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I, Auriel Washburn , hereby submit this original work as part of the requirements for the degree of Master of Arts in Psychology.

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Harmony from Chaos?
Investigations in Aperiodic Visual-Motor and Interpersonal Coordination

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Harmony from Chaos?
Investigations in Aperiodic Visual-Motor and Interpersonal Coordination

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by

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Abstract

Many of our daily behaviors provide evidence that people are capable of coordinating in an effortless manner, even when faced with highly variable, often unpredictable behavioral events. While a substantial amount of research on joint-action has focused on the coordination that occurs between simple stereotyped or periodic movements, a larger proportion of everyday social and interpersonal interaction requires that individuals coordinate complex, aperiodic actions. In fact, many of the actions performed by individuals in an interactive context likely exhibit characteristics synonymous with chaos (i.e., are unpredictable yet deterministic). Although counterintuitive, recent research in physics and human movement science indicates that small temporal feedback delays may actually enhance an individual's ability to synchronize with chaotic environmental events. The current study was designed to determine whether a similar phenomenon might be at work in the interpersonal coordination of aperiodic behaviors and, if so, to examine the underlying anticipatory processes.

In order to evaluate the effect of small perceptual feedback delays on aperiodic interpersonal coordination, three experiments were conducted. Since the phenomenon of anticipatory synchronization had only previously been observed for a single actor coordinating with a computer-generated chaotic stimulus, these experiments were performed in a progressive manner, transitioning from an actor-environment context to an interpersonal, bi-directionally coupled context involving two co-actors. In each experiment, a participant was asked to coordinate their arm movements with another continuous movement sequence displayed to them as a moving dot on a large HD monitor. Perceptual feedback was available to participants via the display of their own movements as a different colored dot. This dot either reflected the behavioral outcomes of a participant’s actions in real time, or at one of three short temporal delays (200 ms, 400 ms, 600 ms). Resulting coordination was measured using four different analyses. The previously established local coordination analyses of maximum cross-correlation and instantaneous relative phase were used to evaluate the occurrence of anticipatory synchronization. Two new analyses of complexity matching, or more global, long-term behavioral similarity, were also conducted in order to gain additional information about the coordinative dynamics between contemporaneous behaviors.

Consistent with previous findings, Experiments 1 and 2 demonstrated that anticipatory synchronization of aperiodic behaviors can be achieved in a visual context, if the coordinating actor experiences a small perceptual feedback delay (200-400 ms). Experiment 3 extends these findings by demonstrating that the same anticipatory phenomenon can occur in an interpersonal context involving two bi-directionally coupled co-actors, again so long as the coordinating actor experiences a small perceptual feedback delay. Furthermore, evidence of complexity matching between observed and produced behavioral movements indicated that the anticipatory synchronization occurring in the current study was likely supported by the coordinative processes of strong anticipation. These findings are some of the first to extend the understanding of visual and interpersonal coordination beyond the study of simple, periodic behaviors. As such, the present work provides new insights about the underlying processes that might provide support for flexible, robust visual and interpersonal coordination and suggests new avenues for investigating the dynamics of social interaction.

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CHAPTER 1

Introduction

The ability of an individual to coordinate with ongoing, ever-changing environmental events, including the actions of other individuals, is fundamental to the performance of many everyday tasks. Research investigating the behavioral dynamics that occur between an individual’s movements and visually-specified environmental events has provided valuable insight into how such behavioral coordination is achieved (Richardson, Marsh, & Schmidt, 2005; Schmidt & O’Brien, 1997; Schmidt, Richardson, Arsenault, & Galantucci, 2007). The majority of this previous research has primarily focused on the visual coordination of simple stereotyped or periodic movements (e.g., rhythmic leg movements; rocking chair movements; see Schmidt & Richardson, 2008 for a review). However, a large proportion of agent-environment interactions require that individuals coordinate their movements with rather complex, aperiodic, and seemingly unpredictable events (Richardson, Dale & Marsh, 2014; Stephen, Stepp, Dixon, & Turvey, 2008). One only has to consider the multitude of actions that must be performed during a daily drive to work, or the interactions that take place when loading a dishwasher or clearing a table with family members, to be reminded that people are often capable of coordinating in an effortless manner, even when faced with highly variable, unforeseeable behavioral events.

Recent work in physics and motor control may help to explain how individuals are able to achieve this kind of complex, aperiodic coordination. The somewhat counter-intuitive finding indicating that small temporal feedback delays can sometimes enhance, rather than hinder, an individual's ability to synchronize with unpredictable (aperiodic) and even chaotic environmental events is especially interesting (Stepp, 2009). Here, an actor experiences a perceptual feedback delay about their own movements – information about the outcome of a behavior is temporally delayed with respect to the production of the behavior – and as a result the actor actually comes to anticipate the environmental sequence of events with which they are trying to coordinate. This phenomenon has previously been referred to as *anticipatory synchronization* (Voss, 2000).

The interactive processes between an agent and an agent's task environment that lead to this phenomenon are not yet readily understood. However, theories about the relative importance of coordination between short-term behavioral events versus long-term behavioral patterns have recently started to surface (Marmelat & Delignieres, 2012). The short-term coordination of events is often referred to as 'local coordination' and can be assessed using various measures of temporal synchronization. The longer-term coordination of behavior has been termed 'global coordination' and can be assessed through a comparison of the patterns of behavioral variability found within each of two concurrent, coordinated behavioral sequences (i.e., requires determining whether the complexity of the two behavioral sequences match; so called *complexity matching*). Thus far, it appears that short-term and long-term associations between an individual's behavior and the external behavior with which they are attempting to coordinate are both valuable in shaping complex, aperiodic behavioral coordination. Questions remain, however, about their relative importance with respect to the locally defined phenomenon of anticipatory synchronization, and how this relationship might be affected by differences between uni-directional coupling, as found in visual actor-environment coordination, and bi-directional coupling, as often exists for interpersonal interactions.

Accordingly, the current study brings together research on visual rhythmic coordination, anticipatory synchronization, and complexity matching in order to determine whether complex visual, interpersonal coordination may be supported by feedback delay-enhanced anticipatory processes of coordination. To investigate this possibility, three separate, yet interrelated experiments were conducted. Experiment 1 was designed to validate a new experimental paradigm for the examination of anticipatory synchronization by replicating the previous finding that small temporal feedback delays can lead to anticipatory synchronization during unidirectional visual coordination (Stepp, 2009). Experiment 2 was designed to determine whether anticipatory synchronization might occur for naturally produced aperiodic behaviors, as opposed to the artificial (computer-generated) chaotic sequences studied previously. Finally, Experiment 3 examined whether anticipatory synchronization might occur between two bi-directionally coupled co-actors. Across these studies, I also explored the potential relationship between complexity matching and anticipatory synchronization (Marmelat & Delignieres, 2012), and how this is influenced by differences in coupling and information exchange between visually coordinated systems.

Visual-Motor and Interpersonal Coordination

Ample research suggests that how we move is heavily influenced by the properties and constraints of the environment that surrounds us, including the movements of environmental objects and other individuals (e.g. Buekers, Bogaerts, Swinnen, & Helsen, 2000; Chartrand & Bargh, 1999; Lopresti-Goodman, Richardson, Silva, & Schmidt, 2008; Richardson, Marsh, & Schmidt, 2010). Of particular relevance for the current study is previous research on visual-motor coordination, which has demonstrated that individuals naturally synchronize and coordinate their limb and body movements with periodic environmental events when they are coupled to them via visual information[1] (Bueckers et al., 2000; Dijkstra, Schöner, & Gielen, 1994; Dijkstra, Schöner, Giese, & Gielen, 1994; Giese, Dijkstra, Schöner, & Gielen, 1996).

A large body of research within the field of visual-motor coordination has demonstrated that visual actor-environment coordination is governed by dynamical processes of entrainment (e.g., Byblow, Chua, & Goodman, 1995; Kelso, Decolle, & Schöner, 1990; Russell & Sternad,

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[1] Evidence suggests that individuals are also capable of coordinating with external events through haptic (Jeka, Oie, Schöner, Dijkstra, & Henson, 1998; Jeka, Schöner, Dijkstra, Ribeiro, & Lackner, 1997) and auditory (Repp, 2004; Repp, 2006; Repp & Penel, 2004) information.

2001; Schmidt & Turvey, 1994; Wilson, Collins, & Bingham, 2005; Wimmers, Beek, & van Wieringen, 1992), and can often be modeled as a system of coupled oscillators (Strogatz & Stewart, 1993). Such visual-motor coordination can arise spontaneously, or can occur as a function of the actor's intent. Evidence for unintentional coordination of rhythmic limb movements has been observed between an actor and their environment both with the coordination of postural sway to visual environmental movements (Dijkstra, Schöner, & Gielen, 1994; Dijkstra, Schöner, Giese, et al., 1994; Giese et al., 1996;), and with the entrainment of rhythmic pendulum swinging to the frequency of an oscillating computer stimulus presented to the actor as a distractor task during the execution of other behaviors (Schmidt et al., 2007). In the context of unintentional entrainment, it appears that rhythmic visual-motor coordination is typically characterized by periods of synchronized behavior interspersed with periods of unsynchronized behavior (Richardson et al., 2005; Schmidt & O'Brien, 1997). This kind of *intermittent* coordination is referred to as *relative* coordination, in contrast to *absolute* coordination which requires that moving components be fully synchronized throughout the interval of coordination.

Both relative and absolute coordination can be identified and described in a number of ways. One common method is to examine the phase relationship between two oscillators or movements (Haken, Kelso, & Bunz, 1985; Lopresti-Goodman et al., 2008; Pikovsky, Rosenblum, & Kurths, 2003; Schmidt, Shaw, & Turvey, 1993). Here, *phase* refers to where an oscillatory movement is in its periodic cycle, as measured in degrees or radians. Similarly, the spatio-temporal coordination between two oscillators can be defined by their relative phase; the simple difference between the phases of each oscillator. Another method of assessing coordination is to establish the maximum cross-correlation between oscillators or movements (Stepp, 2009; Stepp & Frank, 2009). A characteristic phase relationship is established here as well, this time equal to the phase relationship (in space-time) from a range of possible leads or lags for which the greatest amount of synchrony between behaviors is observed. Two specific relative phase patterns have been shown to occur most frequently during rhythmic visual coordination: inphase and antiphase (e.g., Schmidt, Bienvenu, Fitzpatrick, & Amazeen, 1998; Schmidt, Carello, & Turvey, 1990; Richardson et al., 2007). The inphase pattern of coordination is defined as having a stable relative phase value around 0°, with both oscillators simultaneously in the same phase of their respective oscillatory cycles. Conversely, antiphase coordination is characterized by a stable relative phase value around 180°, wherein the oscillators are simultaneously in the opposite phase of their respective oscillatory cycles. When occurring in an actor-environment or interpersonal context, these behaviors are successfully captured and predicted by an adaptation (Liao & Jagacinski, 2000; Russell et al., 2004) of the Haken, Kelso and Bunz (HKB) (1985) model of interlimb coupling, which takes into account the more unilateral coordination processes involved in uni-directional actor-environment coordination as opposed to the bi-directional coupling processes which occur between limbs of a single individual.

The observation of spontaneous coordination between rhythmic limb movements of two individuals who each have visual information about each other's movements provides further evidence for the natural occurrence of interpersonal entrainment (Richardson et al., 2005). In general, the bi-directional coupling inherent to interpersonal coordination results in an increased sensitivity to situational elements known to affect the stability of all visual-motor coordination. As a result, interpersonal coordination is often characterized by relative, intermittent coordination (Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007). Substantial research has been dedicated to determining what factors have the greatest influence on the occurrence and stability of rhythmic visual and interpersonal coordination (see Schmidt & Richardson, 2008, for a review). For instance, decreases in coupling strength between movements, brought about through a reduction in information exchanged between oscillators or increases in movement frequency (e.g., Amazeen, Schmidt, & Turvey, 1995), are known to significantly reduce the likelihood and stability of coordination. Similarly, increased cognitive activity or task difficulty has been associated with a loss of coordination stability resulting from decreases in overall movement stability (Pellecchia, Shockley, & Turvey, 2005; Richardson et al., 2005; Shockley & Turvey, 2005).

The relationship between the natural (i.e., uncoupled) frequencies, or oscillatory periods, of two moving components also has a strong influence on the likelihood and stability of any emerging coordination. Evidence has suggested that the greater the difference between the natural periods of two movements being coordinated, commonly referred to as "detuning", the less likely it is that inphase or antiphase coordination will occur (e.g., Schmidt & O'Brien, 1997; Richardson et al., 2007). More specifically, it has been shown that spontaneous inphase or antiphase visual coordination only occurs when the natural periods of two movements are within approximately +/-15% of each other, with the size of this basin somewhat dependent on the coupling strength between oscillators (Lopresti-Goodman et. al, 2008). However, complex modes of rhythmic visual coordination referred to as "multifrequency" patterns have been found to occur as well, and are characterized by any frequency ratio between oscillating components made up of whole number integers (Peper, Beek, & van Wieringen, 1995a; Peper, Beek, & van Wieringen, 1995b). Interestingly, these studies indicate that frequency detuning may actually facilitate the performance of more complex coordination modes (Sternad, Turvey, & Saltzman, 1999) and mirror how asymmetries in physical and informational constraints can actually induce and support the spontaneous emergence and stabilization of complex behavioral coordination (Lagarde, 2013; Richardson, Garcia, Frank, Gergor, & Marsh, 2012; Richardson, Washburn, & Kallen, in prep; Walton, Richardson, & Chemero, submitted). Indeed, while the intentional performance of multifrequency coordination between two oscillators with no frequency detuning is quite challenging (Fontaine, Lee, & Swinnen, 1997; Kovacs, Buchanan, & Shea 2010; Mechsner, Kerzel, Knoblich, & Prinz, 2001; Rosenbaum, Dawson, & Challis, 2006; Treffner & Turvey, 1993), recent findings indicate that this type of rhythmic visual coordination can emerge spontaneously for specific, divergent natural frequency relationships (Buchanan & Ryu, 2005; Buchanan & Ryu, 2006; Buchanan & Ryu, 2012; Washburn, Coey, Romero & Richardson, in press).

This recent work on multifrequency coordination has helped to broaden the visual coordination literature from a focus on the synchronization of simple, rhythmic behaviors to more complex, interpersonal coordination. However, a large proportion of actor-environment and interpersonal coordination behaviors are still unaccounted for. Exploration of the visually-mediated coordination of aperiodic behaviors has already begun to add valuable information to the field of interpersonal coordination (Stepp, 2009). The objective of the current work is to further examine visually-mediated aperiodic coordination in order to 1) provide evidence about whether visual feedback delays can act to facilitate the visually-mediated, interpersonal coordination of complex behaviors, and 2) establish whether more global coordination processes are also associated with the local coordination phenomenon of anticipatory synchronization for aperiodic behaviors.

Anticipatory Synchronization

The synchronization of physical and biological systems with complex, aperiodic environmental events involves unique challenges relative to the coordination of simple, periodic behaviors, due primarily to the fact that these events are largely unpredictable. Intuitively, one would expect that feedback delays for the coordinating system – that is, temporal delays between the production of a behavior and information about the outcome for that behavior – would increase the difficulty of achieving synchronization with complex environmental events, even to the point of prohibiting coordination altogether. However, it appears that short delays of this nature (~200-400 ms) may actually facilitate coordination (Voss, 2000; Stepp, 2009). In fact, in order to maintain synchrony with a complex aperiodic behavior, the delayed, coordinating system actually comes to anticipate events before they have occurred in a phenomenon referred to as *anticipatory synchronization* (Voss, 2000). In other words, the ostensible challenges to coordination posed by feedback delays (i.e., akin to those that naturally occur in the human nervous system) can be understood as providing the opportunity for a system to achieve an anticipatory relationship with aperiodic external or environmental events (Stepp & Turvey, 2008). It is worth noting that the ability of human agents to anticipate others' actions, or the behavioral outcomes of an environmental event, plays a facilitating role throughout visual coordination, even in the case of simple, periodic behaviors and in the absence of a feedback delay. However, while it may not be difficult to imagine anticipating when a person's foot will next hit the ground during rhythmic walking, evidence for anticipatory synchronization with aperiodic and unpredictable sequences requires further consideration.

Anticipatory synchronization was first observed within the class of unidirectionally coupled dynamical systems collectively referred to as "master-slave" systems, for which a "slave" system often exhibits anticipatory synchronization with respect to the behavior of a "master" system. A schematic representation of this kind of system with and without the inclusion of a feedback loop for the "slave" system (with temporal delay, τ), along with actual time series demonstrating non-anticipatory and anticipatory synchronization by an actor with respect to an aperiodic stimulus, can be found in Figure 1. The collective "master-slave" system can be defined mathematically as.

$$\dot{x} = f(\mathbf{x}) \tag{1}$$

$$\dot{y} = g(\mathbf{y}) + k(\mathbf{x} - \mathbf{y}_{\tau})$$

Here the **x** and **y** vectors represent the states of the master and slave systems, respectively, so that *f*(**x**) and *g*(**x**) specify the intrinsic dynamics of these systems and *k* is the coupling strength between the systems. The term $\mathbf{y}_{\tau} = \mathbf{y}(t - \tau)$, or the state of the slave system delayed by τ in an unspecified unit of time. Work by Stepp and Frank (2009) has demonstrated that anticipatory synchronization also occurs in simulated master-slave systems for a variety of different oscillatory master systems. Subsequently, Stepp (2009) established that the same anticipatory phenomenon can occur for a human actor visually coupled to a simulated chaotic oscillator (wherein the individual is the "slave" and the simulated oscillator the "master").

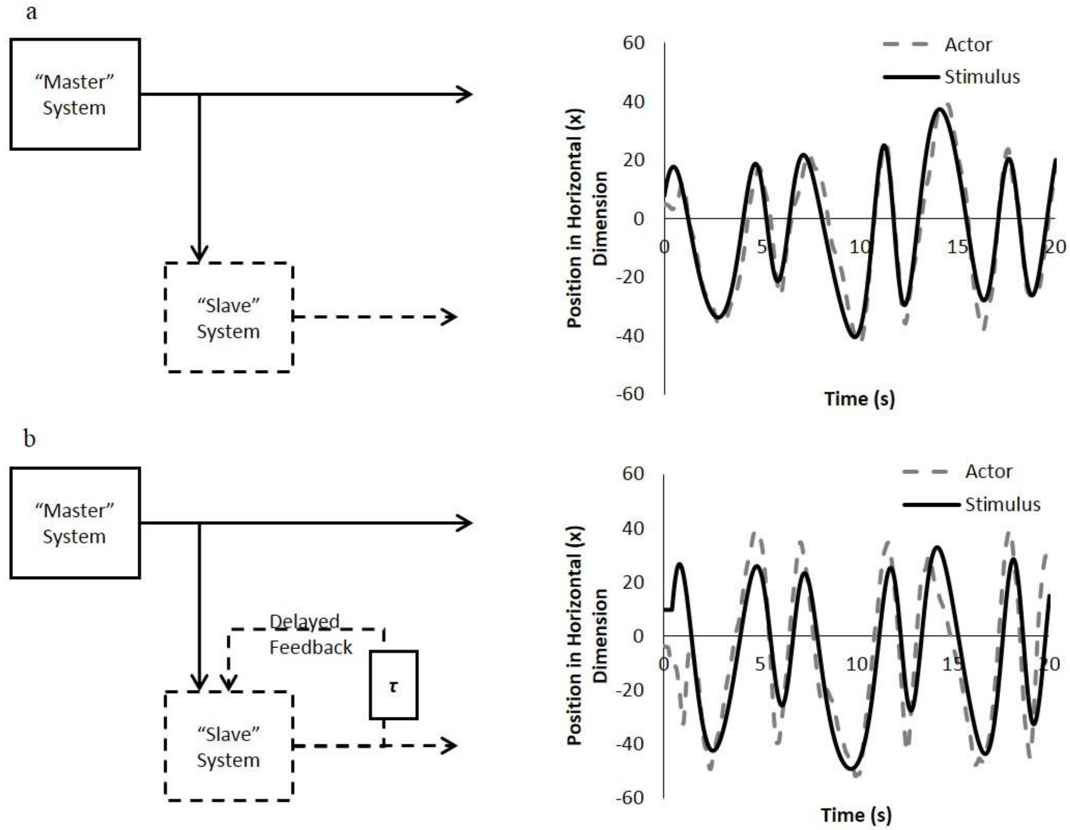

Figure 1. A schematic depiction of master-slave coupling (left), along with time series from one dimension of coordinated stimulus (solid) and participant (dashed) movements (right). Examples of a) non-anticipation and b) anticipatory synchronization are provided. Time series are from Experiment 1, with the example of non-anticipation coming from a trial in which the participant experienced no feedback delay, and the example of anticipatory synchronization coming from a trial in which the participant experienced a 400 ms perceptual feedback delay.

Thus far, all studies demonstrating anticipatory synchronization of aperiodic sequences by an individual have used stimuli which exhibit characteristics of a specific kind of aperiodic behavior referred to as ‘chaotic’ (Stephen et al., 2008; Stepp, 2009). In contrast to inherently stable and predictable time-evolving behavior, such as walking, chaotic behavior is complex and highly variable. Chaotic behavior is not random, however, and the distinction between ‘chaotic’ and ‘random’ behavior is critical here. In a truly random sequence there is no relation between or among events as they occur over time. That is, random behaviors are non-deterministic, so that the state of a random behavior at any point in time is not determined by, nor can it be predicted from, knowledge about the preceding state or event, or any other past or future event. For a chaotic behavior, the events or states that occur over time are completely deterministic. The apparent randomness or aperiodic nature of such behavior is a result of sensitive dependence on initial conditions such that the events which will follow, and the potential relationships between them, are constrained by the context in which the sequence is initiated. These initial conditions can never be known absolutely or with perfect precision, however, hence the *unpredictable determinism* of chaotic behaviors.

The deterministic nature of chaotic sequences provides favorable circumstances for an actor to achieve synchronization, but it appears that for anticipatory synchronization to occur the actor must experience a feedback delay between the production and perceived outcome of their own actions within a temporal range of around 200 to 400 milliseconds (Stepp, 2009). Additionally, continuous movement tasks (e.g. tracing the generally elliptical orbit of a continuous chaotic oscillator) appear to facilitate anticipatory synchronization over the requirement to coordinate with discrete behavioral events (e.g. tapping a key in synchrony with an auditory metronome signal) (Stephen et al., 2008; Stepp, 2009). This was the case even with the introduction of feedback delays for the actor with respect to their own tapping behavior. This outcome has previously been predicted and observed for an actor uni-directionally coupled to a continuous chaotic sequence using model simulations of master-slave systems (Sivaprakasam, Shahverdiev, Spencer, & Shore, 2001; Stepp & Turvey, 2008; Toral, Masoller, Mirasso, Ciszak, & Calvo, 2003; Voss, 2001; Voss, 2002).

Ultimately, in order for anticipatory synchronization to be useful in explaining complex human coordination, either to environmental events or with other individuals, it is important to consider the frequency with which humans embody and exhibit chaotic behavior. In fact, it appears that chaotic structure underlies biological behavior at a variety of levels, as it is implicated in several models of neurophysiological processes, (Chay & Rinzel, 1985; Canavier, Clark & Byrne, 1990), and is also apparent within the variability of human movement (Mitra, Riley & Turvey, 1997). Additionally, it has been demonstrated that inherent structural and functional constraints of human limbs prevent individuals from producing truly random movement, even following explicit training to elicit the behavior that involves substantial performance feedback (Newell, Challis & Morrison, 2000; Newell, Deutsch & Morrison, 2000). It therefore seems likely that many of the aperiodic actions performed by individuals alone and in interactions with the environment, and other individuals, will exhibit characteristics synonymous with chaos, as opposed to randomness. Collectively, findings on anticipatory synchronization and the chaotic nature of aperiodic human movement suggest that anticipatory synchronization may play a significant role in complex actor-environment and interpersonal coordination.

