An Instrumented 6 Minutes Walk Test: Assessment of 3D gait variability for outcome evaluation in elderly population

B. Mariani, A. Paraschiv-Ionescu, and K. Aminian, *Member, IEEE*

***Abstract*—6 minute walk test (6MWT) is a practical test performed in clinic to assess exercise capacity of elderly subjects. This paper aims at providing an instrumented 6MWT (i6MWT) and methods for extracting gait variability metrics in order to characterize walking alteration with age. A new system based on foot-worn sensors and dedicated algorithms providing temporal and spatial parameters in 3 dimensions are proposed to study various aspects of gait variability. Measurements involved 10 young and 10 elderly subjects performing a i6MWT in a 25m-long corridor. Methods for removing walking breaks and turning outliers based on the estimation of standard deviation of gait cycle time or turning angle are proposed. Stride-to stride and long-term variability were also introduced and estimated for stride length, stride velocity, foot clearance and gait cycle time obtained by foot-worn sensors. The extent to which the proposed system can discriminate young and elderly subjects is discussed. The method appears particularly suitable for in-field clinical evaluation of rehabilitation treatment or intervention in elderly subjects.**

I. Introduction

The 6 minutes walk test (6MWT) is a reliable and practical clinical test to assess the exercise capacity of elderly persons [1]. This test measures the distance (6MWD) that a person can quickly walk on a flat, hard surface in a period of 6 minutes. It evaluates the global performance of the subject during exercises but does not provide specific information on the locomotion and its potential limitation such as its variability over walking distance. Actually, gait variability measures have been shown recently to be particularly relevant for the evaluation of gait in elderly for predicting falls and/or age-related changes leading to frailty [2].

In practice, analyzing the intrinsic variability of gait requires adequate straight walking distance, typically more than 200m [3], to obtain information on a stride-to-stride basis without measuring variability due to extrinsic factors such as turning or gait initiation. Generally, long-distance spatio-temporal gait analysis requires large working space, which cannot be obtained with standard laboratory systems such as optical motion capture. Treadmill could be considered as an alternative, but some subjects and particularly elderly individuals are unfamiliar to walking on a treadmill, which might lead to alter their gait pattern and the observed variability. Clinics also rarely have access to straight corridor without obstacles for more than 200m needed for the study of gait variability.

On the other hand, ambulatory devices have overcome some of these limitations by allowing to estimating gait variability using in shoes footswitches [4], but these studies were limited to temporal gait parameters only. More recently, system based on inertial body-worn sensors have proven the possibility to measure both temporal and spatial aspects of gait in long-distance walking by analyzing gait kinematics outside the laboratory environment (in field). However, systems based on Micro-Electro-Mechanical Systems (MEMS) gyroscopes and accelerometers suffer from measurement errors and integration drifts, which make difficult the assessment of velocity, position and orientation during long-term measurements. Therefore, recorded data require dedicated algorithms to compute relevant parameters for clinical use [5]. Estimation of 2D spatio-temporal parameters of gait using a double-pendulum model with sensors on lower limbs has been proposed and used in different populations to estimate spatio-temporal gait parameters and their variability [6]. 3D method was proposed also to find the foot orientation during gait with drift resetting at each step [7]. Such approach used a quaternion-based estimation of foot orientation and position where the drift was corrected periodically by assuming null velocity during foot-flat period at each gait stance. However, those approaches were only applied in condition of straight walking or during short distances.

In the present study, we assume that a 6MWT performed in a 25m-corridor with foot-worn sensors can be used to evaluate the mechanism of gait limitation in elderly. Based on gait parameters derived from a 3D foot kinematic estimation approach, and validated against a gold standard [8], the objective of this study was to design an instrumented 6MWT (i6MWT) to characterize walking alteration with age. First, appropriate outlier removal methods were proposed to aggregate straight walking periods of 6MWT. Then we provide estimators to assess the variability of spatio-temporal gait parameters in young and elderly subjects during the aggregated walking period.

