5-2003

Nonlinear analysis of the development of sitting postural control

Regina T. Harbourne
University of Nebraska Medical Center

Nicholas Stergiou
University of Nebraska at Omaha, nstergiou@unomaha.edu

Nonlinear analysis of the development of sitting postural control

REGINA T. HARBOURNE, MS, PT, PCS, and NICHOLAS STERGIOU, PhD

Regina T. Harbourne, MS PT PCS (Corresponding Author)

Munroe-Meyer Institute

University of Nebraska Medical Center

Omaha, NE 68198-5450

Tel: 402-559-6415; Fax: 402-559-9263; E-mail: rharbour@unmc.edu

and

Nicholas Stergiou, PhD

HPER Biomechanics Laboratory

University of Nebraska at Omaha

Omaha, NE 68182

The development of sitting postural control in five normal infants was examined longitudinally at three stages of sitting: stage 1, when infants could hold up their head and upper trunk, but could not sit independently; stage 2, when infants began to sit independently briefly; and stage 3, when infants could sit independently. Methods from nonlinear dynamics were used to analyze center of pressure (COP) data during sitting in terms of stability of the neuromuscular system (Lyapunov Exponent), movement dimensionality (Correlation Dimension), and complexity/regularity (Approximate Entropy). Results indicated significant changes in the nonlinear measures over time, with increased stability and increased regularity revealing a more stable and periodic strategy of maintaining postural control. Dimensionality decreased from stage 1 to 2, indicating a constraint of the degrees of freedom. Subsequently, dimensionality increased from stage 2 to 3, indicating a release of the degrees of freedom as sitting independence emerged. Nonlinear analysis of the COP time series supports the perspective that the development of postural control is a dynamic process whereby the infant learns to control the body's degrees of freedom to achieve the sitting posture.
KEYWORDS: sitting postural development, infancy, complexity, dimensionality, stability

The achievement of independent sitting appears to be effortless and merely a part of the normal maturation process. Once an infant can control the head and trunk in sitting, the arms are free for exploration and functional activities. However, independent sitting requires dynamic stabilization of all the linked segments of the body, and is a complex process of learning and adaptation to various forces in the environment. Past research (Hirschfeld & Forssberg, 1994; Hadders-Algra, Brogren & Forssberg, 1996a) of the development of sitting has focused on investigating the hypothesis that postural responses are an innate, central pattern generator (CPG) driven activation of muscle groups, rather than a self-organizing, dynamic process. Directionally appropriate muscle responses during support surface translation were noted by the age of 5 months, prior to the achievement of independent sitting (Hirschfeld & Forssberg, 1994; Hadders-Algra et al., 1996a; Hadders-Algra, Brogren & Forssberg, 1996b). Amplitude and temporal ordering of muscle responses became more adult-like as the child matured, which was also attributed to the modification of neural circuitry by continuing sensory input (Hirschfeld & Forssberg, 1994; Woollacott, Assaiante & Amblard, 1996). This viewpoint assumes that posture is controlled at two levels by central pattern generators, one for selection of an appropriate pattern, and one for modulation of that pattern. Therefore, postural control is interpreted as an innate, genetically determined aspect of behavior, which is revealed in its adult form as the nervous system matures.

Another viewpoint of the development of postural control in infancy is one that would agree with the Bernstein (1967) proposition that motor skill acquisition is the process of solving the problem of coordinating the many and redundant degrees of freedom of the body. In contrast to the viewpoint that central pattern generators govern the acquisition of posture control, the dynamic perspective would describe posture control as an emergent skill occurring as a result of the organism interacting with the environment. When posture control is viewed as an emergent, dynamic skill, a nonlinear progression of the skill would be expected, with transitions to new levels of skill characterized by limiting the degrees of freedom for stability of the behavior, or freeing degrees of freedom for increased adaptability of the behavior. As a skill level progresses to a more mature form, the degrees of freedom would be released for a more flexible coordination of body segments within the environmental milieu. It follows that the utilization of tools designed to examine nonlinear properties of systems that evolve over time would be necessary to examine the dynamic process of developing postural control.