Strong Anticipation versus Weak Anticipation. Marmelat and Delignieres (2012) have previously identified three possible explanatory mechanisms for complex interpersonal coordination in which one actor would be able to anticipate the behaviors of another. The first of these relies on the use of internal models to predict events ahead of time (Pezzulo, 2008; Rosen, 1985), with the resulting behavioral anticipation referred to as ‘weak anticipation’ (Dubois, 2003). The other two explanations for anticipatory interpersonal coordination both result in what Dubois (2003) would categorize as ‘strong anticipation’, solely based on the fact that they do not rely on the use of internal models. Generally, strong anticipation is thought to be a result of the fact that all behaviors, exhibited by an individual or found within their environment, follow certain universal dynamical laws (Stepp & Turvey, 2008). In other words, both the individual and the environment are systems that behave according to the constraints of ordinary thermodynamic and physical properties of energy and information flow, so that intrinsic commonalities in behavior between individual and environment allow for the emergence of anticipation during interaction (Barab, Cherkes-Julkowski, Swenson, Garrett, Shaw, & Young, 1999; Kelty-Stephen & Dixon, 2012; Kugler & Shaw, 1990; Walton et al., submitted). Two distinct explanations have arisen for the process by which these shared properties come to shape anticipatory coordinative relationships; advocates of a ‘local’ form of anticipation emphasize the importance of behavioral matching by an individual to environmental events or states on a very short timescale (Stepp & Turvey, 2010), while others have suggested that an adjustment to the overall statistical structure of a series of environmental events, a more ‘global’ form of anticipation, is more meaningful (Stephen et al., 2008). Here the overall statistical structure of a behavior is understood to be a characterization of variability over time, which ultimately provides information about patterns of self-similarity within a given behavior across a wide range of time scales. It is thought that this kind of large-scale structural complexity is prescribed by intrinsic dynamical properties at least as much, if not more, than the progression of short-term behavioral events.

Evidence of anticipatory synchronization for chaotic sequences is generally taken as support for theories of strong anticipation over those of weak anticipation (Stepp & Turvey, 2008; Stepp & Turvey, 2010). Given that chaotic sequences are inherently unpredictable, it is difficult to conceive of how an internal model would make use of information about past events to generate the information about future events necessary for an individual to coordinate. In contrast, proponents of strong anticipation would suggest that the lawful regularities operating within an agent-environment system, along with the determinism of chaotic behaviors, allow the individual to embody the behavioral dynamics of the environment, making coordination possible (Stepp & Turvey, 2008; Stepp & Turvey, 2010). It is perhaps even more difficult to explain the observation that the introduction of temporal feedback delays allow an individual to actually anticipate external chaotic behaviors using a theory of action which depends on internal models (Stepp, 2009). Explanation of this phenomenon as resulting from strong anticipation processes is somewhat different depending on whether the local or global form of strong anticipation is being considered.

The local and global forms of strong anticipation do not interact with anticipatory synchronization in the same way. By definition, the 'synchronization' aspect of this phenomenon involves the coordination of local behaviors, which leads to a natural prioritization of short-term environmental events over long-term characterizations of behavior. However, evidence of coordination occurring on a local scale does not necessarily imply that any underlying strong anticipation process must be of a local form. In fact, it has been noted that the unpredictable nature of chaotic sequences may be similarly difficult to reconcile using the idea of local strong anticipation as it is for weak anticipation (Stephen et al., 2008). The ability of an actor to achieve coordination with an external chaotic behavior solely through short-term adaptation seems unlikely because while the sequence of events is necessarily deterministic (i.e. sensitive to the conditions within which the behavior initiated), the relationship between consecutive events will be inconsistent. On the other hand, global strong anticipation involves the expectation that the long-range patterns of variability and self-similarity of an ongoing external behavior will come to be reflected in the behavior of a coordinating individual, resulting in statistical similarity between the two. This kind of overall similarity in variability structure between behaviors has previously been referred to as *complexity matching*, for which measures used to assess long-term patterns within separate behavioral time series are closely related (West, Geneston, & Grigolini, 2008).

Complexity Matching

Recent work has begun to approach the question of whether the global form of strong anticipation might be associated with the more global coordinative nature of complexity matching. While it is felt that measures of long-range cross-correlation and statistical similarity between behaviors provide support for theories of strong anticipation in general (Marmelat & Delignieres, 2012; Podobnik, Fu, Stanley, & Ivanov, 2007), it is not yet clear that anything other than short-range coupling and adaptation processes are responsible for more global coordination (Delignieres & Marmelat, 2014; Torre et al., 2013). There also remains some debate as to whether the local and global forms of anticipation must necessarily be mutually exclusive, or whether one form or the other is more likely to occur in specific contexts (see Stephen & Dixon, 2011 for further details).

While complexity matching appears to occur for a wide variety of behaviors, sometimes in the absence of any local coordination, it appears to be dependent on pre-existing self-similarity in the environmental behavior with which an actor is coordinating (Delignières & Marmelat, 2014). Ultimately, this allows the actor to exploit the complexity of the environment in order to produce more adaptive and efficient behavior with respect to any task goals (Delignières & Marmelat, 2014; Marmelat & Delignieres, 2012). The same logic holds for a bi-directionally coupled system where complexity within both systems is essential for the development of corresponding fluctuations in variability. This provides an opportunity for mutual adaptation and bi-directional anticipation (Delignières & Marmelat, 2014; Marmelat & Delignieres, 2012). As expressed by West and Grigolini (2010), the exchange of information between systems appears to improve with increases in behavioral complexity. In other words, rather than posing a challenge to the synchronization of local behaviors or the matching of long-term statistical structure, the complexity inherent to many natural behaviors may actually facilitate interpersonal coordination. This idea is consistent with the observation that humans achieve seemingly effortless coordination and cooperation of apparently unpredictable behaviors on a daily basis, and provides motivation for further exploration of the coordination of complex behaviors.

Any method used to identify an instance of complexity matching should theoretically be more sensitive to coordination in a broad sense, by including statistical similarity in the definition of coordination, and less sensitive to the occurrence of synchrony or mimicry of discrete behavioral events. There is some debate as to whether local and global coordination can really be considered independent processes (see Stephen & Dixon, 2011 for further details), but at this time complexity matching is often considered to be the byproduct of local coordination processes. However, even if there does not appear to be synchrony between two behaviors, as established by measures of local coordination, measures of global coordination should theoretically be able to demonstrate that complexity matching has occurred. It is therefore necessary to utilize measures distinct from those used to assess local coordination in order to address the existence of complexity matching.

The idea of performing an analysis to identify complexity matching is relatively recent, and thus far only two methods have been established: correlation of fractal scaling exponents from detrended fluctuation analysis (DFA), and detrended cross-correlation analysis (DCCA). In the first study to evaluate complexity matching, Marmelat and Delignieres (2012) used a fractal analysis of performance variability to gain an initial measure of statistical structure for each individual in an interpersonal, pendulum swinging task. Fractal analyses are designed to address the existence of patterns within the variability of behavioral performance, and have the power to identify self-similarity in fluctuations across multiple timescales (Mandelbrot, 1982). In order to determine what kind of variability is occurring for a given task, it is important to repeatedly measure some aspect of that task as performance unfolds over time. The resulting series can then be broken down into windowed segments or composite sinusoidal series, and are typically submitted to a DFA or a power spectral density (PSD) analysis, respectively (see Holden, 2005 and Ihlen, 2012, for further details). These analyses use slightly different procedures to provide a measure of self-similarity within performance variability. In DFA, the slope of a regression line is fit to a plot of the logarithm of the root mean square deviation from a local least squares line, with the logarithm of the associated window segment size providing a unique scaling relation between the magnitude and scale (i.e. window size) for changes in the performance time series. In PSD, the slope of the regression line is fit to a plot of the logarithm of the power (amplitude squared) of changes with the logarithm of their corresponding frequencies, and provides a unique scaling relation between the size and frequency of changes. This scaling relation (S) is related to a characteristic scaling exponent (α), where $\alpha = -S$. A scaling exponent can then be used to give a quantitative assessment of the type of variability observed or, more specifically, the degree of self-similar fluctuation within one individual’s performance.

While a great amount of information can be gained from considering the kind of performance variability exhibited during the performance of a task, in the context of complexity matching the actual degree of self-similarity within the variability of one individual’s performance is of relatively little importance. Instead, it is most critical to demonstrate that the structure of an individual’s behavioral variability is similar to that of an environmental stimulus, or another individual with whom they are interacting. In order to achieve this, Marmelat and Delignières (2012) used fractal scaling exponents from DFA as a measure of complexity. They then provided a measure of structural similarity between coordinating individuals by finding the correlation between scaling exponents for concurrent behavioral time series. Using this same method of correlating fractal scaling exponents for concurrent behavioral time series, complexity matching has thus far been observed between speech signals of two individuals during conversation, for one individual instructed to synchronize with a variety of periodic and aperiodic auditory sequences, and during interpersonal coordination of rhythmic pendulum swinging (Abney, Paxton, Kello, & Dale, 2013; Coey, Washburn, & Richardson, under review; Marmelat & Delignières, 2012; Torre, Varlet, & Marmelat, 2013). Complexity matching based on this method has even been observed in the absence of any consistent local coordinative relationship between an actor's tapping behavior and a discrete auditory stimulus with chaotic inter-onset intervals (Stephen et al., 2008).

DCCA has also been used to assess complexity matching, as it provides a measure of the long-range cross-correlations between two simultaneously occurring behaviors (Delignières & Marmelat, 2014). This method is an extension of DFA, and follows a very similar process (Podobnik & Stanley, 2008). Initially, each of two behavioral time series of equal length are integrated and divided into non-overlapping windowed segments. The integrated series are then locally detrended, and the covariance between the two detrended series is established. This same process of detrending and calculation of covariance is then repeated for window segments of many different sizes. As in DFA, the slope of a regression line is then fit to a plot of the logarithm of the root mean square deviation from a local least squares line, so that the logarithm of the associated window segment size provides a unique scaling relation between the magnitude and scale (i.e. window size) for changes in covariance between the two behavioral series. The opposite of this scaling relation, λ, functions similarly to the DFA scaling exponent, α. In this case, λ constitutes a single measurement of complexity for the coordinative relationship between the two contemporaneous behaviors being observed, and it is therefore not necessary to conduct a correlation between fractal measures for each of the separate time series as in the DFA method for evaluating complexity matching. This process has been used to assess complexity matching for walking coordination tasks in which an actor is instructed to synchronize with a metronome producing fractal sequences, intrapersonal bimanual movement and tapping tasks, and interpersonal pendulum synchronization tasks (Delignières & Marmelat, 2014).

Like all fractal-based analyses, these newly established methods for identifying complexity matching require long behavioral time series. This makes them unsuitable for assessing complexity matching between the behaviors involved in successful completion of a number of different coordinative tasks. Therefore, as part of the present work I was interested in developing additional measures that could be used to evaluate complexity matching in a wider variety of behaviors, including those involved in the coordinative task used throughout this study. Two new methods of complexity matching are introduced here. Similar to the aforementioned DFA method, both new measures require the user to conduct an initial assessment of complexity for each of two simultaneously occurring behavioral time series, and then to find the correlation between these values to gain a measure of the complexity matching between behaviors. The first of these measures involved the correlation of Largest Lyapounov Exponents (LLEs) between two time series, and provided information about similarities in long-term temporal structure. The second measure was based on the correlation of fractal dimensions (FDs), obtained using a box counting analysis, for two time series and returned a quantification of the global spatial similarities between behaviors. A more thorough explanation of both measures can be found in the *Measures and Analyses* section of Experiment 1.

Current Study

By incorporating work from visual coordination, anticipatory synchronization, and complexity matching, the goal of the current study was to explore aperiodic coordination in greater detail. Although anticipatory synchronization in human behavior has only thus far been observed for an actor coupled to a simulated chaotic oscillator (Stepp, 2009), I was specifically interested in whether it might help to facilitate the coordination of complex, aperiodic behaviors in social, interpersonal situations. I therefore designed three experiments to evaluate this possibility in a progressive manner, transitioning from an actor-environment context to an interpersonal, bi-directionally coupled context involving two co-actors. In each experiment, I examined the coordination of arm movements with visually displayed aperiodic sequences. Coordinating individuals were presented with short perceptual feedback delays, such that they saw a representation of their own movements at a temporal delay, in an attempt to elicit the previously observed phenomenon of anticipatory synchronization of aperiodic behaviors. The use of multiple experiments gave me the opportunity to evaluate the two new methods for assessing complexity matching introduced here, and to examine potential relationships between the local coordination phenomenon of anticipatory synchronization and complexity matching, in three different situations.

In Experiment 1, my aim was to validate a new experimental set-up for evaluating anticipatory synchronization, and examine complexity matching as a counterpart to the local coordination analyses presented previously by Stepp (2009). In Experiment 2, I incorporated pre-recorded, naturally produced aperiodic movement sequences in order to establish whether it was realistic to expect anticipatory synchronization to arise in a truly interpersonal context. In Experiment 3, I investigated real-time interactions between bi-directionally coupled co-actors producing natural aperiodic movements with the expectation that feedback delays would function as they do in an actor-environment context, leading to anticipatory synchronization by one individual with respect the movements of their co-actor.

CHAPTER 2

Experiment 1

The purpose of this first experiment was twofold: 1) to validate a new experimental set-up for investigating anticipatory synchronization which would afford easier adaptation to an interpersonal version than the method used previously (Stepp, 2009); and 2) to determine the relationship between measures of local coordination and measures of complexity matching in the context of anticipatory synchronization. I was interested in demonstrating that an actor's ability to coordinate with computer-generated chaotic sequences is affected by feedback delays with respect to one's own movement. Specifically, I expected that overall coordination would decrease with increases in feedback delay, but also that actor movements would actually come to anticipate the movement of a chaotic stimulus for certain lengths of delay. In addition to replicating the results presented by Stepp (2009) using *maximum cross-correlation*, I also wanted to evaluate behavior using instantaneous *relative phase* as an additional measure of local coordination. Finally, in order to investigate the possible occurrence of complexity matching, calculations of the *Largest Lyapunov Exponent* (LLE) and *fractal dimension* (FD) – assessed using a box counting method – were used to gain initial measurements of complexity for participant and stimulus behaviors.

Method

Participants. Six University of Cincinnati graduate students participated in this experiment. Participants ranged in age from 22 to 29 years.

Procedure and Design. Participants were asked to sit facing a display monitor (50" Plasma HDTV) and were equipped with a motion sensor attached to the middle joint of the first two fingers of their right hand (see Figure 2). They were informed that during the study they would be required to coordinate with a dot on the screen and that their own real time sensor-tracked movements would be displayed on the screen using a different colored dot. The stimulus dot was used to display continuous, computer-generated, chaotic movement sequences. The participants saw these sequences displayed as a blue dot (2 cm in diameter) on a black screen, and saw their own movements displayed using a red dot (2 cm in diameter). They were instructed to "keep the red dot as close to on top of the blue dot as possible" in order to complete the task (see Figure 3a for example movement time series).

Figure 2. General experimental set-up for Experiments 1 and 2. The set-up for Experiment 3 was adapted to include two participants sitting back-to-back, each facing a TV.

Participants experienced eight randomly selected chaotic stimulus movement sequences as test trials. The visual sequences a participant saw corresponding to their own movements were displayed to them at four different lengths of feedback delay, τ, (0, 200, 400, 600 ms; the delays selected here were a subset of those used by Stepp, 2009). Each delay condition was experienced twice over the eight test trials, randomized within blocks of four. Following the test trials, participants were asked to complete four baseline trials. In these trials only the red dot was visible on the screen and participants were instructed to reproduce the kind of movement they had been making during the test trials. All four feedback delays were also experienced for this set of trials, one trial at each delay. As a control measure for coordination between participant and stimulus, analyses of local coordination were performed comparing the position time series of pre-recorded stimulus files to each of the baseline trials. Any degree of coordination apparent between stimulus and participant for these trials was taken to be a baseline level of coordination. Each trial lasted a total of 200 s.

The display was generated by an application written using C/C++ and OpenGL. Data were collected using a magnetic tracking system (Polhemus Liberty, Polhemus Corporation, Colchester, VT). The OpenGL program was also used to record the movement data collected by the tracking system, with a sampling rate of 120 Hz. Horizontal and vertical coordinates of the undelayed participant movements, i.e. the movements of the arm, were captured as y_1 and y_2 with respect to the master-slave system defined in Equation 1. Therefore, all coupling and synchronization is considered to be between the participant's arm and the stimulus dot. The delayed movements of the participant's red dot are synonymous with the term $\boldsymbol{y}_\tau$ in Equation 1. The first 10 s of each time series were discarded to remove transients.

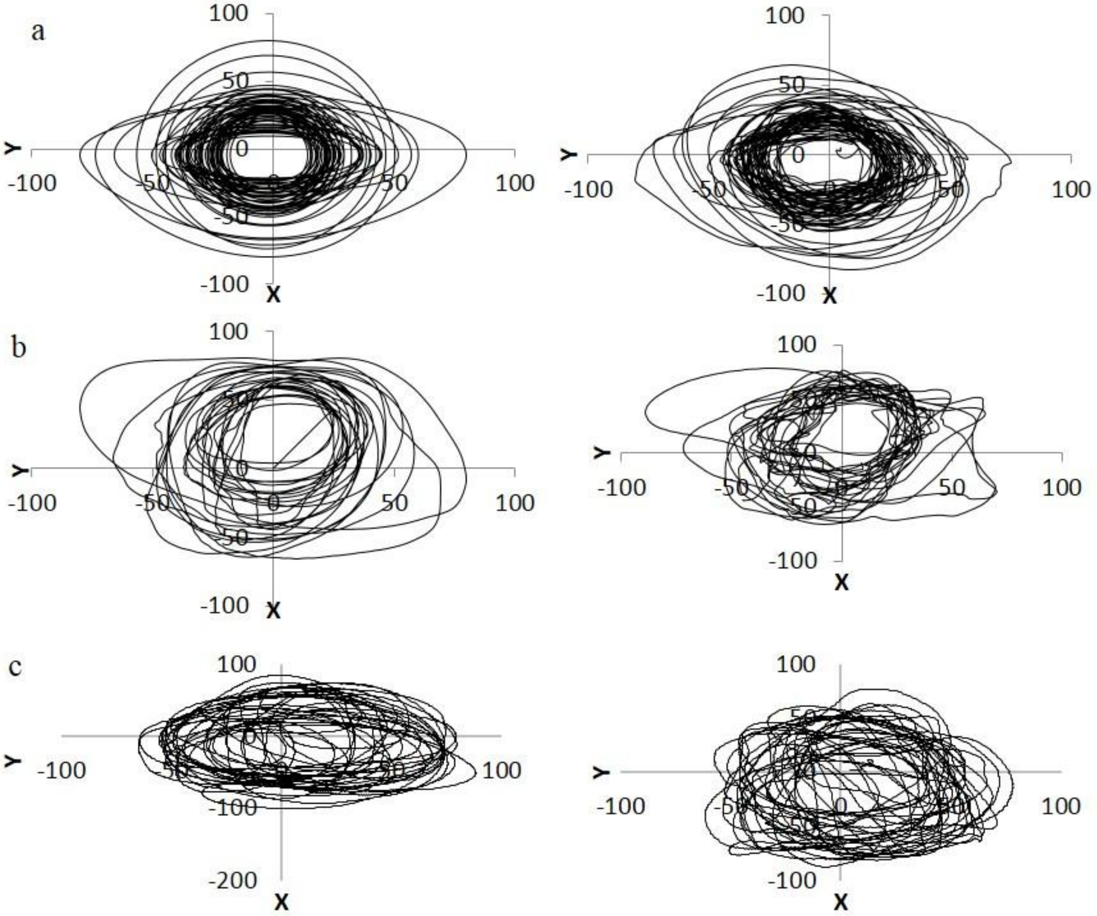

Figure 3. Typical movement time series for both stimulus or producer (left) and coordinator (right) behaviors from a) Experiment 1, b) Experiment 2, and c) Experiment 3. In all examples, participants experienced no feedback delay.

Stimulus Development. A total of 24 stimulus sequences were created for this experiment based on the "chaotic spring" system used by Stepp (2009), and specified by Equation 2. The 'x' and 'y' coordinates for the stimulus dot were generated by the x_1 and x_2 dimensions of the system

$$\dot{x}_1 = x_2 \tag{2}$$

$$\dot{x}_2 = -(2\pi\left(\frac{x_3}{\alpha} + \beta\right))^2 x_1$$

$$\dot{x}_3 = -x_4 - x_5$$

$$\dot{x}_4 = x_3 + \alpha x_4$$

$$\dot{x}_5 = b + x_5(x_3 - c)$$

The x_3, x_4 and x_5 dimensions define a standard Rössler attractor, which produces the chaotic dynamics used to drive the simple harmonic oscillator specified in x_1 and x_2. Ultimately this system maintains an elliptical trajectory while varying chaotically in amplitude and frequency, resulting in movements that are possible for participants to track but difficult to predict. As was established by Stepp (2009), for all stimuli files system parameters were set to $a = b = 0.1$, $c = 14$, $\alpha = 100$ and $\beta = 0.3$. For each stimulus file created, an 800 s (sample rate = 120 Hz) simulated sequence was generated using the initial conditions $x_1 = 1$, $x_2 = 0$, x_3 = taken from uniform distribution of values between [18.5, 19.5], $x_4 = 3.432$, and $x_5 = 20.9$ (from Stepp, 2009). From each 800 s sequence, a 200 s segment was selected for which amplitude remained relatively consistent. These 200 s segments were used as the stimulus time series.

Measures and Analyses. Studies of local anticipatory synchronization typically seek to establish an overall level of sequence similarity, as well as the amount of behavioral lag that is exhibited between the coordinated behaviors. Two different analyses were used to assess local coordination: 1) *maximum cross-correlation*, and 2) *instantaneous relative phase*. In addition to examining local structure in behavior, I was also interested in evaluating the occurrence of any larger scale dynamical processes. Two different analyses were used to assess behavioral complexity in this study: 1) calculation of the *largest Lyapunov exponent*, and 2) box counting to establish *fractal dimension*.

Cross-Correlation and Phase Lead. As presented by Stepp (2009), maximum cross-correlation can be used to assess local coordination and anticipatory synchronization. This analysis provides a measure of synchrony between participant movements and the movements of a stimulus for each experimental trial (Stepp, 2009; Stepp & Frank, 2009). The time series for the ‘x’ dimension of the participant movement and the time series for the ‘x’ dimension of the stimulus dot were each low-pass filtered with a cutoff frequency of 10 Hz using a Butterworth filter, and compared

$$x\text{corr}(h) = \sum_i [x(i) - \overline{x})\ (y(i-h) - \overline{y}] / \sqrt{\sum_i (x(i) - \overline{x})^{2}}\sqrt{\sum_i (y(i-h) - \overline{y})^{2}} \qquad (3).$$

Here the *x* and *y* variables correspond to participant and stimulus positions, respectively, and $x\text{corr}(h)$ represents the normalized cross-correlation function of the two time series taken at a phase shift of the participant with respect to the stimulus equal to *h*. For each trial, the value of the cross-correlation between the two time series was calculated for each of a range of phase shifts of the participant with respect to the stimulus, extending 1 s ahead of and 1 s behind perfect synchrony ($h = [-120, 120]$). The following equation was then used in order to establish both the highest level of synchrony and the associated degree of phase shift for the two time series.

$$\text{degree of synchrony} = x\text{corr}(\text{phase lead}) = \max\ x\text{corr}(h) \qquad (4)$$

The values for *maximum cross-correlation* and *phase lead* were taken to be representative of the relationship between participant and stimulus movements for a given trial. This process was then repeated to compare the time series for the ‘y’ dimension of the participant movement to the ‘y’ dimension of the stimulus movement.

