Predicting the Freezing of Gait in Parkinson's patients based on Machine Learning and Wearable Sensors: A review

MDVAG Jayawardena[1#], PPCR Karunasekara[1] and YVND Sirisena[2]

[1]Department of Electrical, Electronic and Telecommunication Engineering, Faculty of Engineering, General Sir John Kotelawala Defence University, Ratmalana, Sri Lanka.
[2]North Central Teaching Hospital, Ragama, Sri Lanka

#varsha.anarkali@gmail.com

Abstract: *Freezing of Gait (FoG) is a common incapacitating complication in Parkinson's patients, which will temporarily hinder the forward progression and will prevent them from re-initiating their normal gait. This can lead to potentially fatal falls and severely affect the quality of life of the patient. Due to characteristic changes in their gait, FoG can be identified by using wearable sensors such as pressure sensors, Inertial Measurement Units (IMU), and Electroencephalogram (EEG) electrodes. Classification models that run on machine learning algorithms have been frequently used. Prediction of FoG would be highly useful for the patients since this identifies the changes in their gait preceding the event and the patient can be notified. This will allow them to overcome FoG. This systematic review identifies the best sensors, sensor placements, predictive algorithms, and the limitations of the existing prediction systems. Out of all the methods reviewed, combinations of plantar pressure sensors placed on the insoles and IMUs placed on the shank produced the highest accuracies with a specificity of 91.6%. The best algorithm was identified as Convolutional Neural Networks.*

Keywords: *Freezing of Gait, Prediction, Machine learning, Wearable sensors*

1. Introduction

Freezing of Gait (FoG) is identified as a common debilitating neurological complication in patients with Parkinson's Disease (PD), where they are temporarily unable to continue the progression of their normal gait, due to being fixated in a single position (Shalin et al., 2020a) (Mazilu et al., 2015). Despite the patients' efforts, their motion becomes hindered, and their feet will appear to be "magnetized" or "glued" to the surface and are unable to re-initiate the normal gait. This is also termed "Paroxysmal Akinesia" (Chen et al., 2021). The quality of life of 20-80% of Parkinson's patients will be hindered due to the Freezing of Gait (Parakkal Unni et al., 2020a).

It has been observed in a study containing 6629 PD patients that 47% of the sample exhibited symptoms of FoG frequently and 28% of the population exhibited these symptoms daily (Mazilu et al., 2015). 2 out of 3 of the late-stage PD patients will experience FoG (Handojoseno et al., 2014). The severity of this condition lies with the falls resulting from this. This is because the patient will attempt to move forwards by "unfreezing" themselves, and the inability to do so will fixate them despite their efforts. Their upper body momentum will propel them forwards, resulting in a potentially dangerous fall, which could even lead to the death of the patient. 60% of the patients diagnosed with PD will experience falls caused by the FoG. (Chen et al., 2021). No cure has yet been identified to treat the FoG. Pharmaceutical therapy such as Dopamine and Leva-Dopa and treatments such as Deep Brain Stimulation (DBS) will help to alleviate the symptoms (Huang et al., 2018). Nonetheless, chemical-based therapies and DBS does not work for all patients and some patients will develop a resistance to these treatments. This emphasizes the need for drug-free therapy (Mazilu et al., 2015) (Naghavi and Wade, 2019a)

Apart from an individual's physical well-being, their psychological well-being can also be affected by the FoG. The patient will have to live their life with a constant fear of falling, which will further impede their mobility. This will lead to a characteristic change in their gaits, such as trembling of the feet and making shuffling steps, and a reduction in the step length. Due to the patient's hesitancy to move, they will experience secondary health problems such as osteoporosis and constipation (Prasad et al., 2018). Mental health problems such as anxiety could also arise due to FoG. The patients will also be highly dependent on assistance when performing their day-to-day activities, thus, will lose their sense of independence (Reches et al., 2020). This will not only be inconvenient to the patient but will be a burden for the caretakers as well. The reluctance to move out of their retreat will result in reduced amounts of social interactions, which could lead to potential social isolation, and thereby depression. This highlights the severity of FoG and the need for this issue to be addressed (Mazilu et al., 2015).

