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Complexity of Postural Control in Infants: Linear and Nonlinear Features Revealed by Principal Component Analysis

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RUNNING HEAD: Complexity of Postural Control

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Abstract

Nonlinear analysis of standing postural control in healthy adults reveals a chaotic structure of the center of pressure time series. Independent sitting is the first controlled posture during development, and can also be examined for nonlinear dynamics. We performed a principal component analysis on variables extracted from the center of pressure (COP) time series of infants sitting independently. Our purpose was to describe factors that could be interpreted for clinical use in evaluating postural control for infants, and determine if nonlinear measures provide additional information about postural control not quantified by standard linear measures. Four factors were identified: the area or amount of postural sway and the overall variability of the sway (linear); the complexity of the sway in the anterior-posterior direction (nonlinear); power variability or velocity (linear); and the complexity of the sway in the medial-lateral direction (nonlinear). Nonlinear measures, which are used to examine complexity in many physiological systems, describe the variability of postural control that is not described by linear measures. Nonlinear measures may be critical in determining the developing health of the postural control system in infants, and may be useful in early diagnosis of movement disorders. The measurement of nonlinear dynamics of postural control reveals a chaotic structure of postural control in infancy, which may be an indicator of healthy postural control throughout development.
Introduction

Postural control is central to all movement, and is therefore a critical feature controlling or limiting function, and supporting change in motor skill. The center of pressure (COP) at the base of support has been considered a reflection of overall postural control (Massion, 1992). Linear measures such as length of path, range, or area are extracted from the COP time series and are used to quantify features of postural control in standing for children (Raich & Hayes, 1987; Shumway-Cook, 2003), adults (Murray, Seireg, & Sepic, 1975; van Wegen, van Emmerik, & Riccio, 2002), individuals with neurological problems (Winstein et al, 1989), and the elderly (Hughes et al, 1996). Generally, the relative value of these variables is interpreted as quantifying stability and health. A larger value usually indicates instability, while a smaller value indicates greater skill, health, and stability.

In spite of the long-term use in many studies, Palmiere, Ingersoll, Stone & Krause (2002) recently argued that linear measures of the COP do not quantify stability of the postural control system. They argued that it is possible to have a large area of the COP path while having a stable posture (Hughes et al, 1996) or unstable posture (Oppenheim, et al, 1999). Correlations of clinical tests of postural control to the amount of postural sway have been weak and inconsistent (Duncan, Wilson, MacLennan & Lewis, 1992). Because of inconsistency in the interpretation of linear measures of the COP, the lack of clinical correlation to other postural measures, and a lack of standardization, Palmieri et al (2002) maintained that current linear measures are not useful to characterize postural stability, and that new measures are needed to examine the COP and quantify changes in postural control over time.
Because differentiating instability from stability is considered crucial in evaluating postural control, measures of variability have been linked to the construct of instability in order to quantify postural control (van Wegen et al., 2002). Increased variability in the COP time series has been interpreted as noise or instability of the motor control system, related to error within the system, or error in the system’s interaction with the environment (Doyle, Newton & Burnett, 2005). Variability can be measured in many ways, including the standard deviation of the length or range of the COP path, or the root mean square (RMS) of the COP. However, these linear measures are limited because they only indicate the amount of variability and not the nature of the variability in the system. Recently, researchers have postulated that the variability in COP measures is not an indication of noise or instability, but rather information that is important to describe the complexity of postural control (Newell, 1997; Cavanaugh et al., 2005). This variability has a complex structure that is not equivalent to random noise. Researchers using both linear and nonlinear tools have determined that as standard linear measures of variability increase (such as standard deviation or RMS of the time series), measures of randomness in the signal decrease (Riley & Turvey, 2002). Therefore, equating variability with randomness or a lack of control is an erroneous assumption.

Cavanaugh et al. (2005) point out that conventional, linear measures of postural stability such as the length of path, range, and area, may be related to stability, but are not measuring stability of the system itself. Stability is the response of the postural system to a perturbation, which can be internal from the natural sway of the body, or externally generated from the environment. A more important construct to measure is dynamic stability, which can be quantified by measuring the local behavior of trajectories of the system within a state.
space by using a nonlinear measure. Dynamic stability is a feature of a complex system. Increasingly, the variability of other physiological time series is being examined in terms of complexity and measured by using nonlinear mathematical tools (Lipsitz, 2002; Pincus, Cummins, Haddad, 1993; Stergiou et al, 2004). These nonlinear variables reveal the complexity inherent in the system being evaluated and measure different aspects of the system than linear variables can capture. Nonlinear techniques have been used to analyze cardiac rhythms (Fleisher, Pincus & Rosenbaum, 1993), brain activity and neuronal networks (Skarda & Freeman, 1987), as well as other motor control issues (Timmer et al, 2000; Morrison & Newell, 1996). By using nonlinear techniques, all these studies reveal complexity in physiological signals over time, which is a feature of healthy systems.