Nonlinearity has been shown to be a feature of many aspects of development. Physical growth of the human body itself occurs in pulses, with long periods of no detectable growth interspersed with episodic growth pulses of body length between 0.5 and 1.6 cm (Lampl, Veldhuis & Johnson, 1993). Thelen & Fisher (1982) demonstrated that the non-linear progression of infant stepping patterns was related to the infant's increasing leg mass outstripping the development of leg muscle strength, indicating that the behavior emerges through the interplay of many constraints. Early infant leg movements are well coordinated and synchronous (Thelen & Fisher, 1983). As infants begin to walk, they begin to decouple the whole leg synergies seen in kicking to allow crawling and walking (Jensen, Ulrich, Thelen, Schneider & Zernicke, 1995). These studies support the viewpoint that skill acquisition during development proceeds in a nonlinear manner, consistent with dynamic processes.

Recently, nonlinear analysis techniques have been applied to the degrees of freedom problem during standing posture utilizing time series data of the center of pressure (COP). The COP at the base of support in standing has traditionally been considered a reflection of the organization of posture (Massion, 1992). Newell (1997) used COP data to examine the motor control of children, adults and elderly by measuring standing postural sway. Utilizing the nonlinear analysis techniques of Correlation Dimension and Approximate Entropy to assess the time series COP data, the author found that 3 year old children restrict the degrees of freedom by decreasing dimensionality and complexity. The data of the 5 year old children were significantly different from the 3 year olds, and similar to the data of the young adults. Thus, at age 5, the child is able to have more control over the body's degrees of freedom, and shows increased dimensionality and complexity as reflected in the COP time series (an adult like behavior). However, no research has been conducted to examine postural control during various stages of the development of independent sitting using COP data.

Variability of the COP has previously been attributed to noise within the system as well as a consequence of measurement error (Newell, 1997). Techniques of averaging and utilization of variables such as standard deviation, length of path and area of path have been used to reduce the effects of noise. Implicit in the interpretation of such variables is the construct that the information or signal related to the behavior of interest is embedded in other "noise" of the system. Therefore, it was assumed that the data were contaminated by information that was not important to the behavior. This viewpoint ignores the possibility that the variability seen in the time series of the COP may have a structure that can provide information about the strategies used to control the body's degrees of freedom.

INSERT FIGURE 1 ABOUT HERE

Structure in the time series of the COP is not visibly apparent (see Figure 1), and differences between data sets can be difficult to describe. The use of standard averaging procedures (i.e., length of path, excursion in the sagittal or frontal directions) during data analysis of COP time series can create the problem of masking the dynamical properties of the COP data. However, techniques from nonlinear dynamics can solve this problem and can assist in understanding the complexity of posture. The structure of the time series of the COP can provide information regarding the properties of posture that evolve from one moment to the next, when posture is defined as the dynamic stability of a continuously moving body. The natural sway of the body, which is reflected in the COP time series, is a rhythmic activity and produces a limit cycle motion (i.e., closed periodic orbits) in state space. The set of techniques used in nonlinear time series analysis are based on examining the structural characteristics of a time series that is embedded in an appropriately constructed state space. An appropriate state space is a vector space where the dynamical system (i.e., a swaying body during posture) can be defined at any point (Abarbanel, 1996). The characteristics of that state space can then be examined to gain insight into the motor control of posture. In this study of the development of infant sitting, we utilized the nonlinear techniques briefly described below to accomplish this task.

The *Lyapunov Exponent* (LyE) is a measure of the local stability of a dynamical system and its dependence on initial conditions (Abarbanel, 1996). In the present study, stability is defined as the sensitivity of a dynamical system to perturbations (Dingwell, Cusumano, Sternad, Cavanagh, 2000), and local stability is the sensitivity of the system to internal perturbations, such as the natural fluctuations that occur during posture. The effects of these natural fluctuations are what researchers are trying to evaluate with different measures of postural sway (Horak & Diener, 1994; Buchanan & Horak, 2001; Kuo, Speers, Peterka, Horak, 1998). However, local stability can be estimated directly using LyE (Dingwell et al., 2000, Stergiou, Buzzi, Hageman, Heidel, 2000). The LyE quantifies the exponential separation of trajectories with time in state space (Figure 2). As nearby points separate, they diverge rapidly and produce instability. The exponent estimates this instability, which is largely affected by the initial conditions of the system. Specifically, the LyE is calculated as the slope of the average logarithmic divergence of the neighboring trajectories in the state space (Dingwell and Cusumano, 2000; Sprott and Rowlands, 1992). Periodic systems (such as a sine wave) will result in a LyE value of zero, because the trajectories mapped in the state space would completely overlap. A positive LyE may indicate the presence of determinism (order) within a time series. However, completely random data may also produce a positive LyE, because the greater degree of divergence of trajectories results in a larger value of LyE. Thus, it is important to validate results against surrogate data to distinguish a true deterministic origin from randomness (Rapp, 1994).

