Spatiotemporal Symmetry and Multifractal Structure of Head Movements during Dyadic Conversation

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Abstract

This study examined the influence of sex, social dominance, and context on motion–tracked head movements during dyadic conversations. Windowed cross–correlation analyses found high peak correlation between conversants head movements over short ($\approx$ 2s) intervals and a high degree of nonstationarity. Nonstationarity in head movements was found to be positively related to the number of men in a conversation. Surrogate data analysis offsetting the conversants time series by a large lag was unable to reject the null hypothesis that the observed high peak correlations were unrelated to short–term coordination between conversants. One way that high peak correlations could be observed when 2 time series are offset by a large time lag is for each time series to exhibit self–similarity over a range of scales. Multifractal analysis found small–scale fluctuations to be persistent, $\tau(q) < 0.5$ and large–scale fluctuations to be antipersistent, $\tau(q) > 0.5$. These results are consistent with a view that symmetry is formed between conversants over short intervals and that this symmetry is broken at longer, irregular intervals.

Introduction

In order to obtain an understanding of face–to–face conversations, one must examine both verbal content and nonverbal behaviors. Postural shifts, head nods, gestures, and other nonverbal cues are intertwined with speech as part of the communication process. These motor actions complement the verbal stream and can simultaneously serve a number of illustrative or regulatory functions (Ekman & Friesen, 1969). There is evidence that both individual differences (e.g., age, race, or sex) and the context of the conversation (e.g.

conversational goals, mutual attraction, and acquaintanceship of the participants) may influence the patterns of nonverbal behavior observed during a conversation (Benjamin & Creider, 1975; Bull, 1987; Burgoon, Buller, & Woodall, 1996). However, not all conversations are structurally and functionally equivalent — even if the verbal exchange within two different dyads is identical, participants' nonverbal behaviors may provide differing interpretations of the conversation. A gesture or movement executed by one person may impact the flow of a conversation as well as its underlying structure.

One mechanism that could help to achieve this balance is a tendency to complement or match a conversational partner's behavior, creating *symmetry* between partners that may have communicative value (Boker & Rotondo, 2002; Cappella, 1981; Gallese & Goldman, 1998; Lafrance, 1985) and provide what Gallese (2003) has termed a *shared manifold of intersubjectivity.* Evidence for such a mechanism suggests that primates, especially human beings, (Condon, 1980, 1982), are inherently drawn to some sort of rhythmic synchronicity (see Bente, Donaghy, & Suwelack, 1983; Beebe et al., 1982; Byers, 1976; Cappella, 1981; Briton & Hall, 1966; Condon & Sander, 1974; Dabbs, 1969; Hatfield, Cacioppo, & Rapson, 1992; Kendon, 1970; Lafrance & Broadbent, 1976; Scheflen, 1964). However, the dynamic symmetry observed between conversational partners may result in coordination that is substantially different than the rhythm and synchronization observed in the dyadic performance of music or dance.

Symmetry has many forms and has been shown to be a powerful organizing mechanism in perception (Kubovy, 1994; Olivers & Helm, 1998; Palmer & Hemenway, 1978; Pierret & Peronnet, 1994; Shepard, 1994). When two objects exhibit bilateral symmetry around a plane, it is said that they exhibit *mirror symmetry. Temporal symmetry* can be thought of as a form of self–similarity over intervals of time. A simple repeating auditory rhythm produced by a drum machine has a form of temporal symmetry called *translational symmetry.* If a conversant makes a gesture with the left hand and then later makes the same gesture with the right hand, the conversant exhibited *spatiotemporal symmetry.* If two conversants face each other and one makes a movement with the right arm and the other person then mimics that movement with her or his left arm, then this dyad exhibited *spatiotemporal mirror symmetry.* Another form of symmetry is scale–invariant symmetry, a form of self–similarity of motions across scales of time or space. If a conversant were to make small movements such as head nods that were similar in temporal structure to the larger term movements such as speaker–listener floor changes or postural adjustments, then the conversant would be exhibiting self–similarity across temporal scale. Scale–invariant symmetry, whether in space or in time, can be considered as exhibiting *fractal structure* (Mandelbrot, 1967, 1983).

Evidence has been reported in support of neural mechanisms (Iacoboni et al., 1999;

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Rizzolatti & Arbib, 1998; Rizzolatti & Craighero, 2004; Salenius, 1999) that may account for mirroring during conversation. Single cell recordings of these *mirror neurons* from macaque monkeys (Gallese, Fadiga, Fogassi, & Rizzolatti, 1996) have demonstrated that neurons in premotor cortex area F5, show high activity both when an action is performed (such as grasping a grape and bringing it to the mouth) and when a similar action is observed to be performed by another primate. Area F5 of the monkey brain is considered to be homologous to Broca's area in the human brain (Passingham, 1993), an area associated with the production of speech and the interpretation of syntax (Bookheimer, 2002). One aspect of theories derived from the existence of mirror neurons is the prediction that symmetry is a fundamental aspect of communication (Gallese & Goldman, 1998).

If two conversants were to match every movement of the other, this would lead to ever–increasing mirror symmetry and would eventually culminate in a state of close mutual entrainment as is sometimes observed in rhythmic dance (Boker, Covey, Tiberio, & Deboeck, 2005). Since ever–increasing symmetry is not typically observed in conversation, some mechanism for *symmetry breaking* must also be in operation (Boker & Rotondo, 2002).

What communicative purpose does symmetry serve? One possible explanation is that by creating mirror symmetry a conversant is attempting to physically access the somatosensory inner state of his or her conversational partner (Gallese & Goldman, 1998). To the extent that cognitive or emotional states are correlated with postures, gestures and facial expressions, one may be able to trigger the experience of an internal state by assuming a particular posture or making a gesture or expression. Formation of symmetry in conversation might cross–correlate internal states and thus facilitate communication (Bavelas, Black, Chovil, Lemery, & Mullett, 1988).

A framework for understanding symmetry formation and symmetry breaking in conversation derives from information theory (Shannon & Weaver, 1949) where one may consider communication of information to be a problem in prediction. If the listener can exactly predict what is coming in the conversational stream, then the listener already possesses the information that is being transmitted. In other words, if the listener can construct a conversational stream symmetric with that produced by the speaker, then both speaker and listener share the same information. This spatiotemporal symmetry between speaker and listener is a measure of the redundancy between them and thus might be used as a way to signal acknowledgment of communication of information. A dyad might nonverbally signal acknowledgment or agreement through formation of spatiotemporal symmetry in their head movements, posture, or gestures. A repeating head nod is a powerful mechanism for quickly forming symmetry since it is self–similar across time within individual and thus facilitates synchronization (and thus symmetry) between individuals.

However, a speaker must surprise a listener in order for new information to be received by the listener. If a listener can predict a conversational stream, the listener already possesses the information in that stream. But an effective speaker would likely not wish to catch listeners off guard. If a speaker intends an impending increase in new verbal information, this intent could be signaled by a break in nonverbal symmetry between the conversants. Thus a movement that decreases symmetry between individuals may signal an increase in the information content within a verbal stream and facilitate the listener being ready to attend to the new information.

The symmetry exhibited between conversants is likely to have upper and lower acceptable bounds. Conversational partners who exhibit too little symmetry (e.g., seeming uninterested) or too much symmetry (e.g., seeming to mimic or mock the other conversant) may be perceived as socially awkward. Conversations with partners who do not maintain an appropriate degree of symmetry during conversation may be perceived as difficult or uncomfortable to maintain. A continuous process of symmetry formation and symmetry breaking would be consistent with the notion of a "comfortable balance" in conversational symmetry, but would lead to a prediction of *nonstationarity* in motion–tracked time series of nonverbal behaviors. The degree of nonstationarity in the conversation is likely to be a sensitive indicator of how the conversants have adapted to each other in order to form this equilibrium between symmetry formation and symmetry breaking in the conversation. It is also reasonable to expect that social context plays a role in the mutual adaptation that equilibrates between the conversants; and thus the degree of nonstationarity in a conversation may be affected by variables such as social status, gender, and the context of the conversation.

Gender, Dominance, and Nonverbal Behavior

The present study examines symmetry during conversational interaction, with an emphasis on contextual and individual differences factors that may influence the formation of nonverbal displays of symmetry. One motivation for this research was in relation to a theory that males are socially dominant over females (Henley, 1977). A variety of previous research has demonstrated that contextual aspects of a situation (Aries, Gold, & Weigel, 1983; Davis & Gilbert, 1989), personality characteristics (Davis & Gilbert, 1989; Roger & Nesshoever, 1987), and gender composition of the interacting individuals (Henley, 1977; Lafrance & Mayo, 1979; Mulac, Studley, Wiemann, & Bradac, 1987) may influence nonverbal behavior.

Gender is a factor that has been shown to influence nonverbal behavior during conversation. For instance, it has been reported that women use more closed postures and facial expression and tolerate being closer in proximity to their conversational partners (Dovidio, Ellyson, Keating, Heltman, & Brown, 1988; Hall, 1984; Lafrance & Mayo, 1979; Patterson & Schaeffer, 1977; Williams & Best, 1986). Women are reported to be gazed at more often and approached more closely by others (Hall, 1984). Furthermore, there may be an expectation of positivity from females that is not expected from males (Briton & Hall, 1995). In contrast, men are reported to stare away more, be less expressive, be more expansive in their posture, and be more restless (Duncan & Fiske, 1977; Hall, 1984; Mehrabian, 1981; Williams & Best, 1986). There is also evidence that men tend to be less proficient at decoding the nonverbal cues of others, to be worse encoders of negative information than women, and to be more accurate at sending positive information to others (Hall, 1978; Zaidel & Mehrabian, 1969). Additionally, both men and women are reported to exhibit different patterns of nonverbal behaviors (e.g., gazing) based on the gender of their conversational partner (see Bente, Donaghy, & Suwelack, 1998; Weitz, 1976).

One theory used to explain these types of gender differences in nonverbal behaviors was developed by Henley (1977), who proposed that social power in American society is unevenly distributed, as evidenced by nonverbal gestures of dominance and submission. In this *male dominance hypothesis* (Thorne & Henley, 1975), men are labeled as dominant and women and children as submissive in the American social system. According to this view, some gender differences represent efforts by men to wield power over women, while others (such as a lesser sensitivity to nonverbal behaviors in men) are a result of the power differential (Henley & Kramarae, 1991). This theory proposes that gender overlaps a great deal with social dominance, thereby affecting conversations within mixed–gender dyads with the result that males tend to be more dominant than females.

The concept of dominance has been explored extensively. Evidence for a link between status, power, and dominance differences and the production of nonverbal behaviors has been reported by a number of researchers. For example, higher power has been associated with a high visual dominance ratio (i.e., a tendency to look more at the interlocuter while speaking and less while listening) (Dovidio et al., 1988; Dovidio & Ellyson, 1985; Dovidio et al., 1988), the use of more demonstrative hand gestures during a speaking turn (Henley, 1977), the use of more chin thrusts (Henley, 1977; Dovidio et al., 1988), and stoic, unsmiling poses (Keating, 1985). Moreover, dominant individuals are reported to display different visual preferences, such as wanting to be in the position affording the greatest amount of visual access to others (Sommer, 1971) as well as staring at others more directly and steadily (Rosa & Mazur, 1979).

