# Removing obstacles to the analysis of movement in musical performance: Recurrence, mixed models, and surrogates

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**Introduction**

Music is embodied. Musicians bob, weave, and gyrate as they play; listeners move to the sounds of music. One way to understand this intimate relationship is as the product of a dynamical system (Demos, Chaffin, & Kant, 2014). The dynamical systems approach provides a framework for explaining how very different kinds of components can interact to create an integrated complex system. In the case of music, the components include minimally: thought (e.g., music cognition and perception), action (e.g., music production), and social interaction (e.g., music communication) (Hargreaves, MacDonald, Miell, & Miell, 2005; Sawyer, 2005). Each of these component systems has already been the subject of detailed dynamical systems analysis by psychologists (de Bruin & Kästner, 2012; Kelso, 1997; Latash, 2008; Marsh, 2010; Van Gelder, 1998; Warren, 2006). We build on their work in applying dynamical systems to the relationship of music and movement.

The behavior of complex systems often exhibits recurrence, i.e., self-similarity across different time scales (Marwan, 2008; Marwan, Carmenromano, Thiel, & Kurths, 2007). Recurrence has been successfully used in psychology to examine inter-speaker coordination of postural sway (Shockley, Richardson, & Dale, 2009), eye movements (Richardson & Dale, 2005), and word order (Dale & Spivey, 2006). For music performance, recurrence has been used to examine timing (Rankin, Large, & Fink, 2009) and postural sway (Demos, 2013; Demos et al., 2014; Demos, Frank, & Chaffin, 2011). In this chapter, we describe how to measure recurrence in the movements of performers, but the same methods can be applied to the movements of listeners (Demos, 2013).

Dynamical systems approaches treat interactions between components as time-evolving processes constrained by the context – physical, social, and mental. The focus is on change over time, requiring measures and statistical methods that are very different from those traditionally used in psychology. We describe four problems that have impeded the application of the new methods to music, proposing solutions for each. For examples, we draw on a recent study in which we recorded two trombonists as they each played two solo pieces, standards of the trombone literature, written by Marco Bordogni (1789-1856) and transcribed by Joannes Rochut (Rochut, 1928), similar in length and difficulty but differing in musical structure (see Demos, 2013 for details). The trombonists prepared the pieces before coming to the lab, where they played each piece twice in each of three different expressive styles (normal, expressive, non-expressive). We used a force-plate to record their postural sway.

**Music performance as a dynamical system**

The behavior of dynamical systems is often chaotic, producing resultants that are non-linear, i.e., not sums of their parts (Strogatz, 2014). Complex systems can *self-organize,* falling into stable patterns of behavior as a result of the interaction between components of the system, initial conditions, and context. Sudden changes, known as *bifurcations*, occur when the system moves from one stable state to another. Bifurcations often seem unpredictable because they can be triggered by small changes in some distant part of the system that seem both trivial and unrelated.

Music performance exhibits many of these characteristics, combining predictability with sudden change. For example, music relies on repetition to induce expectations in listeners and then disrupts them for emotional effect (Huron, 2006). Moving to music, with different body parts moving at different multiples of the musical pulse (Toiviainen, Luck, & Thompson, 2009), can be understood as an example of spontaneous self-organization (Large, 2000). The swoops and swirls that musicians make as they play can be understood as perturbations of these stable patterns. The fact that movements seem different from one playing to the next reflects the sensitivity of complex systems to initial conditions and context. For example, simply moving a foot or altering the height of the chair can entirely change the sway needed to maintain equilibrium (Balasubramaniam, Riley, & Turvey, 2000).

*Music and methods*

Many of the movements that musicians make as they play are not strictly necessary in order to produce the musical sounds. Instead, their movements seem to reflect their expressive intentions and the music they are playing. Musicians move more when they play more expressively (Davidson, 1994) and larger movements are seen by viewers more expressive and more intense (Davidson, 1993; Nusseck & Wanderley, 2009). Movements reflect properties of the music, synchronizing with rhythmic patterns (Jensenius, Wanderley, Godøy, & Leman, 2009; Wanderley, Vines, Middleton, McKay, & Hatch, 2005) and clustering at musical boundaries and cadences (Davidson, 2007). Compelling examples of movements that seem musically expressive are easy to find (Leman & Godøy, 2010). Unfortunately, it has been more difficult to demonstrate that the apparent relationships are real rather than due to chance.

