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Classification of Human Physical Activity and Energy Expenditure Estimation by Accelerometry and Barometry

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Abstract— **Regular exercise and physical activity are among the most important factors influencing the quality of life and make a significant contribution to the maintenance of health and well-being. The assessment of physical activity via accelerometry has become a promising technique often used as means to objectively measure physical activity. This work proposes a simple and reliable method to assess human physical activity and calculate the energy expenditure (EE) by using an acceleration and an air pressure sensor. Our proposed algorithm differentiates between 7 activities with an average accuracy of 98.2% and estimates the second by second EE with an average percent error of 1.59 ± 8.20% using a single measurement unit attached to the subject's hip.**

I. Introduction

Physical activity classification and energy expenditure (EE) measurement and analysis have been in the past fifteen years a very motivating research field with various applications in the medical research such as therapeutic rehabilitation and disease prevention. Due to the limited accuracy of methods like questionnaires and the obtrusiveness of methods like indirect calorimetry, accelerometry has become a promising widely used technique to assess everyday life physical activity.

Most of the up to now developed algorithms used single or combinations of accelerometers attached to different body locations such as hip, thigh or foot to classify peoples' everyday life physical activity [1-3]. However, single accelerometry has been insufficient to classify activities which include vertical movements such as walking up- or down-hill even though stair climbing requires more than twice the energy of level walking. This limitation can be overcome by using an additional air pressure sensor.

Rulsch et al. [4] proposed a lightweight approach for activity classification using both acceleration and air pressure signals but no EE prediction algorithm, which depicts the intensity of the activity, was presented.

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Ohtaki et al. [5] classified the physical activity and estimated the EE using a single device consisting of an acceleration and an air pressure sensor. However, no results concerning the classification rates were shown and no comparison between the predicted EE and the gold-standard was performed.

An activity-based EE estimation procedure based only on accelerometry was presented by Jatobá et al. [6]. The EE prediction equations were developed by using the intensity of the acceleration measured on the chest and on the left ankle along with some other subject-related features (such as age, weight, height).

Yamazaki et al. [7] and Voleno et al. [8] proposed an EE estimation model based on accelerometer and barometer data. No activity recognition algorithm was presented and the activity-independent estimation model did not include subject-related data, thus providing a limited accuracy.

This paper presents a novel method, which accurately classifies the physical activity and predicts the EE of people's everyday life with an accelerometer and a barometer.

II. Measurement Setup and Data Collection

A. Measurement System

The collection of the acceleration and the air pressure data was done using the Move II sensor (movisens GmbH, Karlsruhe, Germany). The data acquisition device consists of a three-axial acceleration sensor (adxl345, Analog Devices) with a range of ±8 g and a sampling frequency of 128 Hz and an air pressure sensor (BMP085, Bosch GmbH) with a resolution of 0.03 hPa (corresponding to 15 cm at sea level) and a sampling frequency of 8 Hz. The recorded acceleration and air pressure raw data are saved on a micro SD card. The transmission of raw data after a complete measurement is realized by a USB 2.0 interface.

The portable indirect calorimeter Meta Max 3B (Cortex Biophysics GmbH, Leipzig, Germany) was used to assess the energy expenditure. The indirect calorimeter measures the breath by breath CO_2 expiration and O_2 consumption; from which the energy expenditure can be derived.

B. Subject Characteristics

Thirty-six healthy subjects (24 male and 12 female), students and employees of the Karlsruhe Institute of Technology (KIT) participated in the data collection studies. All participants completed an informed consent form prior to enrolling in the study. Descriptive data of the subjects is presented in Table I.

TABLE I. PHYSICAL CHARACTERISTICS OF SUBJECTS (MEAN ± SD)

Subject parameter	Males (N=24)	Females (N=12)	All subjects (N=36)
Age (yrs.)	31.63 ± 9.67	31.58 ± 8.99	31.61 ± 9.46
Height (m)	1.79 ± 0.07	1.67 ± 0.04	1.75 ± 0.08
Weight (kg)	82.70 ± 12.06	65.58 ± 9.60	76.99 ± 13.99
BMI ($kg \cdot m^{-2}$)	25.83 ± 3.04	23.43 ± 3.24	25.03 3.31

C. Measurement Procedure

Each subject was equipped with the activity sensor Move II, attached to the participant's waist over the right anterior axillary line and the indirect calorimeter. The indirect calorimeter was both used to assess the reference data for the EE and to set the start and stop markers for the different activities.

