Classification of walking patterns in Parkinson's disease patients based on inertial sensor data

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6 authors, including:


Milica Djuric-Jovicic
Science Fund of the Republic of Serbia

Nenad Jovicic
University of Belgrade


Saša Radovanović
University of Belgrade


Nikola Kresojevic
Klinički centar Srbije

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Classification of Walking Patterns in Parkinson's Disease Patients Based on Inertial Sensor Data

Milica Djurić-Jovičić, Nenad S. Jovičić, Ivana Milovanović, Saša Radovanović, Nikola Kresojević, and Mirjana B. Popović

Abstract—**The gait disturbances in Parkinson's disease (PD) patients occur occasionally and intermittently, appearing in a random, inexplicable manner. These disturbances include festinations, shuffling, and complete freezing of gait (FOG). Alternation of walking pattern decreases the quality of life and may result in falls. In order to recognize disturbances during walking in PD patients, we recorded gait kinematics with wireless inertial measurement system and designed an algorithm for automatic recognition and classification of walking patterns. The algorithm combines a perceptron neural network with simple signal processing and rule-based classification. In parallel, gait was recorded with video camera. Medical experts identified FOG episodes from videos and their results were used for comparison and validation of this method. The summary result shows that the error in recognition and classification of walking patterns is up to 16%.**

Index Terms—**freezing of gait, gait classification, accelerometers, gyroscopes, neural networks**

I. Introduction

ABOUT one third of Parkinson's disease (PD) patients experience sudden, transient block of movement performance, phenomenon known as freezing of gait (FOG). A FOG episode is defined as the state when the patient is not responding within 1 s to the instruction to walk, or if it appears as he/she is trying unsuccessfully to initiate or continue locomotion, as well as break in gait for no apparent reason. FOG may last even for several minutes, and it is often resistant to therapy [1].

FOG can be manifested in several ways. Patients can come to a complete freezing of gait (akinesia), tremble (festinations), walk with very short steps or walk in place (shuffling) [2]. Investigators commonly distinguish five typical FOG scenarios: start hesitation, turn hesitation, hesitation in tight quarters - FOG through narrow space, destination hesitation, and open-space hesitation [3]. However, in this study, we do not attempt to differ FOGs provoked by various scenarios. We propose an algorithm for the classification of different manifestations of gait pattern that result from different gait disturbances.

FOG represents a common cause of falls and consequent injuries in PD, which stresses the importance of clinical assessment of FOG [4]. However, the assessment has been mostly based on subjective patient reports and questionnaires. Furthermore, FOG episodes are difficult to be elicited in a routine clinical examination, requiring performance of complex walking patterns with turns and obstacles. Still, there is no objective method to identify FOG phenomenon or the type, duration and intensity of disorder episodes.

Inertial sensors (accelerometers and gyroscopes) are often used for gait classification and activity recognition [5]-[10]. In order to classify gait or detect freezing, most algorithms use frequency analysis of signals from triaxial accelerometers placed on various parts of the lower body [11]-[13]. Some investigations suggest the analysis of electromyographic profiles as a method to predict FOG [14]. However, these studies do not offer FOG type classification. In this paper, we propose an algorithm for recognition and classification of different walking patterns (regular walking, small steps, shuffling, intentional standing, festinations and akinesia). This method combines a perceptron neural network and rule-based classification of the signals acquired from gyroscopes and accelerometers placed on leg segments. The algorithm may be implemented in real time.

II. Methods and Materials

A. Sensory System

We used a custom-made wireless sensory system [15]-[16], comprising 6 inertial measurements units (IMUs) placed laterally on each leg segment of both legs. These

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M. Djurić-Jovičić is with the University of Belgrade, School of Electrical Engineering, Belgrade, Serbia, and Fatronik Serbia, Belgrade, Serbia (e-mail: milica.djuric@etf.rs).

N. S. Jovičić is with the University of Belgrade, School of Electrical Engineering, Belgrade, Serbia (e-mail: nenad@etf.rs).

I. Milovanović is with the University of Belgrade, School of Electrical Engineering, Belgrade, Serbia, and Fatronik Serbia, Belgrade, Serbia (e-mail: ivana.milovanovic@etf.rs).

S. Radovanović is with the Institute for Medical Research, Laboratory for Neurophysiology, Belgrade, Serbia (e-mail: sasar@imi.bg.ac.rs)

N. Kresojević with the Institute for Medical Research, Laboratory for Neurophysiology, Belgrade, Serbia (e-mail: nikola_kresojevic@yahoo.com).

