University of New Brunswick

Time Series Analysis
(EE 6563)

Assignment #3

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1. **Explore the dataset and find additional information from the resources listed below.**

   (a) *Activity Recognition from a Single Chest-Mounted Accelerometer:* This dataset was collected from a wearable accelerometer mounted on the chest from 15 participants performing 7 activities. More details about the dataset can be found in this source.

   (b) The dataset can be downloaded from: (This link).

2. **Separate the various activities and visualize the data for the different classes. Next, explore using HMM state modeling for each activity ('Standing Up, Walking and Going up-down stairs') by breaking the activity into different states (for example 3 states, one for 'Standing Up' , a second for 'Walking' and a third for 'Going up-down stairs'). Analyze the results of fitting the model for different HMM states by visual inspection (since no ground truths are available for where a sub-activity starts and ends). Generate these qualitative results for state decoding when training on users 1-10, and testing on users 11-15.**

   The dataset were collected data from an accelerator sensor carried by different users. Data were separated into various CSV files based on participants. Each row in these files contains the information of sequential number (time), x, y, z acceleration, and activity label. The activity label took a number between 1 and 7 according to the user activity. Table 1 shows these activities along with the codes.

   Table 1: The dataset activities and their labels.

Label value	Activity
1	Working at Computer
2	Standing Up, Walking and Going Up-Down Stairs
3	Standing
4	Walking
5	Going Up-Down Stairs
6	Walking and Talking with Someone
7	Talking while Standing

   For the rest of this assignment, we used a Pandas DataFrame for separating and storing the data. Figure 1 shows signals of x, y, z, and label for the last participant.

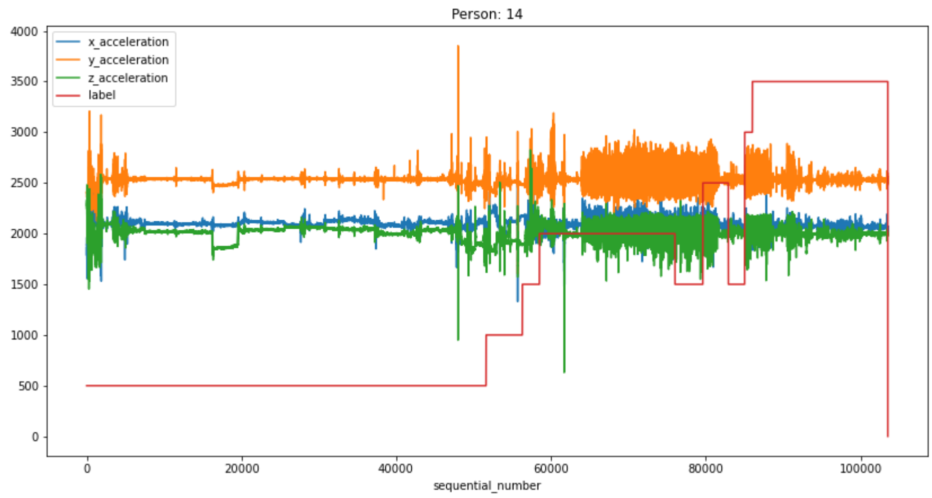

Figure 1: The signals of x, y, z, and label for the last participant. For better understanding, the code of each activity multiply by 500.

Figures 2 and 3 show the raw signal that were filtered based on different users and activities. Based on these two figures, walking or climbing the stairs caused the frequency, variance, and mean of signals to change over time.

Figure 2: The signals of x, y, and z for the first participant and 'Standing Up, Walking and Going up-down stairs' activity.

Figure 3: The signals of x, y, and z for the second participant and 'Going up-down stairs' activity.

The next part of this question is a decoding problem. We had an activity that was included different states (walking, standing, and going up-down stairs). Our goal is that to find the hidden states for this activity based on the observation signals.

Before going into model detail, let first talk about the pre-processing step. In this step, first, we separated and resized all signals of 'Standing Up, Walking and Going up-down stairs' from the dataset. Then, this data were stored in an array with the shape of $15 \times 840000 \times 3$. The dimensions of this array show the number of users, samples, and observation signals, respectively.

For the training part, we separated the array by different users. The first ten users were used as a training set, and the rest were considered for testing the model. Figures 4 to 18 demonstrate the results of HMM on all users data. Besides, normalized data were used for finding the effect of the data scale (see figures 19 to 33). We used the Min-Max algorithm for normalizing data.

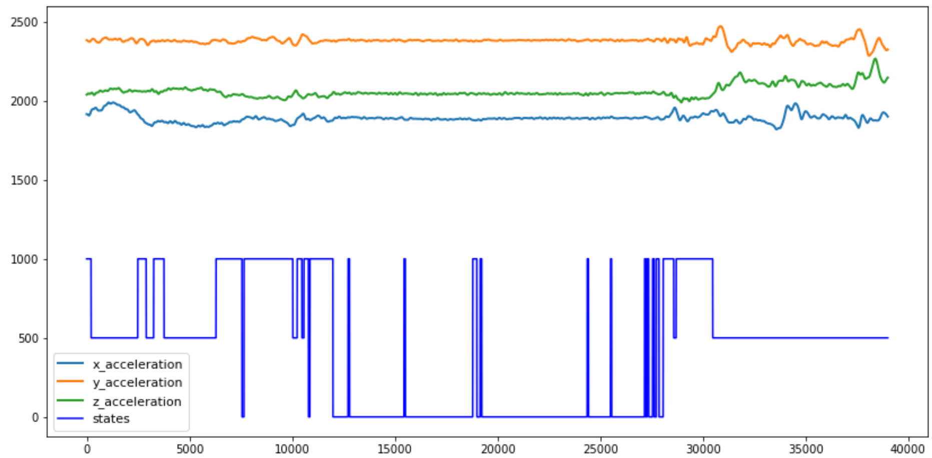

Figure 4: The signals of x, y, and z for participant 1 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

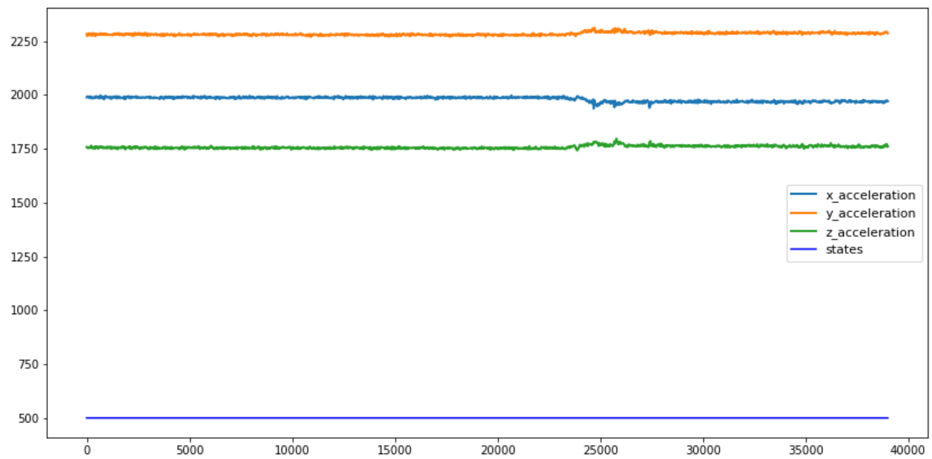

Figure 5: The signals of x, y, and z for participant 2 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

