Cross Recurrence Quantification of Interpersonal Postural Activity

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Measuring interpersonal coordination in the context of conversation has been a challenging problem in psychology for at least three decades. This is an interesting problem because observations of interpersonal coordination in the context of cooperative conversation appear to index the coordination that is required to complete the goals of a particular interaction (Clark, 1996). This type of coordination has been indexed in a number of ways, including the convergence of speaking rate (Street, 1984), vocal intensity (Natale, 1975), pausing frequency (Cappella & Planalp, 1981), and even in the convergence of conversational partners' dialects (Giles, Coupland, & Coupland, 1991). Conversational partners have also been observed to mirror or mimic each others' postures (LaFrance, 1982). Until very recently, however, such indices of coordination have been based on fairly subjective observation procedures. For example, Condon and Ogston (1971) assessed interpersonal coordination by hand scoring video-taped interactions to evaluate the timing of listeners' movements with reference to the rhythmic properties of a speaker.

More recent techniques of quantifying interpersonal coordination have made the visual scoring approach somewhat more systematic by sketching joint angles from video tapes and quantifying the number of joint angle changes (Newtson, 1994; Newtson, Enquist, & Bois, 1977; Newtson, Hairfield, Bloomingdale, & Cutino, 1987). Spectral profiles of periodicity of joint angle changes were then compared across conversers. This strategy has revealed apparent coupling of the *behavioral waves* of conversers. While the Newtson et al. approach is certainly an improvement over previous methods, problems with distortions from scoring 2-dimensional video tapes of 3-dimensional

movements cannot be avoided. The magnitude of angle changes of joints based on visual estimates of a 2-D video is dependent upon the angle of the video-taped person relative to the 2-D viewing plane of the video screen. Thus, visual estimates of angle changes from video will be distorted unless the movements are always aligned with the viewing plane. An additional drawback is that the degree of joint angle change is not measured—all that is measured is that joint angles changed.

Shockley, Santana, and Fowler (2003) introduced a strategy for evaluating the degree of interpersonal coordination that involves submitting measurements of postural sway to cross recurrence quantification (CRQ) analysis. The advantage of CRQ over conventional linear methods is that it requires no assumptions about the nature of the data in question, and it offers an objective method for studying interpersonal coordination. The purpose of this chapter is to provide a tutorial for how to apply this recently developed analysis to postural data using the method and data of Shockley et al. (2003). Before discussing the CRQ technique and its theoretical foundations, however, some understanding of postural sway is necessary to make it clear why such an approach is warranted.

POSTURAL SWAY

Although standing upright seems straightforward and effortless to most of us, it is actually quite challenging to explain how we are able to accomplish this task. Consideration of the underlying anatomical constraints and surrounding physiological processes reveals that the apparently simple act of standing upright is quite complex and yields a correspondingly complex behavior that is not straightforward to

quantify. The fact that postural activity is complex motivates the need for measures that are not restricted by the assumptions of linear methods.

Operationally, upright stance is best understood as the maintenance of the horizontal position of the center of mass of the body within the boundaries of the base of support of the body. Imagine a line drawn straight down to the ground along the direction of gravity from the center of mass of the body (generally in the region of the abdomen). In order to avoid falling down, the projected line from the center of mass must remain within the base of support of the body (usually the anterior-posterior and lateral extents of the feet).

The simplest image of this control requirement is to keep an inverted pendulum upright. To build your intuitions, try to balance an inverted broomstick on one finger. Note that in order to keep the inverted broomstick upright, quick adjustments to the position of the supporting finger are required as the broomstick begins to fall in one direction or another. This is a useful image, but the inverted pendulum image is certainly not an adequate model of postural control, however, given that most animals are of the multi-segmental variety. The consequence of this fact is that the center of mass must effectively be balanced over the base of support across many joints.

One may imagine that simply freezing all joints in a particular position would achieve the desired goal of standing upright. The physiological activity surrounding all of our actions, however, must also be considered. For example, instability in the position of the center of mass is introduced by physiological processes such as the inherent tremor of muscular tensile states, heart compressions, and the

expansion and compression of the chest cavity involved in breathing. These inherent perturbations result in instability of the position of the center of mass over time; this is generally referred to as postural sway (see Figure 4.1).

Postural sway occurs even during so-called *quiet stance* (standing without engaging in other activities; Collins & De Luca, 1994; Newell, Slobounov, Slbounova, & Molenaar, 1997), but occurs especially when supra-postural tasks (e.g., reading, talking, pointing, reaching) are added to the demands of maintaining upright stance (Balasubramaniam, Riley, & Turvey, 1997; Belen'kii, Gurfinkel', & Pal'tsev, 1967; Fel'dman, 1966; Riccio & Stoffregen, 1988; Riley, Mitra, Stoffregen, & Turvey, 1997; Stoffregen, Pagulayan, Bardy, & Hettinger, 2000). For example, the seemingly benign act of raising one's arm compromises postural stability and requires concurrent (and often prior) compensation of the muscles of the thighs, hips, and trunk to keep the center of mass within the base of support (Belen'kii, Gurfinkel', & Pal'tsev, 1967; Pal'tsev & Elner, 1967). Speaking and gesturing are ubiquitous in conversation and, accordingly, add to the instability of the location of the body's center of mass.

CAPTURING THE DYNAMICS OF UNKNOWN NONLINEAR SYSTEMS

The inherent instability of postural activity described above has made the quantification of postural sway quite challenging. The most direct methods for measuring postural sway involve the measurement of the center of pressure of the body using a force platform or the measurement of displacement of the center of mass using a motion
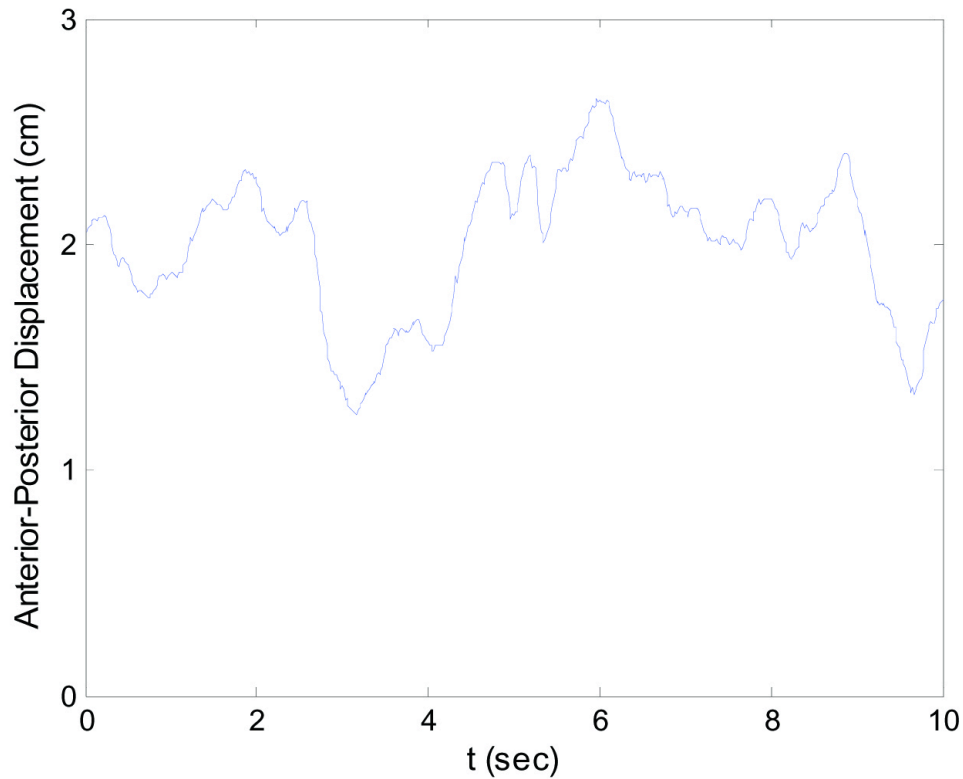
Figure 4.1. Sample postural sway time series during quiet stance. The abscissa corresponds to time (sec) while the ordinate corresponds to anterior-posterior displacement (cm).

