A Perspective on Human Movement Variability With Applications in Infancy Motor Development

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

Yawen Yu
University of Nebraska at Omaha

Anastasia Kyvelidou
University of Nebraska at Omaha, akyvelidou@unomaha.edu

Kinesiology Review, 2013, 2, 93-102

Kinesiology Review
Official Publication of NAK and AKA
www.KR-Journal.com

A Perspective on Human Movement Variability With Applications in Infancy Motor Development

Nicholas Stergiou, Yawen Yu, and Anastasia Kyvelidou

Movement variability is considered essential to typical motor development. However, multiple theoretical perspectives and measurement tools have limited interpretation of the importance of movement variability in biological systems. The complementary use of linear and nonlinear measures have recently allowed for the evaluation of not only the magnitude of variability but also the temporal structure of variability. As a result, the theoretical model of optimal movement variability was introduced. The model suggests that the development of healthy and highly adaptable systems relies on the achievement of an optimal state of variability. Alternatively, abnormal development may be characterized by a narrow range of behaviors, some of which may be rigid, inflexible, and highly predictable or, on the contrary, random, unfocused, and unpredictable. In the present review, this theoretical model is described as it relates to motor development in infancy and specifically the development of sitting posture.

***Keywords*:** posture, nonlinear, sitting

Human movement variability can be defined as the typical variations that are present in motor performance and are observed across multiple repetitions of a task (Stergiou, Harbourne, & Cavanaugh, 2006). This variability is inherent within all biological systems. It can also be observed quite easily, as it is almost impossible for an individual to perform two identical actions of the same task even for elite performers. This has been described quite effectively by Bernstein (1967) as "repetition without repetition" since the repetition of an action involves unique and nonrepetitive neuromotor patterns. For example, when we play a game of throwing darts, we are unable to always hit the center. When we walk, if we observe our footprints on sand or on snow we will see that they never repeat themselves in the exact same fashion. When we stand quietly and especially if we close our eyes, we will observe that we continuously sway without being able to remain completely still. The role of movement variability has attracted significant attention because of its involvement to pathology and performance (Stergiou, 2003).

Theoretical Perspectives Explaining Human Movement Variability

A variety of theoretical perspectives have attempted to explain variability in motor performance in the past decades (Newell & Corcos, 1993). The two most prominent theories are the Generalized Motor Program and the Dynamical Systems Theory. We will briefly review these two theories with respect to human movement variability. There are several others that have been proposed (i.e., Uncontrolled Manifold); however, their review is beyond the scope of this paper and it is our own humble opinion that they are all different versions or byproducts of these two major theoretical perspectives.

The Generalized Motor Program (GMP) theory considers variation in a given movement pattern to be due to *errors* in the ability to predict proper parameters to employ in the general motor program (Schmidt, 2003; Summers & Anson, 2009). Working along with this concept, to optimize the accuracy and efficiency of the movement pattern errors in the control system have to be constantly eliminated. That is, presumably, specificity of practice can better construct the predictability of a given task for better performance. However, this contradicts the fact that variation in training improves performance in movement.

On the contrary, Dynamical Systems Theory (DST) embraces variability as an important component of movement development. Practically, the development of the most stable solution to produce a given movement pattern is based on exploration and the ability to self-organize according to environmental, biomechanical, and morphological constraints (Clark & Phillips, 1993; Kamm, Thelen, & Jensen, 1990; Kelso, 1995; Thelen, 1995; Thelen & Ulrich, 1991). In general, increased variability in a movement pattern indicates loss of stability, while decreased variability indicates a behavior with higher stability. Importantly, both GMP and DST perspectives recognize that the decreased variability results from the

The authors are with the Nebraska Biomechanics Core Facility, University of Nebraska at Omaha. Stergiou (NAK Fellow #510) is also with the College of Public Health, University of Nebraska Medical Center, Omaha, Nebraska.

effective execution of a movement pattern. However, DST provides a particular focus on transitions between behaviors. Specifically, DST suggests that biological systems can change their behavior when movement variability increases and reaches a specific critical point. This is accomplished by the scaling of a control parameter that the system is sensitive. When the control parameter is scaled to a critical level then the system becomes highly unstable and quite variable. At that point the system can switch to a new and more stable movement pattern with less variability. DST proposes that the lack of movement variability may indicate rigid and inflexible systems with limited ability to switch their behaviors and, thus, limited adaptability to changing task or environmental demands.

However, an interesting observation is that several behaviors that appear to be very stable can be performed in quite variable ways. For example, when we observe elite athletes or musicians, we marvel at the amazing number of ways they are capable of performing the same task. In that matter most of us are like these elite individuals when we consider our ability to perform fundamental motor skills, such as sitting on a rocking chair, walking through crowds or diverse challenging terrains, reaching for objects with different orientations and shapes. Thus, in a very stable behavior, to use the phraseology of DST, we observe that variability is closely related with a rich behavioral state. We believe that this is a limitation of DST and that this limitation is due to the lack of appreciation in the past on how variability is being measured and what exactly these measures represent.

Basically, these previous theoretical perspectives used only linear measures (i.e., standard deviation) that can capture error in performance as we are learning to execute a motor skill. As motor learning occurs, the magnitude of variability continuously decreases and eventually will reach a plateau. At that time we have a very stable behavior according to DST or an appropriate selection of parameters to correctly execute the motor program according to GMP. However, the linear measures that are used to reach these conclusions are measures of centrality and thus provide a description of the amount or magnitude of the variability around that central point. This is accomplished by quantifying the magnitude of variation in a set of values independently of their order in the distribution (Figure 1). From this perspective, practitioners, clinicians and scientists believed that the mean is the golden standard of performance and any deviation from this golden standard is error or undesirable behavior or the result of instability. However, the appropriate usage of these traditional linear measures requires that certain

