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Quantitative analysis of nonlinear joint motions for young males during walking

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Abstract

Body motions associated with walking exhibit irregular and complex patterns with time. Chaos analysis methods have been developed to clarify nonlinearity of the lower extremity motions. No research has been reported on chaos analysis of the upper extremity joints. The purpose of this study was to investigate chaotic characteristics of movements of the upper body as well as the lower extremity during level walking. Gait experiments were carried out for eighteen young males. Each subject was instructed to walk on a treadmill at his own natural speed. Flexion-extension angles of eleven joints were obtained by using eight video cameras. To evaluate joint characteristics in a quantitative way, the largest Lyapunov exponent (LLE) was calculated from a reconstructed state space created by time series and embedding dimension. The mean LLE ranged from 0.080 to 0.137 for the upper body, and from 0.090 to 0.182 for the lower extremity joints. The mean LLE of the upper extremity joints was statistically different from that of the lower extremity joints ($p<0.05$). The results obtained can be used as a valuable reference for the normal gait for further studies of abnormal walking.

Keywords: Chaos analysis; Embedding dimension; Largest Lyapunov exponent; Joint motions; Nonlinear dynamics

1. Introduction

Gait is one of the most important issues in biomechanics. In order to determine gait characteristics, motion measurements are indispensable for the analysis of dynamic balancing of human extremities. Quantitative analyses of normal gait would be very helpful to understand how the total body establishes its stability. Researches on stride variability in walking have been done to estimate stability of the total body [1-3]. But such a linear method as the mean analysis has been limited in biodynamic phenomenon analyses [4-6].

Body motions associated with walking show irregular patterns though they seem apparently periodic. A number of researchers have developed chaos analysis methods to understand nonlinearity of the lower extremity motions. Recently, it has been repeated that gait motions exhibit chaotic characteristics during walking [4-8]. Researchers found that the gait signal possesses properties of typical deterministic chaotic systems. Dingwell and Cusumano [4] defined local stability as the sensitivity of the lower extremity to small perturbations and used it to compare between diabetic neuropathic patients and healthy controls. They found their nonlinear approach to be more suitable to explain stability during continuous walking than the traditional method of stride-to-stride variability. The analysis of lower extremity motions has been well established even for clinical applications to patients.

However, the understanding of the upper body motions was not sufficient [9]. Ford et al. [10] re-

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ported that a constrained arm movement resulted in alteration in walking frequency and phase relation between the arm and the leg [10]. They mentioned that persons with upper extremity movement dysfunction may be affected with walking stability problems due to atypical coordination between the upper and lower extremity movements at higher walking velocities. The coordination between the upper and lower extremities for walking stability is still unknown. Few attempts have been made to evaluate quantitatively nonlinear behaviours of the upper body motion during walking.

The purpose of this study was to quantify and investigate nonlinear motions of the upper body as well as the lower extremity. A novel approach attempted is to extend the nonlinear analysis to the total body during level walking. Joints analyzed include the neck, the right and the left shoulders, elbows, hips, knees and ankles. The largest Lyapunov exponent (LLE) was calculated as a chaotic measure from the time series of the flexion-extension angle of every joint. Statistical analyses were performed with the calculated LLEs of the eleven joints for each of eighteen young males involved in gait experiments.

Table 1. Personal information of subjects.

Subject	Age (years)	Height (cm)	Weight (kg)	Walking speed (m/s)
1	20	176	62	1.25
2	25	177	100	0.97
3	32	185	85	1.25
4	27	173	83	0.97
5	25	170	75	0.83
6	20	169	61	0.83
7	19	173	65	0.97
8	20	175	68	1.25
9	29	171	70	0.97
10	23	184	68	1.11
11	24	176	73.5	1.11
12	24	185	70	1.25
13	20	176	74	1.25
14	24	175	63	1.11
15	21	182	80	1.25
16	24	165	73	1.25
17	24	178	71	0.97
18	24	176	73	1.25
Avg.	23.6	175.9	73.0	1.10
STD	3.4	5.5	9.5	0.16

2. Material and method

2.1 Subjects

Eighteen young healthy males volunteered for this study. Their age, weight and height were 23.6±3.4 years, 73.0±9.5 kg and 175.9±5.5 cm, respectively (Table 1). All subjects were asked to walk on a treadmill (KEYTEC® AC9, Taiwan) while eight video cameras (DCR-VX2100, Sony, Japan) were used to capture their motions. To obtain the motions of the eleven joints a total of thirty-one reflective markers were placed on selected bony landmarks of the body (Fig. 1). The markers were carefully positioned on the skin of the subjects by one investigator to remove any possible personal error. The marker coordinates and joint angles were calculated by Kwon3D software (Visol Corp., Korea).

