33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Wireless Gyroscope Suit for Gait Stability Estimation

Darwin Gouwanda, Namal A. Senanayake, *Senior Member, IEEE*

Abstract— **Gait stability is primary in assessing individuals with high risk of falling, particularly the elderly. Custom made self-adjustable wireless gyroscope suit is used as a sensing device to quantify gait stability. A nonlinear time series analysis i.e. maximum Lyapunov exponent (λ*) was employed to estimate the short term and long term stability and it is closely related to the ability of human neuro-muscular control system in maintaining gait stability. Experimental analysis and tests validated the efficacy of this novel approach. The results achieved are comparable with the findings of multiple kinematic and dynamic parameters derived from optical motion capture system and force platform which are widely used as gold standard.**

I. Introduction

DETERIORATION of the ability of an individual to walk in a repetitive and stable manner is a sign of many pathological conditions [1]. Hence, walking stability is one of the important factors in human gait analysis. Walking stability or gait stability is generally referred as the ability of human body to maintain functional locomotion despite the presence of small kinematic disturbances or control errors [2].

In recent years, many researchers had attempted to investigate and to quantify human gait stability. In previous studies, magnitude of kinematic variability was often regarded an estimate of gait stability [3]-[7]. However, little evidences can be found to support this assumption [8]-[9]. Gait stability derived from kinematic variability only quantifies the average differences between strides, independent of the temporal order, in which the strides occur. It also does not contain information on how the locomotor control system responds to perturbations either within or across the strides [8]-[11]. Moreover, it is also limited by its ability to quantify and provide a discrete measure to represent all data points [9].

Due to these reasons, tools from nonlinear dynamical system theory were proposed to examine the point-to-point fluctuations in movement trajectories throughout the gait cycle [2],[8]-[9],[11]. Although the fluctuations in measurement data are often described as error or noise in a system, nonlinear dynamical system theory provides a different explanation. It proposes that the fluctuation might be a consequence of the dynamic self-organization of a complex system. The most popular tool derived from this theory is the maximum Lyapunov exponent (λ*). Dingwell and Kang examined gait stability of older adults using λ* [9].

Despite its wide clinical applications, the kinematic variables used to estimate λ* are generally derived from the optical motion capture system [2],[9],[12]-[17]. Although it is considered as gold standard in capturing human motion, optical motion capture system is expensive, bulky and difficult to operate. With the recent advances in MEMS technology, miniature sensors such as accelerometer, gyroscope, and magnetometer started to gain its popularity among clinicians, biomechanists and researchers as a simple and inexpensive alternative to measure human motion in various activities. Miniature inertial sensors are small, light, and can be easily mounted on human body without hindering human motion [18].

The goal of this study is to explore the advantages offered by the miniature sensor, particularly gyroscope to estimate human gait stability. This paper investigated whether kinematic variable i.e. angular rate measured by gyroscope can be used to determine λ*. This paper also demonstrates how abnormal gait simulated by placing a weight on one side of the limbs can affect λ* and induce gait instability.

II. Wireless Gyroscope Suit

In this research, a wireless gait monitoring system was developed to measure the angular rate of human lower extremity during walking. Custom made self-adjustable wireless gyroscope suit with four wireless gyroscopes (Wireless Inertia-Link from Microstrain, Inc.) were placed on right thigh, left thigh, right shank and left shank as shown in Fig. 1. Each gyroscope has a sampling rate of 200 Hz and measuring range of ±5.235 rad/s with bias stability ±0.00349 rad/s and nonlinearity of 0.2%. Each wireless gyroscope has an onboard microprocessor performing fundamental data filtering therefore no jitter is expected in the data. It is important to mention that no further data filtering is performed to retain spatio-temporal fluctuation and nonlinearities of the signals [2], [19].

Manuscript received April 15, 2011. This work was supported in part by the Ministry of Science, Technology and Innovation (MOSTI), Malaysia under the eScience fund scheme no. 03-02-10-SF0028 with the project title Bio-Inspired Robotic Devices for Sportsman Screening Service (BIRDSSS) 2008-2010.

N. A. Senanayake was with Monash University Sunway Campus, Malaysia (+6737148124; fax: +6732461502; e-mail: aroshas@ieee.org) and currently with University of Brunei.