INSERT FIGURE 2 ABOUT HERE

Surrogation is a technique that can accurately determine if the source of a given time series is actually deterministic in nature (Buzzi, Stergiou, Giakas, Dierks, 2001; Dingwell et al, 2000; Theiler, Eubank, Longtin, Galdrikian and Farmer,1992). The technique compares the actual data and a random data set that has a similar structure to the original data set. 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 (Figure 3). Significant differences in LyE between the original and surrogate counterparts indicate that the original data can be clearly distinguished from a linearly autocorrelated Gaussian noise (Theiler et al,1992). Thus, the original data are not randomly derived, and therefore, they may be deterministic in nature.

INSERT FIGURE 3 ABOUT HERE

The *Correlation Dimension* (CoD) is a method to evaluate the number of degrees of freedom during posture or, in other words, to determine the dimensionality of the COP time series (Newell, 1997). It measures how the data points in a time series from a dynamical system (i.e., the COP time series from a swaying body during posture) are organized within a state space (Sprott & Rowlands, 1992). Specifically, CoD approximates the actual area that the dynamical system occupies in the state space.

The *Approximate Entropy* (ApEn) is a method to determine the complexity of the COP time series (Buzzi et al., 2001; Newell, 1997). Approximate Entropy is a measure that can quantify the regularity of a time series or, in other words, the predictability of a time-series (Pincus, Gladstone, Ehrenkranz, 1991; Pincus and Goldberger, 1994). A more predictable and regular time series is also less complex. A change in complexity may be indicative of learning and a reorganization of the available degrees of freedom (Vaillancourt & Newell, 2000, Newell, 1997). Approximate Entropy 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 et al., 1991). 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. Values typically range from 0 to 2. Values closer to 0 are consistent with greater periodicity (less complexity). Conversely, values near 2 represent greater irregularity (higher complexity).

This study explored the development of independent postural control in sitting from the perspective of dynamic processes. Specifically, the purpose of this study was to investigate whether developing postural control in sitting has deterministic origins, and determine how this can be characterized using techniques to examine the stability, dimensionality and complexity of the COP time series in sitting. We tested the following specific hypotheses: a) the COP time series has a deterministic origin, which can be revealed through the surrogation process, b) infants will show increased local stability (LyE) as sitting develops, c) infants developing the ability to sit independently will show increasing dimensionality (CoD) of the COP time series, indicating increasing control of the degrees of freedom of their bodies, d) infants will show increasing complexity (ApEn) of the COP time series in sitting as development progresses, and e) linear measures of the length of COP path and COP excursion will not change significantly as sitting develops, and, as such, the linear measures will not be able to characterize development.

METHODS

Subjects

Five infants were recruited for this longitudinal study at the mean age of four months (4 females and 1 male). All were within the 25th to 75th percentile for height and weight. Inclusion criteria for the infants at entry (stage 1 sitting) were: the ability of the child to hold up the head when supported at the trunk, beginning ability to reach for objects in supported sitting or lying on the back, and propping on the elbows when in prone for thirty seconds. Exclusion criteria for the infants included prematurity, diagnosed visual deficits, or diagnosed musculoskeletal problems. The infants were followed until they achieved independent sitting. Inclusion criteria for the second data collection session (stage 2 sitting) for typically developing infants were: the infant was able to either prop on the arms for support during sitting, or able to sit for brief periods (10-30 seconds) independently, but was not safe to be left alone in the sitting position. Inclusion criteria for the third data collection session (stage 3 sitting) were: the child sits independently with no danger of falling, but is not yet crawling or moving in and out of the sitting position independently. The parents were interviewed to determine readiness of the child for data collection for each stage, and this information was verified at the beginning of each data collection session. The parents of all the children were told at each session what criteria were necessary for the next session. The children's sitting skills within each stage were very similar, although no standardized motor test was done. Mean ages of the infants were 4.65 months at stage 1 (range 4 to 5.5 months), 5.8 months at stage 2 (range 5 to 6.5 months), and 6.95 months at stage 3 sitting (range 6 to 8 months). A graphical representation of the development stages can be seen in Figure 1.

