

# The Dynamics of Attending: How People Track Time-Varying Events

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A theory of attentional dynamics is proposed and aimed at explaining how listeners respond to systematic change in everyday events while retaining a general sense of their rhythmic structure. The approach describes attending as the behavior of internal oscillations, called *attending rhythms*, that are capable of entraining to external events and targeting attentional energy to expected points in time. A mathematical formulation of the theory describes internal oscillations that focus pulses of attending energy and interact in various ways to enable attentional tracking of events with complex rhythms. This approach provides reliable predictions about the role of attending to event time structure in rhythmical events that modulate in rate, as demonstrated in 3 listening experiments.

Virtually all things in one's environment have extension in time, some too brief to be perceptible and others too long to be imagined. Everyday events, however, occur at time scales over which one can attend. When people hear friends engage in a conversation or listen to a familiar tune, when they watch a basketball game, or when they observe a mother–infant exchange, they are engaged by temporally patterned changes occasioned by natural forces. Such events comprise actions and movements that display distinct beginnings, recognizable rhythms, characteristic tempos, and lawful endings (e.g., Bertenthal & Pinto, 1987; Boltz, 1992; Johansson, 1973; Johansson, von Hofsten, & Jansson, 1980; Jones, 1990; Neisser & Becklen, 1975; Pickett, 1980; Pike, 1945). Yet, there is a fascinating element of flexibility in the time structure of natural events. Temporal relationships modulate as events unfold: Rates change, rhythms vary, and structures transform.

This presents a puzzle. The puzzle is most evident in dynamic events in which a clear temporal structure is apparent, yet the temporal components are not fixed. This happens, for instance, when a song increases in tempo or when a moving basketball player relaxes the rate of a dribble. The puzzle is as follows: Observers appear to apprehend stable rhythmic structures in such events, even as the periodicities that compose these structures fluctuate greatly. Although this phenomenon is common, only

recently has it received much attention, largely in studies of musical events. Typically, musical performers shape the structure of melodies and rhythms to their own ends, playing ahead of an implied beat, modulating tempo, adding expressive emphasis, and so on. Consequently, the acoustic patterns they produce exhibit great temporal flexibility (e.g., Gabrielsson, 1986; Palmer, 1989; Repp, 1992; Shaffer, 1981, 1982). Yet, listeners are readily able to identify the meter, recognize the rhythm, and follow the tempo, as well as perceive meaning in deviations from the implied structure (Epstein, 1995; Palmer, 1989).

Figure 1 illustrates this. Panel A shows a notated sequence of pitches (a melodic phrase); Panel B shows a performance of the pitch sequence (an event) recorded on a computer-monitored piano (Large, Palmer, & Pollack, 1995). The sequence in Panel C illustrates onset times and amplitudes of successive notes. Although the score prescribes a strict rhythmic pattern, the rhythmic proportions actually produced in this performance vary greatly (e.g., to 40% of the mean beat duration), as indicated in Panel D, where the relative duration of each interonset interval (IOI) is plotted.<sup>1</sup> Rate varies locally, first accelerating (relative IOI decreases) and then decelerating (relative IOI increases) as the performer shapes this phrase. Similar distortions occur in speech, in which rate and other timing features vary (e.g., hesitations and expressive contrasts), thus rendering problematic simple and precise descriptions of speech rhythms (e.g., Lehiste, 1977; Remez, Rubín, Berns, Pardo, & Lang, 1994). Yet, in both domains, such variations are often well placed and meaningful. For example, at two points in this event, tempo systematically decreases; this so-called “phrase final lengthening” is a typical marker of phrase endings both in music and in speech (e.g., Lehiste, 1977; Palmer, 1989). People can follow such changes, often anticipating a rate change or a significant rhythmic deviation. Furthermore, despite such temporal fluctuations, people respond to underlying invariants, recognizing rhythm and meter. An aspect of this puzzle, then, is that people seem capable of

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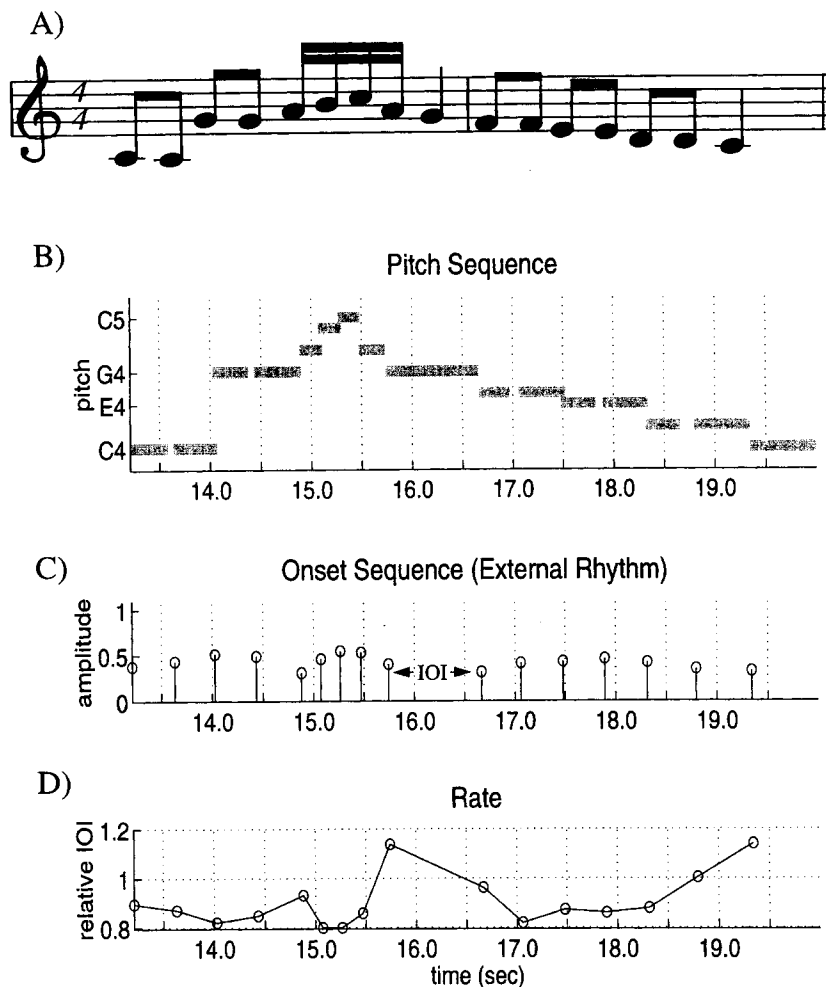
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<sup>1</sup> Relative IOI is performed IOI divided by notated IOI, normalized for average rate (1.0 on the ordinate indicates mean beat duration).



*Figure 1.* A notated melodic phrase (A) performed (B) on a computer-monitored piano (see Large, Palmer, & Pollack, 1995). Onset times and amplitudes of successive pitches produced in B are selected to express the external rhythm as an onset sequence in C. Shown is an interonset interval (IOI), the interval of time from one onset to the next. D: Rate (tempo) as relative IOI; that is, each performed IOI (C) is divided by the corresponding notated IOI and normalized such that 1.00 represents average rate.

comprehending a stable underlying temporal structure while at the same time responding meaningfully and adaptively to changing aspects of the time pattern.

We suggest that the answer to this puzzle lies in understanding how people attend to events that have extent in time. Relatively little is known about how people accomplish these feats, in part because the dynamics of attention are not well understood. Moment-to-moment attending to events in time has not played a significant role in most contemporary attention theories, which tend to concentrate on search responses to static visual arrays. Consequently, the hallmark of attending—selectivity—often refers to a selectivity of visual attention in space postulated to derive from a spatial spotlight (Tsal, 1983), an adjustable focus lens (Ericksen & St. James, 1986), a spatial gradient (LaBerge, 1995), feature integrating glue (A. M. Treisman & Gelade, 1980), or object files (A. Treisman, 1992), among other things. But if William James (1961) was correct in stating that “No one can possibly

attend continuously to an object that does not change” (p. 92), it is imperative to consider how people respond when the object of attention changes in time, a point emphasized by recent research on attentional capture (e.g., Jonides & Yantis, 1988; Yantis, 1992).

In this article, we offer a theory about how people attend to events that change over time. Our theory begins with audition rather than vision because a most persuasive case for positing dynamic attending comes when we consider attending to speech and music. In auditory domains it is evident, as shown later, that attentional selectivity operates in the time dimension. In the end, however, we claim that our framework is a general one, applying to vision as well as to audition.

We take the time structure of events as a point of departure by assuming that, in acoustic patterns, it can capture and maintain attending. We ask two questions: How does event structure guide attending, selectively enhancing attentional focus at certain ex-

pected points in time? and How does attending adapt when event structure begins to change, such that relevant information occurs at unexpected points in time? To answer these questions, we appeal to the idea of attending rhythms that entrain to external events. Entrainment permits selective targeting of attention to expected points (Jones, 1976; Jones & Boltz, 1989; Large, 1994; Large & Kolen, 1995). Attending rhythms comprise recurrent pulses of attentional energy that facilitate a listener's responses not only to expected information but also to temporally unexpected information (Large, 1994).

In the remainder of the introduction, we briefly consider approaches pertinent to two aspects of our theory, namely representational approaches to event time structure and contemporary attending theories. We then introduce a dynamic attending model that builds on the notions of expectancy and entrainment to describe real-time attentional tracking of time-varying events, followed by an assessment of the model using simulations of data from three listening experiments. Finally, we consider broader implications of this approach.

### Temporal Structure of Events and the Role of Attention

Our theory addresses issues that relate to two psychological domains. First, because we assign an important role to the temporal structure of events, research on representation of sequence time structure is relevant. Second, because we are concerned with the activity of attending, the other domain includes research on attention, much of which involves vision.

#### *Theories of Temporal Structure*

Research on representation of time is concerned with how people represent temporal relations among elements composing a serial event (such as a word, a phrase, or a melody). Most of these theories are memory theories designed to explain how a completed event is recalled. Statistical theories of temporal structure rely on statistical description of a sequence of IOIs to explain the nature of memory codes. Beat-based theories of temporal structure rely on clock-timed beats induced from an event's rhythm as a basis for encoding an event's time structure.

#### *Statistical Theories*

Several recent models propose that encoding temporal sequences involves formation of memory traces for (arbitrary) time intervals (Drake & Botte, 1993; Keele, Nicoletti, Ivry, & Pokorny, 1989; Sorkin, 1990). These models continue a long-standing tradition that expresses the duration of single time intervals in terms of counts of random clock pulses that can fill any arbitrary time interval (e.g., Allan, 1979; Creelman, 1962; Getty, 1975, 1976; Killeen & Weiss, 1987; M. Treisman, 1963). Experimental support often comes from time discrimination tasks, because small temporal just-noticeable differences (JNDs) can reinforce the claim that a particular time interval has been encoded. For example, the average Weber model (Monahan & Hirsh, 1990) and the multiple look model (Drake & Botte, 1993) summarize sequence time structure in terms of a mean IOI that affords a referent time interval,  $t$ , for detecting temporal perturbations in a time discrim-

ination task. In the average Weber model, the mean IOI involves only intervals immediately surrounding a to-be-detected time change,  $\Delta t$ , whereas, in the multiple look model, the referent  $t$  is based on the mean of all IOIs in a sequence. The latter model explains memory for tempo (rate) in terms of this mean interval. The strength of the memory trace depends on sequence variability (e.g., IOI standard error). As variability increases, the strength of the memory code decreases, leading to poorer temporal acuity (see also Keele et al., 1989). Drake and Botte (1993) demonstrated the power of this model in experiments designed to test tempo discrimination between two (otherwise identical) sequences. Performance worsened as the standard error of sequence IOIs increased.

The rationale of the multiple look model is compelling and general. If applied to time (rather than tempo) discrimination within sequences, for instance, it implies that the mean of an IOI sequence affords a referent time interval,  $t$ , for detecting a single time change embedded within the sequence; moreover, this representation should degrade as IOI variability increases. Thus, it would appear that a statistical model may offer a tenable approach for explaining responses to temporal flexibility in naturally timed events, as in Figure 1. But caution is required on two fronts. First, such models implicitly assume stationarity, namely that statistical properties are fixed over time.<sup>2</sup> However, for naturally timed sequences, in which changes in global and local structure abound, there is reason to suspect the viability of a statistical approach. Second, statistical approaches do not fully address time discrimination for rhythmically structured sequences, an issue we take up next.

#### *Beat-Based Theories*

Statistical structure may be sufficient to explain sensitivity to rate changes for some sequences, but for more rhythmically complex sequences, the predictions of interval-based statistical models begin to break down. Consider an experiment of Jones and Yee (1997). They created four different rhythmical sequences by varying timings of tones with different amplitudes (loud or soft) and temporal separations (short or long IOIs), as shown in Figure 2. Two patterns, a regular rhythmical (RR) and a regular (R) one, were generated from a regular implied beat; two others (irregular rhythmical [IR] and irregular [I]) contained some irregular beats. However, variability in interval time structure did not directly covary with regularity because the more rhythmical patterns (RR and IR) were more variable than their less obviously patterned counterparts (R and I). If sequences with greater IOI variability convey to listeners a fuzzy memory trace of a referent  $t$ , then the latter two sequences should be more economically encoded than the former. Furthermore, listeners should be better in determining the serial locus of an embedded time change (i.e., a perturbation of the rhythm) with R and I sequences than with RR and IR sequences. This did not occur. As proportion correct (PC) scores in Figure 2 indicate, even listeners with no musical training were

<sup>2</sup> A stationary time sequence is one that can be summarized at any point by fixed statistical properties of IOIs, such as mean, variance, and covariance of these time intervals. Nonstationary patterns are ones with systematic trends, such as gradual rate increases or decreases or certain local IOI patternings that are not described by such statistics.

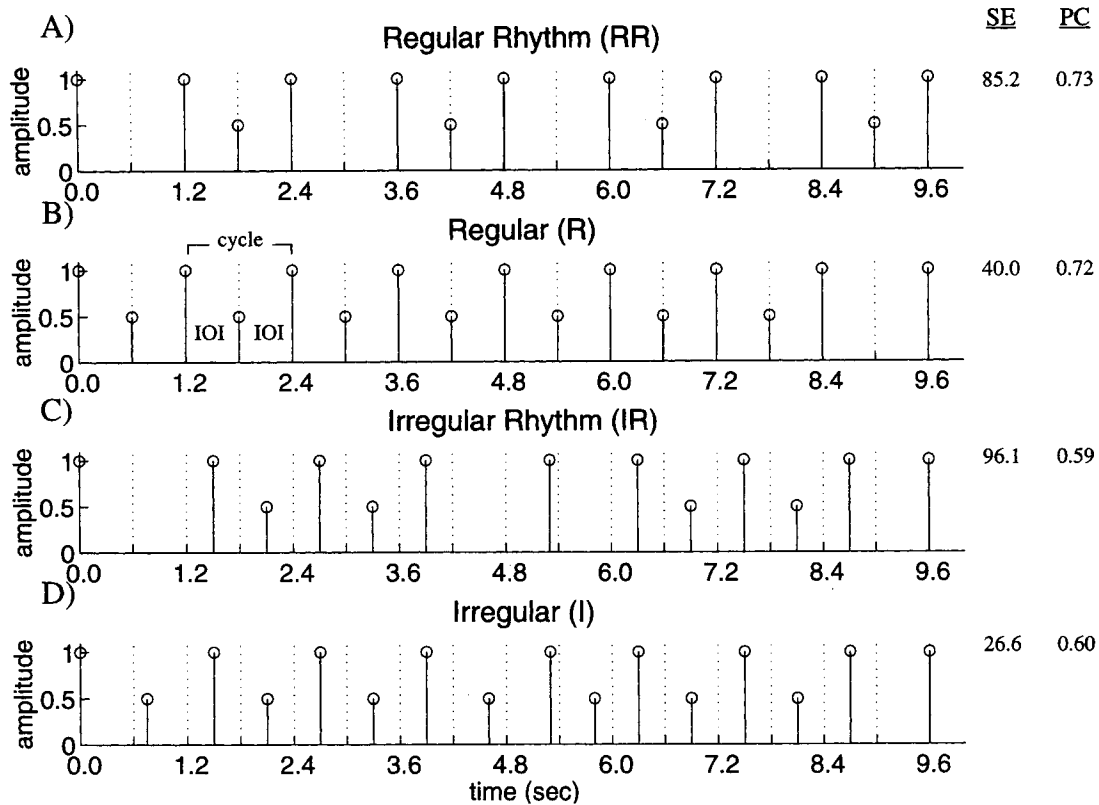


Figure 2. Experimental patterns of Jones and Yee (1997) shown with respective standard errors (SE) of interonset intervals (IOIs) and proportion correct (PC) of time detection responses (far right columns). A and B: Regular patterns. C and D: Irregular patterns. Amplitudes are scaled to the range [0, 1].

better in this task with RR and R than with IR and I sequences. These findings suggest that statistical structure alone cannot explain discrimination responses to rhythmic patterns.

Models specifically designed to explain perception and production of rhythmic patterns have proposed differential encoding of successive time intervals in a sequence (e.g., Lerdahl & Jackendoff, 1983; Longuet-Higgins, 1987; Povel, 1981; Povel & Essens, 1985; Simon & Sumner, 1968). Perhaps the most influential is Povel's clock model. It is a beat-based model: A listener economically encodes time intervals when they form a rhythm sufficient to induce a fixed beat. The beat is mentally represented as a clock grid. The grid supplies the best-fitting beat for a pattern's accent structure and thus determines its memory code; shorter codes correspond to more accurately recalled rhythms. Povel and Essens's (1985) experiments confirmed the model's prediction that time intervals within sequences containing equidistant (isochronous) accents are reproduced best. Thus, Povel's clock model appears more appropriate than a statistical model for the Jones and Yee data (cf. Figure 2). But this prediction comes at a cost. The fixed beat structure of the clock model is not robust even to small perturbations in a rhythmic pattern. Although it correctly predicts that an isochronous pattern is most efficiently encoded, introduction of even modest amounts of temporal jitter would cause most onsets to fall off the beat; consequently, encoding would com-

pletely break down. Systematic trends in sequence rate are more problematic. As shown later, these outcomes do not correspond to listeners' responses.

In brief, both statistical and beat-based theories have been influential in explaining representations of temporal information. Some version of a statistical model seems required to explain responses to temporally variable sequences, whereas some version of a beat-based model seems more appropriate in explaining responses to rhythmically structured events. Yet, this returns us to our original puzzle. When is a difference between two intervals so large as to induce a sense of rhythm or meter, and when is it small enough to be treated as merely a perturbation of an isochronous sequence? What, if anything, does this have to do with responding to systematic changes in the temporal structure of natural sequences? To address these questions, our approach incorporates some features of both statistical and beat-based approaches. But it involves more than simply the memory of temporal structure: It involves active attending.

#### *Attention: The Role of Time*

We aim to describe attention to activities that unfold in time (i.e., attention to events rather than to objects). However, a majority of current research is aimed at understanding visual attention

to objects in space. This research has relevance here because of its emphasis on real-time attentional control. Thus, we first present a brief sketch of pertinent constructs in visual attention to objects. Then we describe dynamic attentional approaches geared to tracking events.

### Visual Attention

Current visual attention theories address attentional control, which in many tasks involves some combination of a long-term, goal-oriented attentional process and a transient, stimulus-driven mechanism (e.g., Egeth & Yantis, 1997). The goal-oriented mechanism reflects expectancy and attentional set; it is concerned with deliberate changes in focal attending (e.g., Folk, Remington, & Johnston, 1992). For instance, an individual may react faster to an object in an attended-to location or may be successfully instructed to ignore certain objects in a forthcoming display. By contrast, the stimulus-driven mechanism reflects fast (some claim automatic) attentional shifts, usually caused by a single salient feature or an abrupt display change. For instance, the abrupt onset of a nontarget object may provoke a rapid attentional shift to it and away from a target object. This phenomenon is known as attentional capture (Jonides & Yantis, 1988; Yantis & Hillstrom, 1994).

In visual attention, both control mechanisms speak to selectivity. There is accumulating evidence that attentional selectivity is connected to the allocation of resources to objects rather than merely to spatial locations (e.g., Duncan, 1984; Rock & Guttman, 1981). This has been a contentious issue, one complicated by the fact that both spatial location and spatial relationships are usually confounded with object form; both space- and object-based processes are probably involved in the maintenance of attentional focus, as current thinking suggests (e.g., Hummel & Biederman, 1992; Logan, 1996). Thus, an object's global structure provides nesting within its spatial boundaries; moreover, within these boundaries, nested subparts, textures, and so forth are relationally configured in space. We distinguish objects, which are patterns in two-dimensional or three-dimensional space, from events, which are patterns in time.

Constructs useful in visual attention, such as expectancy (conveyed by attentional set), attentional capture (conveyed by a sudden or unexpected change), and attentional focus (selectivity in space), are also useful, in altered form, in our framework. Our interpretations are shaped by the inclusion of the time dimension as a source of structure that governs attending to events. In this approach to attending, we identify long-term and transient aspects of attentional control that determine selectivity in time; both processes are influenced by the structure of events in time. Thus, temporally regular patterns guide attending in a goal-oriented way that is manifested by expectancies about the "when" of forthcoming items. By contrast, temporally irregular patterns offer various unexpected items that provoke rapid shifts in the temporal locus of attention. The former parallels a long-term expectancy process, and the latter parallels transient attentional capture. In both, attention in time is responsive to structure in time.

### Dynamic Attending

The dynamic attending approach (Jones, 1976; Jones & Boltz, 1989) shares with visual attention theories an emphasis on the immediacy of attending, the role of expectancy, and focal attending shifts, among other things. At the same time, its emphasis on control of attention by an event's rhythm strongly links it to representational theories of temporal structure. But dynamic attending theory differs from both of these accounts in its reliance on an *entrainment hypothesis*. This hypothesis rests on two assumptions. First, internal oscillations, termed *attending rhythms*, generate expectancies that enable anticipation of future aspects of an event. Second, the external event's rhythm drives attending rhythms, such that attending rhythms entrain to the external rhythm. Thus, an event's temporal structure is salient and useful to an attender.

Recent models pursue the idea of temporal expectancies, instantiated as the behavior of internal rhythmic processes (e.g., Desain, 1992; Large, 1994; Large & Kolen, 1995; McAuley, 1994, 1995). For example, Large described the process of tracking temporally complex, natural events (music and speech rhythms) as nonlinear oscillations that synchronize to event periodicities at various time scales. A complex pattern of expectancies results when several oscillators entrain both to the rhythm of the external event and with one another (Large, 1994). These ideas are further developed later. McAuley (1994, 1995) also used entrainable oscillators. He advanced the idea of a preferred oscillator period, along with period decay, to explain tempo discrimination. His model offers a dynamic alternative to the multiple look model. A characteristic tempo is expressed in an adaptive harmonic oscillator with a preferred period. As with the Large model, this model differs from memory coding models in that the oscillator adjusts to new rates, adapting its characteristic period in real time.

Finally, several of these models have formalized the idea of attentional energy originally suggested by Jones (1976). This continues a tradition of associating attention with energy dating at least from McDougall (1911). Attentional energy has been variously depicted (e.g., Berlyne, 1974; Easterbrook, 1959; Kahneman, 1973; Sanders, 1986; for reviews, see Neumann, 1996; van der Molen, 1996). However, our use of this term is more specific than most. Here energy provides a periodic attentional pulse that is targeted by an internal rhythm. In other words, in the present context, energy differs from the nonspecific resource concept often used to explain attentional selectivity (e.g., Kahneman, 1973).

In sum, recent developments in the application of dynamical systems to complex rhythmic patterns make it possible to extend and formalize hypotheses about the dynamics of attending vis-à-vis event time structure. This is the goal of the next section.

### A Model of Attending Dynamics

As indicated, the dynamic attending framework postulates two entities: external rhythms, which are created by distal events, and internal rhythms, which actively generate temporal expectancies. It also postulates a coordinated relationship between these two entities that arises as a result of entrainment. In this section, we build

on these ideas to develop a model of attentional dynamics that generates predictions about people's sensitivity to interval time properties of an event, specifically, predictions about time judgments that are evaluated later.

### External Rhythms

Our concept of an external rhythm conforms to conventions established for describing time patterns of music and language (Cooper & Meyer, 1960; Cutler & Mehler, 1993; Lehiste, 1977; Liberman, 1975; Lerdahl & Jackendoff, 1983; Yeston, 1976). Used in this sense, "rhythm" refers to a wide variety of explicitly nonisochronous, as well as isochronous, time structures. We assume that an external rhythm involves a sequence of temporally localized onsets, defining a sequence of time intervals that are projected into the flow by some external event.

The acoustic sequence of Figure 1B is a musical event that conveys information about the temporally localized onset of each note as it is created by the pianist's finger impacts on a keyboard. As an external rhythm, such an event is represented by a sequence of discrete onsets stripped of pitch information as in Figure 1C. Within such sequences, explicitly rhythmical patterns can appear in the form of recurrent arrangements of certain IOIs (e.g., long-short-short-long-short-short), thereby implying periodicity on multiple time scales. However, such periodic components rarely remain constant; rather, the phase and period of any component may change systematically over time. The temporal nuances and rate changes that contribute to such perturbations are not noise; they are meaningful, and often communicative, variations on underlying rhythmic forms.

