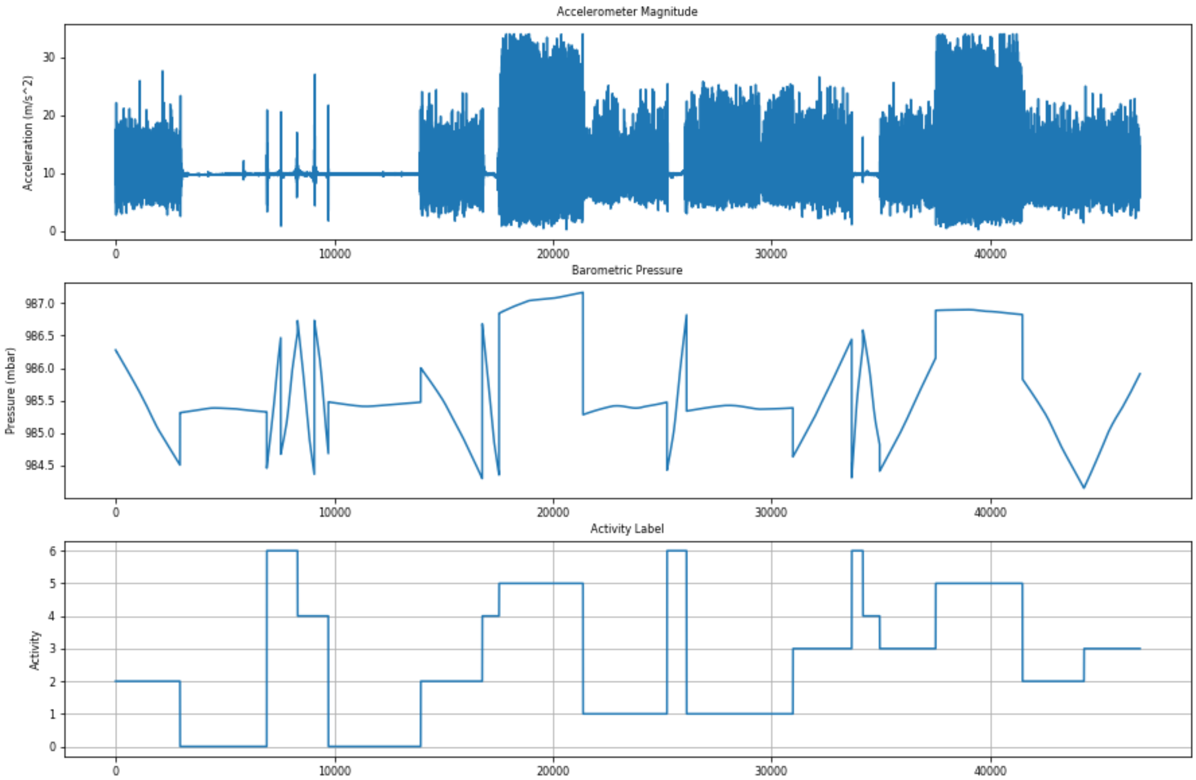
Ubiquitous Computing Assignment: A3: Activity Recognition

Fig 1. Raw Data:



The raw data from activity collection is of limited use when considered by itself. It does however contain general indications of the type of activity even when considered in isolation. This can be seen in the accelerometer magnitude in figure 1 (the summation of all three axis have been converted into a single signal), where it is obvious that activities 1, 2 and 3 contained a lot more movement than 0, 4, and 6. It is clear that activity 5 is ***much*** more movement orientated than all the others.

This is however only possible to deduce when the associated Activity Label graph is available for cross-reference. Without this, the accelerometer data has no context and is unable to be utilised in any meaningful manner.

