



Sensorimotor synchronization with adaptively timed sequences

Bruno H. Repp^{a,*}, Peter E. Keller^b

^a *Haskins Laboratories, 300 George Street, New Haven, CT 06511-6624, United States*

^b *Max Planck Institute for Human Cognitive and Brain Sciences, Leipzig, Germany*

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Abstract

Most studies of human sensorimotor synchronization require participants to coordinate actions with computer-controlled event sequences that are unresponsive to their behavior. In the present research, the computer was programmed to carry out phase and/or period correction in response to asynchronies between taps and tones, and thereby to modulate adaptively the timing of the auditory sequence that human participants were synchronizing with, as a human partner might do. In five experiments the computer's error correction parameters were varied over a wide range, including "uncooperative" settings that a human synchronization partner could not (or would not normally) adopt. Musically trained participants were able to maintain synchrony in all these situations, but their behavior varied systematically as a function of the computer's parameter settings. Computer simulations were conducted to infer the human participants' error correction parameters from statistical properties of their behavior (means, standard deviations, auto- and cross-correlations). The results suggest that participants maintained a fixed gain of phase correction as long as the computer was cooperative, but changed their error correction strategies adaptively when faced with an uncooperative computer.

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* Corresponding author. Tel.: +1 (203) 865 6163x236.

E-mail address: repp@haskins.yale.edu (B.H. Repp).

1. Introduction

1.1. Sensorimotor synchronization in social contexts

Sensorimotor synchronization (SMS) usually takes place in social contexts. All known forms of animal synchronization, such as exhibited by fireflies, crickets, frogs, fish, or birds involve social groups (Greenfield, 2005). Humans, too, synchronize most often with movements or sounds produced by other humans, as in music performance (Repp, 2006), sports (Wing & Woodburn, 1995), applause (Néda, Ravasz, Brechet, Vicsek, & Barabási, 2000), and certain social laboratory situations (Schmidt, Carello, & Turvey, 1990). Although humans are also capable of synchronizing an action with a machine-generated auditory or visual rhythmic sequence, such unilateral synchronization accounts for only a small proportion of all SMS activities in daily life. It is paradoxical, therefore, that research on SMS has focused almost exclusively on this latter situation. Studies typically require participants to synchronize a movement (such as finger tapping) with a computer-controlled stimulus sequence that is either isochronous or perturbed in more or less systematic ways (see Repp, 2005, for a review). This research has yielded useful information about basic principles of SMS, but the time is ripe now to move on and look more closely at interpersonal SMS.

A few studies of piano duet and other musical ensemble performance have been published (e.g., Bartlette, Headlam, Bocko, & Velikic, 2006; Keller, Knoblich, & Repp, 2007; Rasch, 1979; Shaffer, 1984), but none of them has investigated the process of SMS in great detail. These realistic situations are generally too complex to reveal basic processes of entrainment and error correction. Researchers taking a dynamical systems approach have begun to investigate interpersonal coordination during simple oscillatory movements, using techniques and models developed in studies of intrapersonal inter-limb coordination (e.g., Schmidt et al., 1990). However, to the best of our knowledge, coordination between two individuals in the popular tapping task has not yet been studied in detail, although preliminary work has been reported at conferences (Himberg, 2006; Himberg & Cross, 2004).¹ One problem of such studies is that researchers have little control over the participants' characteristics and strategies that affect their interactive behavior, and that may be difficult to tease apart. One promising approach, serving as a preliminary step toward investigating SMS between two individuals, is to study SMS of a single participant with a computer that simulates the potential behavior of a human partner in the task. This makes it possible to control and vary systematically the simulated partner's characteristics, so that there is only one unknown set of parameters and strategies that needs to be inferred from the data. Systematic exploration of the effects that a simulated partner's characteristics have on the SMS behavior of a live participant can yield information that subsequently may be helpful in unraveling the complexities of SMS in a human dyad.

This approach was taken by Vorberg (2005) in an unpublished study that is currently available only as a set of conference slides, posted on the Internet. His goal was to extend the linear model of phase correction in SMS (Vorberg & Schulze, 2002) to the situation of

¹ Mates, Radil, and Pöppel (1992) investigated a situation in which two participants synchronized with a metronome and received auditory feedback from their own or the other participant's taps. They say that "no mutual dynamic influence between simultaneously performing subjects was detected" (p. 691).

an interactive human-computer dyad. In developing the present research, we have benefited greatly from Vorberg's formal derivations and empirical observations. Our experiments partially replicate his work but use a wider range of parameter settings and go on to investigate period as well as phase correction. Before describing our research, it will be good to review some of the predictions and findings of Vorberg and Schulze (2002) for the situation of a human participant synchronizing finger taps with an isochronous or perturbed computer-controlled sequence.

1.2. *The linear phase correction model of SMS*

The linear phase correction model of Vorberg and Schulze (2002) extends the Wing–Kristofferson model of self-paced tapping (Wing & Kristofferson, 1973; Vorberg & Wing, 1996) to SMS by adding an error correction term. The Wing–Kristofferson model assumes open-loop control and postulates two independent sources of variance, one due to a central timekeeper and increasing with interval duration, and another due to peripheral motor delays and largely independent of interval duration. One important consequence of this hierarchical variability structure is that successive inter-tap intervals (ITIs) are negatively correlated, even though there is no error correction. The larger the motor variance is relative to the timekeeper variance, the larger the lag-1 autocorrelation (AC1) of the ITIs will be (maximally $-.5$). To apply this model to SMS, Vorberg and Schulze added a linear phase error correction term whose parameter, α , represents the proportion of each asynchrony (defined as the time of occurrence of a tap minus the time of occurrence of a target event in the pacing sequence) that is subtracted from the currently generated timekeeper interval, without affecting the next timekeeper interval. Alpha theoretically ranges from 0 (self-paced tapping) to 1 (perfect phase correction) to 2 (over-correction), with instability resulting beyond that range. In practice, however, α is generally found to be smaller than 1, with $.5$ being a typical value.

The SMS task yields two correlated time series of data: asynchronies and ITIs. For a small value of α , the AC1 of the asynchronies is predicted to be positive (close to 1), whereas the AC1 of the ITIs is predicted to be negative, as for self-paced tapping. As α is increased, both autocorrelations are predicted to decrease in a nearly linear fashion. A point of special interest is the value of α at which the AC1 of the asynchronies reaches zero and the AC1 of the ITIs (according to the model) simultaneously reaches $-.5$. This point represents optimal phase correction according to the criterion of minimal variance of asynchronies, and interestingly it does not correspond to $\alpha = 1$ but to a value somewhat less than 1 that depends on the ratio of motor variance to timekeeper variance. A reasonable estimate of the optimal α , which we will call α_{opt} , seems to be $.9$ (see Fig. 4D in Vorberg & Schulze, 2002).

Vorberg and Schulze (2002) as well as Vorberg (2005) also considered autocorrelations at longer lags, which shall not concern us in the present study, except (briefly) for the lag-2 autocorrelation (AC2) of the asynchronies. Vorberg and Schulze showed that a participant's α can be estimated by $1 - \text{AC2}/\text{AC1}$, albeit with an estimation bias of unknown magnitude. They further discussed a second-order phase correction model in which both the last and the next-to-last asynchronies are corrected for (see also Pressing, 1998). This model, too, will not figure in the present study, as second-order phase correction is typically negligible unless intervals between sequence events are quite short.

Mates (1994a, 1994b) proposed an error correction model with two components: phase correction and period correction. Repp and Keller (2004) provided some empirical

support for that model and argued that phase correction is largely automatic (see also Repp, 2001b, 2002) whereas period correction is largely under cognitive control. Vorberg and Schulze did not incorporate period correction in their model, in part because of the greater mathematical complexity of such a dual-process model and in part because pacing sequences that do not contain detectable tempo fluctuations are unlikely to elicit period correction. There is always a possibility, however, that cognitively controlled period correction is employed strategically to supplement phase correction. Phase correction seems to be relatively inflexible, although it can be reduced voluntarily to some extent (Repp, 2002; Repp & Keller, 2004).

Vorberg's (2005) extension of the linear phase correction model to SMS with an adaptively timed sequence was straightforward. He showed that all predictions of the model still hold, only now they are a function of the sum of two phase correction parameters, that of the human participant (α_h) and that of the computer (α_c).² Vorberg fixed α_c at several positive and negative values and observed the effects on human participants' SMS performance. When α_c is different from zero, the computer no longer generates a perfectly isochronous pacing sequence, but the tempo nevertheless remains approximately constant because the computer's timekeeper period is fixed. A positive α_c essentially helps the participant synchronize, but when the sum of α_c and α_h values exceeds α_{opt} ($\sim .9$), the asynchronies begin to oscillate because of over-correction (which implies a negative AC1 for asynchronies). Still, SMS remains stable as long as the sum of the two α values is less than 2. By contrast, a negative α_c counteracts the participant's phase correction. As long as $\alpha_h + \alpha_c > 0$, SMS remains stable, but when the sum of the α values becomes negative, large fluctuations in sequence tempo can arise that make SMS difficult. Maintenance of SMS under these unstable conditions may require a strategic deployment of period correction, if it is the case that α_h cannot be changed easily. Systematic variation of α_c in small steps thus can lead to an indirect estimate of α_h : The value of α_c at which the AC1 of the asynchronies reaches zero should be equal to $\alpha_{opt} - \alpha_h$.

One theoretically interesting question is whether a participant's α_h is indeed invariant or whether it is adaptable and context-dependent. Vorberg (2005) suggested in his conclusions that α_h is adaptable, but it is not quite clear what evidence this conclusion was based on. It may have been the ability of some participants to maintain reasonable synchronization when α_c was negative. That, however, may have been due to strategic use of period correction, as suggested above. Nevertheless, some studies have shown that phase correction can be modulated by intentions and context (Repp, 2002; Repp & Keller, 2004). Adaptive behavior of either kind might be reflected in shallow or nonlinear functions relating the AC1 of the asynchronies to α_c .

1.3. *The present study*

The present study included five experiments that can also be regarded as five conditions of a single experiment. Table 1 gives an overview of the simple computer algorithms employed in each. Experiment 1 implemented positive (human-like) phase correction in the computer. Human phase correction compensates for the previous asynchrony by

² Vorberg called the parameters α and β , respectively, but we use β to refer to the period correction parameter in the dual-process model.

Table 1
Overview of computer parameter settings in the five experiments

<i>Experiment 1: Phase correction</i>	
$t_{n+1} = t_n + T + \alpha_c \times \text{asy}_n$	$\alpha_c = 0, .1, .2, \dots, 1; \beta_c = 0$
<i>Experiment 2: Negative phase correction</i>	
$t_{n+1} = t_n + T + \alpha_c \times \text{asy}_n$	$-\alpha_c = 0, .1, .2, \dots, 1; \beta_c = 0$
<i>Experiment 3: Period correction without additional phase correction</i>	
$t_{n+1} = t_n + T_n + \beta_c \times \text{asy}_n$	$\alpha_c = 0$
$T_{n+1} = T_n + \beta_c \times \text{asy}_n$	$\beta_c = 0, .1, .2, \dots, 1$
<i>Experiment 4: Period correction with negative phase correction</i>	
$t_{n+1} = t_n + T_n + (\alpha_c + \beta_c) \times \text{asy}_n = t_n + T_n$	$-\alpha_c = \beta_c = 0, .1, .2, \dots, 1$
$T_{n+1} = T_n + \beta_c \times \text{asy}_n$	
<i>Experiment 5: Period correction with additional phase correction</i>	
$t_{n+1} = t_n + T_n + (\alpha_c + \beta_c) \times \text{asy}_n$	$(\alpha_c + \beta_c) = 0, .2, .4, .6, .8$
$T_{n+1} = T_n + \beta_c \times \text{asy}_n$	$\beta_c = 0$ (for $\alpha_c = 0$ only), $.2, .4$

t_n = time of occurrence of n th tone, T = fixed timekeeper interval (500 ms), T_n = current timekeeper interval (variable), asy_n = asynchrony between tap and n th tone, α_c = phase correction parameter (fixed within each trial) and β_c = period correction parameter (fixed within each trial).

moving the next tap in the opposite direction (assuming a mean asynchrony of zero, without loss of generality). By moving each tone in the same direction as the previous asynchrony (i.e., towards the participant's predicted next tap), the computer "cooperated" with the participant in achieving synchrony. Experiment 2 implemented negative phase correction, whereby the computer moved each tone in the opposite direction from the previous asynchrony (i.e., away from the participant's predicted next tap), thereby counteracting the participant's phase correction. This was expected to result in an unstable situation in which it would be difficult to maintain synchrony, especially when $\alpha_c > \alpha_h$. In Experiment 3, period correction was implemented in the computer without additional phase correction. This condition was expected to be relatively easy for participants, although they now had greater responsibility for maintaining the sequence tempo because the sequence period was malleable. Experiment 4 implemented period correction together with negative phase correction, $\beta_c = -\alpha_c$, equivalent to delayed period correction. This was expected to be a difficult and unstable condition for large values of β_c . Finally, Experiment 5 combined several different values of α_c and β_c to see whether these parameters have independent or interactive effects on participants' behavior.