Maximum cross-correlations between the participant and stimulus time series were calculated separately for the ‘x’ and ‘y’ dimensions. As the same patterns were observed in both dimensions, these values were then averaged across the ‘x’ and ‘y’ dimensions to establish a characteristic maximum cross-correlation and phase lead for each trial.

Instantaneous Relative Phase. An analysis of instantaneous relative phase provided an additional measure of local coordination. The time series for the ‘x’ dimension of the participant movement and the time series for the ‘x’ dimension of the stimulus dot were each centered around zero and low-pass filtered with a cutoff frequency of 10 Hz using a Butterworth filter. Each movement series was then differentiated to create a velocity time series. These resultant series were normalized by angular frequency and the movement phase angles ($\theta°$) were calculated for each time series using

$$\theta_i = \arctan\left(\frac{\dot{x}_i}{x_i}\right), \tag{5}$$

with $\dot{x}_i$ being the normalized angular velocity at sample i (normalized relative to the mean angular frequency for the trial) and x_i being the angular displacement of sample i. The difference between the phase angles was then calculated at each peak ($\phi = \theta_{participant} - \theta_{stimulus}$). The resulting instantaneous relative phase time series was used to compute *mean relative phase* and *standard deviation of relative phase,* as well as the *frequency distribution of relative phase* relationships visited over the course of a trial for each of 37 relative phase regions (-180°-180°, in 5° increments for the regions closest to 0° and 10° increments for all other regions). This process was then repeated to compare the time series for the ‘y’ dimension of the participant movement to the ‘y’ dimension of the stimulus movement.

The instantaneous relative phase between participant and stimulus movements was calculated separately for the ‘x’ and ‘y’ dimensions. As the same patterns were observed in both dimensions, these values were then averaged across the ‘x’ and ‘y’ dimensions to establish relative phase measures for each trial.

An analysis of instantaneous relative phase was also conducted for the relationship between the movement time series of the participant’s onscreen dot and the stimulus dot, specifically to obtain the frequency distribution of relative phase relationships visited over the course of a trial. This allowed me to assess whether anticipation by the participant with respect to the movement of the stimulus dot was actually allowing them to coordinate their onscreen dot with the stimulus dot at close to a 0° phase relationship, as per the instructions for the task.

Again, these measures were calculated separately for the ‘x’ and ‘y’ dimensions. As the same patterns were observed in both dimensions, these values were then averaged across the ‘x’ and ‘y’ dimensions to establish relative phase measures between the participant dot and stimulus dot for each trial.

Largest Lyapunov Exponent. The largest Lyapnuov exponent (LLE) can be calculated for a single time series as a characterization of the attractor dynamics (Eckmann & Ruelle, 1985), with a positive LLE being indicative of chaotic dynamics. For this analysis, the time series for the ‘x’ dimension of the participant movement and the time series, the ‘y’ dimension of the participant movement, the ‘x’ dimension of the stimulus dot, and the ‘y’ dimension of the stimulus dot were each treated separately. The algorithm for establishing the LLE of a time series used here is based on that developed by Rosenstein, Collins and De Luca (1993). The first step of this process is to reconstruct the attractor dynamics of the series. This necessitated the calculation of a characteristic reconstruction delay or ‘lag’, and embedding dimension.

Average Mutual Information (AMI), a measure of the degree to which the behavior of one variable provides knowledge about the behavior of another variable, was used here to establish the appropriate lag for calculation of the LLE. This process involves treating behaviors of the same system at different points in time as the two aforementioned variables (Abarbanel, Brown, Sidorowich & Tsimring, 1993). As a preliminary step to the use of this algorithm, each time series was zero-centered. The calculation for AMI within a single time series was conducted using

$$I(T) = \sum_{n=1}^{N} P\big(s(n), s(n+T)\big) \log_2 \big[P(s(n), s(n+t))/P\big(s(n)\big)P(s(n+T))\big] , \quad (6)$$

where P represents the probability of an event, $s(n)$ is one set of system behaviors and $s(n + T)$ are another set of behaviors from the same system, taken at a time lag T later. In other words, $I(T)$ will return the average amount of information known about $s(n + T)$ based on an observation of $s(n)$. The AMI, $I(T)$, can then be plotted as a function of T in order to allow for the selection of a specific reconstruction delay, T, that will define two sets of behaviors that display some independence, but are not statistically independent. Fraser and Swinney (1986) have previously identified the first local minimum (T_m) of the plot as an appropriate choice for this value. In the current study a plot for each time series was evaluated individually, and the characteristic T_m selected by hand.

In order to find an appropriate embedding dimension for the reconstruction of attractor dynamics, the False Nearest Neighbors algorithm was used (Kennel, Brown & Abarbanel, 1992). As a preliminary step to the use of this algorithm, each time series was zero-centered. The idea behind this process is to project the attractor in an increasing number of dimensions, each time assessing whether apparent crossings of the attractor orbit with itself are an artifact of being projected within too few dimensions, until no 'false neighbors' remain. In practice, the square of the Euclidean distance between a point in a vector time series, $\mathrm{y}(n)$, and its nearest neighbor $\mathrm{y}^{(r)}(n)$ within a given dimension, d, is computed using

$$R_d^2\,(n, r) = \sum_{k=0}^{d-1} [x(n + kT) - x^{(r)}(n + kT)]^2 \,, \quad (7)$$

where T is the time delay used for embedding. When the embedding dimension is increased, to d+1, a new square of Euclidean distance between points can be calculated using

$$R_{d+1}^{2}(n,r) = R_{d}^{2}(n,r) + [x(n+dT) - x^{(r)}(n+dT)]^{2} \tag{8}$$

If the distance between neighbors appears to change significantly with the increase in embedding dimension, an embedding error has likely occurred. This change was quantified using

$$\left([R_{d+1}^{2}(n,r) - R_{d}^{2}(n,r)]/R_{d}^{2}(n,r)\right)^{1/2} > R_{\mathrm{tol}}\,, \tag{9}$$

with any value of R_{tol} greater than 15 being classified as a false neighbor. A plot of the percentage of false neighbors as a function of embedding dimension was then used to identify the minimum embedding dimension, $d_{\mathrm{min},}$ for which the percentage of false neighbors is very close to 0. Similar to the identification of an appropriate reconstruction delay from AMI, a plot for each time series was evaluated individually, and the characteristic embedding dimension selected by hand.

Using the minimum embedding dimension, d_{min}, and reconstruction delay, $T_{m},$ the reconstructed attractor trajectory was defined by the matrix

$$\mathrm{X}_{i} = \left[x_{i}\; x_{i+T_{m}} \ldots x_{i+(d_{min}-1)T_{m}}\right] \tag{10}$$

where X_{i} is the state of the system at a discrete time, i. The LLE algorithm was then used to find the ‘nearest neighbor’ of each point in the series (Rosenstein, Collins, & De Luca, 1993). In selecting the nearest neighbor, the closest point, $X_{j'}$, was taken with respect to a given reference point, X_j, using

$$d_j(0) = \min_{X_{j'}} \left\| X_j - X_{j'} \right\|, \tag{11}$$

where $d_j(0)$ represents the initial distance between the jth point and the closest neighbor, and $\|..\|$ denotes the Euclidean norm. The temporal difference between points was also taken into account, with the requirement that it be greater than the mean period of the time series (also calculated previously as the average time between peaks within the original movement time series). Each neighbor point was then taken to be an initial condition for a unique trajectory, with the mean rate of separation between them constituting an estimate of the LLE for the time series. In other words, the jth pair of nearest neighbors is thought to diverge at a rate approximately equivalent to the LLE, λ_1, as defined by

$$\sim C_j e^{\lambda_1 (i * \Delta t)} \tag{12}$$

with C_j being the initial separation between points. The logarithm of both sides of Equation 12 were then taken to produce

$$\ln d_j(i) \sim \ln C_j + \lambda_1 \, (i * \Delta t) \, , \tag{13}$$

which represents a series of approximately parallel lines for increasing values of j, each with a slope roughly equivalent to λ_1. The LLE can then be calculated by creating a least-squares fit to the "average" line defined by

$$y(i) = \frac{1}{\Delta t} \langle \ln d_j\,(i) \rangle \,, \tag{14}$$

where $\langle .. \rangle$ represents the average over all values of j. This analysis allowed me to detect chaotic dynamics in participant movement, and to look for relationships in the degree of chaos between participant and stimulus, or co-actor, time series.

As in the previous two analyses, the same patterns were observed in both the ‘x’ and ‘y’ dimensions for both participant and stimulus movements, and these values were averaged to establish characteristic LLE values for the participant and stimulus during each trial.

Box Counting. A box counting analysis was used to establish the fractal dimension (FD) for each movement time series (Grassberger & Procaccia, 1983; Kay, 1988). This method provides a measure of scale invariance and self-similarity over time through the analysis of a visual representation of behavior. Analysis involved covering the image with a grid of boxes, and obtaining a count of how many of the boxes contained part of the time series. This was done repeatedly for a single time series using a larger scaling factor, for which the number of boxes was equal to the square of the scaling factor. In the current study, a total of nine iterations were conducted with each successive scaling factor being the square of the previous, progressing from two to 512. The slope of a regression line fit to a plot of the logarithm of the inverse of the box size vs. the logarithm of the number of filled boxes yielded the measure of FD. For a fractal image these values should be non-integers between 1 and 2 (this upper limit of this dimension cannot be higher than that of the box used during measurement), with higher non-integer values indicating greater ‘fractality’. This provided another opportunity for me to compare behavioral complexity across trials and between concurrent movement time series.

In order to calculate the overall FD of each participant and stimulus movement series, I first created a two-dimensional image of each time series with the dimensions 512 × 512 pixels (using both the ‘x’ and ‘y’ dimensions). Images were then submitted to a box counting procedure which returned a unique FD value for each image.

Results

Cross-Correlation and Phase Lead. Means and mean standard deviations for maximum cross-correlation and phase lead can be found in Table 1. A 2 (trial type: test vs. baseline) × 4 (feedback delay) analysis of variance (ANOVA) for the maximum cross-correlation between participant and stimulus movements revealed a significant interaction between the two variables, $F(3, 15) = 14.10$, $p < .001$, $\eta_p^2 = .74$, as well as significant main effects for both trial type, $F(1, 5) = 8807.87$, $p < .001$, $\eta_p^2 = .99$, and feedback delay, $F(3, 15) = 9.09$, $p = .001$, $\eta_p^2 = .65$. As can be seen in Figure 4a, maximum cross-correlation was much lower in the baseline trials than the test trials for all feedback delays, and for the experimental trials maximum cross-correlation generally decreased with an increase in feedback delay. A simple effect analysis of feedback delay for the experimental trials revealed a significant main effect, $F(3, 15) = 24.05$, $p < .001$, $\eta_p^2 = .83$. Fisher’s LSD post hoc comparisons revealed that all differences in average maximum cross correlation between feedback delay conditions were significant ($p < .05$) except for that between the 400 ms and 600 ms feedback delay conditions. There was not a significant simple main effect of feedback delay for the baseline trials.

A one-way ANOVA was conducted for the phase lead of participant to stimulus, at the maximum cross-correlation, for the movement time series. This revealed a significant effect of feedback delay, $F(3, 15) = 41.55$, $p < .001$, $\eta_p^2 = .89$. As can be seen in Figure 4b, phase lead by the participant increased with an increase in feedback delay. Fisher’s LSD post hoc comparisons revealed that all differences in the phase relationship of the participant to the stimulus were significant ($p < .05$) except for that between the 400 ms and 600 ms feedback delay conditions.

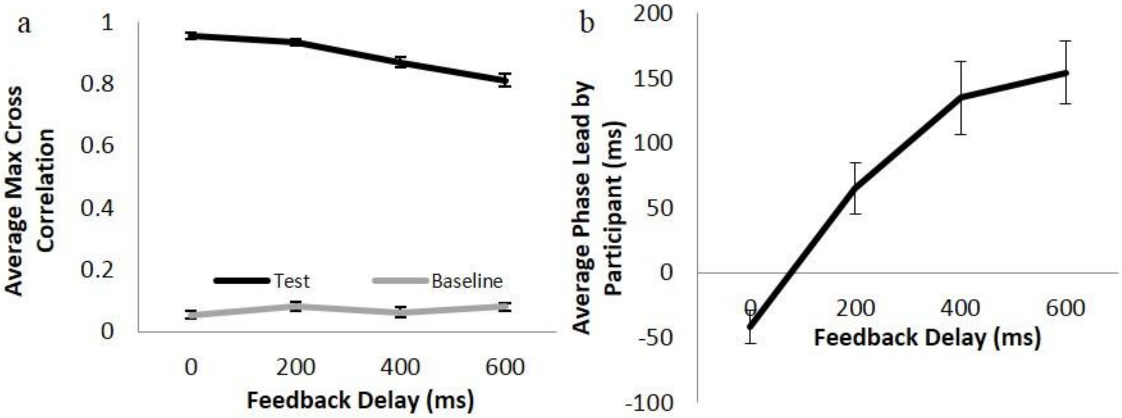

Figure 4. a) Average maximum cross-correlation for experimental and baseline trials and b) phase lead (ms) for participant and stimulus time series associated with each feedback delay condition for Experiment 1. Error bars show standard error.

Instantaneous Relative Phase. Means and mean standard deviations for relative phase and standard deviation of relative phase between the participant movements and the movement of the stimulus dot can be found in Table 1. One-way ANOVAs were conducted separately for mean relative phase and standard deviation of relative phase. The ANOVA on mean relative phase indicated a significant effect of feedback delay on relative phase, $F(3, 15) = 39.06$, $p < .001$, $\eta_p^2 = .89$ (see Figure 5a). Fisher's LSD post hoc comparisons revealed all feedback delay conditions were significantly different (ps < .01) except the 400 ms and 600 ms conditions. This pattern is very similar to that of the phase lead found at the maximum cross correlation in the previous analysis (see Figure 4b).

There was also a significant effect of feedback delay on the standard deviation of relative phase, $F(3, 15) = 22.57$, $p < .001$, $\eta_p^2 = .82$, (see Figure 5b). Fisher's LSD post hoc comparisons indicated that all feedback delay conditions were significantly different from each other (ps < .05) except the 400 ms and 600 ms conditions. Standard deviation was smallest at 0 ms feedback delay, and increased progressively for the 200 ms, 400 ms, and 600 ms delay conditions.

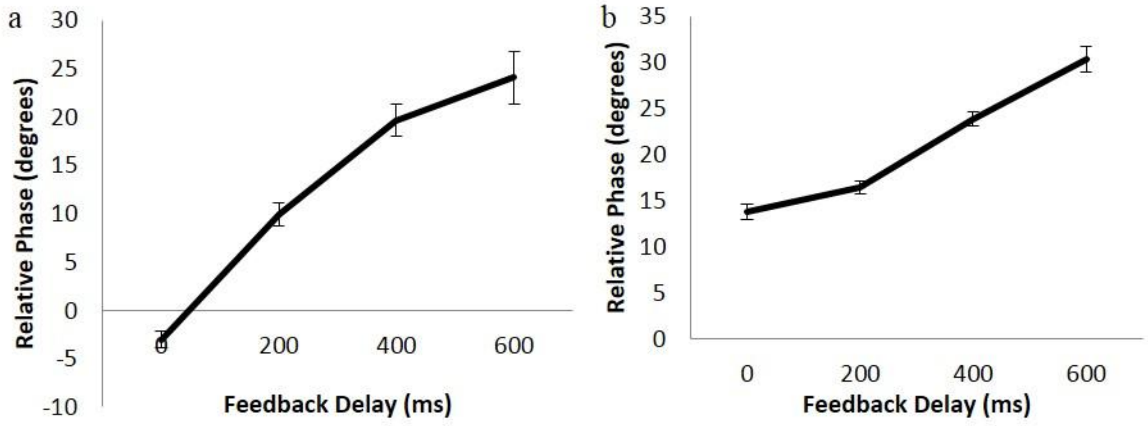

Figure 5. a) Average instantaneous relative phase (degrees) and b) average standard deviation of relative phase (degrees) for participant and stimulus time series associated with each feedback delay condition for Experiment 1. Error bars show standard error.

The average distribution of relative phase values visited over the course of a trial were examined for both the relationship of the participant movement time series to the stimulus time series, and the participant dot time series to the stimulus time series (see *Measures and Analyses* for further explanation). As can be seen in Figure 6, for the 0 ms feedback delay condition there was one large relative phase peak, indicating that most commonly participant movements were about 15° behind those of the stimulus, and one smaller peak at the a relative phase relationship close to 15° ahead of the stimulus (movement time series and dot time series are necessarily identical at no feedback delay). For the movement time series in each of the other three feedback delay conditions, there was also one predominant peak and one smaller peak. The higher peak was indicative of a phase lead by the participant between 15° and 25°, while the lower peak revealed a phase lag between 5° and 15°. The height of both peaks decreased with an increase in feedback delay (from 200 ms to 600 ms), suggesting that as feedback delay increases there is less consistency in the phase relationship between participant and stimulus movements.

For the dot time series, there was also one large peak and one smaller peak at each of the 200 ms, 400 ms, and 600 ms feedback delay conditions. The position of these peaks indicates that the participant’s dot most commonly lagged the stimulus dot on the screen by close to 15° to 25°, but also occasionally lead the stimulus by 5° to 15°. As was seen for the movement series, the height of both peaks for the distribution of relative phase values for the dot series also decreased with an increase in feedback delay.

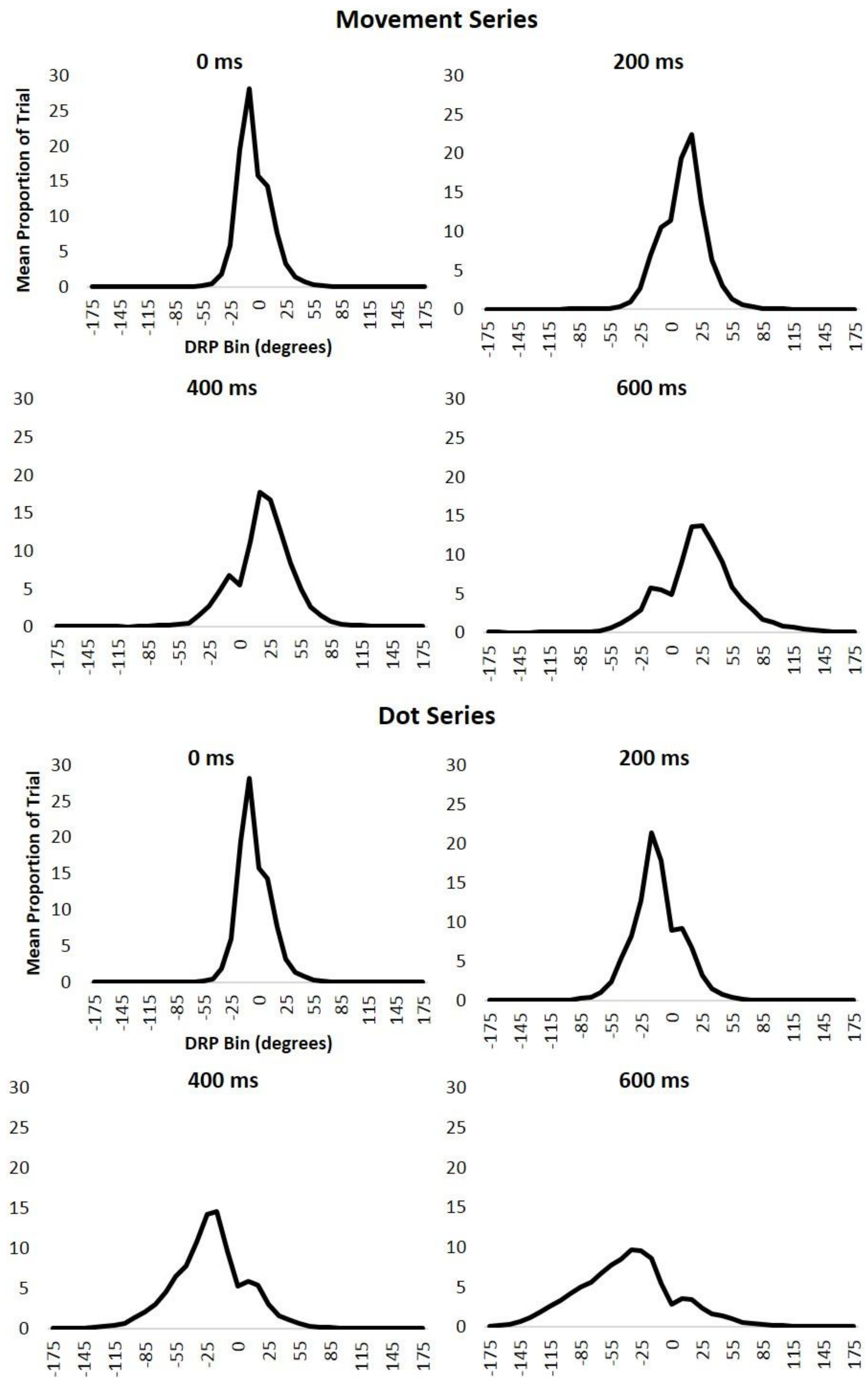

Figure 6. Average distribution of instantaneous relative phase values (degrees) between participant and stimulus movements (top) and average distribution of instantaneous relative phase values (degrees) between participant dot movements and stimulus movements (bottom) over the course of a trial for each feedback delay condition in Experiment 1.

Table 1. *Averaged Results of Local Coordination Analyses: Experiment 1*

	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Maximum Cross-Correlation Test Trials	.95	0.03	.93	0.03	.87	0..04	.81	0.05
Maximum Cross-Correlation Baseline Trials	.05	0.03	.08	0.04	.06	0.04	.08	0.04
Phase Lead Movement Series (ms)	-4.96	3.78	7.79	5.89	16.21	8.28	18.50	7.13
Relative Phase Movement Series (°)	-3.01	3.76	9.97	5.15	19.66	7.18	24.10	8.48
SD Relative Phase Movement Series (°)	13.80	3.51	16.43	2.49	23.89	1.92	30.35	5.58

Largest Lyapunov Exponent. Means and mean standard deviations for LLE can be found in Table 2. A 4 (feedback delay) × 3 (generator: participant, stimulus, participant baseline) factorial ANOVA for LLEs revealed no significant interaction or main effects (see Figure 7).

As can be seen in Figure 8, four separate correlations were conducted (one for each feedback delay condition) (see Table 3). The only significant correlation between stimulus LLE and participant LLE occurred in the 400 ms feedback delay condition ($p < .05$).

Correlations were also evaluated for the difference between participant LLE and stimulus LLE and the maximum cross-correlation in each feedback delay condition. Results indicated that there was no consistent association between the two measures, which suggests that the degree of complexity matching observed between two behaviors was not entirely dependent on the level of local coordination achieved.

