Original article

Multi-scale interactions in interpersonal coordination

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Abstract

Background: Interpersonal coordination is an essential aspect of daily life, and crucial to performance in cooperative and competitive team sports. While empirical research has investigated interpersonal coordination using a wide variety of analytical tools and frameworks, to date very few studies have employed multifractal techniques to study the nature of interpersonal coordination across multiple spatiotemporal scales. In the present study we address this gap.

Methods: We investigated the dynamics of a simple dyadic interpersonal coordination task where each participant manually controlled a virtual object in relation to that of his or her partner. We tested whether the resulting hand-movement time series exhibits multi-scale properties and whether those properties are associated with successful performance.

Results: Using the formalism of multifractals, we show that the performance on the coordination task is strongly multi-scale, and that the multi-scale properties appear to arise from interaction-dominant dynamics. Further, we find that the measure of across-scale interactions, multifractal spectrum width, predicts successful performance at the level of the dyad.

Conclusion: The results are discussed with respect to the implications of multifractals and interaction-dominance for understanding control in an interpersonal context.

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Keywords: Component-dominant dynamics; Interaction-dominant dynamics; Interpersonal coordination; Multifractal; Time series analysis

1. Introduction

To be successful in sports, players must coordinate their actions with others across many different spatial and temporal scales. For example, soccer teammates on an offensive attack must coordinate their more immediate movements in order to complete a pass, while on a longer scale adjust their position and heading to create opportunities to score a goal. On the other side of the coin, defenders must anticipate and match the offense’s strikes and movements, while at the same time making subtle adjustments to steer their opponents to unfavorable positions, thereby reducing the threat of a score. While these cooperation and competition dynamics play out most dramatically in sports, they are present in even the most common of human actions. Indeed, many actions in our work, leisure, and play are similarly best understood as dynamic interactions with others.

An especially fruitful framework for addressing interpersonal or multi-agent coordination of this sort has employed tools and concepts from dynamical systems theory (DST). DST approaches focus on modeling how co-actors may become coupled when performing a shared task—from small-scale interpersonal interactions as when two people rhythmically coordinate their limb movements,1–4 to the types of large-scale coordination dynamics that are present in an attacking side of football players.5 Much of this research has appealed to principles of self-organization to explain how multiple interacting agents may become functionally coordinated without a need for a centralized controller—a significant issue when “control” is spread out among different actors—and how patterns of coordination may spontaneously re-organize to meet changing task demands for both individuals and collectives.

To this end, recent studies have focused on the interpersonal coordination of limb movements when two people engage in a joint supra-postural manual task, one that demands a high degree of manual precision and postural alignment (such as when mutually handling or passing an object). For example, Ramenzoni and colleagues5 asked pairs of co-actors to perform an aiming task where one held a pointer (small rod) inside the bounds of a target ring held by the other. Participants stood facing one another, arms outstretched, and were instructed to

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never allow the objects to come in physical contact with one another. The difficulty of the task was manipulated by varying the size of the ring. Increasing task difficulty (trials with a smaller diameter ring) resulted in increases in interpersonal coordination of hand and postural adjustments, as measured by the number and duration of shared configurations between the two actors. In a follow-up experiment, an additional manipulation was used to challenge the postural stability of each actor. Participants stood either with their feet apart (as before) or with their feet in a tandem stance that reduced postural stability, thereby making the supra-postural aiming task more demanding. This additional task demand resulted in a reorganization of intra-personal coordination at the individual level (between the hand and postural alignments of each individual actor) to preserve the necessary interpersonal coordination required to meet the task. Similar patterns of coordination emerge even in instances where information about the movements of co-actors is limited, and one cannot see their co-actor, but only the movement of the object they are manipulating, suggesting that the emergent coordination may be closely tied to the detection of information related to the task demands rather than an incidental product of visual entrainment.

These studies demonstrate how a nested hierarchy of synergistic intra-personal and inter-personal activity may emerge to meet and adapt to the evolving joint task demands. However, several important questions are left open. First, and perhaps more obviously, we may ask what role (if any) do the individual task demands have on each actor’s relative contribution to achieving the shared goal? For example, in the aforementioned studies the manual (holding ring, holding pointer) or postural (feet apart, feet tandem) demands of the alignment task were different for each actor. As is often the case in cooperative action, co-actors may have adopted complementary roles influenced by their individual constraints in order to meet this shared goal. For example, using a similar paradigm, Nguyen et al. recently demonstrated that coordination between co-actors’ hand movements systematically exhibit a leader–follower dynamic when facing different postural demands (where the person in the stable stance “leads”), indicating that co-actors in this task may spontaneously (without explicit direction) transition into distinct roles provided by their individual constraints.

