

Correlational Methods for Analysis of Dance Movements

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Among the qualities that distinguish dance from other types of human behavior and interaction are the creation and breaking of synchrony and symmetry. The combination of symmetry and synchrony can provide complex interactions. For example, two dancers might make very different movements, slowing each time the other sped up: a mirror symmetry of velocity. Examining patterns of synchrony and symmetry can provide insight into both the artistic nature of the dance, and the nature of the perceptions and responses of the dancers. However, such complex symmetries are often difficult to quantify.

This paper presents three methods – Generalized Local Linear Approximation, Time-lagged Autocorrelation, and Windowed Cross-correlation – for the exploration of symmetry and synchrony in motion-capture data as it is applied to dance and illustrate these with examples from a study of free-form dance. Combined, these techniques provide powerful tools for the examination of the structure of symmetry and synchrony in dance.

INTRODUCTION

The Oxford English Dictionary defines dance in the following manner:

dance *n.* A rhythmical skipping and stepping, with regular turnings and movements of the limbs and body, usually to the accompaniment of music.

dance *v. intr.* To leap, skip, hop, or glide with measured steps and rhythmical movements of the body, usually to the accompaniment of music, either by oneself, or with a partner or in a set.

This definition, while reasonable for the common use case, leaves much to be desired in terms of specificity. More precisely, the terms ‘rhythmical’ and ‘regular’ are left quite unclear, as is the set of possible relationships between

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music and dancer that might acceptably be considered ‘accompaniment’, or more specifically, might constitute dancing *to* a musical selection. Similarly, the concept of dancing *with a partner* is left vague and unanswered. This paper proposes a series of metrics by which these relationships, ‘rhythmical’ stepping and ‘regular’ turnings and movements might be quantified. We extend these techniques to the examination of relationships between the movements of several people dancing together. The tools presented here may also be easily extended to take into account the prospect of musical accompaniment, although we do not extend this last analysis to the general case.

Recent advances in technology, specifically in motion capture technology have made it possible to record and codify dance in a manner previously impossible; dancers’ movements may be recorded every hundredth of a second to the millimeter of movement and fraction of a degree of rotation. This sort of recording provides a wealth of data, but in a format that is difficult to comprehend without additional tools. We propose a set of tools that may help to understand motion capture data from dancers in terms of how ‘rhythmic’ and ‘regular’ a dance may be. We present a means of codifying synchrony and symmetry (how ‘rhythmic’ and ‘regular’ a dance may be), and to provide some quantification of these ideas. The methods presented here are primarily for visualization and are intended to provide a new means of thinking about and making visible the patterns of synchrony and symmetry as they change across time. Through applications of advanced techniques such as surrogate data methods (Theiler, Eubank, Longtin, & Galdrikian, 1992), it is possible to apply statistical tests to these measures and thus to code changes mathematically in the rhythmic structure or regularity of the dance. This allows scientific analyses of a wide variety of manipulations to be performed. Statistical applications are outside the scope of the current paper, which is intended primarily as a basic tutorial of the exploratory and visualization of motion capture data from dancers.

Definitions

We define *symmetry* as identical or near-identical position or behavior at two different locations. For example, if a person were to lift both his left and right arms in the same way at the same time, this would result in a *symmetric* movement. *Symmetry* shows itself in several different forms. If two people facing the same direction raise the same arm at the same time, this would be *translational symmetry*; that is, identical motions shifted along one or more dimensions from one another. In our original example, a dancer raised his left and right arms – this would be *mirror symmetry*, or a motion reflected rather than translated. Mirror symmetry can be thought of in terms of distance; as one moves away from the plane of reflection, one encounters identical shapes in either direction.

These translations and reflections need not be spatial in nature; over the course of a dance it is also possible to show *temporal symmetry*, or symmetry across time. For example, if a dancer made a repeated circle with one hand, then repeated the motion again, this would show *temporal symmetry* of a translational

variety. The dancer has made an identical motion, but shifted forward in time rather than space. A 'regular' motion might be the result of the maintenance of temporal symmetry. The result would be a periodic repetition of a movement or series of movements. The dancer might perform the repeated motion with slight variations each time—imperfect but sustained temporal symmetry. If the person were to first make a motion forward, and then the same motion in reverse, this would be a form of *temporal mirror symmetry*. Like spatial mirror symmetry, the motion would be identical in either direction at the same distance from a reflection point. In temporal mirror symmetry, this means that the motion would look the same two seconds before the reflection time as it would two seconds after the reflection point.

Further, symmetry need not be restricted to position; it could exist similarly in the domain of velocity or acceleration. Here we define velocity as the instantaneous signed rate of change in position, and acceleration as the signed change in velocity. Conceptualizing velocity and acceleration is often best thought of in the context of a vehicle. The location of a vehicle on the road surface is the car's position. The needle on the speedometer shows its speed—the magnitude of the velocity vector. Change in the speedometer needle's angle indicates acceleration. A highly positive rate of acceleration could be achieved by pressing the accelerator pedal hard, while a highly negative rate of acceleration could be achieved by pressing the brake hard.

Two motions that showed identical velocity profiles might show a sort of *translational symmetry of velocity*. For example, if two people began to move with increasing speed over the course of a minute and then slowed suddenly, they would show symmetry of velocity. The same velocity profile could be observed at two different moments in time. From a different perspective, if two people moved such that one always sped up while the other slowed down, this might represent a mirror symmetry of velocity. Similar analyses could be applied for acceleration, or the rate of change of acceleration; however, human movements tend to minimize change in acceleration (Flash & Hogan, 1985). We will therefore discuss the estimation of acceleration, but will focus our examples on position and velocity. The techniques we present can also be applied to acceleration data.

In order to account for the occurrence of two events at a single moment in time, we also define the term *synchrony* to indicate the onset or continuous action of an event at the same time as another. For example, a troupe of dancers might simultaneously begin to move. While each might move in a different way and a different direction, they might all move for the same span of time, thus starting and stopping their movements simultaneously. These would then be considered *synchronous* movements. Movements might be synchronous without being symmetric, or might be symmetric without being synchronous. Similarly, a movement might be timed to correspond with the downbeat of a musical phrase, or a dancer moving to a symphonic rhythm might begin a dance movement at the onset of a musical phrase, say, by a flute. When the flute ended its movement, the dancer might end his movement, thus completing his movement in synchrony with the flute. *Symmetry of velocity* and *symmetry of acceleration* can be considered a

special case of synchrony. To the extent that velocity and acceleration match in time, two movements can be considered to be happening simultaneously.

