Towards Global Aerobic Activity Monitoring

Attila Reiss
German Research Center for Artificial Intelligence (DFKI)
Department of Augmented Vision
Trippstader Str. 122
D-67663 Kaiserslautern, Germany
attila.reiss@dfki.de

Didier Stricker
German Research Center for Artificial Intelligence (DFKI)
Department of Augmented Vision
Trippstader Str. 122
D-67663 Kaiserslautern, Germany
didier.stricker@dfki.de

ABSTRACT
With recent progress in wearable sensing it becomes reasonable for individuals to wear different sensors all day, thus global activity monitoring is establishing. The goals in global activity monitoring systems are amongst others to tell the type of activity that was performed, the duration and the intensity. With the information obtained this way, the individual's daily routine can be described in detail. One of the strong motivations to achieve these goals comes from healthcare: to be able to tell if individuals were performing enough physical activity to maintain or even promote their health. This paper focuses on the monitoring of aerobic activities, and targets two main goals: to estimate the intensity of activities, and to identify basic/recommended physical activities and postures. For these purposes, a dataset with 8 subjects and 14 different activities was recorded, including the basic activities and postures, but also examples of household (ironing, vacuum cleaning), sports (playing soccer, rope jumping) and everyday activities (ascending and descending stairs). Data from 3 accelerometers — placed on lower arm, chest and foot — and a heart rate monitor were analyzed. In this paper, first results are shown on both the intensity estimation and activity recognition tasks, with a performance of 87, 54% and 86, 80%, respectively.

Categories and Subject Descriptors
I.5.4 [**Pattern Recognition**]: Applications—*Signal processing*; J.3 [**Computer Applications**]: Life and Medical Sciences—*Health*; I.5.3 [**Pattern Recognition**]: Clustering—*Algorithms*

General Terms
Algorithms, Measurement, Reliability

Keywords
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1. INTRODUCTION
The health benefits associated with regular physical activity have been investigated in many research studies over the last decades, and strong evidence has been found that physical activity is indeed reducing the risk of many diseases, including diabetes, cardiovascular diseases and certain types of cancer. [2] gives an overview of the most recent studies in this topic, and argues that — apart from not smoking — being physically active is the most powerful lifestyle choice individuals can make to improve their health. A list of all the health benefits, where strong or moderate evidence was found that they can be associated with regular physical activity, can be found e.g. in [12].

The original recommendation of minimum 30 minutes per day of moderate intensity physical activity has been recently updated and refined [9]. According to the updated recommendation statement, "to promote and maintain health, all healthy adults aged 18-65 yr need moderate-intensity aerobic physical activity for a minimum of 30 min on five days each week or vigorous-intensity aerobic activity for a minimum of 20 min on three days each week. Also, combinations of moderate- and vigorous-intensity activity can be performed to meet this recommendation". In addition to aerobic activity, [9] also recommends muscle-strengthening activity for at least twice a week. Moreover, they also point out that greater amounts of activity provide additional health benefits. [9] also provides examples of activities with the aforementioned intensity levels: a table of common physical activities classified as light, moderate or vigorous intensity is given. This table uses the Compendium of Physical Activities [1] as the source of the metabolic equivalent (or MET) of different activities, which is a common reference in the field of energy expenditure estimation of physical activity.

This paper focuses from the recommendations of [9] on the recommendations given for aerobic physical activity. For simplicity and availability reasons, there are a few traditionally recommended aerobic activities: walking, cycling, running and — in certain countries such as Germany — also Nordic walking. Together with the postures lying, sitting and standing, most of an individual's daily routine can be described from the physical activity point of view, thus it is essential to be able to recognize these activities and postures in an activity monitoring system.

Therefore, this paper presents an activity monitoring system with two main goals. On the one hand, the presented system aims to support the monitoring of an individual's daily routine to be able to answer the question in what way the individual meets the recommendations on aerobic activity. For this, the system should classify miscellaneous activities performed by the individual according to their intensity level — in respect of the aforementioned recommendations — as activities of light, moderate or vigorous effort. On the other hand, to give a more detailed description of an individual's daily routine, the system should identify with a high reliability the aerobic activities traditionally recommended and the basic postures.