D. Gouwanda, is with Monash University Sunway Campus, Malaysia as a doctoral candidate. (e-mail:Darwin_gouwanda@yahoo.com).

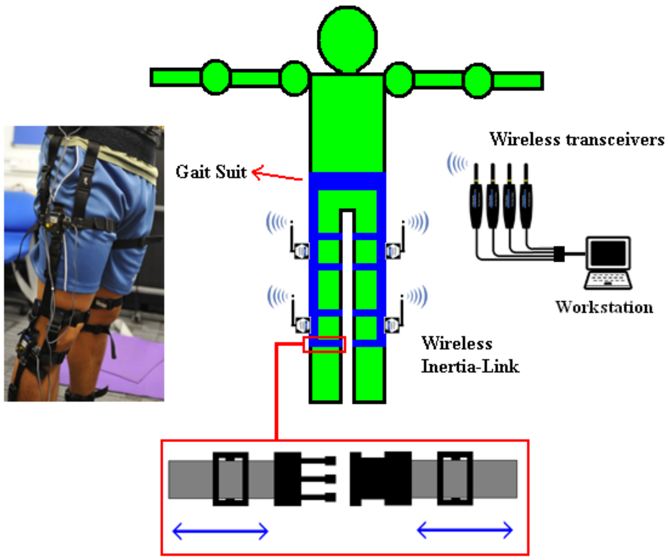

Fig. 1. Wireless gait monitoring system setup

A gait suit was designed to firmly hold the wireless gyroscopes on subject's lower extremity during walking, hence minimizing the measurement errors. This suit is made of bulk straps and Velcro™ straps. Each sensor is placed on top of a bulk strap. Length of the bulk straps can be altered according to the length and circumferences of subject's thigh and shank by unlocking and adjusting the buckler lock and buckler, as illustrated in Fig. An adjustable gait suit allows subject with different anthropometric properties to be able to wear it comfortably without hindering subject's lower extremity motion during walking.

III. Estimation of Maximum Lyapunov Exponent

The gait monitoring system was operated using a software developed under LabVIEW programming platform. This software incorporates real-time data streaming and data recording functionalities based on Inertia-Link data communication protocol developed by Microstrain Inc. It also incorporates several offline processes utilizing tools available in TISEAN (Time Series Analysis) package to estimate λ^* [20].

When this system is in operation, each wireless gyroscope continuously transmits the measurement data to the workstation. Once the data collection is completed, Hybrid Multi-resolution Wavelet Decomposition (HMWD) technique is applied to the shank angular rate in order to identify the occurrences of heel-strike and toe-off in every stride. Since the first 30 continuous strides are required to estimate λ^* [2], the measurement data lie between 2nd heel-strike and 32nd heel-strike are considered only. (As a standard in human gait analysis, the first heel-strike is omitted).

Given that the time to complete one gait cycle varies depending on the walking velocity while the sampling rate is fixed, segmented angular rate of the thigh and shank may have different data length. Therefore, measurement data of the first 30 strides are linearly interpolated to 3000 data points. This approach preserves the stride-to-stride temporal variation which is one of the important elements of Lyapunov stability analysis [1]. It also normalizes the measurement data such that the numbers of data points per stride are similar for every experiment.

Two important parameters are needed to estimate λ^*: the embedding dimension (d_E) and the time delay (τ). In this study, τ was calculated from the first minimum of the Mutual Information (MI) of the data [21].

$$MI(\tau) = -\sum_{h=1}^{j}\sum_{k=1}^{j} P_{h,k}(\tau)\ln\frac{P_{h,k}(\tau)}{P_h P_k} \qquad (1)$$

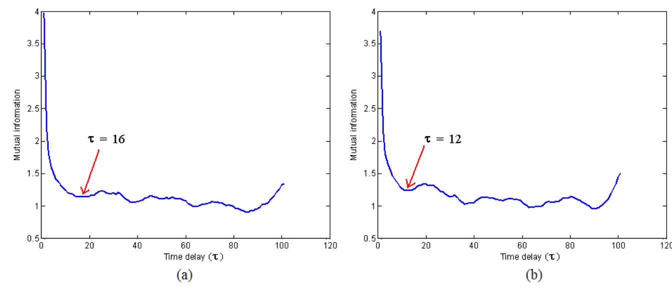

Fig. 2. Determining the first minimum from MI (a) Thigh and (b) Shank of Participant A during walking at speed 3 km/h

Where P_h and P_k denote the probabilities that a time series value x_i in the hth and kth bin respectively and $P_{h,k}$ is the joint probability that x_i is in bin h and $x_{i+\tau}$ is in bin k. Choosing the first minimum from MI provides appropriate τ with minimum redundancy. In this study, the first minimum was found to be ranging from 10 to 20 samples as shown in Fig. 2.. For consistency of the analysis, the mean time delay of $\tau = 14$ sample was selected and applied to all reconstructed state space.

