Synopsis of the B.Tech Minor Project Entitled

Detection and Prediction of Freezing of Gait in Parkinson's Disease

Submitted by

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November 2019

Abstract

Freezing of gait (FoG) is common gait impairment among patients with advanced Parkinson disease. FoG events are associated with falls, interfere with daily life activities and impair quality of life. Wearable systems that detect FoG have been developed to help patients resume walking, but permanent cueing is not advised due to continuous interference. However, the current method of automated detection were not yet ideal. We propose to avoid FoG episodes by predicting when a patient is about to experience FoG and simulating auditory cueing when FoG is detected. This paper we use Random Forest, kNN and Linear SVM as the machine learning algorithms applied. We investigate the features and extract top ranked features from sensors data using Time-Domain and Statistical Analysis. The final system was able to detect FoG events with an average sensitivity of 99.04% and specificity of 93.28% in user dependent settings.

Keywords: Freezing of Gait, Parkinson's disease, supervised learning, machine learning, freezing of gait, feature extraction, prediction, kNN, Linear SVM, Time-Domain and Statistical Analysis

Chapter 1

INTRODUCTION

Freezing of Gait (FOG) is a common deficit in advance Parkinson's disease. Gait refers to the 'manner of movement/walking' of a person. PD is a common neurological disorder caused by the progressive loss of dopaminergic and other subcortical neurons. FOG can be defined as a "Brief, episodic absence or marked reduction of forward progression of the feet despite the intention to walk". FOG occurs more frequently in men than in women (Table 1), and less frequently in patients whose main symptom is tremor. PD patients who experience FOG frequently report that their feet are inexplicably glued to the ground during the FOG episodes. PD patients often suffer from impaired motor skills. Besides a exed posture, tremor at rest, rigidity, akinesia (or bradykinesia), and postural instability, motor blocks area common negative effect of PD. Freezing can be simply termed as the freezing of the movement of the person. FOG events are associated with falls, interferes with the patients' daily life activities and impairs their quality of life. There are some known specic properties that dierentiate the sensor data during FoG episodes from normal walking and the gait of patients with FoG also diers between freezing episodes, compared to patients who do not experience FoG at all. There are even suggestions of a characteristic change in the gait pattern just prior to the occurrence of a FoG episode; however, currently, there is no way of automatically identifying the prodromal state, when the normal gait pattern is about to transform into FoG.

Subject ID	Gender	Age [years]	Disease duration [years]	H&Y in ON	Tested in
01	M	66	16	3	OFF
02	M	67	7	2	ON
03	M	59	30	2.5	OFF
04	M	62	3	3	OFF
05	M	75	6	2	OFF
06	F	63	22	2	OFF
07	M	66	2	2.5	OFF
08	F	68	18	4	ON
09	M	73	9	2	OFF
10	F	65	24	3	OFF
Mean $\pm$ STD		66.4 $\pm$ 4.8	13.7 $\pm$ 9.67	2.6 $\pm$ 0.65	

Figure 1.1: Gender,Age,Disease Duration, and HY rating of the patients (Ref: Wearable Assistant for Parkinson's Disease Patients with the Freezing of Gait Symptom)

According to a survey of 6620 Parkinson's Disease patients, 47% of the subjects reported regular freezing and 28% experienced FOG daily. It is often resistant to pharmacological treatments. Pharmacological management of PD is difcult and often ineffective at relieving FOG. The most common form of treatment used to manage motor symptoms in PD patients is levodopa (LD). The effect of LD on parkinsonian symptoms wears off over time and the effective periods varies between 2 and 6 h. Therefore, effective non-pharmacologic treatments need to be developed as an adjunct therapy to relieve symptoms and improve mobility.

The goals of this work are to improve the detection performance by using machine learning techniques.

The contribution of this work are as follows:
1. We tried to present a methodology for FoG episode detection applying different machine learning techniques exploiting feature sets derived from accelerometer data.

