



University of Nebraska at Omaha
DigitalCommons@UNO

Journal Articles

Department of Biomechanics

6-2003

Nonlinear dynamics indicates aging affects variability during gait

Ugo H. Buzzi

University of Nebraska at Omaha

Nicholas Stergiou

University of Nebraska at Omaha, nstergiou@unomaha.edu

Max J. Kurz

University of Nebraska at Omaha

Patricia A. Hageman

University of Nebraska Medical Center

Jack Heidel

University of Nebraska at Omaha, jheidel@unomaha.edu

Follow this and additional works at: <https://digitalcommons.unomaha.edu/biomechanicsarticles>

 Part of the [Biomechanics Commons](#)

Recommended Citation

Buzzi, Ugo H.; Stergiou, Nicholas; Kurz, Max J.; Hageman, Patricia A.; and Heidel, Jack, "Nonlinear dynamics indicates aging affects variability during gait" (2003). *Journal Articles*. 82.

<https://digitalcommons.unomaha.edu/biomechanicsarticles/82>

This Article is brought to you for free and open access by the Department of Biomechanics at DigitalCommons@UNO. It has been accepted for inclusion in Journal Articles by an authorized administrator of DigitalCommons@UNO. For more information, please contact unodigitalcommons@unomaha.edu.



NONLINEAR DYNAMICS INDICATES AGING AFFECTS VARIABILITY DURING GAIT

Ugo H. Buzzi¹, Nicholas Stergiou^{1*}, Max J. Kurz¹, Patricia A. Hageman², Jack Heidel³,

¹HPER Biomechanics Lab, University of Nebraska at Omaha

²Physical Therapy Education, University of Nebraska Medical Center

³Department of Mathematics, University of Nebraska at Omaha, Omaha, NE, USA

*Corresponding Author:

Nicholas Stergiou, HPER Biomechanics Laboratory, University of Nebraska at Omaha,
6001 Dodge St., Omaha, NE 68182-0216, USA

Tel: (402) 5543247

Fax: (402) 5543693

E-mail: nstergiou@mail.unomaha.edu

ABSTRACT

Objectives: To investigate the nature of variability present in time series generated from gait parameters of two different age groups via a nonlinear analysis.

Design: Measures of nonlinear dynamics were used to compare kinematic parameters between elderly and young females.

Background: Aging may lead to changes in motor variability during walking, which may explain the large incidence of falls in the elderly.

Methods: Twenty females, ten younger (20-37 yr) and ten older (71-79 yr) walked on a treadmill for 30 consecutive gait cycles. Time series from selected kinematic parameters of the right lower extremity were analyzed using nonlinear dynamics. The largest Lyapunov Exponent and the Correlation Dimension of all time series, and the largest Lyapunov Exponent of the original time series surrogated were calculated. Standard deviations and coefficient of variations were also calculated for selected discrete points from each gait cycle. Independent t-tests were used for statistical comparisons.

Results: The Lyapunov Exponents were found to be significantly different from their surrogate counterparts. This indicates that the fluctuations observed in the time series may reflect deterministic processes by the neuromuscular system. The elderly exhibited significantly larger Lyapunov Exponents and Correlation Dimensions for all parameters evaluated indicating local instability. The linear measures indicated that the elderly demonstrated significantly higher variability.

Conclusions: The nonlinear analysis revealed that fluctuations in the time series of certain gait parameters are not random but display a deterministic behavior. This behavior may degrade with physiologic aging resulting in local instability.

Relevance

Elderly show increased local instability or inability to compensate to the natural stride-to-stride variations present during locomotion. We hypothesized that this may be the one of the reasons for the increases in falling due to aging. Future efforts should attempt to evaluate this hypothesis by making comparisons to pathological subjects (i.e. elderly fallers), and examine the sensitivity and specificity of the nonlinear methods used in this study to aid clinical assessment.

Key words: variability; elderly; locomotion; chaos; nonlinear dynamics

INTRODUCTION

Variability is a central characteristic of all human movement. The most common interpretation of this variability is that it is the result of random processes (noise). However, literature from several disciplines, have shown that many apparently noisy phenomena are the result of nonlinear interactions and have deterministic origins (1). As such, the “noisy” component of the measured signal may reveal important information about the system that produced it.

