NYIT School of Engineering and Computing Sciences

Freezing of Gait Detection in Patients with Parkinson's Disease

REU fellow: Maid Husic, mhusic@nyit.edu, School of Engineering and Computing Sciences, NYIT
Faculty Mentor: Huanying (Helen) Gu, hgu03@nyit.edu, , School of Engineering and Computing Sciences, NYIT
Student Mentor: Rajan Khullar, rkhullar@nyit.edu, , School of Engineering and Computing Sciences, NYIT

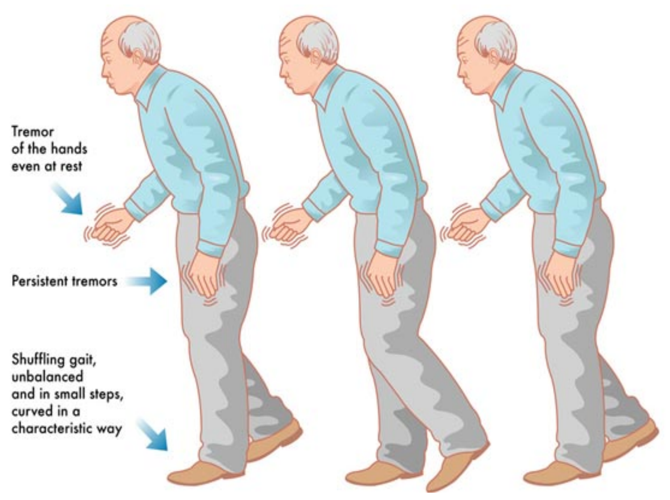
Abstract

Gait detection using Inertial Measurement Units (IMU) and machine learning is a popular topic with potential healthcare applications. We classify and compare two different datasets, one that's completely preprocessed and features were extracted and one that was only filtered with a moving average filter and no features were extracted. The Linear SVM classification algorithm achieved a True Positive Rate (TPR) of 95.55 % and was the best performing model in predicting the actions in the Human Activity Recognition (HAR) dataset. The Complex Tree classification algorithm achieved a low TPR of 46.37 % which was due to the lack of features extracted. Furthermore, the 3-8 Hz band pass filter performed better at filtering and smoothing than the moving average on our dataset.

Background

Parkinson's Disease (PD):

- Nearly one million people in the United States alone are suffering from PD, a progressive motor deficiency or movement disorder [1].
- The symptoms include tremor or shaking of the limbs, bradykinesia or reduced movement, or postural instability.



Freezing of Gait (FOG):

- The sudden inability to walk or move the lower limbs and can last anywhere from a couple seconds to 1 or 2 minutes.
- 70 percent of PD patients also develop FOG, which is one of the more severe symptoms of PD and main cause of falls.

Inertial Measurement Unit (IMU):

- Used to collect gait/motion data from subjects.
- IMU's are usually small and can be integrated into devices such as phones and smart watches so they could be worn easily by PD patients ([2], [3], [4]).

Potential Applications

- Continuous monitoring of daily activities.
- Keep track of the number of occurrences of a specific action such as a tremor or FOG episode.
- Can be applied not only to PD patients but to other patients suffering from movement disorders.
- Useful to physicians or caretakers of patients with movement disorders to help monitor or track progress.

Related Works

- 3-8 Hz band-pass filter can be used to analyze tremors while 1-3 Hz band-pass filter can be used to detect bradykinesia or slowness of movement [5].
- 20 Hz median filter was used to remove noise in accelerometer and gyroscope data from a smartphone [6].
- The lower limbs and wrist were found to be good locations to attach a IMU ([2], [3], [4]).

Methodology

Data Collection:

- The dataset contains 10 subjects.
- The x-IMU was attached securely onto 2 locations on the outer body: Foot and Lower Back
- The subjects were asked to perform three different actions 10 trials for each action separately.

Fig. 1: Internal and External view of x-IMU.

Fig. 2: The x-IMU attached to the two different locations.

HAR Dataset [6]:

- Filtered and contains 561 features that were extracted.
- Includes 30 subjects that performed six different actions.

Preprocessing/Filtering:

- Moving average filter and a 3-8 Hz band pass filter.

Classification:

- The Classification Learner app on Matlab was used to classify the different actions in the HAR Dataset and our dataset.