II. Method

A. Foot-Worn Sensors

A wireless 6 Dimensional-Inertial Measurement Unit (6D-IMU) referred as “S-Sense” has been used [9]. In this study

Manuscript received June 28, 2010.
B. Mariani, A. Paraschiv-Ionescu, and K. Aminian are with the Laboratory of Movement Analysis and Measurements, Ecole Polytechnique Fédérale de Lausanne, Lausanne 1015, VD Suisse

Corresponding author is Kamiar Aminian. Tel: +4121 693 26 17; email: kamiar.aminian@epfl.ch

Fig. 1. Foot-worn sensors module (S-Sense) with compliant foam attached to shoe.

two S-Sense modules were fixed on shoes using double-sided Velcro patches (Fig.1). Raw sensor data was wirelessly transmitted in real time to a PC using “S-Base” receiver plugged in USB. Signals from the two S-Senses were synchronized by considering the absolute real time clock sent by the base station to each module at the start of recording. Data from the two feet were converted to physical units (g or °/s) using in-field calibration method [10].

B. Measurement Protocol

Ten young healthy volunteers (age 26.1±2.8 years), referred as “Young” group, and ten fit elderly volunteers (age 71.6±4.6 years), referred as “Elderly” group, took part in the study. Measurements were scheduled over 2 weeks and the ethical committee of the University of Lausanne approved protocol. Each subject wearing S-Sense modules on shoes performed a 6-Minute Walk Test [1]. The 6MWT was performed indoors, along a long, flat, straight, enclosed corridor, with a hard surface that is seldom traveled. The walking course was 25m. The turnaround points were marked with a cone (Fig.2).

C. Gait Parameters

3D foot kinematics was assessed from the inertial signals by using a dedicated 3D gait analysis algorithm [8]. Five gait parameters were then extracted at each cycle n:

- *Stride length (SL)* was defined as the distance measured between two successive foot-flat positions of the foot. This calculation is valid for curved and turning path as well [11].
- *Foot clearance (FC)* was defined as the maximal foot height during swing phase relative to the height at foot-flat.
- *Stride velocity (SV)* was considered as the mean value of foot velocity in forward direction during gait cycle.
- *Turning Angle (TA)* was defined as the relative change in foot heading (or azimuth), between the beginning and the end of gait cycle.
- *Gait Cycle Time* (*GCT*) was defined as the time between two successive heel-strike events.

D. Detection of outliers and pre-processing of data for variability analysis

For the analysis of gait variability, we focused on the assessment of the ‘intrinsic dynamics’ of continuous and

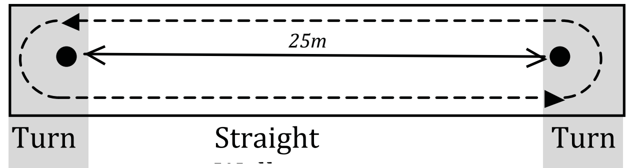

Fig. 2. 6 Minute Walk Test protocol, including turns at the end of the pathway, and straight walking during 25m.

straight walking. Therefore we had to ensure that the analysis was not influenced by those atypical strides outliers i.e. walking breaks and turning periods.

In the following we present two methods for detection and correction of outliers in gait parameters time series.

1) Method 1: statistical approach based on ‘two-sigma rule’

In order to minimize the start-up/end-up effects in the gait acquisition, the samples recorded in the first and the last five 20s were removed before variability analysis. Then gait parameters corresponding to each cycle were detected and their median and standard deviation (STD) were estimated. During the 6MWT, the instant where the subjects stopped to walk or start turning by reaching the end of the 25-meter pathway were detected according to the ‘two-sigma rule’ similar to [12]. According to this rule about 95% of the normally distributed data lie within 2-STD. In the present study, for each gait parameter time series (i.e. *SL, FC, SV, TA, GCT*) we detected outliers, which were distributed outside of median±2STD. These outliers were replaced with the median value of gait parameter time series. The median value was considered rather than the mean because it was observed that some outliers had very large values, and might affect the mean value of the entire time series.

2) Method 2: outlier removal based on turn signal information combined with Method 1

This technique is an improvement of Method 1 consisting of the following steps:

- Detect the gait cycles parameters during turning by applying an empirical threshold on Turning Angle values,
- Remove the gait cycles parameters during turning,
- Apply Method 1 to the new gait parameter time series in order to remove outlier related to other origins such as walking breaks.

E. Gait Variability Analysis

Gait variability was quantified by standard statistics based on mean and standard deviation of gait parameters. This variability expresses the stride-to-stride fluctuations in walking. Moreover in order to consider the dynamic of gait variability and its long-term fluctuations, non-linear metrics were considered as well.