In the present study, the nonverbal movements of dyad partners were measured as they participated in a conversational setting with an inherent asymmetrical dominance context. Dyads were composed of males and females who scored high or low on a personality assessment of dominance, and each was placed in a role consistent with their dominance score. Head movements were recorded with a computerized motion tracking system. In order to examine symmetry between and within individuals, two recently developed techniques were applied. First, windowed cross–correlation (WCC) was applied to calculate a measure for the nonstationarity in the spatiotemporal symmetric relationship between conversants' recorded head movements (Boker, Xu, Rotondo, & King, 2002). Second, a wavelet–based multifractal analysis (Dimitrova & Vitanov, 2004) was used to calculate a measure of the self–similar time structure of the recorded head movements. Since these two analyses may be unfamiliar to many readers, some discussion about each method will precede the application of the analyses to the data.

Experiment: Recorded head movement during a structured–context dyadic conversation

Methods

Participants.

The participants consisted of 64 male and 64 female undergraduates from a midsize, private Midwestern university. Participants were recruited by phone from a pool of eligible students who were taking an introductory course in psychology and had previously completed a dominance scale as part of a department–wide prescreening packet.

All participants were scheduled in groups of four, producing 32 groups (*quads*) of individuals. None of the participants reported being friends with any other quad members. Each quad contained one high–dominant male, one high–dominant female, one low–dominant male, and one low–dominant female (dominance measure described below). Each participant engaged in two conversations, one mixed–sex and one same–sex interaction, and each conversation involved one high– and one low–dominant participant. The quads were counterbalanced for conversation order (i.e., first mixed– then same–sex vs. first same– then mixed–sex).

Apparatus.

The participants' head movements were tracked using an Ascension Technologies MotionStar 16 sensor magnetic motion tracking device. Data were digitally recorded from receivers which sensed position (3 degrees of freedom) and orientation (3 degrees of freedom) at a sampling frequency of 80 times per second (80Hz). The transmitter, a 31cm cube, was positioned on a non–metallic surface approximately one meter from the participants. The transmitter emitted a pulsed magnetic field with an effective recording radius of 3.05m. The sensors, 2.5cm $\times$ 2.5cm $\times$ 2.0cm cubes of approximately 16 grams, were affixed to the participants and acted as receivers measuring flux in response to their position and orientation within the transmitter's field.

Each participant wore eight receivers. One receiver was positioned at each of the following areas: back of the head, middle of the chest, on the back of the right and left hand, just below the right and left elbow, and just below the right and left knee. Each receiver was attached to a piece of neoprene and bolted to a secure device with small aluminum bolts. The head receiver was attached to the back of a baseball cap, the chest receiver to a constructed neoprene vest, and the hand sensors were secured to the back of the hand by weight training gloves. Elbow and knee sensors were bolted onto athletic braces. The sampling rate was set to 80Hz in order to minimize ambient noise. All interactions were held in a 3.7m $\times$ 3.7m specially constructed room containing a minimum amount of ferrous material in order to minimize the effect of the room on the transmitted magnetic field. The sensors were calibrated such that they had less than 1.5 mm RMS error in position. The current work reports results from the angular orientation of the head sensor only.

Conversations were videotaped using three mounted cameras positioned to be unobtrusive yet visible to the participants. One camera captured a full overhead view of both participants, while each of the others recorded facial shots of the participants. Small lavaliere microphones recorded speech from each participant.

Dominance Measure.

A self–report measure of dominance was used as a screening tool for potential subjects from the available pool. Dominance was assessed with 26 items taken from the Dominance Scale of the California Psychological Inventory (Gough, 1956), which has been used widely as a prescreening measure in similar previous research (Aries et al., 1983; Fleischer & Chertkoff, 1986; Hegstrom & Griffith, 1993; Nyquist & Spence, 1986; Richards & McAlister, 1995). Sample items include: "I think I would enjoy having authority over other people," "I think I am usually a leader in my group," and "I would rather not have very much responsibility for other people" (reverse scored). The response scale was lengthened to a 7–point Likert scale format to include greater variability within the sample. Participants were asked to indicate the extent of their agreement or disagreement with the items using this scale.

Responses from all individuals in the participant pool (N = 128) were analyzed using exploratory factor analysis, and two factors were retained. An oblique rotation was performed, resulting in two positively correlated factors (r = .55). One factor contained traits that are more generally associated with leadership skills (e.g., "When I work on a committee, I like to take charge of things"). The second factor appeared to be associated with traits of social dominance (e.g., "When in a group of people I have trouble thinking of the right things to talk about"). The intent of this prescreening measure was to assess an individual's tendency to take the lead of a social situation, so both seemed appropriate composite measures for this goal. Therefore, information from both composite scores was used to determine an individual's level of dominance. Since the two factors were relatively highly correlated, items that loaded most highly on the two factors were selected and summed to produce one composite score. Those scoring in the lowest third on the composite score were labeled "Low Dominant" individuals; those scoring in the highest third were labeled "High Dominant" individuals. A theoretical minimum point total discrepancy between those labeled low and high dominant was set at 20 points, but no pair of individuals was related by only this amount. The minimum point total discrepancy between any pair was 31 points out of a possible 94.

To determine whether this composite score classification differed from the classification that an individual would obtain using only one of the composite scores, the composite score rankings were compared against the rankings obtained when only one factor or the other was used to classify the individuals. Although ranking within a category changed, very few individuals changed categories, and no individuals shifted from the low dominant to the high dominant classifications, or vice versa.

Procedure.

Participants were told that the experiment was designed to examine magnetic fields given off by the body during conversation. If subjects asked for further clarification, experimenters rephrased the original message without including any further information. This deception was necessary to ensure that the individuals did not become self-conscious about their movements or attempt to manipulate their nonverbal behaviors in a biased manner. Since the goal was to capture the naturalistic behaviors displayed in these types of situations, the true nature of the study was not revealed until the debriefing period. No participants revealed that they had determined the true nature of the study before the experimenters informed them of it.

Participants identified as "high" in dominance were assigned the role of "interviewer" and were told that they would be assessing their conversational partners for a hypothetical job working with people with disabilities. The importance of the interviewer's job and their status as interviewer was reiterated several times with sentences like, "Since you will be conducting the interviews, you will be in control of the situation and should structure the time accordingly." Such reminders were used to enhance their sense of status.

Participants identified as "low" in dominance were assigned the role of "interviewee." They were told that they would be interviewing for a potential job placement, but they were not given any special information about the job. To reinforce their role, interviewees were told things like, "The interviewer has been given complete instructions about the job and what it entails, so you should answer his/her questions during the interview to the best of your ability."

Participants were then outfitted with eight receivers (one at each of the aforementioned areas) and asked to wear a lightweight nylon jacket over the sensors. The jacket was used to secure sensor cords during movement as well as diminish distractions due to the equipment or seeing another individual wearing the equipment. To accustom participants to wearing the sensors, we asked them to perform a short block–building task that required gross as well as fine motor movements. All participants completed the task without difficulty prior to beginning their first conversation.

The two participants in a conversation were brought into the experiment room simultaneously. Precautions were taken to minimize their exposure to one another prior to this first meeting. Each participant was seated on a wooden stool, approximately two meters away from his or her conversational partner. The participants were then left alone for seven minutes, during which time they were to conduct the job interview and then use any remaining time for getting to know one another. At the end of the allotted conversation time, the participants were then asked to wait for the next interview or were escorted to a private waiting room until it was time for their second conversation. Upon completion of their second interview, the participants were fully debriefed and thanked for their time.

Preliminary data transformations.

The analyses reported in the current work are based on the angular displacement and velocity about two axes, the vertical axis and the horizontal axis shown in Figure 1. To avoid incorporating movement made in response to the departure or arrival of the research assistants, the first and last 30 seconds of each conversation was deleted from subsequent analyses. The total length of each analyzed conversation was 5 minutes and 50 seconds after this trimming. Since the motion capture equipment sampled at 80Hz, this resulted in 28,000 samples per axis, per individual, per conversation. The mean of each individual time series was subtracted so that all displacements were relative to the mean.

The angular velocity in degrees was estimated using a variant of Savitsky–Golay filtering (Savitzky & Golay, 1964) called Generalized Local Linear Approximation (GLLA) of derivatives (Boker, Deboeck, Edler, & Keel, 2007). This method fits a local quadratic approximation to the neighborhood of each sample x_i defined as $\{x_{i-2}, x_{i-1}, x_i, x_{i+2}, x_{i+2}\}$. The estimated intercept is taken as the low pass filtered angular displacement and the slope from the quadratic approximation is taken as the angular velocity. We used a relatively small filter, only 5 samples wide, since we wished to preserve the microstructure of the head movements and not attenuate the variance in velocities while simultaneously rejecting spurious artifacts.

In order to perform the filtering and derivative estimation, a 5 dimensional time–delay embedded matrix $\mathbf{X}^{(5)}$ of the time series was constructed so that the ith row of $\mathbf{X}^{(5)}$ would be $\{x_{i-2}, x_{i-1}, x_i, x_{i+2}, x_{i+2}\}$. The resulting $N \times 5$ matrix was post–multiplied by a matrix $\mathbf{W}$ defined as

$$\mathbf{W} = \mathbf{L}(\mathbf{L}'\mathbf{L})^{-1} \tag{1}$$

where the matrix $\mathbf{L}$ is given as the loadings for the second order Taylor series approximation to the neighborhood of x_i,

$$\mathbf{L} \;=\; \begin{bmatrix} 1 & -2\Delta t & (-2\Delta t)^2/2 \\ 1 & -1\Delta t & (-1\Delta t)^2/2 \\ 1 & 0 & 0 \\ 1 & 1\Delta t & (1\Delta t)^2/2 \\ 1 & 2\Delta t & (2\Delta t)^2/2 \end{bmatrix} \tag{2}$$

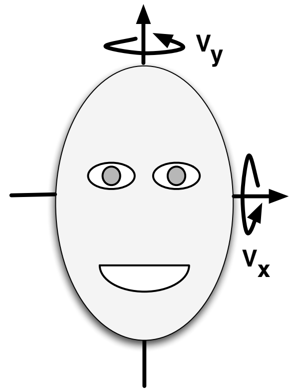

Figure 1. Angular velocity was calculated about two axes of orientation: V_x corresponds to an affirmative head nod and V_y corresponds to a lateral head shake.

where Δt is the elapsed time between samples in the time series. When $\mathbf{W}$ is constructed in this way, the $N \times 3$ matrix $\mathbf{Y}$

$$\mathbf{Y} = \mathbf{X}^{(5)}\mathbf{W} \tag{3}$$

contains the smoothed angular displacements in column 1, the smoothed angular velocities in column 2, and the smoothed angular accelerations in column 3 that are optimal in a least squares sense given that a neighborhood of 5 was chosen and that the second order Taylor series was chosen as the approximating function. The first and second columns of $\mathbf{Y}$ (smoothed angular displacement and smoothed angular velocity) were used in all subsequent analyses.

To give an idea of how well the smoothing operation performed, 5 seconds of a time series are plotted in Figure 2–a and the smoothed equivalent in Figure 2–b. Note that the smoothing algorithm does not reduce major peaks and valleys, (i.e., head shake amplitude), but only removes small artifacts that may be due to high frequency noise. In these data, which have very little high frequency noise relative to the main signal, the smoothed and unsmoothed trajectories appear nearly identical.