Results

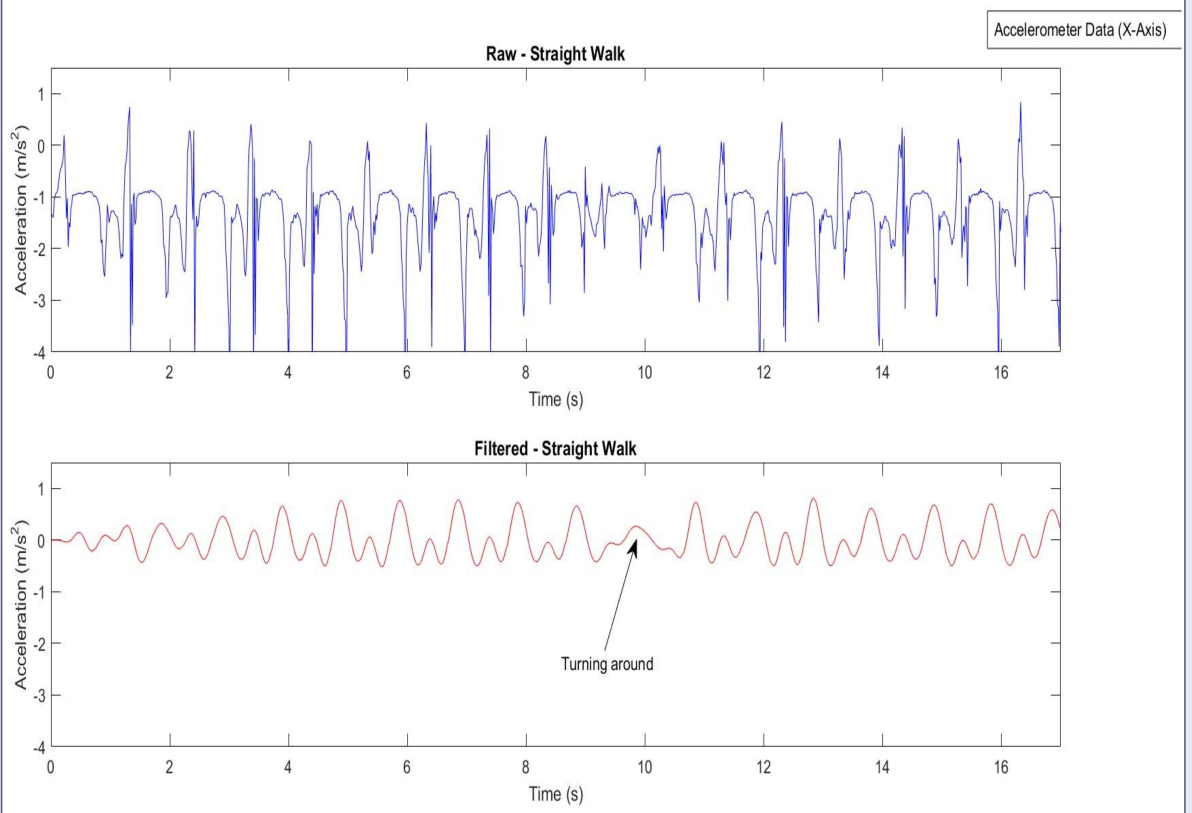


Fig. 3: First graph displays a noisy signal obtained from the foot of one subject while walking in a straight line and back. Second graph is the same signal with a 3-8 Hz band pass filter.

Results (cont.)

