Project Assignment 2 Report
Data Mining
CSE 572
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Submitted to:

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1. INTRODUCTION

This project is aimed at developing a computing system that can understand human gestures. This assignment2 of the project is aimed at extracting the most significant features from the sensor data collected by performing different gestures by different users.

2. TEAM MEMBERS.

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3. TASK 1 – PREPARING FILES FOR FEATURE EXTRACTION.

The purpose of this task is to segment the raw data into 10 separate files using the annotations provided. We are given 37 folders representing the 37 members who performed the gestures. Each folder has 20 files per gesture.

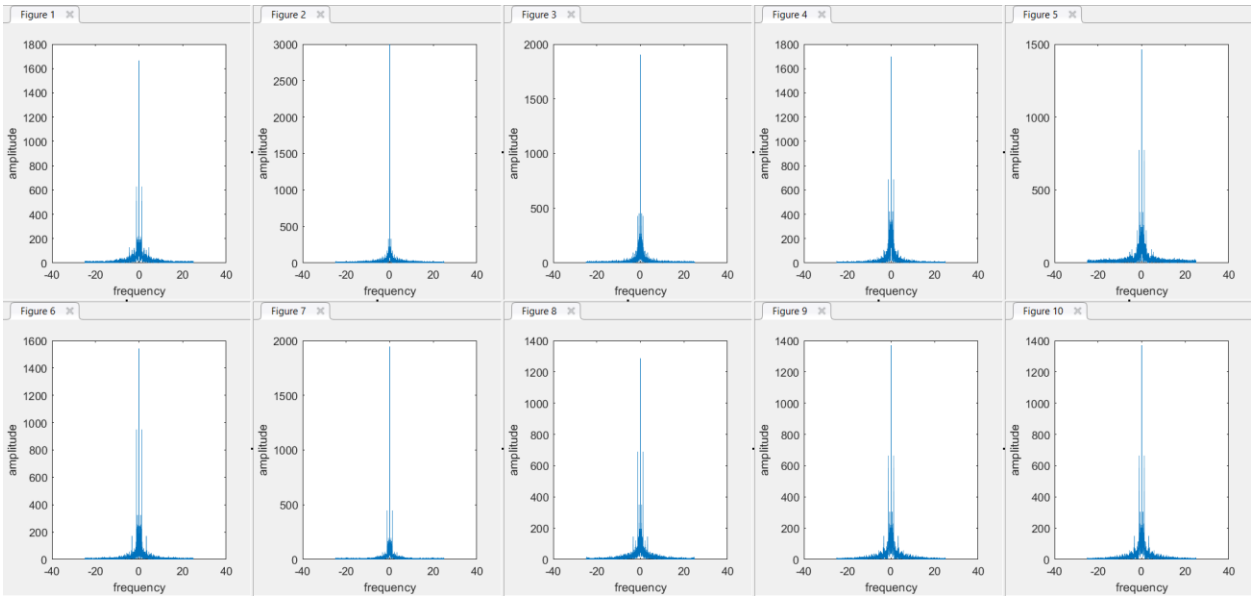
The method we have followed to segment the data into 10 files is as follows.

1. We selected the DM01 to DM10 folders that were provided to us. We took 10 folders because selecting all 37 folders will make it hard to differentiate the gestures. The high density of the data will make the differences less prominent.
2. Files of same gestures were appended vertically, and we created 10 such files corresponding to 10 different gestures.

4. TASK 2 – FEATURE EXTRACTION

The purpose of this task is to find the features that show the maximum variation among the 10 gestures. The first 34 columns were considered for feature extraction as the remaining were from Kinect. Since the task is to find the feature(Sensors) giving the maximum variation, we used feature extraction methods like FFT, DWT etc. on each of the sensors and plotted the graphs of the output. For example, we ran FFT on the ALX data of all the 10 gestures separately and plotted the output in 10 different graphs corresponding to each gesture.

An example graph of FFT on ALX data of all 10 gestures:



This process was repeated for all the 34 sensors/features. Analyzing the graphs will reveal to us the best feature which gives us the maximum variance.