Instrumentation

Data were collected using an AMTI force platform (Advanced Mechanical Technology Inc., Model OR6-7-1000), and a VICON 370 3D Motion Capture System. The force platform was mounted to a sub-floor concrete slab to prevent vibration interference, and was level with the laboratory floor. The VICON 370 Motion Capture System included a 64 channel 12 bit A-D converter and a computer (1 GHz PC; VICON Motion Systems). Data acquisition and processing were controlled through VICON software. Component forces (Fx, Fy, Fz) and moments (Mx, My, Mz) were each sampled at 960 Hz and were amplified using an AMTI Model MCA6 Amplifier. VICON software calculated COP coordinates from the component forces and moments. Data were exported in ASCII format and used for nonlinear analysis. We collected video of each trial using two Panasonic videocameras (Model 5100 HS), one with a rear view and one a side view,   and a Panasonic Digital AV Mixer (Model WJ-MX30). The video and force platform data were synchronised.

Data Collection

The infants were allowed time to get used to the laboratory setting at each session, and were at the parent's side or on the parent’s lap for preparation and data collection. We used a standard set of infant toys for distraction and comfort. The infant was comforted when needed so that a calm, alert state could be maintained.

A blanket was placed over the force plate for warmth and comfort, and the baby was held in the sitting position in the middle of the plate. The investigator and the parent remained at one side and in front of the infant respectively during data collection. The child was held at the trunk for support. A small, flat contact switch was held between the infant and the investigator’s hand. Once the infant was stable and calm, the investigator released the trunk support as much as possible (thus releasing the contact switch which was used as an event marker for the exact time of release), and data were collected for 10 seconds while the child attempted to maintain sitting postural control. The parent either talked to the infant, or displayed toys to hold the infant’s attention to maintain a forward orientation. When the child was too young to sit independently, the investigator maintained contact at the chest area as lightly as possible, to allow the child to attempt the skill but not be in danger of falling. At the 3rd session, when infants could easily sit independently and reach for toys, the parents either held the toys further away, or simply talked to the infant, to keep them from leaning and reaching for the toy. Up to ten trials at each of the 3 data collection sessions were performed in an attempt to capture the child’s best sitting performance.

Data Analysis

We selected segments of the COP data by utilizing the video record to identify a trial in which the infant exhibits at least four seconds of quiet sitting behavior using the following criteria: 1) The infant was not moving their arms, that is, they were not reaching for an object, holding an object, or flapping their arms; 2) The infant was not vocalizing or crying; 3) The infant was not in the process of falling. Other slight movements, such as turning or orienting the head or body slightly to look at the environment, or small movements of the extremities did not necessitate exclusion of the data segment. The data segments selected thus allowed the examination of 3840 points for each COP coordinate (x and y). This number is considered adequate for the analysis performed in this study (Grassberger & Procaccia, 1983; Pincus et al., 1991; Sprott & Rowlands, 1992). The data were analyzed unfiltered so as to get a more accurate representation of the variability within the system (Mees & Judd, 1993). Filtering the data may eliminate important information and provide a skewed view of the system's inherent variability. We 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 could be attributed to changes within the system itself (Mees & Judd, 1993; Kaplan & Glass, 1995).

To evaluate local stability and dimensionality of the COP time series, the LyE and CoD parameters were calculated for each time series using the Chaos Data Analyzer software (Sprott & Rowlands, 1992). To accurately calculate these measures, the number of embedding dimension was chosen (Rapp, 1994) and incorporated in the software. We calculated the embedding dimension using a Global False Nearest Neighbor (GFNN) analysis (Abarbanel, 1996).We used the Tools for Dynamics software (Abarbanel, 1996) for the GFNN analysis of the COP time series. The GFNN analysis describes the minimum number of variables that are required to form a valid state space from a given time series. The embedding dimension is a description of the number of dimensions needed to unfold the structure of a given dynamical system in space (Mitra, Riley, and Turvey, 1997). Our GFNN calculations indicated that five embedding dimensions were the minimum number of variables that are required to form a valid state space from the time series.

We used the procedure of surrogation to validate the LyE and CoD results. Surrogate data sets were generated for all original COP time series. This procedure was performed in Matlab (MathWorks, Natick, MA) using the algorithms developed by Theiler et al (1992) and briefly described in Figure 3. LyE values for all surrogate time series were also computed.

We computed the Approximate Entropy of each time series to evaluate the complexity of the COP time series (Pincus and Goldberger, 1994; Newell, 1997). Approximate Entropy was computed using algorithms written by Pincus and colleagues (Pincus et al., 1991; Pincus and Goldberger, 1994) implemented in Matlab (MathWorks, Natick, MA).

Finally, we calculated the length of path for the COP and the x & y excursion of the COP. These calculations were done using Datapac 2000 Laboratory Applications System (Run Technologies, Laguna Hills, CA). Length of path was normalized to length of path/sec, since the data segments were not of uniform length from trial to trial. These standard descriptive variables were calculated to serve as a point of comparison for linear vs. nonlinear analysis.

