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Association of Stride Rate Variability and Altered Fractal Dynamics with Ageing and Neurological Functioning

Asma Channa

Computer Science Department
University of POLITEHNICA Bucharest
Bucharest, Romania

DIIES Department

University Mediterranea of Reggio Calabria, Italy
asma.channa@stud.acs.upb.ro

Najeeb ur Rehman Malik

Electronics Department
Universiti of Teknologi Malaysia University of POLITEHNICA Bucharest
Johar Bahru, Malaysia
rehman@graduate.utm.my

Nirvana Popescu

Computer Science Department
University of POLITEHNICA Bucharest
Bucharest, Romania
nirvana.popescu@upb.ro

Abstract—Alterations in gait cycle i.e stride rate show fractal dynamics and lower limb walking variability between healthy controls and the controls associated to any neurological disorder. The paper proposes a study in which these stride variability changes in neurological functioning linked with individuals with neurocognitive disorder and accumulation of changes happen in the human body with time called ageing. To validate this research work, we compared the participants' gait cycle in time series: 1) healthy young participants and healthy older adults 2) subjects with Parkinson's disease (PD) and disease-free subjects. Using the Detrended Fluctuation Analysis (DFA) method we computed α , a measure of a degree to which one stride time is compared with the previous and the consecutive intervals over a various time span. The scaling exponent α is exiguently curtailed in older adults as compared to young healthy participants. The scaling exponent α is also lower in the subjects with PD compared with the disease-free participants. Moreover, α seems linearly correlated to the degree of functional impairment in subjects with PD. These findings demonstrate that stride time fluctuations are more arbitrary in elderly subjects and in subjects with PD. Abnormal fluctuations in the fractal properties of lower limb dynamics are clearly related to functioning in central nervous system control.

Index Terms—gait variability, stride interval, detrended fluctuation analysis, neurological disorder

I. INTRODUCTION

Gait cycle variability plays an important role on quality of life (QoL) [1]. The presence of stride interval variability falls in elderly people are frequent, which is considered as the fifth leading cause of demise [2]. Also, an increase in gait alteration in form of stride interval (i.e., between successive heel strikes) in case of PD patients causes a severe effect because of which, around 50% of PD patients experience multiple falls per year [3] and an increasing risk for injuries. According to [4], the gait variability in healthy adults is quite small, 2% around the mean, but it is drastically increased in patients with Parkinson and Huntington's diseases. Despite of the great endeavors of the scientists and medical practitioners to comprehend the pathophysiology of falls in elderly people and build up preventive medicines, there is still a huge gap

in understanding and dealing with this challenging syndrome of gait disability especially when the comparison of elderly person and neurocognitive disorder such as PD patient comes up.

Ageing is associated with declining balance, decreased postural stability or standing on limbs for long time uncomfortable which eventually cause falls and functional impairment in elderly people. In the last decade enormous research has been done in this area and a number of authors proposed numerous solutions in form of wearable devices and artificial intelligence algorithms for fall detection, risk of fall and an emergency alert after falling [5]–[7] using some temporal spatial features i.e maximum amplitude, minimum amplitude, mean amplitude, variance, kurtosis and skewness of the signal. Over the years, a series of research studies [8]–[10] focused on statistical methods for classification of PD gait patterns or extracting the intrinsic features as the number of temporal and spatial domain, using linear and non-linear functions for early diagnose of PD or distinguishing between healthy and PD controls. So in most of the previous research work, the researchers often chunk away some of the not so obvious dynamics and describe the remaining patterns with an average, mean value, standard deviation or median as the first order statistical descriptors although these physiological signals are in general fractal types. In this study we considered Detrended Fluctuation Analysis (DFA) algorithm that represents the properties of the scale dependent variation called as fluctuations. DFA approach determines the fractal scaling properties and the detection of long range correlation in discontinuous time dependent signals. Afterwards Optimize Support Vector Machine (OSVM) classification is performed in identification of young healthy subjects, old aged adults and PD patients. The purpose of the present study is threefold: 1) to determine whether there is any significant correlation between three groups; 2) to evaluate the conditions over which such correlation exists; 3) to distinguish all the participants cohort into three classes using OSVM classifier.

