Gait Monitoring and Analysis for Parkinson's Disease Patients

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Introduction

Parkinson's disease (PD) is a neurodegenerative disorder that affects the dopamine producing neurons in the substantia nigra, an area of the brain, leading to shaking, stiffness and difficulty walking. Parkinson's patients frequently exhibit the debilitating condition freezing of gait (FOG), which is when patients cannot move their feet forward despite the intention to walk. While the feet remain in place, the torso still has forward momentum, making falls very common. At the start, FOG can be triggered by stress, tight spaces or a sudden change in direction. As the disease progresses, this happens more frequently, a fact extremely detrimental to the patient's health and mental well-being.

Aims and Objectives

The aim of this project is to identify the parameter which is most suitable for classification of FOG in PD patients. It also aims to compare multiple machine learning models based on acceleration data from accelerometers placed on the thigh.

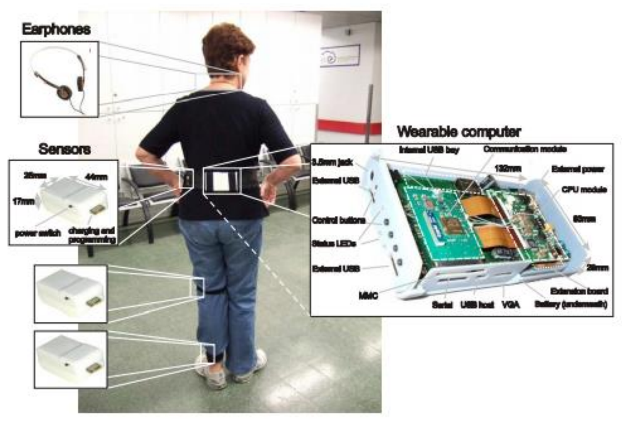
Public datasets of PD patients will be analysed to extract the motion pattern of PD patients. A Freeze Index value is postulated and used to predict FOG based on these parameters. Ultimately, a prototype that fulfils all these requirements will be developed.

Literature Review

1. Utilisation of Inertial Measurement Units (IMUs)

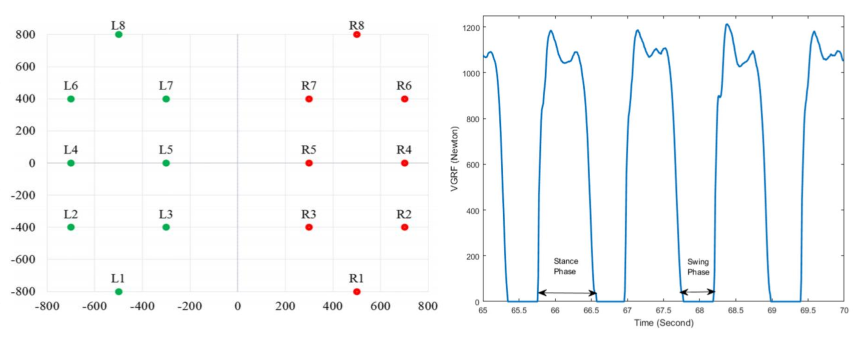
IMU	Purpose	Measured Parameter
Accelerometer	Measuring acceleration	Stride Length, Stride Duration
Gyroscope	Measuring angular velocity	Step Festination, Gait Asymmetry
Flexible Goniometer	Measuring body joint angles	Flat Foot Strike
Force-sensitive Insole	Measuring the tension and compression forces that act on the sensor	Gait Cycle (not accurate for PD patients who suffer from flat footedness)

a. 3D-Accelerometer Wearable System - Bachlin et al.



Sensors are attached to the shank, thigh and lower back where the wearable computer is attached to. There is a notable drop in acceleration.

b. Vertical Ground Reaction Force measurement with force insoles - Alam et al.



The system used to collect gait data consists of eight sensors beneath each foot and a recording unit. A small and light recording unit was carried at the waist. The subjects walked at their natural pace on level ground for two minutes, and data was acquired with a sampling frequency of 100 Hz.

