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Complexity Matching and Coordination in Individual and Dyadic Performance

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Abstract

Complexity matching is a measure of coordination based on information exchange between complex networks. To date, studies have focused mainly on interpersonal coordination, but complexity matching may generalize to interacting networks within individuals. The present study examined complexity matching in a double, coordinated Fitts' perceptual-motor task with comparable individual and dyadic conditions. Participants alternated touching targets with their left and right hands in the individual condition, or analogously with the left hand of one partner and the right hand of another in the dyadic condition. In Experiment 1, response coupling was manipulated by making targets drift either randomly or contingently based on prior responses. Here, drift refers to the variability in the target movements between response locations. Long-range correlations in time series of inter-response intervals exhibited complexity matching between the left and right hands of dyads and individuals. Response coupling was necessary for complexity matching in dyads but not individuals. When response coupling was absent in the dyadic condition, the degree of complexity matching was significantly reduced. Experiment 2 showed that the effect of coupling was due to interactions between left and right responses. Results also showed a weak, negative relationship between complexity matching and performance as measured by total response time. In conclusion, principles and measures of complexity matching apply similarly within and between individuals, and perceptual-motor performance can be facilitated by loose response coupling.

Keywords

complexity matching; long-range correlation; bimanual coordination; interpersonal coordination; Fitts' task

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Introduction

People coordinate their actions to accomplish individual or shared goals. For instance, the two hands of one person can coordinate to juggle three balls, as can the four hands of two people juggling together. Bimanual coordination is necessary in both instances—what differs is whether coordination occurs between the left and right hands of a single person, or across the hands of two separate people. Coordination can sometimes be expressed straightforwardly in terms of coupled oscillators (Haken, Kelso, & Bunz, 1985), but in some cases the variability of interest is more irregular and calls for broader statistical measures and conceptualizations of coordination.

A recently proposed measure of coordination is *complexity matching*, which is based on the principle of maximizing information exchange between complex networks (Abney, Paxton, Dale, & Kello, 2014; Marmelat & Delignières, 2012; West, Geneston, & Grigolini, 2008). Complexity matching is predicted to occur to the extent that participants can satisfy the principle of maximizing information exchange. Complexity matching is operationalized as the convergence in the long-range temporal correlations produced by two interacting systems by correlating estimates of $1/f$ exponents. Typically, the long-range dynamics of each system are quantified using spectral or detrended fluctuation analysis, and then the resulting estimated exponents are correlated across a sampled population of pairs of interacting systems.

To date, complexity matching has been studied in dyadic conversations (Abney et al., 2014; Fusaroli, Raczaszek-Leonardi, & Tylén, 2014), dyadic perceptual-motor coordination (Almurad, Roume, Blain, & Delignières, 2018; Almurad, Roume, & Delignières, 2017; Coey, Washburn, Hassebrock, & Richardson, 2016; Den Hartigh, Marmelat, & Cox, 2017; Fine, Likens, Amazeen, & Amazeen, 2015; Marmelat & Delignières, 2012), perceptual-motor coordination with a metronome (Delignières, Almurad, Roume, & Marmelat, 2016; Stephen, Stepp, Dixon, & Turvey, 2008b; Torre, Varlet, & Marmelat, 2013), and neural networks and brain connectivity (Mafahim, Lambert, Zare, & Grigolini, 2015).

Complexity matching leads one to focus on coordination between two people, or between a person and a device like a metronome (but see Rigoli, Holman, Spivey, & Kello, 2014). In the present study, we examine complexity matching in a perceptual-motor task that has comparable conditions of individual and dyadic coordination. We test whether complexity matching generalizes across individual and dyadic coordination, and whether the role of response coupling operates similarly within and across individuals.

Our study is motivated by the idea that information exchange, as measured by complexity matching, may be a general framework for studying coordination akin to coupled oscillators. Haken, Kelso, and Bunz (1985) introduced a model of coupled oscillators that has proven to describe the dynamics observed in many studies of perceptual-motor coordination within and between people (Black, Riley, & McCord, 2007; Issartel, Marin, & Cadopi, 2007; Riley, Richardson, Shockley, & Ramenzoni, 2011; Schmidt & Richardson, 2008), in movement activity as well as neural activity (Bressler & Kelso, 2001; Fink, Foo, Jirsa, & Kelso, 2000;

Swinnen, 2002). Information exchange may be a similarly general principle for complex networks of interacting components with heterogeneous dynamics.

Bimanual and Interpersonal Coordination

Coordination studies typically employ measures like timing and movement accuracy (Rosenbaum, Dawson, & Challis, 2006; Wel, Knoblich, & Sebanz, 2011), phase relations (Coey, Varlet, Schmidt, & Richardson, 2011), and movement dynamics (Schmidt, Morr, Fitzpatrick, & Richardson, 2012; Schmidt & O'Brien, 1997; Stephen et al., 2008). These measures can be applied similarly within and between individuals. For example, Wel et al. (2011) asked participants to swing a pendulum between two markers by pulling a rope at different amplitudes and frequencies. This task was completed either alone or in cooperation with another person. For the individual condition, each participant had control over both ends of the rope. In the dyadic condition, each participant had control of one end of the rope. Results indicated that members of dyads cooperated by pulling their ends of the rope simultaneously with each other to produce detectable and predictable behaviors that partners could recognize. By contrast, individuals pulled the ends simultaneously only half as often.

Tasks like swinging pendula instruct participants to time their movements relative to each other, but timing relations are not required to perform these tasks—if oscillations fall out of phase with each other, the task continues without penalty or disruption. Other coordinative tasks require certain timing relations to be performed. For example, Fine and Amazeen (2011) extended the individual Fitts' task to investigate whether the Fitts' law tradeoff between speed and accuracy holds when two people cooperate to perform the task. Participants aimed at targets alternately between their left and right hands, and alternation was a required timing relation to perform the task. The authors investigated this double Fitts' task in three different conditions: unimanual, intrapersonal, and interpersonal. In the unimanual condition, participants used either their left or right hands across separate trials; intrapersonal participants used both hands; and interpersonal participants used their dominant hands while standing alongside another participant.

Results showed that coordination between paired individuals arose from perceptual-motor coupling through peripheral vision (Amazeen, DaSilva, & Amazeen, 2008; Mechsner, Kerzel, Knoblich, & Prinz, 2001). Results also indicated that, in both the intrapersonal and interpersonal conditions, when task difficulty varied across hands, movement times for the easy targets slowed down to maintain an in-phase relation with the other hand that responded to harder targets. This result is contrary to the Fitts' law assumption of independence, and it was interpreted as evidence against a centralized control of target aiming and reaching (Marteniuk, Mackenzie, & Baba, 1984).

The study by Fine and Amazeen (2011) required alternation to perform the task, whereas other studies have induced less constrained forms of coordination to perform collaborative tasks (Harrison & Richardson, 2009; Jordan, Schloesser, Bai, & Abney, 2018; Knoblich & Jordan, 2003; Wel et al., 2011). For instance, Jordan et al. (2018) instructed participants to keep a drifting dot inside a narrow rectangular box on a computer screen. The dot was constantly moving and controlled with two keys that interacted to determine the direction of force exerted on the dot. Individuals controlled both keys, whereas each member of a dyad controlled only one of the keys. Timing relations between keypresses were necessary to control the moving dot.

Jordan et al. (2018) found performance was better for individuals because they were able to use precise timing relations between the keys to effect control. Such precision was not available to dyads, so a different coordination pattern emerged in which participants pressed their respective keys quickly and, through feedback, adjusted the phase and frequency of their keypress events to stabilize movement of the dot in the middle of the goal box. Despite dyads being less successful than individuals, partners in dyads utilized the available channels of communication to coordinate with each other.