Statistical Analysis

LyE values of the surrogate data were compared to the LyE values of the original data using a Student T-test ($P < 0.05$). We used a repeated measures ANOVA (developmental stage vs. subject) to compare the mean group values of the following dependent variables: LyE, CoD, ApEn, normalized length of COP path, and x & y COP excursion. The results reported relate to the developmental stage alone for the main effect. COPx and COPy data for each subject were grouped in the analysis to create an N of 10 for each developmental stage. In tests that resulted in a significant F-ratio ($P < 0.05$), we used a Tukey multiple comparison test to identify the location of the significant differences.

RESULTS

Significant differences were found between the original data sets and the surrogate data sets ($P=0.009$ for Stage 1; $P=0.002$ for Stage 2; $P<0.001$ for Stage 3; Table 1). These results indicated the fluctuations observed in the original COP time series were clearly distinguishable from linearly autocorrelated Gaussian noise. Thus, the original data were not randomly derived, and therefore, they may be deterministic in nature. This step validated the application of the rest of the nonlinear techniques.

INSERT TABLE 1 ABOUT HERE

The LyE values showed significant differences ($F[2,18]=7.03$, $P=0.006$) between the three stages of development (Table 2). Post hoc analysis revealed significant differences between stages 1 and 3 ($P=0.007$), and between stages 1 and 2 ($P=0.024$), but not between stages 2 and 3 ($P=0.831$). In general, the mean group values for LyE decreased from stage 1 to stage 2, and decreased further from stage 2 to stage 3.

INSERT TABLE 2 ABOUT HERE

The CoD values showed significant differences ($F[2, 18]=4.99$, $P=0.019$) between the three stages of development (Table 2). The post hoc analysis revealed significant differences between stages 1 and 2 ($P=0.036$), and between stages 2 and 3 ($P=0.034$). There were no significant differences between stages 1 and 3 ($P=1.000$).

The ApEn values showed significant differences ($F[2,18]=3.82$, $P=0.042$) between the three stages of development (Table 2). The post hoc analysis revealed significant differences between stages 1 and 2 ($P=0.041$), but not between stages 2 and 3 ($P=0.784$) or between stages 1 and 3 ($P=0.144$).

The length of path variable decreased with increasing age, but there were no significant differences between stages ($F[2,8]=.71$, $P=0.519$). The x & y excursion variable increased with age, but there was not a significant difference between stages ($F[2, 18]=3.07$, $P=0.071$).

DISCUSSION

The results of this study will be examined from a dynamic perspective. Interpretation of the analysis using linear and nonlinear tools will be followed by a comparison of these results to other studies examining motor skills using a dynamic approach. Finally, the evidence for a dynamic, self-organizing process will be compared to the evidence for an innate, CPG driven mechanism as a basis for the development of independent sitting.

The commonly used variables, length of COP path and x & y excursion summarize the time series, rather than reveal the nature of the dynamic changes that occur throughout the time series. Length of path and excursion of COP variables did not reveal any difference between stages of sitting, although it is obvious that the 3 stages of sitting describe very different degrees of postural control. We believe these linear variables can not help further the understanding of how postural control develops, because they can not capture or describe dynamic processes. Describing the fluctuations within the time series of each trial can reveal developing control strategies, and a successful description necessitates the use of nonlinear tools.

The process of surrogation of the original time series revealed positive LyE values that were significantly different from their surrogate counterparts. This result indicated that the fluctuations observed in the COP time series were not randomly derived, and may reflect deterministic processes by the neuromuscular system. Therefore, the fluctuations in the time series were not noise, but had a structure or order that needed further investigation and description.

The LyE values changed toward zero as the sitting behavior emerged, indicating a more periodic path of the COP. Therefore, as the infants had more experience exploring the sitting position, they increasingly occupied trajectories that were close together within the state space. In other words, the infants became more locally stable. The LyE values decreased as sitting developed, becoming more periodic from stage 1 to stage 2 to stage 3.

The Correlation Dimension provided information regarding how the COP time series data from the swaying infant during sitting posture were organized within a state space (Sprott & Rowlands, 1992). The CoD results showed high dimensionality at stage 1, with a significant decrease in dimensionality at stage 2. This would indicate a reduction in the degrees of freedom of the body, as is often seen when a new skill is attempted. A significant increase in dimensionality occurs from stage 2 to stage 3, indicating an increase of degrees of freedom. This would provide the infant with increased adaptability or flexibility in maintaining postural control over the base of support in sitting.

