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Introducing a Modular Activity Monitoring System

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Abstract— **In this paper, the idea of a modular activity monitoring system is introduced. By using different combinations of the system's three modules, different functionality becomes available: 1) a coarse intensity estimation of physical activities 2) different features based on HR-data and 3) the recognition of basic activities and postures. 3D-accelerometers — placed on lower arm, chest and foot — and a heart rate monitor were used as sensors. A dataset with 8 subjects and 14 different activities was recorded to evaluate the performance of the system. The overall performance on the intensity estimation task, relying on the chest-worn accelerometer and the HR-monitor, was 94.37%. The overall performance on the activity recognition task, using all three accelerometer placements and the HR-monitor, was 90.65%. This paper also gives an analysis of the importance of different accelerometer placements and the importance of a HR-monitor for both tasks.**

I. INTRODUCTION

Activity monitoring systems have been the focus of recent research interest. Simultaneously, with recent progress in wearable sensing, the number of commercially available activity monitoring products is increasing. Most of these products include one sensor, located on the user's body (e.g. as an armband, on the belt or directly integrated in a mobile device), and focus on a few features, usually related to the assessment of energy expenditure. Studies underline the good accuracy of some of these systems, e.g. the Actiheart [4] or the SenseWear [8] system. There exist different needs towards an activity monitoring system. Additional features to the assessment of energy expenditure are introduced in some of the above mentioned products, e.g. the assessment of sleep duration and efficiency in the SenseWear system. However, there is no possibility to extend these systems, e.g. if a higher accuracy or more information is needed in order to introduce new features related to activity monitoring.

This paper presents an extensible activity monitoring system: based on a simple system for physical activity intensity estimation, a more detailed description of daily activities can be acquired with one or two extra sensors. The basic system consists of only one accelerometer worn on the chest, and delivers a reliable coarse intensity estimation of physical activities (results are shown in Section IV). By adding a heart rate monitor, the following benefits can be achieved compared to the basic system: 1) a significantly improved intensity estimation and 2) new features can be added to the system based on the obtained heart rate information (e.g. HR-alerts). By adding two extra accelerometers to the basic or the HR-monitor extended system, besides a further improvement on the intensity estimation, the recognition of basic activities is enabled. As a result, the idea of a modular system for activity monitoring is introduced within this work: a base module is responsible for the basic system functionality (intensity estimation in this case), while two more modules can be added — separately or together — to extend the functionality of the system.

Previous work showed, that 3D-acceleration sensors are the most powerful sensors for estimating intensity of physical activity, e.g. [12], [13]. [4] concludes, that combining accelerometer and HR-data, or using only HR-information provides a good intensity estimation. The goal of the intensity estimation task within this paper is not to estimate e.g. a metabolic equivalent (MET) value of a performed activity, but to estimate whether a performed activity is of light, moderate or vigorous effort. This coarse estimation is sufficient in many applications, e.g. to monitor how people meet health recommendations (defined e.g. in [7]).

Monitored heart rate can extend the functionality of an activity monitoring system in many ways. For cardiac patients for example, a specific HR could be defined individually in the system, and an alarm would be initiated when exceeding this value. For sports applications, a desired range of HR can be defined, and the system can determine how much time was spent in this HR-zone to optimize the benefits from a workout.

The recognition of physical activities is a well researched area (e.g. [5], [9], [10]), and shows that the recognition of basic activities — such as resting, walking, running or cycling — is possible even with just one 3D-acceleration sensor. Current research in this area focuses amongst others on mobile applications (e.g. [3]), personalization (e.g. [11]) and increasing the number of activities to be recognized, which usually involves increasing the number of sensors used, and introducing new classification techniques. As for the latter — which is the focus of the activity recognition task of this paper — apart from a few exceptions (e.g. [2]), usually a similar set of only a few activities is recorded, without any other activities from the background occuring. This limits the applicability of the developed algorithms to the particular scenario with only these few activities switching.