The recognition of basic physical activities — such as resting, walking, running and cycling — is a well researched area (e.g. [4, 7, 11, 13, 14]), and shows that the recognition of these activities is possible even with just one 3D-acceleration sensor. Current research focuses amongst others on mobile applications (e.g. [5], basic activities can be recognized with good accuracy using only the sensors of a mobile phone), personalization (e.g. [16]) and increasing the number of activities to be recognized, which usually involves increasing the number of sensors used and introducing new classification techniques. For instance, a sensor placed by the wrist is preferable when trying to distinguish everyday or fitness activities with similar lower-body, but significantly different upper-body movement, [3, 8], e.g. distinguish walking from Nordic walking [18]. However, apart from a few exceptions (e.g. [3], where a dataset of 20 different everyday activities was recorded and classified), usually a similar set of only a few activities is recorded and used for activity recognition, without any other activities from the background occuring, which limits the applicability of the developed algorithms to the particular scenario with only these few acitivities switching.

Estimating intensity of physical activity using inertial sensors has been the focus of recent studies. In [17], accelerometers and gyroscopes attached to wrist, hip and ankle were used to estimate the intensity of physical activity, and it was found that accelerometers outperform gyroscopes, similar to the activity recognition task. [6] concludes, that lifestyle activities include more components to increase metabolic equivalent than walking or running, thus a different treatment has to be used for them when estimating their energy expenditure. For intensity estimation, physiological signals were also closely examined. However, it was shown that 3D-acceleration sensors are the most powerful sensors also for intensity estimation, e.g. [19] concluded that introducing heart rate related features has no significant improvement on the classification compared when using only features derived from acceleration data.

In this paper, a dataset — including the basic activities, but also others e.g. vacuum cleaning or playing soccer — is presented for the intensity estimation and activity recognition tasks. The sensor setup for data recording and the data collection protocol are described in the next section. Section 3 presents feature extraction, feature selection and the methods used for intensity estimation and activity recognition. Section 4 shows and discusses results achieved on both tasks, and the paper concludes in Section 5.

Figure 1: Placement of IMUs and the data collection unit.

2. DATA COLLECTION

2.1 Sensor setup

To obtain inertial data, 3 Colibri inertial measurement units (IMU) from Trivisio [20] were used. The sensors are lightweight (22 g without cable) and small ($30 \times 30 \times 13$ mm). Each IMU contains a 3-axis MEMS accelerometer, a 3-axis MEMS gyroscope, and a 3-axis magneto-inductive magnetic sensor, all sampled at 100 Hz. For current work, only accelerometer data was used from the IMUs. The accelerometers have a resolution of $0.038\,\mathrm{ms}^{-2}$ in the range of ± 16g. From the 3 IMUs, one was attached over the dominant wrist on the lower arm, one on the chest of the test subjects, and one sensor was foot-mounted.

A Sony Vaio VGN-UX390N UMPC was used as inertial data collection unit, carried by the subjects in a pocket fixed on their belt. The placement of the sensors and this data collection unit is shown in Figure 1. The IMUs were attached to the data collection unit by USB-cables, which were taped to the body so that they did not restrict normal movements of the subjects.

Heart rate information was recorded with the Garmin Forerunner 305 device, a GPS-enabled trainer with integrated HR-monitor. This device was selected since timestamped data was accessible from the device and enables wireless heart rate monitoring. GPS was turned off during data collection.

During data collection, a supervisor accompanied the test subjects and marked the beginning and end of each of the different activities. This timestamped labels were also stored

Table 1: Indoor protocol of data collection

Activity	Code	Intensity level [METs]	Duration [Min]
Lie	07011	1.0	3
Sit	09040	1.8	3
Stand	09050	1.8	3
Iron	05070	2.3	3
Break			1
Vacuum	05043	3.5	3
Break			1
Ascend stairs	17130	8.0	1
Break			2
Descend stairs	17070	3.0	1
Break			1
Ascend stairs	17130	8.0	1
Descend stairs	17070	3.0	1

Table 2: Outdoor protocol of data collection

Activity	Code	Intensity level [METs]	Duration [Min]
Walk very slow	17151	2.0	3
Break			1
Normal walk	17190/17200	3.3-3.8	3
Break			1
Nordic walk	—	4.0-6.0[1]	3
Break			1
Run	12020/12030	7.0-8.0	3
Break			2
Cycle	01010	4.0	3
Break			1
Run	12020/12030	7.0-8.0	2
Normal walk	17190/17200	3.3-3.8	2
Break			2
Soccer	15610	7.0	3
Break			2
Rope jump	15551/15552	8.0-10.0	2

on the data collection unit. Synchronization of the timestamped acceleration data, annotations and heart rate data was done offline. Eight subjects (aged 27.88 ±2.17 years, BMI 23.68 ±4.13 kgm^{-2}, seven males and one female) were recruited among DFKI employees. Approximately 8 h of data were collected altogether.

