Int. J. Mach. Learn. & Cyber. (2017) 8:941–954
DOI 10.1007/s13042-015-0480-0

ORIGINAL ARTICLE

Detection of freezing of gait for Parkinson's disease patients with multi-sensor device and Gaussian neural networks

Ali Saad[1] · Iyad Zaarour[2] · François Guerin[1] · Paul Bejjani[3] · Mohammad Ayache[4] · Dimitri Lefebvre[1]

Received: 9 June 2015 / Accepted: 13 December 2015 / Published online: 26 December 2015

Abstract Freezing of Gait (FoG) in Parkinson Disease (PD) is a sudden episode characterized by a brief failure to walk. The aim of this study is to detect FoG episodes using a multi-sensor device for data acquisition, and Gaussian neural networks as a classification tool. Thus we have built a multi sensor prototype that detects FoG using new indicators like the variation of the inter-foot distance or the knee angle. Data are acquired from PD patients having FoG as a major symptom. The major social challenge is obtaining the acknowledgment of patients to participate in our study, whereas the main technical difficulty is extracting efficient features from various walking behaviors. For that purpose, the acquired signals are analyzed in order to extract both time and frequency domain features that separate the FoG class from the other gaits modes. Due to the complexity of FoG episodes, the optimal features are then extracted using Principal Component Analysis technique. Another contribution is to introduce the combined data into the Gaussian Neural Network (GNN) classification method, that is a new technique used for FoG detection, and has been developed in our previous works. Moreover, the classical thresholding method is implemented to compare and validate the GNN method. Results showed the feasibility of integrating the chosen sensors, in addition to the effectiveness of combining data from different types of sensors on the classification rate. The efficiency rate of classification in the proposed method is about 87 %.

Keywords Detection · Freezing of gait · Gaussian neural network · Parkinson's disease · Thresholding

✉ Ali Saad
ali.saad.bme@gmail.com

Iyad Zaarour
iyad.zaarour@gmail.com

François Guerin
francois.guerin@univ-lehavre.fr

Paul Bejjani
paul_bejjani@usa.net

Mohammad Ayache
mohammad.ayache@iul.edu.lb

Dimitri Lefebvre
dimitri.lefebvre11@gmail.com

1 Laboratory of GREAH (Groupe de Recherche en Electrotechnique et Automatique), University of Le Havre, Le Havre, France

2 Faculty of Business and Economical Sciences, Doctoral School of Science and Technology, Lebanese University, Beirut, Lebanon

3 Neuro-Science Parkinson Center, Holy Spirit University of Kaslik, Notre Dame de Secours University Hospital, Beirut, Lebanon

4 Department of Biomedical, Faculty of Engineering, Islamic University of Lebanon, Khaldeh, Lebanon

1 Introduction

Parkinson's Disease (PD) is one of the most common progressive neurodegenerative diseases with a higher prevalence in older adults with often devastating symptoms. The incidence of occurrence of PD has been reported as 1 % of the population over the age of 50, and 10 % of occurrence over the age of 65 [29]. One of PD symptoms is freezing, which may occur during gait, speaking or a repetitive movement such as handwriting. Freezing of Gait (FoG) has been defined as "a brief episodic reduction of forward progression of the feet despite the intention to walk", and is often described by patients as if their feet are glued to the floor for a short period of time [9]. Over half of patients with PD eventually develop Freezing of Gait (FoG) [28]. This disabling symptom often results in falls [3] and consequent injuries impairing quality of life. Its unpredictable occurrence and sensitivity to external factors such as medication, environmental triggers, or cues make it hard to detect FoG in a clinic or research laboratory [10]. FoG occurs more frequently in men than in women, especially those who report tremor symptoms [25]. Accurate detection and rating of both the severity and impact of FoG is therefore important [7, 33]. In particular, early detection and diagnosis of FoG phenomenon are major challenges for PD patients because such detection and diagnosis will prevent them from falling and hurting. For this reason, analysis of FoG phenomenon has taken an apparent area of interest in research, but a gold standard measure of FoG is currently unavailable. Designing a system that is able to detect FoG episodes accurately in PD patients would lead to the knowledge of the necessary actions that can be taken to overcome and correct each FoG episode. Therefore, careful observation and gait pattern analysis may lead to a successful management of PD patients with FoG. The aim of our research is to design a complete detection, diagnosis and correction system to manage FoG in PD patients. This study is an element of a research that is directed to build a system in order to prevent FoG episodes. The present work concerns detection of FoG. For this purpose, a preliminary multi-sensor prototype has been built to acquire heterogeneous data from different types of sensors: accelerometers, telemeters and goniometers. The other alternative of a multi-sensor device is the single sensor device, but since freezing affects the whole body of patients, a single sensor placed on a single position will not allow assessing the behavioral change of patients during FoG. Moreover, fusing multiple sensor technologies to detect the same FoG event will lead to higher reliability and trustworthiness. One of the contributions of this study is to integrate new types of sensors in the domain of FoG detection (telemeters and goniometers).The variation of the inter-foot distance is measured using the telemeter sensor. From the PD point of view of the PD expert, this measurement defines FoG phenomenon, since during a FoG episode the inter-foot distance of a patient decreases significantly while maintaining movement. All of the mentioned sensors were connected to a National Instrument Data AcQuisition (DAQ) device. Large sets of data have been collected during the imitation of normal and freezing gait behaviors of PD patients. Also, five PD patients were recruited for the collection of real walking data of PD patients including different freezing episodes. The main challenges are to find PD patients that accept to participate to our study and then to acquire data from these patients. This task is very complicated because of the sensitivity of patients to their situation, especially concerning the agonizing freezing disorder that they encounter in their daily life. Thus boosting their morale to participate in this study is essential before starting acquiring data. Moreover, PD patients that agree to participate in the study often feel exhausted very quickly, thus for each patient the acquisition sessions are separated to rest the patients physically and mentally. From the collected data, features from time and frequency domains have been extracted, which contain significant changes during FoG. Another contribution of the study is that the output decision of the detection method is based on the data given by the combination of the optimal features, which are extracted from the different types of sensors. The proposed FoG detection method is based on Gaussian Neural Network (GNN) developed in some previous works in our group and adapted for FoG detection. These networks have some advantages over the traditional artificial neural networks. (1) They can automatically adjust the number of neurons to reflect the complexity of the data to be separated (2) They generate easily non-linear separators between classes (3) Fast learning ability (4) To obtain the same accuracy; they require fewer weights (5) They can build small networks [37]. Moreover, the usual thresholding method is implemented to validate the feasibility of using the GNN method in FoG detection.

The paper is organized as follows: Section II introduces the FoG phenomenon along with a description of the various sensoring approaches that aim to detect it. Section III is divided into four parts. The first one is a short description of the sensors that were integrated in the developed prototype to detect FoG. The second one, states the data acquisition techniques used to collect data from different gait modes. The third one is a study of the acquired signals in order to extract the optimal features that can separate the FoG class from the other modes. This section ends with an analysis of the selected features to validate the signal processing part using a windowing approach. Section IV explains the methodology used for combining the selected indicators using Principal Component Analysis (PCA) technique. Then, the GNN detection method is applied and the results are validated by the classical threshold method. Section V will hold the conclusion and perspectives.

2 Position of the work and state of the art

2.1 Sensoring in FoG detection

Several studies are oriented toward the detection of FoG phenomenon using on-body acceleration sensors to measure the movements and responses of PD patients. Han et al. [12] used signal processing techniques, FFT analysis, to record movement patterns at different sampling rates.