1) Stride to stride fluctuations

Based on statistics defined in Table 1, the following variability metrics were estimated during the continuous and straight walking of 6MWT.

TABLE I
NOTATIONS

Symbol	Quantity
$s(n)$	gait parameter time series (can be Foot clearance, Stride Length, Stride Velocity, Gait Cycle Time), were n corresponds to gait cycle
m_s	mean of s
σ_s^2	variance of s
σ_s	standard deviation of s
σ_d	standard deviation of the first derivative of s

- Coefficient of variation (*CV*):

$$CV = \frac{\sigma_s}{m_s} \times 100$$

- Burstiness parameter (*B*) [13]:

$$B = \frac{\sigma_s - m_s}{\sigma_s + m_s}$$

- Median Absolute Deviation (*MAD)*:

$$MAD_s = median(\left|s - median(s)\right|)$$

- Standard deviation of the first derivative gait/stride time series (σ_d)

- Interquartile range of the second derivative gait/stride time series (*iqr1*)

- Signal Permutation Counts (SPC) [14]. In a given time series (e.g. s(n), n=1,L), a data sample can be identified as a 'signal permutation' (SP) if it satisfies simultaneously the following two criteria: 1) the absolute value of difference between its amplitude and that of the preceding sample should be greater that a specific threshold and 2) it represents an alteration in direction in the signal, i.e., a change in the sign of the derivative. Practically, the detection of a SP is expressed as:

$$s(n) = SP \;\; if \;\; \begin{cases} \left|s(n+1) - s(n)\right| \geq th, 2 \leq n \leq L-1 \\ (s(n) - s(n-1))(s(n+1) - s(n)) < 0 \end{cases}$$

The number of signal permutations (SPC) in a time series represents the degree of signal variability.

2) Long-term fluctuations

The stride-to-stride parameters are not sensitive to changes in the ordering of the stride times or the dynamics. Randomly reordering a time series will not affect the magnitude of the variability but may dramatically alter the dynamic properties. During 6MWT, there can be long-term (i.e. in the order of the minute) fluctuations of gait parameters, that are not directly measured by previously describe variability estimators. To quantify how the dynamics fluctuate over time during the walk, fractal analysis and symbolic entropy measures are applied to the stride time series.

- Fractal scaling exponent (α)

The de-trended fluctuation analysis (DFA) method can quantify the complex temporal organization of the fluctuations in a given time series by a single scaling exponent (α). α is a self-similarity parameter that represents the long-range power-law correlation properties of the signal [15]. A time series with complex fractal-like behaviour has a DFA scaling exponent α=1 (1/f noise). When it becomes more random, the scaling exponent decreases to a minimum of α=0.5 for an entirely random series (white noise). On the other hand, a scaling exponent α=1.5 characterize a smoother time series (Brownian noise) which reflect only trivial complexity [16].

- Symbolic entropy (*SEn*)

Another approach to illustrate the dynamic of gait variability is to quantify the 'complexity' of the gait pattern using methods derived from symbolic dynamics and information theory.

Symbolic time-series analysis [17] involves the transformation of the original time series into symbol sequences that can be valuable to extract useful information about the state of the (physiological) system generating the process. Data symbolization is the first step in symbolic time series analysis and involves the conversion of a data series of many possible values into a symbol series of few distinct values (e.g., binary sequences of 0 and 1). After symbolization, the next step is the construction of words from the symbol series by collecting groups of symbols together in temporal order. This process typically involves definition of a finite word-length template that can be moved along the symbol series one step at a time, each step revealing a new sequence. Quantitative measures of symbolic series include statistics of words (word frequency, transition probabilities between words) and information theoretic based entropy measures such as approximate entropy, multi-scale entropy, Shannon & Renyi entropy [18].

Finally, qualitative observations of long-term fluctuations profiles are made by interpolating the series of gait parameters using cubic-functions.

III. RESULTS

A. Outliers Removal

Fig. 3 illustrates gait parameters time series extracted during a typical 6MWT from an elderly subject. It can be observed that the values of all gait parameters were significantly different (p-values<0.05) during the turning at the end of 25m walking path [8], which justify the relevance of the proposed outlier removal approach.

The analysis of the 20 dataset showed that Method 1 is efficient only if outliers have similar (normally distributed) amplitude. When outliers have various amplitudes (heavy distribution) due to many different sources, for example, turning at different degrees, loss of data samples during acquisition, walking breaks the statistical 'two-sigma rule' is not efficient as shown in the illustrative examples in Fig. 4.

