Task 1:

For Task 1 please refer to the code of MainAlgo and MainAlgo2.

MainAlgo Collects the data for Eating Action

MainAlgo 2 Collects the data for Non Eating Action

Task 2:

We have taken following features:

1. Sum of IMU and EMG for first 30 frames. (18 Features)
2. Max of IMU and EMG (18 Features)
3. Dominant frequency in Fast Fourier Transform of IMU and EMG (18 Features)
4. Variance of IMU and EMG (18 Features)
5. RMS of IMU and EMG (18 Features)

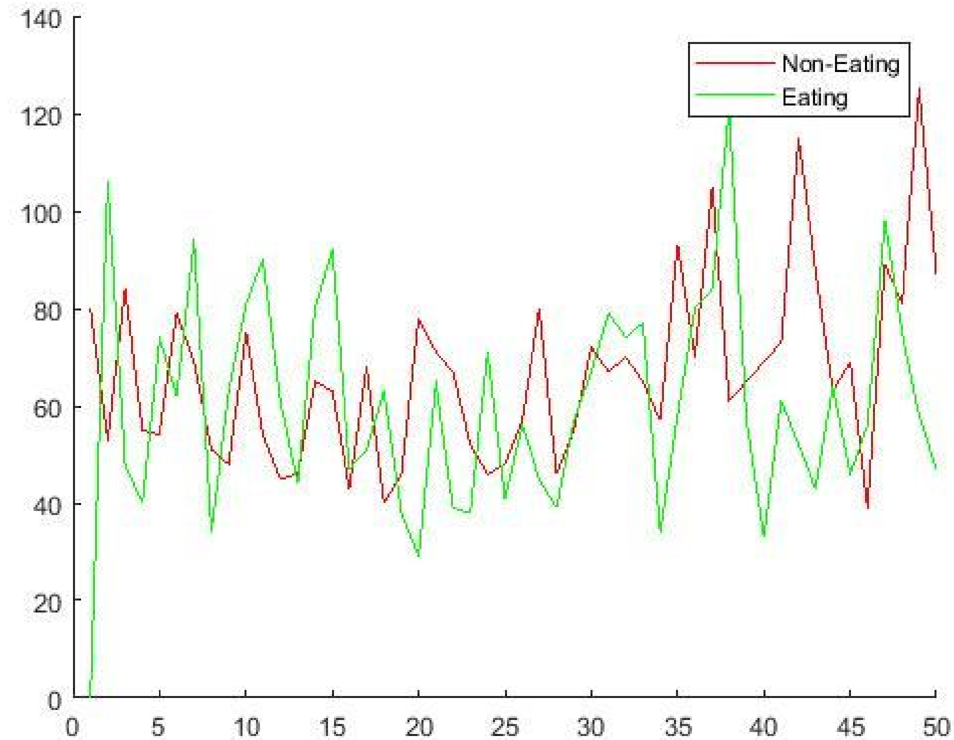
1. **Sum of IMU and EMG for first 30 frames. (18 Features)**
    a. **Method:** We have taken summation of first 30 frames for eating and non-eating actions for all EMG and IMU values.
    b. **Intuition:** When we, initially, pick from fork and spoon, then there is much more muscle tension than any other time while eating; as it takes wrist moment and force is applied. Hence picking motion will have higher absolute inertia and angular velocity for wrist which can be detected from first 30 frames.
    c. **Code Snippet** :

```
eatingMatrix(row+1,column+72)=sum(arrayfun(@(x)abs(x),str(1:min(numel(str),
30))));
```

There can be a case where number of frames are less than 30 for an eating and non-eating action. So for that we have used all the frames.

str is one eating or not eating action time series data.