All subjects were fully informed about the gait experiment. They were given enough time to become warmed up and familiar with walking on the treadmill at their own paces. This testing was based on the report that walking speed at one's own pace was the most stable [6]. The motion data were obtained from every subject for 90 seconds after warming up.

Fig. 1. Markers attached to a subject.

2.2 Joint angles

A time series was constructed for each joint from the flexion-extension angle defined in the sagittal plane. The reason for using this angle is that the flexion-extension remains the most prominent joint motion during gait. Therefore, we excluded the internal-external rotations, adduction-abduction and varus-valgus rotations from the analysis to minimize erroneous signals.

The markers were classified into the primary and secondary ones in Kwon3D software to define joint angles (Fig. 2). The primary markers were placed on the skin and the secondary markers, i.e., virtual ones, represented joint centers. For example, a virtual point between the medial and lateral epicondyle markers becomes a secondary marker to represent the center of a knee joint.

The markers used in defining joint angles are shown in Fig. 2. The vectors of body segments were defined from the marker positions. Each angle was then calculated by the inner product of two vectors of the adjacent segments crossing the joint. In the figure θ_1, θ_2, θ_3, θ_4, θ_5 and θ_6 denote the flexion-extension angles of the neck, shoulder, elbow, hip joint, knee and ankle, respectively.

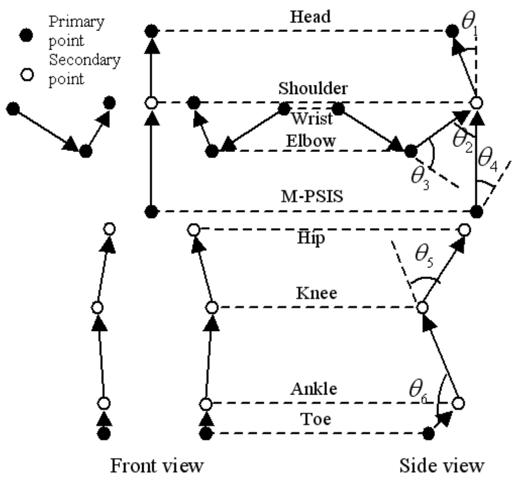


Fig. 2. A human link model constructed with the primary and secondary markers.

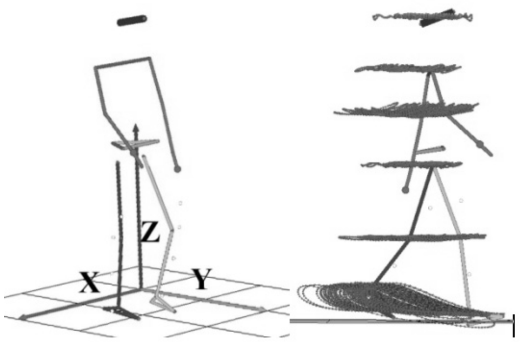


Fig. 3. The stick figures of body model (left) and trajectories of joints during walking (right).

2.3 Chaos analysis

A set of typical time series of flexion-extension angles is shown in Fig. 4. Each time series consisted of a total of 5,430 data points, which is considered sufficient for this type of analysis [11]. The figures show how joint motions changed with time at the neck, shoulder, elbow, hip, knee and ankle of a representative subject, Subject M1. More irregularities were found in the motions of the neck and ankles than those of the shoulders and knees. The neck and the ankle seemed to be more chaotic in flexion-extension than the other joints.

Unfiltered data were analyzed in this study for a more accurate representation of joint variability. Furthermore, since the same instrumentation was used for all subjects, it was assumed that the level of measurement noise would be consistent for all subjects and that any difference could be attributed to changes within the joint itself [12]. Therefore, filtering the data may eliminate important information and provide a skewed view of the inherent joint variability [13].

A state space vector $y(t)$ which consisted of the vector components $[x(t), x(t+T_1), x(t+T_2)...]$ was formed from the original time series. This vector should be made to contain mutually exclusive information about the dynamics of the system [14]. For this, an appropriate time delay was determined by using the average mutual information (AMI) function. This criterion sets the time delay equal to the value of delay corresponding to the first minimum of the AMI function.