A comment is in order on the way in which period correction was implemented in Experiments 3–5. In agreement with previous studies (Mates, 1994a, 1994b; Repp, 2001a, 2001b; Repp & Keller, 2004), we assumed that period correction is immediate, affecting the current timekeeper interval and thus having an immediate effect equivalent to phase correction. This seems reasonable if period adjustment takes place in a timing mechanism (e.g., a counter of pacemaker pulses) that determines the interval endpoint and remains cognitively accessible while the interval is being timed.³ A difference with

³ Alternatively, the immediate effect can also be regarded as constituting phase correction proper, with period correction taking effect only in the next cycle. Formally, these two models are identical; only the values of α_c and β_c would change.

respect to previous studies, however, is that we assumed the informational basis for period correction to be the most recent asynchrony, not the difference between the preceding IOI and the preceding timekeeper interval, as previous studies had assumed. This change was motivated indirectly by various findings (reviewed in Repp, 2005) suggesting that phase correction in turn is not based directly on asynchronies (as has usually been assumed) but represents a form of mixed phase resetting, as originally proposed by Hary and Moore (1985, 1987). Although these two conceptions of phase correction are formally equivalent, the interpretation of phase correction as resting on reference time points (times of occurrence of tones and taps) rather than the interval between them (asynchronies) opens up the theoretical possibility that period correction is based on intervals (asynchronies) rather than on differences between intervals (IOIs and timekeeper periods). This option was also considered recently by Schulze, Cordes, and Vorberg (2005), and we adopted it here.

After the behavioral data had been collected and analyzed, we conducted computer simulations of the human-computer interaction. The purpose of these simulations was to attempt to reproduce certain statistical properties of the data and thereby to estimate the human participants' internal parameter settings. The simulations will be described in more detail in connection with each experiment.

2. Methods

2.1. Participants

The experiments were conducted at the Max Planck Institute for Human Cognitive and Brain Sciences in Leipzig, Germany. The participants were five paid student volunteers (one female, ages 21–25) and the first author (BHR, age 61 at the time). The student volunteers had participated in a previous tapping experiment and were selected on the basis of their low variability in that study. Only BHR had extensive experience with SMS experiments. However, all participants had substantial musical training, and four had played percussion.

2.2. Materials and equipment

Tone sequences were generated and taps were recorded by programs written in MAX 4.5.7 (<http://www.cycling74.com>) running on a Macintosh G5 computer. The tones were specified to be 50 ms in duration, with a fundamental frequency of 2,637 Hz (MIDI pitch = 100) and a constant intensity (MIDI velocity = 60). They were played as piano sounds (from the DLS sample bank) generated by the QuickTime Music Synthesizer. Participants listened over Sennheiser HD 270 headphones at a comfortable intensity and tapped with their index finger on a Roland SPD-6 electronic percussion pad that was connected to the computer via a MIDI interface.⁴ Each tone sequence (trial) consisted of

⁴ Acoustic measurements conducted on similar equipment at Haskins Laboratories have revealed that the combined transmission delays of tap registration and sound output are about 30 ms. This means that the true asynchronies between finger contacts and tone onsets were 30 ms shorter (more negative) than the asynchronies registered by the MAX software. We report the registered asynchronies here because they provided the input to the computer algorithms.

40 tones. Eleven randomly ordered trials, each representing a different constant parameter value (see Table 1) constituted one block, and ten such blocks were presented in each experiment. A few practice trials, at most one whole block, were given at the beginning of Experiments 1, 2, and 4.

As shown in Table 1, computer phase correction was implemented by calculating the last tap-tone asynchrony, multiplying it with $(\alpha_c + \beta_c)$, where either parameter could be zero, and adding the result to the current timekeeper period, T or T_n , to obtain the current tone inter-onset interval (IOI_n). The change in IOI_n was implemented computationally as a cascade of two delays, the first fixed at $0.75 \times T_n$ ($=375$ ms in Experiments 1 and 2, where T was fixed at 500 ms) and the second being variable. The computer's phase correction was limited to registered asynchronies within the range of $\pm 0.25 \times T_n$ ($= \pm 125$ ms in Experiments 1 and 2). Larger asynchronies (which were rare) were ignored. Implementation of period correction (see Table 1) was computationally straightforward, and there was no constraint on changes in the timekeeper period.

It should be noted that the computer algorithms did not include any random noise terms. Adding noise, although making the computer perform more like a human, would merely have introduced additional variability in the data, without contributing any interesting information. Thus, the computer always behaved deterministically.

2.2.1. Procedure

The five experiments were conducted in separate sessions in the order described, with some exceptions.⁵ Intervals between sessions varied from one day to several weeks. Participants sat in front of the computer and held the percussion pad on their lap. After selecting a block of trials, they started each trial by pressing the space bar of the computer keyboard and started tapping on the percussion pad in synchrony with the third tone, thus making 39 taps, the last of which did not coincide with a tone. At the end of each trial, a panel on the monitor reported the number of missing taps (due to late starts, insufficient tapping force, or asynchronies exceeding the limits).⁶ Participants saved the data of each block of trials in a file before proceeding to the next block. They were informed that the tone sequences might exhibit irregularities and might vary in tempo. They were alerted to the difficulty of the tasks in Experiments 2 and 4. In all experiments, they were instructed to synchronize their taps with the tones as accurately as possible and also to maintain the initial tempo, to the best of their ability. Unfortunately, the instruction to maintain the tempo was not heeded by (or not communicated well to) two of the six participants. In Experiments 3–5, where the computer's timekeeper period was not fixed, this led to large drift in ITIs and IOIs, generally towards a slower tempo. This problem was discovered only at the analysis stage, and the data of these two participants are therefore excluded from the analyses in Experiments 3–5.

⁵ A programming error was discovered in Experiment 2 after three participants had been run. The error was corrected, and the sessions were repeated immediately. For one participant, who was unavailable for several weeks, the order of Experiments 4 and 5 was reversed, so as not to start with a very difficult condition after the break. Another participant performed poorly in Experiment 2, perhaps having misunderstood the instructions, and was asked to repeat Experiment 2 after Experiment 5.

⁶ This feature was added after one participant tapped too lightly in Experiment 1, which resulted in the loss of 6.9% of his data. There were no such problems subsequently.

2.2.2. Computer simulations

The simulations of the obtained human data were carried out using programs written in MATLAB. For each experiment, each run of the simulation generated time series of 40 asynchronies, ITIs, and IOIs, comparable to individual trials of empirical data. Each run represented a particular combination of computer and human parameter settings. Typically there were 9 (human parameter values) \times 11 (computer parameter values) = 99 runs in a simulation. Appropriate human parameter settings were found by trial and error in the course of a number of repeated simulations of the same data. The final simulation was repeated 100 times, and statistics comparable to those obtained from the empirical data were derived from each run and averaged across the 100 repetitions. The settings of α_c and β_c were the same as in the experiments (Table 1), whereas α_h and/or β_h were varied over a narrower range, as reported in Table 2. The first asynchrony in every run was assumed to be zero. Human timekeeper variance was simulated by sampling randomly from a normal distribution with mean = 0 and SD = 12 or 10 ms, and adding that value to the current human timekeeper interval (C_n) when computing each inter-tap interval (ITI_n). Motor delays were simulated by sampling randomly from a gamma distribution with $k = 4$ and a scaling parameter set to give SD = 5 ms (see Semjen, Schulze, & Vorberg, 2000). The current value of the motor delay was added and the previous value was subtracted when computing ITI_n .

In general, the empirical data compared to the simulated data were the participant averages. Consideration of each individual participant's data would have led to an excessive amount of detail in the present report. However, there was generally good qualitative agreement among participants in their patterns of results. The simulated data merely constitute approximations to the human data. We did not attempt to derive optimal parameter estimates via automatic computer search procedures because this would have been

Table 2
Overview of human parameter settings in the simulations

<i>Experiment 1:</i>		
SD _C = 12 ms		
$\alpha_h = \alpha_i$		$\alpha_i = .3-.6$ in steps of .05
<i>Experiment 2:</i>		
SD _C = 12 ms		
$\alpha_h = \alpha_i - .5 \times \alpha_c$		
if $\alpha_h < 1.4 \times \alpha_c$:	$\alpha_h = \alpha_i - .1 \times \alpha_c$	$\alpha_i = .4-.6$ in steps of .025
	$\beta_h = -.4 \times \alpha_c$	
	$\alpha_h + \beta_h = \alpha_i - .5 \times \alpha_c$	
<i>Experiment 3:</i>		
SD _C = 10 ms		
$\alpha_h = \alpha_i$		$\alpha_i = .2-.4$ in steps of .05
<i>Experiment 4:</i>		
SD _C = 10 ms		
$\alpha_h = \alpha_i + .5 \times \beta_c$		$\alpha_i = .4-.5$ in steps of .025

SD_C = standard deviation of timekeeper intervals (for motor variability, see text), α_h = phase correction parameter, α_i = value of phase correction parameter for $\alpha_c = 0$, $\beta_c = 0$, and β_h = period correction parameter (zero if not specified).

quite complex and time-consuming, given that there were nine dependent variables (see below).

3. Experiment 1

In Experiment 1, we implemented different degrees of phase correction in the computer by varying α_c between 0 and 1 in steps of .1. Vorberg (2005) investigated the same condition but used only three values of α_c (0, .4, and .8). However, he employed two different timekeeper periods (300 and 450 ms) and three types of induced metrical structure (duple, triple, and quadruple), variables that we did not include in our design. (They had only relatively minor effects on Vorberg's results.) Instead, we aimed to obtain a more detailed picture of the dependence of participants' tapping behavior on α_c .

In this experiment, a negative registered asynchrony (indicating that the tap preceded the tone) resulted in a shortening of the next sequence IOI (the next tone occurring sooner), whereas a positive registered asynchrony resulted in a lengthening of the next IOI. The direction of this computer phase correction was the opposite of the phase correction expected in the participant's taps, as it should be if the computer (controlling the tones) "cooperates" with the participant (controlling the taps). This cooperation was expected to improve the synchronization of the participant's taps with the tones, but only as long as $\alpha_h + \alpha_c < \alpha_{opt}$, presumed to be about .9. Thus, the variability of the asynchronies was expected to vary as a curvilinear U-shaped function of α_c , with a minimum at about $\alpha_c = .9 - \alpha_h$. At the same time, the AC1 of the asynchronies was expected to decrease linearly with α_c and to cross zero at the same point. Thus, there were two potential ways of estimating α_h from the data, in addition to a third estimate that could be derived from the trials with $\alpha_c = 0$, according to the formula $\alpha_h = 1 - AC1/AC2$.

3.1. Results and discussion

3.1.1. Practice effects

We first examined whether there was any significant change in participants' performance across the ten test blocks. Each of nine dependent variables (those shown below in Figs. 1A–F and 2D–F) was subjected to a one-way repeated-measures ANOVA. The Greenhouse-Geisser correction was applied to the p values. None of the variables changed significantly across blocks. All subsequent analyses were performed on data averaged across blocks and, in most cases, also averaged across participants.

3.1.2. Asynchronies and ITIs

All but one participant (see footnote 6) had virtually complete data; missing taps for other participants, due to occasional late starts or weak force, ranged from 0% to 0.3% of their data. No registered asynchronies fell outside the range of ± 125 ms.

Fig. 1A shows the mean asynchronies of individual participants as a function of α_c . Individual data are shown here because one participant differed from the others in that her registered asynchronies were negative, whereas all others had positive asynchronies (but see footnote 4). Each participant's mean asynchrony decreased gradually and almost linearly (though somewhat irregularly in some cases) toward zero as α_c

increased, but did not reach zero. The best-fitting quadratic regression line is shown in each case.

The empirical data are shown against a background of functions (grey lines) that represent regression lines fit to data points derived from computer simulations.⁷ Simulations with the human timekeeper period (C) fixed at 500 ms generated mean asynchronies near zero for all values of α_c and of α_h . To simulate nonzero mean asynchronies, it was necessary to assume that C differed from T , the computer's timekeeper period. Values of 490, 495, 505, and 510 ms were chosen for C , in addition to 500 ms. The resulting asynchronies varied not only as a function of α_c but also as a function of α_h . A lower α_h was associated with more deviant asynchronies at $\alpha_c = 0$ and a steeper decline as α_c increased. The simulated data shown in Fig. 1A are for a fixed α_h value of .4. It can be seen that a mildly curvilinear decrease in mean asynchrony with increasing α_c is predicted by the linear phase correction model, with an asymptote at $C = 500$. Quadratic functions fit the simulated data very well. Some of the empirical functions are less curvilinear than predicted by the model, which may reflect individual values of $\alpha_h < .4$.

Fig. 1B shows the mean ITIs for individual participants as a function of α_c . All participants naturally had a mean ITI of 500 ms when synchronizing with isochronous sequences, but they deviated increasingly from that value as α_c increased. Again, this deviation seemed to be a mildly curvilinear function of α_c . The simulations predicted these deviations from the target tempo quite well. The grey functions shown in Fig. 1B are again for $\alpha_h = .4$, and for C values of 490, 495, 500, 505, and 510 ms. The simulated data were fit very well by quadratic functions.

The direction and relative magnitude of the ITI deviation from the baseline IOI (500 ms) was clearly related to the mean asynchrony (Fig. 1A). The single participant with negative registered mean asynchronies tended to accelerate as α_c increased (because the pacing sequence also accelerated; see Fig. 2A below), whereas the other participants tended to slow down. These tempo changes are a necessary consequence of the sign and magnitude of the registered mean asynchrony: The deviation of the mean ITI from 500 ms is approximately equal to α_c times the mean asynchrony, and it is exactly equal to the mean asynchrony when $\alpha_c = 1$. (Compare the right-most data points in Fig. 1A and B.) This implies that, to achieve a mean asynchrony of zero, participants had to maintain the target tempo exactly (on average), and vice versa.

