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Modeling the gait of normal and Parkinsonian persons for improving the diagnosis

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ABSTRACT

In this study, we present a model for the gait of normal and Parkinson's disease (PD) persons. Gait is semi-periodic and has fractal properties. Sine circle map (SCM) relation has a sinusoidal term and can show chaotic behaviour. Therefore, we used SCM as a basis for our model structure. Moreover, some similarities exist between the parameters of this relation and basal ganglia (BG) structure. This relation can explain the complex behaviours and the complex structure of BG. The presented model can simulate the BG behaviour globally. A model parameter, Ω, has a key role in the model response. We showed that when Ω is between 0.6 and 0.8, the model simulates the behaviour of normal persons; the amounts greater or less than this range correspond to PD persons. Our statistical tests show that there is a significant difference between the Ω of normal and PD patients. We conclude that Ω can be introduced as a parameter to distinguish normal and PD persons. Additionally, our results showed that Spearman correlation between the Ω and the severity of PD is 0.586. This parameter may be a good index of PD severity.

1. Introduction

Early exact diagnosis of Parkinson's disease (PD) is still limited. Diagnosis may be delayed in early stages, as structural neuroimaging methods do not provide characteristic features to allow the diagnosis of PD [10]. Since two cardinal PD symptoms (postural imbalance and rigidity) alter the gait, gait analysis may help PD diagnosis. Simple recording of gait makes it suitable for early diagnosis.

Gait disturbances may be considered as characteristic integral elements of PD. They are caused by muscle rigidity, bradykinesia, abnormal rhythmicity, asymmetry of the two sides of the body, and abnormal scaling of pace length. The gait disorder in PD includes slowed gait, shortened stride length, decreased rhythm and cadence, shuffling and festinating gait, decreased swing of the arms, and disturbed regulation of the stride length. 5 min walking can show these disturbances [8,21].

Different studies have focused on gait analysis. Since 1980s, quantitative differences of normal subjects and PD patients in gait were discussed [13,22]. In 1990s, the stride length variability was shown in PD patients [5,25,28]. Hausdorff et al. observed a fractal structure in gait and showed a stable long-range correlation in stride time interval of normal human gait [14,15] and claimed that the fractal structure is destroyed by neurodegenerative diseases [11]. Asteggiano et al. analyzed the gait variability and showed that gait study may help in early diagnosis of PD [3]. In 1998, Hausdorff et al. used stride time and length variability to separate PD, Huntington's disease and normal persons [16]. In 2003, Paquet et al. assessed the gait disorders of PD and showed decreased velocity and diminished stride length in it [23]. In 2006, Liao and Wang studied the similarity of stride times between left and right legs and showed that the symmetry is decreased in PD patients [19]. Jeon et al. classified PD and healthy persons using spatial–temporal image of plantar pressure. They achieved 91.73% accuracy [18]. In 2009, Henmi et al. presented a spectral analysis of stride signal. They claimed that power spectra can be useful for analyzing PD [17]. Cho et al. studied a vision-based analysis system using PCA [6].

Aziz and Arif studied stride rate variability. They used two complex features of gait to calculate the differences between the healthy and neurodegenerative diseases [4].

Modeling approach is also used for PD evaluation. In 1999, Edwards et al. presented an artificial neural network with a parameter for simulating dopamine level in PD [7]. In 2005, Haeri et al. focused on basal ganglia (BG) structure and presented a

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mathematical model for tremor; while being a simple model and accepting some assumptions, the role of drugs and DBS treatments were simulated fairly suitable and clinically plausible [12]. Asai et al. presented a central pattern generator (CPG) for pedalling. Based on the difference of two input signals to the model, the appropriate output in PD and healthy persons was obtained [1]. In 2008, Mashhadi Malek et al. presented a model of BG structures based on CPG. They showed that rigidity and tremor are correlated. However, the presence of oscillations in the BG internal parts contradicts this hypothesis [20]. Some simple models are introduced for stride, based on CPG theory. These are usually designed for normal persons rather than PD patients [2,26,27].

Based on abovementioned studies, it seems that analyzing and modeling the gait can be suitable for finding new methods to help early diagnosis of PD. In this study, we extracted some characteristic features of the gait and presented a model for it. We tried to extract a parameter from model to separate the normal persons from PD patients.

2. Materials and methods

Gait is a semi-periodic movement. In an ordinary way, we can consider the gait as a sinusoidal behaviour. This behaviour can easily be produced by central pattern generators. However, what makes the gait behaviour more complex is the modulatory effect of the brain on tuning the gait. This effect is the main reason of the difference between healthy and PD patients. The sinusoidal pattern of gait is not changed in the disease state; but, the tuning behaviour of the brain is changed in this state. Brain modulatory effect is observed clearly in the stride time interval variations. Therefore, the brain modulatory effect on gait (stride time interval) was considered as the output of the model. Stride time intervals have a complex behaviour and it is difficult to analyze it. First it is necessary to extract proper features from the gait signal in order to distinguish normal persons from the patients. Some mathematical tools (classifiers) are necessary to determine normal and pathological features.