2.2 Data collection protocol

The protocol for the data collection is described in Table 1 and Table 2. A criterion for selecting activities was on the one hand that the basic activities (walking, running, cycling and Nordic walking) and postures (lying, sitting and standing) to be recognized should be included. On the other hand, everyday (ascending and descending stairs), household (ironing, vacuuming) and fitness (playing soccer, rope jumping) activities were also included to cover a wide range of activities. A total of 14 different activities were included in the data collection protocol. The protocol was split into an indoor and an outdoor scenario, mainly because of the limited battery time of the collection unit, but also to avoid the overloading of the test subjects.

The activity *lying* during the data collection protocol meant lying quietly while doing nothing. This period in the protocol was also used to determine the resting heart rate, which is used for calculating normalized heart rate values (cf. Section 3.1). *Sitting* mainly consists of computer work, while *standing* consists of standing still or standing still and talking, possibly gesticulating. During *ironing*, most of the subjects managed to iron and fold one or two shirts, while during *vacuuming*, one or two office rooms could be vacuumed (which included moving objects, e.g. chairs, placed on the floor). *Ascending stairs* and *descending stairs* was performed in a building between the ground and the top floors, a distance of five floors had to be covered. *Walking very slow* was walking with a speed of less than 3km/h, while *normal walking* was walking with moderate to brisk pace with a speed of 4-6km/h, according to what was suitable for the subject. *Nordic walking* was performed on asphaltic terrain, using asphalt pads on the walking poles. *Running* meant jogging with a suitable speed for the individual subjects. *Cycling* was performed with a real bike with slow to moderate pace, as if the subject would bike to work or bike for pleasure (but not as a sport activity). During data collection, test subjects *played soccer* with the supervisor, which mainly consisted of running with the ball, dribbling, passing to the supervisor or shooting the ball. During *rope jumping*, the subjects used the technique most suitable for them, which mainly consisted of the basic jump (where both feet jump at the same time over the rope) or the alternate foot jump (where alternate feet are used to jump off the ground).

Most of the activities were performed over 3 minutes, except ascending/descending stairs and rope jumping. The shorter performance of ascending and descending stairs was given by the limitations of the building where the indoor scenario was carried out: it toke approximately 1 minute to get from the ground floor to the top floor of the building while using the stairs. As for rope jumping, since this was the most exhausting of all of the activities, a time period of 2 minutes was chosen, so each of the subjects could perform this activity during this interval and nobody had to stop it due to exhaustion.

Since one of the goals of this paper is to estimate the intensity of the performed activities, and for this heart rate related features are also considered, a short break is inserted in the data collection protocol after each of the activities. The duration of the break intervals was chosen so that the heart rate of the subjects returns into the "normal" range after performing an activity, so that the measured heart rate values within an activity are not affected by the previously performed activities. For this purpose, a 1 minute break was sufficient after most of the activities, except for the most exhausting ones (ascending stairs, running and playing soccer), after which activities a 2 minutes break was inserted. However, since in everyday situations the influence of activities on the next performed ones can not be excluded, this influence was also simulated in the data collection protocol with descending stairs directly after ascending stairs (cf. Table 1) and normal walking directly after running (cf. Table 2).

The ground truth for the activity recognition task is provided by the labels made during data collection. The first and last 15 seconds of data from each performed activity was discarded to avoid transient data. Obtaining reference data for the intensity estimation task is not as obvious, hence requires a short explanation. In various previous work on estimating intensity of physical activity (e.g. [6, 17]), reference data was collected with a portable cardiopulmonary system (e.g. Cortex Metamax 3B or Cosmed K4b^2). This method has the advantage, that it provides precise measurements on an individual's oxigen consumption, thus providing measured metabolic equivalents, which is essential if the task is to use this measured MET values to e.g. estimate metabolic equivalent from other features [6, 17]. However, in this paper, as for the intensity estimation, the goal is to only estimate whether a performed activity is of light, moderate or vigorous effort, since for the physical activity recommendations (cf. Section 1) only this information is needed. Therefore, it is sufficient to use the Compendium of Physical Activities [1] to obtain reference data for the intensity estimation task of this paper. [1] contains MET levels assigned to 605 activities, and was also used in the recommendations [9] to provide example activities of moderate and vigorous intensities. The compendium was also used for validation of MET estimation in research, e.g. [15].