Second, interpersonal coordination involves the combined activity of multiple agents across multiple, nested spatiotemporal scales—a pass between teammates is nested within an evolving attack and a volley in tennis is one part of an extended rally. A better understanding of interpersonal coordination requires that we are able to capture the nested structure of coordination across these multiple scales. However, it is often the case that analyses of interpersonal coordination dynamics focus on a single scale, or address the nested structure of coordination in a piecemeal fashion, one scale at a time. While relationships between patterns of short- and long-term activity have been often explored within single actors, only recently has research begun to directly address multi-scale coordination in joint tasks.

In the present study, we address these issues using the interpersonal supra-postural manual task paradigm and characterizing the coordination between actors with a complementary form of analysis that has been explicitly designed to address the possibility of multiply nested, contingent structures: multifractal analysis. A number of accessible tutorials on multifractal methods are available, so we do not present another tutorial here. Rather, we first introduce some basic concepts and related measures from multifractal analysis. Then, we present a short description of multifractal detrended fluctuation analysis (MFDFA), the multifractal method we employ here. Finally, we show how these measures may be profitably applied to the study of relatively complex, joint action, such as the interpersonal supra-postural manual task. Specifically, we test: a) whether the hand-motion time series were multifractals; b) if that multifractal structure was indeed indicative of interactions across scales; and c) whether the multifractal index of across-scale interactions, multifractal spectrum width, predicts performance in the dyadic task.

1.1. A brief introduction to multifractal analysis

Multifractal analysis provides a method for quantifying complex distributions that have non-uniform properties across (usually spatial or temporal) scales. A natural starting place for understanding multifractals is to contrast them with mono-fractals (also, just called fractals). Mono-fractals can be considered a special case of multifractals in which a single power-law is sufficient to describe the relationship between the measured quantity (e.g., movement) and the dimension (e.g., time), where a power-law is a particular type of one-parameter model expressing a non-linear function. Fig. 1A and B shows a canonical example, diffusion of a particle in a heterogeneous medium, which follows the power-law relationship \( x^2 \sim t^\alpha \), where \( x^2 \) is the mean squared displacement, \( t \) is time, and \( \alpha \) is the power-law exponent (\( \alpha = 1.4 \), in our current example). The

![Fig. 1](image-url)
slope of the double-log plot provides an estimate of $\alpha$. Famously, fractals maintain the same relationship regardless of the degree to which you zoom in or out on the measured quantity. For example, with a true fractal, movements on the micrometer scale, millimeter scale, and kilometer scale would all follow the same power-law.

Multifractals, by contrast, require multiple power laws to characterize their structure. Different scales of magnitude will have power-laws with different exponents. For example, movement at the micrometer scale might be much faster than that at the millimeter scale. These differences would be captured by a set of power-law exponents. The range of this set of power-law exponents corresponds to the multifractal spectrum width, although the exponents are traditionally transformed before the multifractal spectrum width is calculated. The multifractal spectrum width has been a central measure in multifractal analysis because it nicely summarizes how much diversity is found across scales of magnitude in the data. In the section below on MFDA, we will present the details of how to go from a time series to the multifractal spectrum. At this point, we hope simply to provide an appropriate intuition about the major purpose of multifractal analysis, assessing the heterogeneity of power-laws across scales, a task accomplished by quantifying the width of the multifractal spectrum (henceforth, mfw).

Multifractal analysis has been applied to a large number of problems, including clustering of galaxies in astrophysics, rainfall in meteorology, the spatial and temporal distributions of earthquakes in seismology, and aggregation in single-celled organisms. In the study of human behavior, multifractals have recently been used to investigate the role of movement fluctuations in haptic perception, the dynamics underlying executive control, and changes in the center of pressure supporting posture. Because biological systems are multi-scale in their anatomical structure, it should come as no surprise that sufficiently fine-grained measurements reveal multi-scale fluctuations. What is perhaps more surprising is that proper quantification of these multi-scale fluctuations has shown that key parameters from multifractal analysis are important predictors of macro-scale properties of human health and performance. For example, mfw distinguishes the center of pressure time series of Parkinson’s patients from that of healthy subjects. Similarly, analyses of inter-heartbeat intervals have shown that mfw distinguishes patients at risk for congestive heart failure from healthy patients.

