Development of an Activity Recognition System for Fitness Trails

Bachelor Thesis of Thomas Pignede
July 17, 2012

TECHNISCHE UNIVERSITÄT DARMSTADT

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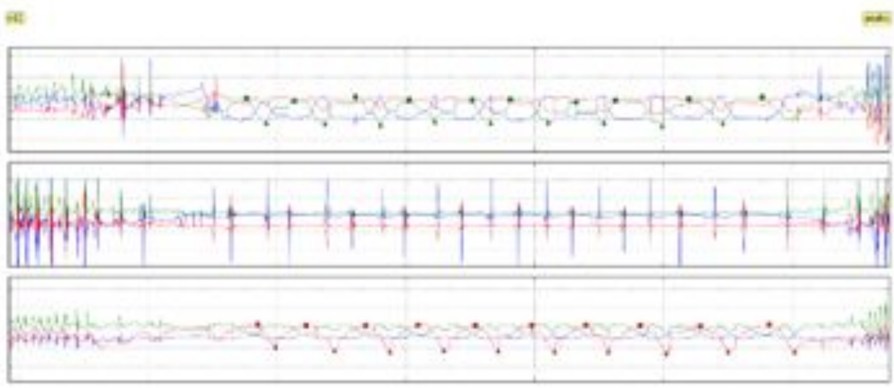

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Darmstadt, July 17, 2012

Thomas Pignede

Zusammenfassung

Trimm-Dich-Pfade sind beliebte Outdoor-Trainingsstätten und können eine wichtige Rolle in der präventiven Gesundheitsvorsorge spielen. Die Begleitung mit einem digitalen Assistenten bei der Durchführung eines solchen Parcours könnte zu einem motivierenderen Erlebnis führen und daher zu einem regelmäßigeren Workout. Hierfür ist das Erkennen und Verfolgen der ausgeführten Übungen zwingend notwendig. Allerdings gibt es noch keine bekannten Projekte, die diesen spezifischen Kontext erforscht haben.

Dieser Bericht gibt eine detaillierte Erklärung über eine vorausgehende Fallstudie, die verschiedene Aspekte dieser Fragestellung untersucht. Nach der Erstellung representativer Datensätze werden unterschiedliche Parameter ermittelt, die sowohl die Erkennung der Aktivitäten als auch die Akzeptanz der Benutzer bezüglich eines solchen Systems betreffen. Am Ende werden die Erkenntnisse der Evaluation zusammengefasst und Vorschläge für die Übertragung dieser Ergebnisse auf einer konkreten Implementierung bereitgestellt.

Abstract

Fitness trails are popular outdoor training sites and can play an important role for preventive health care through physical exercise. Doing such a parcourse accompanied by a digital assistant could lead to a more motivating experience and therefore, to a more regular workout. For this, recognizing and tracking the performed activities is mandatory. However, there are no known projects having explored this specific context yet.

This report gives a detailed explanation about a preliminary case study examining various aspects of this problem. After the acquiring of representative datasets, different parameters concerning both the recognition of the exercises and the user's acceptance of such a system are investigated. At the end the insights of the evaluation process are summarized and recommendations for carrying over these results onto a concrete implementation are provided.

Contents

1 Introduction

During the beginnings of the fitness boom in the 1970s, fitness trails have been particularly popular for people concerned about their health, who want to reduce the risk of chronic diseases by improving their physical strength. These tracks are equipped with obstacles or stations distributed along the path. The equipment can be used for performing specific forms of physiological exercise and the distribution of these stations over the length provides a challenging sort of interval training promoting a good fitness workout for exercising the human body.

For the last couple of years, preventive health care has again obtained an increasing importance, especially in order to cope with medical problems related to overweight or cardiovascular diseases. In this context, regular exercise is a good prevention method and can help reducing the expensive costs of the health care systems. This is one of the main reasons for the growing interest in monitoring a person's physical state using body sensor networks (BSNs).

A BSN consists of wearable sensor nodes for measuring the physiological parameters of a person. The network often assesses the user's current state by using accelerometers. By adding such sensors to fitness accessories, the system is able to monitor not only vital signs but also training activities like the performed exercises. The domain of activity recognition addresses the problem of interpreting and mapping the raw sensor data to the concrete tasks being done by the user. So the goal is to recognize and track the characteristic actions with the aid of the measured physical poses and movements.

One of the most important information about how a user performed on the trail is which obstacles or stations were taken and how many repetitions were done. Hence, a body sensor network using activity recognition and exercise counting could do that automatically and let the trainee focus on the exercises, without having the logging of this information to be done on his/her own. Furthermore, the system could also motivate the user, for instance by giving information about how many repetitions where done the last time.

As previous work ([1], [2]) has shown inertial sensors to be a good choice for detecting and counting gym or free-weight exercises, for the purpose of extending the existing digital training assistants to this particular setup, there is the need of investigation how well the presented methods and resulting concepts from prior research can be reused and adapted for providing a wider range of health care through prevention.

Thus, the aim of this thesis is to do primary research that is required before a future development of a concrete assistant for outdoor training parcourse. For this, both the recognition of activities and the repetition counting as well as the user's acceptance and needs have to be especially investigated. The outcomes of this work could then be used to find out if and how the measurement of the different postures and motions during the fitness trail could help people exercising effectively, and whether the provided information could lead to a better motivation for doing the workout regularly. By the end of this thesis, the results should supply enough knowledge permitting the implementation onto a real system, because these recommendations will eventually be ported for extending *myHealthAssistant*.

Due to the fact that there is no known data from trainees performing such a track with inertial sensors, an important part of this case study will be to create the datasets required for the evaluation, both of the detection of the exercises and of the user's acceptance. The underlying experiments for this part are described in the next section (2).

The remainder of the thesis is then structured as follows: Section 3 gives a detailed explanation of the feature extraction and parameter optimization needed for the activity detection and the exercise counts. The results of the questionnaire for evaluating the comfort and the needs of such wearables from a user's point of view are presented in Section 4. Finally, Section 5 concludes with a brief summary and the consequences of the study and provides an outlook with suggestions on how to deploy the results onto a concrete system.

2 Experiments for Collecting Data

2.1 Task Description

For the development of the activity recognition system for fitness trails, the first mandatory part will be to collect sufficient and representative data from sample runs of the scenario. This chapter shall give a detailed explanation on how the underlying experiments will work and what results are sought through the evaluation of the collected datasets.

2.2 Goals

- evaluating the user's acceptance regarding sensor setup and comfort at different positions
- analyzing potential sensor displacement during the fitness trail (e.g., caused by shifting) and possible consequences for accelerometer data
- collecting training and test datasets to extract good features needed for activity recognition and repetition counting

2.3 Fitness Trails

In order to have enough variety, two different fitness trails will be used: The first one is the "Bewegungsparcours Darmstadt" in the Bürgerpark, a rather new one with modern equipment but where all exercise positions are more or less at the same place. The second trail at the Ludwigsteich in Roßdorf is more traditional with an alternation between fitness exercise and running or walking to the next position (see the pictures of the different activities on the particular tracks at Figures A.1 and A.2).

2.4 Sensors

Since the activity recognition system will rely on the acceleration data measured by the worn sensors during the different exercises, a set of "HedgeHog"-sensors (`http://www.ess.tu-darmstadt.de/hedgehog`) will be used to collect off-line training data from which later on the best features will be extracted and evaluated.

2.5 Preliminary Constraints Regarding the Sensor Positions

Based on previous work ([1], [2], [3], [4], [5], [6], especially those addressing recognition of dynamic and athletic activity), for tracking different movements the following sensor positions (mostly combinations of two of those) were found to work quite well:

- wrist
- upper arm
- chest
- upper leg
- ankle

Hence, the focus will be to find out which combination of those sensor positions leads to the best trade-off between performance of the recognition and acceptance by the user.

2.6 Sensor Setup

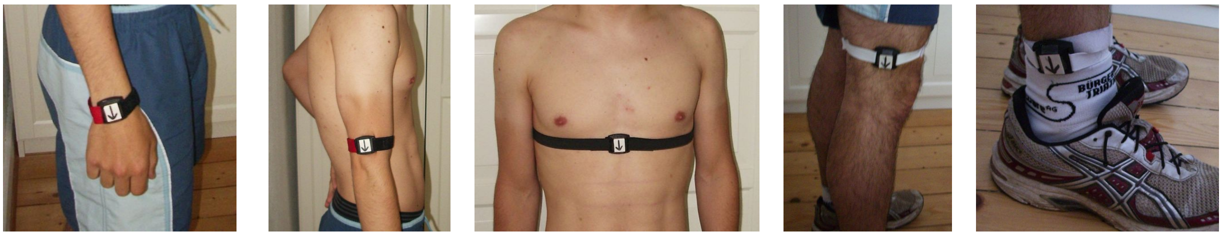
Three sensors with straps will be used, all of them marked with an arrow. The user will be told to put on the sensors on his/her own such that all arrows are pointing towards the bottom when standing still with the arms close to the body (see Figure 2.1).

During the first run, the combination of the positions will be:

- wrist 2.1(a)
- chest 2.1(c)
- ankle 2.1(e)

For the second run, the user will need to remove all sensors and wear them now at following positions:

- upper arm 2.1(b)
- chest 2.1(c)
- upper leg 2.1(d)



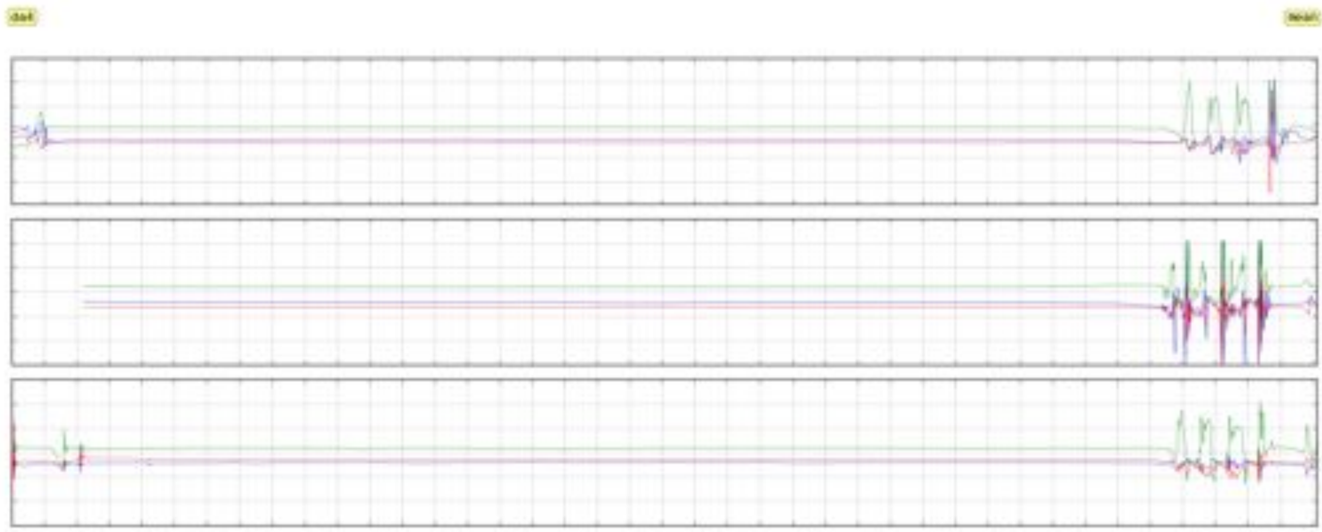
(a) wrist (b) upper arm (c) chest (d) upper leg (e) ankle

Figure 2.1.: Sensor positions

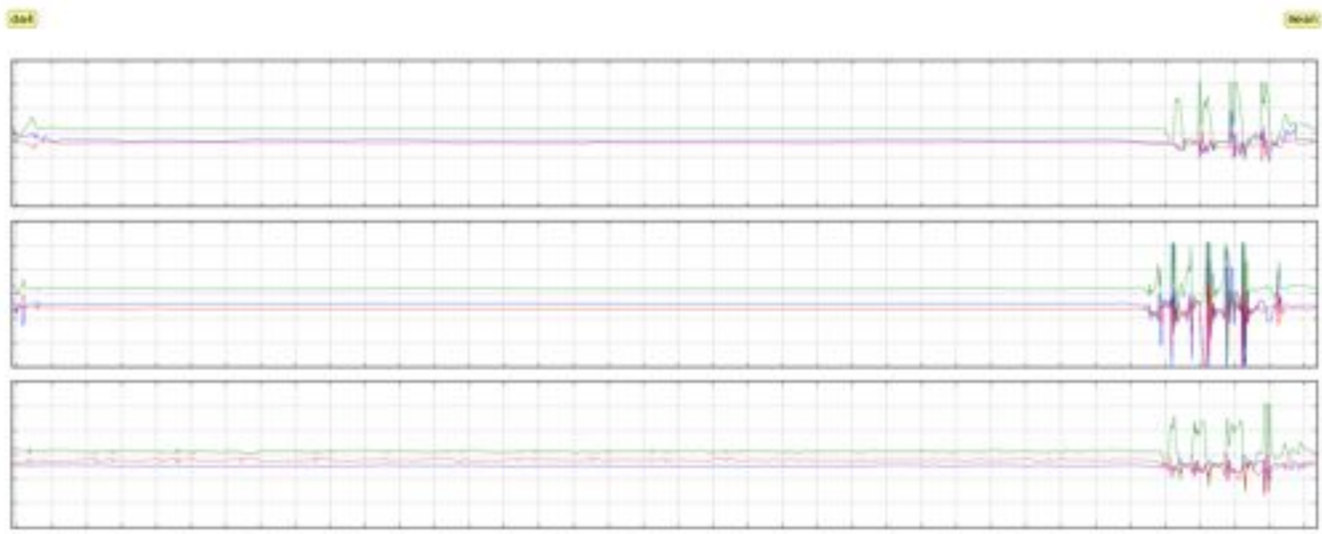
2.7 Synchronizing and Measure of Sensor Slipping

For the purpose of having characteristic accelerometer data for synchronizing the different sensors, both at the beginning and at the end the user will need to stand still for 30 seconds and then to jump three times. Further, this will allow to see the potential impact of slipped sensor positions while performing the fitness trail by analyzing the differences in the measured data of these characteristic movements between the beginning and the end.