In the case of a repetitive motion, *synchrony* takes on a slightly different meaning. Because there is no clear indication when a repetition of the motion begins or ends, two repetitive motions may be considered synchronized if they take the same amount of time to repeat. That is, if the period of *temporal synchrony* is identical between the two, we will consider this a form of synchrony.

Finally, there is no reason to limit either symmetry or synchrony to a single domain. One dancer's legs might show symmetry in velocity with the arms of another. A dancer might begin her movements at the onset of a trumpet solo, increase her velocity as the volume of the solo increased, and decrease it as the sound faded. The result would be a *cross-domain symmetry* between the volume of the trumpet and the velocity of the dancer. Because of the difficulty in directly comprehending *cross-domain symmetry* as a form of symmetric movement, it is often easier to think of it as a special case of *synchrony*.

In the expression of dance, especially between two individuals or between an individual and a musical composition, it is expected that both symmetry and synchrony will be created and destroyed repeatedly. The pattern of *symmetry and synchrony formation* and *symmetry and synchrony breaking* specific to a dance composition provides one way to characterize a particular dance.

Previous work has studied the self-similarity of dancers' movements in the context of music using component transformations such as Principal Components Analysis, Canonical Correlation Analysis (Caramiaux, Bevilacqua, & Schnell, 2010), or classification systems like Linear Discriminant Analysis (Naveda & Leman, 2010) to break dance down into repeating component parts. Others have used methods like periodicity analysis (Naveda & Leman, 2009) or Recurrence Quantification Analysis (Varni, Mancini, Volpe, & Camurri, 2010) to look at periodicity and temporal symmetry in dance. Leman and Naveda (2010) used a combination of autocorrelation and principal components analysis to build a spatio-temporal view of synchronization of dance gestures and movement. A similar system was constructed by Toiviainen et. al. (2009), using a combination of component transformations and velocity-based energy measures to examine the metric structure of movement to music. The current work expands on these endeavors by demonstrating the use of windowing techniques for the visualization of symmetry and synchrony across the structure of the dance, and by introducing new transformations to allow examination of these constructs at the levels of velocity and acceleration.

This paper is intended to present several methods for the examination of symmetry and synchrony in dance movements. The methods presented are equally applicable to any continuous streams of data that is both dense (i.e., sampled often) and numerous (i.e., many samples per person), such as EEC data. The examples presented focus primarily on the comparison of movements in the position and velocity domains; these are used primarily because they are accessible to novice users of these methods. Cross-domain symmetry and symmetry of acceleration may be investigated using the same techniques.

Examples

In order to examine the patterns of symmetry and synchrony exhibited by a dance composition, it is first necessary to record the composition in a format amenable to analysis. This paper will focus primarily on motion-capture data, although data of other formats might be usable in similar analyses.

Example data for this paper come from individuals in an psychology experiment at a small private midwestern USA university. The individuals whose data is to be displayed were untrained dancers dancing to repeated rhythmic stimulus which was presented over headphones. One individual presented here danced alone, while a second pair danced together. In each case, participants were fitted with 8 magnetic motion capture sensors held against the body by neoprene-and-velcro compression straps. More information on the apparatus is available in more detail below. Participants were instructed to ‘Move in whatever way seems natural to you.’ In the dyadic case, one participant was instructed to lead the dance, and the other to follow. For ease of memory, those dancers dancing alone will be referred to in this work as Andrew or Alice, while the two dancing in a dyad will be referred to as David and Donna.¹

Untrained dancers and the designation of a single lead are used for this illustration because the movements made were simple and repetitive, and clearly show several of the features of interest. The measures and techniques presented here should be well-suited to the analysis of dance at any level of expertise. More intricate lead-follow relationships can also be examined, as described in the discussion of windowed cross-correlation, below.

DATA TRANSFORMATIONS AND INITIAL SETUP

One difficult issue in the handling of motion-capture data is the lack of a meaningful coordinate system. Several transformations are often needed to turn motion capture data into a more meaningful form. While a complete discussion of methods for cleaning and normalizing motion-capture data lies outside the scope of this paper, two essential transformations will be discussed: (1) Centering and Hierarchy of Support, and (2) Estimation of Velocity and Acceleration.

Example Setup

In our examples, motion-capture data were recorded using an Ascension Technologies MotionStar magnetic-field-based motion tracking device. Eight sensors were attached to each individual: one at the back of a baseball cap fitted snugly on the head, one held to the sternum with a neoprene and velcro vest, one held to each forearm just below the elbow using a neoprene and velcro compression strap, one held to the back of each hand using an elastic weightlifting glove, and one held to the front of each shin just below the knee using a neoprene and velcro compression strap. Each sensor was an approximately 1.5 cm cube attached by a long, flexible electronic wire to the

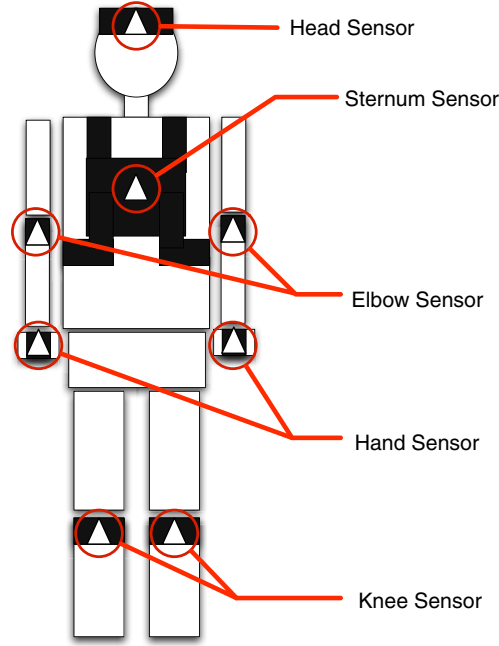


Fig. 1. motion capture sensor placement.

central MotionStar AD converter computer. The sensors were sampled at 80 Hz and recorded position information with 6 degrees of freedom (XYZ position and orientation) with an accuracy of approximately 1.5 mm in position and 2 degrees in orientation. A diagram of the motion capture sensor arrangement as it was used is shown in Figure 1. This arrangement of sensors has been used in the psychological literature for studies of conversation and dance (Boker et al., 2011; Boker & Rotondo, 2003; Ashenfelter, Boker, Waddell, & Vitanov, 2009, for example).