1.2. Multi-fractal structure and interaction-dominant dynamics

In skilled human performance such as pole-balancing, tapping to a complex signal, and hammering to produce beads, multifractal structure has also yielded important insights. A key contrast in analyses of human performance has turned on the distinction between interaction-dominant and component-dominant dynamics. Importantly for our current discussion, both interaction-dominant and component-dominant dynamics can create multifractal time series, but they have very different theoretical implications. Interaction-dominant dynamics are characterized by across-scale effects, whereas component-dominant dynamics are characterized by effects at local scales, although many scales may be in play. Fig. 1C and D show a schematic representation of these two types of dynamics. The panels show the log-log plot from Fig. 1B. The arrows show how effects are distributed across those scales of magnitude. In Fig. 1C, the effects are within relatively local regions of magnitude, consistent with component-dominant dynamics. In Fig. 1D, the effects are distributed across the range of scales, consistent with interaction-dominant dynamics. In the study of human performance, this distinction maps onto theoretical debates about how macro-scale performance results from the activity of the system. Interaction-dominant dynamics implies relatively separable sub-processes that locally handle their assigned tasks. Interaction-dominant dynamics implies that macro-scale behaviors result from complex effects that are distributed across multiple scales of the system.

An important concern in our present investigation turns on demonstrating that the coordination present when two people are engaged in a joint supra-postural task indeed reflects interactions across scales. To this end, we introduce a method of analysis known as Iterated Amplitude Adjusted Fourier Transform (IAAFT) that, when used in conjunction with multifractal analysis, can distinguish interaction-dominant and component-dominant dynamics.

1.3. Implications and predictions for the interpersonal aiming task

In the present study, pairs of participants were asked to perform a precision alignment task similar to Ramenzoni et al., whereby one participant had to keep their manually controlled disk inside the bounds of their partner. Importantly, individuals faced different task demands, or roles—the actor with the smaller disk had to keep his disk within the bounds of his partner’s. Given that multifractal structure has been observed in the corrective movement precision tasks (e.g., Harrison et al.), we expected that analysis of actors’ hand movements in our task would exhibit multi-scale fluctuations. More germane to our present argument, we further expected that actors’ hand movements would exhibit a markedly different mfw depending on the assigned role, as actors faced different demands for precision. In a larger context, this result would add further support to findings that suggest that asymmetries in task demands lead actors to spontaneously settle into patterns of complementary coordination, such as a leader–follower relationship.

2. Methods

2.1. Participants

Sixteen undergraduates (8 pairs) from the University of Connecticut participated in this study for course credit. Informed consent was obtained from all participants. The study was approved by the University of Connecticut-Storrs Institutional Review Board. Participants had normal or corrected to normal vision and were free from recent injury (per self-report).
2.2. Apparatus

We used a short throw projector to display a computer-generated environment onto a vertical white screen. The white screen was translucent so that the display could be viewed from both its sides. Participants were outfitted with two wireless motion tracking sensors (Polhemus Liberty Latus; Polhemus Corporation, Colchester, VT, USA) that collected position data at 188 Hz. Using custom software written by our group, we integrated real-time movement data from the motion sensors with objects and scenes in the computer generated OpenGL graphical environment. This created a “virtual wall” whereby participants’ hand movements were tied to avatars (colored circles) projected onto the screen.

2.3. Procedure

Pairs of participants stood facing one another on opposite sides of the screen (Fig. 2A). Each participant held one motion sensor in their dominant hand while another sensor was attached to their waist. This provided continuous data about their hand and torso movements. The position of each participant’s handheld sensor was mapped to a uniquely colored circle in the display, so that participants could move their respective circles with a hand gesture. The participants could not see one another but only the positions of their avatar circles.