Fig. 1C shows the mean within-trial standard deviation of the asynchronies as a function of α_c . These data, and those in subsequent panels, have been averaged across participants and are plotted with standard error bars. A repeated-measures ANOVA (with Greenhouse-Geisser correction) showed that the variability of the asynchronies tended to depend on α_c , $F(10, 50) = 2.0$, $p < .06$, and decomposition of the effect into polynomial contrasts revealed a significant quadratic effect, $F(1, 5) = 21.9$, $p < .005$. The best-fitting quadratic function is shown, which has its minimum at $\alpha_c = .44$. This is consistent with the prediction that the variability of the asynchronies would be minimal when $\alpha_h +$

⁷ We generally show families of simulated functions, rather than just the single function that fits the empirical data best, in order to give an impression of how the various data statistics change as a function of the computer parameter(s) that were varied. Some of the non-linear curves shown in the figures are shifted to the left by one half-step (0.05) on the X -axis, which is caused by an acknowledged but uncorrected bug in the commercial graphics program used (Deltagraph 5.5). Unequal spacing of curves reflects error variance remaining after 100 repetitions of a simulation.

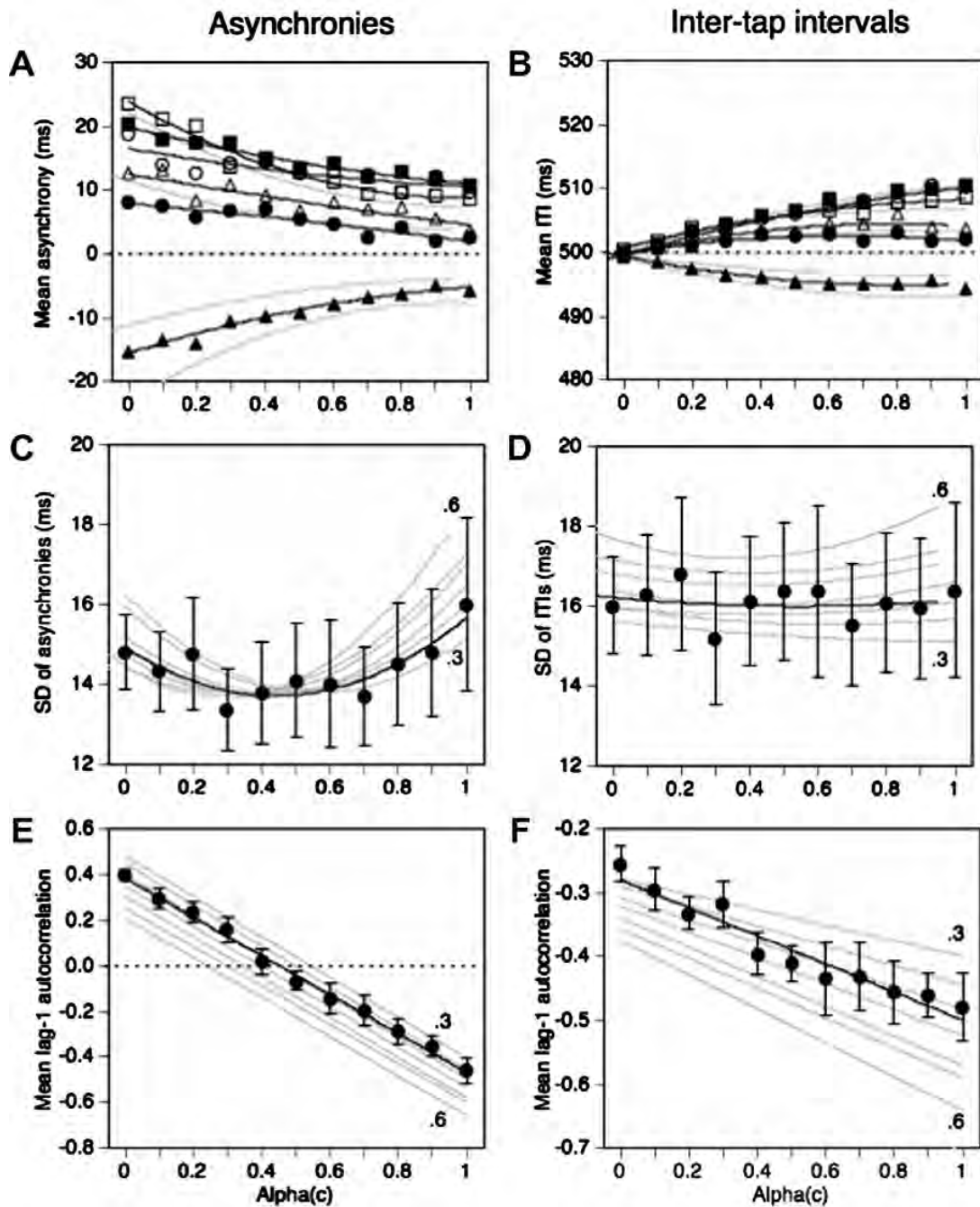


Fig. 1. Experiment 1: Asynchrony and inter-tap interval data as a function of α_c . Solid lines represent functions fit to the data. Error bars represent ± 1 standard error. Gray lines are functions fit to simulated data. Decimal numbers inside panels indicate extreme values of α_i in the simulations (see Table 2). Y-axis labels indicate what is plotted in each figure. (Similarly for all following figures.)

$\alpha_c = \alpha_{opt}$, and it suggests a mean α_h of .46 (assuming $\alpha_{opt} = .9$ and a constant α_h), which seems reasonable given earlier findings in the literature.

The empirical data are shown against a background of a family of seven functions obtained from the computer simulation, in which α_h was varied from .3 to .6 in steps of .05, with $C = 500$ ms. (Varying C had little effect on statistics other than means.) The simulated data were all fit very well by quadratic functions, which are shown. The minimum of the simulated function moved from .58 to .27 as α_h increased from .3 to .6, which

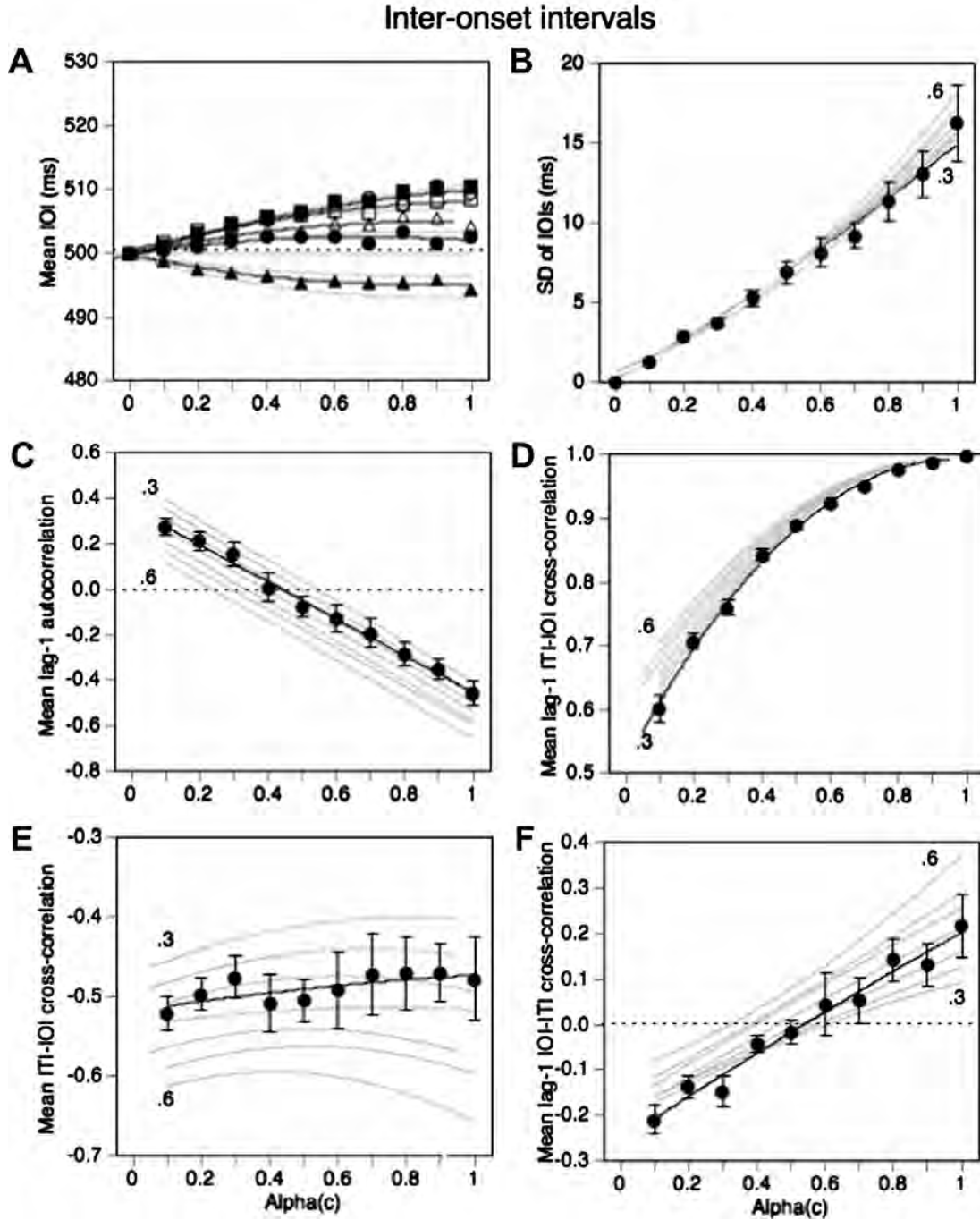


Fig. 2. Experiment 1: Sequence inter-onset interval data as a function of α_c .

implies an α_{opt} ranging from .88 to .87, in good agreement with our assumption that $\alpha_{opt} = .9$. Using linear interpolation between the simulated functions, we find that the best-fitting function has $\alpha_h = .42$, which is very close to the estimate of .43 obtained from the empirical function when α_{opt} is revised from .9 to .87 ($\alpha_h = .87 - .44$).

Interestingly, the simulated data suggest that the variability of asynchronies is independent of α_h when α_c is in the vicinity of .42. In other words, it seems that at that setting of α_c a computer without phase correction capabilities ($\alpha_h = 0$) could be substituted for the human participant without any effect on performance, thus reversing the traditional roles of computer and human participant. For values of α_c below this critical value, a large α_h

reduces variability of asynchronies, whereas for values of α_c larger than the critical value, a small α_h is advantageous. The empirical function seems to represent a good compromise in that it is relatively flat and associated with fairly low variability across the whole range of α_c . This function is compatible with the assumption that α_h did not change as a function of α_c , and that period correction was not engaged.

The variability of the ITIs is shown in Fig. 1D. It was somewhat greater than that of the asynchronies but did not depend on α_c ; the best-fitting function is practically linear and has a slope of zero. The simulated data in the background are slightly curvilinear as a function of α_c and become increasingly nonlinear as α_h increases. Of the functions shown, the one that best fits the empirical data is for $\alpha_h = .4$.

Fig. 1E shows the mean AC1 coefficients of asynchronies as a function of α_c . These correlations were quite consistent across participants, as is revealed by the small standard error bars. The AC1 decreases linearly as α_c increases, moving from positive to negative values and crossing zero at $\alpha_c = .46$, which is close to the minimum of the variability function in Fig. 1C and suggests a mean α_h of .41 if $\alpha_{opt} = .87$. The function is also in good agreement with the AC1 coefficients found by Vorberg (2005) for α_c values of 0, .4, and .8 at a baseline IOI of 450 ms, and with the model predictions of Vorberg and Schulze (2002) for AC1 as a function of α_h (see their Fig. 4D). The AC1 functions generated by the computer simulation are also linear and parallel, with slopes similar to that of the empirical function. The best-fitting simulated function, of the ones shown, is the one with $\alpha_h = .4$, whose zero intercept is at $\alpha_c = .45$. This suggests a value for α_{opt} of .85, just slightly lower than the value estimated from the variability data.

Finally, Fig. 1F shows the AC1 function for ITIs. It tends to be linear also and moves from mildly negative to moderately negative values; it approaches $-.5$ as α_c reaches 1. Vorberg (2005) did not report autocorrelations for ITIs, but the function is in reasonable agreement with the model predictions of Vorberg and Schulze (2002; see their Figure 5D). The simulated functions are linear as well and show the predicted increasing negativity of the correlations as α_h increases from .3 to .6. The best-fitting function is once again the one for $\alpha_h = .4$.

We mentioned earlier that α_h can also be estimated from the asynchronies when $\alpha_c = 0$ according to the formula $\alpha_h = 1 - AC2/AC1$, although this estimate is said to be biased (Vorberg & Schulze, 2002). Table 3 compares these estimates, which were first derived from individual $\alpha_c = 0$ trials and then averaged across those trials for each participant, with estimates of α_h derived from the minimum of a quadratic function fit to the standard deviations of the asynchronies of each participant (cf. Fig. 1C) and from the zero intercept

Table 3

Estimates of α_h (est. α_h , bold face) from AC1 and AC2 when $\alpha_c = 0$ (column 4), from α_c at the minimum of the standard deviation of asynchronies (minSD) (column 6), and from α_c at the zero crossing of the AC1 function (zcAC1) (column 8), assuming $\alpha_{opt} = .87$

Ptcept	AC1	AC2	Est. α_h	minSD	Est. α_h	zcAC1	Est. α_h
BR	.44	.23	.48	.66	.21	.60	.27
IF	.45	.24	.47	.63	.24	.47	.40
JG	.37	.01	.99	.47	.40	.43	.44
JS	.41	.23	.45	.36	.51	.35	.52
JW	.33	.00	.99	.09	.78	.33	.54
SH	.41	.05	.88	.54	.33	.62	.25

of a regression line fit to the AC1 function for asynchronies of each participant (cf. Fig. 1E), with $\alpha_{\text{opt}} = .87$. It can be seen that the three estimates show little agreement. Due to unexpectedly small values of AC2, the estimate of α_{h} derived from the $\alpha_{\text{c}} = 0$ trials was unreasonably high for three of the participants. One of the estimates based on the minimum of the variability function also seems much too high. Only the estimates based on the zero crossing of the AC1 function are credible for all participants, so this appears to be the most reliable way of estimating α_{h} .