    d. **Image:** Plot for **EMG 1**



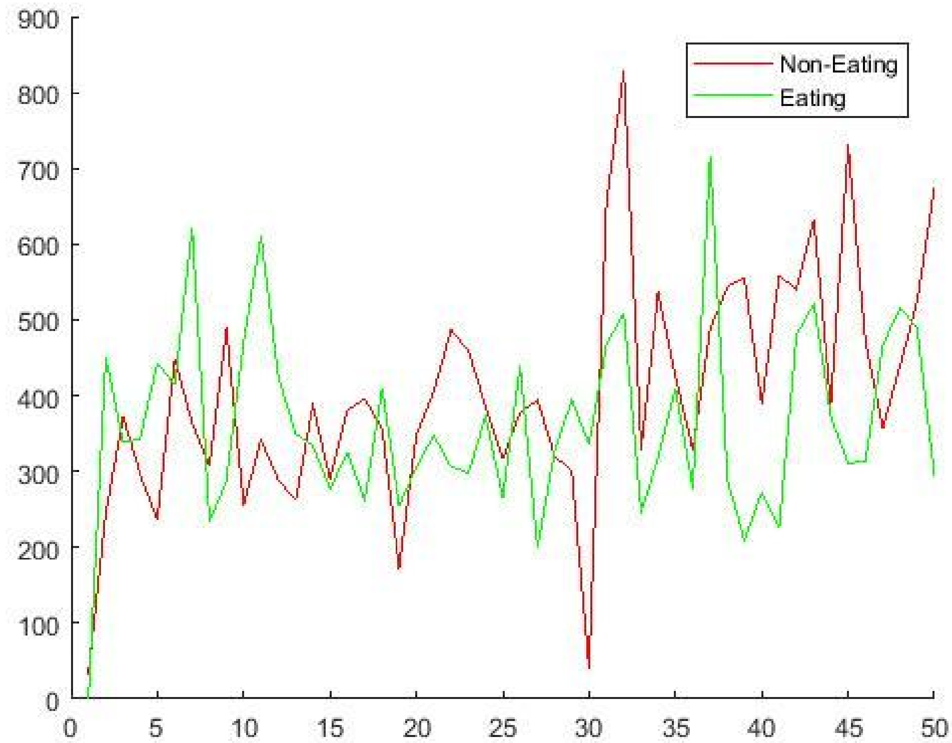
e. Yes, It holds true, as you can see in the graph, the sum of 30 frames of eating actions is higher than the sum of 30 frames of non-eating actions.

2. Max of IMU and EMG. (18 Features)

a. **Method:** In an eating and non-eating action frames, we have taken Max of all EMG and IMU values.
b. **Intuition**: As there are different muscle motion involved during eating and non-eating actions. There must be a significant difference between the highest values that the sensors show.
c. **Code Snippet :** eatingMatrix(row+1,column) = max(arrayfun(@(x) abs(x),str));

   We take the absolute maxima to see where we see the highest peaks in the two actions

d. **Image:** IMU x orientation



e. Yes, It holds true, as you can see in the graph, eating actions are mostly above than non-eating actions. Hence it shows significant muscle moment is evolved while eating.

3. Dominant frequency in Fast Fourier Transform of IMU and EMG (18 Features)

a. **Method**: We have taken Normalized Fourier Transformation of IMU and EMG values for eating and non-eating actions. And we have extracted the dominant frequency of the FFT.
b. **Intuition**: Similar action must have same energy plots. Hence they may have some dominant frequency when converted from time domain to frequency domain.

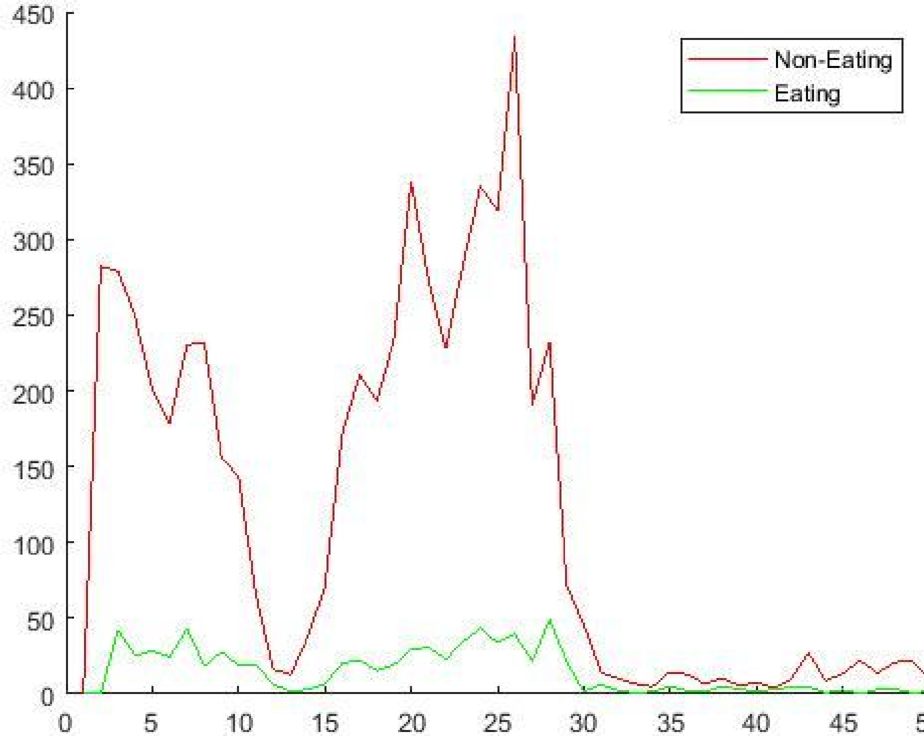
c. **Code Snippet**

```
fftMax = abs(max(fft(str,1024)));

eatingMatrix(row+1,column+18) = fftMax;
```