In the data collection protocol (cf. Table 1 and Table 2), the MET values from [1] are also included together with the 5-digit activity codes used in the compendium.[1] Once again, it has to be noted that this values were not developed to determine the precise energy cost of a specific physical activity within individuals, as also pointed out in [1]. However, these MET levels can be used to distinguish activities of light intensity (< 3.0 METs), moderate intensity (3.0-6.0 METs) or vigorous intensity (> 6.0 METs), which provides the reference data required for the intensity estimation task of this paper: lying, sitting, standing, ironing and walking very slow are regarded as activities of light effort; vacuuming, descending stairs, normal walking, Nordic walking and cycling as activities of moderate effort; and ascending stairs, running, playing soccer and rope jumping as activities of vigorous effort.

3. DATA PROCESSING

3.1 Feature extraction

After the above described data collection and pre-processing steps, synchronized, timestamped and labeled acceleration data from the 3 IMUs and heart rate data is available. From the 3D-acceleration data, standard signal feautures were calculated over a window of 512 samples (about 5 s of data), in both time and frequency domain. Time-domain features were mean, median, standard deviation, peak acceleration and absolute integral (this latter feature was successfully used to estimate the metabolic equivalent in e.g. [17]). For the frequency-domain features, the DC component was first removed, then the power spectral density (PSD) was calculated. Frequency-domain features were peak frequency of the PSD, power ratio of the frequency bands 0–2.75 Hz and 0–5 Hz, energy of the frequency band 0–10 Hz and spectral entropy of the normalized PSD on the frequency band 0–10 Hz.

The signal features extracted from the 3D-acceleration data are computed for each axis separately, and for the 3 axes together, too. Moreover, since synchronized data from the 3 IMUs is available, combining sensors of different placements is possible. From the above mentioned features mean, standard deviation, absolute integral and energy calculated on 3 axes of each of the IMUs are pairwise (e.g. hand + chest sensor placement) weighted accumulated, and a weighted sum for all the 3 sensors together is also added. From this 16 newly derived features it is expected, that they would better describe and distinguish activities with e.g. both upper and lower body movement, or — especially the features containing all 3 sensor placements — could improve the intensity estimation of activities.

From the heart rate data, the features mean and normalized mean (normalization is done on the interval defined by resting and maximum HR) are calculated. The resting HR of a test subject is extracted from the 3 minutes lying task of the data collection protocol, and is defined as the lowest HR value measured over this period. As for the maximum HR, a subject's age-predicted maximum HR ($MHR = 220 - age$) is used [19]. In total, 126 features were extracted from the recorded data: 124 features from IMU acceleration data and 2 features from the heart rate data.

3.2 Intensity estimation of physical activities

For the intensity estimation task, the goal is to distinguish activities of light, moderate and vigorous effort. In this paper, a very simple approach was selected by using the best feature with appropriate thresholds for solving this classification problem. To identify the feature having the best performance in discriminating these intensity classes, the measure presented in [10] was applied. The K-means algorithm with $k = 100$ clusters was used for clustering different features. The fraction for each cluster and intensity class was then computed, and the cluster precisions for each intensity class were obtained from the fractions, as presented in [10]. Results of the classification of samples into the intensity classes are shown and discussed in Section 4.1.

3.3 Activity classification

For activity classification, different approaches exist and yielded good results, such as SVMs, Naive Bayes classifiers, HMMs, ANNs or Boosting. Here the decision fell on custom decision trees, as they also have been successfully applied to activity classification in previous work [3, 4, 7, 8, 11, 16, 18]. The advantages of decision trees include low computation requirements and a simple implementation. The structure of the decision tree used for activity classification in this paper is depicted in Figure 2. The tree has 7 binary decision nodes and 8 leaf nodes, the latter representing the activities.

For selecting features used in the decision nodes, the cluster precisions method mentioned in the previous section was

[1][1] does not contain the activity Nordic walking. Furthermore, since none of the subjects was familiar with this activity, it was performed less intensive as it would have been with subjects skilled in this sport. Therefore, an estimation of the MET value for this activity was made in Table 2, using MET values of similar activities from the compendium (e.g. definitively less intensive than race walking, code 17110, 6.5 METs), and subjective feeling of the subjects (slightly more intensive than normal walking, but comparable with it). Altogether, this activity is considered as an activity of moderate effort within this paper.