Overall Head Angular Amplitude and Velocity

We first examined the extent of angular head movement and the velocity with which those movements were made. Extent of head movement was determined by calculating the root mean square (RMS) amplitude of the orientation of the head with respect to the vertical and horizontal. The smoothed displacement from the mean was taken from the first column of the matrix $\mathbf{Y}$ calculated in Equation 3 for each axis for each person within each conversation. Then the RMS was calculated for each time series as

$$y = \sqrt{1/N \sum_{i=1}^{N} y_i^2} \tag{4}$$

where $N = 28,000$ is the length of each time series. In this way we calculated an RMS vertical displacement, RMS vertical velocity, RMS horizontal displacement and RMS horizontal

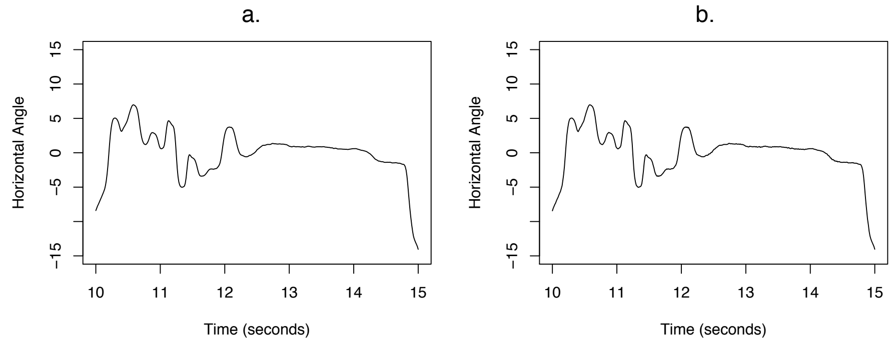

Figure 2. (a) Five seconds of raw horizontal angular displacement (head shake or gaze redirection), and (b) horizontal angular displacement smoothed using Generalized Local Linear Approximation (GLLA). During this 5 second interval the participant can be seen to be shaking his head while moving the center of the oscillation from left to right during the interval 10s to 12s and then holding the head more–or–less steady during the interval 12.5s to 14.5s. However, note that there are micromovements during steady phase that we do not wish to lose during smoothing.

velocity for each person, j, in each conversation, k.

We predicted these four dependent variables using the two independent variables from the experiment, gender (coded male=1, female=0) and dominance (coded high=1, low=0). We chose the unit of analysis as the quad since each individual participated in two conversations with two other individuals in the quad. We used a mixed effects model so as to account for this dependence in the data. We grouped the data by quad ID, q, and allowed a random intercept term to account for mean differences between quads, so that

$$\begin{aligned} y_{jkq} &= c_q + b_1 S_{jkq} + b_2 D_{jkq} + e_{jkq} \\ c_q &= \mu_c + u_q \end{aligned}$$

where y_{jkq} is one of the four dependent measures for person j in conversation k in quad q. The independent variables are the intercept c_q for quad q and the sex S and dominance D. In turn, the intercept is modeled as a combination of a mean intercept value μ_c and a part unique to the quad, u_q.

Results

RMS vertical angular displacement and velocity were related to both gender and dominance of the participant as shown in Table 1. These movements could be due to, e.g., head nods or vertical gaze aversion. Males and high dominant individuals exhibited reduced overall RMS vertical displacement and lower RMS vertical velocities. Thus males' nodding movements tended to be smaller in amplitude than females' nods. In addition, males' nodding movements occurred at about three quarters the RMS velocity of females' nods. This same effect and of approximately the same effect size was observed in high dominant individuals. High dominant individuals tended to nod with a reduced amplitude and at a slower velocity than low dominant individuals. These effects were independent in these data and there was not a significant interaction between sex and dominance.

Table 1: Overall head angular RMS vertical displacement and velocity predicted by the gender and dominance category of the participant. Coefficients for displacement are in units of degrees of angle and velocity coefficients are in degrees per second. (N= 256, Groups= 32; Displacement AIC = 2130 , BIC = 2147; Velocity AIC = 3089 , BIC = 3106)

	Value	SE	DF	t	p
Vertical Displacement					
Intercept	23.945	1.881	222	12.733	< 0.0001
IsMale	-7.055	1.854	222	-3.805	0.0002
IsDominant	-4.172	1.854	222	-2.250	0.0254
Vertical Velocity					
Intercept	116.61	12.30	222	9.481	< 0.0001
IsMale	-41.26	12.41	222	-3.326	0.0020
IsDominant	-43.11	12.41	222	-3.475	0.0006

Horizontal head movements, which could be head shakes or horizontal gaze aversion were related only to gender of the participant as shown in Table 2. Male participants tended to show reduced RMS horizontal displacement and velocity in comparison with female participants. This gender effect was strong in that female participants' RMS horizontal displacement and velocity were both approximately double that of male participants. No effect of dominance was found in horizontal angular movements.

Table 2: Overall head angular RMS horizontal displacement and velocity predicted by the gender and dominance category of the participant. (N= 256, Groups= 32; Displacement AIC = 2377 , BIC = 2395; Velocity AIC = 3291 , BIC = 3309)

	Value	SE	DF	t	p
Horizontal Displacement					
Intercept	24.301	3.009	222	8.077	< 0.0001
IsMale	-10.961	3.042	222	-3.603	0.0004
IsDominant	0.630	3.042	222	0.207	0.8360
Horizontal Velocity					
Intercept	108.78	18.14	222	5.997	< 0.0001
IsMale	-63.31	18.60	222	-3.404	0.0008
IsDominant	-4.42	18.60	222	-0.237	0.8125

Discussion

These data could be interpreted as supporting previous suggestions that females tend to be more expressive of positivity than males (e.g., Briton & Hall, 1995). The vertical angular rotation for females in the present data was greater in amplitude and velocity by a factor of about one third than for males. To the extent that vertical angular rotation was associated with affirmative head nods, we might observe that females were expressing greater positivity. However, since the females also exhibited greater horizontal angular rotation, another interpretation would be that the females simply behaved with greater overall animation and the vertical component of these movements could be perceived as indicative of greater positivity.

In addition, the vertical orientation data could be interpreted as being consistent with reports (e.g., Rosa & Mazur, 1979) of dominance being associated with more steady staring, since the amplitude and velocity of vertical head movements were less for high dominant than for low dominant individuals. On the other hand, the current results are inconsistent with reports of males engaging in greater gaze avoidance. To the extent that gaze avoidance is associated with horizontal head turns, the horizontal displacement and velocity results suggest that males in this experiment engaged in less gaze avoidance than did females. In the absence of eye tracking data, these results remain inconclusive with respect to gaze.

Clearly, females engaged in more energetic head movements both in extent and in velocity than did males. However, only in movements that could be associated with positivity did dominance play a role: High dominant individuals, both male and female, were less energetic in their vertical head movements. But overall amplitude of movements is only a small part of the story of communication. Coordination of movements between individuals is where interpersonal symmetry would be observed.

Interpersonal Coordination

One method for measuring coordinated movement is with a single cross-correlation value, which provides an overall value for the degree of association in position or velocity between individuals. However, overall cross–correlation assumes stationarity in the time series during the interval of interest: The mean, variance and time–lag structure of the time series are assumed to remain constant such that a selected segment of the time series starting at any given time is representative of the whole time series (Kaplan & Glass, 1995).

Nonstationarity might be an indication of a great deal of noise in the data, but it might also be an indicator of a changing pattern in the structure of the coordination between conversants. For instance, cross–correlation may not exhibit same the time–lag structure when a participant is speaking versus listening (see Hendry & Juselius, 2000, for an extended discussion of nonstationarity). Thus, nonstationarity might encode information concerning the formation of coordination during the interaction as speaker and listener roles are alternated.

Another method to examine coordination between individuals engaged in interaction is Windowed Cross–Correlation (WCC)[1]. WCC is a method that estimates the peak Pearson product moment correlation and the associated time lag at the peak correlation between two time series using only an assumption of local stationarity (Boker et al., 2002). Given a selected interval (or *analysis window*) of assumed local stationarity (e.g., 2 seconds), WCC estimates cross–correlation between two time series for each available lagged offset in a range (e.g., ±2 seconds). The peak correlation nearest to an offset of zero is then selected and

[1] A free, open–source implementation of Windowed Cross Correlation and Peak Picking can be downloaded from the web address http://people.virginia.edu/~smb3u or can be obtained by emailing Steven Boker at boker@virginia.edu

that value and its associated time lag is saved. Then the elapsed time base of the analysis window is advanced a small number of samples and the analysis is performed again. Thus, for each elapsed time into the conversation, there is a vector of cross–correlations that could be represented by colors as shown in Figures 3–a and 3–b. The horizontal axes in Figure 3 represent elapsed time during the conversation and the vertical axes represent lagged offset between two individuals' time series. For each combination of elapsed time and offset, there is a cross–correlation represented by a color. At each elapsed time (vertical slice through the graph), there is a peak correlation nearest to a lag of zero represented by the points making up the solid line. If the value of the peak correlation and its associated lag are invariant as elapsed time increases, there will be horizontal stripes through the graph and the solid line will be roughly a straight line with a slope of zero; in other words the association between the two time series will be stationary.

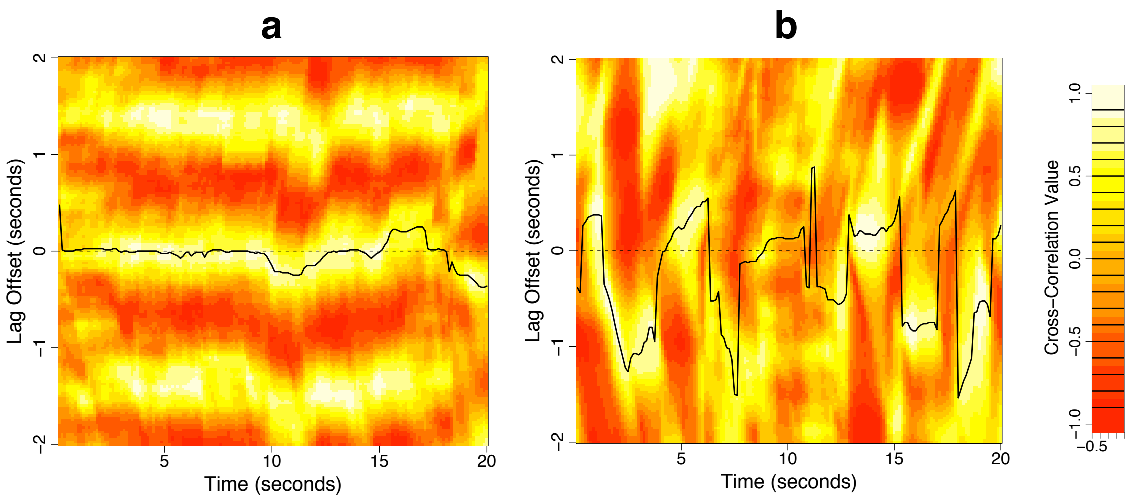

Figure 3. Plots of 20 windowed cross–correlation (WCC) of (a) 20 seconds of total RMS velocity from a pair of dancers and (b) 20 seconds of head vertical angular velocity from a high dominant male speaking with a low dominant male in the current experiment. The horizontal axis plots elapsed time and the vertical axis plots the lead or lag of the cross–correlation for a range of ± 2 seconds. The plotted color represents the value of the estimated cross–correlation for each combination of elapsed time and lead or lag. The solid line plots the peak correlation closest to a zero lag as calculated by the peak picking algorithm described in the text of the article.