Complexity Matching

The studies reviewed thus far used measures of phase relations in behavior, including methods such as recurrence quantification analysis (Coey, Washburn, & Richardson, 2014; Fusaroli, Konvalinka, & Wallot, 2014; Riley, Richardson, Shockley, & Ramenzoni, 2011), to study perceptual-motor coordination in individuals and dyads. Complexity matching has also been used to study perceptual-motor coordination, but unlike recurrence quantification analysis and similar measures, complexity matching does not measure phase relations. Instead it measures the degree to which two measurement series have similarly structured long-range correlations

In one of the first empirical studies of complexity matching, Marmelat and Delignières (2012) instructed pairs of participants to swing separate pendulums back and forth using either their left or right hand. All participants started by completing one trial alone, followed by a practice period of about five minutes as groups of two using the same hand as they did in the individual condition. Afterwards, participants were asked to complete a series of three trials together by swinging the pendulums in synchronous in-phase movements. Response coupling was manipulated in terms of the amount of perceivable information available about the partner’s swinging, at three different levels: weak coupling, intermediate coupling, and strong coupling. The weak coupling condition allowed for only peripheral visual information about the partners’ swinging movements. Intermediate coupling allowed for both visual and auditory information, and strong coupling provided visual, auditory, and haptic information – haptic information was made available by allowing the participants to lock their free arms together.

Marmelat and Delignières (2012) measured fluctuations in the inter-peak intervals of oscillatory movements, whose temporal autocorrelations were found to follow an inverse power law relation. The relation was quantified for each time series by estimating the power law exponent, and complexity matching was measured by correlating exponent estimates across dyads. Results showed complexity matching in the intermediate and strong coupling conditions, and weaker matching in the weak coupling conditions. Thus, the strength of complexity matching was influenced by the amount of perceivable information available (i.e., coupling strength). The goal of the task employed by Marmelat and Delignières (2012) was to swing pendula in synchrony with each other, but participants were not given feedback on their performance, and the degree of synchrony was not used as a performance metric in the reported analyses.

More recently, studies have begun to investigate whether complexity matching might relate to measures of coordinative performance (Abney, Paxton, Dale, & Kello, 2015; Zapata-Fonseca, Dotov, Fossion, & Froese, 2016). For example, Zapata-Fonseca et al. (2016) investigated a task in which pairs of participants interacted with one another by moving virtual "avatars" (points) around an invisible ring, receiving only haptic feedback when their avatars overlapped. The goal was to align the avatars, which was challenging because of decoys placed on the ring that avatars had to avoid. One decoy was a static point located at one spot on the ring, and two others were moving decoys that shadowed the movements of each real avatar. The authors found complexity matching in spectral analyses of the fluctuations in avatar movement, and higher degrees of complexity matching were correlated with higher degrees of avatar alignment.

Another study of complexity matching measured performance indirectly in terms of the likelihood that conversational partners could establish common ground. Abney et al. (2014) analyzed data collected in a prior study (Paxton & Dale, 2013) in which conversational partners had an affiliative conversation and an argumentative conversation. For the affiliative conversation, partners were prompted to talk about popular media, while in the argumentative conversation, partners were prompted to talk about a controversial issue for which they held differing beliefs based on a prior questionnaire. Abney et al. measured power law clustering in the peak amplitude events produced by each speaker, and complexity matching in terms of the relative similarity in Allan Factor functions (Allan, 1966) from which power law exponents can be estimated. The authors found that complexity matching occurred for affiliative but not argumentative conversations. These results suggest that complexity matching reflects conversational "performance" in terms of the degree to which common ground is established.

Current Experiments

In the present study, we use complexity matching to measure perceptual-motor coordination, which removes information about the temporal alignment (or lack thereof) of behaviors, and we compare complexity matching with *correlational matching*, which measures the degree of temporal alignment. Complexity matching measures the degree to which two measurement series have similarly structured long-range correlations, and correlational matching measures the degree to which two measurement series follow each other over time.

We modified the classic Fitts' task to elicit perceptual-motor performance that requires coordination between the left and right hands of one individual, or two partners. Participants reached out and touched targets as they appeared on one or two touch screens with the left or right hands, alternating between targets on the left and right sides of the screen. The task was performed individually by one person reaching for all targets and alternating their left and right hands. The task was performed dyadically by displaying the targets on two touch screens in two separate rooms. One person in one room aimed for the left-side targets with their left hand, and the other person in the other room aimed for the right-side targets with their right hand. In both individual and dyadic conditions, the task forced alternation between left and right responses, and thereby generated series of left and right-hand inter-response intervals (IRIs). We quantified temporal autocorrelations by estimating a spectral exponent for each time series, and we measured complexity matching by correlating the exponent estimates across participants. We measured correlational matching in terms of correlations between left and right-hand IRIs.

Left and right responses were inherently coupled for individuals because responses were controlled by a single brain with two hemispheres connected by a corpus callosum, among other physiological and functional pathways such as ipsilateral projections of M1 (Chen, Cohen, & Hallett, 1997; Kawashima, Roland, & O'Sullivan, 1994). The inherent, internal coupling in the individual condition leads us to expect both complexity matching and correlational matching between the left and right hands of individuals. However, in the dyadic condition, response coupling is only possible through the appearance of targets on the screen. We manipulated the degree of external response coupling by manipulating the inter-dependency of target positions across responses (Experiment 1). In a *dependent drift* condition, the position of each target depended on the precise location of the prior response within the target circle, i.e. the deviation from target center was used to deviate the position of the next target relative to its quadrant. Thus, the left-hand response affected the right-hand response through target positioning, and vice versa. In the *random drift* condition, the position of each next target was sampled randomly and uniformly from anywhere inside the target circle, thereby creating random deviations from target to target. The positional and directional variability in drift is not necessarily matched between the dependent and random drift conditions, so we created a third *playback* condition that controlled for drift variability (Experiment 2).

Our coordinated Fitts' task was designed to address three main research questions. First, does complexity matching generalize across dyadic and individual (bimanual) perceptual-motor coordination, and how does this compare with correlational matching? Second, does external response coupling have the same effect on matching in both dyadic and individual coordination? Third, how does complexity matching and correlational matching in an aiming task relate to performance as measured by total response time? Previous studies suggest a relationship between coordination and performance, but the degree and direction of this relationship are unclear. Matching of movement dynamics has been shown to correlate with better task performance (Abney et al., 2014; Zapata-Fonseca et al., 2016), but also worse performance (Abney et al., 2015). In the latter case, dyads worked together to build a tower and the authors interpreted their results as indicating complementary movements that varied in their phase relations over time to support a loose, flexible kind of coordination.

It is not clear whether performance should improve with increased matching in response timing, or whether left and right-hand responses can be coordinated more effectively when they maintain some independence from each other. Given that prior studies have found differing relationships between performance and coordination, we considered this issue as exploratory in the present study. Examining this relationship will further our understanding of coordination as revealed in the temporal correlations of performance fluctuations.

Experiment 1

METHOD

Participants—In previous related studies (Fine et al., 2011; Marmelat & Delignières, 2012; Jordan et al., 2018; Wel et al., 2011; Zapata-Fonseca et al., 2016), reliable effects were found with 16 to 66 participants per experiment. We ran 90 participants, 30 individuals and 30 dyads, per experiment which should give us ample power to observe similar effects. All students participated from UC Merced for course credit. Each participant signed a consent form explaining that participation was voluntary, and the experiment could be ended at any time without penalty. Of the 90 participants (62 female) who volunteered for this experiment, 59 females and all males were right handed, based on which hand they use for writing. Given the smaller number of males and left-handed individuals, we did not analyze gender or handedness any further.

Apparatus—For each dyad, each participant sat roughly 30 cm (11.81 in) in front of their own 22-inch Planar PCT2235 touch screen monitor at approximately a 65° angle, in separate rooms. The height of each chair relative to the table was set to a comfortable level for each participant. Both rooms were 7 feet by 9 feet in size. For each individual, only one room and monitor were used. A single computer sent the same display to one or both monitors, and it also collected touchscreen responses from one or both monitors via a program written in Python using the Pygame module.