M. B. Popović is with the University of Belgrade, School of Electrical Engineering, Belgrade, Serbia; Institute for Multidisciplinary Research, Belgrade, Serbia; and with the Department of Health Science and Technology, Aalborg University, Aalborg, Denmark (e-mail:mpo@etf.rs).

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units are small and lightweight (50 g), and do not hinder patients walk. The wireless connection allows IMUs to be up to 30 m away from the computer, allowing unobstructed walking and enabling a clinician to monitor the walking from proper distance. For this implementation we used the x-axis of the accelerometer (parallel to the ground, in the direction of walking), yaw axis of the gyroscope foot sensor (measuring foot rotation – dorsiflexion and plantarflexion), and all three axes of the gyroscopes mounted on thigh.

B. *Subjects*

We collected kinematics of gait from 4 patients (age: 60±3 years) diagnosed with idiopatic PD, Hoehn and Yahr (H&Y) stage from 1,5 to 4 (mean ± SD; 2,7 ± 0,87).All patients had a clinical history of FOG, and had no known cognitive impairment. All subjects signed the informed consent approved by the local ethics committee.

C. *Recording Protocol*

Patients walked without any assistance at a self-determined speed along a corridor and a small room, and returned the same way. Patients were asked to stand up from the chair placed in the corridor, walk towards the room and pass a doorway, turn 180° to the right (U-turn), walk the same route back, stand, and sit back in the chair. The complex path included gait initiation, doorway passes, U-turn, and approaching the destination. The distance walked was around 13 m in each direction. Six trials per subject were recorded.

D. *Classification Algorithm*

Based on signals collected from gyroscope yaw axes from the foot, thigh gyroscopes (all three axes), and accelerometer signal (x-axis from the foot segment), we designed an algorithm for gait classification. This algorithm is designed to distinguish between normal and pathological states during locomotion, as shown in Table I. This classification was in parallel performed by the clinicians who examined video files and marked types and durations of each gait state.

TABLE I
CLASSIFICATION OF WALKING PATTERNS

States	Normal	Pathological
WALKING	REGULAR STEPS	SMALL STEPS
		SHUFFLING
STANDING	INTENTIONAL STANDING	AKINESIA
		FESTINATIONS

The flow chart of this algorithm is presented in Fig. 1.

First, the algorithm uses the foot-gyro yaw axis and foot-accelerometer to determine whether there is a foot movement.

Foot movement detection is implemented through calculation of energy of the sensor signals (for both accelerometer and gyro sensors). Assuming that signals have zero mean value, which is reasonable due to the existence of high-pass filters integrated into sensors, the signal energy is being calculated in 200 ms wide time intervals (i.e., the window width is 20 samples) as

$$E(t) = \int_{t-\Delta T}^{t} s^2(t)\, dt\,. \qquad (1)$$

If the energy is above a heuristically determined threshold (slightly above zero), the signal is assumed to be a part of an already initiated movement. The movement is further analyzed until the power falls below the threshold. Thereafter, the neural network is activated in order to perform recognition of the recorded movement.

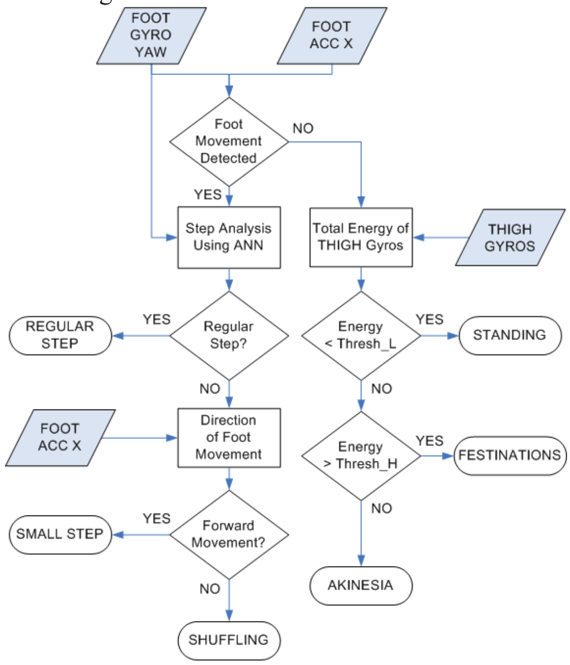

Fig.1. Flowchart of the algorithm for gait classification in Parkinson's disease patients. Input signals are foot gyro yaw and acceleration in the direction of gait propulsion, and thigh gyro signals. Output states are: regular step, short step, shuffling, standing, festination, and akinesia.

Since a neural network (NN) can recognize patterns, the basic idea is to use a NN to identify regular strides. The neural network used for this recognition is one layer perception with one neuron, 100 inputs, and hardlim training function. The network is trained to separate regular strides from other types of foot movements.