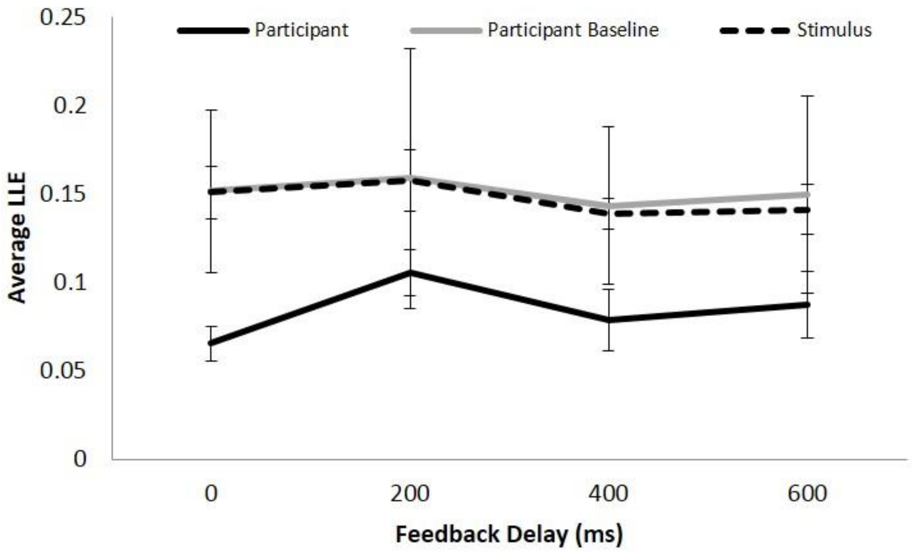

Figure 7. Average LLE values for participant, stimulus, and participant baseline behaviors for each feedback delay condition in Experiment 1. Error bars show standard error.

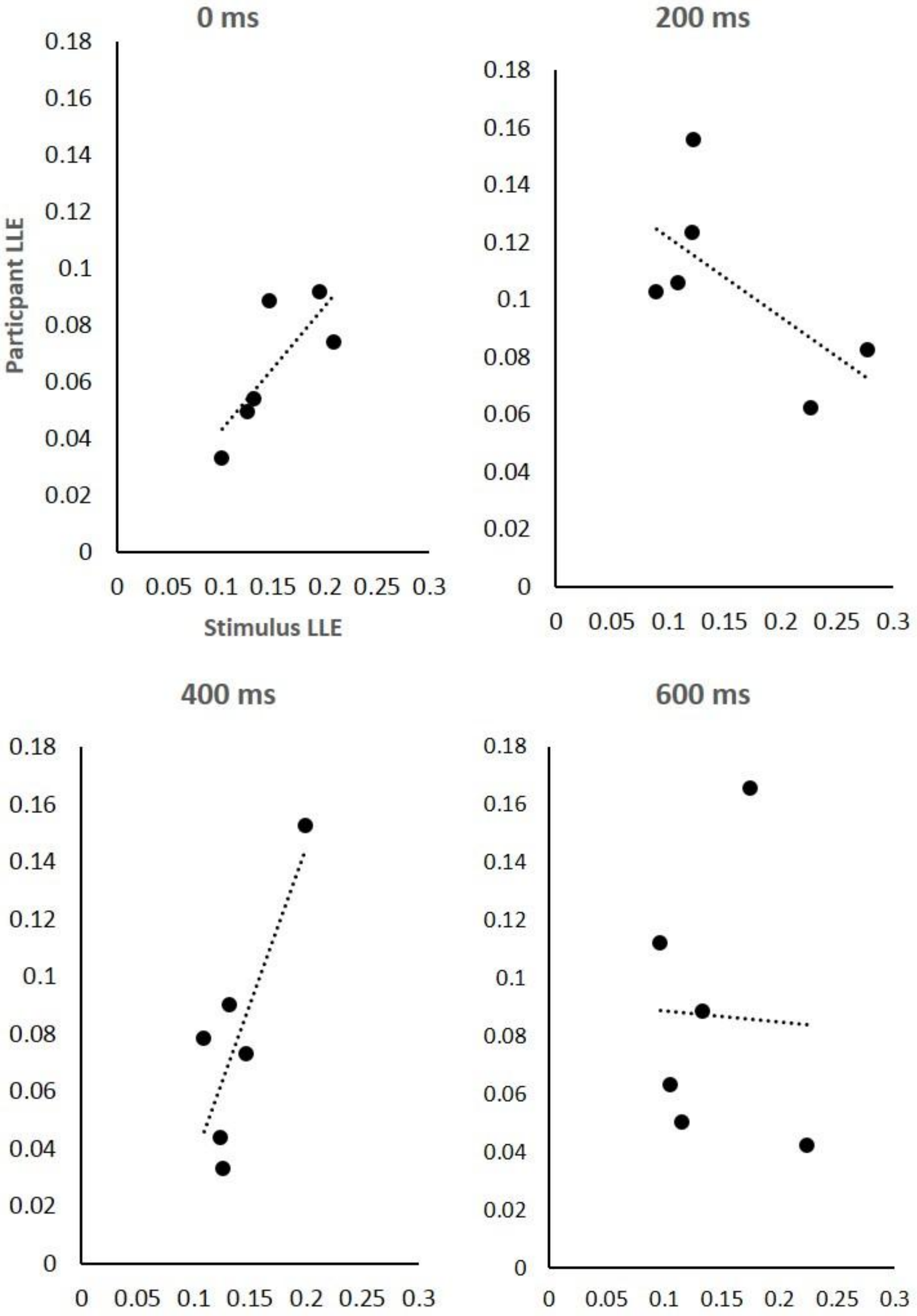

Figure 8. Scatterplots of average participant LLE and average stimulus LLE for each participant, for each feedback delay condition of Experiment 1.

Box Counting. Means and mean standard deviations for FD can be found in Table 2. A 4 (feedback delay) × 3 (generator: participant, stimulus, participant baseline) revealed no significant interaction or main effects (see Figure 9).

As can be seen in Figure 10, four separate correlations were conducted (one for each feedback delay condition) (see Table 3). As was seen for the analysis of LLE, the only significant correlation between stimulus FD and participant FD occurred in the 400 ms feedback delay condition (*p* < .01).

Correlations were also evaluated for the difference between participant FD and stimulus FD and the maximum cross-correlation for each feedback delay condition. Results indicated that there was no consistent association between the two measures. This supports the idea that the degree of complexity matching observed between two behaviors was not entirely dependent on the level of local coordination achieved.

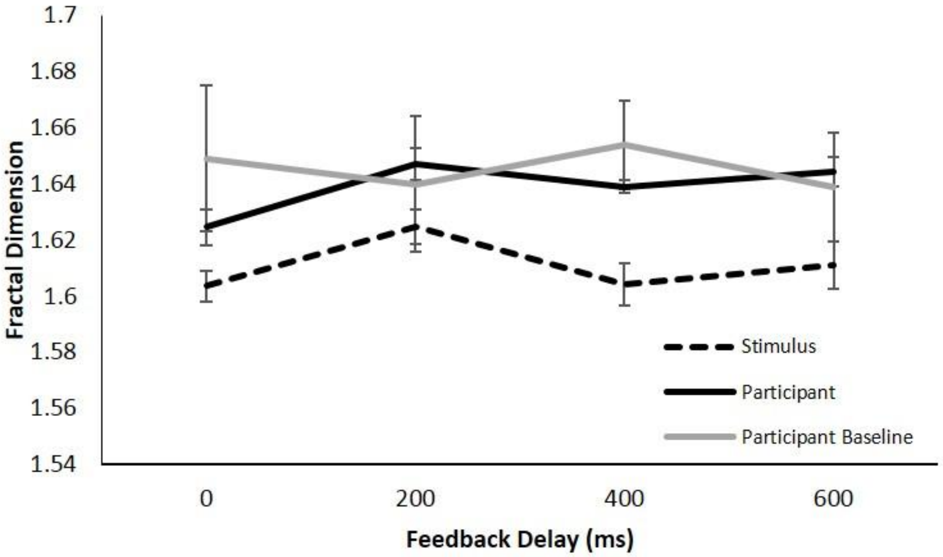

Figure 9. Average FD values for participant, stimulus, and participant baseline behaviors for each feedback delay condition in Experiment 1. Error bars show standard error.

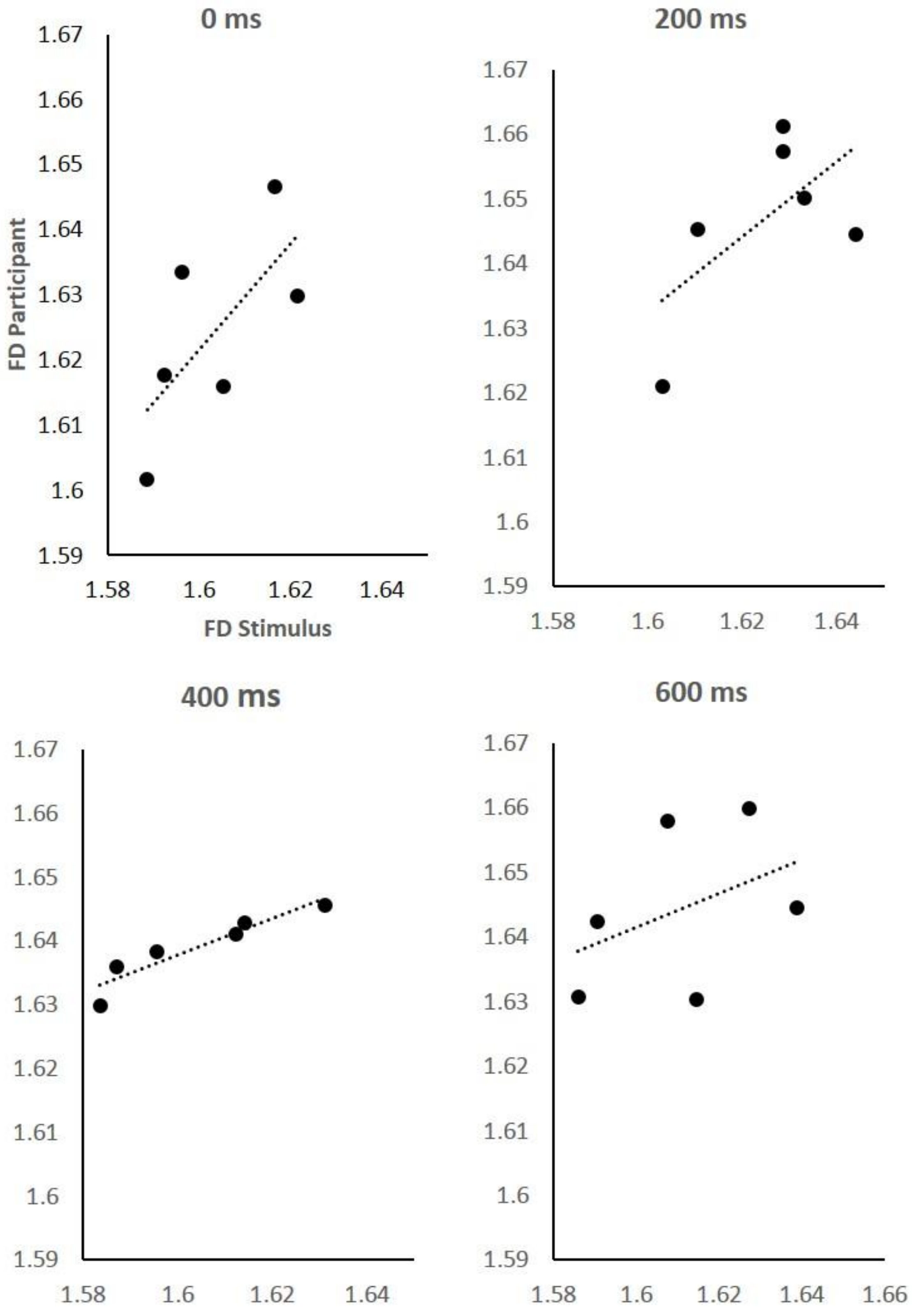

Figure 10. Scatterplots of average participant FD and average stimulus FD for each participant, for each feedback delay condition of Experiment 1.

Table 2. *Averaged Results of Complexity Matching Analyses: Experiment 1*

	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Participant LLE	0.065	.02	0.105	.03	0.078	.04	0.087	.05
Participant FD	1.624	.01	1.647	.01	1.639	.002	1.644	.01

Table 3. *Correlation Results for Complexity Matching Analyses: Experiment 1*

	Feedback Delay			
	0 ms	200 ms	400 ms	600 ms
LLE Correlation	.77	-.65	.82*	-.04
FD Correlation	.68	.61	.94**	.42

**p* < .05
***p* < .01
****p* < .001

Discussion

As a methodological extension of the work presented by Stepp (2009), this experiment was successful in producing consistent results regarding the occurrence of anticipatory synchronization, as assessed by maximum cross-correlation. This measure indicated that overall coordination between the actor and stimulus decreased slightly as feedback delays for the actor increased, and that anticipatory synchronization was achieved for all conditions in which actors experienced a feedback delay, appearing to increase with increases in feedback delay. Without a feedback delay, actors established a high level of coordination with the movements of the chaotic stimulus but with an average phase relationship indicating that the movements of the actor trailed those of the stimulus.

The analysis of instantaneous relative phase provided additional insight into the local coordinative relationship between participant and stimulus throughout the experiment. In considering these results, it is important to note that the measure of phase lead associated with the maximum cross-correlation analysis was the phase relationship between participant and stimulus associated the highest level of coordination between movements, while the measure of phase lead associated with instantaneous relative phase was for the average phase relationship over the course of a trial. Generally speaking, the pattern of average relative phase results across feedback delay conditions is similar to that seen for the phase lead associated with maximum cross-correlation in that the participant appears to have lagged the stimulus when no feedback delay was present, and led the stimulus when there was a feedback delay. For both analyses, this phase lead increased with increases in feedback delay. Standard deviation of relative phase increased with increases in feedback delay, suggesting an increase in variability within the coordinative relationship consistent with the continual decrease in overall coordination as measured by maximum cross-correlation.

The distribution of instantaneous relative phase values visited over the course of a trial was examined for the phase relationship between participant movements and stimulus movements. This supplemented the previous evaluations of anticipatory synchronization made based on both maximum cross-correlation and average relative phase. The associated figures suggest that while participant movements did indeed trail behind those of the stimulus for the majority of the time when there was no feedback delay, they were also ahead of the stimulus for a much smaller proportion of time. Conversely, for each of the conditions in which participants did experience a feedback delay, while participants lead the stimulus for a large proportion of the time, a second peak indicated that their movements were behind those of the stimulus at times.

The 200 ms feedback delay condition was associated with the most time spent leading the stimulus, but participants spent much less time lagging the stimulus with a feedback delay of 400 ms. It therefore appears that neither of these two delays was necessarily better suited to eliciting anticipatory synchronization, but that there may be something unique about a range of feedback delays encompassing both of these delays.

The distribution of instantaneous relative phase was also examined for the phase relationships between the movements of a participant's onscreen dot and those of the stimulus. I was interested in the utility of comparing this distribution to that for the participant movements and stimulus movements in order to determine how the relative phase between a participant's movements and those of the stimulus translated into the visual representation of the two display dots. These figures allow one to see that in all conditions the participant's onscreen dot was behind the stimulus dot for a large proportion of the trial, but was also ahead of the stimulus dot at times. Increases in feedback delay appear to have resulted in a continual decrease in the amount of time for which the participant dot was ahead of the stimulus dot, as well as the amount of time for which the relative phase between dots was actually equal to 0°.

The LLE and box counting analyses were conducted in order to establish measures of complexity within stimulus and participant sequences for each trial, which were then used to assess complexity matching between the two movement series. Results revealed a significant correlation between the LLE of the stimulus and the LLE of the participant for the 400 ms feedback delay condition. The association between the variability structure of the participant's movements and the movements of the stimulus for a given trial appeared to be stronger for the fractal dimension (FD) measure than for the LLEs. However, the 400 ms feedback delay condition was still the only condition to yield a significant correlation between complexity measurements. Correlations between the average difference in participant and stimulus LLEs and the average maximum cross-correlation observed in each feedback delay revealed no consistent relationship. The same was true for correlations between the average difference in participant and stimulus FDs and average maximum cross-correlation. These results suggest that the degree of local coordination between participant and stimulus movements for a given trial was not predictive of similarities in large-scale behavioral complexity. While this does not disprove the local strong anticipation theory that complexity matching is a byproduct of local coordination processes, it does suggest that the degree of similarity between the long-term statistical structure of two concurrent behaviors is not directly dependent on the observed level of local coordination.

With respect to the phenomenon of anticipatory synchronization, the results of this experiment support and extend the findings Stepp (2009). Furthermore, the complementary use of maximum cross-correlation and instantaneous relative phase analyses provided valuable information about local coordinative processes. Results suggest that the optimal range of feedback delays for a participant to experience, with respect to their own movements, in order to elicit anticipatory synchronization of chaotic sequences includes delays of 200-400 ms. With regard to the evaluation of complexity matching between participant and stimulus, it appears that the measures used here have captured aspects of the two movement behaviors which may at times be shared, but that this does not always occur.

Overall, these findings supported the continued use of the current experimental paradigm and analyses for further examination of the phenomenon of anticipatory synchronization in Experiments 2 and 3.

CHAPTER 3

Experiment 2

Experiment 2 was designed to be an intermediate step between evaluating anticipatory synchronization of an actor with a computer-generated chaotic stimulus and investigating whether the phenomenon might also occur between bi-directionally coupled co-actors. I felt that a good preliminary test of this would be to explore whether anticipatory synchronization could be observed for an actor with respect to naturally produced, aperiodic behaviors, but still using an experimental set-up in which one individual was asked to coordinate with a pre-recorded sequence. This maintained the master-slave coupling scenario described earlier, but allowed me to assess whether naturally produced, aperiodic human movement involved the same deterministic dynamics thought to be integral to the occurrence of anticipatory synchronization.

The purpose of this experiment was, therefore, to establish: 1) that anticipatory synchronization can occur with respect to natural, aperiodic human movement; and 2) whether or not temporal delays in coupling enhance coordination with aperiodic sequences, as has been seen with chaotic sequences. Based on the findings of Experiment 1, and previous work in anticipatory synchronization (Stepp, 2009), I predicted that actors would be capable of coordinating with naturally produced, aperiodic movement sequences. More importantly, I expected that when actors were given a feedback delay with respect to their own movements while still being asked to synchronize with a natural, aperiodic stimulus that actor movements would come to anticipate those of the stimulus.

The same four analyses were used here as in Experiment 1 in order to evaluate local coordination between an actor and a stimulus (*maximum cross-correlation, instantaneous relative phase*), and to assess the potential occurrence of complexity matching between actor and stimulus movement dynamics (*Largest Lyapunov Exponent, box counting*). Generally, I expected that measures of local coordination would be consistent in demonstrating that anticipatory synchronization requires the introduction of a feedback delay, with delays of 200-400 ms allowing for the best balance of anticipation and overall coordination. I also expected the complexity measures to reveal some degree of matching between participant and stimulus behaviors, as was seen in Experiment 1.

Method

Participants. Six University of Cincinnati graduate students and three undergraduate students participated in this experiment. Participants ranged in age from 19 to 31 years.

Procedure and Design. The methodology used here was identical to that of Experiment 1, with the exception that the stimulus dot was used to display natural, aperiodic elliptical movement sequences collected as part of that experiment (see Figure 3b for example movement time series). Four different natural aperiodic stimulus movement sequences were created[2], and the visual sequences a participant saw corresponding to their own movements were displayed to them at the same four lengths of feedback delay, τ, (0, 200, 400, 600 ms). Each stimulus sequence was presented to the participants a total of four times, once at each feedback delay, for a total of 16 trials (4 stimulus sequences × 4 feedback delays). Stimulus sequence-feedback delay pairings were randomized within blocks of four trials, with each stimulus sequence being experienced at one of the four feedback delays within each block. Each trial lasted a total of 130 s.

Measures and Analyses. The analyses employed in the current experiment were the same as those used in Experiment 1. *Maximum cross-correlation* and *instantaneous relative*

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[2] As part of Experiment 1, six individuals were asked to coordinate with fully chaotic, simulated sequences for several trials prior to completing one 200 s trial in which they were to make the same kind of movements without seeing a stimulus (see Chapter 2 for further details). In order to select stimulus sequences for the current experiment, each “baseline” sequence from Experiment 1 was normalized and low-pass filtered with a cutoff frequency of 10 Hz using a Butterworth filter in order to remove transients. The first 130 s and last 130 s were then analyzed separately for their respective LLEs. The four 130 s segments chosen to be used as stimuli in the current experiment were those with the highest LLEs observed, while still coming from four unique individuals.

phase were used to assess local coordination, and calculation of the *largest Lyapunov exponent* and use of box counting to establish *fractal dimension* were used to evaluate behavioral complexity (see Chapter 2 for detailed explanations of each analysis).

Results

Cross-Correlation and Phase Lead. Means and mean standard deviations for maximum cross-correlation and phase lead can be found in Table 4. A one-way ANOVA for the maximum cross-correlation between participant and stimulus movements revealed a significant effect of feedback delay, $F(3, 24) = 29.61$, $p < .001$, $\eta_p^2 = .79$. As can be seen in Figure 11a, maximum cross-correlation generally decreased with an increase in feedback delay. Fisher's LSD post hoc comparisons revealed that all differences in average maximum cross correlation between feedback delay conditions were significant ($p < .05$).

A one-way ANOVA was conducted for the phase lead of participant to stimulus, at the maximum cross-correlation, for the movement time series. This revealed a significant effect of feedback delay, $F(3, 24) = 4.72$, $p = .01$, $\eta_p^2 = .37$. As can be seen in Figure 11b, phase lead by the participant increased with an increase in feedback delay up until the 600 ms delay condition. Fisher's LSD post hoc comparisons revealed that the phase relationship of the participant to the stimulus exhibited in the 0 ms feedback delay condition was significantly different from those seen in both the 200 ms ($p < .05$) and 400 ms ($p < .005$) delay conditions, but not significantly different from the 600 ms delay condition. There was also a significant difference between the 200 ms and 400 ms feedback delay conditions ($p < .005$), but not between 200 ms and 600 ms or 400 ms and 600 ms.

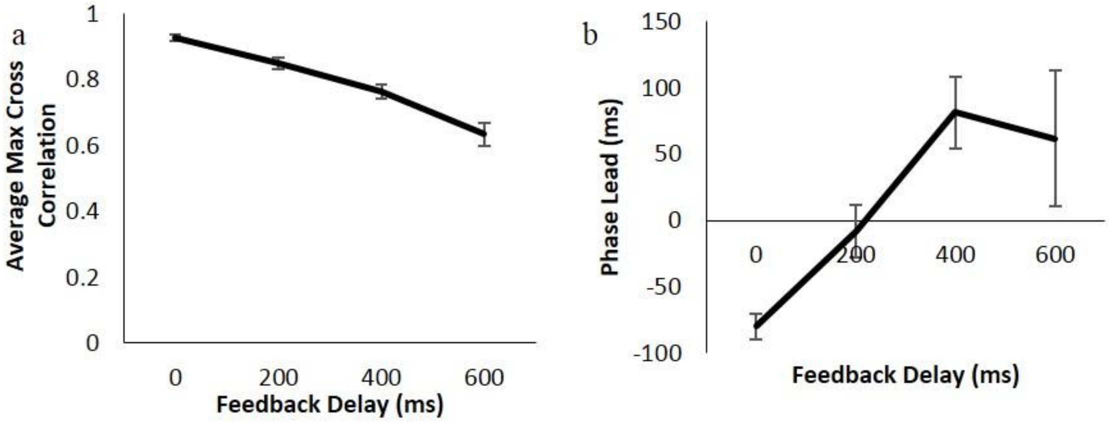

Figure 11. a) Average maximum cross-correlation and b) phase lead (ms) for participant and stimulus time series associated with each feedback delay condition for Experiment 2. Error bars show standard error.