tracking system.[1] These measures yield time series that are typically irregular, non-stationary (i.e., there is drift in the mean and/or standard deviation of the time series over time), and non-periodic (Carroll & Freedman, 1993; Collins & De Luca, 1993). Thus, conventional (linear) analyses that assume normal distributions and stationarity, such as correlational or spectral methods, are not appropriate for postural sway

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[1] The center of pressure corresponds to the point of application of the sum of forces acting between the feet and the surface of support (see Pellecchia & Shockley, Chapter 3).

data (see Riley, Balasubramaniam, & Turvey, 1999; see also Pellecchia & Shockley, Chapter 2, for a comparison of linear and nonlinear methods of analyzing postural sway).

Linearity vs. Nonlinearity

By definition, linear time series analysis methods assume independence and additivity of the multiple degrees of freedom that contribute to a given observable. Nonlinear systems have degrees of freedom that interact multiplicatively. Relatively recent investigations into nonlinear systems have inspired the development of analysis methods that capitalize on the interactive nature of nonlinear systems (see Abarbanel, 1996). In some cases, the variables that contribute to the dynamics of some nonlinear systems are known and can be indexed. Most often, however, the variables that contribute to the dynamics of a system under investigation are not known. The advantage of a nonlinear system, however, is that the dynamical variables interact. Thus, the influence of unknown (or perhaps unmeasurable) variables can be indexed by variables that *are* readily measurable. To illustrate this peculiar feature of nonlinear systems, I will show how the measurement of a single variable from a system with known dimensions can be used to capture the dynamics of the whole system.

The Lorenz Attractor: A Nonlinear System With Known Dynamics

The Lorenz (1963) system is a model of convection (i.e., heat transfer) in the atmosphere. The dynamics (i.e., changes in states) of the Lorenz model can be characterized with three first order differential equations,

$$\dot{X} = a(Y - X) \hspace{4cm} [4.1]$$

$$\dot{Y} = X(b - Z) - Y \hspace{4cm} [4.2]$$

$$\dot{Z} = XY = cZ \hspace{4cm} [4.3]$$

where X, Y, and Z correspond to the three dynamical variables (corresponding to two temperature measures and a velocity measure), the over-dot corresponds to the rate of change (i.e., derivative) of the variable in question, and a, b, and c are constant parameters. What makes the Lorenz system a complex, nonlinear system is the interaction of the three dynamical variables. As can be seen in Equations 4.1-4.3, changes in X are dependent not only upon the value of X, but also upon the values of Y and Z. Therefore, the influences of the variables X, Y, and Z on the current state of the system are not independent and additive, but are instead mutually dependent and multiplicative. The interactive nature of dimensions along which a system may change embodies the complexity of nonlinear systems and is also the key to quantifying systems with unknown or unmeasured dynamical variables.

Phase Space Reconstruction and the Embedding Theorem

Often, the interplay of dynamical variables is best characterized using a phase space (see Figure 4.2). A phase space is essentially a multidimensional scatterplot of each dynamical variable with respect to the other dynamical variables. As is often the case, however, the particular variables that comprise a given nonlinear system may not be known and perhaps may not even be knowable, *a priori*. Fortunately, lack of identification of the dynamical variables does not preclude one

from gaining access to the underlying dynamics of the system in question.
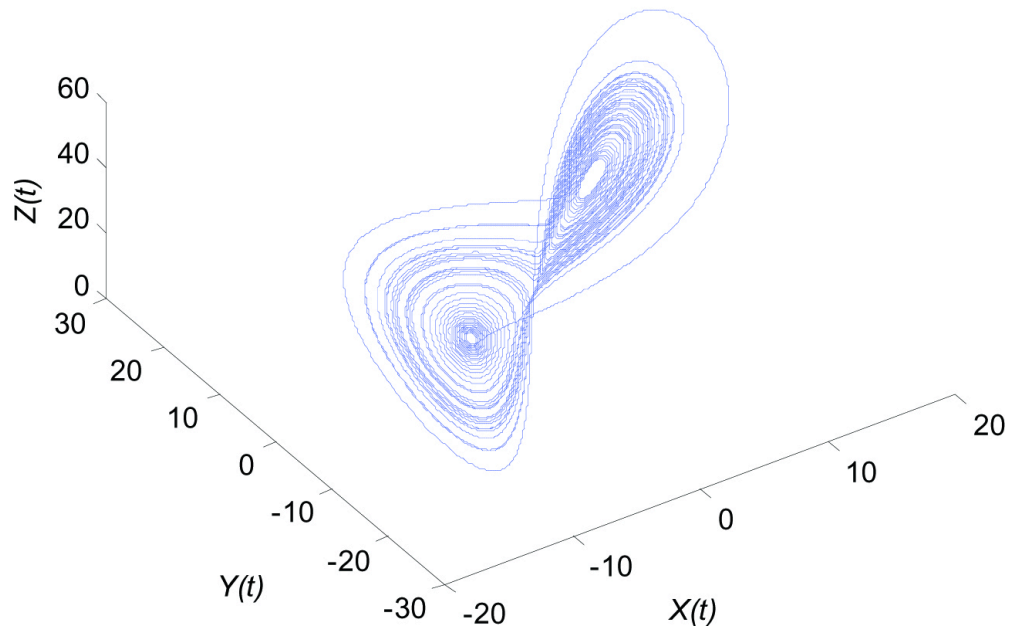
Figure 4.2. A three-dimensional plot (phase space) of the time evolution of the three dynamical variables (X, Y, & Z) of the Lorenz system (Equations 4.1-4.3).