A science of music performance requires there to be commonalities across performances. So far, these have been in short supply for performers' movements. Similarity of movement is higher within than between musicians for performances of the same piece (Teixeira, Yehia, & Lourerio, 2015; Teixeira, Loureiro, Wanderley, & Yehia, 2015). However, even within musician correlations are small. For example, in our study of trombonists, the mean within musician correlation was $R^2 = .12$ across repeated performances (see Demos, 2013). One reason may be that movement reflects musical structure, which may not remain as constant across performances as generally assumed (MacRitchie, Buck, & Bailey, 2013; Palmer, Koopmans, Loehr, & Carter, 2009). In our study, we asked the trombonists to mark their phrasing in the score immediately after each performance, allowing for the possibility that phrasing might vary with the expressive style of the performance (Shaffer & Todd, 1987).

A second problem is how to measure the complexly patterned movements of musicians as they play. Each performer seems to use a limited vocabulary of movement gestures, bobbing, weaving, and gyrating in characteristic ways (Davidson, 2007, 2012; Wanderley et al., 2005). While, the overall degree of movement can be captured by the root mean square, a relative of the standard deviation, standard descriptive statistics do not capture the quality of movement that seems most relevant to the musical expression, *self-similarity*. The discovery that self-similarity across different time scales is a hallmark of complex systems was an important step in the development of complex systems theory. Mandelbrot (1967, 1983) showed that the seemingly random structure of the English coastline can be described by fractal mathematics because the shape of each small region is similar to the larger region in which it is embedded. Our senses respond to self-similarity. Self-similarity is part of what we respond to when we enjoy the swaying of tree branches, the sparkle of sunlight on water, or the coordinated movements of a drill team or corps de ballet (Van Orden, Holden, & Turvey, 2003). Self-similarity is responsible for the patterns that we perceive in musicians' movements.

**Detecting self-similarity in movements**

A popular method for examining self-similarity in a complex system is recurrence quantification analysis (RQA; Marwan, 2008). Conducting RQA on musical movement requires a two-step process. First, the system is represented in phase-space, a mathematical space that contains all possible states of the system. Normally this is impossible to measure, however Takens' (1981) embedding theorem allows one-dimensional data to be transformed into a phase-space representation of the original system (Abarbanel, 1996). For example, postural sway contains information about the movement of arms, head, and torso because each part connects to the others, and so the projection of sway into phase-space reflects the movement of the entire body.

Once the system is represented in phase-space, points of self-similarity, i.e., *recurrence*, can be identified using RQA. Applied to movement, higher proportions of recurrence indicate more repetitive movements, as when playing an oomp-pah-pah accompaniment or playing mechanically and non-expressively. Lower values indicate less repetitive movements of the sort that occur when playing expressively. Figure 1 provides an example, showing three plots of the side-to-side (medio-lateral) sway of one of the trombonist's during an expressive performance. All three panels in Figure 1 show time as elapsed bars from the start of the performance. Panel A shows the raw data for position. Panel B shows the conversion of position data into a recurrence quantification plot with each dot representing a point of recurrence where movement at one point in time overlapped with movement at another point in time (in phase-space). The main diagonal represents a time-lag of zero and so the solid line along the diagonal is the tautological consequence of movements overlapping perfectly with themselves at lag-0. Bumps along the major diagonal represent recurrence of movements (in phase-space) on a short time-scale. Off-diagonal lines reflect the recurrence of movements at longer time lags that increase with distance from the diagonal. The figure is symmetrical, so the lines above and below the diagonal are redundant (Marwan et al., 2007). Solid, dark, straight lines indicate the major sections of the music (A, B, B-Coda, A, Coda) and light, dashed, straight lines the phrase boundaries within each section (Demos, 2013). Panel C is described in the next section.

<FIGURE 1 HERE>

The most important feature of Panel B is that it is not random. If the data were random, dots representing recurrence would be evenly distributed over the plot. The clustering of dots into lines tells us that recurrence (similarity of movement) was not random but was systematically distributed in time. Lines parallel to the diagonal reflect sequences of recurrent movement at consecutive locations in the music. Breaks in the diagonal lines represent periods of non-recurrence during which these recurrent sequences were interrupted. Panel B shows a rich tapestry of recurrence that appears to vary with the musical structure.