Figures 2.2(a) and 2.2(b) show how this task looks like in the plots: the long horizontal lines are the measured inertia when the trainee stands still for 30 seconds. These are subsequently followed by the accelerations when the user jumps three times. The distinct peaks are pretty well synchronized and there is also only a small difference between the measurements before and after performing the track, meaning that there was no really significant sensor displacement while doing the different stations.



(a) 30 seconds standing still followed by three jumps **before** the parcourse



(b) 30 seconds standing still followed by three jumps **after** the parcourse

Figure 2.2.: Synchronizing and Measure of Sensor Slipping

2.8 Experiment Run

The users will be told to do the track consisting of the following activities:

- *running*
- 10x back stretching (Fig. A.1(a) and A.2(a))
- *running*
- 20x diagonal hand to foot moving (Fig. A.1(b) and A.2(b))
- *running*
- 5x pull-ups (Fig. A.1(c) and A.2(c))
- *walking*
- 10x abdominals (Fig. A.1(d) and A.2(d))
- *running*
- 10x alternate one-leg bench jumps (Fig. A.1(e) and A.2(e))
- *running*
- 20x torso turns (Fig. A.1(f) and A.2(f))
- *running*
- 10x squats (Fig. A.1(g) and A.2(g))
- *walking*
- 10x push-ups (Fig. A.1(h) and A.2(h))
- *running*

2.9 Evaluation of the User's Acceptance

The comfort rating of all sensor positions will rely on the methods presented in [7] and [8]. Therefore, the user will need to mark his/her level of agreement for each sensor position on a Likert-scale from 1 to 5 for each of the following questions:

- I feel self-conscious having people see me wear this device (Emotion)
- I feel the device moving on my body (Attachment)
- I feel some pain or discomfort wearing the device (Harm)
- I feel awkward or different wearing the device (Perceived Change)
- I feel that the device affects the way I move (Movement)
- I feel secure wearing the device (Anxiety)

Additionally, the user will be asked:

- for each sensor to rate how difficult it was to wear it (Likert-scale from 1 to 5)
- to give a ranking of the favorite combination of two sensors (name at least 3 different ones)
- to say whether they think the whole system is useful (Likert-scale from 1 to 5)
- to state under which constraints (e.g. maximal number of sensors or no-go positions) they would or would not use the system

Finally, just the following personal data will be collected, because the privacy of the test subjects has to be respected:

- age
- gender
- fitness level (scale from 1 to 5)

So while keeping the answers anonymized, having this extra information would still allow to investigate whether there is a correlation between the provided responses and, for instance, the fitness level.

3 Evaluation of the Datasets

3.1 Activity Recognition

For the detection of the different activities, an approach calculating basic statistics from the time series of the accelerometer data over a sliding window will be used. Thus, the most distinct features for characterizing the activities in a distinct way have to be determined. As previous work ([2], [5], [9] or [10]) has shown that the features mean, variance, maximum and minimum seem to work quite well for distinguishing dynamic movements, the focus will rest upon finding the best window size and the optimal combination of features and sensors while keeping those rather simple statistical terms, that are easy to calculate.

The performance of the different parameters will be evaluated with the “cluster precision” methods presented in [10] and [11]. The main principle of this approach is to assess the parameters leading to the highest cluster precision, meaning that each cluster nearly contains only feature vectors of the same class (i.e. the clusters provide a good separability of the different activities).

The evaluation goes like this: the clustering is done with k-means using a five-fold cross-validation, for which the dataset is divided into five partitions of equal size. Four partitions are used as training data for learning the cluster-centroids and the remaining one serves as test set, where the clustering of each feature vector is done by assigning it to the nearest centroid. Now the precision of these activities can be computed by first measuring the distribution of feature vectors for different activities within the clusters. This is done by calculating the following fraction for each cluster i and activity j:

$$p_{i,j} = \frac{\left|C_{i,j}\right|}{\sum_j \left|C_{i,j}\right|} \tag{3.1}$$

where $\left|C_{i,j}\right|$ is the number of vectors in cluster i labeled with activity j.

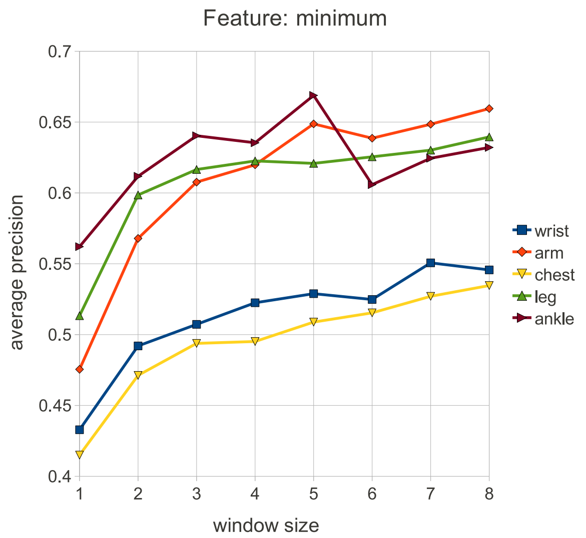
Then the cluster precision p_j for activity j is obtained by computing the weighted sum of these fractions:

$$p_j = \frac{\sum_i p_{i,j} \left|C_{i,j}\right|}{\sum_i \left|C_{i,j}\right|} \tag{3.2}$$

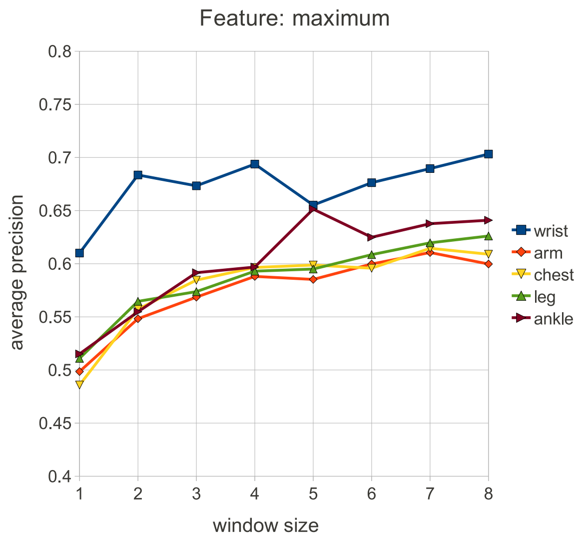
This weighted sum can then be used to compare different parameters and optimize the choices of their values in order to get clusters with a high precision p_j, leading to a clear separability of the distinct activities and subsequently hints at a good recognition later on, using these data and features.

3.1.1 Results of the cluster precision analysis

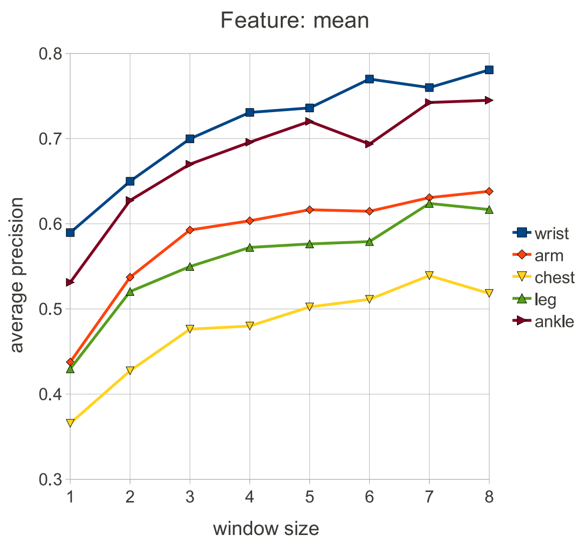
The first step consists of finding good values for the window size, that can be applied during the subsequent feature analysis. As the duration for performing some of the activities does not exceed 8 seconds, this will be the maximal value for the window size that will be considered. For the features minimum, maximum, mean and variance, Figure 3.1 shows the average cluster precision with increasing window size. As further evaluation possibly will influence the value for the optimal window size, for the next steps two different sizes will be kept: 3 seconds as this is the minimum window with an acceptable average cluster precision, and 5 seconds as this is the current overall best value.



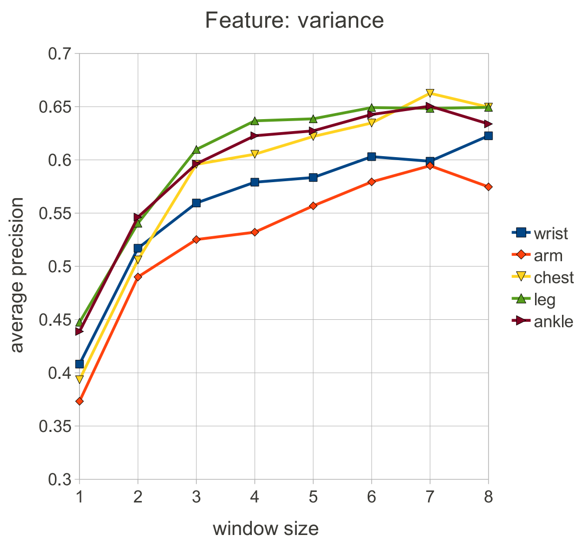
(a) Feature: minimum



(b) Feature: maximum



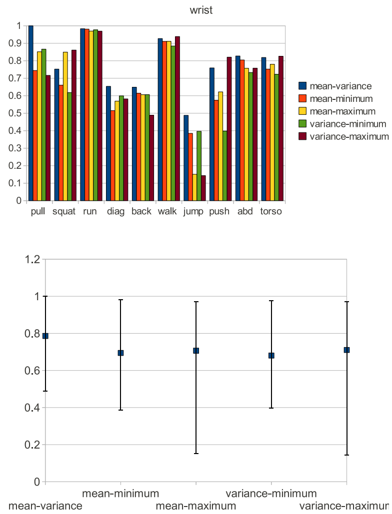
(c) Feature: mean



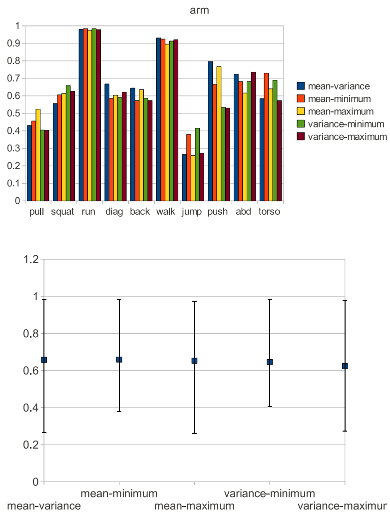
(d) Feature: variance

Figure 3.1.: Average cluster precision with increasing window size for the different sensor positions

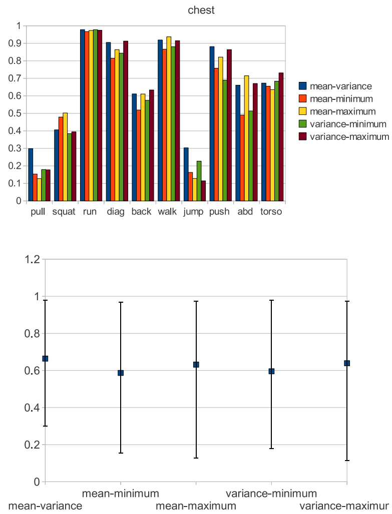
As a next step the best features need to be fixed by comparing the cluster precision for the pairs mean-variance, mean-minimum, mean-maximum, variance-minimum and variance-maximum. Figures 3.2 and 3.3 show the impact of the different feature pairs for each sensor position, with a window size of 3 or 5 seconds respectively. Especially when looking at the averaging plots below the detailed ones, one can see that the optimal feature pair is mean-variance, so these are the features that will be taken from now on.