On a given trial, participants aligned their avatars such that the smaller circle (5 cm diameter) remained within the perimeter of the larger circle (8 cm diameter) for 35 s. The relative sizes of the participants’ circles (their roles) were counterbalanced. The color of the circles changed to red whenever they were out of alignment. This also resulted in a performance meter (projected to the right of the display) decreasing in size. The participants were instructed that they must ensure that this meter was not depleted before the end of the trial.

The participants stood either with their feet apart (A) or in a tandem heel-to-toe stance (T) as they performed the alignment task. This resulted in four possible Participant 1-to-Participant 2 stance configurations: AA, AT, TA, or TT. Two trials were performed in every role (2) × stance (4) condition, resulting in 16 total trials for each pair. Here, we focus specifically on the role manipulation and do not consider the stance manipulation further.

2.4. Analysis techniques

2.4.1. IAAFT

IAAFT is a recently developed surrogate technique that, when used in conjunction with multifractal analysis, can distinguish between interaction-dominant and component-dominant dynamics. IAAFT creates surrogates through a shuffling procedure that preserves the original distributional properties and the linear autocorrelation in the time series. The key idea is that if the multifractal structure is a consequence of skew in the distribution and linear autocorrelation, then the surrogates and the original series will have approximately the same mfw. However, if the multifractal structure is the result of across-scale interactions, consistent with interaction-dominant dynamics, the mfw of the original series and the surrogates will differ significantly.

It is important to note that it is the absolute difference between the surrogate and original series that diagnoses the distinction between interaction and component dominance. That is, the original series may also have an mfw that is less than the surrogates, and that (significant) difference still carries the implication of interaction dominance. This highlights the great variety of possible interaction-dominant scenarios, some of which produce narrower spectrum widths than their surrogates. Thus, the distinction between interaction-dominant and component-dominant processes is established by the absolute difference between the surrogate and original spectrum widths. Given that such a difference has been established, the original series width provides an index of the degree of across-scale interactions.

2.4.2. MF DFA

In the current study, we applied IAAFT to the hand motion time series. The resulting surrogates, and their respective original series, were analyzed independently of each other with MF DFA. The goal of MF DFA is to quantify fluctuations as power-law relationships at multiple scales. This is accomplished by dividing the integrated time series into bins, and computing the local variance for each bin, after detrending. The variances are raised to the power of $q/2$. Larger values of $q$ will emphasize larger fluctuations, while smaller values of $q$ will emphasize smaller fluctuations:

$$F_q(S) = \left[ \frac{1}{2N} \sum_{r=1}^{2N} \left| \sum_{s=1}^{r} F^2(v, s)^{q/2} \right|^{1/q} \right].$$
where $F^2$ is the variance within each bin, $v$ indexes the values in the time series in the bin, and $s$ is the bin size. Fig. 3 shows a schematic example of the binning procedure. Each bin in Fig. 3 would yield a variance, typically the residual variance after linear detrending. For each value of $q$, the slope of the log–log plot gives the scaling relationship between the variance and bin size, known as the Hurst exponent. The plot and resulting slope for $q = 2$ is shown. To the extent that the time series has a multifractal structure, each value of $q$ will yield a different slope, our estimate of the Hurst exponent for that level of $q$. A Legendre transformation of the Hurst exponents and $q$ values yields the traditional multifractal spectrum. Fig. 3 shows an example of how an interpoint distance time series is subjected to multifractal detrended fluctuation analysis (MFDFA). A shows the binning procedure; $F^2$ is meant to represent the local calculation of the residual variance after linear detrending. B shows the calculation of the Hurst exponent for a single level of $q$ ($q = 2$). The arrow from B to C shows the placement of that Hurst value in the spectrum of Hurst values over the levels of $q$ (C). The arrow from C to D shows the placement of that value after the Legendre transformation. The width of the multifractal spectrum (mfw) is calculated as the range of $\alpha$ values (D).

Fig. 3. A schematic example of how an interpoint distance time series is subjected to multifractal detrended fluctuation analysis (MFDFA). A shows the binning procedure; $F^2$ is meant to represent the local calculation of the residual variance after linear detrending. B shows the calculation of the Hurst exponent for a single level of $q$ ($q = 2$). The arrow from B to C shows the placement of that Hurst value in the spectrum of Hurst values over the levels of $q$ (C). The arrow from C to D shows the placement of that value after the Legendre transformation. The width of the multifractal spectrum (mfw) is calculated as the range of $\alpha$ values (D).

