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Title

Easier said than done? Task difficulty's influence on temporal alignment, semantic similarity, and complexity matching between gestures and speech

Running title

GESTURE-SPEECH SYNCHRONIZATION AND TASK DIFFICULTY

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Abstract and key words

Gestures and speech are clearly synchronized in many ways. However, previous studies have shown that the semantic similarity between gestures and speech breaks down as people approach transitions in understanding. Explanations for these *gesture-speech mismatches,* which focus on gestures and speech expressing different cognitive strategies, have been criticized for disregarding gestures' and speech's integration and synchronization. In the current study, we applied three different perspectives to investigate gesture-speech synchronization in an easy and a difficult task: *temporal alignment*, *semantic similarity*, and *complexity matching*. Participants engaged in a simple cognitive task, and were assigned to either an easy or a difficult condition. We automatically measured pointing gestures, and we coded participant's speech, to determine the temporal alignment and semantic similarity between gestures and speech. Multifractal Detrended Fluctuation Analysis (MFDFA) was used to determine the extent of complexity matching between gestures and speech. We found that task difficulty indeed influenced gesture-speech synchronization in all three domains. We thereby extended the phenomenon of gesture-speech mismatches to difficult tasks in general. Furthermore, we investigated how temporal alignment, semantic similarity, and complexity matching were related in each condition, and how they predicted participants' task performance. Our study illustrates how combining multiple perspectives, originating from different research areas (i.e., coordination dynamics, complexity science, cognitive psychology) provides novel understanding about cognitive concepts in general, and about gesture-speech synchronization and task difficulty in specific.

Keywords: gestures; speech; synchronization; gesture-speech mismatches; complexity matching; Multi Fractal Detrended Fluctuation Analysis

1. Introduction

Gestures and speech are two salient aspects of multimodal communication in humans. When people tell a story, explain a difficult problem, or talk about daily affairs, they tend to move their hands in all kinds of ways. Many researchers have therefore proposed that gestures and speech are tightly coupled (e.g. Goldin-Meadow, 2003; McNeill, 1985). Moreover, this tight coupling has been conceptualized as gesture-speech synchronization (e.g. Iverson & Thelen, 1999; Pouw & Dixon, 2019; Treffner & Peter, 2002). Gestures and speech synchronize in time, semantic content, emphasis, and emotional valence (for a comprehensive review, see Wagner et al., 2014).

However, the semantic similarity between gesture and speech has been shown to break down as people approach transitions in understanding (e.g., an insight into a difficult problem; Church & Goldin-Meadow, 1986; Goldin-Meadow, 2003). For instance, in a liquid conservation task a researcher pours equal amounts of water into a wide glass and a narrow glass and asks a child which glass contains more water. When a child is about to learn the concept of conservation, they might say that there is more water in the narrow glass because the level of water is higher, while they gesture about the width of the glasses (Church & Goldin-Meadow, 1986). These instances of semantic dissimilarity are called *gesture-speech mismatches*.

Different explanations exist for the breakdown in semantic similarity between gesture and speech when people approach transitions in understanding. Goldin-Meadow and colleagues' (Church & Goldin-Meadow, 1986; Goldin-Meadow, 2003) explanations center around participants' conflicting cognitive strategies and hypotheses that are thought to exist just before participants achieve a new insight into the problem they are working on (e.g. liquid conversation task). These conflicting strategies and hypotheses are then somehow differently expressed in gestures than in speech, during gesture-speech mismatches. However, Koschmann (2017) questions the existence of gesture-speech mismatches in the first place, and suggests that they are an artefact of the disintegrated methodological coding systems that led to their discovery. Furthermore, Pouw et al. (2017; also see Pouw et al., 2014) highlight an explanatory gap in how an integrated gesture-speech system could produce disintegrated gesture-speech mismatches, and suggest taking a dynamically embodied perspective to address this gap.

From a dynamically embodied, complex system's perspective, a change in understanding can be seen as a system of interrelated components which transitions from one stable state to a new, likely more advanced, stable state (Smith & Thelen, 2003; Stephen, Boncoddo, et al., 2009; Stephen, Dixon, et al., 2009; Thelen & Smith, 1994; Thelen & Smith, 2007; Van Geert, 2008; Van Geert, 2011). A transition from one stable state to another entails a reorganization of a system's components and their relations. This reorganization is elicited by a perturbation, that is, the learning situation. As put forward by De Jonge-Hoekstra et al. (2020), a metaphor for this reorganization is building a new LEGO-structure from an old structure, which is only possible when you break (perturb) the old structure and use the bricks to create a new structure. Taking such a dynamically embodied, complex system's perspective, De Jonge-Hoekstra et al. (2016) suggest that difficult tasks perturb a system, thereby inducing a suboptimal coordination between gestures and speech, which could then lead to various forms of gesture-speech mismatches.

In this study, we empirically address whether task difficulty indeed affects gesture-speech synchronization. We will approach gesture-speech synchronization in three ways: 1) temporal alignment, 2) semantic similarity, and 3) complexity matching (explanation follows below). We will investigate how task difficulty affects temporal alignment, semantic similarity, and complexity matching between gestures and speech, and how these different forms of gesture-speech synchronization are related. In addition, we will investigate how these three gesture-speech synchronization measures predict task performance.

1.1 Synchronization

Synchronization usually means that two (or more) systems start to behave in a similar way due to coupling (Pikovsky et al., 2001). In cognitive science, synchronization comes in different forms, including temporal alignment, semantic similarity, and complexity matching. We will explain these three forms below, and describe how they have been linked to gesture-speech synchronization.

1.1.1 Temporal alignment. Temporal alignment is a well-known form of synchronization. A simple and widely used example of temporal alignment are two asynchronously ticking metronomes, which start to tick in synchrony when they are placed on a shelf on top of two cans that act like wheels (the movement of each metronome is transmitted through the wheels thus providing coupling; see Figure 1). Also within humans, body parts such as fingers (e.g. Haken et al., 1985; Kelso, 1994) and legs (Clark et al., 1988) have been shown to synchronize and temporally align in rhythmic patterns. Moreover, a recent study by Pouw et al. (2018) shows that speech is more rhythmic when it goes together with more gestures, suggesting a rhythmic synchronization between gestures and speech within humans. This paradigm of one-to-one temporal alignment of behavior has been applied to coordination between humans, where it has been found that humans tend to move in synchrony while

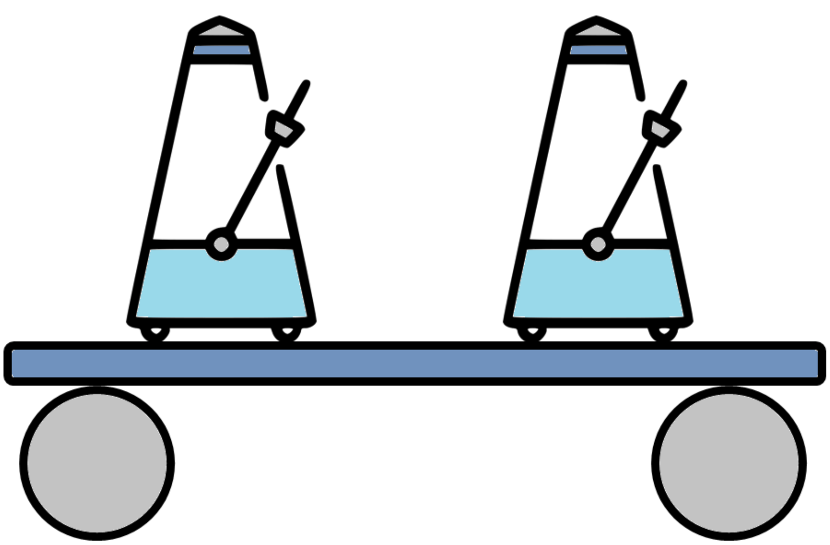

Figure 1. Synchronization of coupled metronomes.

rocking in rocking chairs (Richardson et al., 2007), swinging pendulums (Richardson et al., 2005; Schmidt & O'Brien, 1997), or telling jokes (Schmidt et al., 2014), to name a few examples.

With regard to temporal alignment between gestures and speech, adult's gestures and speech are highly aligned in time (see Wagner et al., 2014, for an overview). In other words, most gestures beat in-phase, and at the same rhythm as speech (Prieto & Roseano, 2018; also see Pouw et al., 2018). For gestures, this rhythm consists of changes in hand-movement velocity over time, while for speech this rhythm refers to the organization and contrast of a sequence of repeated speech events, and can be tracked acoustically through the amplitude envelope of speech (also see Fowler, 2010). To support the existence of temporal alignment between gestures and speech, several studies indicated that the moment of *maximum effort* in gestures goes together with changes in pitch (i.e. relative frequency, "highness" or "lowness") of speech (Kendon, 1972; Kita et al., 1998; Leonard & Cummins, 2011). Recent studies by Pouw and colleagues (Pouw et al., 2018; Pouw & Dixon, 2019a, 2019b) showed that this relation between maximum gestural effort and speech is actually a tight alignment of peak velocity in gestures and peak pitch in speech.

Some circumstances affect the temporal alignment between gestures and speech. Children's age is a robust correlate with the temporal alignment between gestures and speech. According to Iverson and Thelen (1999), the coupling between gestures and speech in infants emerges from natural oscillations of hand movements and vocal acts, which synchronize and become entrained over time (see also Esteve-Gibert & Prieto, 2014; Iverson & Fagan, 2004). As a consequence of this entrainment, the temporal alignment between gestures and speech becomes higher when infants and toddlers grow older (Butcher & Goldin-Meadow, 2000; also see Iverson & Thelen, 1999). Adults' gestures and speech are so tightly coupled in time, that perturbing and delaying speech with a Delayed Auditory Feedback also delays gestures (e.g. Rusiewicz et al., 2013, 2014). Pouw and Dixon (2019) found that a Delayed Auditory Feedback actually increases the temporal alignment between gestures and speech. Lastly, Bergmann et al., (2011) found that gestures and speech were more temporally aligned when their semantic content was more similar.

1.1.2 Semantic similarity. Semantic similarity refers to similarities in *meaning*. Humans can synchronize on a semantic level, whereby they align their "[…] understanding of the world with others […]" (Dumas & Fairhurst, 2019, p. 10). Important to note is that semantic synchronization is not confined to (spoken) language, but can take other action forms involving other body movements as well (Dumas & Fairhurst, 2019). Bodily forms of semantic, meaningful synchronization, such as playing give-and-take-games, or interpersonal movement coordination when a parent dresses their child, seem to be essential for language development. Furthermore, differences in the semantic similarity of two people's words influence their bodily synchronization (see Shockley et al., 2009, for an overview).

Gestures and speech are considered to be semantically similar when a gesture is temporally aligned with a word or phrase, and both gesture and word/phrase convey the same meaning (cf. Wagner et al., 2014). Based on this definition, a distinction has been made between gestures that convey either *redundant*, *complementary*, *non-redundant,* or *mismatching*[1] semantic content to speech. Most of our gestures are either redundant (e.g. saying "The shelf is long" while gesturing that something is long) or complementary (e.g. saying "The shelf is [this] long" while gesturing the length of the shelf) to speech. Studies with participants from different languages show that the typical structure and semantic content of a language influence the semantic content of gestures (Allen et al., 2007; Kita & Özyürek, 2003), highlighting the usually strong semantic similarity between gesture and speech.

However, sometimes the semantic content of gestures and speech does not overlap, and is thus non-redundant in general (Goldin-Meadow et al., 1993). Examples of non-redundant semantic content are a child who points to a cup while saying that they are thirsty, or a teacher who explains two

[1] Studies differ in whether they differentiate between non-redundant or mismatching content (Wagner et al., 2014).

strategies for a problem at the same time: One in speech, and the other in gestures. In these examples, the semantic content of gestures and speech does not overlap, but their meaning is related and falls within an overarching theme (resp. “drinking”, and “problem solutions”). Mismatches between gestures and speech are a specific kind of non-redundant semantic content. As previously described, mismatches are known to occur when a child (or adult) learns a new strategy for a difficult, cognitive problem (e.g. Church & Goldin-Meadow, 1986; Goldin-Meadow et al., 1993; Goldin-Meadow, 2003). Similar to non-redundant semantic content, the meaning of gestures and speech during mismatches does not overlap, but is related.

1.1.3 Complexity matching. Notwithstanding the impact and relevance of the synchronization examples above, involving temporal alignment and semantic similarity, complex systems in the real world often do not synchronize as one-to-one matching of behavior (Delignières et al., 2016). Complex systems, such as gestures and speech, can synchronize on many (time) scales of organization, which is called *complexity matching* (West et al., 2008; Stephen et al., 2008; see also Abney, 2016; Abney, Paxton, et al., 2014; Den Hartigh et al., 2018). During complexity matching, the information exchange between complex systems is maximized (West et al., 2008). Complexity matching occurs when both systems are complex, and the degree of the two systems’ complexity is similar.

1.1.3.1 Gestures and speech as complex systems. Gestures and speech are complex systems. They consist of many different and interacting components and scales, and involve coordination of all these different components and scales of a system over time (e.g., Van Orden et al., 2003). Gestures’ and speech’s scales range from action potentials of neurons to overarching conversational goals, and beyond (see also De Jonge-Hoekstra et al., 2016). For example, numerous muscles and bones in a person’s arms, chest, and even legs, as well as the lungs and central nervous system are involved in each gesture. Importantly, speaking also involves a large number of components; it is estimated that we use more than 70 muscles for each syllable that we utter (e.g., Turvey, 2007).