Healthy systems, whether referring to heart rate or the COP time series, have a “just right” level of complexity, which is not too regular and not too random (Stergiou et al, 2006). This allows the system to have a relatively predictable course which can adapt if a change in the environment occurs. Without this complexity, adaptability would suffer. One of the features of complexity is regularity, which can be measured using Approximate Entropy (ApEn) (Pincus, Gladstone, & Ehrenkranz, 1991; Newell, van Emmerick, Lee, & Sprague, 1993; Georgoulis et al, 2006). Increasing ApEn values are viewed as revealing greater complexity in the signal, with the highest values (close to two) indicating greater irregularity and increased randomness. Conversely, lower values (close to zero) reveal a more regular or periodic signal. ApEn has been useful in identification of differences between young and old in the COP time series in standing (Newell, 1997), in revealing deficits in athletes with a concussion when compared to healthy athletes (Cavanaugh et al, 2006), and in detecting developmental changes in sitting postural control (Harbourne, & Stergiou, 2003).
The largest Lyapunov Exponent (LyE) is another nonlinear measure used to quantify complexity in a time series. As in ApEn, a decrease in the LyE is interpreted as a decrease in complexity, and an increase in LyE reveals greater complexity and more randomness. A random signal features points in the time series that are not related to past or future points (Riley & Turvey, 2002). A completely periodic signal would have points that are completely related or dependent on past and future points. A healthy system requires the complexity of a signal that has some short-term and long-term dependencies on other points in the series, but is also adaptable and changeable to a different pattern when needed. A dynamical system is a system that continuously changes over time such as the swaying body during posture, and this dynamic stability can be measured with the LyE. Yamada (1995) reported chaotic properties in the body sway from COP data during standing in normal adults using the LyE, revealing inherent complexity.

Clinically, the use of the COP for studying postural control has led to the development of methods for differentiating typical from atypical motor control (Prieto et al, 1996), and for evaluating response to treatment (Rocchi et al, 2002). The American Medical Association (2000) and the American Physical Therapy Association (2001) have included force platform and COP testing as components of standard testing for patients with balance disorders. However, the use of force platform technology has been limited to adults and older children who can achieve the standing position, maintain standing under conditions of perturbation, and follow directions (Nashner, Shumway-Cook, & Marin, 1983; Cherng, Su, Chen, & Kuan, 1999). In addition, only linear measures (i.e., range and path length of the COP excursion, root mean square of the COP data) are utilized in current force platform technology used in rehabilitation (Guskiewicz, 2001). The usefulness of this testing has not
yet been shown for very young children, infants, or for examining postural control in positions other than standing, such as the sitting position. Furthermore, the addition of nonlinear variables to the standard linear variables may provide additional valuable information to characterize postural control and assist in directions for treatment. However, it must be established that nonlinear measures provide additional information about postural control that is not currently available through linear measures.

Harbourne and Stergiou (2003), in a longitudinal study of infant sitting development, noted that nonlinear variables show developmental trends in sitting that are not revealed using linear variables. ApEn and LyE decreased over time, reflecting the fact that infants progress from irregular, complex COP tracing when first starting to sit, to a more regular and stable pattern over time as they become independent sitters. Linear variables did not show this trend. A hypothesis stemming from these results is that linear and nonlinear measures differ in the constructs they represent when evaluating the COP time series to quantify postural control. Harbourne and Stergiou (2003) suggested that nonlinear measures can provide a completely different perspective of infant sitting development by evaluating not the amount of variability in the postural sway, but the regularity and the dynamic stability of postural control.

Regularity is the construct measured by ApEn. As a measure of regularity, it reflects a feature of complexity. A more regular, or predictable, signal is less complex. In terms of postural sway, an individual could sway forward and back through an extreme range, but in a very regular, rhythmic pattern; this would result in high values for range and standard deviation from the COP time series, but low values for ApEn. However, if the individual had a different pattern of sway, using a small range of sway (low values of range and standard
deviation), but less repeatable adjustments of COP resulting in higher ApEn values, the postural sway would be more complex.

Dynamic stability is the construct measured by LyE and is also a feature of complexity in a time series. The LyE can characterize the structure or organization of variability in a time series because it measures the divergence of the data trajectories in phase space. The LyE describing purely sinusoidal data, such as a person swaying back and forth rhymically, shows no divergence in the data trajectories. For example, the time series generated from a sine wave which has completely overlapping trajectories with no divergence in the phase space (a perfect circle) will have a LyE value of zero. This indicates no change in the structure of the variability over time in the data. The LyE for random data indicates great divergence in the data trajectories and a time series generated from random data will have no structure when plotted in the phase space; lines will diverge maximally. We have observed relatively large values for LyE from such data that are usually above 0.5. A person that is not making any controlled adjustments of posture and sways forward and back with no divergence will similarly have a value close to zero. If physiological control adjustments are made on-line with environmental changes, then the structure of variability can be deterministic as in mathematical chaos and the LyE values can range somewhere between complete periodicity and randomness. This physiologically normal range can be characterized as dynamic stability or having high complexity.

Complexity is not well described by linear variables. Complexity in postural control requires on-line fine-tuned adjustments that have an optimal amount of regularity and dynamic stability, which allows adaptive adjustments to both internal and external demands. Clinical uses for nonlinear analysis are appearing in a variety of disciplines including
cardiology, neurology, and psychiatry because complexity is not adequately described by linear measures. Heart rate analysis using ApEn has been used to evaluate risk factors for sudden infant death syndrome (Pincus, 1991; Pincus et al, 1993). Nonlinear measures have been useful in verification of implantable cardiac defibrillator interventions by using entropy analysis of heart rate variability (Przybylskia et al, 2004). Therefore, the need for new constructs to explain the features of postural control is similar to other biological signal analysis where the necessity for better description of a time series can benefit diagnosis, treatment, and our understanding of physiological processes.