Takens (1981) introduced the *embedding theorem*, which revealed that the preferred relations of the dynamical variables in a nonlinear system (its attractors) may be discovered by reconstructing a phase space for the system in question using time-delayed copies of a single, observable dynamical variable of the system. That is, the time series of a single dynamical variable can be used to reveal the underlying dynamics of the entire system by using time-delayed copies

of the measured time series. This is possible because (as described previously) in nonlinear systems the multiple dynamical variables interact with one another. The interactive nature of the dynamical variables comprising the nonlinear system generally yields quite messy and unpredictable time series of the variables in question. However, the interactive nature of the degrees of freedom of a nonlinear system dictate that the activity of a single variable will be influenced by the activity of all other dynamical variables. Access to one of the variables of a dynamical system can, accordingly, allow the dynamics of the entire system to be evaluated by unfolding the time series into the appropriate number of dimensions to reveal the underlying dynamics. In the next section I will illustrate how the dynamics of the Lorenz system may be unfolded using time-delayed copies of a single variable.

Distortions Due to Projection

Consider the time series of X in Figure 4.3. The evolution of this variable does not resemble the clearly defined attractor in Figure 4.2. This is because the time series of the observed variable is represented by only one dimension (X), whereas the Lorenz system requires three dimensions to reveal the influence of the three dynamical variables. While the time series depicted in Figure 4.3 does *embody* the dynamics of the entire system, one cannot see the dynamics unfold properly because the dynamics of the 3-dimensional system are 'projected' onto a single dimension. Such a distortion can be illustrated using a less abstract example.

Imagine positioning your two hands such that both hands are between a light source and a wall. Both hands are some distance apart
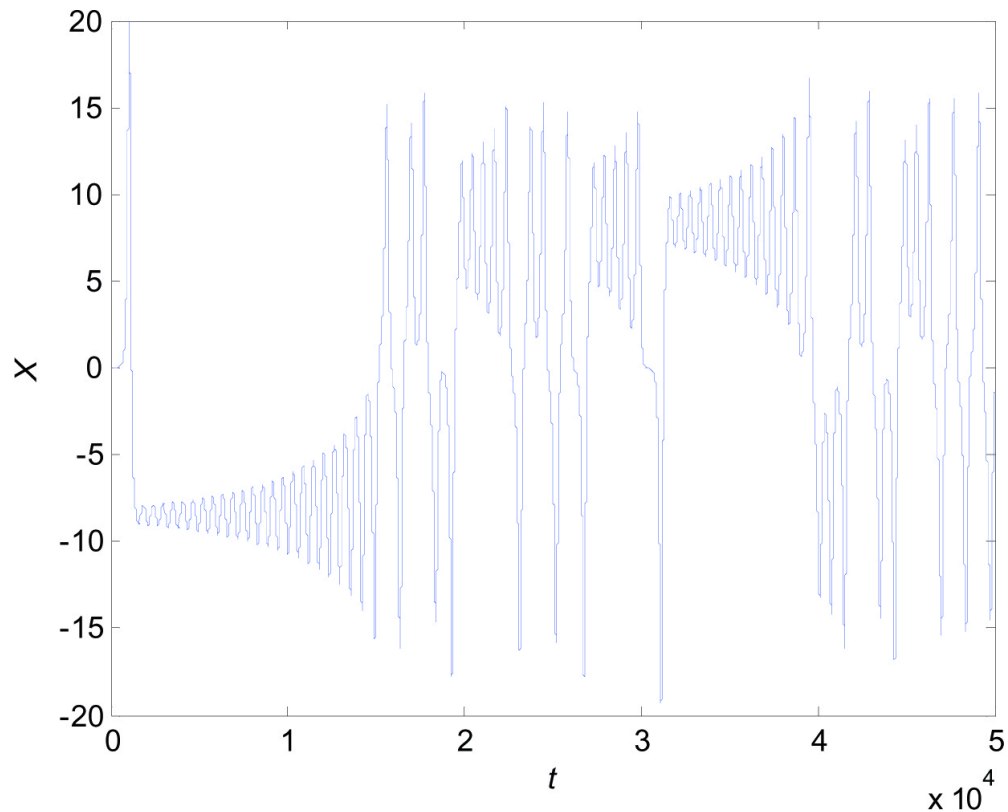
Figure 4.3. The time series X(t) generated from Equations 4.1-4.3. Given that the data are simulated, time (t) corresponds to data points with no particular time units.

along the dimension separating the light source and the wall, but the two hands occupy the same position along the horizontal and vertical dimensions of the wall. In this configuration, the projected shadows of the two hands on the wall will appear to occupy the same space. This shadow example illustrates a distorted, two-dimensional projection of three-dimensional space.

Unfolding the Time Series

The lesson to be learned from Takens' theorem is that the dynamics of a nonlinear system of multiple degrees of freedom (e.g.,
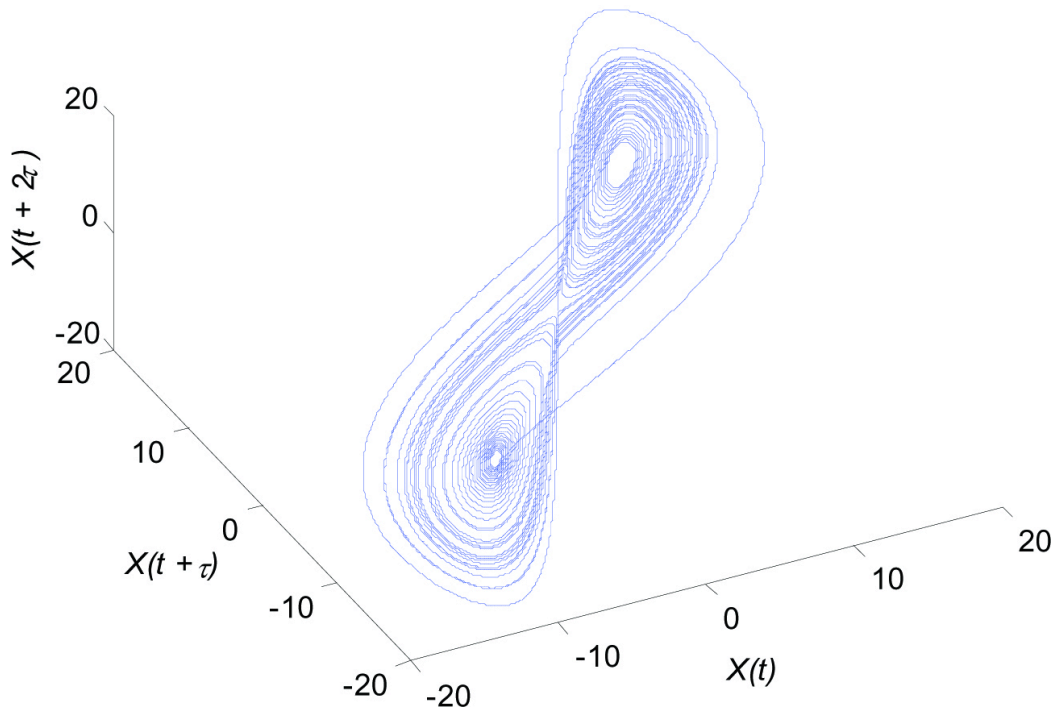
Figure 4.4. A reconstructed phase space of the Lorenz attractor using X(t) to create time-delayed copies to serve as surrogate dimensions. The delay (τ) used was 55 data points.