Then, introducing a mathematical relation (model) to simulate the gait behaviour will be a useful step in investigating the disease. The parameters of such model may be useful for diagnosing and staging of PD. The features utilized in the abovementioned classifier may be used to produce the model.

2.1. Gait features

We chose stride time intervals as the main signal. We tried to extract features from the signals and then to train a classifier which is able to diagnose the differences of normal and PD persons. The chosen features include: variance of the stride signal, mean and variance of phase signal, regression error, and Petrosian dimension [24] for both feet. Brief introduction of Petrosian dimension and phase signal features seems useful:

Phase signal features: Phase signal shows the extent of symmetry between the right and left feet and is calculated as the difference between the stride of the left and the right foot divided by the left foot stride interval. In PD, this symmetry is disturbed, even in the beginning of the disease.

Petrosian dimension: Fractal dimension can be used when a behavioural change is seen in the recorded signal [11]. Since we know that a major behavioural change occurs in the gait of PD patients, we suggested that using this feature may have a good result in separating normal and PD persons. Petrosian dimension is a quick estimate of the fractal dimension. The mathematical method of calculating Petrosian dimension can be found in [24].

2.2. Model structure

Because of the fractal behaviour of stride signal, sine circle map (SCM) relation was used:

$$\theta_{n+1} = \theta_n + \Omega + \frac{k}{2\pi}\sin(2\pi\theta_n) \quad (1)$$

$$y = A\theta + B$$

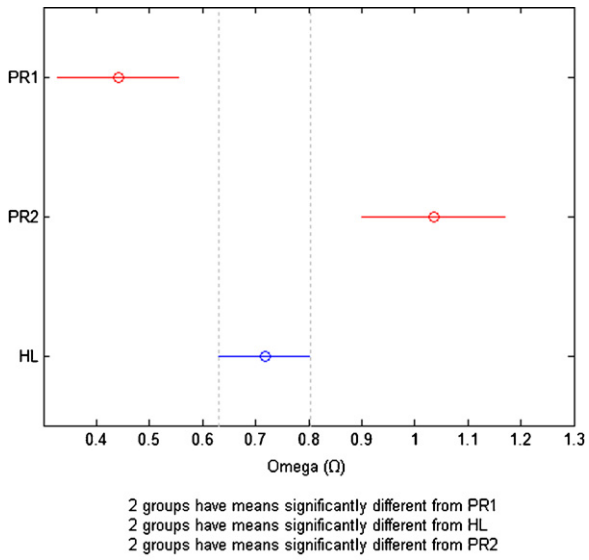

Fig. 1. Tukey–Kramer test showed that the normal and PD groups are significantly different.

The selected parameters for training this model are: θ_0, k, Ω, A and B. n shows the number of paces.

We simulated the stride signal for the left foot and used genetic algorithm for finding model parameters. All of these parameters except θ_0 (initial point) were used for generating right stride time series. θ_0 of the right foot was obtained by subtracting first left stride time from the right one. Because the model is sensitive to initial point, altering the initial point causes time series to appear different at first glance, but the global behaviour is similar in signals.

We used genetic algorithm (GA) for finding proper parameters. In this route, at first chromosomes are defined, which include random numbers that represent the chosen parameters of the model. Some definite members (chromosomes) are selected randomly. Fitness function for each member of the population is calculated. Our fitness function is the difference between features of the model and the real signal features. Based on the amount of fitness function of members, a new population is produced. In the new generation, fitness function is calculated again and this process is repeated until reaching a proper fitness.

Since our goal was producing all the features of model response similar to real cases, we considered each feature of the signal as one object and used GA in multi-object manner. Therefore, each of the model features approached the real features of the stride [9]. The primary population of GA contained 75 members.

For evaluating the results, statistical tests such as Kolmogorov–Smirnov, ANOVA, paired t-test, paired multi-compare test, and Spearman correlation were preformed.

3. Clinical data

We used the gait data of www.physionet.org [16]. This database includes 14 Parkinsonian patients and 16 healthy persons. In this database, there are time intervals of stride, swing, and stand for both legs. Objects were asked to walk 5 min in a 77 m direct path. Patients have not falling or freezing of gate (FOG). Normal subjects had no previous neural diseases or gait disorders.

For measuring time intervals, plantar force sensors were used. The sampling frequency was 300 Hz.

Table 1
The differences between model output features and the clinical data.

Feature error	Left foot variance	Right foot variance	Phase mean	Phase variance	Left foot Petrosian dimension	Right foot Petrosian dimension	Left foot regression mean	Right foot regression mean
Parkinsonian	0.002286	0.002293	0.010654	0.010654	0.002833	0.002235	0.008736	0.008658
Healthy	0.003214	0.003221	0.005511	0.005511	0.006168	0.002885	0.007946	0.007458