Several different external rhythms appear in Figure 3, each illustrating a perturbation of an underlying rhythmic form. Below each rhythm, a corresponding rate curve is shown. Panel A displays an otherwise isochronous rhythm in which the length of a single interval (the fifth IOI) has been perturbed by a fixed amount (15%). Panel B illustrates a similar rhythm with many random phase perturbations (i.e., every interval is perturbed by a small random amount). In Panel C, the isochronous rhythm receives a perturbation that results in an abrupt change of sequence rate (15%) 5 s into the pattern. Finally, the rhythm of Panel D differs from the preceding ones in that it is based on two periodicities. One periodic component,  $P_1$ , is marked by all tone onsets (500-ms mean period), and the other,  $P_2$ , is marked only by louder onsets (1,000-ms period). The disturbance is applied only to  $P_1$ ;  $P_2$  is strictly isochronous, whereas  $P_1$  is variable (with random jitter,  $SD = 50$  ms, applied only to soft tone onsets). These rhythms illustrate the kinds of temporal fluctuations that characterize natural events. Any successful approach to the real-time deployment of attention must be able to explain attentional behaviors in events such as these (and those of Figures 1 and 2). Accordingly, in this article, we focus on such acoustic rhythms.

### Attending Rhythms

Attending rhythms are the building blocks of our theory. This usage of the term *rhythm* contrasts with that applied to an external rhythm, in which many periodic components are considered. Our

concept of an internal rhythm conforms to conventions established in biology, where rhythm commonly refers to a single periodic process carried out by a biological oscillation (Glass & Mackey, 1988; Winfree, 1980). The first two parts of this section describe, respectively, different aspects of a single attentional rhythm: a self-sustaining oscillation and an energy pulse. The self-sustaining oscillation models the generation of temporal expectancies; the energy pulse captures focus of attention and facilitates task-dependent model predictions. A simplified overview of these two basic aspects of a single attentional rhythm appears in Figure 4. The third part of this section generalizes these ideas to multiple attending rhythms.

### Attending Rhythms as Self-Sustaining Oscillations

A self-sustaining oscillation has two important features that make it appropriate for modeling the basic process of attentional dynamics. First, it generates periodic activity, an activity that we refer to as an *expectation*. Expectations are similar to the ticks of a clock, with the important exception that an expectation is an active temporal anticipation, not a grid point in a memory code (cf. Povel & Essens, 1985). Second, when coupled to an external rhythm, a self-sustaining oscillation may entrain, or synchronize, to that rhythm. Therefore, unlike a fixed clock, synchronization between an attending rhythm and an external rhythm is stable, meaning it is robust to both random and nonrandom perturbations of the external rhythm (cf. Figure 3). Finally, an attentional rhythm may adapt its period in response to systematic rate changes in an external rhythm. Thus, an attending rhythm adapts to meaningful temporal fluctuations found in everyday events.

A self-sustaining oscillation is a dynamic system that exhibits, in the limit, a stable cycle, termed a *limit cycle*. Conceptually, the limit cycle describes the periodic generation of a temporal expectation that often intuitively accompanies attending to temporally patterned events (cf. Figure 4). An expectation about "when" an onset should occur is described in terms of a single variable, phase  $\phi(t)$ , which is the position of the oscillation around the limit cycle at time  $t$ . In dynamical systems terminology, phase is one of three state variables in our model; each possible value of phase within a cycle corresponds to a distinct state, so the state space is the space of possible phases. The time required to complete one cycle determines the period,  $p$ , and the phase at time  $t$ ,  $-p/2 < t \leq p/2$ , is denoted by  $\phi(t) = t/p$ . According to this definition, phase is a continuous variable ranging from  $-0.5$  to  $0.5$ , as illustrated in Figure 5.

If we designate the time at which an onset is expected to occur as  $t_x$  and define  $\phi(t_x)$  as 0, then we have the following relation:

$$\phi(t) = \frac{t - t_x}{p}, \quad t_x - \frac{p}{2} \leq t < t_x + \frac{p}{2}. \quad (1)$$

Thus, an expectancy corresponds to zero phase. Furthermore, when an onset occurs at time  $t$ , its relationship to an ongoing attentional rhythm is summarized by the phase of the attentional rhythm at that time,  $\phi(t)$ , calculated according to Equation 1.

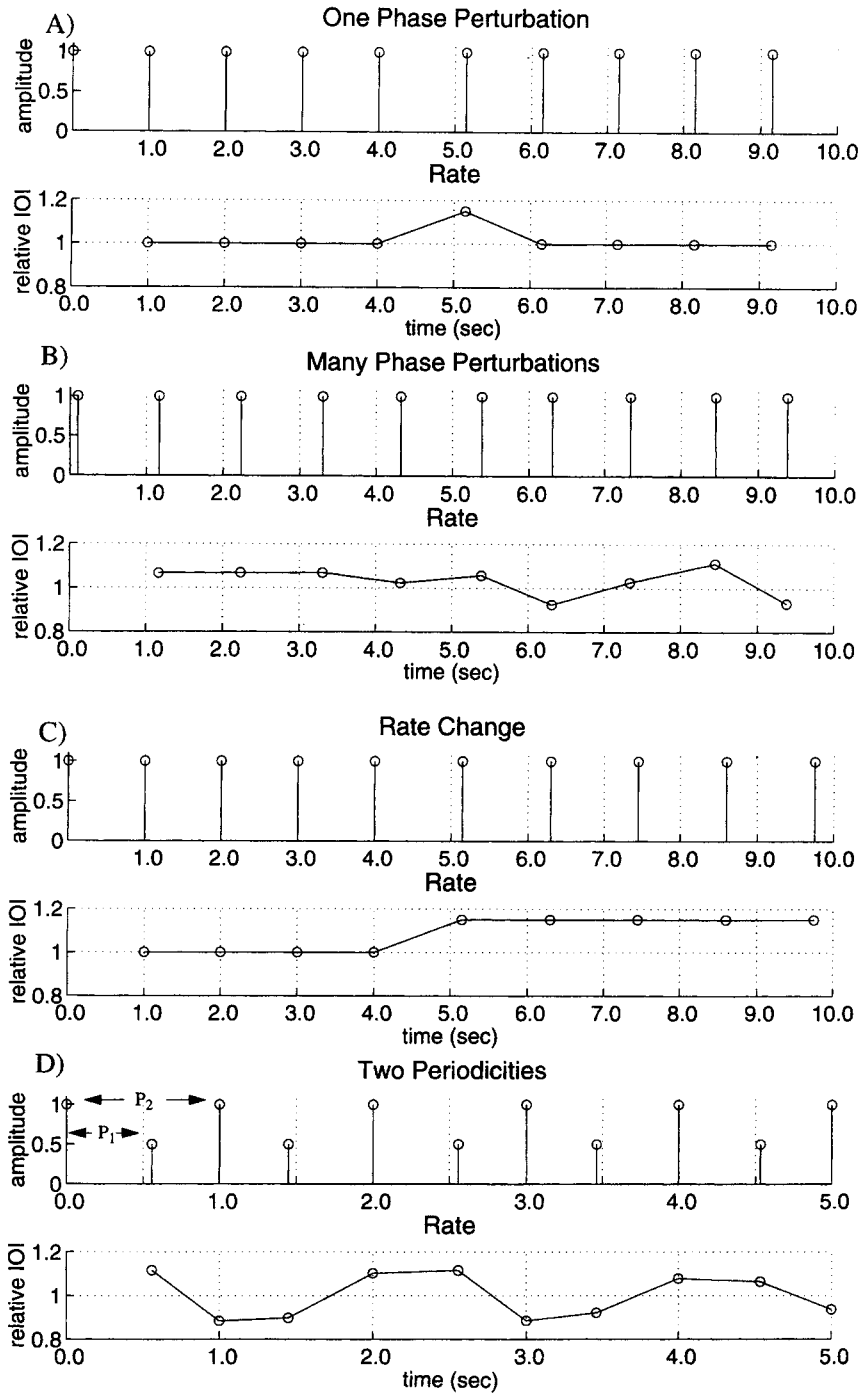


Figure 3. Four external rhythms with different temporal fluctuations. A: One phase perturbation (sixth onset). B: Many random phase perturbations. C: A single rate change (sixth onset). D: A two-periodicity rhythm with random phase perturbations added only at soft tone onsets. Relative interonset intervals (IOIs; rate curves) are calculated with respect to isochrony.

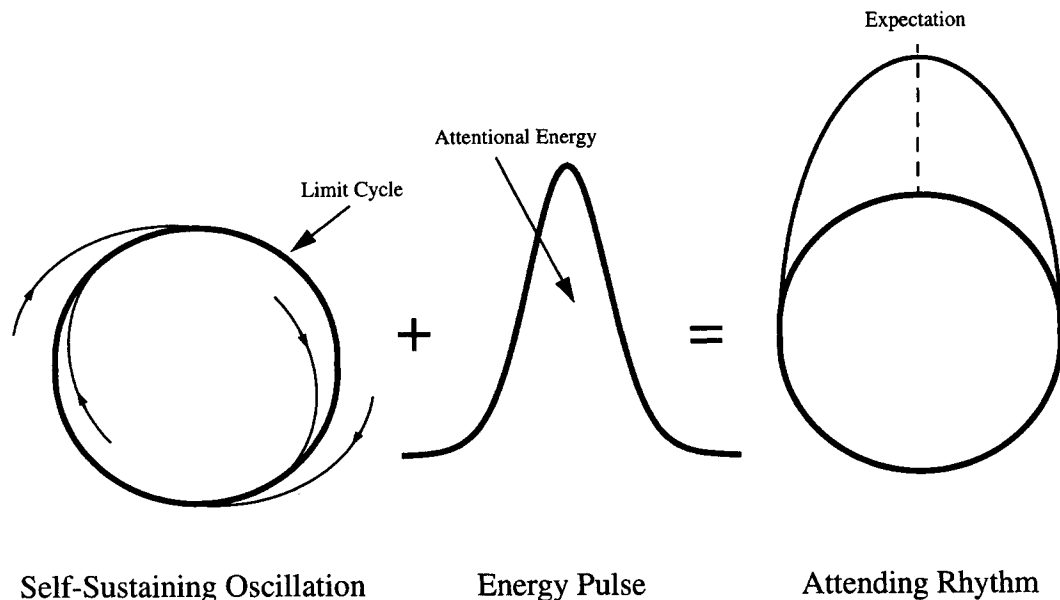


Figure 4. Schematic overview of a single attending rhythm shown as a function of two model components: a self-sustaining oscillation and an energy pulse. Attentional targeting is suggested by mapping a given point on the limit cycle to the modal point of the energy pulse.

Thus,  $\phi(t)$ , or simply  $\phi$ , captures the disparity between the onset and the expectation. Because of the way we have defined *phase* in Equation 1, negative phases correspond to onsets that arrive early relative to expectations, whereas positive phases characterize onsets that arrive late (Figure 5). The term *relative phase* refers to the time of an onset relative to the phase of the attending rhythm.

Because external rhythms can be expressed as onset sequences, it is possible to determine the relative phase for the next onset,  $\phi_{n+1}$ , from the phase at the current onset,  $\phi_n$ ; the interval of time to the next onset,  $t_{n+1} - t_n$ ; and the period,  $p$ :

$$\phi_{n+1} = \phi_n + \frac{t_{n+1} - t_n}{p} \pmod{-0.5, 0.5}. \quad (2)$$

Equation 2 is called a *circle map* because it maps points on the circle ( $\phi_n$ ) to new points on the circle ( $\phi_{n+1}$ ; see Figure 5).<sup>3</sup> The parameter  $p$  is the period of the oscillation. Equation 2 expresses one possible type of relationship between a self-sustaining oscillation and an external rhythm, one in which the oscillation acts as an autonomous referent, or clock, generating ticks (i.e., expectations) at regular intervals independently of the external rhythm. The circle map describes the phase of this clock at which onsets appear in the external rhythm.

Expectations are most useful when they are synchronous with onsets in an external rhythm. In this case, the phase of each onset in a sequence is  $\phi_* = 0$ , indicating that each onset occurs when expected.<sup>4</sup> It is possible to model a simple form of synchronization using Equation 2 by assuming  $t_{n+1} - t_n = p$ , for all  $n$ , and by starting the internal clock simultaneously with the external rhythm, at  $\phi_1 = 0$ . This is similar to two watches that keep perfect time;

once set to the same time, they remain synchronized forever. However, this type of synchronization is fragile in that it can be perturbed by disruptions of the external rhythm. This is illustrated in Panels A–C of Figure 6, where relative phase for a two-rhythm system is plotted (the external rhythms correspond to the onset sequences of Figure 3, Panels A–C). To continue with the watch metaphor, imagine that one watch (corresponding to the external rhythm) is dropped and skips part of one cycle. The resultant series of ticks would correspond to the onset sequence of Figure 3A. Relative phase (Figure 6A) is perturbed by the lengthening of this one IOI (at  $t_{\text{pert}}$ ). According to the second watch (corresponding to the internal clock), not only is the single tick at  $t_{\text{pert}}$  “late,” but all ticks following  $t_{\text{pert}}$  are late as well (i.e.,  $\phi > 0$ ). The system is still phase locked, but synchrony is destroyed because the second watch continues unchanged. Iteration of Equation 2 for a few steps will verify this. A more severe situation arises if the blow to the first watch loosens the works just enough that the length of each cycle differs from the mean by a small random amount, as shown in Figure 3B. Continual random perturbations cause phase drift, as illustrated in Figure 6B. In this case, no phase relationship is stable. Finally, if damage to the first watch creates a systematic change in rate (as in Figure 3C), then the difference in period

<sup>3</sup> The expression  $\pmod{-0.5, 0.5}$  maps the real line (time) onto the circle (phase) by taking the remainder after division by 1 and then remapping the interval (0.5, 1) to the interval (–0.5, 0).

<sup>4</sup> The subscript \* is used when the system is in equilibrium; thus,  $\phi_n = \phi_{n+1} = \phi_*$ . Synchronization is a special form of phase locking. In a phase-locked system, phase is constant (i.e.,  $\phi_* = c$ , but  $c$  is not necessarily zero).



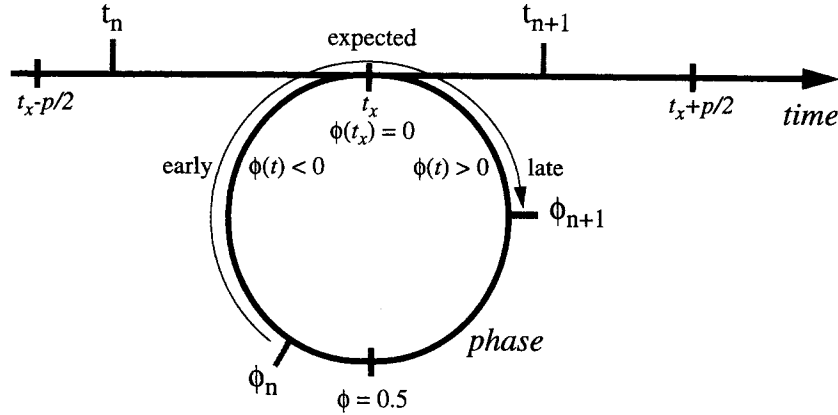


Figure 5. Relative phase and the circle map. Time,  $t$ , is mapped onto phase,  $\phi$ , by Equation 1 such that the expected onset time,  $t = t_x$ , is transformed to an expected phase  $\phi = 0$ . Circle maps such as Equations 2 and 3 work in relative phase directly, mapping points on the circle to new points on the circle ( $\phi_n \rightarrow \phi_{n+1}$ ).

between the two watches causes a relative phase wrap, as shown in Figure 6C: After a time, the first watch will be one cycle behind the second, then two, and so on.

The process by which a system returns to synchrony after a perturbation is called *entrainment*. It arises in coupled systems: Coupling

exerts a force that pulls the two rhythms toward a synchronous relationship. Equation 2 models the relationship of two rhythms that are uncoupled, but it does not model the force exerted by an external rhythm on an attentional rhythm. This force can be modeled with the addition of a coupling term,  $F(\phi_n)$ , to Equation 2:

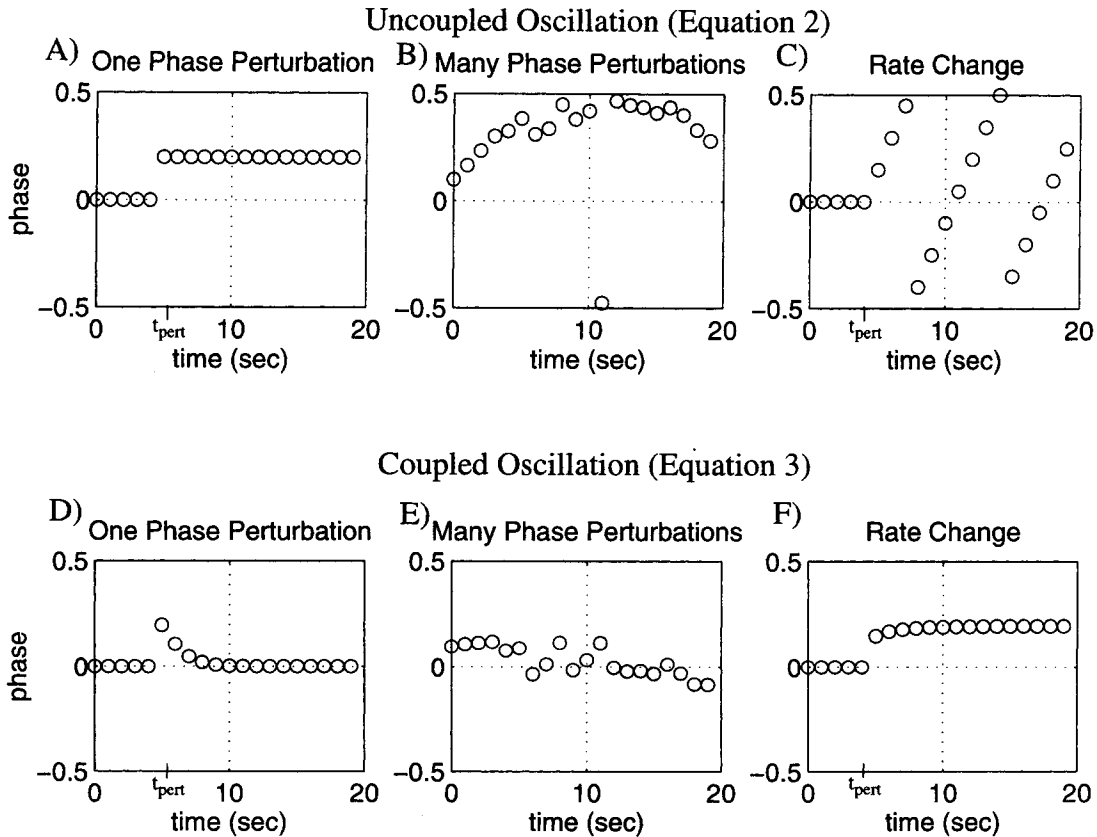


Figure 6. A–C: Responses of an uncoupled oscillator to the fluctuating external rhythms of Figure 3, A–C, respectively, in terms of relative phase (Equation 2). D–F: Responses of a coupled oscillator (Equation 3) to the same stimulus sequences. Single perturbations (pert) occur at time,  $t_{\text{pert}}$ .

$$\phi_{n+1} = \phi_n + \frac{t_{n+1} - t_n}{p} - \eta_\phi F(\phi_n) \pmod{-0.5, 0.5}, \quad (3)$$

where  $F(\phi) = \frac{1}{2\pi} \sin 2\pi\phi$ . The new parameter in this equation,  $\eta_\phi$ , represents coupling strength. Equation 3 is called a *phase attractive circle map* (cf. Kelso, deGuzman, & Holroyd, 1990) because there is an attractor in relative phase created by the addition of the coupling term. It is called an attractor because the system is drawn toward it by coupling. The attractor is called a stable state because it is resistant to perturbations. This is illustrated in Figure 7, where the coupling term is plotted. The location and stability of the attractor depend on the parameters,  $p$  and  $\eta_\phi$ . Synchrony ( $\phi_* = 0$ ) is a stable attractor state for this system when  $t_{n+1} - t_n = p$ , for all  $n$ , as long as coupling strength assumes a value in the range  $0 < \eta_\phi \leq 2$  (see Appendix A). Coupling strength captures the amount of force exerted on the attentional rhythm and determines, among other factors, the speed with which the coupled system relaxes to the attractor. Panels D and E of Figure 6 show the advantage (relative to Equation 2) of coupling the attending rhythm to the external rhythms of Figure 3 (Panels A and B). After a single phase perturbation (Figure 3A), the system quickly returns to synchrony (Figure 6D). In response to random variability in the external rhythm (Figure 3B), the system remains near the attractor at all times (Figure 6E). We refer to this loose form of synchrony as *phase coordination*.

Phase coupling alone, however, is not sufficient to model phase synchrony in the presence of systematic rate changes (Figure 3C). As shown in Figure 6F, when  $t_{n+1} - t_n > p$  an attractor still exists, but its phase changes (see Appendix A); thus, phase synchrony is destroyed. Intuitively, if the period of the oscillation is

shorter than the period of the external rhythm, then onsets will always appear later than expected. To maintain phase synchrony, it is necessary that the attentional rhythm be capable of tracking time-varying events such as these (cf. Large, 1994; Large & Kolen, 1995; McAuley, 1995). To accomplish this, we allow the period of the internal oscillation to adjust in much the same way as phase does:

$$p_{n+1} = p_n + p\eta_p F(\phi_n). \quad (4)$$

The response of the phase-coupled and period-coupled oscillation to the external rhythms of Panels A–C of Figure 3 is illustrated in Panels A–C, respectively, of Figure 8. Panel C, in particular, illustrates the advantage of period adaptation when the external rhythm undergoes a change in rate. After a rate change, relative phase relaxes toward synchrony while the oscillation period adapts to the new period of the external rhythm. In dynamical systems terms, period is promoted from a parameter (Equation 2) to a state variable (Equation 4). Assuming an external rhythm with fixed period  $q$  and an attending rhythm with initial period,  $p_1$ , close to  $q$ , the attractor for this two-dimensional system is  $\phi_* = 0$ ;  $p_* = q$ . The period adaptation rate,  $\eta_p$ , is analogous to coupling strength in Equation 3; together these parameters determine the rate of approach to the attractor.