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3. Results

Time series of hand movements were calculated as the inter-point Euclidean distances in a space defined by the medial–lateral and superior–inferior axes. Fig. 2 shows an example of time series for one trial: the inter-point distance time series for both the small- and large-roles, and the errors for that trial.

In the next section, we describe the epoching procedure we used to assess possible changes in the mfw over time, and how surrogates were generated for each epoch. Then we test whether the original time series and surrogates have different mfw.

3.1. IAAFT and MFDFA

We partitioned the inter-point distance time series measured from the marker on the hand for each participant into eight sequential epochs of 1000 points each, with 200 points overlapping. This allowed us to address the possibility that the multifractal spectrum was changing over the course of a single trial for each individual (and allowed us to assess its relationship to performance, as seen below). We ran MFDFA for each epoch separately, for each participant and trial. The values of the $q$ parameter ranged from −4 to 8 in 0.5 increments. In addition, we performed IAAFT on each epoch (for each participant and trial), generating 10 surrogate time series for each trial. Each of the surrogates was then analyzed via MFDFA independently. In all the analyses that follow, the first epoch
(~5.3 s) was discarded, because for much of this time participants were getting adjusted to the task. The fits of the fluctuation functions were very good, mean $r^2 = 0.98$. Epochs with poor fits, $r^2 < 0.85$, were not considered further in the analyses (less than 1% of MF DFA results).

### 3.2. Distinguishing between component-dominant and interaction-dominant dynamics

An important initial question was whether the original mfw was different from that of the surrogates. A significant difference in width indicates the original series owes a substantial part of its multifractal structure to across-scale interactions, rather than just linear autocorrelations and distributional properties. The top panel of Fig. 4 shows the mean multifractal spectra for the large-circle (left side) and small-circle (right side) role conditions. The blue lines show the spectra for the original series, the red line shows the spectra for the surrogates (averaged over the 10 surrogates per epoch). The width is calculated as the difference along the horizontal axis, the Hölder exponent, $\alpha$, of the maximum and minimum values. The Hausdorff dimension, $f$, is plotted on the vertical axis. As explained above, the Hölder exponents relate to the Hurst exponents that are directly calculated in MF DFA. They give the classic way of quantifying the power-law exponents necessary for describing the relationship between bin size (a time metric) and fluctuation strength (here, hand motion) for fluctuations of different magnitudes. The mfw, the range of $\alpha$, gives an index of how broad the spectrum of power laws must be to describe the data. Narrower spectra are typically interpreted as less complex, because they are tending toward a single power-law. In biological systems, reductions in mfw have typically been associated with less flexible fluid performance. The Fig. 4B shows the mean spectrum width for large- and small-circle conditions, for the original series and surrogates. The original series have significantly wider mfw, indicating that the time series are the result of interaction-dominant processes ($t = 18.15$, $p < 0.001$). This is an interesting result, in and of itself. It suggests that the coordination between the two participants is supported by non-local effects for both the small- and large-circle roles. Put differently, the significant difference here rejects a particular null hypothesis specified by component-dominant dynamics (i.e., that the observed multifractal results are due to linear autocorrelation and distributional properties). Rejecting this null hypothesis puts us in the realm of interaction-dominant dynamics, and supports the interpretation of mfw as a metric of across-scale interactions.

### 3.3. Predicting macro-scale performance with mfw

We were interested in how the degree of multifractality, in the sense of width of the mf spectrum, would predict performance in the task. Performance was measured as the distance between the centers of the two circles (sampled at the same rate as the motion capture markers). For each epoch, we calculated the average distance between the circles over the 1000 samples, henceforth “average error”. Fig. 5A shows the mean average error as a function of epoch. Note that because the pair performs the task jointly (one participant is in the small-circle role, while the other is in the large-circle role), the error scores are at the level of the pair.