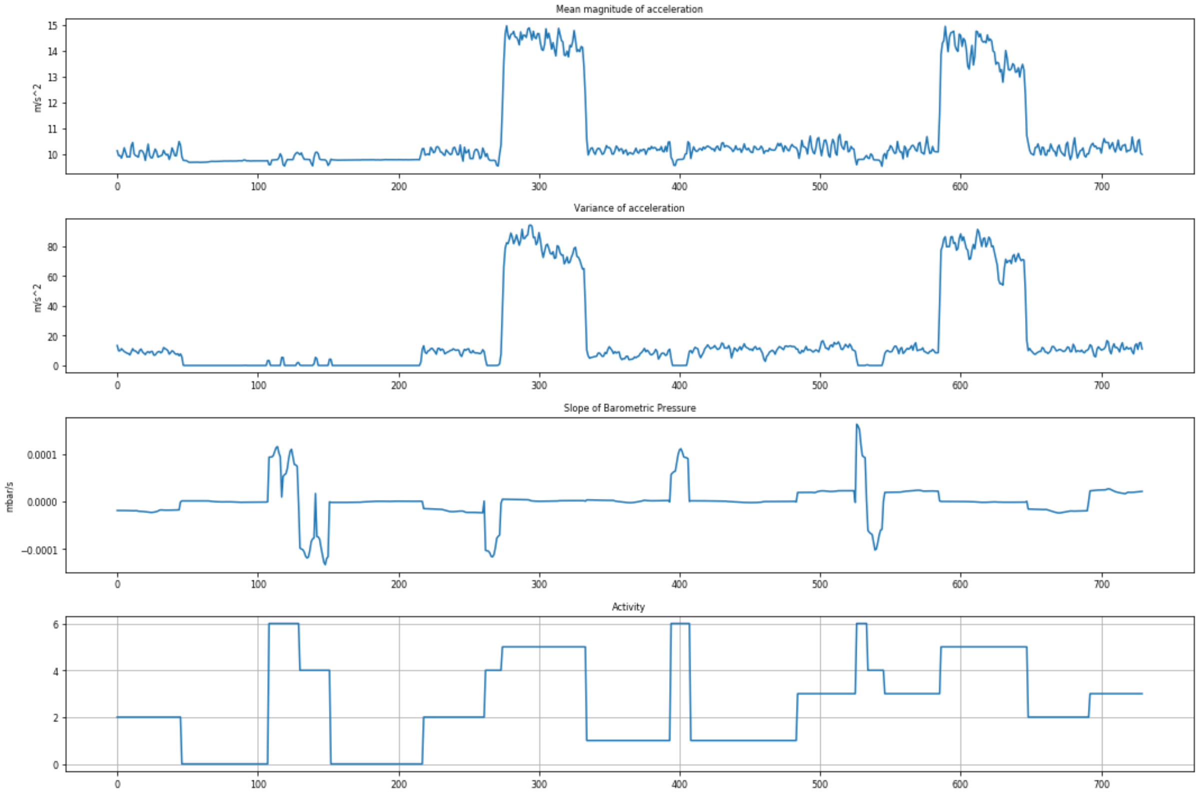
Similarly, the barometer readings alone show the changes in pressure, but lack any context without the Activity Labels.

It is the combination of all three that allows the interpretation of which activity is which, for instance the moderate-physical-activity section with the steadily decreasing barometer pressure reading hints at elevation being physically achieved over a longer period of time (such as walking upstairs), in contrast to the same decrease in pressure being achieved in a shorter period of time with little to no physical movement (hinting at an elevator).

The two periods of high barometric pressure and physical activity suggest quick, rapid motion at a low elevation (such as running at ground-level). This example uses the raw barometer readings to draw this conclusion, rather than any concern with the specific changes in this value (the fact it doesn't change dramatically, shows the approximately flat surface the activity took place on).

The raw data from the accelerometer is however very noisy, making it quite difficult to interpret any specific detail from the reading (other than a general sense of context). This data would be more useful and easier to read after some signal processing (as in figure 2).

Fig 2. Feature Extraction:
(including magnitude of acceleration, variance of acceleration and slope of barometric pressure)



These plots illustrate the same information as in the raw data, after smoothing has been applied. The first sublot uses the time domain mean function of the acceleration (from all three axis) to mor clearly illustrate the amount of movement occurring. It is still obvious that activities 2 and 3 were subject to more motion than other activities, but the contrast between them and activity 5 is much more pronounced.

The following subplot of the variance of accelerometer readings correlate approximately to this pattern (especially in the case of activity 5), however it also shows that there was a fairly consistent rate of change in activities 2 and 3, indicating a steady pace. There are minor fluctuations in this pace however where the variance drops off slightly. They are too few and far apart to be footsteps taken during the 4 floor ascent or decent, but match exactly to the lack of vertical changes occurring (only reading changes in x and y axis) when encountering the flat “turn” sections in the stairwell on and between floors.

The peaks of these changes are closer together over a much shorter duration in activity 3 than those in activity 2. This suggests that activity 3 was the descent of the stairs, the z axis contributing to the higher amount (mean) of the motion due to the more rapid descent, rather than the amount of *change* as this rate was fairly uniform (aside from the flat areas between flights).

