Highlights

- Freezing of Gait (FoG) is a motor symptom of Parkinson's disease
- It negatively impacts on the quality of life of people suffering from this disease
- This study focus on prediction of the onset of a FoG event using machine learning
- The effect of signal features and window size in FoG prediction is investigated
- Balanced classification is attained using RBF-SVM and a 3s transition period

Pattern Recognition Letters
journal homepage: www.elsevier.com

A new machine learning based approach to predict Freezing of Gait

Natasa Kleanthous[a], Abir Jaafar Hussain[a, *] , Wasiq Khan[a] and Panos Liatsis[b]

[a] [a]*Liverpool John Moores University, Computer Science Department, Liverpool, L33AF, UK*
[b]*Khalifa University of Science and Technology, Department of Electrical Engineering and Computer Science, Abu Dhabi, UAE*

ABSTRACT

Freezing of gait (FoG) is a motor symptom of Parkinson's disease (PD) that frequently occurs in the long-term sufferers of the disease. FoG may result to nursing home admission as it can lead to falls, and therefore, it impacts negatively on the quality of life. The focus of this study is the systematic evaluation of machine learning techniques in conjunction with varying size time windows and time/frequency domain feature sets in predicting a FoG event before its onset. In the experiments, the Daphnet FoG dataset is used to benchmark performance. This consists of accelerometer signals obtained from sensors mounted on the ankle, thigh and trunk of the PD patients. The dataset is annotated with instances of normal activity events, and FoG events. To predict the onset of FoG, the dataset is augmented with an additional class, termed 'transition', which relates to a manually defined period prior to the occurrence of a FoG episode. In this research, five machine learning models are used, namely, Random Forest, Extreme Gradient Boosting, Gradient Boosting, Support Vector Machines using Radial Basis Functions, and Neural Networks. Support Vector Machines with Radial Basis kernels provided the best performance achieving sensitivity values of 72.34%, 91.49%, 75.00%, and specificity values of 87.36%, 88.51% and 93.62%, for the FoG, transition and normal activity classes, respectively.

Keywords: Freezing of Gait, Feature Selection, Early Detection, Gait Analysis

* Corresponding author. Tel.: +00-44-151-2312458; e-mail: a.hussain@ljmu.ac.uk

1. Introduction

The world population is rapidly aging with the prevalence of long-term chronic diseases, coupled with reducing numbers of professional carers [1]. Nowadays, many older adults prefer to live independently in their home environment, albeit associated risks due to physical and cognitive decline. Reduction in the care costs and institutionalization is favored by both policymakers and politicians. Moreover, consumers are increasingly questioning the value of services offered by such institutions, e.g., nursing homes. Therefore, many governments advocate the use of Ambient Assisted Living (AAL) technology. AAL refers to a new paradigm of technology, which can enable older people to stay connected to their communities, better manage their health, compensate physical and cognitive impairment and get access to the services they need to enhance their quality of life and live independently in their homes while utilizing the AAL tools and systems supporting the home monitoring, fall detection, and social interaction.

Parkinson's disease (PD) is a neurodegenerative disease characterized by rigidity, muscle weakness, involuntary tremor, bradykinesia, and freezing of gait [2], [3]. In addition to the motor impairment triggered by the disease, patients are also affected by the non-motor symptoms, i.e., anxiety, stress and depression [4]. The degree of motor impairment and disability of PD patients gets worse with the progression of the disease [5]. A common practice to describe the stages of PD is through the Hoehn and Yahr (H&Y) scale [6] that include: 1) one side of the body is affected with some or no functional loss, 2) both sides of the body are affected, however there is no loss of balance, 3) there is loss of balance but the patient is still autonomous, 4) the disease developed further and the person is noticeably disabled, however they can still walk and stand without assistance, 5) there is a need for support, otherwise the patient is restricted to a wheelchair or bed. Previous research related to PD revealed that the disease typically appears between the ages of 50-60, however it could start at an earlier age.

Freezing of gait (FoG) is one of the most distressing motor symptoms of PD, typically occurring in longer term patients or those diagnosed at an advanced disease stage [7],[8]. It is defined as 'a brief episodic absence or marked reduction of the forward progression of the feet despite the intention to walk' [9]. Individuals, affected by FoG often report that they feel as if their feet are glued to the ground. However, most of the times, FoG does not constitute a complete freeze of motion. There is still movement in the legs during FoG, however, patients cannot move onward and prolong walking straight away [10]. In [11], the forces in the feet during FoG were analysed and it was found that the FoG is not an entirely akinetic state, instead forces under the feet diverge in a systematic pattern.

A common pharmacological treatment for PD is Levodopa [12]. Levodopa is a dopamine precursor and can sometimes reduce the number of FoG events, however, it is not always effective. It is unclear whether the side effects of Levodopa contribute in a positive or negative way. For instance, the drug may cause motor complications after some years of treatment leading to the occurrence of FoG [13]. Therefore, non-pharmacological treatment is important for the prevention of FoG.

In recent years, interdisciplinary research efforts from the computer science and health professional communities have emerged to develop the computational methods to further investigate the phenomenon of FoG. One promising direction is the use of machine learning (ML) in gait analysis to classify the human activities, coupled with the pattern recognition for prediction of the gait irregularities [14].

This work proposes a ML approach to classify patterns from the PD gait time series data, which can be used as a predictive and potentially, preventive system, i.e., prior to the occurrence of a FoG event. Such a system may contribute towards an integrated framework for FoG management in the context of AAL. The novelties of this research include:

• The notion of the transition class, i.e., the time period between normal walking and FoG, is utilized in the accelerometer signals dataset for the prediction of FoG prior to its onset. Three window sizes of 2, 3 and 4s prior to a FoG event are evaluated.