We used a linear growth curve model to test whether the spectral width, mfw, predicted average error over epochs. The mfw of the small-circle role (mfw-small) and large-circle role (mfw-large) were entered as effects on both the intercept and slope (epoch). The interaction between mfw-small and mfw-large was entered as an effect on the intercept. Epoch was included as both a fixed effect and a random effect, because change over epochs varied widely across trials and individuals. Random and fixed effects for the intercept were also included. Table 1 shows the resulting coefficients and the ratio of the estimated coefficient to estimated standard error, labeled “t”. All $t$ values greater than 2 are significant by the model comparison, $\chi^2$ test on the change in maximum likelihood. The model predictions are shown in Fig. 5B. Predicted average error is shown on the vertical axis, and epoch is on the horizontal axis. The sub-panel on the left shows the predicted effects when mfw-small is high, the sub-panel on the right shows the
predicted effects when mfw-small is low. The light blue lines show the predictions when mfw-large is low, the dark blue lines show the predictions when mfw-large is high.

When mfw-small is high (left sub-panel), the average error tends to be higher and increases more rapidly than when mfw-small is low (right sub-panel). Both the level and rate of increase in error are moderated by the value of mfw-large. When mfw-large is high, the rate of increase is lower. In Fig. 5B (mfw-small is low), the moderating effect of mfw-large results in error decreasing over epochs. It is important to keep in mind that both mfw-large and mfw-small are time-varying predictors, so the predictions simply describe the set of potential trajectories that a pair of individuals moves across as their mfw values change.

A final issue concerns the relative contribution of interaction-dominant vs. component-dominant dynamics to performance. We showed above that the average mfw for the original series was wider than that of the surrogates, indicating that interaction-dominant dynamics were at work in the task. However, the mfw metrics based on the original series do not eliminate or control for the possible additional contribution of linear local interactions to the mfw values. Thus, we cannot rule out the possibility that some of the effects on performance are due to these local interactions, despite strong evidence for their being non-local (interaction-dominant effects). One simple way to test whether the interaction-dominant processes are contributing to performance is to first control for the component-dominant effects by using the surrogate mfw’s as predictors, and then to see if the mfw’s from the original series continue to contribute significantly to the model. To do this, we took the mfw’s of the surrogates for the small-circle and large-circle series, and created a model exactly parallel to that described above. We then included the set of predictors from mfw’s from the original series, just as described above. Thus, each of the effects in our model now had a parallel surrogate effect in the current model. The crucial issue was whether the set of original effects significantly contributed to the model above and beyond the surrogates. Remarkably, the mfw’s from the original series dramatically improved the fit of the model, even with all the parallel surrogate effects already entered (change in $\chi^2(5) = 33.42$, $p < 0.001$, Table 1). Further, the model predictions themselves were accentuated, not diminished. Fig. 5C shows the predictions, laid out similar to Fig. 4. When the surrogate effects were included to control the linear and distributional properties, the moderating effect of high mfw-large was more similar across levels of mfw-small. When the participant controlling the large-circle had a broader mfw,

Table 1
Growth curve model results.

| Variable | Variance | STD | Correlation | Coefficient | SE | t  |
|----------|----------|-----|-------------|-------------|----|----|
| **Model 1: Effects of mfw on average error**

Fixed effects
- Intercept 0.0089 0.0123 0.723
- mfw-large 0.0119 0.0172 0.691
- mfw-small 0.0022 0.0032 0.942
- epoch 0.0418 0.0216 1.936
- mfw-small*mfw_large 0.0095 0.0024 4.007
- mfw-large*epoch 0.0064 0.0025 2.557

Random effects
- Intercept 0.0000959 0.00979
- epoch 0.0001337 0.01156
- Residual 0.0005079 0.02254

| Variable | Variance | STD | Correlation | Coefficient | SE | t  |
|----------|----------|-----|-------------|-------------|----|----|
| **Model 2: Effects of mfw on average error with mfw for surrogates in model**

Fixed effects
- Intercept 0.0719 0.0176 4.087
- mfw-large 0.0647 0.0212 3.051
- mfw-small 0.0057 0.0251 0.227
- mfw-small-sg 0.1184 0.0431 2.748
- mfw-large-sg 0.1696 0.0364 4.667
- epoch 0.0080 0.0030 2.673
- mfw-small*mfw-large 0.0005 0.0276 0.020
- mfw-large*epoch 0.0148 0.0030 4.987
- mfw-small*epoch 0.0025 0.0037 0.661
- mfw-small-sg*epoch 0.0127 0.0059 2.153
- mfw-large-sg*epoch 0.0191 0.0048 4.019
- mfw-small-sg*mfw-large-sg 0.1807 0.0607 2.714