Infants clearly show how complex gesturing and speaking actually is. Before the first pointing gestures emerge, infants have learned to control their eye movements to focus on an object (Adolph & Franchak, 2017), to use their hands to grasp things, and have learned about distances by crawling forward (Clearfield, 2004). All these actions and perceptions, which are great coordinative accomplishments in themselves, come together in their first pointing gestures. When infant's first words emerge, infants partly 'build' on what they had accomplished for their first gestures (Esteve-Gibert & Prieto, 2014; Goldin-Meadow, 2007). However, uttering their first word involves another set of challenges too. Coordinating all different components to pronounce a specific syllable is a complex task as well, and it usually takes an infant many tries before they grasp the correct configuration. This process is nicely illustrated by Roy (Roy et al., 2015; also see Roy, 2011), who showed how his son went from saying 'gaaaa' to the word 'water', over numerous trials, in about 6 months' time.

***1.1.3.2 Complexity and fractal scaling*.** A complex system's coordination over time (e.g Van Orden et al., 2003) can be more or less fluent. When the coordination of components and layers of a system over time is fluent, the changes of behavior at all different scales are related (e.g. Wijnants, 2014). In other words, variability across time scales is related and dependent, which means that changes on smaller time scales (e.g. neuronal level) influence changes on larger time scales (e.g. conversational goals) and vice versa. If one would plot that system's behavior over time (e.g. time between word onsets during an affective conversation), one would see that small changes in the time series (visible as small *waves*) are nested within larger changes (larger *waves*) (see Figure 2, panel a, for an example). Furthermore, if one would zoom in or out, the plotted time series would look similar at different levels of magnification. In other words, the variability at the level of milliseconds looks like the variability at the level of seconds, which looks like the variability at the level of minutes, etc. Objects that show such self-similarity, such as the Koch snowflake (Figure 2, panel c) or Romanesco broccoli (Figure 2, panel d)

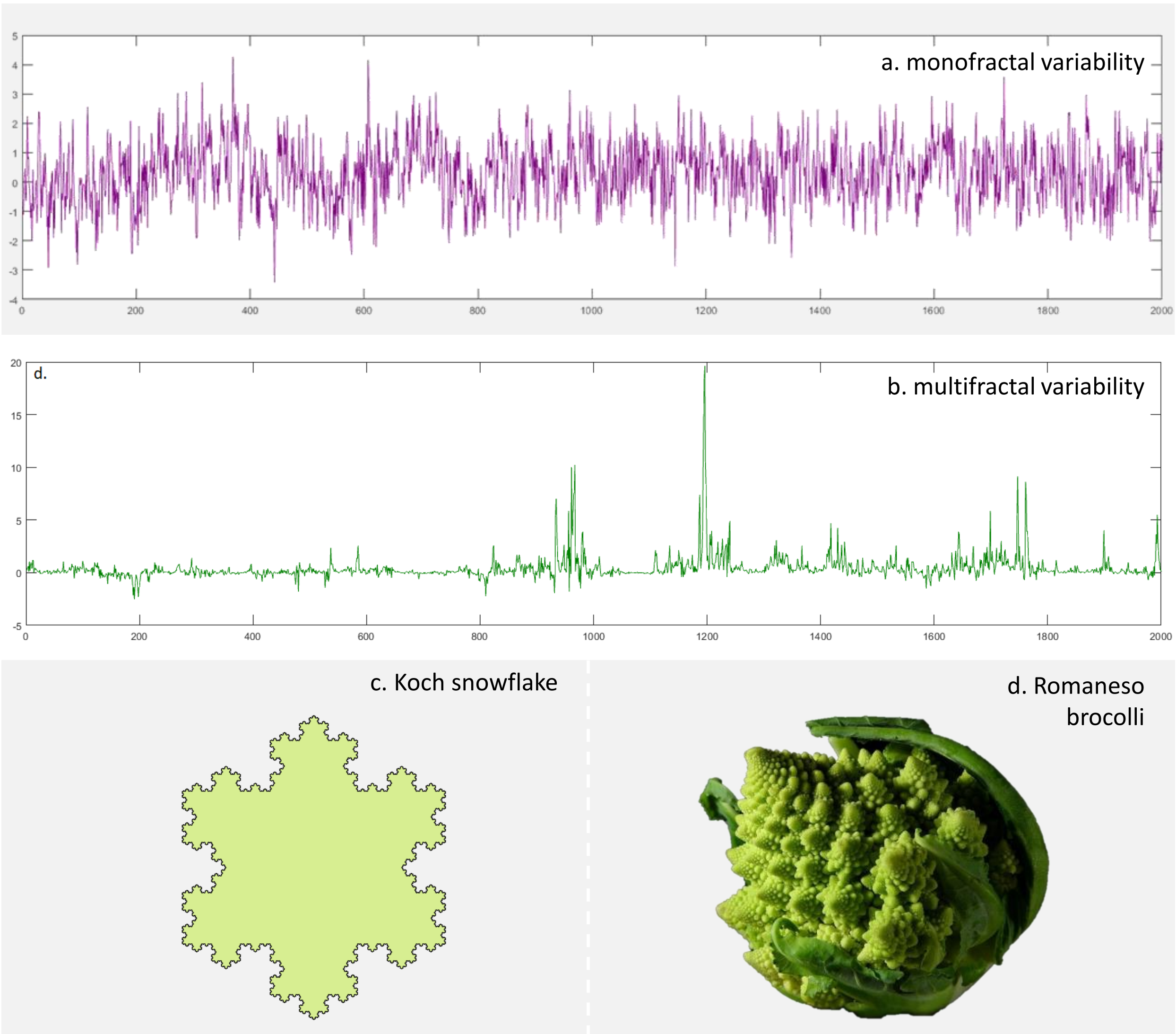

Figure 2. Examples of fractal structures. Panel a shows a timeseries with a monofractal structure of variability (source: script in doi:10.3389/fphys.2012.00141). Panel b shows a timeseries with a multifractal structure of variability, whereby periods of monofractal variability are intermitted by periods of large fluctuations and periods of small fluctuations (source: script in doi:10.3389/fphys.2012.00141). Panel c displays the Koch snowflake (7th iteration; source: bit.ly/2PGeRAd). Panel d displays Romanesco broccoli (source: bit.ly/2wiEccN). The monofractal structures in panel a, c and d are self-similar, which means that they look the same at different levels of magnification. The multifractal structure in panel d is less self-similar.

are also called *fractal* objects. Similarly, a nested, and self-similar[2], structure of variability in the temporal domain is called *(mono)fractal* or *pink noise* (see Figure 2, panel a). Monofractal variability has been proposed as an index of optimal balance between rigid and random behavior, and is often found in complex systems that change over time (Van Orden et al., 2011; Van Orden et al., 2003; Wijnants, 2014). Indeed, many studies found that expert performance on repetitive motor tasks is more *pink* than non-expert behavior (e.g. Den Hartigh et al., 2015; Kloos & Van Orden, 2010; Van Orden et al., 2011). Monofractal variability has thus been considered as an identifying feature of complex systems, corresponding to a systems' degree of complexity.

However, different from relatively repetitive motor tasks, more diverse human behavior shows sudden jumps, and periods of relative stability mixed with intermittent bursts of variability (Dixon et al., 2012; Ihlen & Vereijken, 2010; Kelty-Stephen et al., 2013; Stephen et al., 2012). Moreover, these increases in variability have been related to transitions, which are a hallmark of human (and other complex systems') development. Examples of a sudden jump, which would go along with a burst in variability, are an abrupt change in conversation goals, or the ("aha"-)moment of acquiring new understanding (Dixon et al., 2012). Delignières et al. (2016), Dixon et al. (2012), Ihlen and Vereijken (2010), Kelty-Stephen et al. (2013), and Stephen et al. (2012) argue that timescales *themselves* also interact, and that these interactions between timescales lead to these large changes in variability (for a clear and more in-depth explanation, please see Kelty-Stephen et al., 2013). When variability with a monofractal (pink noise) structure is mixed with periods of changes in variability, these time series display a *multifractal* structure (see Figure 2, panel b). Therefore, identifying complex systems and

[2] Strictly speaking, time series' variability usually is self-affine instead of self-similar, because its dimensions are scaled by different amounts in the x- and y-directions. For purposes of brevity and clarity, we will use the term self-similar throughout the paper.

establishing a system's degree of complexity should also incorporate multifractal variability (Delignières et al., 2016; Dixon et al., 2012; Ihlen & Vereijken, 2010; Kelty-Stephen et al., 2013; Stephen et al., 2012).

1.1.3.3 When does complexity matching occur? As previously described, complexity matching means that the degree of system's complexity is similar, due to coupling. In other words, when coupled systems match their complexity, the fractal structure of their temporal variability is alike.

Circumstances influence complexity matching. Abney et al. (2014) found that type of conversation influences whether complexity matching between two participants in speech occurs. Specifically, when participants discussed things that they had in common, the fractal scaling of participants' acoustic onset events was similar, and their speech thus showed complexity matching. However, no complexity matching was found when participants who discussed issues on which they had different opinions. Furthermore, Almurad et al. (2017) investigated complexity matching between participants who were instructed to walk in synchrony. Participants walked either side-by-side or arm-in-arm (or independently), and the researchers measured the duration of the intervals between their strides. Participants in both (non-independent) conditions showed high levels of complexity matching, whereby arm-in-arm walking led to slightly higher levels of complexity matching than walking side-by-side. With regard to manual coordination between participants in terms intervals between finger taps, fractal hand movements, and a larger magnitude of hand movement's variation, leads to stronger complexity matching between a leader and a follower than random hand movements (Coey et al., 2016). In addition, complexity matching is stronger when participants coordinate movements of both their hands, than when they coordinate the movements of one of their hands to those of a partner (Coey et al., 2018). Most of these studies show that stronger coupling between systems goes together with higher levels of complexity matching (Cox, 2016).

Interestingly, research findings are mixed about whether complexity matching is functional in terms of task performance: While Fusaroli et al. (2013) and Abney et al. (2014) found better task performance with higher levels of complexity matching, Schloesser et al. (2019) and Abney et al. (2015) found an inverse relation. With regard to gestures and speech, De Jonge-Hoekstra et al. (2016) suggest that difficult tasks may influence whether and how gestures and speech synchronize on multiple scales. This would imply that difficult tasks influence complexity matching between gestures and speech.

1.2 Current study

In this study, we investigated how a difference in task difficulty influences the synchronization between participant's gestures and speech, in terms of temporal alignment, semantic similarity, and complexity matching. We asked participants to repeatedly match targets of the same colors presented on a tablet with touch screen, by means of pointing to these targets and saying their location. Participants were assigned to either a predictable, easy condition, or to an unpredictable, difficult condition.

Our first research question is: How does task difficulty influence temporal alignment, semantic similarity, and complexity matching between participant's gestures and speech? With regards to *temporal alignment*, Pouw and Dixon (2019b) found that gestures and speech became more synchronized in the more difficult Delayed Auditory Feedback condition. We therefore expected that gestures and speech would be more synchronized in the difficult than in the easy condition (hypothesis 1A). Regarding *semantic similarity*, Goldin-Meadow and colleagues (e.g. Church & Goldin-Meadow, 1986; Goldin-Meadow et al., 1993; Goldin-Meadow, 2003) found that gestures and speech mismatch in semantic content when people are about to understand a task which they do not understand yet, thus when the task is difficult for them. We therefore expected less semantic similarity between gestures and speech in the difficult than in the easy condition (hypothesis 1B). With respect to *complexity matching*, there are no studies that directly investigated how task difficulty influences complexity matching. As described above, we do know that the level of complexity matching increases when the coupling between systems is stronger (Drew H. Abney et al., 2014; Almurad et al., 2017; Coey, 2016, 2018). Our previously stated hypothesis 1A suggests that gestures and speech become more temporally aligned in the difficult condition, and thus a *stronger* coupling. However, our previously stated hypothesis 1B suggests that gestures and speech become less semantically similar in the difficult condition, and thus a *weaker* coupling. Because of this contradiction, we have no specific hypothesis for the influence of task difficulty on the level of complexity matching between gestures and speech.

Our second research question is: How are temporal alignment, semantic similarity, and complexity matching between gestures and speech related in the easy and difficult condition? Bergmann et al. (2011) found that gestures and speech were more synchronized in time when their semantic content was more similar. This suggests that a higher temporal alignment between gestures and speech would go together with a higher semantic similarity. On the other hand, hypotheses 1A and 1B suggest a higher temporal alignment and a lower semantic similarity in the difficult condition. We therefore expected a positive relation between gestures' and speech's temporal alignment and semantic similarity in the easy condition (hypothesis 2A), and a negative relation between temporal alignment and semantic similarity in the difficult condition (hypothesis 2B). In line with a higher level of complexity matching when coupling is stronger (Drew H. Abney et al., 2014; Almurad et al., 2017; Coey, 2016, 2018), and in line with hypothesis 2A (positive relation between temporal alignment and semantic similarity in easy condition), for the easy condition we expected a positive relation between gestures' and speech's temporal alignment, semantic similarity, and complexity matching as well (hypothesis 2C). Our expected negative relation between temporal alignment and semantic similarity (hypothesis 2B) in the difficult condition suggests an inverse relation in coupling strength. Therefore, we have no specific hypotheses about how complexity matching is related to either temporal alignment or semantic similarity in the difficult condition.

Our third research question is: How do temporal alignment, semantic similarity, and complexity matching between gestures and speech predict task performance? We assessed task performance in terms of *time needed to finish the task*. Our experimental manipulation of task difficulty will influence task performance, as difficult tasks typically take longer to perform. Therefore we controlled for the influence of condition (task difficulty) when we investigated whether temporal alignment, semantic similarity, and complexity matching between gestures and speech predict task performance. According to Iverson and Thelen (1999; also see Butcher & Goldin-Meadow, 2000; Esteve-Gibert & Guellaï, 2018) the temporal alignment between gestures and speech becomes higher when infants and toddlers grow older. As children's language skills change and become more advanced during that time too (e.g. Tamis-Lemonda et al., 1998; Tamis-LeMonda et al., 2001), this could imply that more temporal alignment goes together with a better language performance. Mismatches are a form of semantic dissimilarity, and predict better performance on *subsequent* tasks (e.g. Church & Goldin-Meadow, 1986; Goldin-Meadow et al., 1993; Goldin-Meadow, 2003). Findings about a link between complexity matching and task performance are mixed, whereby some studies found a positive relation (Abney et al., 2021; Abney, 2016; Fusaroli et al., 2013) while others found a negative relation (Schloesser et al., 2019). Taken together, these findings are not sufficiently conclusive to formulate hypotheses about how temporal alignment, semantic similarity, and complexity matching predict task performance.