Within Section A (Bars 1-24) there is a series of diagonal lines reflecting the question and answer structure of the music: cyclical repetition of musical motifs is reflected in the cyclical repetition of movement. In the final phrase of this section (Bars 21-25) and most of section B (Bars 25-32), the diagonals break up and disappear, indicating that the pattern of sway was not repeated elsewhere in the performance. In the following section (Bars 37-44), musical material from section A returns, accompanied once again by diagonal lines representing recurrence.

These correspondences between recurrence and musical material are descriptive, based on visual inspection. Showing that the correspondences are real, and not due to chance, requires use of inferential statistics applied to all 24 complete performances. We will describe two inferential approaches; many others are possible. The first reduces the RQA plot to a one-dimensional time-series (as in Panel C) and uses mixed effect models to do the statistical analysis. The second keeps the data plotted in matrix form and directly compares plots using additional RQA techniques (CRQA and JRQA).

*Time series analysis of RQA*

Generating a meaningful time-series for analysis

Each RQA plot can be converted to a one-dimensional time-series representing recurrence at each point in time, as in Panel C of Figure 1. Just as normal distributions can be summarized by a variety of metrics (e.g., mean and standard deviation), so with recurrence. For recurrence, there are at least nine metrics, of which we will describe three (Marwan, 2008; Shockley & Riley, 2015). The *rate of recurrence* measures the density of recurrent data points (*recurrence)* as a proportion of recurrent to non-recurrent data points (0 -100%). For movement, recurrence indicates repetitiveness. *Stability* of recurrence is measured by the mean length of the off-diagonal lines (*mean line*), and indicates how long sequences of recurrent movements persist. *Predictability* is measured by the ratio of recurrent points that fall into lines to the total number of recurrent points (*determinism)* and indicates how well movements can be predicted.

RQA metrics can be calculated for different sized slices of time. The window size selected depends on the question of interest. Larger window sizes provide smoother time-series, but decreased resolution. For music, time is best calibrated musically, in terms of beats or measures, rather than objectively in terms of clock time. This facilitates the alignment of movements with the musical score, albeit at the cost of allowing the number of samples to differ across beats or measures. Figure 1, Panel C shows the rate of recurrence and stability using the beat (plotted in bars) as the metric of time. Since stability is based on the mean line of the recurrence rate, we partial out recurrence rate to make sure that the fluctuations that we see in stability are not influenced by the rate of recurrence; otherwise the two measures are strongly correlated, making interpretation difficult. This way, stability can be interpreted independently of the patterns for the recurrence rate.

Panel C clarifies the impressions gained from our visual inspection of Panel B. In Panel C we see somewhat cyclical patterns for both recurrence and stability that seem to reflect the phrasal structure of the music. Recurrence appears higher in mid-phrase and lower at starts and ends of phrases. As described earlier for Panel B, the onset of the new musical sections (e.g., in Bars 37-45) seems to change the pattern of recurrence. For example, recurrence reaches its highest rate in Bars 41-45, at which point stability is at a low level. Again, we are describing visual impressions based on inspection of a single performance. Firmer conclusions require the use of statistical techniques.

## Statistics of a recurrence time series

A third source of difficulty in music research has been the inability of traditional inferential statistics to accurately evaluate the reliability of effects in multiple-level temporal hierarchies such as those typically present in musical performance. Traditional statistical tests based on General Linear Models, such as ANOVA and multiple regression, require that observations be independent and variance homogeneous (constant across conditions). For most music and most performances, these conditions are not met. Observations within a piece are not independent because each beat is related to the next, each bar and phrase is related to those that follow, and so on up the temporal hierarchy. Nor can we assume that observations are independent across repeated performances of the same piece by the same musician, since it is likely that each performance affects those that follow. The requirement that variance be constant across conditions is also not met for most music. Since pieces, sections and phrases typically vary in length, segments at each level are likely to provide different numbers of observations, with consequent differences in variability. For these reasons, traditional statistical tests may not accurately assess the reliability of effects in studies of music performance.

