp. 437–451.
[25] J.R. Anderson, L.J. Schooler, Psyc. Sci. 2 (1991) 396.
[26] J.R. Anderson, L.J. Schooler, in: E. Tulving, F.I.M. Craik (Eds.), Handbook of Memory, Oxford University Press, New York, 2000, pp. 557–570.
[27] C.-K. Peng, S.V. Buldyrev, A.L. Goldberger, S. Havlin, F. Sciortino, M. Simons, H.E. Stanley, Nature 356 (1992) 168.
[28] C.-K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Phys. Rev. E 49 (1994) 1685.
[29] C.-K. Peng, S. Havlin, H.E. Stanley, A.L. Goldberger, Chaos 5 (1995) 82.
[30] A. Neuringer, C. Voss, Psychiat. Sci. 4 (1993) 113.
[31] M. Hénon, Comm. Math. Phys. 50 (1976) 69.
[32] M.A. Metzger, M.F. Theisz, Behav. Res. Meth. Ins. Comp. 26 (1994) 387.
[33] R.A. Heath, Nonlin. Dyn. Psyc. Life Sci. 6 (2002) 37.
[34] M.A. Metzger, in: R.F. Port, T. Van Gelder (Eds.), Mind as Motion: Exploration in the Dynamics of Cognition, MIT Press, Cambridge, MA, 1995, pp. 491–526.
[35] H.U. Voss, Phys. Rev. E 61 (2000) 5115.
[36] K. Ikeda, K. Matsumoto, Physica D 29 (1987) 223.
[37] K. Ikeda, H. Daido, O. Akimoto, Phys. Rev. Lett. 45 (709) (1980).
[38] D. Delignières, L. Lemoine, K. Torre, Hum. Movement. Sci. 23 (2004) 87.
[39] L. Lemoine, K. Torre, D. Delignières, Can. J. Exp. Psychol. 60 (2006) 247.
[40] Y. Chen, M. Ding, J.A.S. Kelso, Phys. Rev. Lett. 79 (1997) 4501.
[41] Y. Chen, M. Ding, J.A.S. Kelso, J. Motor. Behav. 33 (2001) 3.
[42] S. Roberts, R. Eykholt, M.H. Thaut, Phys. Rev. E 62 (2000) 2597.
[43] M. Smithson, Organ. Behav. Hum. Decis. Process. 69 (1997) 59.
[44] Code available on-line at http://www.atistar.net/~stepp/anynome/.
[45] A. Dionisio, R. Menezes, D.A. Mendes, Physica A 344 (2004) 326.
[46] R. Kamimura, Network - Comp. Neural. Sys. 4 (1993) 423.
[47] M. Palus, Physica D 80 (1995) 186.
[48] M. Palus, L. Pecen, D. Pivka, Neural. Netw. World 4 (1995) 537.
[49] J.W. Kantelhardt, S.A. Zschiegner, E. Koscielny-Bunde, S. Havlin, A. Bunde, H.E. Stanley, Physica A 316 (2002) 87.
[50] K. Hu, P.C. Ivanov, Z. Chen, P. Carpena, H.E. Stanley, Phys. Rev. E 64 (2001) 011114.
[51] Chen, P.C. Ivanov, K. Hu, H.E. Stanley, Phys. Rev. E 65 (2002) 041107.