As a conclusion, 3D-accelerometers and a HR-monitor are used as sensors in the presented system. For the intensity estimation and activity recognition tasks, a dataset including everyday, household and sports activities is recorded. Data collection — including sensor setup and protocol — is described in the next section. Data processing — including feature extraction and classification algorithm — is described

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TABLE I
PROTOCOL OF DATA COLLECTION

Activity	Duration [Min]	Activity	Duration [Min]
Lie	3	Walk very slow	3
Sit	3	Break	1
Stand	3	Normal walk	3
Iron	3	Break	1
Break	1	Nordic walk	3
Vacuum	3	Break	1
Break	1	Run	3
Ascend stairs	1	Break	2
Break	2	Cycle	3
Descend stairs	1	Break	1
Break	1	Run	2
Ascend stairs	1	Normal walk	2
Descend stairs	1	Break	2
		Soccer	3
		Break	2
		Rope jump	2

in Section III. Results achieved on both tasks are shown and discussed in Section IV. Implementation is briefly presented in Section V, and the paper concludes in Section VI.

II. DATA COLLECTION

Acceleration data was recorded with 3 Colibri inertial measurement units (IMU) from Trivisio [14]. For current work, only the 3-axis MEMS accelerometer was used from an IMU, which has a resolution of $0.038\,\mathrm{ms}^{-2}$ in the range of ± 16g. The IMUs were sampled at $100\,\mathrm{Hz}$. From the 3 IMUs, one was attached over the wrist on the dominant arm, one on the chest of the test subjects, and one sensor was foot-mounted. The IMUs were attached to a data collection unit (a Sony Vaio VGN-UX390N UMPC) by USB-cables, which were taped to the body of the subjects so that they did not restrict normal movements. To obtain heart rate information, the Garmin Forerunner 305, a GPS-enabled trainer with integrated HR-monitor, was used. 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 $8\,\mathrm{h}$ of data were collected altogether.

The protocol for the data collection is described in Table I, the left and right side of the table lists the indoor and outdoor activities, respectively. 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 was included in the data collection protocol. Most of the activities were performed over 3 minutes, except ascending/descending stairs (due to building limitations) and rope jumping (to avoid exhaustion of the subjects).

III. DATA PROCESSING

The data collection provides synchronized, timestamped and labeled acceleration data from the 3 IMUs and heart rate data. From the 3D-acceleration data, standard signal features were calculated over a window of 512 samples (about $5\,\mathrm{s}$ of data), in both time and frequency domain. Time-domain features were mean, median, standard deviation, peak acceleration, absolute integral and correlation between each pair of axes. Frequency-domain features were peak frequency of the PSD, power ratio of the frequency bands 0–$2.75\,\mathrm{Hz}$ and 0–$5\,\mathrm{Hz}$, energy of the frequency band 0–$10\,\mathrm{Hz}$ and spectral entropy of the normalized PSD on the frequency band 0–$10\,\mathrm{Hz}$. 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.

Both the intensity estimation and activity recognition tasks can be regarded as classification problems. For the intensity estimation task, the goal is to distinguish activities of light, moderate and vigorous effort. Reference data is obtained by using [1]: lying, sitting, standing, ironing and walking very slow are regarded as activities of light effort ($<$ 3.0 METs); vacuuming, descending stairs, normal walking, Nordic walking and cycling as activities of moderate effort (3.0-6.0 METs); and ascending stairs, running, playing soccer and rope jumping as activities of vigorous effort ($>$ 6.0 METs).

For the activity recognition task, the goal is to recognize basic activities and postures from a larger set of activities, and classify all other activities into the default "other" class. The classes to be recognized are the following: lying, sitting/standing (forming one class), normal walking, Nordic walking, running and cycling. All other activities belong to the default class, except of the samples labeled as "walk very slow". These samples were removed for the activity recognition task, since this activity was only introduced for the intensity estimation task to have walking related activities in all 3 intensity classes.

From different classification approaches, the performance of some of the widely used base-level (decision trees, K-nearest neighbors, SVM and Naive Bayes) and meta-level classifiers (Bagging, Boosting) was evaluated, using the Weka toolkit [6]. For evaluation, leave-one-subject-out 8-fold cross-validation protocol was used. Best results were achieved with boosted decision trees. The results presented in the next section were all obtained with this classification technique.