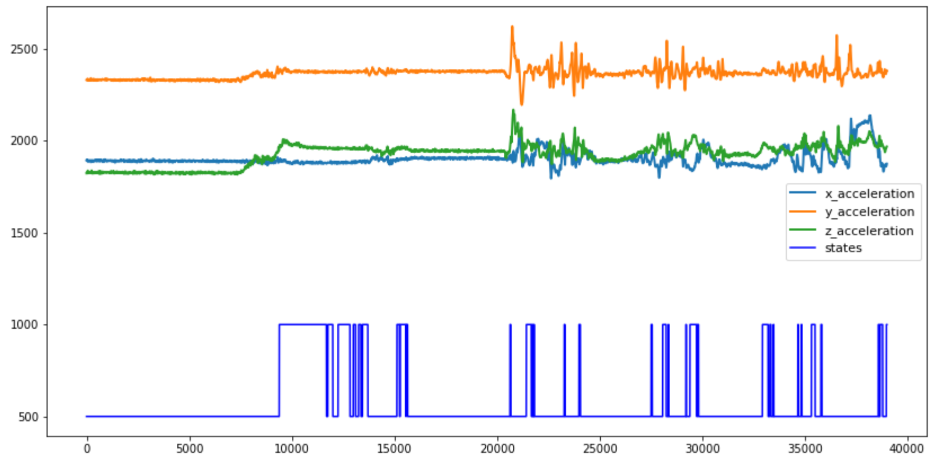

Figure 6: The signals of x, y, and z for participant 3 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

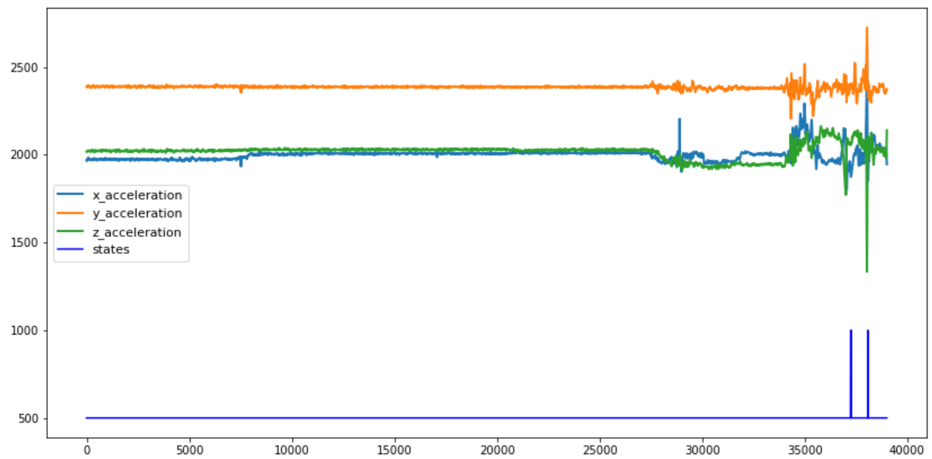

Figure 7: The signals of x, y, and z for participant 4 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

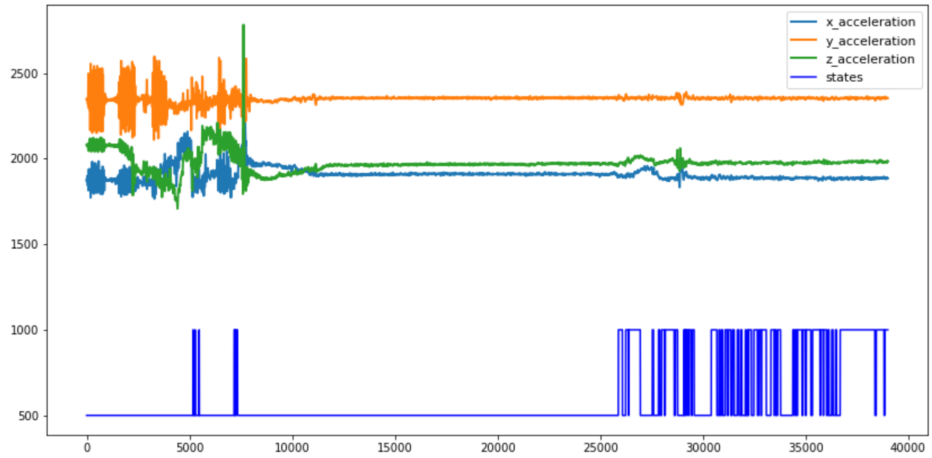

Figure 8: The signals of x, y, and z for participant 5 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

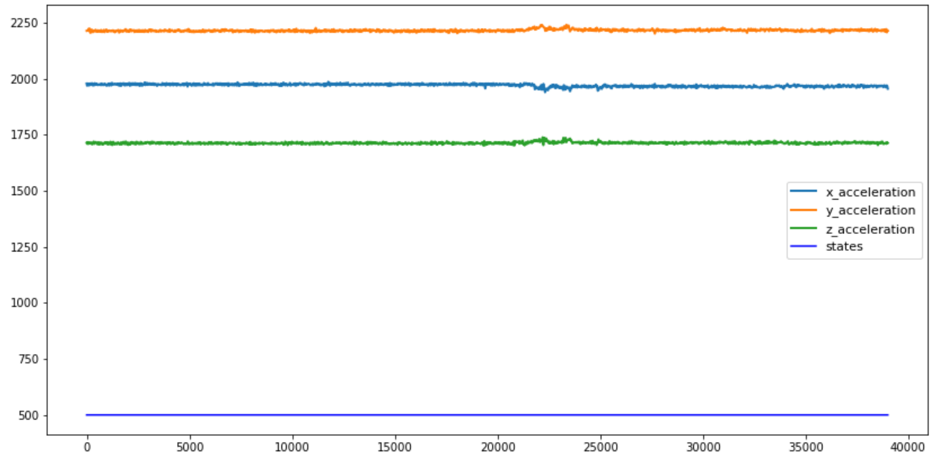

Figure 9: The signals of x, y, and z for participant 6 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