In order to unfold the dynamics of the system, embedding dimension was determined in a proper state space. A reconstructed state vector was formed from the state vector $y(t)$ as follows: $Y(t) = [x(t), x(t+T), x(t+2T), ..., x(t+(d_e-1)T)]$, where T is the calculated time delay and d_e is the calculated number of embedding dimension. A suitable embedding dimension was chosen by using the false nearest neighbour (FNN) method [15]. An inappropriate number of embedding dimensions may yield a projection of the dynamics of the system that has orbital crossings in the state space. These crossings would be due to false neighbours and far from the actual dynamics of the system [15]. Total percentage of false neighbours was computed by FNN method, and the number of dimensions was chosen where this percentage approaches zero. In this study two m-files for calculating the time

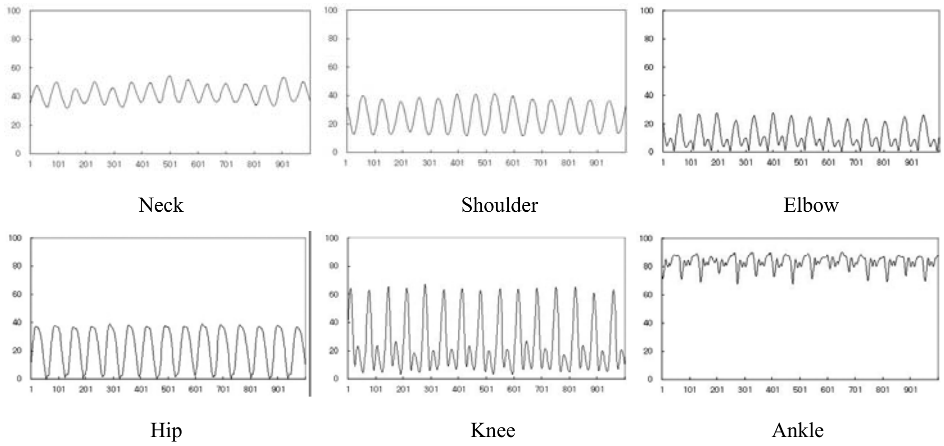


Fig. 4. Time series of flexion-extension angles at six joints.

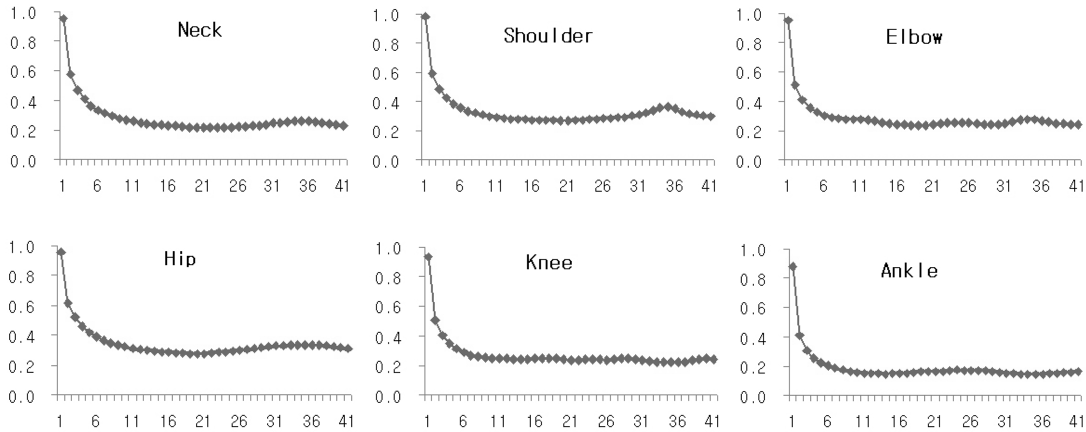


Fig. 5. Selection of delay times for six joints.

delay and the number of embedding dimensions were coded by using MATLAB (The MathWorks Corp., USA).

The Largest Lyapunov exponent (LLE) quantifies the exponential divergence of the neighbouring trajectories in the reconstructed state space. This information is necessary to identify the stability of the time series. Thus, LLEs provide a direct measure of the sensitivity of the system. As nearby points of the state space separate, they diverge rapidly as to produce instability. The LLE for a stable system with little or no divergence is approximately zero as in a sinusoidal wave, while the LLE for an unstable system that diverges is positive.