Pre-recorded accelerometer data were utilized, and results showed that normal movement frequency is close to 2 Hz while FoG frequencies range between 6 and 8 Hz [12]. Moorea et al. [26] have utilized a single vertical linear accelerometer to detect FoG in PD patients during a pre-defined walking and standing test. By analyzing the frequency spectrum of the accelerometer, they have found that FoG is accompanied by high-frequency components in the 3–8 Hz band (freeze) with respect to the 0.5–3 Hz band (locomotor). Thus, a Freeze Index (FI) has been calculated, that is defined as the ratio of power in the 'freeze' band (3–8 Hz) divided by the power in the 'locomotor' band (0.5–3 Hz). During normal movement the FI is relatively stable, while the gait freeze causes it to increase. Thus, a threshold has been selected such that all FI values above it are classified as FoG events. This study is done on seven subjects that experienced a total of 46 FoG events. The method detects 78 % of FoG episodes before being customized to patients [26]. Several researches [1, 18] have extended the previous studies to present a wearable computer system which uses on-body acceleration sensors placed on different body parts (ankle, knee and hip) to measure acceleration data of patients. It automatically detects FoG by calculating the FI inherent in these movements. Once FoG is detected, the assistant provides a rhythmic auditory signal which stimulates the patient to resume walking. Furthermore, the contribution of the prototype that has been done by Jovanov et al. [18] is represented as improvements in the average latency period. They have recorded signals from five experiments, 4 from simulated freezing gait events and one from the real patient and analyzed feasibility of the real-time detection. They have reported 332 ms average latency period and maximum 580 ms latency period for detecting FoG. More advantages are the maximum battery life with minimum system size [18].

Bachlin et al. [1] have reported online FoG detection events with a sensitivity of 73.1 %, a specificity of 81.6 % and latency of 4.5 s (237 FoG episodes from 8 patients). Not all patients found that the auditory cueing made a positive effect in overcoming FoG [1]. For a different approach in detecting FoG, some researches [14, 30] have assessed the forces under the feet of PD patients using Force Sensing Resistors (FSR). These researches are based on the belief that during normal gait, the forces under the feet oscillate in an organized pattern, while during FoG episodes this periodicity diminishes. Popovic et al. [30] have analyzed the time series of ground reaction forces by calculating, the Pearson's Correlation Coefficient (PCC), which is the measure of the linear dependence between two signals (24 FoG episodes from 6 patients). They have selected offline the data of one step from the sequence of normal locomotion. Then this step has been used to compute the correlation coefficient by means of PCC with the entire gait record. They have found that during normal gait PCC values are around ± 1, while during a FoG event the PCC diminishes around zero [30]. Moreover, Mazilu et al. [22] have designed a multimodal sensor system using physical and physiological sensors. They have showed preliminary evidence that a multimodal view can reduce FoG detection latency by considering lower level context (e.g. turning) and physiological data.

Furthermore, recent research [23] have used the collected data from Bachlin et al. [1] to implement the FoG-detection device as an application on a Smartphone. The authors have used supervised machine learning techniques using Weka data mining suit to detect FoG. They have computed time and frequency features using data collected from different placements of acceleration sensors. The selected features are introduced to different classifiers, all classifiers are trained using features selected from N$-$1 subjects and performance has been tested on only the remaining subject. The best classifiers they have used are the AdaBoost and the random forest classifiers. The average sensitivity of their classifiers is 98.35 % while the average specificity is 99.72 %. Correspondingly, Tripoliti et al. [36] have detected FoG using signals from accelerometers and gyroscopes sensors (93 FoG episodes from 5 patients). The proposed methodology is able to detect FoG events with 96.11 % accuracy using the Random Forests classification algorithm. Moreover, [4] have described a two stage FoG detection algorithm during unconstrained and unscripted activities. They have used both wireless, wearable, miniaturized tri-axial accelerometer and electromyographic (EMG) sensors as input features of a dynamic neural network to detect FoG instances (20 FoG episodes from 6 patients). The FoG detector of this study expresses 83 % sensitivity and 97 % specificity on a per-second basis. Also, Handojoseno et al. [13] have presented a method for detection of FOG using electroencephalogram (EEG) signals using discrete wavelet transforms (DWT). Based on DWT, the EEG signal has been decomposed into five EEG sub-bands with different frequency bandwidths: 0–3.9, 3.9–7.8, 7.8–15.6, 15.6–31.3 and 31.3–62.5 Hz). The sub-bands have been used to extract the sub-band Wavelet Energy and the Total Wavelet Entropy. After that a three layer Back Propagation Neural Network (BP-NN) has been used for classification purposes. The classifier identifies the onset of FoG in PD patients during walking with average values of accuracy, sensitivity and specificity around 75 % (10 patients).

2.2 Detection methods

Change detection algorithms are mainly based on signal processing methods or on artificial intelligence methods.

There are some popular state change detectors that can be used in the online detection of FoG, such as the Exponential Weighted Moving Average (EWMA), the CUmulative Sum (CUSUM), and the Dynamic Cumulative Sum (DCS). The EWMA algorithm is used to detect an increase in the mean of a sequence of random variables. The EWMA estimator is essentially a way of forming a 'recent' estimate of the mean at time t, with older data being progressively down weighted [31]. After giving prior knowledge about the mean before and after the change, the estimated mean will allow making a decision whether a change occurred or not. The CUSUM is often considered as the best method for the online state change detection [24]. This algorithm is based on a recursive calculation of the logarithm of the likelihood ratios [27]. At each time t of the signal, the sum of logarithms of the likelihood ratios is computed. The drawback of CUSUM algorithm is that it requires a prior knowledge about the characteristics of the probability density function of the signal before and after the change. To overcome this drawback, Dynamic Cumulative Sum (DCS) technique can be used. It is based on the local cumulative sum of the likelihood ratios between two local segments estimated at the current time t [27]. The two segments are two windows, situated before and after time t, and an estimation of the characteristics of the probability density function of each segment is calculated before computing the likelihood ratio between them. Currently, we are interested to detect FoG using artificial intelligence methods. Soft computing methods are substantially utilized in different real life applications. These applications vary from river forecasting [6, 34], to daily flow prediction [5, 38] and many others. Therefore, we have treated FoG detection as a classification problem, and integrated a new soft computing technique to detect FoG, which is the GNN method. Unlike previous studies, and due to the complexity of FoG episodes, this study aims to detect FoG using the combination of heterogeneous data (e.g. data from different kind of sensors). The classifier decision is based on the data given from a multi sensors system. To the best of our knowledge, there is no previous work that integrates telemeters and goniometers in the detection of FoG for PD patients. Our aim is to design a systematic algorithm that will be implemented for online detection and may lead to obtain the best sensitivity compared to the existing works that are dealing with FoG detection.

3 Data acquisition and signal processing

3.1 Sensors description

Three types of sensors have been integrated: accelerometers, telemeters and goniometers. For the measurement of acceleration during gait, ADXL330 3-axis acceleration board has been used. Besides precision, the additional advantage of this board is its small size, 28.3 mm × 18.5 mm. There are several accelerometer boards that can be used to serve the same purpose (e.g. triple axis accelerometer LSM303). However the ADXL330 3-axis acceleration board is adopted due to its low noise and power consumption, as well as its small size and weight, in addition to its low cost. The measurement range of this accelerometer is ±3 g. Figure 1 shows that two acceleration boards are used. One accelerometer is fixed on the shin, and the other on the foot.