Variability has also been linked to the health of biological systems. Examples include cardiac disease, epileptic seizures, and other neurological impairment conditions (2, 3). Goldberger et al (4), using tools from nonlinear dynamics, observed different variability patterns in heart rhythms among healthy and diseased patients. Goldberger and colleagues suggested that a healthy system has a certain amount of inherent variability. This healthy variability is not random but contains order and can be characterized via nonlinear mathematical descriptors. Pool (1) speculated that this “deterministic” variability might provide a healthy flexibility to the heart, brain, and other parts of the body. Conversely, many ailments may be associated with a loss of this flexibility. Collectively, methods from nonlinear dynamics may be beneficial in describing and understanding variability and subsequently identifying health status.

Differences in motor variability between elderly and young walkers have been previously demonstrated. Hausdorff et al (5) found significant increases in step rate variability in elderly subjects when compared with young controls. Increases in stride-to-stride variability have also been shown in elderly fallers (6). Maki (7) reported that increased variability of several gait parameters is related with an increased risk of falling

in the elderly. This result has been attributed to a possible loss of motor control in the elderly. Guimares and Isaacs (8) found a more variable step length in the elderly when compared to a young group. Although these studies reported greater motor variability in the elderly, the analysis of this variability was usually limited to traditional linear statistical methods.

Traditional linear tools can mask the true structure of motor variability, since during gait analysis biomechanical data from a few strides are averaged to generate a mean ensemble curve. A mean ensemble curve is used to define an “average” picture of the subject’s gait. This averaging procedure is frequently accompanied by time normalization. Time normalizing the data tends to “stretch” or “pull” the original data. As a result, the temporal variations of the gait pattern are lost. On the contrary nonlinear techniques focus on understanding how variations in the gait pattern change over time (9, 10). The structure of the original data is preserved and stride-to-stride variations are studied over multiple gait cycles.

Furthermore, previous studies on motor variability did not attempt to explain the “nature” of the variability found in the elderly gait pattern. In other words, no investigations have determined whether these differences in variability are attributed to biological noise or if these differences are inherent (possibly deterministic) within the system. Random noise within a system may be attributed to several sources, including measurement error and/or a degradation of the neuromuscular control mechanism of the body. Inherent motor variability is the variation within a system that provides the ability to accommodate for possible perturbations the system may experience. It has been suggested that this variability may have deterministic origin and order (9). Quantifying

motor variability may lead to an understanding of the effects of aging on neural control mechanisms during walking.

Thus, the purpose of this study was to quantify the variability present in time series generated from gait parameters of two different age groups via nonlinear analysis. We hypothesized that aging will affect variability in the gait parameters measured.

METHODS

Subjects

Ten healthy young (mean age 25.10, SD 5.30 yrs; mean height 1.70, SD 0.049 m; mean mass 63.93, SD 6.53 kg) and ten healthy older (mean age 74.6, SD 2.55 yrs; mean height 1.59, SD 0.053 m; mean mass 64.07, SD 9.69 kg) women who had prior treadmill walking experience participated in the study. The elderly subjects met the following criteria: independent ambulation, independent living in the community, no neurological pathology, no acute illness, and no restrictions in activities of daily living. Screening of the elderly subjects for neuromuscular deficiencies beyond aging was performed by a licensed physical therapist. Prior to testing, each subject read and signed an informed consent that was approved by the University Institutional Review Board.

Experimental protocol

Subjects walked on a treadmill, while sagittal kinematic data of the right lower extremity were collected using a high-speed (60 Hz) camera (Panasonic, model WV-CL350) interfaced to a high-speed video recorder. Prior to videotaping, reflective markers were placed at the greater trochanter, lateral femoral condyle, and lateral malleolus of the right lower extremity. Subjects were asked to walk on the treadmill at a self-selected pace. This represented their most comfortable and natural walking speed. The usage of a self-selected comfortable pace ensured that any potential discomfort that could have been introduced by using a pre-determined speed for all subjects was minimized (11). Had a pre-determined speed been used, subjects may have been put into a transitioning stage. This stage is marked by increased variability, as opposed to a more stable (less variable) state, that occurs with a self-selected pace (12). The subjects were allowed to warm-up for a minimum of eight minutes. An eight-minute duration of

warm-up has been considered sufficient for individuals to achieve a proficient treadmill movement pattern (13). No fatigue effects were reported as a result of the warm-up for the elderly group. During the warm-up session, each subject established a self-selected comfortable walking pace. Once subjects acknowledged that they were warmed-up, kinematic data were recorded for 30 continuous footfalls/gait cycles.