The LLE is computed from the growth of length; when the length of a vector between two points becomes large, a new point is chosen near the reference trajectory. The calculation starts from the first data point $x(t_0)$ and $x(t_0)+dx$ which is the nearest at a distance $d(t_0)$. If the length $d'(t_1)$ is larger than a small value, then first point $x(t_0)$ is conserved and the algorithm searches the next point $x(t_1)+dx$. This algorithm was proposed by Wolf et al. [12] as:

$$\lambda = \lim_{m \to \infty} \frac{1}{mt} \sum_{i=1}^{m} \log_2 \frac{d'(t_m)}{d(t_{m-1})}$$

where λ is the LLE, t is the time interval, m is the number of total time intervals and d is the nearest distance from the reference trajectory. The LLE depends in general on the initial data point $x(t_0)$, the initial separation distance $d'(t_0)$ and time t.

For the calculation of LLEs and phase plots, the Chaos Data Analyzer (professional version, Physics

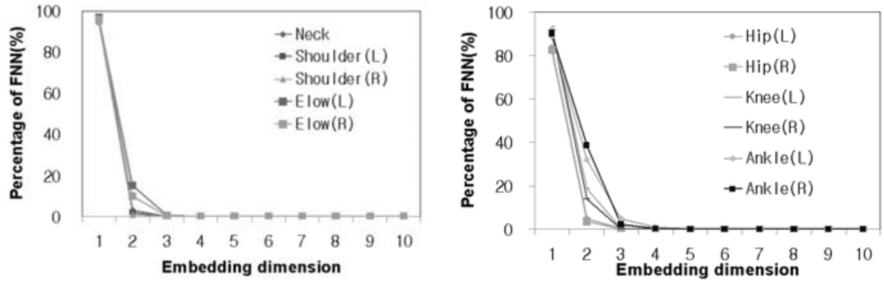
Academy Software, Raleigh, U.S.A.) was used [16]. The Chaos Data Analyzer is special purpose software to analyze nonlinear time series data. The software includes the calculation of LLE in the selection of chaos analysis. Using the software LLEs of known deterministic/chaotic (the Lorenz attractor), random, and periodic (the sine wave) time series were also evaluated as listed in Table 2. The results show the LLEs for the three representative cases, and these values were used as a basis for comparison.

Table 2. The largest lyapunov exponents of known systems.

System	LLE
Random	0.469
Lorenz(σ=10, R=28, b=8/3)	0.100
Sine wave	0.000

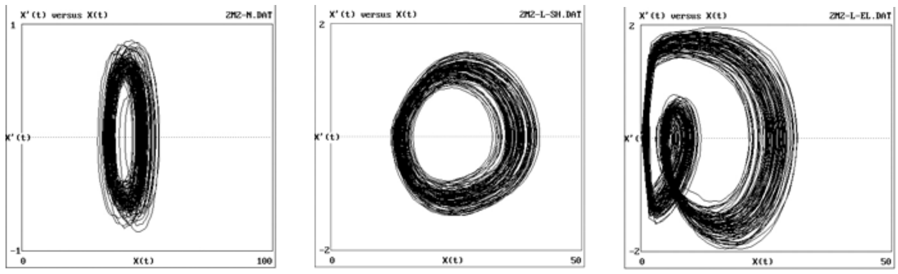
2.4 Statistical analysis

Statistical analyses were performed by using SPSS (version 13.0. SPSS Inc., U.S.A.). A one-way ANOVA test was performed to find any statistical difference in terms of the mean values of LLEs among the body parts. The significance level was set at 0.05 and the Turkey method [fso1] was used as post-hoc analysis. Correlation and regression analyses were carried out to check any relationship between the upper and lower extremity joints. The same sig-

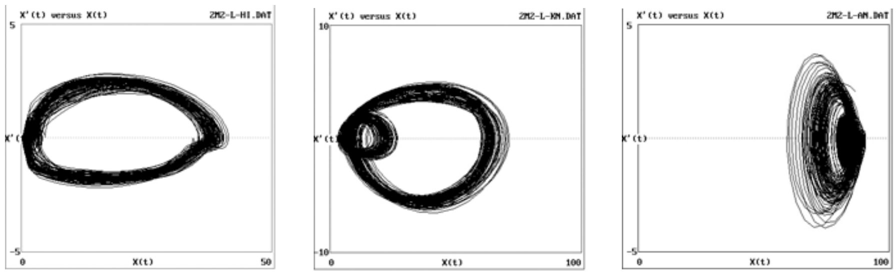


(a) Upper body (b) Lower extremity

Fig. 6. The calculated embedding dimension by the false nearest neighbour algorithm.