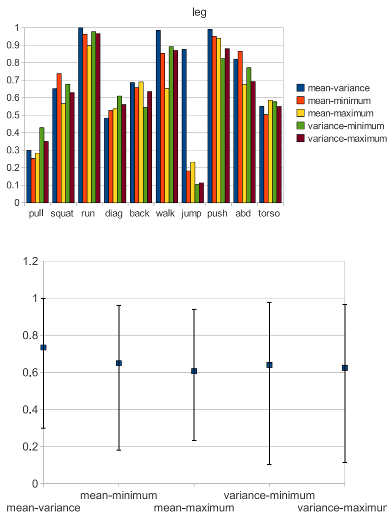
(a) Sensor position: wrist



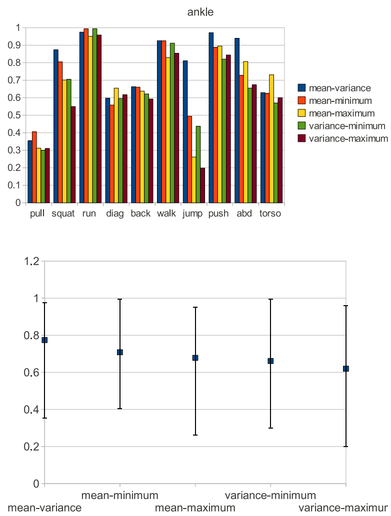
(b) Sensor position: arm



(c) Sensor position: chest

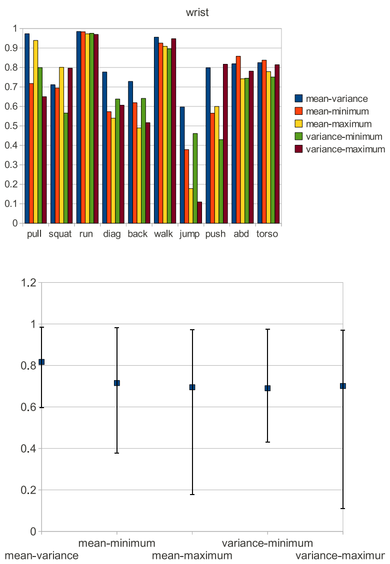


(d) Sensor position: leg

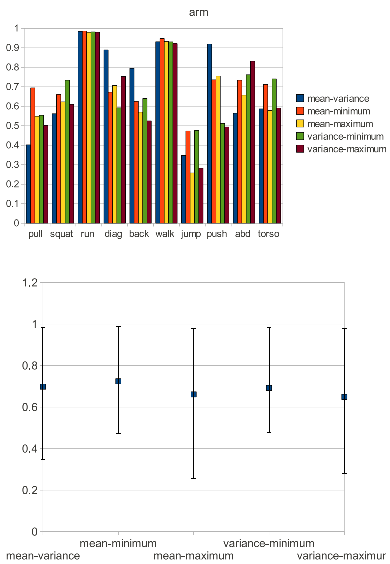


(e) Sensor position: ankle

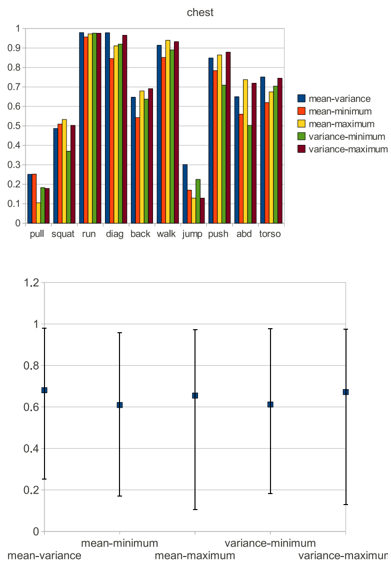
Figure 3.2.: Cluster precision for the different feature pairs with a window size of 3 seconds



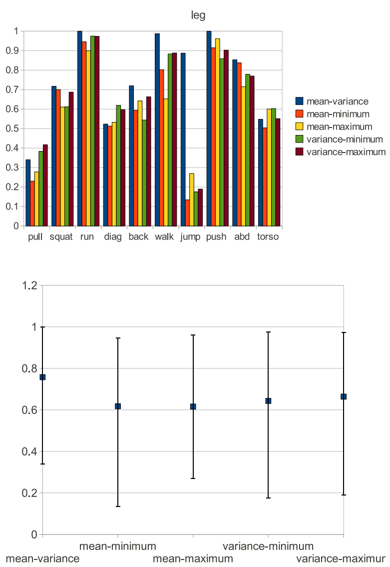
(a) Sensor position: wrist



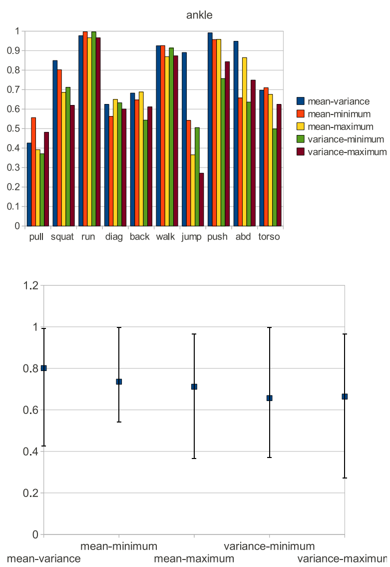
(b) Sensor position: arm



(c) Sensor position: chest



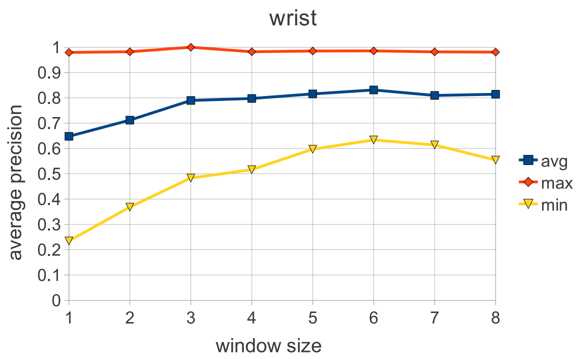
(d) Sensor position: leg



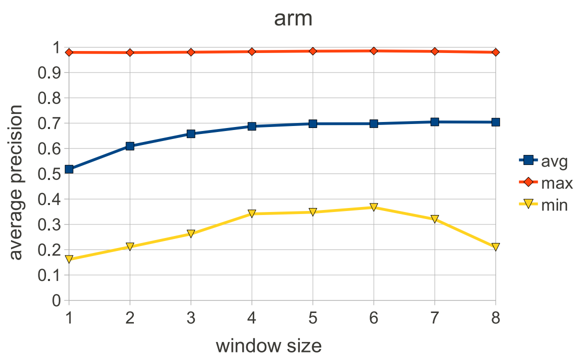
(e) Sensor position: ankle

Figure 3.3.: Cluster precision for the different feature pairs with a window size of 5 seconds

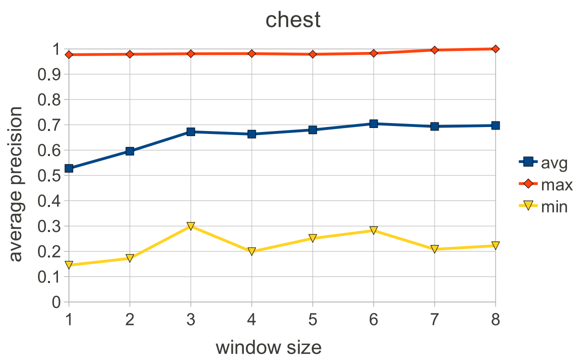
Now, with the features being set to mean-variance, the effect of an increasing window size on the cluster precision will again be analyzed. The results for each sensor position are shown at Figure 3.4 and lead to refine the choices of the optimal window size to the following values: 3 seconds as a minimum value with acceptable precision, and 6 seconds as the current overall best. The main benefit of continuing the evaluation with both window sizes (instead of just keeping the optimal one) is due to the fact that small windows are convenient for systems with small memory and computation resources, therefore it is important to consider them as well.



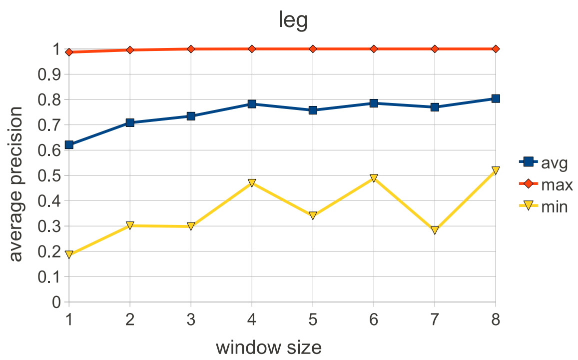
(a) Sensor position: wrist



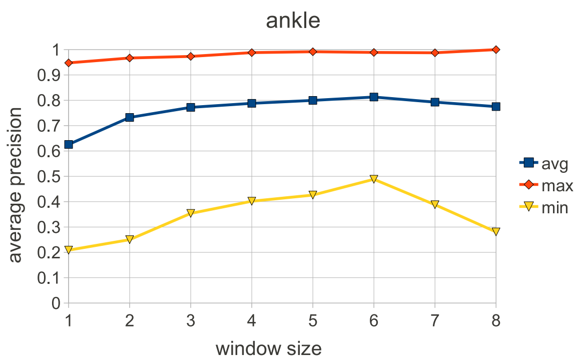
(b) Sensor position: arm



(c) Sensor position: chest



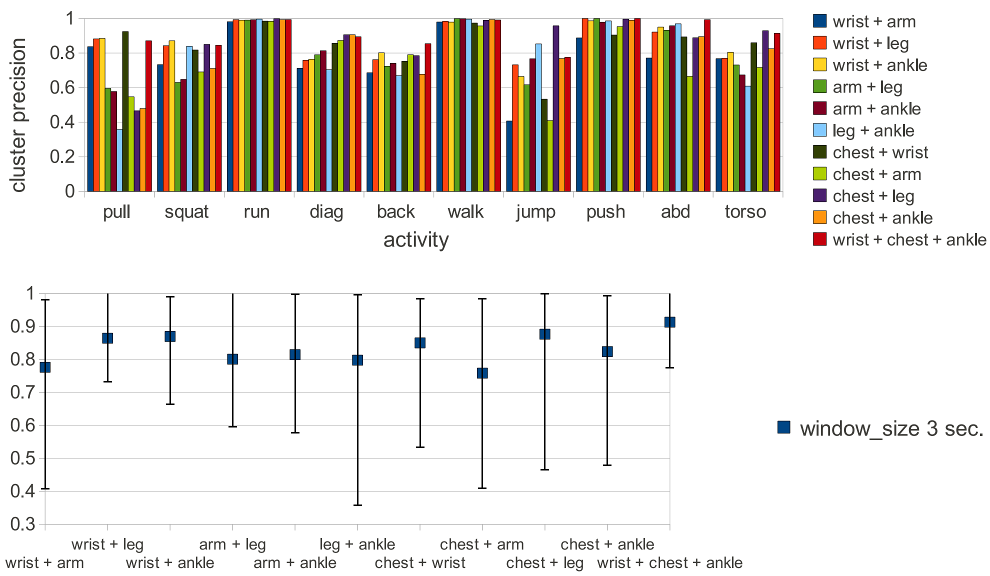
(d) Sensor position: leg



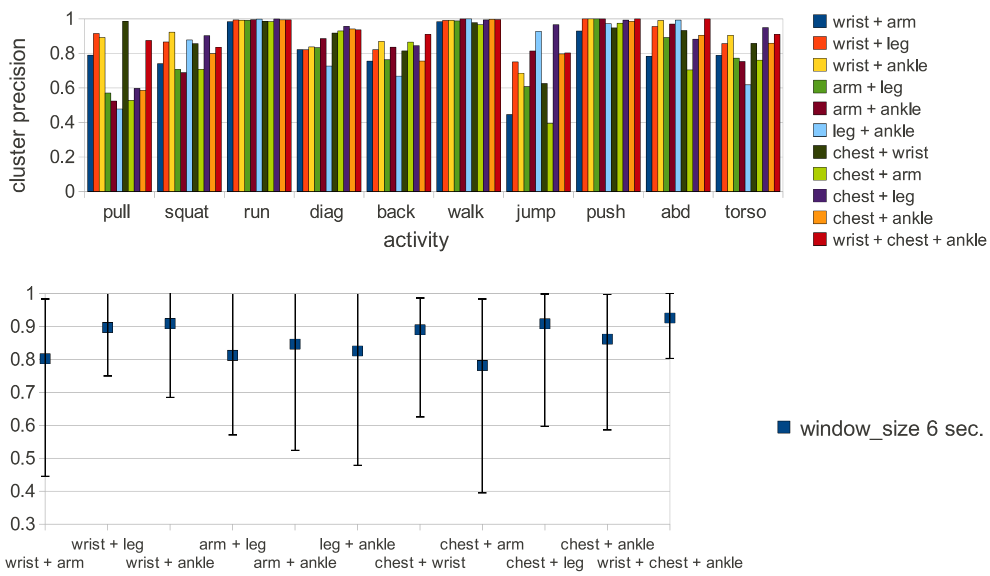
(e) Sensor position: ankle

Figure 3.4.: Average cluster precision with increasing window size for mean-variance feature vectors

The next step will be the determination of the sensor combinations that perform best for detecting the different activities. This is done by calculating the cluster precision of the different activities for each combination of sensor positions (wrist-arm, wrist-leg, wrist-ankle, arm-leg, arm-ankle, leg-ankle, chest-wrist, chest-arm, chest-leg, chest-ankle, wrist-chest-ankle). Both for a window size of 3 and 6 seconds, when looking at the averaging plots of Figure 3.5 below the detailed ones, the overall optimal positions are wrist-ankle and wrist-chest-ankle, so these sensor combinations will be selected for the activity recognition.