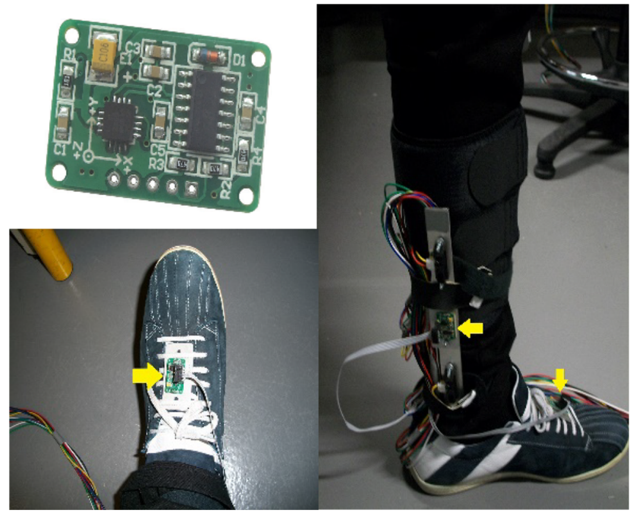

Fig. 1 Acceleration sensor

In this study, the used telemeters are the infrared proximity sensors GP2Y0A21YK made by Sharp. This type of sensors detects distances between 10 and 80 cm with voltages between 3.2 and 0.4 V. Two telemeters are integrated, the "Upper telemeter" which is the one far from the foot, and the "Lower telemeter" which is the one near the foot. Figure 2 shows the position of the two sensors on the leg. The distance between the two telemeters is about 30 cm. Telemeter sensors were used to measure the variation of the inter-foot distance during walking. Telemeters were placed on the inner part of the lower left leg, so that whenever a step is repeated the sensors will detect the instance that the legs are aligned along each other. Other telemeters that can be used for this purpose are: AN1436 proximity sensor, Pololu 38 kHz IR Proximity Sensor and many others. This type of sensor is used because its output can be easily converted to distances. In addition, it is characterized with low cost, reduced size and power consumption. Yet, this sensor is good for applications that do not require high precision which is our case. Note that the exact measured distance between the two feet during an exactly defined timing is not required, and that only

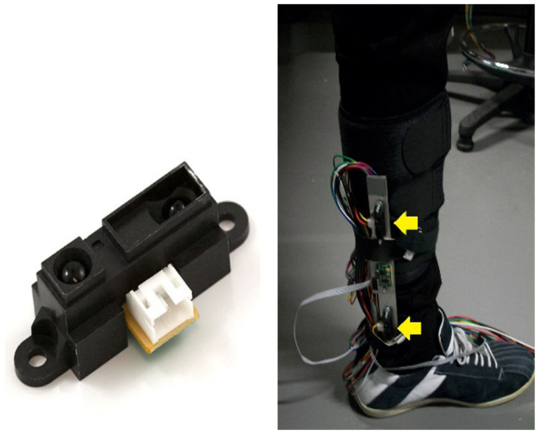

Fig. 2 Telemeter sensor

changes that occur in the signal provided by the telemeter sensors will be used in this study.

The other type of sensor employed is the goniometer. It is employed to the wearable device to measure the angle of the knee during the gait of PD patients (Fig. 3). Thus, the variation of this angle during normal gait, and during FoG is observed. The goniometer has been fixed on the leg using two adjustable neoprene supports, one on the thigh and the other on the shin. The type of goniometer used is the Vishay Spectrol Full 360° Smart Sensor Model 601 HE. The measurement range of this sensor is 0° to 360° with output voltage range not less than 90 % of the supply voltage. Therefore, the sensor is calibrated to give 1 V for 0°, and 2.4 V for 90°. The advantages of this sensor type are: (1) its self-contained package which provides an analog electrical output over a full 360° without the need of external electronics. (2) Low power consumption. (3) Non-volatile output. These advantages make this sensor more effective with less cost over the traditional encoders or potentiometers that measure the angle.

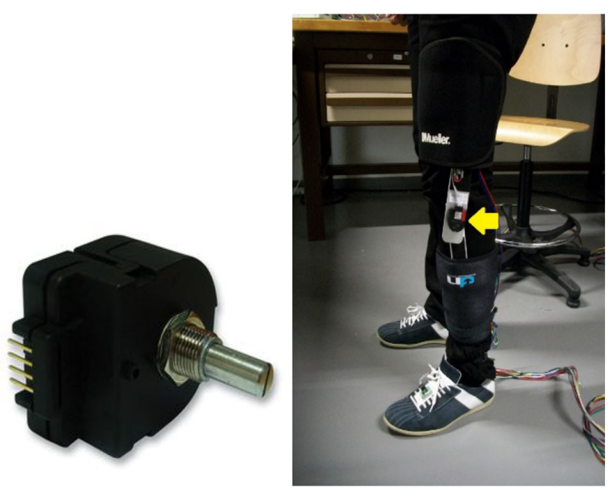

Fig. 3 Goniometer sensor

3.2 Data acquisition

In order to build a preliminary prototype, all of the above mentioned sensors were connected to a National Instrument Data Acquisition (DAQ) device (NI DAQ PCI—6259). Data were saved as '.dat' files using a Visual-Basic computer program, and then signals were processed offline by Matlab program. After studying the gait of PD patients, it is known that PD patients in general walk with short and hasty steps [20], and during a freezing episode their walk can be described as shuffling forward (the patient makes an effort to overcome the block and is partially successful but the steps are very small and rapid and no real step is taken) [15].

Consequently, the first use of our acquisition prototype was to acquire data from different gait modes: (1) walking normally, (2) simulating the short steps of PD patients that is considered as the normal walking of PD patients, and (3) simulating the shuffling forward of PD patients that occurs during their freezing episodes. Table 1 summarizes these test modes and their corresponding duration. Each of the below tests was repeated ten times with sampling frequency of 100 Hz.

In the last test mode, different gait behaviors are simulated (normal short steps, and FoG). Thus, it is important to label the acquired data points. This is done by observing each run, and selecting manually the five seconds of simulated FoG episode in each run. Therefore, all data points of the FoG episodes are labeled as "1" and the rest of the data points are labeled as "0".

Experiments took place in "Neuro Science Clinic: Parkinson Memory and Movement Disorder Center", Beirut, Lebanon, under the supervision of a clinical specialist. Five patients (four males and one female) were taken voluntary. All patients are diagnosed with PD without evidence of other form of Parkinsonism (dementia, multiple system atrophy, and progressive supranuclear palsy) [35] and with history of FoG episodes. After

Table 1 Description and duration of all test modes in FoG episodes simulation

	Description	Duration
Test mode 1	Walking with normal steps	15 s
Test mode 2	Walking with short steps to simulate the normal gait of PD patients	15 s
Test mode 3	Simulating FoG by imitating the shuffling forward behavior of PD patients during FoG episodes	15 s
Test mode 4	Walking with normal short steps for 10 s, and then simulating FoG for 5 s, and finally another 5 s of normal short steps	20 s

understanding the study and the test protocol, all patients agree to participate anonymously in the tests. The patients have an average age of 73 years, and average disease duration of 8 years. All patients were taking anti-parkinsonian medications.

We designed a set of scenarios with different types of motor activities that patients are asked to perform. The chosen activities stimulate the occurrence of FoG (e.g. turnings, passing narrow paths). Since patients will be physically tired throughout the experiments, patients were asked to rest between sessions. In the following, details about the protocol session are provided:

- *Straight walking with turns* The subject needed to complete 6 m of straight walking, turn, and then walk again in the opposite direction. The performed task is simple. But sometimes, complications is added to the task by adding a cognitive load (holding a ball), or by narrowing the straight path, or by placing an additional obstacle for patients to turn around it.
- *Straight walking above cones with turns* The subject needed to complete the same tasks as mentioned above in the presence of cones as barriers to pass across it as shown in Fig. 4.
- *Clinic tour* A real-life session that included random unscripted walking through the hall of the clinic and in the garden with involuntary stops, turns, changes of direction, and walking in narrow spaces.