2. We perform a detailed analysis of features (and feature combinations) extracted from the sensors' time series.

3. Our experimental results on a real-world benchmark data sets indicate that Top-10 Features (obtained from from mutual information) yield the best result . Furthermore, the proposed approach outperforms our baselines, i. e., state-of-the-art approaches significantly

Chapter 2

Preliminary Literature Survey

Having understood the meaning of Freezing of Gait in the Parkinson's disease, several research papers have been published on this topic. Most of the early research papers emphasised on Rhythmic Auditory Stimulation (RAS) upon detection of FOG. RAS is applied to produce a rhythmic ticking sound upon detection of FOG episode. Wearable system based on motion sensors have been proposed for the detection and treatment of FOG with auditory stimulation.

While RAS upon detection helps to shorten the duration of FOG episodes, it cannot avoid them altogether due to the latency of the detection, which is at best on the order of hundreds of milliseconds. A step further is to predict when a patient is about to experience FOG, thus enabling pre-emptive RAS, with the goal of avoiding the FOG episodes. We call this FOG prediction as opposed to FOG detection. Then, with the emergence and popularity of machine learning, several research papers were written with emphasis on the feature recognition, extraction and detection. [2] formulated the FOG detection problem as a two-class classication problem: FOG versus normal locomotion and similarly, treat FOG prediction problem as a three-class classication problem. Beside FOG and normal locomotion, some papers consider the walking periods before FOG episodes as a third-class called pre-FOG. They hypothesize that there is a detectable deterioration of gait in this phase which precedes FOG.

Several research groups have proposed wearable systems for the detection of FoG episodes. Most sensor setups involve accelerometers and/or gyroscopes, extended with electroencephalography (EEG) or electromyography (EMG).According to a study,it was observed that continuous RAS can be annoying and that a context-aware triggering of the RAS would be preferable. [1] proposed a wearable system, that provides rhythemic auditory signal when a FoG is detected. They also deduced that content-aware automatic cueing was more beneficial to the patients. [4] also explored the use of smartphones as wearable device for FoG detection and treatment because of the several merits (Economical, User-Friendliness, Tele-Medicine, Social aspects) involved with it. The algorithm presented in [4] worked much better in user-dependent environment. Therefore, patients using this system should record a set of training data for labelling FoG episodes, so that the classifer can be trained online.

Certain limitations were also associated with the researches. Even though machine learning techniques classified the FoG episodes, but the results were highly patient dependent like some FoG episode start when subject starts walking, and pre-FoG duration will also probably vary. Another limitation was that patient did not experience FoG during the study but reported many FoG events at home, the presence of a physiotherapist may have reduced the likelihood of FoG. Another reason may have been the controlled environment, instead of an actual daily life environment for the experiment.

Chapter 3

Proposed methodology

3.1 Data description

The Daphnet Freezing of Gait Dataset is a dataset devised to benchmark automatic methods to recognize gait freeze from wearable acceleration sensors placed on ankle, legs and hip. The dataset was recorded in the lab with emphasis on generating many freeze events. This dataset is the result of a collaboration between the Laboratory for Gait and Neurodynamics, Tel Aviv Sourasky Medical Center, Israel and the Wearable Computing Laboratory, ETH Zurich, Switzerland. Recordings were run at the Tel Aviv Sourasky Medical Center in 2008. The study was approved by the local Human Subjects Review Committee, and was performed in accordance with the ethical standards of the Declaration of Helsink.

It contains data collected from three wireless accelerometer sensors placed on the ankle, thigh, and trunk of 10 PD patients. The sensors recorded 3D accelerations at 64Hz and transferred their data to a wearable computer, which was attached to the trunk of the subjects (along with the third sensor) and provided RAS upon the detection of a freeze episode.

The research protocol was based on two sessions, both designed to replicate a normal daily walking routine. During the first session, the wearable computer collected all the data and conducted online FoG detection, without RAS feedback. In the second session the same procedure was followed, however, the RAS feedback was activated. The subjects performed three basic walking tasks in both 10-15 minutes sessions, more specifically, (1) Walking back and forth in a straight line, including several 180-degrees turns; (2) Random walking with a series of initiated stops and 360 degrees turns; (3) Walking simulating activities of daily living, which included entering and leaving rooms, walking to the kitchen, getting something to drink and returning to the starting room with a cup of water.