Random effects
- Intercept 0.00033 0.0057
- epoch 0.000110 0.0106
- Residual 0.000493 0.0222

Note: Estimated coefficients and standard errors (SE) for the fixed effects, and estimated variances of the random effects for two models predicting average error at the level of the pair. The multifractal spectrum width (mfw) for the small role (mfw-small) and large role (mfw-large) are the primary predictors in Model 1. In Model 2, the mfw’s of their respective surrogates (mfw-small-sg, mfw-large-sg) are also included in a parallel set of effects.
error decreased sharply. Conversely, when the participant controlling the small-circle had a broader mfw, error increased. It appears that successful performance (i.e., lower error) was supported by increased across-scale effects for the large-circle role, but decreased across-scale effects for the small-circle role.

4. Discussion

Interpersonal coordination is a key element for many aspects of social functioning, and of central concern for skilled performance in team sports. Using a simple dyadic manual precision task, we showed that interpersonal coordination is a multi-scale phenomena in three important ways. First, the movements of the players’ hands, regardless of whether they were in the small- or large-circle role, showed a multifractal structure. This suggests that interpersonal coordination is supported by multiple scales of the system. Second, the comparison of the surrogates and original series showed that the multifractal structure observed in the original series was consistent with interaction-dominant dynamics. That is, a major source of multifractality appears to be across-scale effects, rather than isolated local-scale effects. The implication is that the control of the system is distributed across scales, as opposed to having a single scale governing the others.

Third, the mfw, a measure of the breadth of power-laws necessary to describe the observed behavior, predicted average error, a measure of performance. Typically, increases in mfw correspond to greater differences between periods of large (irregular) variability and periods of small (regular) variability in the movement time series. Our data suggest that greater mfw for the large-circle role predicts decreases in average error, and less mfw predicts decreases in error in the small-circle role. This result may reflect differences between each paired actor’s movement strategy or online adaptation to meet the individual task demands. For example, mfw of the hand movement time series has been shown to increase when actors aim at relatively smaller targets—as when actors in the current experiment controlled the larger circle. At the same time, differences in the relationship between mfw and performance for each role may reflect the mutual influence, constraint, and compensation of coupled actors as they perform the task. While the relative influence of these sort of “joint task effects” remains an open question, at minimum this result supports our original hypothesis that different roles, as defined by their distinct task demands, are jointly specifying how participants organize to perform the task, even at the level of the microstructure that is supporting the goal-directed behavior (i.e., “keep the circles centered on each other”).

More broadly, the present results add support to recent efforts to understand interpersonal coordination and social cognition as a multi-scale affair. More, the results stress an important lesson for those investigating movement coordination between co-actors. While one can pick out a particular spatio-temporal scale, such as movements in the 1–2 cm range, and focus on how movements at that scale support interpersonal coordination, this choice is not only arbitrary but also likely to misrepresent the phenomenon, because many other scales are

Fig. 5. A shows the mean average error for each epoch. B shows the model predictions for the effect of multifractal spectrum width (mfw) on average error. The separate subpanels show two levels of mfw-small (high on the left, and low on the right). The separate curves show two levels of mfw-large. (In all cases, the third quartile was used as the level for high, and the first quartile was used as the level for low). C shows the analogous set of predictions, but with the mfw values for the respective surrogates also in the model.
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contributing. Thus, multifractals are not just a fancy mathematical toolbox that one can employ if one enjoys complex analyses. Rather, multifractals are set of methods that are capable of handling the nested, multiscale structure produced during human performance. In a very real sense, techniques such as multifractals are motivated by the structure of the data itself, and when employed carefully they can allow us to address fundamental questions of how behavioral systems are organized to the task. For example, in the current case, we showed that performance on the task is predicted by measures of across-scale interactions. This suggests that control during interpersonal coordination is distributed across the system. As we try to understand how complex phenomena occur in coupled biological systems, it will be increasingly important to have the right statistical tools for the job.

Authors’ contributions
TJD conceived of the study, designed the experiments, built the apparatus and program, collected the data, and drafted the manuscript. TRB carried out the MF DFA and performed the statistical analysis. JAD carried out the MFDFA and performed the statistical analysis, and drafted the manuscript. All authors have read and approved the final version of the manuscript, and agree with the order and presentation of the authors.

Competing interests
None of the authors declare competing financial interests.

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