3.1.3. IOIs

Results for the IOIs of the pacing sequence and their relations with the participants' ITIs are shown in Fig. 2. Fig. 2A plots the mean IOI as a function of α_{c} for individual participants. It can be seen that the mean IOIs are virtually identical with the mean ITIs (Fig. 1B), which proves that all participants were able to stay in synchrony with the pacing sequence at all levels of α_{c} . The simulated functions for $\alpha_{\text{c}} = .4$ are very similar to those in Fig. 1B also.

Fig. 2B shows the mean standard deviation of the IOIs as a function of α_{c} . This function starts at zero for an isochronous sequence and increases linearly with α_{c} at first but then becomes curvilinear. The standard error, representing between-participant differences, increases at the same time. The function is fit well by a quadratic function through zero. For $\alpha_{\text{c}} = 1$, the mean standard deviation of the IOIs equals the magnitude of the mean standard deviation of the ITIs (Fig. 1D), about 16 ms. (The reason for this will become clear shortly.) The simulated data are also fit very well by quadratic functions. The simulated function that provides the best fit to the data is the one with $\alpha_{\text{h}} = .3$, but the function with $\alpha_{\text{h}} = .4$ provides an excellent fit as well.

Fig. 2C shows the mean AC1 of the IOIs as a function of α_{c} . (There is no data point for $\alpha_{\text{c}} = 0$ in Fig. 2C-F because the IOI was constant at 500 ms in that condition.) This AC1 function is nearly identical with the AC1 function of the asynchronies (Fig. 1E). The reason for this can be found in the fact that the IOIs are linearly dependent on the asynchronies, according to the phase correction algorithm: $\text{IOI}_n = t_{n+1} - t_n = T + \alpha_{\text{c}} \times \text{asy}_n$ (cf. Table 1). Therefore, they also must have the same autocorrelations as the asynchronies. The simulated functions are likewise identical with those in Fig. 1E.

The same linear relationship is also responsible for the functions shown in Fig. 2D, which depict the lag-1 cross-correlation (CC1) between ITIs and IOIs (i.e., the dependency of IOIs on immediately preceding ITIs). These functions increase in a negatively accelerated fashion as α_{c} increases; the correlation is perfect for $\alpha_{\text{c}} = 1$. This means that the IOIs track the ITIs precisely when $\alpha_{\text{c}} = 1$. This follows from the fact that when $\alpha_{\text{c}} = 1$, $\text{IOI}_n = T + \text{asy}_n$. By definition, $\text{ITI}_n = \text{IOI}_n - \text{asy}_n + \text{asy}_{n+1}$ (see Vorberg & Schulze, 2002), so that $\text{ITI}_n = T + \text{asy}_{n+1} = \text{IOI}_{n+1}$. This also explains the identity of standard deviations of ITIs and IOIs when $\alpha_{\text{c}} = 1$. The empirical CC1 function is fit very well by a quadratic function, and individual differences vanish as α_{c} increases. The simulated functions are all quadratic, too. The best-fitting function here is the one with $\alpha_{\text{h}} = .3$, but the function for $\alpha_{\text{h}} = .4$ also provides a good fit.

Fig. 2E shows the mean lag-0 cross-correlation (CC0) between the IOIs and ITIs, which changes little with α_{c} and is nearly constant at values close to $-.5$. A positive correlation would indicate that participants were able to anticipate the next IOI and adjust their ITI accordingly; clearly, this was not the case, nor was it in participants' interest to do so because this would have counteracted the computer's cooperative phase correction.

The empirical data follow a shallow linear function, whereas the simulated functions are somewhat more curvilinear. The best-fitting function is the one with $\alpha_h = .4$.

Finally, Fig. 2F plots the mean CC1 of the IOIs and ITIs (i.e., the dependence of ITIs on immediately preceding IOIs). It increases linearly as a function of α_c and crosses zero at $\alpha_c = .54$. This means that participants began to track the IOIs with their ITIs as α_c grew large, though this remained a weak tendency. It is presently not clear how this zero crossing might be related to α_h , as it is at a higher value than the estimates of α_h derived from Fig. 1C and E. The best-fitting simulated function is the one with $\alpha_h = .4$, although it is somewhat shallower than the empirical function; the function for $\alpha_h = .45$ comes closer in terms of slope.

3.1.4. Summary

The results of Experiment 1 are approximated quite well by simulated functions based on the assumption that α_h remained fixed throughout the experiment. Thus there is little evidence to suggest that participants change their phase correction adaptively in response to variations in α_c , or that they engage in period correction at all. The zero crossing of the AC1 function for asynchronies (or, equivalently, for IOIs) provides a good estimate of α_h (.42 on average), and it also yields an estimate of α_{opt} (.87 on average). To account for non-zero mean asynchronies and mean deviations from the baseline tempo in ITIs and IOIs, a deviant setting of the human timekeeper period has to be assumed, which may reflect either a perceptual time estimation error (Wohlschläger & Koch, 2000) or attraction toward a preferred motor tempo (McAuley, Jones, Holub, Johnston, & Miller, 2006).

4. Experiment 2

In this experiment we investigated participants' synchronization behavior in response to an uncooperative computer whose phase correction strategy was opposed to that of the participant. The task was expected to be manageable as long as $\alpha_c < \alpha_h$, but to become unstable when $\alpha_c > \alpha_h$. The question of main interest was whether participants would be able to deal with such instability by adopting a compensatory strategy (either increasing their α_h or employing period correction in addition to phase correction), or whether they would fail to maintain synchrony.

4.1. Results and discussion

It emerged that all six participants were able to maintain synchronization at all values of α_c , with only occasional difficulties. Three participants missed no more than 2–4 taps during the whole experiment. The other three participants had from 0.7% to 2.2% of their taps missing in the data. Most likely, the missing taps reflected asynchronies exceeding the ± 125 ms limits (which were not recorded), although some could have been deliberate or accidental omissions. They occurred mainly with high values of α_c and in the initial blocks of the experiment. In the later blocks, there were hardly any missing taps, which indicates that participants quickly learned to deal with the unstable situations.

4.1.1. Practice effects

Repeated-measures ANOVAs on the nine dependent variables showed that the variability of asynchronies and ITIs decreased significantly across blocks, $F(9,45) = 7.40$,

$p = .007$, and $F(9,45) = 5.45$, $p = .014$, respectively. None of the other variables changed significantly, although some individual participants appeared to exhibit changes. Subsequent analyses were conducted on data averaged across blocks.

4.1.2. Asynchronies and ITIs

Fig. 3A shows the individual mean asynchronies as a function of $-\alpha_c$. (We prefer this way of plotting the data over the mirror-image alternative, with α_c on the X-axis.) The individual differences seen in Experiment 1 (Fig. 1A) are again present, but the asynchronies do not change systematically with $-\alpha_c$. Linear functions fit the data reasonably well, although there are some irregularities.

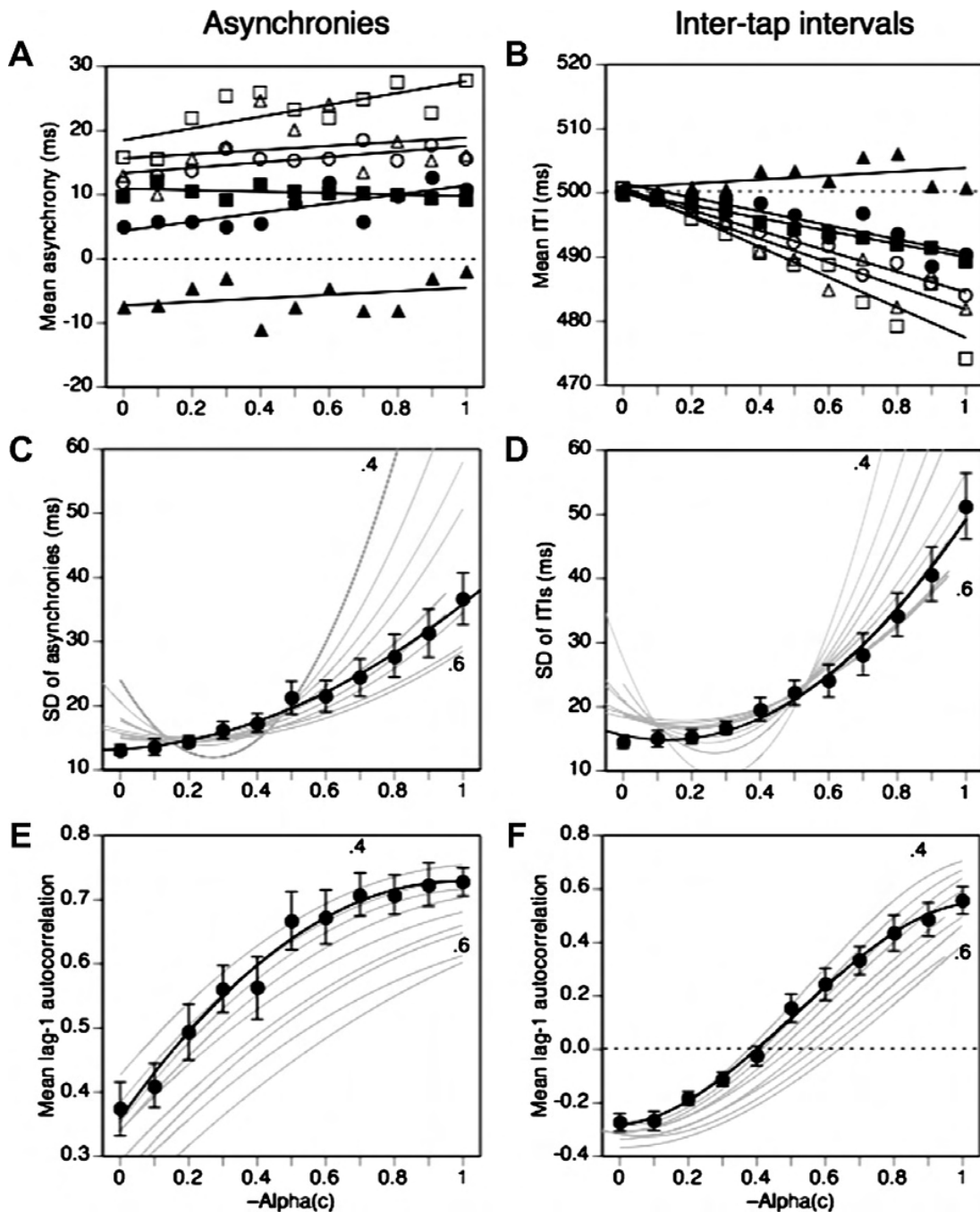


Fig. 3. Experiment 2: Asynchrony and inter-tap interval data as a function of $-\alpha_c$.

The simulation of the mean asynchronies proved problematic. If the human timekeeper period C is set at 500 ms, mean asynchronies close to zero are predicted. If different values of C are assumed, as in Experiment 1, the asynchronies start out differently but converge onto zero as $-\alpha_c$ increases. The reason for this is that we found it necessary to invoke human period correction to simulate other aspects of the data (see below), and a non-zero β_h seems to drive asynchronies to zero, just as a non-zero β_c does (as became evident in Experiments 3–5). We leave this issue unresolved.

Fig. 3B shows the individual mean ITIs as a function of $-\alpha_c$. Naturally, the mean ITIs are 500 ms when $\alpha_c = 0$, but then they deviate increasingly from 500 ms in a roughly linear fashion. It can be seen that the ITI deviations are in the opposite direction of the mean asynchronies, and at $-\alpha_c = 1$ they are their almost exact inverses. This is easily explained by the relationship discussed already in connection with Fig. 1B, with only a change in sign: The deviation of the mean ITI from the baseline IOI (500 ms) is approximately equal to $-\alpha_c$ times the mean asynchrony. This implies again that, to maintain the target tempo exactly, participants would have to tap with a mean asynchrony of zero, and vice versa.

Before discussing the other statistics derived from the human data, we should point out that it was immediately evident that the data could not be modeled by assuming a constant α_h . To achieve stability and match the shapes of the various functions, α_h had to increase with $-\alpha_c$, such that $\alpha_h > -\alpha_c$, and in addition it seemed that period correction had to be invoked when $-\alpha_c$ got large. (Keep in mind that $-\alpha_c$ assumed positive values.) By trial and error, we arrived at the following parameter settings for the simulations: Starting with initial values of α_h (α_i) ranging from .4 to .6 in steps of .025, α_i was increased by $-\alpha_c \times .5$ to yield α_h . In addition, as soon as α_h became less than $-\alpha_c \times 1.4$, the human period correction parameter β_h was changed from zero to $-\alpha_c \times .4$ and α_h was reduced to $\alpha_i - \alpha_c \times .1$. This had the consequence of maintaining an immediate phase adjustment of $\alpha_h + \beta_h = \alpha_i - \alpha_c \times .5$. The resulting fits were still not as good as those in Experiment 1, but they were satisfactory on the whole.