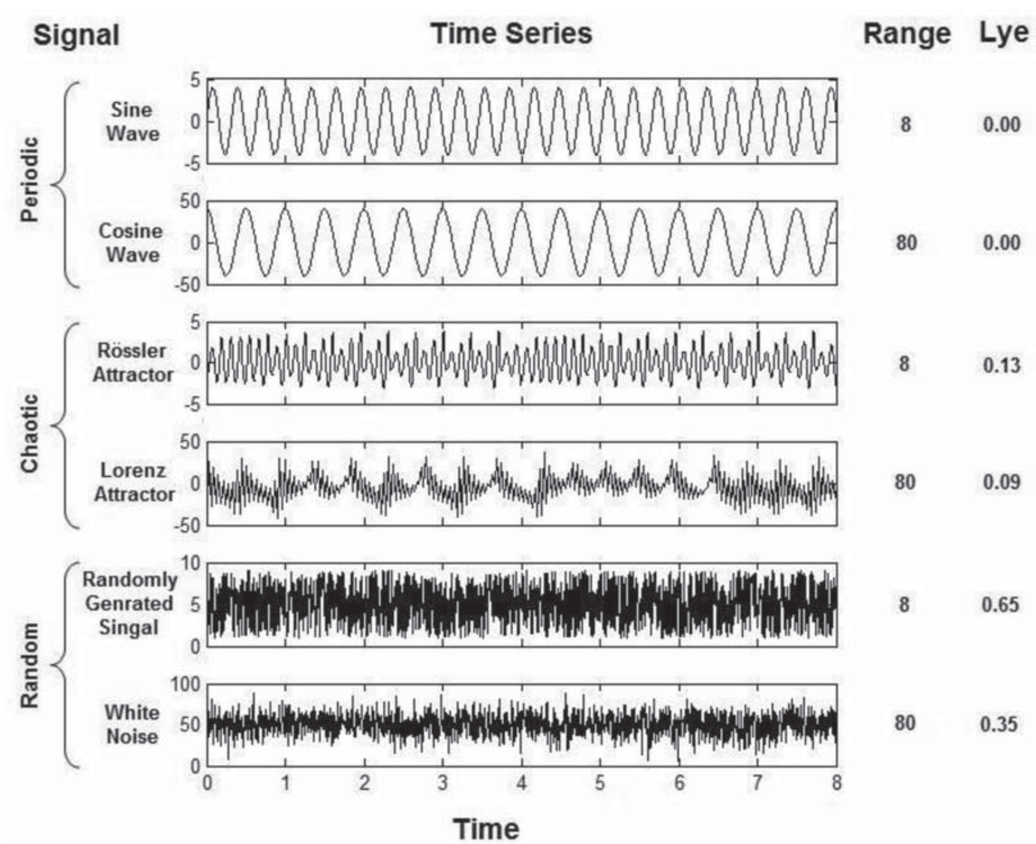

Figure 1 — Demonstration of the complimentary use of linear and nonlinear measures from different signals; six signals are displayed with the respective values for range and largest Lyapunov Exponent (LyE). The first two time series are periodic while the following two time series are chaotic. The last two time series are random. The figure exhibits that signals can have the same range but differ in terms of LyE or vice versa.

assumptions are obeyed. In particular, it is assumed that variations between repetitions of a task are random and independent (of past and future repetitions; Lomax, 2007). This is not true since previous studies have shown that such variations are not noise (Delignières & Torre, 2009; Dingwell & Cusumano, 2000; Dingwell & Kang, 2007; Harbourne & Stergiou, 2009; Hausdorff, 2007; Stergiou, Buzzi, Kurz, & Heidel, 2004, Stergiou et al., 2006). Importantly, several studies have also found that these variations are deterministic in nature (Dingwell & Cusumano, 2000; Dingwell & Kang, 2007; Harbourne & Stergiou, 2009; Hausdorff, 2007; Miller, Stergiou, & Kurz, 2006; Stergiou et al., 2006).

Such observations became possible using nonlinear tools, such as entropy measures, fractal measures, or tools developed from the mathematical theory of chaos, that have allowed the evaluation of the temporal structure of variability or how a set of values in a particular distribution are organized in time or even across a range of time scales (Sosnoff, Valantine, & Newell, 2006; Stergiou et al., 2004). The two approaches are truly complimentary since each investigates different aspects of variability (Figure 1; Harbourne & Stergiou, 2009; Stergiou et al., 2004). However, neither one should be ignored as it was the case in the past. Nonlinear tools that have been used in the literature for this purpose include Approximate Entropy, Sample Entropy, Correlation Dimension, largest Lyapunov Exponent, and Detrended Fluctuation Analysis (Bruijn, van Dieën, Meijer, & Beek, 2009; Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Cavanaugh, Kochi, & Stergiou, 2010; Delignières & Torre, 2009; Dingwell & Cusumano 2000; Dingwell, Cusumano, Sternad, & Cavanagh, 2000; Dingwell & Kang, 2007; Dingwell & Marin, 2006; Donker, Roerdink, Greven, & Beek, 2007; Gates, Su, & Dingwell, 2007; Gates & Dingwell, 2007, 2008; Harbourne & Stergiou, 2009; Hausdorff, 2007, 2009; Hausdorff, Zemany, Peng, & Goldberger, 1999; Jordan, Challis, & Newell, 2006, 2007a, 2007b; Liao, Wang, & He, 2008; Kurz & Hou, 2010; Kurz, Markopoulou, & Stergiou, 2010; Kyvelidou, Kurz, Ehlers, & Stergiou, 2008; Sosnoff et al., 2006; Sosnoff & Voudrie, 2009; Stergiou et al., 2004; Stins, Michielsen, Roerdink, & Beek, 2009; Vaillancourt & Newell, 2002).

These nonlinear tools are being used increasingly to describe complex conditions in which linear tools have been inadequate, confounding scientific study and the development of meaningful therapeutic options. For example, nonlinear analysis has recently appeared in research of heart rate irregularities, sudden cardiac death syndrome, blood pressure control, brain ischemia, epileptic seizures, and several other conditions to understand their complexity and eventually develop prognostic and diagnostic tools (Amato, 1992; Buchman, Cobb, Lapedes, & Kepler, 2001; Goldberger, Rigney, Mietus, Antman, & Greenwald, 1988; Goldstein, Toweill, Lai, Sonnenthal, Kimberly, 1998; Slutzky, Cvitanovic & Mogul, 2001; Toweill & Goldstein, 1998; Wagner, Nafz, & Persson, 1996). In cardiology, significant advances have been made using this approach. For example, heart rhythms where the variations in the time interval between successive QRS waves are either periodic or random (Figure 2) have