False Nearest Neighbors (FNN) analysis is used to calculate d_E. FNN compares the distances between neighboring trajectories in the reconstructed state space at successively higher dimensions. Given a point *p(i)* in the m-dimensional embedding space , *p(j)* is *p(i)* nearest neighbor if the normalized distance R_i is smaller than a given threshold R_t. *p(i)* is marked as having a false nearest neighbor if R_i is larger than R_t. R_i can be computed as follows in (2).

$$R_i = \frac{\left|x_{i+m\tau} - x_{j+m\tau}\right|}{\left\|p(i) - p(j)\right\|} \qquad (2)$$

The selection of d_E is based on the percentage of false neighbors' approaching zero to provide a sufficient number of coordinates that define the system state at all points in time. The results of FNN analysis are presented in Fig. 3 [22].

An embedding dimension of d_E = 9 was selected because the percentages of false neighbor were less than one percent for both thigh and shank.

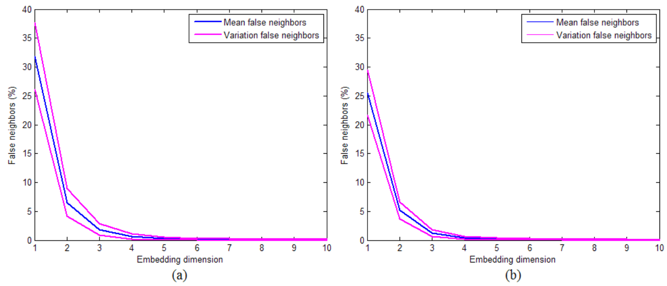

Fig. 3. FNN analysis results of (a) Thigh and (b) Shank

Lyapunov exponents quantify the average exponential rate of divergence of neighboring trajectories in the state space. They are a sensitivity measure of a system to infinitesimal perturbation. For a complete description of the effects to such perturbation, the system needs to be described in all directions of the reconstructed state space thus yields to multiple Lyapunov exponents, which are called Lyapunov spectrum [23]. However, in practice, analysis of the dynamic stability is restricted to λ^* because the behavior of entire system is dominated by λ^*. In gait analysis, the main significance of λ^* is that it provides a direct indicator of human body dynamic stability [1]-[3]. It is defined as follows in (3).

$$\ln d_j(i) \approx \ln C_j + \lambda^*(i\Delta t) \tag{3}$$

Where Δt is the sampling time ($t = i\Delta t$), $d_j(i)$ is the Euclidean distance between the jth pair of nearest neighbors after ith discrete time steps and C_j is the initial separation between the jth pair of nearest neighbors. The jth pair of nearest neighbors at the ith discrete time step is obtained by pairing a data point of a reference trajectory after fixing the ith discrete time step and with another data point of the jth nearest neighbor trajectories in the whole range of data. Using the algorithm proposed by Rosenstein et al. [23], λ^* can be found by estimating the linear slopes of the curves generated by (4).

$$y(i) = \frac{1}{\Delta t}\langle \ln dj(i) \rangle \tag{4}$$

Where $\langle . \rangle$ denotes the average over all values of j. Since each subject exhibited a different average stride time, the time axes of these curves are rescaled by multiplying the average stride frequency of each subject. A graphical illustration on how to estimate λ^* is depicted in Fig. 4.