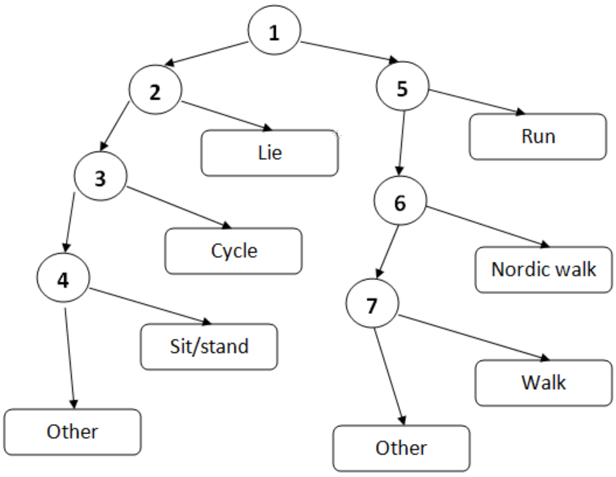

Figure 2: Structure of the custom decision tree.

used, since this method can also be utilized to identify the best features to separate 2 groups of activities, or just to find the best feature to distinguish 2 different activities. Questions like "what is the best feature to separate running from all other activities including footsteps?" or "what is the best feature to distinguish lying and sitting?" can be easily answered by using the cluster precisions method only on the 2 groups of activities as a binary classifier. The selected signal features for activity classification are the following:

1. absolute integral of the accelerations summarized for the 3 axes measured on the foot-mounted sensor
2. peak absolute value of the up-down (transversal) acceleration measured on the chest sensor
3. energy of the accelerations summarized for the 3 axes measured on the foot-mounted sensor
4. standard deviation of the up-down (transversal on initial position) acceleration measured on the lower arm sensor
5. median value of the forward-backward (horizontal) acceleration measured on the foot-mounted sensor
6. peak absolute value of the forward-backward (coronal on initial position) acceleration measured on the lower arm sensor
7. peak frequency value of the up-down acceleration measured on the foot-mounted sensor

The numbers of the selected features in the above list correspond to the numbers in the decision nodes in Figure 2. The first decision node divides all activities into activities with and without footsteps, all other decisions are used to separate one activity from the remaining other activities. If the current sample is not recognized into any of the activities while passing the decision tree, it falls through to the default "other" class. Classification results are shown and discussed in Section 4.2.

Table 3: Confusion matrix of the intensity estimation task for the feature: standard deviation of the up-down acceleration on the chest sensor

Annotated intensity	Estimated intensity 1	2	3	Performance [%]
1	10414	1838	0	85.00
2	319	10924	44	96.78
3	0	1512	4751	75.86

Table 4: Detailed confusion matrix of the intensity estimation task for the feature: standard deviation of the up-down acceleration on the chest sensor

Annotated activity	Estimated intensity 1	2	3	Performance [%]
Lie	2329	33	0	98.60
Sit	2259	0	0	100.00
Stand	2429	110	0	95.67
Iron	3093	128	0	96.03
Vacuum	196	2393	0	92.43
Ascend stairs	0	1319	12	0.90
Descend stairs	0	865	25	97.19
Walk very slow	304	1567	0	16.25
Normal walk	0	3462	19	99.45
Nordic walk	0	2055	0	100.00
Run	0	0	2913	100.00
Cycle	123	2149	0	94.59
Soccer	0	178	1078	85.83
Rope jump	0	15	748	98.03

4. RESULTS AND DISCUSSION

4.1 Intensity estimation of physical activities

For the intensity estimation task, the following feature was identified as the feature having the best performance to classify samples into the intensity classes: standard deviation of the up-down (transversal) acceleration measured on the chest sensor. Table 3 shows the confusion matrix for this feature, the overall performance is 87.54%. It is worth to note, that misclassifications only appear into "neighbour" intensity classes, thus no samples annotated as light intensity were classified into the vigorous intensity class, and vice versa.

More information can be obtained from Table 4, which shows how samples of different activities were classified into the intensity classes. For instance it shows, that the selected feature performed very well on estimating the intensity of samples belonging to postures (lying, sitting and standing). Good to very good results were achieved on samples of household activities (ironing and vacuuming), and of sport activities (running, cycling, playing soccer and rope jumping). In contrast, performance was poor on samples of the activities walking very slow and ascending stairs. The reason is, that the characteristics of these activities overlap with normal walking from the selected feature's point of view. Moreover, due to the similarity of the movement, it is reasonable to expect that the samples of ascending stairs can not be distinguished from walking related activities of moderate effort with only features derived from acceleration data, which implies the need for features extracted from physiological measurements, e.g. heart rate data.