Detection of FoG can be beneficial to the patients since this will help them overcome the event and re-initiate their normal gait. Abnormal changes in the gait will be detected to identify events of FoG. After the event is detected, FoG episodes can be overcome by either changing the original path of motion, by auditory stimulations such as humming or using metronomes, or by making high steps. Current clinical modes of detection are done using video-recorded data of their gait and performing an offline analysis process. This will not be highly beneficial to the patient since they cannot be monitored continuously. (Rahman et al., 2008) (Tips to Overcome "Freezing" | ParkinsonsDisease.net, 2017).

Increasingly engineering-based solutions such as using wearable sensors are used for the detection of FoG. EEG (Electroencephalogram) and EMG (Electromyography) electrodes, skin conductance sensors, pressure sensors, and Inertial Measurement Units are commonly used since they can be easily and comfortably worn by the patient for a long period, enabling continuous patient monitoring. They are better than motion capture systems since they work in real-time and are easy to set up. To identify and analyze the swift changes in the Gait characteristics during FoG, machine learning algorithms such as Support Vector Machines, Neural Networks, and Decision Trees have been developed (Pardoel, 2021a) (Aich et al., 2018a) (Palmerini et al., 2017a).

Prior to the occurrence of FoG, a progressive deterioration of the spatial-temporal gait patterns of individuals is observed (Borzì et al., 2021). This enables early detection or prediction of this event. Predictive systems are more desirable than detection systems since they identify FoG a time window ahead of its occurrence, thereby addressing the latency issue associated with detection systems. Detection of the event will not allow sufficient time for the patient to respond and overcome FoG. Individuals can independently identify FoG events during their medication "OFF" stage, so the use of detection systems will be limited. Prediction systems paired with pre-emptive cueing will notify the patient well ahead of the event. The predictive systems will use gait characteristics during a time window ahead of the event, known as "Pre-FoG", for analysis. Together with the FoG and Non-FoG gait characteristics, Pre-FoG data will be used in the identification of characteristic motor changes in PD patients before the Freezing of Gait (Mazilu et al., 2015) (Pardoel, 2021a). Thus, the analysis and development of FoG predictive systems would be highly beneficial to PD patients. Therefore, the aim of this literature review is to explore and analyze the methods of predicting FoG. This review will focus on the existing FoG predictive systems, that use wearable sensor hardware systems and predictive software developed based on machine learning algorithms. An analysis will also be done on the accuracy and feasibility of the systems developed.

2. Methodology

This review takes a systematic approach to analyze the existing literature. (Wright, 2007) (Aromataris and Pearson, 2014). The scope of the review was initially identified as the existing predictive technologies of Freezing of Gait in Parkinson's patients, that followed engineering-based approaches. The area of interest was studied by exploring peer-reviewed articles and scientific journals based on this topic. The databases Google Scholar, Science Direct, PubMed, and Research Gate were used to obtain the relevant literature. The keywords used for this quest, along with their synonyms, were recorded as "Freezing of Gait", "Parkinson's Disease", "Machine learning", "Prediction", "Detection", "Wearable sensors", and "Predictive algorithms". Using Boolean operators such as "And" and "Or", the keywords were combined to scale down the search results. This yielded combinations such as "Prediction of Freezing of Gait and Machine learning", "Detection or Prediction of Freezing of Gait", "Prediction algorithms and Freezing of Gait", "Parkinson's disease and Machine learning" and "Wearable sensors and Freezing of Gait".