For the data collection two different studies with a variety of indoor (e.g. walking in treadmill) and outdoor (e.g. cycling) predefined activities have been carried out. The data collection protocol for the first (N=16) and the second (N=20) study can be seen in Table II and III respectively.

TABLE II. FIRST STUDY-DATA COLLECTION PROTOCOL

Activity	Duration
lying (2 times)	2 min
sitting (2 times)	2 min
standing (2 times)	2 min
walking slow in treadmill	3 min
walking fast in treadmill	3 min
jogging in treadmill	3 min
walking slow	3 min
walking fast	3 min
jogging	3 min
cycling	app. 5 min
walking up- /downhill (2 times)	app. 4 min
walking stairs up/ down	app. 2 min

TABLE III. SECOND STUDY -DATA COLLECTION PROTOCOL

Activity	Duration
sitting	5 min
standing	5 min
walking slow	app. 5 min
walking fast	app. 5 min
jogging	app. 5 min
cycling	app. 5 min
walking up- /downhill (4 times)	app. 8 min
walking stairs up/ down (3 times)	app. 6 min

III. SIGNAL PROCESSING

A. Signal Preprocessing

The following signal processing has been done with MATLAB. Both the acceleration and the air pressure signals were preprocessed and segmented in intervals of 4 seconds.

The acceleration sensor can measure both movement and posture. Therefore the AC (dynamic) and the DC (static) parts of the acceleration were separated by subtracting the mean value of the signal. The air pressure signal was converted into altitude using the barometric formula [9]. To suppress noise that is not relevant to the vertical movements a Butterworth lowpass filter [4] with cutoff frequency 0.2 Hz was used.

The output signal from the indirect calorimeter was characterized by a non-uniform sampling frequency since it was sampled at every breath. Therefore, linear interpolation was used in order to resample to a uniform 1 Hz sampling frequency.

B. Parameter Extraction

Each interval (4 sec) of the acceleration and the air pressure data was transformed into a feature vector. The feature vector was the input for the activity recognition and the EE estimation. In the following, the vectors $ax_{AC}(i)$, $ay_{AC}(i)$ and $az_{AC}(i)$ stand for the AC parts of the ax, ay and az-acceleration during the i^{th} interval, whereas $ax_{DC}(i)$, $ay_{DC}(i)$ and $az_{DC}(i)$ for the DC parts. The features extracted are the following:

Acceleration magnitude (EEAC): The mean of the total acceleration represents the intensity of the movement in this interval and was used to distinguish between periods of activity (e.g. walking) and inactivity (e.g. sitting). A threshold between activity and inactivity according to [4] was selected. The acceleration magnitude was calculated as:

$$EEAC(i) = mean(sqrt(ax_{AC}^2(i) + ay_{AC}^2(i) + az_{AC}^2(i))) \quad (1)$$

Acceleration variance (VAR): The variance of the total acceleration is a measure of how widely the acceleration signals fluctuate from their mean values and was used to separate less dynamic (e.g. walking) from more dynamic (e.g. jogging) activities. The variance of the total acceleration was calculated as:

$$VAR(i) = var(sqrt(ax_{AC}^2(i) + ay_{AC}^2(i) + az_{AC}^2(i))) \quad (2)$$

Step count: Using the magnitude of the acceleration per sample, the number of steps in every interval was calculated. The step detection was performed by using a peak-detection algorithm. Fig. 1 illustrates the detection of steps.

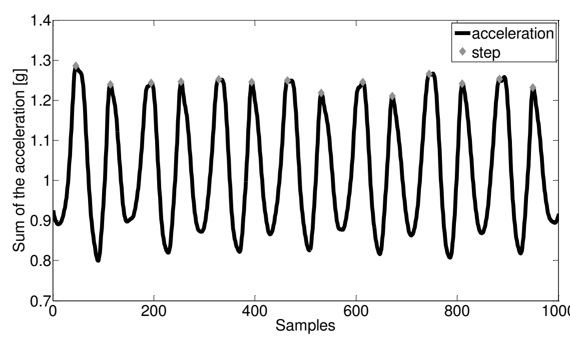

Figure 1. Step detection algorithm

Peak frequency (f_{max}): If the person was active the frequency of the strongest Fourier component of the magnitude of the acceleration signal was calculated as following:

$$f_{max}(i) = \begin{cases} 0, & EEAC(i) < 0.1 \\ f_{max}, & EEAC(i) \geq 0.1 \end{cases} \quad (3)$$

Angle of inclination (θ): Using the DC components of the acceleration signals the angle of each axis relative to the gravity was calculated. This value enabled the distinction between lying and upright activities like sitting [2].

$$\theta_y(i) = \cos^{-1}\left(\frac{ay_{DC}(i)}{\sqrt{ax_{DC}^2(i) + ay_{DC}^2(i) + az_{DC}^2(i)}}\right) \tag{4}$$

Altitude change (Δh): The altitude change corresponds to the direction of the vertical movements. Therefore the change in altitude Δh for each segment was calculated. By means of this value it was possible to differentiate between level and up- and down-hill walking.