The ApEn analysis indicated that a significant decrease in complexity occurred from stage 1 to stage 2 sitting. This decrease may be indicative of the child homing in on the strategy that is most successful for maintaining posture control. There was a slight increase of ApEn values from stage 2 to stage 3, although this was not significant statistically. Infants at stage 3 of sitting have discovered a strategy for stable postural control, and may be starting a transition to a new behavior, the ability to get in and out of the sitting position. This may be indicated by the increase in complexity, which may be a reflection of increased exploration and increasing dynamic control of the sitting posture.

Taken together, the differences in the variables of LyE, CoD and ApEn over the time period during which sitting develops reflect changes in the dynamics of postural control. Stability (LyE) and regularity (ApEn) increase over this time period, as the child discovers a successful strategy for maintaining the upright body segments over the base of support. Dimensionality

(CoD) initially decreases from stage 1 to stage 2 sitting, in order to freeze some degrees of freedom for control, then increases as the child discovers how to flexibly link body segments for dynamically stable posture control.

The strategy of decreasing the degrees of freedom, as a skill is initially formed, is common both in infants and in older children. Thelen, Corbetta, Kamm, Spencer, Schneider, & Zernicke (1993) described the development of reaching in infants as a discontinuous process, in which the skill of moving the arm and hand close to a desired object is initially softly assembled, with high variability and many degrees of freedom. Through exploration of the dynamics of the reaching task, the infants discover solutions to the degrees of freedom problem within the specific task, and reduce the variability of their movement for improved reaching success. Fitzpatrick (1998) studied clapping in children of various ages, and described the same process of assembling the task using a variety of different strategies, followed by a process of fine tuning and refining to a best solution. Fitzpatrick (1998) postulates that children assemble and disassemble intralimb linkages as they perform more complex clapping games. In other words, they freeze degrees of freedom to assemble a skill, then release degrees of freedom to explore the dynamics of a new perceptual motor skill. The process appears the same in the development of sitting skill; as the infant begins to sit independently the skill is softly assembled, with an initial strategy of freezing degrees of freedom. The infant then discovers a solution to the problem of controlling the linkages of body segments in upright, and is able to release degrees of freedom to adaptively interact with the environment.

Variability reflects specific, individual solutions to solve specific, individual problems (Thelen et al, 1993; Adolph, 1998). Using the surrogation technique, the variability of the COP time series was found to be different than noise. This evidence of specific solutions to the individual's task is contradictory to the idea of a common neural circuitry, or CPG. Further description of the structure of the time series showed a non-linear progression of the variables ApEn and CoD over time, also indicating adaptations to the task and environment, rather than revelation of a neural circuit that was constantly present.

Although the neuromaturationist perspective of an innate, CPG driven postural control mechanism is a possible explanation for the muscle synergies seen in infants prior to the ability to sit independently, the dynamic perspective can also be used to explain this phenomenon. Prior to independence in sitting, infants exhibit a variety of muscle response patterns to either a support surface translation (Hadders-Algra et al., 1996a), or a perturbation caused by a release of trunk support (Harbourne, Giuliani, Mac Neela, 1993). The most situationally appropriate response is only one of several responses, or muscle synergies, that is elicited in the youngest infants. The dynamic view that the infant assembles responses, and in a process of trial and error, discovers the response which is most successful and valuable to the goal, can also be used to explain muscle synergies which occur at first sporadically, then increase in consistency over time. In fact, more consistent muscle responses can be trained by practicing sitting activities with infants (Hadders-Algra et al., 1996b), indicating a discovery process by which the infant selects the most successful strategy for linking body segments together and maintaining the center of mass over the base of support.

There are several limitations of this study. We have reported the data of only 5 subjects, too small a number from which to draw broad conclusions. Also, we relied on the parents to report the sitting skills of the infants, which led to some variability within the stages of sitting that were described. Future investigations using this methodology should include increased numbers of subjects, more discrete selection of measurement intervals, and a longer time period of following the infants.

The process of learning to sit independently involves multiple systems including rapidly changing body proportions and dimensions, perceptual abilities, varying ability to generate force, and environmental restrictions. A centrally determined program of specific muscle responses is unlikely to provide successful postural control within the changing context of a growing infant. The results of this study add to the evidence that infants dynamically assemble the sitting posture by increasing the stability and regularity of their strategy, and controlling the degrees of freedom first to approximate the skill, then to explore adaptations to function in the environment. The methodology utilized in this study may be a simple means of assessing the control of dynamic postural control in infants, which may then be useful in evaluating the efficacy of treatments for infants with developing movement disorders.