The search results were refined by scanning the titles and the abstracts of the research articles and the latest and the most relevant literature was given priority. The duplicate articles were discarded. Following the process of screening, the literature was completely examined to identify those that used only wearable sensors and machine learning. To refine the eligible articles, 9 characteristics were observed: the number of patients used in the experiment, their age ranges, the freeze-inducing activities performed, types of sensors used, the sensor placements, number of trials for each activity, features extracted, the algorithms used for the classification process and the results obtained. A table was compiled consisting of the references for each article and the criteria observed (Table 1). Finally, the data obtained were used to develop a critical analysis of the literature that was reviewed.

Table 1. Summary of the literature.

Reference	**No. of patients**	**Age**	**Activities**	**Sensor, Algorithms, Results**
(Chen et al., 2021)	24	males- 62.827 ± 8.82, Females- 69.20 ± 5.89	gait initiation, 360- and 180-degree turns and walking through crowded halls and narrow corridors	IMU sensor, Random forest algorithm, Hit rate of 68%
(Shalin et al., 2020)	5	67-80 years	walking in a freeze-inducing path, 90/180 degree turns	plantar pressure sensors, CNN classifier, Sensitivity- 82.3%, Specificity- 94.2%
(Mazilu et al., 2015)	11	68.9 ± 10.2	180 and 360-degree turns, walking on a straight line and through narrow corridors	9 IMUs, IR sensors, ECG and SCR electrodes, patient-specific cross-validation, 71.3% prediction accuracy
((Borzì et al., 2021)	11	73 ± 7	7m Timed Up and Go Test (TUG)	2 IMUs, Decision Trees and Support Vector Machines, sensitivity-84.1%, specificity -85.9%

Source: Author

3. Results

256 research articles were obtained from the initial search from all the databases collectively. The screening process yielded 21 articles on prediction and 50 articles on the detection of FoG. Only 22 articles that satisfied the eligibility criteria were used to compile the review. 5 review articles and 2 theses were used in the review process as well. Only the key findings for the 4 articles, with the highest number of citations, were presented in Table 1, due to space constraints. The following sections will present the results of the literature review.

A. Sensor types and Placements

Table 2 summarizes the types of sensors used, parameters measured, the common sensor placements, and the highest reported prediction accuracy when for different sensors.

Table 2. Summary of the types of sensors used

Sensor	**Parameter**	**Placements**	**Accuracy (%)**	**References**
Inertial Measurement Units (IMU)- Accelerometers, Gyroscopes, Magnetometers	Acceleration, angular motion, fluctuations of the magnetic field	Shin, shank, thigh, lower back, ankles, above the knee, hip	85.5	(Mazilu et al., no date b) (Chen et al., 2021) (Borzì et al., 2021) (Shalin, 2021) (Naghavi and Wade, 2019b) (Assam and Seidl, 2014)(Aich et al., 2018b) (Palmerini et al., 2017b)(Pardoel et al., 2021)(Yuan and Chakraborty, 2020) (Pardoel, 2021b)
Pressure sensors	Pressure	Plantar pressure sensors placed as an insole in shoes	92.0	(Shalin et al., 2021) (Pardoel et al., 2021)
Force plate	Ground reaction force	Beneath the feet	Not provided	(Parakkal Unni et al., 2020b)
EEG electrodes	Electrical activity -brain	Motor control regions-Brain	72	(Naghavi, Miller and Wade, 2019b)(Handojoseno et al., 2018b)
ECG electrodes	Electrical activity -heart	Chest	71.3	(Mazilu et al., 2015)
Skin conductance sensors	Electrical conductance-skin	Index and middle fingers, wrist	71.3	(Mazilu et al., 2015)

Source: Author

Some of the commonly used sensors are displayed in Figure 1.