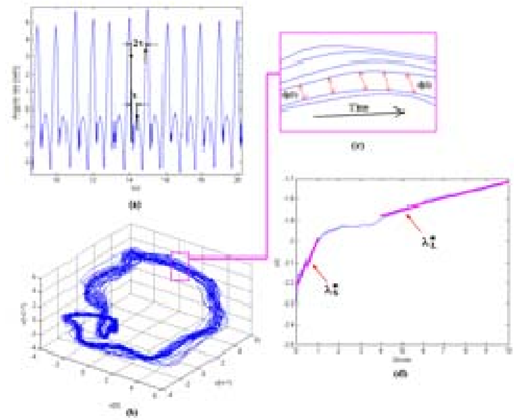

Fig. 4. Schematic representation of local dynamic stability analysis. (a) original time series data i.e. shank angular rate (b) reconstructed state space with embedding dimension d_E of 3 and time delay τ of 10 (c) A closer view of a section of the reconstructed state space; for each data point, the nearest neighbor is calculated and divergence from this point was calculated as *dj(i).* (d) Average logarithmic rate of divergence, from λ_S^* and λ_L^* which are determined.

Two different time scales [9],[13],[15] are used to estimate λ^*. Short-term λ^* (λ_S^*) is calculated from the slope of a linear fit to the divergence curve between zero and one stride. Long term λ^* (λ_L^*) is calculated from the slopes between four and ten strides. Periodic systems result in zero or negative λ^*, whereas non periodic or random systems result in a positive λ^*. Systems that are more dynamically stable exhibit lower λ^* values whereas systems that are less dynamically stable exhibit higher λ^* values [11]-[12] and [14].

IV. EXPERIMENTAL STUDY

A. *Participants*

Eleven healthy individuals (Age: 25.3 ± 1.7 years old; Height: 173.9 ± 4.8 cm; Weight: 70.5 ± 9.3 kg) were recruited from Monash University Sunway campus. Participants with known gait abnormalities were excluded. Participants were briefed on the purpose of the study and its procedure before they gave their consents. The experimental procedures were carried out based on the approval given by Monash University Human Ethic Committee.

B. *Experimental Procedures*

Two experimental sets were conducted in this study. In the first set, participants were requested to walk on a treadmill at the speed of 3 km/h, 4 km/h and 5 km/h for duration of one minute. Participants were allowed to rest in between experiments for a maximum of three minutes. Only one trial was recorded on every experiment.

In the second set, participants were requested to load their lower shank and walked on the treadmill at the speed of 3 km/h, 4 km/h and 5 km/h for one minute. Loading one of the limbs was intended to change the inertial properties of the loaded limb hence altering the spatio-temporal parameters of the loaded limb during walking. This study selected 2.5 kg load to be placed on the left or right lower shank to induce abnormal gait. As reported in [17], 2.5 kg load shall alter both timing and magnitude of the lower limb kinematic parameters.

C. Statistical Analysis

One way ANOVA was performed to examine the statistical differences of λ^* in different walking conditions. The alpha level/statistic significance, α was set at 0.01. If the null hypothesis is rejected, Tukey-Kramer multiple comparison test is conducted to assess the differences between each level of that factor.

V. Results

One of the significances of these results is the linear relationship between walking speed and λ_S^*. When participants walked at speed of 3 km/h, λ_S^* for thigh and shank were ranging from ≈0.30 to ≈0.44 and from ≈0.63 to ≈0.74 respectively. When the participant walked at speed of 5 km/h, λ_S^* for thigh and shank increased and were found to be ranging from ≈0.30 to ≈0.45 and from ≈0.75 to ≈0.87 respectively. Similar observations were found in other experimental results, particularly when participants walked with a load placed on one side of the limbs. These findings were consistent with the results reported in [2], [13].

However, when a load was placed on one side of the limbs, the loaded limb exhibited smaller λ_S^* whereas the non-loaded limb exhibited greater λ_S^* with $p < 0.01$. These results were expected as over short period of time, particularly during the first few strides, participants' neuromuscular locomotor system tried to maintain walking stability despite the significant differences between left limb and right limb inertial properties.

Different behavior was exhibited in λ_L^*. No statistical differences were found in λ_L^* ($p > 0.01$). These were anticipated as walking on a treadmill could reduce gait variability hence improving participants' walking stability [8]. More importantly, over long period of time, the participants' neuromuscular locomotor systems might have accustomed to the load placed on either side of the limb. Thus, they did not encounter much difficulty in maintaining walking stability. These results agreed with findings reported in [9] and [13].

It is important to note that based on the comparison of the similar walking speeds, one can notice that λ_S^* and λ_L^* found in thigh were smaller than λ_S^* and λ_L^* found in shank ($p<0.01$).These results were expected as the superior body segment i.e. thigh was less sensitive to small perturbations, thus its motion was more stable than the inferior body segment i.e. shank. These results were consistent with findings reported in [13] and [14].