• An exhaustive set of features from the time and frequency domains is extracted. The Boruta algorithm is used to select the most informative features in the context of real-time performance.

• Five state-of-the-art ML classifiers, specifically, Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting Machine (GMB), Support Vector Machines with Radial Basis Function kernels (RBF-SVM) and Multilayer Perceptrons (MLP) are systematically evaluated for varying window sizes and feature sub-sets in FoG prediction.

The reminder of this work is organized as follows. Section 2 presents a thorough analysis of ML methods used for FoG detection. Section 3 describes the proposed methodology including signal preprocessing, the introduction of the transition class in the dataset, and feature extraction. Section 4 presents a performance comparison of the use of different feature sets, time windows and the five ML classifiers. Section 5 discusses the results, and compares them to relevant findings in the state-of-the-art techniques. Section 6 presents the conclusions and avenues for further research.

2. Related work

A variety of approaches were proposed for the detection of FoG, exploring the suitability of wearable devices, feature extraction and ML algorithms. For instance, in [15], the significance of features for FoG detection under normal living conditions was investigated. Varying window sizes (i.e. 0.8, 1.6, 3.2 and 6.4s) were considered with feature sets including mean, frequency domain features, skewness and kurtosis, and the high order principal components. Support Vector Machines (SVM) with a window size of 1.6s achieved the best results with a sensitivity of 91.7% and a specificity of 87.4%, respectively. A wearable technological assistant for real-time FoG detection through a smartphone using supervised ML was proposed in [16]. The Daphnet dataset [17] was used in their research which is also employed in the current study. It was found that the most discriminative features were the mean, standard deviation, the Freeze Index and the power of the signal in the 3-8Hz and 0.5-3Hz bands [18]. Both window sizes of 1s and 4s achieved sensitivities and specificities of over 95%, although the 4s window demonstrated a slightly higher performance. While these results are very encouraging, the classifiers were trained and tested using data from the same patient. In an extension of their work [19], [20], a wrist-mounted sensor was proposed for detection of FoG using a combination of accelerometers and gyroscopes. Both studies compared the wrist movements of the subject, while experiencing freezing to investigate whether wrist movements are associated with the freezing episodes. The FoG hit rates were 0.85 and 0.9, respectively, for subject- dependent and independent classification using C4.5 decision trees.

Regarding specificity, the results were 0.8 and 0.66, for subject-dependent and independent classification, respectively. Work in [21] presented a training and support system, named 'GaitAssist', based on the C4.5 classifier that was developed for the patients suffering with PD. The authors claim that this approach is able to provide auditory cueing in the occurrence of FoG, and supports training through FoG provoking exercises. A detection rate of 99 out of 102 FoG events was reported with less than 0.5s latency, for a window size of 2s and 0.25s overlap.

Similar techniques were used in [22] exploring the use of 6 accelerometer and 2 gyroscope signals for FoG detection. Following the pre-processing, the entropy is extracted and used by multiple MLclassifiers. The best results were achieved with the RF with accuracy over 90%. [23] performed a comparative study of varying features, window sizes and ML techniques in FoG detection. Accelerometer signals from sensors mounted on the waist were used. A variety of algorithms were used. The majority of higher performance results were observed with a window size of 256 samples. The most informative features were the mean, mean of the difference between the x, y, z axes, standard deviation, correlation between the 3 axes, frequency standard deviations in 0.1-0.68 Hz, 0.68-3 Hz, 3-8 Hz, 8-20 Hz and 0.1-8 Hz bands, maximum harmonic amplitude, frequency center of mass, integrals, auto-regressive coefficients using the Bourg method, skewness and kurtosis. The best performing classifier was Support Vector Machines. In [24], an alternative approach was explored, using features the Wavelet cross spectrum, Wavelet cross frequency energy ratios, and statistical features (e.g., mean, standard deviation, skewness, kurtosis, maximum, and minimum) from EEG signals. The performance of multilayer perceptrons and k nearest neighbor was compared. Three classes were considered, specifically walking, FoG, and transition, which related to a group of data 5s prior to the occurrence of a FoG event. Recently, a study focused on the detection of FoG events using deep learning methods [25] and achieved accuracy, sensitivity, and specificity values of 94.3%, 96.1%, and 95.5%, respectively. In our previous work, we performed an initial investigation of the use of ML for FoG detection, using a window size of 5s to detect the transition event [26]. Promising results were obtained, however, the need for systematic analysis of the problem was identified. Specifically, in the current study, we focus on the early detection of a FoG event, through classification of the transition class (i.e., prior to the presence of FoG), contrary to the majority of previous studies that recognize FoG once it has occurred.

3. Methodology

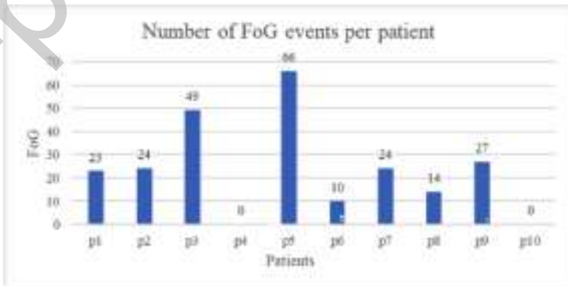
In this research, we use the Daphnet Freezing of Gait dataset [17] comprising the data from 10 PD patients (7 males and 3 females) who experience regular FoG. The data was attained using wearable sensors, located on the ankle, thigh, and trunk, which collect accelerometer signals, sampled at 64Hz. Participants were required to perform a number of tasks:

- Walking back and forth in a straight line, including 180° turns.
- Random walking, including a series of initiated stops and several 360° turns.
- Walking typical of daily living activities.