(a) Neck (b) Shoulder (c) Elbow



(d) Hip (e) Knee (f) Ankle

Fig. 7. Two-dimensional phase plots for six joints.

nificance level was used when Pearson correlation coefficient and regression coefficient were calculated.

3. Results

Time delayed data calculated by the AMI function are shown in Fig. 5. The first minimum value was selected in each graph and the case of the neck was selected as 16. Using the time delays obtained the number of embedding dimensions was calculated for each joint. Fig. 6 shows how the percentage of false nearest neighbours decreased to zero. For every subject the minimum embedding dimensions were four and five for the upper body and the lower extremity joints, respectively. Consequently, the suitable embedding dimension for all the joints was selected as five.

Fig. 7 shows typical two-dimensional phase plots of six joints for subject M1. The shapes of chaotic signals were clearly different from joint to joint. A group of seemingly concentric circles was observed in the plots of the shoulder and hip. The shapes of the elbow and knee were of partially twisted annuli. The neck and ankle had narrowing ellipsoid forms. If a joint motion were a periodic, the shape of the plot would be a perfect circle.

Table 3 lists the mean values and standard deviations of the LLEs. The mean LLEs of the eleven joints lay from 0.080 to 0.182. In the upper body joints the neck had a maximum of 0.137 and the right shoulder had a minimum of 0.080. In the lower extremity joints the left ankle had a maximum of 0.182 and both hip joints had a minimum of 0.090. The higher values of LLE at the neck and ankles are due to the finding that the neck had the smallest range of angle with larger irregularity and higher sensitivity to the initial condition as in Fig. 4, and that stability of the ankle was established with larger angular variation when the heel began to strike the ground.

Table 3. The calculated largest Lyapunov exponents in mean ±SD.

Joint	Left	Right
Neck	0.137±0.039	
Shoulder	0.082±0.016	0.080±0.013
Elbow	0.115±0.022	0.111±0.018
Hip	0.090±0.028	0.090±0.017
Knee	0.099±0.020	0.110±0.018
Ankle	0.182±0.039	0.163±0.035

The mean LLEs for six joints are illustrated in Fig. 8. The mean LLEs for the upper and lower extremities became larger as the joints become more distal. Such unexpectable movements as heading up and down frequently observed in the experiment caused the neck to have a higher value of LLE. A correlation was found between the shoulder and the hip in a significant level ($p<0.05$) as denoted by an asterisk in the figure. No other statistically significant correlations were found among the upper and lower joints. We attempted to obtain causality of the relation, but a regression analysis yielded a low regression coefficient, $R^2=0.124$.

In order to find any statistical difference among body parts, the body was categorized into three parts: the neck, upper extremity, and lower extremity joints. Their mean values of LLEs were compared as shown in Fig. 9. The ANOVA test revealed that statistical differences existed with a significant level ($p<0.05$) between the neck and the upper extremity, between the upper and lower extremities. The mean LLE of the upper extremity was 79.5% of that of the lower extremity. It means that the motion was likely to be periodic as a pendulum in the upper extremity while the higher LLE of the lower extremity was strongly influenced by the ankle joint.

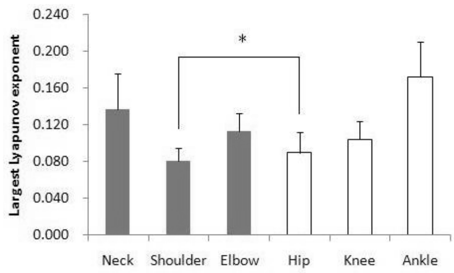


Fig. 8. The mean largest Lyapunov exponents for six joints (* Pearson coefficient R=0.352, p=0.035).

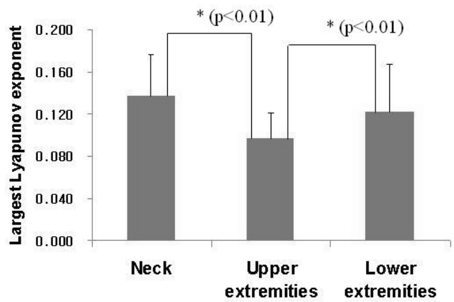


Fig. 9. The mean largest Lyapunov exponents for three groups.