Toward the goal of more clearly differentiating linear and nonlinear variables, we chose to perform a Principal Components Analysis (PCA) as a data reduction method to aid in the interpretation of the COP time series. We assumed that the nonlinear variables of ApEn and LyE that evaluate complexity in terms of regularity and dynamic stability are two features that characterize variability in the COP time series. PCA should reveal distinct factors that group related variables within the task of postural control in infants. As such, the nonlinear variables should load onto different factors than the linear variables, indicating measurement of different features of the COP time series. In addition, reducing the variables into a few factors would serve to simplify the classification and description of skill in postural control. Therefore, the primary purpose of this study was to reduce several linear and nonlinear variables extracted from the COP time series into factors that better describe the COP. These factors can serve as useful clinical measures with more clarity of interpretation. In addition, a second purpose of this study was to verify that linear and nonlinear variables load onto different factors, indicating the characterization of different features of the time series COP, and thus different components of postural control. Lastly, we
wanted to know if nonlinear measures correlated negatively with linear measures of variability in this early postural task, commensurate with findings in adult postural control studies (Schmit et al, 2005).
Method

Participants and Procedures

Participants were 33 typically developing infants, recruited at approximately 5-months-old, and 8 infants with delayed development of sitting, ranging in age from 8 months to 18 months at recruitment. This study was a portion of a larger longitudinal study examining the development of sitting over a period of 16 weeks. The data for this portion of the study was collected at the last session, when the infants were able to sit independently. At the initiation of the larger study, typical infants were screened for development by scoring above -0.05 SD on the Peabody Test of Infant Development (Folio & Fewell, 2000). Infants who were delayed in development were referred from local early intervention programs, and scored lower than -1.50 SD to qualify for the atypical group. For the current analysis, data were collected when the infant was able to sit for over 10 seconds without falling and without using the arms to prop for support. No other skill restrictions were used for inclusion, so the group of infants exhibited a range of postural control. The typical infants were between 6 and 7 months old. The infants with delays were between 9 and 18 months of age. Infants came to the lab twice within one week, and at each session we attempted to collect 3 trials of unassisted sitting where the infant was relatively quiet (no arm flapping, kicking, rocking or vocalizing). We calculated each variable for each trial, and then averaged these 6 trials for each variable. We reasoned that the mean of these 6 trials was a valid representation of each infant’s sitting skill. Thus, for each variable we used an averaged value from each of the 41 infants for analysis.

COP analysis for sitting posture was done using an AMTI force plate (Advanced Mechanical Technology Inc., Model OR6-7-1000) integrated with a Vicon 370 3D Motion
Capture System. The force plate is embedded in the floor of the motion analysis lab. A small absorbent cloth was taped to the plate for warmth and absorption. Infants were held in the sitting position in the middle of the plate. When the infant was stable, support was withdrawn and the infant’s attention was held by watching an age-appropriate video or looking at toys held by the mother.

**Analysis**

Component forces \((F_x, F_y, F_z)\) and moments \((M_x, M_y, M_z)\) were each sampled at 240 Hz and were amplified using an AMTI Model MCA6 Amplifier. Calculation of COP X and Y coordinates from the forces and moments occurred through Vicon software (Vicon 370 3D Motion Capture System). Data was exported in ASCII format which was then used for linear and nonlinear analysis. A frequency analysis of both the medial-lateral and anterior-posterior components of the COP time series from our data indicated that the range of signal frequencies that contain 99.99% of the overall signal power is between 1 and 29 Hz. Therefore, the sampling frequency was set at 240 Hz in order to stay a factor of ten above the highest frequency contained in the signal. Based on our pilot data collections, we found a balance between the length of time an infant could tolerate sitting relatively quietly on the force plate and the sampling frequency needed to best analyze the signal that was identified from our spectral analysis. The data were analyzed unfiltered so as to get a more accurate representation of the variability within the system. It was assumed that since the same instrumentation was used for all subjects, the level of measurement noise was consistent for all subjects and that any differences were attributed to changes within the system itself (Kaplan & Glass, 1995). Filtering the data may eliminate important information and provide a skewed view of the system’s inherent variability (Rapp, 1994).). Video of each trial was
collected using two Panasonic videocameras (Model 5100 HS) at 30 Hz and a Panasonic Digital AV Mixer (Model WJ-MX30).

*Data selection:* Segments of COP data were selected by utilizing the video record to identify trials in which the infant exhibited at least 10 seconds of quiet sitting behavior. The trials were cropped so that all trials were of equal length (8.3 seconds), with 2000 data points per trial. Variables were calculated using custom MatLab software (MathWorks, Natick, MA). Linear measures were calculated using customized MatLab software from the COP time series, using the methodology of Prieto, Myklebust, Hoffmann, Lovett, and Myklebust (1996), and included the root-mean-square (RMS), the maximum minus minimum (range) length of the path traced by the COP, the sway path (the length of the COP movement over 2000 time steps), and the frequency dispersion.

The calculation of the LyE measure is based on examining the structural characteristics of the investigated data set that is embedded in an appropriately constructed state space. An appropriate state space is a vector space where the dynamical system can be defined at any point in time (Abarbanel, 1996). To properly reconstruct a state space, it is essential to quantify an appropriate time delay and embedding dimension for the investigated data set. Investigation of the characteristics of the state space is a powerful tool for examining a dynamic system because it provides information that is not apparent by just observing the data (Abarbanel, 1996; Baker & Gollub, 1996). To reconstruct the state space, a state vector was created from the data set. This vector was composed of mutually exclusive information about the dynamics of the system (Equation 1).

\[
y(t) = [x(t), x(t-T_1), x(t-T_2),...] \quad \text{Equation (1)}.
\]
where $y(t)$ was the reconstructed state vector, $x(t)$ was the original data and $x(t-T_i)$ was time delayed copies of $x(t)$. The time delay ($T_i$) for creating the state vector was determined by estimating when information about the state of the dynamic system at $x(t)$ was different from the information contained in its time-delayed copy. If the time delay was too small then no additional information about the dynamics of the system would be contained in the state vector. Conversely, if the time delay was too large then information about the dynamics of the system may be lost and can result in random information (Abarbanel, 1996; Baker & Gollub, 1996). Selection of the appropriate time delay was performed by using an average mutual information algorithm (1)

$$I_{x(t), x(t+T)} = \sum P(x(t), x(t+T)) \log \left[ \frac{P(x(t), x(t+T))}{P(x(t))P(x(t+T))} \right]$$