REFERENCES

Abarbanel HDI (1996). Analysis of observed chaotic data. New York, NY: Springer-Verlag.

Adolph KE, Vereijken B, Denny MA (1998). Learning to crawl. Child Development, 69(5), 1299-1312.

Bernstein N (1967). The coordination and regulation of movements. London, Pergamon Press.

Buchanan JJ, Horak FB (2001). Transitions in a postural task: do the recruitment and suppression of degrees of freedom stabilize posture? Experimental Brain Research, 139, 482-494.

Buzzi UH, Stergiou N, Giakas G, Dierks TA (2001). The effect of ACL reconstruction on locomotor variability. Proceedings of the 25th Annual Meeting of the American Society of Biomechanics, San Diego, CA, pp. 295-296.

Dingwell JB, Cusumano JP (2000). Nonlinear time series analysis of normal and pathological human walking. Chaos, 10, 848-863.

Dingwell JB, Cusumano JP, Sternad D, Cavanaugh PR (2000). Slower speeds in patients with diabetic neuropathy lead to improved dynamic stability of continuous overground walking. Journal of Biomechanics, 33, 1269-1277.

Fitzpatrick P (1998). Modeling coordination dynamics in development. In K. M. Newell & P. M. C. Molenaar (Eds.), Applications of nonlinear dynamics to developmental process modeling (pp. 39-62). Hillsdale, NJ: Erlbaum.

Grassberger P, Procaccia I (1983). Measuring the strangeness of strange attractors. Physica D, 9, 189-208.

Hadders-Algra M, Brogren E, Forssberg H (1996a). Ontogeny of postural adjustments during sitting in infancy: variation, selection and modulation. Journal of Physiology, 493, 273-288.

Hadders-Algra M, Brogren E, Forssberg H (1996b). Training affects the development of postural adjustments in sitting infants. Journal of Physiology, 493, 289-298.

Harbourne RT, Giuliani C, Mac Neela J (1993). A kinematic and electromyographic analysis of the development of sitting posture in infants. Developmental Psychobiology, 26, 51-64.

Hirschfeld H, Forssberg H (1994). Epigenetic development of postural responses for sitting during infancy. Experimental Brain Research, 97, 528-540.

Horak FB, Diener HC (1994). Cerebellar control of postural scaling and central set in stance.

Journal of Neurophysiology, 72, 479-493.

Jensen JL, Ulrich BD, Thelen E, Schneider K, Zernicke RF (1995). Adaptive dynamics of the leg movement patterns of human infants:III. Development. Journal of Motor Behavior, 27, 366-374.

Kaplan D, Glass L (1995). Understanding Nonlinear Dynamics. New York: Springer-Verlag.

Kuo AD, Speers RA, Peterka RJ, Horak FB (1998). Effect of altered sensory conditions on multivariate descriptors of human postural sway. Experimental Brain Research, 122, 185-195.

Lampl M, Veldhuis JD, Johnson ML (1992). Saltation and stasis: a model of human growth. Science, 258, 801-803.

Massion J (1992). Movement, posture, and equilibrium: interaction and coordination. Progress in Neurobiology, 38, 35-56.

Mees AI, Judd K (1993). Dangers of geometric filtering. Physica D, 68, 427-436.

Mitra S, Riley MA, Turvey MT (1997). Chaos in human rhythmic movement. Journal of Motor Behavior, 29, 195-198.

Newell KM (1997). Degrees of freedom and the development of center of pressure profiles. In K. M. Newell & P. M. C. Molenaar (Eds.), Applications of nonlinear dynamics to developmental process modeling (pp. 63-84). Hillsdale, NJ: Erlbaum.

Pincus SM, Gladstone IM, Ehrenkranz RA (1991). A regularity statistic for medical data analysis. Journal of Clinical Monitering, 7, 335-345.

Pincus SM, Goldberger AL (1994). Physiological time-series analysis: what does regularity quantify? American Journal of Physiology, 266 (Heart Circulatory Physiology, 35), H1643-H1656.

Rapp PE (1994). A guide to dynamical analysis. Integrative Physiological and Behavioral Science, 29, 311-327.

Ryan SM, Goldberger AL, Pincus SM, Mietus J, Lipsitz LA (1994). Gender and age-related differences in heart rate dynamics: are women more complex than men? Journal of American Coll Cardiology, 24, 1700-1707.