Data analysis

The hip, knee, and ankle joint markers were digitized using the Peak Performance Technologies' Motus 4.0 system (Peak Performance Technologies, Inc., Englewood, Colorado, USA). The coordinates of these joint markers were also used for calculating the relative knee angle. The continuous data, or time series, from the 30 gait cycles for the hip, knee, ankle Y-coordinates (vertical displacement) and the relative knee angles for each subject were analyzed. This allowed for the evaluation of both linear and angular kinematic parameters during gait. The 30 continuous gait cycles allowed the examination of an average of 2441 data points for each variable. This number is considered adequate for the nonlinear analysis performed in this study (14-17). The data were analyzed unfiltered to get a more accurate representation of the variability within the system (15). It was assumed that since the same instrumentation was used for all subjects, the level of measurement noise would be consistent for all subjects. Therefore, any differences could be attributed to changes within the system itself (18). In addition, it has been suggested that filtering of time series should be avoided because it can affect calculations of nonlinear tools (19).

To quantify motor variability during gait in terms of nonlinear dynamics we initially examined "local stability". Local stability is defined as the sensitivity of the system to small perturbations, such as the natural stride-to-stride variations present during

locomotion (9, 20). We sought to understand how elderly subjects compensate to these variations. If motor variability is related to local stability, then the increased variability that was reported in the literature for the elderly should also result in increased local instability. Local stability was quantified using nonlinear time-series methods (9, 20). These methods are based on examining the structural characteristics of a time series that is embedded in an appropriately constructed state space (Figures 1A, 1B). An appropriate state space is a vector space where the dynamical system can be defined at any point (21). The first step in using nonlinear methods is to properly reconstruct the state space that the system occupies by calculating the number of embedding dimensions (21). A dynamical system can be extracted from a single time series and the topological structure of the system can be created (21). The number of dimensions that this structure represents in state space is the embedding dimension. Incorporating an accurate number of embedded dimensions when calculating nonlinear parameters ensures that the dynamical properties of the system remain unchanged when deriving multidimensional dynamic information from a unidimensional time series (18, 21). In the present study, the estimation of the embedded dimensions was performed using the Global False Nearest Neighbor (GFNN) analysis (21). Our GFNN calculations indicated that five embedded dimensions is the minimum number of variables that is required to form a valid state space from a given time series. Similar results were found for all time series for all subjects in both groups.

INSERT FIGURE 1 ABOUT HERE

After determining the embedded dimension of the time series, the estimation of local stability can be conducted by calculating the largest Lyapunov Exponent (LyE) (17). The calculation of the LyE was performed for all time series using the Chaos Data Analyzer software (15). The LyE is a measure of the stability of a dynamical system and

its dependence on initial conditions. A dynamical system is a system that continuously changes over time such as the human during walking. Such a system is highly dependent on initial conditions, which are the constraints (e.g. strength limits, joint laxity, sensory abilities) that underline its function (18). The LyE quantifies the exponential separation of trajectories with time in state space (Figure 1C). As nearby points separate, they diverge rapidly and produce instability. The LyE 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 (9,17). Periodic systems will result in LyE that are negative or zero. Positive LyE typically indicates the presence of determinism within a time series. However, completely random data will also produce positive LyE. Thus, it is important to validate results against surrogate data to distinguish a true deterministic origin from randomness (19, 22).

Surrogation is a technique that can accurately determine if the source of the stride-to-stride variations in a given time series is actually deterministic in nature (9, 19, 22). The surrogation technique removes the deterministic structure from the original time series, generating a random equivalent with the same mean, variance, and power spectra as the original (Figure 2). Therefore, all the time series generated for all conditions were surrogated using a phase randomization analysis (22). This analysis was performed in Matlab (MathWorks, Natick, MA, USA) using the algorithms developed by Theiler et al (22). Surrogate data sets were generated for all original time series. The LyE for all surrogate time series were computed and statistically compared to the LyE of their original counterparts. Significant differences in LyE between the original and their

surrogate counterparts indicate that the stride-to-stride variations observed in the original data are not randomly derived and may be deterministic in nature.

INSERT FIGURE 2 ABOUT HERE

The last technique that we used from nonlinear dynamics was the Correlation Dimension (COD). The calculation of the COD was performed for all time series using the Chaos Data Analyzer software (15). The COD is a measure of how the data points of a dynamical system are organized within a state space (Figure 1A and 1B). This measure approximates the fractal dimension of the region in state space occupied by the dynamical system (23, 24). The COD is typically considered to be an accurate measure when working with small data sets because it focuses efficiently on the areas of space that actually contain data points (15, 16, 23). Completely random data will be characterized by a large COD along with a large LyE (15, 23), while chaotic/deterministic data usually have smaller COD and LyE values.