We will designate the location of motion sensor i at time t along x, y, and z coordinates as the column vector $\mathbf{P}_i(t) = [x_i(t), y_i(t), z_i(t), 1]^T$, and the orientation as $\mathbf{O}_i(t)$, a matrix with four rows and four columns². The entire uncentered orientation and location can be represented by the matrix $\mathbf{P}_i^*(t)$, created by multiplying the two together.

Many other motion-capture systems are in use today, using a wide variety of technologies. Most are capable of at least reporting position and orientation of the tracked points. Many will also automatically perform transformations into a centered frame of reference.

Provided the system is able to provide position and orientation information for the various points in some manner, the mechanisms here can all be used. Transformation into the representations used here are specific to the motion tracking system used, but are widely available.

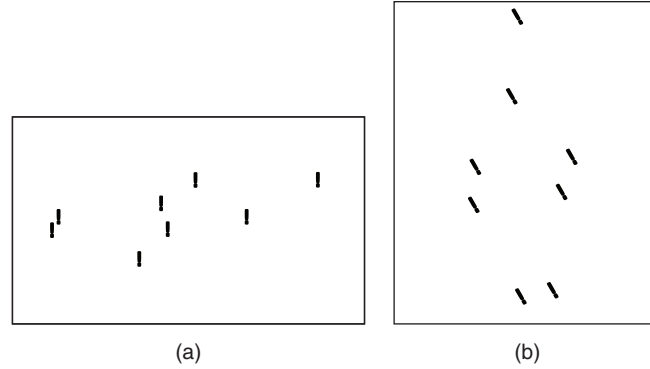


Fig. 2. A visualization of motion-capture data (a) before centering and (a) after centering. The shape of a human figure is much more noticeable after centering. Each motion-capture sensor is represented by a short line showing the sensor's location and orientation.

Centering and Hierarchy of Support

Figure 2(a) shows a plot of raw motion capture data from a person standing, wearing the sensors. At first, it is not clear what arrangement the sensors have to each other, or where they lie on the human figure. In order to induce a clear coordinate system, we must first define a coordinate system. In this case, we will use the initial position of the chest sensor to be our $(0, 0, 0)$ location, and use its orientation to be the orientation of our coordinate grid. This computation can be carried out using Equation 1. The result is a much more comprehensible parameterization of the data, as visualized in Figure 2(b).

$$\mathbf{P}_i = \mathbf{P}_i^* \mathbf{P}_{chest}^{-1} \quad (1)$$

A problem may arise in the use of data centered in such a way. When comparing the movements of a person's arm and hand, for example, a great deal of symmetry in motion will be detected—that is, when the arm moves, the hand moves with it. This is because of the hierarchy of support that structures the human body—it is difficult to move one without the other. In order to remove this common motion, we will center each sensor on the body to show its difference from the sensors to which it is connected. Continuing to use the chest as our best measure of overall body movements, we will center the elbow, head, and knee sensors to the chest, and the wrist sensors to the elbow. In this way we ensure that shoulder movement will be measured only by the arm sensor and not by both the arm and wrist.

More advanced methods exist for transforming raw motion capture data. The most common approaches uses an error-minimization approach such as least-squares to fit the raw sensor data to a model of the human body (O'Brien, Bodenheimer, Brostow, & Hodgins, 2000) or a less-constrained model of joint motion (Schwartz & Rozumalski, 2005; Ehrig, Taylor, Duda, & Heller, 2006). While a full discussion of these transformations is outside the scope of this paper,

it is worth noting that data resulting from such transformations can be utilized in the analyses discussed here.

Estimation of Velocity and Acceleration

In order to examine symmetry and synchrony of velocity and acceleration, it is first necessary to extract a measure of these quantities. To do so, we will utilize a method known as Generalized Local Linear Approximation (GLLA) (Boker, Deboeck, Edler, & Keel, 2010). GLLA is a variant of a mathematical filter known as a Savitzky–Golay filter (Savitzky & Golay, 1964), and uses the measurements of position across a short window of time to estimate the position, velocity and acceleration, at the center of the window. GLLA has been used previously in the analysis of motion-capture data (Ashenfelter et al., 2009; Boker et al., 2009, 2011).

In order to apply the GLLA transformation, we must first convert the time series of each of our measurements into a series of short windows through a process known as *time-delay embedding* (Sauer, Yorke, & Casdagli, 1991). To illustrate time-delay embedding, first consider a single measurement, the position along the x-axis. Across the duration of the dance, a large number of measurements of this position will be collected. We will designate the measurement at time t as $x(t)$. Our initial measurement thus appears as a column vector $\mathbf{X}$, as shown in Equation 2.

$$\mathbf{X} = \begin{bmatrix} x(1) \\ x(2) \\ x(3) \\ x(4) \\ \vdots \\ x(n) \end{bmatrix} \quad (2)$$

Time-delay embedding expands this matrix by transforming each row into a short window of time-points rather than a single time point. In this case, we will use window made up of 3 time points, also referred to as an *embedding dimension* of 3, as shown in Equation 3.

$$\mathbf{X}^{(3)} = \begin{pmatrix} x(1) & x(2) & x(3) \\ x(2) & x(3) & x(4) \\ x(3) & x(4) & x(5) \\ x(4) & x(5) & x(6) \\ \vdots & \vdots & \vdots \\ x(n-2) & x(n-1) & x(n) \end{pmatrix} \quad (3)$$

Conceptually, GLLA estimates velocity using a weighted average of the changes in position at the surrounding measurements. To illustrate, we will use an example with an embedding dimension of 3. In this example, GLLA estimates the velocity at time first t by calculating the difference in position between time

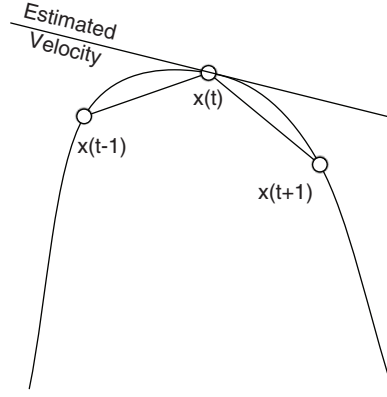


Fig. 3. An illustration of generalized local linear approximation.