Fig. 4 A view where a patient (*left*) is stepping over cones while wearing the prototype whereas the physiotherapist (*right*) is monitoring the gait the patient

- The total number of freezing episodes is 64 for the five patients divided as follows:
  - Patient 1: 14 FoG episodes.
  - Patient 2: 15 FoG episodes.
  - Patient 3: 7 FoG episodes.
  - Patient 4: 10 FoG episodes.
  - Patient 5: 18 FoG episodes.

The acquired data are synchronized with video recordings that are captured during each test. Then with the help of the physiotherapist, FoG data were labeled for each patient as well as the state of the patient (e.g. walking, turning, standing, sitting etc.). Since our aim is to detect freezing during the gait of patients, data that are not related to walking state have been removed from our datasets.

3.3 Signal processing

In this section, the simulation data are used to make a comparative study between signals acquired from the three different gait modes (normal gait, short steps, and FoG). The aim is to extract features that can separate the FoG class from the other modes (one against all). Therefore, each sensor signal is divided into several sub-segments, and time and frequency domain characteristic features were computed. Table 2 summarizes the extracted characteristic features and their descriptions. The intention is to extract features with minimum complexity, to allow their implementation in a wearable computer for online FoG detection. The most simple and obvious features to be tested in time domain are the mean and standard deviation. Furthermore, we extracted standard frequency based features which are the mean frequency and the frequency power. As

Table 2 Summary and description of the extracted features

Characteristic feature	Description
Mean	Mean value of the selected data
Standard deviation	Standard deviation value of the selected data
Power spectral density (PSD)	Power (S) carried by the wave, per unit frequency (f)
Power of the signal[a]	Calculated using the spectral Moment formula ($M_r = 2\int_0^\infty f^r S_x df$) such that (M0) is the power of the signal
Mean frequency[a]	Calculated using the spectral Moment formula such that (M1/M0) is the mean frequency
Freeze index (FI)[a]	Inspired from Jovanov et al. [18], and defined as the ratio of power in the freeze band (3–8 Hz) divided by the power in the normal walking band (0.5–3 Hz)

[a] Parameters estimated using PSD

for the Freezing Index feature, it is extracted due to its importance in previous work.

At this stage, test modes have been compared to each other to detect changes in the waveforms of each measured signal. Each sensor was studied separately, in order to extract the optimal features that may lead to detect FoG.

Upon visualizing and comparing the raw signals of the three test modes, a change appears in the behavior of the signals especially during the FoG test mode. For instance, the goniometer signal has an increased frequency accompanied with a decreased angle variation during FoG. In addition, FoG episodes are characterized by a deformation of the walking rhythm and step magnitude that leads to specific features in the telemeter sensor voltage measurements. In both short steps and normal walking modes (Fig. 5a, b) voltage peaks occur shortly, this shows that the person is walking with complete steps. As for FoG signals (Fig. 5c), the width of the voltage peaks increases while the time between different peaks decreases. This shows that the person is walking with incomplete steps, while legs are near each other. It is also important to conclude how much this change in the signal will reflect changes in the selected features.

Following the extraction of all features for each sensor signal, the histograms of the features for the three test modes are compared. Starting by the goniometer signal, it is observed that the most important features that have a significant change in its values during FoG are the FI and mean frequency. Both features show a noticeable increase during FoG mode. Figure 6 represents the goniometer FI histogram for each test mode.

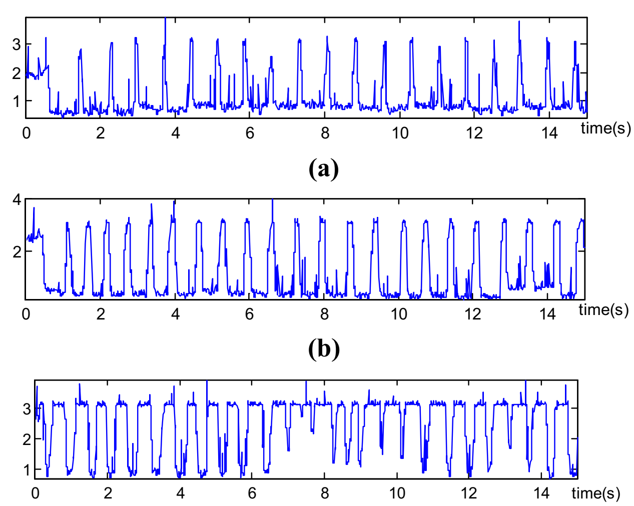

Fig. 5 Upper telemeter signals (Volts) during the three test modes. **a** Normal walking; **b** Normal small steps; **c** FoG simulation

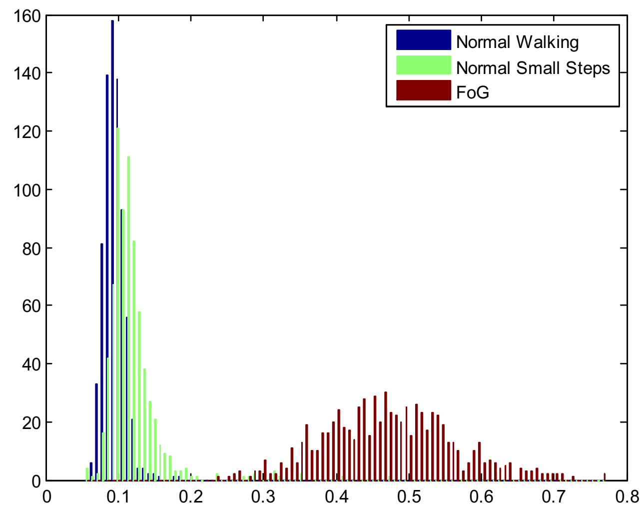

Fig. 6 Freezing Index histogram of goniometer data

For both upper and lower telemeter signals, the main characteristic feature that has a significant change in FoG is the mean. This significant change in the telemeter signal allows more investigation to extract more features and analyze them. For example, one of the features that may have more accurate discrimination is calculating the duty cycle of each period of the signal which theoretically may lead to evaluate how dominant the high state is in the signal.

The analysis of the accelerometer signals acquired from the shin shows that features extracted from the frequency components of the signal are important. Furthermore, in x-axis the FI and mean frequency show a very significant increase during FoG. Moreover, in y-axis the sensor provides only an increase in PSD power during FoG test mode. Finally, the z-axis shows a significant increase of the mean frequency during FoG.

3.4 Feature analysis and selection

In this section, the fourth test mode (Table 1) is used to validate the signal processing part where abrupt changes in signals occur during walking. This is done by applying a small window of length 2 s, with step size of 0.2 s that slides throughout the whole signal and extracts from each window the optimal selected features. The aim is to observe the ability of the optimal features to detect the appearance of FoG episodes when it is merged with a normal gait mode. Figure 7 shows signals from all sensors during one run of the fourth test mode.