There are similar dips in the rate of change over task 1 (walking on a flat surface) which accurately reflect the 180 degree turns performed at the ends of the corridor where this activity took place.

The slope of barometric pressure similarly removes the nose from the raw data and leaves us with the *change* of pressure over time. From this we can confirm the rate of ascent or decent suggested by the accelerometer variance. Activity 2 (walking up stairs) shows a more gradual drop in pressure, easing back to zero once the final step as been achieved, where as activity 3 (walking down stairs) shows a slightly quicker climb in pressure (compared to the drop observed in activity 2) which suddenly levels off to zero at the bottom step, much more abruptly as there is no slowing down before conclusion of activity as there is present in climbing the final few steps.

The change in pressure is also the first obvious indication that the first instances of activity 6 and 5 are recoded in duplicate (the x axis is not chronological for unknown reasons). There are two, short, iterations of activity 6, followed by two short instances of activity 5 (with a further single instance of each spread across the middle, and another grouped pair toward the end of the x axis). While there are suggestions of this patterns in the mean and variance of the accelerometer, it is *far* more pronounced in the slope of barometric pressure. This not only brings it to the attention of the viewer more readily but will also greatly assist in the accuracy of machine prediction of activity.

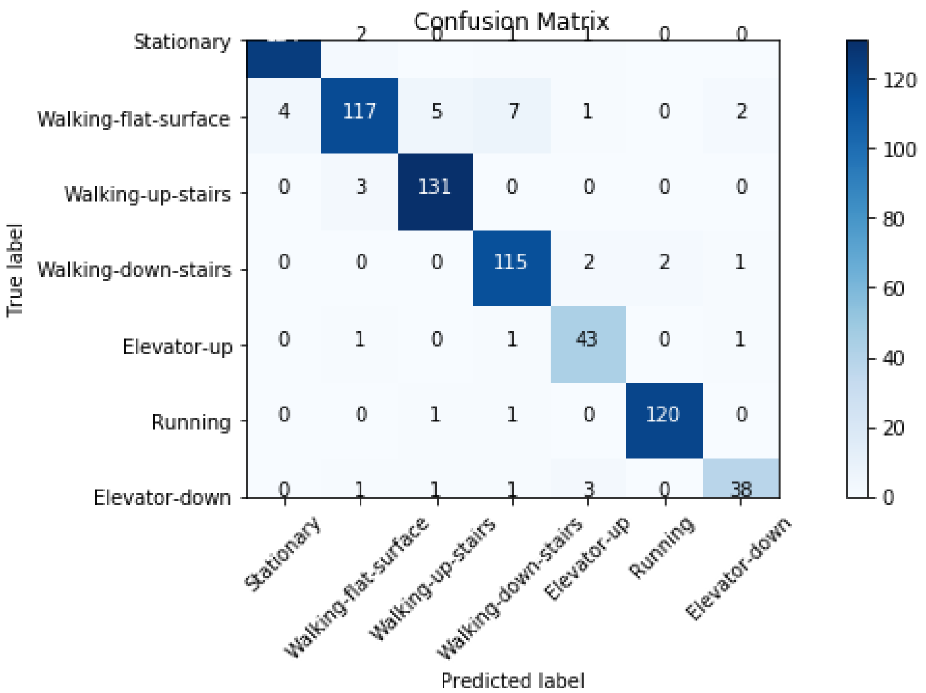
Overall these readings accurately reflect the activities performed, even to the deviations from the task being performed (such as the 180-degree walking turn or mid-flight turn platforms in the stairwell). The running (activity 5) barometric change recorded on this plot does surprise me as I had assumed this would show the small bridge that was passed over during the activity. This can however be seen in the raw data values of the barometer (shown as the early climb in the first instance, not reflected in the second journey due to a slight deviation in route length).

The amount of accelerometer motion and variance could have been lessened if the device was placed in a different location (such as jacket pocket) instead of in the front-left-trouser-pocket. This location was chosen to emphasise the motion of the target activities (if placed on the torso, only a continuous vertical motion would be observed when climbing the stairs, rather than the up-down oscillation of each footfall).