$t - 1$ and time t , and averaging that with the change in position between time t and time $t + 1$, as shown in Figure 3. If the acceleration across the very short time period of measurement is close to constant, then this average should produce a very accurate estimate of the speed at time t . The acceleration is then estimated as the difference in slope between the $(t - 1) \rightarrow t$ and $t \rightarrow (t + 1)$ segment. The resulting equations would look like Equation 4 and Equation 7, below. Note that in these equations, $\dot{x}(t)$ represents the velocity of x at time t , and $\ddot{x}(t)$ represents the acceleration at time t .

$$\dot{x}(t) = \frac{(x(t) - x(t - 1)) + (x(t + 1) - x(t))}{2} \quad (4)$$

$$= \frac{x(t + 1) - x(t - 1) + (x(t) - x(t))}{2} \quad (5)$$

$$= \frac{x(t + 1) - x(t - 1)}{2} \quad (6)$$

$$\ddot{x}(t) = (x(t) - x(t - 1)) - (x(t + 1) - x(t)) \quad (7)$$

$$= -x(t + 1) - x(t - 1) + x(t) + x(t) \quad (8)$$

$$= -x(t + 1) + 2x(t) - x(t - 1) \quad (9)$$

Mathematically, the derivatives can be estimated in a single step by multiplying the embedded matrix $\mathbf{X}^{(3)}$ by a carefully constructed weight matrix $\mathbf{W}$. Element w_{ij} at row i and column j of $\mathbf{W}$ can be calculated using Equation 10. The resulting matrix $\mathbf{W}$ for the three-dimensional example case is

$$\mathbf{W} = \begin{pmatrix} 0 & -0.5 & -1 \\ 1 & 0 & 2 \\ 0 & 0.5 & -1 \end{pmatrix} \quad (10)$$

Postmultiplying $\mathbf{X}^{(3)}$ by $\mathbf{W}$,

$$\mathbf{X}^* = \mathbf{X}^{(3)}\mathbf{W} \quad (11)$$

results in a matrix with three columns: position, $(x(t))$ in column 1, velocity, $(\dot{x}(t))$, in column 2, and acceleration, $(\ddot{x}(t))$, in column 3.

A similar result can be calculated for higher rates-of-change (for example, the rate of change of acceleration, known as *jerk*). While it is possible to use these higher moments in the analyses that follow, human movement often minimizes sudden changes in acceleration, so jerk is generally quite low (Flash & Hogan, 1985). As a result, we will focus our analyses at the levels of position, velocity, and acceleration.

The large number of columns of motion capture data can often be overwhelming. To reduce the dimension of the data examined, it is sometimes helpful to use aggregate measures of motion. For example, the *Root Mean Square* (RMS) velocity can be used to measure the ‘quantity of motion’ made by a person across their entire body. The RMS velocity therefore provides reasonable measure of overall activity, and can be helpful for locating regions of synchrony between individuals. RMS velocity of the n sensors on a single person can be calculated as

$$RMSV(t) = \sqrt{\frac{\sum_{i=1}^n (\dot{x}_i(t)^2 + \dot{y}_i(t)^2 + \dot{z}_i(t)^2)}{n}}. \quad (12)$$

RMS acceleration can be calculated similarly, and provides a measure of the amount of change in velocity across the entire body. RMS position is less helpful; it is recommended that the sternum sensor position be used instead.

In order for GLLA to approximate velocity and acceleration accurately, we must make the assumption that the movement of each sensor is *locally linear*; within the time window examined the motion of the sensor is assumed to be smooth, with no discontinuities. Because motion capture systems generally function at speeds much faster than human movement, this assumption is not unreasonable.

Encoding Music

In order to make comparisons between the musical form and the movements in dance, it is also necessary to transform the music into a numerical sequence. For the majority of the paper, we will focus only on the rhythmic aspects of music, and will denote synchronization with the music in terms of matching the measure structure only. Other common methods of digitizing a musical score

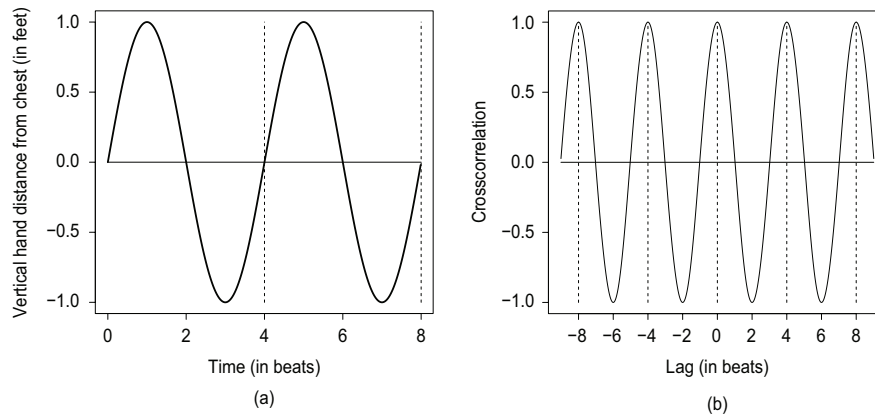


Fig. 4. A perfect repetitive motion, (a) shows a perfect simulated motion capture signal, graphed as position against time, (b) shows the global lagged autocorrelation function. Peaks at an autocorrelation of 1 indicate a perfect repetition of the movement at a given lag.

include measuring pitch contour, pitch set, intensity, beat structure, fundamental frequency, or the raw sonic waveform (Dowling, 1994; Boersma, 1993; Drake, 1998; Shaffer & Todd, 1994). If one of these methods is used, it is recommended that the sampling rates of the musical and motion capture data be resampled to be the same rate. Once this is done, the musical data can be included in analyses the same way as any other stream of motion data.

SYMMETRY

To continue our exploration of symmetry and synchrony, we begin with the detection of the simplest forms of symmetry. Consider a dancer making rhythmic motions with her left arm. If we plot the horizontal position of her hand relative to her body across time, we might see a curve that look something like the idealized curve shown in Figure 4(a). Note that individual movement curves are unlikely to look exactly the same. This is, at least in part due to the fact that the arms of two dancers are unlikely to be exactly the same length. The longer the dancer's arm the larger the range of motion.