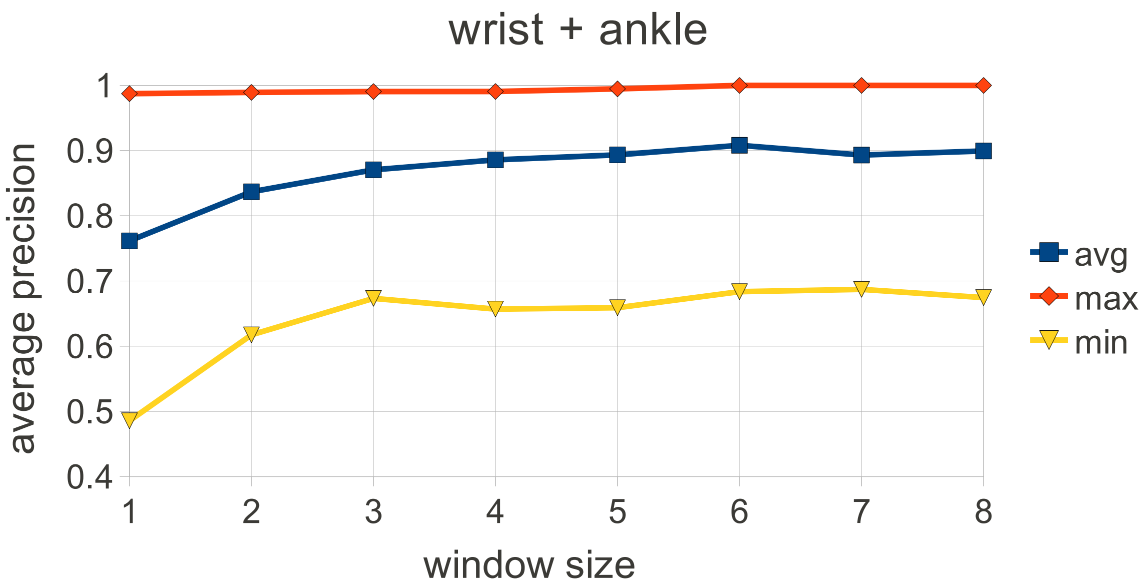
(a) Window size: 3 seconds



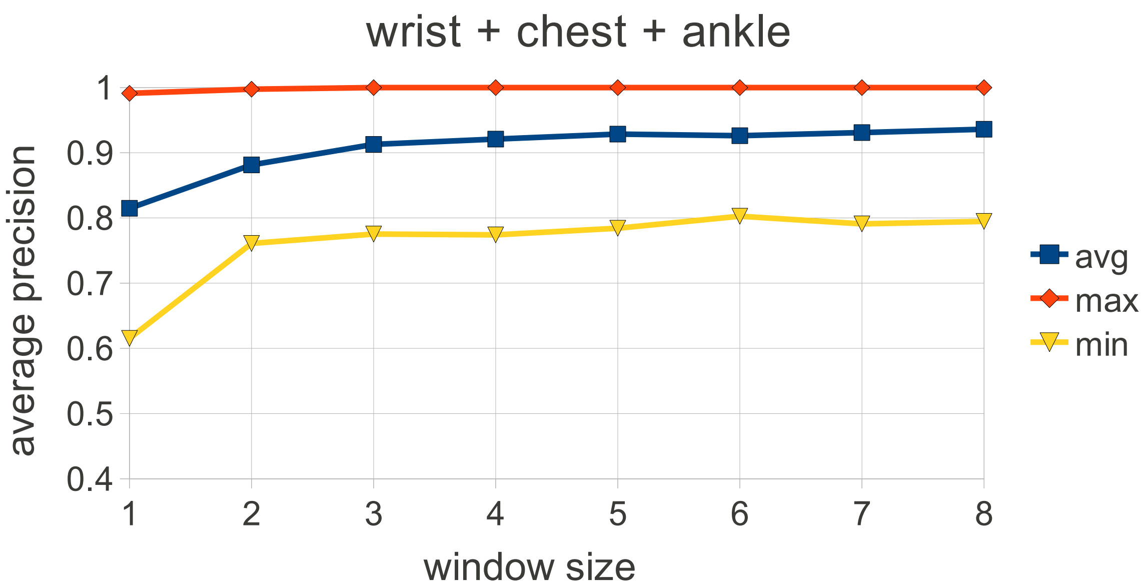
(b) Window size: 6 seconds

Figure 3.5.: Cluster precision for the different sensor combinations

After having fixed the optimal combinations of sensor positions, the cluster precision dependence on an increasing window size is evaluated one more time in order to set the window size to the best value when all other parameters are chosen like described above. Figure 3.6 suggests to refine the window size one more time to a value of 4 seconds, because this is the minimal length with an acceptable cluster precision (shortest window size with approx. 90% average precision in both cases). So this leads to a good tradeoff between a performant activity extraction and a short window length, that is favorable for small memory and computation resources.



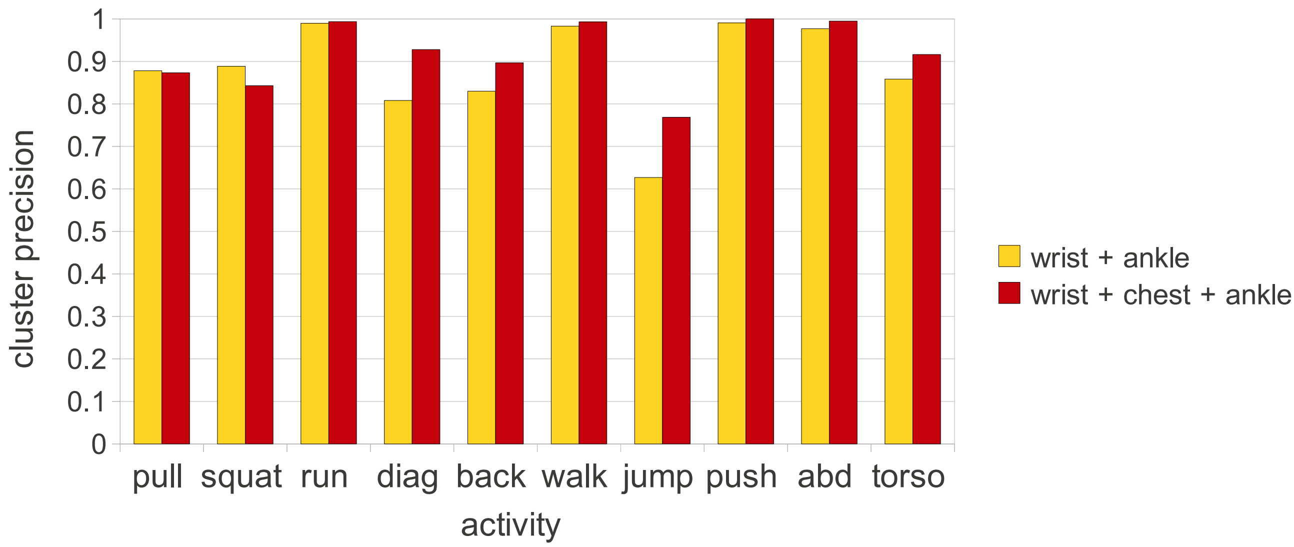
(a) Sensor combination: wrist-ankle



(b) Sensor combination: wrist-chest-ankle

Figure 3.6.: Average cluster precision with increasing window size for the best sensor combinations

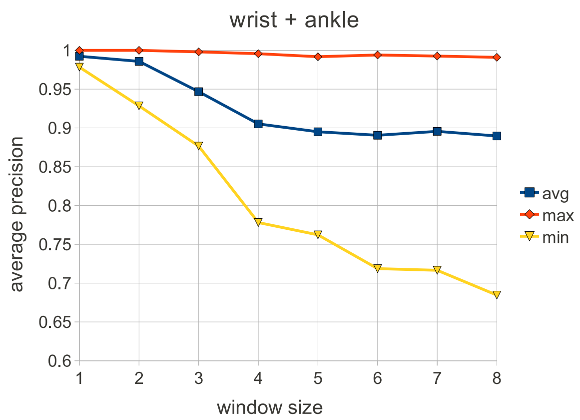
Finally, for both best sensor combinations wrist-ankle and wrist-chest-ankle and with a window size of 4 seconds and with mean-variance feature vectors, Figure 3.7 demonstrates that these parameters work quite well for recognizing the different activities, as the resulting cluster precision almost always is above 80%.



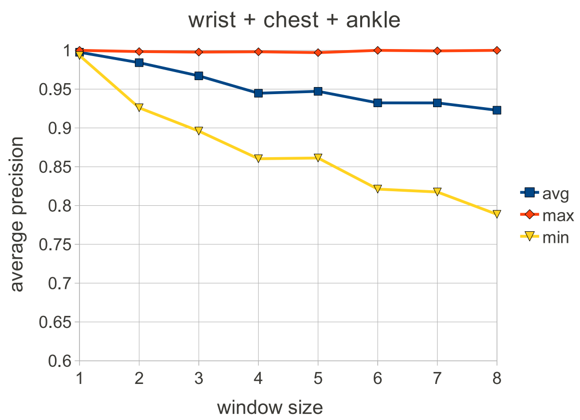
(a) Sensor combinations: wrist-ankle and wrist-chest-ankle

Figure 3.7.: Resulting cluster precision for each activity with mean-variance feature vectors and a window size of 4 seconds

The fact that the average cluster precision with the assessed parameters from above seem to converge with increasing training and test data, indicates that probably the number of test subjects is sufficient for this preliminary analysis, even if of course more data is always good for claiming strong results from an evaluation of a user's case study. Beyond that, a higher number of users would probably help in being more robust against outlier participants.



(a) Sensor combination: wrist-ankle



(b) Sensor combination: wrist-chest-ankle

Figure 3.8.: Convergence of the average cluster precision with increasing number of datasets

3.2 Repetition Counting

As a visual analysis of the collected data has shown that the number of repetitions within an activity is highly correlated to the measured data from the sensors, and due to the fact that previous work ([1], [2]) also used peak-detection algorithms for solving a similar issue, the general idea will be to count repetitions by finding the significant peaks in the acceleration of the different sensors along the dominating axes.

Since in the previous section the best sensor positions for the activity recognition have been determined to be wrist, chest and ankle, only these ones will be used for trying to count repetitions appropriately. The other sensor positions arm and leg will not be evaluated.

The algorithm for finding the global minima and maxima of the accelerometer data for a specific axis is adapted from `http://billauer.co.il/peakdet.html` and described at Alg. 1. The parameters to be adapted are highlighted in red and describe the following:

- $delta\_val$ → the least difference in the acceleration values between a maximum and a minimum
- $delta\_time$ → the least time difference between two peaks.

In a first step, for each activity (except running and walking) the dominating axes on every sensor's data have to be figured out. For this both prior knowledge and plots of the measured accelerations will be used. For instance, the ankle-sensor can be neglected for counting repetitions of activities where one has to be standing on the ground without moving the feet (e.g. back-stretching). Furthermore, the two different trails in Darmstadt or Roßdorf will be evaluated separately, because the activities sometimes have to be performed differently, depending on the actual equipment (e.g. abdominals).

Afterwards, for these characteristic axes the parameters of the algorithm will be optimized in order to find the best recognition of those peaks that correlates with a single repetition of an activity. Possibly the choice of the best sensors and axes for counting the repetitions of a specific activity will also be refined during this evaluation.