Known deterministic/chaotic (the Lorenz attractor), random, and periodic (the sine wave) time series were also evaluated using the same nonlinear algorithms as the experimental data (surrogation, LyE and COD). These data sets were used as a basis of comparisons. Linear statistical analyses were also employed for comparison purposes with the available literature. The maximum and minimum values for the hip, knee, ankle vertical displacement, and the knee angle for each gait cycle were identified. Standard deviations (SD) and coefficients of variation (CV) for each parameter, for each subject, were calculated. SD and CV were then averaged across each group to determine overall mean group variability. Finally, independent student t-tests were performed on the subject values for LyE, COD, SD, CV, and the walking speed. The level of significance was set at $P < 0.05$.

RESULTS

The group mean SD and CV values for both age groups are presented in Table 1. For CV, significant differences were found between the young and elderly groups for all parameters except the maximum of the hip vertical displacement. For the SD, significant differences were found for the minimum of the hip vertical displacement, and the minimums and maximums of the ankle vertical displacement and the knee angles. For all comparisons, the young group exhibited smaller SD and CV values than the elderly.

INSERT TABLE 1 ABOUT HERE

The group mean values of the nonlinear parameters for both age groups are presented in Table 2. Significant differences were found for the LyE and COD across all parameters evaluated. Both LyE and COD values were greater for the elderly group in all instances. A graphical evaluation provided further support to these results. Representative phase portraits from both groups and for all the parameters analyzed are presented in Figure 3. Marked differences can be seen between the two groups. The elderly plots show more divergence in their trajectories, while the young group trajectories are confined within a tighter space.

INSERT TABLE 2 AND FIGURE 3 ABOUT HERE

All LyE values were found to be positive (Table 2). Except for the hip vertical displacement in the young, significant differences were found between the LyE values for all original time series and the LyE values for their surrogate counterparts. This result suggested that the fluctuations observed in the original time series may be deterministic in nature, and not randomly derived (Table 2).

To establish a basis for comparison, known deterministic/chaotic (the Lorenz attractor), random, and periodic (the sine wave) time series were also analyzed. Table 2

reports the values calculated for these series. Positive values were obtained for both chaotic and random time series. LyE for the chaotic time series was smaller than that of the random time series and was also associated with a substantially smaller COD. The periodic time series had a negative LyE that was very close to zero. As expected, the periodic and chaotic time series were significantly different from their surrogate counterparts (Table 2). This was not the case with the random time series.

Lastly, the group means for the walking speeds were 1.140 (SD 0.247) $\text{m}\cdot\text{s}^{-1}$ for the young and 0.849 (SD 0.218) $\text{m}\cdot\text{s}^{-1}$ for the elderly group. The statistical analysis indicated that the elderly group walked significantly slower than the young.

DISCUSSION

The results of the traditional linear measures of variability used in this study, demonstrated significant differences between the young and the elderly. These results are in agreement with other studies (5-8) that showed increased variability in gait parameters in elderly populations. This has been attributed to a loss of motor control in the aging population. However, from the traditional linear measures we cannot distinguish between increases in noise within the system and inherent variability. Quantifying the nonlinear dynamics of a system may help us to understand changes in the actual motor control mechanisms that result from aging. The SD and the CV, while giving accurate measures of motor variability within the system, are not explanatory of the underlying neural processes of human movement. The nonlinear measures helped us to understand the motor variability within a system, and not just provide a measure of the amount of variability that is present. Furthermore, as stated previously, traditional linear tools can mask the true structure of motor variability, since few strides are averaged to generate a “mean” picture of the subject’s gait. In this averaging procedure, the temporal variations of the gait pattern may be lost. On the contrary nonlinear techniques focus on understanding how variations in the gait pattern change over time (9, 10).

To quantify motor variability during gait in terms of nonlinear dynamics we examined “local stability”. Local stability is defined as the sensitivity of the system to small perturbations, such as the natural stride-to-stride variations present during locomotion (9, 20). We sought to understand how elderly subjects compensate to these variations. If motor variability is related to local stability, then the increased variability that was reported in the literature for the elderly should also result in increased local instability. The estimation of local stability can be conducted by calculating the LyE.