Similar problems occur in any study involving time-series data, including that staple of cognitive psychology, the repeated-measures design. In repeated-measures designs, observations are not independent because they are made sequentially on the same individual, and so performance on one trial may affect performance on the next. The normal solution is to counterbalance stimuli with order of presentation across participants, eliminating order effects with respect to comparisons of experimental interest. This strategy is not available when studying music, which must be played in the order written. Random ordering destroys musical structure, eliminating the musical properties of interest when relating musicians' movements to the music they are playing.

Fortunately, mixed effects models now provide a generalized form of multiple regression analysis suitable for short-time-series and longitudinal data with unbalanced numbers of observations in hierarchical nested/crossed designs (Pinheiro & Bates, 2000; Singer & Willett, 2003). Mixed models make it possible to examine serial position effects in composed music containing phrases of varying lengths. Mixed models can also simultaneously test for effects at multiple levels of a musical hierarchy (beats within bars, within phrases, within sections, within pieces) and model the interleaving of temporally nested and crossed factors of the sort that occurs when a musician gives multiple performances of the same piece. This allows us to accurately partition variance in the data to its different sources, such as differences between musicians, musical pieces, and levels of musical structure, allowing us to pinpoint effects of interest. Mixed models allow the researcher to treat each independent variable as fixed, random or both, making it possible to increase sensitivity by statistically holding constant variables that obscure effects of interest (e.g., amount of practice, pitch height, inter-note/beat interval). Mixed models also allow testing of "growth curve" serial position effects, such as bow-shaped changes of dynamic level across the length of a phrase (Mirman, 2014). Mixed models also make it possible to examine such effects while controlling both time-variant predictors, such as practice, and time-invariant predictors, such as serial-position in a phrase.

We used mixed models with linear, quadratic (U-shaped), and cubic (S-shaped) polynomial functions to examine the effects of musical structure, i.e., phrasing, and expressive style across the 24 performances recorded by our two trombonists (Demos, Chaffin, & Logan, under review). Each of the 24 performances was treated in the way shown in Figure 1 (position → recurrence plot → metrics for rate of recurrence and stability). Phrase boundaries were taken directly from the performers' reports of their phrasing, made immediately after each performance. Recurrence changed systematically across phrases, producing S-shaped functions when plotted against serial position in a phrase (as in Figure 1, Panel C). Rate of recurrence was lowest at the beginning of a phrase, increasing sharply to a peak shortly before the middle, and then tailing off gradually to the end of the phrase. The S-shapes of these phrasing profiles were more pronounced in normal and expressive than in non-expressive performances, and more pronounced for longer than for shorter phrases. The phrasing functions identify statistically reliable relationships between the musicians' movements and the music they played. It was important that the musicians reported their phrasing after each performance because phrasing differed with the musician, the expressive style of the performance, and, in one case, from one performance to another by the same performer in the same style.

*Direct analysis of RQA plot*

RQA of more than one performance

When RQA is extended from one performance to two (or more), it comes in two flavors: cross (CRQA) and joint (JRQA). Both are available in the Matlab CRP Toolbox (Marwan & Kurths, 2002). Each answers a different question. CRQA, like cross-correlation, asks, "did the same pattern repeat across the two performances, regardless of location in the piece". JRQA is more like overlaying two auto-correlations; it, asks, "Did some patterns repeat at the same places in both performances?". JRQA is tied to the score, while in CRQA is not.

CRQA can be considered a generalized form of cross-correlation (Marwan et al., 2007). When two (and only two) time-series (of any type) are examined in phase-space, we look for locations where the two signals come to the same state. These locations are where the two systems are in alignment with each other. As with RQA, these locations can be considered at all possible time lags or only at lag-0 (Marwan et al., 2007). In CRQA, the movements must cross in shared phase space. This means that you are looking for repeats of the same movement pattern in both performances. JRQA asks a different question. JRQA takes two (or more) RQA plots and overlays them and asks when recurrence occurs at exactly the same time. The recurrent points that overlay each other may reflect different movements, but they show that the performer did something recurrent at the same point in each performance. JRQA results in a new plot that shows where the two (or more) RQA plots have identical recurrent patterns. JRQA helps solve the initial conditions problem of complex systems by identifying similarities between performances in recurrence rather than similarities in the movements themselves.