Preliminary runs of a prototype implementation have already lead to surprisingly good results, that, at least for this evaluation, encourages not to use additional preprocessing filters, because the noisy acceleration data (mostly due to human impreciseness or trembling while performing the different activities) seems to be generalized quite well already with this rather simple algorithm.

Algorithm 1 Peak-Detection Algorithm

Input: $time\_series$ of (t, a)-pairs ▷ t: timestamp, a: acceleration
Output: lists max_list and min_list of (t, a)-pairs with maxima and minima

```
Initialization
max_val ← −∞                                   ▷ last maximum acceleration value
max_time ← 0                                   ▷ last maximum time position
min_val ← +∞                                   ▷ last minimum acceleration value
min_time ← 0                                   ▷ last minimum time position
lookformax ← true
max_list ← [ ]                                 ▷ [ ]: empty list
min_list ← [ ]

Iteration
for i = 1 → length(time_series) do
    cur_val ← time_series.a[i]                 ▷ current acceleration value
    cur_time ← time_series.t[i]                ▷ current time position

    if cur_val > max_val then
        (max_val, max_time) ← (cur_val, cur_time)
    end if
    if cur_val < min_val then
        (min_val, min_time) ← (cur_val, cur_time)
    end if

    if lookformax is true then
        diff ← (cur_time − max_time)
        if cur_val < (max_val − delta_val) and diff > delta_time then
            max_list.append{(max_time, max_val)}
            (min_val, min_time) ← (cur_val, cur_time)
            lookformax ← false
        end if
    else
        diff ← (cur_time − min_time)
        if cur_val > (min_val + delta_val) and diff > delta_time then
            min_list.append{(min_time, min_val)}
            (max_val, max_time) ← (cur_val, cur_time)
            lookformax ← true
        end if
    end if
end for
```

3.2.1 Visual Evaluation of the Acceleration Data

After having evaluated the graphical plots of the measured accelerations, Table 3.1 shows for each activity the most promising sensors and axes that will be considered in the further evaluation of the repetition counting.

Table 3.1.: Most promising sensors and axes for repetition counting after visual evaluation

activity	Roßdorf	Darmstadt
back stretching	wrist: x/y/z , chest: y/z	wrist: x/y/z , chest: y/z
diagonal hand to foot moving	wrist: x/y/z , chest: x/y/z	wrist: x/y/z , chest: x/y/z
abdominals	wrist: y , chest: y/z	ankle: y
torso turns	wrist: x/y/z	wrist: y/z , chest: x
squats	wrist: y/z , ankle: x/y/z , chest: y/z	wrist: z , chest: y/z
push-ups	wrist: x , chest: z	wrist: x/z , chest: z

An illustration how this analysis has been done can be found at Figure 3.9, showing squats in Darmstadt: the three subplots are the inertia of the wrist, ankle and chest sensors respectively. The blue lines are the accelerations in x-direction, the green ones the accelerations in y and the red lines in z-direction.

One can see that for the wrist-position the red z-acceleration and that for the chest the green y and the red z-acceleration have all ten regularly distributed maxima and minima, while the other ones do not have the same kind of a characteristic frequency. Therefore, those axes are expected to be the most appropriate ones for counting this specific activity.

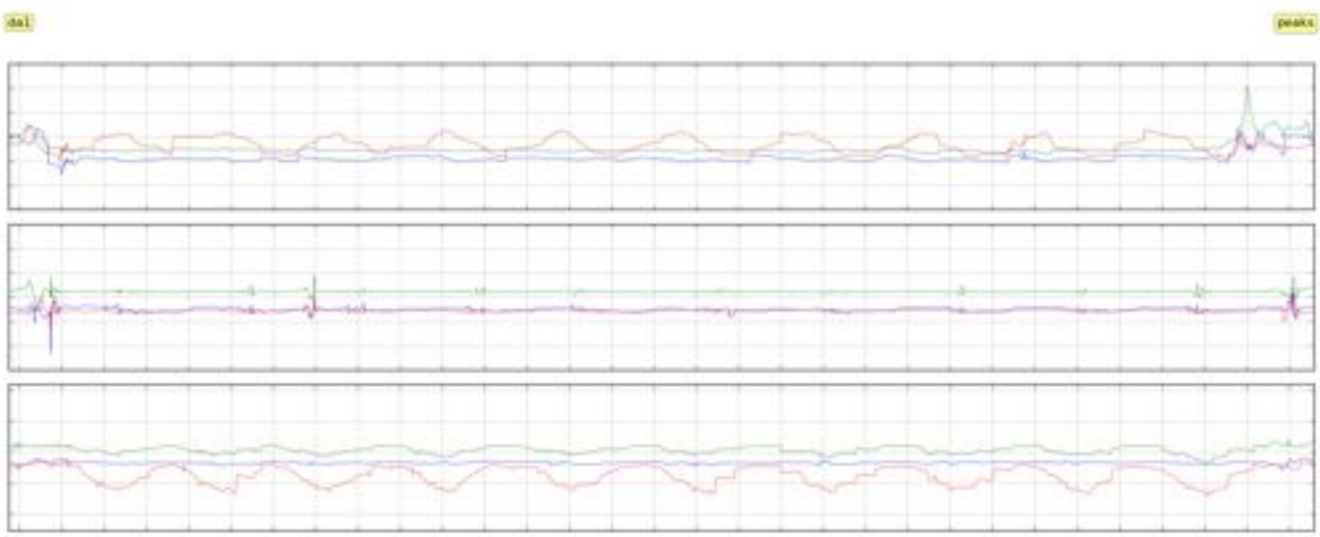


Figure 3.9.: Raw sensor data for squats in Darmstadt

Note that for the next steps the activities “pull-ups” and “alternate one-leg bench jumps” will be left out, because there were no recognizable similarities in the measured accelerations of how the different users performed this action. Further evaluation of different approaches would probably be needed in order to be able to count the number of movements for these specific activities.

3.2.2 Optimization of the Parameters

As already mentioned before, the parameters of the algorithm that need to be optimized are:

- $delta\_val$ → the least difference in the acceleration values between a maximum and a minimum
- $delta\_time$ → the least time difference between two peaks.

The first parameter $delta\_val$ actually will not be optimized directly, but computed according to:

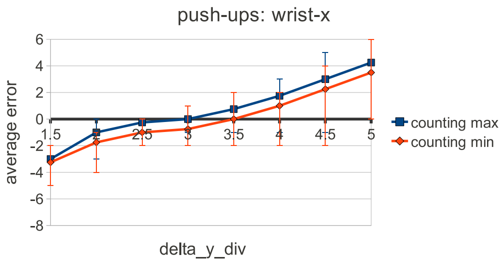
$$delta\_val = \frac{\max(time\_series.acceleration) - \min(time\_series.acceleration)}{delta\_y\_div} \tag{3.3}$$

so eventually the best value for the parameter $delta\_y\_div$ (controlling which proportion of the overall distance between the highest and the lowest acceleration value has to be the least difference between a maximum and a minimum) will need to be determined instead.

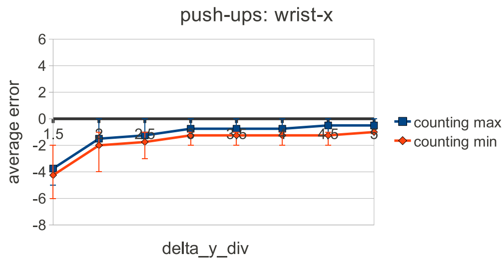
In order to optimize the parameters, plots showing the average difference between the actual number of repetitions and the computed one dependent on the factor $delta\_y\_div$ will be used, with different fixed values for the parameter $delta\_time$ (blue: counting the detected maxima, red: counting the detected minima).

First, the optimal value for the parameter $delta\_time$ is figured out by comparing the resulting plots for $delta\_time$ varying between 0.1 and 1.5 seconds. It turns out that a value of 0.5 seconds is the overall best for an accurate counting, and furthermore a low value for this parameter helps keeping the window small.

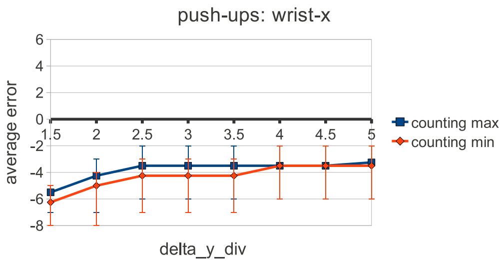
Figure 3.10 provides a representative example of this process: the comparison of counting push-ups in Roßdorf with the acceleration in x-direction of the wrist sensor has the least average error when $delta\_time$ is 0.5 seconds, regardless of the value for $delta\_y\_div$.



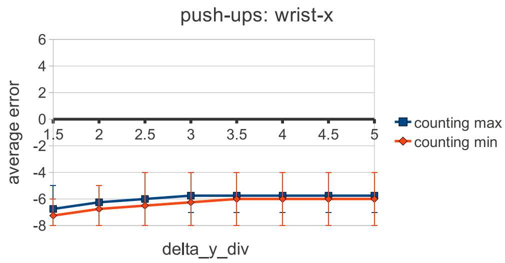
(a) $delta\_time$ = 0.1 seconds



(b) $delta\_time$ = 0.5 seconds



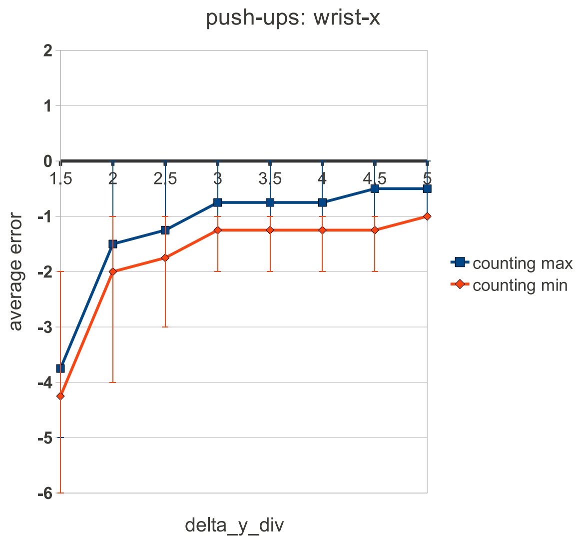
(c) $delta\_time$ = 1.0 seconds



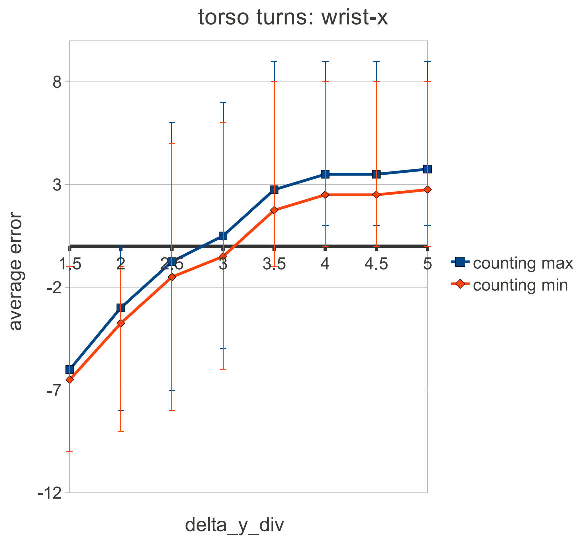
(d) $delta\_time$ = 1.5 seconds

Figure 3.10.: Average error when counting push-ups in Roßdorf with wrist sensor acceleration in x-direction

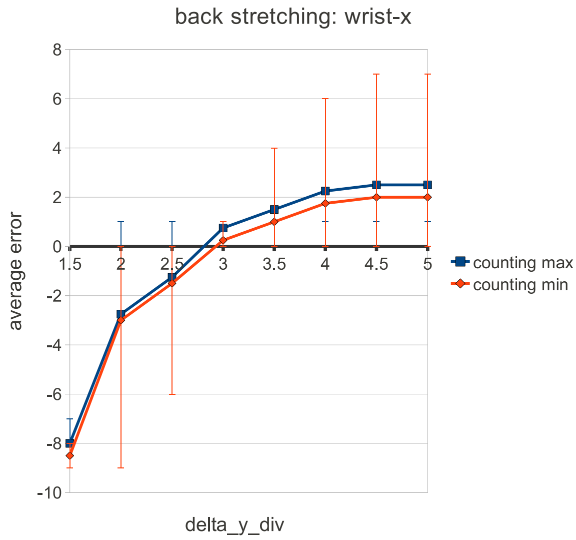
Next, with $delta\_time$ fixed to 0.5 seconds, the best value for the factor $delta\_y\_div$ (determining the parameter $delta\_val$) has to be evaluated. Figures 3.11 and 3.12 illustrate the effect of increasing $delta\_y\_div$ when counting the repetitions of different activities at both tracks. Altogether it seems that a value of 3 for $delta\_y\_div$ is most appropriate, leading to the least average error in the repetition counts.