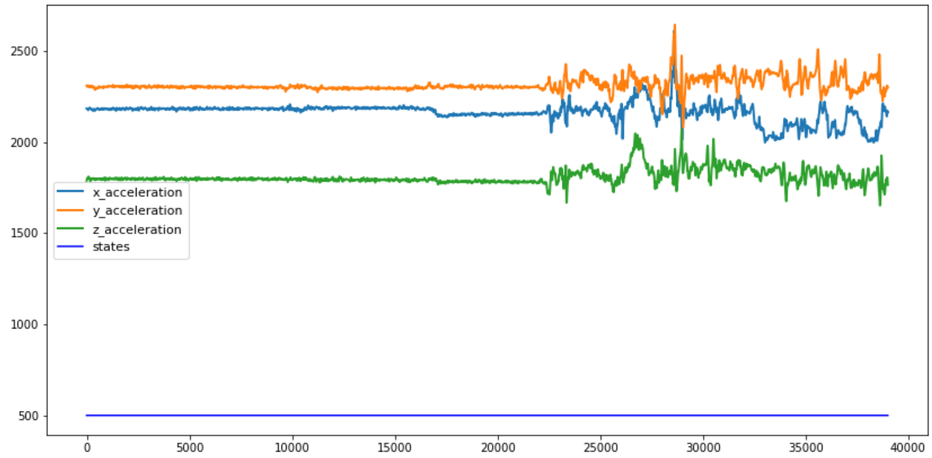

Figure 10: The signals of x, y, and z for participant 7 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

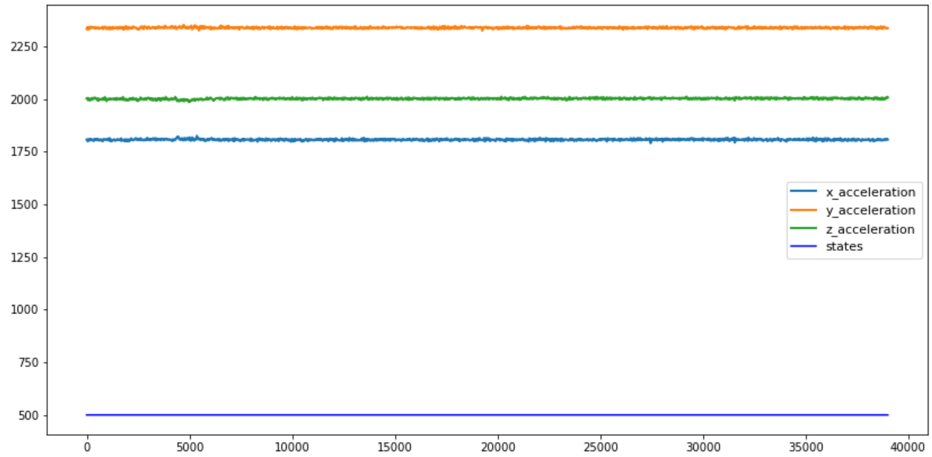

Figure 11: The signals of x, y, and z for participant 8 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

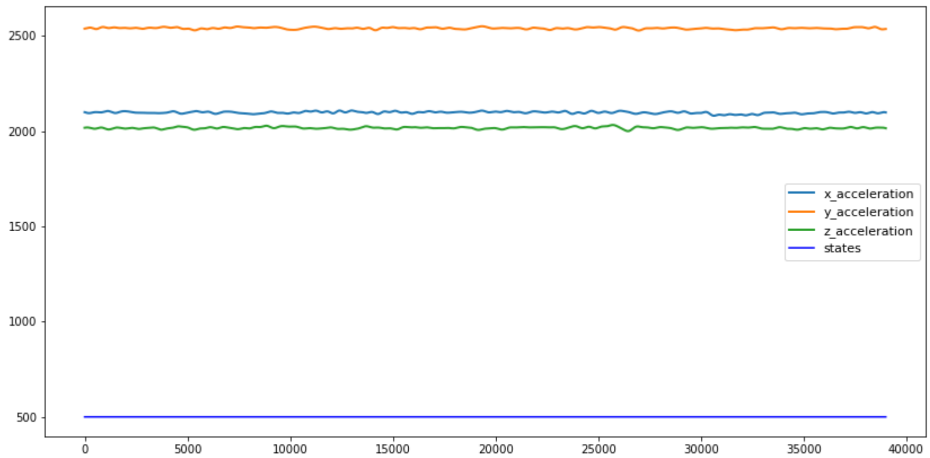

Figure 12: The signals of x, y, and z for participant 9 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

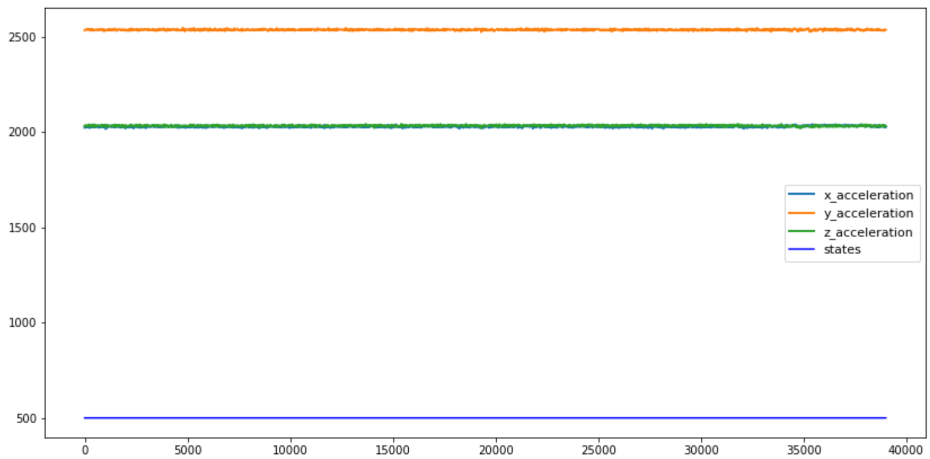

Figure 13: The signals of x, y, and z for participant 10 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

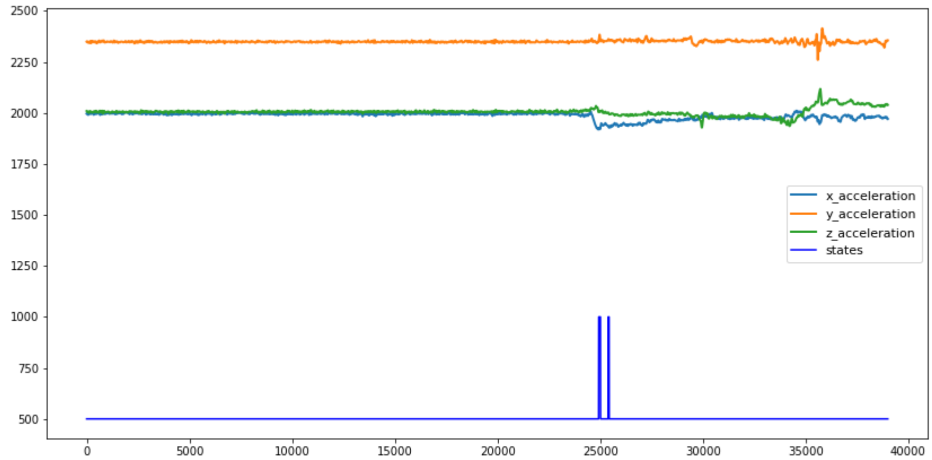

Figure 14: The signals of x, y, and z for participant 11 and ‘Standing Up, Walking and Going up-down stairs’ activity. The dark blue signal indicates the different states.