If the recorded movement is not a regular stride, the algorithm investigates whether the movement is shuffling or a small step. This classification is based on the double integrated accelerometer signal from the foot, and distinguishing between shuffling and small steps is performed by simple thresholding of the movement displacements.

In the case when there is no detection of the foot movements, gyroscope signals from the thigh are included in the FOG classification algorithm. The total energy of all gyroscopes signals is calculated as the sum of energies of all gyro axes. The energy is averaged in 100 samples wide window (1 s) in order to gain smoother line that could be thresholded. Comparing it to two heuristically determined thresholds (Thresh_L and Thresh_H), the algorithm decides if the movement belongs to standing, akinesia, or festinations.

III. RESULTS

One example of the recorded kinematics with characteristic gait disturbances according to Table I is presented in Fig. 2. The classification was first performed by the clinicians based on the recorded video files.

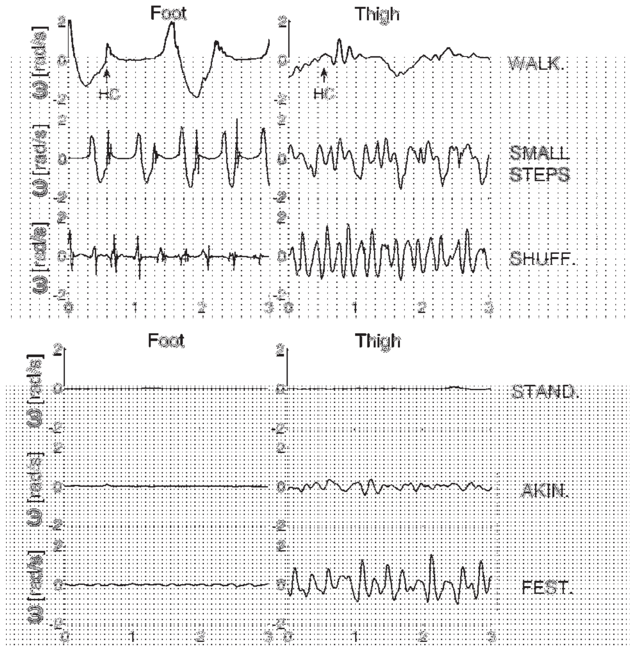

Fig.2. Classification of walking pattern according to states in Table I determined visually by clinicians from video file. One example of recorded data: signals from thigh (left column) and foot (right column) for two normal states (WALKING, STANDING) and respective pathological states (SMALL STEPS, SHUFFLING, FESTINATION, and AKINESIA). HC stands for heel contact during normal locomotion. Horizontal axis is time in seconds.

One example of classification performed automatically by the algorithm is presented in Fig. 3.

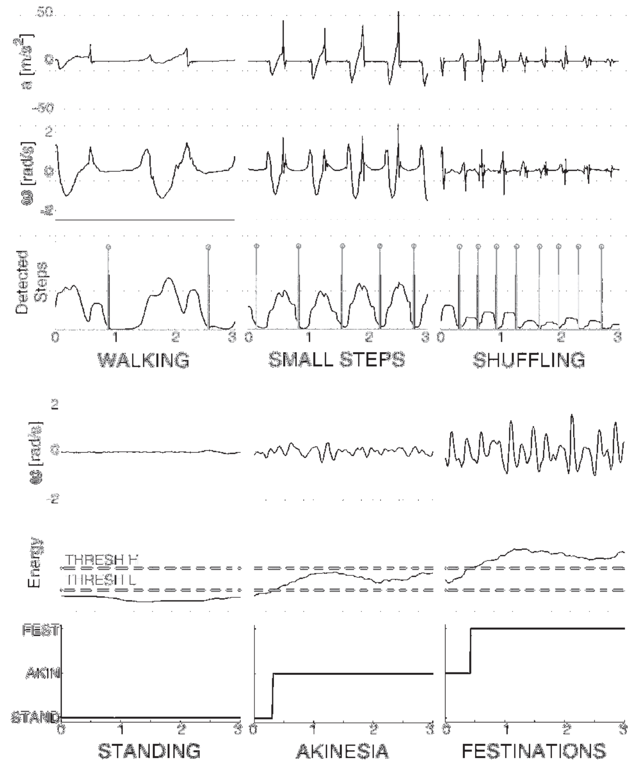

Fig.3. Classification of walking pattern according to the states in Table I determined automatically with the proposed algorithm from Fig.1. One example of classified states – for normal: WALKING and STANDING (left column panels), - for pathological patterns of walking: SMALL STEPS and SHUFFLING (middle and right column panels of top three rows), and for - pathological patterns of standing: AKINESIA, and FESTINATION (middle and right column panels of lower three rows). Horizontal axis is time in seconds.