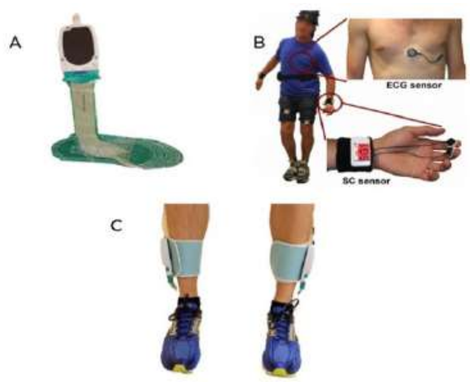

Figure 1. Types of sensors used

Sources: A) A pressure sensor insole B) 2 IMUs worn as bands on the shank (Shalin et al., 2020a) C) An ECG electrode placed on the chest and a Skin conductance electrode worn on the wrist (Mazilu et al., 2015)

Figure 2 depicts some of the common sensor locations.

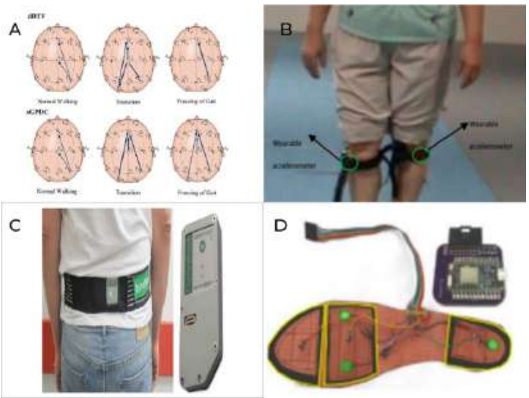

Figure 2. Sensor placements

Sources: A)EEG electrodes placed on the motor regions of the brain (Handojoseno et al., 2014) B) Accelerometers placed on the shank (Aich et al., 2018a) C) An IMU worn as a band on the waist (Weiss et al., 2013) D) 3 pressure sensors placed in an insole (Prado et al., 2020)

C. Feature Extraction

Features are measurable quantitative data extracted from the manipulation of raw sensor data. Some of the commonly used time domain features are Mean, Standard deviation, angular velocity, angular jerk, and foot velocity (Mazilu et al., 2015) (Pardoel, 2021a) (Handojoseno et al., 2013b) (Naghavi, Miller and Wade, 2019a) (Borzì et al., 2021) (Shalin et al., 2020a). Some of the commonly used frequency domain features are spectral density and the power of the signal obtained from Fourier Transform and Approximation and Detail Coefficients obtained from Wavelet Transform (Pardoel, 2021a) (Naghavi and Wade, 2019a) (Handojoseno et al., 2013a) (Mazilu et al., 2015) (Borzì et al., 2021).

D. Algorithms

Implementations of the commonly used algorithms are done through:

1) Supervised pattern classification: Uses labeled data to develop the classification model and categorizes the data into training and testing groups. Labeled training data is used to develop the classification model and unlabelled testing data is used to validate the model (Mazilu et al., 2015) (Borzì et al., 2021).

2) Unsupervised pattern classification: Yields better results for prediction rather than the supervised models. Uses unlabelled data, thus this will eliminate the subjective biases. The model itself will perform the labeling process and cluster the data into freezing and non-freezing groups (Mazilu et al., 2015) (Borzì et al., 2021).

3) Semi-supervised pattern classification: This is a composite of the supervised and unsupervised models, so uses the advantages of both methods. A major portion of the unlabelled data and a minor portion of the labeled data is used for the development of this classifier. This eliminated the need for laborious labeling processes and allows the development of generalized and subject-specific models too. The highest reported sensitivity and specificity using this classifier were 95.9% and 95.6% respectively (Mazilu et al., 2015) (Borzì et al., 2021).

A few of the commonly used algorithms are:

1) Neural Networks: Convolutional Neural networks allow independent identification of spatial patterns and are favorable since feature extraction is not a necessity for this algorithm. They develop images using the data and work on pattern recognition principles. Minor disadvantages of this model are its complexity and time consumption. Sensitivities and specificities of 98.8% and 95.1% have been reported using this algorithm (Shalin et al., 2021) (Pardoel, 2021a).