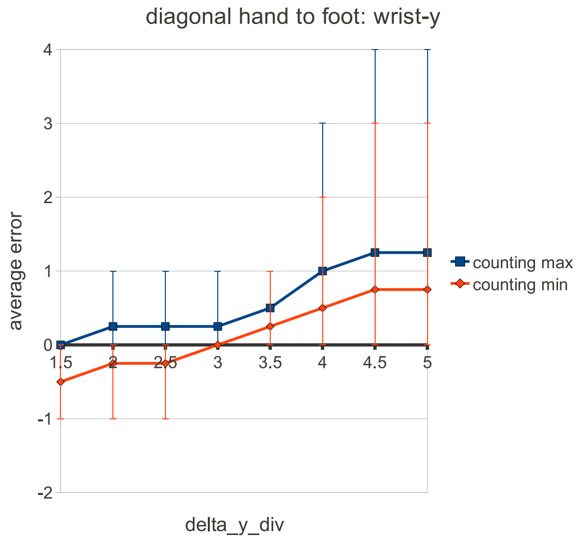
(a) Push ups: x-axis on wrist sensor



(b) Torso turns: x-axis on wrist sensor

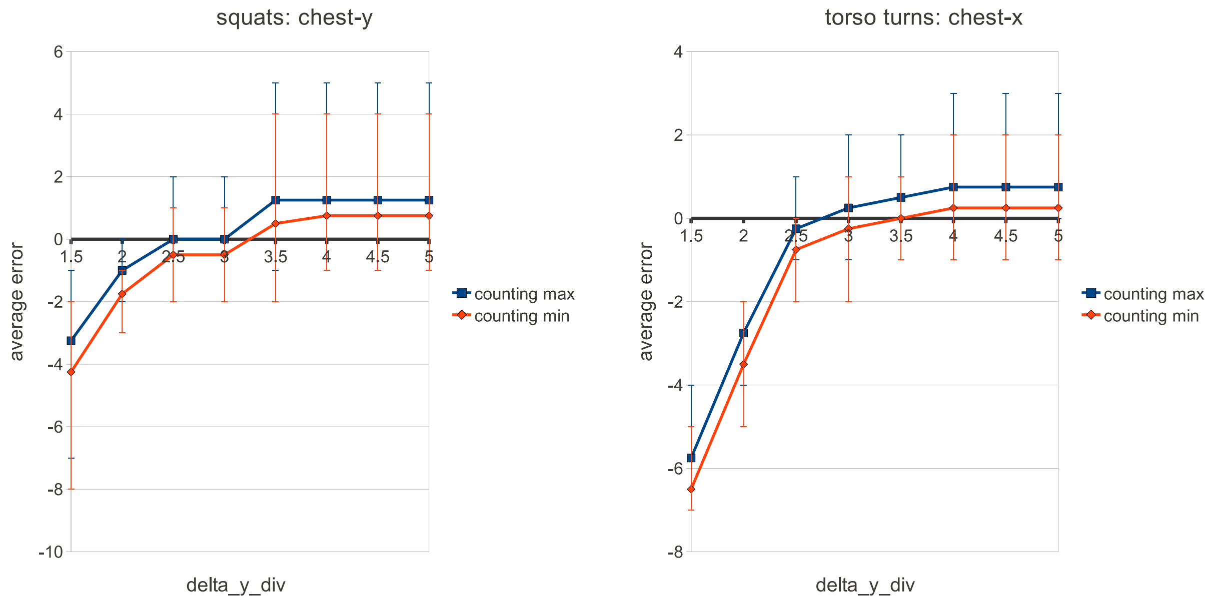


(c) Back stretching: x-axis on wrist sensor

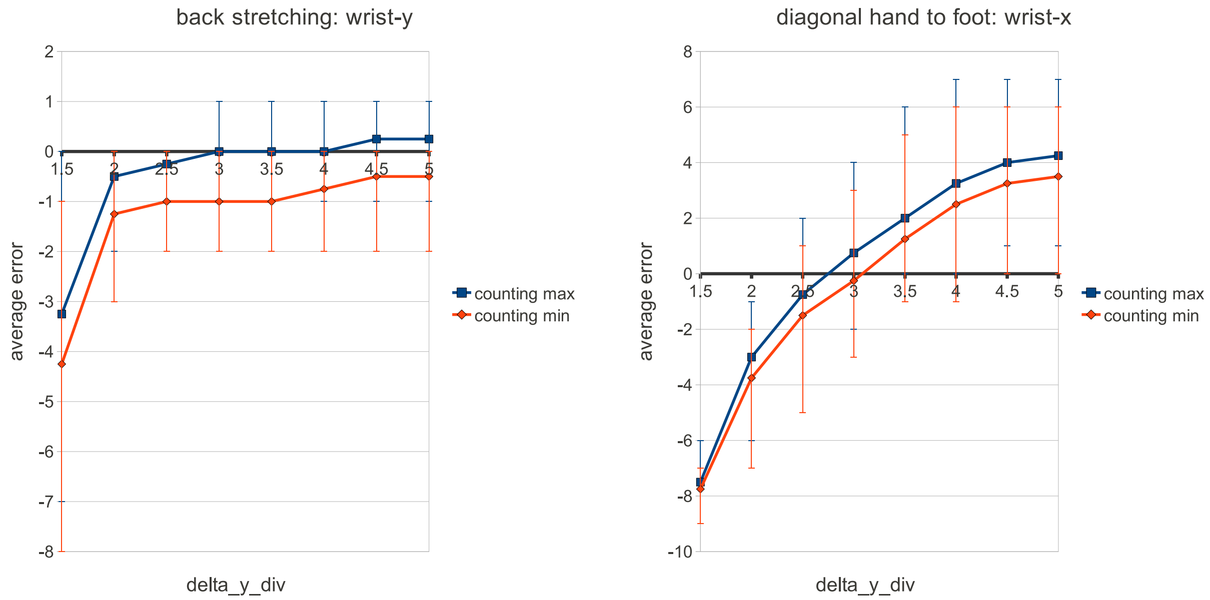


(d) Diagonal hand to foot moving: y-axis on wrist sensor

Figure 3.11.: Effect of increasing $delta\_y\_div$ for counting repetitions in Roßdorf



(a) Squats: y-axis on chest sensor (b) Torso turns: x-axis on chest sensor



(c) Back stretching: y-axis on wrist sensor (d) Diagonal hand to foot moving: x-axis on wrist sensor

Figure 3.12.: Effect of increasing $delta\_y\_div$ for counting repetitions in Darmstadt

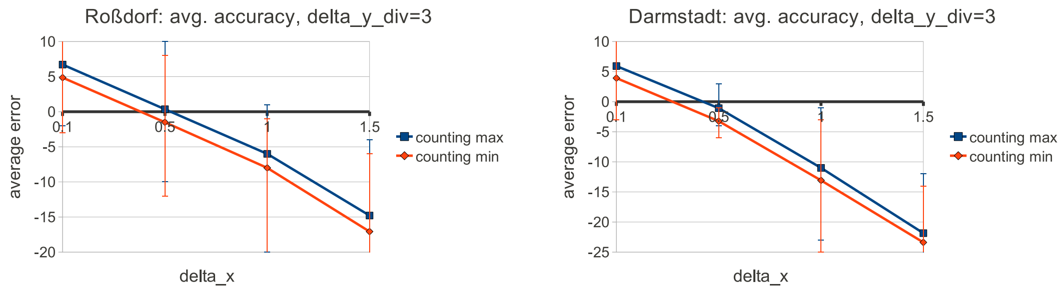
Now, after having determined the optimal values for the parameters, for each activity the best sensors and axes can be fixed by choosing those having the least average error when counting the repetitions. Table 3.2 shows the resulting selection of sensors and axes.

Table 3.2.: Best sensors and axes for repetition counting after parameter optimization

activity	Roßdorf	Darmstadt
back stretching	wrist: x/y , chest: z	wrist: y/z , chest: z
diagonal hand to foot moving	wrist: y/z , chest: x	wrist: x/y , chest: x
abdominals	wrist: y , chest: z	ankle: y
torso turns	wrist: y/z	wrist: z , chest: x
squats	wrist: y , ankle: y , chest: z	wrist: z , chest: y
push-ups	wrist: x , chest: z	wrist: z , chest: z

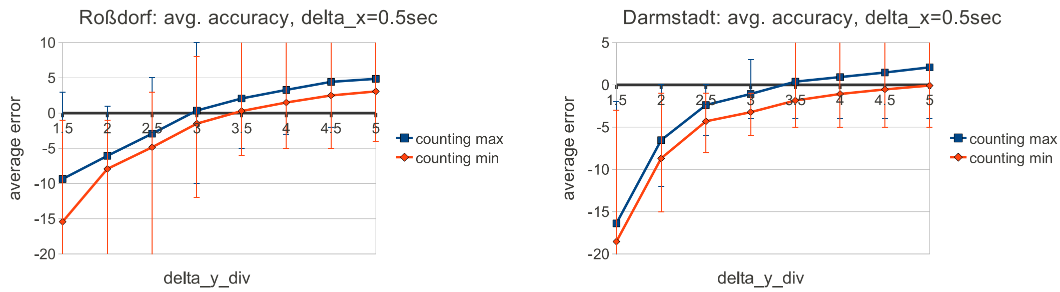
Indeed, the algorithm with the determined parameters described above leads to a good correlation between the detected peaks in the acceleration and the corresponding repetition counts, when using the selected sensors and axes. For both fitness trails, the resulting repetition counts through peak-detection for every activity is visualized in the Figures B.1, B.2, B.3 and B.4.

Finally, Figures 3.13 and 3.14 show the average accuracy of the counted repetitions for both Roßdorf and Darmstadt, when varying either $delta\_y\_div$ or $delta\_time$ while letting the other one fixed at its best value. The plots confirm that the best average accuracy is reached if $delta\_time$ is set to 0.5 seconds and $delta\_y\_div$ equals 3.



(a) Counting in Roßdorf (b) Counting in Darmstadt

Figure 3.13.: Average accuracy when varying $delta\_time$



(a) Counting in Roßdorf (b) Counting in Darmstadt

Figure 3.14.: Average accuracy when varying $delta\_y\_div$

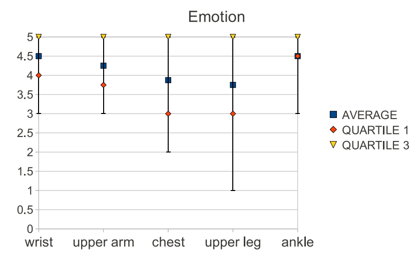
4.1 Test Subjects

Each track has been performed by four different persons: Two of them were female subjects and the remaining six were male. Overall six persons had an age of $\sim$ 22 and two were $\sim$ 50 years old. Three persons had a low fitness level, three were regularly exercising users and also two high-performance athletes performed the trails.

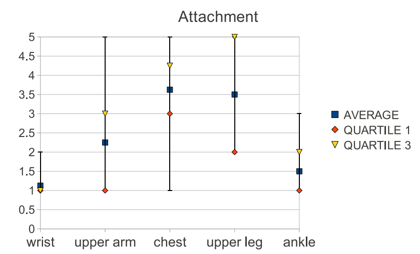
4.2 Comfort of Wearables according to Knight et al. [7]

The first important result regarding the comfort assessment is that for each sensor the question "I feel secure wearing the device" has always been answered with a "1" (i.e. "I do not agree at all"). Furthermore, some of the users mentioned that this question concerning "anxiety" is not relevant in this whole context, as the sensors are not providing any additional assurance while performing the activities. Hence, this dimension will not be considered for rating the comfort of the different sensor positions.

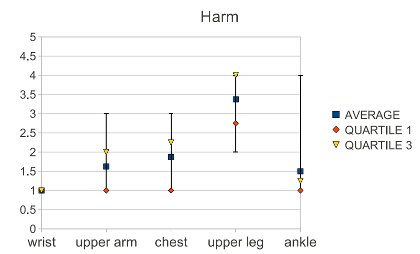
For the remaining comfort dimensions Figure 4.1 shows the average value (surrounded by the 0.25 and 0.75 quartiles) that the users provided on the five-point Likert-scale for every sensor position. One can clearly see that overall the wrist and ankle positions seem to be accepted best. Additionally, especially the attachment and the convenience of the sensors should be improved, because these aspects have been rated worst.