CRQA and JRQA require that the performances compared be on the same time scale, which requires converting clock time to musical time, by time warping the performances. There are many methods of time warping, including functional data analysis (FDA) (Ramsay, 2006), and more classically derived methods, such as linear resampling to standardize each musical note length across performances (see Demos, 2013). FDA is a good candidate when paired with CRQA. When using JRQA, classical methods will be more precise and more assumption free as individual notes can be aligned. Once the data are time-warped and undergo C/JRQA there are two options. A time-series can be extracted and analyzed with mixed models, as described above. Alternatively, the level of correspondence between two performances provided by the C/JRQA plots can be directly assessed for statistical significance.

## Assessing significance

A final difficulty that has impeded the scientific study of music performance is that there is no obvious way of determining what to expect by chance. For example, if performers' movements are related to the music, they should overlap across performances. How do we determine whether overlap is greater than chance? In traditional experiments, control groups generally provide a baseline for making such assessments. For music performance, chance levels must be determined by *bootstrapping* (Efron & Tibshirani, 1994). The data is shuffled a predetermined number of times (typically 500 or more) to create *surrogate* data sets, and the statistic of interest is computed for each shuffle to build a distribution for the statistic. Then, we test the observed value of the statistic against the distribution using the percentile method. If the observed value falls outside the confidence intervals provided by the surrogates, then it is significant.

Simple, random shuffling the data is not, however, sufficient because it destroys the autoregressive structure of the original data. Significant effects show only that the observed value was not generated by a stochastic (white noise) process – often a trivial conclusion. Of course, human movement and musical sound are not white noise. They are highly autoregressive, with each data point strongly related to its predecessor. When plotted over time, the data take the form of wave-like undulations. Randomly chosen pairs of undulating time series of this sort often exhibit substantial correlation. Such correlations are merely products of chance, providing no evidence that the two sequences are related. To provide evidence of a relationship, the correlation must be greater than the chance levels that occur when comparing two unrelated time series.

Phase-shuffling is an alternative shuffling method, more appropriate for time-series data, because it retains the autoregressive properties of the original data. The time-series is converted into its Fourier components, the phase is shuffled, and the time-series reassembled (Thiel, Eubank, Longtin, Galdrikian, & Farmer, 1992). Iterative Amplitude Adapted Fourier Transform (IAAFT) is a method of phase shuffling that preserves both the autoregressive structure and the frequency distribution of the original time series (Schreiber & Schmitz, 2000). When the observed value of a statistic differs from its value for IAAFT surrogates, we can conclude that two time-series have more in common than just their autoregressive parameters.

IAAFT surrogates provide similar output to bootstrapping, i.e., confidence intervals (CI). Each surrogate is processed as if it were the original time-series, first undergoing PSR and C/JRQA. When two time-series are compared, surrogates are computed for one and compared to the other (real) time-series. This process is repeated, say 500 times, and a distribution of each of the metrics of C/JRQA is created. This distribution can be treated statistically as a source of CIs for one-tailed or two-tailed tests in the same way as for traditional statistical metrics.

Here, we provide an example where we took two performances of the same piece by the same performer and asked whether or not their movement patterns were more similar (cross-recurrence) than expected by chance, as determined by IAAFT surrogates. The CRQA analysis showed a cross-recurrence rate between the two performances of .092 and the IAAFT surrogates yielded a 95% CI [lower bound = .081, upper bound = .095]. The actual recurrence rate falls within the CI, so we conclude that the movement patterns in the two performances did not overlap more than expected by chance. In other words, the movement of the performer was not significantly different from one performance to the next. As always, we should be cautious interpreting null results.

JRQA provides a different test, asking whether recurrence occurred at the same point in the musical score in each of the two performances. The JRQA analysis showed a joint-recurrence rate of .025 and the IAAFT surrogates yielded a 95% CI [lower bound = .010, upper bound = .016]. Since the obtained value was outside the CI, we can conclude the joint-recurrence value was higher than chance. Since JRQA asks, "Did some patterns repeat at the same places in both performances?", we conclude that they did; the performer moved in the same ways at the same places in the music more than expected by chance. Again, this is expected for two performances of the same piece, in the same style, by the same musician.