Procedure—The experiment began with verbal instructions about the overall nature of the task, which was to reach out and touch red circle targets as they appeared on the touch screen monitor, one at a time, as quickly as possible. Each target was 2.3 cm (0.9 in) in diameter, and the targets appeared in a repeated order (see Figure 1). The first target started in the top left quadrant, the next appeared in the top right quadrant, then lower left quadrant, and finally the lower right quadrant. All targets immediately appeared at the next quadrant following an accurate touch response. This cycle repeated 300 times in each block.

An auditory tone 200 ms in duration followed each target response to indicate the response time. The frequency of the tone was linearly related to the response time within a bounded range. The lower bound was 250Hz at 1750 ms or longer, and the upper bound was 2000Hz at 0 ms. The tone indicated performance to participants, with higher frequency meaning faster performance, and lower frequency meaning slower performance.

The left hand responded to targets in the left two quadrants, and the right hand responded to targets in the right two quadrants (see Figure 1). Participants in the individual condition used their left and right hands to respond to all targets, whereas participants in the dyadic condition responded to only half the targets. One dyadic participant was chosen at random to respond to left sided targets with their left hand and the other responded to right sided targets with their right hand (see Figure 1). All participants saw all the targets in all four quadrants, and dyads could see their partner’s touch responses as brief gray concentric rings centered on the response location.

Target drifted within their quadrants from one response to the next, and drift was either random or based on participant responses. In the random drift condition, the position of each next target was shifted in a random direction, by a deviation sampled uniformly between zero and the target radius. The new position was translated to the next quadrant to position the next target, and drift outside the quadrant boundary was reflected to keep targets within bounds. In the dependent drift condition, the new center of each target was determined by the previous response location within the previous target, which was also bound within the target radius. Also, target positions were restricted from drifting off the screen, in that at least half the target circle was always visible.

Altogether, the task was identical for individuals and dyads, except individuals responded to all the targets whereas each member of a dyad responded to only half the targets. Each experimental block of 1200 targets was preceded by 40 practice targets. Each individual participant and each dyad completed one random drift block and one dependent drift block. The order of blocks was counterbalanced across participants.

Data Analyses—Responses both inside and outside the target areas were recorded, but only accurate responses counted towards response times and dependent drift. The primary dependent variable of interest was the time between consecutive responses, i.e. IRI. All left-hand IRIs started with a right-hand response and ended with a left-hand response, and vice versa for right-hand IRIs. Everyone response had an associated IRI because each next target appeared only after each prior response, i.e. responses were forced to be interleaved. The IRI represents performance given the goal of completing each block as quickly as possible. Inaccurate touches outside the target radius (errors) necessarily caused longer IRIs because the next target did not appear until the current target was touched. Therefore, IRIs captured both the speed and accuracy of performance because inaccurate responses necessarily increased IRIs.

IRIs that were above or below 2.5 standard deviations were replaced with the mean IRI for the corresponding block—on average, 2.9% of responses were replaced. The 1200 responses in each block were separated in half by the left and right hands. The last 512 responses of each hand for each block were retained and analyzed. Figure 2 shows example IRI time series for the left and right hands from each of the four different conditions.

The time series show that IRI fluctuations tend to rise and fall together, indicating visual evidence of correlational matching. However, closer examination reveals that fluctuations covary over timescales of multiple trials, and not necessarily trial-to-trial. We explored the scale at which to measure correlational matching by correlating IRI series after convolving them with a moving average window of several different widths. Correlational matching on longer timescales was measured by correlating series convolved with wider moving average windows. We tested windows in multiples of four, to correspond with one cycle of responses over the four quadrants. Correlations began to asymptote at a window size of 16 responses, so for the results reported herein, we measured correlational matching by correlating IRI series after being smoothed by a moving average window 16 responses wide.

We used spectral analysis to measure temporal autocorrelations in IRI time series as a function of condition, and to measure the degree of complexity matching in response time fluctuations between the left and right hands (next section). Temporal autocorrelations in response time series are commonly expressed as an inverse relation between frequency and spectral power (Gilden, 2001; Holden, Van Orden, & Turvey, 2009; Kello, Beltz, Holden, & Van Orden, 2007). When temporal correlations extend over many trials (i.e. long-range correlated), the spectral function often resembles a power law as expressed by a linear relation between spectral power and frequency in log-log coordinates.

For long-range correlated time series, power estimates in the raw spectrum become less reliable as frequency increases (Thornton & Gilden, 2005). We used logarithmic binning of spectral power as a function of frequency to standardize the statistical reliability of power estimates. The number of estimates averaged per bin doubled from bin to bin, moving from lowest to highest frequency, with the log-binned spectral power for the highest frequency averaged 128 power estimates in the raw spectrum. Statistical tests have shown that power laws usually provide the best fits to behavioral time series compared with short-range correlations (Gilden, Thornton, & Mallon, 1995; Kello, Anderson, Holden, & Van Orden, 2008; Wagenmakers, Farrell, & Ratcliff, 2004), but here we are only interested in capturing variability in the degree of autocorrelation across timescales, rather than determine the best fitting statistical function. Therefore, it will suffice to estimate degrees of autocorrelation by fitting polynomial functions to log-binned spectra in log-log coordinates.

Complexity matching is commonly measured in terms of correlations in the linear coefficients of fits to log-log spectra (or analogously for detrended fluctuation functions; Delignières & Marmelat, 2012; Marmelat & Delignières, 2012). In analyses of speech (Ramirez-Aristizabal, Médé, & Kello, 2018), complexity matching has been based on fits to the long and short frequencies of variation separately, rather than all measured timescales. The reason is that speakers match prosodic features of their speech that span longer timescales (e.g. phrases and other large units of language), and the utilized measures of clustering in speech timing are sensitive to prosodic variations (Falk & Kello, 2017). However, the perceptual-motor task employed herein is not like a conversation. Speakers have relatively few constraints on how they coordinate their utterances because conversational turns may vary widely in length, as well as pauses and even periods of overlap in speaking. By contrast, the target aiming task requires strict timing and sequencing between the left and right hands. It is possible that the hands are too constrained to vary freely and match their correlations over long timescales like those observed for speech. Therefore, we tested complexity matching over three overlapping windows of timescales shifted from low to middle to high frequency ranges.

Out of eight logarithmically binned estimates of spectral power, we shifted a window of six timescale bins from the lowest six frequency bins, to the middle six, to the highest six frequency bins. The ranges roughly corresponded to fluctuations over as many as 256 responses for the low range, 128 responses for the middle range, and 64 responses for the high range. A complexity matching measure was computed for each estimate by correlating the corresponding left- and right-hand slopes. As expected given the difference in constraints between conversations and the Fitts' task, the high range yielded the strongest mean correlation across conditions, $r(118) = 0.421$, followed by the middle range, $r(118) = .184$, and then the low range, $r(118) = .118$. All remaining spectral analyses were conducted on the high range of frequency bins.

Finally, testing the relationship between complexity matching and performance required a measure of complexity matching per trial, which is not afforded by the correlational measure that spans over samples of trials (our measure of correlational matching is per trial by nature). We measured complexity matching for a given trial by taking the absolute difference between the left- and right-hand linear coefficients, with smaller differences meaning closer matching of autocorrelations in left- and right-hand response series.

RESULTS

Total Time and Errors—We first analyzed overall performance for each condition in terms of the total amount of time it took to complete each block. A two-way analysis of variance was conducted with Group Type as a between-subjects factor (individual versus dyadic), Movement Type as a within-subjects factor (random versus dependent drift), and participants as a random factor. We found a significant main effect of Group Type, $F(1, 58) = 17.71$, $p = .001$, $\eta_p^2 = .234$, a main effect of Movement Type, $F(1, 58) = 66.01$, $p < .001$, $\eta_p^2 = .532$, and a significant interaction, $F(1, 58) = 4.73$, $p = .034$, $\eta_p^2 = .075$, (see Figure 3). Individuals were faster than dyads, the dependent drift supported faster responses compared with random drift, and individuals were better able to take advantage of dependent drift compared with dyads.