max gives maximum complex number and abs gives the magnitude

d. **Image** : IMU X orient sensor



e. Yes, It holds true, as you can see in the graph, non-eating actions are mostly above than eating actions. Hence Non-eating actions have higher frequency than eating actions which tells actions excluding eating can be any motion which may result in higher energy.

4. Variance of IMU and EMG (18 Features)

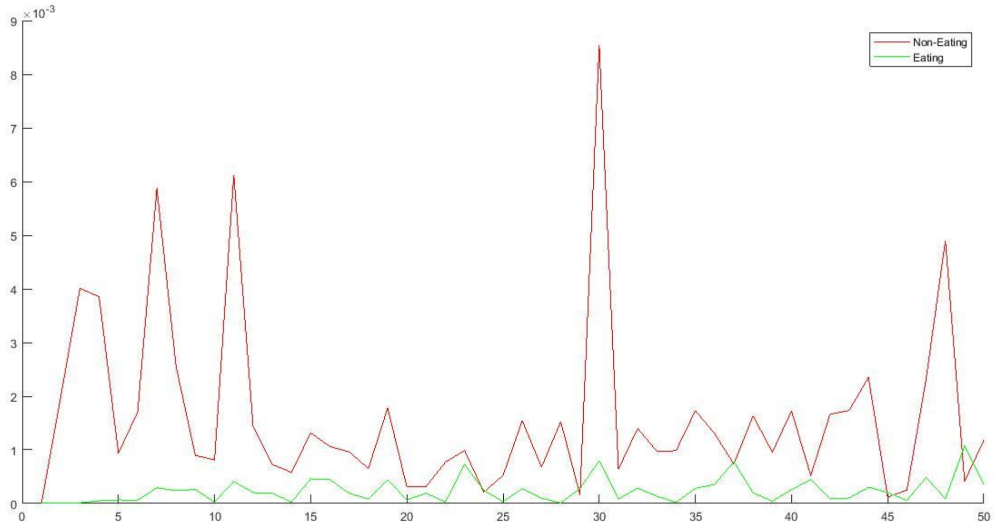
a. **Method**: We have taken the variance of IMU and EMG values for eating and non-eating actions.

b. **Intuition**: Eating action has one definite path hence their variance must be different from than any random action (non-eating).

c. **Code Snippet**:

```
eatingMatrix(row+1,column+36) = var(str);
```

d. **Image**: IMU orient x



e. Yes, It holds true, as you can see in the graph, the variance of eating actions are mostly below than non-eating actions. Hence we can say eating actions have low variance than non-eating. As non-eating are random moment must have higher variance.