**Conclusion**

The intuition that music and movement are closely related is widely shared by performers and audiences alike. However, providing empirical evidence for this intuition has proved difficult. Two decades of research into the relationship of movement and music have provided many examples of movements that seem musically expressive, but has not succeeded in showing that the apparent relationships were due to more than chance. Progress has been limited by the lack of ways of measuring complex movements and statistical methods for assessing them. Fortunately, the development of the complex systems approach has provided music researchers with the tools they need. Our research with the trombonists showed that their postural sway was systematically related to their musical phrasing. The existence of such a relationship between phrasing and movement was obvious, but now we can demonstrate it rigorously. Finally, we can begin to ask interesting questions about the embodiment of thought and feeling in music performance.

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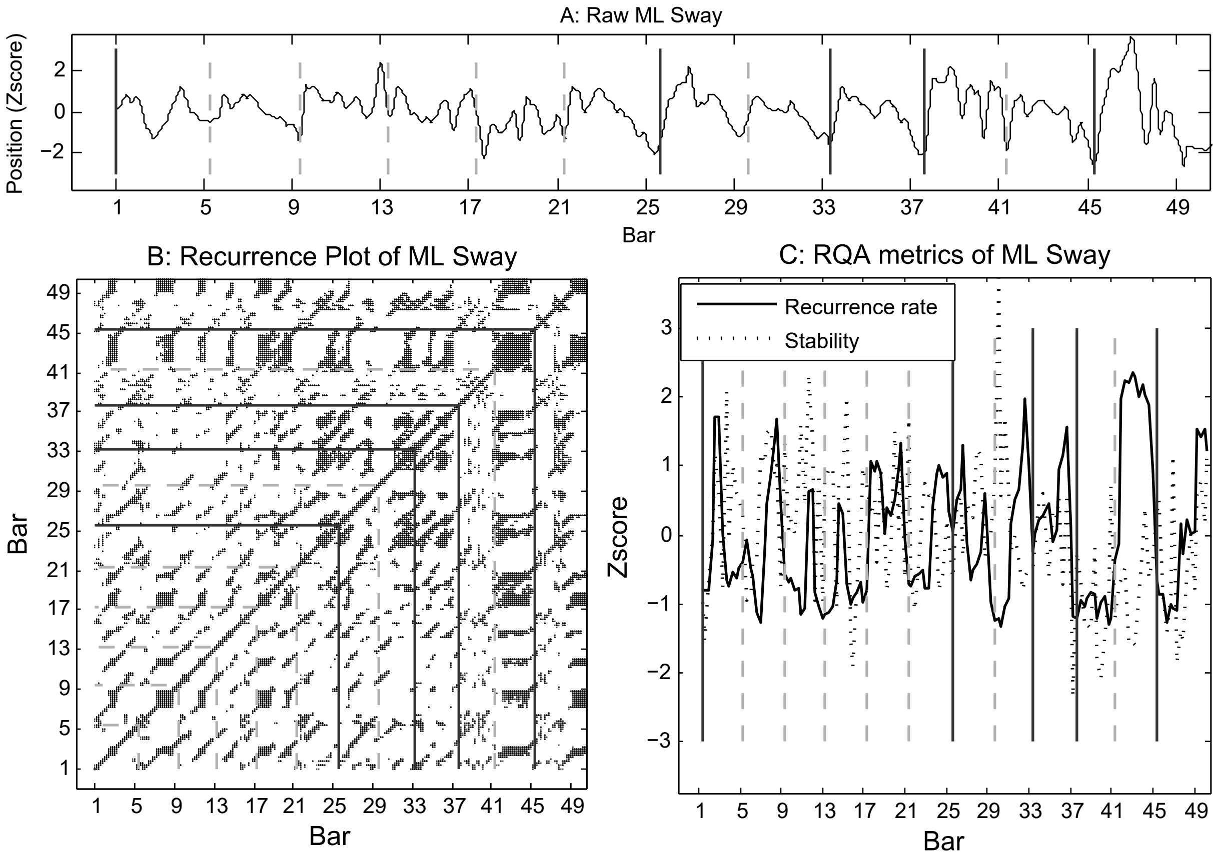

A: Raw ML Sway
Position (Zscore)
Bar
B: Recurrence Plot of ML Sway
Bar
Bar
C: RQA metrics of ML Sway
Recurrence rate
Stability
Zscore
Bar