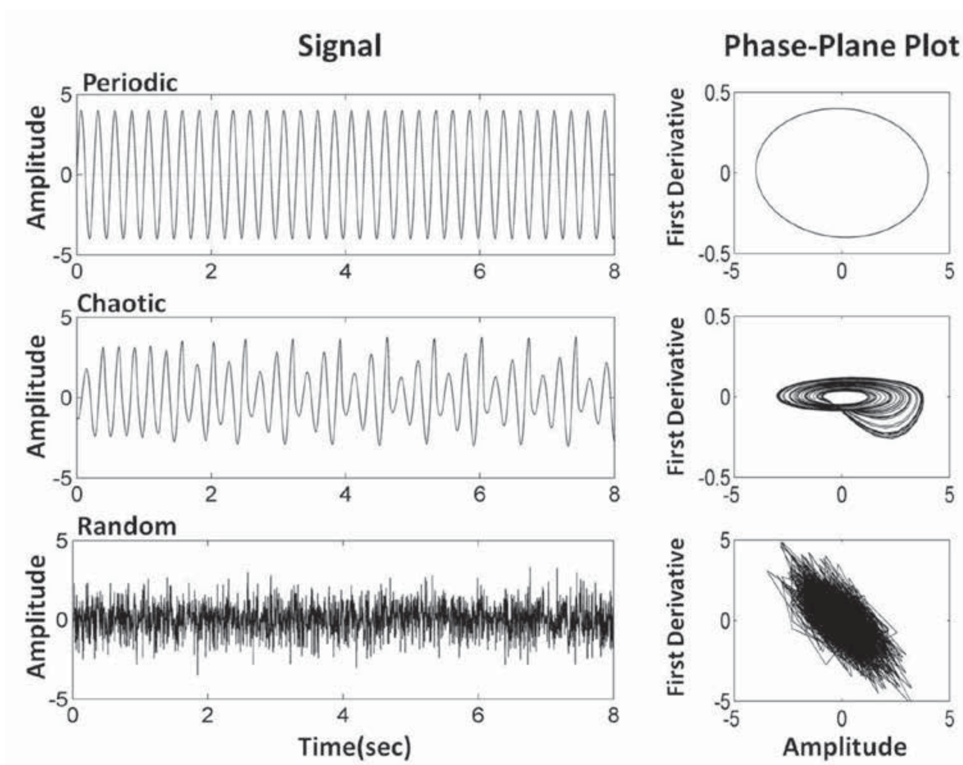

Figure 2 — Periodic, chaotic, and random time series and their corresponding two-dimensional phase space plots. The phase space plot is obtained by plotting the original time series versus its first derivative.

been associated with heart problems (Denton, Diamond, Helfant, Khan, & Karagueuzian, 1990; Glass & Mackey, 1988). Conversely, heart rhythms where these variations are characterized by chaotic patterns are associated to a healthy heart (Figure 2). It is important to mention that the specialized concept of “chaos” discussed here is distinct from, and contrary to, the English language notion of chaos which means confusion and disorder. In fact, when we refer to mathematical chaos in a system, we are pointedly referring to an underlying order or pattern that is contained within a complex, variable system. Chaotic properties of a system are described using nonlinear techniques.

While chaos is a mathematical construct, its properties have been found to proliferate in nature, art and music (Didier, 2004; Madden, 2007; Mandelbrot, 1982; Mureika, 2005). Our laboratory and others have also shown that such deterministic variations are linked to the health of biological systems such as the cardiovascular, respiratory, cognitive and locomotor systems, while pathologic systems generate less complex (i.e., either more ordered or more random) outputs (Buzzi et al., 2003; Decker, Moraiti, Stergiou, & Georgoulis, 2011; Hausdorff, Cudkowicz, Firtion, Wei, & Goldberger, 1998; Hausdorff, Rios, & Edelberg, 2001, Myers, Johanning, Stergiou, Celis, Robinson, & Pipinos, 2009). Based on such investigations, Stergiou et al. (2006) and Stergiou and Decker (2011) have recently proposed a new theoretical model to explain human movement variability. Their model states that optimal variability of a biological system is when a system demonstrates stability but with a capacity to change when required. The stability is associated with a repeated pattern that may not be readily identifiable, except over long time series. This property is known as statistical self-similarity. The capacity to adapt to an ever-changing environment is associated with the richest, most complex outputs (i.e., signals with the highest information content over multiple temporal or spatial scales as depicted in Figure 3). When variations in a system exhibit these properties (i.e., self-similarity and complexity) it can be inferred that the system is exhibiting a fractal and chaotic structure.

We should also mention here that Stergiou and colleagues also proposed that motor development and motor learning processes obey this model. In other words, the development of healthy and highly adaptable systems relies on the achievement of the optimal state of variability. Alternatively, abnormal development may be

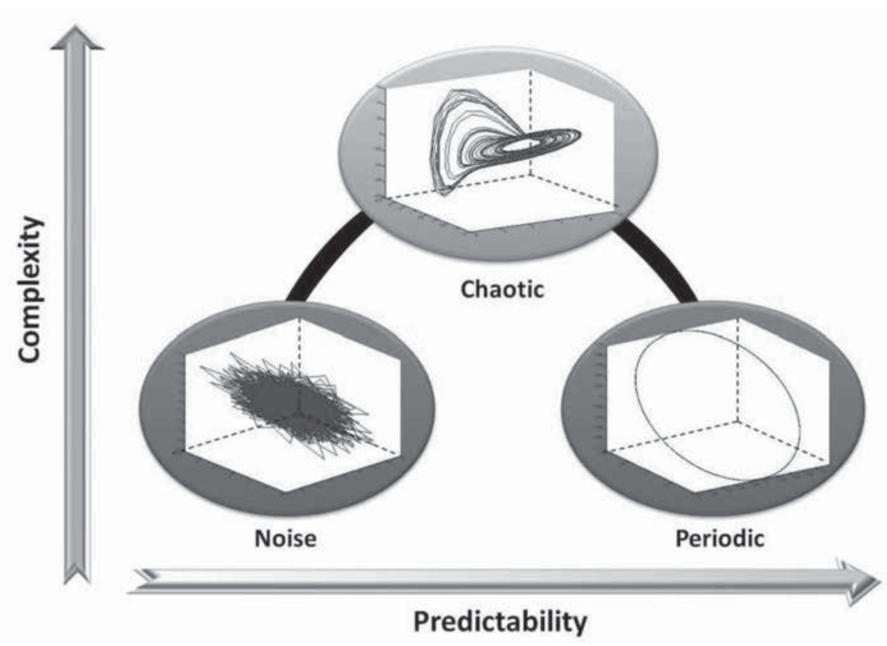

Figure 3 — This model is based on the idea that mature motor skills and healthy states are associated with optimal movement variability that reflects the adaptability of the underlying control system. The principle of optimality in movement variability is pioneering in the sense that it relates in an inverted U-shape relationship the concept of complexity with the concept of predictability. Practically at this optimal state of movement variability the biological system is in a healthy state and is characterized by the largest possible effective complexity (i.e., the uppermost point along the inverted U-shaped function), attaining high values only in the intermediate region between excessive order (i.e., maximum predictability) and excessive disorder (i.e., no predictability). Thus, this variability has deterministic structure and reflects the adaptability of the system to environmental stimuli and stresses. Decrease or loss of this optimal state of variability renders the system more predictable, rigid and with a robotic type of motor behavior. Increases beyond optimal variability render the system more noisy and unpredictable, similar to what is observed for example in a very frail elder or a drunken sailor walking. Both situations result in decreased complexity, flexibility and adaptability to perturbations and are associated with lack of health.

characterized by a narrow range of behaviors, some of which may be rigid, inflexible and highly predictable or, on the contrary, random, unfocused and unpredictable. Motor disabilities many times are described as such. In agreement with this proposition the authors also propose that enhancement of the development of this optimal state of movement variability should be the objective of neurologic physical therapy.