<u>Fig 3. Confusion Matrix</u>

(including text depiction for clarity: image vertical cutoff is a known bug in matplotlib 3.1.1):

```
===== Confusion Matrix (within subject) =====
Confusion matrix, without normalization
[[124.   2.   0.   1.   1.   0.   0.]
 [  4. 117.   5.   7.   1.   0.   2.]
 [  0.   3. 131.   0.   0.   0.   0.]
 [  0.   0.   0. 115.   2.   2.   1.]
 [  0.   1.   0.   1.  43.   0.   1.]
 [  0.   0.   1.   1.   0. 120.   0.]
 [  0.   1.   1.   1.   3.   0.  38.]]
```



<u>Precision, recall and accuracy:</u>

Key:

- True positive (TP)
- True negative (TN)
- False positive (FP)
- False negative (FN)

Formulas used:

Precision =	TP / (TP + FP)
Recall =	TP / (TP + FN)
Accuracy =	(TP + TN) / (TP + TN + FP + FN)

(All values have been rounded to 3 decimal places.)

<u>Stationary:</u>

TP:	124	
TN:	598	
FP:	4	
FN:	4	
Precision:	124 / (124 + 4) =	0.969
Recall:	124 / (124 + 4) =	0.969
Accuracy:	(124+598) / (124 + 598 + 4 + 4) =	0.989

<u>Walking:</u>

TP:	117	
TN:	587	
FP:	7	
FN:	19	
Precision:	117/ (117 + 7) =	0.944
Recall:	117/ (117 + 19)=	0.860
Accuracy:	(117 + 587) / (117 + 587 + 7 + 19) =	0.964

<u>Walking up stairs:</u>

TP:	131	
TN:	589	
FP:	7	
FN:	3	
Precision:	131 / (131 + 7) =	0.949
Recall:	131 / (131 + 3) =	0.978
Accuracy:	(131 + 589) / (131 + 589 + 8 + 3) =	0.986

<u>Waking down stairs:</u>

TP:	115	
TN:	599	
FP:	11	
FN:	5	
Precision:	115 / (115 + 11) =	0.927
Recall:	115 / (115 + 5) =	0.958
Accuracy:	(115 + 599) / (115 + 599 + 11 + 5) =	0.978

Elevator up:
TP: 43
TN: 677
FP: 7
FN: 3

Precision:	43 / (43 + 7) =	0.860
Recall:	43 / (43 + 3) =	0.935
Accuracy:	(43 + 677) / (43 + 677 + 7 + 3) =	0.986

Running:
TP: 120
TN: 606
FP: 2
FN: 2

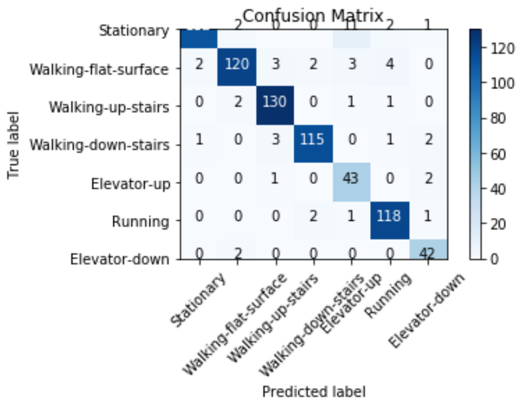
Precision:	120 / (120 + 2) =	0.984
Recall:	120 / (120 + 2) =	0.984
Accuracy:	(120 + 606) / (120 + 606 + 2 + 2) =	0.994

Elevator down:
TP: 38
TN: 682
FP: 6
FN: 4

Precision:	40 / (40 + 3) =	0.930
Recall:	40 / (40 + 4) =	0.909
Accuracy:	(38 + 682) / (40 + 682 + 6 + 4) =	0.986

Fig.4 Confusion Matrix 2: 7 additional datasets
(including true/false) results of the feature selection function)

```
Processing data from sgj17quu
Processing data from ssq26shu
===== Confusion Matrix (between subjects) =====
Confusion matrix, without normalization
[[112.   2.   0.   0.  11.   2.   1.]
 [  2. 120.   3.   2.   3.   4.   0.]
 [  0.   2. 130.   0.   1.   1.   0.]
 [  1.   0.   3. 115.   0.   1.   2.]
 [  0.   0.   1.   0.  43.   0.   2.]
 [  0.   0.   0.   2.   1. 118.   1.]
 [  0.   2.   0.   0.   0.   0.  42.]]
```




```
===== Mask of Top-5 Features =====
[ True  True False False False  True False False False False False False
  True  True]
```

Stationary:
TP: 112
TN: 599
FP: 3
FN: 16
Precision: 112/ (112+ 3) = 0.974
Recall: 112/ (112+ 16) = 0.875
Accuracy: (112+599) / (112+ 599+ 3 + 16) = 0.974