As is shown in Fig. 3C, the variability of asynchronies increased systematically with $-\alpha_c$, reflecting increasing task difficulty. The data are fit very well by a positively accelerated quadratic function. The simulated functions show similar, nearly quadratic shapes; their minima at low values of $-\alpha_c$ are a curve-fitting artifact. The best-fitting function corresponds to an α_i (when $-\alpha_c = 0$) of .525 or .55, which is unexpectedly high, given the results of Experiment 1 where the estimated $\alpha_i = \alpha_h$ was .42. It is possible that the context of difficult conditions in other trials (when $-\alpha_c > 0$) within a block raised α_i . However, the α_i estimates from the correlational data in this experiment are lower than those from the variability data.

Fig. 3D shows that the variability of the ITIs is larger than that of the asynchronies but likewise increases in a smooth, quadratic fashion with $-\alpha_c$. The simulated functions are approximately quadratic also, and the best-fitting function is the one for initial $\alpha_h = .55$, although it overestimates the initial variability.

The mean AC1 as a function of $-\alpha_c$ is shown in Fig. 3E. This function, too, is fit well by a quadratic function, but a negatively accelerated one in this case. The AC1 increases initially with $-\alpha_c$ but then approaches an asymptote near a value of .7. This contrasts with the linearity of the AC1 for positive α_c (Fig. 1E). The AC1 values obtained by Vorberg (2005) for $-\alpha_c = .25$ and .5 (the only values of $-\alpha_c$ used in that study) are in good agreement with the present data. The simulated functions are quadratic and very similar in shape to the

empirical function. The best-fitting function is the one for $\alpha_i = .425$, which is in excellent agreement with Experiment 1.

Finally, Fig. 3F shows the mean AC1 of the ITIs as a function of $-\alpha_c$. This function is S-shaped and is fit well by a cubic function. The AC1 changes from negative to positive, with an apparent asymptote on either side and with a zero crossing in the vicinity of .4. The zero crossing may constitute an estimate of α_i , although this remains to be proven. The simulated data, although fit well by cubic functions, fail to capture the positive asymptote of the empirical function. However, the best-fitting function again corresponds to an initial α_h of .425 or .45.

4.1.3. IOIs

Fig. 4A shows the individual mean IOIs, which are virtually identical with the mean ITIs (Fig. 3B), as they should be if participants maintained synchrony on the whole. In Fig. 4B we see the standard deviation of the IOIs as a function of $-\alpha_c$. This parabolic function through zero is quite similar to that for the variability of the ITIs (Fig. 3D), but the variability is lower here because of the absence of timekeeper variability. The simulated data are also roughly parabolic, and the best-fitting function is the one for an initial α_h of .55.

Fig. 4C plots the mean AC1 of the IOIs as a function of $-\alpha_c$. It follows a negatively accelerated parabolic function that is highly similar to that of the mean AC1 of the asynchronies (Fig. 3E), except for the missing data point at $-\alpha_c = 0$. The explanation of this near-identity is the same as was given in connection with Figs. 1E and 2C (see above). The simulated data, too, match those in Fig. 3E.

Fig. 4D shows the mean ITI-IOI CC1, a measure of the degree to which the computer tracked the participants' ITIs. This function is mildly parabolic in shape and rises from negative to positive values, with a zero crossing in the vicinity of $-\alpha_c = .5$. This point is again a possible estimate of α_h , although a formal proof of this remains to be given. It is interesting to compare this function to that for positive α_c in Fig. 2D. The two functions are by no means mirror images of each other, as one might naively predict from the change in the sign of α_c . While the IOIs track the ITIs perfectly when $\alpha_c = 1$, there is merely a weak tendency in the same direction when $-\alpha_c = 1$. The simulated data are fit well by quadratic functions and closely resemble the empirical function. The best-fitting function is the one for an initial α_h of .45.

Fig. 4E plots the ITI-IOI CC0, a measure of participants' prediction or matching of the computer's IOIs. This quadratic function increases from about .55 to .88, and the very small inter-individual variability should be noted, which suggests that this correlation, like that in Fig. 2D, is determined by the computer's negative phase correction algorithm. In other words, the algorithm forced participants to produce ITIs that increasingly matched the computer's simultaneous IOIs; or, put differently, the computer produced IOIs that increasingly matched the participants' ITIs. This contrasts with the total lack of such matching when α_c was positive (Fig. 2E). The simulated data here give rise to clearly quadratic functions as well, but they overestimate the correlations for small values of $-\alpha_c$. The best-fitting function would have an α_i well below .4, which cannot be right. This reveals another shortcoming of the current simulation.

Finally, Fig. 4F shows the IOI-ITI CC1, a measure of the degree to which participants tracked the computer's IOIs with their ITIs. The function is once again quadratic. It starts at a lower value than the function in Fig. 4E but reaches a similarly high value, though

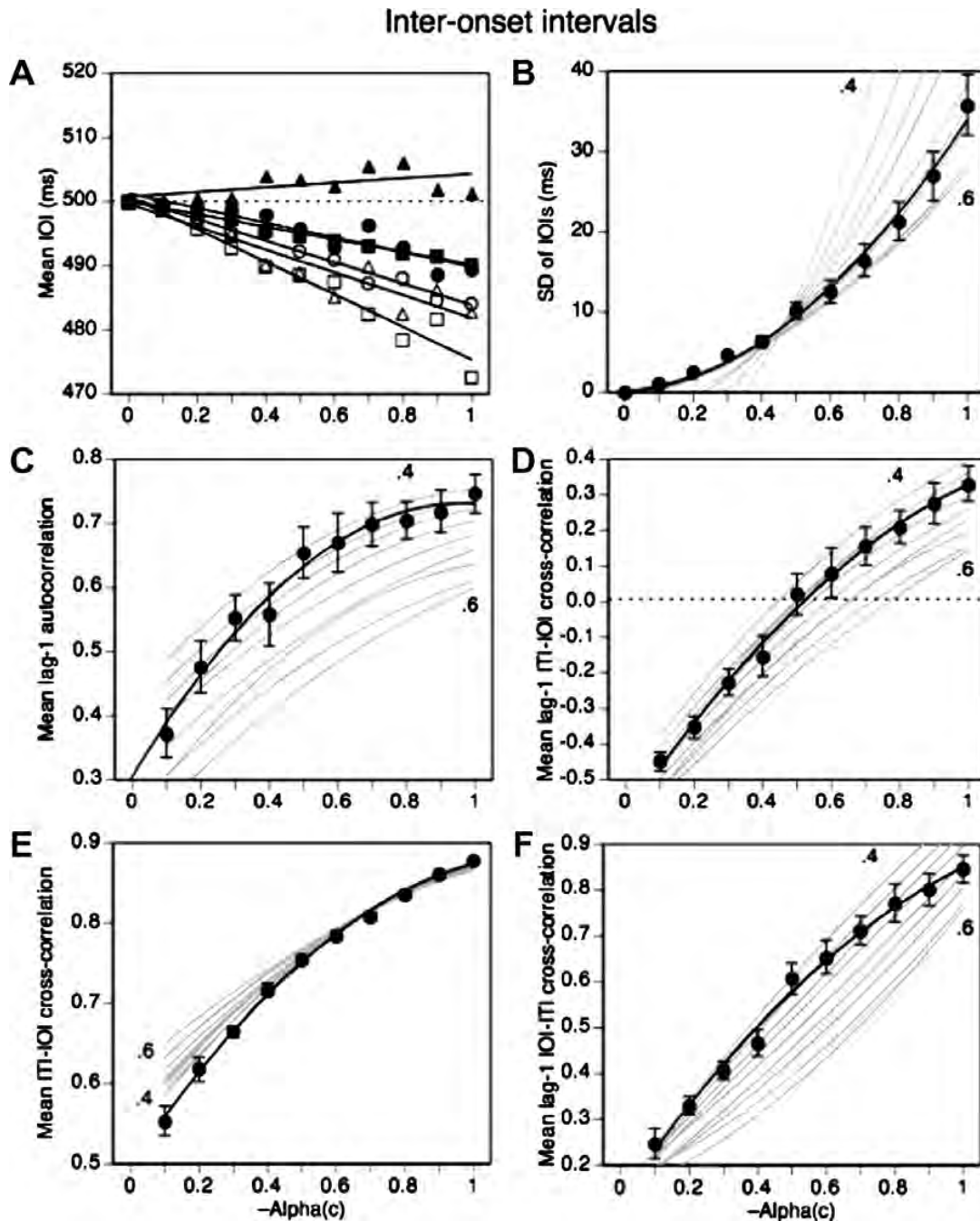


Fig. 4. Experiment 2: Sequence inter-onset interval data as a function of $-\alpha_c$.

with greater inter-individual variability. The simulated data here fail to capture the curvilinearity of the empirical data at high values of $-\alpha_c$. The best-fitting function has an α_i of about .45.

Although all correlation data were fit well by smooth functions, there is a suggestion of a discontinuity between $-\alpha_c$ values of .4 and .5. This may signal the adoption of a new strategy by human participants, such as the engagement of period correction.

4.1.4. Summary

One important finding of this experiment is that all (musically trained) participants were able to cope with potentially unstable situations, resulting from a highly uncooperative

computer. They quickly found strategies that enabled them to maintain synchrony, albeit with increased variability. These strategies apparently required not only the engagement of period correction (assumed to be largely under cognitive control) but also substantial increases in the gain of phase correction, which we previously thought was mostly automatic and rather inflexible (Repp & Keller, 2004). Previous studies have suggested that phase correction can be decreased voluntarily, though not suppressed completely (Repp, 2002; Repp & Keller, 2004). The present data suggest that phase correction can also be increased substantially when the situation requires it (though see the General Discussion for a qualification of that conclusion). This amounts to an increased sensorimotor coupling, which is consistent with the finding that all autocorrelations and cross-correlations are positive and, for the most part, quite high when $-\alpha_c$ is high. It results in an irregular slow oscillation of the interval time series, with the computer leading the participant (because the correlations in Fig. 4F are much higher than the ones in Fig. 4D). Plots of raw time series exhibiting such oscillations can be found in Vorberg (2005).

5. Experiment 3

Experiment 3 introduced period correction to the computer's capabilities and thereby went beyond the conditions explored by Vorberg (2005). No additional phase correction was specified, which means that the computer's immediate phase adjustment in response to any asynchrony was the same as in Experiment 1, but there was an aftereffect of the phase adjustment on the computer's period. The main difference between Experiment 3 and Experiment 1 thus was that the computer's timekeeper period was flexible in Experiment 3. This was not expected to pose any problem to participants, but they had now an increased responsibility of controlling and maintaining the tempo. To be successful in this, their internal period had to be close to 500 ms, and period correction had to be suppressed.

The best strategy might have been simply to tap as regularly as possible and let the computer do the synchronization. It is known from earlier studies, however, that phase correction cannot be disengaged completely (Repp, 2002; Repp & Keller, 2004). Therefore, we expected that the human data would follow a pattern that could be simulated with a fixed α_h , as in Experiment 1, but that the best-fitting value of α_h might be lower than in Experiment 1.

5.1. Results and discussion

5.1.1. Practice effects

There were no significant changes in any of the dependent variables across trial blocks. Performance was generally stable.

5.1.2. Asynchronies and ITIs

No participant had any trouble with the tasks in Experiment 3, and there were no missing data. As mentioned earlier, however, two participants had to be excluded in this and subsequent experiments because they did not maintain the tempo. Although their performance was by no means unsystematic, separate discussion of their results would lead too far here.

Fig. 5A shows the individual mean asynchronies of the remaining four participants as a function of β_c . There are two interesting findings here. First, the small mean asynchronies observed in the baseline condition ($\beta_c = 0$) converge onto zero as soon as $\beta_c > 0$. These data demonstrate that even minimal period correction by the computer results in a symmetric distribution of the tone onsets around the taps. The second interesting result is that the baseline asynchronies differ from those in Experiments 1 and 2 (see Figs. 1A and 3A), even though the isochronous baseline condition is exactly the same in all experiments. Three participants who showed positive baseline asynchronies in Experiments 1 and 2 now have negative baseline asynchronies. This finding demonstrates that the experimental context can change the asynchronies for isochronous sequences. This change may be