Next we analyzed the mean number of errors in each condition. There was only a significant main effect of Group Type, $F(1, 58) = 43.24$, $p < .001$. Individuals responded more quickly but also made more errors. Mean error rates are as follows: Individual Dependent ($M = 154$, $SD = 85.9$); Individual Random ($M = 172$, $SD = 105$); Dyadic Dependent ($M = 56.6$, $SD = 46.4$); and Dyadic Random ($M = 52.2$, $SD = 35.6$). This result indicates faster responses from individuals were partly at the cost of errors, but the time lost recovering from errors did not exceed the gain in speed. Dyads did not benefit from speed gains accompanied by increased errors, possibly because of real or perceived social costs of errors when performing the task with a partner, and possibly because it was harder to recover from errors when coordinating with another person.

Complexity Matching—Figure 4 shows the mean log-binned spectra for left- and right-hand time series as a function of condition. The functions follow the inverse relation between spectral frequency and power that is characteristic of long-range autocorrelations in all four conditions, with flattening in the higher frequencies due to random measurement noise and timing errors. The figure also shows that spectral functions were steeper for dyads and dependent drift compared with individuals and random drift, respectively. We do not analyze these differences further because they are not relevant our interests in complexity matching, correlational matching, and perceptual-motor performance.

Complexity matching was first measured by positive correlations between linear coefficients of left- and right-hand spectra. We found complexity matching in terms of significant positive correlations for individuals in both movement conditions and the dyadic dependent drift condition, but not for dyadic random drift (see Figure 5). Correlations coefficients and statistics for each condition are as follows: Individual Dependent, $r(28) = .59$, $p = .001$; Individual Random, $r(28) = .41$, $p = .023$; Dyadic Dependent, $r(28) = .63$, $p < .001$; and Dyadic Random, $r(28) = .06$, $p = .772$. These correlations indicate that complexity matching occurred when the hands were coordinated *either* within an individual, *or* through dependencies in the positions of targets across left and right hands. When neither channel of coupling was available, then complexity matching was inhibited.

Correlational Matching—We measured correlational matching per response series by correlating the left- and right-hand IRI series, after convolving each one with a moving average window 16 responses wide. The mean and variance of Pearson's *r* values following a Fisher's z-transformation is shown in Figure 6 below, separated by condition. The graph shows that nearly all correlations were > 0 in all four conditions, indicating that correlational matching was a general feature of performance in our coordinated Fitts' task, even when coupling was inhibited in the dyadic random drift condition.

To test whether correlational matching varied by condition, we conducted a two-way analysis of variance with Group Type as a between-subjects factor (individual versus dyadic), Movement Type as a within-subjects factor (random versus dependent drift), and participants as a random factor. We found a significant main effect of Group Type, $F(1, 58) = 8.10$, $p = .006$, $\eta_p^2 = .122$, and a main effect of Movement Type, $F(1, 58) = 5.16$, $p = .027$ $\eta_p^2 = .082$, but there was no significant interaction between Group Type and Movement Type, $F(1, 58) = 0.80$, $p = .374$, $\eta_p^2 = .014$. Figure 6 shows that correlational matching was greater for individuals and dependent drift compared with dyads and random drift. This pattern of results indicates an additive effect of internal coupling and response coupling for correlational matching, whereas the complexity matching results indicated a multiplicative effect because spectral coefficients were equivalently correlated when either coupling was present, but uncorrelated when neither coupling was present.

Matching and Performance—Next we tested whether performance was correlated with our two measures of matching using a 2×2 mixed effects model with total time as the dependent variable, and movement type and per-series complexity matching as the predictors. Complexity matching exhibited a non-statistically significant, negative relationship with total time, $F(1,57) = 3.27$, $p = 0.07$, $\eta_p^2 = .054$. The weak trend suggests that better performance is, if anything, associated with *less* complexity matching, but the lack of reliability means that we cannot draw any conclusions based on these results alone. The same analysis conducted with correlational matching as the dependent measure yielded no reliable relationship with performance.

Distance and Angle Variability—To this point, the drift manipulation employed in Experiment 1 has been framed in terms of response coupling—dependent drift is a channel for left and right responses to affect each other, and random drift eliminates this channel while preserving target movement. The two different drift conditions were designed to be roughly equivalent in terms of drift magnitude, mainly by virtue of bounding them within the same radius. However, random drift steps were drawn from a uniform distribution, without directional bias, whereas dependent drift may be corrective and hence autocorrelated with smaller step sizes. If so, complexity matching may be facilitated by less variability and greater predictability in dependent drift rather than response coupling *per se*.

We measured each angular and distance deviation in target position and plotted their histograms aggregated over response series, as a function of group type and movement type (see in Figure 7). The random drift conditions showed uniform distributions, as expected. The dependent drift conditions were far from uniform, showing large biases towards smaller steps in corrective directions *opposite* the prior target movement. This anti-persistence in drift direction indicates that participants used their control over drift to stabilize the targets in the middle of the screen, somewhat more so for individuals than dyads. Individuals as a group responded much faster overall compared with dyads, trading off speed for larger drift deviations as shown in Figure 7, which they counteracted somewhat through increased negative feedback.

The directions and sizes of dependent drift deviations indicate that the effect of dependent drift on complexity matching may have been due to increased predictability in target positions. The other possibility, which we originally hypothesized, is that dependent drift facilitates response coupling between left and right responses. In turn, this coupling was hypothesized to provide a channel of information exchange that facilitates in complexity matching.

Experiment 2

In Experiment 2, we tested two competing explanations of the effect of movement type by dissociating the possible effect of target predictability from response coupling. We created a “playback” condition in which the series of target positions from each block of the dependent condition of Experiment 1 were used to display targets to new participants in Experiment 2. The new participants experienced the same exact target predictability that occurred in Experiment 1, but without the response-to-response interactions across hands. If the effect of dependent drift on matching (complexity or correlational) is due to target predictability, then the degree of dyadic matching should be the same for dependent drift and playback drift conditions in Experiment 2. By contrast, if matching depended on interactions in Experiment 1, then playback drift should be like random drift, and the playback drift condition in Experiment 2 should replicate the random drift condition in Experiment 1.

METHOD

Participants—To maintain equivalent sample sizes to those of Experiment 1, we collected another 90 students from UC Merced who all participated for course credit. All participants signed a consent form which explained that participation was voluntary, and the experiment could be ended at any time. Of the 90 participants (68 female) who volunteered for this experiment, 75 were right handed, based on which hand they use for writing. We did not analyze handedness further.

Apparatus, Procedure, and Data Collection/Processing—The experimental set up was the same as Experiment 1, as was the experimental protocol and design. Conditions were also the same, except random drift was replaced with playback drift. Each series of playback target positions corresponded to one of the series generated by participants in Experiment 1, such that every series was played back once. Data collection and pre-processing procedures were the same as in Experiment 1.

RESULTS

Distance and Angle Variability—Before reporting the main results, we first verify that dependent drift in Experiment 2 was comparable to playback drift, which was equal to dependent drift in Experiment 1. As shown in Figure 8, variability in drift distance and angular change was highly similar between the Dependent and Playback conditions. This equivalence allows us to ascribe the upcoming effects of dependent drift to response coupling as opposed to target variability / predictability.

Total Time and Errors—A 2 (Group Type – Individual or Dyad) × 2 (Movement Type – Dependent or Playback) two-way ANOVA was conducted with individual or dyad as a random factor. The results indicated a marginally significant main effect of Group Type, $F(1, 58) = 3.7$, $p = .059$, $\eta_p^2 = .06$, and a significant two-way interaction between Group Type and Movement Type, $F(1, 58) = 6.11$, $p = .016$, $\eta_p^2 = .095$, (see Figure 9). Individuals were again faster than dyads, especially with dependent drift, but both drift conditions supported the same overall levels of performance when controlling for group type. These results suggest that target predictability is more relevant to accounting for performance than bimanual interactions created by response coupling. Whether it is more relevant for our measures of matching is addressed after we report the spectral analyses.