The LyE values for all gait parameters analyzed, except the hip vertical displacement for the young group, were positive and found to be significantly different from their surrogate counterparts (Table 2). This indicates that the fluctuations observed in the time series may reflect deterministic processes by the neuromuscular system. The fact that the original time series were significantly different from their surrogate counterparts even for the elderly, indicated that despite any aging degradation of the neuromuscular system, the deterministic behavioral properties of the motor variability were preserved. These deterministic behavioral properties may provide the neuromuscular system with the necessary mechanisms to adapt to changing conditions, while generating effective movement patterns.

Despite the fact that the deterministic properties of gait were maintained, changes in the underlying variability were apparent. The LyE values for the elderly were found to be significantly higher (i.e. more locally unstable) than the young (Table 2). These results indicated that changes in local stability were present. As it was mentioned previously, a time series consisting of random or noisy data can also produce a positive LyE. As indicated in Table 2, the random time series has an LyE value that is larger than the one produced from the chaotic data. Thus, the larger LyE values in the elderly may be interpreted as revealing more noise and more local instability within their time series when compared to the young. This interpretation can also be supported by the COD results. The COD values for all time series analyzed were significantly lower in the young group (Table 2). As it can be observed in Table 2, the known chaotic data had smaller COD values than the random data. Therefore, the coupling of the LyE and the COD results may be indicative of less noise and more local stability in the young group. This conclusion is also supported by previous studies in cardiology where significant

differences were found due to aging. Specifically, Kaplan et al (25) found that the cardiovascular system of a group of healthy young subjects was more complex and chaotic, than a healthy elderly group. They concluded that there were genuine changes in the cardiovascular system associated with age.

It has been previously reported (5-8) that there are differences in gait patterns between young and elderly walkers. More specifically, it is believed that the elderly make certain alterations in their gait to avoid falling. Maki (7) reported that the most common alterations are increased double support time and reduced stride length and velocity. Hageman (26) made similar remarks and suggested that these adaptations are made in order to undergo a safer, more stable gait. Slower walking speeds provide individuals with increased time to avoid obstacles or any other perturbations, which may cause falling (7). In the present study, we also found that the elderly walked with a slower speed. Winter (27) suggested that these adaptations might be a result of an inability in the elderly to regulate motor control. An adaptation by the elderly toward a slower and safer gait is made in order to avoid falling. Thus, it is generally accepted that elderly individuals tend to walk in a safer, more careful manner. However, falls continue to be a leading cause of morbidity in the elderly, which poses an interesting question. If older adults are walking more carefully, then why do they continue to fall? The results of the present study may provide an intriguing explanation for this phenomenon. The fact that the elderly were significantly more “noisy” and more locally unstable than the young, may be attributed to a decrease in motor control. Deficiencies in the ability to actively control joint motion may manifest itself in increased noise and more local instability at these given joints. This may be the cause of elderly falls, despite safer walking patterns. In support to this explanation, Hausdorff et al. (6) reported that variability in temporal

gait parameters was significantly increased in the elderly compared to the young and it was even larger in a group of elderly fallers. Based on the above, it can be proposed that the increased falls due to aging may be due to the inability of the elderly to compensate to the natural stride-to-stride variations present during locomotion. In other words, the elderly may have increased local instability.

The above results provide also ground for an interesting hypothesis regarding motor variability. It is possible that changes in motor variability may in fact be the consequence of modifications not only in the deterministic operation of the adaptive complex control systems, but also in intrinsic stochasticity (noise). For example in the elderly, while the deterministic properties of gait were preserved, an increase in noise was also observed. It is possible that motor variability can actually be represented by a continuum. The two ends of the continuum are complete regularity and complete randomness. A “healthy” optimal motor variability is somewhere between the two ends. Decreases or losses of this variability can make the system more rigid and less adaptable. Increases can make the system more noisy and unstable, like in the elderly. This theoretical model needs to be tested in the future via carefully planned experiments possibly using diverse and pathological populations.

An additional observation from the results of the present study is that the LyE increased from the ankle toward the hip. This may indicate an increase in local instability in the system, which can be due to the ground restriction at the lower end and the decrease in the available degrees of freedom. The knee and especially the hip, are also associated with a greater amount of musculature, producing an increasing variety of movements. These joint and musculature factors increase the degrees of freedom available at the hip and knee, and may affect local stability.