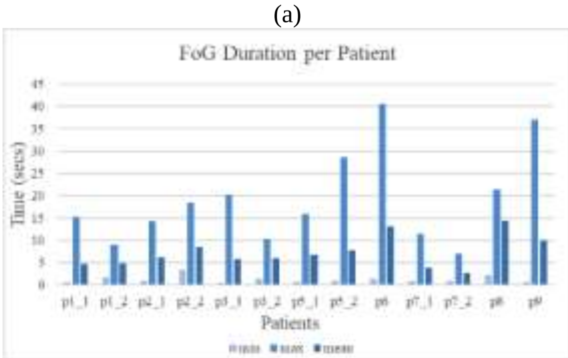
The recruited subjects were capable of walking without assistance in OFF[1] periods. Patients 2 and 8 were the only subjects, who took part in the experiment in ON[1] periods. Patients with a diagnosis of hearing/vision loss, dementia, or other neurological disorders were excluded. Gait variability for each patient in the dataset is quite large. For some patients, gait differentiation between healthy and PD participants was poor. Throughout the study, 8 out of the 10 patients experienced a FoG event. Patients 4 and 10 did not experience any FoG events during the experiments. A total of 8.20 hours of recordings were logged, producing a total of 237 FoG events. Algorithm 1 provides the definition of variables used in the experiments.

Algorithm 1: Variable definitions for the experiments
Let PD be a set of Parkinson disease patients
Let R represent the set of data of PD
Let T represent the index of time
T = {t | t in ms at 64Hz}
Let A represent the ankle gait measurements
A = {AnkleHorizontal, AnkleVertical, AnkleLateral}
Let G represent a set of gait measurements
$G = \{g | g \in A\}$
Let FoG = {0, 1} represent the presence of FoG, where 0/1 corresponds to the patient performing tasks in the absence/presence of a FoG event, respectively.
$R = T \cup G \cup A$ such that:
$\forall p \in PD, \exists r \in R \rightarrow r$ represents p data

---



(a)



(b)

Fig. 1. FoG events (a) number and (b) duration per patient. Patients 1, 2, 3, and 7 had 2 recordings. Patients 6, 8 and 9 had only 1 recording.

3.1. Data Preparation

The aim of this research is to early predict the occurrence of a FoG event by identifying the 'transition' period from a normal walking event to FoG. Statistical reports for all patients with event counts, mean duration, range, maximum and minimum duration, and standard deviation were produced. The FoG event statistics per patient are shown in Figure 1. As previously

[1] ON-OFF period: Levodopa is the medication used for Parkinson's disease treatment. ON/OFF periods refer to times when the medication is effective/no longer effective in controlling the effects of motor response fluctuations due to PD, respectively.

mentioned, patients 4 and 10 did not experience any FoG events during the experiments and were therefore excluded. It is observed that the maximum duration of the freezing episodes varies considerably (i.e., 5-40s) between patients, compared to the minimum duration values, which are mostly in the range of 3-4s.

Algorithm 2: Transition class between walking and FoG
$\forall p \in PD, \exists s \in S \rightarrow s\ sampled\ at\ rate = 64HZ$ and S is a set of PD gait signals
Let w represent a time window $in\ seconds \rightarrow w = t \times 64,\ t = 2, \ldots, n$, where t is the desired transition time in seconds
Let Events = {Walking, Transition, FoG} be the events set
Let T = {twalking, ttransition, tFoG} represent the time set and T $\in w$
If twalking < t → twalking = 0 ∧ ttransition = t

3.2. Signal Filtering

Previous studies indicated that the majority of information in human gait signals contained the frequencies under 20Hz [27], [28]. We utilize a third order low pass Butterworth filter [23] at 20Hz, for the noise reduction. Figures 2 and 3 illustrate raw and filtered signals of FoG and normal walking.

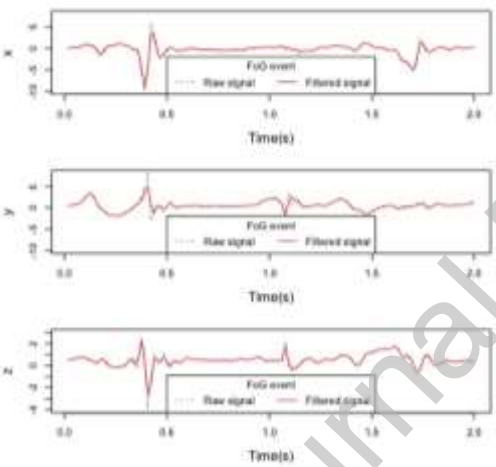


Fig. 2. Raw and filtered signals of a FoG event. Horizontal forward acceleration (x), vertical acceleration (y), horizontal lateral acceleration (z)

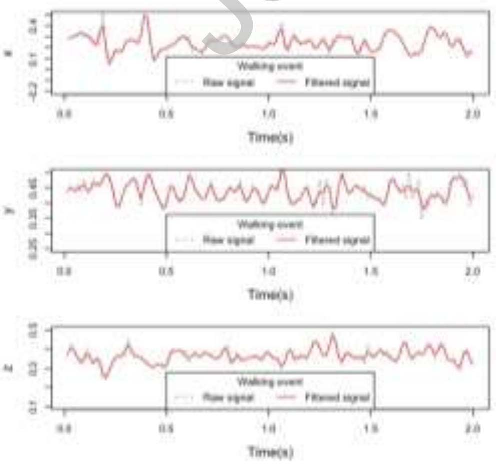


Fig. 3. Raw and filtered signals of a normal walking event. . Horizontal forward acceleration (x), vertical acceleration (y), horizontal lateral acceleration (z)

3.3. Data Manipulation and Segmentation

Prediction of the onset of a FoG event is posed as a classification problem by augmenting the original two classes of events, i.e., 'walk' and 'FoG', with a new class, i.e., 'transition'. Events 'walk', 'transition' and 'FoG' were segmented into periods of 2, 3 and 4s, so as to investigate which period produces the best results. The state-of-the-art indicates that these intervals suffice for patients to be warned for the onset of a FoG event. Algorithm 2 shows the proposed method for class augmentation.