Suppose a fixed amount of spatiotemporal symmetry existed between conversants, i.e., the cross–correlation between their movements exhibited long–term stationarity. This would suggest that the movements of one partner could be predicted from the other partner's movements for the duration of the conversation. This sort of stationarity in spatiotemporal symmetry can be observed when two individuals dance and one participant is instructed to follow the movements of the other (Boker et al., 2005). As an example, see Figures 3–a and 3–b. Figure 3–a is a WCC plot of 20 seconds of two participants' RMS velocity while dancing to a fixed auditory rhythm (Boker et al., 2005) and exhibits a relatively high degree of stationarity in the coordination between the dancers. On the other hand, Figure 3–b is a

WCC plot of the lateral angular velocity (V_y) from one 20 second segment from the current experiment. The head lateral angular velocity in this segment of a dyadic conversation does not exhibit the same time invariant association as is found in the dance example. The coordination (as estimated by peak cross–correlation) is still strong, but the lag at which that peak correlation is occurring changes rapidly during the conversation. Sometimes person A is leading, sometimes person B is leading, sometimes a smooth transition occurs from leading to lagging, and sometimes there is a short interval of low association that might indicate symmetry breaking.

Data from a previous study in dyadic conversation (Boker et al., 2002) suggested that the length of time during which local stationarity was likely to hold is approximately 2 seconds, that the minimum temporal resolution required to capture leads and lags in head coordination was approximately 0.10 seconds, and that changes in lead and lag could be observed within 250ms. Given that, WCC analysis was performed using an analysis window of 2 seconds (160 observations), with a maximum lead and lag of 2 seconds (160 observations). The lag increment, or the number of observations between successive changes in the lead and lag between windows, was set at 2 observations (25ms). The elapsed time window increment, or the number of observations between one fixed window and the next, was set to 10 observations (125ms).

The resulting plots of the windowed cross-correlation technique are similar to that shown in Figure 3–b. Temporally synchronous correlations are plotted along the horizontal slice through the graph where the Y axis value is zero. Positive Y axis values indicate correlations obtained when the low–dominant person's measurements were temporally leading those of the high–dominant person. Negative values on the Y axis indicate correlations obtained when the high–dominant person's movements were in the lead. The legend provides a reference for the strength of the correlations.

In Figure 3–b, patterns of high correlations cross from one side of temporal synchrony to the other. Consider the section of the graph during elapsed time $t = 2$s to $t = 7$s. At $t = 2$s the head lateral angular velocity initiated by the high–dominant individual were subsequently matched or mirrored by the low dominant individual about 1.2s later, so the peak WCC at $t = 2$s is at lag -1.2. As elapsed time increases to about $t = 6$s, the lead passes from the high–dominant to the low–dominant individual as indicated by the diagonal stripe from (2, -1.2) to (6, 0.5). Then there is a rapid transition from the low–dominant individual leading at $t = 6$ to the high–dominant again leading at $t = 7$. Sudden transitions in lead (also observed at $t = 13$, $t = 15$, and $t = 17$) are likely to be indications of symmetry breaking in the conversation.

The peak picking algorithm described by Boker et al. (2002) was used to track the lag and offset of the peak WCC nearest a lag of zero. The algorithm was run using a peak noise rejection interval of 8 observations, insuring that there was consistent decline for 4 observations on each side of a selected peak. The lag times of the peak WCC during 20 seconds of conversation are plotted as the solid lines overlaid onto the graphs in Figures 3 and 4. Since these lag times are associated with a maximum correlation value nearest to a lag of zero for a given analysis window, these plots provide an estimate of the time lag with greatest association between the two time series.

The value of the peak WCC, its associated lag, and the variance of that lag were predicted using a mixed effects model in which participants were grouped by dyad in order

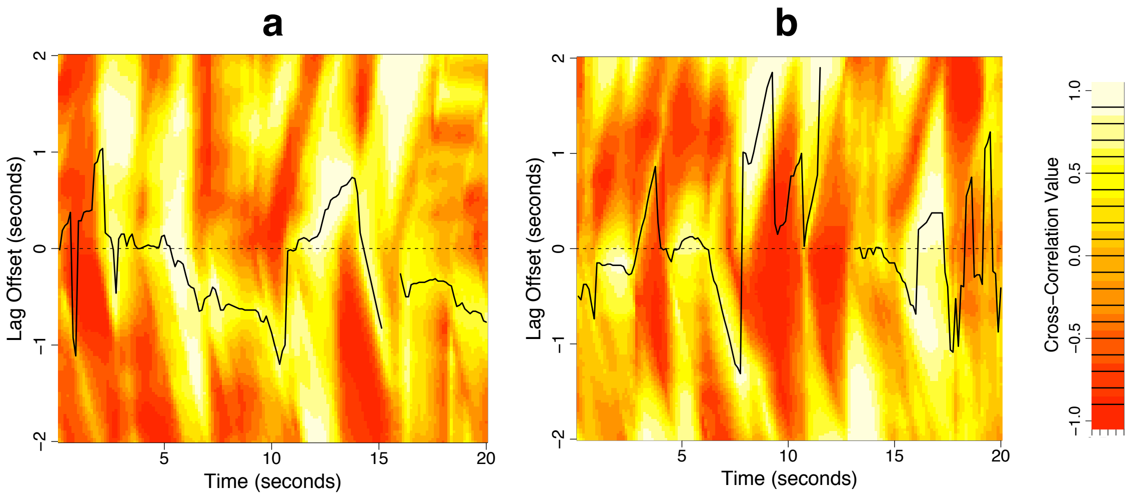

Figure 4. Plots of 20 seconds of windowed cross–correlation (WCC) of head vertical angular velocity (head nod) from (a) a high–dominant female speaking with a low–dominant female and (b) the same high–dominant female speaking with a low–dominant male.

to account for the fact that each participant in a dyad contributed data to two conversations. Each conversation was split into 16 non–overlapping 20 second sections and the mean value of the peak WCC, the mean lag and the variance of the lag was calculated for each section. Mixed effects models were fit using the linear mixed effects function in the statistical software R (Ihaka & Gentleman, 1996; Pinheiro & Bates, 2000) such that

$$\begin{aligned} y_{ij} &= b_{i0} + b_1 x_{ij} + b_2 z_{ij} + e_{ij} \\ b_{i0} &= c_0 + u_{i0} \end{aligned} \tag{5}$$

where y_{ij} represents the selected outcome variable (mean peak WCC, mean peak lag, variance of peak lag, or derivative with respect to time of the peak lag) for quad i in conversation section j. The predictor variables x_{ij} and z_{ij} are the sex of the high–dominant person and low–dominant person respectively coded as male=1 and female=0. The intercept term b_{i0} was composed of an overall fixed effect c_0 and a component u_{i0} unique to quad i. The two tables in the next section (Tables 3 and 4) present results for Equation 5 applied to the selected outcome variable.

Results

The overall mean peak WCC was estimated to be $r_{wcc} = 0.54$ for the vertical (head nod) and $r_{wcc} = 0.55$ for the horizontal (head shake) angular displacements; and for velocity was estimated to be $r_{wcc} = 0.25$ in both the vertical and horizontal directions as shown in Table 3. Small but statistically significant effects of the sex of the dominant individual were found for horizontal and vertical angular displacements and for vertical velocities such that when the high–dominant individual was male, the peak WCC was likely to be higher.

In addition, there was a significant effect of sex in the low dominant position for vertical velocity only.

Table 3: Fixed effects from mixed effects model predicting mean peak correlation of vertical and horizontal head angular displacement and velocity. (N= 2048, Groups= 32; Vertical displacement AIC = -2897.1 , BIC = -2869.0; Vertical velocity AIC = -5663.5 , BIC = -5635.4; Horizontal displacement AIC = -3000.5 , BIC = -2972.4; Horizontal velocity AIC = -5833.2 , BIC = -5805.0)

	Value	SE	DF	t	p
Vertical Displacement					
Intercept	0.5447	0.00541	2014	100.69	< 0.0001
Male High	0.0157	0.00517	2014	3.04	0.0024
Male Low	0.0053	0.00517	2014	1.03	0.3049
Vertical Velocity					
Intercept	0.2457	0.00427	2014	57.31	< 0.0001
Male High	0.0170	0.00261	2014	6.50	< 0.0001
Male Low	0.0136	0.00261	2014	5.21	< 0.0001
Horizontal Displacement					
Intercept	0.5503	0.00524	2014	104.98	< 0.0001
Male High	0.0130	0.00506	2014	2.57	0.0101
Male Low	0.0009	0.00506	2014	0.19	0.8531
Horizontal Velocity					
Intercept	0.2502	0.00373	2014	67.03	< 0.0001
Male High	0.0040	0.00251	2014	1.60	0.1103
Male Low	0.0002	0.00251	2014	0.08	0.9356

Statistically significant means ($p < 0.0001$) of the lag of the peak WCC were found for vertical and horizontal angular displacement and velocity. Since these means were positive, the peak association occurred when the low–dominant participant was leading by a grand mean of 1.25ms (.2/160). While this mean effect was statistically significant, it is considerably less than the time accuracy of the motion tracking equipment ($1/160 =$ 6.25ms), and so we treat these results with skepticism.

The variability of the time lag of peak WCC for displacement and velocity was estimated by calculating the variance in the lag during each 20 second segment of each conversation. The overall standard deviation of the lag was estimated as $\sigma = 342$ms ($\sqrt{2989.0}/160$) for vertical displacement and $\sigma = 345$ms ($\sqrt{3055.8}/160$) for horizontal angular displacement as shown in Table 4. Smaller standard deviations of the lag were found when velocity was used as the target for the WCC algorithm: $\sigma = 207$ms ($\sqrt{1096.2}/160$) for vertical and $\sigma = 210$ms ($\sqrt{1126.4}/160$) for horizontal velocity. Effects for sex were found for both high–dominant ($p < 0.001$) and low–dominant ($p < 0.01$) participants in vertical angular displacement and velocity and for high–dominant individuals only ($p < 0.01$) in horizontal angular displacement and velocity. These effects had a positive sign, suggesting that conversations including any male high–dominant participants were likely to have more variability in the lag of the peak WCC of head nods, while only the sex of the high–dominant participant was likely to affect head shakes.

Table 4: Fixed effects from mixed effects model predicting variance of the lag of the peak correlation for vertical and horizontal head angular displacement and velocity. (N= 2048, Groups= 32; Vertical Displacement AIC = 33752.6, BIC = 33780.7; Vertical velocity AIC = 30646.6, BIC = 30674.7; Horizontal Displacement AIC = 33868.9, BIC = 33897.0; Horizontal velocity AIC = 30851.3, BIC = 30879.4)

	Value	SE	DF	t	p
Vertical Displacement					
Intercept	2984.4	41.79	2014	72.08	< 0.0001
Male High	142.8	40.47	2014	3.53	0.0004
Male Low	128.6	40.47	2014	3.18	0.0015
Vertical Velocity					
Intercept	1096.2	21.37	2014	51.30	< 0.0001
Male High	104.6	18.90	2014	5.53	< 0.0001
Male Low	49.6	18.90	2014	2.62	0.0088
Horizontal Displacement					
Intercept	3058.4	38.25	2014	79.96	< 0.0001
Male High	113.8	41.61	2014	2.74	0.0063
Male Low	59.9	41.61	2014	1.44	0.1502
Horizontal Velocity					
Intercept	1126.4	23.62	2014	47.68	< 0.0001
Male High	78.7	19.84	2014	3.97	0.0001
Male Low	14.9	19.84	2014	0.75	0.4537

Surrogate Data Tests

The WCC analyses report relatively high peak correlation between participants as well as considerable variability in the lead/lag structure of the time series. In addition, effects of gender were found for both mean peak correlation and variability of the lag. But it is reasonable to ask whether these coefficients are due to the coordination between people as they act in a mutual perception–action cycle or if these values might be due to the overall context of the conversation. After all, the participants were both seated, facing each other, and engaging in speaking and listening behavior. To the extent that each individual is self–similar in their behavior over the duration of the conversation, the WCC analysis might return similar results if the two time series were offset by a large interval. Thus if the movements of A's first minute of the conversation were similar to A's movements in the fourth minute of the conversation, the WCC analysis might report a relatively high peak correlation and lag variability with B's movements in the first minute of conversation. But only the first minute of A's movements analyzed with the first minute of movements from B could possibly be due to interpersonal coordination from perception and action.