Figure 8a shows a significant increase of the mean frequency for the goniometer when an episode of FoG occurred. As for FI, it is noticed that all previous studies applied this feature only on acceleration sensors. But our

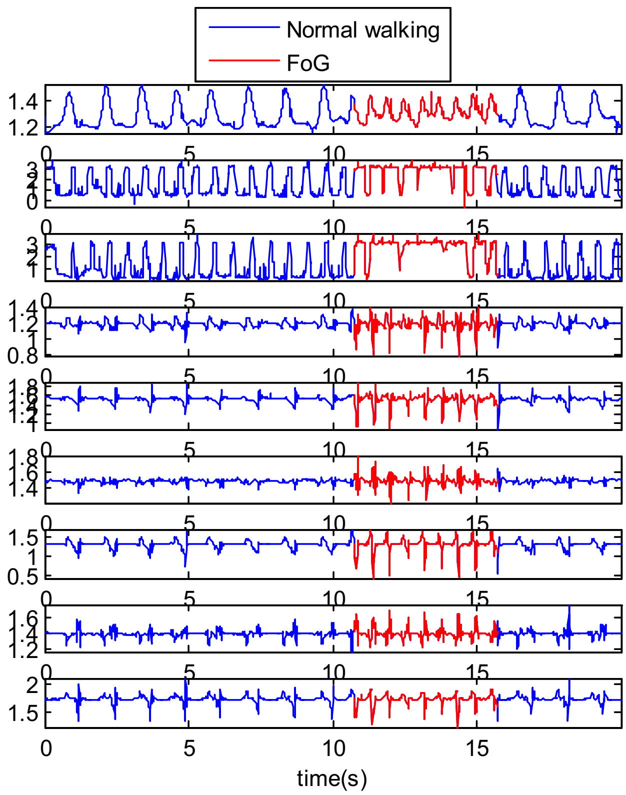

Fig. 7 Signals (Volts) from all sensors during a randomly picked run. Starting from *top to bottom*: goniometer, upper telemeter, lower telemeter, x-axis shin accelerometer, y-axis shin accelerometer, z-axis shin accelerometer, x-axis foot accelerometer, y-axis foot accelerometer, z-axis foot accelerometer

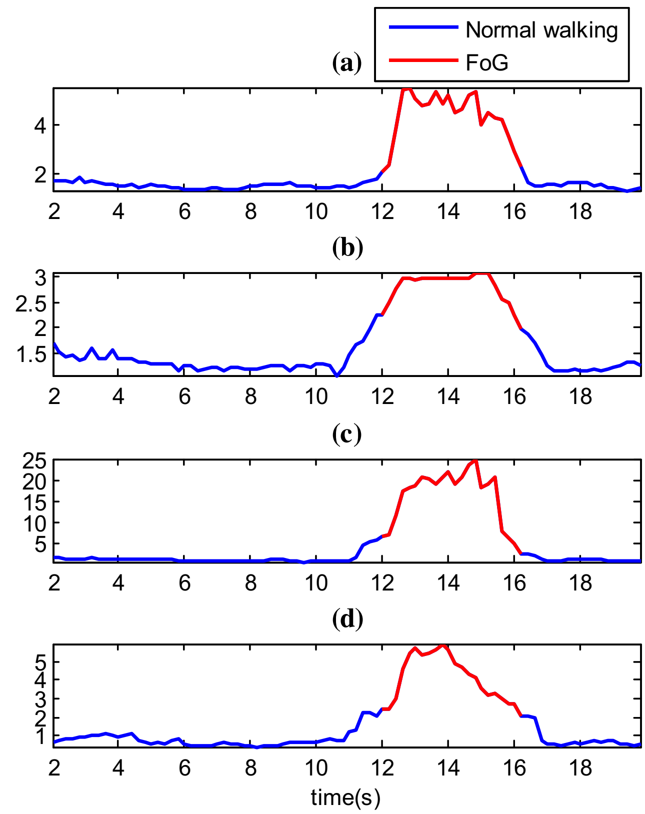

Fig. 8 Different features as function of time: **a** Mean frequency (Hertz) of goniometer data; **b** Mean (Volts) of telemeter data; **c** Freezing Index of x-axis shin acceleration data; **d** Freezing Index of x-axis foot acceleration data

result shows that this feature can be used to detect FoG using the goniometer also. Signals of both upper and lower telemeter sensors showed a significant change of their mean during FoG episodes (Fig. 8b). This result is very advantageous especially in order to design a system for online detection of FoG, since the mean of the telemeter signal, which is a time domain feature, needs less computational time. Thus an online detection system can be implemented with minimum latency period. For the shin acceleration data, the features that allow to detect FoG in both x and y axis are the standard deviation (time domain), PSD power and FI (frequency domain). It is worth mentioning that FI has the most significant change during FoG when compared to the other two indicators (Fig. 8c).On the other hand, z-axis of the shin accelerometer shows less significance when compared to the other two axes. With respect to the foot accelerometer (Fig. 8d), FI is the best indicator that can be used to detect FoG. Furthermore, standard deviation and PSD power can be considered but with much less significance. The changes of all three indicators in the foot accelerometer during FoG are less than that in the shin accelerometer. To conclude, positioning the accelerometer on the shin is better than placing it on the foot. This matches the result of previous work [1, 21, 36]. Thus, the most informative features, which are the best features to detect FoG for certain sensors, are selected after studying the change of the mean of their distribution during FoG. Table 3 summarizes the best indicators for each sensor that can be used to detect FoG.

4 FoG detection

4.1 Feature combination with PCA

Data combination is an essential task in our study that is needed to extract the most significant components of the features. The aim of this step is to combine the above mentioned indicators using PCA technique. The central idea of PCA is to reduce the dimensionality of a data set consisting of a large number of variables, without losing too much information. As a result, new attributes will be discovered, called “Principal Components” (PCs) that will be introduced to detect FoG with respect to change detection. Other alternatives for PCA are Exploratory Factor Analysis (EFA) and Fischer Discriminant Analysis

Table 3 Summary of all indicators that best detect FoG

Feature	Best indicators (*with less significance)
Goniometer	Mean frequency
	Freezing Index*
Upper and lower telemeter	Mean
	Standard deviation*
Shin accelerometer	Freezing Index
	Standard deviation*
	PSD power*
Foot accelerometer	Freezing Index
	Standard deviation*
	PSD power*

(FDA) that also can be used as variable reduction techniques [8, 11]. PCA is selected since in our case it is not important to determine the correlation among the observed variables, which is done using EFA. The aim is simple, just combine and reduce multidimensional data to lower dimensions while retaining most of the information. Moreover another important advantage for PCA in our case is the decreased requirements for capacity and memory. This allows the implementation of the algorithm on a wearable computer with minimum complexity. The calculations of PCs are based on the eigenvectors and eigen values of the covariance matrix. Note that there is a drawback of the PCA method, which is the sensitivity of the PCs to the units of measurement. This drawback may be very important in our study since our extracted attributes are collected from heterogeneous sensors and have different units of measurement. To overcome this drawback it is preferable to use the PCA from the correlation matrix. This will avoid that PCs are arranged according to the size of the variances of the original data [17]. For correlation matrices, the standardized variables are all dimensionless and can be combined to give suitable PC scores [19]. After applying the PCA technique to the FoG simulation dataset, data are normalized in range [0: 1] × [0: 1]. Also, the percentage of the total variance explained by each principal component is calculated (Fig. 9). It is obvious that the first two PCs that contain about 87 % of the information are the most important components. Figure 10 shows the distribution of the first two PCs in a plane (PC1, PC2). It is observed that in both components the FoG data have higher values when compared to the noFoG data which are near to zero.