Instantaneous Relative Phase. Means and mean standard deviations for relative phase and standard deviation of relative phase between the participant movements and the movement of the stimulus dot can be found in Table 4. A one-way ANOVA was conducted for mean relative phase and standard deviation of relative phase. The ANOVA on mean relative phase indicated a significant effect of feedback delay on relative phase, $F(3, 24) = 3.71$, $p = .03$, $\eta_p^2 = .32$ (see Figure 12a). Fisher's LSD post hoc comparisons revealed that the phase relationship of the participant to the stimulus exhibited in the 0 ms feedback delay condition was significantly different from those seen in both the 200 ms ($p < .05$) and 400 ms ($p < .005$) delay conditions, but not significantly different from the 600 ms delay condition. There was also a significant difference between the 200 ms and 400 ms ($p < .005$) feedback delay conditions, but not between 200 ms and 600 ms or 400 ms and 600 ms. This pattern is very similar to that of the phase lead found at the maximum cross correlation in the previous analysis (see Figure 11b).

There was also a significant effect of feedback delay on the standard deviation of relative phase, $F(3, 24) = 47.31$, $p < .001$, $\eta_p^2 = .86$, (see Figure 12b). Fisher's LSD post hoc comparisons indicated that all feedback delay conditions were significantly different ($p < .05$).

Standard deviation was smallest at 0 ms feedback delay, and increased progressively for the 200 ms, 400 ms, and 600 ms delay conditions.

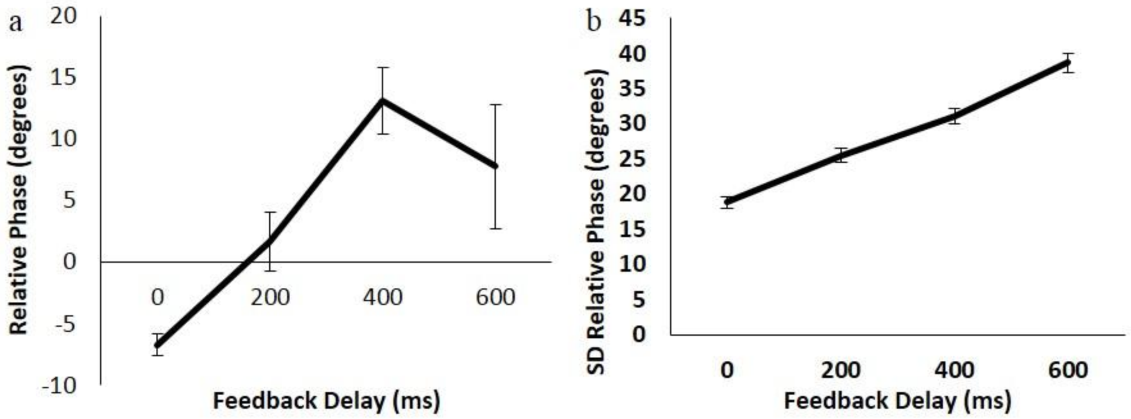

Figure 12. a) Average instantaneous relative phase (degrees) and b) average standard deviation of relative phase (degrees) for participant and stimulus time series associated with each feedback delay condition for Experiment 2. Error bars show standard error.

The average distribution of relative phase values visited over the course of a trial were examined for both the relationship of the participant movement time series to the stimulus time series, and the participant dot time series to the stimulus time series (see the *Measures and Analyses* section of Chapter 2 for further explanation). As can be seen in Figure 13, in the 0 ms feedback delay condition there was one large relative phase peak, indicating that most commonly participant movements were behind those of the stimulus by about 15°, and one smaller peak indicating a phase lead by the participant close to 15° (movement time series and dot time series are necessarily identical at no feedback delay). For the movement time series, there were two distinct relative phase peaks for the other three feedback delay conditions. The higher peak was indicative of phase lead close to 15°, while the lower peak suggests a phase lag between 5° and 15°. The height of both of these peaks decreased with an increase in feedback delay (from 200 ms to 600 ms), suggesting that as feedback delay increases there is less consistency in the phase relationship between participant and stimulus movements. For the dot time series, there was one predominant peak at each of the 200 ms, 400 ms, and 600 ms feedback delay conditions. The position of these peaks indicates that the participant dot most commonly lagged the stimulus dot on the screen by close to 15°. A substantially shorter peak also appears at each of these feedback delay conditions, suggesting that the participant dot was sometimes ahead of the stimulus dot by less than 15°. As was seen for the movement series, the height of both peaks for the distribution of relative phase values for the dot series also decreased with an increase in feedback delay.

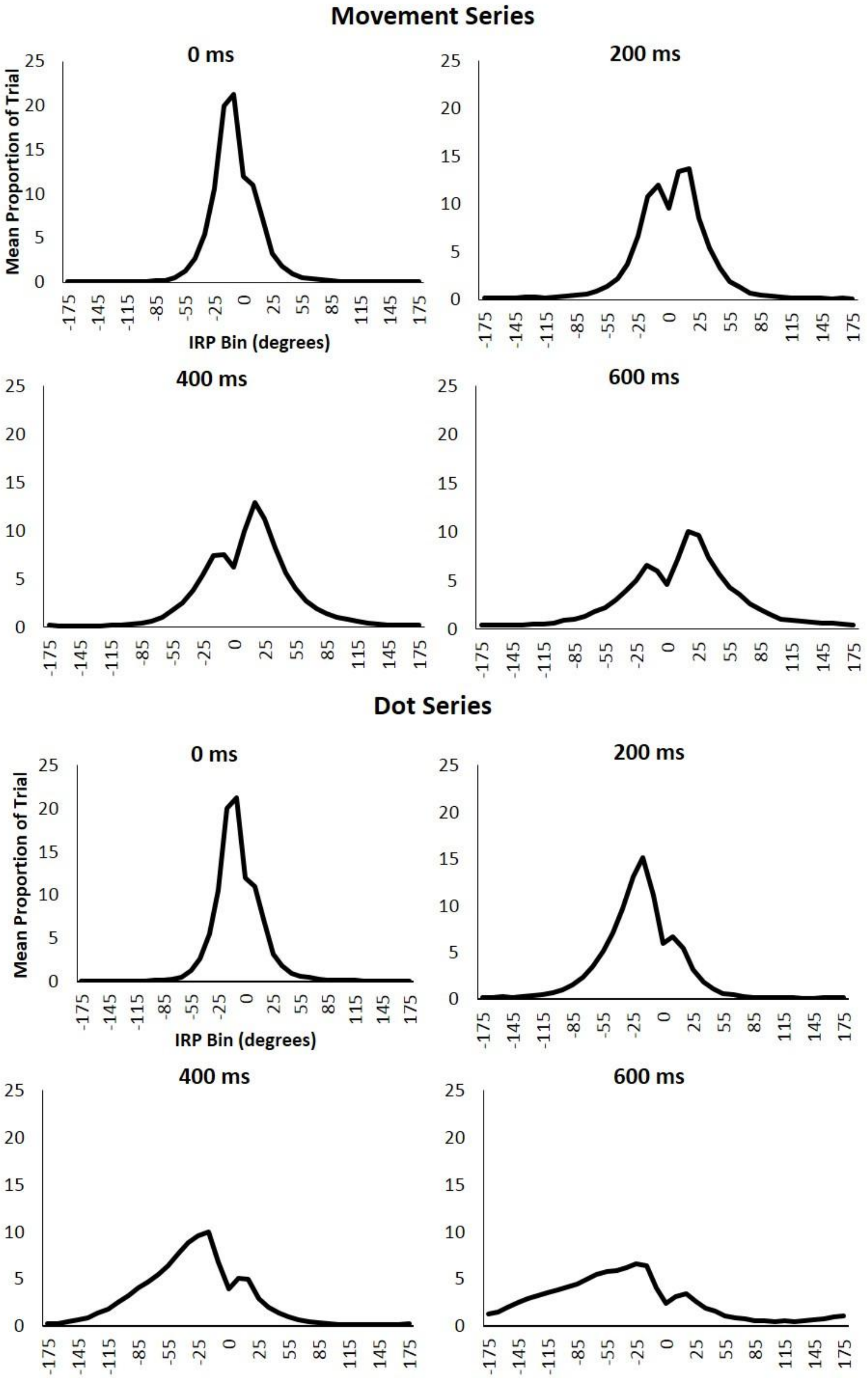

Figure 13. Average distribution of instantaneous relative phase values (degrees) between participant and stimulus movements (top) and average distribution of instantaneous relative phase values (degrees) between participant dot movements and stimulus movements (bottom) over the course of a trial for each feedback delay condition in Experiment 2.

Table 4. *Averaged Results of Local Coordination Analyses: Experiment 2*

	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Maximum Cross-Correlation	.93	0.04	.85	0.08	.76	0.10	.63	0.18
Phase Lead Movement Series (ms)	-79.75	38.40	-7.87	95.01	81.13	149.63	61.57	256.85
Relative Phase Movement Series (°)	-6.75	4.66	1.67	13.63	13.10	18.52	7.76	33.81
SD Relative Phase Movement Series (°)	18.80	5.25	25.47	6.55	31.11	7.09	38.68	10.89

Largest Lyapunov Exponent. Means and mean standard deviations for LLE can be found in Table 5. A 4 (feedback delay) × 4 (stimulus file) factorial ANOVA for participant LLE revealed a significant interaction between feedback delay and stimulus file, $F(9, 72) = 2.90$, $p = .006$, $\eta_p^2 = .27$, as well as a significant main effect of stimulus file, $F(3, 24) = 31.71$, $p < .001$, $\eta_p^2 = .80$, but no significant main effect of feedback delay. As can be seen in Figure 14, the interaction between feedback delay and stimulus file is being driven by the differences in LLE across feedback delay conditions when participants were presented with Stimulus File 3. Simple effects analyses for the influence of feedback delay on participant LLE during coordination with each of the stimulus files revealed a significant effect of delay for Stimulus File 3 only, $F(3, 24) = 4.85$, $p = .009$, $\eta_p^2 = .38$. More specifically, Fisher's LSD post hoc comparisons identified a significant difference between the 0 ms feedback delay condition and both the 200 ms and 600 ms delay conditions ($p < .05$) for this stimulus file.

As can be seen in Figure 15, participant LLE generally increased with increases in stimulus LLE. Correlations were evaluated for the difference between participant LLE and stimulus LLE and the maximum cross-correlation in each feedback delay condition. Results indicated that there was no consistent association between the two measures. As noted in Experiment 1, this implies that the degree of complexity matching observed between behaviors was not entirely dependent on the level of local coordination achieved.

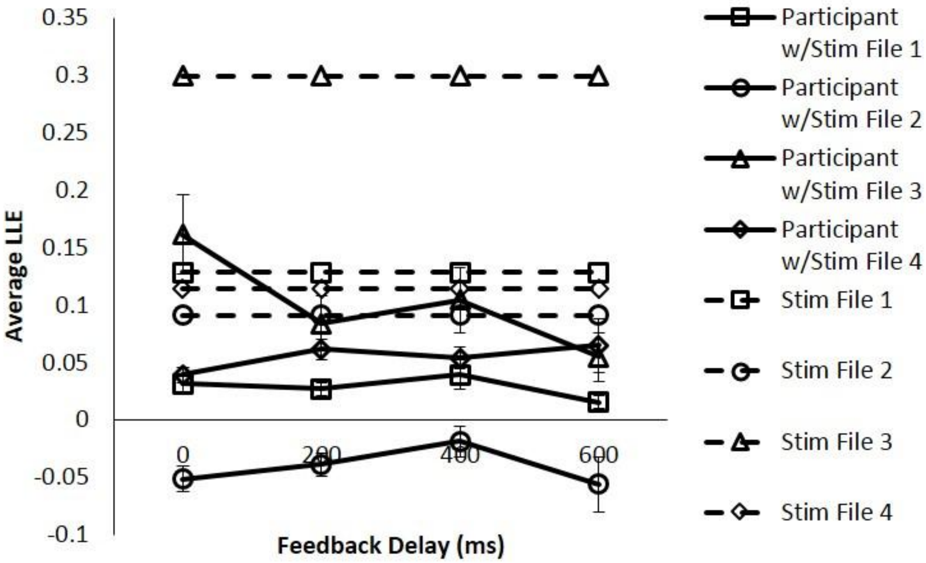

Figure 14. Average LLE values for participants coordinating with each stimulus file for each feedback delay condition in Experiment 2. LLE values for each stimulus file are also included for reference. Error bars show standard error.

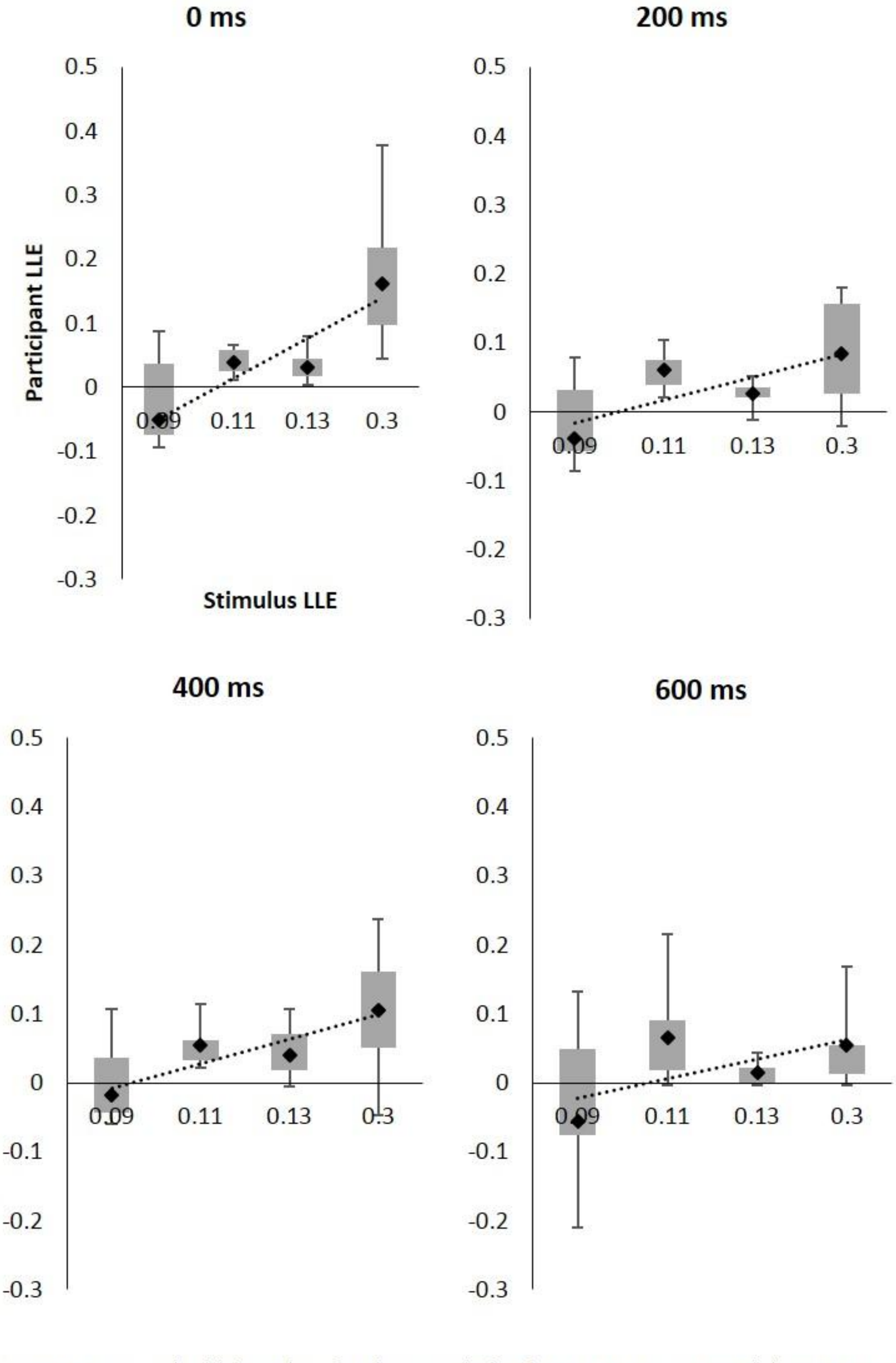

Figure 15. Box and whisker plots for the association between average participant LLE and average stimulus LLE for each participant, within each feedback delay condition of Experiment 2.

Box Counting. Means and mean standard deviations for FD can also be found in Table 5. A 4 (feedback delay) × 4 (stimulus file) factorial ANOVA for participant FD revealed a significant interaction between feedback delay and stimulus file, *F*(9, 72) = 3.68, $p = .001$, $\eta_p^2 = .32$, as well as a significant main effect of stimulus file, *F*(3, 24) = 98.53, $p < .001$, $\eta_p^2 = .93$, and a significant main effect of feedback delay, *F*(3, 24) = 3.12, $p = .045$, $\eta_p^2 = .28$. As can be seen in Figure 16, the interaction between feedback delay and stimulus file appears to be driven by the differences in FD across feedback delay conditions exhibited when participants were presented with Stimulus File 2. Simple effects analyses for the influence of feedback delay on participant FD during coordination with each of the stimulus files revealed a significant effect of delay for Stimulus File 2 only, *F*(3, 24) = 6.79, $p = .002$, $\eta_p^2 = .46$. More specifically, Fisher's LSD post hoc comparisons identified a significant difference between the 0 ms feedback delay condition and both the 200 ms and 600 ms delay conditions, as well as between the 400 ms and 600 ms delay conditions ($p < .05$) for this stimulus file.

As can be seen in Figure 17, participant FD generally increased with increases in stimulus FD. Correlations were evaluated for the difference between participant FD and stimulus FD and the maximum cross-correlation in each feedback delay condition. Results indicated that there was no consistent association between the two measures. This supports the idea that the degree of complexity matching observed between behaviors was not entirely dependent on the level of local coordination achieved.

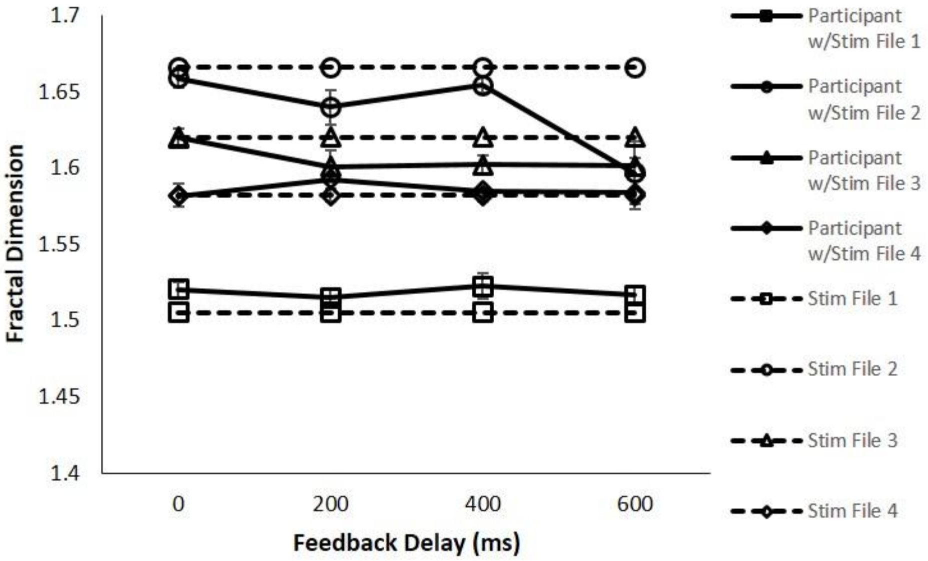

Figure 16. Average FD values for participants coordinating with each stimulus file for each feedback delay condition in Experiment 2. FD values for each stimulus file are also included for reference. Error bars show standard error.

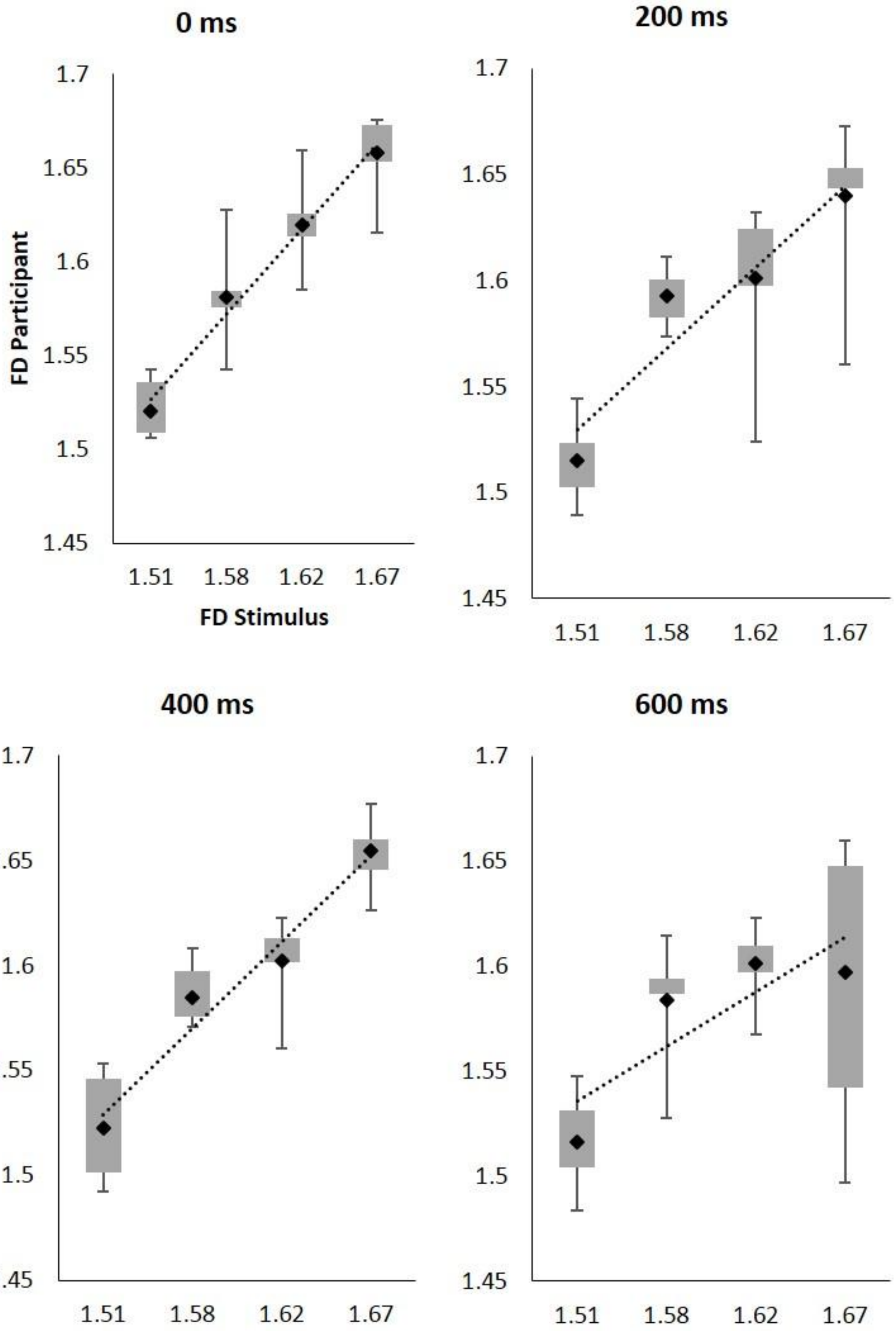

Figure 17. Box and whisker plots for the association between average participant FD and average stimulus FD for each participant, within each feedback delay condition of Experiment 2.