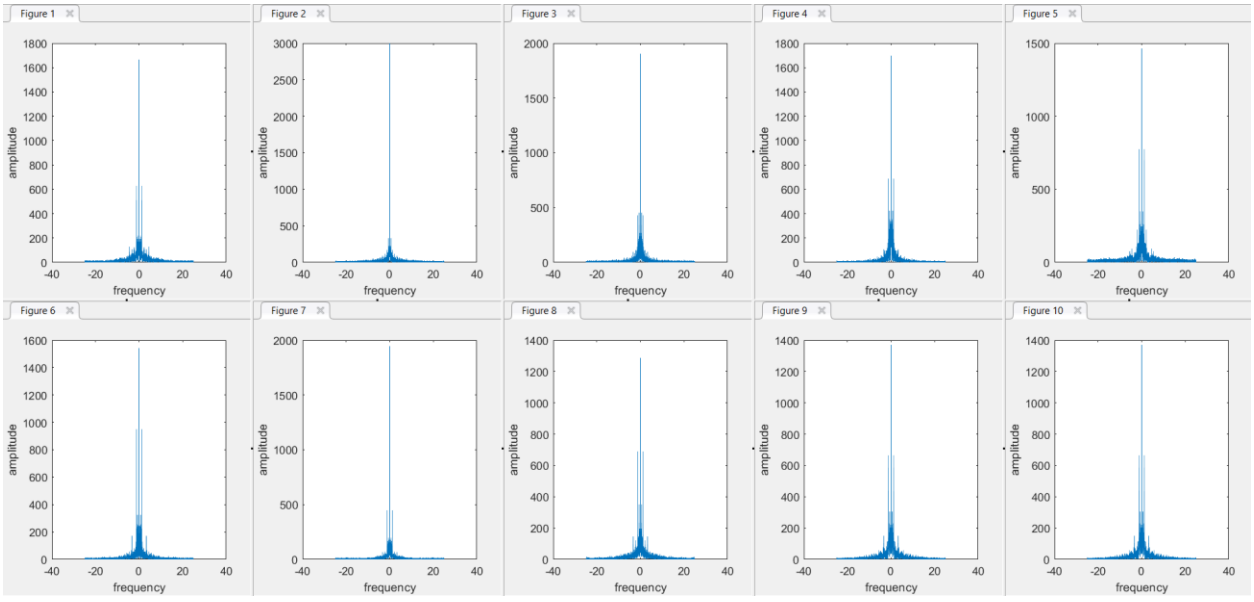
The following feature extraction methods were selected.

a. Fast Fourier Transform
b. Discrete Wavelet Transform
c. Discrete Cosine Transform
d. Mean
e. Standard Deviation

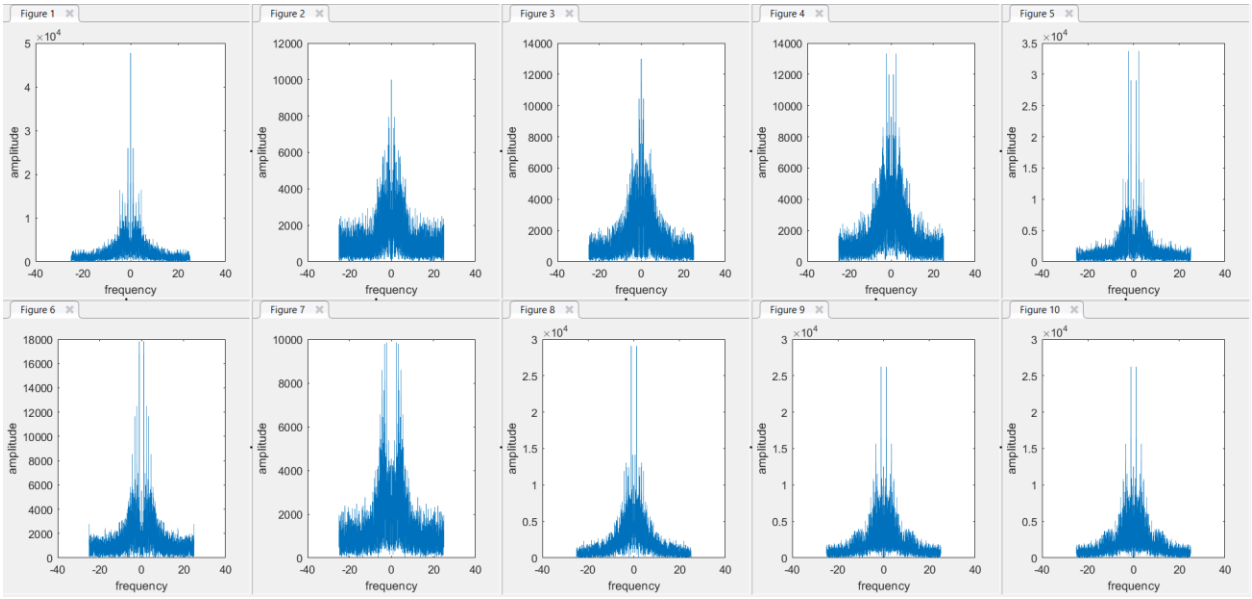
a. Fast Fourier Transform

A fast Fourier transform is an algorithm that samples a signal over a period of time (or space) and divides it into its frequency components.