the Lorenz system) may be seen properly by unfolding the system into the appropriate number of dimensions using time-delayed copies of one measured dimension as surrogate dimensions in reconstructed phase space. This can be accomplished by using the original time series, $X(t)$, as the first dimension, $X(t + \tau)$ as the second dimension, and $X(t + 2\ \tau)$ as the third dimension, and so on for four and higher dimensions. In this example, I used a delay of 55 data points. So, the first dimension, $X(t)$, begins at data point 1 of the original time series. The second dimension, $X(t + 55)$, begins at data point 56 of the original time series. The third dimension begins at data point 111 of the original

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time series. What Takens demonstrated is that the reconstructed phase space is isomorphic to the true phase space of the system and, accordingly, allows the system in question to be evaluated in the appropriate number of dimensions (compare Figures 4.2 and 4.4). The purpose of the Lorenz example is to show that a phase space of a system can be reconstructed even with access to only one of the many possible dimensions of change.

QUANTIFICATION OF POSTURAL SWAY

How can one take advantage of the technique of phase space reconstruction to quantify what appears to be terribly complex postural activity? Recent efforts have made headway in this regard and have demonstrated that nonlinear methods of quantification are useful in differentiating among postural sway time series that correspond to subtly different activities of the person standing (see Riley et al., 1999; Riley & Clark, 2003). For example, Riley et al. (1999) detected deterministic structure in postural sway time series that cannot reliably be differentiated from stochastic noise using conventional methods. The method they used was recurrence quantification analysis (RQA; Webber & Zbilut, Chapter 2), which capitalizes on Takens' embedding theorem.

Recurrence Analysis

Webber and Zbilut (1994) introduced the basic RQA strategy, which involves reconstructing a phase space for a given time series, in the manner described above for the Lorenz system, and then tallying the number of instances that an unfolded time series visits each location in reconstructed phase space (i.e., how often a value recurs). The

degree of deterministic structure in the system may be assessed by quantifying how many sequences of recurrent points are repeated (i.e., repeating patterns of recurrent points). The variety of differing lengths of these sequences of recurrent points (number of data points forming a recurring sequence) may be used to determine the complexity of the signal by computing the Shannon entropy (see below) of the distribution of the lengths. The stability of the system may be measured by the longest of these sequences of recurrent points (maxline) (Eckmann, Kamphorst, and Ruelle, 1987). Finally, the degree of stationarity of the system may be assessed by determining the slope of the density of recurrent points as the points become more separated in time (trend). This procedure is known as auto-recurrence since a time series is compared to itself. See chapters in this volume by Webber and Zbilut (Chapter 2) and Pellecchia and Shockley (Chapter 3) for more extensive discussion and illustration of RQA measures.

CROSS RECURRENCE QUANTIFICATION AS A MEASURE OF COUPLING

Cross Recurrence Quantification (CRQ) was introduced by Zbilut, Giuliani, and Webber (1998) as an extension to RQA (see also Webber & Zbilut, Chapter 2). This extension involves effectively embedding two synchronous time series in a reconstructed phase space. Rather than tallying the recurring locations of a single embedded time series (auto-recurrence), the number of instances for which locations are shared by the two time series is tallied in CRQ (see Figure 4.5). Measures comparable to those of RQA are available with CRQ. *Percent recurrence* (%REC) in CRQ corresponds to the ratio of
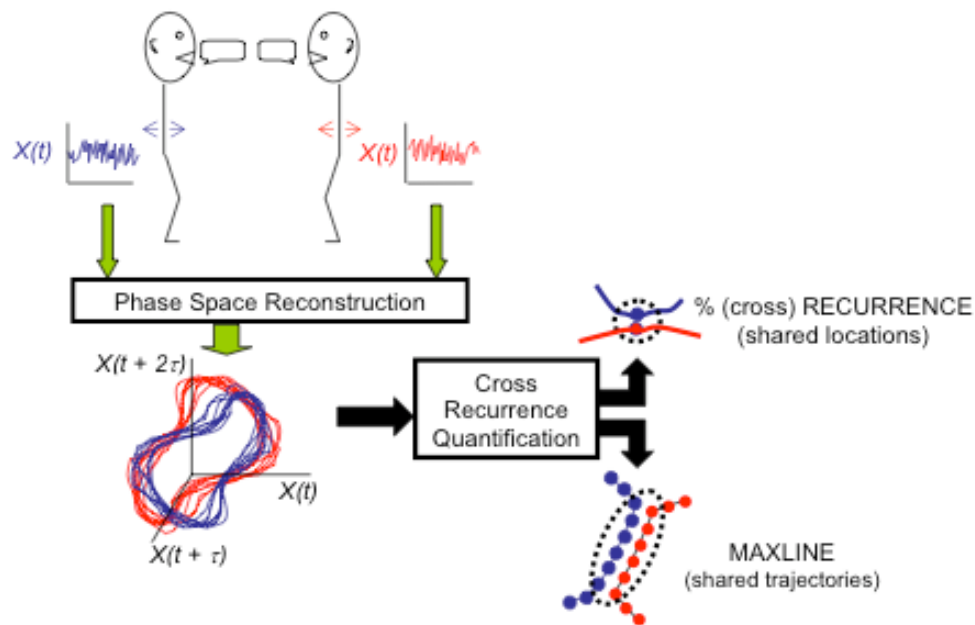
Figure 4.5. Illustration of time series collection, phase space reconstruction, and CRQ measures %REC and MAXL. Blue corresponds to data from one member of the participant pair and red corresponds to data from the other member of the participant pair. %REC quantifies shared locations in reconstructed phase space of two points from the two time series. MAXL quantifies the longest of parallel trajectory of the two time series in reconstructed phase space.

the number of shared location relative to the number of possible shared locations (see Figure 4.5). *Percent determinism* (%DET) is the ratio of the number of shared locations that are part of a sequence of shared locations relative to the total number of shared locations. *Maxline* (MAXL) is the longest shared trajectory and is a measure of the stability of the shared activity (see Figure 4.5). *Entropy* (ENT) is the Shannon entropy of the distribution of lengths of sequences of shared locations.