3.4. Feature Extraction

Feature extraction uses time and frequency domain approaches to extract a set of distinctive features from the filtered data. We apply feature extraction on the filtered signals of the horizontal forward (x), vertical (y), and horizontal lateral (z) accelerations from the ankle sensor. This provides sufficiently rich information in regards to gait variations for the detection of FoG [27].

Table 1: Features extracted from the x, y, z acceleration signals

Time domain features	
Mean	Signal average value
Standard Deviation	Signal standard deviation
Min, max	The minimum and maximum signal values
Quartile1, Quartile3	Quartile 1 is the middle value between the minimum and the median of the signal. Quartile 3 is the middle value between the median and the maximum value of the signal
Median	The median value of the signal (Quartile2)
skew, kurt	The skewness and kurtosis of the signal
Zero crossing Rate	The rate of the sign changes of the signal
Peak-to-Peak	The minimum minus the maximum of the signal
Crest Factor	The ratio of the peak value to the RMS value
Root Mean Square (RMS)	The square root of the mean of the square of the signal (known as quadratic mean)
Velocity Root Mean Square	The quadratic mean of the speed of the signal in the time domain
Entropy	Entropy of the signal in the time domain
Frequency Domain Features	
Freeze Index	The power in the 3-8Hz band divided by the power in the 0.5–3 Hz band
Power difference	The difference of the sum of the powers in the bands 3 - 8 Hz and 0.5–3 Hz
Fast Fourier Transform mean magnitude	Fast Fourier Transform features from the acceleration magnitudes of the signal
Fast Fourier Transform mean phase	Mean signal phase in the frequency domain
Power spectrum	The distribution of the power of the first stronger frequencies of the signal in the window
Features extracted from x, y, z acceleration	
Integrals	The sum of the integrated acceleration signals in the x, y, z directions
Centre of Gravity of x, y, z components	The center of gravity in the x, y, and z components of the accelerometer signal
Angles of x, y, z components	The angles of the x, y, and z components of the accelerometer signal

Table 1 lists the extracted feature set consisting156 parameters. Skewness and kurtosis were estimated to provide information about the shape of the distribution, thus supporting the detection of differences between acceleration measurements

[29], [30]. As this study, for the first time, targets a three-class problem (i.e., normal walk, transition and FoG), we will investigate the contribution of these features in the classifier performance.

3.5. Feature Selection

Feature selection is performed on the extracted features in an iterative process, as shown in Figure 4. First, the Boruta algorithm [31], a wrapper built around the RF classifier was used. This uses the Z score [32] and the notion of a 'shadow' attribute as a means of estimating feature importance. Boruta reduces the original feature set to the 91 most relevant features.

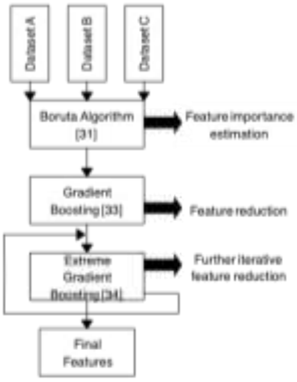


Fig. 4. Overview of feature selection process

Table 2: Top 30 predictors

Transition Duration	Number of Features	Feature
2s	30	Entropy (x, y, m) RMS Velocity (x, y, m) Integrals Freeze Index (y, x, m) Power (x, PC3) Phase (PC2, PC3, y, z, x) FFT 2nd coefficient (PC2, PC3, y) FFT 1st coefficient (y, x, PC2) Skewness (m) Kurtosis (m, x) Mean (PC3) Center of Gravity (y) Angle (y) Zero-crossing rate (x)
3s	30	Entropy (y, m, PC1) RMS Velocity (y, z, PC1) Freeze Index (x, y, z, m, PC1-3) Mean (PC3) Integrals Phase (PC1, PC3, z, x, y) FFT 1st coefficient (x, y) Crest Factor (PC3) Quartile1 (PC3) Zero crossing rate (PC2) Kurtosis (m, x)
4s	30	Entropy (y, z, m, pc1, pc3) RMS Velocity (x, y, z, m, pc1, pc2, pc3) Freeze Index (x, y, m, pc1, pc2, pc3) Mean (pc3) Integrals Center of Gravity (y) Phase (m, pc3, z, x) FFT 1st coefficient (x) FFT 2nd coefficient (z) Kurtosis (y, m, pc3)

Next, gradient boosting was employed on the reduced feature set to provide a greedy approximation to the feature selection cost [33], which resulted to the top 30 features. Extreme gradient boosting was used to further reduce the number of features to the most important 15 and 5, respectively [34]. This process was applied to the 3 labelled datasets, which include transition events of 2, 3, and 4s, and termed datasets A, B and C, respectively. Each of the datasets contains instances of the 3 classes, i.e., 'walk', 'transition' and 'FoG'. Overall, the three datasets are fairly distributed with balanced proportions of the three classes. Dataset A consists of 220 walk, 237 transition and 237 FoG events. Dataset B consists of 200 walk, 237 transition and 237 FoG events. Dataset C consists of 189 walk, 237 transition and 237 FoG events. Dataset C is the least balanced and this will be considered in result interpretation. The feature selection model of Figure 4 is used to reduce feature dimensionality into sets of 30, 15 and 5 features, as shown in Tables 2-4, respectively. The parameter m in the Tables corresponds to the magnitude of the x,y,z accelerometer signal, while PC1-3 correspond to the first three principal components.