In order to test the null hypothesis that no perception action effects were being detected by the WCC analysis, we constructed *surrogate data sets* (Prichard & Theiler, 1994; Theiler, Eubank, Longtin, & Galdrikian, 1992) using a modified form of resampling (Efron, 1979) that ensures that this null hypothesis is true. For each conversation one of the conversant's time series was offset by 14,000 samples and the last half of the time series was then used to replace the first half of the conversation. So, while the time series for person B was indexed by the numbers $i = \{1 \dots N\}$, person A's time series was indexed by the numbers $j = \{(N/2) \dots N, 1 \dots (N/2-1)\}$. In this way, the same values from both time series were used for the analysis, but the values were always separated by an interval of 175 seconds, i.e., almost 3 minutes. In so doing, we have preserved the local time structure within each person's time series, but have guaranteed that interpersonal perception–action coordination could not be occurring.

The WCC analysis was run on the surrogate data in exactly the same fashion as in the previous section, and the results are shown in Table 5. The surrogate results are the same as for the time synchronized data. Thus it is concluded that the mean peak correlation results are unlikely to be due to perception–action coordination within the short time intervals of $\approx \pm 2$s that we would expect during conversation.

Table 5: Surrogate data fixed effects from mixed effects model predicting mean peak correlation of vertical and horizontal head angular displacement and velocity.

	Value	SE	DF	t	p
Vertical Displacement					
Intercept	0.5427	0.00467	2014	116.26	< 0.0001
Male High	0.0138	0.00527	2014	2.62	0.0090
Male Low	0.0089	0.00527	2014	1.70	0.0897
Vertical Velocity					
Intercept	0.2483	0.00426	2014	58.23	< 0.0001
Male High	0.0222	0.00266	2014	8.34	< 0.0001
Male Low	0.0140	0.00266	2014	5.27	< 0.0001
Horizontal Displacement					
Intercept	0.5514	0.00489	2014	112.82	< 0.0001
Male High	0.0122	0.00530	2014	2.30	0.0214
Male Low	0.0068	0.00530	2014	1.29	0.1967
Horizontal Velocity					
Intercept	0.2533	0.00373	2014	67.97	< 0.0001
Male High	0.0076	0.00257	2014	2.97	0.0030
Male Low	0.0001	0.00257	2014	0.05	0.9610

When the variability of the lag from the WCC analysis on the surrogates was modeled using the same mixed effects model as shown in Table 6, there were no effects of gender in either the vertical or horizontal direction. Thus, since time shifting the data eliminated the gender effects on variability of the lag, these gender effects must require the data to be time aligned. Thus, the null hypothesis that the effects on variability of the lag were not due to short term coordination of action is unlikely in these data.

Discussion

There were several notable results from the WCC analysis. The mean peak correlation between the conversantants head orientation was relatively high for both displacement and velocity in the vertical and horizontal directions. However, a surrogate analysis could not

Table 6: Surrogate data fixed effects from mixed effects model predicting variance of the lag of the peak correlation for vertical and horizontal head angular displacement and velocity.

	Value	SE	DF	t	p
Vertical Displacement					
Intercept	3013.3	38.01	2014	79.28	< 0.0001
Male High	70.8	41.36	2014	1.71	0.0869
Male Low	55.2	41.36	2014	1.33	0.1825
Vertical Velocity					
Intercept	1099.1	21.40	2014	51.36	< 0.0001
Male High	65.5	18.97	2014	3.45	0.0006
Male Low	37.3	18.97	2014	1.97	0.0494
Horizontal Displacement					
Intercept	3036.7	42.02	2014	72.26	< 0.0001
Male High	51.2	40.25	2014	1.27	0.2033
Male Low	53.8	40.25	2014	1.34	0.1813
Horizontal Velocity					
Intercept	1102.2	20.63	2014	53.43	< 0.0001
Male High	56.9	19.33	2014	2.94	0.0033
Male Low	29.6	19.33	2014	1.53	0.1265

reject the null hypothesis that these peak correlations were due to overall behavior and not closely coupled perception–action during the conversation. There was an effect of the high dominant conversational role being occupied by a male such that there were slightly higher peak correlation in both the vertical and horizontal directions for displacement and in the vertical direction for velocity. But these effects were also present in the time shifted surrogate data. How could these effects persist when the surrogate data was time shifted by nearly 3 minutes? One possible explanation is that both participants were producing behaviors that were self–similar over time and that the degree of this self–similarity varied with gender.

High variability in the lag of the peak WCC ($\sigma \approx$ 350ms) indicated a high degree of nonstationarity in the cross–correlation between participants' head angular velocities. The variability in the lag of peak WCC for head nods was predicted by the sex of both high–dominant and low–dominant participants such that for each male present in the conversation, the variability increased. The degree of variability in the lag for head shakes also increased a male was in the high–dominant role, but not the low–dominant role. These gender–specific effects were not present in the analysis of the time–shifted surrogate data; thus the evidence is consistent with a hypothesis that gender effects on nonstationarity are due to interpersonal coordination.

Overall, over short ($\approx$ 2s) intervals, there is a high degree of peak correlation between conversants' head movements, but there is a high degree of nonstationarity in the time lags of these peak correlations. This nonstationarity may be an important clue to understanding nonverbal behavior. One way of interpreting such a time series is that there exist periods of high interpersonal symmetry along with intermittent symmetry breaks. If these periods of high symmetry between participants occur in a self–similar manner over time, but the intervals between symmetry breaks do not follow a simple linear structure, a pattern of results similar to that observed in the WCC and surrogate analyses would be obtained. This would suggest a pattern of conversational movements that exhibited high local predictability (i.e., local redundancy) along with a global pattern of reduced predictability (i.e., global information). In other words, there may be two distinct regions of self–similarity in these data, one associated with high short–term temporal symmetry and longer term region associated with lower temporal symmetry.

The results of the WCC analysis are consistent with time series that are nonstationary and self–similar, but with at least two degrees of self–similarity associated with two different temporal scales. Nonstationary self–affine time series have been analyzed using nonlinear methods such as empirical calculation of fractal dimension (Hentschel & Procaccia, 1983; Kantz & Schreiber, 1995). Multifractal analyses were developed to account for different degrees of self–similarity within different temporal or spatial scaling regions (e.g., Muzy, Bacry, & Arneodo, 1991). We will employ a recently developed measure of self–similarity, multifractal dimension, in the next section in order to test the viability of this hypothesis. A wavelet analysis of the participants' head angular velocities was performed in order to estimate the multifractal dimension of these movements. In this way, the presence of time–scale invariance in the self–similarity of head movements could be estimated and dominance and gender contributions to this invariance could be modeled.

Multifractal Scaling in Horizontal Head Movements

It has been increasingly appreciated that human data may be highly complex with feedback mechanisms leading to nonlinear behavior. Recognizing the complex properties of natural phenomena like human data, it is reasonable to implement nonlinear analyses, such as fractal analysis (Capra, 1996; Shanon, 1993). Analysis of fractals provides a way to describe the data in a manner beyond the traditional approach that assumes highly complex phenomena are derived from random processes (Doyle, Dugan, Humphries, & Newton, 2004). When fractal structures can be dissociated from random processes, constraints on the form of the underlying dynamics of that data can be revealed. Natural language has been reported as exhibiting fractal behavior (Shanon, 1993), so fractal analysis of verbal and nonverbal behavior during conversation provides an extension of this observation.

Fractal dimension is a geometrical measure of self–similarity (Holden, 2002) and has been used to characterize facets of nature such as the spreading of tree branches (Oppenheimer, 1986), the scaling of tree trunk diameters within a forest (G. B. West & Brown, 2004), the organization of the circulatory systems of animals (B. West & Goldberger, 1987), cellular architecture (Keough, Hyam, Pink, & Quinn, 1991), and firing patterns of neurons (Usher, Stemmler, & Koch, 1994). A fractal has the characteristic of being self–affine (self–similar but not necessarily identical) at a range of scales of measurement — thus the structure is scale–independent over some range of scales. When we speak of scales of measurement, these could be measuring extent in space, extent in time, or some combination of extent in space and time.

A *fractal*, as the term is generally used, refers to a *monofractal*. That is, only one measure of fractal dimension is necessary for the signal/time series because the structure is (at least roughly) scale-independent. But in the case of head movements during conversation, one measure of fractal dimension may be inadequate. The WCC analysis indicates that there may be different fractal structures for different scales or more than one governing process at work. These type of fractals are known as a *multifractal*. When there is evidence for a multifractal structure, there may be two or more fractal structures within the data (Oświęcimka, Kwapień, Drożdż, & Rak, 2005).

Evidence for the presence of multifractal structures has been found in human data. From recordings of the human heartbeat (Ivanov et al., 1999), to normal and abnormal EEGs of human brain activity (Song, Lee, Kim, Lee, & Kim, 1999), to human gait (B. West & Scafetta, 2003), a number of studies analyzing time series data taken from human participants have reported multifractal structure. Even when attempting to perform a behavior that would seem likely to be monofractal in nature because of its regularity, like the pattern of human gait, human participants data still exhibited a multifractal structure (B. West & Scafetta, 2003). A logical progression from these studies is the investigation of the multifractal structure of human head motion during conversation.

An analysis was undertaken in order to examine the multifractal geometry of horizontal head movement time series. The time series for each participant consisted of a series of fluctuations in the angular velocity of lateral head movement (see Figure 5). A wavelet transform modulus maxima (WTMM) analysis was performed on the lateral angular velocity time series. WTMM makes use of a continuous one-dimensional wavelet transform that takes a time series that is discrete in nature due to the nature of the equipment's sampling rate and outputs a continuous series of $\tau(q)$ estimates, which are indicative of the multifractal structure of the time series.

Suppose there is a time series $x(t)$, which contains a measurement at time t_i, where $t_i{=}i\Delta t$ (i.e., the data are sampled at regular intervals). The fluctuation of the time series around $x(t_i)$ is:

$$\Delta x_i(t_k) = x(t_i + t_k) - x_i(t_i) \qquad (6)$$

where k is the number of time steps away from t_i. The value t_k defines the scale and is therefore a crucial element required to differentiate between monofractal and multifractal structures. These fluctuations will have the same magnitude over all scales when a monofractal structure exists. Likewise, the probability distribution function of $\Delta x_i(t_k)$ also has the same form for different t_k if there is a monofractal structure, meaning that the distribution of fluctuations is scale-independent. This concept of mono- versus multi-fractality is at the root of the importance of wavelet transforms for the investigation of the fractal structure of the time series. Basically, monofractal structure is one that shows the same fractal structure for all scales. For example, a leaf with a monofractal structure might have one stem that branches into six veins, which each branch into six veins, which also each branch into six more veins, and so forth. A multifractal structure might be a tree where one trunk branches into three branches, which branch into three more branches. However, at the leaf, one stem branches into six veins; the fractal structure differs at varying scales of measurement.