Walking:
TP: 120
TN: 590
FP: 6
FN: 14
Precision: 120/ (120 + 6) = 0.952
Recall: 120/ (120 + 14)= 0.896
Accuracy: (120 + 590) / (120 + 590 + 6 + 14) = 0.973

Walking up stairs:
TP: 130
TN: 589
FP: 7
FN: 4
Precision: 130 / (130 + 7) = 0.949
Recall: 130 / (130 + 4) = 0.970
Accuracy: (130 + 589) / (130 + 589 + 7 + 4) = 0.985

Waking down stairs:
TP: 115
TN: 604
FP: 4
FN: 7
Precision: 115 / (115 + 4) = 0.966
Recall: 115 / (115 + 7) = 0.943
Accuracy: (115 + 604) / (115 + 604 + 4 + 7) = 0.985

Elevator up:
TP: 43
TN: 668
FP: 16
FN: 3
Precision: 43 / (43 + 16) = 0.729
Recall: 43 / (43 + 3) = 0.935
Accuracy: (43 + 668) / (43 + 668 + 16 + 3) = 0.974

Running:
TP: 118
TN: 600
FP: 8
FN: 4

Precision:	118 / (118 + 8) =	0.937
Recall:	118 / (118 + 4) =	0.967
Accuracy:	(118 + 600) / (118 + 600 + 8 + 4) =	0.984

Elevator down:
TP: 42
TN: 680
FP: 6
FN: 2

Precision:	42 / (42 + 6) =	0.875
Recall:	42 / (42 + 2) =	0.955
Accuracy:	(42 + 680) / (42 + 680 + 6 + 2) =	0.962

Comparison of 1 and 8 data set calculations

	Single data set			8 data sets			differences		
	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy
Stationary	0.969	0.969	0.989	0.974	0.875	0.974	0.005	-0.094	-0.015
Walking	0.944	0.860	0.964	0.952	0.896	0.973	0.008	0.036	0.009
Stairs up	0.949	0.860	0.964	0.949	0.970	0.985	0	0.11	0.021
Stairs down	0.927	0.958	0.978	0.966	0.943	0.985	0.039	-0.015	0.007
Elevator up	0.860	0.935	0.986	0.729	0.935	0.974	-0.131	0	-0.012
Running	0.984	0.984	0.994	0.937	0.967	0.984	-0.047	-0.017	-0.01
Elevator down	0.930	0.909	0.986	0.875	0.955	0.962	-0.055	0.046	-0.024

Overall the differences between the calculations from the single dataset and eight datasets is relatively small. There were more improvements than expected using the larger dataset, however these can be explained due to the machine learning gaining a larger data pool (and therefore more accurate picture of what data was expected). This does not hold true for all the sections however as there are many variables that are either unaccountable for (such as the recording device being located in a different pocket, if the device was located on the subject's dominant side or not, the subject's gait, environmental conditions such as a change in the weather, and so on), or simply do not conform to the ideal pattern of the supplied training data.

The most misidentified activity in either matrix was walking on a flat surface using the 8 data sets. This could be due largely to the location chosen by each subject to perform their data gathering. The single set training data was performed on a 2nd storey building (at the bottom of a hill), in an empty sealed corridor, at a leisurely pace. This environment offered little by way of velocity changes (other than the 180 degree turn at each end), vertical changes, or any change in barometric pressure. If the other datasets had been performed in a vastly different setting, such as an open space with higher activity from other people or even outside while exposed to the elements, this variety in conditions may be interpreted by the machine to be closer to another task (closer matching conditions of the environment during the training data).
Similarly, the biggest change seen in the calculations was a large (.131) drop in the precision of the elevator-up task. This is a little more difficult to explain by the above variation in behaviour or