IV. RESULTS AND DISCUSSION

This section presents and discusses results achieved on both the intensity estimation and the activity recognition task. Classification performance was evaluated with different combinations of the sensors to analyze how many and which sensors are needed for a reliable intensity estimation and activity recognition, which sensors and sensor placements are more important than others, etc.

A. Intensity estimation

Table II shows results on the intensity estimation task with various sets — combinations which are considered to be interesting for this task — of sensors. One row in the table represents one setup, crosses in the four columns indicate which sensors are included in a specific setup. The

TABLE II
RESULTS ON THE INTENSITY ESTIMATION TASK

chest IMU	arm IMU	foot IMU	heart rate	Performance [%]
X				90.47
	X			86.47
		X		88.08
			X	82.06
X			X	94.37
	X		X	93.07
		X	X	91.36
X	X	X		94.07
X	X	X	X	95.65

TABLE III
CONFUSION MATRIX OF THE INTENSITY ESTIMATION TASK USING THE CHEST IMU AND THE HR-MONITOR

Annotated intensity	Estimated intensity 1	2	3	Performance [%]
1	23485	854	0	96.49
2	1009	17287	967	89.74
3	0	264	11114	97.68

results in this table justify the definition of the modules (cf. Section I) of the current activity monitoring system: 1) from the three investigated IMU positions, the chest placement performs best and 2) adding the HR-monitor to the basic module significantly improves the intensity estimation (this is true for the other two IMU placements as well). Table II also shows, that adding two more accelerometers — on arm and foot placement — further improves the performance of the system on intensity estimation. However, if the activity monitoring system is only used for intensity estimation, it is not worth to add the module containing these two IMUs: a minor improvement in performance does not justify the usage of two extra sensors.

The results in Table II also indicate, that — in contrast to the conclusion of [13] — heart rate information combined with accelerometers improves the intensity estimation of physical activities compared to systems only relying on inertial data. By analyzing the selected features in the decision tree nodes of the trained classifier it is clear, that — especially for normalized HR — it is worth to take features extracted from HR data into account.

Table III shows the confusion matrix of the intensity estimation task when using the chest IMU and the HR-monitor. This setup is considered the most efficient for the intensity estimation task within this paper: using only these two sensors gives a highly reliable (the overall performance is 94.37%) intensity estimation. It is also worth to mention, 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.

B. Activity recognition

Table IV shows results on the activity recognition task with various sets of sensors. Compared to Table II it is clear, that the activity recognition task defines a more difficult classification problem, than the intensity estimation task does. With the basic module, or the basic plus HR-module, only a relatively low performance can be achieved. This justifies the definition of the third module in the current activity monitoring system, containing two extra accelerometers, placed at arm and foot position. An interesting conclusion from the results of Table IV (from the performance results on the setups containing two IMUs and the HR-monitor) is, that the chest and foot IMU placements behave similarly for activity recognition, while the arm IMU placement is complementary. Comparing the activity type of misclassified samples with and without using the arm IMU reveals, that distinguishing normal walking and Nordic walking is effectively not possible without using the arm IMU.

TABLE IV
RESULTS ON THE ACTIVITY RECOGNITION TASK

chest IMU	arm IMU	foot IMU	heart rate	Performance [%]
X				83.36
	X			73.55
		X		74.67
			X	45.64
X			X	83.85
	X		X	77.55
		X	X	76.45
X	X		X	88.11
X		X	X	81.70
	X	X	X	89.95
X	X	X		88.90
X	X	X	X	90.65

TABLE V
CONFUSION MATRIX OF THE ACTIVITY RECOGNITION TASK USING THE CHEST, ARM AND FOOT IMUS AND THE HR-MONITOR

Annotated activity	Estimated activity Lie	Sit/ Stand	Normal walk	Nordic walk	Run	Cycle	Other	Performance [%]
Lie	4640	0	0	0	0	0	0	100.00
Sit/Stand	0	7913	54	0	0	25	1570	82.75
Normal walk	0	0	5009	24	204	0	517	87.05
Nordic walk	0	0	39	2665	173	0	487	79.22
Run	0	0	0	0	4493	0	153	96.71
Cycle	0	117	0	0	0	3131	527	82.94
Other	0	855	7	8	25	16	18672	95.35