A sample output, when FFT was applied to feature 1:



A sample output, when FFT was applied to feature 24:



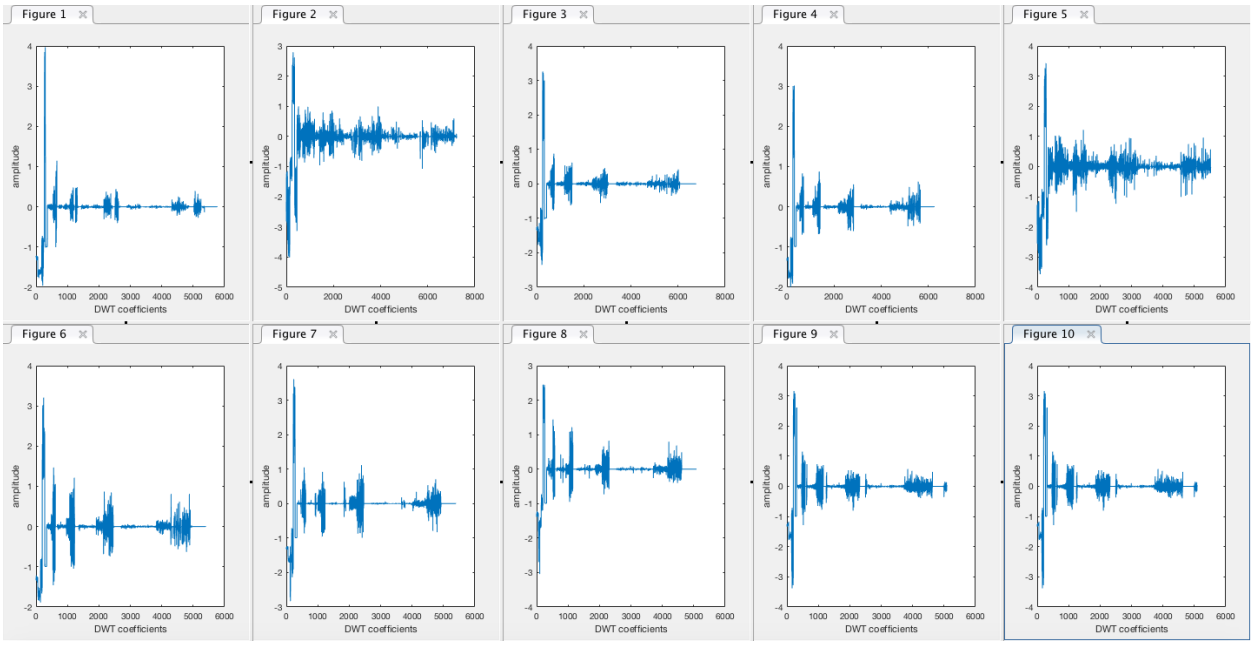
As we can see here, the variation in the data for feature 24 is considerably more compared to the variation in the data for feature 1. According to our observation for all the 10 gestures, features 23 to 28 gives the maximum variation, which is the gyroscope data. But for the remaining features, it remains considerably less. One of the possible reasons for this could be that for many of the gestures, either left hand is not used or right hand is not used, or the other sensors may not even be capturing the data, but gyroscope is used for all the gestures. So, FFT gives an intuition regarding which feature is more important.

b. Discrete Wavelet Transform

A discrete wavelet transform is any wavelet transform for which the wavelets are discretely sampled. We applied DWT at fourth level on

each of the 34 columns of each of the 10 gestures. While we found some considerable variation in the data for features 23 to 28 in case of FFT, for DWT, there was no variation.