4. Discussion

The objective of this study was to quantify the dynamic signal of the upper body as well as the lower extremity. The results showed that the LLE of upper extremity was statistically lower than that of the lower extremity. This indicates that the upper extremity has more stable dynamic pattern during walking. It is possible to walk with constrained arms; however, their contribution to natural gait could not be neglected because the walking inherently includes the upper extremity motion. The quantitative results obtained from this study can explain how the upper extremity contributes to the stability of walking. If the upper extremity were more chaotic in its motion, the walking perturbed by nonlinearity would become more unstable. More periodic movements of the shoulder and the elbow make walking rhythmical and well balanced. Dingwell and Cusumano [4] noticed that falling was not due to the upper body movements. They argued that the reason for falling was a low response time to adjust dynamic variability of the lower extremities to perturbations from sudden obstacles or ground status. Their observations make sense with the findings of this study.

As mentioned by Ford et al. [10], the motion of the upper body affects the gait pattern of the lower body motion. For this reason we performed a statistical analysis to find any effect of upper body joint motions. Though the shoulder and hip joints had a statistically meaningful relationship, there was not an obvious causality of the regression between the two joints. It is likely that the nonlinearity of the most proximal joints of the upper and lower extremities is evenly related to the body control strategy.

In order to establish a database for nonlinearity associated with gait, young males were selected since they have the most stable movement. This study is of great importance in its first presentation of values of LLE for major joints related to normal level walking. Up to now no other published data have been found to compare the values of LLE for the upper body movements. On the other hand, some information on the nonlinear dynamic behavior for the lower body movements can be obtained. Dingwell and Cusumano [4] defined dynamic stability and evaluated it using the LLE. They analyzed the lower body movement using such parameters as speed, age, walking environment. Buzzi et al. [5] investigated aging effect of gaits by using chaos analysis. Their results showed that the dynamic stability decreased when speed was reduced compared to self-selected speed, and the elderly group had low LLE values compared to the younger group. Because the knee joint has a lower LLE value and a smaller standard deviation than the other lower extremity joints, its LLE has been widely used to compare with other researches. Stergiou et al. [6] and Ko et al. [8] calculated their LLEs for the knee joint as 0.108 and 0.109, respectively. These were consistent with our result of 0.104, the average of the right and left knees.

Embedding dimension is the minimum value that trajectories of the reconstructed state vector may not cross over each other in state space. With respect to the dimension of five, if a lower dimension is chosen, the results will be incorrect due to the collapse of trajectories. Or if a higher dimension is set, the calculation time will become highly increased due to the redundancy of dimension. The value of LLE is sensitive to the embedding dimension as in Fig. 10. It shows how the LLEs vary with the number of dimensions from 2 to 10 in case of the left shoulder of Subject M1. The dimensions calculated were four and five for the upper and lower extremities, respectively. The values of embedding dimension were the same as the previous studies [4,6]. As in Fig. 10 little difference in LLE was found between the results using dimensions four and five. But the values of LLE were increased or decreased up to 30% when the number of dimension became away from five. Thus, it is recommended to carefully choose the appropriate embedding dimension in the comparison of other LLEs.

Analyses of the chaotic signal of human motion have been recently started. In the past, gait analyses have mainly focused on the variability of the stride-to-stride and several parameters. For it was thought that walking stability can be explained by speed and variability. However, the results from these studies led to a paradoxical problem that reduction in speed to obtain stable walking increases the stride variability although real walking stability is enhanced. Thus the linear variability was not an index to elucidate walking stability. Dingwell and Cusumano [4] reported that it was a mistake considering that variability was the same concept with the stability. Such linear methods as the mean and standard deviation analyses have a limitation in their explanation of the stability of dynamic systems. So the chaos analysis technique is more suitable for analyzing irregular and complex body signals of walking.

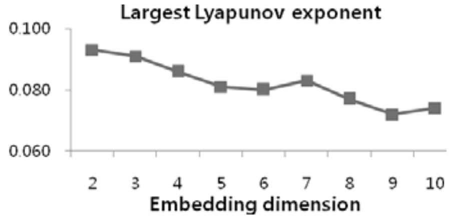


Fig. 10. The dependence of LLE on embedding dimension.