It should be noted that the results of this study are derived from a relatively small sample size. Measures of variability may be more conclusive using a larger number of subjects. Also, fractal and spectral analysis were not performed in this case, nor were several other measures of nonlinear dynamics (i.e. approximate entropy), which may serve to more accurately quantify actual differences between the young and the elderly.

CONCLUSIONS

In summary, we have found that fluctuations in the time series of certain linear and angular kinematic parameters during gait are not random but display a deterministic behavior. This behavior may degrade with physiologic aging resulting in local instability. Elderly subjects showed increased inability to compensate to the natural stride-to-stride variations present during locomotion. We hypothesized that this may be one of the reasons for the increases in falling due to aging. Future efforts should attempt to evaluate this hypothesis by making comparisons to pathological subjects (i.e. elderly fallers), and examine the sensitivity and specificity of the nonlinear methods used in this study to aid clinical assessment.

REFERENCES

1. Pool R. Is it healthy to be chaotic? *Science* 1989; 243: 604-607.
2. Goldberger A, Bhargava V, West B, Mandell AJ. Some observations on the question: is ventricular fibrillation “chaos”? *Physica* 1986; 19: 282-289.
3. Rapp PE, Zimmerman ID, Albano AM, deGuzman, GC, Greenbaun, NN, Bashore, TR. Experimental studies of chaotic neural behavior: cellular activity and electroencephalographic signals. *Nonlinear Oscillations in Biology and Chemistry*. Berlin, Germany: Springer-Verlag, 1986; 175-205.
4. Goldberger AL, Rigney DR, Mietus J et al. Nonlinear dynamics in sudden cardiac death syndrome: heart rate oscillations and bifurcations. *Experientia* 1998; 41: 983-987.
5. Hausdorff JM, Forman DE, Ladin Z et al. Increased walking variability in elderly persons with congestive heart failure. *J Am Geriatr Soc* 1994; 42: 1056-1061.
6. Hausdorff JM, Edelberg HK, Mitchell SL et al. Increased gait unsteadiness in community dwelling elderly fallers. *Arch Phys Med Rehabil* 1997; 78: 278-283.
7. Maki BE. Gait changes in older adults: predictors of falls or indicators of fear. *J Am Geriatr Soc* 1997 45: 313-320.
8. Guimares RM, Isaacs B. Characteristics of gait in old people who fall. *Int Rehabil Med* 1980; 2: 177-180.
9. Dingwell JB, Cusumano JP. Nonlinear time series analysis of normal and pathological human walking. *Chaos* 2000; 10: 848-863.

10. Hausdorff JM, Mitchell SL, Firtion R et al. Altered fractal dynamics of gait: reduced stride-interval correlations with aging and Huntington's disease. *J Appl Physiol* 1997; 82: 262-269.
11. Sekiya N, Nagasaki H, Ito H, Furuna T. Optimal walking in terms of variability in step length. *J Orthop Sports Phys Ther* 1997; 27: 266-272.
12. Diedrich FJ, Warren WH. Why change gaits? Dynamics of the walk-run transition. *J Exp Psychol* 1995; 21: 183-202.
13. Jeng SF, Liao HF, Lai JS, Hou JW. Optimization of walking in children. *Med Sci Sports Exerc* 1997; 29: 370-6.
14. Abraham NB, Albano AM, Das B et al. Calculating the dimension of attractors from small data sets. *Phys Lett A* 1986; 144:217-221.
15. Sprott JC, Rowlands G. *Chaos Data Analyzer*. New York, NY: American Institute of Physics, 1992.
16. Grassberger P, Procaccia I. Characterization of strange attractors. *Phys Rev Lett* 1983; 50: 346-349.
17. Wolf A, Swift JB, Swinney HL, Vastano JA. Determining Lyapunov exponents from a time series. *Physica* 1985; 16: 285-317.
18. Kaplan DT, Glass L. *Understanding Nonlinear Dynamics*. New York, NY: Springer-Verlag, 1995.
19. Rapp PE. A guide to dynamical analysis. *Integr Physiol Behav Sci* 1994; 29: 311-327.
20. Dingwell JB, Cusumano JP, Sternad D, Cavanagh PR. Slower speeds in patients with diabetic neuropathy lead to improved local dynamic stability of continuous overground walking. *J Biomech* 2000; 33: 1269-1277.