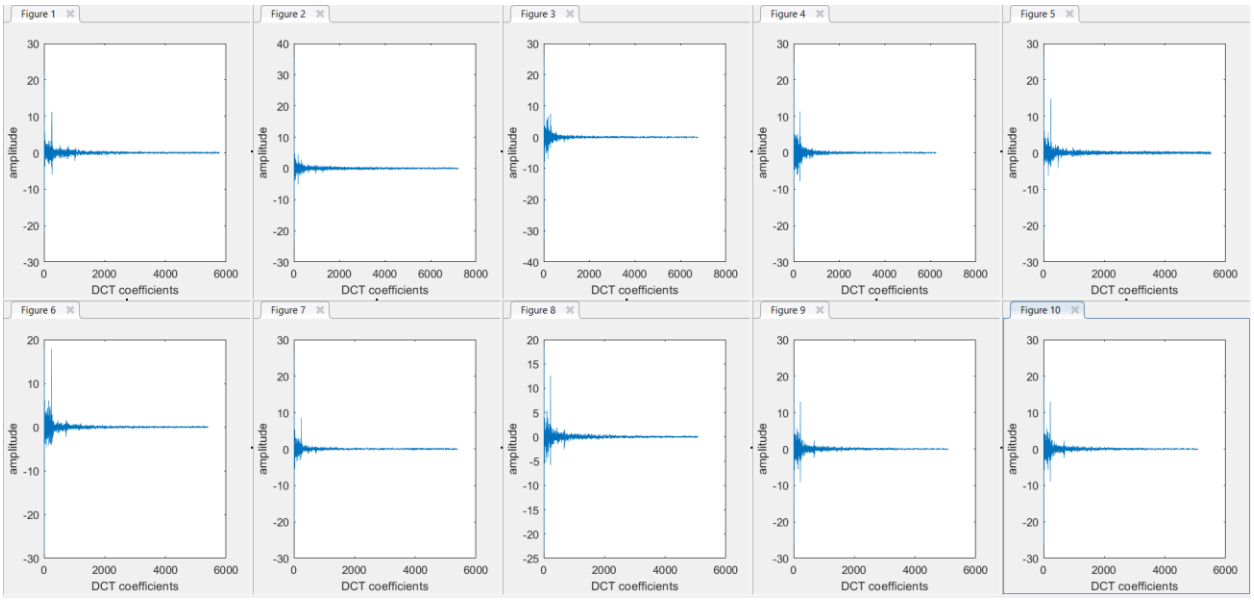
A sample plot for all of the 10 gestures for feature 1:



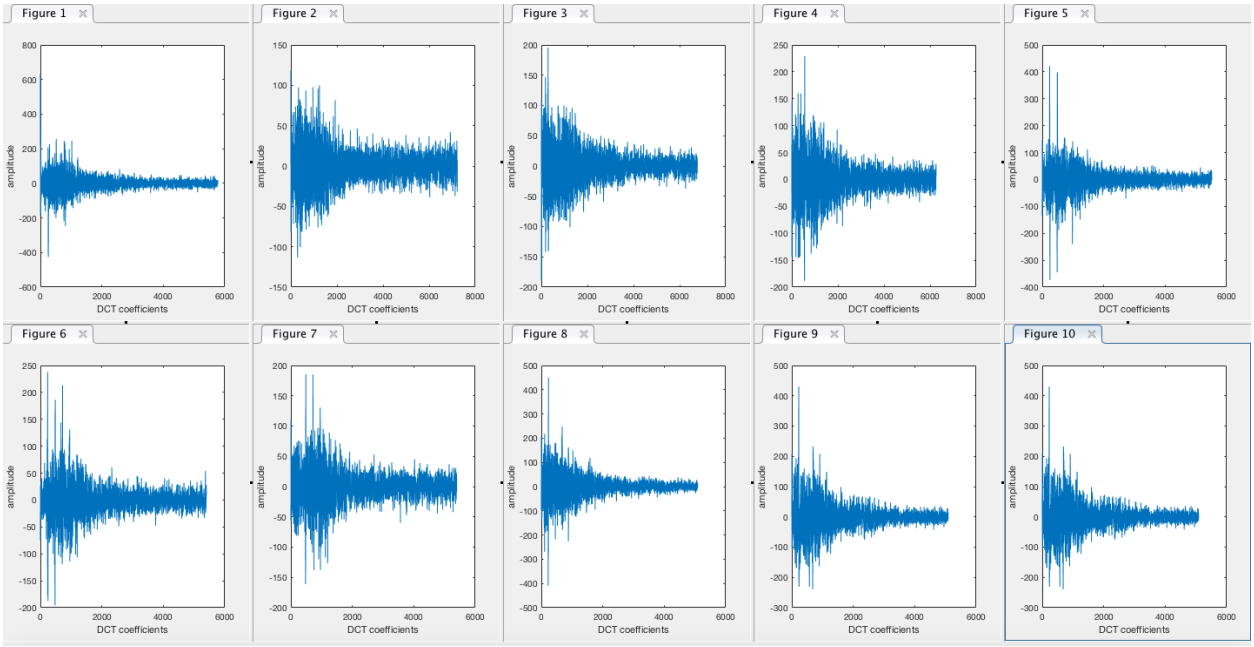
c. Discrete Cosine Transform

A discrete cosine transform expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. For DCT, the observations are same as that of FFT. We find more variance for feature 23 to 28 compared to other features.

A sample plot for feature 1:



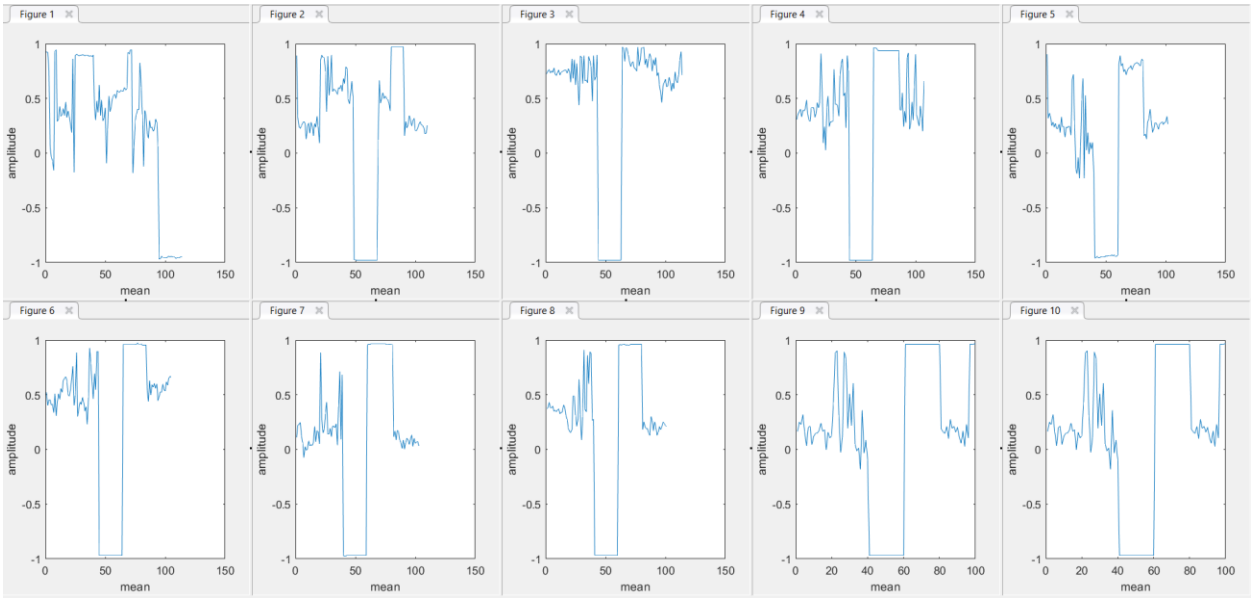
A sample plot for feature 24:



d. Mean

For every gesture, we have taken average of each feature for each file, hence we get one row of data with 34 columns for a single file. We appended all the rows corresponding to a gesture vertically and stored it in a separate file. Hence, we have 10 files for 10 gestures. We plot mean of a particular feature from each gesture file. Hence there will be 10 plots corresponding to a feature. We plotted these graphs for all 34 features. We observed that mean does not show any significant variation in the data.

