Exercise PC Design & Development / Systems and Environments

Assignment 2

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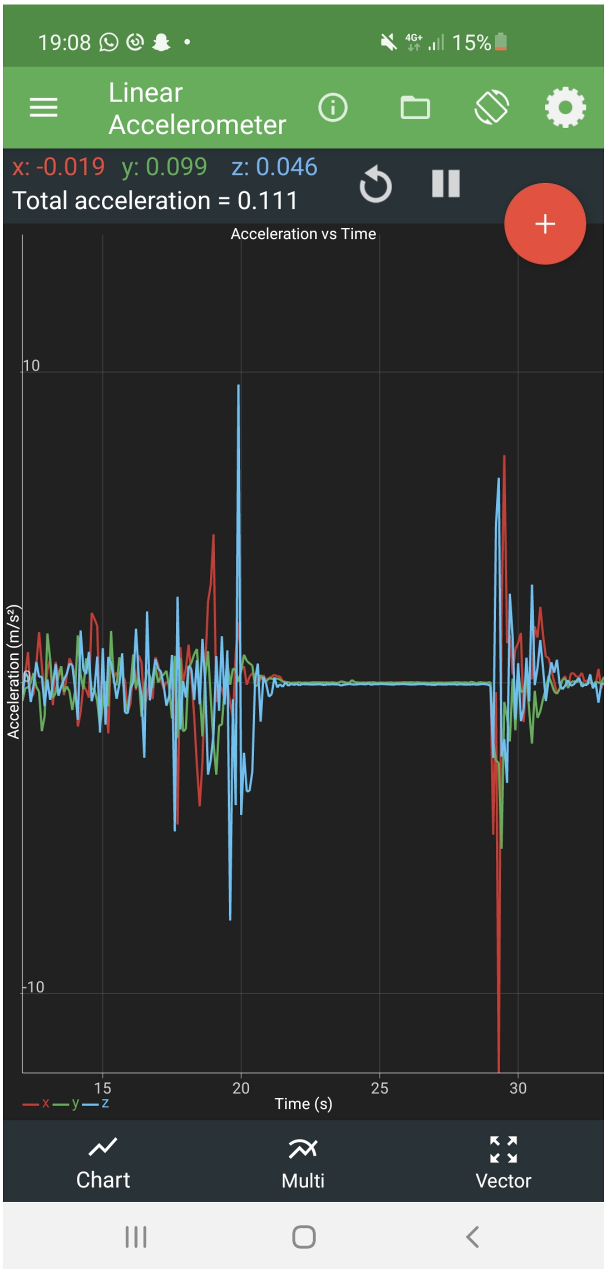
1. Remarks

The data was acquired by walking the same street up and down to have similar recording conditions.

Python code: https://github.com/StefanHaslhofer/PervasiveComputing/tree/main/Assignment2