Together, the concepts of self-sustained oscillation, phase entrainment, and period adaptation describe how an attending rhythm can generate periodic expectations that are well coordinated with an external rhythm amid the fluctuations that are characteristic of natural events. The concept of a stable attractor state implies the existence of a special sustaining relationship between internal and

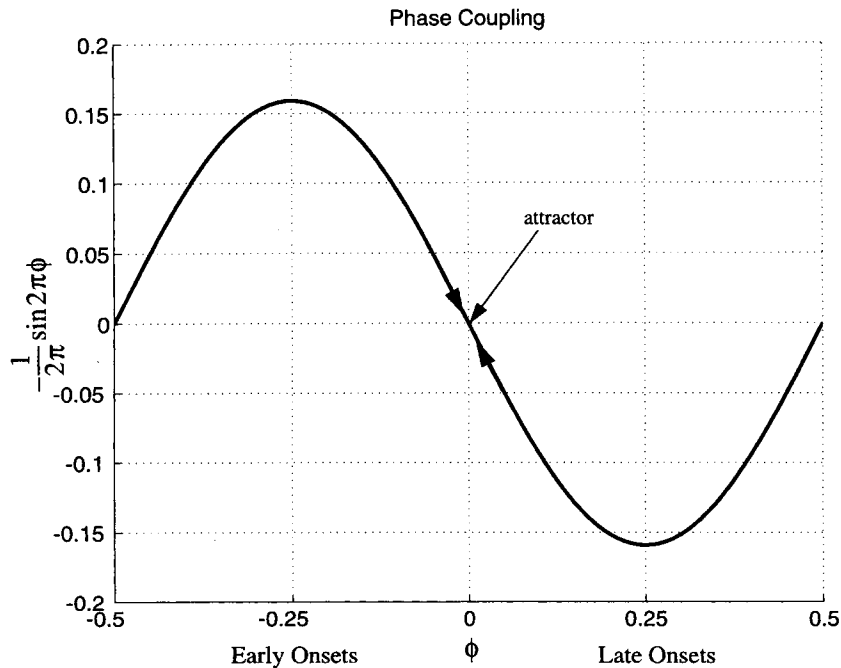
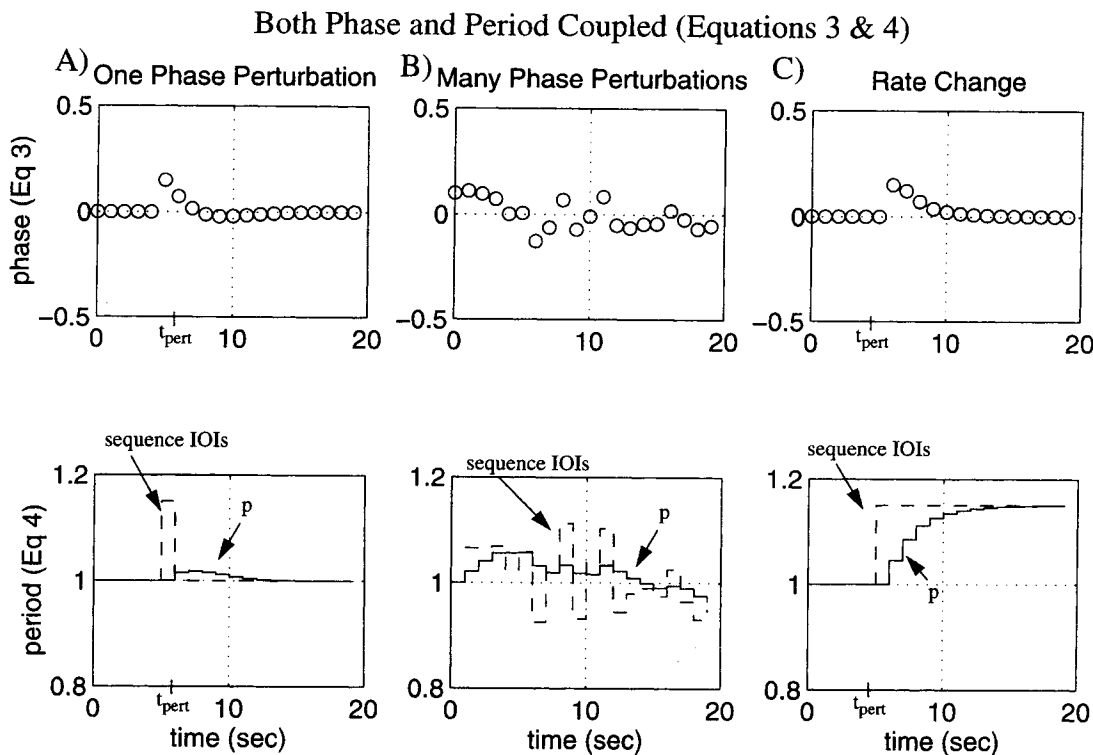


Figure 7. Phase coupling,  $F(\phi) = 1/2\pi \sin 2\pi\phi$ , shown as a function of  $\phi$  within a single attending rhythm cycle. Arrows indicate that the system moves toward the attractor,  $\phi = 0$ .



*Figure 8.* Responses of an adaptive oscillation (A–C) to the three external rhythms of Figure 3, A–C. Oscillator responses in all cases are based on the two-dimensional system of Equation (Eq) 3 and Equation 4 (i.e., coupling of both phase and period). Compare with predictions shown in Figure 6, A–C (from Equation 2 alone), and Figure 6, A–C (from Equation 3 alone). IOI = interonset interval; pert = perturbation.

external rhythms. This relationship continually “hovers” in the background while the attending rhythm adjusts to momentary event changes. The attractor exerts long-term control over attending, summarizing the influence of a simple, underlying rhythmic form. Alternatively, when phase perturbations or rate changes occur in the external rhythm, the attending rhythm adapts with transient shifts of attention that constitute a form of attentional capture.

#### *Attending Rhythms and Attentional Focus*

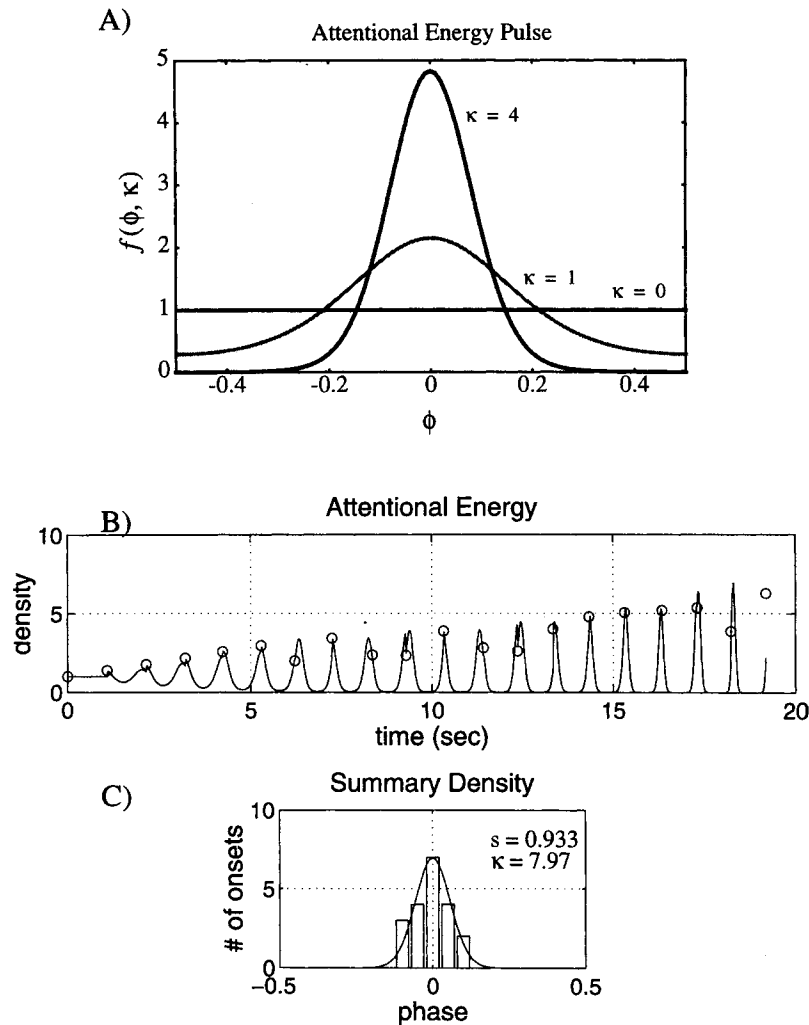
The model, as we have thus far described it, has one important shortcoming. It associates an expectation with a single point in time and, therefore, with a single point in the state space of the coupled system. It is evident that this is not appropriate for situations in which natural rhythmic fluctuations come into play. That is, even when coupling does a good job of maintaining coordination (Figure 8B, for example), none of the onsets occur precisely at this expectation point. It is necessary to quantify expectancy violations to precisely predict responses to unexpected as well as expected onsets. Therefore, we move from the informal notion of expectation to a model of the allocation of attentional energy within each cycle of an attentional rhythm. We develop the notion of *focus of attention*, embodied as a third state variable that describes concentration of attentional energy within each cycle.

Adaptation of this state variable over time models changes in attentional focus that depend on context. Attentional focus accommodates effects of temporal expectancies on overt responding, enabling predictions of judgments about both expected and unexpected happenings.

We begin with the idea of a “pulse” of attentional energy, modeled as a periodic probability density function. The pulse is linked to the dynamical system of Equations 3 and 4 through the phase of an attending rhythm (the periodic variable,  $\phi$ ). The variable  $\kappa$  captures attentional focus. The pulse has both locus and extension in time. Phase ( $\phi = 0$ ) determines the locus of a pulse, whereas focus determines its extent. The pulse is defined as follows:

$$f(\phi, \kappa) = \frac{1}{I_0(\kappa)} \exp \kappa \cos 2\pi(\phi), \quad (5)$$

where  $I_0(\kappa)$  denotes the modified Bessel function of the first kind of order zero. Equation 5 corresponds to the periodic density first introduced by von Mises to describe statistical inference on the circle (see Appendix B). For fixed  $\kappa > 0$ , energy varies as a function of  $\phi$ , with larger absolute values of  $\phi$  corresponding to less attentional energy. Figure 9A illustrates how focus determines the distribution of attentional energy over one cycle. The mode of the pulse is at  $\phi = 0$  (the expectation



*Figure 9.* The attentional pulse. A: Distribution of energy (a von Mises distribution; Equation 5) as a function of  $\phi$  for three different focus ( $\kappa$ ) values. Larger  $\kappa$  values correspond to a greater concentration of energy about the expected phase,  $\phi = 0$ . B: How the probability density evolves over time as  $\kappa$  adapts in response to an external rhythm that contains many random perturbations (i.e., Figure 3B). Values between discrete onsets are interpolated according to Equation 5; circles show where onsets fall relative to the evolving density. C: Comparison of a histogram of observed relative phases and a predicted (summary) density based on the final value of  $\kappa = 7.97$ . The observed distribution of relative phases ( $r = 0.937$ ; see Figure 10A) is nicely summarized by this density ( $s = 0.933$ ).

point), and the antimode is at 0.5. The pulse contributes an expectancy region about the mode where attentional energy is nonzero. It reflects the idea that “something is anticipated around this point in time.” Figure 9A indicates that, as  $\kappa$  increases, the pulse narrows concentrating energy near the mode, modeling a more focused temporal expectation. As  $\kappa$  decreases, the pulse widens, reflecting greater uncertainty about external happenings. When  $\kappa = 0$ , the pulse function is flat, indicating a uniform dispersion of attentional energy.

The attentional pulse permits quantification of attentional responses to variability in an external rhythm. Unlike the multiple look model, however, which treats IOI as the random variable, our

model treats relative phase,  $\phi$ , as the random variable (see also McAuley & Kidd, 1998). Attentional focus increases (i.e., the pulse narrows) as synchronization improves and decreases (the pulse widens) as synchronization degrades. This implies that attentional focus comes to reflect the accumulated effect of expectancy violations rather than sequence variability. Figure 9B illustrates how the shape of the attentional pulse might evolve over several cycles in response to the randomly perturbed rhythm of Figure 3B, through adaptation of attentional focus,  $\kappa$  (described subsequently). The pulse begins flat and then narrows to reflect degree of synchronization.

Adaptation of attentional focus is incorporated into the model by

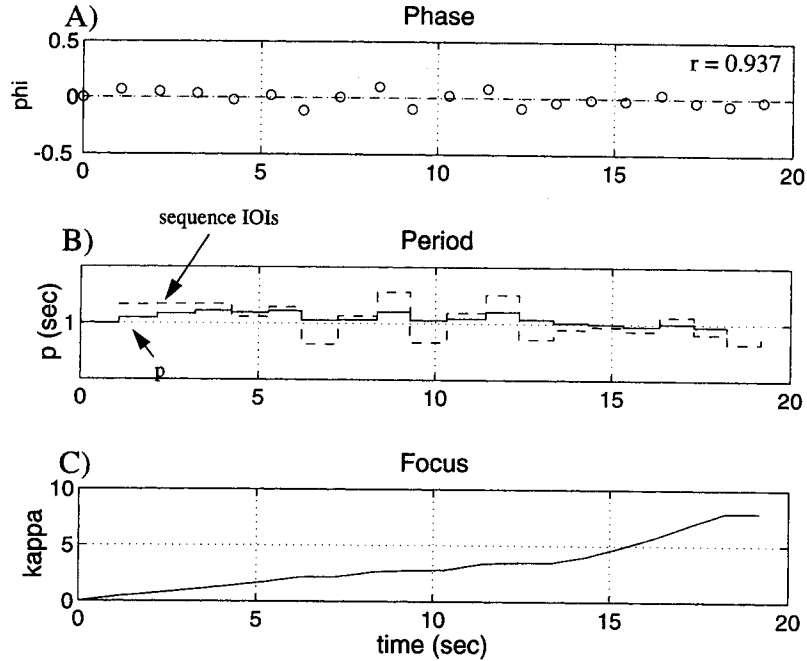


Figure 10. Response of an attentional rhythm to a stimulus sequence containing many random perturbations. (i.e., Figure 3B). The full model comprises three state variables: phase,  $\phi$ ; period,  $p$ ; and focus,  $\kappa$ . Predicted changes in these variables over time (for this rhythm) are shown, respectively, in A, B, and C. IOI = interonset interval.

a method similar to finding the maximum-likelihood estimate of  $\kappa$  for the von Mises distribution (Batschelet, 1981). The maximum-likelihood estimate is given by the solution to the equation

$$A(\kappa) = r, \quad (6)$$

where  $r$  is a statistic, called *mean vector length* (Appendix B), that can be used to measure degree of synchronization (Goldberg & Brown, 1969) by gauging variability in relative phase. It ranges from 0 to 1, where 0 indicates no synchronization and 1 indicates complete synchronization.  $A$  is a monotonic function of  $\kappa$  such that, as  $r$  goes from 0 to 1,  $\kappa$  goes from 0 to  $\infty$ . Because the function  $A$  cannot be inverted analytically, the corresponding value of  $\kappa$  is found numerically (or by table lookup) for a given estimate of  $r$ . Thus, the problem of adapting attentional focus reduces to finding an incremental approximation to  $r$ , which we call *synchronization strength*,  $s$  (see Appendix B).

$$s_{n+1} = s_n - \eta_s (s_n - \cos 2\pi\phi_n)$$

and

$$\kappa_{n+1} = A^{-1}[H(b, s_{n+1})]. \quad (7)$$

Equation 7 describes real-time adaptation of attentional focus. Intuitively, it states that the measure of synchronization strength on the next onset ( $s_{n+1}$ ) depends on the current measure ( $s_n$ ) as well as the phase of the current onset (i.e., the  $\cos$  term);  $\kappa$  is a function of synchronization strength such that as  $s_n$  increases, so does  $\kappa$ . Equation 7 is derived in Appendix B. Two parameters are involved in adaptation of  $\kappa$ . The adaptation rate,  $\eta_s$ ,  $0 \leq \eta_s \leq 1$ ,

determines how quickly attentional focus changes. If  $\eta_s = 1$ , each estimate of  $\kappa$  is based solely on the phase of the current onset; if  $\eta_s < 1$ , focus adapts more slowly because previous context is taken into account. The auxiliary parameter  $b$  places a limit on the maximum value of  $\kappa$  through the hard limit function  $H(b, s)$  (Appendix B). It determines an upper limit on attentional focus and, hence, specifies how narrow a pulse can become.<sup>5</sup>

Figure 10 depicts adaptation of phase, period, and focus in response to a stationary external rhythm in which small random deviations perturb the length of each cycle (Figure 3B). Adaptation of attentional focus depends on strength of synchronization of the attending rhythm to the external rhythm. Panels A and B of Figure 10, respectively, show that phase and period adjust to maintain coordination with the external rhythm. Panel C shows that attentional focus adapts to reflect the resultant distribution of relative phase values. By comparing Figure 10C with Figure 9B, one can observe that as focus increases, the width of the attentional pulse decreases, whereas changes in phase and period determine slight shifts in the temporal locus of the attentional pulse. Attentional focus reaches an asymptotic value of  $\kappa = 7.97$  ( $s = 0.933$ ). Comparison of this value with a statistical estimate of synchronization strength ( $r = 0.937$ ) verifies that incremental adaptation of attentional focus captures the quality of coordination between internal and external rhythms. A predicted density function (Equa-

<sup>5</sup> The value of  $b$  was held fixed at 0.95 for all simulations described in this article. This value corresponded to an upper limit for attentional focus of  $\kappa = 10.27$ .

tion 5), based on this value of  $\kappa$ , is compared with a relative phase histogram in Figure 9C. It fits the empirical distribution of observed relative phase values, reflecting the quality of synchronization between the attending rhythm and the external rhythm.

The attentional pulse construct complements that of a limit cycle oscillation in offering probabilistic quantification of people's judgments about unexpected as well as expected aspects of an external rhythm. Attentional focus allows one to quantify time-change noticeability in terms of the size of an expectancy violation relative to an observed distribution of relative phase: Large deviations from expectancy ( $|\phi| \gg 0$ ) are more noticeable than small ones, and a given deviation is more likely to be noticed when attention is highly focused (large  $\kappa$ ) than when it is broadly focused (small  $\kappa$ ). In other words, noticeability of any perturbation depends on both the temporal locus and width of an attentional pulse. Finally, the probability of noticing a time change is quantified as area under the density (pulse) function from the mode ( $\phi = 0$ ) to the relative phase of a perturbed onset. Following this rationale, Appendix B derives response probabilities for two different tasks.

To briefly summarize, the full model of a single attending rhythm reveals both long-term and short-term control of dynamic attending. It is grounded in the behavior of three state variables: phase, period, and focus. Near equilibrium phase is coordinated with the external rhythm, period approximates a pattern's mean IOI, and focus reflects synchronization quality. This attractor state models goal-oriented attentional control in that it represents the long-term behavior of the attending rhythm. In addition, the attentional rhythm reacts to momentary changes in the external rhythm with a speed determined by three parameters that correspond, respectively, to the three state variables; they are phase coupling strength, period adaptation rate, and focus adaptation rate. The response to these changes is transient, representing a short-term control of attending by event structure; it constitutes a form of attentional capture. Together, the state variables and model parameters describe targeting of attentional pulses; in turn, a pulse summarizes one's expectations about an unfolding rhythm and allows quantitative predictions about responses to the rhythm.

### Multiple Attending Rhythms

Events in the world typically give rise to complex rhythms containing multiple pseudoperiodicities. The patterns of Figure 1, Figure 2, and Figure 3D, for instance, exhibit characteristic rhythmic forms. Rhythmic forms involve ratio relationships among the phases and periods of temporal components. We assume that, in attending to complex rhythms, listeners enlist multiple attending rhythms that track distinct pseudoperiodic components. Accordingly, in this section we generalize the notions of limit cycle oscillation and attentional pulse to the case of two attending rhythms. Each of several attending rhythms has a potential for coordinating with a single distinct periodicity in the external rhythm. In this more general model, attending rhythms not only respond to the exigencies of external rhythms; they are also constrained by relationships with one another. Specifically, internal oscillations are coupled to one another so as to preserve certain phase and period relationships. These interrelationships offer the potential for expressing relational information about the rhythm's underlying temporal form.

*Coordination between two self-sustaining oscillations.* Internal coupling gives rise to phase and period relationships among attending rhythms that can express certain psychologically persisting or compelling rhythmic relationships (see also Jones, 1976). However, coupling among internal oscillations differs from the coupling between a single attentional rhythm and an external rhythm in two important ways. First, external-internal coupling is unidirectional; the external rhythm affects the internal rhythm, but not vice versa. Internal-internal coupling, however, can be bidirectional, so that internal oscillations affect each other. Second, with external-internal coupling, we are interested mainly in 1:1 coupling (i.e., one attentional pulse corresponding to each onset). With internal coupling, we are interested in more complex ratios. For example, a 2:1 phase relationship means that one attending rhythm completes two cycles in the same time required for the other to complete one cycle. This implies a 1:2 period relationship, the former having one half the period of the latter. The existence of long-term internal relationships such as these enables dynamic representation of the structure of more complex rhythms.

We describe phase and period coupling of internal oscillations using the simplest possible linear model. We also assume a simple long-term relationship between  $O_1$  and  $O_2$ , one in which the average period ratio,  $p_1/p_2$ , is 0.5. First we consider phase coupling for two oscillations,  $O_1$  and  $O_2$  (see Appendix C). We assume that both respond to the same external rhythm, which comprises at least two distinct periodicities. For instance, Figure 3D shows a rhythm comprising two periodicities,  $P_1$  and  $P_2$  ( $P_2$  is strictly isochronous;  $P_1$  is variable). The idea is that  $O_1$  should synchronize with  $P_1$  and  $O_2$  should synchronize with  $P_2$ ; however, both oscillators respond to all onsets. Figure 11 (Panels A and B) shows the phase of onsets for the sequence of Figure 3D relative to  $O_1$  and  $O_2$ , respectively, as each oscillation adapts to this sequence.

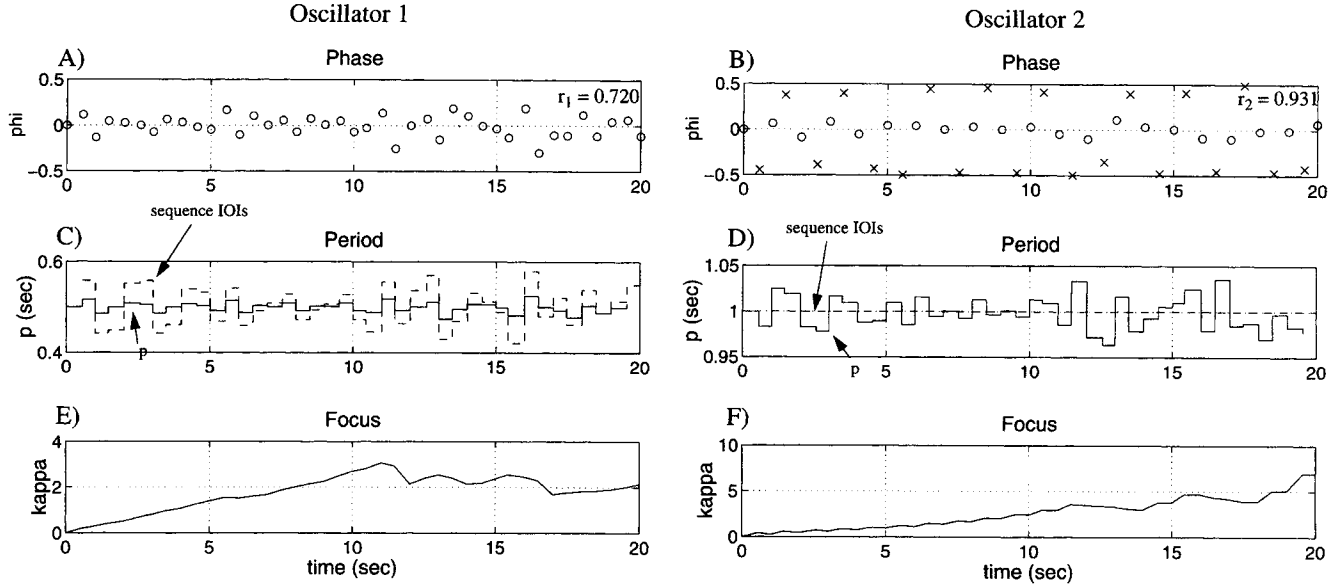
To express such behavior, two phase equations are necessary, one for each oscillation. The subscript  $i$  is used to denote the phase,  $\phi_i$ , and period,  $p_i$ , of  $O_i$  ( $i = 1, 2$ ). As before, the index  $n$  counts onsets in the external rhythm, but now it is a superscript. The two phases are coupled internally:

$$\phi_1^{(n+1)} = \phi_1^{(n)} + \frac{t_{n+1} - t_n}{p_1^{(n)}} - \eta_\phi F(\phi_1^{(n)}) - \alpha G_{21}(\boldsymbol{\phi}^{(n)}, \boldsymbol{\kappa}^{(n)}) \pmod{-0.5, 0.5, 1}$$

and

$$\phi_2^{(n+1)} = \phi_2^{(n)} + \frac{t_{n+1} - t_n}{p_2^{(n)}} - \eta_\phi F(\phi_2^{(n)}) - \alpha G_{12}(\boldsymbol{\phi}^{(n)}, \boldsymbol{\kappa}^{(n)}) \pmod{-0.5, 0.5, 1}. \quad (8)$$

The first three terms on the right-hand side of each equation correspond to the three terms on the right-hand side of Equation 3. The final term is a second, internal coupling term that describes the force exerted by internal oscillations on one another. This force continually pulls the two oscillations toward a 2:1 phase-locked relationship. Here  $\boldsymbol{\phi} = [\phi_1, \phi_2]$  represents the phase of both oscillators, and  $\boldsymbol{\kappa} = [\kappa_1, \kappa_2]$  represents focus (see Appendix C). The new parameter,  $\alpha$ , represents the strength of internal phase



**Figure 11.** Response of two self-sustaining oscillations ( $O_1$ ,  $O_2$ ) to the external rhythm of Figure 3D, a rhythm with two periodicities ( $P_1$ ,  $P_2$ ), one of which fluctuates randomly. Predicted changes in phase, period, and focus over time are shown for each oscillator in the top (A and B) middle (C and D), and bottom (E and F) panels, respectively (cf. Equations 8, 9, and 11). In A, mean vector length,  $r_1$ , reflects the relative phase of onsets from periodicity  $P_1$ ; in B,  $r_2$  reflects the relative phase of onsets from periodicity  $P_2$  (shown as open circles;  $P_1$  onsets are shown as xs). IOI = interonset interval.

coupling,  $0 \leq \alpha \leq 2$ . If  $\alpha$  is 0, the model implements two independent oscillations; if  $\alpha$  is 1, any phase difference is corrected in one iteration.