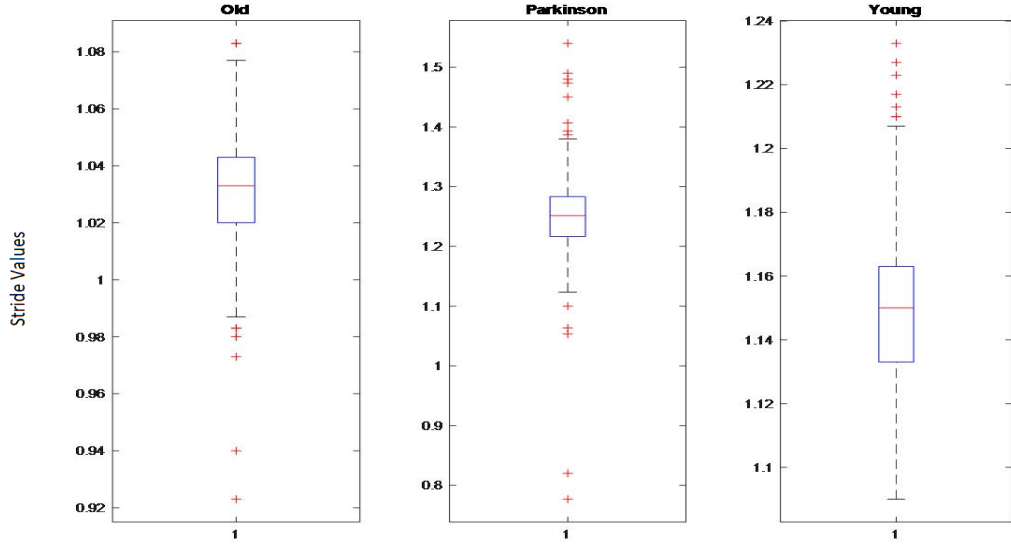


Fig. 1. Group comparison of variability of stride time between different groups of subjects

II. METHODS

A. Subjects

In this present study, the data of walking stride interval based on time series from 15 participants is included, the data being available in [11]. From 15 subjects, 5 subjects have PD with mean and standard deviation (SD) age 70.4 ± 6.406 , 5 healthy old adults with mean and SD age 74.6 ± 2.05 and 5 disease-free young participants with mean and SD age 24.4 ± 2.8 . For each subject, the recordings are based on two columns. The first column initiates the time stamp (in seconds) and the second one represents the stride time. The details of participants with respect to their age is illustrated in Table 1.

TABLE I
DEMOGRAPHIC DETAILS OF THE PARTICIPANTS

Patients Age	Disease free participants age	
	Old adults	Young adults
60	76	23
66	74	29
75	75	23
67	77	21
77	71	26
mean \pm SD	mean \pm SD	mean \pm SD
70.4 ± 6.4062	74.6 ± 2.05126	24.4 ± 2.8

B. Data Collection

Data is collected using ultra-thin force sensitive resistors placed inside the shoe of subjects. The analog force signals are sampled at rate of 300 Hz and converted to digital signal using twelve bit ADC (analog to digital converter) by employing an ambulatory, ankle worn microcomputer that also store the data.

Consequently, the duration in time at foot touch is ineluctably computed. The data is collected into two phases. 1) The data from the subjects with PD is collected as subjects walked for 6 minutes up and down along a hallway. 2) The data from the healthy subjects is collected as subjects walked in roughly circular path for 15 minutes. All the members walked persistently on level ground around a snag free way.

C. Assessment of gait cycle duration using DFA

Gait abnormality is observed in PD patients and older adults. According to [12], fluctuations in the stride interval show fractal dynamics and long-range correlations in disease-free young individuals. In this study we investigated the changes in gait cycle by changes in neurological function of adults and ageing factor using DFA. It detects long range correlation and scaling components of non-stationary signals. It is a non-parametric approach that avoids the spurious detection of seemingly long-range correlations which are the artifact of nonstationarity. DFA is composed of two parts as illustrated in [13]

- 1) the data series $B(k)$ is shifted by the mean and integrated (cumulatively summed),

$$x(k) = \sum_{i=1}^k [B(i) - \langle B \rangle] \quad (1)$$

then it is segmented into a window of Δn various sizes. In this way we have illustrated our data profile i.e. $x(k)$. $\langle y \rangle$ is the mean of the time series. The global trend of the signal is eliminated using subtraction of the mean. The advantage of applying scaling analysis to the signal