4.2 Gaussian neural network method

GNN artificial neural network with Gaussian activation functions is used according to our previous works [2]. For FoG detection, the GNN learning algorithm is simplified by

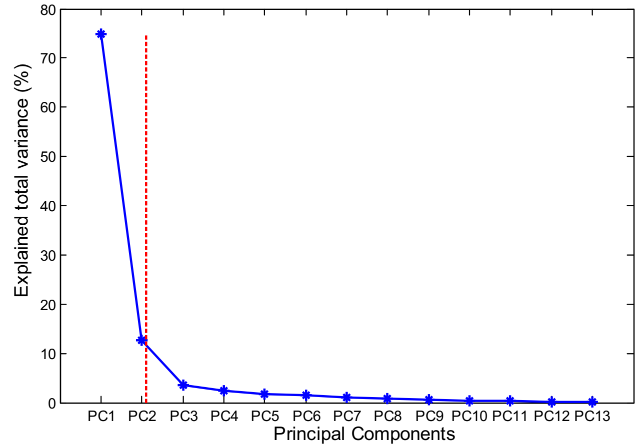

Fig. 9 The percentage of the total variance explained by each output pc

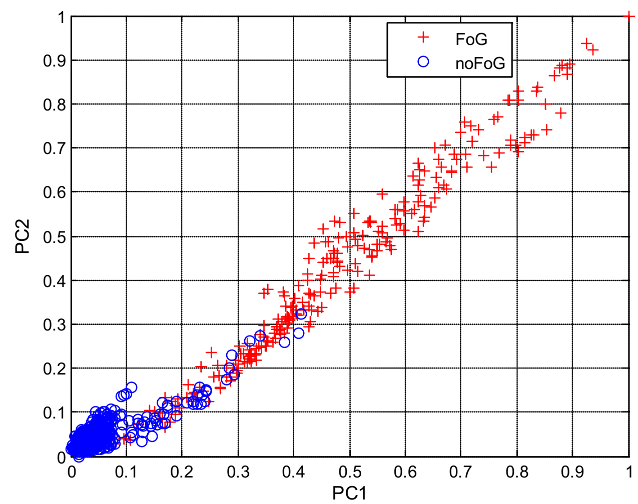

Fig. 10 Representation of simulation data in plane (PC1, PC2)

using a fixed structure without adding extra nodes to it during the learning process. The input data for the GNN is the first two principal components that have been extracted from the optimal features of the different sensors after being normalized to the domain [0:1] × [0:1]. The use of such model is motivated by the ability to approximate nonlinear parametric fields, and because the separation of the Gaussian surfaces are either arcs of circle or straight lines depending on the value of the learned Gaussian function parameters [32]. The idea is to use the learning PC data to represent each class (FoG/noFoG) by a specific Gaussian function. The Gaussian functions are defined by Eq. (1):

$$G_j(X''(P)) = \frac{1}{d_j\sqrt{2\pi}} e^{-\frac{\|X''(P)-c_j\|^2}{2d_j^2}} \quad j = 1, \ldots, N_c \tag{1}$$

where $X''(P)$ is defined as the normalized principal components. N_c is the number of activation nodes that correspond to the number of classes. c_j and d_j are respectively the center and the dispersion of the jth Gaussian function. For the learning of both parameters c_j and d_j, a supervised classification algorithm is proposed for the GNN [32]. These parameters are calculated iteratively. At each iteration, the misclassification rate of the classifier is evaluated by calculating the mean error of classification which is given by Eq. (2)

$$E_m = \frac{1}{N_c \cdot (N_c - 1)} \left(\sum_{j=1,\ldots,N_c, k=1,\ldots,N_c, k \neq j} E(j,k) \right) \tag{2}$$

where $E(j, k)$ is defined as the proportion of samples of type j that activate the representative Gaussian function of class k.

4.2.1 Center learning

Initially the Gaussian centers are equal to the center of gravity of the data for each class. The aim is to adjust these centers, so that each center will best represent the data of its class. If $g(X''(P))$ is defined as the most representative Gaussian function for the data sample X, it is computed using Eq. (3), and thus the position of the center is updated with Eq. (4).

$$g(X''(P)) = arg\left(max_{j=1,\ldots,N_C}\left\{G_j(X''(P))\right\}\right) \tag{3}$$

$$c_{g(X''(P))} = \alpha . \frac{\left(C_{g(X''(P))} - X''(P)\right)}{N_L(g(X''(P)))} \tag{4}$$

where $\Delta c_{g(X''P))}$ represents the variation of the center $c_{g(X''P))}$, and $N_L(g(X''P)))$ is the number of samples in the learning set, that belong to the domain of activation of the function $G_{g(X''(P))}$, and α is a gain parameter selected by the user. The process stops when the center converges, or when the maximum number of iterations is reached.

4.2.2 Dispersion learning

Initially the dispersions are equal to the standard deviation of the data representing each class. This value is adjusted by using a simple trial and error measurement method because it is really difficult to evaluate the sensitivity of the classifier performance with respect to the standard deviation. The difficulty is that a small variation of the standard deviation for a single node changes the perimeters of all classes. Thus, the dispersion is increased or decreased in order to improve the discrimination between classes, and consequently to minimize the mean error E_m. The dispersion is updated with Eq. (5):

$$\Delta d_{\beta *} = \gamma . \beta^* . d_{j*} \tag{5}$$

where γ is a gain parameter close to 0 selected by the user and the couple (j^*, β^*) is defined in Eq. (6):

$$(j^{\beta *}, \beta^*) = \arg\left(min_{j,\beta}\left\{E_m\left(d_j \cdot (1 + \beta \cdot \gamma)\right), \beta \in \{0, +1, -1\}, j = 1, \ldots, N_c\right\}\right) \tag{6}$$

In this study, the two components that are calculated from the simulation data will be introduced as a learning dataset to the GNN in order to learn the centers and dispersions of the Gaussian functions that represent the data. The eigenvectors calculated from the simulation data are saved, and used to project the new data (e.g. data from real PD patients) then introduced to the GNN as a testing dataset. The reasons to use simulation data for calibration and learning are (1) the few number of PD patients, which impose us to save their data for validation, (2) the physical difficulties for PD patients to participate to a quite long and tiring learning phase. For new input X, $Prob_j(X)$ which is the probability of belonging to class j is computed using Eq. (7), and X is classified as $class(X)$ = FoG or $class(X)$ = noFoG according to the maximum of the probability computed for each class.

$$Prob_j(X) = \frac{G_j(X)}{\sum_{k=1}^{N_c} G_k(X)}, \quad j = 1, \ldots, N_c \tag{7}$$

Furthermore a classification confidence coefficient is calculated after each decision. Since two classes (FoG and noFoG) are considered, then there will be two Gaussian activation functions: $G_1(x)$ having a center c_1 and dispersion d_1 and $G_2(x)$ having a center c_2 and dispersion d_2. Then the confidence coefficient can be computed using Eq. (8).

$$Conf(x) = \begin{cases} |D - R| \; if \; class(X) = FoG \\ \dfrac{d_2}{d_1} * |D - R| \; if \; class(X) = noFoG \end{cases} \tag{8}$$

where X is a new classified point, D is the Euclidian distance between this point and the center of the Gaussian function associated to the FoG class, and R is the radius of the FoG class. More details can be found in Sidibé et al. [32]. This coefficient is used to evaluate the belief of the classification for each new input.

4.3 Thresholding method

This method is integrated in our study to validate the GNN method and to highlight on the advantages of using such method compared to the usual thresholding method. Huang and Chau [16] propose other alternative for calculating the optimal threshold. They used the Expectation Maximization (EM) algorithm to find a number of Gaussian mixtures that allow computing the optimal threshold for a specific gray image histogram [16]. In our case, since the thresholding method is utilized for comparison reasons only, the traditional trial and error thresholding method is used. For this purpose, thresholds that separated FoG from noFoG data are computed using the first two PCs of simulation data. Moreover, the PCs from real PD data are projected using the eigenvectors from simulation data. The optimal threshold for each PC is the one that gives the highest accuracy value. The accuracy is computed according to Eq. (13).

$$\text{Accuracy} = \frac{[\text{Number of correct decisions}]}{[\text{Number of cases}]} \tag{13}$$

Table 4 represents the optimal threshold for each PC and its corresponding accuracy. The thresholds allowed transforming the two PCs into binary vectors with "1" where FoG is detected and "0" elsewhere. The final step of the thresholding method is to input the binary PCs into a binary decision process (AND operator). This means that a data point is classified as: (1) FoG if both PCs classified it as FoG, (2) noFoG if both PCs classified it as noFoG, (3) outlaw if there is a negation between the classifications of the PCs.