Analysis Description

When there is reason to believe that the time series of interest shows nonstationarity, as is the case with this data set, a wavelet transform method designed for such nonstationarity may be a more appropriate analytical tool (Oświęcimka et al., 2005) that the

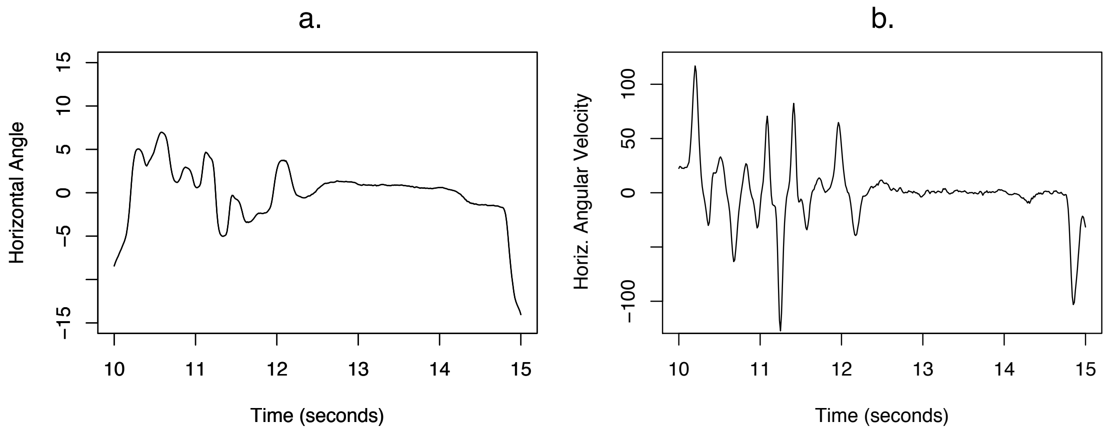

Figure 5. Time series data for 5 seconds of horizontal angular motion capture for a high dominant male participant. (a) Smoothed angular displacement from the mean (in degrees). (b) Smoothed angular velocity (in degrees per second).

Fourier. While a Fourier transform calculates the sum over the entire time series of a signal multiplied by an periodic functions at different frequencies, a continuous wavelet transform (CWT) calculates the sum of the signal as multiplied by scaled and shifted versions of the chosen wavelet (Misiti, Misiti, Oppenheim, & Poggi, 1996). The Fourier transform keeps a fixed time window and varies the number of peak oscillations in that window, but wavelet transforms keep the peak oscillations fixed and vary the window size. More specifically, wavelets utilize a mother wavelet that is stretched and compared locally to segments of the time series and captures that local information at different scales (Misiti et al., 1996). Thus, wavelets simultaneously pick up the fine details and the broad trends. Another way to conceptualize this distinction is that while the wavelet transforms and Fourier transforms are related, the main difference between them is that the Fourier transforms provide a time-frequency analysis of a time series, while a wavelet transform analyzes its time-scale properties (Misiti et al., 1996). While it is possible to track the scaling of a leaf visually with the naked eye, human nonverbal behavior is considerably more difficult to characterize without a tool like wavelet analysis for analyzing its fractal structure.

For this study, the Wavelet Transform Modulus Maxima (WTMM) was chosen as a flexible way to estimate fractal dimension in time series where one does not wish to rule out the possibility of multifractal scaling. The WTMM was performed using Matlab (Mathworks, 2006) and a supplemental package called Wavelab (Donoho, Duncan, Huo, & Levi, 2006). The WTMM has three major steps: (1) a continuous one-dimensional wavelet transform is performed, (2) a thermodynamic partition function is used to locate the presence of local maxima, (3) from that partitioning, a function is calculated, $\tau(q)$, where q is a statistical moment index. The function $\tau(q)$ allows the estimation multifractal dimension as will be described in detail below. The WTMM reduces the otherwise intensive computational burden by following a small fraction of the transformed data. More specifically, this method focuses on the maxima — the places where a scaled wavelet has local maxima or singularities in the correlation with the time series data. We next describe each of the three steps in detail.

For the analysis of a one–dimensional time series, WTMM applies a one–dimensional continuous wavelet transform (CWT) to the fluctuations in the time series. A one–dimensional CWT computes the sum over time as multiplied by scaled and then shifted versions of the chosen wavelet (Rao & Bopardikar, 1998). For this anlaysis, the second derivative of the negative Gaussian function (commonly called the “Mexican Hat” wavelet) was used (Misiti et al., 1996; Rao & Bopardikar, 1998; Starck, Murtagh, & Bijaoui, 1998)

$$\Psi_x = \left(\frac{2}{\sqrt{3}} \pi^{-1/4} \right) (1 - x^2) e^{-x^2/2} \tag{7}$$

The chosen one-dimensional wavelet is compared to a section of the original time series and a wavelet coefficient, c, is calculated that indicates how similar the wavelet shape is to the selected section (see Figure 7). Large coefficients indicate a high degree of similarity between the wavelet and that section of the time series. Next, the wavelet is compared to successive sections of the time series until c has been calculated for all sections. After the whole time series has been analyzed, the scale of the wavelet is changed (which is akin to stretching it out to fit a larger window of view) and c is again calculated for each segment of the time series. This process is repeated for all scales. The result is a set of coefficients that contain information about the time series for a range of sections and scales. Although the original time series was not continuous due to the discrete sampling of the equipment, the transformed dataset is now continuous. This transformation is key to the WTMM, since empirical data are generally discrete, while multifractality is continuous and its analysis requires a continuous dataset (Turiel, Perez-Vicente, & Grazzini, 2005).

The analytic process proceeds in three parts. The first part can be characterized as follows:

$$c(s, t_i) = \int x(t) \frac{1}{\sqrt{s}} \psi(\frac{t - t_i}{s}) dt, \tag{8}$$

where s is the scale, $x(t)$ is the time series data, and t_i is the location within the time series that is being measured. This is the step of the analysis that transforms the data from a discrete to a continuous signal. It uses a constant interpolation between $x(k)$ for all values $k = 1$ to $k = length(x)$ and calculates c_{s,t_i} for $t_i = 1$ to $t_i = length(x)$ (Misiti et al., 1996). Note that the larger the scale, the more “stretched out” a wavelet becomes, and it is compared to a longer section of a time series (Misiti et al., 1996). Therefore, at large scales, only fluctuation peaks of extended duration will be detected and large, abrupt fluctuations would make the signal very dissimilar to the wavelet. The list of scales chosen should include both very small and very large values in order to get a more complete picture of the structure of the data.

The choice of scales for a wavelet analysis is often based on equations defined by terms from the field of music. For this analysis, the number of scales to be used and their values were calculated using the equation(Turiel et al., 2005; Donoho et al., 2006)

$$s = 2 * (2 + (1 : nscale)/nvoice) \tag{9}$$

$$
\begin{aligned}
nscale &= nvoice * noctave \\
noctave &= floor(log2(N)) - 1
\end{aligned}
$$

where N is the length of the time series being analyzed, nscale is the number of scales to be calculated for the analysis, noctave is the number of octaves, and nvoice is the number of voices per octave chosen for the analysis. The output in Matlab for the CWT is a matrix of N by nscale of wavelet coefficients. The free parameter in the equations used for this analysis is the number of voices. The use of 12 scale voices is a standard for wavelets such as the Mexican Hat function (e.g., Aller, Habetler, Harley, Tallam, & Lee, 2002; Najmi & Sadowsky, 1997; Tomassini et al., 2001; Donoho et al., 2006). This selection is related to the scale of notes on a standard piano (Alm & Walker, 2002), which J.S. Bach termed a "A Well-Tempered Klavier" (Alm & Walker, 2002; Donoho et al., 2006). The scales used in this study can be seen in Fig. 6.

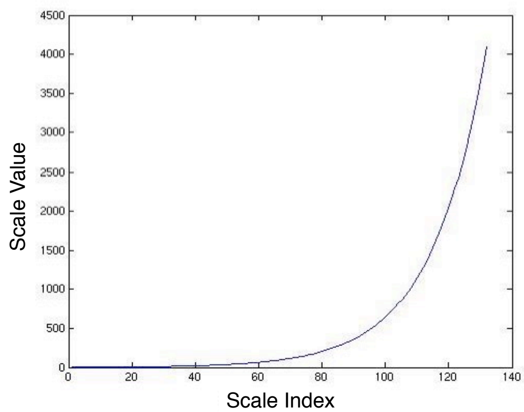

Figure 6. The 132 scales used for WTMM. Very large and very small scales were chosen to get a complete picture of the data's underlying structure

The coefficients extracted from the CWT can be seen in Figure 7–a. Here, the light regions indicate large coefficients, where the wavelet was very similar to the section of the time series to which it was being compared. From looking at these coefficients, it appears that there is no section of the time series where the wavelet was either very similar or very dissimilar at every scale, which indicates that this signal is most likely not monofractal. Note that at the largest scales, the dark regions occur in regions of fluctuations that are much smaller than the scale size. Here, the head movements go back and forth several times during the window scale, and the correlation to a large wavelet is weak at best. At other scales, a dark region may also arise from fluctuations that are larger than the scale's size or offset from center of a fluctuation of that scale. In the case of these data, the strong correlations (light regions) at large scales occur when the time between sudden changes are of the same order as the large time scale. In between those changes, the fluctuations are much smaller. This would occur if the participant was looking away from the other participant, then returned to eye contact, then maintained eye contact for a long period of time, and then looked away. The dark lines at small scales occur during abrupt changes in head movements. This plot also indicates that the scale around $log_2(s) = 5$ has strong regularity with light and dark regions fairly evenly spaced. This may indicate a fundamental unit of time during dyadic conversation (it appears to be about roughly 12 seconds in duration).

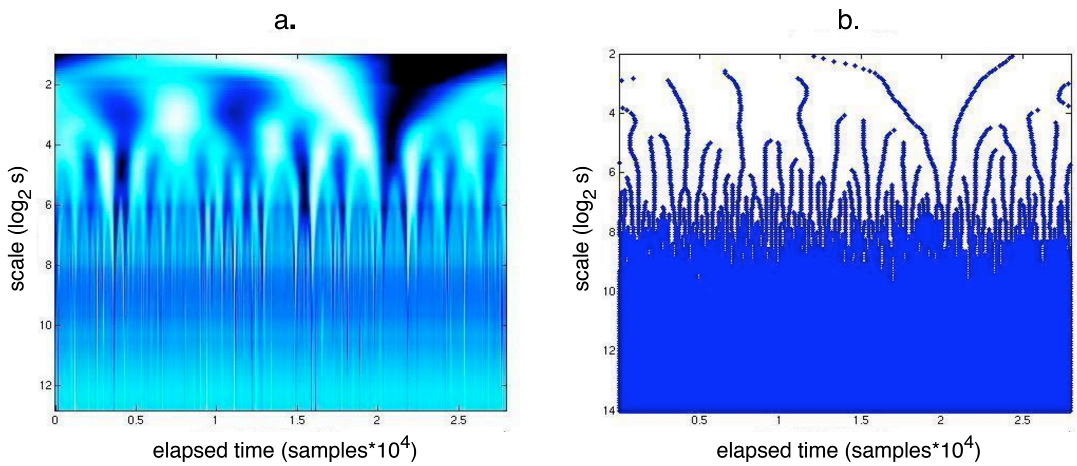

Figure 7. (a) Continuous wavelet transform of one participant's horizontal head angular velocity time series. The log base 2 of the scale value, s, is represented on the y-axis and the x-axis plots elapsed time in samples of the entire 5 minute and 50 second conversation. Small scales are represented at the bottom of the figure and large scales at the top. (b) Maxima skeleton map created by WTMM. The plot shows the time location for the local maxima of the wavelet coefficients. These correspond to times when fluctuations of that scale are occurring. Because there are many more opportunities (more partitions) for maxima to occur at small scales, the number of maxima increases as the scale decrease as is observed. Exactly how the number of maxima changes as a function of scale is determined by the underlying fractal structure of the data.