Here we should also mention that we are not unique in the proposition of a U-shaped model of complexity as it relates with predictability. Our uniqueness lies in its adaptation to explain phenomena with respect to human movement variability and how it relates with health and skillful performance. West (2006) introduced a theoretical measure of complexity in general science that starts at zero, increases to a maximum value, and then decreases to zero again. The measure is plotted in a figure that is similar with our Figure 3. However, the x-axis utilizes an increasing parameter, which the author calls number of variables. When there are a low number of variables, the author suggests that the mathematics that explains what is going on include nonlinear dynamics and control theory. However, when the number of variables is large, the mathematics that describes these phenomena is renormalization group theory, scaling and random walks. The area of maximum complexity is suggested to be unknown with respect to its mathematics and is characterized by lack of experimentation to uncover it. The author suggests that here is "where the secrets of DNA are hidden and the mysteries of neurophysiology take root," making its description generic and allegorical. In 1994, Gell-Mann (1994) also included, what the author called, "a sketch that was showing roughly" possible effective complexity as related with algorithmic information content (AIC). In this generic model, the author attempted to explain how a child learns a language with respect to the information provided. In the model, complexity started from a minimum which was very near to zero where AIC for a given message length was in complete order or completely regular. Then complexity increased linearly to a maximum and then decreased again to a minimum near zero where however AIC for a given message length was completely random or characterized with complete disorder.

Lastly, Tononi, Edelman, and Sporns (1998) related complexity as a notion of integration of information and coherence. They defined neural complexity in terms of integration, utilizing the ensemble average of integration values for subsets composed of increasing numbers of neural elements. They included also a schematic, which has similarities with our Figure 3. In their schematic the y-axis was named complexity and the x-axis regularity. They included three cartoons that symbolized gas molecules, molecules in a crystal lattice, and interactions of neurons in the brain. They stated that any system of elements arranged in a random (e.g., gas molecules) or completely homogeneous way (molecules in a crystal lattice) is not complex. Therefore these two cartoons were placed low on the y-axis and to the right and left, respectively. By contrast, the arrangement and interactions of neurons in a brain or of molecules in a cell is obviously extremely complex. Therefore, this cartoon was placed at the top of the schematic with respect to the y-axis, but also in the middle with respect to the x-axis.

Armed with the above theoretical model and its related methodological advances, we have explored for the last 10 years motor development in infants. In the following section, we will present our empirical work as it relates to this particular domain in terms of specific questions/steps that exhibit our strong inference (Platt, 1964).

Motor Development in Infancy

Our interests in this area were focused from the very beginning on the development of variability. We were particularly interested to understand how (and if) we develop into the above described model. Several questions were generated, such as a) is such a model hard-coded in our genetic code? b) Can the above nonlinear methodology to examine variability provide reliable measures to investigate motor development? c) if the above model is acceptable, can it be harnessed to develop therapeutic interventions to address motor developmental disabilities? To explore these questions we decided to focus on a specific motor milestone, the development of the sitting posture.

The achievement of independent sitting appears to be effortless and merely a part of the normal maturation process. Sitting is the first upright posture achieved in life, with independent sitting occurring by six to seven months of age in the typically developing child (Folio & Fewell, 2000). Early postural control in sitting is an important prerequisite for standing balance, and sitting by the age of two years is a marker for potential independence in walking in children with cerebral palsy (Bleck, 1975). Once an infant can control the head and trunk in sitting, the arms are free for exploration and functional activities. Researchers have linked the ability to sit independently to greater success in reaching and maintaining contact with objects and improved eye-hand coordination of infants learning to reach (Out, van Soest, Savelsbergh, & Hopkins, 1998; Rochat, 1992). Poor postural control can limit the attainment of functional skills such as mobility and manipulation during the developmental process (Shumway-Cook & Woollacott, 1993; Amiel-Tison, & Grenier, 1986). Hence, the study of the development of postural control in sitting is an important component in the study of movement control that affects the developmental outcome of a child.

Traditionally, the center of pressure (COP) at the base of support during standing has been thought of as a mirror representation of how we organize posture (Massion, 1992). Researchers have used the COP in studies of postural control in children developing standing skills (Odenrick & Sandstedt, 1984; Riach & Hayes, 1987). However, there have been conflicting interpretations of the COP data using the standard linear measures to identify sway variability such as length of path, excursion in the sagittal or frontal directions, and the area of the path of the COP during stable standing. For example, different researchers have interpreted an increased sway variability to suggest greater motor control because the individual can recover from disruptions to posture (Hughes, Duncan, Rose, Chandler, & Studenski, 1996), while others interpret an increased sway variability as a lack of postural control (Riach & Hayes, 1987). Our group has used this experimental paradigm to investigate the development of independent sitting (Figure 4).

Based on the above conflicting results we immediately realized that nonlinear measures could provide important information about emerging postural abilities and the evolution and adaptive nature of sitting postural control. However, we first wanted to identify if we have sufficient reliability regarding the measures of sway variability for assessing the development of sitting postural control. In two studies from our laboratory (Kyvelidou, Harbourne, Stuberg, Sun, & Stergiou. 2009; Kyvelidou, Harbourne, Shostrom, & Stergiou, 2010), we investigated the intrasession and intersession reliability of linear and nonlinear measures when used to analyze COP data during the development of infant sitting postural control in both typically developing and infants with or at risk for cerebral palsy (CP). The infants were tested twice in one week at each of the four months of the study. Three trials at each session were used to determine intrasession reliability. The repeat testing within one week of each month was used for the estimation of the intersession reliability. We found that the evaluation of COP data using linear and nonlinear measures is a reliable method for quantifying incremental change across the development of sitting postural control in both typically developing infants and in infants with or at risk for CP. The nonlinear tools specifically presented high intrasession and intersession ICC values with values increasing as the sitting skill improved. Thus, the evaluation of COP data are a reliable method of investigating the development of sitting postural control.