2. Method

2.1 Participants

We included[3] 30 participants (20 F, 10 M) between 18 and 27 years (*M* = 20.70, *SD* = 2.39) in our study. All participants were students with a Dutch nationality at a University in the Netherlands, who participated in the experiment in exchange for course credit or monetary compensation. The participants provided written consent. The ethical committee of Psychology department of the University of Groningen approved of the study.

2.2 Materials

Participants performed the task on a tablet (Lenovo MIIX 320-10ICR 1.44GHz x5-Z8350) with a 10.1 inch touchscreen (1280 x 800 pixels) and Windows 10 operating system. To facilitate pointing, the tablet was positioned in a 45 degree angle from the table using a tablet stand (see Figure 3). The experiment was programmed using OpenSesame [version 3.0.0] (Mathôt et al., 2012), which is an open-source program to build (social science) experiments. Using OpenSesame, we could run the task at the tablet (a detailed description follows below), and simultaneously record the time and x- and y-coordinates of participants' pointing (touching) at the screen, as well as participants' speech-signal.

Participants' speech was recorded at 44.1 kHz using a basic, hands-free microphone that was plugged into the 3.5mm audio jack of the tablet. We used Audacity [version 2.2.2] to normalize the volume of the speech-signal and to filter out background noise. Furthermore, we used Praat (Boersma &

[3] We recruited a total of 59 participants to participate in this experiment. However, due to technical issues with the tablets, for 29 participants the audio was either not recorded, or recorded with insufficient quality (e.g. loud ticks on the screen, background noise). After rigorous checks of the quality of all the audio recordings, we decided to include the 30 participants of which the audio-recordings were of high quality. For the analyses that we will conduct, with many data points, a sample of 30 participants is sufficiently large. We have the pointing data for all 59 participants, and we will use this data for other studies and research questions that do not involve speech.

Figure 3. Set-up of experiment.

Weenink, 2018) [version 6.0.42] and RStudio [version 1.1.456] to calculate the *amplitude envelope* of the speech signal (resp. He & Dellwo, 2016; Pouw & Trujillo, 2019; a detailed description follows below). The amplitude envelope that is calculated by the R-script is identical to the amplitude envelope that is calculated by the Praat-script (Pouw & Trujillo, 2019). We used a custom script in Matlab [version 2018a] to identify the start of syllables in the speech signal, and to cut the audio recordings into smaller parts of one syllable each (a detailed description follows below). We used OpenSesame [version 3.0.0] (Mathôt et al., 2012) to manually code the semantic content of these syllables.

We used Matlab to carry out the analyses on the time series of pointing and the amplitude envelope of speech. We specifically used the MFDFA-package by Ihlen (2012) to perform Multifractal Detrended Fluctuation Analysis, to estimate the *temporal multifractality* of participant's gestures and speech. Furthermore, we used RStudio to carry out inferential statistics, and the R-package ggplot2 (Wickham, 2016) to create plots of our data.

2.3 Procedure

Participants performed a tablet task (see Figure 3 and 4), which can be found here: osf.io/dj5vr/ (Scripts & Materials > Tablet task). We instructed the participants to repeatedly (virtually) put a ring on a bar of the same color, by first pointing (touching) to the ring on screen and thereafter to the top of the corresponding bar. Furthermore, each time that a participant pointed, we instructed them to say out-loud the location of the ring and bar (left, middle, right) that they were pointing to, in Dutch ("links", "midden", "rechts", resp.). In addition, we instructed participants to perform the task as fast and accurate as possible (in accordance with Fitts, 1954). We randomly assigned the participants to either the easy (n = 14; see Figure 4, left panel) or the difficult condition (n = 16; see Figure 4, right panel). In the easy condition, the color of the ring always corresponded to the color of the above bar (see Figure 4, left panel). In the difficult condition however, the color of the rings was random (see Figure 4, right panel). Participants were not informed about the pattern being either random or non-random. Since it is

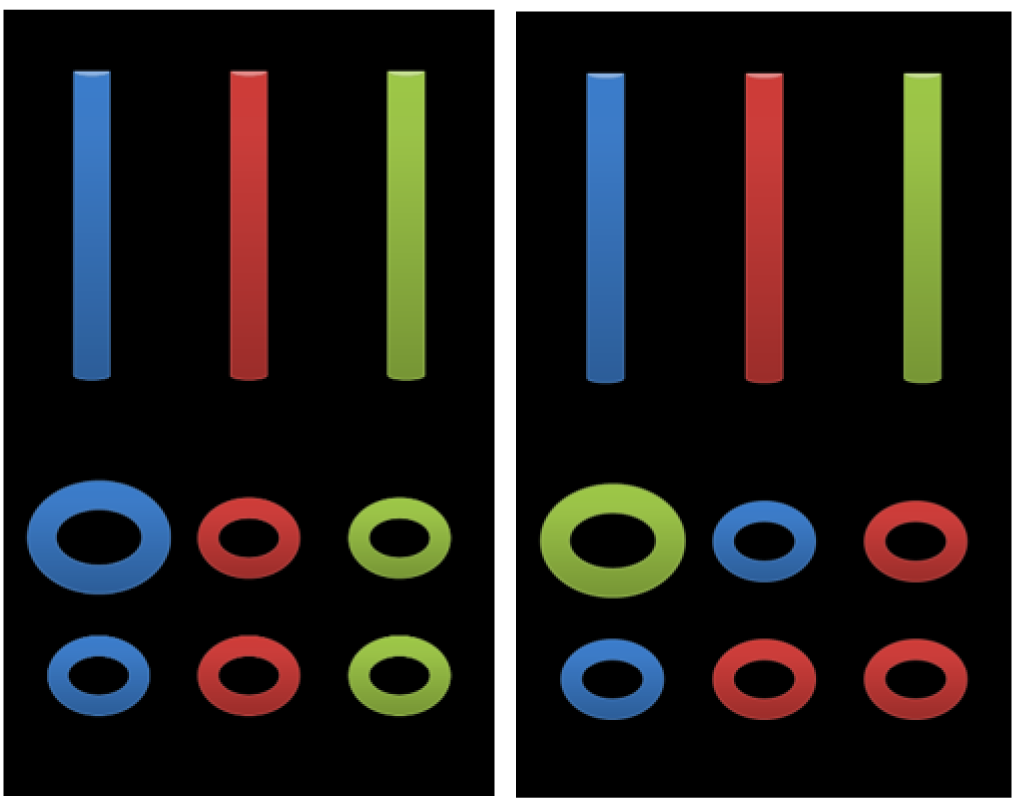

Figure 4. Example of tablet task. The left panel displays the easy task, and the right panel displays the difficult task.

impossible to understand a random pattern, participants in in the difficult condition were constantly needed to reorganize to the new spatial arrangement. This state of reorganization shares similarities with the state of reorganization that precedes learning something new (see Kello et al., 2007; Stephen, Dixon, et al., 2009).

To register participants' pointing, we divided the screen into 3 X 6 = 18 (invisible) areas. Each top of the bar was positioned in an area at the top row of the screen, while each ring was positioned in an area at the second row from the bottom of the screen. The correct ring, that is, the ring that participants needed to point to during that trial, appeared larger on screen, as shown in Figure 4 (upper left ring in both panels). Please note that the participants did not have to point to the correct ring or bar for the task to proceed. However, if participants failed to click on a *ring-area* or a *top of the bar-area*, the task did not proceed and the time and location of every first error was recorded.

During the task, the order in which the rings were presented alternated between left to right and right to left. For example, the correct order of the task in the left panel of Figure 4 would be: [first row] left – left – middle – middle – right – right – [second row] right – right – middle – middle – left – left. The correct order of the task in the right panel of Figure 4 would be: [first row] left – right – middle – left – right – middle – [second row] right – middle – middle – middle – left – left. Each time a participant finished with the last ring of a row, that row disappeared from screen, the second row moved up, and a new row appeared at the bottom of the screen. The participants performed 540 repetitions of the task, which is identical to 180 rows of 3 rings and corresponding bars, or a total of 1080 times pointing and saying the location of either a ring or a bar. Before starting with the actual task, the participants completed a trial phase with 15 repetitions of the task, to get used to the set-up. The recordings of this trial phase were not included in the analysis.

2.4 Data preparation

To investigate the coupling between participants' gestures and speech, we recorded the time (ms), location (left/middle/right) and position (x- and y-coordinates) of their pointing, and their speech signal.

2.4.1 Gestures. For gestures, the above resulted in a time series[4] of a) the duration between pointing to rings and bars, and vice versa, b) a time series of the location of the pointing, and c) a time series of distances between the exact locations that participants pointed to. With regards to distances between rings and bars, there are three possible distances[5] that participants' fingers needed to travel while pointing: 1) a short distance of 608 pixels, when the ring and bar are vertically aligned, 2) a middle distance of 664 pixels, when the ring and bar are one location off (i.e. from the left ring to the middle bar), or 3) a long distance of 809 pixels, when the ring and bar are two locations off (i.e. from the left ring to the right bar). This third, long distance can only occur in the difficult condition, and therefore the frequency distribution of distances between targets differs between the two conditions.

From the work by Fitts (1954) we know that the distance (D) between targets, combined with the width (W) of targets (ring: 167 pixels; bar: 61 pixels), influences how difficult the movement between two targets (i.e. from ring to bar or vice versa) is to perform. Fitts referred to this as the Index of Difficulty (ID), which is given by the following formula: $ID = log_2\left(\frac{2D}{W}\right)$. Using this formula, from ring to bar the index of difficulty for the short, middle and long distance is 4.317, 4.444, and 4.729, respectively. From bar to ring the index of difficulty for the short, middle and long distance is 2.864, 2.991, and 3.276, respectively. In the current study, we aim to manipulate task difficulty by changing the overall task demand of matching targets of the same color when one of the targets' color was either random (difficult) or non-random (easy). However, any difference in movement time could potentially result from the difference in ID between targets. To remove this possible confound, and standardize this

[4] A time series is a sequence of datapoints in chronological order.

[5] The distances are calculated between the middle of the ring-area and the middle of the top of the bar-area.

influence of the ID on each duration in our movement timeseries, we divided each duration between pointing to two targets (Movement Time; MT) with the Index of Difficulty of that particular movement. These corrected durations between pointing to two targets corrected with the Index of Difficulty of each movement yielded a time series of MT/ID.

2.4.2 Speech. We recorded participant's speech from the moment that the first experimental trial was presented until the moment that the participant finished with the last experimental trial. This yielded one long sound recording of what the participant said during the task. To increase the quality of the sound recording, we used Audacity to normalize the sound volume and to filter out background noise. We subsequently used PRAAT (He & Dellwo, 2016) or R (Pouw & Trujillo, 2019) to calculate the *amplitude envelope* of the speech signal. The amplitude envelope basically is a smoothed outline of a speech signal's intensity (He & Dellwo, 2016), and it's structure corresponds to the lower lip kinematics (He & Dellwo, 2017). In addition, we calculated the velocity of the speech signal's amplitude envelope, which captures how the amplitude envelope increases and decreases.

We identified the start of syllables by extracting the peaks in velocity of the amplitude envelope, using a custom MATLAB script (osf.io/dj5vr/; Scripts & Materials > Data preparation), and saved the audio between two velocity peaks as audio segments (i.e. one syllable per audio segment). The Dutch word "links" has one syllable, "midden" has two syllables, and "rechts" has one syllable. Due to individual differences in speaking, extracting one word or syllable per audio segment did not work perfectly for each participant, however[6]. To ensure that MATLAB was not too sensitive, so as to cut one

[6] Some participants pronounced a very loud "s" at the end of "links" and "rechts", and therefore the MATLAB script identified two syllables within these words, instead of one. Conversely, some participants mumbled the word "midden" (which is quite typical for people from the Northern part of the Netherlands), and therefore the MATLAB script identified one syllable within this word, instead of two. In addition, participants differed in their range of speech amplitude during the task: Some spoke evenly loud during the whole task, while others intermitted softer and louder periods of speaking. Therefore, for some participants, a velocity peak in a softer part of the audio

syllable into multiple audio segments, yet sensitive enough, so as to aggregate a maximum of five words into one audio segment, we manually tweaked a sensitivity parameter in the script (osf.io/dj5vr/; Scripts & Materials > Data preparation) for each audio recording. We subsequently coded the semantic content of the audio segments to identify the starting times of actual words.

We coded the semantic content of the audio segments using OpenSesame (osf.io/dj5vr/; Scripts & Materials > Data preparation). We loaded the audio segments into OpenSesame and coded whether a segment was A) [the first half of] “links”, B) [the first half of] “midden”, C) [the first half of] “rechts”, D) the second half of a word, E) a sequence of multiple words, or F) something else (i.e. other speech, a sigh). If a segment was E) a sequence of multiple words, we coded the semantic content of the sequence of words in that segment. This coding of audio segments yielded a time series of word (segments) and their starting time. For E) sequences of multiple words, we used the amount of words in an audio segment to extract the same amount of velocity peaks of the amplitude envelope in that particular audio segment. We replaced the word sequences in the time series with the individual words and their velocity peaks. We removed the F) other speech/sighs from the time series.