Once the wavelet coefficients have been extracted, the second step in in the process is to construct a multiresolution skeleton of the original time series (Figure 7–b). This skeleton consists of maxima lines, which represent the local maxima (singularities) found by the CWT. These lines are informative because they depict the relative positions of maxima (i.e., modulus) according to scale and magnitude in a scale-space plane, and the singularity exponents that we are interested in calculating for this study can be extracted from them (Turiel et al., 2005). In order to accomplish this, Wavelab (Donoho et al., 2006) employs a binary coding algorithm, which outputs a data series where 1 indicates the presence of a maxima and 0 indicates the absence of maxima across the CWT data. This output is then entered into the thermodynamic partitioning function. The "branching" of these maxima lines depicts the hierarchy of singularities across scales (Muzy et al., 1991; Turiel et al., 2005).

The scale–space thermodynamic partitioning function (Alber & Peinke, 1998; Manimaran, Panigrahi, & Parikh, 2004; Turiel et al., 2005) can be written as

$$Z_q(s) = \left[\frac{1}{N}\sum_{k=1}^{N}|Z(s)|^q\right]^{\frac{1}{q}} \sim s^{\tau(q)} \tag{10}$$

where s is the scale, q is the statistical moment index (i.e., order of the scaling function), and $Z(s)$ is the coefficient of wavelets at the maxima only ($Z(s) = c$). In other words, the partition function extracts the wavelet coefficient at each maxima based on the binary output described above. So, the partition function reads both the number of maxima and how strong they are (i.e., values of wavelet coefficients) at each scale for each value of q specified.

Finally, the third part of the WTMM estimates $\tau(q)$ from the partitioning $Zq(s) \sim S^{h(q)}$ and $\tau(q) = qh(q) - 1$ where $h(q)$ is the power law scaling of the wavelet coefficients. For $q > 0$, the larger scale fluctuations (i.e. the large, abrupt changes in velocity) are being captured, while for $q < 0$, small singularities (i.e., small changes in velocity) are characterized. This is because the $\tau(q)$ values for $q > 0$ weight the magnitude of distribution changes with increasing importance as a function of increasing q. The $\tau(q)$ values for $q < 0$ weight the probability distribution of small fluctuations (i.e., plateaus in the time series data) with increasing importance as a function of decreasing q, which become dominated by the most minuscule changes in velocity. Nearing this level, measurement/numerical resolution play decisive roles. It should be pointed out that these small fluctuations could be strongly affected by undersampling or the length of the time measurement (Alber & Peinke, 1998). As q gets progressively larger at the other extreme, the statistical moments are subsequently dominated by largest fluctuations.

The slope of $\tau(q)$ versus q plot is the Hölder exponent for the data, which indicates the strength of a singularity (Manimaran et al., 2004; Oświęcimka et al., 2005), and q is the statistical moment index. For a monofractal structure, the values of $h(q)$ are linear and have the same slope for all scales. When the data have two different slopes for $q > 0$ and $q < 0$, there is evidence of a multifractal structure. The generalized Hurst exponent is $H = h(q = 2)$ because when the statistical moment index $q = 2$, m_q quantifies the variance of the fluctuations. The Hölder exponent characterizes the strength of a singularity (i.e., attractor) (Oświęcimka et al., 2005) and is a local version of the generalized Hurst exponent (Muzy et al., 1991). In other words, the Hölder exponent is the scaling of the WTMM coefficient across scales.

If $H = 0.5$, then the data can be considered random Brownian motion. If $H > 0.5$, then the data are persistent (or correlated), meaning that feedback grows in the system. If $H < 0.5$, then the data show antipersistence (or anticorrelation), which means that fluctuations die off in a manner similar to damping or if the system is self-correcting. The significance of the Hurst exponent can be conceptualized with respect to a one dimensional random walk. If $H = 0.5$ and the data is a random walk, one is just as likely after taking the first step forward to either move forward again or to move back. If $H > 0.5$ and the data is persistent, then there is a preference for moving forward; one is more likely to move forward again after the first step forward than to move backward. Likewise, if $H < 0.5$ and the data is antipersistent, one has the reverse preference for the backward direction.

Results

The results of the application of WTMM to one participant's head horizontal angular displacement time series can be seen in Figure 8, which plots the $\tau(q)$ values versus q. These data were estimated to be persistent for $q < 0$ and antipersistent for $q > 0$ and neither exponent is equal to 0.5, indicating that this signal is not a Brownian random walk. The difference in $\tau(q)$ central tendency for $q < 0$ and $q > 0$ indicates that there is a different fractal structure for the strong singularities than there is for the weak singularities. Strong singularities are large fluctuations, which correspond to sudden changes in horizontal head angular displacement. Likewise, weak singularities are smaller fluctuations, which correspond to slow, gradual changes in velocity. The results can be visualized in a manner similar to the leaf described above. The structure of lateral head motions appears self–similar for small scales (short intervals between maxima and minima of angular displacement), but as the size of the scale increases, there is a point where that structure changes. The self–similarity for large scales (long intervals between maxima and minima of angular displacement) has a different structure than for small scales.

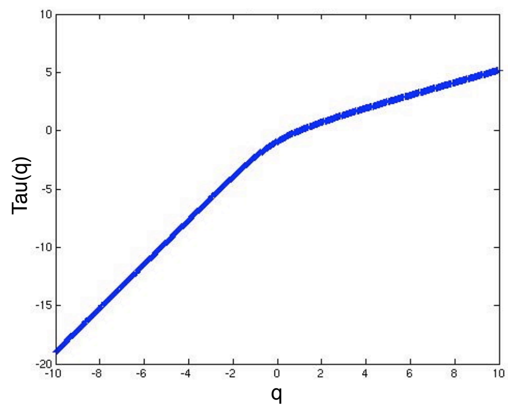

Figure 8. The $\tau(q)$ spectrum from one participant. The difference in slopes for the $q < 0$ and $q > 0$ suggest multifractality in horizontal angular head displacement. The $q < 0$ progressively quantify smaller magnitude changes in displacement as q becomes more and more negative. Alternatively, $q > 0$ progressively measures larger fluctuations in displacement as q becomes more positive. At the largest positive q value (scaling exponent), $\tau(q)$ is dominated by the largest fluctuations.

The large fluctuations ($q > 0$) occur when there are relatively long intervals between maximum and minimum head angle (as in Figure 5-b from elapsed time 10s to 12.5s) and are antipersistent ($\tau(q) < 0.5$) in Figure 8. Thus while these movements exhibit self–similarity, they are not likely to persist for many repetitions. The small fluctuations ($q < 0$) appear persistent in nature ($\tau(q) > 0.5$), which means that a period of short intervals between maxima and minima in displacement is most likely maintained for many repetitions, such as when the participant is maintaining (or possibly avoiding) eye contact (see Figure 5-b from elapsed time 12.5s to 14.5s). These small microadjustments in head position appear to have self–similar structure and thus may be useful indicators of behavioral constructs in conversation. In addition, these micromovements appear to have a different structure than movements such as head nods, head shakes, and head movements associated with change in gaze direction.

The distributions for the Hölder exponents ($\tau(q)$) for all participants are graphed as boxplots in Figure 9. The horizontal and vertical directions have essentially indistinguishable distributions within each of the four conditions (displacement versus velocity and $q < 0$

versus $q > 0$). However, there is no overlap between the distributions for $q < 0$ and $q > 0$ for either displacement or velocity. Thus, there is strong evidence for multifractality in these head movements — every individual shows a greater slope for $q < 0$ than every other individual's slope for $q < 0$. Note also that the mean difference between slopes for $q < 0$ and $q > 0$ is approximately the same within displacement as it is within velocity. Thus, the multifractal structure exhibits itself in approximately the same way whether we measure displacement or velocity.

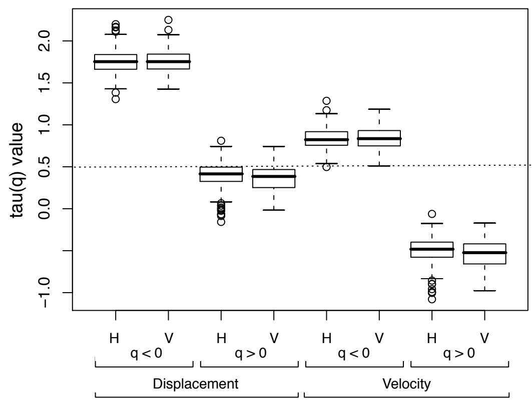

Figure 9. Box plots of the distribution of all participants' displacement and velocity split by $q < 0$ and $q > 0$ split by horizontal and vertical movements. Note that horizontal and vertical values of $\tau(q)$ are essentially equal within condition, but that there are large differences between $q < 0$ and $q > 0$ within displacement and within velocity.

Mixed effects models were used to estimate the effect of participant dominance and gender on the value of the Hölder exponents for each of eight outcome variables (horizontal versus vertical, displacement versus velocity, and $q < 0$ versus $q > 0$) using the statistical software R (Ihaka & Gentleman, 1996). Participants were again grouped by quad in order to account for each participant being a part of two conversations (Pinheiro & Bates, 2000) such that

$$\begin{aligned} y_{ij} &= b_{i0} + b_1 x_{ij} + b_2 z_{ij} + e_{ij} \\ b_{i0} &= c_0 + u_{i0} \end{aligned} \tag{11}$$

where y_{ij} represents the selected Hölder exponent outcome variable for quad i in conversation section j. The predictor variables are the sex of the the participant, x_{ij}, coded as male=1 and female=0 and the dominance of the participant, z_{ij}, coded as high–dominant=1 and low–dominant=0. The intercept term b_{i0} is comprised of an overall fixed effect c_0 and a component u_{i0} unique to quad i. The results of these analyses can be found in Tables 7 and 8.

Dominance of the participant is a significant negative predictor all of the Hölder exponent outcome variables for the small fluctuations ($q < 0$) shown in Table 7. Thus, the

Table 7: Hölder exponent for $q < 0$ predicted by dominance and sex

	Value	SE	DF	t	p
Horizontal Displacement					
Intercept	1.793	0.0196	218	91.648	< 0.0001
Dominance	-0.071	0.0205	218	-3.452	0.0007
Sex	-0.020	0.0205	218	-0.959	0.3387
Vertical Displacement					
Intercept	1.801	0.0159	222	112.977	< 0.0001
Dominance	-0.070	0.0174	222	-4.016	0.0001
Sex	-0.014	0.0217	222	-0.632	0.5280
Horizontal Velocity					
Intercept	0.857	0.0190	222	45.218	< 0.0001
Dominance	-0.042	0.0162	222	-2.583	0.0104
Sex	-0.002	0.0184	222	-0.107	0.9150
Vertical Velocity					
Intercept	0.870	0.0183	222	47.590	< 0.0001
Dominance	-0.056	0.0194	222	-2.862	0.0046
Sex	0.004	0.0207	222	0.200	0.8419

high–dominant individuals have smaller Hölder exponents than low–dominant individuals. Sex does not appear to predict these small fluctuation values of the Hölder exponent. Note also that the intercept and dominance coefficients for the horizontal and vertical are very similar within the displacement Hölder exponents and also within the velocity Hölder exponents. Thus, there does not appear to be much differentiation between the prediction of horizontal and vertical Hölder exponents when looking at the small fluctuations.