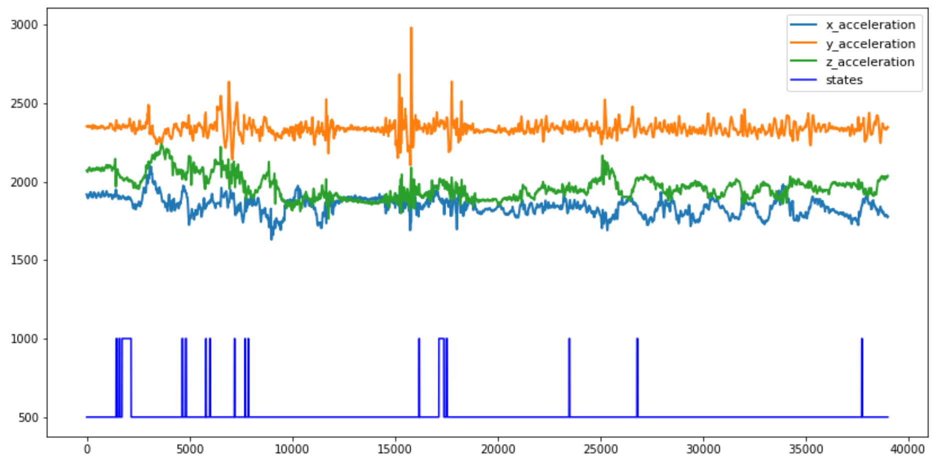

Figure 15: The signals of x, y, and z for participant 12 and ‘Standing Up, Walking and Going up-down stairs’ activity. The dark blue signal indicates the different states.

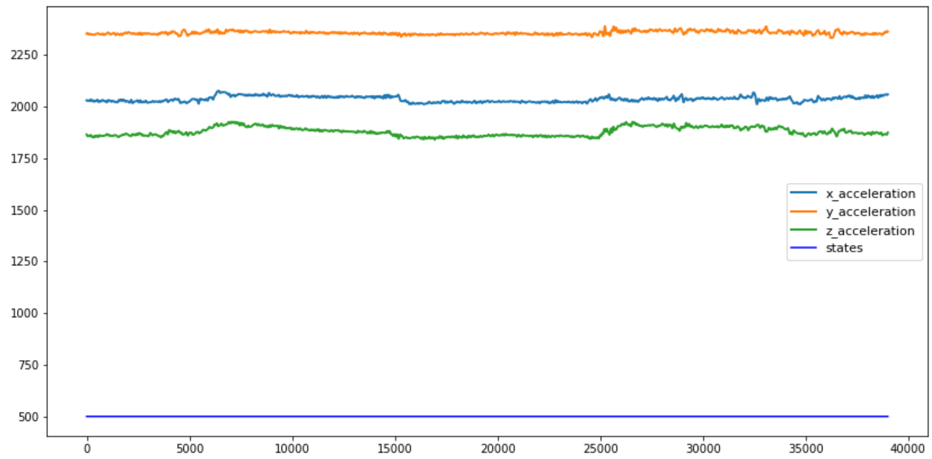

Figure 16: The signals of x, y, and z for participant 13 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

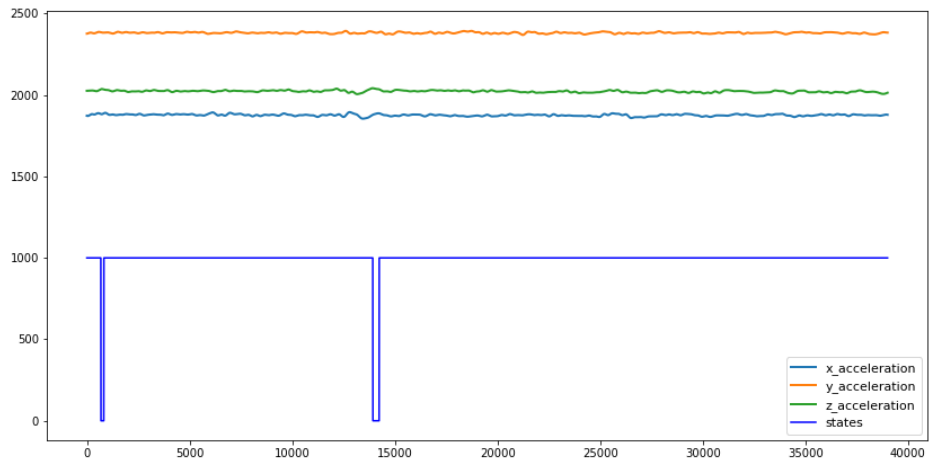

Figure 17: The signals of x, y, and z for participant 14 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

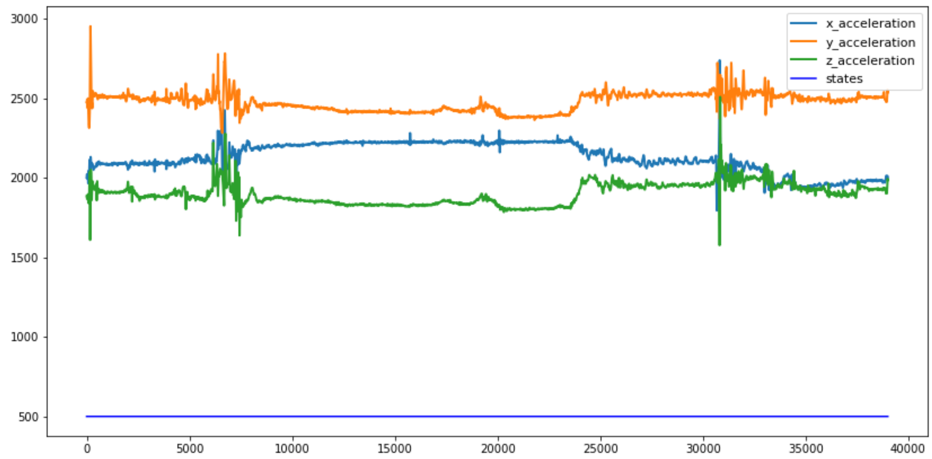

Figure 18: The signals of x, y, and z for participant 15 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