2. Machine learning approaches

a. Support Vector Machine (SVM)
   i. Considered the most accurate by Aich et al.
b. K-Nearest Neighbour (kNN)
c. Decision Tree (DT)
d. Naive Bayes (NB)
e. Threshold/ Logistic Regression
f. Time Series Analysis

3. Summary of Gait parameters

Gait abnormalities	Definition
Step Festination	Shortening of steps
Decrease in Stride Duration	Decrease in the time difference between two consecutive detected acceleration peaks of the same leg
Postural Instability	Loss of balance
Increase in step-to-step time variability	Difference in time taken between each stride
Stride Length Reduction	Reduction in distance between each stride/step
Decreased Cadence	Decrease in number of steps taken per unit time
Gait Asymmetry	Difference in gait between the two legs of patient

4. Gait Equations

Gait Parameters	Equation
Stride Length	Stride velocity (m/min) /0.5 cadence (steps/min)
Gait Variability	(*Standard deviation/Mean) x 100

*Standard Deviation: $\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$

for the stride length and step width of each participant

Public Dataset Analysis

1. Dataset used

DAPHNet dataset:

The result of a study done by Bachlin et al., carried out by the Laboratory for Gait and Neurodynamics, Department of Neurology, Tel Aviv Sourasky Medical Center (TASMC). In this experiment, 10 PD patients with varying Hoehn & Yahr (H&Y) scales were made to do various walking tasks, including walking back and forth in a straight line, doing several 180 degrees turns, random walking including a series of initiated stops and 360 degree turns and walking simulating daily activities.

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 ± STD		66.4 ± 4.8	13.7 ± 9.67	2.6 ± 0.65	

The table above depicts the patients. Patient 08 and Patient 01 both suffered from walking difficulties due to disease severity and foot drop respectively.

2. Gait parameters focused

Although PD patients suffer from a variety of gait abnormalities, previous researchers have reported the importance of five parameters for the detection of PD. Most notably, Hollman et al. have proposed five major domains of gait based on factor analysis:

i. Rhythm - step and stride time

ii. Phase - gait cycle

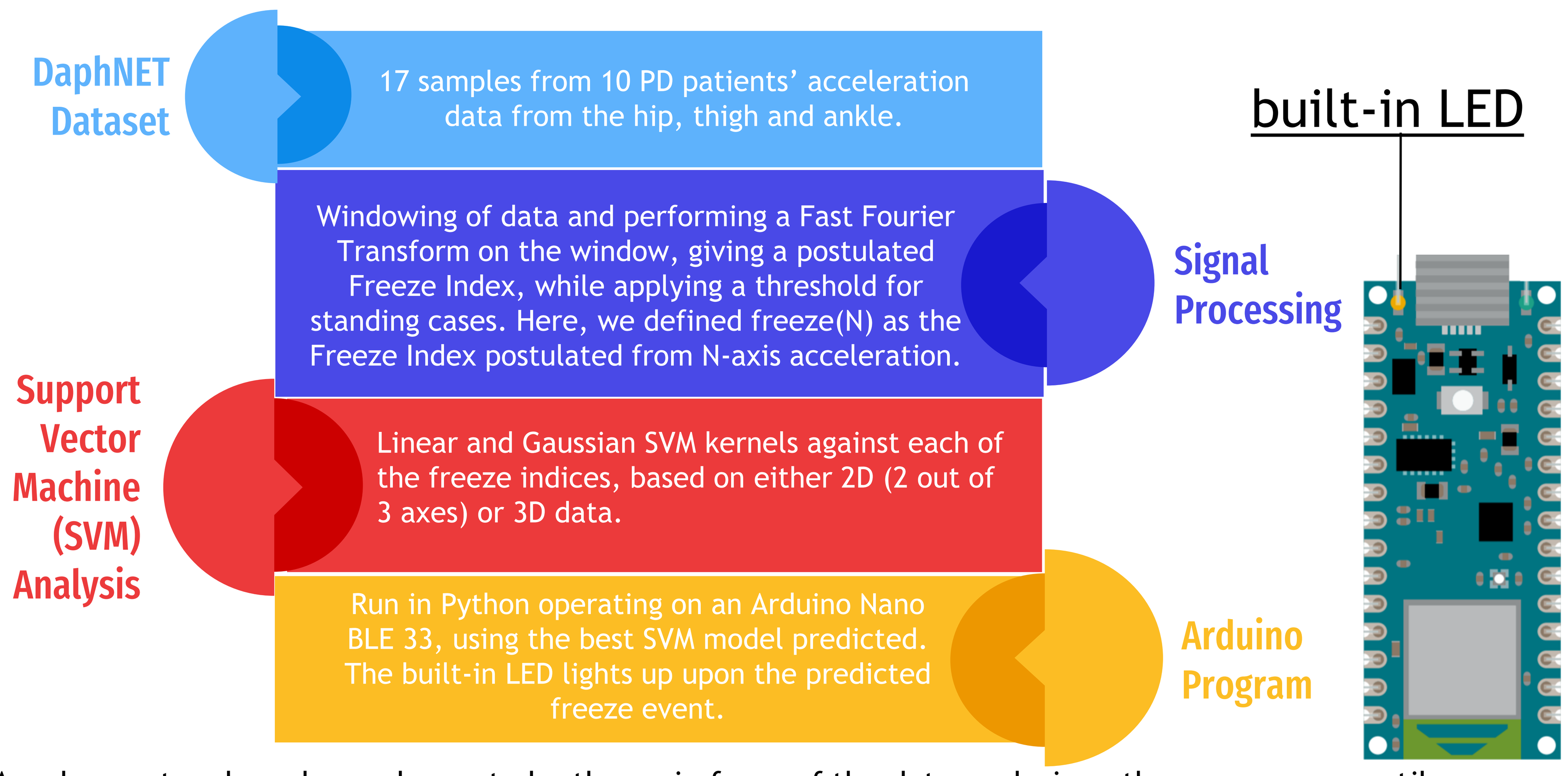
iii. Variability - step-to-step variability

iv. Pace - gait speed, stride and step length

v. Base of support - step width.

Others have confirmed the importance of determining the spatiotemporal parameters. Hence, in this study, the focus will be on gait velocity, stride time and gait cycle.