Global Correlation

Because of these differences between people, it is not advisable to simply measure the difference between their motions as a measure of symmetry. Instead, we need a measure that is invariant to scale—that is, a measure that will not be biased by the slightly larger reach of person 1. Correlation (specifically, the Pearson product-moment correlation coefficient) is just such a measure. Correlation provides a scale-invariant method of determining the extent to which two streams of data covary; that is, if one always rises when the other rises and sinks when the other sinks, the correlation will be near one. If the two streams are independent,

the correlation will be near zero. If one rises when the other sinks and vice – versa, as would be the case in the event of mirror symmetry, their correlation will be near negative one. The correlation can be calculated using Equation 13 (Cohen, Cohen, West, & Aiken, 2003).

$$r_i(t) = \frac{n \sum_{t=1}^n x_i(t)y_i(t) - \sum_{t=1}^n x_i(t) \sum_{t=1}^n y_i(t)}{\sqrt{n \sum_{t=1}^n (x_i(t))^2 - (\sum_{t=1}^n x_i(t))^2} \sqrt{n \sum_{t=1}^n (y_i(t))^2 - (\sum_{t=1}^n y_i(t))^2}} \quad (13)$$

Correlations are not linear measures and cannot be combined by addition or averaged with a mean because they are bounded between positive and negative one. If several correlations need to be combined into a single grand correlation value, this can be done by converting the correlations into Fisher's Z scores, averaging the transformed values, and converting them back into correlations. Note that using this technique, a limb with one dimension of perfect symmetry and one dimension of perfect mirror symmetry will show a grand correlation of zero, since the two will cancel out. To provide a better estimate of the amount of precision in such a comparison, the root mean square of the Z transformed values (shown in Equation 15) may be a better measure. The Z scores and RMS_Z can be calculated as

$$Z = \frac{1}{2} \ln \left(\frac{1 + r_i}{1 - r_i} \right) \quad (14)$$

$$RMS_Z = \sqrt{\frac{\sum_{i=1}^n \left(\frac{1}{2} \ln \left(\frac{1 + r_i}{1 - r_i} \right) \right)^2}{n}} \quad (15)$$

where r designates the correlation.

The overall correlations can give a rough measure of how similar two dances were. The correlation between two recordings of a dancer performing the same routine will give some information about how precisely the two performances matched in both space and time.

In many cases it will be unhelpful to know simply whether one dancer is performing the same motions as another at the same time. Instead, it is helpful to see mirroring and symmetry across time. In order to answer these sorts of questions, we must introduce a new technique.

Lagged Autocorrelation and Self-symmetry

Imagine a simple dance: a dancer simply rocks back and forth at a steady rhythm, reaching the same point in her rotation at each measure of the music. To examine the rhythmicity of this movement, we must search for *temporal self-symmetry*. That is, we are seeking those times at which the dancer's movements look most similar to themselves a previous time.

Self-symmetry can be identified using the same correlation metric described above. Instead of correlating two different streams of movement, however, we

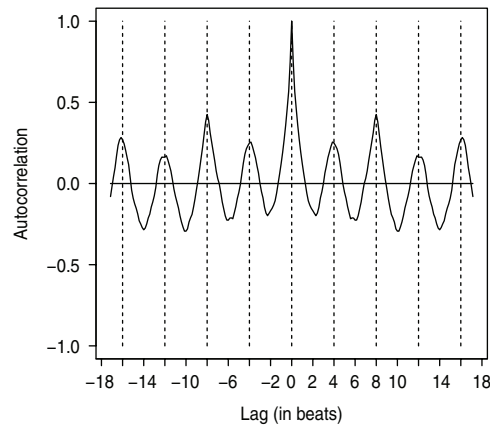


Fig. 5. Autocorrelation from Andrew's dance.

examine how a single stream correlates with itself across time. To do this, we make a copy of the original movement, and delay it in time against itself, first by one, then two, then three samples, and so on. At each level of delay, we can calculate a new correlation coefficient, which we will call the *lagged autocorrelation* at that delay.

At a lag of 0, the autocorrelation will always be a perfect 1.0—a sequence always perfectly matches itself. As we move further and further out from lag 0, the correlation will fall away from a perfect correlation of 1.0. If there is rhythmicity in the movement, at even longer lags, the correlation will begin to increase again; the dance will again resemble itself. The plot in Figure 4 shows movements similar to what our hypothetical dancer might make if she were perfectly matching her movement each time, and the autocorrelation plot that goes with it. In the autocorrelation plot, the y-axis denotes the correlation coefficient, while the x-axis denotes the delay between the original data and the lagged data. Negative delay means that the lagged data is shifted the other way; it begins earlier than the original data stream³. The timing of the music is simplified here, represented as dotted lines for each musical measure. Notice that the motion repeats once for each measure, as shown by the peaks in correlation at that interval. The distance between peaks indicates the period of the rhythmic movement—the time taken for the motion to repeat itself.

Analyzing two example dancers from our experiment, we are now able to deduce a few properties of their movements. In one trial, Andrew moves rhythmically to the music provided, matching the beat almost exactly, but often a few milliseconds too late (see Figure 5). In a different dance, Alice moves at twice the meter of the music, matching her own movements at every measure and half-measure (see Figure 6). We can also see that as the lag increases, the correlation at the peaks drifts slowly downward. This indicates that as time goes on, our dancers' movements drift from their original locations, so their later movements look less and less like their original ones. Here, she exhibits a decaying *temporal symmetry*; her movements are highly, but not perfectly symmetrical across time.

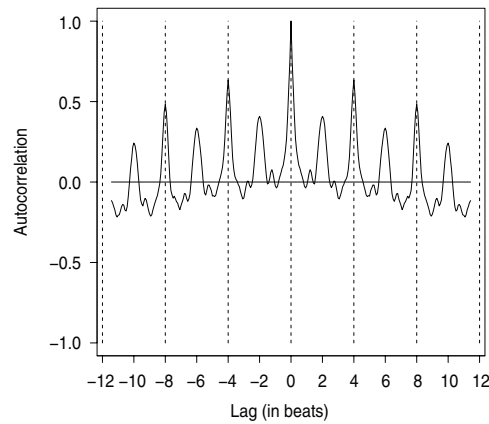


Fig. 6. Autocorrelation from Alice's dance.

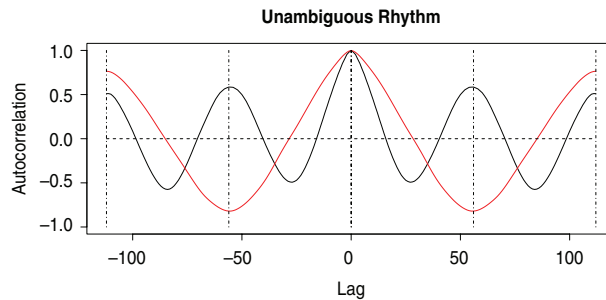


Fig. 7. Autocorrelation of left arm and torso from Alice's dance.