Afterward, the physiotherapists analyzed the recorded video along with the manual labels to identify the ground truth labels, the duration, the onset, and the end of the FoG episodes as well. The onset of a FoG episode was detected when the locomotion pattern, more specifically the alternation from left to right step, was decelerating, and the end of the FoG episode was considered as the moment that the pattern was accelerating. The physiotherapists labeled manually four activities, specifically standing, walking, turning, and freezing. However, after the video analysis, they categorized the activities standing, walking, and turning as “no freezing”. Consequently, for each 3D accelerometer sensor reading of the DAPHnet dataset, the final ground truth class labels are 1 for “no freeze” and 2 for “freeze”. It is worth pointing out that there is an extra class label (annotation) in the DAPHnet dataset with the value 0, which is not part of the experiment, for instance the subject war performing activities unrelated to the protocol.

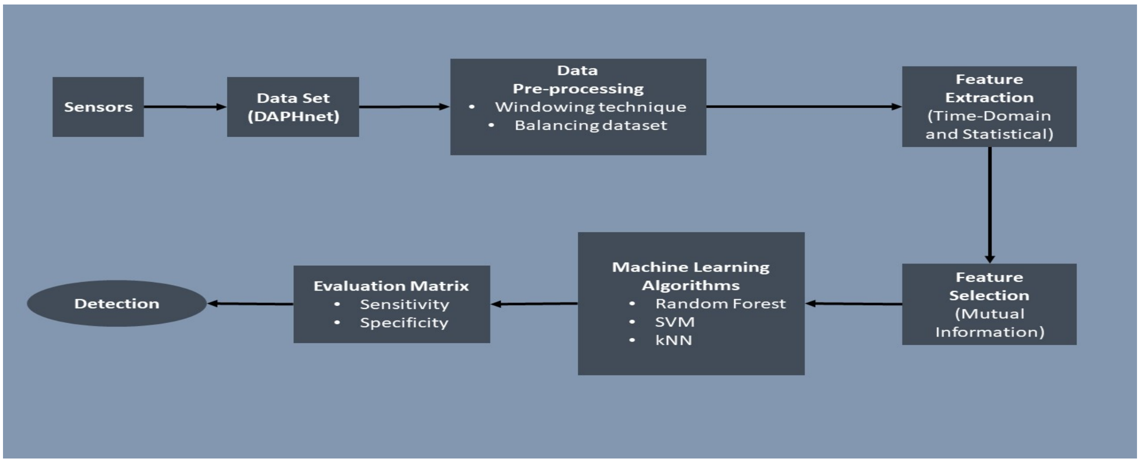

Figure 3.1: Flow Chart

3.2 Data Pre-processing

One of the essential steps in the data mining process is data preprocessing. In our setting, we first deleted annotation 0, because it is not relevant to the experiment. The next step of data preprocessing involves a balancing of unbalanced data only 5% of the data was FoG.

3.2.1 Windowing

The next fundamental step is the application of windowing techniques, where the sensor signals are sliced into partially overlapping windows. We used a windowing function with a window length of 4 seconds (256 samples) and an overlap of 0.5 seconds (32 samples). A window was labeled as a FoG-Window if more than 50% of the samples were labeled as FoG. After segmentation, relevant features are extracted from each window and the resulting feature vectors are used as training data.

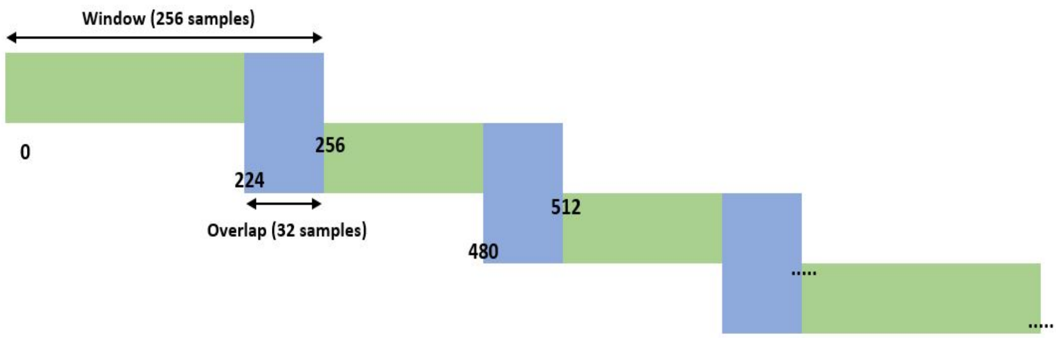

Figure 3.2: Windowing

3.2.2 Balancing of data

After windowing technique, the features selected were tested on the model. Then we observed that the accuracy was very high but low sensitivity. Therefore, it was always predicting 0 (Non-FoG class) and completely ignoring the minority class in favour of majority class. It indicates that our data is unbalanced where only 5% of the data was recorded as FoG events, and the remaining 95% of the data was recorded as normal locomotion. This happens because the model is inclined to inflate the accuracy by default. So we needed to handle the unbalanced data.