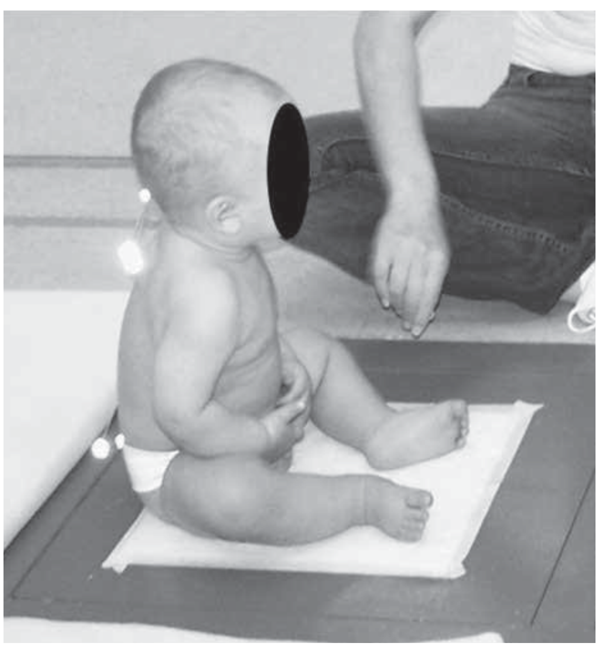

Figure 4 — Illustration of the experimental paradigm of infant sitting postural control.

As soon as we established our reliability, we further wanted to get into the heart of the above mentioned conflicting results with respect to the evaluation of COP data and what they mean with respect to motor control. Thus, our next step was to investigate if nonlinear and linear variables describe different features of sway variability. In a series of studies (Deffeyes, Harbourne, Kyvelidou, Stuberg, & Stergiou, 2009; Harbourne, Deffeyes, Kyvelidou, & Stergiou, 2009; Cignetti, Kyvelidou, Harbourne, & Stergiou, 2011) with typically developing infants we found that as we were expecting linear measures of sway variability acquired during sitting posture were positively correlated with other linear measures and nonlinear measures were positively correlated with other nonlinear measures. In addition, linear measures were negatively correlated with nonlinear measures. Practically they tell us different stories about sway variability, namely that the amount and temporal structure of sway variability are two different things. We also found that linear measures increased during development of sitting in typically developing infants while nonlinear measures decreased in the anteriorposterior (front-to-back) direction, while the exact opposite occurred in the mediolateral (side-to-side) direction showing an interesting de-coupling. We felt that this de-coupling is probably due to biomechanical factors such as the presence of increased fat around the infant's buttocks at this age that restricts motion in the mediolateral direction (at least initially). Lastly, we also found that linear and nonlinear measures load on different factors using a principal component analysis indicating that they explain different aspects of sitting postural control.

Based on the above information regarding the mechanisms of sitting postural control, we then turned our focus on infants with developmental delays. A delay in achieving the milestone of sitting independently is one sign that a child's development is not following a normal course. A disruption in postural control significantly affects the development of a child, and can limit the ability to develop eventual independent movement. Thus, as our next step we asked if measures of sway variability can discriminate between typically developing infants and infants with developmental delays. The results from several studies from our laboratory (Deffeyes, Harbourne, Dejong et al., 2009; Deffeyes, Kochi et al., 2009) showed that nonlinear measures provide information about small improvements in postural control over time that were not apparent with standard clinical tests such as the Gross Motor Function Measure. In addition, nonlinear measures revealed significant differences between infants with typical versus delayed development. In our infants with delayed development we found that they had more rigid and less complex patterns of postural sway as compared with typically developing infants. These results were also supported by studies that we performed with our collaborators with respect to the development of gait and the supine posture (Smith, Stergiou, Ulrich, 2011; Smith, Teulier, Sansom, Stergiou, Ulrich, 2011; Dusing, Kyvelidou, Mercer, Stergiou, 2009) in children with developmental delays.

The fact that the infants with delayed development were found to have more rigid and less complex patterns as predicted by our theoretical model, led us to consider as our next step translating our model in designing therapies to improve sitting postural control for infants with motor developmental delay. As such we mapped variability problems that are associated with certain behavioral expressions, with certain possible interventions (Harbourne & Stergiou, 2009). Specifically, an infant that exhibits reduced amount of variability with maximum predictability and rigidity also exhibits very little active movement in comparison with typically developing infants. Thus, we recommended a complexity improving intervention with increased sensory input that can be provided with nature based physical guidance to take full advantage of the presence of chaos and fractals in nature. An infant that exhibits increased amount of variability with minimum predictability and very noisy movement patterns also exhibits continuous pushing and pulling into the extreme ranges of the possible effective movement. Thus, we recommended a complexity improving intervention with the introduction of soft constraints to suggest reduced range of movement.

Of course we wanted to put the above proposed interventions into action and as our next step we explored if this model can be put to test through a clinical trial (Harbourne, Willett, Kyvelidou, Deffeyes, & Stergiou, 2010). Thus we performed a clinical trial and we found that our therapeutic model, which facilitates the exploration of the environment through natural based paradigms, enhanced the complexity of sitting postural control in infants with cerebral palsy and allowed their developmental trend to resemble the one found in infants with typical development. This was not the case with a home based program that constituted the standard care of treatment for these infants. Even though that program improved clinical tests, nonlinear measures acquired pre and posttreatment showed that the home based program moved the developmental trajectory of the infants with cerebral palsy in the opposite direction as the one found in typically developing infants.

Conclusion

In conclusion, even though almost ten years have passed in this scientific trip in infancy motor development, we do not have the answers to all of our questions. We still want to find out how severity affects the implementation of our therapy and if we can have similar results with children that have mild CP versus severe CP. We also want to identify if the implementation of our therapy can translate to benefits in other milestones like standing and walking or if we can extend our therapy beyond CP and address other motor developmental disabilities. Lastly, it will be very interesting to investigate how different milestones are related in terms of development of complexity and how we can incorporate in our theoretical model other important aspects of development like motivation or cognitive changes.