The asymmetry compounds as the dance continues, so that the movement four cycles later may be qualitatively different, although each individual movement is quite similar to the one before.

Comparisons across limbs can be interesting at this level as well; symmetry, especially in terms of velocity, can be common between limbs. In Figure 7, we notice that Alice is moving her torso in time with the measure of the music, but her arm (in this case, her left elbow) at twice that rate. Both movements synchronize to the same rhythmic stimulus, but show different periods of movement. Note that these movements may be very different in character; it is only the structure of temporal symmetry that they exhibit that shows this doubling relationship.

Windows

Our examples and techniques so far have been global examinations of an entire dance as a unit, as though the dance were a single movement repeated numerous times. While this may be accurate for the controlled space of our example, it is certainly not the case for professional dancers, where in some dances each movement may be unique. Figure 8 shows a situation in which

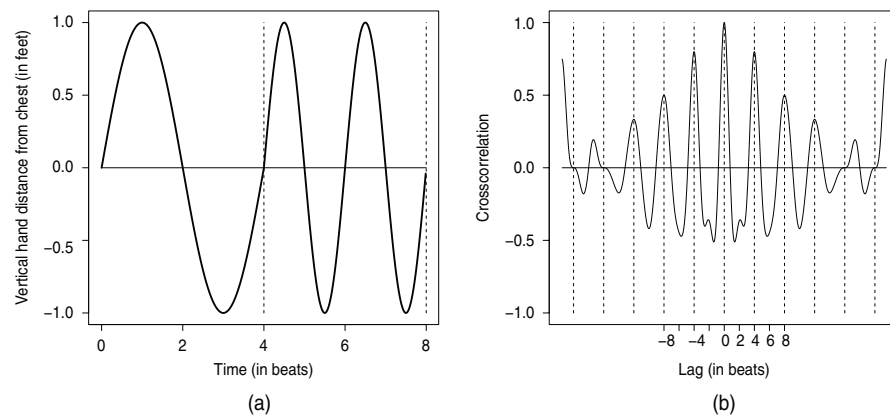


Fig. 8. An illustration of the problems with global correlations. The movement shown in (a) is poorly captured by the global autocorrelation (b).

global autocorrelation ceases to be functional. The movements in Figure 8(b) change over time, as would happen in a real dance scenario. For illustration purposes, our example shows only a single change in frequency. It is not clear from the global autocorrelation function exactly what is happening. The slow decrease in peaks in the global autocorrelation function in Figure 8(b) show that the dance changes; movements closer together in time are more similar. There is still an obvious rhythmic movement, but it goes away over time. The global autocorrelation function aggregates across the entire dance, and so shows a complicated ‘average’ pattern of temporal symmetry. While this aggregate view is useful for getting a sense of the overall rhythmicity of the dance, and how well a set of highly rhythmic movements match each other’s timing, a better method is needed to see the dance in detail.

In order to examine the changes in symmetry across the course of the dance, we must look at each part of the dance as its own series of movements. To do this, we split the dance into short windows of time, and examine the lagged autocorrelation of each of those windows separately.

While manually examining thousands of windows would be prohibitively difficult, it is possible to stack a large number of *windowed time-lagged autocorrelation* graphs together, as shown in Figure 9. These graphs take some practice to understand, but reveal numerous patterns in rhythmicity to the trained eye. Each vertical slice of the graph is a single time-lagged autocorrelation function. The changing lags are on the y-axis of the graph, again with dotted lines to indicate a single measure of the musical score. Colour indicates the magnitude of the correlation – the similarity of the reference window to a window lagged by that amount. Moving right along the x-axis moves the reference window forward in time. Rhythmic behavior shows up as horizontal bars, with changes in the timing of the rhythm showing up as diagonal or vertical changes in those bars. Figure 9(a) shows the simulated example of a perfect dancer. The result is perfect horizontal lines, spaced evenly at the timing of the dance; in this case,

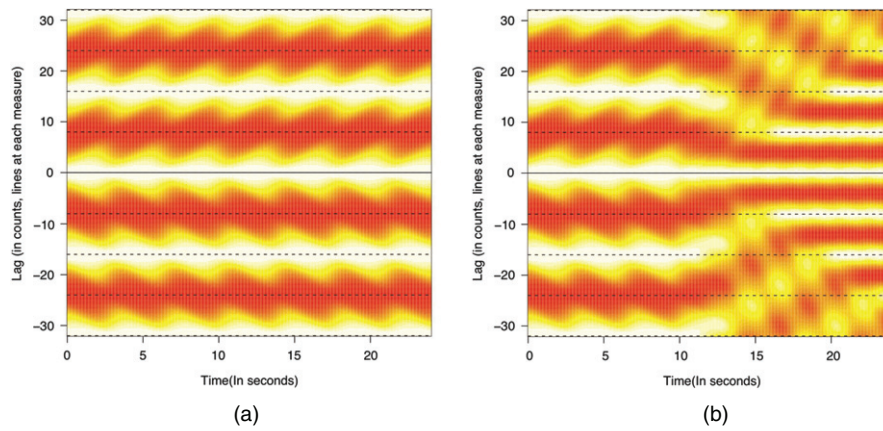


Fig. 9. Differences visible in Windowed Autocorrelation. Both figures show rhythmic motion at the beginning, (a) shows a constant repetitive motion, while the motion in (b) changes to a faster rhythm partway through.

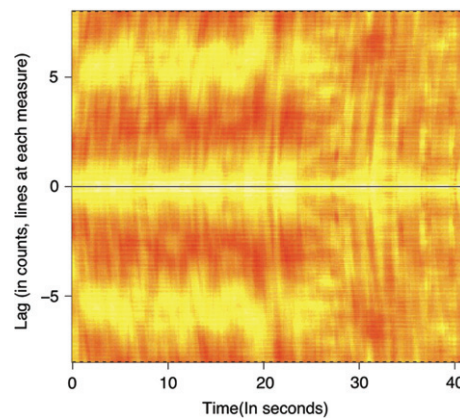


Fig. 10. Windowed autocorrelation of Andrew's RMS velocity.

the movement repeats every two measures of the music in perfect synchrony. Figure 9(b) shows a windowed cross-correlation plot of the simulated data shown in Figure 8(b). Here, the dance begins with a rhythmic motion that takes two measures to complete, but changes into a motion that repeats with every measure. These changes are visible on the windowed autocorrelation graph.