VI. Discussion

Optical motion capture system and force plates are the common methods to quantify human motion during walking. However, these approaches pose several limitations. They have to be properly calibrated prior to an experiment. They can only capture human motion in a laboratory environment. Due to these limitations, wireless gyroscope was proposed to capture human lower extremity motions in real-time. Unlike conventional instruments, gyroscope is inexpensive, small, light-weight, and relatively easier to use. It produces similar results regardless of the minor differences in the attachment sites on human body. Lastly, it is suitable for wearable applications that continuously monitor human's gait.

Equipping the gyroscope with wireless technology also offers additional advantages. It allows the subject to move freely without being obstructed by wires that connect the sensors to the workstation. Subject's movement space is also not restricted by the length of the wires. This technology enables the motion to be captured in both indoor and outdoor environments.

Since human walking is not strictly periodic, traditional linear analysis may not be a suitable tool to examine human gait [12]. This analysis can diminish the true structure of kinematic/dynamic variability when few strides are averaged to produce an overall picture of a person's gait. Moreover, temporal variations of the gait may be lost. On the other hand, nonlinear analysis i.e. λ^* provides better illustration on how these variations change over the time [8],[11]-[12]. λ^* can estimate human dynamic stability during walking by measuring the local divergences of human motion in a state space. More importantly, λ^* can quantify how the neuromuscular locomotor system responds to perturbations. For these reasons, many researchers have adopted this approach [8],[11],[14] and [16]. Their findings suggested that positive λ^* was an indication of chaotic characteristic lying between completely periodic and completely random characteristics. Lower positive implied that human lower extremity exhibited higher resistance to stride-to-stride variability and was less flexible and adaptable when variations from one stride to another occurred.

Two different time scales i.e. λ_S^* and λ_L^* were determined to quantify walking stability. Short-term stability is represented by λ_S^* because it only examines the stability over the first gait cycle. Long-term stability is represented by λ_L^* as it evaluates the stability over the fourth to the tenth gait cycles. Despite using different method to capture human motion during walking, the experimental results are similar to the findings reported in [2][13]. All participants exhibited lower λ_S^* for both thigh and shank when they walked slower. They exhibited larger λ_S^* when they walked faster. Thus, it can be deduced that the human neuromuscular locomotor systems can control kinematic disturbances better during slow walking than during fast walking [2]. These results agreed with basic perception that individuals with higher risk of falling walk slower to improve their stability [13]. However, λ_L^* exhibited different behavior, λ_L^* had the lowest values when the participants walked at speed of 4 km/h. These results signified that over the long period of time, participants controlled their neuromuscular locomotor system better when they walked at this speed. In the second experimental set, when abnormal gait was simulated, loaded limb exhibited lower λ_S^* and then λ_L^* than the non-loaded limb. These results suggested that due to changes in the loaded limb inertial property, non-loaded limb neuromuscular system was challenged to balance the perturbations induced on the other limb, which in turn increased both λ_S^* and λ_L^* of the non-loaded limb.

VII. CONCLUSION

The results achieved prove that the angular rate of human lower extremity shall be a valid kinematic parameter to estimate λ^*. It also derives a normative baseline for young and healthy individuals who walk at different speed i.e. 3 km/h, 4km/h and 5 km/h. With this baseline, this system is expected to employ in clinical research to assist clinicians and biomechanists in order to analyze the influences of λ_S^* and λ_L^* in walking stability, particularly on which neuromuscular locomotor system is responsible for the changes in λ_S^* and λ_L^*, hence permits clinicians and biomechanists to conclude appropriate strategies that can improve human gait stability and reduce the risk of falls in the elderly.