Methodology

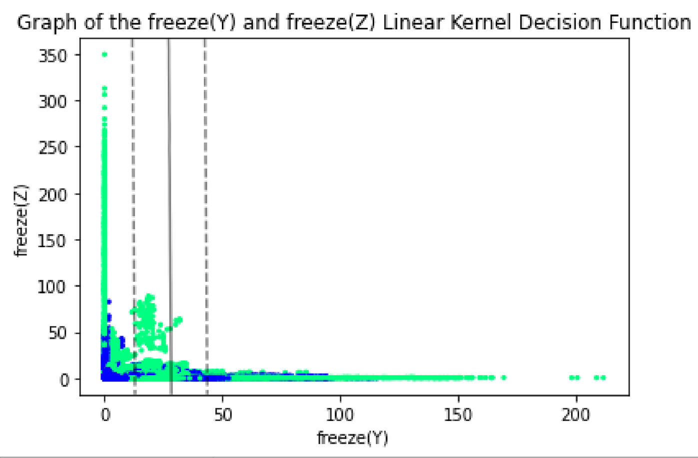


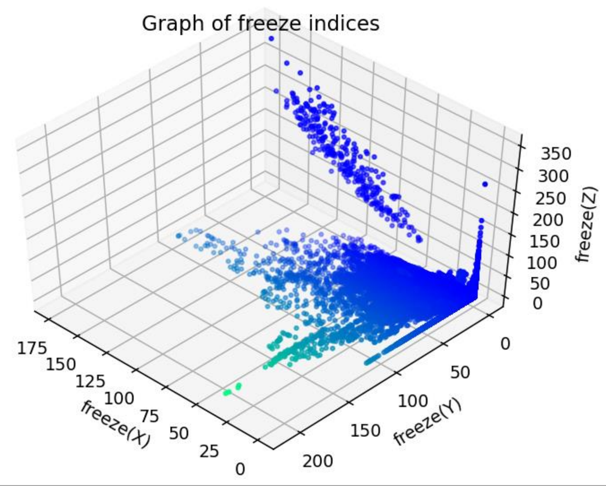
Accelerometers have been chosen to be the main focus of the data analysis as they are very versatile. Research has shown that accelerometers can be used to determine stride time, gait cycle and gait velocity. Hence, they would be a good starting point. The axis used is based on X being horizontal forward, Y being vertical and Z being horizontal lateral with respect to the user.

Results

Upon performing the Signal Processing Algorithm on the DaphNET dataset data, the freeze indices are plotted against one another as shown on the right. This data is then tested using multiple parameters and 2 kernels, achieving the results below.

Based on the results, it is believed that the **Linear kernel with parameters freeze(Y) and freeze(Z)** is the best since it is highly **accurate**, **specific** and **precise**. After conducting an analysis, it is found that the weighted average value for precision and sensitivity/recall as 0.90 and F_1 score as 0.86. The decision boundary function is shown below on the left.





Kernel	**Linear Kernel**				Radial Basis Kernel			
Parameters	freeze(X) and freeze(Y)	freeze(X) and freeze(Z)	**freeze(Y) and freeze(Z)**	All 3 Parameters	freeze(X) and freeze(Y)	**freeze(X) and freeze(Z)**	freeze(Y) and freeze(Z)	All 3 Parameters
Specificity	1.000	0.975	**1.000**	1.000	0.990	**0.990**	0.991	0.989
Sensitivity/ Recall	0.000	0.243	**0.006**	0.002	0.174	**0.183**	0.163	0.260
Precision	0.000	0.509	**0.889**	0.867	0.650	**0.664**	0.665	0.723
Accuracy	0.903	0.904	**0.904**	0.904	0.911	**0.912**	0.911	0.918
F_1 Score	0.000	0.329	**0.011**	0.005	0.275	**0.286**	0.262	0.382

Table of Algorithm Evaluation Functions with regards to kernels and parameters

Prototype

In the end, a prototype has been developed to verify the effectiveness of parameters based on public dataset analysis.

It consists of an Arduino Nano BLE 33 board with a built-in 3D accelerometer and 3D gyroscope attached to an elastic band. It is small, light, very comfortable and is meant to be wrapped around the thigh.

Conclusion

An algorithm has been developed to identify the most suitable parameter for the classification of FOG in PD patients. Multiple machine learning models have also been compared based on acceleration data from accelerometers placed on the thigh. After analyzing, the most suitable parameters for classification are freeze(X) and freeze(Z) based on the acceleration data in the public datasets and the best model is the linear kernel model in terms of sensitivity. To make the result more reliable, freeze(Y) and freeze(Z) might also be considered.

Besides that, a prototype has been implemented to test the performance of the identified most suitable parameters.

Discussion and Future Work

Due to time limitations, only accelerometers were studied in this experiment. Multiple sensors can be worked on to achieve maximum accuracy. Additionally, only postulated freeze index values have been analysed based on the public datasets. Parameters such as Stride Length and Stride Duration have not been worked on. In the future, such parameters can be taken into account when computing the general gait freeze moment. The sensitivity of the algorithm should also be improved. Since the prototype has already been built, the next phase is to test it in a laboratory.

Furthermore, by connecting this system to earbuds and implementing biofeedback via audio, the system will also be able to mediate FOG. Another method involves connecting the system to an App such that notifications can be sent to the caregiver's phone to alert them to a fall. This can be developed via Android App Development with Java/Kotlin or via frameworks like Kivy or Flutter for Python and Dart Programming respectively.

Acknowledgements

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