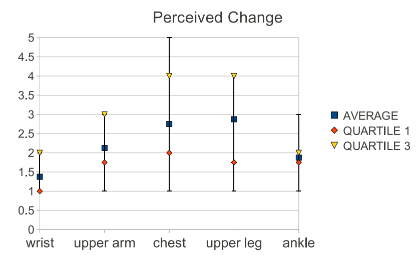
(a) I feel self-conscious having people see me wear this device



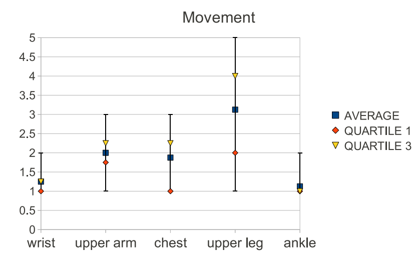
(b) I feel the device moving on my body



(c) I feel some pain or discomfort wearing the device



(d) I feel awkward or different wearing the device



(e) I feel that the device affects the way I move

Figure 4.1.: Comfort rating evaluation

4.3 Further Results of the Questionnaire

Regarding the difficulty of wearing the sensors, Figure 4.2 demonstrates that at least the chest and the upper arm seem to be a bit more complex to attach. Thus, the current system using simple straps should be improved for helping the user with putting on the sensors.

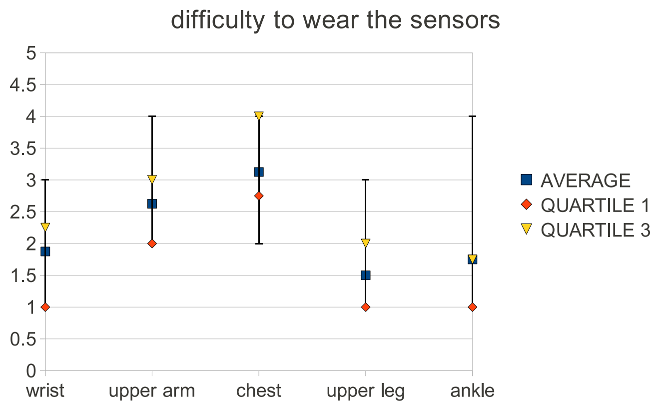


Figure 4.2.: Difficulty to wear the sensors

Concerning the favorite sensor combinations, 100% of the users have chosen “wrist/ankle” as their preferred one. This combination is followed by “chest/ankle”, “upper arm/ankle” and “wrist/chest”. So surprisingly, this fits quite well with the sensor positions that have been determined to work best in the previous chapter.

The maximal number of accepted sensors varies between two and four, but the fact whether the sensors hurt or not has been stated as much more important regarding the decision whether the test subjects would use the system or not. Therefore, the development of a comfortable sensor attachment should clearly be a main point of interest when creating a concrete setup, in order to mitigate the risk that the system would not be adopted, which would defeat the objective of the whole study work.

Another point worth to mention is that most of the regularly exercising users stated that they would not make use of this system for their own, as they rather “prefer to train by instinct”. Only high-performance athletes could imagine to possibly use this additional information if it could help them to revise and enhance their training results when doing the track.

Nevertheless, many test subjects said that instead of rather “uninteresting” repetition counts, they would be much more interested in getting feedback whether they perform the movements correctly. So further investigation in learning to differ “good” from “bad” or “unhealthy” moves could maybe lead to a system that is more motivating, as it could help the athlete to correct the way of doing the fitness trail on his/her own.

Last but not least, it is important to note that this case study probably needs many more users in order to claim strong results.

5 Conclusions

The aim of the thesis was to do primary research required before a future development of a training assistant for fitness trails. This report described the realization of the case study and the acquired insights through the evaluation process. Since the results eventually will be used for extending *myHealthAssistant*, the conclusion will start by summarizing the general results obtained during the thesis and finish by giving some recommendations for an implementation of an actual system.

5.1 Summary and Consequences of the Study

The activity recognition seems to work best for mean-variance feature vectors calculated over a sliding window of 4 seconds. If using just two different sensors, the most appropriate combination would be wrist-ankle. These sensors are also the most accepted ones regarding the comfort rating. Working with three sensors can increase the precision of the recognized movements: in this respect, the wrist-chest-ankle combination was determined to be the optimal one. But especially the chest sensor tends to lower the users' acceptance of using such a system. Hence, the improvement of the sensor attachment and comfort should be a main topic for further investigation.

For counting the repetitions within an activity, the "Peak-Detection Algorithm" Alg. 1 is expected to provide encouraging results. The best accuracy should be reached when setting the parameter $delta\_time$ to a value of 0.5 seconds and computing the parameter $delta\_val$ according to Eq. 3.3 with $delta\_y\_div$ being set to 3. For the distinct activities done on a specific track, Table 3.2 shows along which sensors and dominating axes the numbers of movements should be counted.

Beside this repetition counting, an important result of the case study was that many users stated to be more interested in a system correcting their way of performing the movements. Thus, a more in-depth study in distinguishing "good" from "bad" or "unhealthy" moves could really be worth it, leading to a motivating digital training assistant.

5.2 Outlook: Suggestions for the Deployment onto a Concrete System

The following indications have solely arisen from the whole evaluation process described above and have not been tested further on any prototype implementation.

As both the sliding window approach for getting the mean-variance feature vectors and the peaks detection algorithm are not highly complex, they should directly run on the sensors. This could help reducing the amount of data as well as the frequency rate the sensors have to send to the mobile device, because for every axes only the mean, the variance and the counted number of peaks within the last window need to be sent instead of the whole acceleration measurements. A window size of 4 seconds should still be small enough for limited memory and computation resources, and clearly more energy-saving than sending more data at a higher frequency rate.

The concrete classification of the performed exercise and the selection of the dominating axes for the repetition counting could then be left to the mobile device, as much more hardware resources are needed for this process. In a first step, the mean-variance feature vector should be classified by assigning it to the nearest cluster centroid (those have to be set up once as it was done in Section 3.1). Since the assigned cluster determines the most likely activity, this knowledge can be used afterwards to count the movements within the last window by selecting only the sent number of peaks along the relevant axes for that specific activity (according to the results from Section 3.2).

A Pictures of the Different Activities on Both Tracks

(a) back stretching

(b) diagonal hand to foot moving

(c) pull-ups

(d) abdominals

(e) alternate one-leg bench jumps

(f) torso turns

(g) squats

(h) push-ups

Figure A.1.: Exercises in Roßdorf

(a) back stretching

(b) diagonal hand to foot moving

(c) pull-ups

(d) abdominals

(e) alternate one-leg bench jumps

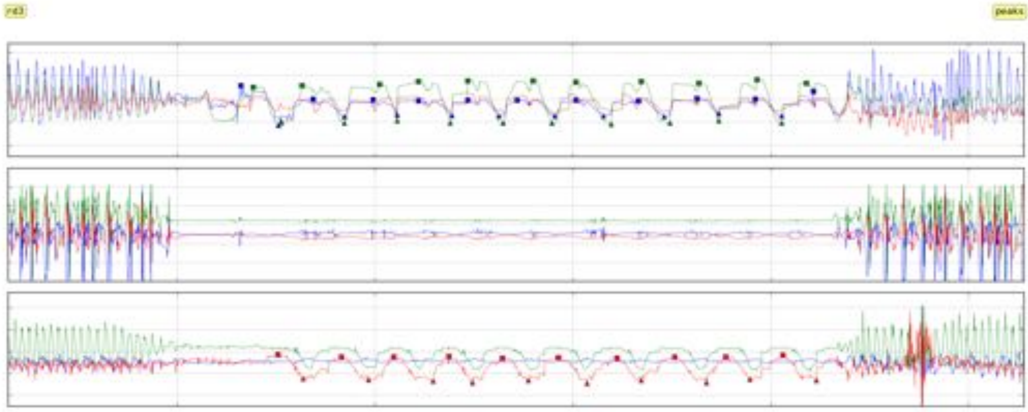
(f) torso turns

(g) squats

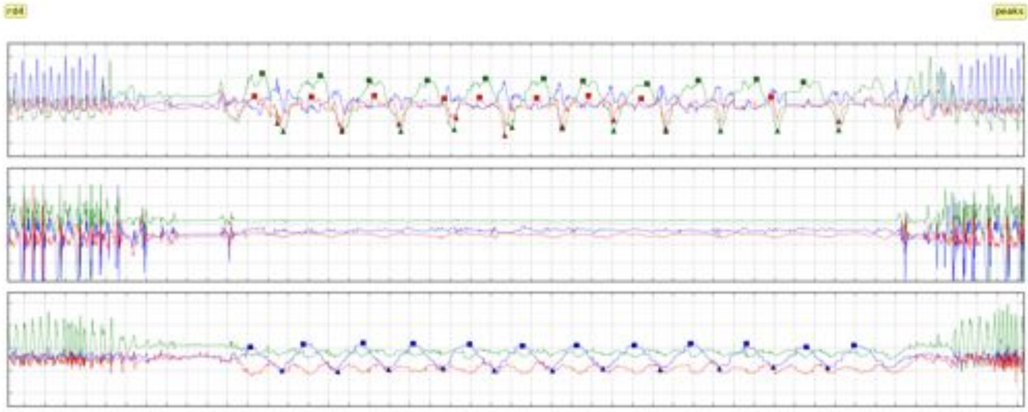
(h) push-ups

Figure A.2.: Exercises in Darmstadt

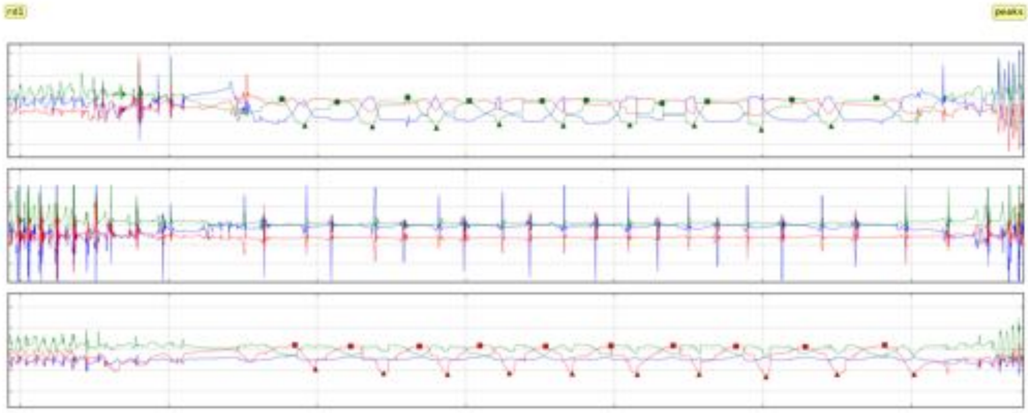
B Visualization of the counted repetitions with the detected peaks