4.4 Discussion and results

The collected data from the five PD patients is introduced to the GNN classifier. The classifier detected the occurrence of all FoG episodes for the different patients. Figure 11 represents the first two components of a sample of the data acquired from Patient 1 (P1) where a FoG episode occurred to him during walking. It is shown that during FoG both PCs increase significantly while they maintain a near zero distribution while the patient walks normally. The figure also represents the boundary of the Gaussian functions that are learned from the simulation data as well as the thresholds that are obtained from the thresholding method. It has been noticed that the boundary of Gaussian function can clearly separate the FoG data from normal walking data. This proves that the acquired simulation data can be considered as an acceptable representation of the real patient data. In other words, this proves that the extracted features from the simulated data can be used for the analysis of patient data. It has been noticed that for the GNN the separation is non-linear, while the thresholding method gives linear separators.

Table 4 Detection accuracy for each attribute

PCs	PC1	PC2
Optimal threshold	0.825	0.15
Accuracy (%)	96.33	96.11

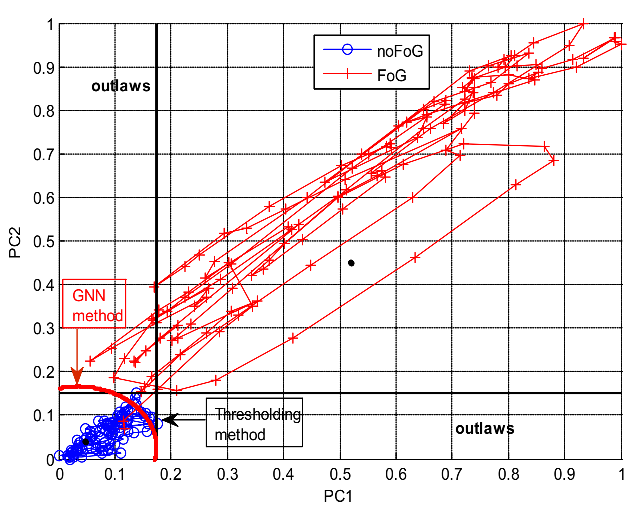

Fig. 11 GNN limit versus thresholding limit for P1 in plan (PC1, PC2)

Table 5 gives the FoG detection performance of the data from P1. The average performance is the mean value resulting from the rate of FoG data points that are correctly classified in FoG class and the rate of noFoG data points that are correctly classified in noFoG class. The average classification rate is 0.89 for the proposed GNN method. Despite the similar performances of the GNN method and the thresholding method, the advantages of the proposed GNN method are the autonomous adaptation process and its ability to take into account new data, as well as the absence of outlaws that are present in thresholding method. The presented rates stand for the detection accuracy in terms of data points. So the GNN classifier detected all FoG episodes for each patient, but with specific detection accuracy. To enhance these performances a confidence coefficient is calculated (see Sect. 4.2). Figure 12 shows the change of the classification belief coefficient during two consecutive FoG episodes. It is noticed that in each false classification the confidence coefficient tends to reach the zero value. This coefficient can be used to remove any decision with very low confidence and retain the previous decision.

Finally, similar results are evident in all patients, yet a slight difference in the average detection performance is observed as shown in Table 6. Knowing that every patient has different gait behaviors and different ways of freezing, our system has been proven to be able to detect the occurrence of the different FoG episodes. This suggests the robustness of the implemented method, and this proves also the feasibility of implementing the proposed detection classifier for online detection of FoG.

5 Conclusion

We have described a new method to detect FoG in PD patients. We use our previously implemented method and adapt it in a new field of application, which is FoG detection. We have designed a preliminary multi sensor

Table 5 Performance of the Gaussian and thresholding methods for patient 1

	Classified as FoG	Classified as noFoG	Classified as outlaw	Average perf.
GNN				
Class FoG	0.99	0.01	N/A	0.95
Class noFoG	0.08	0.92	N/A	
Thresholding				
Class FoG	0.89	0.01	0.1	0.93
Class noFoG	0	0.98	0.02	

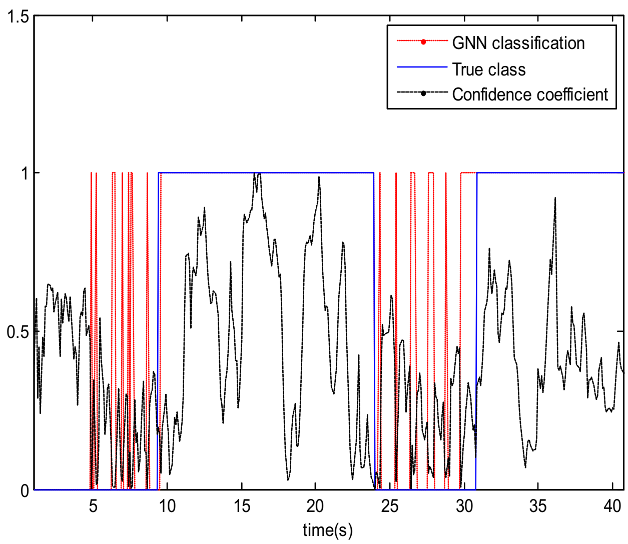

Fig. 12 GNN classification (*dotted line*) versus the true class (*full line*) including the classification confidence coefficient (*dashed line*)

Table 6 Average performance of GNN classifier for all patients

Patient	GNN average performance
P1	0.95
P2	0.84
P3	0.87
P4	0.82
P5	0.89

system that is able to acquire data from PD patients. Five PD patients have been recruited for FoG data acquisition. New sensors in the field of FoG detection are integrated in our system: particularly, the telemeter that allowed measuring the variation of the inter-foot distance, which is a novel measurement in the evaluation of gait for PD patients. From all the sensors, we have extracted optimal features that made a significant change during FoG. Due to the complexity of FoG episodes, the optimal features are then combined using PCA technique. The two principal components explained about 87 % of the whole data. After that, the principal components are introduced into a new detection method, which is the Gaussian Neural Network in which Gaussian activation functions are trained using patterns extracted from the learning data. The average classification rate for the five PD patients using the Gaussian method is 0.87. We notice that the position of the accelerometer on the leg is very important, where the shin position is more appropriate since it had better results in FoG detection. One limitation in our conclusions is due to the small number of patients that participate in the test. We expect that more patients will participate in future tests. Other limitation in our study is the wired connection between the integrated sensor and the acquisition device. This problem will be solved upon implementing the detection algorithm to a wearable computer. This task will increase the patient comfort during the data acquisition tests.

The future steps of this study are to complete the work in designing a whole system that prevents FoG episodes using measurements obtained from PD patients that suffer from FoG. First, the designed online detection algorithm (GNN) will be improved by considering the uncertainty of each decision to increase the detection performance. The detection approach will also be compared to existing efficient change detection algorithms (EWMA, CUSUM, DCS…), as well as other machine learning algorithms (e.g. Bayesian Belief Networks).

On the other hand, a diagnostic model will be developed based on probabilistic models (i.e. Bayesian Belief Networks). The structure of the Bayesian model will be graphical and qualitative illustration of the essential causal relationships among the causal factors that would lead to the appearance of FoG episodes. The diagnosis model will combine different useful information from the statistical studies done in this paper in addition to the knowledge of the PD experts. The aim is to design a model that may predict the appearance of freezing episodes using all information that particularly affect the freezing phenomena.

After completing our detection and diagnosis system, methods that would overcome FoG will be implemented and tested. The decision given by the detection and diagnosis system will trigger actions that may lead to overcome FoG. In particular we will investigate the stimulation of the tibialis anterior muscle that may be more effective than visual or auditory cueing. However this task needs more extensive effort to study the effect of such action on patients.

Finally the perspectives are also to implement the whole system in a wearable computer "RASPBERRY PI" and used for online detection, diagnosis and correction of FoG.