2. Data recording

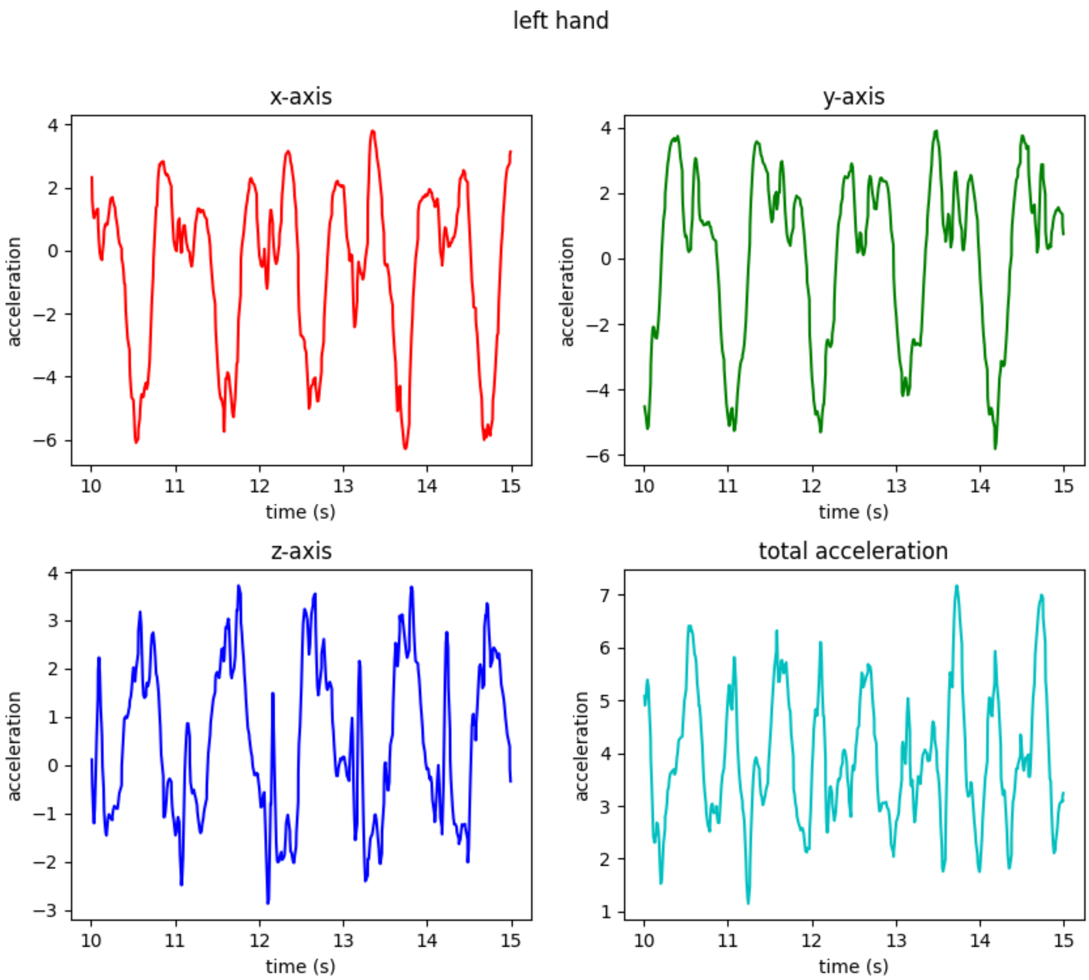
I recorded the acceleration over time on my mobile phone with an app called *Physics Toolbox Sensor Suite*.
The app allows access to the phone's built-in linear accelerometer and displays acceleration on x, y and z axis as well as a total acceleration value.

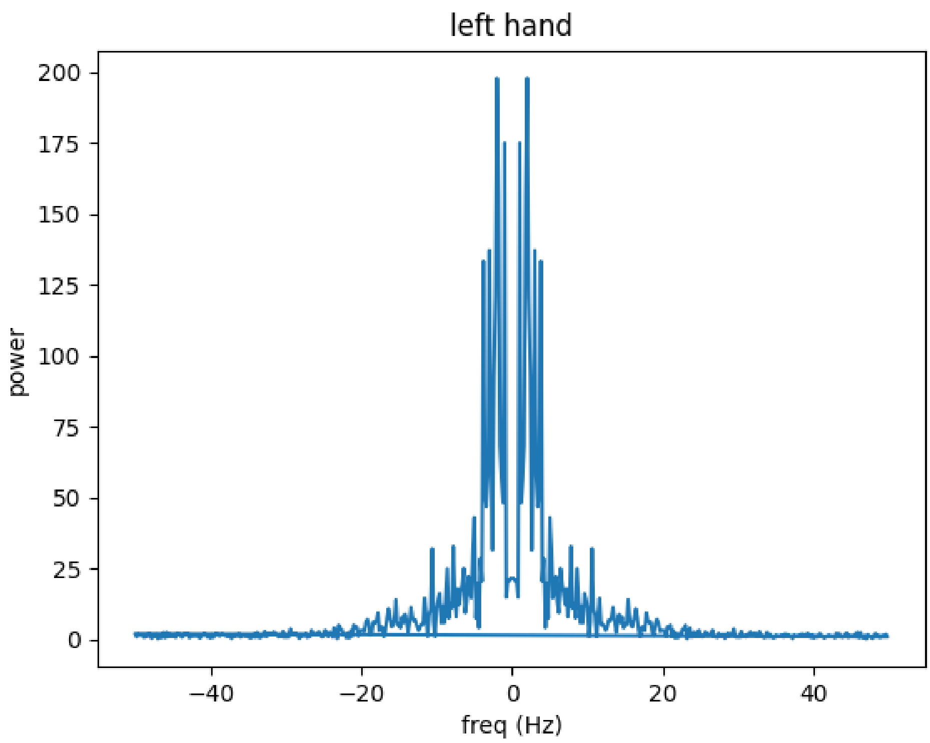


The data can be exported as *csv*. Each row contains a timestamp and all axis values plus the total acceleration.