2) Decision Trees: The observed studies used a binary classification tree method. This method prevents overfitting of the data and exhibits greater transparency in comparison with the other algorithms. Compares the data with a threshold and categorizes it along the nodes. Uses boosting techniques such as Logistic, Adaptive, and Robust boosting to enhance the performance. Can produce sensitivities and specificities of 83.8% and 82.1% (Pardoel, 2021a).

3) Support Vector Machines: Based on principles of binary or multiclass classification and classifies the data by constructing a hyperplane. The planes and the classes are given the maximum disparity and new data points are classified based on their positions on the plane. Can yield sensitivities as high as 89.2% (Pardoel, 2021a) (Borzì et al., 2021) (Naghavi and Wade, 2019a) (Handojoseno et al., 2013b).

4. Discussion

The findings of the review will be summarized, discussed, and analyzed in-depth in this section. Prediction of FoG is identified as the detection of FoG during a period preceding its incidence and warning them using pre-emptive signaling. Most recent studies focused on prediction algorithms since they assist Parkinson's patients in overcoming FoG more effectively than detection systems. Thus, this review will mainly focus on the results obtained pertaining to the prediction of FoG.

A. Sensor types

The variations in the gait of a PD patient will result in fluctuations in the kinetics and the kinematics during and prior to the event (Parakkal Unni et al., 2020a). These can be effectively captured by wearable sensors. Different physiological parameters respond to FoG in different ways, thus different types of sensors will capture different characteristics of FoG, depending on the type of data that it collects. Increasingly, multimodal sensors have been used for the detection and prediction of FoG, since all the variations cannot be captured by a single type of sensor. (Shalin et al., 2020a). This also maximizes the chance of identifying the event, by compensating for the patient-specific differences. Figure 1 and Table 2 refer to the commonly used types of sensors.

It is evident that IMUs were the most widely used sensors and pressure sensors yielded the highest accuracy out of all the sensors reviewed. IMUs are lightweight and compact devices that could be easily accessed and worn on the patient's body, with minimal inconvenience. This makes IMUs preferable compared to the other wearable sensors. They are usually combinations of accelerometers, gyroscopes, and magnetometers. Accelerometer data were more commonly used in comparison with other IMU data. Pressure sensors are among those that emerged recently, and these sensors yielded the highest reported prediction accuracy. They are more comfortable to be worn on the body and are less intrusive. All pressure sensors observed were used as plantar pressure sensors on the insole of the shoe. Thus, pressure sensors can capture data more conveniently from the patients, with greater accuracy. Pairing pressure sensors with IMUs yielded the highest reported sensitivity (78.0%) and specificity (91.6%), in comparison with single sensors, and multimodal sensors produced the best overall performance. (Shalin et al., 2021) (Pardoel, 2021a). To analyze the use of other sensors like force plates, EEG electrodes, ECG electrodes, and skin conductance sensors, limited literature was available.

A. Sensor Placements

Several studies compared the best sensor placements for the IMUs, which produced a greater prediction accuracy compared to EEG, ECG, and skin conductance electrodes. Figure 2 and Table 3 depict the common sensor placements. Wearable accelerometers that were sported on the shank and the thigh yielded the highest prediction rates, which were 95.7 and 96.7 respectively (Naghavi and Wade, 2019a) (Assam and Seidl, 2014). Sensors which were worn on the waist were unable to capture a large portion of FoG data since it is distal from the lower body that is mostly affected by FoG. It was only able to capture 5.1% of the FoG data. Out of all the sensor positions reviewed, it was evident that the shank was the optimal sensor location due to the highest prediction accuracy and the least patient dependency. Plantar pressure sensors were not used as single pressure units, but multiple sensors were used to capture point pressure data. Most of the studies using pressure sensors used the commercial F-Scan sensing system, which had 3.9 sensors per cm2, and yielded sensitivities of 82.1% and specificities of 89.5% (Pardoel, 2021a). One study used 3 pressure sensors placed on the metatarsals, calcaneus, and phalanges. This yielded a mean sensitivity of 96% and a mean specificity of 99.6% (Prado et al., 2020). Thus, individual pressure sensing cells can capture more accurate FoG data, in comparison with the commercial F-Scan system. All the systems placed sensors on the left and right regions of the body, and no detectable differences between the data recorded from the 2 regions were identified (Palmerini et al., 2017a).