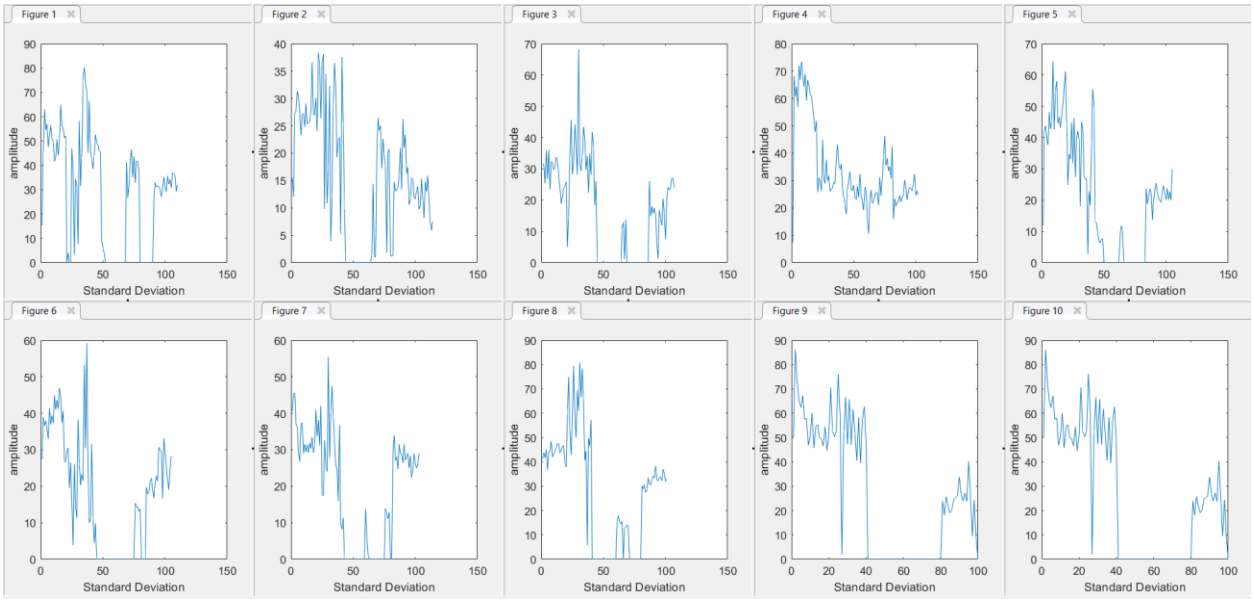
A sample plot for feature 1:



e. Standard Deviation

For Standard Deviation, the same steps are followed as that for mean.

A sample plot for feature 1:



f. Conclusion from Task 2

Gyroscope data is the most significant one and we expect it to give maximum variance.

5. TASK 3 – FEATURE SELECTION

We can apply PCA to find the features containing the maximum variance. Also, when we know the features of maximum variance, we can use dimensionality reduction to reduce the size of the dataset.

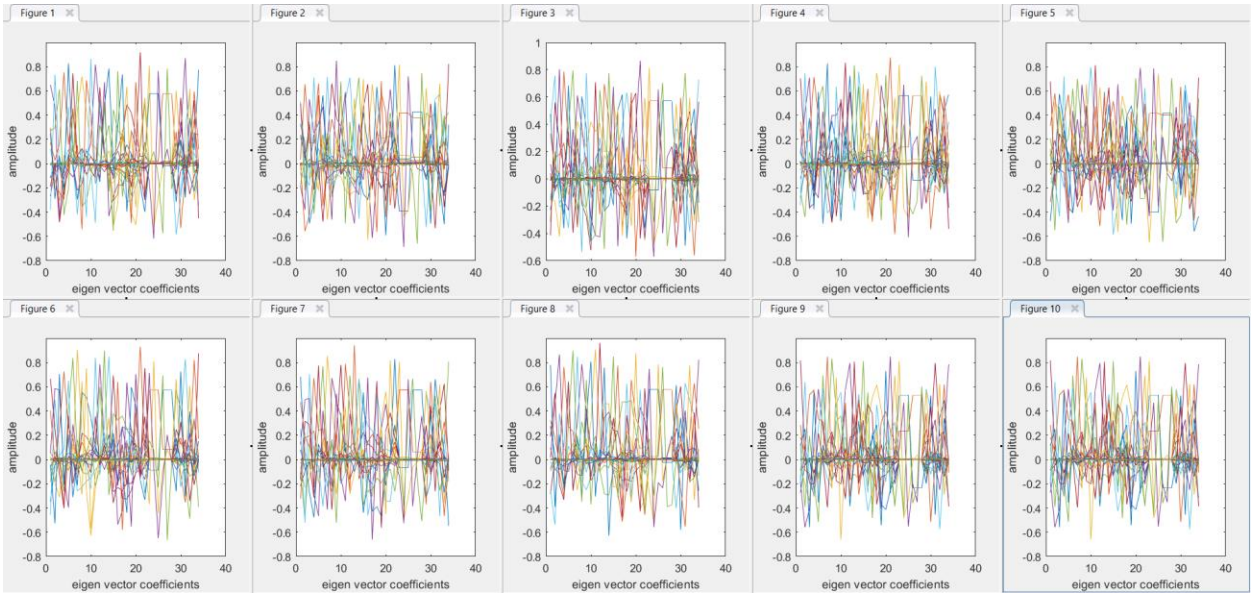
a. Arranging the feature matrix.