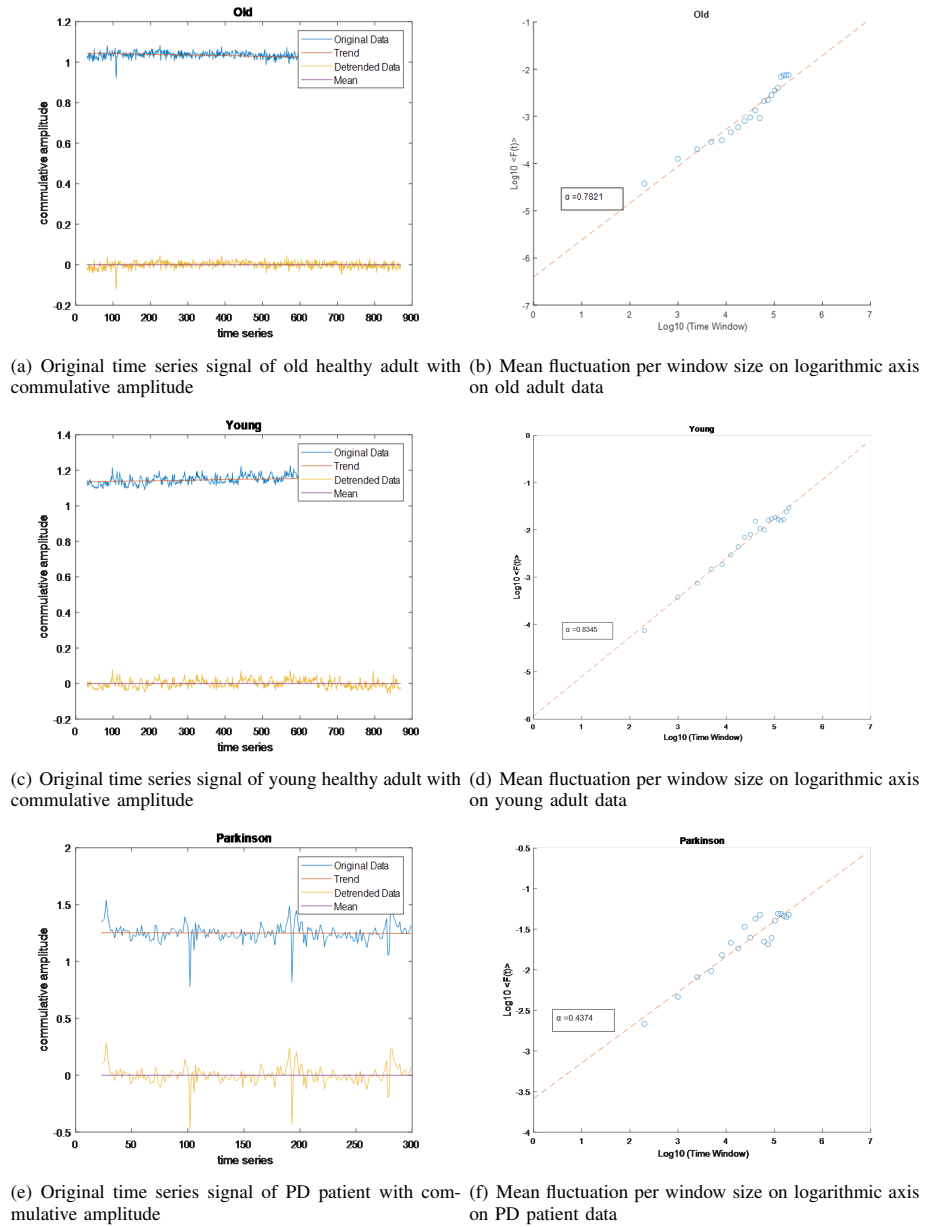


Fig. 2. Original time series signal along with the commulative amplitude displaying fluctuations away from the mean; the mean fluctuation per window size on logarithmic axis.

TABLE II
DEMOGRAPHIC DETAILS OF PARTICIPANTS

Subjects Group	coefficient α	Fluctuations corresponding to window	mean absolute error
Old	0.7821	-6.4026	Mean absolute difference between old and PD subjects = 44%
Parkinson	0.4374	-3.5858	Mean absolute difference between PD subjects and young controls =47%
Young	0.8345	-5.9349	Mean absolute difference between young and old subjects = 6.2%

profile instead of the signal is that it makes no a prior assumptions about the stationarity of the signal. When computing the scaling of the signal profile, the resulting scaling exponent, α , is an estimation of H.

