KIT-AR

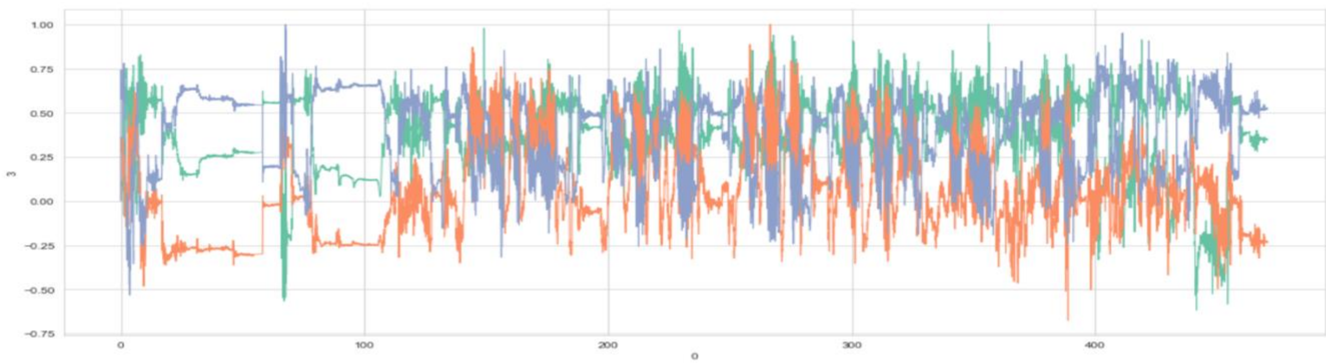
Use Case (1) - Activity Recognition and Analysis:

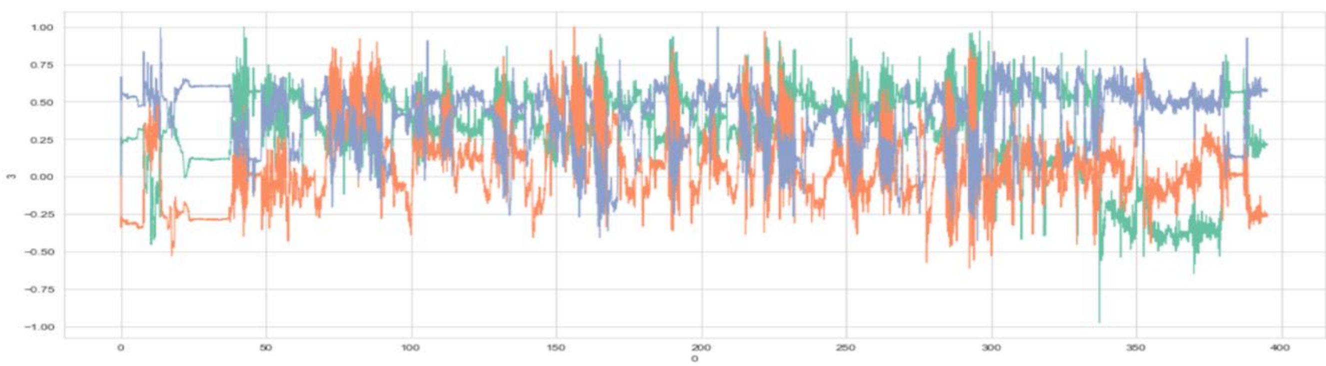
Task 1:

From my analysis, I can say that there are 13 unique participants. Each participant has taken an average of 2 trials.
The exact participant and trial are listed below

- Participant 1 – Trials 1,2,3
- Participant 2 – Trials 4,5,6,7,8
- Participant 3 – Trials 9,10,11
- Participant 4 – Trials 12,13
- Participant 5 – Trials 14,15,16
- Participant 6 – Trials 17
- Participant 7 – Trials 18,19
- Participant 8 – Trials 20,21,22
- Participant 9 – Trials 23,24,25
- Participant 10 – Trials 26
- Participant 11 – Trials 27,28
- Participant 12 – Trials 29,30
- Participant 13– Trials 31,32