Files of same gestures were appended vertically, and we created 10 such files corresponding to 10 different gestures. This is same as Task1.

b. Execution of PCA

Run the mat file and select the folder containing the input data. Then select option 5, we shall get the plot of all eigen vectors. Kindly go through the readme.txt for more information to run the code.

A sample plot for PCA:



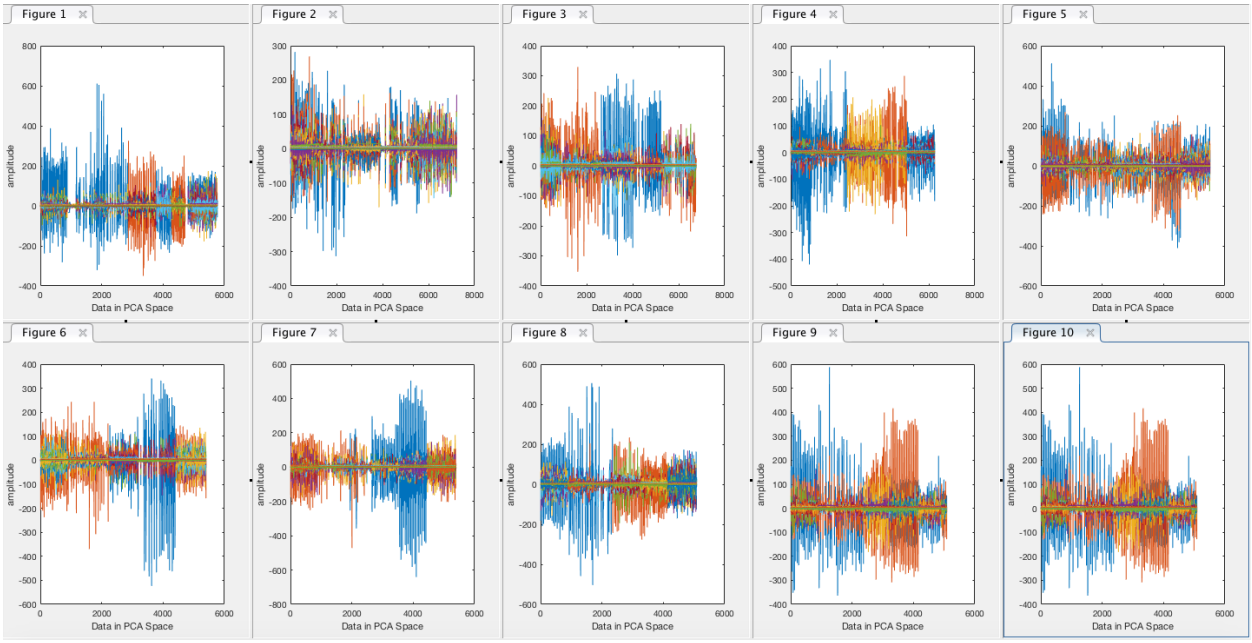
c. Make sense of the PCA Eigen vectors

We examine the ‘latent’ and ‘explained’ values from the output of PCA. From the ‘explained’ data we observe that the first two principal components capture 99% of the total variance. From the ‘latent’ data we observe the same trend that the first two eigenvalues are very large when compared to others. This is a bit different conclusion from task2 where we concluded that the features 23 to

28 shows the maximum variance. This might be because the users who did the gestures were predominantly right handed and the most variation would be from right hand gyroscope. Also, only two of the three axes (X, Y, Z) of the gyroscope captures the maximum percentage of total variance.

d. Results of PCA.

Plot for data in PCA Space:



e. Argument for effectiveness of PCA.

PCA gives more validation to the conclusion made in task2. Also, it narrows down the maximum variation to the right-hand gyroscope.

6. CONCLUSION

Right hand gyroscope gives the maximum variance.