- 2) in each segmentation, the integrated data is locally fit to a polynomial $xn(k)$ (originally and typically, linear) and the mean-squared residual $F(n)$ (“fluctuations”) is found:

$$F(\Delta n) = \sqrt{\frac{1}{N} \sum_{k=1}^N [x(k) - x_{\Delta n}(k)]^2} \quad (2)$$

In equation (2), N represents the total number of the data points and $F^2(\Delta n)$ is counted as the average of the summed squares of the residual raised in the windows. The n-th order polynomial regressor in the DFA family is typically denoted as DFA_n. This process checks for self-similarity i.e. fractal dynamics as it operates estimating (the dispersion of the residual of integrated fluctuations about a regressor) at different resolutions (window sizes). If power law scaling is present then a double logarithmic (“log-log”) plot of $F(n)$ versus n, often termed the fluctuation plot, is conventional to be linear.

$$F(\Delta n) = C(\Delta n)^\alpha \Rightarrow \ln(F(\Delta n)) = \alpha \ln(\Delta n) + \ln(C) \quad (3)$$

In relation (3), C is a constant and a scaling exponent α can be estimated from a least-squares fit. This scaling exponent α is a measure of correlation in the signal and is simply an estimation of the Hurst exponent H. So here we used DFA method over the stride intervals of the young healthy adults, old healthy adults and PD patients to find their correlation in gait cycle and process it. If $\alpha = 0.5$, there is no correlation; if $\alpha < 0.5$, the data is anticorrelated; if $\alpha > 0.5$, the data is long-range correlated.

D. Time Series Classification Using Optimizable SVM

For classifying the time series biomedical signals, a number of classifiers are available. Out of these, the support vector machine (SVM) is powerful and uses kernel methods for classification purpose. In this study we trained SVM optimally, so that it can produce excellent separating hyperplanes. The training quality of this classifier is not just confide on the available data but also on additional learning parameters, which are not easy to regulate, especially for unbalanced datasets.

III. RESULTS AND DISCUSSION

Sharp transients spikes are common in wearable sensors data hence, before analyzing the data, it is first pre-processed and visualized. For pre-processing the outliers are removed and the first 30 seconds of data is filtered out as it may include hallway rounds or unwanted noises. Afterwards the records of three cohorts are separately visualized and compared in the form of box plots as shown in Fig 1. From box plot it is

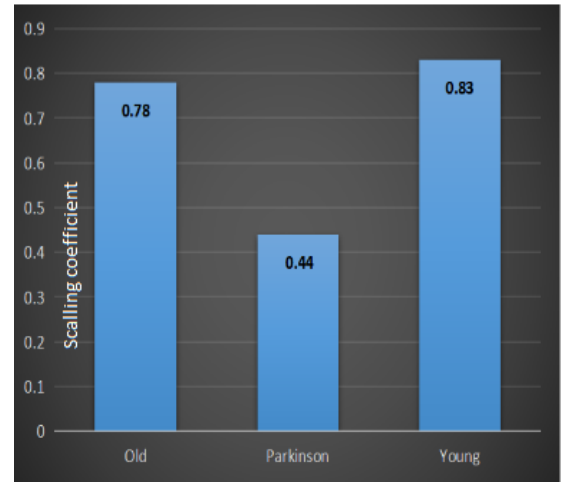


Fig. 3. Scaling coefficient of each group

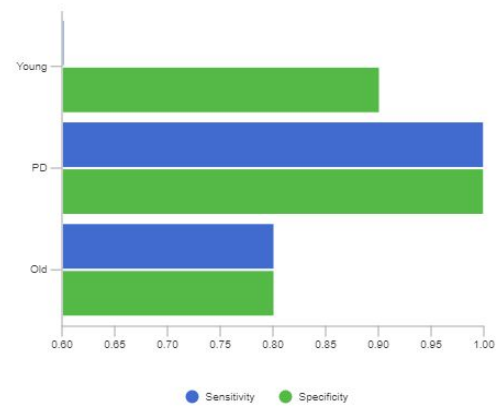
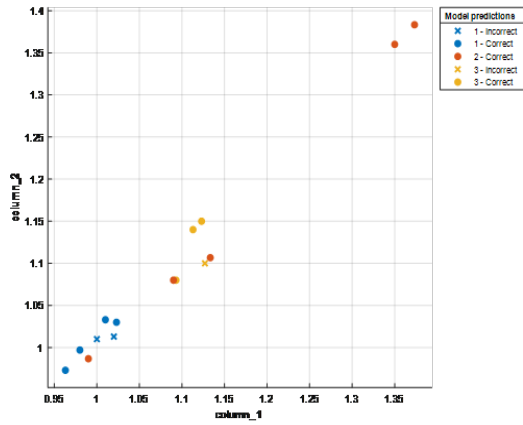
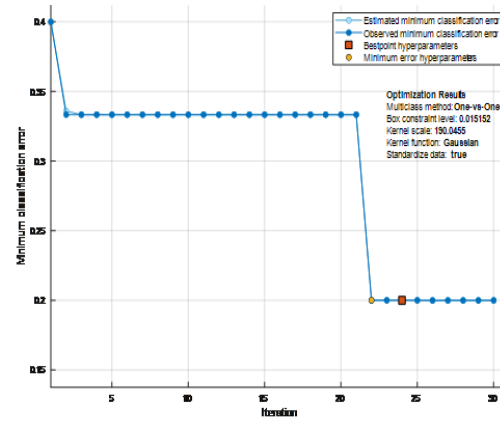