Equation (2).

where $T$ was the time delay, $x(t)$ was the original data, $x(t+T)$ was the time delay data, $P(x(t), x(t+T))$ was the joint probability for measurement of $x(t)$ and $x(t+T)$, $P(x(t))$ was the probability for measurement of $x(t)$, $P(x(t+T))$ was the probability for measurement of $x(t+T)$. The probabilities were constructed from the frequency of $x(t)$ occurring in the time series. Average mutual information was iteratively calculated for various time delays and the selected time delay was at the first local minimum of the iterative process. This selection was based on previous investigations that have determined that the time delay at the first local minimum contains sufficient information about the dynamics of the system to reconstruct the state vector (Abarbanel, 1996; Wolf et al, 1985). It was additionally necessary to determine the number of embedding dimensions to unfold the dynamics of the system in an appropriate state space. An inappropriate number of embedding dimensions may result in a projection of the dynamics of the system that has orbital crossings in the state space that are due to false
neighbors and not the actual dynamics of the system (Abarbanel, 1996). To unfold the state
space we systematically inspected x(t) and its neighbors in various dimensions (e.g.
dimension = 1, 2, 3, … etc.). The appropriate embedding dimension occurred when neighbors
of the x(t) stopped being un-projected by the addition of further dimensions of the state
vector (Equation 3).

\[ y(t) = [x(t), x(t + T), x(t + 2T), \ldots x(t + (d_E - 1) T)] \quad \text{Equation (3).} \]

where \( d_E \) was number of embedding dimensions, \( y(t) \) was the \( d_E \)-dimensional state vector,
x(t) was the original data, and T was the time delay. A global false nearest neighbors
algorithm with the time delay determined from the local minimum of the average mutual
information was used to determine the number of necessary embedding dimensions to
reconstruct the COP data series (Abarbanel, 1996). The calculated embedding dimension
indicated the number of governing equations that were necessary to appropriately reconstruct
the dynamics of the system (Abarbanel, 1996). The Tools for Dynamics (Applied Chaos
LLC, Randle Inc., San Diego, CA, USA) software was used to calculate the embedding
dimension for our data sets, and it was found to be six. This embedding dimension was used
for all data files.

The largest Lyapunov exponent was calculated to quantify the variations of the COP
movement trajectories in the reconstructed state space. Lyapunov exponents quantify the
average rate of separation or divergence of points in the state space over time (Abarbanel,
1996). Lets assume that two neighboring points in the reconstructed state space are separated
by an initial Euclidean distance of \( s(0) \). As time evolves, the two points diverge rapidly and
now \( s(i) \) is the Euclidean distance between the two points \( i \) times later. The larger the \( s(i) \) will
be in comparison with \( s(0) \), the larger the divergence of the two points over time. The
Lyapunov Exponent is a measure of the logarithmic divergence of the pairs of neighboring points in the state space over time. The larger the Lyapunov Exponent, the greater is the divergence in the reconstructed attractor. The largest Lyapunov Exponent values for the COP time series were numerically calculated using the *Chaos Data Analyzer Professional version* (American Institute of Physics, Raleigh, NC, USA) using an embedding dimension of six.

We should mention here that periodic systems (i.e. a sine wave) will result in Lyapunov Exponents that are negative or zero. A positive Lyapunov Exponent may show that the variations in a time series are deterministic/chaotic. However, completely random data will also produce a positive result. Thus, validating results against surrogate data to distinguish a true deterministic origin from randomness is important. Therefore, we validated our LyE results with the procedure of surrogation. Surrogation removes the deterministic structure from the original data set, generating a random equivalent with the same mean, variance, and power spectra as the original. Surrogate data sets were generated for all original COP time series using algorithms by Theiler et al (1992) implemented in Matlab (The MathWorks, Inc., MA). LyE values for all surrogate time series were computed and compared to the LyE values of their original counterparts. As in our previous work (Harbourne & Stergiou, 2003), we found again significant differences in the Lyapunov Exponents values between the original and surrogate counterparts (the surrogated had significantly larger values) indicating that variations in the original data are not randomly derived, and therefore, may be deterministic/chaotic in nature. This procedure allowed us to confidently proceed with the utilization of the LyE values in the present study.

ApEn quantifies the regularity of a time series (Pincus & Goldberger, 1994). Specifically, ApEn measures the logarithmic probability that a series of data points a certain
distance apart will exhibit similar relative characteristics on the next incremental comparison within the state space (Pincus & Goldberger, 1994). Time series with a greater likelihood of remaining the same distance apart upon comparison will result in lower ApEn values, while data points that exhibit large differences in distances between data points will result in higher values. The ApEn mathematical definition is described in great detail in Pincus & Goldberger (1994) and Pincus & Kalman (1997). Here, we will present a shorter version of this definition, adapted from these publications. Thus, to define ApEn (better identified as ApEn \((m, r, N)\):

1) we start with our \(N\) input data points \(u(1), u(2), \ldots, u(N)\) and we incorporate two input parameters, \(m\) and \(r\). The input parameter \(m\) is the length of compared runs, and \(r\) is a tolerance.