As in Experiment 1, we analyzed the mean number of errors in each condition. Again, there was only a significant main effect of Group Type, $F(1, 58) = 17.72$, $p < .001$. Mean error rates are as follows: Individual Dependent ($M = 107$, $SD = 50.3$); Individual Playback ($M = 144$, $SD = 99.8$); Dyadic Dependent ($M = 62.1$, $SD = 65.6$); and Dyadic Playback ($M = 62.5$, $SD = 44.6$). Replicating Experiment 1, individuals responded more quickly but made more errors.

Complexity Matching and Correlational Matching—Mean spectral functions shown in Figure 10 followed the same overall trend as in Experiment 1. The effects of condition were also similar, in that spectral slopes were steeper for dyads compared with individuals, and dependent drift compared with random drift, although the latter difference was attenuated in Experiment 2.

Complexity matching analyses replicated the results from Experiment 1: Linear coefficients for left-and right-hand spectra were positively correlated for both individual conditions and the dyadic dependent drift condition, but not for the dyadic playback drift (see Figure 11). The strength of the correlations for each condition is as follows: Individual Dependent, $r(28) = .57$, $p = .001$; Individual Playback, $r(28) = .71$, $p < .001$; Dyadic Dependent, $r(28) = . 37$, $p = .046$; and Dyadic Playback, $r(28) = .16$, $p = .398$. These results indicate that complexity matching is facilitated by response coupling as afforded by dependent drift, and not target predictability. If predictability was the operative factor, then we would expect complexity matching in all four conditions since target predictability was equated across them.

Correlational matching analyses also replicated Experiment 1, as shown in Figure 12: nearly all smoothed time series correlations were positive in all four conditions, indicative of pervasive correlational matching. An analysis of variance yielded a significant main effect of Group Type, $F(1, 58) = 33.53$, $p < .001$, $\eta_p^2 = .366$, but no significant main effect of Movement Type, $F(1, 58) = 1.26$, $p = .266$, $\eta_p^2 = .021$, and no significant interaction, $F(1, 58) = 0.38$, $p = .542$, $\eta_p^2 = .006$, (see Figure 12). Unlike complexity matching, playback drift facilitated correlational matching to the same degree as dependent drift. Therefore, it appears that correlational matching was affected by target predictability in Experiment 1, and *not* the lack of response coupling in Experiment 2.

Matching and Performance—As in Experiment 1, the relationship between total time and matching was subtle for both measures, but also consistent enough with Experiment 1 that we combined the data from the two experiments into a single analysis. We combined Random and Playback Drift into a single "Uncoupled" condition, and we compared it with Dependent Drift. We conducted an ANOVA with Total Time as the dependent variable, and Drift Type and either complexity matching or correlational matching as the independent measures. Results showed that correlational matching was not reliably related to performance, $F(1, 117) = 2.13$, $p = .147$, $\eta_p^2 = .017$, but complexity matching was marginally related to performance in the dependent drift condition: $F(1, 117) = 3.49$, $p = .064$, $\eta_p^2 = .029$, (see Figure 13). Once again, there was a weak, negative relationship between complexity matching and performance, whereas no such effect was apparent in correlational matching.

DISCUSSION

The main goal of our study was to examine complexity matching and correlational matching as measures of coordination that may generalize across individuals and dyads. In a coordinated Fitts' task, we found both types of matching for individuals and dyads, but the two measures reflected different aspects of coordination. Complexity matching appeared to be more sensitive to response coupling, whereas correlational matching was more sensitive to target predictability. One caveat of this conclusion is that the effect of complexity matching was not fully replicated in Experiment 2, because it was weaker in the dyadic dependent condition compared with Experiment 1. The two conditions were identical, so the difference in reliability may indicate an unknown source of variability that affects complexity matching.

The divergence of complexity matching and correlational matching was also observed in another study that compared complexity matching and correlational matching within individuals. Rigoli, Holman, Spivey, and Kello (2014) asked participants to tap to a visual metronome, and they measured long-range correlations in two fluctuations of tapping responses (keypress times and durations) and two fluctuations of the autonomic nervous system (pupil dilation and heart rate). They found complexity matching between the two keypress measures and also between the two autonomic measures, but no reliable correlational matching among any measured time series. They concluded that complexity matching reflected the interacting networks of activity that produce keypress responses, and likewise within the autonomic nervous system, but that these two sets of networks do not exchange information during a simple, relaxed task of tapping to a metronome.

Results of the current study, taken together with those of Rigoli et al. (2014), support the theory of complexity matching as a measure of information exchange between complex networks. We now have evidence that complexity matching holds equally for interactions both within and between individuals. We also have additional evidence that complexity matching requires coupling between networks to facilitate information exchange, whereas correlational matching does not. These results encourage future investigations into models of information exchange between complex networks that may illuminate principles of intra- and inter-personal coordination.

We also found that individuals performed better overall compared with dyads, which indicates an advantage when one hand can anticipate the response of the other—that is, when the left hand knows what the right hand is doing, so to speak. Also, performance was better overall when there was dependent drift, and this advantage appeared to derive from response coupling as well as target predictability. Finally, there was no relationship between performance and correlational matching, and only a suggestion of a relationship between performance and complexity matching. In particular, complexity matching was related to performance only when responses were coupled via dependent drift, yet better performance was associated with *less* complexity matching. The subtly of this relationship is consistent with previous studies that have found weak or conflicting relationships between matching and performance. Some have shown inverse relationships between performance and measures of coordination, like the current study (Abney et al., 2015; Wiltshire, Steffensen, & Fiore, 2018), and others have shown positive relationships (Abney et al., 2014; Fine et al., 2015; Zapata-Fonseca et al., 2016). Altogether, the evidence suggests that, if there is a reliable relationship between matching and performance, it depends on the nature of the task or other factors yet to be determined, such as the degree or types of constraints on interaction.

Future studies of coordination may advance our methods for measuring coordination and its relationship to performance. For instance, recent advances in studies of human dynamics have introduced multifractal measures of time series (Delignieres & Marmelat, 2012; Ihlen & Vereijken, 2010). Multifractal analyses provide more in-depth measures of long-range temporal dependencies in behavioral dynamics, and recent studies generalized complexity matching to correlate functions of estimated multifractal exponents (Almurad et al., 2018, 2017; Coey et al., 2016; Delignières et al., 2016). Based on prior results, we expected multifractal complexity matching to pattern with the reported complexity matching results, and they did, but not reliably (results not reported here). Future studies may formulate new tasks that require a multifractal measure of matching to see the relationship between coordination and performance.

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Public Significance Statement

Coordination is fundamental to human behavior, and many human activities require complex coordination to be successful—imagine the movements and interactions among two or more sailors working together to tack and jibe through the wind. We studied perceptual-motor coordination in a very simple, alternating aiming task that allowed us to examine the underlying dynamics of two people performing together, versus one person performing the same task alone. We found that individuals coordinate their two hands to aim quickly and precisely in the same way that two people coordinate their four hands to perform the same task. In both cases, we found that the better performers maintain a relatively loose timing relationship between their alternating responses. The results provide evidence for advancing theories of coordination dynamics that apply to both simple and complex instances of human coordination and performance.