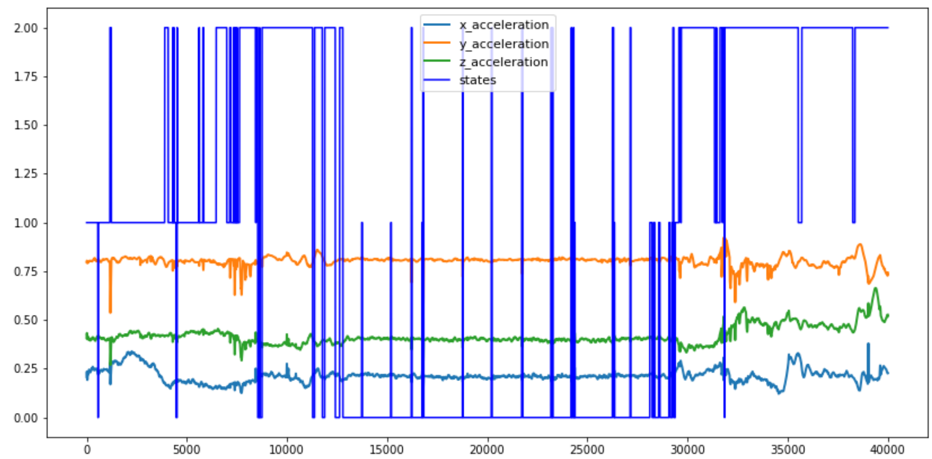

Figure 19: The normalized signals of x, y, and z for participant 1 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

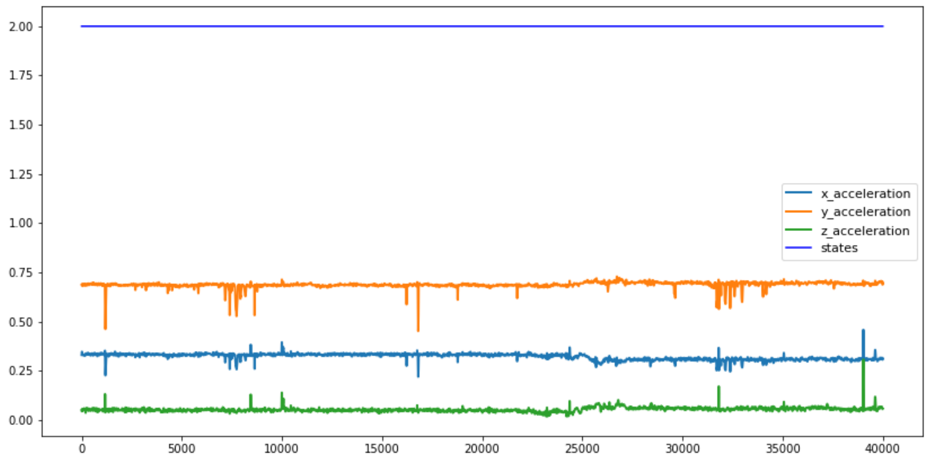

Figure 20: The normalized signals of x, y, and z for participant 2 and ‘Standing Up, Walking and Going up-down stairs’ activity. The dark blue signal indicates the different states.

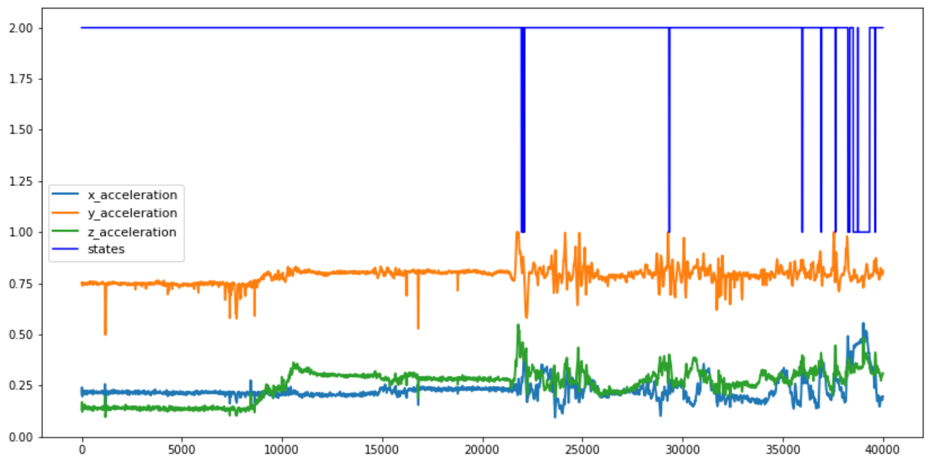

Figure 21: The normalized signals of x, y, and z for participant 3 and ‘Standing Up, Walking and Going up-down stairs’ activity. The dark blue signal indicates the different states.

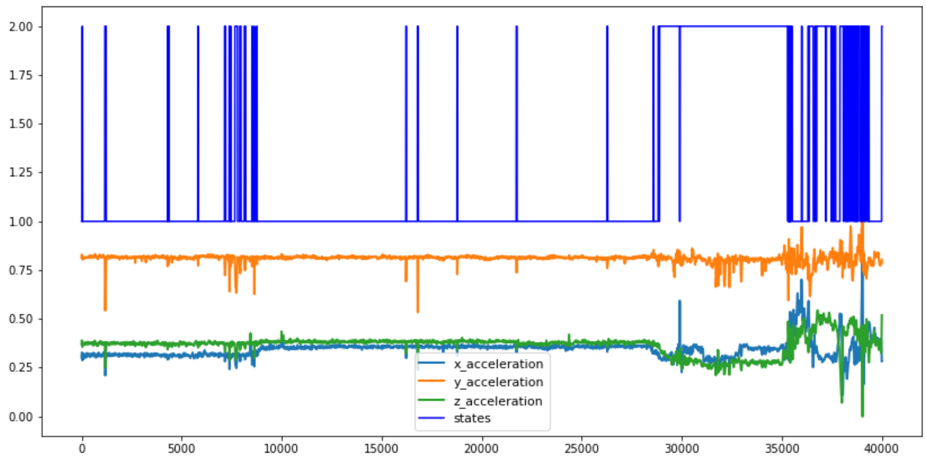

Figure 22: The normalized signals of x, y, and z for participant 4 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

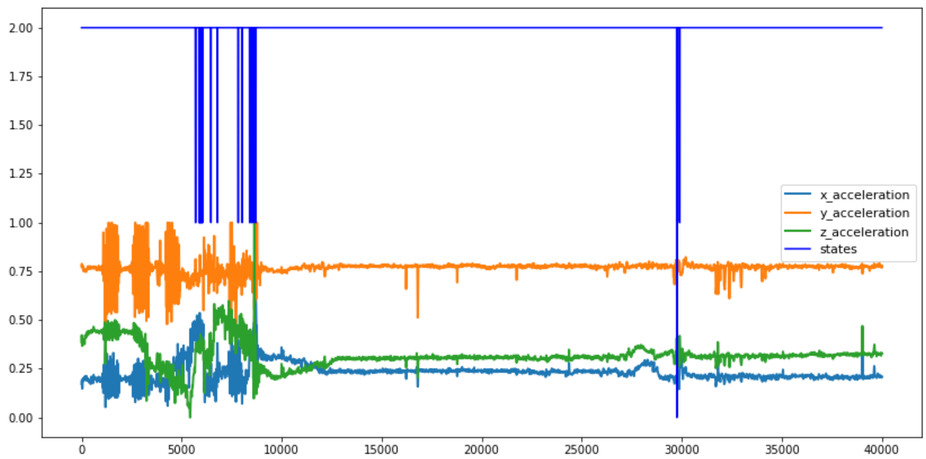

Figure 23: The normalized signals of x, y, and z for participant 5 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