C. Activity Classification

The classification algorithm differentiated between the following activities: lying, rest (sitting/standing), cycling, uphill, downhill, level walking and jogging. The classification was performed in the following steps (Fig. 2).

Using the angle of inclination, the postural orientation was determined; thus distinguishing between lying and upright activities. If the upright criterion was fulfilled and no steps were detected, the activity was further classified either as sitting/standing or as cycling. If on the other hand steps were detected, the altitude change Δh was used in order to differentiate between level walking and walking uphill/upstairs and downhill/downstairs. The variance of the total acceleration in this interval was then used to distinguish between jogging and walking. Since the frequency peak for walking lies between 1 and 3 Hz [5], activities with peak frequency inside this interval were classified as level walking and the rest as cycling. Fig. 2 shows the flowchart of the activity classification algorithm. The thresholds were not person-specific and were defined based on a preliminary study.

D. Estimation of Energy Expenditure

For the EE estimation the activities were divided in 3 groups. The first group included all the passive activities (lying, sitting and standing), the second all the walking activities and the third one the cycling.

For the first activity-group the EE estimation was done using the basal metabolic rate (BMR) formulas published in [10]. BMR is defined as the calories the body needs for its main functions (e.g. breathing). The EE for the passive activities was calculated as shown in (5).

$$EE = BMR \cdot 1.2 \tag{5}$$

The EE estimation for the other two activity-groups was performed by using multi-linear models. The features used for the multi-linear models were the acceleration magnitude (EEAC) and the altitude change. The altitude change was split into two separate features, the positive and the negative altitude change (Δh_{pos} and Δh_{neg} respectively).

Along with the features extracted from the acceleration and the air pressure signal, other subject-related features such as body height, body weight and age were used as well.

Using the features mentioned above two separate linear models (one for women and one for men) were trained for each activity group. The model parameters were estimated by using the least square estimator between the model output and the output from the indirect calorimeter.

IV. Results

Table IV summarizes the results of the activity classification algorithm. The ground truth was annotated by a researcher, who always walked behind the subject and based on the study protocol gave instructions when to start and stop. All the activities are classified with a mean classification rate of 98.2%. The activity with the smallest classification rate was cycling (95.1%).