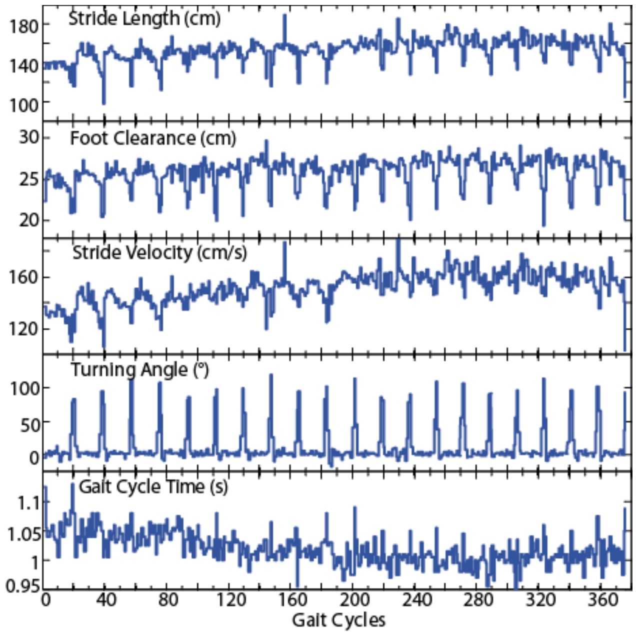

Fig. 3. Typical series of gait parameters extracted during 6 Minute Walk Test from an Elderly Subject.

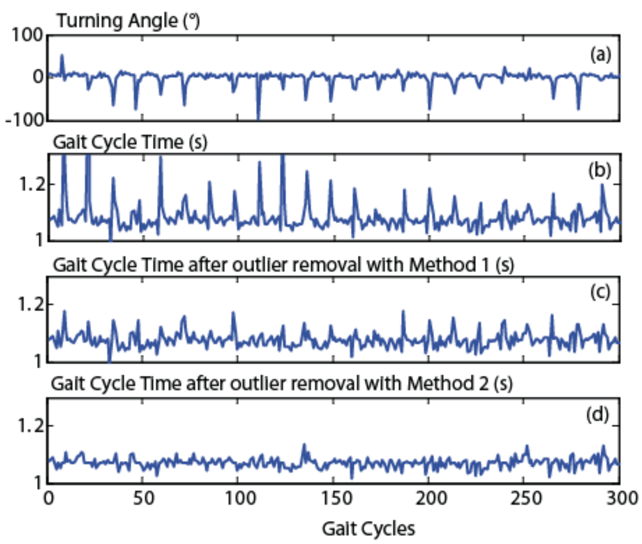

Fig. 4. Detection and correction of outliers in gait cycle time series: typical example when turning angle and outliers in gait cycle time series have a heavy amplitude distribution (a,b) and correction performance obtained with Method 1(c) and Method 2 (d).

As it can be observed on Figs. 3 and 4, an absolute threshold value of 10 to 15° qualitatively allow a good discrimination of the turning and straight walking gait cycles. Therefore, the efficiency of Method 2, which combines the information from the turn signal with the statistical approach, is illustrated in Fig. 4.

B. Gait Variability in Young and Elderly subjects

Stride-to-stride variability

The data series (after outlier removal) corresponding to each of the extracted gait parameters, namely SL, SV, FC and GCT were considered for analysis in Young and Elderly group of subject. Comparative analyses were conducted by considering gait data from Physionet [19] as a reference with Healthy young controls (n=15) and Healthy Elderly (n=5, age 74±2). Results are presented in Table II, and indicate that stride-to-stride variability of different gait parameters increases with aging.

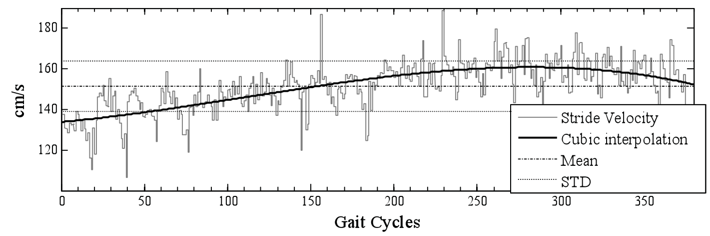

Fig. 5. Long-term trend obtained by cubic interpolation of Stride Velocity series that is not measure by classical linear variability such as STD.