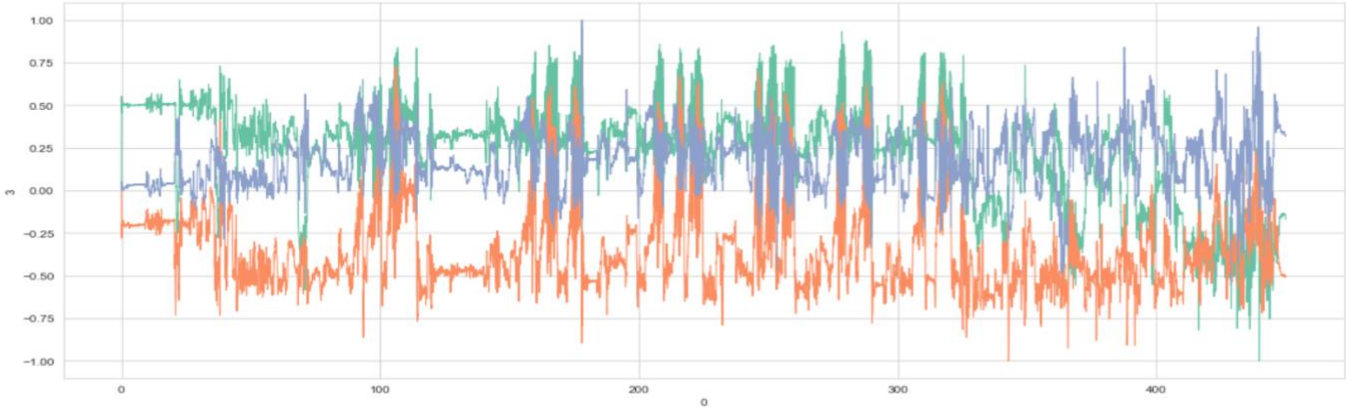
I plotted the accelerometer_fft.csv, gyro_fft.csv and orientationEuler_fft.csv as seaborn lineplots.
The reasoning for this is because the same participant would have similar hand movements/gestures and would take the same amount of time in completing the task.
So, by plotting and comparing the data as graphs we can get an idea of the number of participants and the trials that they undertook
An e.g. of the graphs has been shown below(The graph is a time series of the accelerometer data)





From the graphs above represent trials 21 and 22 from the accelerometer data. We can see that they X,Y,Z

Values are very similar to each other. From this we can draw an initial pairing.
We then compare the mean and median values for the X,Y,Z data and check the standard deviation to further solidify our initial pairing.
Another example graph is shown below



Task 2:

After reading the data pre-processing documentation and a few research papers I can say that the steps taken by the students were necessary and desirable.
Detection of EMG signals is useful and improve the essential methodologies in many applications. Such applications are becoming increasingly in demand, such as biomedical engineering), robotics arm and automation control systems

The measurements and precise representations of the EMG signals depend on the characteristics of the electrodes and their relationship with the skin of the forearm or shoulder and are affected by the amplifier design and the transition of the EMG signals from analog to digital format (A raw EMG signal has the maximum voltage of (0–2) mV, and a range of frequency approximately between (0–1000) Hz. Nonetheless, the vital frequency that contains useful information lies between (20–500) Hz). The EMG signals can be acquired by positioning surface electrodes on the arm or the shoulder.

The data acquisition represents the first stage in detecting EMG signals and recording them, processing them by removing noise and unwanted parts of the signal. The pattern recognition represents the backbone of EMG signals analysis and processing. The pattern recognition system is mostly used to obtain gestures of the muscle activity. It consists of three main stages: segmentation, feature extraction selection, and classification

The feature extraction stage is when suitable features are selected to extract information from each window of the EMG signals. The characteristics of EMG signals can be categorized by Time Domain (TD), Frequency Domain (FD), and Time-Frequency domain (TF). TD features extraction is easy to implement and does not require a high computational cost. TD features, such as WL, MAV, AR, SSC, ZC, and RMS are extracted from the data that rarely related to the amplitude and frequency of the raw EMG signals. In contrast, FD features are extracted widely using Power Spectral Density (PSD). The FD features include median frequency, mean power, peak frequency, maximum amplitude and variance of the central frequency. The TF features which depend on TF domain like Wavelet Transform (WT) and Fourier Transform (FFT) require higher computational cost and are more complex compared to TD features but are more accurate.

Task 3:

Human activity recognition, or HAR, is a challenging time series classification task.

It involves predicting the movement of a person based on sensor data and traditionally involves deep domain expertise and methods from signal processing to correctly engineer features from the raw data in order to fit a machine learning model.

Recently, deep learning methods such as convolutional neural networks and recurrent neural networks have shown capable and even achieve state-of-the-art results by automatically learning features from the raw sensor data.

There are two main approaches to neural networks that are appropriate for time series classification and that have been demonstrated to perform well on activity recognition using sensor data from commodity smart phones and fitness tracking devices.

They are Convolutional Neural Network Models and Recurrent Neural Network Models.

Convolutional Neural Network models, or CNNs for short, are a type of deep neural network that were developed for use with image data, e.g. such as handwriting recognition.

They have proven very effective on challenging computer vision problems when trained at scale for tasks such as identifying and localizing objects in images and automatically describing the content of images.

They are models that are comprised of two main types of elements: convolutional layers and pooling layers. Convolutional layers read an input, such as a 2D image or a 1D signal, using a kernel that reads in small segments at a time and steps across the entire input field. Each read results in an the input that is projected onto a filter map and represents an internal interpretation of the input.

Pooling layers take the feature map projections and distil them to the most essential elements, such as using a signal averaging or signal maximizing process.

The convolution and pooling layers can be repeated at depth, providing multiple layers of abstraction of the input signals. The output of these networks is often one or more fully connected layers that interpret what has been read and map this internal representation to a class value.