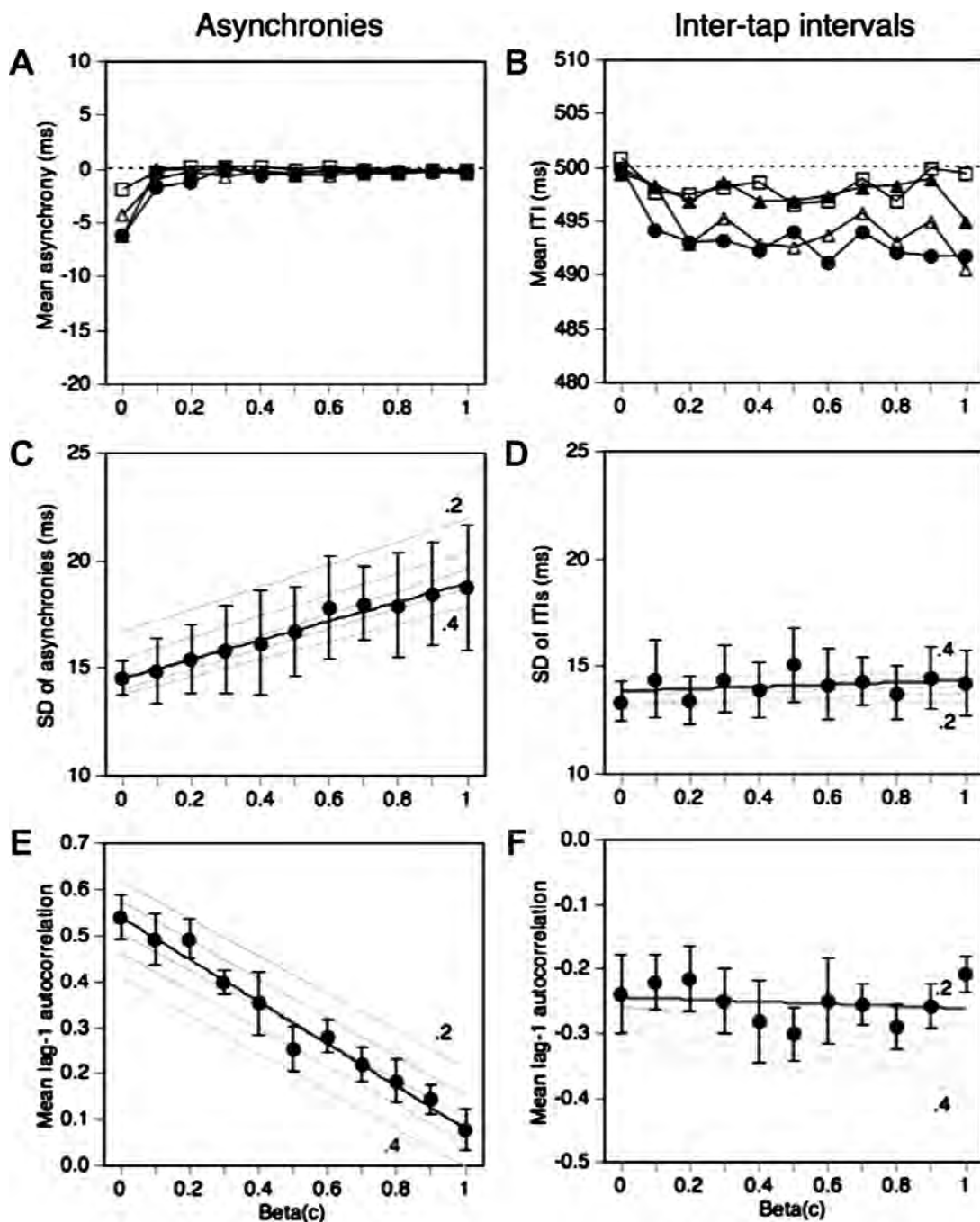


Fig. 5. Experiment 3: Asynchrony and inter-tap interval data as a function of β_c .

related to participants' intention to keep the tempo and "lead" the computer, for the two excluded participants (who clearly did not adopt a leading role) continued to show positive baseline asynchronies.

Different baseline asynchronies can easily be simulated by setting $C \neq 500$, and we found that the simulated mean asynchronies indeed converge rapidly onto zero when $\beta_c > 0$. However, the value of α_h also affects the baseline mean asynchrony. In general, the mean baseline asynchrony was at least twice as large as $500 - C$ (cf. Fig. 1A, where asynchronies are plotted for $C = 490, 495, 505,$ and 510 ms, with $\alpha_h = .4$), and it increased further as α_h decreased. Therefore, the obtained baseline mean asynchronies suggest only very small deviations of C from 500 ms.

Fig. 5B depicts the mean ITIs as a function of β_c . All four participants were quite accurate in maintaining the tempo. They showed a slight acceleration that was roughly the same for all values of $\beta_c > 0$. This contrasts with the linear change in their mean ITI as a function of α_c in Experiment 1 (Fig. 1B). As one might expect, setting C to a value less than 500 ms in the simulations resulted in mean ITIs equal to C . In other words, participants tapped at a tempo that corresponded to their internal period. We just noted, however, that the simulated baseline asynchronies were at least twice as large as $C - 500$. Thus, the obtained initial asynchronies (Fig. 5A) seem rather too small compared to the deviations of the mean ITI from 500 ms. It seems that participants' internal period was closer to 500 ms in the baseline condition than in the other conditions.

Fig. 5C shows the variability of the asynchronies as a function of β_c . The mean standard deviation increases linearly with β_c , although the increase is rather small. The simulated functions are linear as well and have similar slopes. The best-fitting function is the one for $\alpha_h = .3$ or $.35$. To achieve this fit, the standard deviation of the human timekeeper (C) had to be reduced from 12 to 10 ms; this may reflect either an effect of practice or the exclusion of two participants whose variability was relatively high.

The variability of the ITIs (Fig. 5D), by contrast, is lower and quite independent of β_c . This is also reflected in the simulations. The best-fitting functions are again the ones for $\alpha_h = .3$ and $.35$.

Fig. 5E shows that the AC1 of the asynchronies decreases linearly as β_c increases. Unlike the linear AC1 function in Experiment 1 (Fig. 1E), however, it starts out higher and does not cross zero. Thus, α_h cannot be estimated from a zero crossing here. The simulated functions are linear and parallel, and the best-fitting function is the one for $\alpha_h = .3$.

Finally, as can be seen in Fig. 5F, the AC1 values for the ITIs are somewhat variable but relatively constant at a small negative value, in contrast to those in Experiment 1 (Fig. 1F), which decrease linearly as α_c increases. This suggests that the participants adopted the appropriate strategy of self-pacing their taps and leading the computer. The AC1 values are similar to those expected in self-paced (unsynchronized) tapping, according to the well-known model of Wing and Kristofferson (1973); see also Vorberg and Wing (1996). The simulated data suggest a very mild dependency on α_c . They also miss their target in this case. The best-fitting function would be one with $\alpha_h = .15$, which is clearly too low a value.

5.1.3. IOIs

The results of the IOI analyses are shown in Fig. 6. The mean IOIs (Fig. 6A) are again almost exactly equal to the mean ITIs (Fig. 5B), which demonstrates that all participants were able to maintain synchrony.

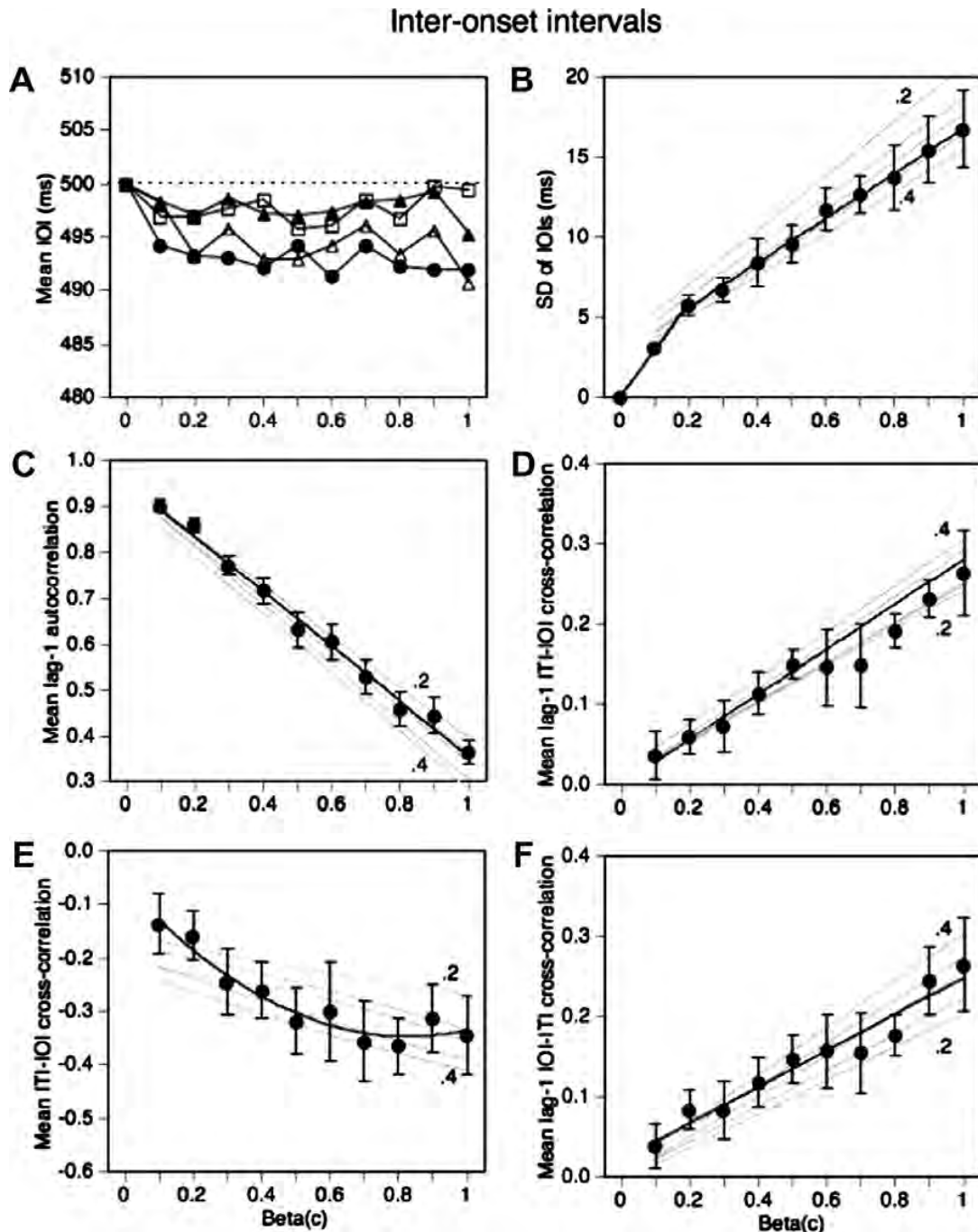


Fig. 6. Experiment 3: Sequence inter-onset interval data as a function of β_c .

Fig. 6B shows that the variability of the IOIs increased linearly with β_c between values of .2 and 1. The clearly steeper initial increase between values of 0 and .2 has been excluded from the linear fit here. The simulated functions are linear also and include the data point for $\beta_c = .1$, but not the one for $\beta_c = 0$. The best-fitting function is the one for $\beta_c = .35$. It is noteworthy that IOI variability increased steadily whereas ITI variability remained constant in this experiment (Fig. 5D). A similar finding was reported by Madison and Merker (2004), where the variability of ITIs began to increase only when the variability of the IOIs reached about the same magnitude.

Fig. 6C shows the AC1 of the IOIs as a function of β_c . In Experiments 1 and 2, where only α_c was varied, this AC1 function was the same as that for the asynchronies. Now that

β_c is varied, this is no longer the case. The function is similarly linear with a negative slope, but the absolute values are much higher for IOIs than for asynchronies, presumably reflecting the oscillations of the computer-controlled tones around the taps. The computer simulations generated similar functions, and the best-fitting function is the one for $\beta_c = .25$.

The CC1 functions for ITIs and IOIs (Figs. 6D and F) can be considered together because they are almost identical. In other words, it does not matter much which time series is lagged in computing these correlations. The function starts out near zero and increases linearly with β_c . The simulated functions are linear as well, and the best-fitting function appears to be the one for $\beta_c = .3$. These data are in stark contrast to the lag-1 cross-correlation functions in Experiment 1 (Figs. 2D and F), which differ radically from each other.

Finally, the CC0 between ITIs and IOIs (Fig. 6E) is mildly negative and seems to decrease first and then reach an asymptote as β_c increases. The simulated functions are fairly linear, however. Thus the fit to the empirical data is not very good here, but the function for $\beta_c = .3$ comes closest.

5.1.4. Summary

The results of this experiment are consistent with the prediction that participants would basically take the lead and tap steadily while letting the computer follow them. As in Experiment 1, the data can be modeled quite well by assuming that a fixed value of α_h was maintained throughout. As expected, phase correction could not be suppressed completely, but the estimated mean value of about .3 is lower than the mean estimated α_h (.37) of the same four participants in Experiment 1 (BR, IF, JW, and SH in Table 1). Although the computer engaged in period correction, there was no need for human participants to engage in period correction or even to adjust their α_h . The computer cooperated by following the pace set by participants and by nulling their mean asynchronies.

6. Experiment 4

Experiment 4, like Experiment 2, implemented a condition that was challenging for participants. The phase correction effected by immediate period correction was canceled by negative phase correction (i.e., $-\alpha_c = \beta_c$), so that period correction took effect in the next cycle without any phase adjustment in the current cycle. Thus the computer reacted to participants behavior in a delayed, essentially uncooperative fashion.

6.1. Results and discussion

Participants indeed found this task challenging when β_c approached 1, but all of them were nevertheless able to maintain synchrony in all conditions, with only occasional taps that fell outside the tolerance limit for asynchronies, which was set at $\pm 25\%$ of the current IOI. Asynchronies exceeding these limits were not recorded and thus resulted in missing taps. A significant number of such missing taps occurred with only two participants, the highest individual percentage being 6.6% when $\beta_c = 1$. There were no phase slips, and no trials had to be excluded from analysis.

The data proved to be difficult to approximate via simulation, however. Similar to Experiment 2, α_h needed to increase as β_c increased (see Table 2). As will be seen in the

figures below, the resulting auto- and cross-correlation functions generally matched the empirical functions in slope, but they were uniformly too low. Attempts to achieve better matches by introducing human period correction were not successful. (It should be noted that introducing human period correction is problematic in this experiment because it is the human participant's task to keep the baseline tempo.) Yet, it is clear that the higher values of the empirical auto- and cross-correlations must reflect either a slow modulation or (less likely) a unidirectional drift of the asynchronies and ITIs. An effective way of generating this slow modulation in simulations remains to be determined. For example, it could be due to intermittent period correction or resetting, which may be triggered by large deviations from the target tempo. This would require a β_h parameter that can vary within a trial and a separate stable tempo memory.

6.1.1. Practice effects

Despite the relative difficulty of the task, there was no significant change in any of the dependent variables across blocks.