2) we form vector sequences \(x(1)\) through \(x(N - m - 1)\) from the \(\{u(i)\}\), defined by \(x(i) = [u(i), \ldots, u(i + m - 1)]\). These vectors are basically \(m\) consecutive \(u\) values, beginning with the \(i\)-th point.

3) we define the distance \(d[x(i), x(j)]\) between vectors \(x(i)\) and \(x(j)\) as the largest difference in their respective scalar components.

4) we use the vector sequences \(x(1)\) through \(x(N - m - 1)\) to create (for each \(i \neq N - m + 1\))

\[
C_i^m(r) = \frac{\text{(number of } x(j) \text{ such that } d[x(i), x(j)] \leq r)}{(N - m + 1)}
\]  
Equation 1.

The \(C_i^m(r)\) values measure (within the tolerance \(r\)) the regularity of patterns similar to a given pattern of window length \(m\).
5) we define \( \Phi^m(r) \) as the average value of \( \ln C_i^m(r) \), where \( \ln \) is the natural logarithm. Lastly, we define Approximate Entropy as

\[
\text{ApEn}(m,r,N) = \Phi^m(r) - \Phi^{m+1}(r)
\]

Equation 2.

Using ApEn we basically calculate the logarithmic probability that runs of patterns that are close (e.g., within tolerance \( r \)) for \( m \) observations remain close (with the same tolerance) on the next incremental comparisons.

ApEn was computed for all COP time series using these algorithms implemented in Matlab (The MathWorks, Inc., MA). We used a lag value of 4, an \( r \) value of 0.2 times the standard deviation of the data file, and a vector length \( m \) of 2. These \( r \) and \( m \) values are typically used in the calculation of ApEn for physiologic time series (Pincus & Goldberger, 1994; Stergiou et al, 2004). The lag value is usually set at 1. However, we utilized a lag value of 4 due to slight contamination of the 240 Hz signal with 60 Hz sinusoidal line noise which was identified in the spectral analysis. By utilizing a lag value of 4, we removed this noise from the COP time series for the ApEn calculation which was sensitive to this line noise. For the rest of the parameters utilized in this study, we did not treat the data for this line noise, because our results identified that the data were not affected.

Ten variables were selected for inclusion in the analysis. Six variables were linear variables, based on time, frequency, or distance measures of the COP path that have been commonly used in COP analysis in standing (Prieto et al, 1996; Table 1). Four variables were nonlinear variables, based on techniques of nonlinear dynamical analysis of time series data (Stergiou et al, 2003; Table 2). Where possible, variables describing the anterior/posterior and medial/lateral directions were used separately, because postural control is clinically
thought to develop differently in the anterior/posterior direction than in the medial/lateral direction (Stengel, Attermeier, Bly, & Heriza, 1984).

Statistical Analysis: Bartlett’s Test of Sphericity was performed to determine the appropriateness of applying a principal components analysis (Tobias & Carlson, 1969). Chi-square was significant for 45 degrees of freedom at P<0.001. This indicated that the correlation matrix of our sample was not an identity matrix, and therefore justified proceeding with the principal components analysis. Principal component analysis was performed using SPSS, Version 13. The correlation matrix of linear and nonlinear variables (Table 3) was used to estimate the principal components (Joliffe, 1986). Varimax rotation with Kaiser normalization was performed to ease interpretation of the principal components (Kaiser, 1958). In addition, Quartimax rotation was implemented as an alternative procedure to determine if a change in the factor loadings occurred.

The first 4 components were selected because their eigenvalues were greater than 1 (Kaiser, 1960). The total variance accounted for by all 4 factors was 87.2%. Any additional component accounted for 6% or less of the total variance.
Results

The ten variables were reduced to 4 principal components. The rotated component matrix in Table 4 shows the correlation of each variable with each principal component; the highest correlations indicate which variables load most strongly onto each component. Rotating the factor solution eased interpretation of each component, and provided support for our hypothesis that linear and nonlinear variables measure different underlying features of postural control. We used the original Varimax rotation results because the Quartimax rotation results did not differ in which variables loaded onto each factor. Thus, our first purpose, to reduce multiple COP variables into fewer factors, was accomplished. The following describes each factor, the variables loaded onto that factor, and an interpretation of the factor meaning.

a) The first component included the linear variables of range and RMS in both directions. These variables describe the quantity or amount of movement/sway reflected on the COP. In addition, both directions of the ApEn variable loaded negatively onto this factor, with the strongest loading in the medial/lateral direction. Therefore, as linear variables increase together, the ApEn variables decrease, as depicted in Figure 1. This factor explains 42.6% of the variance in the data set.

b) The LyE and the ApEn in the anterior/posterior direction loaded primarily on the second factor. This accounted for 15% of the variance. This factor can be seen as a possible measure of complexity and stability in the anterior/posterior direction. In contrast to factor one, the ApEn variable in the anterior/posterior direction loaded positively onto this factor, in the same direction as the LyE. No other variables loaded strongly onto this factor.
c) The third factor included the variables of SwayPath, a measure of velocity, and Frequency dispersion, a unitless measure of the dispersion of the different frequencies in the signal (power spectrum variability). These are both linear measures based on time and distance. Both loaded positively, indicating that they tend to increase together, so that increased power variability and increased velocity are related. 15% of the variance is explained by this factor.

d) The fourth and final factor included primarily the variables of the LyE and the ApEn in the medial/lateral direction. This factor accounted for 14.6% of the variance, and can be described as representing complexity and stability as in the second factor. However, because these variables loaded onto a separate factor from the anterior/posterior direction, we assume they are explaining a different portion of the variance (Table 4).