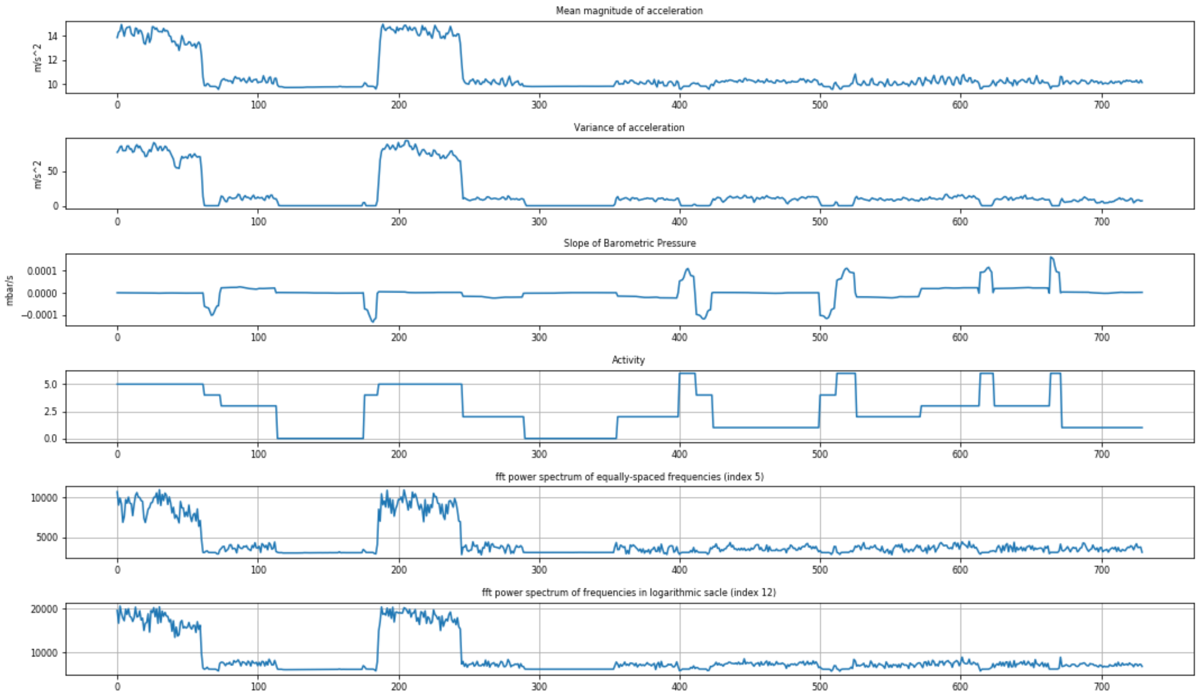
conditions. For example, the slope of barometer pressure should be easy to distinguish from other activities, especially when combined with motion data (that on its own could be easily misinterpreted: the stationary, elevator-up and elevator-down tasks all have similar horizontal accelerometer-interpreted physical activity levels). Neither of the other similar (horizontal) physical-activity tasks should share such a sudden drop in pressure combined with vertical movement. This could be explained in part however by the inclement weather conditions (resulting in bursts of low pressure) interfering with these readings if any of the other activities were recorded in locations affected by these changes.
Another interesting anomaly is the four instances of misinterpretation of walking as running. While this would be affected by the running/walking style, speed and even grace of the person recording the data, the comparatively violent nature of movement during even a light running motion should be easily distinguishable from walking (far more vertical movement, even if the device was located in a pocket not connected to the legs).

<u>Feature Evaluation</u>
The decision tree has provided categorisation of the 13 features (as seen the bottom of fig.4):

<u>Top discriminative features:</u>

- Mean magnitude of acceleration
- Variance of acceleration
- Slope of barometric pressure
- FFT power spectrum of equally spaced frequencies (index 5)
- FFT power spectrum of frequencies in logarithmic scale (index 12)

Fig.5: additional feature plots:



This plot shows what are deemed to be the top five features by the decision tree (plus the corresponding activity labels in sub plot 4). The sub plots have been grouped according to their previous inclusion in this report: the bottom two have been isolated below the activity labels as they have not previously been referred to.

Each of these Fourier Transformations offer additional insight into the frequencies present in the raw data, however from an activity identification standpoint they are of limited value. First, they are difficult for an observer to interpret due to their time domain mapping (corresponding to the activities and their duration), rather than being a representation of the specific frequencies present(x), mapped against their power(y) on a single graph. From an automated analysis standpoint, they offer little in the way of additional identification of activities (correlating greatly with the magnitude and variance of acceleration plots), while simultaneously introducing additional noise into the previous readings (as can be most clearly seen in the peaks of activity 5).
It is also worth noting that introducing these additional features (that offer little benefit) introduces the various complications associated with the consideration of these additional dimensions, along with the fact it is likely to have a detrimental effect of blurring the (potentially better) results obtained without them.
Therefore, due to the lack of useful additional input from these features for our objective (even when considering the combination of these two features into a single plot of power and specific frequencies), I do not agree these should be considered as two of the top features in this specific use.