6.1.2. Asynchronies and ITIs

The baseline mean asynchronies (Fig. 7A) are again somewhat different from previous experiments, which suggests effects of context. As in Experiment 3, the mean asynchronies approach zero as soon as $\beta_c > 0$. The mean ITIs (Fig. 7B) are close to 500 ms throughout for two participants but diverge increasingly as β_c increases for the other two. Setting C to a value different from 500 ms yields results similar to those in Experiment 3: a constant deviation of the ITI from 500 ms when $\beta_c > 0$, and asynchronies that are at least twice as large as the ITI deviation. The obtained asynchronies thus appear too small for the two participants who did not keep the tempo precisely. Thus, the asynchrony and ITI data are not well explained at present.

The standard deviations of the asynchronies and ITIs (Figs. 7C and D, respectively) increase as a quadratic function of β_c , quite similar to the functions observed in Experiment 2 (Figs. 3C and D), though a bit steeper. The simulated function for an α_i of .45 provides a good fit to the ITI function, but it is initially shallower and later steeper than the empirical function for asynchronies.

The convex AC1 function for asynchronies (Fig. 7E) is different from that in Experiment 2, and its downward turn at higher values of β_c is not captured by the simulation. The AC1 function for ITIs (Fig. 7F) is S-shaped (cubic) and similar to the one in Experiment 2. The asymptote at high values of β_c again is not modeled well, but otherwise the simulated slope seems right.

The results for IOIs are shown in Fig. 8. As usual, the mean IOIs (Fig. 8A) are practically identical with the mean ITIs (Fig. 7B), which confirms that all participants were able to maintain synchrony in all conditions. The standard deviation of the IOIs (Fig. 8B), like that of the ITIs, follows a quadratic function of β_c , which is fit reasonably well by the simulated function for $\alpha_i = .45$.

As in Experiment 3, but unlike Experiments 1 and 2, the AC1 function for the IOIs (Fig. 8C) is quite different from the AC1 function for the asynchronies (Fig. 7E). It is linearly decreasing and shows only very small individual differences (standard errors). The simulation predicts the slope exactly. The CC1 of the ITIs and IOIs (Fig. 8D) is fairly irregular and not fit so well by a straight line. The CC0 (Fig. 8E), too, is not perfectly linear but, like the AC1, shows only minimal individual differences. The slopes of these

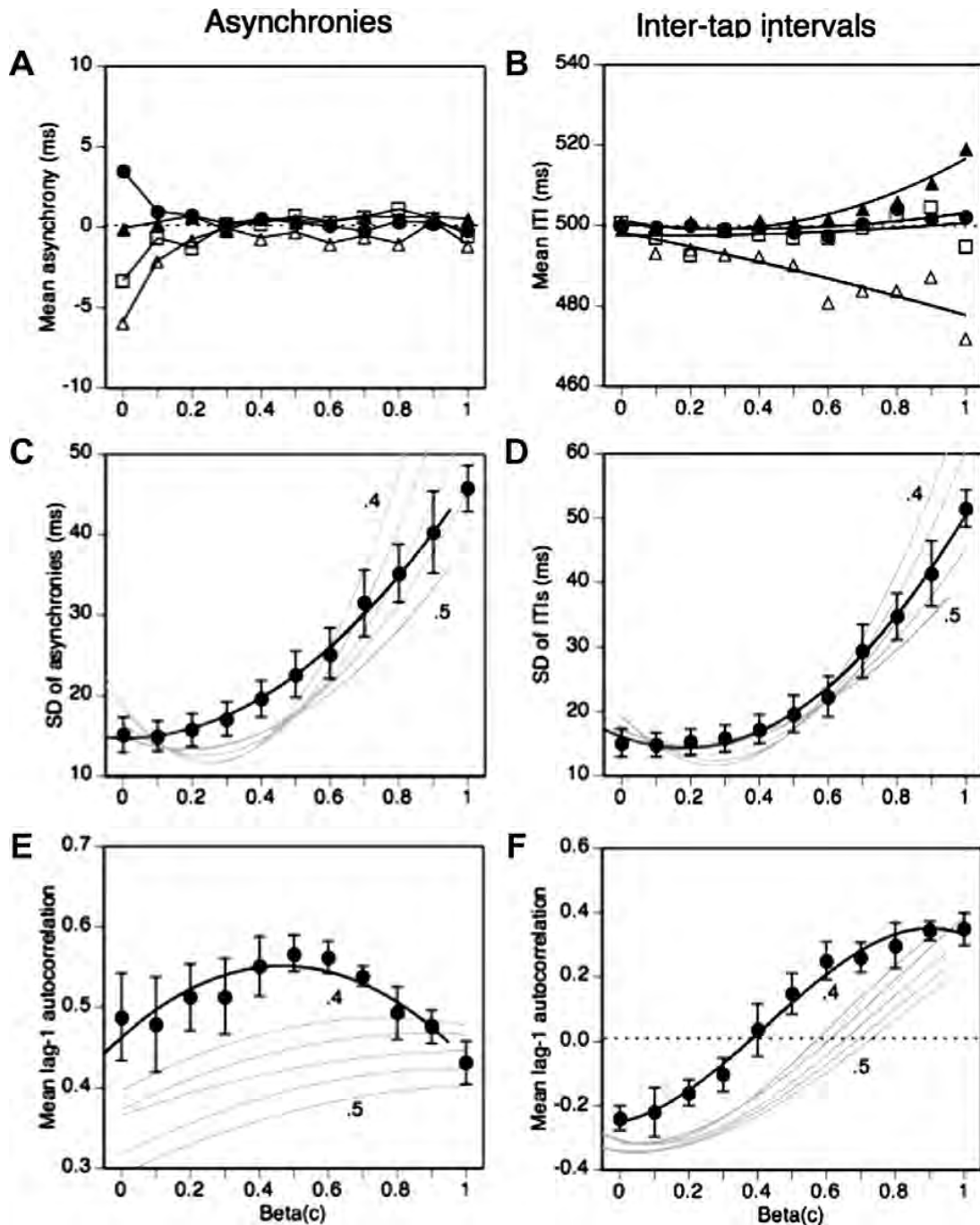


Fig. 7. Experiment 4: Asynchrony and inter-tap interval data as a function of β_c .

functions are again matched very well by those of the simulated functions, but the absolute values are way off. Finally, the CC1 of the IOIs and ITIs (Fig. 8F) shows a curvilinear pattern whose general slope, but not the asymptote, is captured by the simulation.

6.1.3. Summary

Although the computer was using an uncooperative strategy that was different from that in Experiment 2, participants were again able to cope and produced systematic and sometimes remarkably congruent patterns of data. In part, they achieved this by increasing their phase correction as β_c increased. However, there were also slow modulations in the asynchronies and ITIs that were not captured by the simulations.

Inter-onset intervals

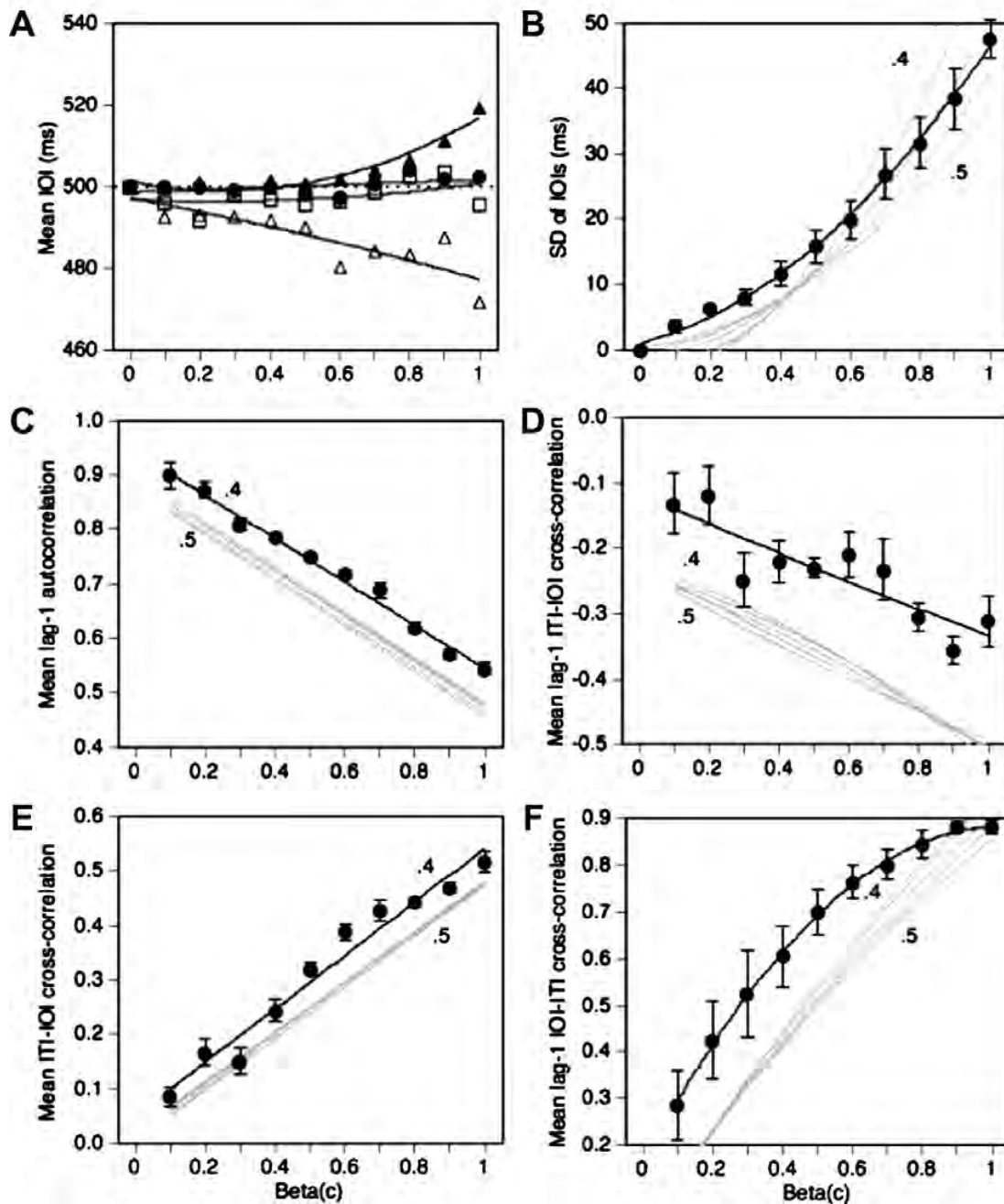


Fig. 8. Experiment 4: Sequence inter-onset interval data as a function of β_c .

7. Experiment 5

Our final experiment combined several values of $(\alpha_c + \beta_c)$ and β_c to create situations that perhaps are closest to what may be encountered in an interaction with another human participant. Typically, there will be both phase and period correction, but phase correction is likely to be stronger than period correction. We considered $(\alpha_c + \beta_c)$ rather than α_c as the relevant variable in our factorial design because $(\alpha_c + \beta_c)$ represents the immediate phase adjustment. In other words, the specific effect of period correction takes place only in the following cycle. None of the parameter combinations was expected to pose any difficulties for the participants. The main theoretical question of interest was whether

$(\alpha_c + \beta_c)$ and β_c would have independent or interactive effects on the various statistics derived from the data. In this experiment we did not conduct any simulations, and we also did not analyze the IOIs. We merely conducted 2-way repeated-measures ANOVAs on the data to test main effects and potential interactions of $(\alpha_c + \beta_c)$ and β_c .

7.1. Results and discussion

As expected, participants had no difficulties and also did not show any practice effects. The results for asynchronies and ITIs are shown as a function of $(\alpha_c + \beta_c)$ in Fig. 9. Each