5. RMS of IMU and EMG (18 Features)

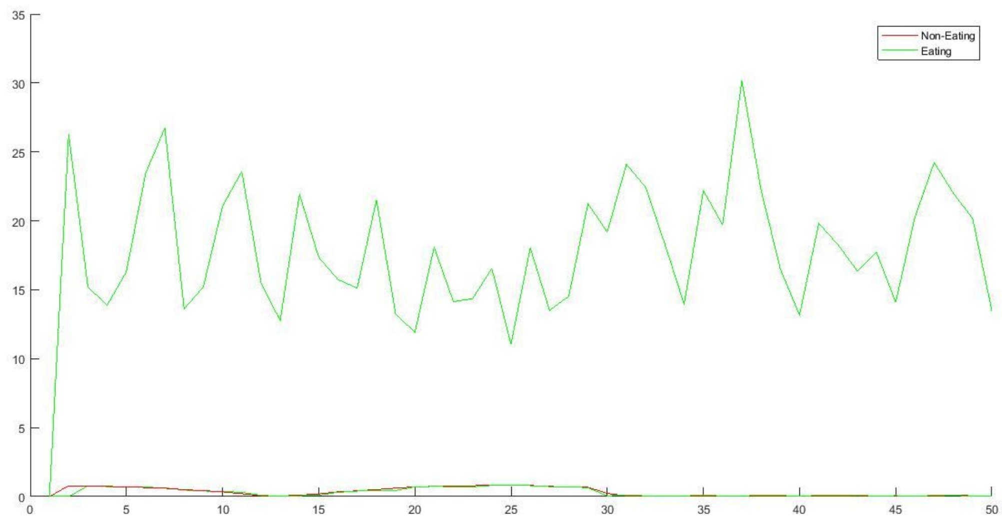
a. **Method:** We have taken RMS of IMU and EMG values for eating and non-eating actions

b. **Intuition**: As there are different muscle motion involved in during eating and after eating actions. There must be a significant difference between their generalized mean (RMS). RMS also tells the total power of the signal.

c. **Code Snippet**

```
eatingMatrix(row+1,column+54) = rms(str);
```

d. **Image**: EMU 1



e. Yes, It holds true, as you can see in the graph, RMS of eating actions are mostly above than non-eating actions. Hence we can say eating actions have high RMS than not-eating as eating action involve significant moment and energy.

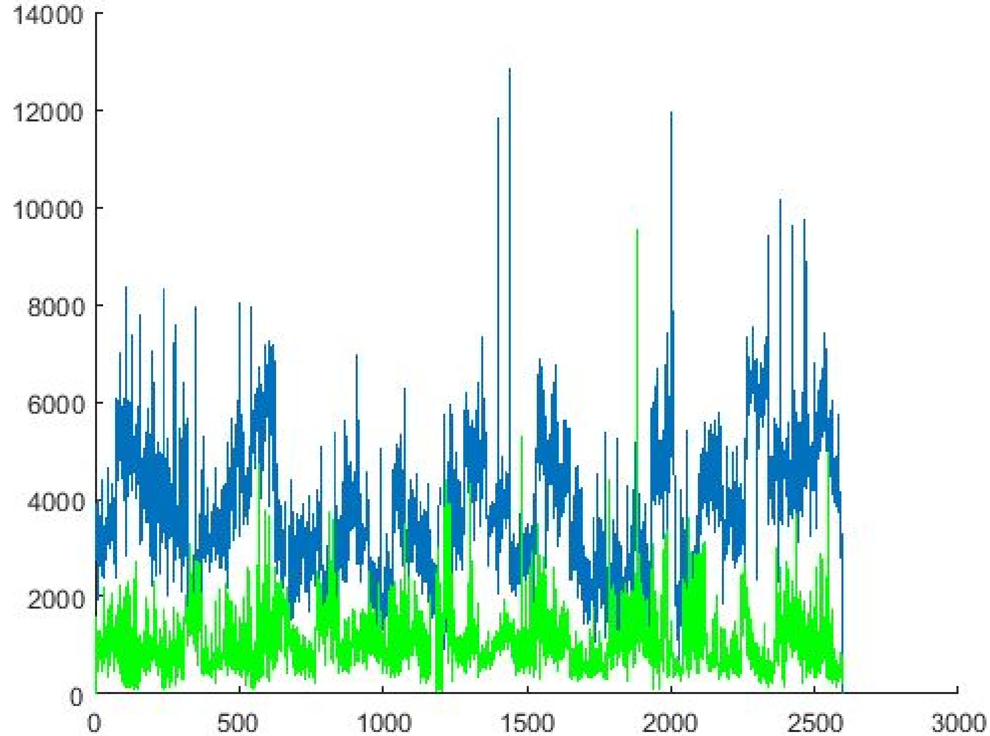
Task 3:

a. We have extracted the feature matrix and is kept in files NonEatingFeatures.csv and EatingFeatures.csv. The logic to extract this is kept in file FeatureReader.m file.
b. Out of 90 eigenvectors we have only chosen 3 and the plots for them are shown below. They can surely help in making clear distinction between the two actions