Table 3: Top 15 predictors

Transition Duration	Number of Features	Feature
2s	15	Entropy (y, m) RMS velocity (x, y, m) Freeze Index (x, y, m) Integrals Power (PC3) FFT phase (x, PC3) FFT 2nd coeff (PC3) Mean (PC3) Skewness (m)
3s	15	RMS velocity (y) Entropy (y, m, PC1) Freeze Index (m, x, PC1, PC3) FFT phase (y, x, z, PC3) FFT 1st coefficient (x) Kurtosis (m) Quartile 1 (m)
4s	15	RMS velocity (y, z, m) Entropy (y, PC1), Freeze Index (x, m, PC1-2) FFT 1st coefficient (x) FFT 2nd coefficient (z, y) Kurtosis (y, PC3) Phase (z)

Table 4: Top 5 predictors

Transition Duration	Number of Features	Feature
2s	5	RMS velocity (y), Entropy (y), Freeze Index (x, y), FFT phase (x)
3s	5	RMS velocity (y), Entropy (y, PC1), Freeze Index (x, magnitude)
4s	5	RMS velocity (magnitude, y, z), Entropy (y), Freeze Index (magnitude)

4. Simulation Results

Experiments are conducted using ML classifier-set consists of RF, XGB, GMB, RBF-SVM and MLP with two hidden layers. The datasets were split into training and test sets with 80% and 20% ratios, respectively where the training was performed using 10-fold cross-validation. Statistical measures are used to evaluate the performance of the 5 ML models on the test datasets with respect to transition times and feature sub-sets.

Table 5 shows the results obtained with the XGB algorithm. Accuracy ranges from 75.76% to 79.10%, and on average around 78%. A more balanced class separation was observed, when 30 features were used on the 4s dataset, with a sensitivity values of 78.72%, 80.85% and 73.68% for FoG, transition and walk events, respectively. The highest sensitivity for the transition event was achieved using 5 and 30 features on the 2s dataset at 93.62%. The lowest sensitivity for the transition event was 76.60%, with the 15 features set and the 4s dataset. Overall, performance for the transition period was consistent.

Table 5: **XGB results**

	30 Predictors		15 Predictors		5 Predictors		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	82.98	78.02	89.36	80.22	80.85	82.42	2 secs
Transition	93.62	94.51	91.49	92.31	93.62	90.11	
Walk	56.82	94.68	54.55	95.74	59.09	94.68	
Acc. (%)	**78.26**		**78.99**		**78.26**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	78.72	80.46	80.85	78.16	89.36	75.86	3 secs
Transition	87.23	96.55	85.11	96.55	87.23	95.40	
Walk	67.50	90.43	67.50	92.55	57.50	96.81	
Acc. (%)	**78.36**		**78.36**		**79.10**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	78.72	85.88	80.85	77.65	89.98	80.00	4 secs
Transition	80.85	88.24	76.60	91.76	78.72	91.76	
Walk	73.68	92.55	68.42	93.62	68.42	93.62	
Acc. (%)	**78.03**		**75.76**		**77.27**		

Table 6 presents the results with the RF method. The highest sensitivity for the transition event was achieved using 30 and 15 features with the 2s dataset. With 30 features, RF resulted in a sensitivity of 93.62% and a specificity of 94.51%. Similarly, with 15 features for the 2s dataset, sensitivity was 93.62% and specificity was 95.60%, while also achieving a sensitivity of 85.11% for the FoG event, for both 30 and 15 feature sets. Observing the results of the walking events, it is noted that classification of this type of event does not achieve sensitivity values higher than 65.79%, however, specificity values higher than 90% are achieved for all feature sets. The highest accuracy was 79.85%, obtained for a 3s transition period, irrespective of the number of features. The most balanced results were yielded with the 3s transition period and 15 features.

Table 6: RF results

	30 Predictors		15 Predictors		5 Predictors		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	85.11	78.02	85.11	74.73	76.60	81.32	2 secs
Transition	93.62	94.51	93.62	95.60	91.49	95.60	
Walk	56.82	95.74	52.27	95.74	65.91	90.43	
Acc. (%)	**78.99**		**74.54**		**78.26**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	80.85	81.61	82.98	79.31	85.11	78.16	3 secs
Transition	89.36	93.10	87.23	95.40	87.23	96.55	
Walk	67.50	94.68	67.50	94.68	65.00	94.68	
Acc. (%)	**79.85**		**79.85**		**79.85**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	89.36	76.47	85.11	78.82	80.85	78.82	4 secs
Transition	78.72	92.94	80.85	89.41	78.72	90.59	
Walk	65.79	97.87	65.79	97.87	65.79	93.62	
Acc. (%)	**89.36**		**76.47**		**85.11**		

Table 7 presents the results with the GBM algorithm. The highest accuracy was 79.55%, using a 4s transition period with the 30 and 15 feature sets. For 15 features, FoG sensitivity and specificity values were 87.23% and 80%, respectively. Sensitivity and specificity values for the walk and transition events were 71.05%, 78.72% and 96.81%, 91.76%, respectively. The highest transition sensitivity was achieved using a 2s period with the 30 feature set at 91.49% and specificity of 94.51%. For walking, a sensitivity of 61.36%, and a specificity of 92.55% were obtained.