C. Feature Extraction

Features that exhibit characteristic differences in the gait patterns of FoG, Non-FoG, and Pre-FoG events should be used in the prediction of FoG. Threshold-based detection methods are less complex, so they can be processed faster (Pardoel, 2021a). This allows threshold-based classification methods to be used in the real-time prediction of FoG. It has been identified that frequency domain data allows the mapping of minute changes in the Pre-FoG windows. Time domain features allow distinct differences to be observed between the gait patterns. By performing a time-frequency analysis of the data, using the optimum number of parameters, the best results can be obtained (Pardoel et al., 2019) (Shalin et al., 2020b).

D. Algorithms

Predictive systems were mostly based on 3 class classification techniques, since the FoG, Non-FoG, and Pre-FoG classes have to be taken into consideration. Subject-specific models yield greater prediction accuracies as opposed to models that are generalized for the whole population. However, limited data is available to generate models specific to each individual, therefore generalized models are more desirable. All the studies used for the review used machine learning models to classify the data and produce predictions. (Mazilu et al., 2015). The algorithms that yielded the best performances were identified as Convolutional Neural Networks, Adaptive Boosted Decision Trees, Support Vector Machines, and Random Forests (Pardoel, 2021a).

E. Limitations

Most of the existing predictive systems have not focused on producing real-time results and are based on offline processing techniques. Without real-time analysis, feedback cannot be provided to the patient with a minimal time delay, thereby making the existing systems less useful. FoG manifests in different ways for different PD patients, therefore generalized models are less effective. The feasibility of the existing systems cannot be guaranteed due to patient-specific differences. This poses a risk of incorrect classification and classification metrics, thereby producing incorrect validations for the model (Pardoel et al., 2019) (Palmerini et al., 2017a).

5. Conclusion

review, the need for an accurate FoG prediction system has been identified, which was to address the latency issues posed by the detection system. This will be more useful for the patients to overcome events of FoG. Out of the literature reviewed, the best wearable sensors were identified as multimodal sensors that used Plantar pressure sensors and Inertial Measurement Units, with the sensitivities and specificities reported as 78.0% and 91.6%. The optimal sensor placements for the IMU were identified as the shank and for the plantar pressure sensors, the positions of calcaneus, metatarsals, and phalanges yielded a greater accuracy. Classification models that used time-frequency domain features were better than individual time or frequency domain features since they combined the advantages of the two domains. The best classification algorithm out of the commonly used ones was identified as the Convolutional Neural Networks, with the highest reported sensitivity of 98.8%. A degree of personalization could be added by incorporating semi-supervised classification techniques. Thus, a system based on plantar pressure sensors and Inertial Measurement Units would open a promising avenue for the prediction of Freezing of Gait.

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Author Biography

Varsha Jayawardena is currently a final year Biomedical Engineering Undergraduate at the Faculty of Engineering of

General Sir John Kotelawala Defence University. Her final year research is based on the Prediction of Freezing of Gait in Parkinson's patients using wearable sensors.

Dr. PPCR Karunasekara is a senior lecturer of the Biomedical Engineering degree program at the Department of Electrical, Electronic, and Telecommunication Engineering at General Sir John Kotelawala Defence University, Sri Lanka. Her research interests include Neural Engineering, Biomechanics, and Rehabilitation Engineering.

Dr. Darshana Sirisena (MBBS, MD (Col.)) is a consultant Neurologist with a special interest in Movement disorders. He is currently the president of the Association of Sri Lankan Neurologists.