Our second purpose was to determine whether linear and nonlinear variables would load onto different factors. Factors 1 and 3 included linear variables, and factors 2 and 4 included nonlinear variables. There was a clear differentiation of the linear and nonlinear factors into separate factors, indicating the measurement of different features of postural control. Interestingly, the linear variables did not exhibit loading onto different factors by direction (anterior/posterior vs. medial/lateral) as noted for the nonlinear variables.

Our third purpose was to verify that nonlinear measures of complexity in the time series did not correlate positively with linear measures of variability. The negative loadings of ApEn onto the first factor, in contrast to the strong positive loading of RMS, indicate that as the linear measures of variability increased, the nonlinear measures decreased. This relationship can also be noted by the negative correlations of ApEn to RMS in the correlation matrix (Table 3).
Discussion

Our primary purpose for this study, to reduce multiple variables into factors that clarify and quantify the variability in sitting postural control for clinical description, was achieved; these factors will be discussed below. Our second purpose, to determine whether linear and nonlinear variables describe different features of the COP, was also supported, by virtue of the fact that linear and nonlinear variables clearly load onto separate components. And finally, the third purpose, to verify that linear measures of variability increase as nonlinear measures of complexity decrease in sitting postural control, was also supported. We will first discuss the results related to each of these purposes; then, we will present support from other studies of postural control, discuss the importance of viewing postural control from this nonlinear perspective, and describe limitations of the presented work along with future directions.

Our first purpose was to reduce multiple variables into a few factors to achieve a parsimonious description of sitting postural control. There are several benefits to this model. First, assuming that each factor reflects a unique facet of sitting postural control, we can speculate that different factors might contribute to a loss or change in postural control if variations from the normative range occur, such as in pathology with a disease state. Secondly, it is possible that specific components could be targeted to assist in differentiating typical from atypical postural control. And lastly, measuring changes that occur over time due to developing skill or as a result of intervention can be more accurately measured if a specific component is targeted in treatment. We will now focus on the interpretation of each factor, and possible uses in differentiating problems in postural control.
Linear measures of distance or area covered by the COP during a postural control task, and the variability of that area, are strongly related to each other, and were reflected in the first factor. These measures quantify the distance covered by the COP, but are not measures of the stability of postural control when taken alone. Recall that these measures have not been consistently interpreted in past studies (Palmieri et al, 2002), and that the clinical correlates to sway measures are weak (Duncan et al, 1992; Oppenheim et al, 1999). It is likely that linear measures are best interpreted when used in conjunction with nonlinear measures for improved description and quantification of the time series. Linear measures may represent the amount and overall variability of postural sway, but not the coordination or the time-dependent structure of that sway. Viewed thusly, a large range of sway could be present with stable postural control, as in a person who can go to the limits of the boundaries of the base of support safely; conversely, a large range could be present in a person who has trouble keeping the center of mass within the base of support, and who is more likely to lose balance. Both directions of ApEn loaded negatively onto this factor, reflecting a different relationship of this nonlinear measure to the data. As noted by the negative versus positive polarity of the nonlinear to the linear, as linear measures increase, the ApEn measure decreases. We interpret this to mean that as variability measured by range and RMS increases, ApEn values tend to decrease, indicating increasing regularity for greater control. If regularity did not increase with increasing range and variability, the individual would likely be unable to cope with wide excursions of the COP, and would be unstable. It is worth noting here that while infants are learning to sit, they seem to “play” with anterior-posterior shifts of the trunk or pelvis, using rather stereotypical, repetitive movements in a rocking or rhythmical motion. Repetitive movements like this are common in infancy prior to the
emergence of skilled movement, such as rocking on hands and knees before the emergence of crawling (Thelen, 1979). These rhythmical movements do not appear related to a functional task, but are pervasive in normal development, and may reflect some necessary mapping of the system while postural control is developing.

The nonlinear variables LyE and ApEn in the anterior/posterior direction are represented in factor two. We interpret this factor as providing a measure of the structure of the sway of the COP time series or how postural control evolves over time in the anterior/posterior direction. ApEn may be an indicator of the predictability/regularity of the postural control system. LyE indicates whether the system generally has small deviations of the trajectories of movement within the state space, making the system stable overall. This component might be targeted in an individual needing dynamic stability, needed when maintaining a posture over time while visually monitoring the environment, and requiring small changes in stability to respond to environmental events.

The third factor includes the velocity measure, sway path, and the frequency dispersion measure. Velocity of postural sway has been found to be clinically correlated to falling and differences between young and old (Prieto et al, 1996). Changes in the power spectrum have also been linked to clinical signs in Parkinson’s disease (Rochi, Chiari & Horak, 2002). This factor may be related to the speed of sway and the necessary regulation of that sway by the nervous system. This factor could possibly be described as quantifying the speed and coordination of body sway.

The fourth factor, in which LyE and ApEn in the medial/lateral direction loaded primarily, may provide a measure of complexity in movements from side to side. As in factor two, the nonlinear measures describe the structure of the varying movement of the COP, and
describe stability and regularity in the medial-lateral direction. The fact that LyE and ApEn load onto different factors for the two directions of sway raises the possibility that the two directions are controlled separately. It has been noted that infants develop protective reactions in sitting in the anterior direction prior to the lateral direction (Stengel, Attermeier, Bly, & Heriza, 1984). This sequence of developing protective reactions may also be related to biomechanical alignment in the sitting position, and the changing configuration of the infant’s legs as the infant gains greater postural control.

Taking the linear and nonlinear measures together, we have a comprehensive description of postural control, with the ability to describe specific deficits in the system. Both the amount of the COP excursion and the characteristics of that excursion are described. Because ApEn is correlated negatively with the linear measures of distance and variability, a low ApEn and high range of the COP would indicate regularity of the movement of the COP, part of the control system necessary to keep the COM within the base of support. If the sway is predictable, the system is better able to manage routine balance without calling upon resources needed to attend to an unpredictable sway pattern.