Table V shows the confusion matrix of the activity recognition task when using all three IMUs and the HR-monitor. The overall performance of the system is 90.65%. Most of the misclassifications can be explained with the introduction of the "other", background activities, which significantly increases the difficulty of the classification problem. For example, the activities *standing* (especially when talking and gesticulating during standing) and *ironing* have similar characteristics that are difficult to distinguish. This is the main reason for the more than 15% of sitting/standing-samples misclassified into the default "other" class, and similarly the false positives in the sitting/standing class coming from the default class. Similar to ironing, the characteristic of *playing soccer* also overlap with some of the activities to be recognized, e.g. it is not trivial to distinguish running with a ball from just running.

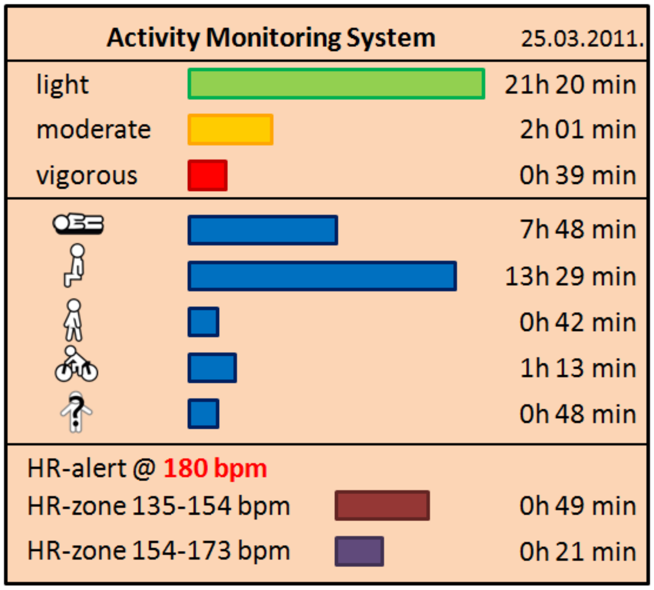

Fig. 1. Representation of the summary of an exemplar output of the activity monitoring system

V. Mobile application

The modular activity monitoring system presented in this paper was implemented as a mobile application. Compared to the data collection, some modifications were done concerning the hardware setup, to receive a completely portable system: 1) the Sony Vaio UMPC is replaced by a Viliv S5 device, mainly to increase the battery time of the system 2) to obtain HR-data directly online, a BM-CS5SR heart rate monitor is used from BM innovations GmbH and 3) Colibri-Wireless IMUs from Trivisio are replacing the originally used wired IMUs, although the latter inertial sensors are still supported by the system. Figure 1 represents the summary of an exemplar output of the full system (thus all three modules are active): estimated intensity of activities over a day, a summary of recognized activities (the icons refer to the activities lying, sitting/standing, walking, cycling and other activities; in this example the subject did not perform running or Nordic walking during the selected day), and time spent in defined HR-zones to receive information about training sessions performed during a day.

VI. Conclusion

In this paper, the idea of a modular activity monitoring system has been presented. A basic module, consisting of a chest-worn 3D-accelerometer provides coarse intensity estimation. The performance on this functionality can be improved by adding a further module, consisting of a HR-monitor. This module also provides additional features related to HR-information. A third module, consisting of two accelerometers — placed on lower arm and foot — extends the system with an additional feature: the recognition of basic activities and postures. The analysis of different sets of sensors and sensor placements in Section IV justifies the definition of these three modules. Following the idea of modularity, additional modules could be defined. A possible extension to the presented system is e.g. a module providing full upper-body tracking. Therefore, besides the already provided monitoring of aerobic activities, the monitoring of muscle-strengthening activities would become available.

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