Fig. 4. Sensitivity and specificity of each class



(a) Model predictions



(b) Classification error

Fig. 5. OSVM classifier results

clearly observed that the median, minimum and maximum value of each group is different. Hence for proper fractal analysis of stride interval parameters, the data is detrended, the scaling component is calculated and the correlations are demonstrated using the DFA approach. After calculating the α for each group, the mean absolute difference is calculated as illustrated in Table II and Fig 2. The DFA implementation for determining the scaling coefficient characterizes the self affinity of the input data. For the interpretation of the outputs and the algorithm, when applying DFA to non-stationary signals, the purpose is to find how the amplitude of an oscillation changes over time.

First, the cumulative sum of the signal is computed to constitute the signal profile as defined in (1). Then a set of window sizes T is defined, which are uniformly spaced on a logarithmic scale according to the length of the signal. Afterwards the signal profile is split into a set (W) of separate time series of length t , which have 50% overlap. For each window, we use a least-squares fit from the time series to create w detrend; then the standard deviation of the detrended signal is calculated and finally, the fluctuation function is constituted as the mean standard deviation of all identically sized windows: $F(t) = \text{mean}(\alpha(W))$. The plots from Fig. 3 show the fluctuation function for all window sizes, T , on logarithmic axes and also their DFA fluctuation exponent, α . The fluctuation component α for healthy old adults is 0.78, for PD subjects is 0.44 and for healthy young adults is 0.68. According to [14], α of PD patients is smaller than 0.5 so there is no correlation; however α of healthy subjects is higher than 0.5 which is interpreted as long range correlation as shown in Fig. 3 and Table II.

An automatic classification is performed on the data collected from all three groups of subjects to distinguish them into three classes. An OSVM classification is performed. The Support vector machine (SVM) is one of the most effective classification method and the OPSVM classifier is able to

select appropriate input features and optimize SVM parameters to increase classification accuracy. In this study the OSVM classifier gives an accuracy of 80%. Fig. 4 shows the sensitivity in blue and specificity in green of each group. The PD class has maximum sensitivity and specificity with 1 in contrast with healthy cohort of young and old participants. The the cohort of young subjects has 0.6 sensitivity and 0.9 specificity incase of old group subjects the sensitivity and specificity both lies at 0.8. The Fig. 5 (a) shows how many predictions were correct and incorrect. The cross shows the wrong predictions and dot proves correct predictions and from Figure it is clear that for second class there is no wring predictions. For the second group there is not any incorrect prediction as it performed 100% accurately. However Fig. 5 (b) presents how the optimizing decreases the classification error: initially the error was 0.4 and after optimization it is reduced up to 0.2. The yellow circle shows when the error hits the minimum value and the red rectangle represents the best point hyper-parameters.

IV. CONCLUSION

This study validates the applicability of fractal approach and the optimizable SVM method in stride rate analysis of healthy subjects cohort and PD patients group. This research methodology illustrates the presence of any correlation between healthy young and old adults and PD patients. From the analysis using DFA, it has been proved that the long range correlation exists between the old and young participants as the value of α is greater than 0.5 and for PD subjects it appears that there no similarity exists. Hence, by analyzing the gait cycle, using DFA on short walkways of subjects and getting sufficient result, the optimizable SVM is implemented to differentiate these cohorts of subjects using their stride intervals. The optimizable SVM classifier performed well and differentiated the subjects with accuracy of 80%. These investigations provide a first insight into the elaborating gait

impairments for subjects with PD and ageing using stride cycle with future possibility to make it more standardized considering long-walkways and fast or moderate stride intervals with patients having neurocognitive disorder.

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