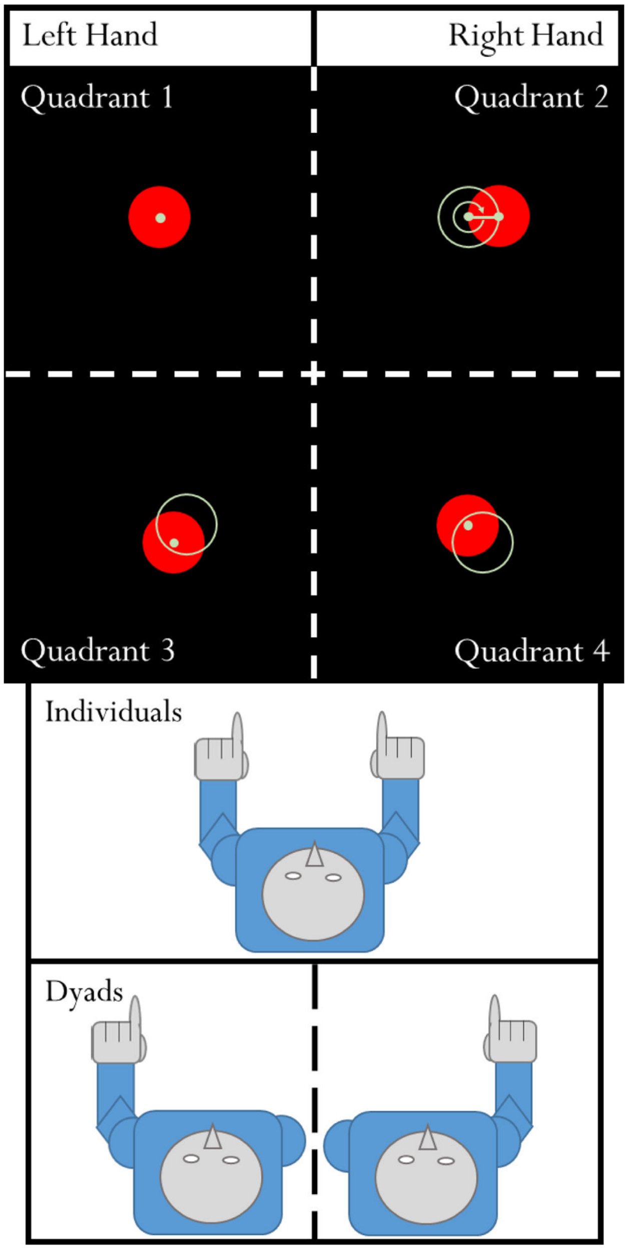

Figure 1.

Top: Four initial response locations are depicted in the individual and dyadic conditions (the white dashed lines were not visible in the experiment). Bottom: Response positions are depicted for individual and dyadic conditions.

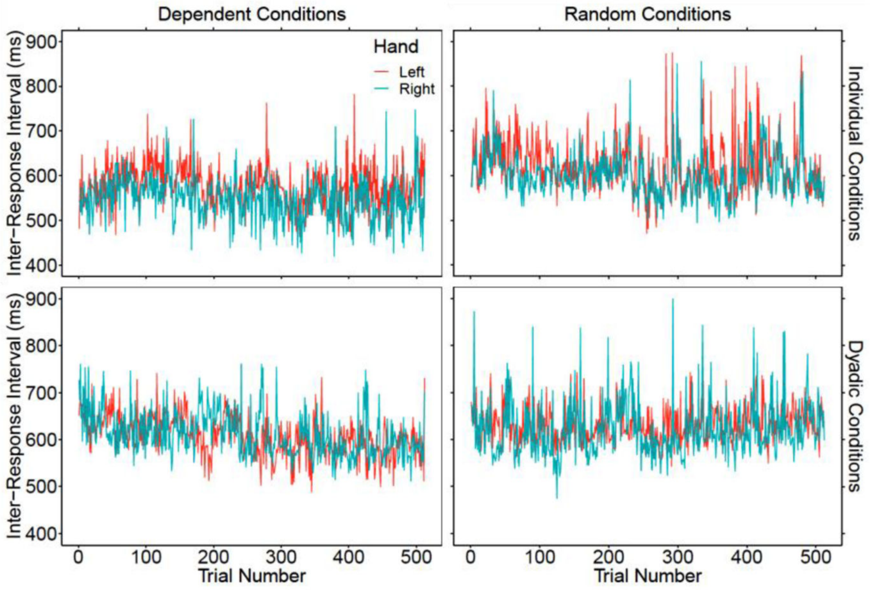

Figure 2.

Example time series for each of the four conditions: Individual dependent (top left), individual random (top right), dyadic dependent (bottom left), and dyadic random (bottom right).

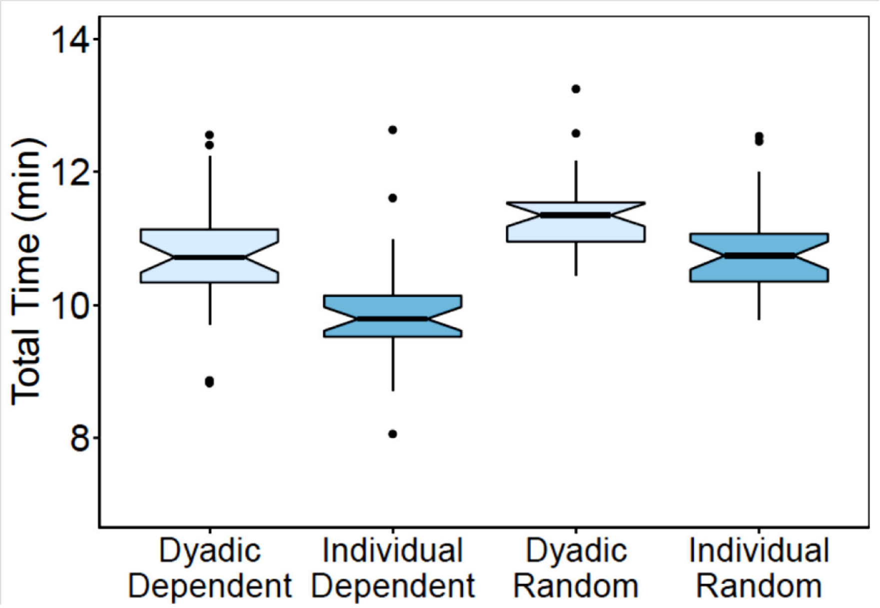

Figure 3.
Total time to complete each block as a function of Group Type and Movement Type. Boxes correspond to group means, and individual points correspond to outliers.

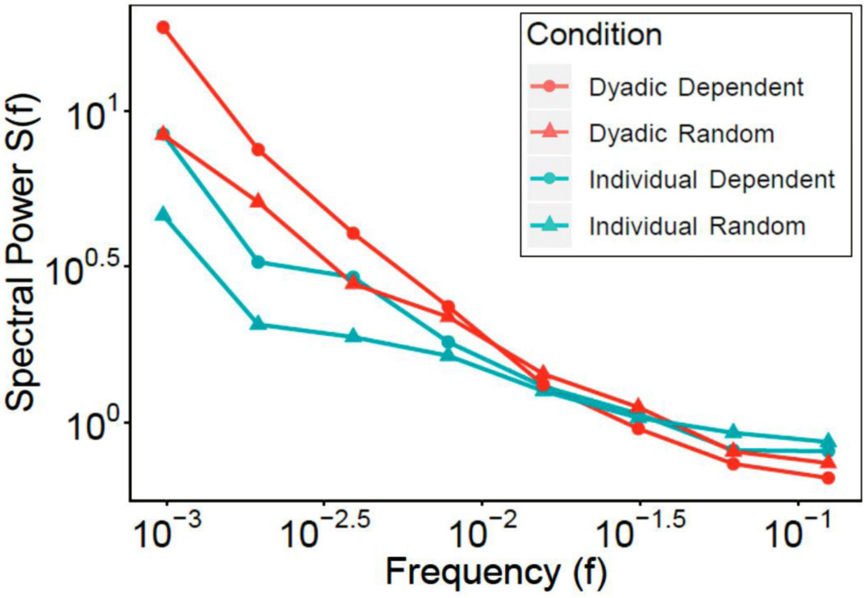

Figure 4.

Logarithmically binned, mean spectra as a function of Group Type and Movement Type. On the x-axis, each bin is equal to one over the frequency of responses. Approximately, the first bin corresponds two responses, the second bin to four responses, third bin to eight responses, etc. The frequency of the log-log bins is roughly equal to the timescale different cycles of responses made in the task.