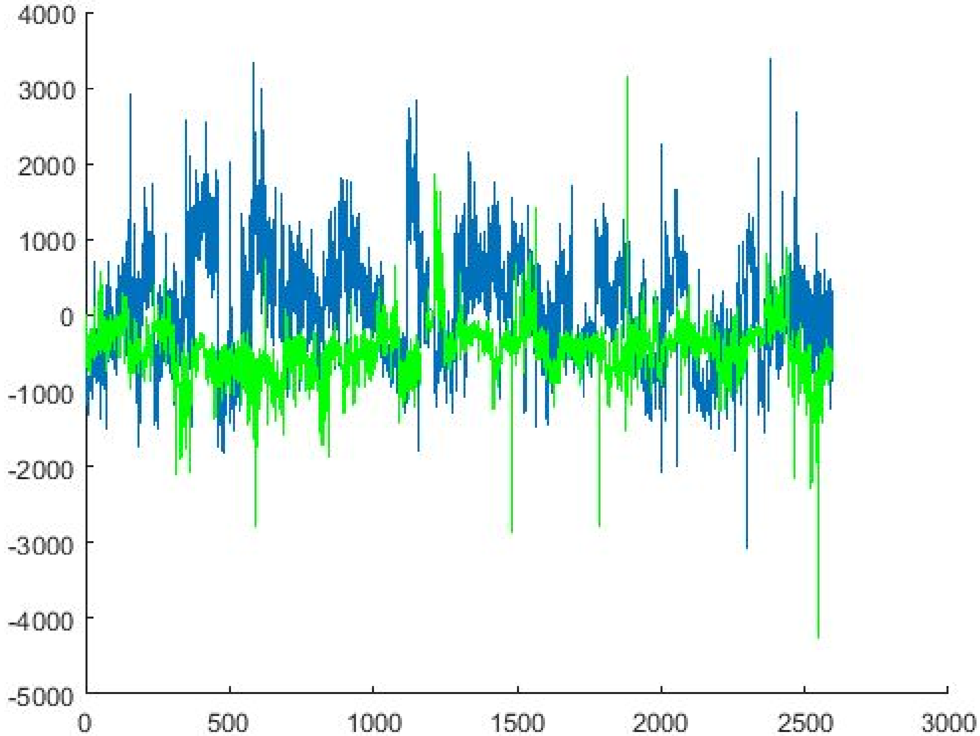
   Blue is for non eating

   Green is for eating

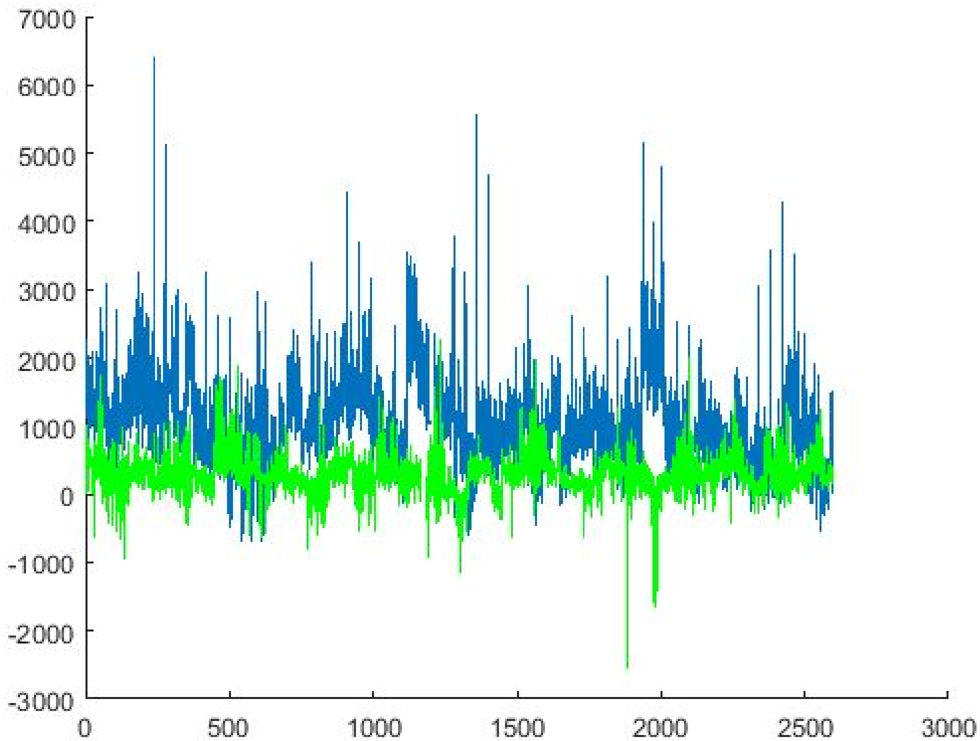
   First


14000
12000
10000
8000
6000
4000
2000
0
0
500
1000
1500
2000
2500
3000

Second


4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
-5000
0
500
1000
1500
2000
2500
3000

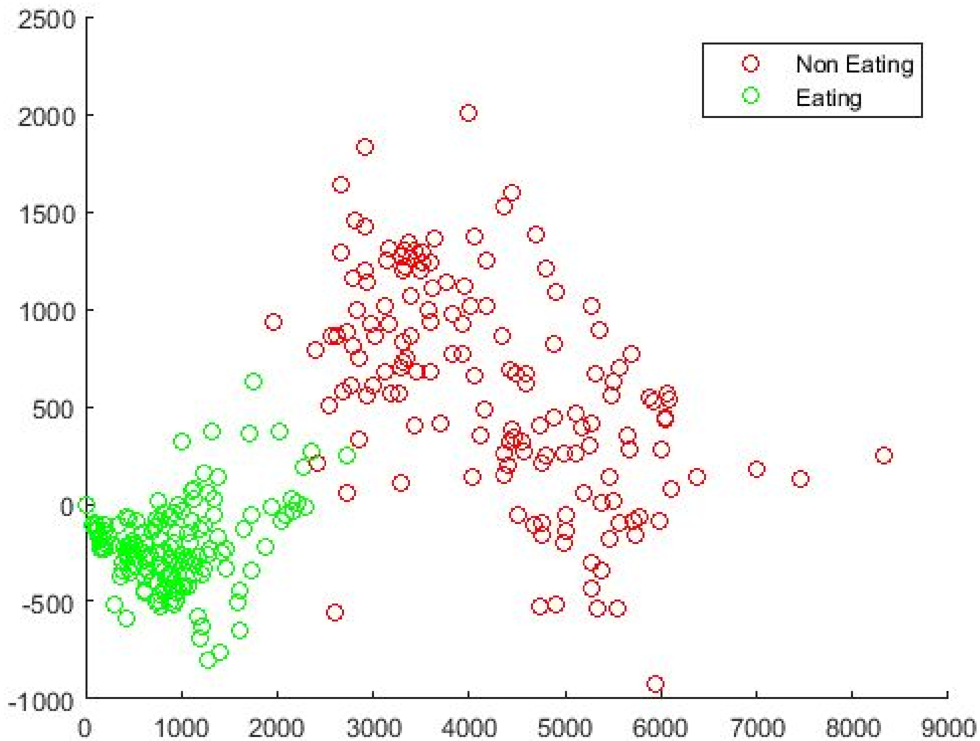
Third



c. We have chosen features that can help in determining randomization in the movements so we can expect something in which randomization would be high. This turns out right in eigenvector also. Non-eatings have higher values. That shows higher randomization movements in non-eating.
d. The below image is a scatter plot between first and second dimensions of the resultant matrix and you can clearly create a classifier in the two actions.

   x is dimension 1 for eating and non eating

   y is dimension 2 for eating and non eating



There are little outliers but the result is still showing clear distinction.

e. Yes. PCA did help in the problem as we started with a huge set of features and the result is parsed into 3 dimensions only. Plus we are able to see clear classifier development after this. So PCA, has chosen the features that affect the most in distinction.