Adaptation in this two-oscillation system involves both external and internal relative phase. Figure 11A shows that large deviations from isochrony in  $P_1$  cause  $O_1$  to experience relatively large expectancy violations. Accordingly, large adjustments to  $\phi_2$  result via external phase coupling. By contrast, external phase relative to  $O_2$ , shown in Figure 11B, clusters near 0 and 0.5. The latter causes negligible adjustments to  $\phi_2$ . This is because the shape of the coupling function (Figure 7) implies that onsets near  $\phi = 0.5$  are effectively ignored. The phases clustering near zero, however, reflect occurrences of regularly spaced onsets corresponding to the isochronous periodicity  $P_2$ , but note that sometimes these relative phase values are significantly different from zero. This discrepancy is caused mainly by internal phase coupling:  $O_2$  adapts its phase in response to  $O_1$ , which is responding to a highly variable onset sequence. In this case, internal coupling has a slight desynchronizing effect, distracting  $O_2$  from its target periodicity  $P_2$ . Conversely, the presence of  $O_2$  cushions the blows of large expectancy violations to  $O_1$ , and so adjustments are smaller than they would otherwise be.

Attending rhythms also respond to systematic rate changes in external rhythms by adapting their intrinsic periods (Figure 11, Panels C and D). This, in turn, can affect their internal relationship. Thus, we also consider period coupling between two attending rhythms. Through internal period coupling, two oscillations can maintain an appropriate relative period as they simultaneously respond to rate modulations in an external rhythm. Our expression

of period adaptation for two oscillations parallels that of the one-oscillation model (Equation 4):

$$p_1^{(n+1)} = p_1^{(n)} + p_1^{(n)} \eta_p F(\phi_1^{(n)}) - \alpha P_{21}(\phi^{(n)}, \mathbf{p}^{(n)}, \boldsymbol{\kappa}^{(n)})$$

and

$$p_2^{(n+1)} = p_2^{(n)} + p_2^{(n)} \eta_p F(\phi_2^{(n)}) - \alpha P_{12}(\phi^{(n)}, \mathbf{p}^{(n)}, \boldsymbol{\kappa}^{(n)}). \quad (9)$$

For simplicity, we assume that the strength of internal period coupling is identical to that for phase coupling. This system estimates periods of two different external periodicities within a sequence while maintaining an invariant 1:2 ratio between the periods of  $O_1$  and  $O_2$ . Panels C and D of Figure 11 illustrate period adaptation in response to both external and internal forces. External forces cause large period changes in  $O_1$ , which are passed along to  $O_2$  via internal coupling. Thus, in Figure 11D,  $p_2$  changes even though external forces acting on it are negligible. Conversely, deviations of  $p_1$  are smaller than they would otherwise be as a result of a steadying influence of  $O_2$ .

*Two trains of attentional pulses: Two time scales.* We have assumed that there are two periodicities,  $P_1$  and  $P_2$ , present in the external rhythm (e.g., Figure 3D) and two oscillations,  $O_1$  and  $O_2$ , that synchronize to them. Each oscillation targets attentional energy to expected times consistent with its intrinsic period. These pulses occur at two different time scales given by periods conforming to a 1:2 ratio. Furthermore, two focus variables ( $\kappa_i$ ,  $i = 1, 2$ ) adapt to the external rhythm, one for each attentional pulse. We wish to measure synchronization to  $P_1$  and  $P_2$ , respectively, as suggested in Figure 12. How-

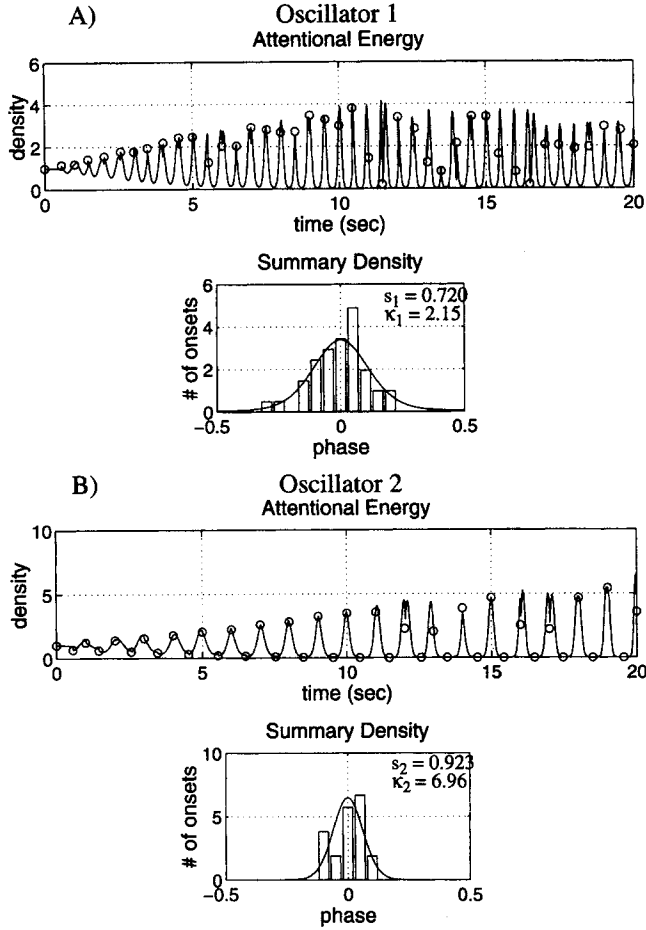


Figure 12. A:  $O_1$  pulses adapting over time to the randomly perturbed periodicity,  $P_1$ , nested within the rhythm of Figure 3D. Beneath is a relative phase histogram for  $P_1$  and summary density for  $O_1$ ; note that incrementally estimated synchronization strength ( $s_1 = 0.720$ ) matches the mean vector length for  $P_1$  (Figure 11A;  $r_1 = 0.720$ ) well. B: Pulses for  $O_2$  to the fixed periodicity,  $P_2$ , in the same rhythm. Summary density for  $O_2$  captures the relative phase histogram for  $P_2$ ; again, incrementally estimated synchronization strength ( $s_2 = 0.923$ ) matches the mean vector length for  $P_2$  (Figure 11B;  $r_2 = 0.931$ ).

ever, we assume that information about which onset marks which periodicity is not available to the estimation process. Such problems can be dealt with via the expectation-maximization algorithm (Dempster, Laird, & Rubin, 1977; McLachlan & Krishnan, 1997), which we adapt to incremental estimation:

$$s_i^{(n+1)} = s_i^{(n)} - \eta_s a^{(n)} \tau_j(\phi^{(n)}; \kappa^{(n)})(s_i^{(n)} - \cos 2\pi\phi_i^{(n)}), \quad i = 1, 2$$

and

$$\kappa_i^{(n+1)} = g^{-1}[H(b, s_i^{(n+1)})]. \quad (10)$$

Equation 10 is similar to Equation 7 with the addition of an expectation-maximization coefficient,  $\tau_j(\phi; \kappa)$ , to the adaptation term; this coefficient is the essential contribution of the expectation-

maximization estimation (see Appendix C). It scales the contribution of the  $n$ th onset to the next estimate of  $\kappa_i$  according to the conditional probability that this onset marks  $P_i$ . The factor  $a^{(n)}$  is the amplitude of the  $n$ th onset, scaled to the range [0 1], reflecting the fact that onset amplitudes differ within a sequence.

To illustrate, consider the two-periodicity stimulus of Figure 3D. Figure 11 (Panels E and F) shows changes in attentional focus as it adapts according to Equation 10. In both cases,  $\kappa$  increases over time, implying narrowing widths of both attentional pulses. The two trains of attentional pulses are illustrated in Figure 12 (Panels A and B, respectively) as the densities evolve over time. Also, the relative phase histograms for stimulus onsets corresponding to  $P_1$  and  $P_2$ , respectively, are compared with summary densities for  $O_1$  and  $O_2$ . Without any information about which onsets mark which periodicities, each focus variable,  $\kappa_i$ , comes to summarize the synchronization of  $O_i$  with  $P_i$ .

### Summary

This section has described three aspects of attending rhythms. First, temporal targeting of attentional energy to external rhythms was shown to arise from a self-sustaining oscillation that entrains to external rhythms. Second, an attender's response to unexpected as well as expected event timings was explained via the construct of an attentional energy pulse modeled as a periodic probability density. Finally, these notions were generalized to multiple interacting attending rhythms. This enables description of a pair of oscillations that jointly track a complex time pattern while dynamically representing its underlying rhythmic form.

### Responses to Event Time Structure: Experiments and Models

This section describes three listening experiments along with simulations of listeners' performance based on the dynamic attending model described earlier. The experiments focused on the three main aspects of our theory: attentional coordination (Experiment 1), attentional focus (Experiment 2), and the two-oscillation model (Experiment 3). Two experiments involved time discrimination (Experiments 1 and 3), and the other involved a time interval classification task (Experiment 2). Experiment 1 addressed hypotheses about attending to the rate-modulated sequences. Experiment 2 addressed hypotheses about attentional pulse and the role of attentional focus. Experiment 3 addressed the coordination of two internal oscillations and the dynamic representation of more complex rhythmic forms.

#### Experiment 1: Attentional Coordination and Time Discrimination

Experiment 1 examined the way in which event time structure regulates attending through the coordination of attending and external rhythms. We used a time discrimination task because it is well suited to evaluation of predictions derived from the attentional model. It permitted assessment of attentional coordination with rate-modulated sequences because it can gauge an attender's sensitivity to fine time changes. This task requires listeners to detect small time changes embedded within isochronous, higher pitched test regions of rate-modulated sequences, such as in Fig-



ure 13. Contextual rate modulations of various degrees mimic tempo fluctuations of natural events in that they might slow (decelerate) or speed (accelerate) pattern rate locally.

We tested the hypothesis that time discrimination in isochronous test regions within rate-modulated patterns is best in sequences that allow good attentional coordination. According to the attending rhythm model, both isochronous sequences and sequences with small rate modulations should provide for good attentional coordination. In addition, for any model to be a serious contender for explaining people's sensitivity to time interval information, it must pass two benchmark tests. First, it must adequately describe effects of temporal context (rate modulations). Second, it must predict differences in the noticeability of time changes. Accordingly, we manipulated both degree of rate modulation and magnitude of to-be-detected time changes.

### Method

**Participants.** Ninety-six undergraduate Ohio State University students participated in this experiment in return for course credit in introductory psychology. None had more than 2 years of musical training.

**Apparatus.** All stimuli were programmed via version 5.0 of the MIDILAB software (R. Todd, Boltz, & Jones, 1989) on a 486 IBM PC compatible computer interfaced by a Roland MPU-401 MIDI processing unit controlling a Yamaha TX81Z FM tone generator set to a sine wave

voice. Stimulus patterns were recorded and played on a cassette deck to listeners equipped with AKG headphones (Model K240).

**Stimuli and conditions.** A basic 25-tone sequence comprising 24 IOIs was used to create 177 experimental sequences. In all, IOIs were marked by tones of equal amplitudes (ca. 76 dB SPL) following the format for context and test regions shown in Figure 13. The context and test tone frequencies were 261 Hz (C4) and 329 Hz (E4), respectively. All test region IOIs were 600 ms (with the exception of changed IOIs).

Two variables, modulation and pattern type, determined the temporal structure of context regions. The four levels of rate modulation, indexed by the standard deviation of 15 context IOIs, were 21, 39, 57, and 76 ms. These comprised (roughly) equal numbers of positive and negative deviations from the mean IOI (600 ms). The same set of IOIs was arranged in three different ways, determining three nonstationary (termed *nonisochronous*) pattern types: rate-increasing sequence, rate decreasing, and alternating IOI magnitudes within the 5 IOIs of a context region. Finally, a fourth pattern type, an isochronous one, functioned as a control.

Two additional variables determined test region structure: magnitude of the to-be-detected (target) time change and type of time change. On all but 24 catch trials, a nonzero time change occurred with equal likelihood in one test region:  $\Delta t = 21, 39, \text{ or } 57 \text{ ms}$  (Weber fractions,  $\Delta t/\text{IOI}$ , of 0.035, 0.065, or 0.095, respectively, assuming that the referent IOI is 600 ms). The type of time change was determined by the direction (advance vs. delay) of a shift in the onset time of the fourth tone within a test region. This change affected two IOIs (the third and fourth; see Figure

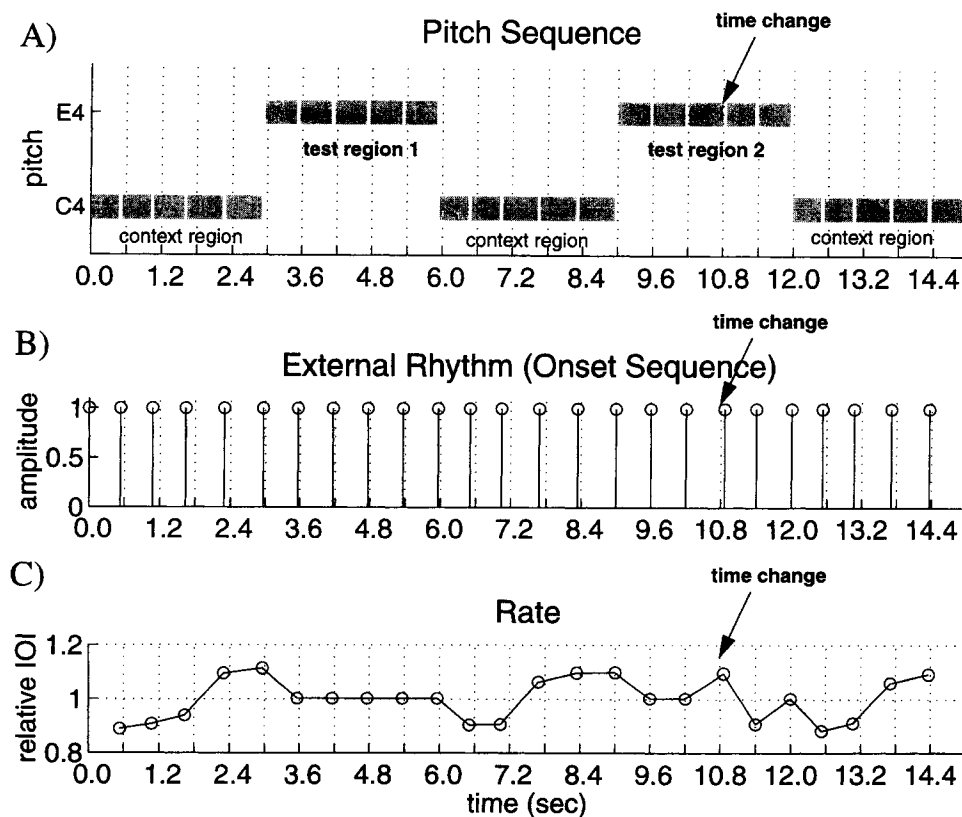


Figure 13. A: An auditory stimulus in Experiment 1 that interleaves test and context regions. B: Successive interonset intervals (IOIs) as well as the locus of a to-be-detected time change. C: Nature of rate modulation in context regions.

13B), creating a short-long (advanced or early) or a long-short (delayed or late) rhythmic deviation.

**Design.** The design was a  $4 \times 4 \times 3 \times 2$  mixed factorial. The single between-subjects variable was modulation, with four levels ( $SD = 21, 39, 57, \text{ or } 76 \text{ ms}$ ). The three within-subject variables were pattern type (isochronous, increasing, decreasing, or alternating rate), time-change magnitude, (21, 39, or 57 ms), and type of time change (advanced or delayed). Twenty-four participants were randomly assigned to each of the four different levels of the rate modulation variable.

**Procedure.** On each of a series of prerecorded trials (sequences), a 2-alternative forced choice (AFC) procedure required listeners to indicate (in writing) whether a sequence contained a time change in its first or second test region. Each trial began with a 500-ms warning tone that preceded the initial tone in a pattern by 2 s. The interval between the onset of a pattern tone and that of the next warning tone was 3.6 s. Listeners received 8 training trials with 100% feedback, followed by session trials with 10% sporadic feedback. Each modulation condition comprised 168 trials (with two brief rests). Each of the three time changes occurred within

each of the four patterns, equally often as advanced ( $-\Delta t$ ) and delayed ( $\Delta t$ ) targets, thereby creating 24 experimental conditions. These 24 patterns, along with 4 catch patterns (0 ms), were randomized within six blocks of 28 trials each; thus, each condition occurred six times within an 80-min session.

**Results and Discussion**

Generally, listeners found it more difficult to detect a time change in nonisochronous (nonstationary) than in isochronous (stationary) patterns. Accuracy increased as rate modulations decreased and as the magnitude of the time change increased. Mean proportions of correct responses, as a function of modulation condition and time-change magnitude, appear in Figure 14 (averaged over the three nonisochronous pattern types).

An analysis of variance (ANOVA) performed on PC scores indicated that the main effect of modulation was significant,  $F(3,$

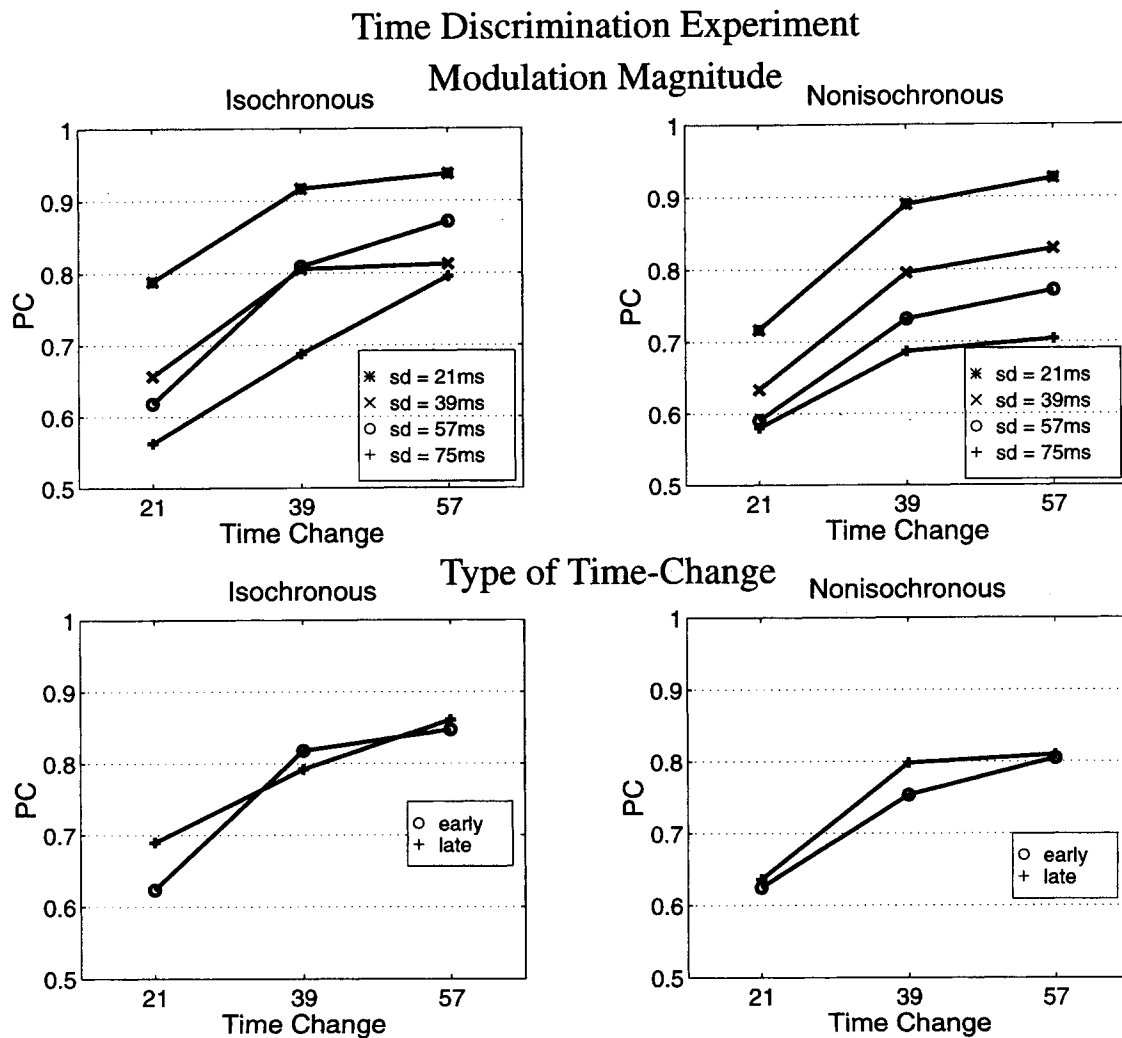


Figure 14. Mean proportion correct (PC) for isochronous and nonisochronous sequences in Experiment 1. Mean PC is given as a function of the magnitude of the to-be-detected time change (abscissa) and, respectively, magnitude of rate modulation (top) and type of time change (bottom).

92) = 6.96,  $MSE = 0.5364$ ,  $p < .0003$ , as was that of time-change magnitude,  $F(2, 184) = 117.24$ ,  $MSE = 0.0612$ ,  $p < .001$ . The interaction of these two variables was not significant.

Although pattern type influenced performance, this effect was entirely due to the fact that listeners were better with isochronous patterns (mean PC = 0.78) than with nonisochronous patterns (mean PC = 0.74),  $F(3, 276) = 5.89$ ,  $MSE = 0.03012$ ,  $p < .001$ . Follow-up analyses confirmed that there were no reliable differences within the nonisochronous patterns.

Time-change type (early vs. late) produced both main effects and several interactions. Although statistically reliable, these effects were small relative to others observed. Late targets were more noticeable than early ones,  $F(1, 92) = 9.85$ ,  $MSE = 0.0227$ ,  $p < .005$ . The long-short rhythmic deviation was especially noticeable in small rate modulation conditions, leading to an interaction of these two variables,  $F(3, 92) = 2.72$ ,  $MSE = 0.227$ ,  $p < .05$ . Time-change type also interacted with pattern type (isochronous vs. nonisochronous) and time-change magnitude,  $F(6, 552) = 2.36$ ,  $MSE = 0.0239$ ,  $p < .05$  (see Figure 14, Panels C and D). This three-way interaction indicates that listeners were more sensitive to late targets (the long-short rhythmic perturbation) in isochronous sequences than in nonisochronous ones, especially with small time changes (e.g., 21 ms). With nonisochronous sequences, a larger time change (e.g., 39 ms) was required to make the early targets more noticeable. Follow-up analyses indicated that the focus of this interaction was between isochronous and nonisochronous sequences; pattern type did not play a role.

Finally, a curious finding is revealed by listeners' responses to the isochronous patterns. The data of Figure 14 indicate the presence of substantial trial-to-trial carryover effects within a session. Isochronous pattern performance gauges this because these patterns appear in all four modulation conditions. Mean PC scores for these sequences, within each modulation condition, are shown in Figure 14. Performance on isochronous and nonisochronous sequences across rate modulation conditions was quite similar. This is remarkable because isochronous patterns contain no modulation. Nevertheless, performance on isochronous patterns differed significantly with modulation condition,  $F(3, 92) = 7.09$ ,  $MSE = 0.1368$ ,  $p < .00025$ . This indicates that effects of rate modulation not only carry over from context to test region within a single nonisochronous pattern (i.e., pattern context effects) but transport over trials from one pattern to another (i.e., session context effects).

Temporal acuity thresholds were determined via a Probit procedure (Finney, 1971) applied to group data within each modulation condition. This procedure used a modified Newton-Raphson algorithm to fit the cumulative form of the normal density function over the three absolute magnitudes of time change (21, 39, or 57 ms) for all pattern types. The 24 listeners within each modulation condition together contributed 1,728 and 576 observations for nonisochronous and isochronous patterns, respectively. For a 2AFC, the Probit base response rate parameter,  $c$ , is fixed at 0.50, and a threshold criterion is PC = 0.75. Resulting threshold values, presented in Table 1, were based on interpolations for all but one condition (isochronous in the 21-ms modulation condition) in which a modest downward extrapolation was required. These

Table 1

*Relative Difference Limens (Probit Analyses) for Isochronous and Nonisochronous Sequences Averaged, Respectively, for Each Group of Listeners Receiving One of the Four Different Rate Modulation Conditions in Experiment 1*

Modulation (SD)	Difference limen (Probit)	
	Isochronous	Nonisochronous
21 ms	.023	.037
39 ms	.060	.067
57 ms	.067	.083
76 ms	.083	.105

values were consistent with accuracy scores in that temporal acuity was best for isochronous pattern contexts presented in the lowest modulation condition and worst for the nonisochronous patterns with greatest modulations.

Overall, the data are consistent with the dynamic attending hypothesis that regular sequences that create few violations of temporal expectancies (e.g., isochronous and small rate modulations) should yield good performance, with listeners displaying acute sensitivity to deviations from an underlying rhythm. In these conditions, performance is well above chance, and Weber fractions (0.03 to 0.07) correspond to those reported elsewhere when rate modulations were absent (e.g., Drake & Botte, 1993; Getty, 1975, 1976; Halpern & Darwin, 1982; Monahan & Hirsh, 1990).

The data are also consistent with statistical models of temporal event structure. It is not clear how conventional psychophysical models address this task (e.g., Allan, 1979; Creelman, 1962; Getty, 1975, 1976; Killeen & Weiss, 1987; M. Treisman, 1963), but the multiple look model correctly predicts observed decreases in acuity with increases in rate modulation. In contrast to the dynamic attending approach, this is due to sequence variability, which yields fuzzy rate encoding. Statistical models have more difficulty with findings related to type of time change, however. This is because IOI mean and variance are identical for sequences containing early and late time changes. Others, using different tasks, have reported similar acuity differences as a function of type of time change (McAuley, 1995; McAuley & Kidd, 1998). Finally, the session context effect, wherein performance with isochronous sequences changes as a function of neighboring patterns, remains challenging for all perspectives.