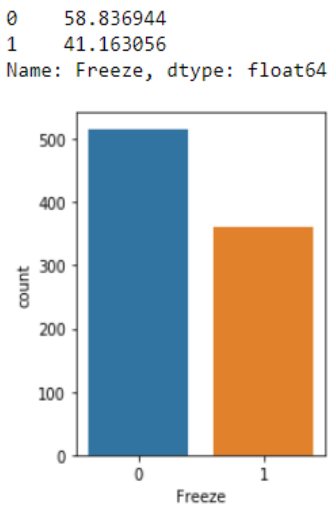

Figure 3.3: Balancing

The data can be balanced using oversampling of minority class, down sampling of majority class and cost sensitive training. In context of our experiment, we performed over sampling of minority class which gave us a better performance in comparison to under sampling of majority class because under sampling of a majority class leads to the decrease in the recall value of the majority class.

3.3 Feature Extraction and Selection

In present work the total signal consists of 9 components where each sensor consists of 3 signals: horizontal, vertical and lateral. The top ranked features were: Mean, Variance, Standard Deviation, Kurtosis and Skewness. We, then evaluated the above mentioned features for all the axes (X,Y and Z) and magnitude for each sensor – ankle, thigh and trunk. Altogether, we then obtained a total of 45 columns, for determining feature vectors. A target value of 1 is labeled for freezing cases and 2 is assigned for no-freezing cases using extracted statistical information. We ran the features based on Mutual Information (MI) computed on the entire data window. In the training phase, the obtained k-ranked features (k ranging from 5 to 20) were subject dependent. The features with 0 as a Mutual Information were removed as they did not have any dependence on the target variable and features with high MI score were retained. For feature selection we consider the MI score and tested our model by selecting highly discriminative features. We observed that MI score improved for the top-ranked features.

3.4 Experiments and Evaluation

We evaluated the data based on the following classifiers: Random Forest, Linear Support Vector Machine and kNN. The machine learning algorithm is tuned for obtaining the optimal hyperparameters based on GridSearchCV approach.These parameters express important properties of the model such as its complexity or how fast it should learn. We performed N-cross validation on the training dataset, and on hyperparameter tuning, the estimator with best average cross-validation score was selected. The value of N, that is number splits to be done on the training data before testing was obtained using GridSearchCV. We defined our grid of parameters to search over and then run the grid search and obtained the best parameter and estimator. The parameters taken into account for each model are as follows:

- Random Forest: n_estimators, max_depth
- Linear SVM: C
- KNN: n_neighbours, class_weights

Random Forest based classifier works best with unbalanced data, as observed previously the classification on unbalanced data was giving very high accuracy but low sensitivity. The computational cost of random forest is less than other classifier models SVM and logistic regression.

We measure Sensitivity, which proportion of correctly detected FoG windows to total number of actual FoG windows. And Specificity measures the proportion of correctly detected no-FoG windows to actual no-FoG windows. Furthermore, we evaluated the model in terms of classification algorithm and number of selected features.

Chapter 4

Result and Discussion

For evaluation, we considered subject-dependent settings on all the machine learning techniques using different selected features for constructing the respective training and test datasets. We give the results in terms of overall patient dataset average sensitivity and specificity, in window-to-window comparison.

As our setting is user dependent therefore, the training and testing data will be from the same patient. The top ranked features varied patient wise. We report the comparative performance of top 5,10,15,20 ranked features on the whole dataset for classification algorithms.