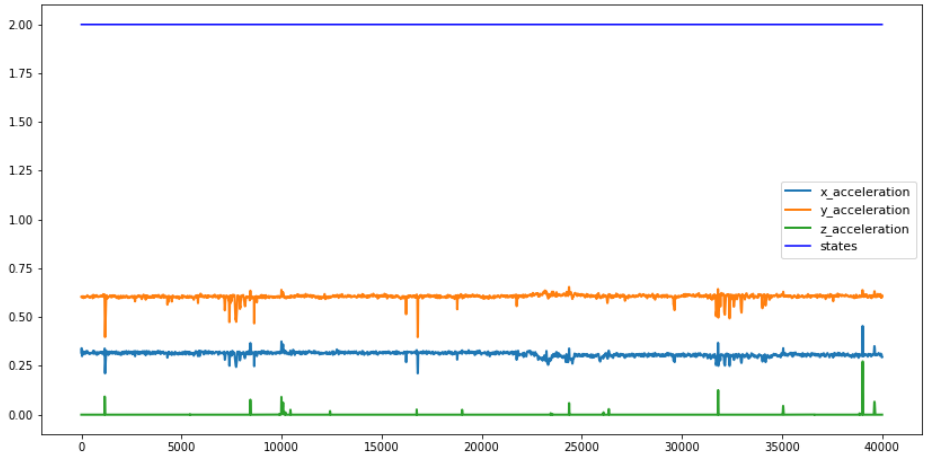

Figure 24: The normalized signals of x, y, and z for participant 6 and ‘Standing Up, Walking and Going up-down stairs’ activity. The dark blue signal indicates the different states.

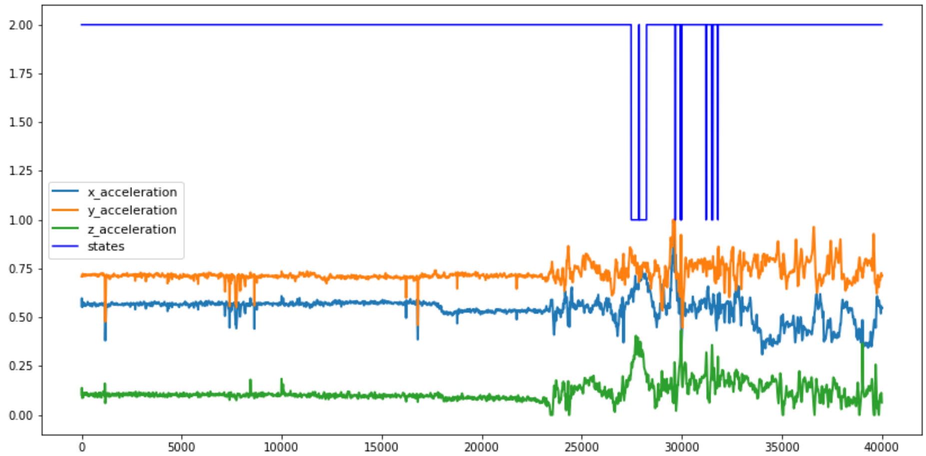

Figure 25: The normalized signals of x, y, and z for participant 7 and ‘Standing Up, Walking and Going up-down stairs’ activity. The dark blue signal indicates the different states.

Figure 26: The normalized signals of x, y, and z for participant 8 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

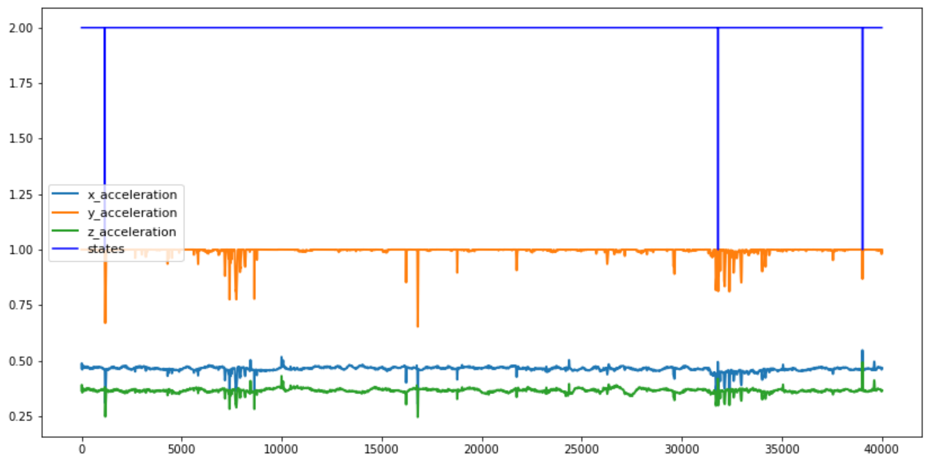

Figure 27: The normalized signals of x, y, and z for participant 9 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

Figure 28: The normalized signals of x, y, and z for participant 10 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

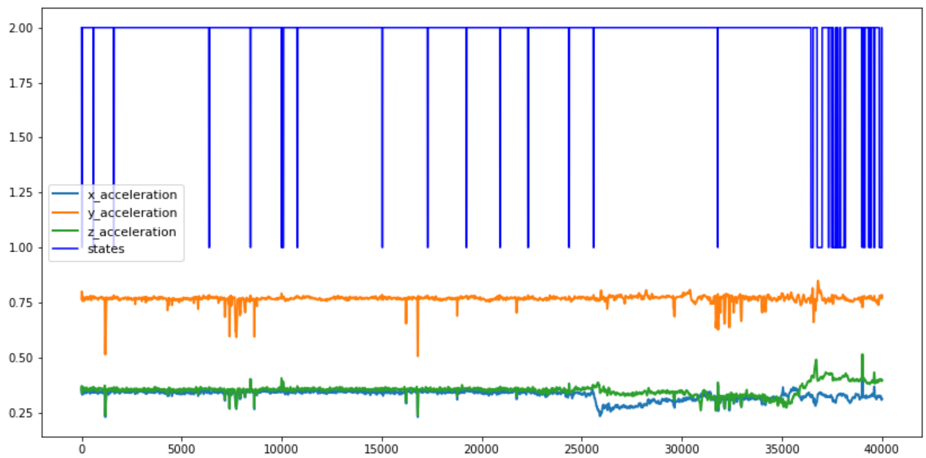

Figure 29: The normalized signals of x, y, and z for participant 11 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