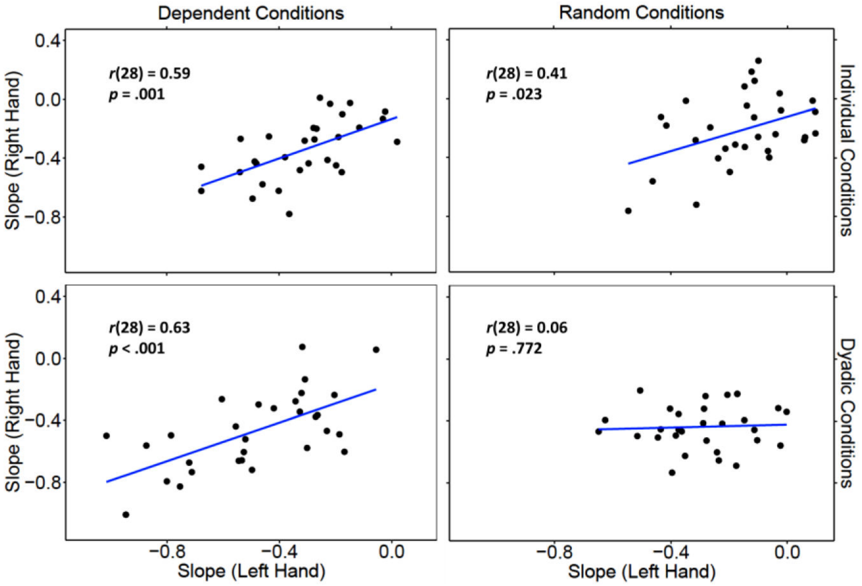

Figure 5.

Left-hand slope plotted against right-hand slope per block, separated by Group Type and Movement Type.

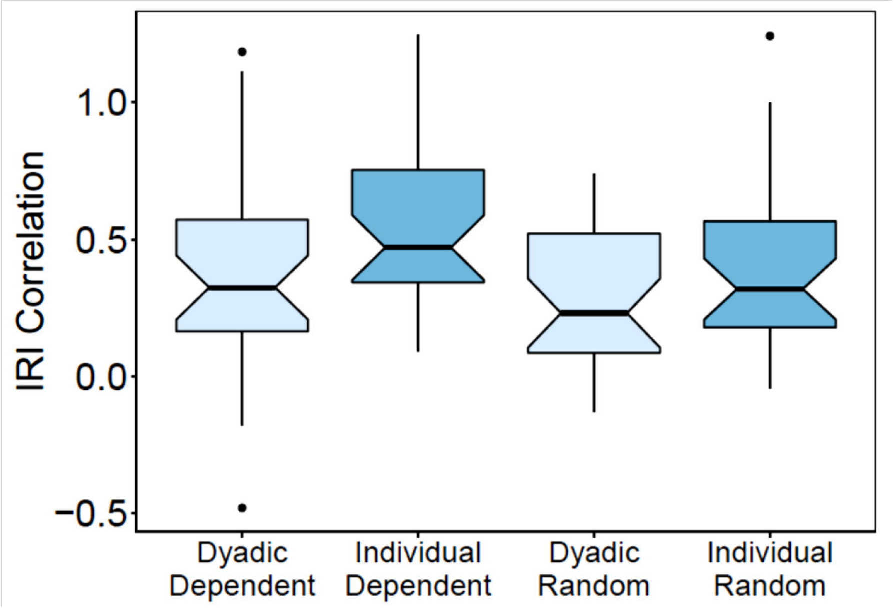

Figure 6.

Correlational matching of smoothed IRI series in each block as a function of Group Type and Movement Type.

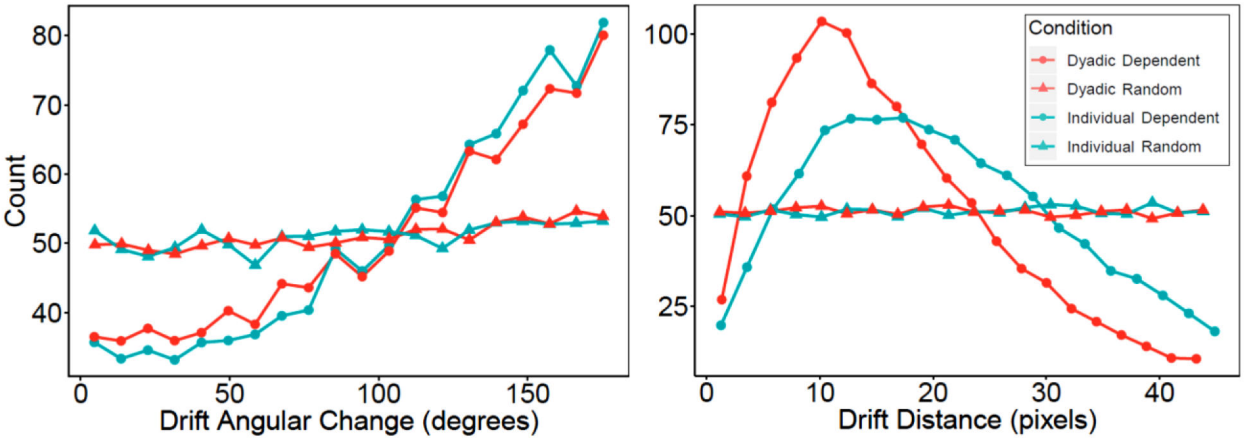

Figure 7.

(Left) Direction in degrees (0°−180°) of target movements from one target to the next by Group Type and Movement Type. (Right) Movement distance of the target (measured in pixels) on the x and y-axis from one target to the next by Group Type and Movement Type.

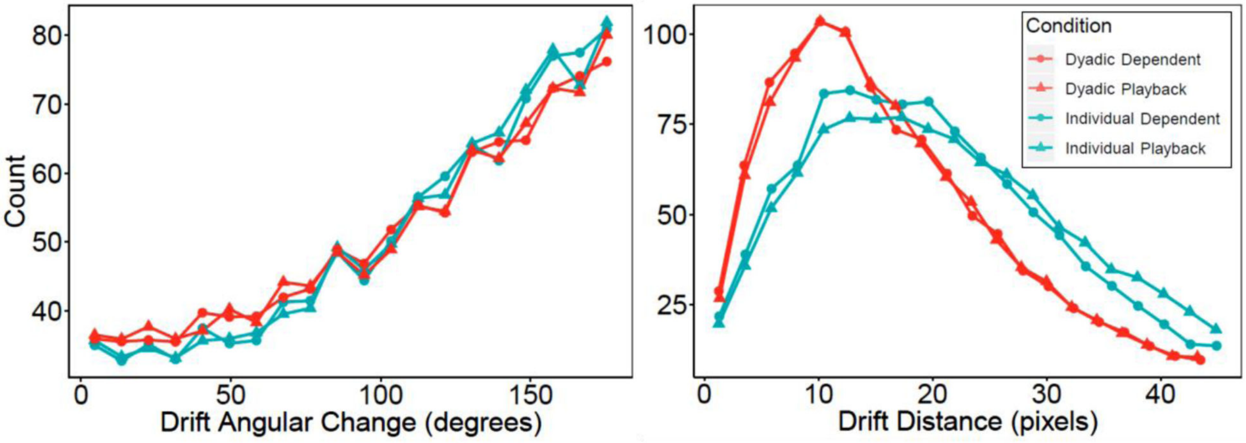

Figure 8.

(Left) Direction in degrees (0°−180°) of target movements from one target to the next by Group Type and Movement Type. (Right) Movement distance of the target (measured in pixels) on the x and y-axis from one target to the next by Group Type and Movement Type.