Table 7: GBM results

	30 Predictors		15 Predictors		5 Predictors		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	80.85	80.22	80.85	73.63	78.72	75.82	2 secs
Transition	91.49	94.51	89.36	95.60	91.49	94.51	
Walk	61.36	92.55	50.00	91.49	54.55	92.55	
Acc. (%)	**78.26**		**73.91**		**75.36**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	82.98	78.16	76.60	80.46	82.98	75.86	3 secs
Transition	85.11	94.25	91.49	91.95	85.11	95.40	
Walk	62.50	93.62	62.50	93.62	65.00	95.74	
Acc. (%)	**77.61**		**77.61**		**78.36**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	93.62	75.29	87.23	80.00	82.98	81.18	4 secs
Transition	76.60	92.94	78.72	91.76	80.85	85.88	
Walk	65.79	100.00	71.05	96.81	60.53	95.74	
Acc. (%)	**79.55**		**79.55**		**75.76**		

Table 8 summarises the results with the RBF-SVM algorithm. The highest accuracy was observed using 5 predictors and the 3s dataset, at 79.85%. Sensitivity and specificity values for the transition event were 91.49% and 88.51%, respectively. Moreover, FoG events have a sensitivity of 72.34% and a specificity of 87.36%. Walk events can be detected with a sensitivity of 75% and a specificity of 93.62%. The highest sensitivity and specificity values for the transition class were obtained using the 4s dataset and 5 features, at 93.62% and 95.60%, respectively. For the same configuration, classifier performance in the walk events was comparatively low, with sensitivity and specificity values of 50% and 92.55%, respectively. For FoG events, a sensitivity and specificity of 80.85% and 74.73% were obtained, respectively.

Table 8: RBF-SVM results

	30 Predictors		15 Predictors		5 Predictors		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	68.09	80.22	72.34	80.22	76.60	84.62	2 secs
Transition	91.49	83.52	85.11	83.52	91.49	90.11	
Walk	54.55	93.62	56.82	93.62	65.91	92.55	
Acc. (%)	**71.74**		**71.74**		**78.26**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	70.21	82.76	65.96	80.46	72.34	87.36	3 secs
Transition	85.11	88.51	93.62	86.21	91.49	88.51	
Walk	67.50	90.43	57.50	92.55	75.00	93.62	
Acc. (%)	**74.63**		**73.13**		**79.85**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	80.85	81.18	78.72	80.00	80.85	74.73	4 secs
Transition	78.72	87.06	80.85	80.00	93.62	95.60	
Walk	65.79	94.68	57.89	98.94	50.00	92.55	
Acc. (%)	**75.76**		**73.48**		**75.36**		

The best results with the MLP were observed when using the 4s dataset and 30 features, shown in Table 9. Accuracy was 78.79%, while FoG event sensitivity and specificity were 82.98% and 82.35%, respectively. For the transition and walk events, sensitivities of 78.72%, 73.68% and specificities of 89.41%, 95.74% were observed, respectively. The lowest sensitivity was achieved using 30 features and the 2s dataset at 43.18% and high specificity of 92.55%. MLP is the top performer in the case of transition events using 30 features and the 3s dataset. However, accuracy is lower for the FoG and transition classes.

Table 9: MLP results

	30 Predictors		**15 Predictors**		**5 Predictors**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	70.21	72.53	78.72	76.92	76.60	81.32	2 secs
Transition	89.36	86.81	89.36	90.11	91.49	95.60	
Walk	43.18	92.55	54.55	94.68	65.91	90.43	
Acc. (%)	**68.12**		**74.64**		**78.26**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	63.83	88.51	72.34	85.06	85.11	73.56	3 secs
Transition	95.74	81.61	95.74	88.51	85.11	94.25	
Walk	60.00	90.43	65.00	93.62	57.50	96.81	
Acc. (%)	**73.88**		**78.36**		**76.87**		
	Sen %	**Spec %**	**Sen %**	**Spec %**	**Sen %**	**Spec %**	**Period**
FoG	82.98	82.35	82.98	82.35	89.36	77.65	4 secs
Transition	78.72	89.41	85.11	83.53	76.60	92.94	
Walk	73.68	95.74	60.53	98.94	68.42	96.81	
Acc. (%)	**78.79**		**77.27**		**78.79**		

5. Discussion

FoG is a symptom of PD which attracted considerable research interest due to its unpredicted and transient nature. In our investigations, we focused on prediction of the transition class, i.e., the period between normal walking and the occurrence of FoG. We considered three time periods of 2, 3 and 4s, respectively, prior to the onset of FoG.

A detection accuracy between 77%-97% for the transition class was achieved in the simulation experiments in the testing datasets. These results are comparable with the recent study of [24], where a sensitivity of ~85% was reported. We considered window sizes of 2, 3, and 4s, in contrast to [24], where a 5s transition period was adopted. Contrary to [24], which uses EEG, our study is based on accelerometer signals similar to [35]. We obtained a better performance than [35] that reported an F1-measure of ~55%. However, the features used in this work are different, and thus, a fair comparison between the two approaches is not possible.

Classification of the walk class achieved notably low results in terms of sensitivity in almost all experiments, with a least sensitivity of 43.18%, when using the MLP with a 2s transition period and 30 features. The highest sensitivity for the walk class was 75%, using the RBF-SVM with 5 features and the 3s dataset. The top results in FoG event classification were attained with the use of the MLP on the 5 feature, 4s dataset.

An uneven classification performance for the three classes was observed, which could be either due to the lack of sufficiently informative features, or variations in FoG and transition periods. This was also observed in previous studies [15], [18], [35]. Indeed, lack of a clear segmentation of the onset of FoG and transition gait events is one of the challenges addressed in this study.

Table 10 summarizes the comparison of results for four scenarios, where event classification is reasonably balanced. In these instances, although the classification performance for the transition class is lower, the overall performance is comparatively high. In RBF-SVM, it can be observed that the transition class has a sensitivity of 91.49% and a specificity of 88.51%, with the 5 feature, 3s dataset. In this case, the sensitivity for the walk class is 75%, which is the highest in our studies. The GBM model using 15 features and the 4s transition events has a FoG sensitivity of 87.23% and a specificity of 80%. Most ML models perform well in classification of transition events with the 2s dataset, while event classification is more balanced with the 4s dataset.