2.4.3 Combining gestures and speech. To investigate the temporal alignment and semantic similarity between gestures and speech, we aligned the time series of gestures and speech by linking the gestures to the word that was closest in time. To find the correct delay for each participant, we aligned the time series of gestures and speech for every delay between 10 ms and 1000 ms, with steps of 10 ms, and calculated the amount of semantic content-differences, and the average asynchrony, between gestures and speech (for overview, osf.io/dj5vr/; Data). Since the amount of semantic content differences for each participant went down to a minimum and then went up again, we decided that the

recording is not recognized as a velocity peak in a louder part of the audio recording. This resulted in MATLAB identifying multiple words as one syllable in the loud periods of speaking, and multiple words per audio segment in the softer periods.

delay with the least amount of semantic content-differences was the correct delay. If there were more delays with least amount of semantic content-differences, we picked the delay with the lowest average asynchrony between gestures and speech. The data files with the maximally aligned gestures and speech can be found here: osf.io/dj5vr/; Data > For analyses.

We calculated the difference between *amplitude* peaks (not *velocity* peaks) in the aligned time series to create a duration-time series for speech, and we used this time series to analyze temporal alignment between gestures and speech. The amplitude peak of the amplitude envelope corresponds to the stressed syllable in a word (see Figure 5). In each of the three words that the participants said, the first syllable of the word is stressed ("links", "mid-den", "rechts"). The amplitude peak therefore yielded a similar time point for each of the three words. Furthermore, to analyze semantic similarity, we used the semantic content-time series of speech. We divided the duration-time series of speech with the Index of Difficulty for that particular movement between ring and bar or vice versa to create a MT/ID

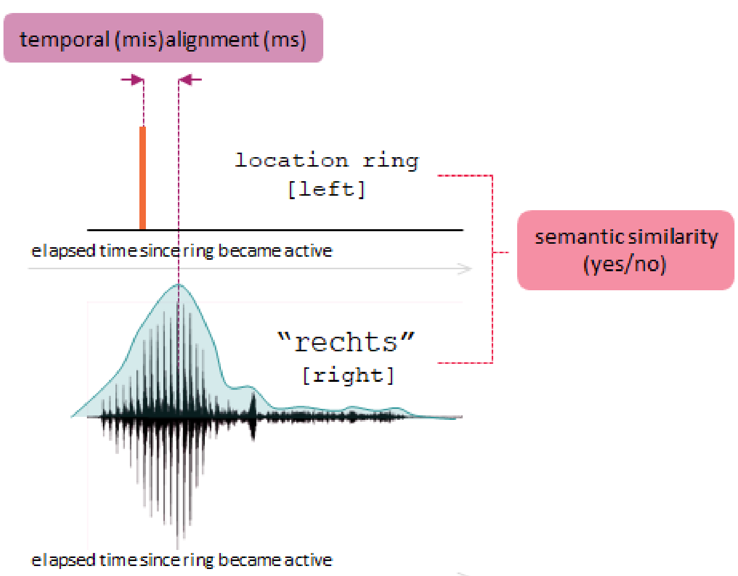

Figure 5. Illustration of how we calculated temporal alignment and semantic similarity within a trial. The orange vertical line indicates the moment the participant's finger touched the screen when the participant pointed at the ring. The peak of the blue curve corresponds to the amplitude peak of the word that the participant said.

time series for speech. We used this time series for speech to analyze complexity matching between gestures and speech.

2.5 Analysis

2.5.1 Calculating temporal alignment. For each trial, from ring to bar or from bar to ring, we know the time between the moment the ring or bar became activated, and a) the moment that participants pointed to and touched a bar or ring, and b) the amplitude peak of the word the participant said to indicate the ring's or bar's location. We compared these durations between the moment of pointing and the moment of the amplitude peak. For each participant, we calculated the average absolute difference between moments of pointing and amplitude peak, and used this as our measure of temporal alignment. Please note that higher values correspond to lower temporal alignment. Figure 5 displays how we estimated temporal alignment and semantic similarity within a trial. To check whether participant's temporal alignment was significantly higher than chance level, for each participant we compared the empirical temporal alignment with the temporal alignment between their repeatedly shuffled durations of gestures and speech.

2.5.2 Calculating semantic similarity. For each trial, from ring to bar or from bar to ring, we know whether participants' pointed to the left, middle, or right object, and which location they mentioned in speech. We compared the location in gestures and in speech location and identified whether they did or did not match. We calculated the sum of mismatches in location, and used this as our measure of semantic similarity. Please note that higher values correspond to lower semantic similarity. To check whether participant's semantic similarity was significantly higher than chance level, for each participant we compared the empirical semantic similarity with the semantic similarity between their repeatedly shuffled (mentioned) location of gestures and speech.

2.5.3 Calculating complexity matching. We applied Multifractal Detrended Fluctuation Analysis (Ihlen, 2012; Ihlen & Vereijken, 2010; Kantelhardt et al., 2002; Wallot et al., 2014) to the time series of gestures and speech. MFDFA is a method to reliably approximate a time series *temporal multifractality*. MFDFA is an extension of Detrended Fluctuation Analysis (DFA), which is a method to reliably approximate a time series' *temporal fractality*. An accessible explanation of MFDFA can be found in Appendix A.

In short, performing MFDFA on a timeseries yields a so-called multifractal spectrum (see Figure 6; the details of going from timeseries to multifractal spectrum can be found in Appendix A). The width of this multifractal spectrum indicates the degree of temporal multifractality of the timeseries, and is a measure of the multifractal structure of the timeseries' variability. In short, a higher degree of multifractal structure leads to a wider multifractal spectrum, while a lower degree of multifractal structure (or higher degree of monofractal structure) leads to a narrower multifractal spectrum. As previously described, complexity matching requires that the fractal structure of variability of the behavior of two complex systems matches. To investigate the degree of complexity matching between gestures and speech, we therefore calculated the difference in gestures' and speech's multifractal spectrum width. To check whether complexity matching between gestures and speech was significant, for each participant we compared the actual difference in multifractal spectrum width with the difference in repeatedly sampled, random pairs of gestures' and speech's multifractal spectrum width.

2.5.4 Monte Carlo permutation testing. We calculated all *p*-values using Monte Carlo (MC) Permutation tests (Ninness et al., 2002; Todman & Dugard, 2001), because MC permutations tests do not require a specific underlying distribution of the data. By drawing 10,000 random samples from the original data, the probability that differences are caused by chance was measured. We used custom made R scripts to calculate *p*-values using MC permutation tests (osf.io/dj5vr/; Scripts & Materials).

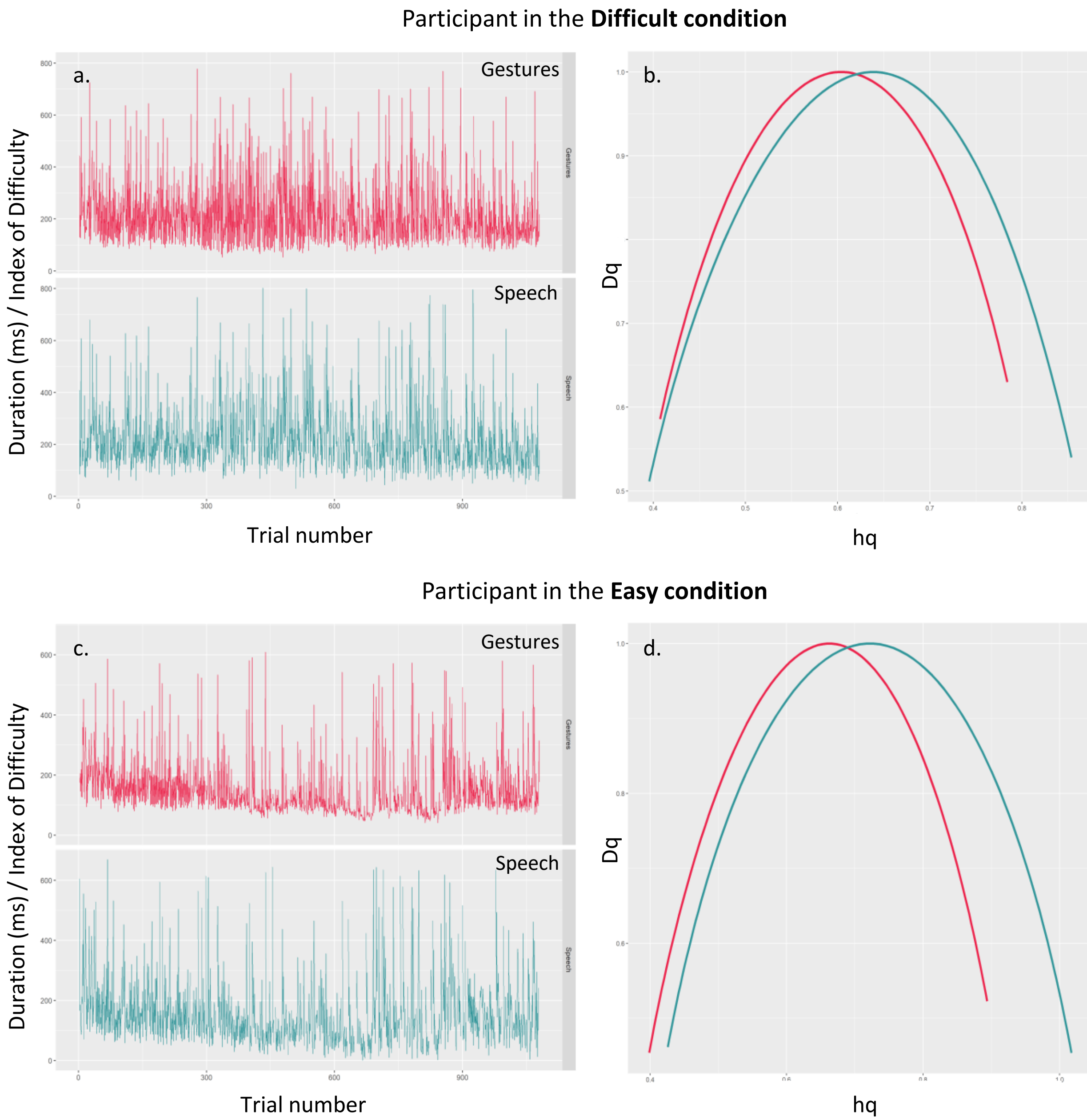

Figure 6. Timeseries of duration (ms) divided by Index of Difficulty (panel a and c), and corresponding multifractal spectrums (panel b and d, resp.), for gestures (red) and speech (blue). Panel a and b illustrate the MT/ID of timeseries gestures and speech and corresponding multifractal spectrums of a participant in the Difficult condition, and panel c and d of a participant in the Easy condition. The difference in multifractal spectrum width is 0.081 for the participant in the difficult condition and 0.096 for the participant in the easy condition. We interpret this as more complexity matching between gestures and speech for the participant in the difficult condition, compared to the participant in the easy condition.

3. Results

3.1 Descriptives

Participants in the difficult condition performed the task on average within 987 sec. (*SD* = 138 sec.). While they always pointed to the correct location of the bar and ring, they said the incorrect location on average 119.8 out of 1080 trials (*SD* = 29.6), i.e. 11%. A semantic dissimilarity was thus always a combination of a correct gesture and an incorrect utterance. In the difficult condition, gestures' width of the MFDFA-spectrum was on average .473 (*SD* = .203), and speech's width of the MFDFA-spectrum was on average .432 (*SD* = .178).

Participants in the easy condition performed the task on average within 749 sec. (*SD* = 151 sec.). Similar to the difficult condition, they always pointed to the correct location of the bar and ring, but they said the incorrect location on average 45.8 out of 1080 trials (*SD* = 47.3), i.e. 4%. Gestures' width of the MFDFA-spectrum was on average .618 (*SD* = .169), and speech's width of the MFDFA-spectrum was on average .496 (*SD* = .104), in the easy condition.

3.2 RQ1: Task difficulty's influence on temporal alignment, semantic similarity, and complexity matching

With regard to temporal alignment, we found significantly less temporal alignment between participants' gestures and speech in the difficult condition (*M* = 218.538 ms, *SD* = 43.652) than in the easy condition (*M* = 167.182 ms, *SD* = 62.322), *p* = .009 (Δ_M = 51.356, 95% $CI_{\Delta\text{-MC}}$= -34.598, 35.322), with a large effect size, *d* = .955 (see Figure 7, left panel). This finding is opposite from our hypothesis 1A, as we expected that gestures and speech would be more temporally aligned in the difficult than in the easy condition. For all participants, the empirically observed temporal alignment between gestures and speech throughout the task was significantly higher than the temporal alignment between random pairs of their gestures' and speech's duration ($p < .001$).

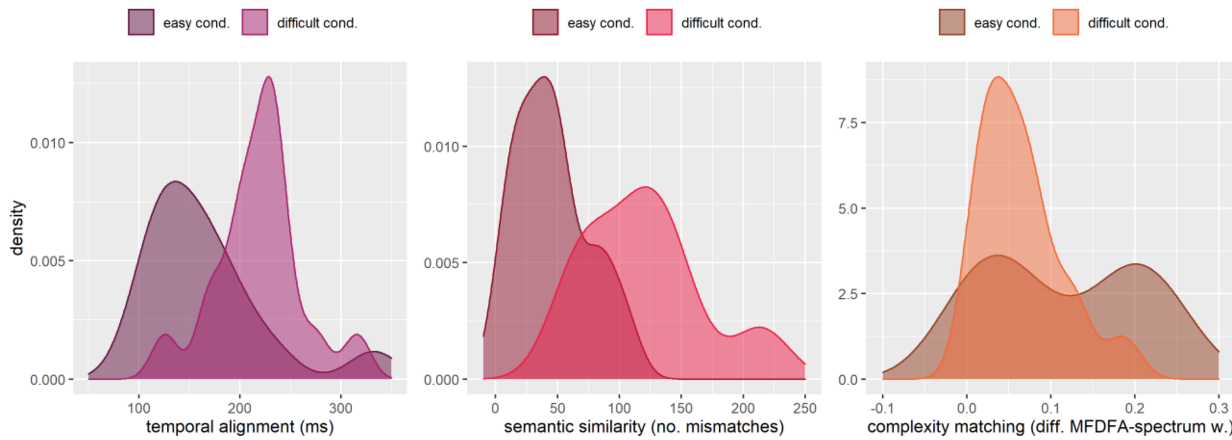

Figure 7. Density plots of temporal alignment, semantic similarity, and complexity matching in the difficult and easy condition.