Long-term variability

The results of long-term variability analysis quantified by the symbolic entropy *SEn* and the fractal scaling exponent α are shown in Table II. The estimated values indicated a decrease of long-term variability of gait parameters with aging. In addition, to stride-stride variability and long-term variability, the speed profile in particular can illustrate interesting long-term trend. See for example fig 5, where maximum stride velocity is observed after 250 seconds from the beginning of the test.

TABLE II
TEMPORAL AND 3D SPATIAL GAIT VARIABILITY
Y: Young group, ***E*** : Elderly group

		GCT (Physionet)	GCT	SV	SL	FC
CV	***Y***	2.33±0.53	2.6±0.97	5.1±1.7	4±1.4	4±0.9
	E	2.45±1.22	3±0.9	7±2.8	5.7±2.6	4.4±1.9
B	***Y***	-0.94 ±0.01	-0.94±0.02	-0.89±0.03	-0.92±0.02	-0.9±0.02
	E	-0.94±0.02	-0.9±0.01	-0.81±0.18	-0.89±0.05	-0.9±0.03
MAD	***Y***	0.015±0.005	0.015±0.012	0.04±0.02	0.022±0.02	0.007±0.002
	E	0.014±0.005	0.02±0.004	0.074±0.08	0.043±0.022	0.008±0.002
σ_d	***Y***	0.028±0.007	0.03±0.01	0.077±0.03	0.066±0.02	0.013±0.002
	E	0.03±0.02	0.04±0.01	0.09±0.04	0.09±0.05	0.014±0.004
iqr1	***Y***	0.036±0.009	0.038±0.021	0.089±0.057	0.06±0.04	0.017±0.003
	E	0.03±0.01	0.044±0.013	0.1±0.07	0.11±0.07	0.0168±0.005
SPC	***Y***	5±5.8	14±9	9±10	2±2	1±2
	E	16±29	20±10	15±21	10±21	3±6
SEn	***Y***	1.8±0.2	1.74±0.34	0.92±0.28	1.25±0.47	1.24±0.5
	E	1.7±0.4	1.5±0.4	0.8±0.4	0.9±0.4	1.05±0.47
α	***Y***	1.00±0.15	0.9±0.1			
	E	0.83±0.11	0.82±0.13	-	-	-

IV. DISCUSSION

In this study, we have considered a familiar and well-established test of mobility, i.e. 6MWT, and technically evolved it to "i6MWT". One of the major contributions of this work was to provide a method for extracting gait cycles parameters and their variability with automatic exclusion of non-relevant gait cycles due to artifacts such as walking breaks, loss of data and turning periods. With our 25m-based test, mean amount of data classified as outliers was approximately 15% for the entire datasets. So the remaining information should be long enough for correct variability estimations [3]. In practice, that makes the i6MWT an easy and convenient test to perform with elderly subjects in the framework of routine clinical tests.

Based on this test, which can measure up to several hundreds of walking steps, gait variability was assessed by wearable IMU sensors attached on shoes. We provided two types of gait variability metrics, those expressing the stride-to-stride regularity of walking and those reflecting the non-linear behavior of gait variability, also referred as "complexity" of walking.

Stride-to-stride variability is always present in walking, allowing a certain adaptability to external perturbations (e.g. change in direction and speed, obstacle avoidance). However, when this variability is too high, it has been shown to be associated with impaired motor function. As such, we expected higher stride-to-stride variability with age and that was confirmed in this study by higher stride-to-stride variability in elderly subjects compared to healthy young subjects (i.e. higher CV, MAD, σ_d, iqr1, SPC and B).

When considering walking as a dynamic biological system, higher dynamic range and complex variability enable the organism to rapidly respond to internal and external perturbation. The non-linear gait variability metrics (i.e. SEn and α) in this study corroborated this aspect as we found that those metrics tend to decrease with age, implying a less complex and frailer behavior. This is in agreement with a well-known loss of complexity with aging.

The ranges of gait variability obtained in this study are in agreement with other preliminary existing data. However, we have also proposed gait variability measures in some new spatial parameters (i.e. SV, SL and FC).