On the other hand, the results of the models for large fluctuations presented in Table 8 exhibit a more complicated picture. For all outcome variables, sex appears to be a significant positive predictor of the Hölder exponent. Thus, in both the horizontal and vertical direction, males have greater values of Hölder exponent than do females. However, there is a differentiation between the horizontal and vertical angular movements since in the vertical direction dominance again is a significant negative predictor, while in the horizontal direction, the dominance coefficients do not reach significance. Interestingly, the signs of the dominance and sex coefficients are always opposite of one another such that males' Hölder exponents are reliably greater in value than females, while the opposite effect holds for high–dominant individuals in the vertical direction.

Discussion

These WTMM analyses presented clear evidence of multifractal structure in head movements during conversation. There was no overlap at all in the distributions of Hölder exponents ($\tau(q)$) for values of q less than zero with the equivalent distributions for q greater than zero. Overall, values of $\tau(q)$ for $q < 0$ were approximately 1.2 greater than for $\tau(q)$ for $q < 0$ within both the vertical and horizontal axes and within displacement and velocity. Thus, there appears to be strong evidence of multifractal structure in head movements. For

Table 8: Hölder exponent for $q > 0$ predicted by dominance and sex

	Value	SE	DF	t	p
Horizontal Displacement					
Intercept	0.379	0.0172	218	22.093	< 0.0001
Dominance	-0.034	0.0216	218	-1.597	0.1117
Sex	0.075	0.0238	218	3.145	0.0019
Vertical Displacement					
Intercept	0.386	0.0155	222	24.927	< 0.0001
Dominance	-0.088	0.0188	222	-4.678	< 0.0001
Sex	0.052	0.0219	222	2.384	0.0179
Horizontal Velocity					
Intercept	-0.531	0.0207	222	-25.630	< 0.0001
Dominance	-0.030	0.0212	222	-1.433	0.1533
Sex	0.092	0.0244	222	3.761	0.0002
Vertical Velocity					
Intercept	-0.525	0.0186	222	-28.267	< 0.0001
Dominance	-0.084	0.0224	222	-3.774	0.0002
Sex	0.059	0.0245	222	2.387	0.0178

both displacement and velocity, the scaling exponent for small fluctuations, $q < 0$, tends to be persistent, $\tau(q) < 0.5$, and the scaling exponent for large fluctuations, $q > 0$ appears to be antipersistent, $\tau(q) > 0.5$.

All participants exhibited the same type of multifractal structure across several outcome variables (horizontal versus vertical and displacement versus velocity) and the scaling exponents occurred in a relatively narrow distribution within outcome variable. These two results indicate a high degree of self–similarity across time within person that might help explain the surrogate data results from the WCC analysis. Thus, time shifting one individual when calculating a WCC might not reveal a difference in the mean peak cross correlation since each individual shows high self–similarity across time.

The antipersistent results for the large fluctuations are consistent with a view of symmetry breaking occurring within each participants' time series. That is to say, movements with relatively long intervals between maxima and minima tended to occur at irregular intervals even though that irregularity itself exhibits a self–similarity across a range of scales. This result fits with results from WCC analysis for the variance of the lag of the peak correlation. In the WCC analysis, males tended to exhibit greater nonstationarity than females and in the WTMM analysis, males tended to exhibit greater antipersistence than females.

In the vertical large fluctuations, the coefficients for sex were positive and the coefficients for dominance were negative. This interesting differentiation indicates that while males were more antipersitent than females, high–dominant individuals were less antipersistent than low–dominant individuals. This result is evidence against a view that high–dominance and male gender can be treated as a unitary dimension, and thus is evidence against the male dominance hypothesis.

Overall, displacement and velocity showed the same patterns of results, although the means of the distributions of $\tau(q)$ for displacement were about 0.9 greater than the means of the $\tau(q)$ distributions for velocity. Once these mean differences in distributions were taken into account, the pattern of coefficients predicting $\tau(q)$ from gender and dominance was indistinguishable for displacement and velocity. While the WTMM results are consistent across displacement and velocity and thus only one of these outcome variables need be examined, the WCC results indicate that displacement and velocity each contribute independently to the pattern of results and thus we recommend that both displacement and velocity continue to be analyzed.

General Discussion

These analyses show converging evidence that both sex and dominance play a role in the structure of head movements during conversation. They all offer evidence that indicates that older theories such as the male dominance hypothesis are incomplete for explaining the complex nature of the behavior, the symmetry between conversational partners, or the self–similar structure of these time series. We found both a high degree of coordination between speaker for short periods of time and different underlying structures for small and large head movements. Additionally, there is evidence that both of these phenomena are influenced by the dominance score and sex of the participants.

The windowed cross-correlation analysis of the two head movement time series showed that over short ($\approx$ 2s) intervals, there is a relatively high peak correlation between conversants' head movements, but that there is also high degree of nonstationarity in the lag of that peak correlation. The surrogate data analysis demonstrated that a similar high degree of correlation is observed even if two conversants' time series are offset by an large time interval; this indicated that there may be high degrees of self–similarity within person over time and thus large time offsets would continue to produce high degrees of peak correlation between conversants.

A wavelet analysis of individuals' head angular displacement and velocity provided evidence that there are scaling regions of self–similarity within persons over time and that there are different fractal structures for large– and small–scale fluctuations in head movements. The mixed effects models indicated that these fractal scaling exponents can be predicted by dominance for small fluctuations and by both sex and dominance for large fluctuations. When both sex and dominance were significant predictors of the scaling exponent (horizontal large fluctuations), the coefficients for male sex and high dominance were of opposite sign, contradicting the prediction of a unitary dimension for maleness and dominance.

Taken together, these two analyses provide evidence that human head movements during conversation are both nonstationary and multifractal, indicating that there is a complex and changing structure to head movements during conversation. When two people converse, there are two roles that each conversant takes: speaker and listener. One explanation for the observed changing structure of head movements during a conversation could be related to the shifting speaker–listener role of the conversants, i.e., turn–taking (McInnes & Attwater, 2004; Pincus & Guastello, 2005).

Another possible explanation consistent with these data is that the small fluctuations in head angle are micromovements indicative of symmetry formation between individuals as opposed to larger fluctuations indicative of intention that serves to break symmetry. It may be that the smaller fluctuations in head angle are a result of incomplete suppression of a low–level mirror system such that head movements between conversants become correlated over short intervals as one person speaks and the other person listens while both exhibit some mirroring of the other in a feedback loop. Thus large fluctuations would exhibit antipersistence due to their symmetry breaking function and small fluctuations would exhibit persistence due to their symmetry formation function.

The possibility exists that these observed structures in the head movement time series are highly coupled to the time structure of the semantics of the conversation. That is to say, in order for meaning to be communicated between people a serial temporal ordering of the meaning must be constructed. This temporal ordering is likely to contain some redundancy, but not too much. How much redundancy is necessary? This might be estimated on–the–fly by the conversants and one channel for improving that estimation may be head movements. Thus, the moment to moment information content of the time ordered meaning within a conversation may be highly coupled to the head movements of the conversants. If this is so, the analyses presented here may provide clues to how semantic streams are constructed between conversants in order to achieve mutual understanding.

Knowing how people communicate nonverbally and the reasons why they do so are key to improving the quality of human communication. The more we know about differences between people due to sex or personality factors like dominance, the better this knowledge can be applied to real–life situations where effective communication is vital. For example, teachers may tailor their nonverbal communication with students based on their sex and personality so that the student can more easily learn the material. Understanding differences in nonverbal behaviors between groups of people might improve the classroom environment (Anthony, 1979). In addition, findings like those from this study may be implemented in computer–simulation of human behavior and thus improve the quality of human–machine interaction.

Limitations

Although the results of these analyses are interesting, there are still much to be done to provide a better picture of the nonverbal head movement behavior. For instance, the context of the conversations was highly structured, unstructured conversation may not show the same pattern of results. In addition, the high dominant participant was always the interviewer and the low dominant participant was always the interviewee. This created a planned asymmetry in dominance. Future work should address the relative contributions of personality dominance versus situational dominance.

The current study raises a perplexing question concerning coordination between individuals in conversation. Since the surrogate data windowed cross correlations are not significantly different than the time synchronized windowed cross correlations, observed coordination between individuals in conversation could be simply an artifact of stereotypical movements made during the act of speaking and listening. This conjecture seems counterintuitive, so further experiments and better methods for analysis of these highly nonstationary data are certainly indicated.

With the ever-expanding list of options for data analysis, using more than one in a study provides different prospectives that can combine to form a more complete picture. The three data analysis techniques used in this study are by no means an exhaustive list, and other statistical and wavelet techniques could be used to look at the symmetry between participants and the underlying structure of the data. One alternative might be recurrence quantification analysis (e.g., Shockley, Butwill, Zbilut, & Webber, 2002), which is one possible way to investigate the possible relationship between the different structures found for different types of lateral head movements to symmetry breaking and turn-taking.

Future Directions

Finding that there are different fractal structures for large- and small-scale fluctuations opens the door for a closer examination of what this means with relation to the psychological data. Again, the different structures found for different types of head movements may be related to turn-taking. It is reasonable that people make different head movements when speaking as opposed to when they are actively listening to their conversational partner. The movements that they make while speaking and listening also may be affected by the conversant's dominance score and sex. As previously discussed, males and females behave differently with respect to other nonverbal behaviors, so it may be the case that there is also a large difference in they way they move their heads during speaking and listening. Again, an analysis of the data while coding for whether the individual is speaking versus listening may help explain the different underlying structures found for small and large head movements

Having captured information about the physical motions of those in conversation, these data can be used to model physical movements in a computer-generated, interactional avatar. Future research might include developing an artificial intelligence simulation of the hypothesized difference between active speaking versus passive listening to see if the behavior that emerges resembles the real psychological data. Also, a similar analysis of the auditory data associated with the nonverbal motion data analyzed could potentially provide more information about the coordination between conversants and the fractal structure of their utterances.

Given the current results, future studies will include a greater examination of full-body symmetry formation across time. The current study was limited to head motion, but data concerning the physical motion of the hands, arms, legs, and chest was also collected. Over time, these data could be used to estimate the degree of overall body coordination, cross-correlation of joint angular velocity, and timing patterns related to postural shifts and backchannels. Also, further cross–correlation analyses may be performed to examine whether people are highly correlated at the beginning, middle, or end of the conversational segment in between turn switches. Future research which monitors the turn-taking with respect to the time series data might be able to address as to when this coordination occurs with respect to turn-taking. Analysis of the video and audio components of the current data in order to examine turn–taking is planned.

The results of the current study could be expanded into further research to examine whether similar results could be observed under different conversational contexts. In addition, another measure of social and conversational dominance might be used as a predictor. Also, social dominance is most likely not the only personality trait that is predictive of behavior during a conversation. For example, self-esteem and self-image with respect to their conversational partner might also play a role in predicting the coordination between conversants as well as the underlying structure of their movements.

The results of the current study could be expanded into further research to examine whether similar results could be observed under different conversational contexts. One such future direction might examine real-world interviewer-respondent dynamics, such as those between Census field representatives and the residents with whom they interact.

In summary, conversants' head movements show correlation over short intervals and nonstationarity over longer intervals. Fractal analysis of these movements shows persistence over short intervals and antipersistence over longer intervals. These results are consistent with a view that symmetry is formed between conversants over short intervals and this symmetry is broken at longer, irregular intervals. The notion of a rhythm to conversation appears to hold, but not in the sense of a rhythm in music. The temporal structure is irregular, but exhibits self–similar scaling with two distinct scaling regions. The existence of two fractal scaling constants for head movements offers a new perspective on the structure of face-to-face conversation. Now that these scaling regions have been identified, the next step is to investigate reasons why they exist and what pragmatic functions they serve.

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