For semantic similarity, we found significantly less semantic similarity between participants' gestures and speech in the difficult condition ($M_{mismatches}$ = 119.750, *SD* = 47.301) than in the easy condition ($M_{mismatches}$ = 45.769, *SD* = 29.601), $p < .001$ (Δ_M = 73.981, 95% $CI_{\Delta\text{-MC}}$= -32.661, 32.506), with a very large effect size, d = 1.875 (see Figure 7, center panel). This finding is in line with our hypothesis 1B, as we expected less semantic similarity between gestures and speech in the difficult than in the easy condition. For all participants, the empirically observed semantic similarity between gestures and speech throughout the task was significantly higher than the semantic similarity between random pairs of their gestures' and speech's semantic content ($p < .001$).

With regard to complexity matching, we found more complexity matching between gestures and speech for participants in the difficult condition ($M_{diff.\ MFDFA\text{-}spectrum\ wdith}$ = 0.065, *SD* = 0.049) than in the easy condition ($M_{diff.\ MFDFA\text{-}spectrum\ wdith}$ = 0.123, *SD* = 0.102), p = 0.026 (Δ_M = -.058, 95% $CI_{\Delta\text{-MC}}$= -0.049, 0.047), with a medium to large effect size, d = .726 (see Figure 7, right panel). When we visually inspected the density plot, participants in the difficult condition showed a striking peak around 0.0 and 0.1 in difference of MFDFA-spectrum width. However, participants in the easy condition showed no clear peak in difference in MFDFA-spectrum width, but instead showed a wide range of values. In line with this, for 15 out of 16 participants in the difficult condition we found the difference in MFDFA-spectrum width to be significantly smaller ($p < .05$) than the difference in MDFA-spectrum between random pairs of participants' gestures and speech, while we found this to be true for only 8 out of 14 participants in the easy condition. Note that we did not make a prediction about the difference in complexity matching between the two conditions.

3.3 RQ2: Relations between temporal alignment, semantic similarity, and complexity matching

In the difficult condition, we found a significant, moderate, positive correlation between average temporal alignment (ms) and semantic similarity (no. of gesture-speech mismatches), $r = .555$, $p = .014$ (95% $CI_{r\text{-}MC}$= -.422, .433; see Figure 8, panel a). This finding is opposite from our hypothesis 2B, as we expected a negative relation between temporal alignment and semantic similarity in the difficult condition. We found a significant, moderate, negative correlation between average temporal alignment (ms) and complexity matching (difference in MFDFA-spectrum width), $r = -.481$, $p = .031$ (95% $CI_{r\text{-}MC}$= -.430, .433; see Figure 8, panel b). We did not state a hypothesis about the relation between temporal alignment and complexity matching. We found a non-significant, low, negative correlation between semantic similarity (no. of gesture-speech mismatches) and complexity matching (difference in MFDFA-spectrum width), $r = -.125$, $p = .336$ (95% $CI_{r\text{-}MC}$= -.414, .448; see Figure 8, panel c). We did not state a hypothesis about the relation between semantic similarity and complexity matching. An overview of our findings with regards to research question 2 can be found in Figure 9.

In the easy condition, we found a significant, moderate, positive correlation between average temporal alignment (ms) and semantic similarity (no. of gesture-speech mismatches), $r = .653$, $p = .013$ (95% $CI_{r\text{-}MC}$= -.438, .511; see Figure 8, panel d). This finding is in line with our hypothesis 2A, as we expected a positive relation between temporal alignment and semantic similarity in the easy condition. We found a non-significant, low, negative correlation between average temporal alignment (ms) and

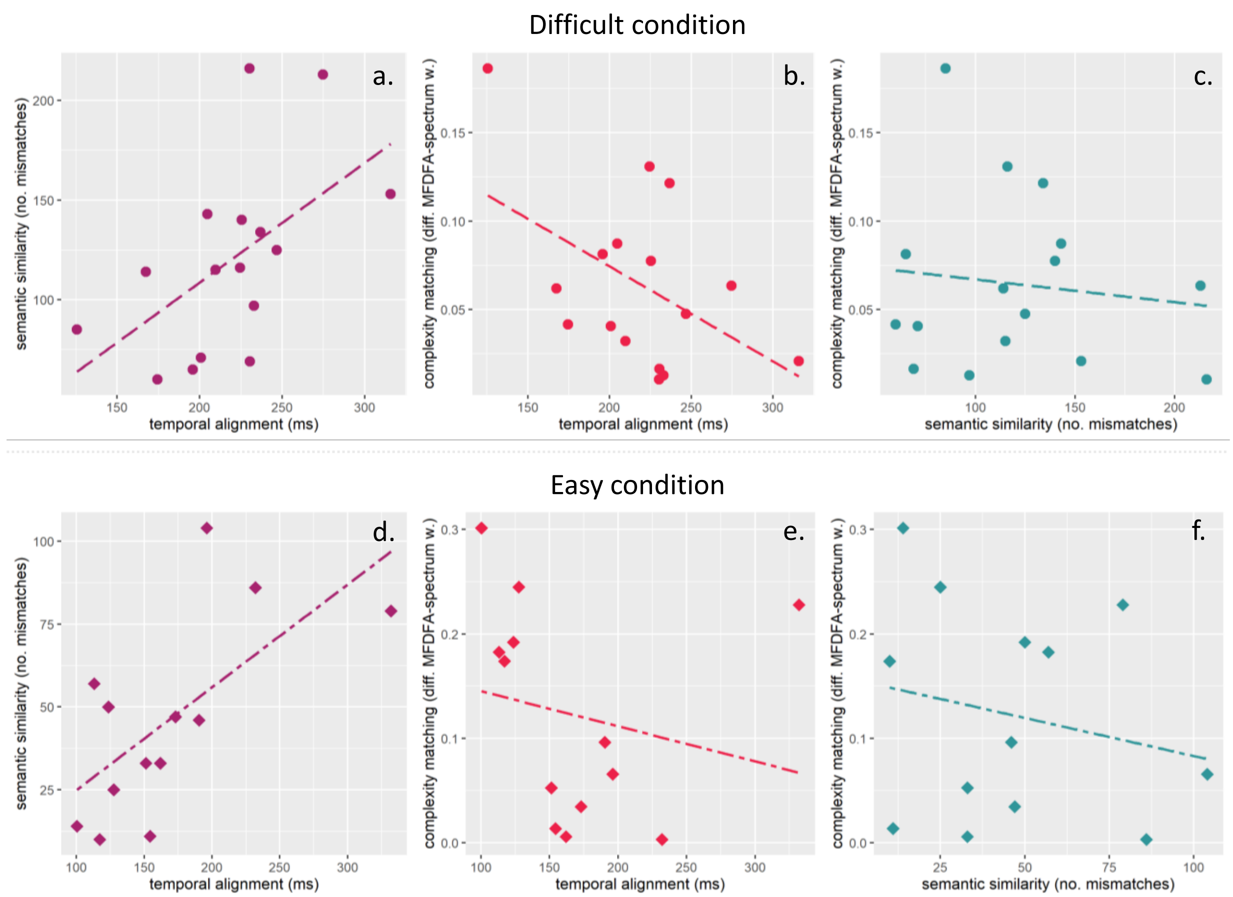

Figure 8. Scatterplots of relations between the variables temporal alignment (ms), semantic similarity (no. of mismatches), and complexity matching (difference in MFDFA-spectrum width). Panels a, b, and c display the relations in the difficult condition; panels d, e, and f display the relations in the easy condition.

complexity matching (difference in MFDFA-spectrum width), r = -.205, p = .269 (95% $CI_{r\text{-}MC}$= -.444, .489; see Figure 8, panel e). This finding is not in line with our hypothesis 2C, as we expected a positive relation between temporal alignment and complexity matching. We found a non-significant, low, negative correlation between semantic similarity (no. of gesture- speech mismatches) and complexity matching (difference in MFDFA-spectrum width), r = -.211, p = .253 (95% $CI_{r\text{-}MC}$= -.475, .477; see Figure 8, panel f). This finding is not in line with our hypothesis 2D, as we expected a positive relation between semantic similarity and complexity matching.

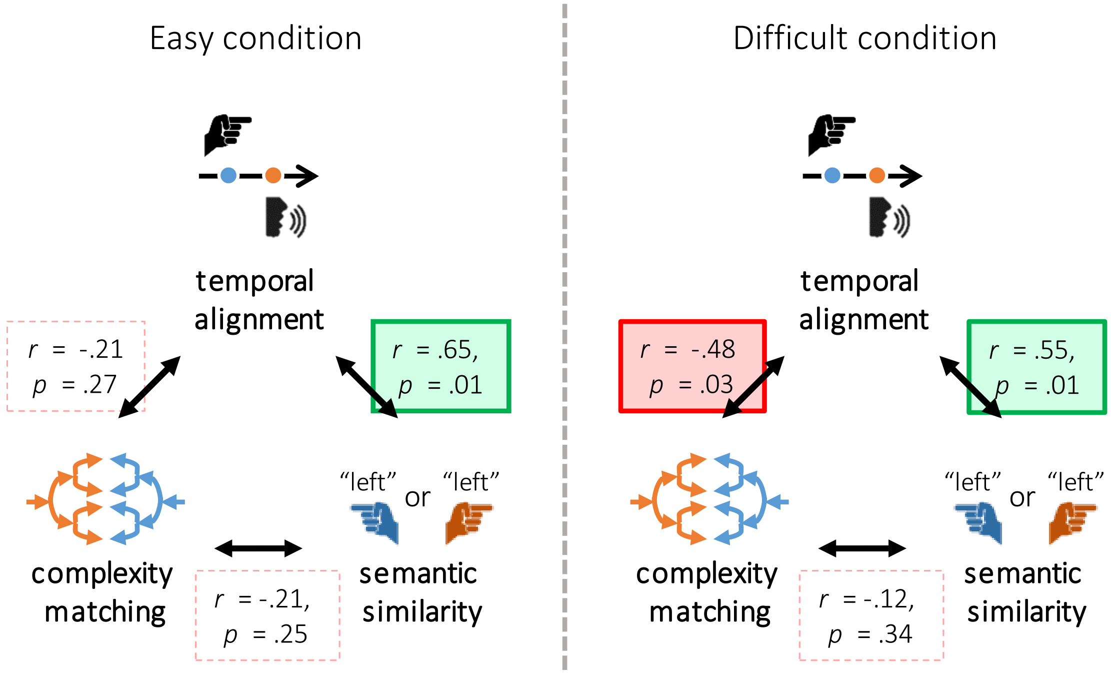

Figure 9. Overview of the empirical relations between temporal alignment, semantic similarity and complexity matching, in the easy and difficult condition.

3.4 RQ3: Predict task performance with temporal alignment, semantic similarity, and complexity matching

We performed a multiple linear regression to predict task performance (total time), based on temporal alignment, semantic similarity, and complexity matching.

With regard to the individual variables, greater temporal alignment significantly predicted better (i.e. a more speedy) task performance than condition alone, with R^2 increasing from .423 to .616, $p <$ .001 (Δ_{R^2} = .192, 95% $CI_{\Delta\text{-}MC}$= .000, .082). Less semantic similarity did not significantly predict better task performance than condition alone, with R^2 increasing from .423 to .425, p = .764 (Δ_{R^2} = .002, 95% $CI_{\Delta\text{-}MC}$= .000, .082). Less complexity matching did not significantly predict better task performance than condition alone, with R^2 increasing from .423 to .456, p = .214 (Δ_{R^2} = .033, 95% $CI_{\Delta\text{-}MC}$= .000, .079).

Given that temporal alignment was a predictor of performance with only condition in the model, we asked whether semantic similarity and complexity matching would contribute additional unique variance. When semantic similarity was included in the model with condition and temporal alignment, we obtained a significant increase in R^2 from .616 to .734, p = .003 (Δ_{R^2} = .118, 95% $CI_{\Delta\text{-}MC}$= .000, .057), whereby greater temporal alignment and less semantic similarity significantly predicted task performance. When we added complexity matching to the model containing condition and temporal alignment, we obtained a non-significant increase in R^2 from .616 to .619, p = .628 (Δ_{R^2} = .004, 95% $CI_{\Delta\text{-}MC}$= .000, .057). Furthermore, when we added complexity matching to the model containing condition, temporal alignment, and semantic similarity, we obtained a non-significant increase in R^2 from .734 to .737, p = .601 (Δ_{R^2} = .003, 95% $CI_{\Delta\text{-}MC}$= .000, .040).

4. Discussion

In this study, we investigated how a difference in task difficulty influences the synchronization between participant's gestures and speech, in terms of temporal alignment, semantic similarity, and complexity matching.

4.1 Summary of results

Our first research question was: How does task difficulty influence temporal alignment, semantic similarity, and complexity matching between participant's gestures and speech? We found significantly less temporal alignment, less semantic similarity and more complexity matching in the difficult condition than in the easy condition. With regard to complexity matching, we additionally observed a more peaked distribution of differences in MFDFA-spectrum widths in the difficult condition, while the distribution was clearly flatter in the easy condition. This suggests that, for participants in the difficult condition, the fractal structure of variability of gestures' and speech' matches to a similar degree, which also points to complexity matching. Participants in the easy condition show a more variable degree of this matching, so no clear complexity matching.

Our second research question was: How are temporal alignment, semantic similarity, and complexity matching between gestures and speech related in the easy and difficult condition? In the difficult condition, we found (a) a moderate and significant positive relation between temporal alignment and semantic similarity, (b) a moderate and significant negative relation between temporal alignment and complexity matching, and (c) a low and nonsignificant negative relation between complexity matching and semantic similarity. In the easy condition, we found (A) a moderate and significant positive relation between temporal alignment and semantic similarity, (B) a low and nonsignificant negative relation between temporal alignment and complexity matching, and (C) a low and nonsignificant negative relation between complexity matching and semantic similarity.