Table 5. *Averaged Results of Complexity Matching Analyses: Experiment 2*

	Stimulus File 1							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
LLE	.031	0.02	.027	0.02	.039	0.04	.015	0.02
FD	1.520	0.02	1.515	0.02	1.523	0.02	1.516	0.02

	Stimulus File 2							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
LLE	-.052	0.03	-.039	0.03	-.019	0.04	-.056	0.07
FD	1.659	0.02	1.640	0.03	1.654	0.02	1.597	0.06

	Stimulus File 3							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
LLE	.161	0.10	.084	0.07	.104	0.08	.054	0.06
FD	1.620	0.02	1.601	0.03	1.602	0.02	1.601	0.02

	Stimulus File 4							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
LLE	.039	0.02	.061	0.03	.054	0.03	.065	0.07
FD	1.581	0.02	1.592	0.01	1.585	0.01	1.584	0.03

Discussion

This experiment successfully demonstrated that anticipatory synchronization can be achieved by a participant with respect to naturally produced, aperiodic movements, as has previously been observed for simulated chaotic movements. Results also provided evidence of complexity matching by participants to naturally produced, aperiodic behaviors. Together these findings supported the continued investigation of anticipatory synchronization and associated complexity matching within a truly interpersonal context to be carried out in Experiment 3.

Analyses of local coordination produced a similar pattern of results to those seen in Experiment 1. As measured by maximum cross-correlation, overall coordination appeared to decrease as a function of increasing feedback delay, and phase lead by the participant to the stimulus was observed when a participant experienced a feedback delay in the display of their onscreen dot with respect to their own movements. However, the amount of phase lead exhibited in each of the feedback delay conditions was slightly different than what was observed in Experiment 1. Here, the average phase relationship within the 200 ms feedback delay condition was negative, suggesting that actor movements were generally trailing those of the stimulus when coordination was the highest. This is contrasted with the average phase relationship exhibited during the 400 ms feedback delay condition which indicates the participant movements led those of the stimulus dot when coordination was highest. Additionally, while there was a continued increase in phase lead by the participant to the stimulus between the 400 ms and 600 ms feedback delay conditions in Experiment 1, here the average phase lead in the 600 ms feedback delay condition, while still positive, was lower than that for the 400 ms condition.

The analysis of instantaneous relative phase provided additional insight into the phase relationship between the participant and the stimulus in each of the feedback delay conditions. As noted in Experiment 1, while the phase lead results associated with maximum cross-correlation were for the phase relationship between participant and stimulus which was associated with the highest level of coordination, the results associated with instantaneous relative phase are for the average relationship or the distribution of relationships visited over the course of a trial. It is therefore not surprising to find that while the pattern of average relative phase values over the feedback delay conditions is similar to that seen for the phase lead at maximum cross-correlation, the average values give a slightly different impression of the underlying coordination. Here the no feedback delay condition still results in a phase lag by the participant to the stimulus, but in the 200 ms feedback delay condition the average relative phase is positive, indicating that anticipatory synchronization did occur with this shortest amount of delay. This difference highlights the value of analyzing instantaneous relative phase, in addition to maximum cross-correlation, in order to assess the local coordinative relationship between participant and stimulus. Consistent with the phase lead results associated with maximum cross-correlation, the average relative phase for the 600 ms feedback delay condition was lower than that for the 400 ms condition. Combined with the fact that overall coordination was lowest for the 600 ms feedback delay condition, this indicates that a feedback delay of 600 ms or longer may be too great to provide suitable conditions for eliciting anticipatory synchronization of natural aperiodic sequences. The measure of standard deviation of relative phase allows us to see a steady increase in variability with increasing feedback delay which is consistent with the continual decrease in overall coordination seen for increasing values of feedback delay (demonstrated in the results for maximum cross-correlation).

As in Experiment 1, the distribution of instantaneous relative phase values visited over the course of a trial was also examined for the phase relationship between participant movements and stimulus movements. This supplemented the previous evaluations of anticipatory synchronization made based on both maximum cross-correlation and average relative phase. These figures suggest that while participant movements did indeed trail behind those of the stimulus for the majority of the time when there was no feedback delay, they were also ahead of the stimulus for a much smaller proportion of time. Conversely, for each of the conditions in which participants experienced a feedback delay, they spent nearly equivalent proportions of the trial leading and lagging the stimulus (200 ms), or a large proportion of the trial leading the stimulus and a smaller proportion of the trial lagging the stimulus (400 ms and 600 ms). As in Experiment 1, the 200 ms feedback delay condition was associated with the most time spent leading the stimulus, but participants spent much less time lagging the stimulus with a feedback delay of 400 ms. This supports the idea posed in Experiment 1 that there may be something unique about a range of feedback delays encompassing 200-400 ms with respect to the phenomenon of anticipatory synchronization.

The distribution of instantaneous relative phase was also examined for the phase relationships between the movements of a participant’s onscreen dot and those of the stimulus. This allowed me to determine how the relative phase between a participant’s movements and those of the stimulus translated into the visual representation of the two display dots. In all conditions, the participant’s onscreen dot was behind the stimulus dot for a large proportion of the trial, but was also ahead of the stimulus dot at times. Increases in feedback delay appear to have resulted in a continual decrease in the amount of time for which the participant dot was ahead of the stimulus dot, as well as the amount of time for which the relative phase between dots was actually equal to 0°.

The Largest Lyapunov Exponent (LLE) and box counting analyses were conducted here, as in Experiment 1, in order to establish measures of complexity within the individual participant and stimulus movement sequences for each trial. In turn, these complexity measures were used to evaluate potential associations between the statistical structure of participant and stimulus movement sequences. Evaluating the LLE also allowed me to determine whether participant movements were characterized by the dynamics associated with chaotic behavior. Results indicated that the degree of “chaoticness” exhibited by a participant was somewhat dependent on the LLE of the stimulus they were coordinating with, with the LLE of the coordinating participant always being somewhat lower than that of the stimulus. In the current Experiment, participant movements coordinated with Stimulus File 2, which had the lowest LLE of the four stimulus files used, were characterized by negative average LLEs. It therefore appears that there is a value of the LLE for the stimulus below which the movements of a coordinating participant will not exhibit chaotic dynamics. While the association between participant LLE and stimulus LLE existed across feedback delay conditions, as seen in Experiment 1, results suggest it is strongest when there is no feedback delay or when a feedback delay of 400 ms is present.

Assessments of complexity matching between participant and stimulus behaviors were even stronger for the fractal dimension (FD) measure than for the LLE measure. As for the LLEs, the association between participant FD and stimulus FD was strongest when there was no feedback delay, and when there was a feedback delay of 400 ms. As was seen in Experiment 1, correlations between the average difference in participant and stimulus LLEs and the average maximum cross-correlation observed in each feedback delay revealed no consistent relationship between these measures. The same was true for correlations between the average difference in participant and stimulus FDs and average maximum cross-correlation. As suggested with regard to the results of Experiment 1, it appears that the degree of local coordination between participant and stimulus movements for a given trial was not predictive of similarities in large-scale behavioral complexity. This provides continued support for the idea that the degree of similarity between the long-term statistical structure of two concurrent behaviors is not directly dependent on the level of local coordination observed.

Overall, this experiment demonstrated that anticipatory synchronization can occur for an actor coupled to naturally produced, aperiodic events while also establishing that the complexity of an actor movement sequence is often strongly associated with that of a natural, aperiodic behavior with which they are coordinating. These findings invited Experiment 3, designed to evaluate anticipatory synchronization and complexity matching in a truly interpersonal context, with bidirectional coupling between actors.

CHAPTER 4

Experiment 3

This final experiment was designed to investigate whether the anticipatory synchronization and complexity matching previously observed: 1) for an actor unidirectionally coupled to a computer-generated chaotic movement sequence and 2) for an actor unidirectionally coupled to naturally produced, aperiodic movements, can also occur within a truly interpersonal context. This provided me with the opportunity to investigate how variations in the bidirectional coupling between actors might affect these phenomena.

I expected that in an interpersonal context where one actor was designated as the movement "producer" and another actor as the "coordinator", co-actors would be capable of coordinating aperiodic, elliptical movements. Additionally, I thought that when a coordinator was given a feedback delay with respect to their own movements, while still being asked to synchronize with the movements of a producer, coordinator movements would come to anticipate those of the producer. I also predicted that this local coordination between coordinator and producer would be accompanied by some degree of complexity matching between behaviors.

As in the previous two experiments, analyses of *maximum cross-correlation*, *instantaneous relative phase*, *Largest Lyapunov Exponent*, and *fractal dimension* were conducted here in order to gain information about local coordination between actors, and to assess the potential occurrence of complexity matching between co-actor movement dynamics. Judging by the findings from Experiments 1 and 2, I thought that the length of phase lead by the coordinator to the producer (associated with the maximum cross-correlation) would increase continuously with increases in feedback delay from 0 ms to 400 ms, followed by a decrease in phase lead in the 600 ms feedback delay condition. I also expected that overall levels of coordination between the coordinator and producer would decrease continuously with increases in feedback delay. I predicted that measures of instantaneous relative phase would reveal that when experiencing a feedback delay with respect to their own movement, coordinators would spend the largest proportion of each trial slightly ahead of the producer and another substantial proportion of the trial slightly behind the producer, with the stability of these relative phase relationships decreasing with increases in feedback delay. Additionally, I expected the correlation between the LLEs and FDs of producers and coordinators to be high in all feedback delay conditions.

As this is the first study to examine anticipatory synchronization in the context of bi-directional coupling, I was interested in the opportunity to examine any effects of variation in informational coupling on the resulting movement coordination. By using two visual conditions for the producer, I expected to get an impression of how critical the master-slave coupling relationship is to the phenomenon of anticipatory synchronization, as well as to complexity matching between systems. A *congruent* visual condition closely matched the unidirectional coupling relationship used in the previous two studies, while an *incongruent* condition provided the movement producer with more real time information about coordinator movements. I expected to see some differences between these conditions to occur but did not categorically expect to find evidence of anticipatory synchronization or complexity matching in one condition over the other.

Method

Participants. Twenty-one University of Cincinnati undergraduate students and one graduate student participated in this experiment. Participants ranged in age from 18 to 27 years.

Procedure and Design. The experimental set-up used here was very similar to that used in Experiments 1 and 2, adjusted to include two participants. Each participant was asked to sit facing their own display monitor (50” HD Plasma TV) and was equipped with a motion sensor, attached to the middle joint of the first two fingers of their right hand.

Pairs of participants acted together in Experiment 3. Upon arrival, one participant from each pair was randomly chosen to be a ‘producer’ while the other was assigned the role of ‘coordinator’. Participants were not informed of these roles, but they were told that one of them would have the opportunity to practice briefly before they both would be asked to perform the experimental task together. The producer was then asked to come into the room first while the coordinator waited outside. During this practice period, the producer was asked to complete two trials, each lasting 100 s, in which they were to coordinate with fully chaotic, simulated sequences based on the equation for a “chaotic spring” system. The same two sequences[3] were provided to all producers, but were presented in alternating order by participant pair. The producer saw these sequences displayed as a blue dot (2 cm in diameter) and their own real time, sensor-tracked movements displayed using a red dot (2 cm in diameter), on the right half of a white screen[4] (the other half of the screen was covered). They were instructed to “keep the red dot as close to on top of the blue dot as possible” in order to complete the task. Once they had completed the two practice trials, the producer was told that their goal for the duration of the study would be to produce the same kind of movements they had been making: “generally circular and always in the same direction, but somewhat unpredictable in terms of the speed of movements and where they go”. They were also informed that the goal of the other participant would be to coordinate with their movements, as they had had to do with the computer stimulus during the practice trials.

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[3] Stimuli sequences for the practice trials were selected from those created for Experiment 1 (see Chapter 2 for further details), based on their high LLE values (~0.32). The first 100 s of each stimulus sequence were used here.

[4] The screen color in Experiment 3 was initially black, as in Experiments 1 and 2, but this was changed to white after four participant pairs due to the fact that participants reported being able to see the reflection of their partner’s screen in their own. This change does not appear to have had any significant effect on the qualitative patterns observed in the data.

The coordinator was then brought into the room and situated in front of their own display screen so that the two participants were back-to-back. They were then told that their co-participant had just practiced the kind of movement they would be making for the duration of the study and that their own goal was going to be to coordinate with that person's movements. The coordinators were informed that their co-participant's movements would be displayed using a red dot (2 cm in diameter), while their own real time, sensor-tracked movements would be reflected on the screen as a blue dot (2 cm in diameter). They were instructed to "keep the blue dot as close to on top of the red dot as possible" in order to complete the task (see Figure 3c for example movement time series). The coordinator would see these dots displayed on the left half of white screen (the other half of the screen was covered).

Both participants always saw the producer's movements displayed in real time, but the visual sequences a coordinator saw corresponding to their own movements were displayed to them at four different lengths of feedback delay, τ, (0, 200, 400, 600 ms). Two different display conditions were employed with respect to what the producer saw as the coordinator's movements. In a 'congruent' condition the producer saw exactly what the coordinator saw; if the coordinator experienced a feedback delay with respect to their own movements, the producer saw the delayed series displayed as the coordinator's dot. In an 'incongruent' condition the producer saw the coordinator's movements in real time, irrespective of the feedback delay the coordinator experienced with respect to their own movements. Each feedback delay for the coordinator was experienced once in each display condition for a total of eight trials, with display condition-feedback delay pairings randomized within participant pairs. Each trial lasted a total of 100 s.

Procedures for display generation and data collection were identical to those used in Experiments 1 and 2.

Measures and Analyses. The four analyses used to examine participant and stimulus behaviors in Experiments 1 and 2 were used here in Experiment 3 to examine coordinator and producer behaviors. Two of these analyses were used to measure local coordination: 1) *maximum cross-correlation*, and 2) *instantaneous relative phase*, while the other two analyses were meant to assess behavioral complexity: 1) calculation of the *largest Lyapunov exponent*, and 2) box counting to establish *fractal dimension*.

Results

Cross-Correlation and Phase Lead. Means and mean standard deviations for maximum cross-correlation and phase lead can be found in Table 6. A 2 (visual condition) × 4 (feedback delay) factorial ANOVA for the maximum cross-correlation between coordinator and producer movements revealed a significant main effect of feedback delay, F (3, 30) = 50.69, $p < .001$, $\eta_p^2 = .84$, but no main effect of visual condition or interaction between the two variables. As can be seen in Figure 18a, maximum cross-correlation generally decreased with an increase in feedback delay. Fisher’s LSD post hoc comparisons revealed that all differences in average maximum cross correlation between feedback delay conditions were significant ($p < .005$).

A 2 (visual condition) × 4 (feedback delay) factorial ANOVA for the phase lead of the coordinator to the producer movements also revealed a significant main effect of feedback delay, F (3, 30) = 6.65, $p = .001$, $\eta_p^2 = .40$, and no main effect of visual condition or interaction between the two variables. As can be seen in Figure 18b, phase lead by the participant increased with an increase in feedback delay up until the 600 ms delay condition. Here, Fisher’s LSD post hoc comparisons revealed significant differences in phase lead between the 0 ms feedback delay condition and both the 200 ms and 400 ms delay conditions ($p < .001$), as well as between the 200 ms delay condition and the 400 ms delay condition ($p < .05$).

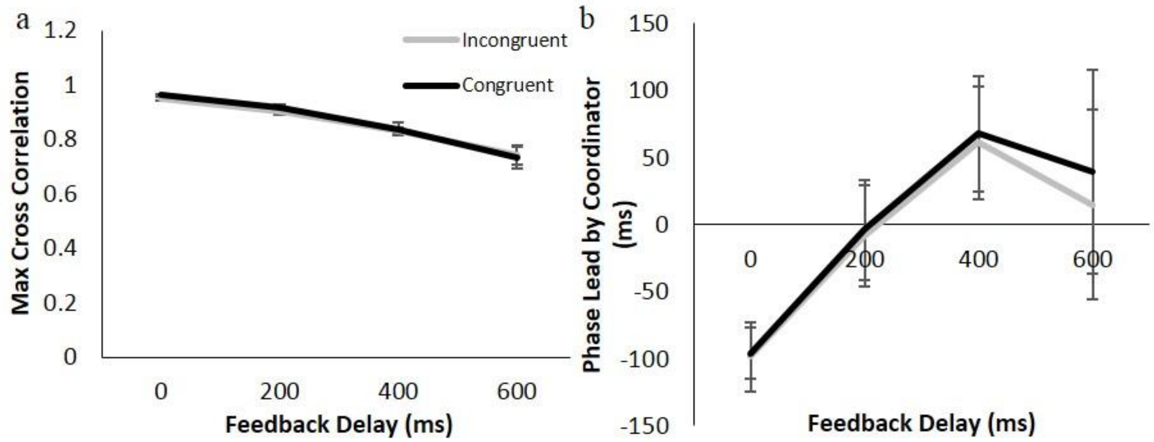

Figure 18. a) Average maximum cross-correlation and b) phase lead (ms) for coordinator and producer time series associated with each combination of visual conditions and feedback delay conditions for Experiment 3. Error bars show standard error.

Instantaneous Relative Phase. Means and mean standard deviations for relative phase and standard deviation of relative phase can be found in Table 6. A 2 (visual condition) × 4 (feedback delay) factorial ANOVA for the mean relative phase between the coordinator and producer revealed a significant main effect of feedback delay, F (3, 30) = 6.91, p = .001, η_p^2 = .41, but no main effect of visual condition or interaction between the two variables. As can be seen in Figure 19a, these patterns are very similar to those found for the phase lead associated with the maximum cross correlation in the previous analysis (see Figure 11b). Here, Fisher's LSD post hoc comparisons revealed significant differences in phase lead between the 0 ms feedback delay condition and all three of the 200 ms, 400 ms, and 600 ms delay conditions (p < .05), as well as between the 200 ms delay condition and the 400 ms delay condition (p < .05).

There was also a significant main effect of feedback delay on the standard deviation of relative phase, F (3, 30) = 60.60, p < .001, η_p^2 = .86, but no main effect of visual condition and no interaction between the two variables. Overall, standard deviation in relative phase appeared to increase with increases in feedback delay (see Figure 19b). Fisher's LSD post hoc comparisons revealed that all differences in average maximum cross-correlation between feedback delay conditions were significant (*p* < .005).

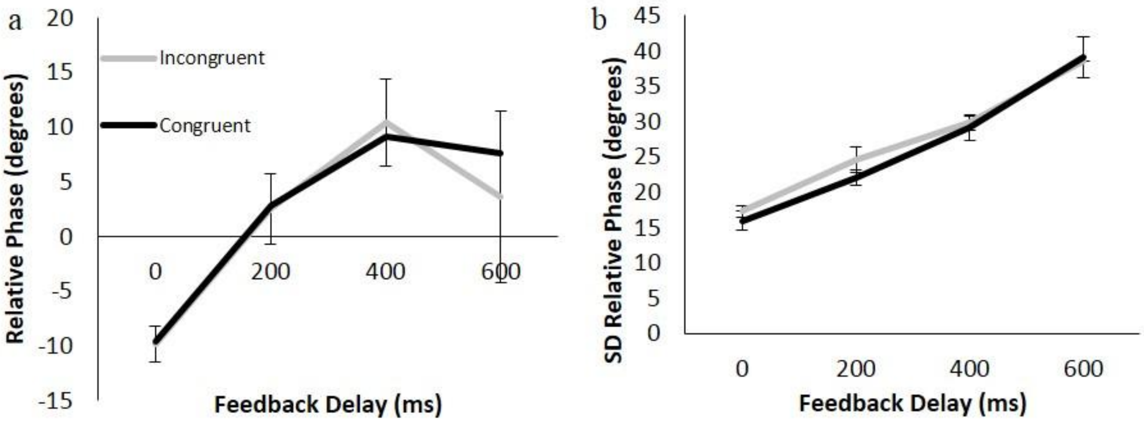

Figure 19. a) Average instantaneous relative phase (degrees) and b) average standard deviation of relative phase (degrees) for coordinator and producer time series associated with each combination of visual conditions and feedback delay conditions for Experiment 3. Error bars show standard error.

The average distribution of relative phase values visited over the course of a trial were examined separately for the two visual conditions. As can be seen in Figure 20, in the 0 ms feedback delay condition there was one main relative phase peak, indicating that most commonly participant movements were slightly behind those of the stimulus. In both visual conditions, there were two distinct relative phase peaks for the other three feedback delay conditions. The higher peak is indicative of phase lead close to 15°, while the lower peak suggests a phase lag around 15°. The height of both of these peaks decreases with an increase in feedback delay (from 200 ms to 400 ms), suggesting that as feedback delay increases, there is less consistency in the phase relationship between coordinator and producer movements. The only apparent difference in relative phase distribution between the two visual conditions occurs for the 600 ms feedback delay condition, as the larger peak is similar in height to those for the 200 ms and 400 ms feedback delay conditions in the incongruent visual condition, but substantially lower in the congruent visual condition.

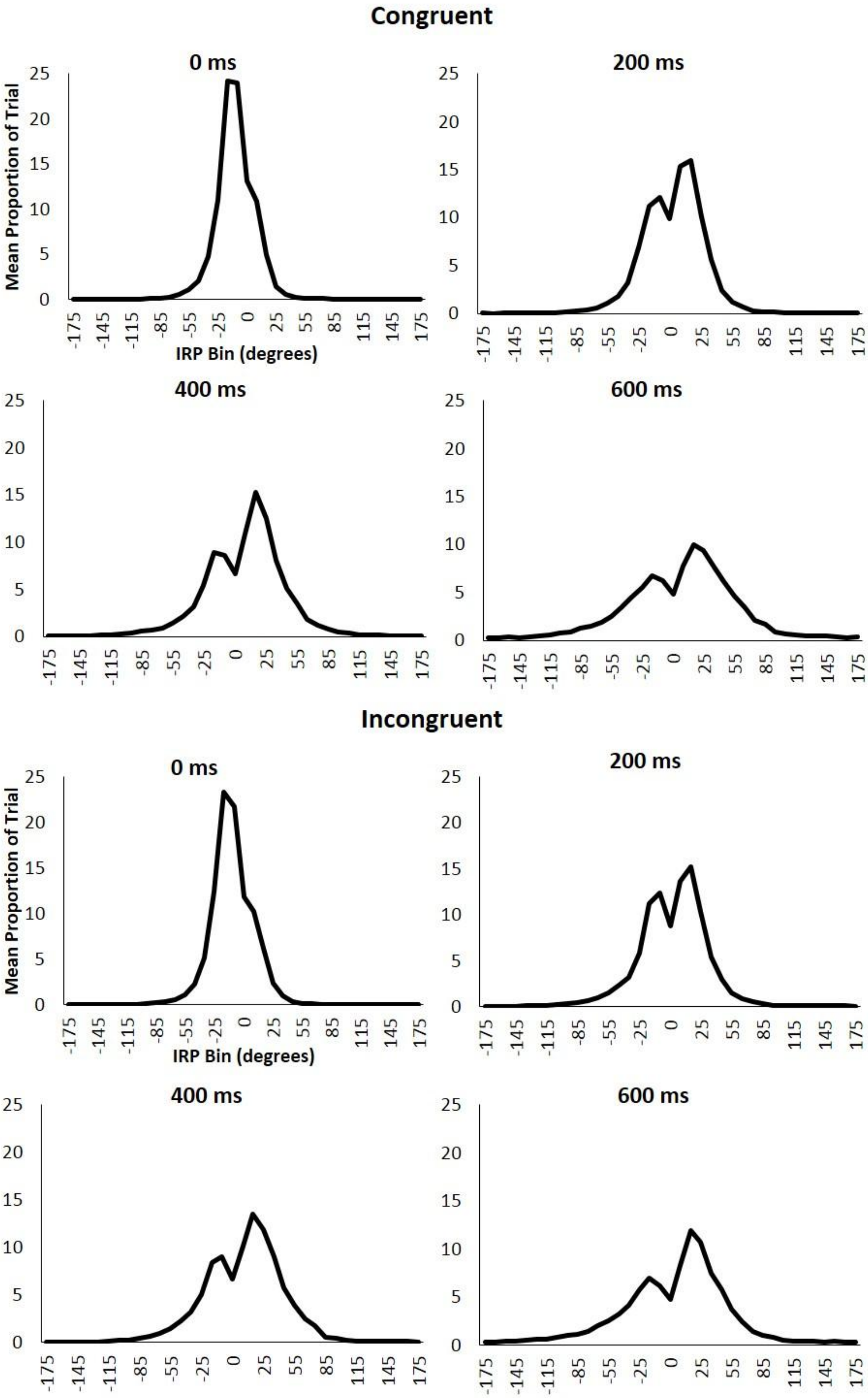

Figure 20. Average distribution of instantaneous relative phase values (degrees) between coordinator and producer movements for the congruent visual condition (top) and average distribution of instantaneous relative phase values (degrees) between coordinator and producer movements for the incongruent visual condition (bottom) over the course of a trial for each feedback delay condition in Experiment 3.