21. Abarbanel HDI. Analysis of Observed Chaotic Data. New York, NY: Springer-Verlag, 1996.
22. Theiler J, Eubank S, Longtin A et al. Testing for nonlinearity in time series: the method of surrogate data. *Physica D* 1992; 58: 77-94.
23. Grassberger P, Procaccia I. Measuring the strangeness of strange attractors. *Physica D* 1983; 9: 189-208.
24. Theiler J. Spurious dimensions from correlation algorithms applied to limited time series data. *Phys Rev* 1986; 34: 2427-2433.
25. Kaplan DT, Furman MI, Pincus SM et al. Aging and the complexity of cardiovascular dynamics. *Biophys J* 1991; 59: 945-949.
26. Hageman PA. Gait characteristics of healthy elderly: a literature review. *Issues Aging* 1995; 18: 14-18.
27. Winter DA, Patla AE, Frank JS, Walt SE. Biomechanical walking pattern changes in the fit and healthy elderly. *Phys Ther* 1990; 70: 340-347.

Table 1. Group means for SD and CV for both groups (standard deviation). Significant differences ($P < 0.05$) between groups are marked with an asterisk (*). Standard deviation units marked with † are reported in degrees.

<i>Variables:</i>	<i>SD</i> (cm)	<i>CV</i>
Hip min. – Young:	0.349* (0.067)	0.330* (0.067)
Hip min. – Elderly:	0.446* (0.125)	0.501* (0.147)
Hip max. – Young:	0.255 (0.139)	0.235 (0.136)
Hip max. – Elderly:	0.276 (0.100)	0.298 (0.111)
Knee min. – Young:	0.295 (0.099)	0.454* (0.164)
Knee min. – Elderly:	0.366 (0.081)	0.669* (0.164)
Knee max. – Young:	0.267 (0.088)	0.347* (0.130)
Knee max. – Elderly:	0.329 (0.097)	0.540* (0.154)
Ankle min. – Young:	0.105* (0.034)	0.360* (0.142)
Ankle min. – Elderly:	0.188* (0.485)	0.940* (0.253)
Ankle max. – Young:	0.298* (0.106)	0.672* (0.261)
Ankle max. – Elderly:	0.621* (0.279)	1.814* (0.820)
Knee angle min. – Young[†]:	1.246* (0.595)	1.117* (0.562)
Knee angle min. – Elderly[†]:	2.040* (0.799)	1.761* (0.622)
Knee angle max. – Young[†]:	1.332* (0.472)	0.782* (0.282)
Knee angle max. – Elderly[†]:	1.997* (0.715)	1.167* (0.426)

Table 2. Group means from both groups for the nonlinear measures used in the present study (standard deviation). Significant differences ($P < 0.05$) between groups are marked with an asterisk (*). Significant differences ($P < 0.05$) between the original times series and their surrogate counterparts are marked with a plus sign (+). LyE = Lyapunov Exponent from the original time series; S- LyE = Lyapunov Exponent from their Surrogated counterpart; COD = Correlation Dimension from the original time series.

<i>Variables:</i>	<i>LyE</i>	<i>S-LyE</i>	<i>COD</i>
Periodic:	-0.001	0.113+	1.167
Chaotic:	0.100	0.341+	1.941
Random:	0.469	0.470	4.723
Hip – Young:	0.179* (0.030)	0.199 (0.032)	3.018* (0.346)
Hip – Elderly:	0.219* (0.021)	0.279+ (0.039)	3.437* (0.259)
Knee – Young:	0.127* (0.037)	0.213+ (0.023)	2.938* (0.268)
Knee – Elderly:	0.145* (0.054)	0.286+ (0.031)	3.542* (0.484)
Ankle – Young:	0.078* (0.020)	0.241+ (0.031)	2.886* (0.243)
Ankle – Elderly:	0.098* (0.033)	0.270+ (0.029)	3.346* (0.346)
Knee angles – Young:	0.107* (0.027)	0.265+ (0.012)	2.348* (0.335)
Knee angles – Elderly:	0.154* (0.027)	0.288+ (0.023)	2.633* (0.226)

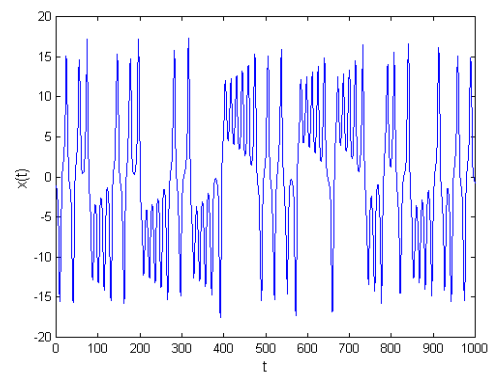
LEGENDS TO FIGURES

Figure 1. A graphical representation of the state space and the calculation of the LyE. A) An original time series adopted from a known chaotic data set (the Lorenz attractor). B) From this time series a state space is created (26). For a better visual display, this state space is plotted here in three dimensions. C) A section of the state space where the divergence of neighboring trajectories is outlined. The LyE is calculated as the slope of the average logarithmic divergence of the neighboring trajectories.