### *Modeling Time Discrimination Performance*

The dynamic attending model addressed, via two simulations, the main features of Experiment 1 results. We fit PC predictions about the effects of rate modulation, time-change magnitude, and other variables. These predictions rest on attentional focus (the width of the attentional pulse) relative to the magnitude of a time change. A given time change is more noticeable when focus is strong (narrow pulse) than when it is weak (wide pulse), because the former represents violation of a more focused expectation. Finally, focus is pegged to the phase and period of an adapting temporal referent.

The complete model comprises three main parameters: phase coupling strength,  $\eta_\phi$ ; period adaptation rate,  $\eta_p$ ; and focus adaptation rate,  $\eta_s$ . No additional parameters are involved in mapping state variables onto predicted PC values for this 2AFC task. Details of the task-specific PC calculations are found in Appendix B. Values of parameters used in all simulations are summarized in Table 2.

In both simulations, the model predicted mean PC for each condition (individual differences were not considered). It was exposed to four complete experimental sessions, one session per modulation condition. This allowed us to factor in effects of session context. On each trial, the PC calculation yielded a predicted PC value for a given pattern; these values were averaged over all repetitions of that pattern in a session.

### Simulation 1A: No Attentional Coordination

This simulation generated PC predictions for an attentional rhythm that is not coupled to an external rhythm.

**Parameters.** We turned off phase and period coupling by setting  $\eta_\phi$  (phase coupling strength) and  $\eta_p$  (period adaptation rate) both to zero. The resulting model was similar to that of Equation 2, in that it approximated a clock that is not coupled to—and therefore cannot entrain to—the external rhythm. In addition, adaptation rate for attentional focus was set to  $\eta_s = 0.005$ , modeling very slow adaptation to relative phase variability.

**Initial conditions.** On each trial, initial phase,  $\phi_1$ , was set to a small random value ( $M = 0.00$ ,  $SD = 0.01$ ); initial period,  $p_1$ , was set to a random value near 600 ms ( $M = 600$  ms, coefficient of variation [cv] = 0.01). Attentional focus,  $\kappa$ , was set to zero on the first trial of each session, but its final value for a pattern was allowed to carry over from trial to trial within a session. We reasoned that this simple form of memory, in addition to the slow adaptation of attentional focus, might accommodate session context effects.

**Results.** Figure 15A displays mean PC predictions. Clearly, this simulation failed to predict any aspects of these data; in fact, chance performance was predicted in all conditions. Correspondingly, root-mean-square deviation (RMSD) with these data was large (0.289), indicating that the absence of coupling hurts performance. Thus, we move to Simulation 1B.

### Simulation 1B: Good Attentional Coordination

The second simulation generated PC predictions for an attentional rhythm coupled to an external rhythm.

Table 2  
Parameter Values and Root-Mean-Square Deviation (RMSD)  
Fits for All Simulations

Simulation	Phase coupling strength ( $\eta_\phi$ )	Period adaptation rate ( $\eta_p$ )	Focus adaptation rate ( $\eta_s$ )	RMSD
1A	0.0	0.0	0.005	0.289
1B	0.6	0.1	0.005	0.055
2A	0.6	0.1	0.000	0.213
2B	0.6	0.1	0.005	0.063
3A	1.0	0.3	0.005	0.104
3B	1.0	0.3	0.005	0.064

**Parameters.** For the second simulation, we enabled phase and period coupling, setting  $\eta_\phi = 0.6$  and  $\eta_p = 0.1$ . The adaptation rate for attentional focus was again set to  $\eta_s = 0.005$ .

**Initial conditions.** As in Simulation 1A, initial phase,  $\phi_1$ , was set to a small random value ( $M = 0.00$ ,  $SD = 0.01$ ) at the beginning of each trial, and attentional focus,  $\kappa$ , was allowed to carry over from trial to trial within a session. Because period adaptation was enabled for this simulation, final period was carried over from the previous trial. Thus, as in the previous simulation,  $p_1$  usually differed slightly from 600 ms. No additional noise was added to this initial estimate.

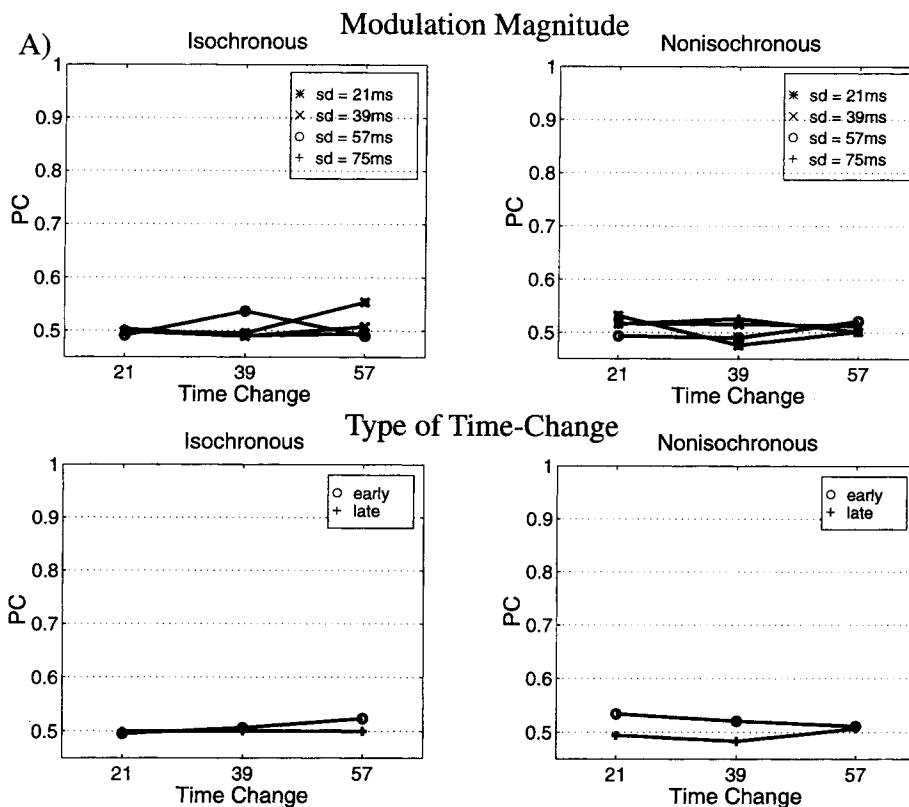
**Results.** Figure 15B displays mean PC predictions. It is evident that this simulation was far superior to the first in predicting the performance of our listeners. This was confirmed by the much smaller RMSD (0.055). The model correctly predicted that large time changes are easier to detect than small time changes. It also predicted a large effect of contextual modulation: Discriminability gradually falls off with increasing contextual modulation. A small effect of time change (i.e., early-late) was also predicted by this simulation. Interestingly, it was very nearly opposite to the small effect observed in our experiment; the model found early time changes easier to notice than late time changes (we return to this point shortly). Finally, a large session context effect was predicted. The model's performance on isochronous sequences was greatly influenced by the modulation session in which they occurred, just as it was for listeners.

### Discussion

The preceding simulations indicate that coordination of attention with external events is crucial. The first simulation, in which the attentional rhythm was not coordinated with the attentional oscillation, predicted chance performance in this task. The reason is evident in Figure 16 (Panels A–C), which displays the time course of the state variables in an actual trial from a high rate modulation session ( $SD = 57$  ms) of Simulation 1A. When a slightly mistuned initial period is combined with a rate-modulated sequence, phase drifts and finally wraps around (much as predicted by a simple clock model; see Figure 6, Panels B and C). And because this general state of affairs obtains throughout the session, focus remains correspondingly low (Panel D). By contrast, when phase and period coupling enter the picture, model fits improve dramatically. Figure 16 (Panels E–H) displays the state variables for the corresponding trial from the same session of Simulation 1B. The initially mistuned period (Panel F) now adapts to the period of the sequence. In addition, phase (Panel E) is well coordinated with the event onsets, and accordingly attentional focus (Panels G and H) is high. Focus is estimated over several trials, accounting for the session carryover effect.

The entrainment of an internal oscillation to an external rhythm (Equations 3 and 4) is important in explaining its superiority over an uncoupled (i.e., fixed clock) model (Equation 2). In the latter, lack of coupling precludes its responding adaptively to various rate perturbations in the different sequences of this experiment. These perturbations continue to produce large deviations from the expectations generated by the attending rhythm, and large expectancy violations keep attentional focus low as a result of a lack of synchronization. Thus,

Simulation 1A — No Attentional Coordination



Simulation 1B — Good Attentional Coordination

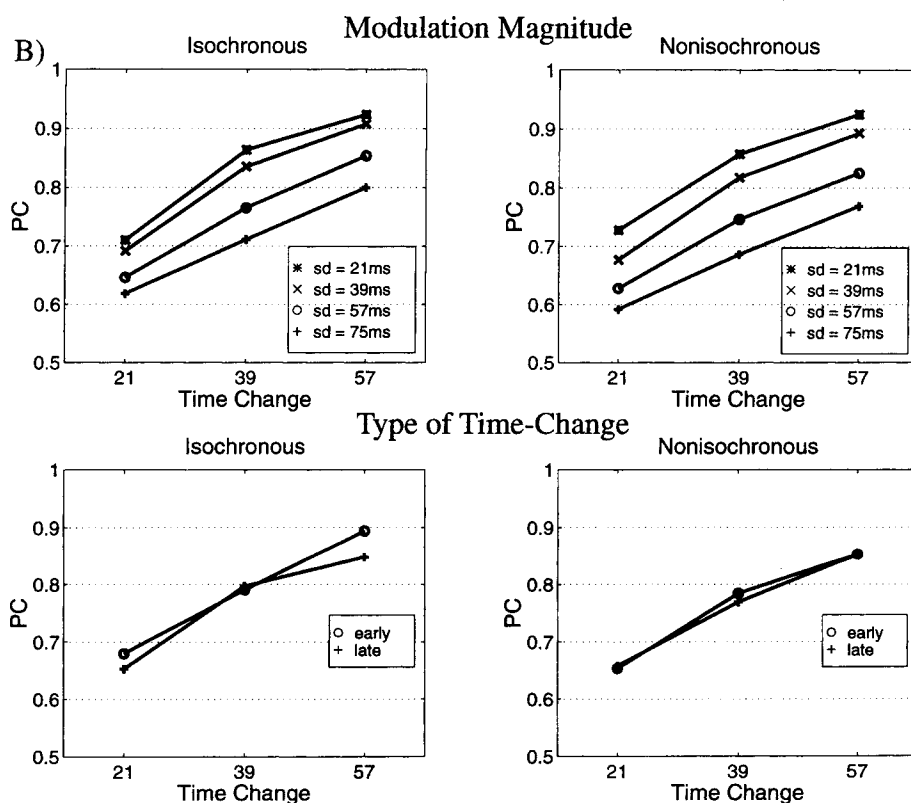


Figure 15. A: Predicted proportion correct (PC) from Simulation 1A (no attentional coordination), which involved no coupling,  $\eta_\phi = \eta_p = 0$ . B: Corresponding predictions from Simulation 1B (good attentional coordination), which incorporated coupling,  $\eta_\phi = 0.6$ ,  $\eta_p = 0.1$ . Compare predicted PCs for these conditions with observed PCs in Experiment 1, shown in Figure 14.

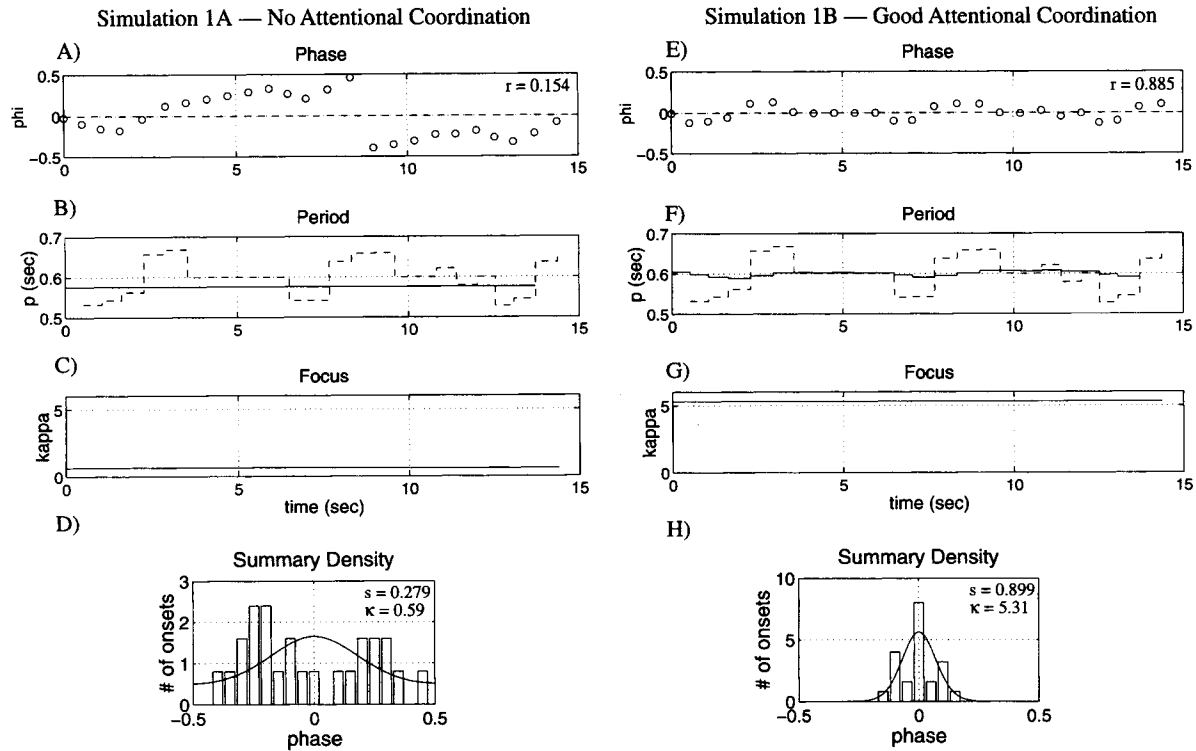


Figure 16. Characteristic model predictions for an actual trial in a high rate modulation condition of Experiment 1. Predictions are shown as time series for the three state variables of the model, phase, period, and focus. A relative phase histogram and summary density are also shown. The histogram shows the observed distribution of relative phase on the current trial, whereas the summary density (solid line) shows predicted pulse width based on previous trials. A–D: Predictions from Simulation 1A (no attentional coordination). E–H: Corresponding predictions from Simulation 2A (good attentional coordination).

for rate-modulated patterns, fixed clock models do not suffice. Statistical models, on the other hand, do generate the correct rank order of predicted PC scores for nonisochronous patterns. Their success derives from a dependence on a sequence's IOI variability; in the patterns of this experiment, IOI variability was strongly correlated with quality of synchronization. However, statistical models do not adequately predict session context effects with isochronous patterns.

One outcome none of the models predicts is the difference between early and late time changes (and the resulting interactions). Overall, late onsets were slightly easier to detect than early ones, with this more evident for small time changes in isochronous sequences and for larger ones in nonisochronous patterns. Currently, our model weighs late and early onsets equally in an isochronous context. There is reason to question this assumption, however. McAuley (1995) found that, with isochronous sequences, late onsets are more noticeable at slow rates and early ones are more noticeable at fast rates; his model handles these findings. Similar assumptions could be incorporated in our model. Because the bulk of evidence on this remains inconclusive, however, we refrain from a theoretical commitment.

### Experiment 2: Duration Judgments and the Attentional Pulse

The single-oscillation model rests on two major assumptions, only one of which, attentional coordination, was addressed in Experiment 1. The other concerns the attentional pulse: Attentional focus is assumed to reflect a concentration of energy at particular points in time. Experiment 2 addressed the second assumption. The incorporation of pulsed energy implies that performance should be better when a time interval begins and ends at expected rather than unexpected times, because the former represent points of maximum attentional energy. In light of this, the outcome of Experiment 1 may seem surprising: Time discrimination performance was best with large time changes, meaning that performance improved as a to-be-detected time interval (or tone onset) departed from an expected point in time. Although the model neatly describes time discrimination data, how does its success in this case square with the idea that pulses of attentional energy center about expected locations? Should not discrimination performance be best when the markers of time intervals fall within the region of maximum attentional energy concentration?

The answer is found in the way model predictions accommodate different tasks. In a 2AFC time discrimination task, best performance is associated with correct responses to novelty (i.e., to expectancy violations) because listeners have only two choices, both differences. The versatility of our approach is its quantification of responses to unexpected as well as expected time intervals. The model implies that “different” responses are more likely to be correct when sequences are highly regular and attention is highly focused so that a time change “pops” out. This is precisely what happened with isochronous sequences in Experiment 1, in which listeners indeed performed best. In short, people should most reliably notice a changed tone onset when it has violated a strong expectancy about “when” the tone should occur.

The flip side of this coin is relevant to the present question. Specifically, should not time judgments be better when they involve expected rather than unexpected onset times? The answer is yes, but a different task is required to test this. With the invaluable assistance of Ralph Barnes, we devised a categorization task similar to one used by McAuley and Kidd (1998): Listeners judged target time intervals as the same as, longer than, or shorter than a preceding standard interval. In fact, the target was equally often the same as, longer than, or shorter than the standard. A highly focused expectancy for the standard was created by preceding it with a sequence of isochronous IOIs. Sometimes the standard interval confirms this expectancy, but more often it does not. Figure 17 depicts the latter, where the standard IOI is unexpected. We anticipate that people will be better at judging these two

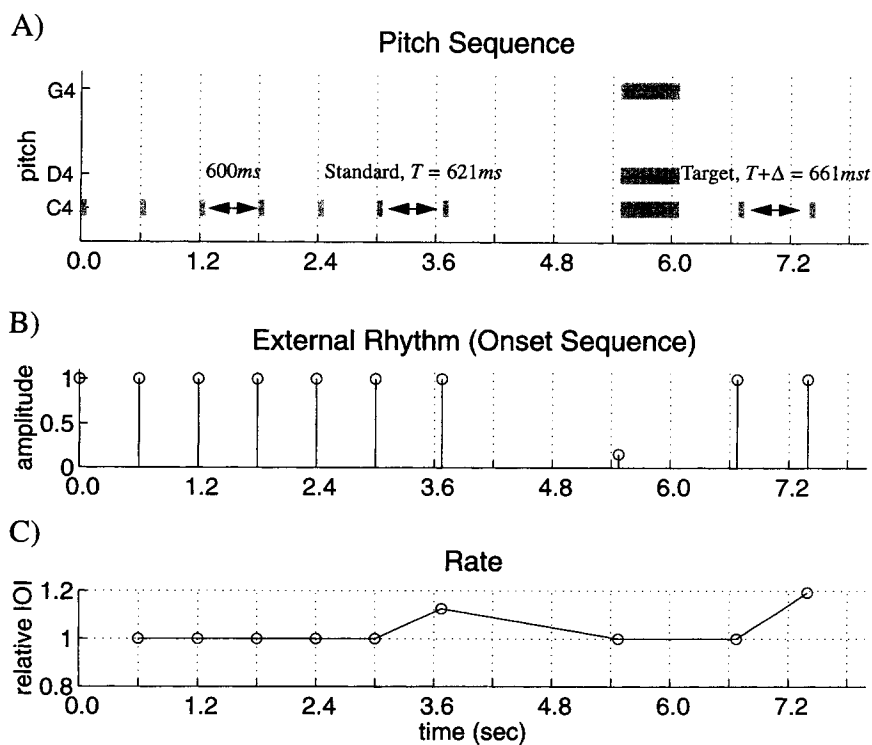
intervals when the standard is expected rather than unexpected. In this experiment, we used three expectancy conditions: *expected*, where the standard duration,  $T$ , equals the IOI of preceding durations (600 ms); *unexpected*, where  $T$  ends either early or late by 21 ms; and *very unexpected*, where  $T$  ends either 76 ms early or late. The model predicts that categorization performance will be best when the standard is expected and worst when it deviates markedly from expectation.

### Method

**Participants.** Of the 48 original participants, the data from 10 were eliminated for reasons described shortly. Analyses were based on 38 listeners, all of whom met the same criteria as in Experiment 1.

**Apparatus.** The apparatus was identical to that of Experiment 1.

**Stimuli and conditions.** All auditory sequences comprised a series of context IOIs followed by one standard and one target IOI arranged as in Figure 17. The context sequence was always isochronous, composed of five 600-ms IOIs marked by onsets of 60-ms tones (264 Hz). The IOIs of standard,  $T$ , and target,  $T + \Delta t$ , intervals varied according to expectancy conditions (described later). The time between onset of the final standard tone and the first target tone was 3 s, 600 ms of which was filled with a soft chord (component frequencies: 262, 294, and 392 Hz) designed to signal the forthcoming target interval; the onset of this tone occurred 1,800 ms after the onset of the second tone of the standard interval. The target interval followed the chord (see Figure 17). Equally often, the standard IOI assumed one of the following values:  $T = 600$  ms (*expected*),  $T = 600$  ms  $\pm$  21 ms (*unexpected*), or  $T = 600$



**Figure 17.** A and B: Stimulus sequence from the unexpected condition of Experiment 2; the standard interonset interval (IOI),  $T$ , follows an isochronous sequence and is followed by the target IOI,  $T + \Delta t$ . C: Rate curve for this stimulus pattern.

Table 3  
Results of Experiment 2

Measure	Expected		Unexpected		Very unexpected	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Percentage correct	0.625 <sub>a</sub>	0.122	0.588 <sub>a</sub>	0.084	0.490 <sub>b</sub>	0.078
<i>d'</i>	1.443 <sub>a</sub>	1.274	1.168 <sub>a</sub>	1.054	0.508 <sub>b</sub>	0.572
False alarm rate	0.320	0.183	0.361	0.175	0.380	0.125

Note. Means with different subscripts differ (honestly significant difference) at  $p < .01$ .

ms  $\pm$  76 ms (very unexpected), resulting in a range of *T* values (in ascending order) of 524 ms, 579 ms, 600 ms, 621 ms, and 676 ms. For any standard *T*, the target interval was  $T + \Delta t$ ; equally often, it was shorter than ( $\Delta t = -40$  ms), equal to ( $\Delta t = 0$ ), and longer than ( $\Delta t = 40$  ms) the standard. These three categories occurred an equal number of times with each type of target. They were combined to form three expectancy conditions in which the standard interval ended on time or was deviant by either 21 ms or 76 ms; over the three expectancy conditions, the Weber fraction was identical:  $\Delta t/T = 0.067$ , which substantially exceeded the relative time discrimination threshold for an isochronous context of this length (between 0.02 and 0.04; Drake & Botte, 1993; Jones & Yee, 1997; Schulze, 1989; see also Table 1).

**Procedure.** Listeners heard recorded instructions and demonstration patterns and studied a diagram of the task (similar to Figure 17, without times indicated). They were told to listen only for the standard and target intervals and that the onset of the latter was signaled by a very soft chord. Initially, they completed 20 practice trials with corrective feedback regarding short, same, and long targets on each trial; these trials contained roughly equal numbers of the three expectancy conditions (expected, unexpected, and very unexpected). To ensure that only listeners who clearly understood the task were included in the data analysis, we included only experimental session data from listeners who scored 60% correct or better on the last 10 practice trials (chance was 33%); in addition, all of the data of any listener who pressed a response button before the onset of the target interval on more than 5% of the trials were eliminated. A posttest questionnaire verified that listeners followed instructions.

An experimental session comprised 180 trials, on each of which listeners judged the final IOI (target) relative to the standard by pressing one of three buttons labeled shorter, same, or longer. They received noncorrective feedback (i.e., correct vs. incorrect) on each trial. Stimuli were presented over trials in 10 trial blocks; within each block, two of each of the five expectancy conditions appeared in succession. The order in which the five different pairs were presented was randomly determined over the 18 blocks of trials, such that none of the three response categories (shorter, same, and longer) were correct for more than four successive trials. Equal numbers of the three categories occurred over 60 trials. Each of the five expectancy conditions (i.e., different *T* values) occurred 36 times; thus, the relative frequency of each *T* was 0.20, and the relative frequency of any unexpected *T* value was 0.80.

## Results and Discussion

Results indicate that expectancy systematically affects time judgments. Table 3 presents means and standard deviations of PC,

*d'*, and false alarm rates for the expected, unexpected, and very unexpected conditions. As predicted, listeners were most accurate (as indexed by PC) when the standard interval could be anticipated on the basis of preceding context (the expected condition) and least accurate when this interval was very unexpected,  $F(2, 74) = 29.96$ ,  $MSE = 0.006$ ,  $p < .00001$ . A Tukey honestly significant difference value of 0.059 ( $\alpha = .01$ ) indicates that expected and unexpected conditions did not significantly differ, but both differed from the very unexpected conditions. Similarly, discriminability (*d'*) decreased as the standard became less expected,  $F(2, 74) = 29.18$ ,  $MSE = 0.124$ ,  $p < .00001$ , and the false alarm rate<sup>6</sup> increased,  $F(2, 74) = 29.99$ ,  $MSE = 0.047$ ,  $p < .00001$ . Mean PC values exceeded chance (.33) in all conditions ( $p < .01$ ).