In the present study angular displacements for eleven joints were examined in a quantitative way. A question still remains about how the upper and the lower extremities are coordinated during walking. Further studies with a wide variability of subjects will be helpful to understand how gait depends on the severity of body damage, recovery levels of rehabilitation, clinical treatments and so on.

5. Conclusions

The chaos analysis technique was applied to the quantification of nonlinear dynamic signals of the human joints during level walking. The motion data were obtained to establish a database for chaotic characteristics associated with gait from the normal young males. The results obtained lead to the following conclusions: The LLEs were calculated and statistically analyzed for the eleven joints of the upper body and the lower extremity joints. The mean LLEs lay from 0.080 to 0.182: the neck had the maximum and the right shoulder had the minimum in the upper body; the left ankle had the maximum and both hip joints had the minimum in the lower extremity. The mean LLEs for the upper and lower extremities exhibited a tendency to become larger as the joints become more distal. A correlation between the shoulder and the hip was found, while regression analysis yielded a low regression coefficient, R^2=0.124. No other statistically significant correlations were found among the upper and lower extremity joints. Statistical differences were found between the neck and the upper extremity as well as between the upper and lower extremities. The mean LLE of the upper extremity was 79.5% of that of the lower extremity.

Acknowledgment

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References

[1] J. B. Dingwell and P. R. Cavanagh, Increased variability of continuous overground walking in neuropathic patients is only indirectly related to sensory loss, *Gait Posture* 14 (2001) 1-10.

[2] M. D. Lewek, J. Scholz, K. S. Rudolph and L. Snyder-Mackler, Stride-to-stride variability of knee motion in patients with knee osteoarthritis, *Gait Posture* 23 (2006) 505-511.

[3] V. Dubost, R. W. Kressig, R. Gonthier, F. R. Herrmann, K. Aminian, B. Najafi and O. Beauchet, Relationship between dual-task related changes in stride velocity and stride time variability in healthy older adults, *Hum. Mov. Sci.* 25 (2006) 372-382.

[4] J. B. Dingwell and J. P. Cusumano, Nonlinear time series analysis of normal and pathological human walking, *Chaos.* 10 (4) (2000) 848-863.

[5] U. H. Buzzi, N. Stergiou, M. J. Kurz, P. A. Hageman and J. Heidel, Nonlinear dynamics indicates aging affects variability during gait, *Clin. Biomech.* 18 (5) (2003) 435-443.

[6] N. Stergiou, C. Moraiti, G. Giakas, S. Ristanis and A. D. Georgoulis, The effect of the walking speed on the stability of the anterior cruciate ligament deficient knee, *Clin. Biomech.* 19 (9) (2004) 957-963.

[7] P. Matjaz, The dynamics of human gait, *Eur. J. Phys.* 26 (2005) 525-534.

[8] J. H. Ko, K. Son, B. Y. Moon and J. T. Suh, Gait study on the normal and ACL deficient patients after ligament reconstruction surgery using chaos analysis method, *Trans. KSME A.* 30 (4) (2006) 435-441.

[9] G. Rau, C. Disselhorst-Klug and R. Schmidt, Movement biomechanics goes upwards: from the leg to the arm, *J. Biomech.* 33 (2000) 1207-1216.

[10] M. P. Ford, R. C. Wagenaar and K. M. Newell, Arm constraint and walking in healthy adults, *Gait Posture.* 26 (2007) 135-141.

[11] N. B. Abraham, A. M. Albano, B. Das, G. D. Guzman and R. S. Yong, Calculating the dimension of attractors from small data sets, *Phys. Lett. A* 114 (5) (1986) 217-221.

[12] A. Wolf, J. B. Swift, H. L. Swinney and J. A. Vastano, Determining lyapunov exponents from a time series, *Phys. D Nonlinear Phenom.* 16 (3) (1985) 285-317.

[13] P. E. Rapp, A guide to dynamical analysis, *Integr. Physiol.Behav. Sci.* 29 (3) (1994) 311-327.

[14] F. Takens, Detecting Strange Attractors in Turbulence, Lecture Notes in Math 898, Springer, New

York, USA, (1981).
[15] M. B. Kennel, R. Brown and H. D. I. Abarbanel, Determining embedding dimension for phase-space reconstruction using a geometrical construction, *Phys. Rev. A* 45 (6) (1992) 3403-3411.
[16] J. C. Sprott and G. Rowlands, Chaos Data Analyzer: The Professional Version 2.1 Manual, Physics Academic Software, USA, (1998).