However, as the greatest developmentalist of our times, Esther Thelen, once told the first author of this paper that we would have never embarked on this trip if we did not have a map or, in other words, a theoretical model. Such a map can allow for the application of the scientific method as originally described by Bacon a few centuries ago and reiterated by Platt in 1964. However, we should never be "married" to our theoretical model because usually models are modified and change significantly over time. We, as scientists, should remain open-minded to be able to recognize such changes and apply modifications that are necessary to develop better experiments that can improve kinesiology and better serve humanity.

References

Amato, I. (1992). Chaos breaks out at NIH, but order may come of it. *Science, 257,* 1763–1764. doi:10.1126/science.1615321

Amiel-Tison, C., & Grenier, A. (1986). *Neurologic assessment during the first year of life*. New York, NY: Oxford University Press.

Bernstein, N.A. (1967). *The coordination and regulation of movements*. Oxford: Pergamon Press.

Bleck, E.E. (1975). Locomotor prognosis in cerebral palsy. *Developmental Medicine and Child Neurology, 17,* 18–25. doi:10.1111/j.1469-8749.1975.tb04952.x

Bruijn, S.M., van Dieën, J.H., Meijer, O.G., & Beek, P.J. (2009). Is slow walking more stable? *Journal of Biomechanics, 42,* 1506–1512. doi:10.1016/j.jbiomech.2009.03.047

Buchman, T.G., Cobb, J.P., Lapedes, A.S., & Kepler, T.B. (2001). Complex systems analysis: a tool for shock research. *Shock (Augusta, Ga.), 16,* 248–251. doi:10.1097/00024382-200116040-00002

Buzzi, U., Stergiou, N., Kurz, M., Hageman, P., & Heidel, J. (2003). Nonlinear dynamics indicates aging affects variability during gait. *Clinical Biomechanics (Bristol, Avon), 18,* 435–443. doi:10.1016/S0268-0033(03)00029-9

Cavanaugh, J.T., Kochi, N., & Stergiou, N. (2010). Nonlinear analysis of ambulatory activity patterns in community-dwelling older adults. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences, 65,* 197–203. doi:10.1093/gerona/glp144

Cignetti, F., Kyvelidou, A., Harbourne, R.T., & Stergiou, N. (2011). Anterior-posterior and medial-lateral control of sway in infants during sitting acquisition does not become adult-like. *Gait & Posture, 33*, 88–92. doi:10.1016/j.gaitpost.2010.10.002

Clark, J.E., & Phillips, S.J. (1993). A longitudinal study of intralimb coordination in the first year of independent walking: a dynamical systems analysis. *Child Development, 64,* 1143–1157. doi:10.2307/1131331

Decker, L.M., Moraiti, C., Stergiou, N., & Georgoulis, A.D. (2011). New insights into anterior cruciate ligament deficiency and reconstruction through the assessment of knee kinematic variability in terms of nonlinear dynamics. *Knee Surgery, Sports Traumatology, Arthroscopy, 19*, 1620–1633. doi:10.1007/s00167-011-1484-2

Deffeyes, J.E., Harbourne, R.T., Dejong, S.L., Kyvelidou, A., Stuberg, W.A., & Stergiou, N. (2009). Use of information entropy measures of sitting postural sway to quantify developmental delay in infants. *Journal of Neuroengineering and Rehabilitation, 6,* 34. doi:10.1186/1743-0003-6-34

Deffeyes, J.E., Harbourne, R.T., Kyvelidou, A., Stuberg, W.A., & Stergiou, N. (2009). Nonlinear analysis of sitting postural sway indicates developmental delay in infants. *Clinical Biomechanics (Bristol, Avon), 24,* 564–570. doi:10.1016/j.clinbiomech.2009.05.004

Deffeyes, J.E., Kochi, N., Harbourne, R.T., Kyvelidou, A., Stuberg, W.A., & Stergiou, N. (2009). Nonlinear Detrended Fluctuation Analysis of Sitting Center-of-Pressure Data as an Early Measure of Motor Development Pathology in Infants. *Nonlinear Dynamics Psychology and Life Sciences, 13*, 351–368.

Delignières, D., & Torre, K. (2009). Fractal dynamics of human gait: A reassessment of the 1996 data of Hausdorff et al. *Journal of Applied Physiology, 106,* 1272–1279. doi:10.1152/japplphysiol.90757.2008

Denton, T.A., Diamond, G.A., Helfant, R.H., Khan, S., & Karagueuzian, H. (1990). Fascinating rhythm: a primer on chaos theory and its application to cardiology. *American Heart Journal, 120*, 1419–1440. doi:10.1016/0002-8703(90)90258-Y

Didier, S. (2004). *Critical phenomena in natural sciences: chaos, fractals, self-organization, and disorder: concepts and tools*. Berlin: Springer.

Dingwell, J.B., & Cusumano, J.P. (2000). Nonlinear time series analysis of normal and pathological human walking. *Chaos (Woodbury, N.Y.), 10,* 848–863. doi:10.1063/1.1324008

Dingwell, J.B., Cusumano, J.P., Sternad, D., & Cavanagh, P.R. (2000). Slower speeds in patients with diabetic neuropathy lead to improved local dynamic stability of continuous overground walking. *Journal of Biomechanics, 33*, 1269–1277. doi:10.1016/S0021-9290(00)00092-0

Dingwell, J.B., & Kang, H.G. (2007). Differences between local and orbital dynamic stability during human walking. *Journal of Biomechanical Engineering, 129,* 586–593. doi:10.1115/1.2746383

Dingwell, J.B., & Marin, L.C. (2006). Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. *Journal of Biomechanics, 39*, 444–452. doi:10.1016/j.jbiomech.2004.12.014

Donker, S.F., Roerdink, M., Greven, A.J., & Beek, P.J. (2007). Regularity of center-of-pressure trajectories depends on the amount of attention invested in postural control. *Experimental Brain Research, 181,* 1–11. doi:10.1007/s00221-007-0905-4

Dusing, S.C., Kyvelidou, A., Mercer, V.S., & Stergiou, N. (2009). Infants born preterm exhibit different patterns of center-of-pressure movement than infants born at full term. *Physical Therapy, 89*, 1354–1362. doi:10.2522/ptj.20080361

Folio, M.R., & Fewell, R. R. (2000). *Peabody developmental motor scales* (2nd ed). Pro-ed, Inc.; Austin, TX.