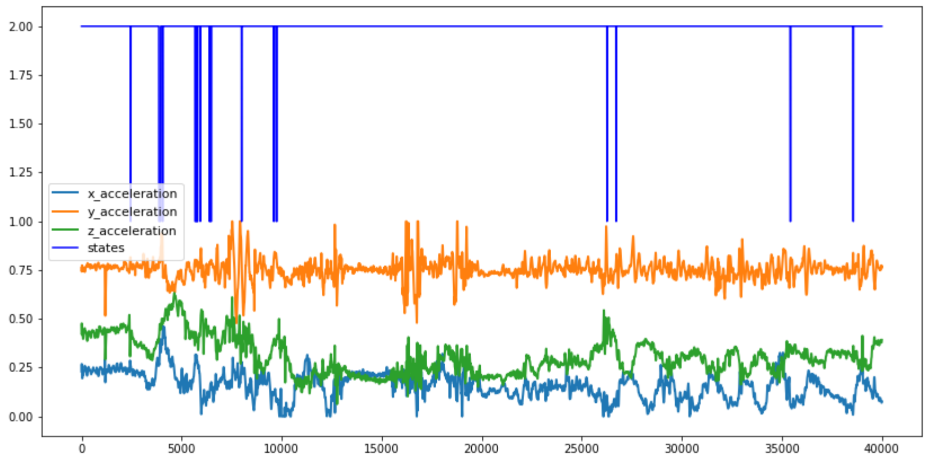

Figure 30: The normalized signals of x, y, and z for participant 12 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

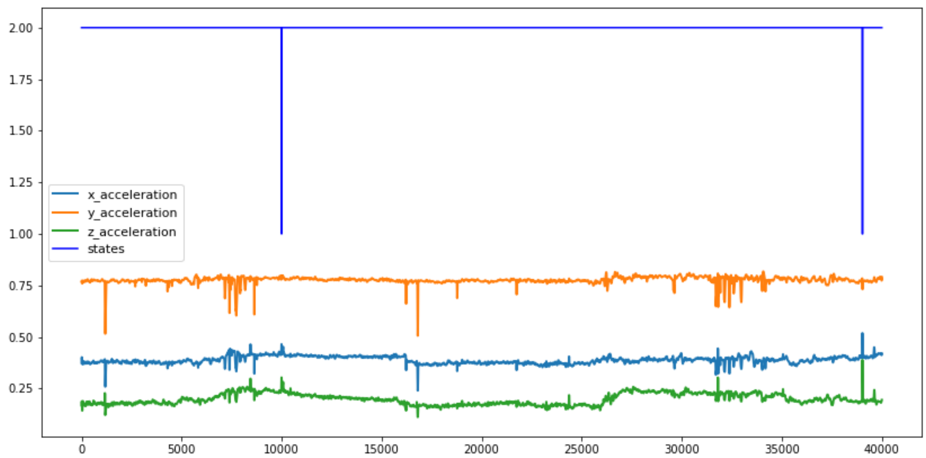

Figure 31: The normalized signals of x, y, and z for participant 13 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

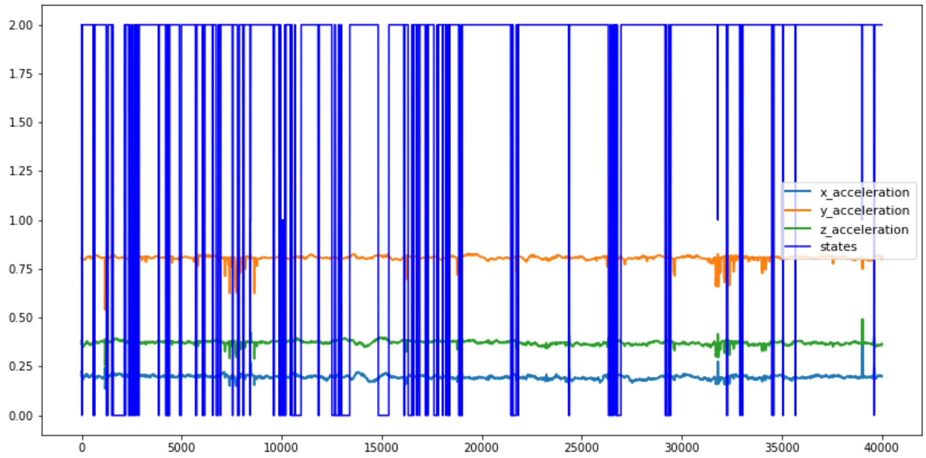

Figure 32: The normalized signals of x, y, and z for participant 14 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

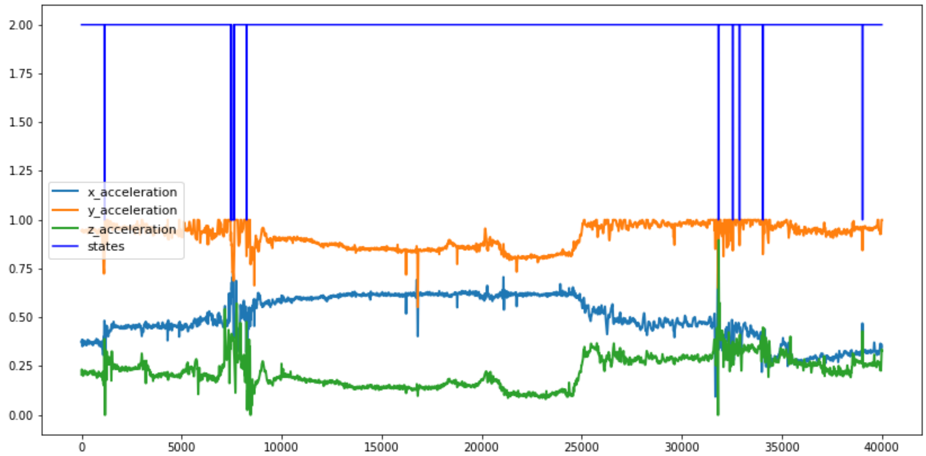

Figure 33: The normalized signals of x, y, and z for participant 15 and 'Standing Up, Walking and Going up-down stairs' activity. The dark blue signal indicates the different states.

3. **Walk/non-Walk Classification: Train an HMM model to detect the activity 'Walk' using users 1-10 for training. Then, use the model to detect 'walk' activity patterns in the data from users 11-15. The goal here is to label during which parts of the data the user were walking. You can adjust the selection criteria by varying the likelihood threshold. Compute the system performance/accuracy across different thresholds (hint: explore ROC curves).**

   This question is a learning problem. Figure 34 indicates the pipeline of my solution. For pre-processing part, we used *the re-sampling function* to resize all observations.

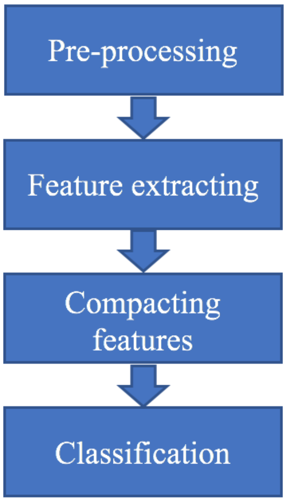

Figure 34: The pipeline of question 3.