Table 6. *Averaged Results of Local Coordination Analyses: Experiment 3*

	Visual Condition: Congruent							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Maximum Cross-Correlation	.96	0.02	.92	0.03	.84	0.08	.73	0.14
Phase Lead Movement Series (ms)	-95.83	63.66	-3.79	122.64	67.80	141.50	39.77	252.74
Relative Phase Movement Series (°)	-9.56	5.48	2.84	10.72	9.11	13.35	7.62	13.35
SD Relative Phase Movement Series (°)	15.94	4.45	22.02	3.66	29.04	5.86	39.00	9.60
	Visual Condition: Incongruent							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Maximum Cross-Correlation	.95	0.02	.90	0.04	.83	0.04	.74	0.12
Phase Lead Movement Series (ms)	-98.33	85.68	-8.33	126.19	61.36	139.79	14.77	234.41
Relative Phase Movement Series (°)	-9.85	7.30	2.53	13.21	10.39	14.27	3.66	24.08
SD Relative Phase Movement Series (°)	17.26	2.84	24.59	5.74	29.84	3.46	38.51	10.34

Largest Lyapunov Exponent. Means and mean standard deviations for LLEs can be found in Table 7. A 2 (participant) × 2 (visual condition) × 4 (feedback delay) factorial ANOVA was conducted on the LLEs for producer and coordinator movements. This analysis revealed a significant main effect of participant, $F(1, 10) = 37.72$, $p < .001$, $\eta_p^2 = .79$, but no other main effects or interactions (see Figure 21). Follow up tests indicated that producer LLEs were significantly greater than coordinator LLEs in both visual conditions and at all feedback delays ($p < .01$).

As can be seen in Figure 22, four separate correlations were conducted (one for each feedback delay condition) in each visual condition for a total of eight correlations (see Table 8). The strongest correlation between producer LLE and coordinator LLE occurred in the congruent visual condition for the 0 ms feedback delay condition ($p < .0001$). The correlation in the 0 ms feedback delay condition in the incongruent visual condition was also significant, as were the correlations in the 200 ms feedback delay condition for both visual conditions (ps < .05).

Correlations were also evaluated for the difference between coordinator LLE and producer LLE and the maximum cross-correlation for each combination of feedback delay conditions and visual conditions. Results indicated that there was no consistent association between the two measures. As for the previous two experiments, this suggests that the degree of complexity matching observed between behaviors was not entirely dependent on the level of local coordination achieved.

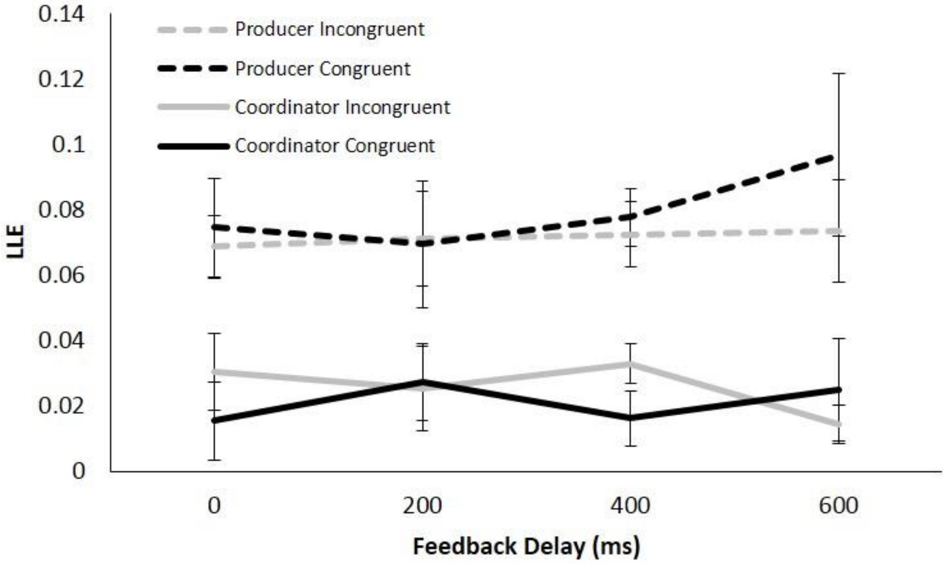

Figure 21. Average LLE values for coordinator and producer behaviors in each of the congruent and incongruent visual conditions for each feedback delay condition in Experiment 3. Error bars show standard error.

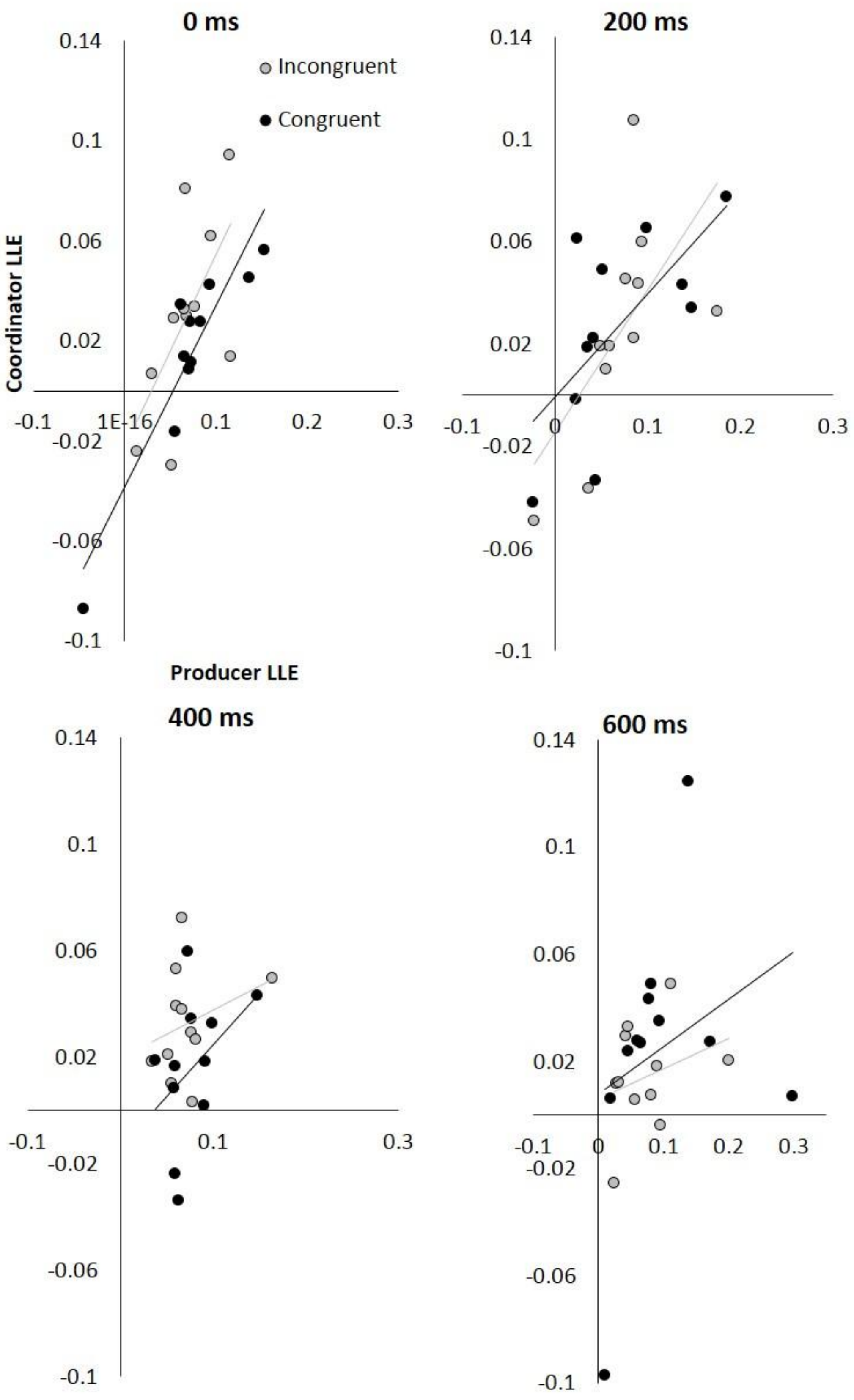

Figure 22. Scatterplots of average producer LLE and average coordinator LLE, by participant pair, for each feedback delay condition of Experiment 3.

Box Counting. Means and mean standard deviations for FD can be found in Table 7. A 2 (participant) × 2 (visual condition) × 4 (feedback delay) factorial ANOVA was conducted on the FD for producer and coordinator movements. This analysis revealed a significant interaction between participant and feedback delay, *F* (3, 30) = 8.23, $p < .001$, $\eta_p^2 = .45$, as well as a main effect of feedback delay, *F* (3, 30) = 12.53, $p < .001$, $\eta_p^2 = .56$ (see Figure 23). This interaction appears to have been driven by the fact that coordinator FD was significantly higher than producer FD in the 0 ms feedback delay condition ($p < .05$), while the reverse was true in the 600 ms feedback delay condition ($p < .05$). A simple effect analysis of feedback delay for producer FD was significant, *F* (3, 30) = 6.20, $p < .01$, $\eta_p^2 = .38$. Fisher's LSD post hoc comparisons revealed that FD was significantly different between all feedback delay conditions except 0 ms and 200 ms, and 400 ms and 600 ms for both the producer (*p*s < .05). A simple effect analysis of feedback delay for coordinator FD was also significant, *F* (3, 30) = 14.65, $p < .001$, $\eta_p^2 = .59$. Fisher's LSD post hoc comparisons revealed that FD was significantly different between all feedback delay conditions except 0 ms and 200 ms, and 400 ms and 600 ms for both the producer (*p*s < .05), as was seen for the producer FDs.

As can be seen in Figure 24, four separate correlations were conducted (one for each feedback delay condition) in each visual condition for a total of eight correlations (see Table 8). All correlations between the stimulus and participant FD were significant (*p*s < .01), with the strongest being in the 0 ms, 200 ms, and 400 ms feedback delay conditions for the congruent visual condition, and the 0 ms and 200 ms feedback delay conditions for the incongruent visual condition.

Correlations were also evaluated for the difference between coordinator FD and producer FD and the maximum cross-correlation for each combination of feedback delay conditions and visual conditions. Results indicated that there was no consistent association between the two measures. This provides additional support for the idea that the degree of complexity matching observed between behaviors was not entirely dependent on the level of local coordination achieved.

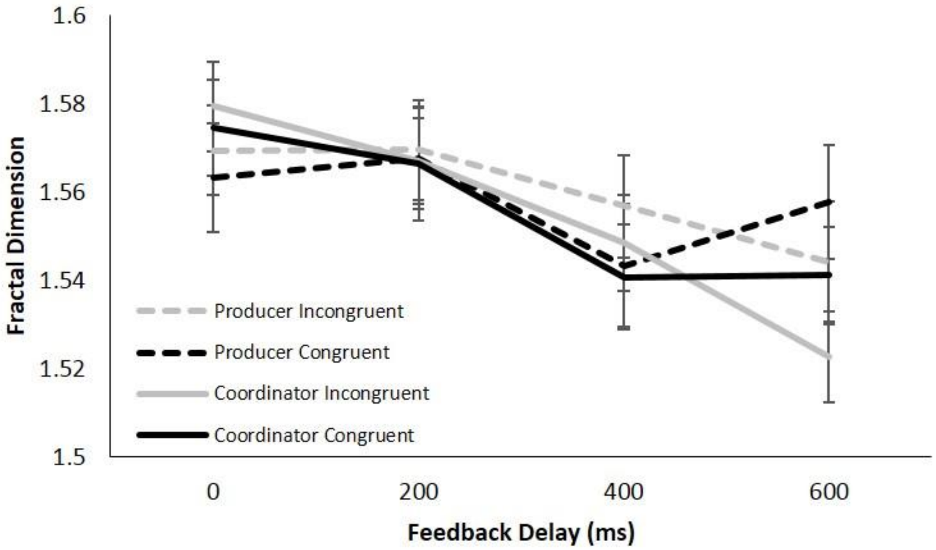

Figure 23. Average FD values for coordinator and producer behaviors in each of the congruent and incongruent visual conditions for each feedback delay condition in Experiment 3. Error bars show standard error.

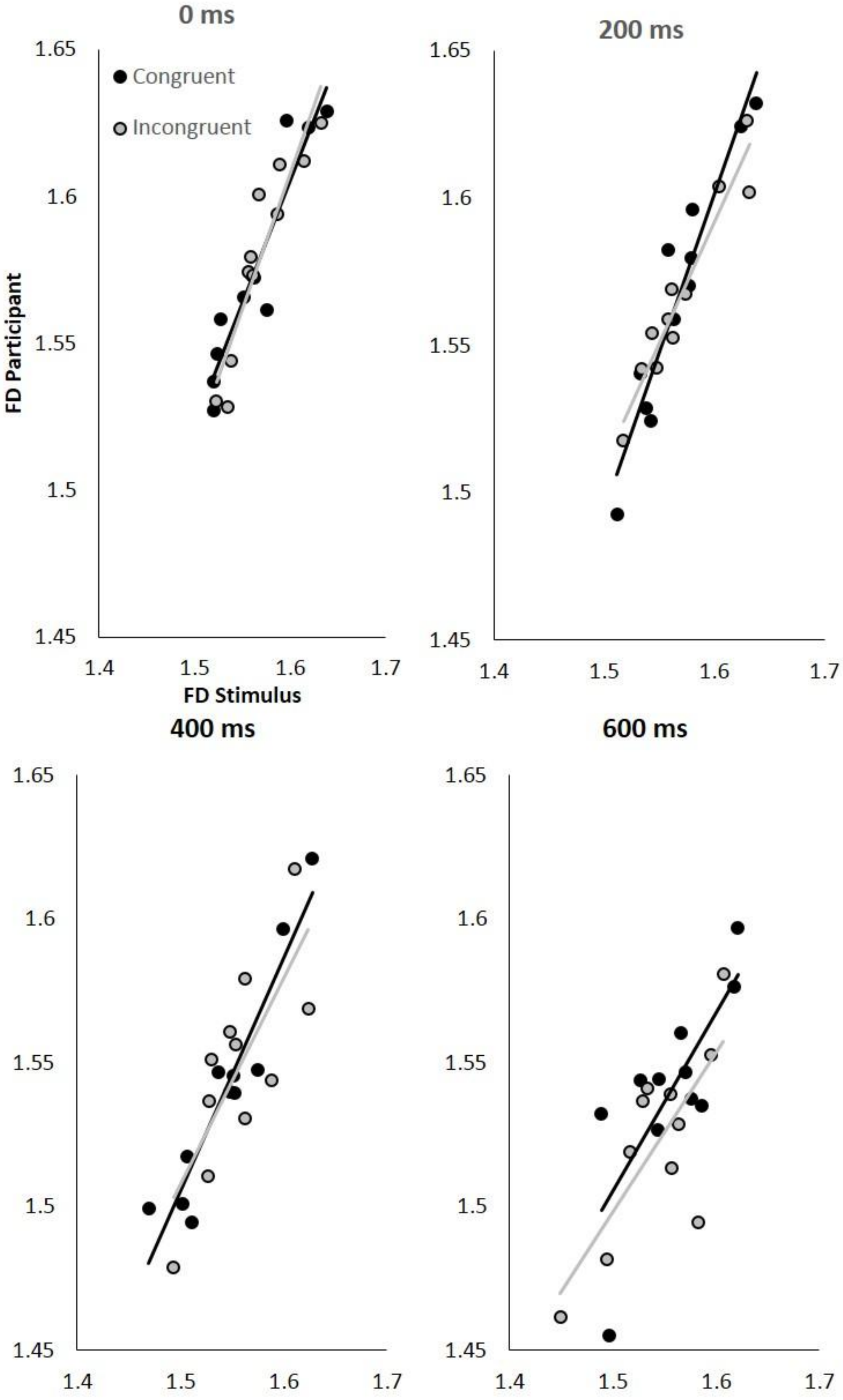

Figure 24. Scatterplots of average producer FD and average coordinator FD, by participant pair, for each feedback delay condition of Experiment 3.

Table 7. *Averaged Results of Complexity Matching Analyses: Experiment 3*

	Visual Condition: Congruent							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
LLE Producer	.075	0.05	.069	0.06	.078	0.03	.097	0.08
LLE Coordinator	.015	0.04	.027	0.04	.016	0.03	.025	0.05
FD Producer	1.563	0.04	1.568	0.04	1.543	0.05	1.558	0.04
FD Coordinator	1.575	0.04	1.567	0.04	1.541	0.04	1.541	0.04

	Visual Condition: Incongruent							
	Feedback Delay							
	0 ms		200 ms		400 ms		600 ms	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
LLE Producer	.069	0.03	.071	0.05	.073	0.03	.073	0.05
LLE Coordinator	.030	0.04	.025	0.04	.033	0.02	.014	0.02
FD Producer	1.569	0.03	1.570	0.04	1.557	0.04	1.544	.0.5
FD Coordinator	1.579	0.03	1.567	0.03	1.549	0.04	1.523	0.03

Table 8. *Correlation Results for Complexity Matching Analyses: Experiment 3*

	Visual Condition: Congruent			
	Feedback Delay			
	0 ms	200 ms	400 ms	600 ms
LLE Correlation	.92***	.66*	.41	.28
FD Correlation	.94***	.95***	.95***	.76**
	Visual Condition: Incongruent			
	Feedback Delay			
	0 ms	200 ms	400 ms	600 ms
LLE Correlation	.64*	.62*	.29	.30
FD Correlation	.93***	.96***	.76**	.76**

$^{*}p < .05$
$^{**}p < .01$
$^{***}p < .001$

Discussion

This final experiment successfully demonstrated that anticipatory synchronization can be achieved in an interpersonal context, with bi-directional coupling between co-actors. Findings also indicated that complexity matching developed between participants during the coordination task even more often in this context than was observed in the previous two experiments where the participant was uni-directionally coupled to an environmental stimulus.

The pattern of findings for local coordination and phase lead of the coordinator to the producer, as assessed through maximum cross-correlation, were very similar to those found for the participant to the stimulus in Experiment 2; coordination decreased with increases in feedback delay and a maximum phase lead was observed for the 400 ms feedback delay condition. As in Experiment 2, the coordinator still appeared to lag the producer when coordination was highest for the 200 ms feedback delay condition, and phase lead decreased between the 400 ms and 600 ms feedback delay conditions. Also similar to Experiment 2, the instantaneous relative phase analyses revealed that the average relative phase between coordinator and producer movements in the 200 ms feedback delay condition was actually positive, indicating that anticipatory synchronization did occur at this feedback delay. Here there was a slight difference between the two visual conditions; the results for the incongruent condition more closely matched those of Experiment 2, in that the average relative phase was higher in the 400 ms feedback delay condition than any of the others, while in the congruent condition there was not as much difference between the average relative phase in the 400 ms and 600 ms feedback delay conditions. In both conditions, as was seen in Experiments 1 and 2, the standard deviation in relative phase increased continually with the increase in feedback delay, indicating an increase in relative phase variability consistent with the overall decrease in coordination.

The distribution of relative phase was examined here for the coordinator movements with respect to the producer movements. As the relative phase of the onscreen dots would have been different for each participant’s display in the incongruent visual condition, I did not assess that measure here as was done in Experiments 1 and 2. The pattern of results for the distribution of relative phase in the congruent visual condition was very similar to that seen in Experiment 2, with there being a slightly greater amount of time for which the coordinator movement was ahead of the producer movement during the 200 ms feedback delay condition than was previously seen for the participant with respect to the stimulus. For both visual conditions, in the 400 ms feedback delay condition the amount of time the coordinator spent ahead of the producer was almost equivalent to that seen for the 200 ms feedback delay, but the smaller peak representing a lag by the coordinator was associated with a smaller proportion of time than seen in the 200 ms condition. Additionally, in the incongruent visual condition there was a greater amount of time for which the coordinator was ahead of the producer in the 600 ms feedback delay condition than in the congruent visual condition. This actually seems somewhat contradictory to the finding that the average relative phase was higher in the congruent visual condition than the incongruent visual condition for the 600 ms feedback delay, but generally it still appears that this delay resulted in the least stable coordination between the coordinator and producer.

As in Experiments 1 and 2, LLE and box counting analyses were conducted in order to evaluate complexity matching between the two participants' movements. Results revealed moderate correlations between the LLE of the producer and the LLE of the coordinator in the no feedback delay conditions and the 200 ms feedback delay conditions, with correlations being higher for the congruent visual condition in both cases. Similar to the previous two experiments, measurements of complexity matching were stronger for the fractal dimensions (FDs), than for LLEs. Here, correlations between the FD of the producer and the FD of the coordinator were very strong for both visual conditions in the no feedback delay condition and the 200 ms feedback delay condition. In the 400 ms feedback delay condition the correlation between FDs was much higher for the congruent visual condition, and in the 600 ms feedback delay condition correlations for both visual conditions were moderate (but still significant). Overall, the highest correlation for both visual conditions was observed for the 200 ms feedback delay condition.

The results of the complexity matching analyses used here are somewhat more complicated than for the previous two experiments, and the differences observed between visual conditions are worth further consideration. Overall, the results associated with the congruent visual condition very closely resembled the results from Experiments 1 and 2, with the exception that complexity matching in the current experiment appeared to be as common in the 200 ms feedback delay condition as for the 400 ms feedback delay condition (in Experiment 2 complexity matching was less common in the 200 ms condition). For the incongruent visual condition, the 200 ms feedback delay condition supported more complexity matching between behaviors than the 400 ms feedback delay condition. One possible explanation for this finding is rooted in the fact that the producer can see the timing of the coordinator’s actual movements. They were therefore able to see that they were sometimes ahead, which may have resulted in the coordinator intermittently taking on more of a leader role in the coordination process. If this were the case, it could interrupt the long-range statistical structure of producer ultimately resulting in less matching between the two participants. Further exploration of anticipatory synchronization and complexity matching within these and other variations of bi-directional coupling would be necessary to build upon this idea.