Table 10: Summative performance results

Class	**Sen**	**Spec**	**Period**	**Model and Features**
FoG	82.98%	82.35%	4 secs	MLP / 30 features
Transition	78.72%	89.41%		
Walk	73.68%	95.74%		
FoG	**87.23%**	80.00%	4 secs	GBM / 15 features
Transition	78.72%	**91.76%**		
Walk	71.05%	**96.81%**		
FoG	78.72%	85.88%	4 secs	XGB / 30 features
Transition	80.85%	88.24%		
Walk	73.68%	92.55%		
FoG	72.34%	**87.36%**	**3 secs**	**RBF-SVM / 5 features**
Transition	**91.49%**	88.51%		
Walk	**75.00%**	93.62%		

An aspect of this work that merits further investigation relates to the selection of the transition period. Specifically, the time periods considered for the transition class may not be sufficiently representative since a transition event can be considered as an event of a variable nature [35]. A clear limitation of this work is the size of the dataset, which consists of data from only 10 PD patients. Furthermore, the data collection experiments were conducted in a controlled environment, which may not be sufficiently representative of daily living activities.

6. Conclusions

FoG affects the quality of life of PD patients due to falls, collisions, etc., and consequently has socioeconomic impacts in terms of increased healthcare costs, and decreasing independence of sufferers. The detection and prediction of the FoG is a challenging task because of the variability of the event’s duration and frequency. Improved discrimination of the state of walking using ML can be achieved on a patient-dependent basis. The results of the current study are in line with those reported in the literature, indicating that FoG and walk events can be misclassified as the transition period increases.

In further work, we intend to explore the hypothesis that transition events do not purely belong to the transition phase, but instead, they may be part of FoG events. A thorough analysis of the frequencies for such events needs to be considered. It is possible to use complementary sensor technologies, e.g., sound, in the context of real-time FoG prediction systems.

Finally, there is a need for further investigations with larger datasets for the analysis of frequency variations of transition events in order to improve the identification of optimal sets of features and appropriate ML models for robust prediction of FoG.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