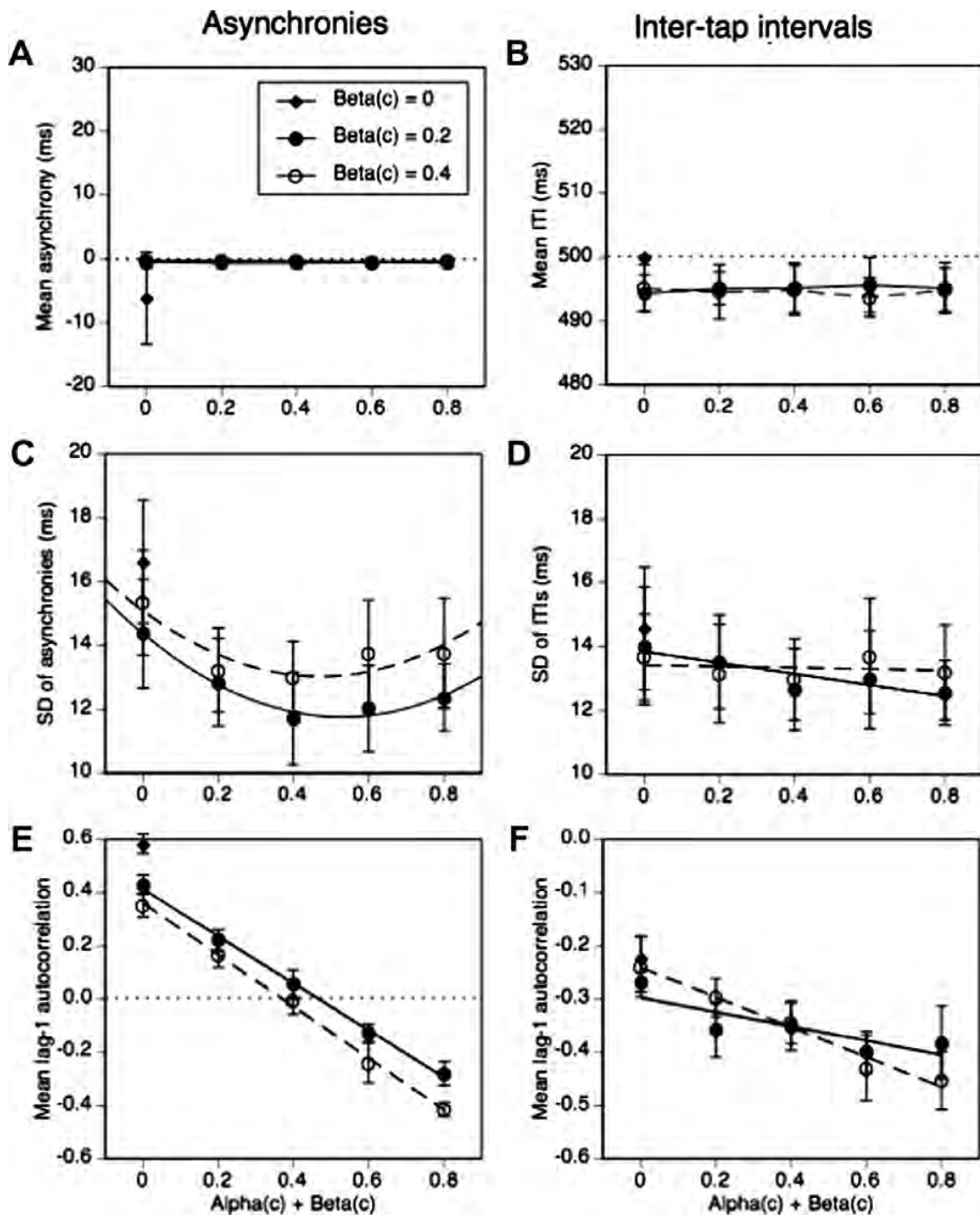


Fig. 9. Experiment 5: Asynchrony and inter-tap interval data as a function of $(\alpha_c + \beta_c)$ and of β_c .

graph contains separate functions for the two values of β_c (.2, .4), as well as an additional isolated data point for the baseline condition, $\alpha_c = \beta_c = 0$.

Fig. 9A shows the mean asynchronies, here averaged across participants. The mean asynchronies are slightly negative in the baseline condition (with considerable individual differences) but zero whenever $\beta_c > 0$, in agreement with Experiments 3 and 4. Fig. 9B shows the mean ITIs, which are constant at about 495 ms, except for the baseline condition, where the mean ITI is 500 ms. Clearly, there are no main effects or interactions here, so that ANOVAs are superfluous.

The standard deviations of the asynchronies (Fig. 9C) vary as a nonlinear (quadratic) function of $(\alpha_c + \beta_c)$, which replicates one crucial result of Experiment 1 (cf. Fig. 1C). The main effect of $(\alpha_c + \beta_c)$ is significant, $F(4, 12) = 6.22$, $p = .029$, although the quadratic component only approaches significance here, $F(1, 3) = 8.30$, $p = .063$, due in part to the small number of participants. Variability also increases as β_c increases from .2 to .4, as in Experiment 3 (Fig. 7C), $F(1, 3) = 32.05$, $p = .011$. The interaction is not significant. Unexpectedly, the variability in the baseline condition is the largest. The minima of the quadratic functions are located at $(\alpha_c + \beta_c) = .53$ and .47, respectively, which suggests values of $\alpha_h = .34$ and .40, respectively (assuming $\alpha_{opt} = .87$). Note that the α_h estimates would not make sense if the data were plotted as a function of α_c rather than $(\alpha_c + \beta_c)$; they would be .14 and 0, respectively.

Fig. 9D shows the variability of the ITIs, which exhibits little influence of either $(\alpha_c + \beta_c)$ or β_c , in agreement with the results of Experiments 1 (Fig. 1D) and 3 (Fig. 5D). There are no significant effects in the ANOVA.

The AC1 functions for asynchronies (Fig. 9E) show a linear decrease from positive to negative values as $(\alpha_c + \beta_c)$ increases, just as in Experiment 1 (Fig. 1E), $F(4, 12) = 152.71$, $p < .001$. There is also a significant decrease as β_c increases, $F(1, 3) = 18.29$, $p = .023$, in agreement with Experiment 3 (Fig. 5E). The interaction is not significant. The zero crossings of the functions are at $(\alpha_c + \beta_c) = .47$ and .37, respectively, which suggests $\alpha_h = .4$ and .5, respectively – values higher than the ones suggested by the variability functions in Fig. 9C. However, the increase in α_h is consistent with that assumed in the simulations of Experiment 4, namely $\alpha_h = \alpha_i + .5 \times \beta_c$, if $\alpha_i = .3$.

Finally, the AC1 functions for the ITIs (Fig. 9F) show a slight decrease as $(\alpha_c + \beta_c)$ increases, $F(4, 12) = 11.67$, $p = .012$, as in Experiment 1 (Fig. 1F), and there is no clear effect of β_c , in agreement with Experiment 3 (Fig. 5F). There is a suggestion of an interaction in the data, but it is far from significant in the ANOVA, $F(4, 12) = 1.93$, $p = .242$.

7.1.1. Summary

This experiment produced orderly data that match those of preceding experiments. Moreover, the data suggest that $(\alpha_c + \beta_c)$ and β_c have independent effects on human participants' behavior, at least within the range investigated.

8. General discussion

The present study replicates and extends Vorberg's (2005) pioneering research on SMS of a human participant with a computer capable of error correction. Vorberg investigated only phase correction. Experiments 1 and 2 resemble his studies but used a wider range of more narrowly spaced parameter values; the results were more detailed but quite similar

where they could be compared. This despite the fact that Vorberg used only the final data of a highly practiced group of participants, whereas the present participants were given little task practice prior to data collection. Except for a reduction of variability in the course of Experiment 2, there was little evidence of change as a function of practice in the present experiments. The participants were all musically trained, however, and one of them (author BHR) had extensive experience with SMS tasks. (His results were generally similar to those of the other participants.)

Experiments 3–5 went beyond Vorberg's experiments in that they added period correction to the computer's capabilities. There has been much less research on period correction than on phase correction, and consequently that process is less well understood. In theory, period correction can be based on either differences in intervals ($IOI_n - C_n$) or on differences in time points (asynchronies). This distinction concerns the informational basis of period correction, and it results in models that are not formally identical. We have chosen the second model here over the first one (cf. Schulze, Cordes, & Vorberg, 2005), for reasons stated earlier. The results of simulations using one or the other model do not seem to differ greatly, but this observation is based on limited explorations.

One major finding of the present study is that SMS with a cooperative computer can be modeled quite successfully by assuming that human participants adopt a fixed value of α_h and do not engage in period correction, regardless of whether the computer carries out phase correction (Experiment 1) or period correction (Experiment 3). This implies that human participants do not adopt any strategies to prevent phase under-correction (if α_c is low) or over-correction (if α_c is high). If the computer engages in immediate period correction (without additional phase correction), participants seem to reduce their α_h somewhat, as was suggested by the comparison of the α_h estimates emerging from Experiments 3 and 1. This amounts to a reduced sensorimotor coupling and suggests some degree of (not necessarily cognitive) control over phase correction, particularly in reducing α_h , as shown in some previous studies (Repp, 2002; Repp & Keller, 2004). What remains is presumably an automatic component of α_h that cannot easily be turned off, at least as long as synchronization is intended.

This mandatory phase correction may be sufficient for maintaining synchrony in the context of ensemble music characterized by rubato (i.e., systematic variations in local tempo). Here, while the musician acting as leader modulates his or her timekeeper period with expressive intentions, it would be counterproductive for the other musicians to engage in period correction (except in cases of extreme rubato), as this could lead to large-scale tempo drift affecting the ensemble as a whole. (The two devious participants who did not maintain the correct tempo in Experiments 3–5, and whose data were excluded from the reported analyses, presumably were actively engaging in period correction.) In this regard, it is also worth noting that when the computer was programmed to implement period correction, the human participants were forced to assume responsibility for maintaining the correct tempo and thereby to play the role of the leader. Our participants apparently adopted this leadership role rather zealously, as the results of Experiments 3 and 5 suggest that they set their timekeepers to be slightly faster than the target periodicity. In real musical contexts, this strategy may serve to counteract the tendency for tempi to drag, rather than rush, during performance of challenging music. (Note that this was in fact the fate of our devious participants, whose tempo slowed down substantially as they let themselves be led by the computer.) Adopting faster-than-target tempi may reflect an attempt to lead, quite literally, by acting before one's

partner(s) or by generating greater movement velocities in order to produce louder sounds (though this of course would have been an ineffectual strategy in our experiments).

In the simulations of Experiment 2, we found it necessary to assume human period correction when $-\alpha_c$ got large, but the major human strategy seemed to be an increase in α_h . Similarly, in simulating the results of Experiment 4, we found it necessary to assume that α_h increased linearly as a function of β_c . Period correction could not be introduced in the simulations of Experiment 4 because the participants had to maintain the tempo, and period correction by definition results in an unstable tempo. So, the second major finding of our study is that human participants seem to be able to increase their α_h very substantially (up to 1 at least) when the situation requires it. This is a new finding (although [Vorberg, 2005](#), reached the same conclusion), and it suggests that people have much more control over phase correction than was previously assumed. The control is not necessarily cognitive; the adjustment of α_h may occur automatically in response to task requirements. Adjusting the gain of phase correction may be useful when playing in ensembles where it is initially difficult to anticipate upcoming expressive timing because the stylistic idiosyncracies of other ensemble members, or the music itself, are unfamiliar. Phase correction gain may be reduced as familiarity grows.

It could be argued that, rather than increasing their phase correction, participants actually carried out period correction while at the same time maintaining a long-term memory of the target tempo. This seems like a contradiction, but it is exactly what music performers are doing when they are modulating tempo expressively while maintaining a constant overall tempo. In a synchronization task, however, “local” period correction amounts to phase correction and would show up as an increase in α_h . Therefore, this is not an alternative explanation of our findings but just another (perhaps, better) way of saying that participants adapted their coordinative strategies to the situation. It is likely that participants engaged in local period correction (i.e., augmented phase correction) intermittently rather than continuously, namely whenever they detected an asynchrony. This could be investigated in future work by simulating performance at the individual trial level.

The present research was conceived as preparatory to an investigation of synchronization between two human participants. One way in which our experiments differed from a true dyadic situation was that the computer algorithms were deterministic, without any random noise components. This was deliberate; we thought we would obtain more systematic results that way. In a realistic dyad, however, both participants are fraught with biological noise, so that their behavior is more difficult to predict. The predictability of the computer’s behavior within each trial, and to some extent within each experiment, may have facilitated the tasks for the present participants. It would be straightforward to add noise to the IOIs in the computer simulations and examine its effects on the results; this remains to be investigated. It could also be argued that different forms of noise should be considered in the simulations. For example, timekeeper noise might be drawn from a gamma distribution rather than a normal one (as done by [Semjen et al., 2000](#)), whereas motor noise might be drawn from a normal distribution (as is done in most applications of the Wing–Kristofferson model). We have chosen a gamma distribution for motor noise here because motor delays probably have an absolute minimum, but a normal distribution for timekeeper noise because timekeeper intervals are not obviously constrained in their variation. Furthermore, one might consider introducing a form of timekeeper noise that

generates long-term dependencies in asynchronies, which have been observed in several studies (Chen, Ding, & Kelso, 1997, 2001; Chen, Repp, & Patel, 2002). In the present simulations we simply added noise to a constant (or adjustable) timekeeper interval duration, but it would perhaps be more realistic to let the noise affect the memory of the timekeeper interval. (We tried this in some simulations and found it did not affect the results much.)

When two (or more) human participants are required to coordinate their actions, they may adopt the role of leader or follower. The intricacies of such role-taking in realistic music performance and dance have recently been discussed by [Maduell and Wing \(2007\)](#). In the present study, participants' role-taking was not manipulated directly, but the computer's programmed behavior had definite consequences in that regard. When the computer's timekeeper period was inflexible, the computer could follow a human leader only to a limited extent. Basically, therefore, the human participant had to assume the role of follower, letting the computer set the pace. When the computer was capable of period correction, its human partner could either take the lead in setting the pace or (like the two excluded participants) take a more passive attitude and let the tempo drift. In the former case, human phase correction was somewhat reduced but by no means eliminated; human period correction was absent. In the latter case (which we did not attempt to model via computer simulations), human period correction would clearly occur together with normal or possibly enhanced phase correction. The two participants who did not keep the tempo were nevertheless quite accurate in keeping synchrony. Thus the results of the present study outline the strategies that people have available in an interactive situation that requires temporal coordination.

In conclusion, the present study presents a preliminary step towards investigating synchronization between individuals and had the following main findings: When faced with a cooperative partner, human participants (musically trained) do not change their synchronization strategies but rather operate with a constant gain of phase correction. When faced with an uncooperative partner, however, they appear to be capable of increasing the gain of their phase correction considerably. An additional engagement of period correction seemed to occur when the computer could be relied upon to maintain the tempo. When the computer's period was flexible, however, human period correction would have led to instability, although the human behavior was not sufficiently explained by phase correction alone. The simple linear two-process model of error correction applied here may have to be expanded to deal with this last case. Potential avenues for expansion include the introduction of hierarchically arranged timekeepers to allow for intermittently applied period correction or slow modulations in timekeeper period (analogous to *rallentandi* and *accelerandi* observed in music; cf. [Schulze et al., 2005](#)).

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