Taken together with the distance/area measures, and the regularity measure of the ApEn, LyE may quantify dynamic postural stability under specific conditions, such as those present during the testing condition. If different testing situations are used, such as maintenance of postural control when a cognitive load is placed on the subject, posture may be controlled differently (Schmid, Conforto, & Lopez, 2007).

As in other postural control studies of adults using nonlinear and linear measures of a physiological time series, we found that as linear measures of variability increase, nonlinear measures decrease, indicating that variability and complexity are not the same (Riley &
Turvey, 2002). Rocchi et al (2004) performed a principal components analysis on stabilometry variables taken from adults in quiet standing. Because the authors did not include nonlinear measures, a direct comparison cannot be made, but some parallels can be drawn to our findings. The first component in the Rocchi et al study was related to distance/area of sway, as in this study, and the largest proportion of the overall variance was attributed to this factor. In another principal component analysis by Rocchi et al (2006) examining individuals with Parkinson’s disease, the factor that included the largest percentage of the variance was also related primarily to distance and area of the path of sway. The final component in the Rocchi (2004) study with typical adults was defined primarily by the frequency dispersion variable, similar to factor three in this study. This is related to spectral characteristics of the signal, and the frequencies imbedded in the time series.

Considering the commonalities of our findings with these other studies, the conclusions from our study appear consistent with previous literature, and appear to add to the knowledge base regarding the analysis and interpretation of the COP in postural control studies.

The importance of utilizing nonlinear as well as linear measures to describe the COP is evident. Other studies have shown that LyE and ApEn decrease over time as a posture becomes more developed and adaptive, while linear measures are unchanged (Harbourne & Stergiou, 2003; Newell, 1997). Newell (1997) also found differences in ApEn between the COP time series of young and old standing adults, and interpreted this decrease as a loss of complexity. Thus, nonlinear measures may be useful in identifying instability that is not apparent with linear variables.

Additional studies provide evidence that postural control may not be adequately reflected in linear measures (Cavanaugh et al, 2005, 2006; Newell, 1997; Sabatini, 2000;
Stergiou et al., 2006). Using the information gained from the principal component analysis, postural control may be better defined as a complex system which dynamically stabilizes the center of mass within the borders of the base of support, allowing variable adaptations based on changing conditions. Problems in the system may occur when one or more of several components are compromised, such as a deficit in dynamic stability, a change in complexity, or a problem in utilizing the area of the base of support. From this perspective, the quantification of postural control in the development of sitting in infancy has commonalities with postural control in standing adults.

It is important to mention here that our conclusions are based only on the examination of sitting postural control in infants. Therefore, this analysis needs to be expanded to older children, standing adults, and a variety of patient types, to determine if linear and nonlinear variables, in combination, provide a more complete picture of the health of the postural control system. If larger numbers of subjects are available, a larger number of variables could be examined to determine whether postural control can be adequately described by the four factors identified here, or whether other factors need to be included.

In the future we plan to utilize these linear and nonlinear variables to differentiate typical from atypical postural control, which would provide a unique diagnostic tool. Discriminant analysis would be the next step to determine whether variables from the COP time series may be useful in diagnosis of postural and movement disorders, or in prognosis of future movement problems. As other physiologic signals have shown differences between health and non-health using nonlinear variables, so may this be with the COP. There is growing evidence that complexity is commensurate with good health, and the evaluation of
the COP should be done using some of the same nonlinear techniques that are proving to be important in detecting health in other physiologic signals.
References


Principal component analysis


Principal component analysis


ACKNOWLEDGEMENTS

This work was supported by the NIH (K25HD047194), the NIDRR (H133G040118), and the Nebraska Research Initiative. We would like to thank the infants and their parents, as well as Stacey DeJong, PT, MS, PCS, Sandy Willett, PT, MS, PCS and Wayne A. Stuberg, PhD, PT, PCS for their assistance in this project.
Table 1. **Linear variables: acronyms and brief descriptions**

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSAP</td>
<td>Root-mean-square: the standard deviation of the length samples in the anterior-posterior direction</td>
</tr>
<tr>
<td>RMSML</td>
<td>Root-mean-square: the standard deviation of the length samples in medial-lateral direction</td>
</tr>
<tr>
<td>RangeAP</td>
<td>Range of distance covered in the anterior-posterior direction</td>
</tr>
<tr>
<td>RangeML</td>
<td>Range of distance covered in the medial-lateral direction</td>
</tr>
<tr>
<td>SwayPath</td>
<td>Total length of the center of pressure path in 2000 steps (samples)</td>
</tr>
<tr>
<td>Frequency</td>
<td>Frequency dispersion: unitless measure of variability of power; closer to 0 is sinusoidal, closer to 1 is a large mix of signals (more random)</td>
</tr>
</tbody>
</table>
### Table 2. Nonlinear Variable: acronyms and brief descriptions