It was recently demonstrated that CRQ is a useful measure of the coupling of two signals by evaluating physically coupled oscillators (Shockley, Butwill, Zbilut, & Webber, 2002). An apparatus was

constructed that immersed a rotor with a paddle into a container filled with viscous fluid. The container (i.e., the driver) was then oscillated in a translational fashion at a fixed frequency while the immersed rotor was allowed to spin in the fluid at its natural frequency. The idea was to vary the strength of the coupling of the two oscillators by changing the viscosity of the fluid. In this coupled-oscillator system, the coupling strength of the signals was directly manipulated so that the efficacy of CRQ for detecting shared activity could be evaluated. Very subtle couplings between two signals were detected by CRQ measures that remained undetected by conventional, linear measures of coupling, such as cross-spectral analysis. For example, in medium and low coupling conditions, CRQ was able to detect the influence of the driver tray on the rotor oscillation to which linear spectral analysis was blind. Having CRQ as a tool for quantifying the shared activity between two signals allowed Marie-Vee Santana, Carol A. Fowler, and I to turn our attention to the problem of quantifying interpersonal coordination (Shockley et al., 2003). We endeavored to evaluate the utility of CRQ in detecting subtle postural coupling that may exist between two people engaged in conversation.

## VERBAL COORDINATION OF INTERPERSONAL POSTURAL ACTIVITY—THE EXPERIMENT

The Task

The strategy of Shockley et al. (2003) was to track the postural activity of two people engaged in a conversation. In order to generate conversation, a puzzle task was used that required participants to determine the differences between two similar cartoon pictures.

Similar types of puzzles can often be found in puzzle books or newspapers. Typically, however, the task involves a single person comparing two pictures. The innovation we introduced was to give each member of a participant pair one of the two similar cartoon pictures. We did not allow participants to visually inspect each other's picture during the course of a trial. This constraint left only verbal interaction to facilitate finding differences between the two pictures. This method was quite effective in generating normal conversation. Furthermore, the participants expressed genuine interest in the task both during and after data collection, as indicated by their reluctance to stop at the end of a trial and their unsolicited positive comments following the data collection session.

In recognition that visual interaction may influence postural sway in addition to the verbal interaction required by the task, two independent variables were factorially combined, *Task Partner* and *Body Orientation*. There were two levels of each variable (see Figure 4.6). A participant's *Task Partner* could be either the other member of the participant pair (*Participant*) or one of the experimenters (*Confederate*), who was seated out of view. The *Body Orientation* of the participant pairs involved either facing each other (*Facing*) or facing away from each other (*Away*). In all conditions, participants were instructed to discuss their pictures with their task partner and determine as many differences as possible between the two pictures over the course of two minutes. In all trials, the dependent measures were the postural sway of the two members of a given participant-pair, irrespective of the *Task Partner* on a given trial. Thus, the shared postural activity between two persons engaged in conversation with
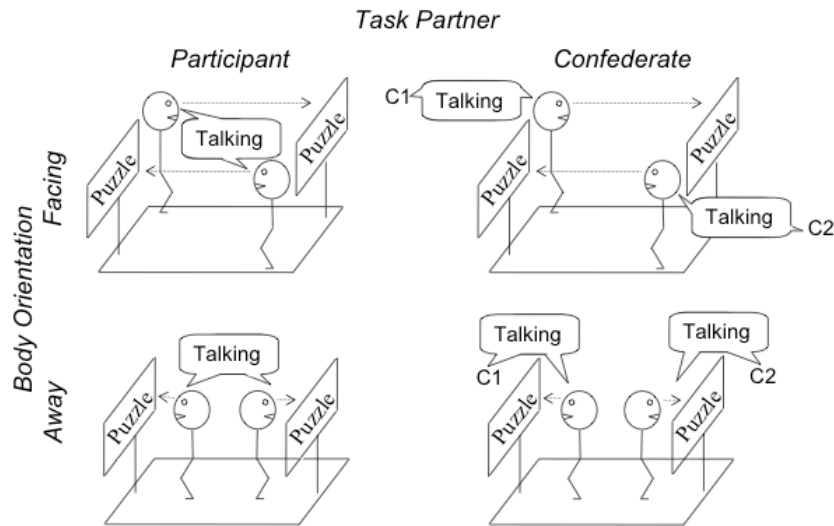
Figure 4.6. Method for evaluating interpersonal postural constraints involved in cooperative conversation. Participants faced toward or away from one another and conversed with each other or a confederate (C). Figure adapted from Shockley, Santana, and Fowler (2003).

each other could be compared to the shared postural activity of the same two persons engaged in conversation with others. Greater shared postural activity (i.e., greater %REC) was expected when participant pairs were conversing with each other than when participant pairs were conversing with confederates.

Data Collection and Reduction

A Polhemus FasTrak magnetic motion capture system (Polhemus, Inc., Colchester, VT) was used with *6-D Research System* software (Skill Technologies, Phoenix, AZ) to track the participants' movements in the anterior-posterior direction. Sensors were placed using Velcro straps at the waist and the forehead. For the purposes of this chapter I am only reporting data measured at the waist. Participants stood on opposite sides of the magnetic field emitter and were each

approximately 18 inches away from the emitter. Data columns of displacement in the anterior-posterior direction were extracted from the data file recorded by the motion capture software.

Unless otherwise indicated, for the subsequent analyses *Recurrence Quantification Analysis* software was used (the package is available free of charge from http://homepages.luc.edu/~cwebber/). Detailed instructions for how to use the recurrence analysis software can be found in the *README.TXT* file, which is provided with the software. It is assumed that the user has a working knowledge of an *MS-DOS* environment. The program *ZSCORE.EXE* was used to convert our displacement data into z-scores to ensure a common scale for all participants.

CRQ Parameters

Prior to calculating recurrence quantities, one must select the settings for seven parameters (embedding dimension, delay, range, norm, rescaling, radius, and line length). Embedding dimension, delay, and radius are among the most challenging parameters to determine. When the system in question is of unknown dimensionality and periodicity (e.g., postural sway data), one method for estimating these parameters is to evaluate the number of recurrent points for a range of these parameter settings (Zbilut & Webber, 1992; Riley et al., 1999; see Pellecchia & Shockley, Chapter 3). For a range of parameter settings it is important that there are smooth changes in the number of recurrent points in response to small changes in parameter values (see Trulla, Giuliani, Zbilut, & Webber, 1996). A large, discontinuous change in the number of recurrent points may correspond to a change in the scale of activity in the system to which the recurrence measures

are sensitive. Selecting parameters that are near such a threshold of sensitivity could, therefore, yield changes in recurrence values due to crossing the threshold, rather than changes due to experimental manipulations. Thus, it is safer to use parameter values within a range that exhibits smooth changes in %REC.

The program *KRQS.EXE* may be used to calculate %REC for a range of the three parameters in question. For each execution of the program, one inputs the file names corresponding to the two time series to be compared as well as an output file name to which the recurrence measures are saved. In our case, the input files corresponded to the z-score time series for Person A and Person B, respectively, of a given participant pair for a given 2-minute trial. After entering the command to execute *KRQS.EXE*, one is prompted for the minimum and maximum values for delay, embedding dimension, and radius.