Our third research question was: How do temporal alignment, semantic similarity, and complexity matching between gestures and speech predict task performance? With regard to individual variables, we found that temporal alignment significantly predicted task performance, whereby more temporal alignment went together with better (i.e. a more speedy) task performance. Neither semantic similarity nor complexity matching significantly predicted task performance. With regard to combinations of variables, we found that temporal alignment and semantic similarity together predicted task performance better than temporal alignment alone, whereby more temporal alignment and less semantic similarity went together with better task performance. Adding complexity matching to the model did not significantly increase the model's exploratory power.

4.2 Phase synchronization

When two (weakly) coupled *oscillating* systems interact, their rhythm adjusts and their frequency entrains. This phenomenon is called *phase synchronization* (e.g. Pikovsky et al., 2003; Warren, 2006), and results in temporal alignment. We have viewed gestures and speech as two coupled systems throughout this paper. Akin to oscillating systems, we observed that participants in the easy condition rapidly got into a regular rhythm of gesturing and speaking. However, participants in the difficult condition struggled to get into and maintain a rhythm. In line with the higher temporal alignment that we found in the easy condition, we believe that participant's gestures and speech also exhibited phase synchronization in the easy condition. Similarly, Pouw et al. (2019) found that rhythmical arm beating, but not wrist beating, entrained the amplitude envelope of speech. Although less pronounced than beating, participants in the easy condition of the current study also rhythmically moved their arm.

Pouw and Dixon (2019b) investigated temporal alignment between gestures and speech while participants told a story. As previously described, Pouw and Dixon (2019b) found an increase in temporal alignment between participants' gestures and speech under Delayed Auditory Feedback. Delayed Auditory Feedback is a delayed stimulus that entrains both gestures and speech, and gestures and speech become more synchronized to each other because they are entrained together. Pouw and Dixon (2019b) reasoned that Delayed Auditory Feedback perturbs hand movements and speech, and that the increase in gesture-speech synchrony is a way to stabilize rhythmic activity (such as gestures and speech) under disrupting circumstances (also see Pikovsky et al., 2001), i.e. "stability through synergy" (Pouw & Dixon, 2019b, p. 28).

While the difficult task in our study did *disrupt* gestures' and speech's rhythm, task difficulty did not *entrain* gestures and speech. The nature of our perturbation was different from Pouw and Dixon (2019), and indeed we did not find more temporal alignment in the difficult condition than in the easy condition. However, we did find more complexity matching in the difficult condition than in the easy condition. Extending Pouw and Dixon's (2019) notion of "stability through synergy", in the difficult condition, gestures and speech may have stabilized together by means of complexity matching, which entails coordination at multiple timescales, instead of entrainment, that is, coordination at a single timescale. Metaphorically speaking, the difficult condition might elicit a form of gesture-speech coordination which shares similarities with the coordination between a jazz-saxophonist and a jazz-pianist while improvising together, which is characterized by "…a multitude of simple and complex rhythms, all interwoven extemporaneously into one cohesive sound" (i.e. complexity matching; Herby Hancock Institute of jazz, https://bit.ly/2FIypCm; also see Walton et al., 2015, 2018). The easy condition might elicit a form of gesture-speech coordination similar to clapping one's hands in a regular, monotonous rhythm (i.e. entrainment). Furthermore, in the easy condition, entrainment may overrule complexity matching. This might suggests a trade-off between phase synchronization and complexity matching, which could be reflected in the negative relation between temporal alignment and complexity matching in the difficult condition that we found (also see Marmelat & Delignieres, 2012). In terms of our metaphor, if either the saxophonist or the pianist start playing a regular, monotonous rhythm, the other musician will be drawn to that regular and monotonous rhythm and will have a very hard time to maintain improvisation in all its complexity. We will discuss our findings' implications for the concept of complexity matching in the next paragraphs.

4.3 Complexity matching

While a body of research has shown that complexity matching exists between different human systems and under different circumstances (e.g. Abney, 2016; Abney et al., 2014; Almurad et al., 2017; Coey, 2016, 2018; Den Hartigh et al., 2018; Fusaroli et al., 2013; Marmelat & Delignieres, 2012; Ramirez-Aristizabal et al., 2018; Schloesser et al., 2019; Schneider et al., 2019), we are still grappling with what complexity matching *actually does* for people. In our study, we found more complexity matching between gestures and speech in the difficult condition than in the easy condition, and we interpreted this as a way for gestures and speech to stabilize together when entrainment is difficult to impossible. However, complexity matching did not predict participant's task performance in terms of time to finish the task, and complexity matching was also not related to semantic content-alignment (i.e. number of speech errors). Apart from gestures and speech potentially being more stable, as we proposed, it is unclear whether and how participants benefited from more complexity matching.

Different studies about complexity matching during dyadic tasks do show that participants who demonstrated complexity matching benefited from this, in terms of reaching a collaborative goal (Abney, Paxton, et al., 2014; Fusaroli et al., 2013; see also Schloesser et al., 2019). Important to note is that the performance measures in the studies by Abney, Dale, et al. (2014) and Fusaroli et al. (2013) are more sophisticated and captured higher-order goals, than our simple performance measure of total time to perform the task did. In line with our findings, Schloesser et al. (2019) also found a weak and slightly negative relation between complexity matching - both within and between participants - and performance in terms of total time.

From a theoretical point of view, West et al. (2008) showed that complexity matching increases the information exchange between complex networks. However, as argued before by Abney (2016), we know little about what this *information* actually is, and how to operationalize it. We could speculate that complexity matching only increases performance on tasks that involve the (re)organization of components to a higher-order structure. This higher-order structure could be the *common ground* that interacting people needed to establish during a conversation involving many different utterances (Drew H. Abney et al., 2014), or the *joint decision* that people needed to converge to during a series of joint decision making (Fusaroli et al., 2013). If it is true that complexity matching only increases performance on tasks that involve the (re)organization of components to a higher-order structure, this could hint that the information as proposed by West entails *interactions between components that form a synergy*.

An interesting study by Rigoli et al. (2014; also see Schloesser et al., 2019) similarly suggests that information in complexity matching entails interactions between components that form a synergy. Rigoli et al. (2014) investigated participants who were asked to tap to a visual metronome, by pressing a key. Rigoli et al. (2014) found complexity matching between the time series of participants' key press times and durations [*key press synergy*], and they found complexity matching between the time series of participants' pupil dilation and heart rate [*anatomic synergy*]. However, Rigoli et al. (2014) did not find complexity matching between key press time series and the anatomic time series. Rigoli et al. (2014) therefore concluded that the key press network and anatomic network did not exchange information during the simple and relaxed task of tapping to the visual metronome. Similarly, in the easy (simple and relaxed) condition of the current study we did not find complexity matching between gestures and speech, which suggests that these systems did not exchange information either. We did find complexity matching in the difficult condition however, which suggests that the gestures and speech exchanged information and (re)organized as a synergy under these difficult task constraints. Future studies could investigate whether difficult tasks, involving higher-order goals, indeed elicit more complexity matching between systems than simple tasks. With regard to difficult tasks involving higher order-goals for children, one example are Piagetian conversation tasks, which have been used to study the interplay between gestures and speech before (e.g. Alibali et al., 2000; Church & Goldin-Meadow, 1986; De Jonge-Hoekstra et al., 2020; Pine et al., 2004, 2007).

4.4 Gesture-speech mismatches

As previously described, Goldin-Meadow and colleagues (e.g. Church & Goldin-Meadow, 1986; Goldin-Meadow et al., 1993; Goldin-Meadow, 2003) found that children make gesture-speech mismatches (i.e. semantic *dissimilarities*) when they are on the verge of learning something new. Moreover, during these gesture-speech mismatches, children show a more advanced understanding in gestures than in speech. In the current study, we found more gesture-speech mismatches (i.e. less semantic similarity) in the difficult than in the easy condition, and these gesture-speech mismatches were always due to speech errors in semantic content. With our findings, we thus extend the phenomenon of gesture-speech mismatches from tasks in which people acquire understanding about cognitive problems, to difficult, cognitive tasks in general. Since a transition between “old” understanding and “new” understanding was impossible in our experiment, participants’ gesture-speech mismatches were due to something different than competing cognitive understanding.

First, both in the current study and in previous studies, gestures had a clear spatial component that was directly linked to the physical properties of the task material (e.g. Bergmann & Kopp, 2010; De Jonge-Hoekstra et al., 2020; Hostetter & Alibali, 2008; Yeo & Alibali, 2018). This is not true for speech, however, and Smith and Gasser (2005) even propose that a too close resemblance between the physical structure of the environment and the structure of speech would limit speech’s functionality. Maybe difficult, cognitive tasks amplify this difference between gestures and speech in how they are coupled to the physical properties of the spatial environment, which could result in gesture-speech mismatches. Furthermore, we could question the extent to which speech actually needed to be functional in the current study. Participants performed the task individually and their speech did not have to be understandable for someone else (also see Fowler, 2010). Future studies could investigate how task constraints related to spatial structure and social context influence the occurrence of gesture-speech mismatches.

Second, participants had to verbally discriminate left from right in our experiment, which is known to be notoriously difficult for children and adults alike (e.g. Fisher & Camenzuli, 1987; McKinley et al., 2015; Vingerhoets & Sarrechia, 2009). To our knowledge, no studies have investigated whether people find it difficult to discriminate between left and right using gestures as well. However, Abarbanell and (2020) recently found that instructing children to use gestures to discriminate between left and right benefits their performance on a rotation task more than instructing children to say the (Spanish) words (for) “left” and “right”. The authors explain this effect by gestures being directly linked to the spatial properties of a task, similar to our reasoning in the previous paragraph. This direct link between gestures and spatial properties of a task is particularly evident for deictic gestures, like the pointing of participants in our study. Therefore discriminating between left and right using gestures was probably easier for the participants than using speech. Furthermore, while participants in the easy condition could just repeat the same sequence of words without much thought about their meaning, participants in the difficult condition needed to think about the words' meaning constantly. Participants in the difficult condition were therefore more prone to confuse the words "left" and "right", while they could correctly differentiate between left and right by means of pointing. This could explain why we found more gesture-speech mismatches in the difficult condition than in the easy condition. Future studies need to investigate whether this phenomenon is more evident in tasks which require left-right discrimination, as compared to spatial temporal tasks in general, as we argued in the previous paragraph.

Third, in line with Bergmann et al. (2011), we found a positive relation between temporal alignment and semantic similarity in both the difficult and easy condition, which suggests that more temporal alignment goes together with less gesture-speech mismatches. However, it is yet unclear whether temporal alignment is causally related to gesture-speech mismatches and what the direction of this potential relation would be . According to the Information Packaging Hypothesis (Kita, 2000; also see Kita et al., 2017), gestures help to organize and "package" spatial information to both enable verbalization about this spatial information, and to ensure that the spatial information "fits" within the structure of speaking. When verbalization is challenging, speakers take more time to "package" information by means of gesturing. This would result in low temporal alignment between gestures and speech in the during gesture-speech mismatches, as well as low temporal alignment in the difficult condition. This is in line with the positive relation between temporal alignment and semantic similarity and less temporal alignment, and also with less temporal alignment in the difficult condition, that we found. Follow-up studies could research the relation between gestures, speech, and gesture-speech mismatches in more detail, using methods to quantify the temporal direction of gesture-speech coupling, such as Cross Recurrence Quantification Analysis (see also De Jonge-Hoekstra et al., 2016). Moreover, in previous studies, temporal information usually has been disregarded when coding gesture-speech mismatches (e.g. Alibali et al., 2000).

4.5 Limitations

Our study has a number of limitations. We will address the limitations that we deem most important.

First, participant's utterances during the experiment were very limited in scope and syntactic complexity (i.e. "left", "middle", "right"), which leaves open the question of how our findings will correspond to more typical, fluent, and syntactically complex speaking and gesturing. Previous studies have found complexity matching between participant's fluent speech (Drew H. Abney et al., 2014; Fusaroli et al., 2013). Furthermore, Abney et al. (2018) created spike trains of participant's language and gesture events during fluent conversations and subsequently calculated the *burstiness* of both language and gesture events. Bursty processes are typical for complex dynamical systems (Barabási, 2005; Karsai et al., 2012), and in this sense, burstiness shares similarities with multifractality (albeit the scope of burstiness analysis is not multi-scaled). The methods used by Abney and colleagues (Drew H. Abney et al., 2014, 2018; Fusaroli et al., 2013) provide viable directions for investigating complexity matching between gestures and speech in more typical and fluent speaking and gesturing.

Second, instead of changing the physical lay-out and order of the task, we could have increased task difficulty in a way that is closer to cognitive problem solving. For instance, we could have asked participants to follow sets of rules about when to put which color ring on which color bar, and investigate how rules of varying difficulty influence gesture-speech coupling. However, such a manipulation would not have perturbed participants continuously as participants get used to rules, while the random order that we used in the current study did continuously perturb them.