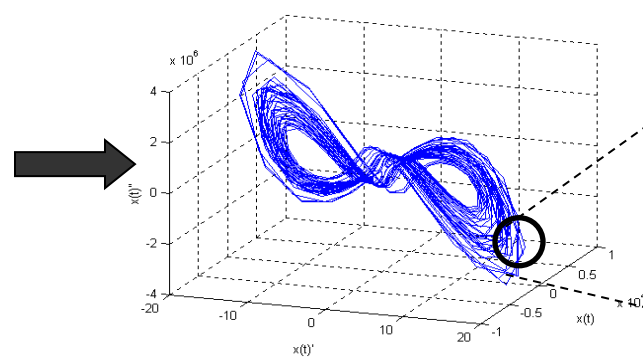
Figure 2. A graphical representation of the surrogation procedure. A) An original time series. B) A description of the algorithm applied. C) The surrogate counterpart of the original time series. This surrogate time series has the same mean, variance and power spectra as the original time series. The algorithm used is from Theiler et al (28).

Figure 3. Representative phase portraits from one elderly and one young subject for hip, knee, and ankle Y-coordinates and knee angles.

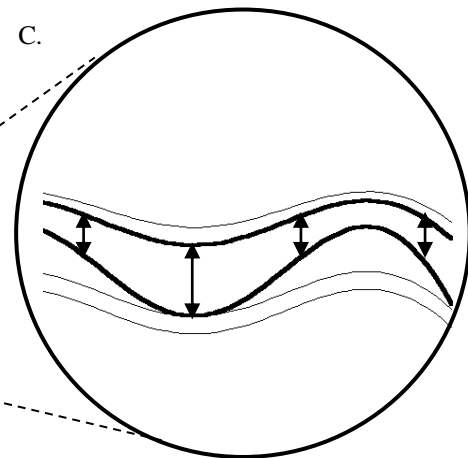
A.



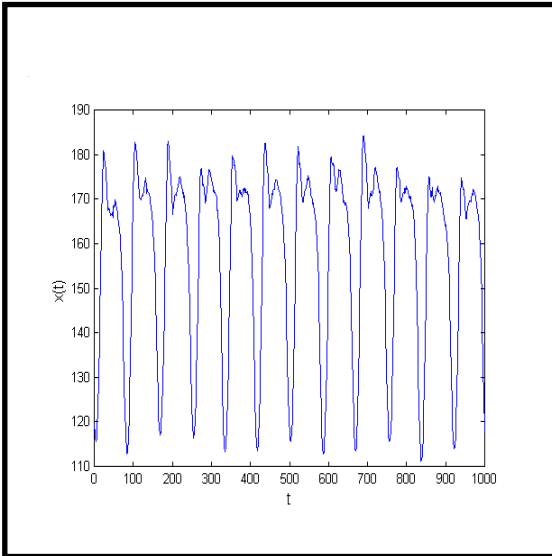
B.



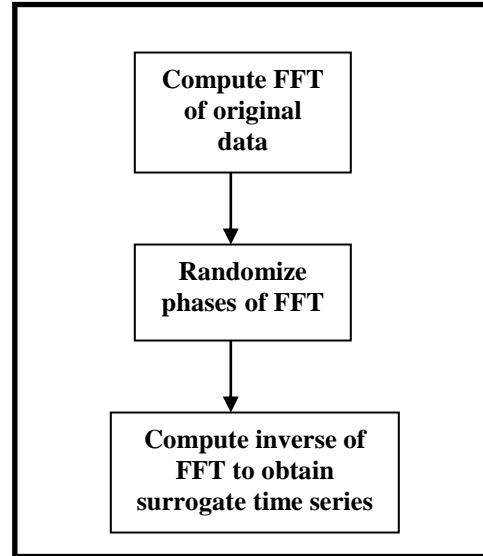
C.



A.



B.



C.