As shown in Fig. 3, when foot movements are detected, the neural network and the foot displacement calculations are used to distinguish stride types: walking, small steps, and shuffling. Due to the short duration of both shuffling and small steps, the integration drift does not jeopardize the calculated foot displacement. For each of the recognized "steps" (SMALL STEPS and SHUFFLING in Fig. 3, middle and right upper panels and Fig. 4, left panel), classification is performed based on heuristically determined threshold (Fig. 4, right panel).

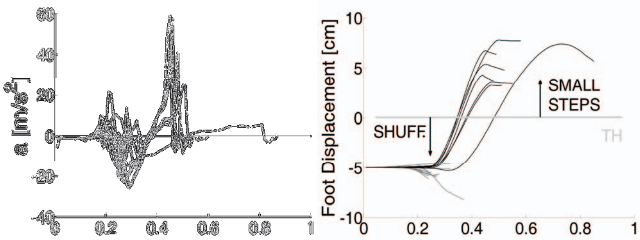

Fig.4. Acceleration recorded from foot in the direction of walking for shuffling steps (grey lines) and small steps (black lines) on left, and corresponding derived foot displacements on right panel. Classification uses heuristically determined threshold to separate small steps from shuffling as shown in this example on right panel. Horizontal axis is time in seconds.

In the case when the foot is at rest, algorithm applies threshold on the total energy from gyroscopes placed on thigh. Classification enables distinguishing three states: standing, akinesia, and festination as explained in Method and Materials section.

For detection of walking, small steps, and shuffling, error was defined regarding the number of false detections, as

$$\text{Error} = \frac{\text{Number of false detections}}{\text{Total number of detections}} 100\%,$$

while for standing, akinesia, and festinations, it was defined through time duration of each state:

$$\text{Error} = \frac{\text{Duration of false detection}}{\text{Duration of the state}} 100\%.$$

Results of this classification are shown in Table II.

TABLE II
AVERAGE CLASSIFICATION ERRORS FOR GROUP OF SUBJECTS

States	Error [%]		Detected as:
	mean[%]	range%	
STANDING	4	3-7	AKINESIA
WALKING	5	0-15	SMALL STEPS
FESTINAT.	11	4-20	AKINESIA
SHUFFLING	3.2	0-5.2	FESTINAT.
AKINESIA	16	13-23	FEST. (5%), STAND. (11%)
SMALL STEPS	6	0-15	WALKING
Not Detected	0.8	0-2	Not Classified

IV. Discussion and Conclusion

At first, we should stress that capturing of all types of FOG for every patient was not possible in six trials even if they manifest all types of disturbances.

Here we discuss the cases of false classifications.

Normal *versus* small steps. The very first step during sequence of normal strides is usually shorter and different from the following steps. As a consequence, this step, although belongs to the normal WALKING state, often is classified as SMALL STEP. However, this is systematic and thus acceptable.

Shuffling *versus* small steps. The distinction between these two types is based on an arbitrary threshold. Due to the fact that these signal levels differ significantly, this type of error was very rare and only present for cases when it was also visually very difficult to differentiate between them.

Standing, akinesia, and festination. Classification of these three states is based on empirically determined thresholds applied for the calculated energy from thigh movement. As a consequence inconsistent results across subjects may be present. These thresholds need to be adapted for each person individually due to different energy levels of the movements during walking. Our future goal is to make it automatically performed by the algorithm. Also, as explained in Method and Materials section, the calculated energy was averaged in 1 s wide window. For this reason, the algorithm has about 0.5 s delay during recognition of these states, as shown in Fig. 3, middle and right lower panels in the bottom row, energy plots. Distinguishing of the intentional standing from akinesia was possible for the recorded gait sequences because there were still some trembling movements during freezing. However, we are aware that there might be no differences between the intentional standing and akinesia.

The performance of this algorithm should be tested and validated on a larger number of patients. A real-time system for gait classification should be designed. The algorithm uses basic arithmetic operations that could be implemented on a microcontroller. Finally, standalone device could be used as a holter monitor and also a gait "defreezer", as described in [17]. Once FOG is detected, it is possible to use different sensory tricks to cease the FOG: touch, sudden sound, and light push [18]-[19]. Hence, it is of paramount importance to have an algorithm that can perform in real time, because it can be used for unfreezing the gait by delivering vibrating and/or acoustic stimulation to the patient at the moment when FOG episode occurs, as demonstrated in [17].

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