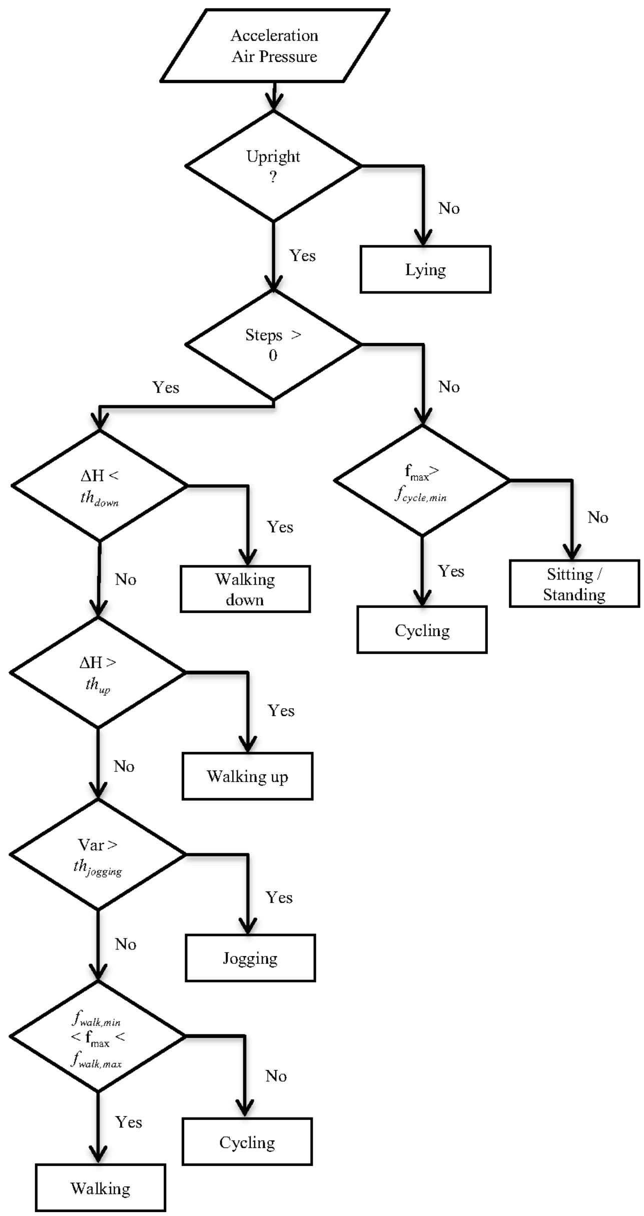

Figure 2. Activity recognition flowchart

TABLE IV. THE RESULTS OF THE ACTIVITY CLASSIFICATION

	Lying	Rest	Cycling	Uphill	Jogging	Downhill	Walking	Sensitivity
Lying	3648 s	124 s	0	0	0	0	0	96.7%
Rest	16 s	19388 s	0	0	0	0	0	99.9%
Cycling	0	116 s	9076 s	0	0	0	356 s	95.1%
Uphill	0	0	28 s	3752 s	0	0	64 s	97.6%
Jogging	0	0	12 s	0	8528 s	0	36 s	99.4%
Downhill	0	4 s	0	0	0	3212 s	32 s	98.9%
Walking	0	16 s	12 s	0	8 s	0	16208 s	99.8%
Pos. prediction	99.6%	98.7%	99.4%	100.0%	99.9%	100.0%	97.1%	

The validation of the EE prediction models was performed by using the leave-one-subject-out cross validation. Using this method the generalization of the models can be tested. In our approach we first separated the data in 2 groups according to the gender and then we performed the cross validation. The difference between the output from the indirect calorimeter and the prediction of the EE was computed for each subject and each activity.

Table V shows the results of the second-by-second estimation of EE using the rms error (RMSE) and the percent error for each activity and over the whole duration of the protocol (including the time to reach the steady state). The mean value of the RMSE for all the activities is 1.19 ± 0.37 [kcal/min]. The biggest prediction error is observed for the cycling activity, this is both due to the fact that cycling was sometimes falsely recognized as rest or walking and due to the position of the sensor, which was not always able to detect the intensity of the movement. Fig. 3 shows a sample plot of the EE measured with the portable indirect calorimeter and the estimated values for one subject.

TABLE V. PREDICTION ERRORS (MEAN ± SD) FOR THE ENERGY EXPENDITURE

Activity	RMSE [kcal/min]	Percent error [%]
Lying/ Rest	0.38 ± 0.15	-3.15 ± 13.63
Walking	0.85 ± 0.41	-3.90 ± 14.71
Jogging	1.31 ± 0.68	2.82 ± 10.44
Cycling	1.43 ± 1.05	4.48 ± 19.46
Walking up-/downhill	0.87 ± 0.32	-3.06 ± 9.40
Walking upstairs	1.05 ± 0.53	0.27 ± 14.76
All activities	1.19 ± 0.37	1.59 ± 8.20

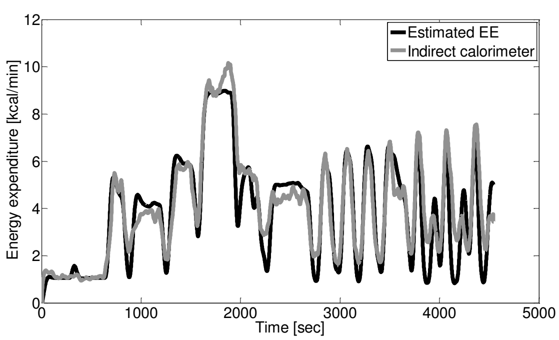

Figure 3. Energy expenditure. The black line is the estimated energy expenditure and the gray line is the gold standard measure obtained by the portable indirect calorimeter.

V. CONCLUSION

An algorithm for activity recognition and EE estimation was presented and evaluated. The results from the activity classification are very satisfactory but should be tested under real life conditions and for longer time periods. The results achieved by the EE estimation are of rather good quality as well, but the performance of the algorithm should be further tested for other daily living activities (e.g. household) and other populations (e.g. elderly people, children) in order to optimize the model parameters for the EE estimation.

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