3. Pre-processing and Segmentation

At first, I plotted the recordings in the time domain and in the frequency domain to get a feeling for the data.
Looking at the time domain plot, one can see that it takes approximately 1 second to take a step. The frequency domain confirms that frequencies in movement are (unsurprisingly) rather low. Hence, I choose to only consider frequencies lower than 50Hz for further processing.
I also split the data recordings into windows of 5 seconds to get enough samples. I used a jumping window approach, where windows do not overlap.





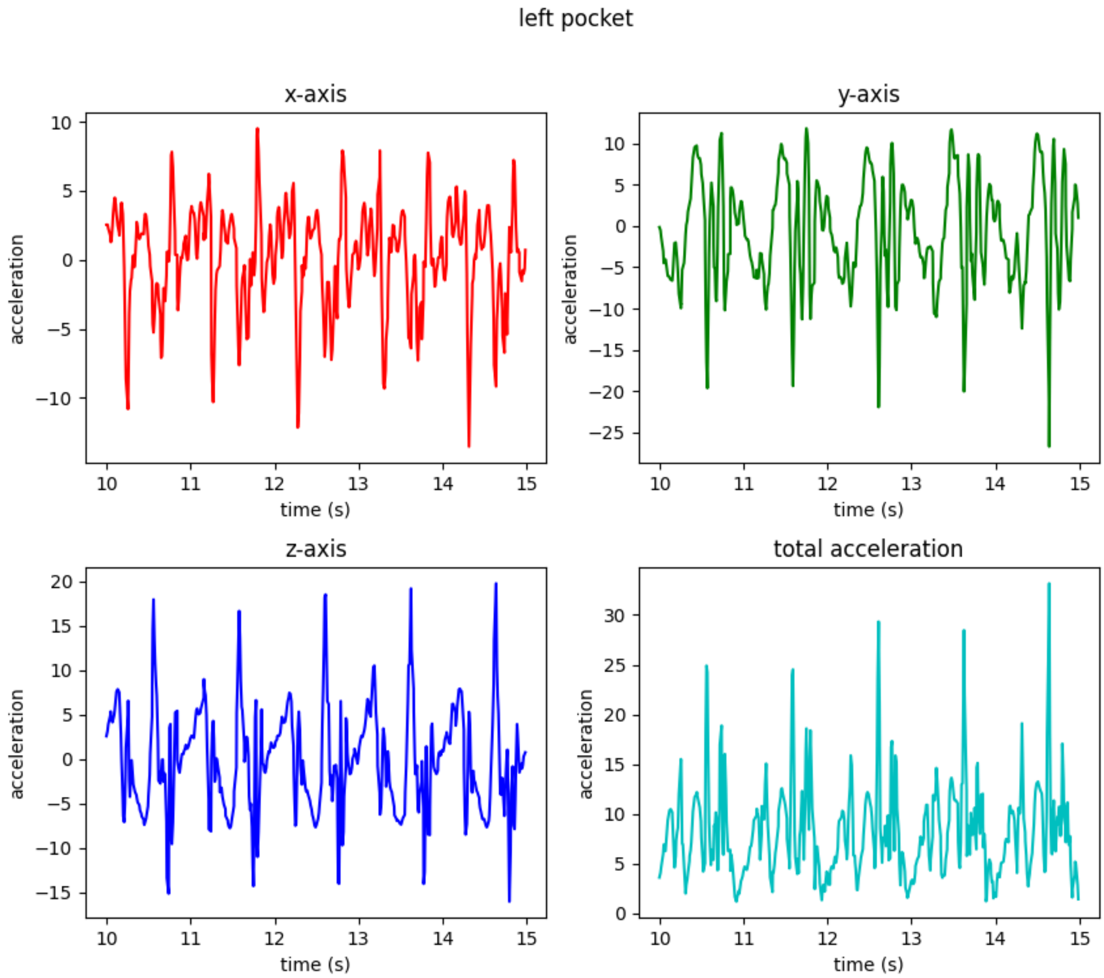
Above you can see the two plots:

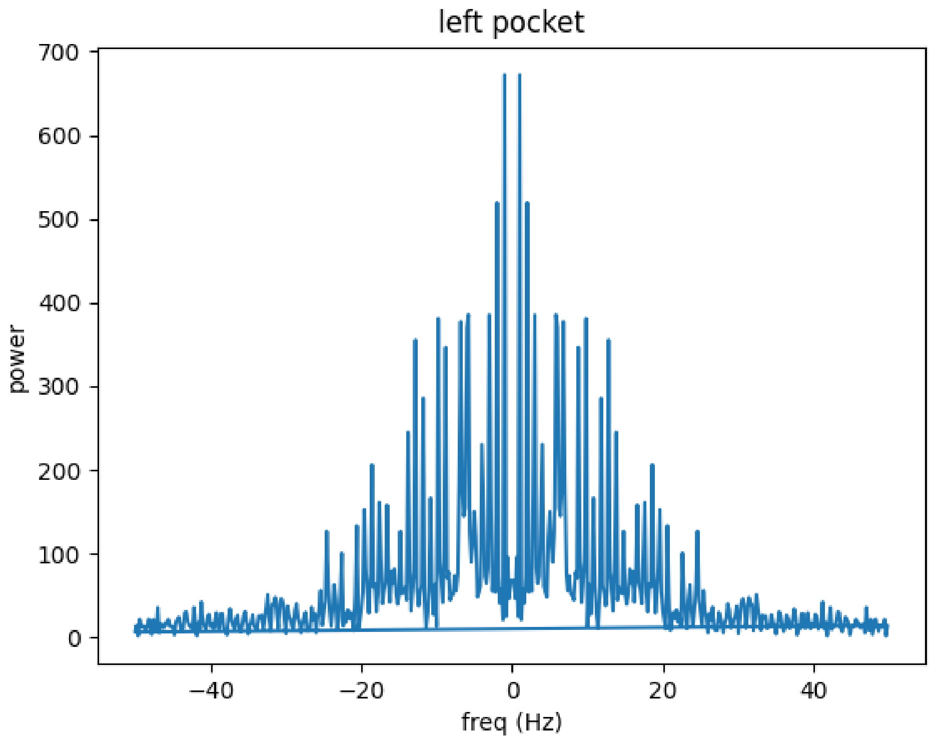
1. x, y and z-axis plus total acceleration over time
2. frequency composition of total acceleration

4. Feature extraction

Next, I implemented a python script to extract the features and save it to an *arff*-file

First, I calculated statistical features over the absolute signal values such as mean and variance for all axes including the total acceleration. I also noticed that the phone accelerates faster in my pockets than in my hands. Additionally, the frequencies recorded in my pockets seem to span over a wider spectrum compared to the recordings in my hands which can be seen when comparing the following two plots with the left hand's plots in section 3:





The significant difference in frequencies gave me reason to believe that I can extract viable information from the frequency domain as well. I used scipy's fft implementation for that.

However, at first glance the frequencies only seem to make suitable distinction between hands and pockets but not between left and right of each class.

The following table lists all extracted features with some remarks:

feature	remark
mean of x-axis	mean acceleration of feet tends to be higher than those of hands, also right hand accelerates faster than left hand
mean of y-axis	(see mean of x-axis)
mean of z-axis	(see mean of x-axis)
mean of total Acc	(see mean of x-axis)
var of x-axis	variance of feet acceleration also tends to be larger than those of hands
var of y-axis	(see var of x-axis)
var of z-axis	(see var of x-axis)
var of total Acc	(see var of x-axis)
max x-axis Acc	the maximum acceleration seems to be higher in the pockets (for all axes), also right hand accelerates faster than left hand

feature	remark
max y-axis Acc	(see var of x-axis)
max z-axis Acc	(see var of x-axis)
max total Acc	(see var of x-axis)
max x-axis freq	max frequency is slightly higher for pockets
max y-axis freq	(see max x-axis freq)
max z-axis freq	(see max x-axis freq)
max total freq	(see max x-axis freq)
max x freq energy	dominant frequency of pockets has more energy than dominant frequency of hands, also right hand's dominant frequency has more energy than dominant frequency of left hand
max y freq energy	(see max x freq energy)
max z freq energy	(see max x freq energy)
max total freq energy	(see max x freq energy)
sum of x-axis energy	overall energy of frequencies seem to differ between pockets, which is particularly helpful as I did not find a good distinction between left and right pocket yet
sum of y-axis energy	(see sum of x-axis energy)
sum of z-axis energy	(see sum of x-axis energy)
sum of total energy	(see sum of x-axis energy)
q1 frequency	frequency distribution differs widely between pockets and hands (see plots)
q2 frequency	frequency distribution differs widely between pockets and hands (see plots)

5. Classification

Weka was used for classifications.