Embedding Dimension. Embedding dimension specifies how many dimensions will be used in reconstructing the phase space. As discussed previously, the goal is not to determine exactly how many dimensions the system has. The goal is to be confident there are sufficient embedding dimensions to allow the dynamics of the system to be revealed without distortions. Webber (2004) suggested, for physiological data, starting with embedding dimensions between 10 and 20 and working downward. Based on Webber's suggestion and previous investigations of postural activity using recurrence analysis (e.g., Balasubramaniam, Riley, & Turvey, 2000; Riley et al., 1999), I elected a range of 8 through 14 embedding dimensions for the present discussion.

Delay. The delay parameter specifies the time lag to use for the time-delayed copies of the original time series (i.e., the surrogate dimensions in the reconstructed phase space). For illustrative purposes of this chapter and data processing economy, I selected delays ranging between 15 and 25 data points. A larger range, however, would certainly be appropriate. The sampling rate of the motion capture system used in the present study was 60 Hz. This means that delays of 15 to 25 data points would correspond to time delays of 0.25 to 0.42 s.

Radius. The radius parameter specifies the Euclidean distance within which points from the two time series are considered neighbors (i.e, recurrent) in the reconstructed phase space. The selected radius should yield a sparse recurrence matrix. That is, %REC should remain low (no larger than 5%), but not so small as to produce a floor effect (%REC at or near 0%). I selected radii ranging between 20 and 40, with a step size of 2. Given that mean distance rescaling will be selected (see below), the radius corresponds to the percentage of the mean distance separating points in reconstructed phase space.

Norm. The norm parameter specifies how distances are normalized in reconstructed phase space. I selected Euclidean normalization, which is consistent with previous studies using recurrence analysis to evaluate postural activity (see Riley, et al., 1999; Riley & Clark, 2003).

Rescale. The rescale parameter determines the method used to rescale the distance matrix (i.e., matrix of all distances among postural data points of person A and person B). Given that each participant pair may have had different distance magnitudes, Shockley et al. (2003) elected to rescale the distances among the points to the mean distance.

This served to intrinsically define the inclusion radius (see above) to a percentage of the average distance separating the postural trajectories of a given participant pair, rather than using an arbitrarily defined threshold (e.g., an absolute Euclidean distance). A distance corresponding to the mean distance separating postural locations in reconstructed phase space would, therefore, have a value of 100. Mean distance rescaling also serves to minimize the influence of an outlier value (e.g., large postural excursion due to laughing or sneezing)—as compared to rescaling to the maximum distance, for example.

Range. Each time series consisted of 7200 data points (120 seconds of data at 60 Hz). In the present study, there is no reason not to include as many data points as possible. Therefore, the first data point should be 1 and the last point should be 6875 (given a maximum embedding dimension of 14 and a maximum delay of 25). These values guarantee the use of the maximal number of data points and the same number of data points within each surrogate dimension in the phase space (see Pellecchia & Shockley, Chapter 3, for a detailed explanation of how to determine the last data point). The value for the last data point does not need to be determined, however. The software will provide a range of values, and the user can simply enter the maximum in the range presented by the software.

Line Length. Line length specifies the number of consecutive recurrent points required to define a line segment. This parameter should be set to two points (the minimum option) unless one has reason to believe that a more conservative estimate of a line is warranted.

The next step in determining parameters for CRQ is to randomly select a few trials from each experimental condition and execute the

program *KRQS.EXE* to compute recurrence measures for the selected parameter ranges for the selected trials. For illustrative purposes, I selected four sets of data to submit to *KRQS.EXE*.

Surface Plots for Parameter Selection in CRQ

One method of evaluating the %REC values for the selected range of parameter values is to use surface plots, which can be generated in the *MatLab* software environment (Mathworks, Inc., Natick, MA). For each embedding dimension, one can plot the %REC values returned from *KRQS.EXE* for a given data set as a surface (see Figure 4.7). A surface corresponds to a numeric matrix (stored in a *MatLab* variable that I arbitrarily named "rec"). The number of rows of the matrix corresponds to the number of values of radius used by *KRQS.EXE* and the columns of the matrix correspond to the number of values of delay used by *KRQS.EXE*. The values in the matrix correspond to the %REC values for one set of data (generated by *KRQS.EXE*) for each radius (rows) and delay (columns) for a given embedding dimension. To review, the extents of the two sides of each surface correspond to the range of radius and delay, respectively.

To create a surface plot in *MatLab*, one needs two vectors—one of extents corresponding to the numbers of columns and rows of the *%REC* matrix, respectively, and the matrix that I called "rec" in *MatLab*. First, create two *MatLab* vectors—"radius" [20 22 24 26 28 30 32 34,36 38 40] and "delay" [15 16 17 18 19 20 21 22 23 24 25]—to be used for all surfaces plotted. As discussed above, the matrix should be created from the %REC values returned from *KRQS.EXE*. The values of %REC will, therefore, be different for each trial analyzed. The matrix will, accordingly, need to be re-created for each surface to be plotted. Each
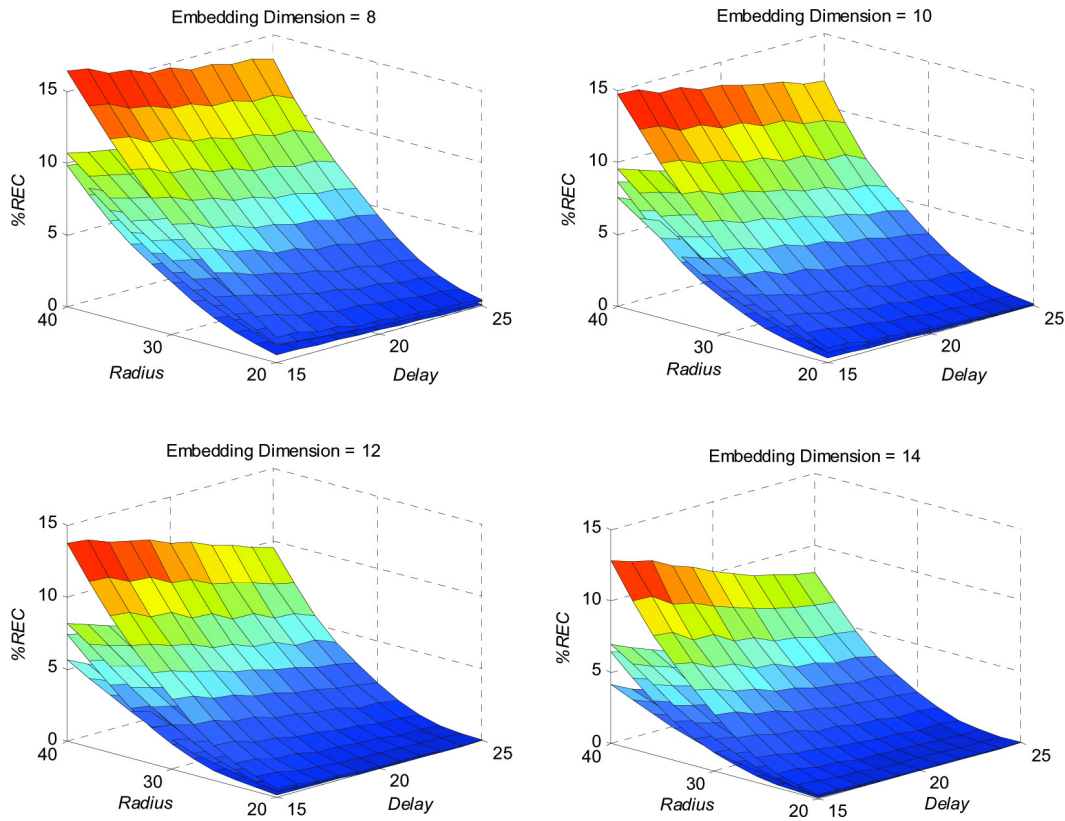
Figure 4.7. Shared postural locations (%REC) in reconstructed phase space for a randomly selected subset of data from Shockley, Santana, & Fowler (2003) for a range of values of the following parameters: Embedding dimension, delay, and radius. Each surface in a given plot corresponds to a different data set and each plot represents the same data sets for the parameter ranges.