(a) back stretching

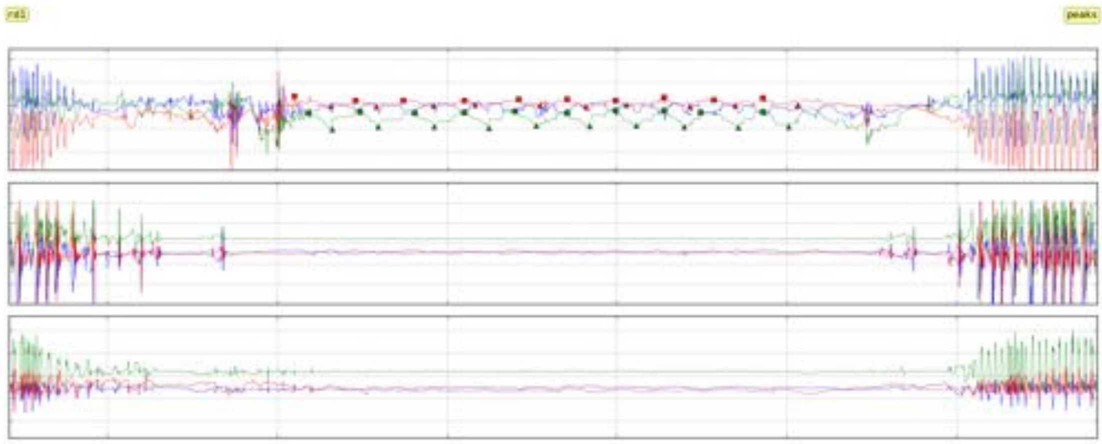


(b) diagonal hand to foot moving

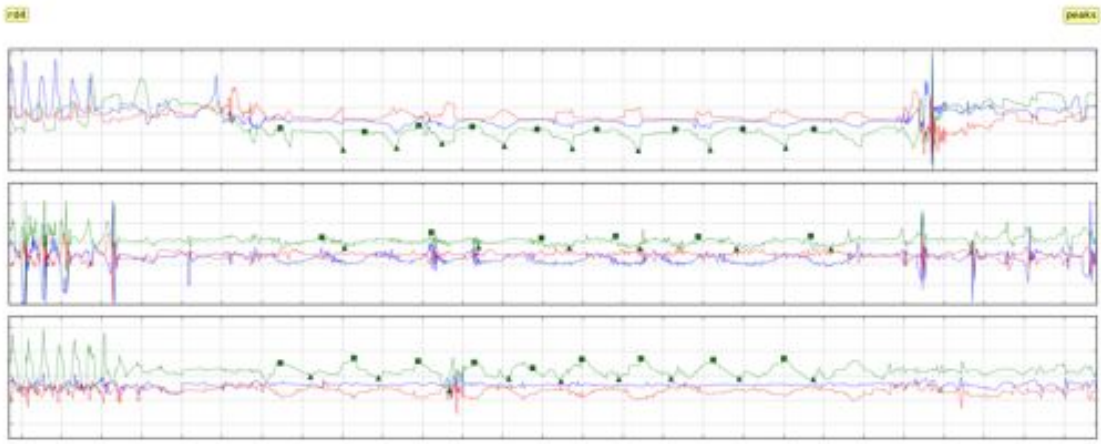


(c) abdominals

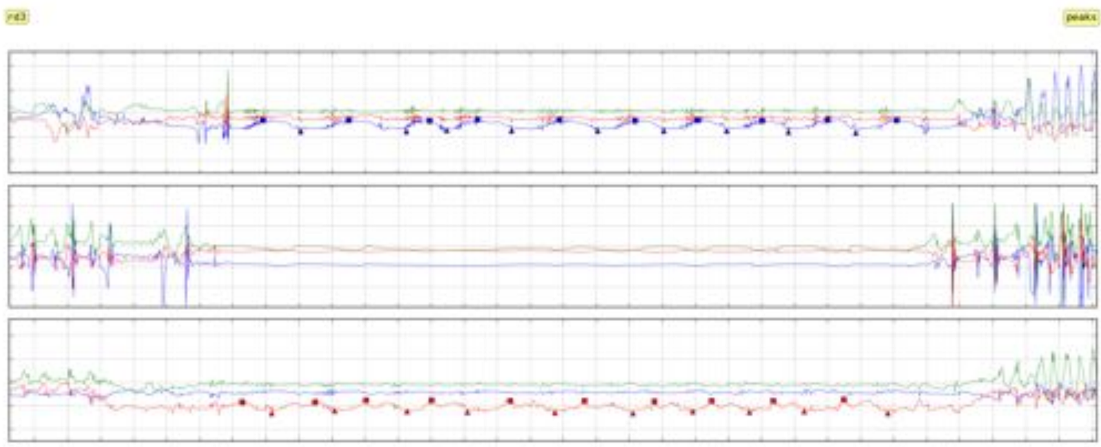
Figure B.1.: Visualization of the counted repetitions with the detected peaks for each activity in Roßdorf (part 1)



(a) torso turns

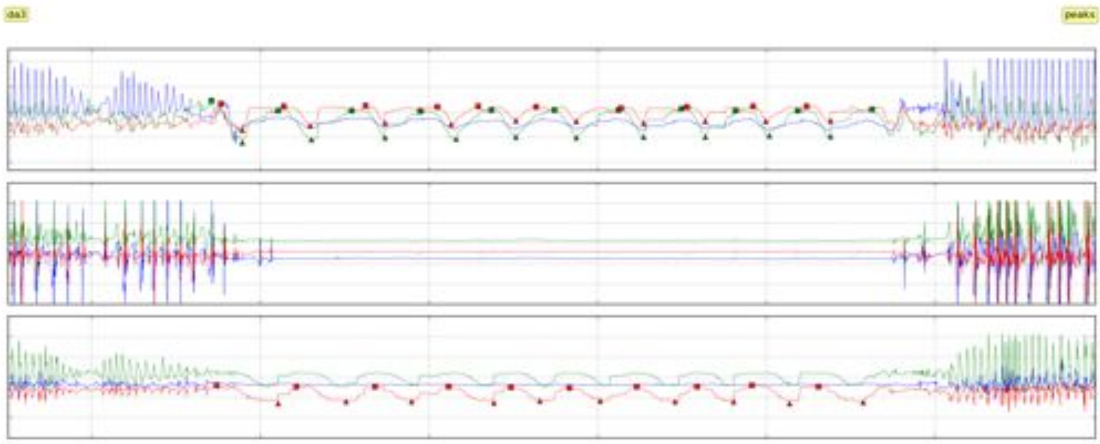


(b) squats

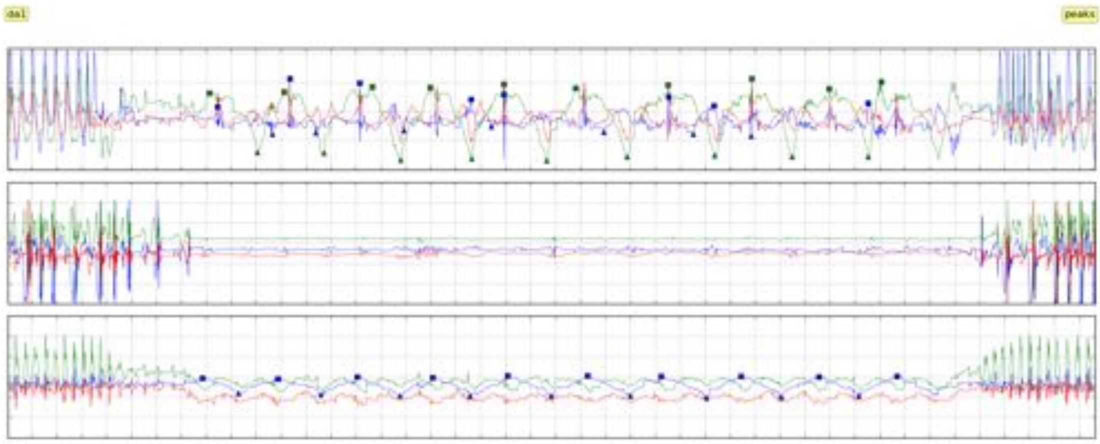


(c) push-ups

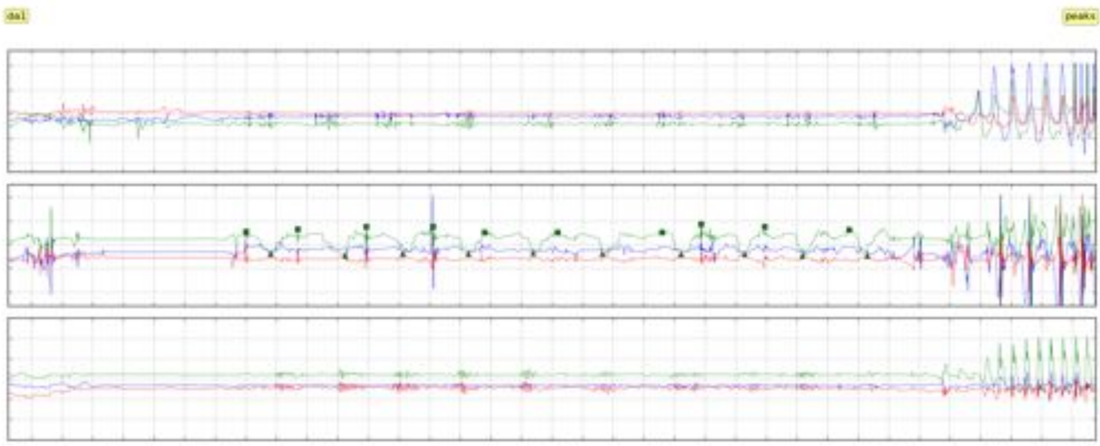
Figure B.2.: Visualization of the counted repetitions with the detected peaks for each activity in Roßdorf (part 2)



(a) back stretching

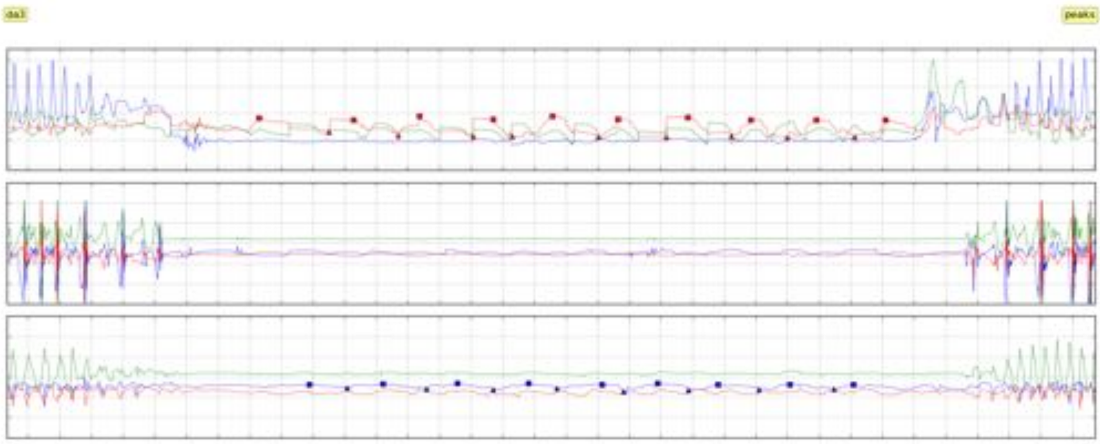


(b) diagonal hand to foot moving

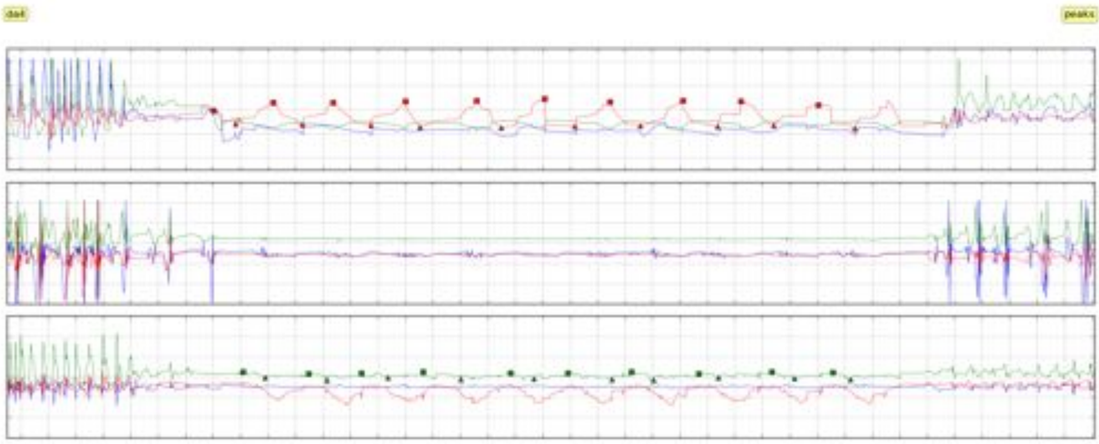


(c) abdominals

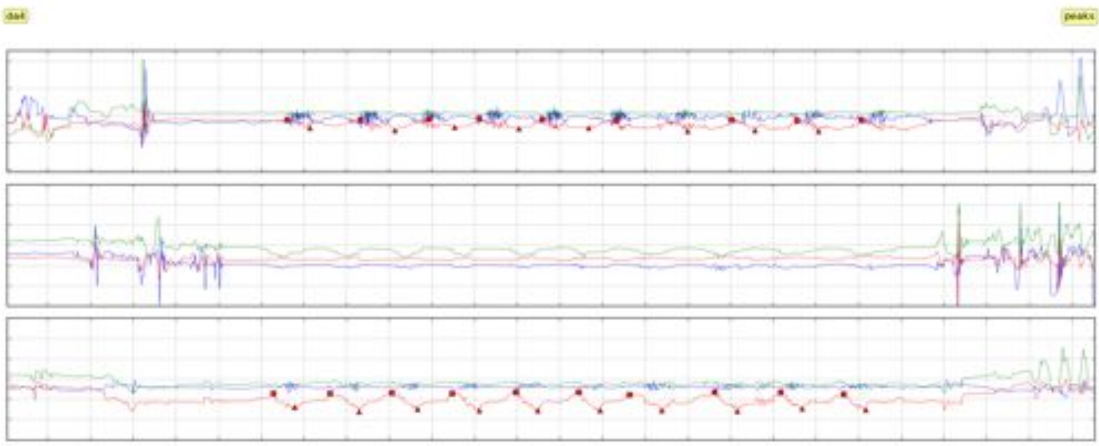
Figure B.3.: Visualization of the counted repetitions with the detected peaks for each activity in Darmstadt (part 1)



(a) torso turns



(b) squats



(c) push-ups

Figure B.4.: Visualization of the counted repetitions with the detected peaks for each activity in Darmstadt (part 2)

Acknowledgements

I gratefully would like to thank Svenja Stark, Max Pignede, Christian Seeger and Kristof Van Laerhoven for helpful discussions, critical comments and providing many suggestions.

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