I used the Weka visualization to filter out less significant features by hand. However, this proved to be an incorrect approach as removing some features results in a slightly worse classification and is therefore unnecessary.

a) J48

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,853	0,059	0,829	0,853	0,841	0,787	0,924	0,789	left_hand
	0,824	0,039	0,875	0,824	0,848	0,801	0,910	0,811	right_hand
	0,912	0,020	0,939	0,912	0,925	0,901	0,983	0,907	left_pocket
	0,941	0,039	0,889	0,941	0,914	0,885	0,968	0,917	right_pocket
Weighted Avg.	0,882	0,039	0,883	0,882	0,882	0,843	0,946	0,856	

Parameter tuning:

- C (confidenceFactor): Changing the parameter *C* has no effect on the result.
- M (minNumObj): Changing the parameter *W* only worsens the result.

b) Naïve Bayes

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	0,020	0,944	1,000	0,971	0,962	1,000	1,000	left_hand
	0,941	0,000	1,000	0,941	0,970	0,961	1,000	1,000	right_hand
	0,912	0,010	0,969	0,912	0,939	0,921	0,960	0,934	left_pocket
	0,971	0,029	0,917	0,971	0,943	0,924	0,958	0,901	right_pocket
Weighted Avg.	0,956	0,015	0,957	0,956	0,956	0,942	0,979	0,959	

Naive bayes has no parameters in *Weka*.

c) kNN

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1,000	0,029	0,919	1,000	0,958	0,944	0,996	0,978	left_hand
	0,941	0,010	0,970	0,941	0,955	0,941	0,982	0,931	right_hand
	0,912	0,000	1,000	0,912	0,954	0,941	0,957	0,939	left_pocket
	0,971	0,020	0,943	0,971	0,957	0,942	0,984	0,946	right_pocket
Weighted Avg.	0,956	0,015	0,958	0,956	0,956	0,942	0,980	0,949	

Parameter tuning:

- k: I experimented with the parameter *k* (number of nearest neighbors) until I hit the sweat spot at 3. This allowed me to increase accuracy from 94.9% to 95.6%.
- W: Increasing *W* was not effective. A lower number decreased accuracy drastically, however choosing a large value for *W* (e.g. 300) happens to deliver nearly the same results with slightly worse ROC Area.

d) Multilayer perceptron

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0,971	0,010	0,971	0,971	0,971	0,961	0,999	0,996	left_hand
	0,971	0,010	0,971	0,971	0,971	0,961	0,998	0,996	right_hand
	0,941	0,010	0,970	0,941	0,955	0,941	0,999	0,996	left_pocket
	0,971	0,020	0,943	0,971	0,957	0,942	0,969	0,974	right_pocket
Weighted Avg.	0,963	0,012	0,963	0,963	0,963	0,951	0,991	0,991	

Parameter tuning:

- L (learningRate): A small decrease of the parameter *L* leads to a slight increase in ROC Area (+0.1%) and PRC Area (+0.1%).
- M (momentum): Increasing the *momentum* effects the result negatively. However, a slight decrease leads to a better ROC- (+0.1) and PRC Area (+0.2%). Nonetheless, the accuracy stays the same.
- N (trainingTime): Changing the parameter *N* has no effect on the result.
- V (validationSetSize): Setting *V* = 10 increases the TP rate by 1.4% and the ROC Area by 0.1%. Additionally, it decreases the FP Rate by 0.5%.
- S (seed): I increased the *S* which at first did not change the outcome, however I found that for the randomly entered value *1111* the ROC Area got increased by 0.1%. I could not find a better input.
- E (validationThreshold): Changing the parameter *E* has no effect on the result.

Generally speaking, the standard parameters seem to perform good enough on the dataset.

Summary

In summary, the multilayer perceptron performed best with an accuracy of 96.3%. It also achieved the lowest FP rate at 0.12%. It is also worth mentioning that kNN and the naive bayes deliver nearly indistinguishable results. Because the dataset is balanced the ROC Area is also a suitable metric. But even in this category the multilayer perceptron comes out on top.