surface plot is created by the following command: surf(delay, radius, rec). To plot multiple surface plots on one graph (as seen in Figure 4.7), type 'hold' after the first surf command. I have found that it is most useful to create a different plot for each embedding dimension. To generate new plots, open a new figure window and repeat the procedure. For illustrative purposes I have plotted four of the eight embedded dimensions (see Figure 4.7).

Inspection of Surface Plots

Embedding Dimension. Notice in Figure 4.7 that the recurrence values for the sampled data files tend to bottom out (%REC equals 0) for higher values of the delay and low values of the radius for embedding dimensions 12 and 14. Thus, an embedding dimension of 10 allows sufficient unfolding of the time series and still yield a sparse recurrence matrix (i.e., recurrence values just above 0%).

Delay. The particular delay selected is often arbitrary for postural data. What is most important is that the patterning of recurrence measures is consistent across a range of delay values. If so, one can be confident that any observed differences across experimental conditions are not artifacts of the delay. Shockley et al. (2003) selected a delay of 25 data points, which fits these criteria.

Radius. As discussed above, the radius is the maximum Euclidean distance by which points can be separated in reconstructed phase space and still be considered recurrent points. One should choose a value of radius that ensures that the number of recurrent points is reasonably low (so as to avoid global recurrence, i.e., all points recurrent). Webber (personal communication, June 2000) suggested that recurrence should be approximately 1%. Given that CRQ must be performed on multiple trials of multiple participants, however, Webber's prescribed recurrence range tends to be a bit too low. This is so because data from some trials may yield %REC = 0 for the same parameter settings that yield 1% recurrence for other participants. For biological movement data, I have found that recurrence of around 3%-5% for a randomly selected subset of data

tends to yield non-zero %REC values for all subjects, but still offers sufficiently low recurrence.

In summary, Shockley, et al. (2003) selected a delay of 25 data points, an embedding dimension of 10, and a radius of 30% of the mean distance separating points in reconstructed phase space. Modest changes of each of the values of those parameters does not change the patterning of results found by Shockley et al. (2003).

Full Analysis

After the parameters to be used for the analysis have been selected, the next step is to run the CRQ with the selected parameter settings on the entire set of experimental data. Shockley et al. (2003) used *KRQE.EXE* to compute the recurrence variables—%REC, %DET, MAXL, and ENT—for each participant pair. The reason for using *KRQE.EXE*, rather than *KRQD.EXE*, for example, is that the former allows multiple analyses to be executed in batch mode, rather than waiting for each file to be analyzed and then typing the next command for the next file to be analyzed.

To review, the following parameter settings were used with *KRQE.EXE*: delay = 25, embedding dimension = 10, range = 1-6875, norm = Euclidean, rescaling = mean distance, radius = 30, and line length = 2. The program *KRQEP.EXE* was used to generate a parameter file to be accessed by the commands in the batch file. This obviates the need to type in the parameters for each file to be analyzed. An ASCII (text), tab-delimited batch file (*filename.bat*) was set up such that each row corresponded to the *MSDOS* command for analyzing one file using *KRQE.EXE*. The number of rows corresponded to the number of files to be analyzed (see *README.TXT* file for complete instructions). Program

run time for the present data was several hours. Mean values for the recurrence measures were calculated for the four trials of each condition. Separate ANOVAs were conducted on each recurrence measure for postural time series pairs.

Results of Shockley, Santana, & Fowler (2003)

Among the measures derived from the tallied cross recurrence values, %REC (the ratio of the number of recurrent points to the number of possible recurrent points) and MAXL (the length of the longest trajectory of consecutive parallel recurrent points; a measure of the stability of the shared activity) were found to be significantly influenced by the experimental manipulations. Representative cross recurrence plots are provided in Figure 4.8A and 4.8B. The plots are organized such that the postural time series of one member of a participant pair (A) is indexed along the abscissa while the postural time series of the other member of a participant pair (B) is indexed along the ordinate. Points are plotted in the cross recurrence plot when the trajectories of the unfolded time series, A and B, occupy the same area of the reconstructed phase space within some radius of inclusion. That is, if a given position (i) in time series A occupies the same position in reconstructed phase space as the position (j) of time series B (i.e., $A[i] = B[j]$), then the point is considered recurrent (see Figure 4.5). Shockley et al. (2003) found greater shared postural activity among pairs of participants engaged in conversation with each other as compared to the activity shared among the same participants engaged in conversation with confederates, regardless of visual interaction.