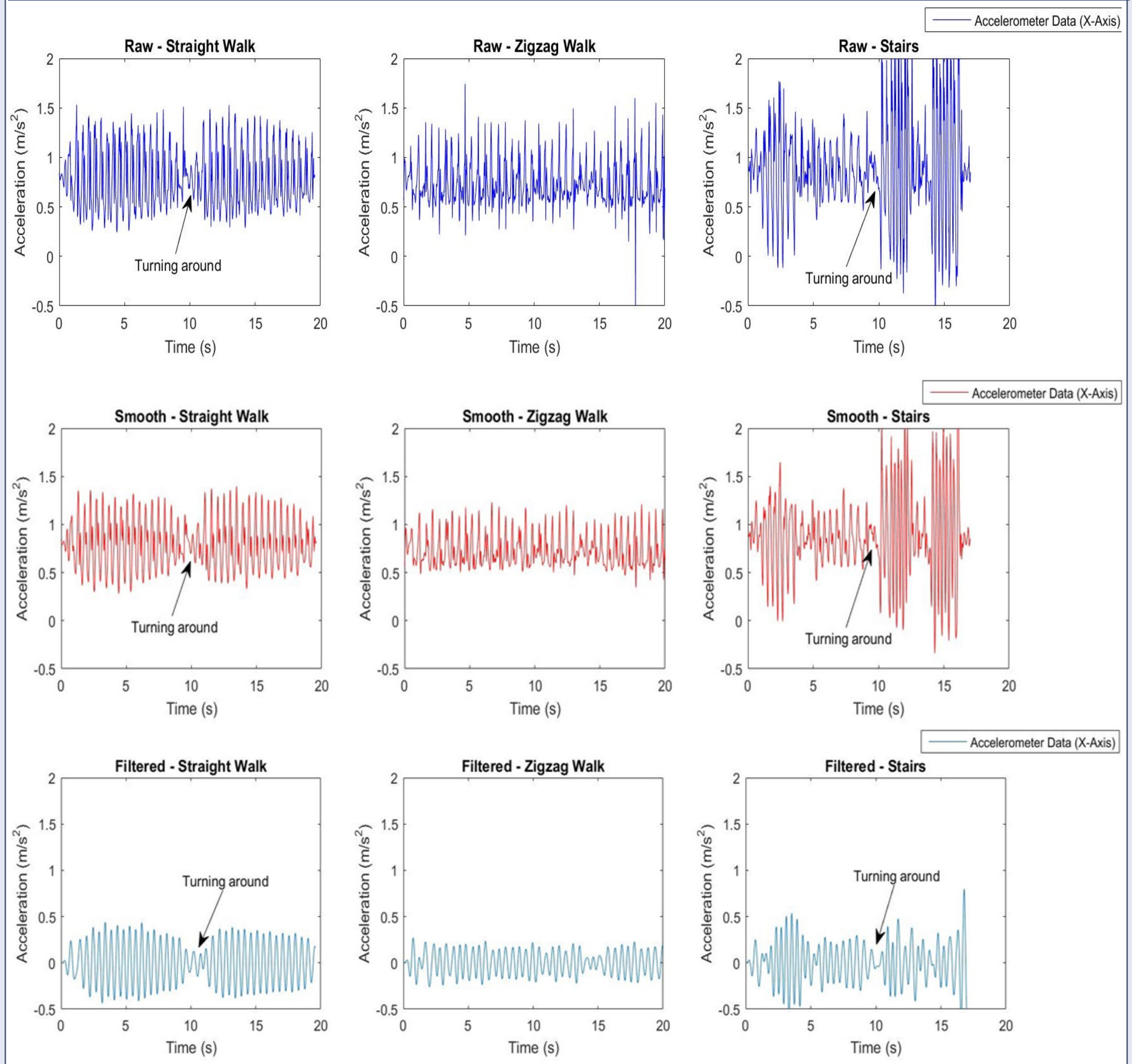


Fig. 4: Three different actions are shown, straight walk, zigzag walk, and stairs. For each of the three actions, a graph of the acceleration in the x-axis in its raw, smoothed, and filtered forms are shown to compare the three signals. Also the graphs point out where the turns happened. The signals were obtained from one subject with the x-IMU attached to the lower back.

TABLE I: OVERALL PRECISION RATES IN PREDICTING THE ACTION FOR EACH OF THE CLASSIFICATION ALGORITHMS USED FOR THE HAR DATASET

Classifier	True Positive Rate
Linear SVM	95.55 %
Quadratic SVM	95.48 %
Complex Tree	87.04 %
Simple Tree	72.21 %
Fine KNN	85.34 %
Medium KNN	89.11 %
Linear Discriminant	81.37 %
Cubic KNN	86.12 %