Figure 10 shows the previous example of Andrew's RMS velocity, now in windowed format. Notice that his movements do not quite fit twice within a beat—he slightly lags behind the rhythm. Instead, the peak is consistent, but follows along about a half beat after one half of the length of the repeating rhythm. This is indicated by the strong peak line just above the y-axis mark indicating one-half of the rhythmic sequence. The strength of the correlation, combined with its regularity shows that he is performing a rhythmic motion, but that it does not repeat precisely with the beat of the music. After about twenty

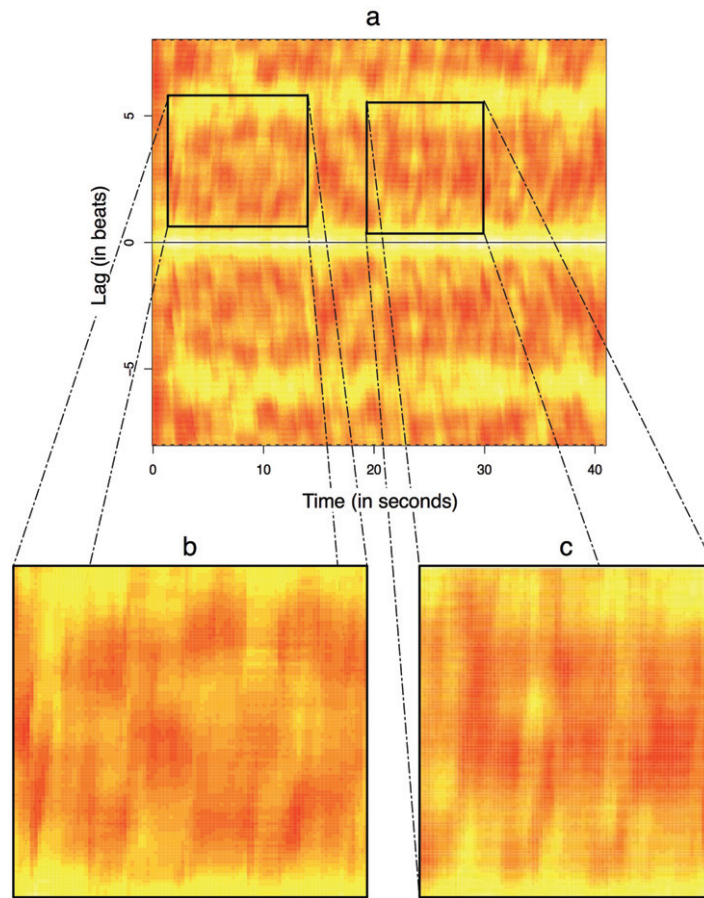


Fig. 11. (a) Autocorrelation from Alice's Dance. (b) Detail of oscillatory behavior. (c) Detail of vertical feature.

five seconds, the rhythmicity of his movements begins to change drastically – he no longer shows a regular rhythmic movement.

Alice's movements from above are shown in Figure 11. More intricacy in the dance is now visible. Notice the widening and narrowing of the central band and its contrast with the smaller peak between, as shown in detail in Figure 11(b). This implies switching between motions that are more constant near the downbeats (as in our simulated example), and motions that are changing near the downbeats. Similarly, the long vertical strokes seen in Figure 11(c) indicate a movement that continues at near-constant velocity over an entire measure of music. For example, Alice might be performing a spin.

Synchrony can be examined to some extent by simply aligning autocorrelation plots for comparisons. For example, if we align the autocorrelation plots of David and Donna as they dance together, we can notice patterns of synchrony between the two dancers. Peaks that line up horizontally

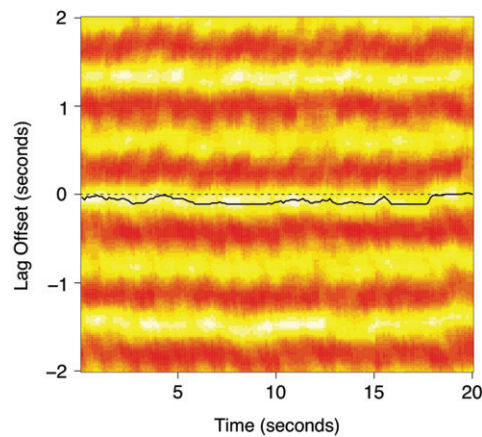


Fig. 12. Windowed autocorrelation of a dancer's RMS velocity.

(that is, have the same location on the vertical axis) imply identical periodicity in the dancer's movements; they are repeating their movements at the same rate. Changes that line up vertically indicate synchronous change; both dancers are altering their movements at the same time. Aligned autocorrelation plots can provide insight into the differences in rhythmicity between two dancers, but it is difficult at times to compare the movements of the two. If both dancers follow a similar rhythmic pattern, the autocorrelation plots will show similar peak structures. Visual features of the plots (for example, the vertical bars shown in Figure 11(c)) can also be coded and used as a measure of comparison. Automatic coding of these features is also possible.

Windowed Time-lagged Cross-correlation

One drawback of comparing autocorrelation plots, however, is that the plots do not reflect differences in the *phase* of movements. If David begins a motion at the start of a measure, and Donna begins hers two beats later, the autocorrelation will still show the same rhythmicity. After all, they are still repeating their movements in the same way. To compare their phases directly, we must look to a different method.

The same technique used above may be applied to two separate streams of movement rather than two copies of a single stream, provided the two streams have the same rate of measurement and span the same amount of time. David and Donna's RMS velocities are compared in this way in Figure 12. Again, moving right on the x-axis moves forward in time. Color again indicates the degree of correlation, and height along the y-axis indicates the lag between the two movements. A peak exactly at the lag 0 line indicates that the two are moving in synchrony. Above the y-axis, a peak indicates that Donna has repeated a movement made previously by David. Below the y-axis, David has repeated a motion made by Donna. Stripes parallel to the x-axis but above it imply that Donna is following David's movements at a lag determined by the distance to the

y-axis. Stripes below imply that David is following Donna. Finally, parallel stripes both above and below indicate that the couple is making rhythmic movements: Donna making a motion, David repeating it, and then Donna repeating it again.