Figure 18 presents mean PC levels for the three expectancy conditions with respect to the three time categories. Two features of these data are evident. First, in the expected condition, listeners were accurate, with roughly equal likelihood, in categorizing short, same, and long target intervals (although best with the same intervals). Second, in other conditions, there was a tendency to judge targets based on early standards as shorter than their standards and those with late standards as longer. This tendency was more marked in the very unexpected conditions. These findings agree with those of McAuley and Kidd (1998).

### Modeling Categorization Judgments

The sequences of Experiment 2 were shorter and simpler than those used in Experiment 1; at most, they contained one perturbation of an IOI before the target IOI. Accordingly, the single-oscillation model predicts a narrow attentional focus as a listener approaches the standard interval. With this model, we simulated mean PC performance for the three response categories of this task; details of PC derivations from the von Mises distribution are provided in Appendix B. Our strategy was to model attending by requiring the model to respond to all Experiment 2 stimulus

<sup>6</sup> In this context, false alarm rate for a particular type of time change of the comparison IOI was determined separately for each of the three types of changes (longer, same, or shorter). It was the rate at which a listener used the response term for that time change (e.g., same) inappropriately when the comparison manifested a different change (i.e., as in responding "same" to a longer comparison).



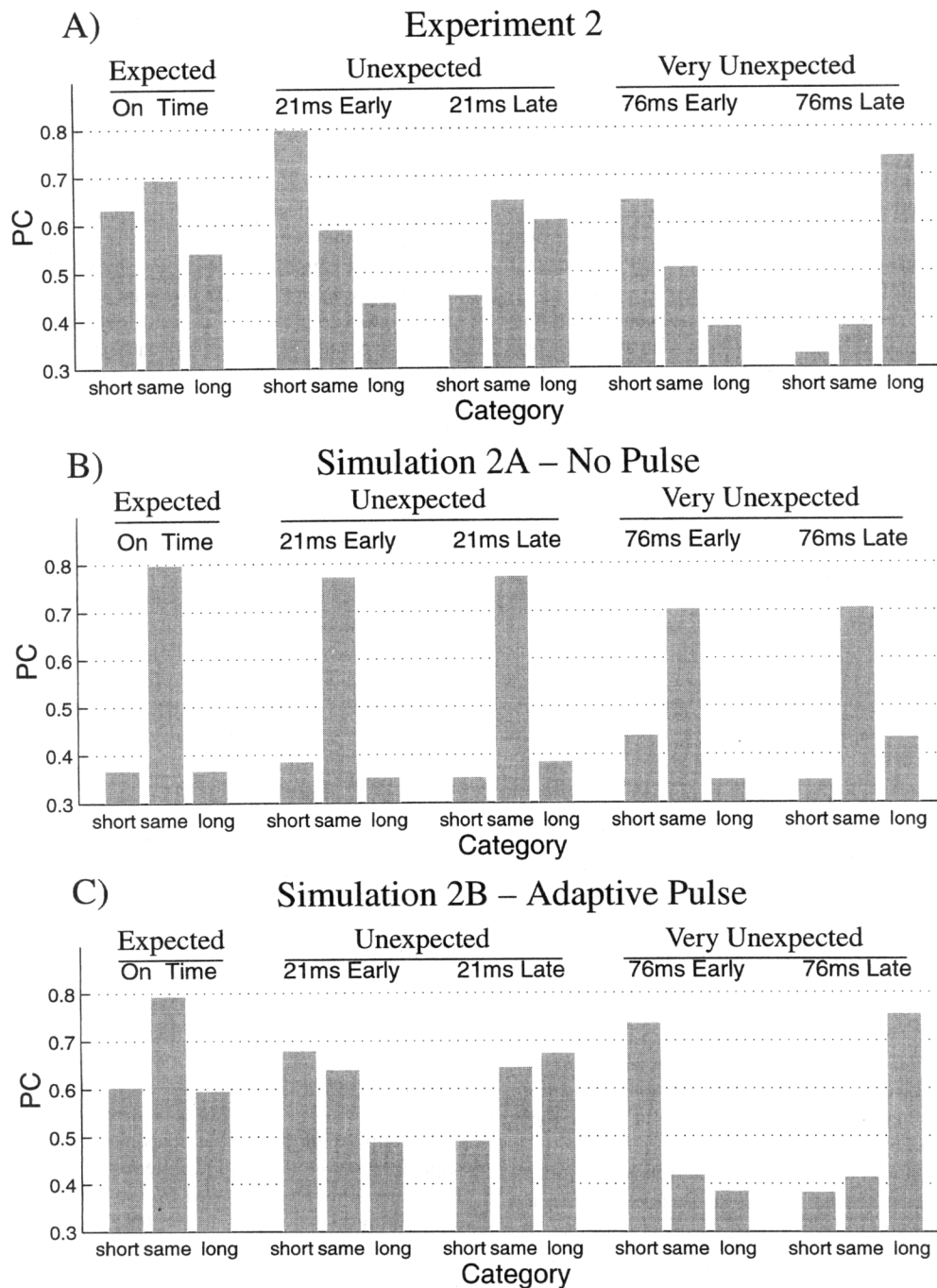


Figure 18. A: Mean proportion correct (PC) values over the three categories in each of the five expectancy conditions of Experiment 2. B and C, respectively, show predictions of Simulation 2A (no attentional pulse;  $\eta_s = 0$ ) with widely distributed attending energy and Simulation 2B (adaptive attentional pulse;  $\eta_s = 0.005$ ) with focused energy.

sequences. We aimed to explain both observed expectancy effects and the role of attentional focus. To accomplish this, we predicted performance using two simulations, one with a fixed-width attentional focus (Simulation 2A) and one with an adaptive focus (Simulation 2B).

#### Simulation 2A: No Attentional Pulse

If an attentional pulse is important in explaining attending, we anticipate that PC predictions will not jibe with observed ones when attentional energy is widely distributed over a cycle. To

simulate diffuse attentional focus, we set  $\kappa$  to zero, modeling a uniform distribution of attentional energy over each cycle.

*Parameters.* We enabled both phase coupling and period adaptation, setting  $\eta_\phi = 0.6$  and  $\eta_p = 0.1$ . Adaptation rate for attentional focus was set to  $\eta_s = 0$ , modeling fixed focus.

*Initial conditions.* On each trial, phase,  $\phi_1$ , was set to a small random value ( $M = 0$ ,  $SD = 0.01$ ), and period,  $p_1$ , initially 600 ms, carried over from trial to trial. Attentional focus,  $\kappa$ , was set to zero. Because adaptation of focus was disabled, the pulse was effectively disabled, modeling a uniform distribution of energy throughout each cycle of the attentional rhythm.

*Results.* Figure 18B displays mean PC predictions for all nine conditions of Experiment 2 ( $RMSD = 0.213$ ). The strongest prediction was that performance is best when judging two identical intervals, regardless of condition. Although this prediction was not completely at odds with the experimental findings, the PC scores generated for the same category were disproportionately high relative to others. This simulation also predicted that, in the early conditions, judgment accuracy should be greater for a shortened than a lengthened interval. Conversely, in the late conditions, it should be easier to classify a lengthened than a shortened interval, but with lower accuracy scores than observed. None of these predictions quite fit the data, so we turn to Simulation 2B.

### *Simulation 2B: Adaptive Attentional Pulse*

The full model unleashes attentional focus; it is free to adapt to sequence and standard IOIs. With Experiment 2 sequences, we expected focus to increase, provided that a high concentration of attentional energy is targeted to an expected ending time of the standard IOI. This also means that the ending time of a very unexpected standard will fall outside the pulse and receive little energy.

*Parameters.* For the second simulation, we enabled phase and period coupling as in Simulation 2A, setting  $\eta_\phi = 0.6$  and  $\eta_p = 0.1$ . Focus adaptation was enabled, setting  $\eta_s = 0.005$ .

*Initial conditions.* In a manner similar to that of the previous simulation, phase,  $\phi_1$ , was set to a small random value ( $M = 0$ ,  $SD = 0.01$ ), and period carried over from trial to trial. Attentional focus,  $\kappa$ , was set to zero at the outset of the session and carried over from trial to trial, allowing an adaptation of attentional focus within a sequence and over several trials.

*Results.* Figure 18C displays mean PC predictions ( $RMSD = 0.063$ ). In contrast to the simulation with no attentional pulse, the adaptive pulse simulation nicely described observed outcomes. As evident from predictions regarding expected sequences, same intervals were still easier to identify than long or short intervals, but by a smaller margin than in the previous simulation, in agreement with the data. Furthermore, the tendency of listeners to classify an interval as shortened (or lengthened), when it was in fact the standard that was shortened (or lengthened), was predicted here.

### *Discussion*

Two interesting outcomes are predicted by the adaptive pulse model. The first concerns the effect of the expectancy condition on categorization accuracy and the role of the attentional pulse. In Simulation 2A, attentional energy was unfocused; energy was so

widely distributed that even suprathreshold differences were not responded to. This led to the incorrect prediction that even very large expectancy violations are the same as synchronous onsets. Neither differences between the standard and the preceding IOIs of 600 ms nor those between the standard and the target IOIs were reliably noticed. Everything seems similar.

By contrast, a focused pulse, which was predicted by Simulation 2B, concentrates energy narrowly around  $\phi = 0$ , given the isochronous context preceding the standard. This correctly predicted that judgments in the expected and unexpected conditions should be relatively accurate. However, when the standard is very deviant from a preceding context, it is difficult to accurately compare it with a target interval. This is because the comparison ultimately depends on the phase of the attentional rhythm. Small violations of expectancy (e.g., unexpected) are tolerated, but large violations (e.g., very unexpected) are not.

The second pattern of responding predicted by the adaptive pulse model involved listeners' tendency to judge a target long (or short) when its standard ends late (or early). This is due to the fact that the phase adjustment and period adjustment to the first deviation (the standard interval) were only partial. Furthermore, although the intervening chord and first onset of the comparison interval reinforce the phase adjustment, they effectively eliminate the period adjustment. This means that memory for the standard is dominated by the context of surrounding IOIs (600 ms). The model predicts that a standard functions like one of the context IOIs in determining the locus of the pulse for judging a target. Thus, in a very simple way, the model explains apparent biasing effects of a standard on categorization judgments.

### *Experiment 3: Responding to Rhythmical Patterns*

The final experiment returned to the issue of temporal event structure. We relied on the more complex, rhythmical patterns studied by Jones and Yee (1997; Experiment 3) to address this question. In the introduction, we indicated that these data rule out a purely statistical treatment of memory for rhythmical time intervals (see Figure 2). Models that enlist an underlying referent period, or beat, are more plausible. Povel and Essens (1985), for instance, proposed that regular sequences induce a fixed beat period that enables encoding of a series of patterned IOIs.

We aim to illustrate that responses to temporally patterned sequences can be understood in terms of two attending rhythms. The patterns involved differed from those of the first two experiments in that both amplitude and IOIs were systematically varied to create rhythmical sequences falling into two categories: regular (RR and R) and irregular (I and IR), as shown in Figure 2. Within such patterns are two identical test regions; listeners had to judge which of the two regions contained a to-be-detected time change.

### *Method*

Only the main features of the Jones and Yee experiment are presented; a complete description appears in Jones and Yee (1997, Experiment 3). The methodology was identical to that of earlier experiments with the following exceptions.

*Participants.* Sixty-four undergraduate students participated in return for course credit.

*Stimuli and conditions.* Figure 2 shows the four basic patterns (RR, IR,

R, and I), all of equivalent duration (9,600 ms), that were used to create pairs of standard and comparison monotone sequences (pitches of G4 and D4, respectively). All patterns consisted of eight loud-soft (two beat) cycles with an average cycle duration of 1,200 ms. In all patterns, when a soft tone occurred within a cycle, it always subdivided that cycle into two equal parts. The louder tone (80 dB SPL) in each cycle served as the initial beat opening each cycle, and the softer tone (76 dB when present) supplied the second beat. All tones lasted 60 ms.

Two pattern categories were regular (RR and R) and irregular (IR and I). In each category, one pattern instance was more explicitly rhythmical (and hence more variable, statistically) than the other; the more rhythmical patterns were termed RR and IR. Less rhythmical sequences were R and I. The R sequence was isochronous except for a final lengthened IOI created by omitting the soft tone in the last cycle. The I sequence was identical to the R pattern with respect to four of its eight cycles; the remaining four cycles had the same mean duration (1,200 ms), but their individual durations varied: 1,500 ms (Cycle 1), 1,400 ms (Cycle 4), 1,000 ms (Cycle 5), and 900 ms (Cycle 8). These soft tones subdivided cycle durations into two equal IOIs (except for the final cycle). The RR and IR patterns were developed, respectively, from the R and I sequences. Each contained four lengthened IOIs created by omitting soft tones from the four cycles in R and I sequences.

*Apparatus and stimulus generation.* These were identical to Experiments 1 and 2.

*Procedure.* After hearing a standard-comparison pair, listeners had to localize (in writing) a small time change,  $\Delta t$ , in one of two test regions of the comparison sequence (2AFC). The time change always shifted the onset of the soft tone within these (otherwise isochronous) test cycles (Cycle 2 or 6). Assuming that the referent IOI is the average IOI (600 ms) within a test region,  $\Delta t/\text{IOI} = 0.075$ . Test regions were identical in all four patterns. Thus, the four basic sequences differed only with respect to the contextual time structure surrounding test regions.

Listeners completed 7 practice trials involving representative sequences containing relatively large time changes; these were followed by 48 experimental trials. Feedback occurred only on practice trials.

*Design.* The design was a  $4 \times 2$  mixed factorial. Four levels of session context (a between-subjects variable) involved the following sets of patterns: RR and R, RR and I, IR and R, and IR and I. Pattern instance, referring to the two pattern levels (rhythmical vs. nonrhythmical) in each of the four sets, was a within-subject variable. In any given session, half of the trials involved standard comparisons based on either RR or IR; the remaining trials involved pairs from R or I pattern types.

### Results: An Overview

Two main findings in the ANOVA of PC scores are of interest. First, the effect of session (RR-R, RR-I, IR-R, or IR-I) was significant,  $F(1, 60) = 4.73$ ,  $MSE = 0.040$ ,  $p < .005$ . Second, the session variable interacted with pattern type in a session,  $F(3, 60) = 5.27$ ,  $MSE = 0.018$ ,  $p < .005$ . Mean PC scores as a function of pattern and session context are shown in Figure 19. They indicate that, overall, regular patterns produced better performance than irregular ones; performance was best in the RR-R session and worst in the IR-I session.

More interesting is performance on individual patterns and the way it changes as a function of session context, as reflected by the preceding interaction. Figure 19 presents the performance of listeners on the same sequence when it appeared with another pattern in the two different session contexts (see abscissa). Note that although both regular patterns produced good performance and both irregular ones produced poor performance, there were intriguing carryover effects due to the accompanying session pattern.

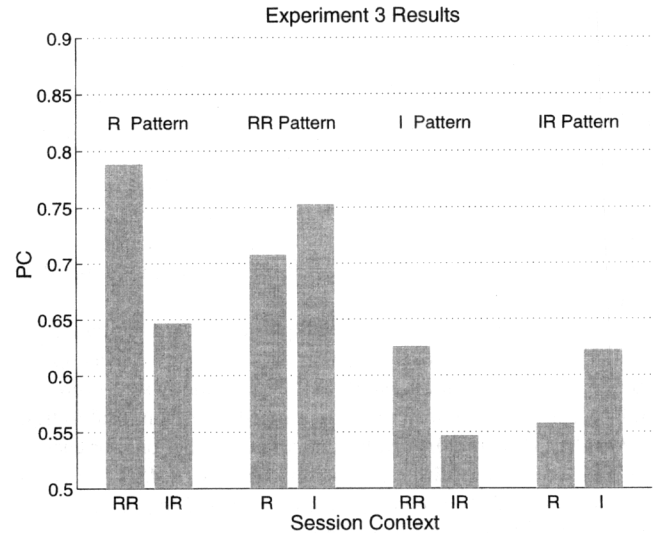


Figure 19. Results of Experiment 3 (from Jones & Yee, 1997; Experiment 3 with nonmusicians). Mean proportion correct (PC) is shown for each of the four patterns (regular [R], regular rhythm [RR], irregular [I], and irregular rhythm [IR]) as a function of two alternate session partners. Thus, for example, in Pattern R, mean PC = 0.79 when accompanied by RR but only 0.65 with a different session partner, namely the IR pattern.

Two such effects are worth noting. First, statistically significant improvement in performance on the R pattern occurred in the session context of the RR pattern relative to that of the IR context. Second, even the I pattern appeared to benefit from the RR context relative to the IR (although this only approached significance). Curiously, neither RR nor IR patterns seemed as vulnerable to carryover effects as the R and I sequences.

### Modeling Sensitivity to Rhythmic Form

Although a single oscillation can respond to changing periodicities within a pattern, it is less well equipped than two or more oscillations to capture relational information about complex rhythmic forms. Accordingly, we describe two simulations of the data presented in Figure 19. They reflect performance of the model based on a single oscillation (Simulation 3A) and two oscillations (Simulation 3B). We continued to rely on time-change noticeability as a gauge of a listener's sensitivity to a pattern's time structure. To accomplish this, we assumed in both simulations, that the oscillation whose period corresponds to the modal IOI, denoted by  $O_1$ , supplies the referent for time-change detection. In effect,  $O_1$  supplies the underlying beat for detecting the time change. Unlike fixed beat models, however, the oscillator adjusts phase and period. Moreover, in the two-oscillation model,  $O_1$  must respond not only to exigencies of an external rhythm but also to the simultaneous pull of a second attentional rhythm,  $O_2$ . In both simulations, we presented the model with pairs of standard-comparison sequences. To address session context effects, we simulated each of the four session conditions by exposing the given model to entire sessions.

### Simulation 3A: The Single-Oscillation Model

A single-oscillation model predicts mean PC scores for the present data by assuming that, in these rhythmical patterns, stronger (louder) markers corresponded to higher amplitude markers ( $a = 1.0$  in simulation) and weaker (softer) markers corresponded to markers of lower amplitude ( $a = 0.5$  in simulation).

*Parameters.* We enabled both phase coupling and period adaptation, setting  $\eta_\phi = 1.0$  and  $\eta_p = 0.3$ . Adaptation rate for attentional focus was set to  $\eta_s = 0.005$ , again modeling slow adaptation of attentional focus.

*Initial conditions.* On each trial, phase  $\phi^{(1)}$ , was initialized to a small random value ( $SD = 0.01$ ) and period,  $p^{(1)}$ , was initialized to 600 ms. Attentional focus,  $\kappa^{(1)}$ , was initially set to zero. As in Experiment 1, memory for focus carried over from trial to trial.

*Results.* Figure 20A displays mean PC predictions for each of the four patterns in different session contexts ( $RMSD = 0.104$ ). The single-oscillation model correctly predicted the largest effect in this experiment: that the regular patterns (R and RR) were much more conducive to time-change detection than were the irregular patterns (I and IR). In addition, the single-oscillation model correctly predicted significant negative carryover from the IR to the R pattern. Unfortunately, the model also predicted considerable negative carryover from the I to the RR pattern, an effect not observed. Furthermore, the marginally significant carryover effect of RR on the I pattern was not captured, although a slight trend in this direction was evident. Overall, the model predicted better performance for the regular patterns and poorer performance for the irregular patterns than observed. Thus, we turn to the predictions of the two-oscillation model.

### Simulation 3B: A Two-Oscillation Model

Our second simulation added a second oscillator to the system of Simulation 3A. The oscillator of the previous simulation is denoted here as  $O_1$ , and the additional oscillator is denoted as  $O_2$ . Following Equations 8 and 9, the two oscillations were phase coupled with a 2:1 ratio and period coupled in a 1:2 ratio.  $O_1$  continued to serve as the referent oscillation; thus,  $p_1$  supplied the temporal referent for time discrimination. This enabled direct comparison of performance in the two-oscillator simulation with performance in the single-oscillator case.

*Parameters.* The parameters specifying the effect of the external signal,  $\eta_\phi$ ,  $\eta_p$ , and  $\eta_s$ , were identical to those of the single-oscillator simulation and the same for both oscillators. The parameter specifying internal phase and period coupling was set to  $\alpha = 0.5$ .

*Initial conditions.* On each trial, initial phases,  $\phi_1^{(1)}$  and  $\phi_2^{(1)}$ , were set to small random values ( $SD = 0.01$ ), and initial periods,  $p_1^{(1)}$  and  $p_2^{(1)}$ , were set to 600 and 1,200 ms, respectively. At the beginning of each new session, attentional focus for both oscillations,  $\kappa_1^{(1)}$  and  $\kappa_2^{(1)}$ , was set to zero. As in previous simulations, memory for focus carried over from trial to trial.

*Results.* Predicted PC values are shown in Figure 20B as a function of pattern structure and session context condition ( $RMSD = 0.064$ ). The two-oscillator simulation did a better job of predicting the main effect of pattern structure than did the single-oscillator simulation. As with Simulation 3A, it correctly predicted

better performance with regular than irregular patterns, but it did so with greater precision.

Simulation 3B also nicely captured observed session context effects. The significant decrement in listeners' performance observed for the R sequence when accompanied by IR (vs. RR) patterns was predicted by the two-oscillation model. In addition, the model captured the slight advantage observed for the I sequence when accompanied by RR (vs. IR) patterns. The small, nonsignificant advantage in listeners' performance observed for the RR sequence when accompanied by I (vs. R) patterns was not captured by the model. However, the large effect in the opposite direction (predicted by the single-oscillator simulation) disappeared: The two-oscillation model correctly predicted no carryover effect for the RR sequence. Finally, this simulation also correctly predicted no carryover effect for the IR patterns, although predicted performance on this pattern, overall, was somewhat lower than observed.

### Discussion

We make two observations about these fits to the Jones and Yee data. First, the single-oscillation model (Simulation 3A) does a remarkably good job of predicting the results of this experiment involving rhythmic patterns. This is not too surprising, because the experiment demonstrated that regular patterns, which afford greater opportunity for entrainment, yield improved time discrimination performance regardless of overall pattern variability. This general prediction follows equally well from a single- or a multiple-oscillation model. Second, it is also remarkable that a two-oscillation model should predict these results better than the single-oscillation model. Although rhythmic sequences were used, there is no obvious reason for the two-oscillator simulation to fit these data any better than a one-oscillator simulation, because regular patterns should be trivially easy and irregular patterns should be intractably difficult for both models. Thus, we direct our attention to two questions: Why does the single oscillation correctly predict both the main effect and the most important carryover effect in the Jones and Yee data? and Why does the two-oscillation model predict the specific pattern of results more precisely than the one-oscillation model?

Insight into both questions is gained from Figure 21. Panel A shows focus,  $\kappa$ , as it evolves over trials within the four sessions for the single-oscillator simulation; Panel B shows two focus variables,  $\kappa_1$  and  $\kappa_2$ , for the two-oscillator simulation in the same conditions ( $\kappa$  of Panel A should be compared with  $\kappa_1$  of Panel B). For both the one- and the two-oscillation models, note that attentional focus was greatest in the RR-R session, lowest in the IR-I session, and intermediate in the mixed sessions. Greater focus in the RR-R session means greater temporal acuity than in other conditions. The fact that  $\kappa$  values persist over trials involving different patterns explains why both models predict the main effect of session context as well as certain carryover effects, such as IR to R patterns. Of course, attentional focus depends on attentional coordination, which is good with regular patterns and very poor with irregular ones.