A major limitation of this study was the small sample size of population, which did not allow statistical comparisons. Other investigations are in progress with a larger elderly population in order to estimate the performance of the proposed variability metrics in the assessment of rehabilitation and training intervention efficiency. Notably, intervention with a motorized shoes generating non-linear stimulation (SMILING shoes) aiming at improving gait and balance through neuro-motor rehabilitation will be consider.

The potential applications of i6MWT are not just limited to elderly subjects. Gait variability measured by i6MWT could be relevant for assessment of Parkinson disease, orthopedics impairment and some other pathology associated with gait impairment.

Acknowledgment

The project "Self Mobility Improvement in the eLderly by counteractING falls" (SMILING) is part of the European Commission's 7th RTD Framework Programme – Specific Programme Cooperation, Theme 3 "Information and Communication Technologies", Objective ICT2007.7.1 "ICT and Ageing", contract number 215493.

References

[1] Crapo, R. O., Casaburi, R., Coates, A. L., Enright, P. L., MacIntyre, N. R., McKay, R. T., Johnson, D., Wanger, J. S., Zeballos, R. J., Bittner, V., Mottram, C., 2002. ATS statement: Guidelines for the six-minute walk test. American Journal of Respiratory and Critical Care Medicine 166, 111-117.

[2] Rochat, S., Büla, C.J., Martin, E., Seematter-Bagnoud, L., Karmaniola, A., Aminian, K., Piot-Ziegler, C., Santos-Eggimann, B., 2010. What is the Relationship Between Fear of Falling and Gait in Well-Functioning Older Persons Aged 65 to 70 Years? Archives of Physical Medicine and Rehabilitation, 91 (6), pp. 879-884.

[3] U. Lindemann, B. Najafi, W. Zijlstra, K. Hauer, R. Muche, C. Becker, K. Aminian, Distance to achieve steady state walking speed in frail elderly persons, Gait & Posture, 91–96, 2008

[4] 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

[5] Aminian, K., 2006. Monitoring Human Movement with Body-Fixed Sensors and its Clinical Applications. Invited chapter in "Computational intelligence for movement sciences : neural networks and other emerging techniques". Idea Group Pub., p. 101-138

[6] Aminian, K., Najafi, B., Bula, C. J., Leyvraz, P. F., Robert, P., 2002. Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. Journal of Biomechanics 35, 689-699.

[7] Sabatini, A. M., Martelloni, C., Scapellato, S., Cavallo, F., 2005. Assessment of walking features from foot inertial sensing. IEEE Transactions on Biomedical Engineering 52, 486-494.

[8] Mariani B, Hoskovec C, Rochat S, Bula C, Penders J, Aminian K, 3D Gait assessment in young and elderly subjects using foot-worn inertial sensors, Journal of Biomechanics, In Press.

[9] Penders J, Van de Molengraft J, Masse F, Mariani B, Aminian K, S-sense: a wireless 6D inertial measurement platform for ambulatory gait monitoring, submitted to ICABB, 2010

[10] Ferraris, F., Grimaldi, U., Parvis, M., 1995. Procedure for effortless in-field calibration of three-axis rate gyros and accelerometers. Sensors and Materials 7, 311-330

[11] Huxham, F., Gong, J., Baker, R., Morris, M., Iansek, R., 2006. Defining spatial parameters for non-linear walking. Gait and Posture 23, 159-163

[12] G J Hanh and S.S. Shapiro, Statistical Models in Engineering, Hoboken, NJ: Wiley, 1994

[13] K-I. Goh, A-L. Barabasi, Burstines and memory in complex systems, EPL 81 48002, 2008.

[14] R.M. Rangayyan, Biomedical Signal Analysis: A case-study approach. New York, NY: IEEE and Wiley, 2002

[15] Goldberger A L (1996) Non-linear dynamics for clinicians: chaos theory, fractals, and complexity at the bedside. Lancet 347:1312–1314

[16] Hausdorff J M, Peng C K, Ladin Z et al. (1995) Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. J Appl Physiol 78:349–358

[17] W. Aziz and M. Arif, Complexity analysis of stride interval time series by threshold dependent symbolic entropy, Eur J Appl Physiol, 98: 30-40, 2006.

[18] A. Paraschiv-Ionescu, K. Aminian, Nonlinear analysis of physiological time series, in Advanced Biosignal Processing, Springer, 307-334, Chapter 15, 2009

[19] PhysioNet: http://www.physionet.org/