Third, while we treated the trials from ring to bar and from bar to ring equally, the instruction for these trials differed. For the trials from ring to bar, participants were instructed to select the bar which has the same color as the ring. For the trials from bar to ring, participants were instructed to select the enlarged ring. This difference in instruction could potentially lead to a different pattern of multifractal scaling for the trials from ring to bar and for the trials from bar to ring. In an interesting study, Kello et al. (2007) investigated a task whereby participants needed to press a key on a keyboard when they saw a stimulus on screen, thereby responding as fast as they could. Participants were allocated to either an easy, predictable condition, whereby the time between the stimuli was constant, or to a difficult, unpredictable condition, whereby the time between stimuli was random within a certain range. Kello et al. (2007) analyzed two time series: 1) A time series of the time between the appearance of the stimuli and pressing the key (reaction time), and 2) a time series of the time between pressing the key and releasing the key again (key-contact duration). The authors argue that participants only received an instruction about reaction time (responding as fast as possible), while they received no instruction about key-contact duration. Kello et al. (2007) found the reaction times and key-contact durations in both conditions to be not or only weakly correlated. Furthermore, they found fractal scaling in both the reaction time series and the key-contact duration time series and in both conditions. The fractal scaling of the reaction time series of the difficult, predictable condition was lower than the fractal scaling of the other three time series. Although the study by Kello et al. (2007) shares some similarities with our study, there are notable differences as well. While pressing down a key as fast as possible and releasing a key correspond to a simple instruction vs. no instruction, respectively (Kello et al., 2007), selecting a bar with the same color and selecting an enlarged ring correspond to a more complicated instruction vs. a simple instruction, respectively (current study). Furthermore, while pressing down and releasing a key are two different motions, involving the contraction of different muscles (Kello et al., 2007), trials from bar to ring and from ring to bar *both* involved pointing to a target and saying the location of that target (current study). A follow-up study could investigate whether the ring to bar trials differ from the bar to ring trials with regard to duration and multifractal scaling.

Fourth, our sample size is relatively small, which is largely due to failed audio-recordings. However, we do have many datapoints per participant. Fifth, the number of measurements per participant (1024) was on the small side for performing MFDFA (Ihlen & Vereijken, 2010), yet sufficient. Albeit challenging, we need to come up with ways to increase the number of measurements per participants while still keeping the task feasible for participants to do. Furthermore, Almurad and Delignières (2016) propose an alternative way of performing DFA (the monofractal variant of MFDFA) which allows for timeseries which are even shorter than 1024 datapoints.

4.6 Conclusions

We aimed to investigate how task difficulty affects the synchronization between gestures and speech, thereby empirically addressing De Jonge-Hoekstra et al.'s (2016) proposal. By doing so, we brought together different perspectives on and ways of investigating gesture-speech synchronization. We found that task difficulty indeed influences gesture-speech synchronization in terms of temporal alignment, semantic similarity, and complexity matching. With our findings of less semantic similarity in the difficult condition, we extended the phenomenon of gesture-speech mismatches to difficult, cognitive tasks. Furthermore, we found more temporal alignment in the easy condition, which we related to phase synchronization between gestures and speech. We found more complexity matching between gestures and speech in the difficult condition, which we related to gestures and speech forming a more stable synergy under the influence of more difficult task constraints. Our findings add another piece to the puzzle of why complexity matching between occurs in complex dynamical systems.

In sum, our study demonstrates how this perspective can be used to study the relation between gestures and speech, and gesture-speech mismatches – subjects that primarily have been studied from within cognitive psychology. While the body of research that tries to bridge between complex dynamical systems and coordination research, and cognitive psychology is steadily growing, we acknowledge that many gaps between the two perspectives still remain. We look forward to future work that continues to build connections between the two fields, and we hope that these future studies can build on our study.

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Appendix A

Detailed and accessible description of Multifractal Detrended Fluctuation Analysis (MFDFA)

To provide an accessible introduction to Multifractal Detrended Fluctuation Analysis (MFDFA) to readers from diverse academic backgrounds, we will introduce the method in three main steps. First, we will illustrate how the box counting method is used to approximate the fractal dimension of objects. Second, we will illustrate how Detrended Fluctuation Analysis (DFA), which shares similarities with the box counting method, is used to approximate the temporal fractality of time series. Third, we will illustrate how MFDFA extends from DFA, and how it is used to approximate time series' temporal multifractality. For the first step, we largely follow David Feldman's (2019) highly accessible explanation of the box counting dimension, which is part of the *Fractals and Scaling course* from the Sante Fe Institute. For the second and third step, we largely follow the clear and recommended explanation by Ihlen (2012), which includes a script to perform MFDFA in Matlab.

Box counting method

As described in the Introduction of the main paper, objects that show self-similarity, i.e. that look similar at different levels of magnification, are *fractal*. However, the relation between level of magnification (s) and number of perfect "copies" (n) of the object differs for different fractal objects. For example, if we would dissect a line into two equal line segments, we would need to magnify the two line segments by a factor of two ($s = 1/2$), to see two perfect copies ($n = 2$) of our initial line (see Figure A1, left panel). Similarly, if we would dissect a line into three equal line segments, we would need to magnify the three line segments by a factor of three ($s = 1/3$), to see three perfect copies ($n = 3$) of our initial line. However, if we would dissect the lines of a square into two equal line segments each, we would create four smaller squares (see Figure A1, right panel). We would need to magnify these four smaller squares by a factor of two ($s = 1/2$), to see four perfect copies ($n = 4$) of our initial square. Similarly, if we would dissect the lines of a square into three equal line

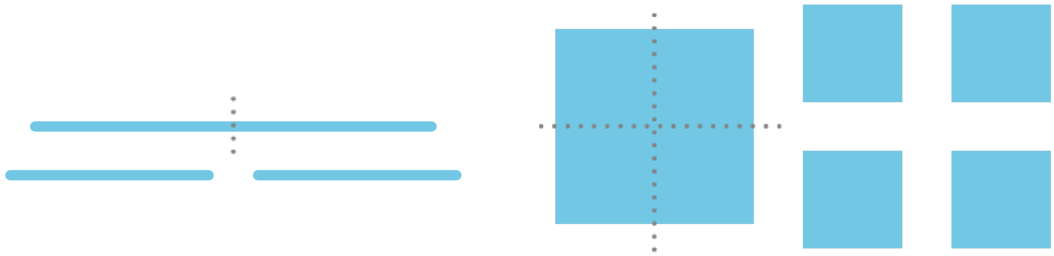

Figure A1. Dissecting the lines of a line and a square into 2 equal line segments ($s = \frac{1}{2}$). For the line, this creates 2 self-similar copies ($n = 2$). For the square this creates 4 self-similar copies ($n = 4$).

segments each, we would create nine smaller squares. We would need to magnify these nine smaller squares by a factor of three ($s = 1/3$), to see nine perfect copies ($n = 9$) of our initial square.

This relation between level of magnification (scaling factor) and number of copies (segments) is captured by the Hausdorff dimension, which is a form of fractal dimension. For mathematical objects, such as a line, a square, or the Koch snowflake (see Figure 2 in main paper, panel c), we can calculate the fractal dimension D by means of the following formula: $D = \frac{\log n}{\log 1/s}$, whereby $n =$ number of segments, and $s =$ scaling factor. When we apply this formula to the previous examples of dissecting objects' lines into two equal line segments, D of a line is 1, and D of a square is 2. Using this same formula, D of the Koch snowflake is calculated to be around 1.26. Roughly speaking, the fractal dimension D is a measure for an object's complexity.

Next to mathematical objects, which show *perfect self-similarity*, many real world objects, such as Romanesco broccoli (see Figure 2 in main paper, panel d) or the coast of Britain (see Figure A2), are self-similar and thus fractal too, which is called *statistical self-similarity*. Different from mathematical objects, we cannot calculate the fractal dimension of real world objects exactly. Instead, we need to estimate their fractal dimension. The box counting method is a widely used method to estimate an object's fractal dimension. If we apply the box counting method to estimate an object's fractal dimension, we basically draw a grid of boxes of a certain size over that object and count the number of boxes of that particular size that are necessary to completely overlay the object. We repeat this procedure for grids with different box size (i.e. different side length). We subsequently plot the number of boxes that are needed to cover the object on the y-axis, and 1/box

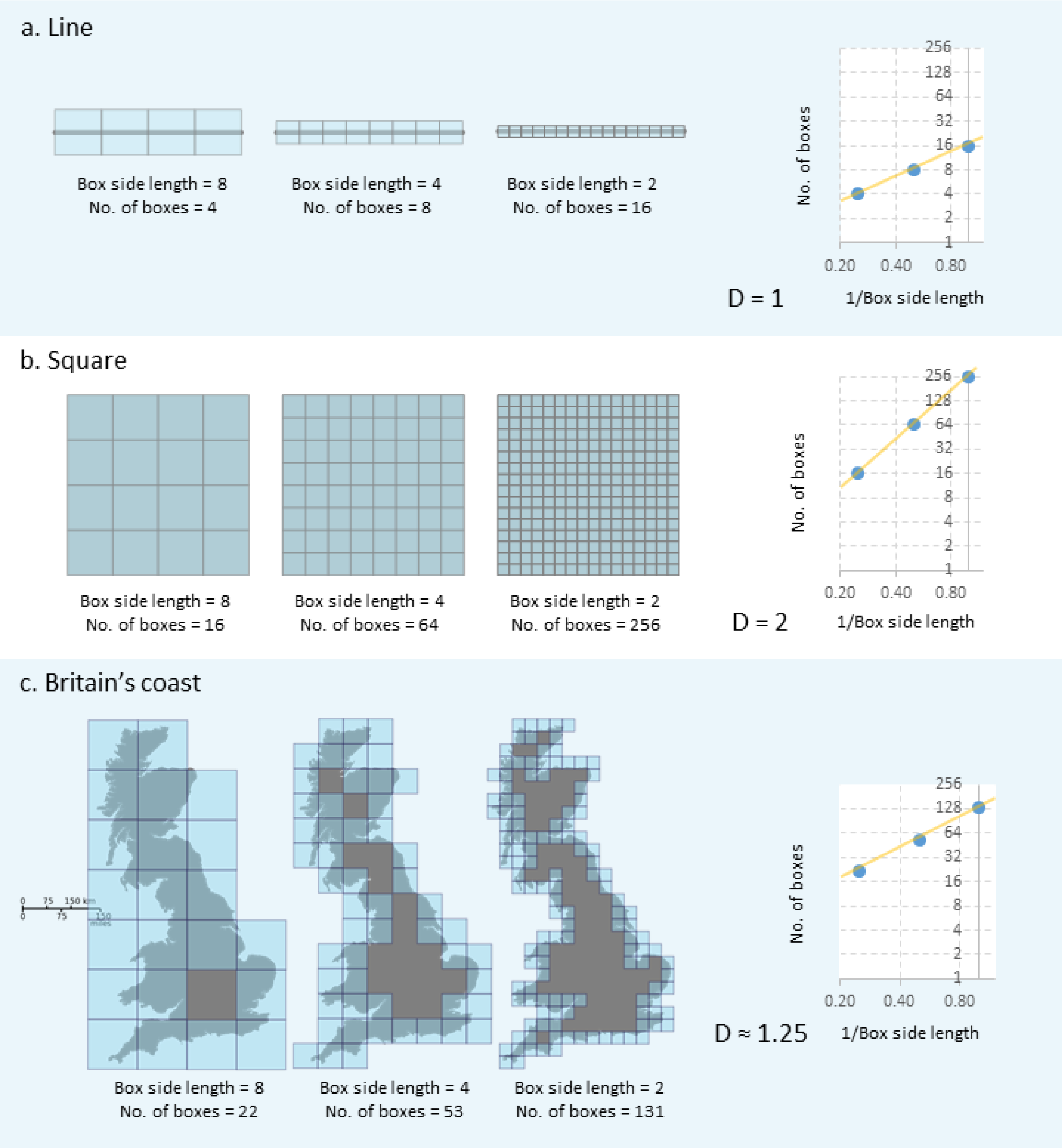

Figure A2. The box counting method to estimate the fractal dimension of a line (panel a), a square (panel b), and Britain's coast (panel c). We can estimate the fractal dimension by plotting the box side length against [1/(the number of boxes that are needed)] on a log-log plot, and calculating the slope of the resulting regression line. The fractal dimension D of a line is 1, of a square is 2, and Mandelbrot (1967) estimated the fractal dimension of Britain's coast to be 1.25.

side length on the x-axis, on log-log scales. We can find the fractal dimension D of the object by drawing a regression line through the dots on the log-log plot, and calculating the slope of that line, that is the scaling relation. Figure A2 illustrates how we can use the box counting method to estimate the fractal dimension of a line, a square, and Britain's coast. Due to specific characteristics of biological time series, which we will explain next, we cannot directly apply the box counting method to estimate the fractal dimension of time series, however.

Detrended Fluctuation Analysis

DFA is a method to determine the statistical self-similarity of a time series' variability (Ihlen, 2012; Peng et al., 1995). DFA's first step (Ihlen, 2012) is to transform the raw, noise-like, time series (see Figure A2, panel a) to an integrated, random-walk like time series (see Figure A2, panel b). The second step is to divide the time series into non-overlapping bins and calculate the variability within these bins, and repeat this for different bin sizes (see Figure A2, panel c). This second step has similarities with the box counting method, where now the bin size refers to the size of temporal window ('box') etc.

However, for biological time series, calculating the variability is not as straightforward as it may seem. Biological time series are typically non-stationary, which means that they stem from systems of which behavior changes over time (Peng et al., 1995). One part of these changes comes from random influences in the environment that we do not intend to measure. The other part of the changes comes from the system's internal dynamics, that we do want to measure. Peng et al. (1995) showed that accidental changes present themselves as changing trends in the biological time series. To calculate the scale-invariant variability for bins of non-stationary time series, we need to measure the variability *around these trends*, instead of the raw variability. For each bin, we therefore fitted a linear trend to the data (see the orange lines in Figure A2, panel c) and calculated the variability as the Root Mean Square of the residual variability (see orange, transparent, area around the orange lines in Figure A2, panel c), i.e. the *detrended fluctuation* or $RMS_{bins-scale}$.