Next, we attack the more subtle issue of why Simulation 3B predicted the results of this experiment more precisely than Simulation 3A. Both attentional focus and attentional coordination

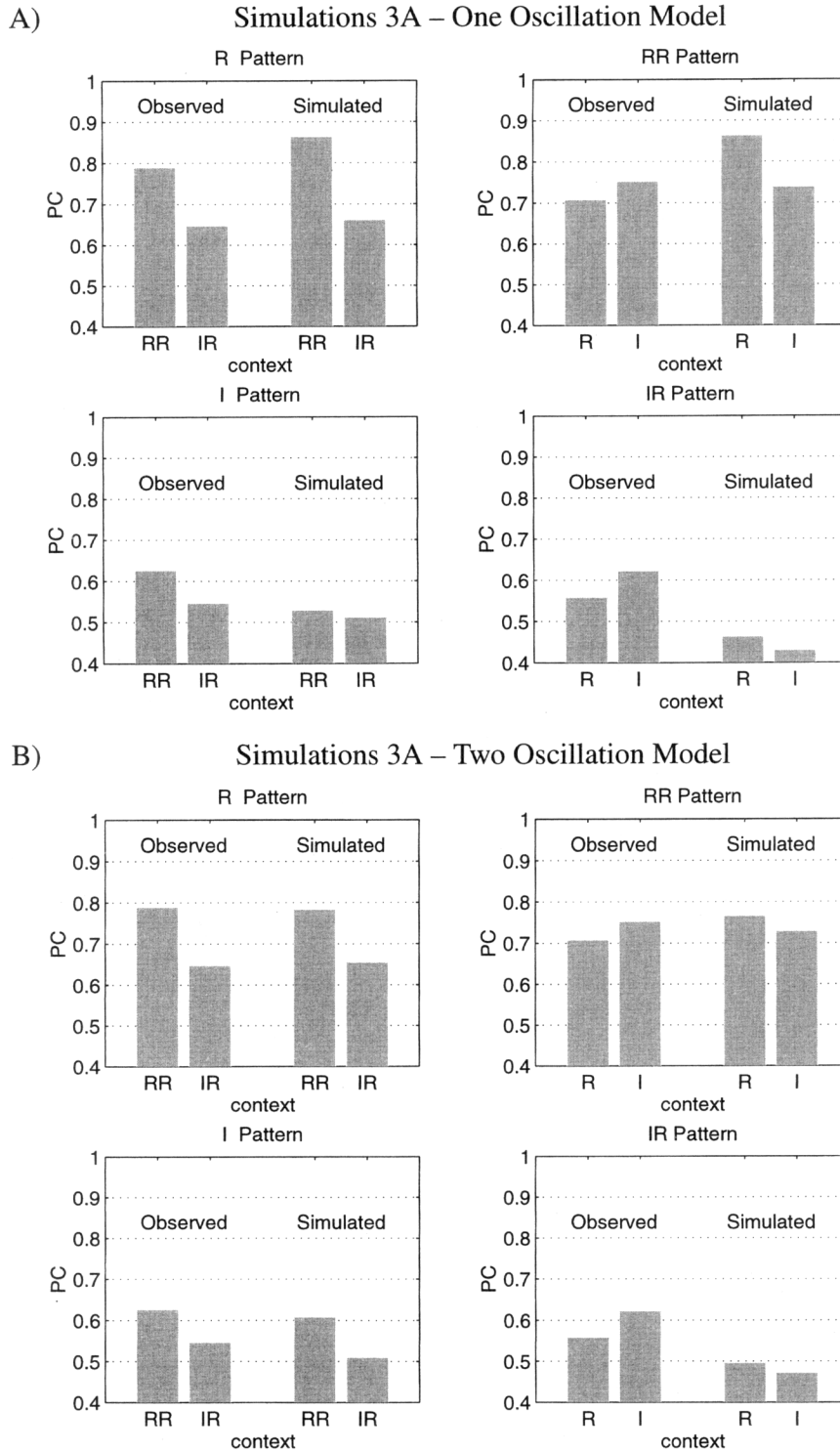


Figure 20. Predictions of two models for data presented in Figure 19. A: Simulation 3A, the single-oscillator model. B: Simulation 3B, the two-oscillator model. R = regular; RR = regular rhythm; PC = proportion correct; I = irregular; IR = irregular rhythm.

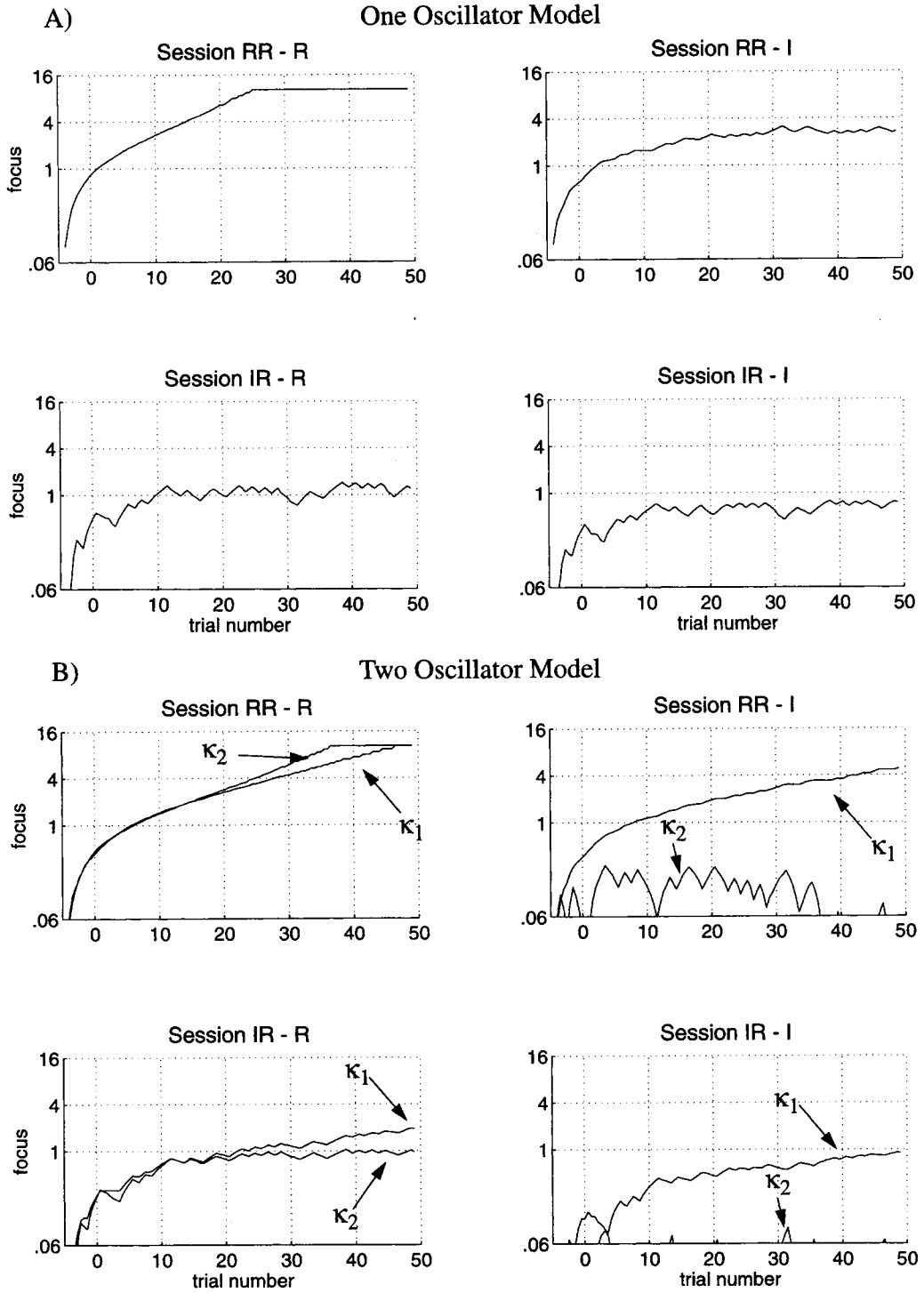


Figure 21. Predicted changes in focus over the 48 trials in a session for each of the four session conditions of Experiment 3 as the model responds to both pattern types within a session. Values of the focus variable,  $\kappa$ , for the one-oscillator model (A) should be compared with those of  $\kappa_1$  for  $O_1$  in the two-oscillator model (B). RR = regular rhythm; R = regular; I = irregular; IR = irregular rhythm.

play a role here. Consider first that the two-oscillation model predicted poorer performance than the one-oscillation model on regular patterns. The main reason for this is attentional focus. Note that in Figure 21 focus,  $\kappa$ , for the single oscillation (Panel A; RR-R session) assumes higher preasymptotic values than the corresponding focus variable for the two-oscillator simulation,  $\kappa_1$  (Panel B; RR-R session). Attentional focus adapts more slowly in the two-oscillation model because the two oscillations share available information about phase variability, a constraint added by the expectation-maximization coefficient of Equation 10.

Next, consider that the two-oscillation model also predicts better performance on irregular sequences than does the one-oscillation model. Differences in attentional focus figure into the explanation as well, but they arise from a different source. Note, for instance, that in the RR-I session,  $\kappa_1$  ultimately reaches a higher value than  $\kappa$ . In this case, however, the increment in performance cannot be attributed to this final value alone, because  $\kappa_1$  adapts more slowly than  $\kappa$ . Rather, this higher asymptotic value points to the true reason: improved synchronization with the irregular sequences. In the one-oscillation model, synchronization with irregular sequences is almost equivalent to performance of an uncoupled oscillator (e.g., Simulation 1A). However, in the two-oscillation model, internal coupling between  $O_2$  and  $O_1$  improves the synchronization of  $O_1$  to  $P_1$ . In other words, with irregular sequences, the two-oscillation model is superior mainly because the presence of  $O_2$  renders the temporal targeting of the pulse by  $O_1$  more effective.

In summary, a two-oscillation model nicely accommodates the effects of both pattern and session context on time discrimination. Although the present model represents the simplest form of internal coupling between attending rhythms, it correctly described both differences between regular and irregular rhythmical sequences and some important session context effects. Most intriguing is the discovery that the two-oscillation model actually—and correctly—predicts poorer performance on regular patterns (RR and R) than does the single-oscillation model.

### General Discussion

At the outset, we asked how listeners apprehend rhythmic structure in natural events while at the same time responding meaningfully and adaptively to temporal fluctuations. By adopting a dynamic attending approach, we think we have made progress in answering this question. The approach maintains that external rhythms drive attending, permitting enhanced selective attending in time. It also assumes that attending can be “tuned” in that it adapts over time to changes in event structure. This implies that the temporal structure of events governs the ability to attend. But temporal event structure is seen to have systematic effects on human behavior that differ depending on the task (e.g., time discrimination, time judgment, real-time tracking, or recall). In this section, we focus largely on implications of the theory for issues of temporal structure, attentional control, and general models of attending oscillations.

#### *Temporal Structure*

Because our model is rooted in the time domain, a logical first step is to apply it to judgments about that domain and, in partic-

ular, to listeners’ sensitivity to an event’s interval time structure. Although our primary aim has been to use perceptions of time intervals and related tasks as barometers of attentional entrainment, the resulting theory also offers a new slant on the psychophysics of time discrimination and the Weber fraction.

Psychophysical methodologies commonly treat the observed Weber fraction,  $JND/t$ , as a ratio of two relatively invariant quantities within a session or trial. Nevertheless, it is already well established that temporal acuity improves with practice (e.g., Watson, 1987). Our theory implies that both the numerator and denominator of a Weber fraction change not only with experience but also with event structure. For example, a JND may be considered to be a function of changing attentional focus associated with an ongoing oscillation. In addition, we have assumed (Experiments 1 and 3) that a listener’s temporal referent, usually denoted by  $t$ , is in fact the period of a prominent oscillation (i.e.,  $t = p$ ). In short, both referent period and attentional focus adapt in our model. Furthermore, the model incorporates phase, which is not commonly addressed in Weber-law models. This rationale leads to predictions of the time discrimination thresholds observed in Experiment 1. More generally, this approach offers a dynamic framework within which to study listeners’ changing perceptions of event time structure.

#### *Is Entrained Oscillation Warranted?*

The adaptive qualities of driven nonlinear oscillation distinguish our approach from beat-based coding models involving fixed time intervals (e.g., Povel & Essens, 1985). Because the oscillation is inherently flexible, it offers malleable phase and period absent in typical temporal coding models. Experiment 1 most clearly illustrates this. Assuming that the referent oscillation carries the “beat,” phase and period adapt in response to changes in tempo. Experiment 3 shows that similar flexibility resides in the tracking behavior of internally coupled oscillations, but here additional constraints on adaptability are evident in the operation of internal couplings that ensure rhythmic ratios. The two-oscillation model simultaneously responds to rate modulations and other forms of rhythmic flexibility while incorporating constraints that reflect rhythmic form.

These features enable us to address questions about oscillators and time discrimination, namely that a referent oscillator is necessarily unresponsive to out-of-phase event markers (e.g., Ivry & Hazeltine, 1995; Keele et al., 1989). According to this criticism, oscillator models of time perception incorrectly predict poor temporal acuity in sequences comprising IOI repetitions that contain a single phase shift. Presumably, this is because a repeated interval induces an oscillator of fixed phase and period that is thrown permanently off track by a single phase perturbation. Consequently, Keele et al. (1989) argued that a repeating time interval evokes neither an internal clock (e.g., Povel & Essens, 1985) nor an oscillator mechanism. In fact, they maintained that repetitions of a given IOI produce good acuity not because they form an isochronous pattern but because each repetition strengthens a memory code for a single time interval.

Two points are relevant to this criticism. First, effects of phase shifts on temporal acuity are by no means clear cut. McAuley (1996) has shown that a single phase shift can influence acuity

judgments; moreover, the experiments presented here all illustrate, in various ways, the effect of phase on temporal acuity. Second, coupled oscillation is not the same concept as a fixed clock. Whereas an uncoupled oscillation, or fixed clock, is indeed thrown off track by a single phase shift (as indicated in Figure 6, Panels A–C), a coupled oscillation (e.g., Figure 8, Panels A–C) quickly adapts to such perturbations. In Experiment 1, for instance, the model remained on track by adjusting in real time to successive perturbations. Simulated acuity remains fairly good in conditions with relatively small phase shifts (low rate modulations), declining only with many relatively large perturbations. This prediction matches the responses of listeners well. Models that incorporate two (or more) jointly active oscillations are still more flexible in these respects (see also Large, 1994; Large & Palmer, 1999).

### *Temporal Order and Sequence Structure*

An alternative explanation of the perception and tracking of dynamic events suggests that our treatment of time and temporal structure is misguided. Perhaps the necessary structure resides not in the time domain at all but in the structure of the sequences that occupy time.

Lashley (1951) proposed an overarching mental scheme in which rhythm directs serial behavior. By contrast, Chomsky's (1957) manifesto on transformational grammars emphasized the complexity of sequential structures. Chomsky's approach has influenced many thinkers to abstract out interval and ratio time relationships and focus exclusively on the temporal order of elements in a complex event such as a word or sentence. This approach was embodied in early memory models that linked sequence retention to the encoding of sequences via sets of grammatical rules (Deutsch & Feroe, 1981; Estes, 1972; Martin, 1972; Restle, 1970; Simon, 1972; see Jones, 1974, 1981, for reviews). Although more recent connectionist models have shifted away from explicit grammatical rules and memory-based explanations, they retain a focus on sequence structure (e.g., Elman, 1990; Jordan, 1986; Mozer, 1992; Williams & Zipser, 1989). Elman's (1990) simple recurrent network (SRN) represents serial order relationships among, say, words of a sentence as a pattern of activations spatially distributed over a set of short-term memory (context) nodes. For example, Elman (1991) focused exclusively on the ability of the network to learn complex grammatical structures; the job of the network is to learn to predict what the next word of the sentence will be. However, no attempt is made to model, for example, when the next element is expected to occur.

This emphasis on ordinal relationships to the exclusion of other temporal relationships leads to difficulties if such models are adapted to natural events that unfold in real time (e.g., events that display the types of temporal flexibility investigated here). Experimental investigations into the temporal processing capabilities of the SRN, for example, reveal that for complex sequences such networks do not show temporal generalization (Liu, Wang, & Ahalt, 1996). When trained at one or two sequence rates, they fail to recognize the same sequence presented at novel rates.

Extensions of these models have been proposed to deal with such timing issues (e.g., Cottrell, Nguyen, & Tsung, 1993; de Vries & Principe, 1992; Tank & Hopfield, 1987). For example, one account of acquired rate sensitivity uses an augmented SRN

network to describe adaptive tracking of temporally modulated events (Cottrell et al., 1993; Nguyen & Cottrell, 1994). This network is trained on stationary events (e.g., locomotion or speech patterns) presented at some "normal" rate. Unlike the typical SRN, however, once it has learned a sequence it can adapt to changes in presentation rate. This is accomplished by predicting the next element in the sequence and using the difference between predicted and actual onset time of that element to adapt time constants that control processing rate. In other words, the network relies on sequence structure (i.e., the ordering of elements) to determine changes in sequence rate. The main drawback of this approach, of course, is that it works only for learned sequences. But there are other difficulties as well. First, learning a sequence requires the presentation of a canonically timed training sequence, which is problematic. Second, a change in rhythm cannot be distinguished from a change in rate because the network uses only the order of sequence elements to determine timing (i.e., the network is both rate and rhythm invariant). Thus, it does not capture people's sensitivity to the rhythm of a previously learned event (e.g., Boltz, 1992; Jones & Ralston, 1991).

Undeniably, serial competency is crucial to language, music, and other temporal events. Clearly, it is adaptive that people often continue to recognize an event when its rate changes. Nevertheless, a disregard of the richness of event time structure in favor of serial order seems premature. Even when serial ordering does not change, variations in rhythm (as well as large rate changes) significantly affect recognition (Boltz, 1992; Handel, 1989; Jones & Ralston, 1991; Kidd & Watson, 1990). In addition, anticipatory order errors often occur in productions of speech and music, reflecting a temporal importation of future elements into the present. Significantly, it appears that these mistakes are more common among elements occupying similar rhythmical locations (Ryan, 1969a, 1969b), suggesting an intimate connection between temporal structure and serial order.

Lashley's prescient observations emphasized that rhythm and interval time structure play a role in anticipatory errors (also see Martin, 1972). Perhaps he was on the right track. But time structure is important not simply for insights into the serial order problem; it is important in its own right. Time is an integral part of event structure and of meaning. Many events (e.g., speech, music, and body gestures) are not merely serially ordered but are temporally coherent as well. A change in the rhythm of such sequences can signal a change in meaning and implication. Thus, a sense of rhythmic structure is necessary to interpret a speaker's hesitations, to recognize a variation on a melodic theme, and so forth.

### *Attention*

We have described attending in terms of the dynamics of attentional entrainment. Because the external rhythm is based on the time structure of a distal event, our approach views attention as heavily influenced by environmental patterning. It is possible to identify two related ways in which event structure exerts control over dynamic attending. These derive, respectively, from the way a driven nonlinear oscillation generates expectancies in time and from its subsequent reactions to violations of these expectancies.



### *Long-Term Attentional Control: Expectancies*

The self-sustaining oscillation is an engine for generating goal-oriented expectancies. That is, each attending rhythm displays an underlying predisposition, or attentional set, that guides anticipations every step of the way. Over the long haul, an attractor controls this process, ensuring that expectancies are well coordinated with an event. Thus, attractor states establish long-term control of attending; they reflect a goal state of minimum disparity between the period and phase of an attentional rhythm and those of the unfolding event. When multiple oscillations come into play, a stable relationship also emerges among internal oscillations, one that can reflect the form of the external rhythm dynamically, for instance, in certain phase and period ratios.

The attentional tuning that emerges from long-term behavior is reminiscent of Gibson's unconventional view of attending as a mode of "educating of the senses." Gibson (1966) saw attention as a vehicle for perceptual refinement in that it served to position a perceiver optimally for detecting finer and finer differences (pp. 51–52, 269–271). In a parallel way, attentional targeting becomes more and more focused as temporal expectancies gravitate to an optimal temporal positioning of attentional energy. Effectively, this means that successively finer discriminations of temporal nuances within an attended event become possible.

This aspect of the theory also echoes the more current idea that attentional set introduces slow and persisting selective responding. However, the picture we offer connects long-term attentional control to environmental structure itself. That is, we do not consider how attentional set is determined, for instance, by instructions to ignore certain aspects of an unfolding event. In principle, such a feature can be accommodated, but current evidence using auditory sequences, in which both attentional set (instructions to attend selectively vs. nonselectively) and pattern structure was varied, suggests that structural manipulations of attending far outweigh those introduced by attentional set instructions (e.g., Jones, Jagacinski, Yee, Floyd, & Klapp, 1995). Accordingly, our model has focused on control of attention and adaptation to external time structure. We assume that such oscillations rhythmically carry attention into the future over both long and short time periods, realizing future-oriented attending (Jones & Boltz, 1989).

### *Short-Term Attentional Control: Expectancy Violations*

The movement toward an attractor comprises many small adaptations. These adaptive responses represent fast, transient adjustment to novel or unexpected timing. Thus, if long-term attentional control reflects expectancies, then short-term control of attending reflects expectancy violations. Both are influenced by event structure. That is, in spite of the persistent pull of an attractor on the system, any momentary impact of an unexpected onset within an external rhythm can perturb the attending rhythm, forcing it in a different direction. To be sure, in the long run, stability ensures that an adaptive oscillation returns to its goal. But two aspects of the transient response to sudden or unexpected onsets are worth underlining.

The first aspect is simply that a temporal contrast, arising from an advanced or delayed onset in the external rhythm, is the occasion for disturbing the attending rhythm. The magnitude of

such an expectancy violation at any point in time in an unfolding sequence is gauged by the attentional pulse. In a detection task, for instance, this magnitude determines how noticeable or novel an unexpected onset seems, with large deviations more likely than small ones to be judged as changes in an event's time structure. A second aspect of the transient response to a time change is its adaptive character. Following Equations 3 and 4, the subsequent reaction to such a "surprise" is a rapid attentional shift in time. Specifically, the shift is operationalized as an adjustment of phase and period in the direction of the unexpected time change. Moreover, the degree of shift is related to the degree of change in timing. In these respects, the response to expectancy violations instantiates a time-domain version of attentional capture.

The dual aspects of expectancy and expectancy violations, as they are displayed by the way an external rhythm drives an attending rhythm, echo classic features associated with attention. In other terms, they embody, respectively, anticipation and surprise. This is a dichotomy found in various theories in which attention is associated with preparation, on the one hand, and with response to change (or novelty), on the other (Neumann, 1996; van der Molen, 1996). For instance, the response to novelty is fundamental to Berlyne's theory (1974) and Sokolov's (1975) analysis of the orienting response, both of which have been interpreted in terms of involuntary attention to change (Eimer, Nattkemper, Schroger, & Prinz, 1996; cf. Posner, 1980). The response to novelty is clear in our approach: It is an attentional rhythm's adaptation in response to an unexpected time change. At least with respect to timing, this quantifies and clarifies that a response to novelty is predicated on a defined expectancy. Thus, in Experiment 1 patterns with little or no rate modulation generated strong, narrowly focused expectancies for "when" future onsets should occur, thereby setting the stage for a listener to notice even quite small time changes as deviant or novel.

### *Attention or Perception?*

We claim to be describing the dynamics of attending, but is this really a theory of attending? After all, time discrimination is a perceptual task. So why is this not a theory of perception? As we have acknowledged, our theory addresses both perception and attention. However, as in many cases, these constructs are interdependent and difficult to tease apart (cf. Bregman, 1990; Kahneman, 1973; A. Treisman, 1992). Defining either attention or perception is daunting because such definitions quickly become theories. In this vein, our approach suggests new ways to conceive of standard attentional and perceptual phenomena.

In spite of its name, the attentional pulse expresses important aspects of perceiving because it suggests circumstances that are most likely to render accurate perceptual reports. Specifically, given a particular difference between two time intervals, correct reports about whether they are similar (same) or not (different) depend on two aspects of the attentional pulse. First, perceiving both identity and distinctiveness among time intervals involves the locus of an attentional pulse. Listeners are best at these judgments when both standard and comparison intervals begin or end at expected temporal locations. This is evident from the data of Experiment 2, in which time judgments were poor with unexpected standard intervals. Simply put, if one is appropriately primed for

when something will occur, overall perceptual categorization is enhanced.

The second feature of the pulse that influences perceiving is its extent relative to some time change. Good attentional coordination leads to a narrow attentional pulse, meaning that in these contexts a given time change becomes more noticeable. Conversely, in sequences that afford only moderate coordination, the pulse widens such that the same time change may go unnoticed. In other words, regular rhythms encourage sharper selective attending in time; this, in turn, establishes more rigorous criteria for similarity and differences among time intervals. Thus, in Experiments 1 and 3, contextual irregularities in some patterns produced poorer focus. Unruly sequences in Experiment 1 produced poor attentional focus and low temporal acuity (thresholds as high as 0.10), whereas the more regular sequences produced greater attentional focus and better acuity (thresholds between 0.02 and 0.03). We underscore that changes in focus derive from variability in relative phase, not variability of the IOI sequence. Thus, in Experiment 3, the clear rhythmic regularity of RR patterns introduced marked IOI variability, but this neither adversely affected synchronization nor lowered performance. This view of perception clearly emphasizes the relational nature of perceiving: A to-be-detected time change is gauged relative to the maximally expected phase of a single oscillation.

Clearly, anticipation and expectancy play into this approach to perception. Variations in attentional focus correspond to variations in the width of an expectancy region and the selective distribution of attentional energy in time. Others have also proposed a variable attentional focus (e.g., Ericksen & St. James, 1986), but these proposals concern the distribution of visual attention in space. Our theory describes attentional energy distributed in time; it is unusual in linking focal variability to violations of temporal expectancies.

### *Attention Tasks*

Attentional tracking involves attentional targeting and the coordination of internal and external rhythms. It is difficult to directly evaluate because it involves momentary and unobservable changes in postulated internal states. Most real-time tracking situations involve either overt motor tracking or event-related potential (ERP) monitoring of cortical activity. However, both paradigms present difficulties for the present approach.