ACKNOWLEDGMENT

This research was partially supported by the Ministry of Science, Technology and Innovation (MOSTI) Malaysia under e-Science grant No. 03-02-10-SF0028 with the title "Bio-Inspired Robotic Devices for Sportsman Screening Service (BIRDSSS)

REFERENCES

[1] Y. Hurmuzlu, and C. Basdogan, "On the measurement of dynamic stability of human locomotion", *Journal of Biomechanical Engineering*, vol. 116, pp. 30-36, February 1994

[2] S. A. England, and K. P. Granata, "Influence of gait speed on local dynamic stability of walking", *Gait and Posture*, 2007, vol. 25, pp. 172-178

[3] J. M. Hausdorff, L. Zemany, C. K. Peng, and A. L. Goldberger, "Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children", *Journal of Applied Physiology*, 1999, vol. 86, pp.1040-1047

[4] J. M. Hausdorff, Y. Ashkenazy, C. K. Peng, P. C. Ivanov, H. E. Stanley, and A. L. Goldberger, "When human walking becomes random walking: Fractal analysis and modeling of gait rhythm fluctuations" *Physica A:Statistical Mechanics and its Applications*, 2001, vol. 302, no. 1-4, pp. 138-147

[5] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: A 1-year prospective study", *Archives of Physical Medicine and Rehabilitation*, 2001, vol. 82, no. 8, pp. 1050-1056

[6] B. E. Maki, "Gait changes in older adults: Predictors of falls or indicators of fear?", *Journal of American Geriatric Society,* 1997, vol. 45, no. 3, pp. 313-320

[7] D. A. Winter, "Biomechanics of normal and pathological gait:implication for understanding human locomotor control", *Journal of Motor Behavior*, 1989, vol. 21, pp. 337-355

[8] J. B. Dingwell, J. P. Cusumano, P. R. Cavanagh, and D. Sternad, "Local dynamic stability versus kinematic variability of continuous overground and treadmill walking", *Journal of Biomechanical Engineering*, vol. 123, pp. 17-32, February 2001

[9] H. G. Kang, and J. B. Dingwell, "Effects of walking speed, strength and range of motion on gait stability in healthy older adults", Journal of Biomechanics, 2008, vol. 41, pp. 2899-2905

[10] U. H. Buzzi, and B. D. Ulrich, "Dynamic stability of gait cycles as a function of speed and system constraints", *Motor Control*, vol. 8, no. 3, pp. 241-254, July 2004

[11] J. B. Dingwell, and J. P. Cusumano, "Nonlinear time analysis of normal and pathological human walking", *Chaos*, 2000, vol. 10, pp. 848-863

[12] 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", *Clinical Biomechanics*, 2004, vol. 19, pp. 957-963

[13] H. G. Kang, and J. B. Dingwell, "Dynamic stability of superior vs inferior segments during walking in young and older adults" *Gait and Posture*, 2009, vol. 30, pp. 260-263

[14] K. Son, J. Park, and S. Park, "Variability analysis of lower extremity joint kinematics during walking in healthy young adults", *Medical Engineering and Physics*, 2009, vol. 31, pp. 784-792

[15] H. G. Kang, and J. B. Dingwell, "A direct comparison of local dynamic stability during unperturbed standing and walking", *Experimental Brain Research*, 2006, vol. 172, pp. 35-48

[16] M. Schablowski, and H. J. Gerner, "Comparison of two measures of dynamic stability during treadmill walking" *Lecture Notes in Control and Information Sciences*, 2006 vol. 340, pp. 345-360

[17] D. J. Miller, N. Stergiou, and M. J. Kurz, "An improved surrogate method for detecting the presence of chaos in gait", *Journal of Biomechanics*, 2006 vol. 39, pp. 2873-2876.

[18] Y. Ohtaki, K. Sagawa, and H. Inooka, "A method for gait analysis in daily living environment by body-mounted instrument", *JSME International Journal Series C*, 2001, vol. 44, no. 4, pp. 1125-1132

[19] J. B. Dingwell, and L. C. Marin, "Kinematic variability and local dynamic stability of upper body motions when walking at different speeds", *Journal of Biomechanics*, 2006, vol. 39, pp. 444-452

[20] R. Hegger, H. Kantz, and T. Schreiber, "Practical implementation of nonlinear time series methods: the tisean package", Chaos, 1999, vol. 9, pp. 413-435.

[21] M. Perc, "The dynamic of human gait", *European Journal of Physics*, 2005, vol. 26, pp. 525-534.

[22] M. B. Kennel, R. Brown, and H. D. Abarbanel, "Determining embedding dimension for phase-space reconstruction using a geometrical construction", *Physical Review A*, 1992, vol. 45, pp. 3403-3411.

[23] M. T. Rosenstein, J. J. Collins, and C. J. DeLuca, "A practical method for calculating largest Lyapunov exponents from small data sets" *Physica D*, 1997, vol. 65, pp. 117-134.