Sprott JC, Rowlands G (1992). Chaos Data Analyzer. New York, American Institute of Physics.

Stergiou N, Buzzi UH, Hageman PA, Heidel J (2000). A chaotic analysis of gait parameters in different age groups. Proceedings of the 24th Annual Meeting of the American Society of

Biomechanics, Chicago, IL, pp. 75-76.

Theiler J, Eubank S, Longtin A, Galdrikian B, Farmer JD (1992). Testing for nonlinearity in time series: the method of surrogate data. Physica D, 58, 77-94.

Thelen E, Corbetta D, Kamm K, Spencer JP, Schneider K, Zernicke RF (1993). The transition to reaching: mapping intention and intrinsic dynamics. Child Development, 64, 1058-1098.

Thelen E, Fisher DM (1982). Newborn stepping: an explanation for a “disappearing reflex”. Developmental Psychology, 18, 760-775.

Thelen E, Fisher DM (1983). The organization of spontaneous leg movements in newborn infants. Journal of Motor Behavior, 15, 353-377.

Vaillancourt DE, Newell KM (2000). The dynamics of resting and postural tremor in Parkinson’s disease. Clinical Neurophysiology, 111, 2045-2056.

Woollacott MH, Assaiante C, Amblard B (1996). Development of balance and gait control. In M. Bronstein, T. Brandt, and M. H. Woollacott (Eds.), Clinical Disorders of Balance, Posture and Gait (pp. 43-61). London: Arnold Press.

FIGURE CAPTIONS

Figure 1: Stages 1, 2, and 3 of sitting development, each with a corresponding example of a center of pressure tracing during one sitting trial. Data represent one trial for a single infant through each stage of sitting.

Figure 2. A schematic of the estimation of the Lyapunov Exponent using data from a well known time series, the Lorenz attractor (Abarbanel, 1996). We start with the original time series that we can see in A. From this time series, a three-dimensional state space is created that we can see in B. In C, we observe a section of the state space where the divergence of the neighboring trajectories is identified. The Lyapunov Exponent is the slope of the average logarithmic divergence of the neighboring trajectories (Dingwell, 2000; Sprott and Rowlands, 1992).

Figure 3. A schematic of the surrogation procedure using data from a well known time series, the Lorenz attractor. We start with the original time series that we can see in A. Then we generate phase-randomized surrogate fluctuations from the original data using the process described in B. The surrogate time series that we can see in C has the same mean, variance and power spectra as the original time series. The algorithm used is from Theiler (1992).

TABLE 1

	Original Data		Surrogate Data				
Variable	Mean	SD	Mean	SD	t	df	P
LyE stage 1	0.0868	0.0803	0.1640	0.0221	-2.941	18	0.009
LyE stage 2	0.0345	0.0380	0.0907	0.0307	-3.634	18	0.002
LyE stage 3	0.0240	0.0268	0.1550	0.0450	-7.907	18	<0.001

Results of t-test between actual data and surrogate data.

TABLE 2

Variable	N	Mean	SD	SEM	F value	P
LyE1*#	10	0.087	0.080	0.025		
LyE2#	10	0.035	0.038	0.012	7.029	0.006
LyE3*	10	0.024	0.027	0.008		
*significant difference between LyE1 and LyE3, P=0.007						
#significant difference between LyE1 and LyE2, P=0.024						
CoD1*	10	4.144	0.192	0.061		
CoD2*#	10	3.800	0.467	0.148	4.99	0.019
CoD3#	10	4.148	0.238	0.075		
*significant difference between CoD1 and CoD2, P=0.036						
# significant difference between CoD2 and CoD3, P=0.034						
ApEn1*	10	0.626	0.380	0.120		
ApEn2*	10	0.231	0.211	0.067	3.816	0.042
ApEn3	10	0.330	0.426	0.135		
*significant difference between ApEn1 and ApEn2, P=0.041						
LengthCOP1	5	0.902(meters)	0.165	0.074		
LengthCOP2	5	0.801	0.190	0.085	0.712	0.519
LengthCOP3	5	0.781	0.189	0.085		
x&yexc1	10	0.028(meters)	0.0134	0.004		
x&yexc2	10	0.050	0.0373	0.012	3.071	0.071
x&yexc3	10	0.052	0.0218	0.007		

Results of repeated measures ANOVA and post-hoc testing for non-linear variables of LyE, CoD and ApEn and linear variables of COP length and COP x&y excursion. All variables have df=18, except lengthCOP, which has df=8.