Correlations between the average difference in coordinator and producer LLEs and the average maximum cross-correlation observed in each feedback delay revealed no consistent relationship. The same was true for correlations between the average difference in coordinator and producer FDs and average maximum cross-correlation. Consistent with the first two experiments, this suggests that the level of local coordination between coordinator and producer movements was not directly predictive of similarity in large-scale behavioral complexity. These findings do not provide conclusive evidence against the theory of local strong anticipation, or the associated idea that complexity matching is a byproduct of local coordination processes, but they do indicate that differences in global behavioral similarity can not be entirely accounted for by incremental differences in the level of local coordination between movements. Relatedly, bi-directional coupling between co-actors led to the highest levels of complexity matching observed in the current study, but did not have an analogous effect on the general strength and stability of local coordination. The collective findings of the current study therefore suggest that there is some dissociation between local and global coordinative processes for the aperiodic behaviors being performed.

With respect to the phenomenon of anticipatory synchronization, the results of this experiment support and extend the findings of Experiments 1 and 2 in indicating that it is possible for an actor to achieve anticipation of a naturally produced aperiodic sequence of events while bi-directionally coupled to the producer of the sequence. Additionally, it appears that in this context the optimal feedback delays for a coordinator to experience with respect to their own movements in order to facilitate anticipatory synchronization include the range of delays 200-400 ms.

Ultimately this experiment demonstrated that anticipatory synchronization of aperiodic behaviors can indeed occur in an interpersonal context between bi-directionally coupled actors, while maintaining that the complexity of an actor’s movements is often strongly correlated with that of behavior with which they are coordinating.

CHAPTER 5

General Discussion

The present study was designed to extend the current understanding of aperiodic coordination processes, based on existing research in anticipatory synchronization, complexity matching, and visual coordination. A series of three experiments were conducted in order to examine aperiodic coordination in 1) an actor-environment context with computer-generated movement sequences, 2) an actor-environment context with pre-recorded naturally produced movement sequences, and 3) an interpersonal context with bi-directionally coupled co-actors. During each experiment the coordinating actor experienced a variety of short perceptual feedback delays -- for which information about the outcome of each behavior was delayed with respect to its production -- in order to determine whether this would facilitate anticipatory synchronization by the coordinator, as has been observed previously for computer-generated chaotic sequences (Stepp, 2009). Coordination between the arm movements of the coordinating actor and the aperiodic sequence with which they were instructed to synchronize was assessed using measures of both local coordination and more global behavioral similarity, or complexity matching.

In Experiment 1, I was able to replicate Stepp's (2009) observation of anticipatory synchronization for computer-generated chaotic movements using a new experimental paradigm. An initial evaluation of anticipatory synchronization was made using a maximum cross-correlation analysis, as demonstrated by Stepp (2009), which identifies the phase relationship (in ms) at which the actor is most highly coordinated with the movements of the stimulus. In order to gain further information about the local coordinative processes occurring throughout the experiment, an analysis of instantaneous relative phase was also conducted. This afforded valuable insight about the frequency of different phase relationships (in degrees) between actor and stimulus movements over the course of each trial. As the assessment of anticipatory synchronization was enhanced by the complementary use of both analyses of local coordination, I continued to use these two methods together in the latter two experiments.

In Experiment 1, calculation of Largest Lyapunov Exponents (LLEs) and fractal dimensions FDs (found using a box counting method) were used to provide measures of complexity matching for the first time. Results indicated that both analyses were capable of revealing some similarity in global movement dynamics between two contemporaneous behaviors, and both were used again for this purpose in Experiments 2 and 3. In Experiment 2, I established that anticipatory synchronization and complexity matching could be achieved by an actor with respect to the pre-recorded, naturally produced aperiodic movement sequences of an another individual. Finally, in Experiment 3 I was able to show that anticipatory synchronization of aperiodic movements can be achieved in an interpersonal context by one (coordinating) actor bi-directionally coupled to another (producing) actor. I also found that of the three experiments, this interpersonal context resulted in the highest levels of complexity matching.

Anticipatory Synchronization

Prior to the current study, anticipatory visual synchronization had only been investigated for a single individual attempting to coordinate with a computer-generated chaotic stimulus (Stepp, 2009). It is clear, however, that people are highly capable of coordinating with many naturally occurring, seemingly unpredictable environmental events, including the behaviors of other individuals (Richardson et al., 2014; Stephen et al., 2008). Additionally, it has been established that many complex biological behaviors, including human movement processes, exhibit the kind of unpredictable determinism characteristic of chaos (Mitra et al., 1997; Newell, Challis et al., 2000; Newell, Deutsch et al., 2000). This observation, that naturally produced movements can be chaotic, suggests that processes similar to the previously observed anticipatory synchronization of computer-generated chaotic sequences may also underlie some instances of complex interpersonal coordination.

In previous studies of anticipatory synchronization for chaotic behaviors, the phenomenon has occurred as a function of small perceptual feedback delays experienced by the coordinating actor (e.g. 200-400 ms) (Voss, 2000; Stepp, 2009). While one might expect these delays to prohibit the emergence of coordination, it appears that they may instead create the opportunity for a coordinating system to embody the dynamics of another system exhibiting chaotic behavior. In turn, this embodiment is thought to provide the coordinating system with the ability to achieve an anticipatory relationship with the other system's chaotic behaviors (Stepp & Turvey, 2008). In all three experiments presented here, it was necessary for the coordinating individual to experience a perceptual feedback delay with respect to the outcomes of their own actions in order for anticipatory synchronization to be observed. For each of the two actor-environment contexts (Experiment 1: actor-computer-generated stimulus, Experiment 2: actor-pre-recorded naturally produced sequence) and the interpersonal context (Experiment 3) examined, feedback delays in a range around 200 ms to 400 ms were most effective in facilitating anticipation, with a significant break down in coordination being observed for delays of around 600 ms .

For Experiments 2 and 3, the results from the maximum cross-correlation analysis appeared to indicate that the 200 ms feedback delay did not actually result in anticipatory synchronization by the coordinator. An examination of the distribution of instantaneous relative phase, however, revealed that the coordinator did actually spend a substantial amount of time ahead of the stimulus or producer movements at this delay. This discrepancy between the maximum cross-correlation and instantaneous relative phase analyses in terms of assessing anticipatory synchronization can be understood through careful consideration of the information provided by each analysis. While maximum cross-correlation identifies a single characteristic phase relationship associated with the highest level of coordination for each trial, the distribution of instantaneous relative phase relationships visited over the course of a trial gives a broader impression of the evolving relationship between coordinating actor and stimulus or producer. An examination of this distribution at each feedback delay within Experiments 2 and 3 revealed that the relationship of coordinator movements to stimulus or producer movements over the course of a trial always involved both anticipatory and lagged coordination.

Ultimately, while the greatest stability of coordination may have been achieved when the coordinator's movements were lagged with respect to those of the stimulus or producer for the 200 ms feedback delay, a more accurate interpretation of both local coordination analyses together in Experiments 2 and 3 leads to the conclusion that anticipatory synchronization by the coordinator occurred *intermittently*. In fact, an evaluation of the distribution of instantaneous relative phase for the 400 ms feedback delay condition revealed a similar magnitude of both anticipatory and lagging behavior in Experiments 2 and 3. Additionally, even though, the analyses of maximum cross-correlation and instantaneous relative phase both indicated that anticipatory synchronization was achieved at the 200 ms and 400 ms feedback delay conditions in Experiment 1, distributions of instantaneous relative phase for each condition revealed that the coordinator likewise spent time anticipating and, lagging the stimulus. These distributions also revealed that coordinators spent the greatest amount of time anticipating the stimulus by a small phase interval in the 200 ms feedback delay condition, and less time lagging the stimulus overall in the 400 ms condition.

The intermittency of anticipatory synchronization observed here is characteristic of the relative coordination found frequently in everyday interpersonal and visual environmental coordination, as well as biological coordination in general. In the context of the current study, this suggests that an actor does not always have to be ahead of the aperiodic behavior with which they are attempting to coordinate in order to achieve anticipatory synchronization, they just need to lead the other behavior often enough to maintain a functional level of coordinative activity.

Strong Anticipation versus Weak Anticipation. Theories of the underlying processes for anticipatory coordination (i.e. for periodic or aperiodic behaviors) fall into two broad categories. Explanatory mechanisms that depend on the use of internal models to predict upcoming events have previously been referred to as ‘weak anticipation’, while those based on the idea that all behaviors follow the same, universal dynamical laws (Stepp & Turvey, 2008) have been categorized as ‘strong anticipation’ (Dubois, 2003). Furthermore, theories of ‘local’ strong anticipation have been developed as distinct from the theories of ‘global’ strong anticipation. Here the local form prioritizes the synchronization of behaviors on a very short time scale (Stepp & Turvey, 2010), while the global form highlights the importance of similarities in long-term statistical structure between two contemporaneous behaviors (Stephen et al., 2008).

The observation of anticipatory synchronization is typically taken as support for theories of strong anticipation over weak anticipation, as it is hard to explain how an internal model could provide an actor with information about unpredictable, chaotic events, especially for an actor experiencing perceptual feedback delays (Stepp & Turvey, 2008; Stepp & Turvey, 2010). I therefore expected that the processes underlying any anticipatory synchronization observed in the current study would be consistent with strong anticipation. Although I did not have any specific predictions about whether it was more likely for the local or global form of strong anticipation to occur for this phenomenon, or whether one of these might be better-suited to the coordination and cooperation of aperiodic behaviors in general, I was aware that the use of a task which required local coordination for successful completion would likely have an influence on the relative prominence of local vs. global coordinative processes.

The occurrence of complexity matching in all three experiments, as evidenced by the correlation of coordinator and stimulus/producer LLEs and the correlation of coordinator and stimulus/producer FD (see next section for further details), is generally suggestive of strong anticipation processes. However, these analyses alone provide no evidence as to whether matching arose as a result of consistent local coordinative processes or more global behavioral similitudes. Instead, a comparison of LLE values between coordinator movements and stimulus or producer movements indicated that the anticipation processes observed here might be of the local, rather than global, strong variety. Across all three experiments presented here, the LLE of the coordinating participant was consistently lower than that of the stimulus or producer behavior with which they were attempting to coordinate. Coordinating behavior was, therefore, generally less chaotic, and more predictable, than driving behavior. This suggests that the coordinator was continuously in the act of predicting the driving behavior, rather than simply producing their own behavior based on an embodiment of the chaotic dynamics of the driving behavior. This finding is more consistent with the ideas inherent to the local form of strong anticipation rather than the global form, as the actor appears to be attending to short-term changes in the behavior with which they are trying to coordinate, rather than using information to reproduce more long-term behavioral patterns.

Complexity Matching

The examination of associations between long-term behavioral patterns of contemporaneous time series, or complexity matching (West et al., 2008), is a relatively recent pursuit. As with the assessment of local coordination phenomenon, complexity matching could be evaluated using a number of different measures, with the stipulation that the measures should be able to detect global forms of coordination even in the absence of local synchronization processes. Previous studies have focused on the correlation between fractal scaling exponents from detrended fluctuation analysis (DFA) for simultaneously occurring behavioral time series, and detrended cross-correlation analysis (DCCA) as measures of complexity matching (Abney, Paxton, Kello, & Dale, 2013; Coey, Washburn, & Richardson, under review; Delignières & Marmelat, 2014; Marmelat & Delignières, 2012; Torre, Varlet, & Marmelat, 2013).

As a fractal analysis, DFA is used to identify patterns within behavioral variability in order to establish whether fluctuations exhibit self-similarity across timescales (Mandelbrot, 1982). This leads to the calculation of a characteristic scaling exponent, which provides a quantitative assessment of the degree of behavioral self-similarity within a single performance. In order to evaluate complexity matching using DFA, the scaling exponents of two concurrent performances can be submitted to a correlation (Marmelat & Delignières, 2012). In the case of DCCA, a similar analysis to DFA is conducted but instead of measuring variability within a single behavioral time series, the analysis measures self-similarity in the covariance of two simultaneously occurring behaviors (Delignières & Marmelat, 2014). Unfortunately, like many fractal-based analyses, these methods of evaluating complexity matching between two behaviors are limited in that they can only be performed on long behavioral time series, which are not possible to obtain for all tasks.

In the current study, I evaluated the use of two new measures for complexity matching. As with the previously used DFA method, both of these measures require the initial calculation of a value associated with each of two contemporaneous time series, followed by the correlation between these two values. The correlation between the LLEs of two time series provided information about similarities in long-term temporal behavioral structure, and the correlation between the FDs of the same two time series (as established using a box counting analysis) provided an assessment of the global spatial similarities. Both analyses allowed me to examine complexity matching for the task used in this study, which was not suited to the previously established measures of complexity matching.

The association between coordinator and stimulus/producer LLE values and the association between coordinator and stimulus/producer FD values were assessed within each experiment of this study. In Experiment 1, LLE correlations and FD correlations were significant in the 400 ms feedback delay condition, and were also high in the no feedback delay condition. These findings established that both new analyses were capable of detecting global similarities in contemporaneous behavioral time series, distinct from local behavioral similarities. Due to the fact that all participants experienced the same four aperiodic stimulus sequences in Experiment 2, it was not possible to perform correlations on the complexity measures for concurrent participant and stimulus movements. However, box and whisker plots of these associations revealed similar patterns of complexity matching to those observed in Experiment 1, with the strongest associations occurring in the 400 ms feedback delay condition and the no feedback delay condition for both LLE and FD measures. These findings even seem to indicate that greater complexity matching occurred in Experiment 2 for participants coordinating with pre-recorded, naturally produced aperiodic behaviors than was seen in Experiment 1 for participants coordinating with computer-generated, chaotic stimuli. In Experiment 3, FD correlations were significant in all feedback delay conditions, and LLE correlations were significant in the 200 ms feedback delay condition and the no feedback delay condition.

The association between the degree of local coordination and the differences in behavioral complexity between participant and stimulus, or coordinator and producer, was examined for both complexity matching analyses. Across all three experiments, results indicated that there was no consistent relationship between the level of local coordination and the degree of similarity in behavioral complexity for coordinated movements. This confirms that both new methods of assessing complexity matching are capable of identifying global similarities in movement dynamics distinct from local coordination phenomena. Furthermore, these findings suggest that in the context of the current experimental task, the degree of complexity matching observed was not entirely dependent on the level of local coordination achieved. This may seem to be at odds with the earlier statement that the coordinative processes observed in the present study appear to be most consistent with those of local strong anticipation. However, further development of the existing theory of local strong anticipation might provide a more satisfying account of the present observations. As required by the experimental task, participants in the current study were always locally coordinated to a stimulus or co-participant. It seems possible that even very low levels of local coordination may result in substantial complexity matching, which would still be consistent with the expectations of local strong anticipation. Additional research is needed to address whether there might be a characteristic degree of local coordination that categorically impacts the emergence of complexity matching. Ultimately, the observation of complexity matching throughout this study suggests that the anticipatory processes underlying coordination are more likely to be synonymous with strong anticipation than weak anticipation. In other words, it seems likely that the occurrence of complexity matching is based on similarities in intrinsic physical and dynamical properties between systems rather than the use of internal models.

In all three experiments, associations between coordinator and stimulus/producer behaviors were stronger for the FD measure than the LLE measure. A reminder of what each measure is actually capturing helps to explain why there was some inconsistency between assessments of complexity matching provided by the two new methods. While the LLE is a measure of the unpredictability and divergence of behavior from one time step to the next, the FD captures the spatial self-similarity of a behavioral trajectory over time. Both can be understood to provide information about the collective movement dynamics of a behavior, but clearly capture distinct aspects of these dynamics. These analyses should therefore not be regarded as equivalent or interchangeable, and should instead continue to be used in a complementary fashion in order to gain an array of information about similarities in global movement dynamics during the coordination of complex behaviors.

Despite the differences between the two complexity matching measures introduced in the current study, both revealed that complexity matching occurred in all three experiments of the current study. West and Grigolini (2010) have previously suggested that the exchange of information between systems may actually improve with increases in behavioral complexity. This is reflected in the current study through the fact that the complex, aperiodic behaviors examined supported both local and global forms of coordination, and is also consistent with Delignières and Marmelat's (2014) idea that complexity matching is dependent upon pre-existing self-similarity in the behavior with which an actor is trying to coordinate. Complexity matching then occurs as the actor comes to produce the same statistical structure within their own behaviors, making their own actions adaptive and efficient within the current environmental context (Delignières & Marmelat, 2014; Marmelat & Delignieres, 2012). A similar process of mutual adaptation is thought to occur within the bi-directional coordinative systems which emerge during interpersonal coordination (Delignières & Marmelat, 2014; Marmelat & Delignieres, 2012). In the current study, the strongest associations between measures of complexity for two coordinated behaviors occurred in Experiment 3. The fact that the highest levels of complexity matching observed here were found in an interpersonal context involving bi-directional coupling provided the basis for a new idea, that the matching of behavioral complexity improves with increases in information exchange.

Visual-motor and Interpersonal Coordination

A large body of research has demonstrated that individuals naturally coordinate with environmental events, including the behaviors of other individuals, via visual information (e.g. Buekers, Bogaerts, Swinnen, & Helsen, 2000; Chartrand & Bargh, 1999; Lopresti-Goodman, Richardson, Silva, & Schmidt, 2008; Richardson, Marsh, & Schmidt, 2010). Findings from the field of visual-motor coordination, indicate that this actor-environment coordination is often governed by dynamical processes of entrainment (e.g., Byblow, Chua, & Goodman, 1995; Kelso, Decolle, & Schöner, 1990; Russell & Sternad, 2001; Schmidt & Turvey, 1994; Wilson, Collins, & Bingham, 2005; Wimmers, Beek, & van Wieringen, 1992). Entrainment can occur spontaneously or as a result of actor intent, and can be either absolute -- wherein behavioral events are perfectly synchronized -- or more intermittent. Results from previous studies have indicated that interpersonal coordination is more often characterized by the latter intermittent, or relative, coordination (Richardson et al., 2007). Relative and absolute coordination are both necessarily descriptors of local coordination processes, and can be measured using a number of different analyses. In the current study, analyses of maximum cross-correlation and instantaneous relative phase were used to evaluate the occurrence of the local coordinative processes associated with anticipatory synchronization.

Anticipatory synchronization has previously been understood as a visual-motor coordination phenomenon arising from the coupling dynamics inherent to a master-slave system, in which the slave system experiences a perceptual feedback delay with respect to the outcome of its’ own behaviors (Stepp, 2009). In the current study, I was interested in establishing whether anticipatory synchronization might also occur in an interpersonal context, such that it could help to further our understanding of how individuals come to coordinate and cooperate with the unpredictable, aperiodic behaviors of others in a seemingly effortless fashion. The first two experiments in this study replicated the master-slave coupling previously associated with anticipatory synchronization, but the third experiment allowed me to evaluate whether this phenomenon might be achieved in a bi-directional coupling situation, in which both actors received information about the others' movements.

When co-actors are bi-directionally coupled, the movement producer (i.e. 'master') actually has the opportunity to see the coordinator's (i.e. 'slave') behaviors with respect to their own. The use of two visual conditions in Experiment 3 provided an opportunity to examine how the information available to the movement producer about a coordinator's movements might affect the producer's behaviors and, subsequently, the occurrence of anticipatory synchronization and complexity matching. The design of the *congruent* visual condition more closely matched a unidirectional coupling relationship, as the producer saw the coordinator's movements at the same perceptual delay that the coordinator himself experienced. However in the *incongruent* condition, where the producer always saw the coordinator's movements displayed in real time, the producer would have perceived the coordinator's movements as intermittently leading and lagging their own. Contrary to what might have been expected, this did not lead to a breakdown in the pre-established producer-coordinator relationship, or the subsequent disintegration of coordinative processes. Instead, this information did not appear to have any substantial effect on the occurrence of anticipatory synchronization compared to what was observed in the *congruent* condition, or to what was found in Experiment 2. There were also only very small differences in complexity matching between the two visual conditions. Ultimately, these findings imply that it is not actually necessary for one to be "ahead" in order to be driving coordinated joint-action. On the contrary, it appears that functional, complex coordination between co-actors is varied, flexible and robust to small fluctuations in the phase relationship between movements. This intermittent nature might also make naturally occurring anticipatory synchronization less obvious during everyday behaviors, as people naturally move ahead or behind one another.

The stable coordination of aperiodic behaviors appears to have been as successfully achieved in an interpersonal context as it was in the coordinative context involving an actor coupled to a computer-generated stimulus. Perceptual feedback delays do seem to be as critical for a coordinating actor to achieve anticipatory synchronization with aperiodic behaviors in an interpersonal context as they have been shown to be in an actor-environment context (Stepp, 2009). Still, the overall instance of local and global coordination -- both with and without the involvement of perceptual feedback delays – was as prevalent in Experiment 3 as in the other two experiments presented here. The current study successfully demonstrated that co-actors are capable of coordinating aperiodic behaviors as assessed by both local and global measures, and identified conditions under which anticipatory coordination can be achieved by one actor with respect to the other's behaviors.

In addition to the fact that visual-motor coordination between an individual's movements and environmental events factors heavily in the successful completion of many tasks, it has also been shown that the coordination of movement patterns between two individuals via visual information can increase interpersonal rapport, reduce prejudice, and facilitate social awareness (e.g., Miles, Griffiths, Richardson & Macrae, 2010; Miles, Lumsden, Richardson, & Macrae, 2011). The findings from Experiment 3 therefore suggest that positive social outcomes are likely to result from natural, anticipatory synchronization processes. Additionally, these are some of the first results to extend the understanding of interpersonal visual coordination beyond the study of simple, periodic behaviors. In integrating theories and methodologies from a diverse range of scientific disciplines (e.g., physics, kinesiology, neuroscience, cognitive science, psychology) the present work provides new opportunities for the modeling of many aspects of emergent visual, interpersonal coordination and for the further examination of the self-organizing dynamics of social synergies.

Conclusions

The findings of the current study suggest that neither behavioral complexity, nor perceptual feedback delays, should be considered challenges to visual or interpersonal coordination. Individuals asked to coordinate with semi-unpredictable chaotic movements or naturally produced aperiodic movements were able to achieve both local coordination and complexity matching. Additionally, short perceptual feedback delays (around 200-400 ms) appear to have actually been critical to the emergence of anticipatory synchronization across actor-environment and interpersonal contexts. While complexity matching was not dependent on the introduction of these feedback delays, the same lengths of delay that facilitated anticipatory synchronization also appear to have supported the emergence of long-term statistical similarities in behavior.

It is worth noting that these critical lengths of feedback delay are very similar to the reaction times commonly observed for a variety of tasks, as well the delays found within the human nervous system (see Thorpe, 2002; Wallot, & Van Orden, 2012). The results of the current study suggest that delays between 200-400 ms may consistently be providing opportunities for a system to achieve coordination with ongoing external events, or between multiple internal processes. Given my current interest in exploring the role of feedback delays and anticipatory synchronization within interpersonal interaction, it is interesting to consider the fact that others' reactions during social interaction provide a form of delayed perceptual feedback with respect to one's own behaviors. If these reactions are occurring on the same timescale as the perceptual delays introduced in the present study, they may be facilitating coordination and cooperation of non-stereotyped behaviors. Further consideration and investigation of similar, naturally occurring temporal delays would help to establish their seemingly integral role for many kinds of coordination.

The identification of complexity matching for chaotic and aperiodic behaviors seen throughout this study is reflective of West and Grigolini's (2010) idea that the exchange of information between systems may improve with increases in behavioral complexity. The fact that associations in global dynamic structure were highest between two bi-directionally coupled co-actors has also led to the idea that the matching of behavioral complexity improves with increases in information exchange. Ultimately, much remains to be understood about commonly occurring aperiodic coordination processes, but this study should serve as motivation for further exploration of complex interpersonal movement coordination.

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