References

[1] United Nations, (https://www.un.org/en/sections/issues-depth/ageing/), Accessed: 2019-12-24.
[2] P. Rea, Chapter 3 - Forebrain, in Essential Clinical Anatomy of the Nervous System, San Diego: Academic Press, 2015, pp. 77–87.
[3] J. A. Ross and S. S. Singer, Parkinson’s disease, Magill’s Medical Guide (Online Edition), 2016.
[4] P. J. Garcia-Ruiz, K. R. Chaudhuri, and P. Martinez-Martin, Non-motor symptoms of Parkinson’s disease A review…from the past, Journal of the Neurological Sciences, Vol. 338, No. 1–2, pp. 30–33, 2014.
[5] G. Alves, T. Wentzel-Larsen, D. Aarsland, and J. P. Larsen, Progression of motor impairment and disability in Parkinson disease: a population-based study, Neurology, Vol. 65, No. 9, pp. 1436–1441, 2005.
[6] M. M. Hoehn and M. D. Yahr, Parkinsonism onset, progression, and mortality, Neurology, Vol. 17, No. 5, pp. 427–427, 1967.
[7] N. Giladi, R. Kao, and S. Fahn, Freezing phenomenon in patients with parkinsonian syndromes, Mov. Disord., Vol. 12, No. 3, pp. 302–305, 1997.
[8] M. Amboni, F. Stocchi, G. Abbruzzese, L. Morgante, M. Onofrj, S. Ruggieri, M. Tinazzi, M. Zappia, M. Attar, D. Colombo, L. Simoni, A. Ori, P. Barone and A. Antonini, Prevalence and associated features of self-reported freezing of gait in Parkinson disease: The DEEP FOG study, Parkinsonism & Related Disorders, Vol. 21, No. 6, pp. 644–649, 2015.
[9] J. G. Nutt, B. R. Bloem, N. Giladi, M. Hallett, F. B. Horak, and A. Nieuwboer, Freezing of gait: moving forward on a mysterious clinical phenomenon, The Lancet Neurology, Vol. 10, No. 8, pp. 734–744, 2011.
[10] J. Parkinson, An Essay on the Shaking Palsy, JNP, Vol. 14, No. 2, pp. 223–236, 2002.
[11] J. M. Hausdorff, Y. Balash, and N. Giladi, Time series analysis of leg movements during freezing of gait in Parkinson’s disease: akinesia, rhyme or reason?, Physica A: Statistical Mechanics and its Applications, Vol. 321, No. 3–4, pp. 565–570, 2003.
[12] W. Poewe, K. R. Chaudhuri, L. Bergmann, A. Antonini, Levodopa-carbidopa intestinal gel in a subgroup of patients with dyskinesia at baseline from the GLORIA Registry, Neurodegenerative Disease Management, Vol. 9, No. 1, pp. 39-46, 2019.
[13] S. Fahn, J. Jankovic, and M. Hallett, Chapter 6 - Medical treatment of Parkinson disease, in Principles and Practice of Movement Disorders (Second Edition), Edinburgh: W.B. Saunders, pp. 119–156, 2011.
[14] W. Khan W, A. Badii, Pathological Gait Abnormality Detection and Segmentation by Processing the Hip Joints Motion Data to Support Mobile Gait Rehabilitation, Research Medical & Engineering Sciences, Vol. 7, No. 3, pp.754-762, 2019.
[15] A. Samà, D. Rodriguez-Martin, C. Perez-Lopez, A. Catala, S. Alcaine, B. Mestre, A. Prats, M. C. Crespo, A. Bayes, Determining the optimal features in freezing of gait detection through a single waist accelerometer in home environments, Pattern Recognition Letters, Vol. 105, pp. 135-143, 2017.
[16] S. Mazilu, M. Hardegger, Z. Zhu, D. Roggen, G. Troester, M. Plotnik, and J. Hausdorff, Online detection of freezing of gait with smartphones and machine learning techniques, in Proc. 6th International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health) & Workshops, pp. 123-130, 2012.
[17] UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets/Daphnet+Freezing+of+Gait#) Accessed: 2019-12-24.
[18] S. T. Moore, H. G. MacDougall, and W. G. Ondo, Ambulatory monitoring of freezing of gait in Parkinson’s disease, Journal of Neuroscience Methods, Vol. 167, No. 2, pp. 340–348, 2008.
[19] S. Mazilu, U. Blanke, and G. Tröster, Gait, wrist, and sensors: Detecting freezing of gait in Parkinson’s disease from wrist movement, in Proc. IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), pp. 579–584, 2015.
[20] S. Mazilu, U. Blanke, A. Calatroni, E. Gazit, J. M. Hausdorff, and G. Tröster, The role of wrist-mounted inertial sensors in detecting gait freeze episodes in Parkinson’s disease, Pervasive and Mobile Computing, Vol. 33, pp. 1–16, 2016.
[21] S. Mazilu, U. Blanke, M. Hardegger, G. Tröster, E. Gazit, and J. Hausdorff, GaitAssist: A Daily-life Support and Training System for Parkinson’s Disease Patients with Freezing of Gait, in Proc. SIGCHI Conf Human Factors in Computing Systems, pp. 2531-2540, 2014.
[22] E.E. Tripoliti, A.T. Tzallas, M.G. Tsipouras, G. Rigas, P. Bougia, M. Leontiou, S. Konitsiotis, M. Chondrogiorgi, S. Tsouli, and D.I. Fotiadis, Automatic detection of freezing of gait events in patients with Parkinson’s disease, Computer Methods and Programs in Biomedicine, Vol. 110, pp. 12–26, 2013.
[23] D. Rodríguez-Martín, A. Sama, C. Perez-Lopez, A. Catala, B. Mestre, S. Alcaine and A. Bayes, Comparison of Features, Window Sizes and Classifiers in Detecting Freezing of Gait in Patients with Parkinson’s Disease Through a Waist-Worn Accelerometer, in Vol. 288: Artificial Intelligence Research and Development, Frontiers in Artificial Intelligence and Applications, pp. 127-136, 2016.
[24] A. M. A. Handojoseno, J. M. Shine, T. N. Nguyen, Y. Tran, S. J. G. Lewis, and H. T. Nguyen, Using EEG spatial correlation, cross frequency energy, and wavelet coefficients for the prediction of Freezing of Gait in Parkinson’s Disease patients, in Proc. 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4263–4266, 2013.
[25] Y. Zhang and D. Gu, A Deep Convolutional-Recurrent Neural Network for Freezing of Gait Detection in Patients with Parkinson's Disease, in Proc. 12th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Suzhou, China, pp. 1-6, 2019.
[26] N. K. Orphanidou, A. Hussain, R. Keight, P. Lishoa, J. Hind and H. Al-Askar, Predicting Freezing of Gait in Parkinsons Disease Patients Using Machine Learning, in Proc. 2018 IEEE Congress on Evolutionary Computation (CEC), Rio de Janeiro, pp. 1-8, 2018.
[27] M. Bächlin, M. Plotnik, D. Roggen, N. Giladi, J. M. Hausdorff, and G. Tröster, A Wearable System to Assist Walking of Parkinson´s Disease Patients, Methods Inf Med, Vol. 49, No. 1, pp. 88–95, 2009.
[28] I. Killane, C. Fearon, L. Newman, C. McDonnell, S.M. Waechter, K. Sons, T. Lynch and R.B. Reilly, Dual Motor-Cognitive Virtual Reality Training Impacts Dual-Task Performance in Freezing of Gait, IEEE Journal of Biomedical and Health Informatics, Vol. 19, No. 6, pp. 1855–1861, 2015.
[29] L. Bao and S. S. Intille, Activity Recognition from User-Annotated Acceleration Data, in A. Ferscha and F. Mattern (eds) Pervasive Computing, Lecture Notes in Computer Science, Vol. 3001, Springer, pp. 1-17, 2004.
[30] C. C. T. Clark, C. M. Barnes, G. Stratton, M. A. McNarry, K. A. Mackintosh, and H. D. Summers, A Review of Emerging Analytical Techniques for Objective Physical Activity Measurement in Humans, Sports Med, Vol. 47, No. 3, pp. 439–447, 2017.
[31] M. B. Kursa and W. Rudnicki, Feature Selection with Boruta Package, Journal of Statistical Software, Vol. 36, No. 11, pp. 1-13, 2010.
[32] R. Zhang, P. Xu, L. Guo, Y. Zhang, P. Li and D. Yao, Z-score linear discriminant analysis for EEG based brain-computer interfaces, PLOS One, Vol. 8, No. 9, e74433, 2013.
[33] J. H. Friedman, Stochastic gradient boosting, Computational Statistics & Data Analysis, Vol. 38, No. 4, pp. 367–378, 002.
[34] Y. Wang and X.S. Ni, A XGBoost risk model via feature selection and Bayesian hyper-parameter optimization, arXiv: 1901.08433, 2019.
[35] S. Mazilu, A. Calatroni, E. Gazit, D. Roggen, J. M. Hausdorff, and G. Tröster, Feature Learning for Detection and Prediction of Freezing of Gait in Parkinson’s Disease, in P. Perner (ed.) Machine Learning and Data Mining in Pattern Recognition, Springer pp. 144–158, 2013.

Graphical Abstract (Optional)

Fonts or abstract dimensions should not be changed or altered.

A new machine learning approach to predict Freezing of Gait

Leave this area blank for abstract info.

Natasa Kleanthous, Abir Jaafar Hussain, Wasiq Khan, Panos Liatsis