Table 5: Confusion matrix of the intensity estimation task for the feature: normalized mean HR

Annotated intensity	Estimated intensity 1	2	3	Performance [%]
1	12345	485	0	96.22
2	1495	9231	949	79.07
3	26	1613	4951	75.13

Table 6: Detailed confusion matrix of the intensity estimation task for the feature: normalized mean HR

Annotated activity	Estimated intensity 1	2	3	Performance [%]
Lie	2590	0	0	100.00
Sit	2593	2	0	99.92
Stand	2571	27	0	98.96
Iron	2996	216	0	93.28
Vacuum	376	2215	0	85.49
Ascend stairs	26	986	344	25.37
Descend stairs	90	643	182	70.27
Walk very slow	1595	240	0	86.92
Normal walk	785	2217	767	58.82
Nordic walk	91	1995	0	95.64
Run	0	542	2387	81.50
Cycle	153	2161	0	93.39
Soccer	0	70	1463	95.43
Rope jump	0	15	757	98.06

Table 7: Confusion matrix of the activity classification task

Annotated activity	Estimated activity: Lie	Sit/ Stand	Normal walk	Nordic walk	Run	Cycle	Other	Performance [%]
Lie	2341	12	0	0	0	4	0	99.32
Sit	0	2035	0	0	0	0	155	92.92
Stand	0	1754	0	0	0	11	729	70.33
Normal walk	0	0	2916	0	0	0	32	98.91
Nordic walk	0	0	242	983	5	0	419	59.61
Run	0	0	0	37	2275	0	23	97.43
Cycle	0	0	0	0	0	1351	513	72.48
Iron	0	350	0	0	0	0	2956	89.41
Vacuum	3	0	0	0	0	150	2150	93.36
Ascend stairs	0	0	18	0	0	59	1300	94.41
Descend stairs	0	0	23	0	0	66	807	90.07
Soccer	0	0	78	145	227	0	801	64.03
Rope jump	0	0	40	39	4	11	660	87.53

Two other features, extracted from acceleration data, performed — for both the overall performance as for the detailed results on the different activities — similarly, as the above presented feature: the peak absolute value summarized for the 3 axes measured on the chest sensor, and the weighted sum of the standard deviation for all the 3 sensors together. The latter underlines, that if synchronized data from different sensor placements is available, it is worth to extract and investigate features calculated from multiple sensors for the intensity estimation task.

The overall performance of the features mean HR and normalized mean HR on the intensity estimation task was 83.53% and 85.31%, respectively. On the one hand, these results confirm the applicability of heart rate related features for intensity estimation. On the other hand, the results also underline the importance and benefits of personalized features, since by only normalizing (thus personalizing with the subject's resting and maximum HR) the heart rate values, a significant improvement in the overall performance can be observed. Table 5 and Table 6 show the confusion matrices when using the normalized mean HR as selected feature. Comparing these results with Table 4, a remarkable improvement is observable on activities, where all acceleration-related features failed (ascending stairs and especially walking very slow). The still low performance on samples of ascending stairs can be explained with the short duration of performing this activity in the data collection protocol: the heart rate of the subjects increased continuously during the 1 minute while ascending stairs, but only reached the threshold of vigorous intensity towards the end of this period. The lower performance on some other acitivities can be explained similarly, e.g. the performance on samples of running dropped with nearly 20% compared to the best acceleration-related features. Moreover, the increase of performance with nearly 10% on samples of soccer achieved with the feature normalized mean HR has also similar reasons: during playing soccer, the test subjects were sometimes moving slower or just holding position, thus samples of these intervals were not classified into the vigorous intensity class with features derived from acceleration data. In contrast, since heart rate does not adapt so fast, if the less intensive period did not last too long, heart rate still stayed above the threshold of vigorous intensity.

As described in Section 2.2, the influence of activities on the next performed ones was also simulated in the data collection protocol. The effects of this are observable on the lower performance of descending stairs and normal walking in Table 6 compared to Table 4. Since one part of these activities are preceded by ascending stairs and running, respectively, the heart rate of those samples is affected and still exceeds the threshold of vigorous intensity.

The above presented results show, that some of the benefits and weaknesses of acceleration-related and HR-related features differ, thus an increased performance is to be expected by combining these features, as pointed out in Section 5.