Of particular interest in a windowed cross-correlation is the location of the closest peak to the line of zero lag. This indicates the time difference between the leader and follower in a lead/follow dance. If there is a peak along the zero-lag line, the two movements are in perfect synchrony. If there is a peak close to the zero-lag line but not on it, the two movements are in near but not precise synchrony. Finally, if the peak follows the zero-lag line and then moves off of it or disappears, synchrony has been formed and then broken. The height of the peak indicates the strength of coupling; that is, the closer to 1 or -1 the peak is, the more exactly the follower is imitating the leader, either in translational or mirror symmetry, respectively. A peak dropping drastically from 1 or disappearing entirely is an example of a *symmetry break* the pattern of leader and follower has disappeared. Tracking the location and height of the closest peak to the zero-lag line in a cross-correlation analysis can often be very informative about the variation in synchrony and symmetry of the dancers' movements.

DISCUSSION

The techniques shown here are exploratory in nature. They represent a new way to visualize the overall architecture of a dance, its relationship to the musical score, and the relationships of dancers to each other. The techniques provide means of classifying all or part of a dancer's movement to a specific movement.

Although primarily exploratory in nature, these techniques have previously been used to examine experimentally the effects of manipulations on unchoreographed dance (Boker & Rotondo, 2003). The results, specifically the height and location of the nearest peak in auto- and cross-correlation plots, can be modeled using standard regression techniques. The height of the correlation should first be transformed by the Fisher's Z transformation listed in Equation 14.

The windowed methods here are all naturally dependent on the size of the window chosen for the analysis. A larger window will provide more smoothing, reducing the amount of influence that movements with short time durations have on the correlations. Smaller time windows provide a view of smaller movements, but allow noise in measurement to become more visible. Larger windows also reduce the number of windows available for the analysis. In working with untrained dancers in unconstrained and unchoreographed dance, we have found windows between one-half and two musical measures to be sufficient. Given the greater complexity and more intricate planning demonstrated by professional or choreographed dance, in most cases a larger range is helpful. It is even possible to extend the lag structure to encompass the entire dance. This larger display would also make it possible to see long-term relationships such as repeated sequences of movements or patterns of change between rapid and slow movements. If other data than movements are used, the window size must be appropriately tuned to the timescale of the effect under study.

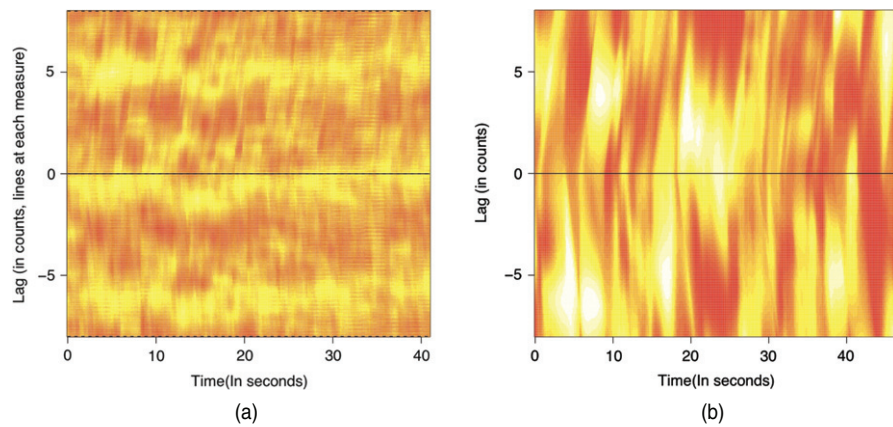


Fig. 13. An example comparison of coordination using Windowed Cross-Correlation. Differences are apparent in structure of coordination of movements in dance (a) as compared to conversation (b).

Human interaction and movement provide a wide range of characteristic patterns in the creation and breaking of symmetry. For example, compare the two windowed, time-lagged cross-correlation plots shown in Figure 13. In Figure 13(a), two dancers show a relatively continuous synchronized symmetry, with one dancer leading and the other following, despite regular breaks in symmetry where one or the other dancer performs a movement separately. Figure 13(b), a very different pattern of synchronization is apparent, where symmetry making and symmetry breaking are both apparent. In fact, this pattern is not from a dyadic dance, but rather from the head movements of participants in a verbal conversation.

Because the windowed methods are also localized in time, it is possible to observe, indirectly, the music to which the dancers move. If a large percentage of independent dancers change their motions twenty seconds into the presentation of a piece of music, for example, this implies the existence of an event in the music that precipitates such a change. Early analyses of the data used as an example in this paper have been used to study the perception of rhythmic stimuli. The evidence suggests that alternative interpretations of ambiguous rhythmic stimuli can still have an effect on dancers' movements (Boker, Covey, Tiberio, & Deboeck, 2005), even though the dancers do not report hearing those interpretations. While little other work has been done with these structures in the field of dance, similar analyses in the field of conversation may provide some insight into the effectiveness of these techniques. For example, these analyses have been used to examine the structure of dominance and sex in the lead-lag relationship of movements (Boker & Rotondo, 2003) or in the structure of symmetry in velocity at different timescales.

CONCLUSION

Dance can be viewed as a series of movements that create and break symmetry across both space and time, and that create and break synchronicity among

themselves, with other dancers, and with the music. The pattern of creation and breaking of symmetry is one way to characterize a dance. Modern technologies such as motion capture provide a means of analyzing these patterns of synchrony and symmetry creation and destruction.

We have presented autocorrelation and cross-correlation techniques for the visualization of synchronization and symmetry over the course of the dance. These techniques can be combined with generalized local linear approximation to detect synchronous behaviours that show symmetry only in their patterns of velocity and acceleration.

We hope that these tools will allow researchers who study dance to better codify the ‘rhythmicity’ and ‘regularity’ of dance in terms of symmetry and synchrony of movements.

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NOTES

1. We use these designations to make it easier to discuss specific dances over the course of the text. In order to maintain the complete anonymity of participants, no promise is made that the dances referred to as a single person's are performed by a participant of the assumed gender of the example, or even all by a single participant. Gendered names are used to help differentiate the dancers in the surrounding text, and to ease memory in the case of the lead/follow relationship in the dyad. Not all the cases shown are necessarily led by the male partner.
2. The last row and column on the orientation matrix are generally each $[0, 0, 0, 1]$. They and the final 1 on the coordinate vector provide a representation of position and orientation in *homogenous coordinates*. The homogeneous coordinate representations are used so that position and orientation can be combined into a single matrix, and transformations easily applied.
3. While an autocorrelation stream will always be symmetric about a lag of zero, we include the negative lags here for instructional purposes. When we generalize to cross-correlation, this symmetry will no longer always hold.