They also found that trajectories of participant pairs stayed parallel longer when the participant pairs were engaged in
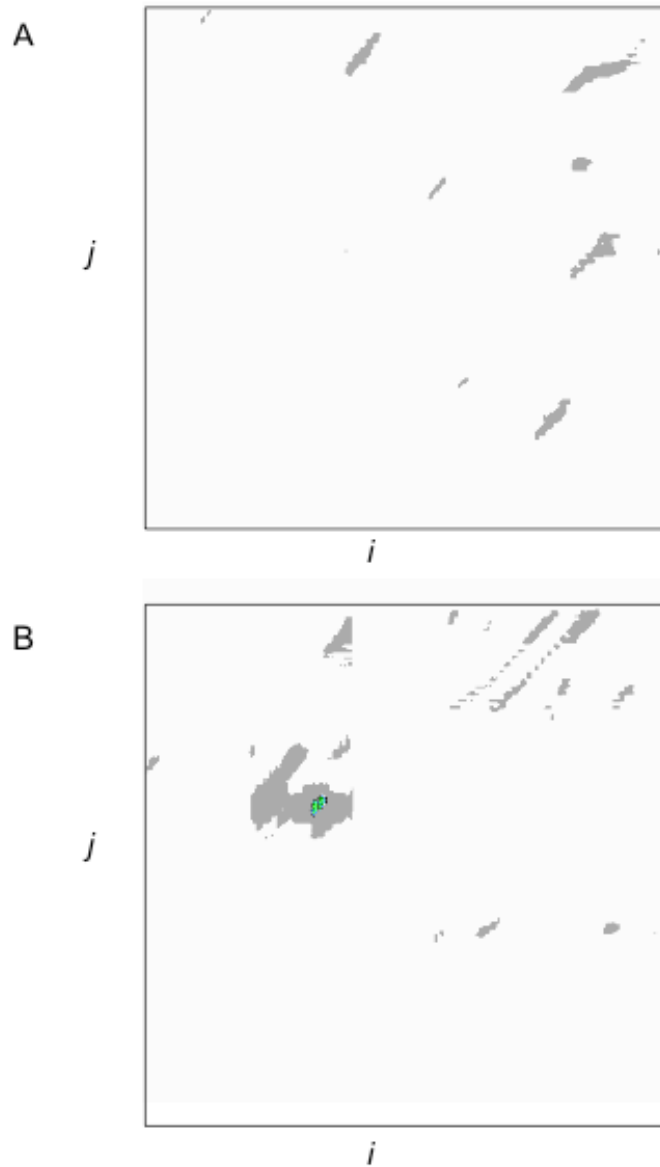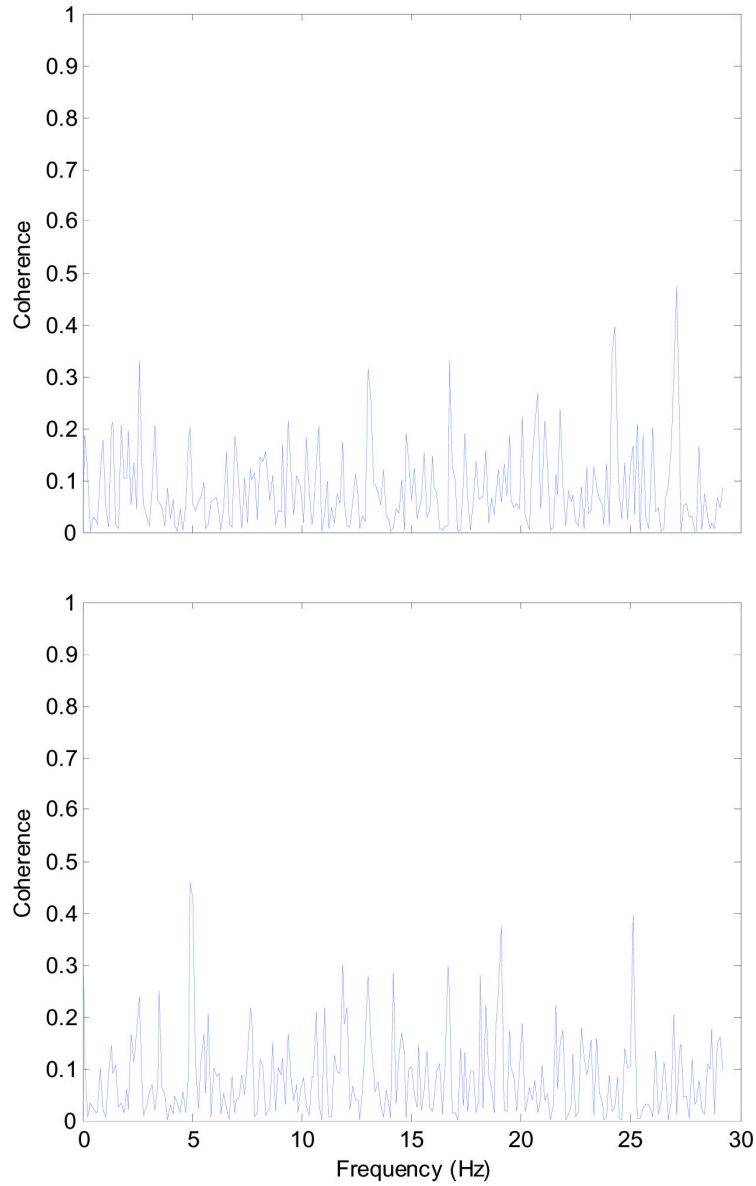
Figure 4.8. (A) Sample cross recurrence plot of the postural activity of two persons engaged in conversation with confederates. (B) Sample cross recurrence plot of the postural activity of two persons engaged in conversation with each other. Both are examples of the participant-pair facing away from each other. Indices along the abscissa (i) and the ordinate (j) corresponds to data points of person A and B, respectively of a participant-pair. Illuminated pixels correspond to shared postural locations in reconstructed phase space.

conversation with each other than when participant pairs were engaged in conversation with others. As far as the authors could determine, their observations mark the first objective measures of interpersonal postural coordination. Representative examples of a linear method of shared signal activity—coherence analysis—are provided in Figure 4.9. In Figure 4.9A, the participants were speaking to each other. In Figure 4.9B, the participants were each speaking to a confederate. Coherence analysis is effectively a correlation of Fourier spectrum power estimates compared across two signals for a range of frequencies. Note that there are not distinct frequencies at which power is correlated in either plot. Furthermore, on average the coherence for the two plots is the same (~0.085). This is consistent with the Shockley et al. (2002) finding that CRQ is a more sensitive measure of coupling than linear measures. Perhaps of greater importance, however, is the fact that CRQ is a more appropriate method for quantifying shared postural activity than linear methods, given that CRQ does not require the assumptions of normal distributions and stationarity of the data required by linear methods. That is, any significant effects that may have been discovered with linear methods would be suspect due to violations of the assumptions of those methods.

It is encouraging that recurrence strategies continue to prove their usefulness for the study of postural control. It remains to be seen how sensitive of a measure CRQ may prove to be. For example, is the degree of postural coordination scaled by the degree of cooperation of a given verbal interaction? Giles (1973) recognized changes in coordination among conversers with his observation that conversers in a cooperative and friendly setting show convergence of dialects, while

Figure 4.9. (A) Representative example of a coherence plot of the postural activity of two persons engaged in conversation with confederates. (B) Representative example of a coherence plot of the postural activity of two persons engaged in conversation with each other. Both are examples of the participant pair facing away from each other. Frequency (Hz) is plotted along the abscissa and the ordinate corresponds to the coherence between the power of the Fourier spectra of the individual time series of the participant pair.

hostile conversations show divergence of dialects. Will %REC decrease in a less cooperative situation as compared to a more cooperative situation? Furthermore, it remains to be seen what is the mechanism of coupling that was observed by Shockley et al. (2003). Investigations are currently under way to determine what aspects of the interaction (e.g., speaking rhythms, conversational turn-taking, word similarity) facilitate the type of shared postural activity that was observed. I leave these questions to future investigations.

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