4.2 Activity classification

For the activity classification task, the goal was to recognize basic aerobic activities and postures from a larger set of activities, and classify all other activities into the default "other" class. Two restrictions were made for this task. On the one side, the activities sitting and standing form one class, as shown in Figure 2. This is a common restriction made in this research area (e.g. [7, 8, 16, 18]), since an extra IMU on the thigh would be needed for a reliable differentiation of these postures. On the other side, the samples labeled as "walk very slow" were removed for the activitiy classification task. This activity was only introduced for the intensity estimation task to have walking related activities in all 3 intensity classes (walk very slow, normal walk and run).

The results of the classification are shown in the confusion matrix of Table 7, the overall performance is 86.80%. The results demonstrate, that the classifier works very good-good on the basic recommended activities (like normal walking or cycling), and also performs good on other activities (like ironing or rope jumping). Most of the misclassifications can be explained from the data collection and the characteristic of certain activities, as discussed below.

Lying was recognized with over 99%, due to the different upper body orientation compared to all other activities. The classification of the samples *sitting* and *standing* demonstrate how background activities increase the difficulty of the classification task, especially the nearly 30% of standing-samples misclassified into the default "other" class. The main reason for the misclassifications is the introduction of the activity *ironing* in the data collection protocol: ironing has a similar characteristic as e.g. when talking and gesticulating during standing. The overlapping of the characteristic of ironing and standing also explains the more than 10% of ironing-samples misclassified into the "standing" class. *Normal walking* and *running* was identified with high reliability, while the performance on *Nordic walking* was much lower. The latter can be partly explained with the low experience of the subjects with this activity (as mentioned in Section 2), but also implies the need of improving the classification method. The only moderate results on *cycling* also urge for a more complex classification algorithm, as pointed out in Section 5. Good results were achieved on the activities *vacuuming*, *ascending stairs*, *descending stairs* and *rope jumping*, all belonging to the "other" class. Finally, it is worth to shortly analyze the only moderate results on *playing soccer*. Similar to ironing, the characteristics of playing soccer also overlap with some of the activities to be recognized. For instance, it is not trivial to distinguish running with a ball from just running, thus a high level classification algorithm would be necessary to recognize playing soccer more reliably.

5. CONCLUSION AND FUTURE WORK

In this paper, an activity monitoring system, focusing on aerobic activities, was presented. There are countless different activities (605 different activities are listed in [1]), therefore it is not feasible to recognize all of them. However, in a global activity monitoring system, at least the intensity of any activity should be estimated to be able to monitor how people meet the recommendations of [9] on aerobic physical activity. Moreover, to give even more information about an individual's daily routine, a global activity monitoring system should also recognize the most common activities. Therefore, this paper focuses on two main goals: to classify miscellaneous activities according to their intensity level, and to recognize basic aerobic activities and postures. For both purposes, a dataset with 8 subjects performing 14 different activities was recorded. Compared to previous work, this dataset is for both intensity estimation and activity recognition interesting in the way that it contains — besides the common basic activities — examples of household, sport and other everyday activities, too.

For the intensity estimation task, this paper presented a very simple first approach by using only the best feature with trained thresholds. However, even this approach achieved good overall results, especially since no grave misclassifications appeared, thus no confuses were observed between the light and vigorous intensity classes. The good results on various household and sport activities are also promising, since they suggest that the proposed methods are applicable for an even wider set of different activities. Nevertheless, more complex algorithms should be investigated in future work, combining different features, e.g. from different sensor placements, or combining acceleration and heart rate related features. Especially from the latter, a significant increase of the performance can be expected, as suggested from the results of Table 4 and Table 6.

For the activity classification task, a custom decision tree based approach was presented to identify basic activities and postures from a larger set of activities. Although some of the activities (e.g. Nordic walking) exposed the limits of this approach, good overall results were achieved. However, it has to be mentioned, that the custom decision tree used as classifier does not necessarily provide the most suitable classifier for a given set of features, thus it is planned in future work to investigate automatically generated decision trees or other methods (such as SVMs or artificial neural networks) in order to exhaustively explore the solution space. Related to the activity classification task, it also has to be mentioned, that current work also shows how background activities occuring in the dataset increase the difficulty of the classification problem.

Apart from improving the classification methods of both the intensity estimation and activity recognition tasks, an interesting problem in future work remains to investigate how the monitoring of muscle-strengthening activities can be included in the presented system. This is motivated by the recommendations also existing for muscle-strenthening activity in [9], thus with such a system it could be entirely monitored how an individual meets the recommendations.