		Sensitivity		
Features	5	10	15	20
RF	97.78	99.26	95.735	99.04
Linear SVM	77.99875	80.26875	85.84125	89.66125
		Specificity		
Features	5	10	15	20
RF	91.91	93.83	90.81	93.28
Linear SVM	82.65875	85.4725	87.74375	87.565

Figure 4.1: Average Sensitivity and Specificity for classifiers for different values of no of features selected

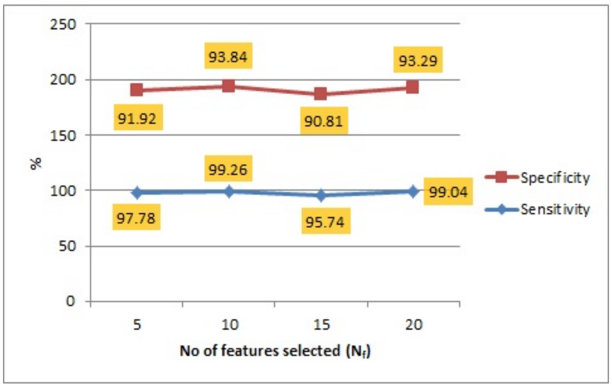

Figure 4.2: Sensitivity and Specificity for RF for different number of features selected

The best results were obtained from top 10 and 20 features with on a average specificity and sensitivity of 99% and 93%. We take into consideration top 20 features for further experiments, as we obtain better overall performance on all the classifiers for it, as shown in Fig 4.1 and Fig 4.2. The detection performance highly decreased for top 5 ranked features with average sensitivity and sensitivity of 87%. So for further evaluation, we will be taking into account only Top-20 features for the comparison of classifiers.

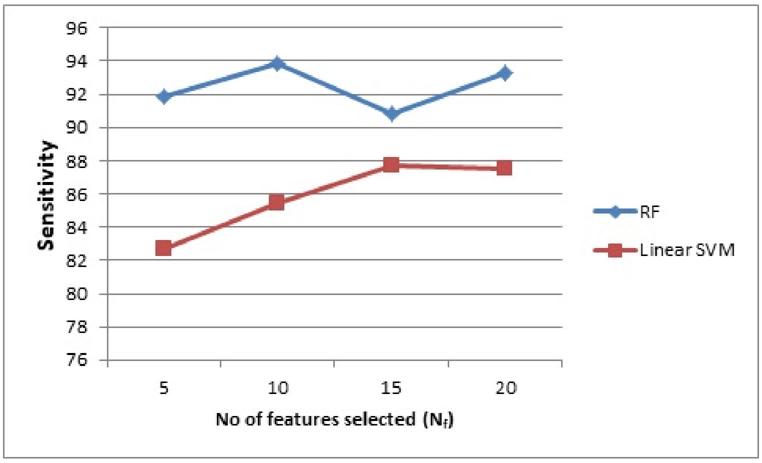

Figure 4.3: Comparison of Classifiers based on Sensitivity and Specificity of Top-20 features

Comparative results for algorithms are shown in Fig 4.3 and report that Random Forest(RF) performs better than other algorithms. Random forest gives an overall sensitivity of 99.04% and specificity of 93.28%. Random Forest was evaluated on the patients Fig 4.4 and observed that Patient 1,2,6,7,10 had the highest sensitivity 100% and Patients 7 had the highest specificity 98.93%. Overall the performance of Patient 7 was highest for Random Forest Classifier.

	Top 20	
	Sensitivity	Specificity
Patient 1	100	97.48
Patient 2	100	94.05
Patient 3	98.93	87.7
Patient 4	-	-
Patient 5	100	88.57
Patient 6	100	91.11
Patient 7	100	98.93
Patient 8	95.45	93.02
Patient 9	97.97	95.45

Figure 4.4: Patient wise performance analysis based on Random Forest

Following detailed algorithm evaluation presented above, we chose Random Forest Classifier for our project. As they obtain good results in terms of FoG detection performance. For feature selection, we chose Top-20 ranked features based on mutual information.In future, we will analyse the data based on subject-independent settings.

Chapter 5

Conclusion and Future Work

In this project we investigated the performance of different classifiers approach to detect the accuracy for FoG Detection. In our experiment we observe the performance of different features which are more relevant and informative for the detection study.We created models by keeping window size of 4s and overlapping of 0.5s seconds. The accuracy, specificity and sensitivity were noted.

Future work should be to predict FoG and the start of Rhythmical Cueing during such situations the gait performance in PD, both on Short-Term and Long-Term periods. We propose to increase the performance of our system, and recognising the patients from their symptoms.

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