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ApenAP</td>
<td>Approximate Entropy: a measure to quantify the regularity or predictability of a time series, in the anterior-posterior direction.</td>
</tr>
<tr>
<td>ApenML</td>
<td>Approximate Entropy: a measure to quantify the regularity or predictability of a time series, in the medial-lateral direction.</td>
</tr>
<tr>
<td>LyEAP</td>
<td>Lyapunov Exponent: a measure that quantifies the stability of the system within a dynamical system by quantifying the divergence of the trajectories within the state space in the anterior-posterior direction.</td>
</tr>
<tr>
<td>LyEML</td>
<td>Lyapunov Exponent: a measure that quantifies the stability of the system within a dynamical system by quantifying the divergence of the trajectories within the state space in the medial-lateral direction.</td>
</tr>
</tbody>
</table>
Table 3. The correlation matrix of all variables examined.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS_AP</td>
<td>1</td>
<td>.766**</td>
<td>.978*</td>
<td>.768*</td>
<td>.116</td>
<td>-.038</td>
<td>-.590*</td>
<td>-.436*</td>
<td>.019</td>
<td>.279</td>
</tr>
<tr>
<td>RMS_ML</td>
<td>.766*</td>
<td>1</td>
<td>.771*</td>
<td>.966*</td>
<td>.078</td>
<td>-.142</td>
<td>-.465*</td>
<td>-.666*</td>
<td>.157</td>
<td>.067</td>
</tr>
<tr>
<td>Range_AP</td>
<td>.978*</td>
<td>.771*</td>
<td>1</td>
<td>.801*</td>
<td>.103</td>
<td>.009</td>
<td>-.538*</td>
<td>-.403*</td>
<td>.078</td>
<td>.356*</td>
</tr>
<tr>
<td>Range_ML</td>
<td>.768*</td>
<td>.966*</td>
<td>.801*</td>
<td>1</td>
<td>.069</td>
<td>-.103</td>
<td>-.434*</td>
<td>-.600*</td>
<td>.191</td>
<td>.127</td>
</tr>
<tr>
<td>Sway_Path</td>
<td>.116</td>
<td>.078</td>
<td>.103</td>
<td>.069</td>
<td>1</td>
<td>.449*</td>
<td>.089</td>
<td>-.041</td>
<td>.017</td>
<td>-.166</td>
</tr>
<tr>
<td>Frequency</td>
<td>-.038</td>
<td>-.142</td>
<td>.009</td>
<td>-.103</td>
<td>.449*</td>
<td>1</td>
<td>.199</td>
<td>-.034</td>
<td>-.010</td>
<td>-.013</td>
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<tr>
<td>ApEn_AP</td>
<td>-.590*</td>
<td>-.465*</td>
<td>-.538*</td>
<td>-.434*</td>
<td>.089</td>
<td>.199</td>
<td>1</td>
<td>.620*</td>
<td>.458*</td>
<td>.057</td>
</tr>
<tr>
<td>ApEn_ML</td>
<td>-.436*</td>
<td>-.666*</td>
<td>-.403*</td>
<td>-.600*</td>
<td>-.041</td>
<td>-.034</td>
<td>.620*</td>
<td>1</td>
<td>.131</td>
<td>.287*</td>
</tr>
<tr>
<td>LyE_AP</td>
<td>.019</td>
<td>.157</td>
<td>.078</td>
<td>.191</td>
<td>.017</td>
<td>-.010</td>
<td>.458*</td>
<td>.131</td>
<td>1</td>
<td>.597*</td>
</tr>
<tr>
<td>LyE_ML</td>
<td>.279</td>
<td>.067</td>
<td>.356*</td>
<td>.127</td>
<td>-.166</td>
<td>.013</td>
<td>.057</td>
<td>.287*</td>
<td>.597*</td>
<td>1</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
Table 4. The four principal components are listed, with each variable and the corresponding correlation to each component. Highlighting indicates the variables most highly correlated with the related component, and the factor that the variable loads onto most strongly. For example, RMS_AP, RMS_ML, Range AP and Range ML load onto the first factor. Bold indicates the negatively correlated but strong loading of both directions of ApEn onto the first factor.

Rotated Component Matrix

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS_AP</td>
<td>.868</td>
<td>-.200</td>
<td>.071</td>
<td>.383</td>
</tr>
<tr>
<td>RMS_ML</td>
<td>.959</td>
<td>.146</td>
<td>-.050</td>
<td>-.047</td>
</tr>
<tr>
<td>Range_AP</td>
<td>.864</td>
<td>-.186</td>
<td>.092</td>
<td>.412</td>
</tr>
<tr>
<td>Range_ML</td>
<td>.964</td>
<td>.075</td>
<td>-.023</td>
<td>-.007</td>
</tr>
<tr>
<td>Sway_Path</td>
<td>.108</td>
<td>.048</td>
<td>.841</td>
<td>-.128</td>
</tr>
<tr>
<td>Frequency</td>
<td>-.095</td>
<td>-.006</td>
<td>.855</td>
<td>.062</td>
</tr>
<tr>
<td>ApEn_AP</td>
<td>-.609</td>
<td>.691</td>
<td>.176</td>
<td>-.051</td>
</tr>
<tr>
<td>ApEn_ML</td>
<td>-.697</td>
<td>.148</td>
<td>-.007</td>
<td>.497</td>
</tr>
<tr>
<td>LyE_AP</td>
<td>.111</td>
<td>.944</td>
<td>-.026</td>
<td>.133</td>
</tr>
<tr>
<td>LyE_ML</td>
<td>.153</td>
<td>.101</td>
<td>-.075</td>
<td>.923</td>
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</tbody>
</table>
Figure 1. COP plots from the same child from the same session, but from two different trials. The COP plot in both directions is plotted on the left; beside each plot the anterior-posterior direction is on the top, and the medial-lateral plots are on the bottom. The variable values adjacent to the plots quantify only the medial-lateral direction. These values demonstrate that Range and RMS describe that the top trial has a greater quantity of COP movement, and greater variability from a linear perspective. However, the nonlinear variable of ApEn shows more irregularity in the bottom trial, which cannot be determined from visual inspection of the graph.