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7. REFERENCES

[1] B. E. Ainsworth, W. L. Haskell, M. C. Whitt, M. L. Irwin, a. M. Swartz, S. J. Strath, W. L. O'Brien, D. R. Bassett, K. H. Schmitz, P. O. Emplaincourt, D. R. Jacobs, and a. S. Leon. Compendium of physical activities: an update of activity codes and MET intensities. *Medicine and science in sports and exercise*, 32(9 Suppl):S498–504, Sept. 2000.

[2] L. Alford. What men should know about the impact of physical activity on their health. *International journal of clinical practice*, 64(13):1731–4, Dec. 2010.

[3] L. Bao and S. Intille. Activity recognition from user-annotated acceleration data. In *Proc. 2nd Int. Conf. Pervasive Comput*, pages 1–17, 2004.

[4] G. Bieber and C. Peter. Using physical activity for user behavior analysis. *PETRA'08*, 282, 2008.

[5] G. Bieber, J. Voskamp, and B. Urban. Activity Recognition for Everyday Life on Mobile Phones. In *HCI 2009*, pages 289–296, 2009.

[6] S. E. Crouter, K. G. Clowers, and D. R. Bassett. A novel method for using accelerometer data to predict energy expenditure. *Journal of applied physiology*

(Bethesda, Md. : 1985), 100(4):1324–31, Apr. 2006.

[7] M. Ermes, J. Pärkkä, and L. Cluitmans. Advancing from offline to online activity recognition with wearable sensors. In *30th Annual International IEEE EMBS Conference*, volume 2008, pages 4451–4454, Jan. 2008.

[8] M. Ermes, J. Pärkkä, J. Mäntyjärvi, and I. Korhonen. Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE Trans. Inf. Technol. Biomed.*, 12(1):20–26, Jan. 2008.

[9] W. L. Haskell, I.-M. Lee, R. R. Pate, K. E. Powell, S. N. Blair, B. a. Franklin, C. a. Macera, G. W. Heath, P. D. Thompson, and A. Bauman. Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. *Medicine and science in sports and exercise*, 39(8):1423–34, Aug. 2007.

[10] T. Huynh and B. Schiele. Analyzing features for activity recognition. In *sOc-EUSAI '05*, pages 159–163. ACM Press, 2005.

[11] D. Karantonis, M. Narayanan, M. Mathie, N. Lovell, and B. Celler. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *IEEE Trans. Inf. Technol. Biomed.*, 10(1):156–167, 2006.

[12] M. O. Leavitt. 2008 Physical Activity Guidelines for Americans, 2008.

[13] M.-h. Lee, J. Kim, K. Kim, I. Lee, S. H. Jee, and S. K. Yoo. Physical activity recognition using a single tri-axis accelerometer. In *WCECS 2009*, volume I, 2009.

[14] X. Long, B. Yin, and R. M. Aarts. Single-accelerometer based daily physical activity classification. In *31st Annual International IEEE EMBS Conference*, volume 1, pages 6107–6110, Jan. 2009.

[15] J. Mattila, H. Ding, and E. Mattila. Mobile tools for home-based cardiac rehabilitation based on heart rate and movement activity analysis. In *31st Annual International IEEE EMBS Conference*, pages 6448–6452, 2009.

[16] J. Pärkkä, L. Cluitmans, and M. Ermes. Personalization algorithm for real-time activity recognition using PDA, wireless motion bands, and binary decision tree. *IEEE Trans. Inf. Technol. Biomed.*, 14(5):1211–5, Sept. 2010.

[17] J. Pärkkä, M. Ermes, K. Antila, M. van Gils, A. Mänttäri, and H. Nieminen. Estimating intensity of physical activity: a comparison of wearable accelerometer and gyro sensors and 3 sensor locations. *29th Annual International IEEE EMBS Conference*, 2007:1511–4, Jan. 2007.

[18] J. Pärkkä, M. Ermes, P. Korpipää, J. Mäntyjärvi, J. Peltola, and I. Korhonen. Activity classification using realistic data from wearable sensors. *IEEE Trans. Inf. Technol. Biomed.*, 10(1):119–128, Jan. 2006.

[19] E. M. Tapia, S. S. Intille, W. Haskell, K. Larson, J. Wright, A. King, and R. Friedman. Real-Time Recognition of Physical Activities and Their Intensities Using Wireless Accelerometers and a Heart Rate Monitor. *2007 11th IEEE International Symposium on Wearable Computers*, pages 1–4, Oct. 2007.

[20] Trivisio. http://www.trivisio.com.