References

1. Bachlin M, Plotnik M, Roggen D, Maidan I, Hausdorff J, Giladi N, Troster G (2010) Wearable assistant for Parkinson's disease patients with the freezing of gait symptom. IEEE Trans Inf Technol Biomed 14(2):436–446
2. Barakat M, Druaux F, Lefebvre D, Khalil M, Mustapha M (2011) Self adaptive growing neural network classifier for faults detection and diagnosis. Neurocomputing 74(18):3865–3876
3. Bloem BR, Hausdorff JM, Visser JE, Giladi N (2004) Falls and freezing of gait in Parkinson's disease: a review of two interconnected, episodic phenomena. Mov Disord 19(8):871–884
4. Brayan TC, Sergy HR, Hamid N (2011) Detecting freezing-of-gait during unscripted and unconstrained activity. In: 33rd annual international conference of the IEEE engineering in medicine and biology society, Boston, USA, 30 Aug–03 Sept 2011
5. Chau KW, Wu CL (2010) A hybrid model coupled with singular spectrum analysis for daily rainfall prediction. J Hydroinform 12(4):458–473
6. Cheng CT, Chau K, Sun Y, Jianyi Lin (2005) Long-term prediction of discharges in Manwan reservoir using artificial neural network models. Lect Notes Comput Sci 3498:1040–1045
7. Fahn S (1995) The freezing phenomenon in parkinsonism. Adv Neurol 67:53–63
8. Ghravian MH, Almas GF, Ohadi AR, Heidari BH (2013) Comparison of FDA-based and PCA-based features in fault diagnosis of automobile gearboxes. Neurocomputing 121(9):150–159
9. Giladi N, McMahon D, Przedborski S, Flaster E, Guillory S, Kostic V, Fahn S (1992) Motor blocks in Parkinson's disease. PubMed Neurol 42:333–339
10. Giladi N, Nieuwboer A (2008) Understanding and treating freezing of gait in Parkinsonism, proposed working definition and setting the stage. Mov Disord 23(11):23–25
11. Grimm LG (2002) Reading and understanding more multivariate statistics. American Psychological Association, Washington, DC
12. Han JH, Lee WJ, Ahn TB, Jeon BS, Park KS (2003) Gait analysis for freezing detection in patients with movement disorder using three dimensional acceleration system. In: Proceedings of the 25th conference in engineering in medicine and biology society, Cancun, Mexico, 17–21 Sept 2003
13. Handojoseno AM, Shine JM, Nguyen TN, Tran Y, Lewis SJ, Nguyen HT (2012) The detection of freezing of Gait in Parkinson's disease patients using EEG signals based on Wavelet decomposition. In: 34th annual international conference of the IEEE engineering in medicine and biology society, San Diego, CA, USA, 28 Aug–01 Sept 2012
14. Hausdorff JM, Balash Y, Giladi N (2003) Time series analysis of leg movements during freezing of gait in Parkinson's disease: Rhyme or reason? Phys A 321(3–4):565–570
15. Horak F (1992) Postural inflexibility in Parkinsonian subjects. J NeurolSci 111(1):46–58
16. Huang ZK, Chau KW (2008) A new image thresholding method based on Gaussian mixture model. Appl Math Comput 205(2): 899–907
17. Jolliffe IT (2002) Properties of Population Principal Components. In: Bickel P, Diggle P, Fienberg SE, Gather U, Olkin I, Zeger S (eds) Principal component analysis, 2nd ed. Springer Science & Business Media, New York
18. Jovanov E, Wang E, Verhagen L, Fredrickson M, Fratangelo R (2009) deFOG: a real time system for detection and unfreezing of gait of Parkinson's patients. In: 31st annual international IEEE engineering in medicine and biology society Conference, Minneapolis, Minnesota, 3–6 Sept 2009
19. Legendre L, Legendre P (1983) Numerical ecology: developments in environmental modeling. Elsevier Scientific Publication Co, Amsterdam
20. Lewis SJ, Dove A, Robbins TW, Barker RA, Owen AM (2003) Cognitive impairments in early Parkinson's disease are accompanied by reductions in activity in frontostriatal neural circuitry. J Neurosci 23(15):6351–6356
21. Mazilu S, Blanke U, Hardegger M, Tröster G, Gazit E, Hausdorff JM (2014) GaitAssist: a daily-life support and training system for Parkinson's disease patients with freezing of gait. In Proceedings of the 32nd annual ACM conference on human factors in computing systems (CHI '14). ACM, New York, USA, 28 April–1 May 2014
22. Mazilu S, Blanke U, Roggen D, Tröster G, Gazit E, Hausdorff J (2013) Engineers meet clinicians: augmenting Parkinson's disease patients to gather information for gait rehabilitation. In: Proceedings of the 4th augmented human international conference, Stuttgart, Germany 7–8 Mar 2013
23. Mazilu S, Hardegger M, Zhu Z, Roggen D, Troster G, Plotnik M, Hausdorff J M (2012) Online detection of freezing of gait with smartphones and machine learning techniques. In: Proceedings of the 6th international conference on PervasiveHealth, San Diego, CA 21–24 May 2012
24. Montgomery DC (2008) Introduction to statistical quality control. Wiley, New York
25. Moore O, Peretz C, Giladi N (2007) Freezing of gait affects quality of life of peoples with Parkinson's disease beyond its relationships with mobility and gait. Mov Disord 22(15): 2192–2195
26. Moorea S, MacDougall H, Ondoc W (2008) Ambulatory monitoring of freezing of gait in Parkinson's disease. J Neurosci Methods 167(2):304–308
27. Mustapha O, Lefebvre D, Khalil M, Hoblos G, Chafouk H (2009) Fault detection algorithm using DCS method combined with filters bank derived from the wavelet transform. Int J Innov Comput 5(5):1313–1327
28. Nutt JG, Bloem BR, Giladi N, Hallett M, Horak FB, Nieuwboer A (2011) Freezing of gait: moving forward on a mysterious clinical phenomenon. Lancet Neurol 10(8):734–744
29. Okuma Y, Yanagisawa N (2008) The clinical spectrum of freezing of gait in Parkinson's disease. Mov Disord 23:S426–S430
30. Popovic MB, Jovicic MD, Radovanovic S, Petrovic I, Kostic V (2010) A simple method to assess freezing of gait in Parkinsons disease patients. Braz J Med Biol Res 43(9):883–889
31. Ross GJ, Adams NM, Tasoulis DK, Hand DJ (2012) Exponentially weighted moving average charts for detecting concept drift. Pattern Recognit Lett 33(2):191–198
32. Sidibé Y, Druaux F, Lefebvre D, Leon F, Maze G (2013) Outils d'aide à la décision pour le diagnostic des structures immerges. JESA 47(4–8):339–360
33. Snijders AH, Nijkrake MJ, Bakker M, Munneke M, Wind C, Bloem B (1995) Clinimetrics of freezing of gait. Mov Disord 23:S468–S474
34. Taormina R, Chau KW (2015) Neural network river forecasting with multi-objective fully informed particle swarm optimization. J Hydroinform 17(1):99–113

35. Tison F (1997) Other causes of parkinsonism. Baillieres Clin Neurol 6(1):205–218
36. Tripoliti E, Tzallas A, Tsipouras M, Rigas G, Bougia P, Leontiou M, Konitsiotis S, Chondrogiorgi M, Tsouli S, Fotiadis D (2013) Automatic detection of freezing of gait events in patients with Parkinson's disease. Comput Methods Progr Biomed 110(1):12–26
37. Vikas C, Anil K, Ahlawat RS Bhatia (2011) Growing neural networks using soft competitive learning. Int J Comput Appl 21(3):1–6
38. Wu CL, Chau KW (2009) Methods to improve neural network performance in daily flows prediction. J Hydrol 372(1–4):80–93