Motor performance, by definition, engages overt responding, thus offering the advantages of direct measurement of a behavioral time series. This has enabled demonstrations of bistability and hysteresis in rhythmic movement (e.g., Kelso & Scholz, 1985), as well as other features that directly implicate nonlinear dynamics (e.g., Haken, Kelso, & Bunz, 1985; Schöner, Haken, & Kelso, 1986). Other studies lend support to the hypothesis that neuromotor oscillations follow the timing of input signals (e.g., Schmidt, Carello, & Turvey, 1990). Dynamical models have been proposed to describe coordinated motor responses to simple auditory patterns (cf. Kelso et al., 1990; Schöner & Kelso, 1988a, 1988b). In spirit, the latter approaches are similar to ours, but they differ in at least two critical ways. First, our model describes tracking of more complex, rhythmically patterned sequences that may be nonstationary. Second, we address attentional tracking of auditory pat-

terns. Indeed, the dynamics of attending may be preliminary to those of actions in that they prepare the motor system to respond (cf. Allport, 1989). We aim to show that entrainment is not specific to overt motor responding but, rather, occurs in various attention tasks as well. In short, we seek to tap directly into the dynamics of attending using paradigms that are uncontaminated by motor activity.

Tracking tasks that appear less contaminated by overt responding are those involving ERPs. These tasks rely on paradigms such as the odd-ball paradigm (Donchin, Ritter, & McCallum, 1978) or attentional filtering (Hillyard, Hink, Schewent, & Picton, 1973; see Naatanen, 1990, for a review) in which the recorded components of attentional cortical responses (e.g., N1, P2, or P300) are linked to probabilistic aspects of stimulus sequences (Donchin & Coles, 1988; Verleger, 1988). Thus, Naatanen and his colleagues (Naatanen, Schroger, Karakas, Tervaniemi, & Paavilainen, 1993) recorded attentional tracking of tone sequences and found that listeners' ERPs to standard (frequent) and deviant (infrequent) sequences differed systematically; the ERP component reflecting this difference (i.e., mismatch negativity) peaked at 100–200 ms from the onset of a changed tone frequency in the deviant sequence. Although these tasks offer great potential for evaluating the entrainment hypothesis, they also present three obstacles. First, the mapping of different ERP components to the model variables (phase, period, and focus) is unclear. Second, clean assessments of ERPs emerge only when electroencephalograph changes are averaged over hundreds of presentations of a single stationary event, whereas our most informative tracking predictions derive from moment-to-moment adaptations of the oscillation in response to nonstationary events. Finally, it is unclear how ERP components relate to detection of small time changes.

### *Toward General Oscillation Models*

The most general version of our theory posits the joint activity of several attending rhythms. We expect that such models will be especially useful in explaining responses to complex rhythmical events, as Experiment 3 illustrates. The most important distinction between a multiple-oscillation model and a single-oscillation model is that only the former can display complex forms of coordination among internal attending rhythms. Internal interactions among attending oscillations offer great explanatory potential that can yield both unusual and powerful predictions. An unusual prediction is illustrated in our discovery that a two-oscillation model provides a better fit to performance with rhythmical sequences than a single-oscillation version because the latter predicts performance that is too good. It turns out that interactions among oscillations can moderate performance. Alternatively, patterns of internal couplings can provide predictions about subgroups of oscillations that mutually interact in beneficial ways. The multiple-oscillation approach also holds significance for understanding other phenomena such as the perception of metrical relationships and the perception of figure versus ground.

### *Meter and Expressive Nuance*

The puzzle posed at the outset of this article is at the heart of meter perception. In musical performances, neither strict period-

icity nor precise metrical time ratios (e.g., 2:1 or 3:1) are realized. The challenge facing current theories of meter perception is that performers flexibly modulate the rate of the performance to create emphasis and expressive nuance (Clarke, 1985; Drake & Palmer, 1993; Palmer, 1989; Shaffer, Clarke, & Todd, 1985; N. P. M. Todd, 1985).

The solution proposed by Large and Kolen (1995; Large, 1994) assumes that multiple, simply coupled oscillators track multiple periodicities in complex rhythms. Meter is associated with phase and period ratios; the duple meter rhythm used in Experiment 3, for instance, corresponds to a 2:1 ratio among periodicities. This and other simple integer ratios are more likely to result in stable metric perceptions (Large & Kolen, 1995; see also Jones, 1976). However, these models did not address time discrimination. Our account does address this factor. It suggests that the noticeability of various temporal nuances is affected by musical rubato, namely rate modulation (Experiment 1), and also by higher order rhythmic patterning (Experiment 3). In the latter case, interactions among internal oscillations not only affect the noticeability of certain time changes but dynamically express the metrical structure. Related work also suggests that the perception of metrical patterns can be modeled as multiple oscillations and that expectancy violation figures in the perception of phrase structure and in the identification of a melody among several voices (Large & Palmer, 1999). Such models offer substantial explanatory power for understanding how people perceive and produce time patterns within complex rhythmical events.

### *Binding and Figure–Ground Phenomena*

Neural oscillation has been proposed as a solution to the binding problem that arises in distributed representation theories of visual object and scene perception. In these theories, mental features (e.g., vertices or edges) that denote the same object are spatially distributed. To perceive an integrated object, neurally distributed features are presumed to coalesce (i.e., bind) whenever outputs of the relevant feature units oscillate in phase. Thus, phase synchrony of oscillating feature-specific units is a binding agent. The flip side of the binding problem, the segregation problem, concerns the perception of a figure as distinct from its background. This problem is also solved if it is assumed that oscillating feature units that represent a figure (a single object) are out of phase with those of the background (or other objects; e.g., Hummel & Biederman, 1992; Terman & Wang, 1995; see also von der Malsberg & Schneider, 1986).

Our approach differs from theories of visual feature binding in its interpretation of the relationship between internal oscillations and stimulus structure. To our knowledge, distributed representation theories do not propose that the time structure of the stimulus (e.g., frequency or phase relationships of light that falls on the retina) meaningfully relates to the frequency or phase of internal oscillations involved in binding. Features such as proximity, texture, and color, which are essentially nontemporal, have no direct bearing on oscillator phase and period. Rather, they are simply cues postulated to generate internal synchronization. Synchrony itself is proposed to stem from adjacency in “feature topic” neural maps (e.g., see Terman & Wang, 1996). In other words, internal oscillations do not entrain to external time patterns; instead, they

provide an on–off implementation for feature integration in which integration itself derives from other principles (Tesar & Smolensky, 1994). Thus, our approach is quite different in its stance that organisms are directly sensitive to the temporal structure of events.

Our view of multiple attending rhythms agrees with the binding rationale in the sense that synchrony forms a basis for perceptual integration. However, phase and period relationships within the stimulus itself provide the basis for integration. In dynamic events, an integrated figural form usually involves the presence of a stable rhythmic pattern comprising various related periodicities. Thus, to perceive a time pattern as an intact figure, one experiences its constituent event periods as bound together in a stable and integrated way. For instance, the compelling RR rhythm of Experiment 3 comprised two phase-locked periodicities in which the period of one component was twice that of the other. These properties directly lead to its perception as a stable rhythmic form. In attending to such events, the perception of an integrated figure derives from synchronous activities of internal oscillations. Synchronicity among different external periodicities within a rhythmic figure drives the establishment of stable synchronous relationships among internal oscillations; these relationships, in turn, determine integrated percepts (Jones, 1976).

### Concluding Remarks

In the larger scheme, this framework suggests that attending has a participatory quality. Whether one is captivated by an amusing story, excited by a fast-moving soccer game, or inspired by a masterfully conducted symphony, one is engaged by distal happenings that project complex rhythmic flow patterns comprising multiple related temporal components. The time pattern of an event reliably shapes a rhythm in the ambient flow, and the coordination of attention with the pulsating flow pattern connects the attender to the originating event in a rather direct fashion. Such patterns afford multiple opportunities for the engagement of attention because they comprise lawfully related component periodicities. At each of several time scales, these events project flexibly evolving periodicities comprising a series of distinct onsets that parallel the patterns studied here with single- and multiple-oscillation models. Effectively, the presence of many different periodicities within structured rhythms provides a means of tethering an attender to a distal event. Via entrainment, a complex of internal oscillations may be shaped by the time structure of rhythmically intricate events, and events can be attended to more or less efficiently depending on their timing properties. Furthermore, the joint coordination of active oscillations tracking different flow periods offers a means of directly “knowing” about that event. That is, coordinated attending rhythms fashion a crude mime of an event’s rhythm, an adaptive attentional cartoon of its shape in time. Thus, by virtue of dynamic mimicry, the attender “participates” in the rhythm of a remote event. Entrainment means that parts of an attender literally “match up” with certain time spans in the remote event, and in this sense attending is participatory. The resulting synchrony with temporally structured events functions as a form of direct knowing.

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## Appendix A

## Circle Map Dynamics

We first consider the one-dimensional phase-coupled system of Equation 3. To simplify this system for analysis, we replace the series of interonset intervals  $t_{n+1} - t_n$  with the single interonset interval  $q$ , representing a stationary driving rhythm with a fixed period. Equation 3 becomes

$$\phi_{n+1} = \phi_n + \frac{q}{p} - \frac{\eta_\phi}{2\pi} \sin 2\pi\phi_n \pmod{-0.5, 0.5}, \quad (\text{A1})$$

which is the well-known sine circle map. To determine the location (phase) of the fixed points, we assume equilibrium (i.e.,  $\phi_{n+1} = \phi_n = \phi_*$ ) and define  $\Omega = q/p \pmod{-0.5, 0.5}$ . We then solve

$$\phi_* = \phi_* + \Omega - \frac{\eta_\phi}{2\pi} \sin 2\pi\phi_* \quad (\text{A2})$$

for  $\phi_*$ . This gives fixed points at

$$\phi_* = \frac{1}{2\pi} \text{asin}\left(\frac{2\pi}{\eta_\phi} \Omega\right). \quad (\text{A3})$$

In general, the location of the fixed points depends on both  $\eta_\phi$  and  $\Omega$ . However, when  $p = q$ ,  $\Omega = 0$ , and there is an attractor at  $\phi_* = 0$  and a repeller at  $\phi_* = 0.5$ .

Next, consider the two-dimensional system described by the addition of period coupling (Equation 4) to the model. The equation

$$p_* = p_* \left(1 + \frac{\eta_p}{2\pi} \sin 2\pi\phi_*\right) \quad (\text{A4})$$

yields  $\phi_* = 0$ , and substituting this result into Equation A2, we find

$$p_* = q. \quad (\text{A5})$$

Thus, the attractor for the phase-coupled and period-coupled model (Equation 3 plus Equation 4) is  $\phi_* = 0$ ,  $p_* = q$ .

## Appendix B

## Circular Statistics and the von Mises Distribution

Because relative phase is a circular variable, it is described via circular statistics (thorough discussions can be found in Batschelet, 1981; Fisher, 1993; and Mardia, 1972). The most important difference between circular and linear statistics is that, in circular statistics, each sample point is treated as a unit vector. Thus, the mean of a set of sample points is a vector,  $\mathbf{m}$ , with polar coordinates  $r$  and  $\bar{\phi}$ , representing the mean vector length and mean phase angle, respectively, of the sample. Mean vector length,

$$r = \frac{1}{n} \sum_{i=1}^n \cos 2\pi(\phi_i - \bar{\phi}), \quad (\text{B1})$$

is a measure of dispersion about the mean. It can also be used as a measure of synchronization strength (Goldberg & Brown, 1969).

We model attentional energy as a periodic probability density, the von Mises distribution:

$$f(\phi) = \frac{1}{I_0(\kappa)} \exp[\kappa \cos 2\pi(\phi - \theta)], \quad (\text{B2})$$

with two parameters,  $\theta$  and  $\kappa$  ( $0 \leq \kappa$ ). The function takes on its maximum value at  $\phi = \theta$  (i.e.,  $\theta$  is the mode), and the distribution is symmetric about the mode. Because, in our application,  $\phi$  represents the phase of a phase-coupled and period-coupled oscillation, we assume that  $\theta = \bar{\phi} = 0$  (i.e., that the system is in equilibrium). The larger the  $\kappa$ , the more concentrated the distribution about the mean; hence,  $\kappa$  is called the *concentration parameter* (Figure 9A). In our model,  $\kappa$  captures focus of attention; it is a third state variable that adapts in response to the structure of an external rhythm. The process of adaptation is related to maximum-likelihood estimation of the concentration parameter of a von Mises distribution.

## Adaptation of Attentional Focus

The maximum-likelihood estimate of the concentration parameter,  $\hat{\kappa}$ , of a von Mises distribution is given by the solution to the equation

$$A(\hat{\kappa}) = \frac{I_1(\hat{\kappa})}{I_0(\hat{\kappa})} = \frac{1}{n} \sum_{i=1}^n \cos 2\pi\phi_i \quad (\text{B3})$$

(Batschelet, 1981). The right-hand side of this equation is the mean vector length of the sample,  $r$ , introduced earlier (Equation B1). In this case, however, we estimate vector strength incrementally using

$$s_{n+1} = s_n - \eta_s (s_n - \cos 2\pi\phi_n). \quad (\text{B4})$$

We call this measure *synchronization strength*, written  $s$ , to emphasize that it is an incremental approximation to vector strength,  $r$ . Next,  $\kappa$  is determined as

$$\kappa_{n+1} = A^{-1}[H(b, s_{n+1})], \quad (\text{B5})$$

where  $A^{-1}(x)$  can be solved numerically or by table lookup (Batschelet, 1981). The adaptation rate  $0 \leq \eta_s \leq 1$  determines an adaptation time constant, with smaller values approximating  $r$  over longer time periods. Equation B4 has a fixed point at  $s_* = \cos 2\pi\phi_*$ , so when there is no variability in the stimulus,  $s = 1$ . Because  $A^{-1}(1) = \infty$ , we fix a bound  $s$  using a hard limit function  $H(b, s)$ . Thus, the maximum value of  $\kappa$  is  $A^{-1}(b)$ , placing an upper limit for attentional focus. The simulations described in the text used a value of  $b = 0.95$ .

According to the current model, an event onset is perceived as the phase of the onset relative to an ongoing oscillation. The von Mises model of an attentional pulse permits predictions about the relative noticeability of time changes, taking into account both relative phase and level of uncertainty. Here certainty corresponds to attentional focus,  $\kappa$ , which reflects the quality of synchronization with an external rhythm.

## Predicting Performance in a 2AFC Task

In Experiments 1 and 3, participants were asked to judge in which of two locations a time change occurs. We modeled their responses by developing an expression for the proportion of tones in location  $n$  whose onset times

will be detected as deviating from expected onset times. This is twice the area under the curve from the mode of the attentional pulse to  $|\phi_n|$ :

$$P_{D(n)} = 2 \int_0^{|\phi_n|} f(x) dx. \quad (\text{B6})$$

Two proportions are calculated in this way, one for each of two test regions. The proportion of time shifts that will be detected in the test region where the shift truly occurs is notated  $P_{D(T)}$ , and the proportion of “false shifts” (induced by contextual modulations) that will be detected in the alternate test region is notated  $P_{D(F)}$ . Scores for each of two test regions are converted to a single PC score for each 2AFC trial by combining the two measures to calculate the overall proportion of correct responses on a given trial:

$$P_C = \frac{P_{D(T)} - P_{D(F)} + 1}{2}. \quad (\text{B7})$$

### Predicting Performance on an Interval Classification Task

Next we describe how to predict performance on a task in which the participant is asked to judge whether a comparison interval is the same as, longer than, or shorter than a standard interval (Experiment 2). First, the proportion of intervals heard to be the same as, early, or late is derived

from  $P_D$  (Equation B6), the proportion of intervals detected to deviate from the standard:

$$P_S = 1 - P_D,$$

$$P_L = P_D \left( \int_{-0.5}^{\phi_n} f(x) dx \right),$$

and

$$P_E = P_D \left( 1 - \int_{-0.5}^{\phi_n} f(x) dx \right).$$

Next, the proportion of intervals correctly classified based on what the participant hears is as follows:

$$P_H = \begin{cases} P_S & \text{if interval same as standard} \\ P_E & \text{if interval shorter than standard} \\ P_L & \text{if interval longer than standard.} \end{cases}$$

Finally, the proportion of correct responses is  $P_C = .33 + P_H(P_{\max} - .33)$ , where .33 is the proportion of guessed classifications and  $P_{\max}$  is the maximum proportion of correct classifications observed over all sessions in the experiment.

## Appendix C

### A Two-Oscillator Model

When a stimulus comprises more than a single periodicity, we assume that more than a single oscillation participates in attentional tracking. Here we present a simple two-oscillation model useful in modeling responses to patterns that comprise two periodicities. First we analyze

$$\phi_1^{(n+1)} = \phi_1^{(n)} + \frac{q}{p_1} - \alpha_1(\phi_1^{(n)} - 2\phi_2^{(n)}) \pmod{-0.5, 0.5, 1}$$

and

$$\phi_2^{(n+1)} = \phi_2^{(n)} + \frac{q}{p_2} - \alpha_2(\phi_2^{(n)} - 0.5\phi_1^{(n)}) \pmod{-0.5, 0.5, 1}, \quad (\text{C1})$$

which corresponds to the system of Equation 8 without external phase coupling. If we define internal relative phase as  $\psi = \phi_1 - 2\phi_2$  and assume that  $p_2 = p_1$ , then this system can be rewritten as

$$\phi_1^{(n+1)} = \phi_1^{(n)} + \Omega - \alpha_1\psi^{(n)} \pmod{-0.5, 0.5, 1}$$

and

$$\phi_2^{(n+1)} = \phi_2^{(n)} + \frac{\Omega}{2} + \alpha_2\psi^{(n)} \pmod{-0.5, 0.5, 1}.$$

We are interested in the evolution of internal relative phase. Using the identity  $\phi_1 = \psi + 2\phi_2$ , we write  $\psi^{(n+1)} + 2\phi_2^{(n+1)} = \phi_1^{(n)} + \Omega - \alpha_1\psi^{(n)}$ , and, after some manipulation, we arrive at

$$\psi^{(n+1)} = \psi^{(n)} - (\alpha_1 + \alpha_2)\psi^{(n)}. \quad (\text{C2})$$

Thus, this system has a fixed point at  $\psi^* = 0$  that is stable for  $0 < \alpha_1 + \alpha_2 < 2$ . When  $\alpha_1 + \alpha_2 = 1$ , the system relaxes to the attractor after one cycle. We use this discrete, linear internal coupling to approximate a system in which internal coupling brings internal oscillation into coordination within a single stimulus cycle. The full system is similar to Equation C1 with the addition of the external coupling. We think of external

coupling as delivering perturbations to the internally coupled system (Equation C1):

$$\phi_1^{(n+1)} = \phi_1^{(n)} + \frac{q}{p_1} - F(\phi_1) - \alpha\tau_2(\phi^{(n)}, \kappa^{(n)})(\phi_1^{(n)} - 2\phi_2^{(n)}) \cdot \pmod{-0.5, 0.5, 1}$$

and

$$\phi_2^{(n+1)} = \phi_2^{(n)} + \frac{q}{p_2} - F(\phi_2) - \alpha\tau_1(\phi^{(n)}, \kappa^{(n)})(\phi_2^{(n)} - 0.5\phi_1^{(n)}) \cdot \pmod{-0.5, 0.5, 1}. \quad (\text{C3})$$

We assume a single coupling parameter,  $\alpha$ , and the term  $\tau_i(\phi, \kappa)$  is defined in the next section. Here we simply note that  $\sum \tau_i(\phi, \kappa) = 1$ , satisfying the preceding stability condition.

Period coupling is defined similarly to phase coupling, and the attractor for internal relative period can be worked out similarly to internal relative phase:

$$p_1^{(n+1)} = p_1^{(n)} + p_1^{(n)}\eta_p F(\phi_1^{(n)}) - \alpha\tau_2(\phi^{(n)}, \kappa^{(n)})(p_1^{(n)} - 0.5p_2^{(n)})$$

and

$$p_2^{(n+1)} = p_2^{(n)} + p_2^{(n)}\eta_p F(\phi_2^{(n)}) - \alpha\tau_1(\phi^{(n)}, \kappa^{(n)})(p_2^{(n)} - 2p_1^{(n)}). \quad (\text{C4})$$

### Estimating Two Concentration Parameters

To estimate the concentration parameters for two von Mises distributions simultaneously, we first define a mixture of von Mises distributions. The unimodal von Mises distribution is given by

$$f_j(\phi) = \frac{1}{I_0(\kappa_j)} \exp[\kappa_j \cos 2\pi j \phi],$$



and a mixture of two multimodal (assuming  $\phi_1 = 2\phi_2$ ) von Mises distributions is given by

$$f(\phi; \kappa) = \sum_{j=1}^2 w_j f_j(\phi). \tag{C5}$$

Here the vector  $\kappa = [\kappa_1, \kappa_2]$  contains the unknown concentration parameters. The  $w_j$  are the mixture weights; we assume  $w_1 = w_2 = 0.5$  for simplicity. The log-likelihood function for Equation C5 is

$$\log L = \sum_{i=1}^N \log \left\{ \sum_{j=1}^2 w_j f_j(\phi_i) \right\}. \tag{C6}$$

Taking the derivative of Equation C6 with respect to  $\kappa_j$  and equating the result to zero, we obtain the likelihood equation

$$\sum_{i=1}^N \frac{0.5 f_j(\phi_i)}{f(\phi_i)} \left[ \cos 2\pi \phi_i - \frac{I_1(\kappa_j)}{I_0(\kappa_j)} \right] = 0 \tag{C7}$$

for  $j = 1, 2$ , which does not yield an explicit solution. Therefore, we adapt the expectation-maximization algorithm to the estimation of the concentration parameters for our von Mises mixture. To do this, we pose the problem as an incomplete-data one by introducing the unobservable or missing data vector  $\mathbf{z} = (z_1^T, \dots, z_M^T)^T$ , where  $\mathbf{z}_j$  is an  $M$ -dimensional vector of zero-one indicator variables such that  $z_{ji} = (z_i)_j$  is one or zero according to whether  $\phi_i$  did or did not arise from the  $j$ th component of the mixture.

If the  $z_{ji}$  were observable, then the maximum-likelihood of estimate  $\kappa_j$  would be given by the solution to the equation

$$\frac{I_1(\kappa_j)}{I_0(\kappa_j)} = \left( \sum_{i=0}^N z_{ji} \cos 2\pi \phi_i \right) / \sum_{i=0}^N z_{ji}. \tag{C8}$$

The intuition behind Equation C8 is that it is a version of Equation B3 calculated only for those samples (onsets) that arise from the  $j$ th component

of the mixture. In other words, the right-hand side of Equation C8 estimates the mean vector length,  $r$ , for those onsets that belong to periodicity  $j$ .

Next, the expectation step requires calculation of the current conditional expectation of  $z_{ji}$  given the observed data,  $\Theta$ , where  $Z_{ji}$  is the random variable corresponding to  $z_{ji}$ . Now

$$E_{\kappa^{(n)}}(Z_{ji} | \Theta) = p r_{\kappa^{(n)}}\{Z_{ji} = 1 | \Theta\} = z_{ji}^{(n)}$$

and, by Bayes's theorem,

$$z_{ji}^{(n)} = \tau_j(\phi_i; \kappa^{(n)}) / f(\phi_i; \kappa^{(n)}),$$

where  $\tau_j(\phi_i; \kappa^{(n)})$  represents the posterior probability that the  $i$ th member of the sample  $\phi_i$  belongs to the  $j$ th component of the mixture. The maximization step requires replacing  $z_{ji}$  with  $z_{ji}^{(n)}$  to give

$$\frac{I_1(\kappa_j^{(n+1)})}{I_0(\kappa_j^{(n+1)})} = \left( \sum_{i=0}^N z_{ji}^{(n)} \cos 2\pi \phi_i \right) / \sum_{i=0}^N z_{ji}^{(n)}. \tag{C9}$$

Thus, our incremental estimate of synchronization strength (corresponding to the right-hand side of Equation C9) is

$$s_j^{(n+1)} = s_j^{(n)} - \eta_s a^{(n)} \tau_j(\phi^{(n)}; \kappa^{(n)}) (s_j^{(n)} - \cos 2\pi \phi_j^{(n)}). \tag{C10}$$

Note that Equation C10 is similar to Equation B4, with the addition of the expectation-maximization coefficient,  $\tau_j(\phi, \kappa)$ . The intuitive interpretation of Equation C10 is that the contribution of the  $n$ th onset to our incremental estimate of synchronization strength,  $s$ , is weighted by the (currently assessed) posterior probability that event  $n$  belongs to periodicity  $j$  (this expectation-maximization coefficient also weights internal coupling in Equations C3 and C4). Once  $s$  has been determined,  $\kappa$  is found by using Equation B5. The additional factor  $a^{(n)}$  is the amplitude of the  $n$ th onset, scaled to the range [0 1]. This reflects that fact that, for complex multi-periodicity rhythms, onset amplitudes differ.

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