Resizing could delete the effect of zero padding (having the same features for zero values). After that, nine various features were extracted from each observation signal. We also considered a window with the size of 256 samples and an overlap portion of 20 percent. Based on the observation signals, the mean and variance of signal were calculated as features. Also, we found six peak values in the Short-time Fourier transform, with the same algorithm used in the tutorial. Figure 35 shows the peak values for a subset of a signal.

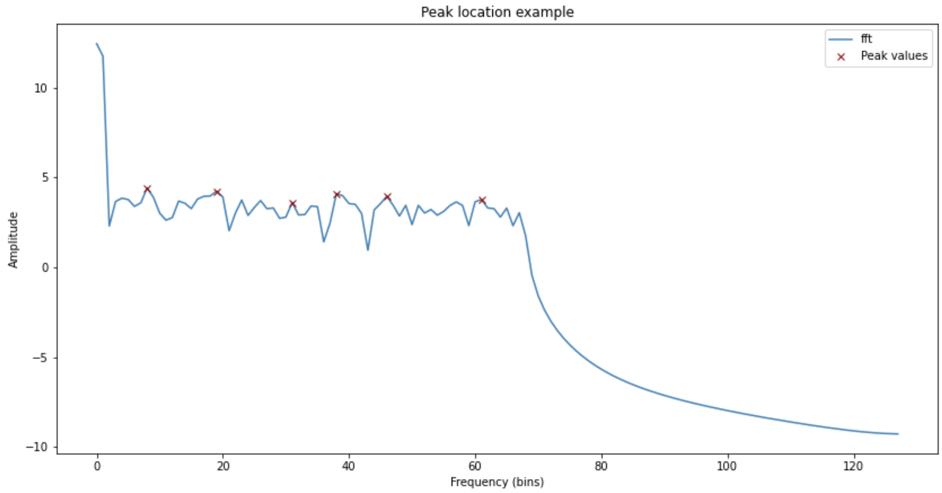

Figure 35: The magnitude of STFT and its peak values.

The output of feature extracting is a matrix with dimension of $3 \times 411 \times 9$ for each activity. Then features of each observation (x, y, and z) concatenated to each other to produce a matrix of 411×27 for each user activity. Finally, features were separated based on their activities. The shape of the final array is $15 \times 411 \times 27$; Where 15, 411, and 27 indicate the number of users, windows, and features, respectively.

In the classification part, the array was divided into train and test array. Based on the question, we used users 1 to 10 for training and others for the test. Also, we set the state variable as a loop variable to find the effect of the HMM state in the accuracy.

Because we have only one HMM model trained for walking activity, the output is a probability value. This probability shows whether or not the test features belonged to this activity. To find the best threshold, we used a *for loop*. The results of this model are illustrated below.

Table 2: The results of HMM for different states and threshold values.

Test accuracy of 2 states HMM for threshold -10000 :	64.29%
Test accuracy of 2 states HMM for threshold -20000 :	57.14%
Test accuracy of 2 states HMM for threshold -30000 :	57.14%
Test accuracy of 2 states HMM for threshold -40000 :	50.00%
Test accuracy of 2 states HMM for threshold -50000 :	50.00%
Test accuracy of 2 states HMM for threshold -60000 :	71.43%
Test accuracy of 2 states HMM for threshold -70000 :	**85.71%**
Test accuracy of 3 states HMM for threshold -10000 :	64.29%
Test accuracy of 3 states HMM for threshold -20000 :	50.00%
Test accuracy of 3 states HMM for threshold -30000 :	50.00%
Test accuracy of 3 states HMM for threshold -40000 :	42.86%
Test accuracy of 3 states HMM for threshold -50000 :	50.00%
Test accuracy of 3 states HMM for threshold -60000 :	50.00%
Test accuracy of 3 states HMM for threshold -70000 :	57.14%
Test accuracy of 4 states HMM for threshold -10000 :	57.14%
Test accuracy of 4 states HMM for threshold -20000 :	57.14%
Test accuracy of 4 states HMM for threshold -30000 :	50.00%
Test accuracy of 4 states HMM for threshold -40000 :	57.14%
Test accuracy of 4 states HMM for threshold -50000 :	50.00%
Test accuracy of 4 states HMM for threshold -60000 :	50.00%
Test accuracy of 4 states HMM for threshold -70000 :	57.14%
Test accuracy of 5 states HMM for threshold -10000 :	64.29%
Test accuracy of 5 states HMM for threshold -20000 :	64.29%
Test accuracy of 5 states HMM for threshold -30000 :	64.29%
Test accuracy of 5 states HMM for threshold -40000 :	64.29%
Test accuracy of 5 states HMM for threshold -50000 :	57.14%
Test accuracy of 5 states HMM for threshold -60000 :	57.14%
Test accuracy of 5 states HMM for threshold -70000 :	57.14%

Based on table 2, the best result belonged to 2 states HMM with threshold -70000.

4. **Summarize your findings and observations briefly in a final discussion. Submit both the developed code and your document to the Assignment 3 folder on D2L.**

   (a) Although re-sampling has some positive effects on features extracting part (deleting zeros padding parts), it could decrease the quality of spectral features. For example, the algorithm could not find any features for this part of the signal because the scale of STFT was changed (see figure 36). Therefore, we need to update our algorithm for finding peaks or extract other features.

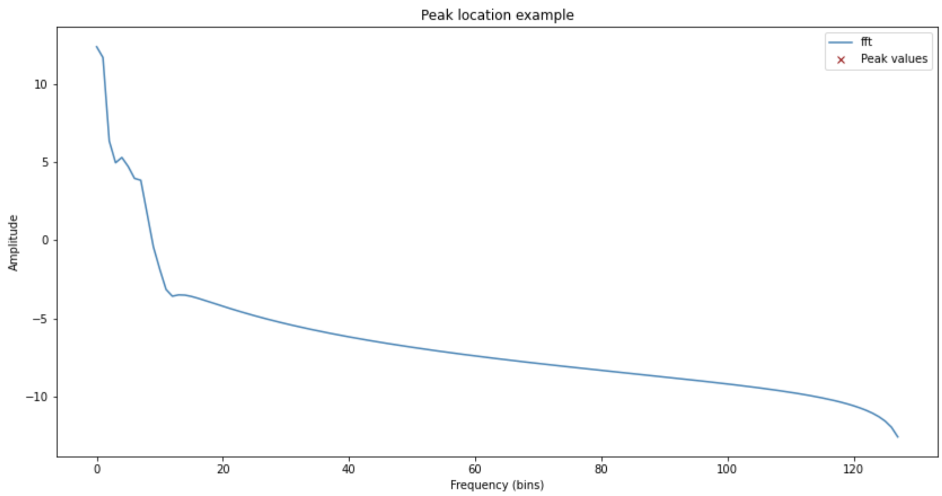

Figure 36: The magnitude of STFT and its peak values.

   (b) Data normalization had a significant effect on the result of HMM (compare figures 7 and 14 with 22 and 29, respectively)

   (c) The decoding result was not good enough for finding different states in raw data. The reason for this result could be either the re-sampling of data or the size of the training set.