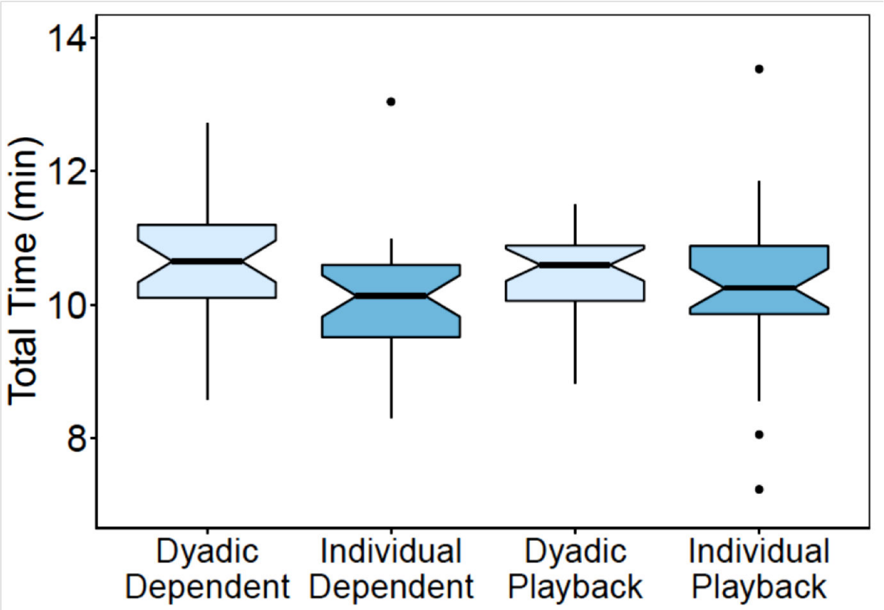

Figure 9.

Mean time to complete each block of targets plotted as a function of Group Type and Movement Type.

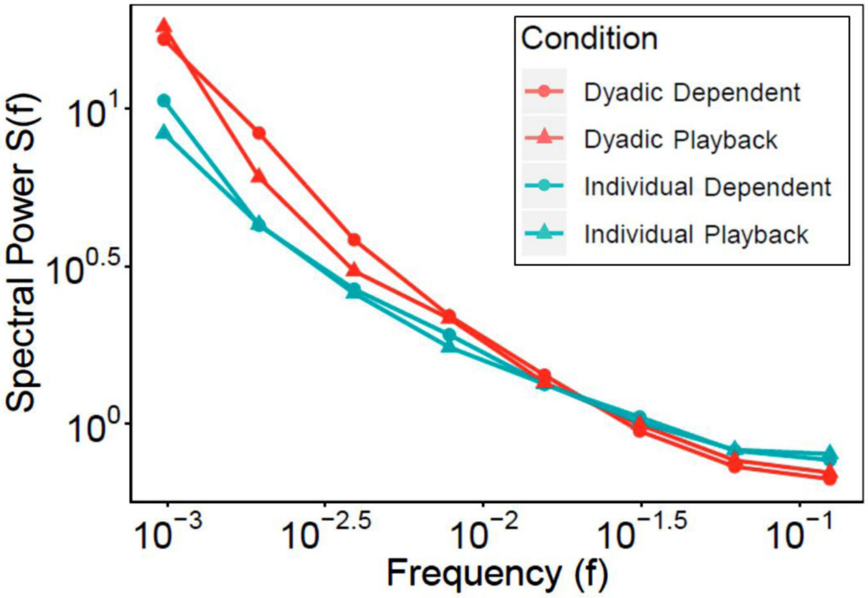

Figure 10.

Mean log-log spectra as a function of Group Type by Movement Type

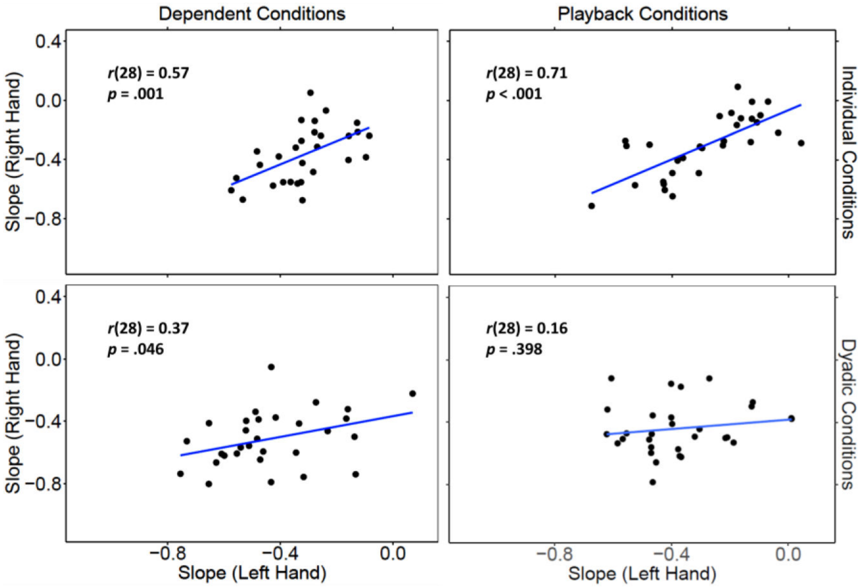

Figure 11.

Complexity matching as a function of Group Type and Movement Type in Experiment 2.

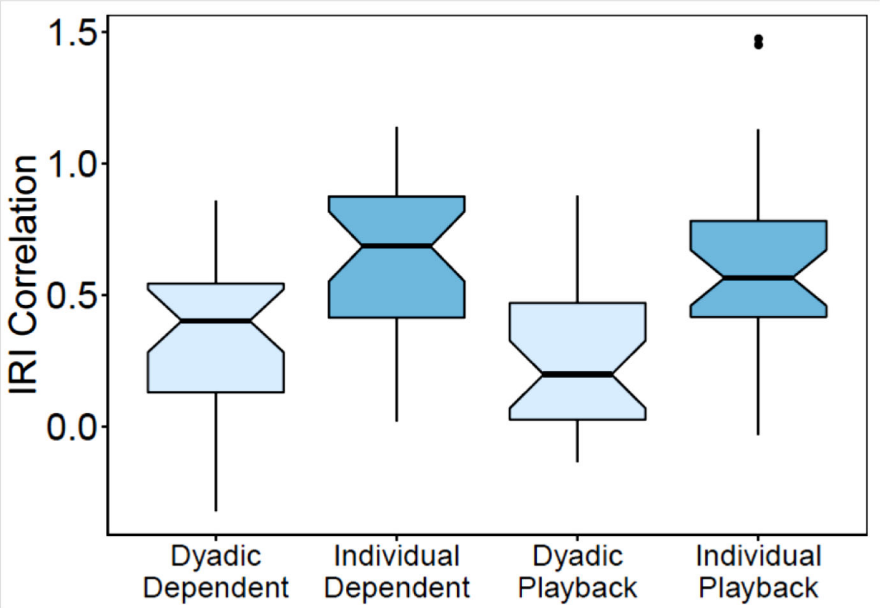

Figure 12.

Correlational matching in Experiment 2 as a function of Group Type and Movement Type.

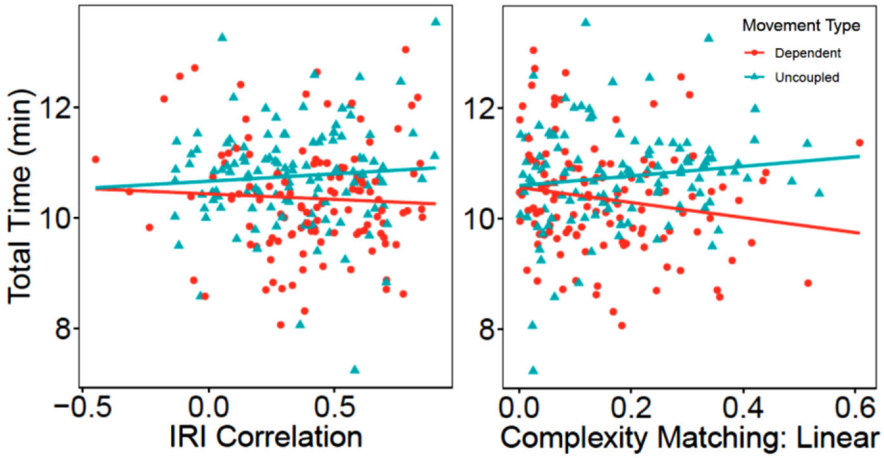

Figure 13.

Correlational Matching (left) and Complexity Matching (right) plotted as a function of Movement Type and combined across Experiments 1 and 2 (Random and Playback Drift combined).