Gates, D.H., & Dingwell, J.B. (2007). Peripheral neuropathy does not alter the fractal dynamics of stride intervals of gait. *Journal of Applied Physiology, 102,* 965–971. doi:10.1152/japplphysiol.00413.2006

Gates, D.H., & Dingwell, J.B. (2008). The effects of neuromuscular fatigue on task performance during repetitive goal-directed movements. *Experimental Brain Research, 187,* 573–585. doi:10.1007/s00221-008-1326-8

Gates, D.H., Su, J.L., & Dingwell, J.B. (2007). Possible biomechanical origins of the long-range correlations in stride intervals of walking. *Physica A, 380,* 259–270. doi:10.1016/j.physa.2007.02.061

Gell-Mann, M. (1994). *The quark and the jaguar: adventures in the simple and the complex*. New York, NY: Owl Books.

Glass, L., & Mackey, M.C. (1988). *From clocks to chaos: the rhythms of life*. Princeton, NJ: Princeton University Press.

Goldberger, A.L., Rigney, D.R., Mietus, J., Antman, E.M., & Greenwald, S. (1988). Nonlinear dynamics in sudden cardiac death syndrome: heartrate oscillations and bifurcations. *Experientia, 44,* 983–997. doi:10.1007/BF01939894

Goldstein, B., Toweill, D., Lai, S., Sonnenthal, K., & Kimberly, B. (1998). Uncoupling of the automatic and cardiovascular systems in acute brain injury. *The American Journal of Physiology, 275,* R1287–R1292.

Harbourne, R.T., Deffeyes, J.E., Kyvelidou, A., & Stergiou, N. (2009). Complexity of postural control in infants: Linear and nonlinear features developed by principal component analysis. *Nonlinear Dynamics Psychology and Life Sciences, 13,* 123–144.

Harbourne, R.T., & Stergiou, N. (2009). Perspective on movement variability and the use of nonlinear tools: Principles to guide physical therapy practice. *Physical Therapy, 89,* 1–15.

Harbourne, R.T., Willett, S., Kyvelidou, A., Deffeyes, J., & Stergiou, N. (2010). A comparison of interventions for children with cerebral palsy to improve sitting postural control: A clinical trial. *Physical Therapy, 90*, 1881–1898. doi:10.2522/ptj.2010132

Hausdorff, J.M. (2007). Gait dynamics, fractals and falls: finding meaning in the stride-to-stride fluctuations of human walking. *Human Movement Science, 26*, 555–589. doi:10.1016/j.humov.2007.05.003

Hausdorff, J.M. (2009). Gait dynamics in Parkinson's disease: common and distinct behavior among stride length, gait variability, and fractal-like scaling. *Chaos (Woodbury, N.Y.), 19,* 026113. doi:10.1063/1.3147408

Hausdorff, J.M., Cudkowicz, M.E., Firtion, R., Wei, J.Y., & Goldberger, A.L. (1998). Gait variability and basal ganglia disorders: stride-to-stride variations of gait cycle timing in Parkinson's disease and Huntington's disease. *Movement Disorders, 13*, 428–437. doi:10.1002/mds.870130310

Hausdorff, J.M., Rios, D.A., & Edelberg, H.K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of Physical Medicine and Rehabilitation, 82*, 1050–1056. doi:10.1053/apmr.2001.24893

Hausdorff, J.M., Zemany, L., Peng, C., & Goldberger, A.L. (1999). Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children. *Journal of Applied Physiology, 86,* 1040–1047.

Hughes, M.A., Duncan, P.W., Rose, D.K., Chandler, J.M., & Studenski, S.A. (1996). The relationship of postural sway to sensorimotor function, functional performance, and disability in the elderly. *Archives of Physical Medicine and Rehabilitation, 77,* 567–572. doi:10.1016/S0003-9993(96)90296-8

Jordan, K., Challis, J.H., & Newell, K.M. (2006). Long range correlations in the stride interval of running. *Gait & Posture, 24,* 120–125. doi:10.1016/j.gaitpost.2005.08.003

Jordan, K., Challis, J.H., & Newell, K.M. (2007a). Speed influences on the scaling behavior of gait cycle fluctuations during treadmill running. *Human Movement Science, 26*(1), 87–102. doi:10.1016/j.humov.2006.10.001

Jordan, K., Challis, J.H., & Newell, K.M. (2007b). Walking speed influences on gait cycle variability. *Gait & Posture, 26*(1), 128–134 10.1016/j.gaitpost.2006.08.010.

Kamm, K., Thelen, E., & Jensen, J.L. (1990). A dynamical systems approach to motor development. *Physical Therapy, 70,* 763–775.

Kelso, J.A.S. (1995). *Dynamic patterns: the self-organization of brain and behavior*. Cambridge, MA: MIT Press.

Kurz, M.J., & Hou, J.G. (2010). Levodopa influences the regularity of the ankle joint kinematics in individuals with Parkinson's disease. *Journal of Computational Neuroscience, 28,* 131–136. doi:10.1007/s10827-009-0192-0

Kurz, M.J., Markopoulou, K., & Stergiou, N. (2010). Attractor divergence as a metric for assessing walking balance. *Nonlinear Dynamics Psychology and Life Sciences, 14,* 151–164.

Kyvelidou, A., Harbourne, R.T., Shostrom, V.K., & Stergiou, N. (2010). Reliability of center of pressure measures for assessing the development of sitting postural control in infants with or at risk of cerebral palsy. *Archives of Physical Medicine and Rehabilitation, 91,* 1593–1601. doi:10.1016/j.apmr.2010.06.027

Kyvelidou, A., Harbourne, R.T., Stuberg, W.A., Sun, J., & Stergiou, N. (2009). Reliability of center of pressure measures for assessing the development of sitting postural control. *Archives of Physical Medicine and Rehabilitation, 90,* 1176–1184. doi:10.1016/j.apmr.2009.01.031

Kyvelidou, A., Kurz, M.J., Ehlers, J.L., & Stergiou, N. (2008). Aging and partial body weight support affects gait variability. *Journal of Neuroengineering and Rehabilitation, 5,* 22. doi:10.1186/1743-0003-5-22

Liao, F., Wang, J., & He, P. (2008). Multi-resolution entropy analysis of gait symmetry in neurological degenerative diseases and amyotrophic lateral sclerosis. *Medical Engineering & Physics, 30,* 299–310. doi:10.1016/j.medengphy.2007.04.014

Lomax, R.G. (2007). *Statistical concepts: A second course for education and the behavioral sciences*. Mahwah, NJ: Lawrence Erlbaum Associates.

Mandelbrot, B.B. (1982). *The fractal geometry of nature*. New York: W.H. Freeman and Company.

Madden, C. (2007). *Fractals in music*. Salt Lake City, UT: High Art Press.