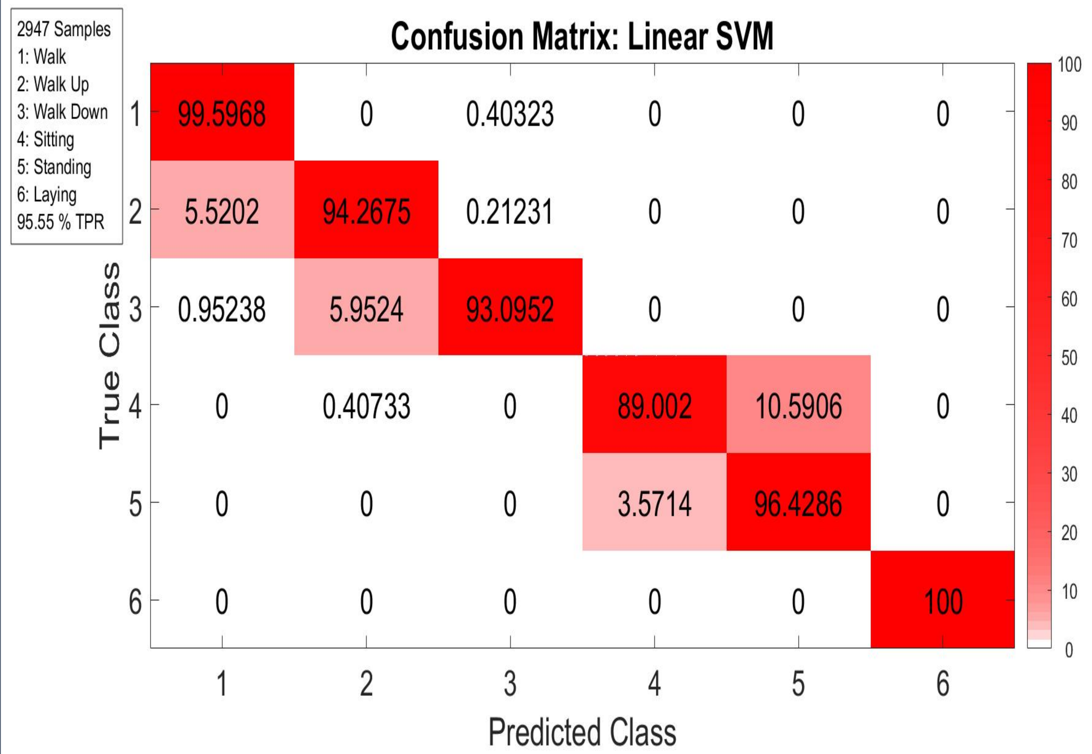


Fig. 5: Confusion Matrix of the classification results on the HAR test data using the Linear SVM classification algorithm, which was the most accurate at predicting the six different actions in the test dataset.

Results (cont.)

TABLE II: OVERALL PRECISION RATES IN PREDICTING THE ACTION FOR EACH OF THE CLASSIFICATION ALGORITHMS USED FOR OUR DATASET

Classifier	True Positive Rate
Fine KNN	44.10 %
Coarse KNN	46.04 %
Complex Tree	46.37 %

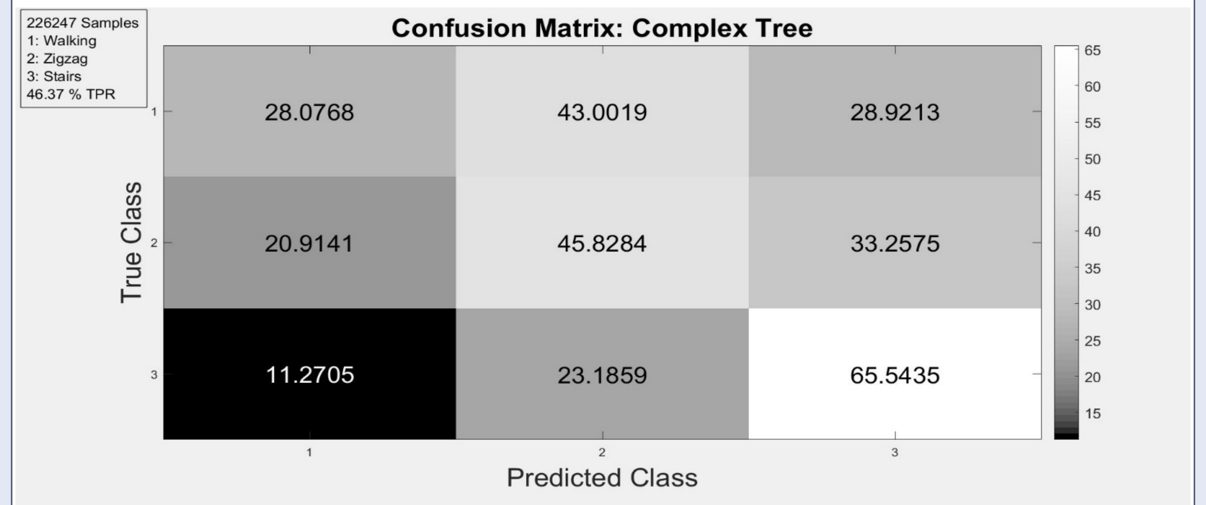


Fig. 6: Confusion Matrix of the classification results on the test data using the Complex Tree classification algorithm, which was the most accurate at predicting the three different actions in the test dataset.

Discussion

The Linear SVM classification algorithm achieved the highest TPR out of the eight classification algorithms used on the HAR dataset with a TPR of 95.55 %. The lack of extracted features was evident in the TPR's of the three classification algorithms used on our dataset. The Complex Tree achieved the highest TPR on our dataset with 46.37 %. As shown in Fig. 4, the moving average filter removed some of the noise in the original raw signal. In addition, the 3-8 Hz band pass filter applied removes noise and smooth the signals. We noticed in our dataset, the data from the foot contained more noise than the data from the lower back. However, the noise can still be filtered out as shown in Fig. 4 which shows an example of a raw signal from the foot and the filtered signal when a 3-8 Hz band pass filter was applied.

Future Work

Applying different types of filters at different frequency ranges on the raw data set will be done to find the right filter needed for our specific dataset. Features also need to be extracted to obtain higher classification accuracies.

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