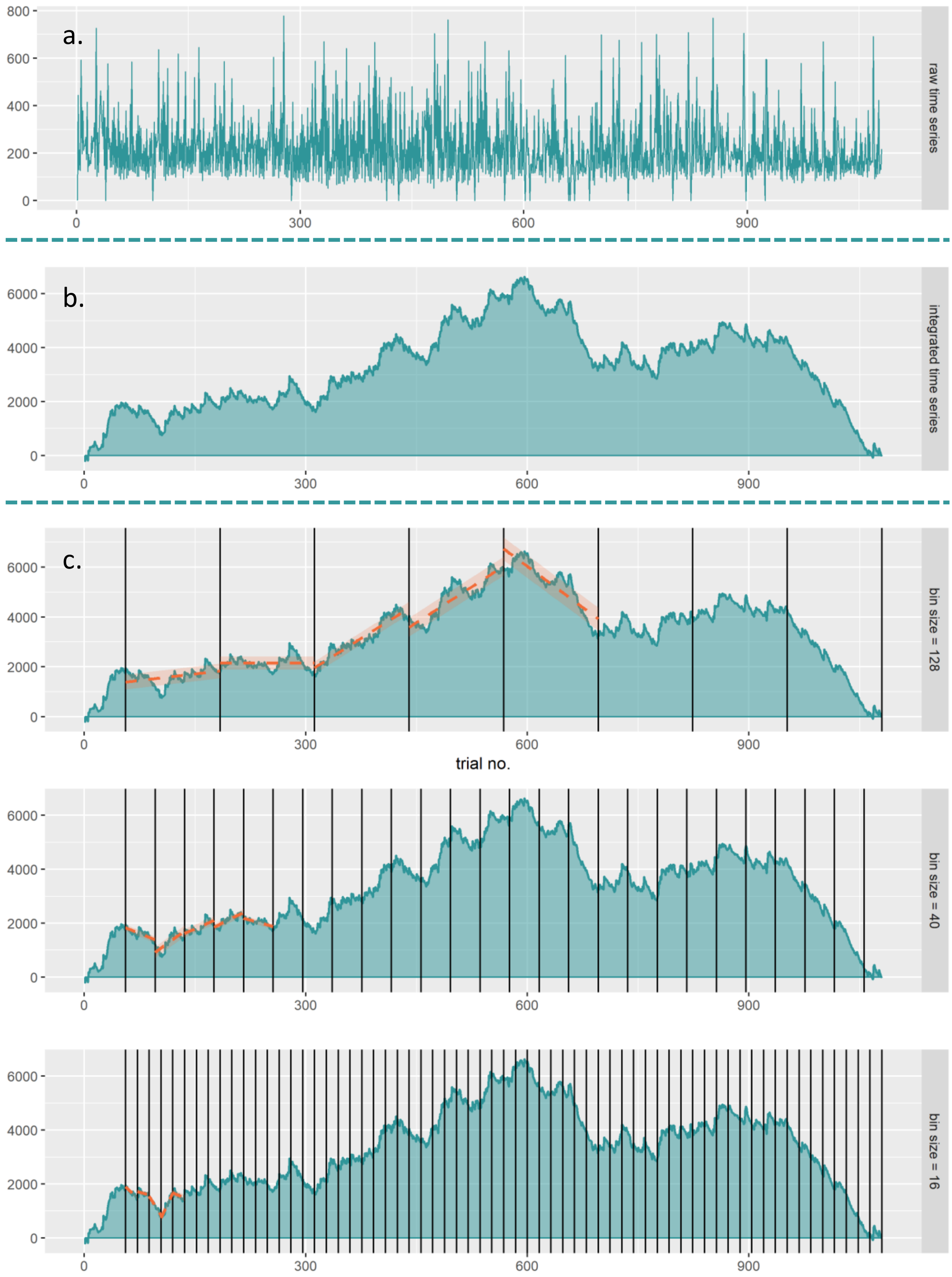

Figure A3. Steps of Detrended Fluctuation Analysis, illustrated with data from one participant in our experiment. Panel a shows the raw time series. This raw time series is then transformed to an integrated time series, which is shown in panel b. Panel c shows how the integrated time series is divided in increasingly smaller bin sizes, and the detrended fluctuation in each bin is calculated (orange lines).

After calculating the variability of all the bins with different sizes, DFA's next step is to calculate the overall Root Mean Square of each bin size scale, by means of the following formula: $RMS_{overall-scale} = \sqrt{\overline{RMS_{bins-scale}}\hat{}2}$. We subsequently need to plot the $RMS_{overall}$ for the different scales on the y-axis, and the bin size on the x-axis, on log-log scale (see Figure A5, panel a). When we draw a regression line through this dots in the plot, the slope of this line corresponds to the Hurst exponent H. The Hurst exponent is a measure for the interdependence of datapoints in a time series. For example, for more random timeseries (i.e. Gaussion white noise) the datapoints are more independent, which corresponds to a $H \approx 0.5$. For time series with datapoints that are in between dependent and independent (i.e. pink noise; see Figure 2, panel a, in the main paper), $H \approx 1.0$. Following Wijnants et al. (2012), the Hurst exponent H is related to the fractal Dimension D according to the following formula: $D = 0.4H^2 - 1.2H + 2$.

Multifractal Detrended Fluctuation Analysis

Strictly speaking, only mathematical objects can be monofractal, that is, can be captured perfectly by *one* fractal dimension only. Real-world objects, such as Romanesco broccoli or Britain's coast, are more irregular and therefore better described by a range of fractal dimensions, although the size of this range varies from object to object. Cumulonimbus clouds, which usually develop into a thunderstorm, are a clear example of a multifractal natural object (see Figure A4). Different parts of the cloud are self-similar and fractal, with a different fractal dimension, and yet the fractality of these different parts is also related and intertwined. Also time series can have a multifractal structure. When time series are multifractal, periods of pink noise-like variability are intermitted by periods of much larger and much smaller fluctuations. These intermittent periods of larger and smaller fluctuations stem from processes at intertwined time series, and are thus not random but occur systematically. MFDFA is a method to approximate the range of fractal dimensions that characterize the variability of a time series.

Figure A4. Cumulonimbus cloud. The self-similarity of this cloud cannot be captured by one fractal dimension only, but varies for different parts of the cloud. This cloud is thus a multifractal object.

To approximate the range of fractal dimensions of a time series, we need to measure and quantify it's periods of larger and smaller fluctuations – something that DFA is unable to. MFDFA deals with this 'problem' by means of extending DFA with the *q-order*. As a brief reminder, for DFA, we calculate the overall Root Mean Square of each bin size scale by means of the following formula: $RMS_{overall-scale} = \sqrt{\overline{RMS_{bins-scale}}\text{^}2}$. We thus calculate the variation at a bin size scale using the *second order* statistical moment (^2). For MFDFA, we calculate the variation at a bin size scale using a range of *q-order* statistical moments. As a first step, we transform $RMS_{bins-scale}$ to $RMS_{bins-scale[q]}$, by means of the following formula: $RMS_{bins-scale[q]} = RMS_{bins-scale}\text{^}q$. As a second step, we calculate the overall q-order RMS: $RMS_{overall-scale[q]} = \overline{RMS_{bins-scale[q]}}\text{^ }1/q$. The *q-order* essentially weights the influence of segments with large and small fluctuations on the overall q-order RMS. For negative q's, $RMS_{overall-scale[q]}$ is influenced by small fluctuations, while for positive q's, $RMS_{overall-scale[q]}$ is influenced by large fluctuations, whereby increasingly negative q-values emphasize increasingly smaller fluctuations, and increasingly positive q-values emphasize increasingly larger fluctuations. We subsequently can plot the $RMS_{overall[q]}$ for the different scales

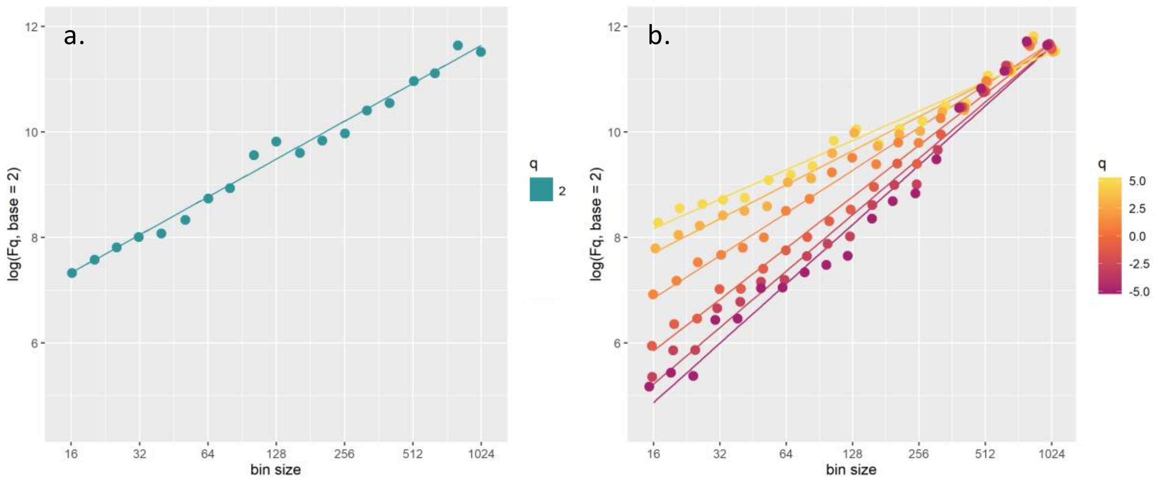

Figure A5. Log-log plots with $RMS_{overall}$ (Fq) on the y-axis and bin size on the x-axis, for one participant in our experiment. Panel a displays the dots and regression line of $q = 2$, as is the procedure for DFA. Panel b displays the dots and regression line of $-5 \leq q \leq 5$, as is the procedure for MFDFA.

and different q-orders on the y-axis, and the bin size on the x-axis, on a log-log plot (see Figure A5, panel b). When a timeseries is multifractal, the slope of the regression line is different for different values of q.

While DFA uses the slope of the regression line as the outcome measure, i.e. the Hurst exponent H, MFDFA converts the q-order Hurst exponents $H(q)$ to the so-called multifractal spectrum. Researchers typically use the multifractal spectrum width as the outcome measure of MFDFA. We can create the multifractal spectrum in four steps. First, we convert $H(q)$ to the q-order mass exponent $t(q) : t(q) \; = H(q) \; * (q-1)$. Second, we convert $t(q)$ to the q-order singularity exponent $h(q) : h(q) = \frac{dt(q)}{dq}$. Third, we convert $t(q)$ and $h(q)$ to the singularity dimension $D(q)$: $D(q) = \; 1 + qh(q) - t(q)$. Fourth, by plotting $h(q)$ on the x-axis and $D(q)$ on the y-axis, we create the multifractal spectrum (see Figure A6 for the multifractal spectrums of gestures and speech of one participant in the difficult condition and one participant in the easy condition).

The multifractal spectrum is an arc (see Figure A6), and it’s shape informs us about the fractality of the timeseries (for a complete overview, see Ihlen, 2012). The central tendency of the multifractal spectrum (i.e. top of the arc) is closely related to the average fractal structure of the timeseries, or the Hurst exponent that is the outcome measure of DFA. The width of the arc informs

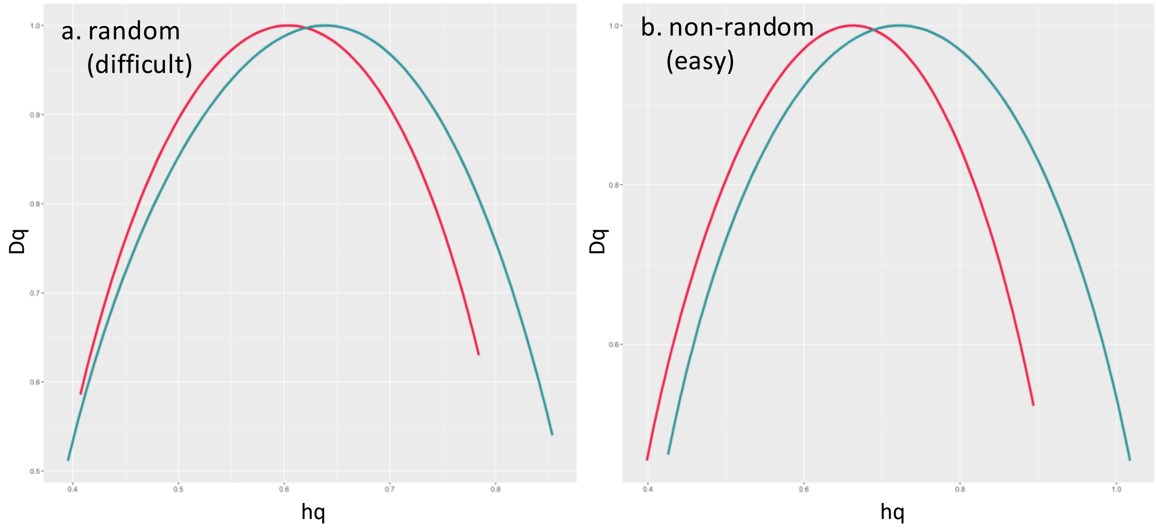

Figure A6. Multifractal spectrums of gestures (blue arc) and speech (red arc) for a participant in the difficult condition (panel a) and a participant in the easy condition (panel b). The difference in multifractal spectrum width is 0.081 for the participant in the difficult condition and 0.096 for the participant in the easy condition. We would interpret this as more complexity matching between gestures and speech for the participant in the difficult condition, compared to the participant in the easy condition.

us about the degree to which the timeseries' large and small fluctuations diverge from this average fractal structure. This means that timeseries that can be mostly characterized by one scaling relation will have a small multifractal spectrum width, while timeseries that can characterized by a whole range of scaling relations will have a large multifractal spectrum width.

Complexity matching as difference in multifractal spectrum width

In the current study, we define complexity matching between gestures and speech as the difference in multifractal spectrum width. Similarly, Davis, Brooks and Dixon (2016) performed MFDFA and compared multifractal spectrum widths to investigate how two participants coordinate their hand movements during a joint task. Furthermore, using a different technique to create the multifractal spectrums, Stephen and Dixon (2011) compared multifractal spectrum widths to investigate how participants coordinate their finger tapping with a metronome that beats in a particular, and sometimes multifractal, pattern. It should be noted that Delignières, Almurad, Roume and Marmelat

(2016) proposed a different method than comparing multifractal spectrum widths to investigate multifractal complexity matching.

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