Massion, J. (1992). Movement, posture, and equilibrium: interaction and coordination. *Progress in Neurobiology, 38,* 35–56. doi:10.1016/0301-0082(92)90034-C

Miller, D.J., Stergiou, N., & Kurz, M.J. (2006). An improved surrogate method for detecting the presence of chaos in gait. *Journal of Biomechanics, 39,* 2873–2876. doi:10.1016/j.jbiomech.2005.10.019

Mureika, J.R. (2005). Fractal dimensions in perceptual color space: a comparison study using Jackson Pollock's art. *Chaos (Woodbury, N.Y.), 15*, 043702. doi:10.1063/1.2121947

Myers, S.A., Johanning, J.M., Stergiou, N., Celis, R.I., Robinson, L., & Pipinos, I.I. (2009). Gait variability is altered in patients with peripheral arterial disease. *Journal of Vascular Surgery, 49*, 924–931. doi:10.1016/j.jvs.2008.11.020

Newell, K.M., & Corcos, D.M. (1993). Issues in variability and motor control. In K.M. Newell & D.M. Corcos (Eds.), *Variability and motor control* (pp. 1–12). Champaign, IL: Human Kinetics.

Odenrick, P., & Sandstedt, P. (1984). Development of postural sway in the normal child. *Human Neurobiology, 3,* 241–244.

Out, L., van Soest, A.K., Savelsbergh, G.J.P., & Hopkins, B. (1998). The effect of posture on early reaching movements. *Journal of Motor Behavior, 30,* 260–272. doi:10.1080/00222899809601341

Platt, J.R. (1964). Strong inference. *Science, 146*, 347–353. doi:10.1126/science.146.3642.347

Riach, C.L., & Hayes, K.C. (1987). Maturation of postural sway in young children. *Developmental Medicine and Child Neurology, 29,* 650–658. doi:10.1111/j.1469-8749.1987.tb08507.x

Rochat, P. (1992). Self-sitting and reaching in 5-to-8-month-old infants: The impact of posture and its development on early eye-hand coordination. *Journal of Motor Behavior, 24,* 210–220. doi:10.1080/00222895.1992.9941616

Schmidt, R.A. (2003). Motor schema theory after 27 years: Reflections and implications for a new theory. *Research Quarterly for Exercise and Sport, 74,* 366–375.

Shumway-Cook, A., & Woollacott, M. (1993). Theoretical issues in assessing postural control. In I.J. Wilhelm (Ed.), *Physical therapy assessment in early infancy* (pp. 161–171). New York: Churchill Livingstone.

Slutzky, M.W., Cvitanovic, P., & Mogul, D.J. (2001). Deterministic chaos and noise in three in vitro hippocampal models of epilepsy. *Annals of Biomedical Engineering, 29,* 607–618. doi:10.1114/1.1380419

Smith, B.A., Stergiou, N., & Ulrich, B.D. (2011). Patterns of gait variability across the lifespan in persons with and without down syndrome. *Journal of Neurologic Physical Therapy; JNPT, 35*, 170–177.

Smith, B.A., Teulier, C., Sansom, J., Stergiou, N., & Ulrich, B.D. (2011). Approximate entropy values demonstrate impaired neuromotor control of spontaneous leg activity in infants with myelomeningocele. *Pediatric Physical Therapy, 23*, 241–247. doi:10.1097/PEP.0b013e3182289ae4

Sosnoff, J.J., Valantine, A.D., & Newell, K.M. (2006). Independence between the amount and structure of variability at low force levels. *Neuroscience Letters, 392*, 165–169. doi:10.1016/j.neulet.2005.09.010

Sosnoff, J.J., & Voudrie, S.J. (2009). Practice and age-related loss of adaptability in sensorimotor performance. *Journal of Motor Behavior, 41,* 137–146. doi:10.3200/JMBR.41.2.137-146

Stergiou, N. (2003). *Innovative analyses of human movement*. Champaign, IL: Human Kinetics.

Stergiou, N., Buzzi, U.H., Kurz, M.J., & Heidel, J. (2004). Nonlinear tools in human movement. In N. Stergiou (Ed.), *Innovative analyses of human movement* (pp. 63–90). Champaign, IL: Human Kinetics.

Stergiou, N., & Decker, L.M. (2011). Human movement variability, nonlinear dynamics, and pathology: Is there a connection? *Human Movement Science, 30*(5), 869–888. doi:10.1016/j.humov.2011.06.002

Stergiou, N., Harbourne, R.T., & Cavanaugh, J.T. (2006). Optimal movement variability: A new theoretical perspective for neurologic physical therapy. *Journal of Neurologic Physical Therapy; JNPT, 30,* 120–129.

Stins, J.F., Michielsen, M.E., Roerdink, M., & Beek, P.J. (2009). Sway regularity reflects attentional involvement in postural control: Effects of expertise, vision and cognition. *Gait & Posture, 30,* 106–109. doi:10.1016/j.gaitpost.2009.04.001

Summers, J.J., & Anson, J.G. (2009). Current status of the motor program: Revisited. *Human Movement Science, 28,* 566–577. doi:10.1016/j.humov.2009.01.002

Thelen, E. (1995). Motor development. A new synthesis. *The American Psychologist, 50,* 79–95. doi:10.1037/0003-066X.50.2.79

Thelen, E., & Ulrich, B. D. (1991). Hidden skills: a dynamic systems analysis of treadmill stepping during the first year. *Monographs of the Society for Research in Child Development, 56*, 1–98 (discussion 99–104).

Tononi, G., Edelman, G.M., & Sporns, O. (1998). Complexity and coherency: integrating information in the brain. *Trends in Cognitive Sciences, 2,* 474–484. doi:10.1016/S1364-6613(98)01259-5

Toweill, D.L., & Goldstein, B. (1998). Linear and nonlinear dynamics and the pathophysiology of shock. *New Horizons (Baltimore, Md.), 6*(2), 155–168.

Vaillancourt, D.E., & Newell, K.M. (2002). Changing complexity in human behavior and physiology through aging and disease. *Neurobiology of Aging, 23,* 1–11. doi:10.1016/S0197-4580(01)00247-0

Wagner, C.D., Nafz, B., & Persson, P.B. (1996). Chaos in blood pressure control. *Cardiovascular Research, 31,* 380–387.

West, B.J. (2006). *Where medicine went wrong: rediscovering the path to complexity, studies of nonlinear phenomena in life science* (Vol. 11). Teaneck, NJ: World Scientific.