A Person-Centered Measurement System for Quantification of Physical Activity and Energy Expenditure at Workplaces

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Abstract. Accurate quantification of physical activity (PA) and energy expenditure (EE) is a basic prerequisite to evaluate activity promoting measures. A novel approach for determining EE by a person-centered measurement system which operates with motion sensors is presented. The new EE prediction model combines information on the type and intensity of PA as well as personal characteristics. For model calibration eight subjects performed standardized office and locomotion tasks while wearing the measurement system and an indirect calorimeter simultaneously. Via multiple regression analyses different EE prediction equations for sitting, standing, walking, climbing downstairs and climbing upstairs are developed. Model fit statistics revealed good results (adjusted $R^2 = 0.51 - 0.90$). The developed model seems promising for precise EE prediction during the investigated activities.

Keywords: physical activity, inactivity, office tasks, energy expenditure, prediction equation, motion sensors, CUELA Activity System, MetaMax 3B.

1 Introduction

Work with computers means a heavy burden on the employees' well-being: Continuous sitting, inadequate static postures and strong focus on screen and keyboard hardly allow physical activity (PA). Static work tasks and lack of PA constitute a serious health hazard which can be reduced by preventive strategies that promote PA and the variation between sitting, standing and moving at workplaces. To evaluate such measures, a method which provides objective, reliable and detailed information on PA in field studies is required.

Motion sensors are currently seen as the most suitable practice for long-term activity monitoring [4, 6, 11]. In case of adequate data processing, they provide information on type, intensity, duration and frequency of the performed activities as well as estimation of the energy expenditure (EE). Particularly in the context of inactivity, EE – which is often disproportionate to energy intake – has an increased significance. There are basically two approaches in determining EE by means of motion sensors:

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1. *Estimation of EE via the intensity of PA (PAI, physical activity intensity):* This approach is based on the assumption that the intensity of human movement is related linearly with activity induced EE. As far as thirty years ago it was discovered that during walking the integrated sums of the accelerations measured on the body are proportional to EE [7]. Today's devices designed for recording PAI and EE are also based on this assumption (e.g. Caltrac, MTI Actigraph or RT3 Activity Recorder). Movement intensity is usually recorded by a single uni- or triaxial accelerometer placed on the hip (as rough representation of the body's centre of mass). The procedure used to determine PAI is always the same: first of all, the raw acceleration signals are high-pass filtered and afterwards the absolute values are subsequently averaged in different ways. The so calculated PAI values are either internally converted into EE or they are displayed as "activity counts" and have to be processed further externally. Both, the internal and the external calculations are based on calibration studies with indirect calorimetry, in which equations for the conversion of activity counts into EE were ascertained via linear regression methods. In many cases, the prediction models include personal characteristics like age, sex, and/or body size.

   Validation studies yielded very heterogenous results. The estimations can be used to distinguish between different levels of activity. However, the precise prediction of EE according to this approach seems difficult [4, 5, 6 ,11]. This may be due to the inability of one hip mounted sensor to reflect the energy cost of arm activities or walking upstairs. Additionally, the relationship between PAI and EE depends highly on the type of activity. Prediction equations which are, for example, developed only on the basis of locomotion activities (e.g. walking and running at different speeds), tend to underestimate the energy cost of everyday activities like household or office tasks [10, 11]. Therefore, it is concluded, covering all possible activities with just one equation seems unlikely, and alternative strategies are needed to obtain more precise estimations of EE which are valid for a broad range of activities [10].

2. *Estimation of EE via the type of PA:* A different approach is pursued by the measurement system IDEEA (Intelligent Device for Energy Expenditure and Activity). By means of five movement sensors, which are placed at the sternum, at both thighs and under both feet, different activities, like sitting, standing, lying, walking, climbing stairs or running, are detected automatically. The IDEEA software contains equations for the determination of EE for the identifiable activities as well as for resting metabolic rate. These equations are taken from especially conducted measurements as well as large databases [1, 2]. As the IDEEA system records accurately type, onset, duration and frequency of PA [15], a more differentiated estimate of EE compared to the first approach can be expected.

   Validated against direct and indirect calorimetry, a high overall accuracy has been shown [14]. Anyhow, there were overestimations and underestimation up to 10%. The authors explain the overestimation of the IDEEA with the fact, that some of the subjects had a high fitness level which is ignored in the prediction equations. The underestimations probably arise because activities of the upper limbs are disregarded again. Furthermore, additional movements during static postures (e.g. fidgeting during sitting) are not considered.

The test protocol for validation against indirect calorimetry solely consisted of static body postures as well as walking and running on a treadmill; everyday activities were not investigated. The main difficulty of this approach is that, even if more sensors were applied, it would not be possible to detect all conceivable activities to consult the respective exact equation for EE determination.

In order to solve the described problems, we developed a new EE prediction model which combines the two presented approaches: The model considers the type of activity as well as PAI. Additionally, personal characteristics are taken into account. For model calibration, we conducted a study in which the required activity information was determined by the multi-sensor CUELA Activity System (computer-assisted recording and long-term analysis of physical activity) and a portable gas exchange analyzer (MetaMax 3B) provided the criterion measure of EE.

2 Methods

2.1 Subjects

Eight subjects (4 females, 4 males) participated in this calibration study. The participants were free from known cardiovascular and metabolic disorders. The physical characteristics are given in Table 1. Besides sex, age and BMI, the activity level was assessed as supposed determinants of EE [12]. The activity level was rated by the subjects themselves on a five-stage scale (1 = inactive, 2 = low, 3 = moderate, 4 = high and 5 = very high) [3]. The sample represents a wide range of physical characteristics: age between 23 and 48 years, BMI between 20.1 and 31.2 kg/m^2 and activity level between 1 and 5.

Table 1. Characteristics of the sample

	Female (n = 4)		**Male (n = 4)**		**Total (n = 8)**			
	Mean	SD	Mean	SD	Mean	SD	Min	Max
Age (years)	29.5	8.7	39.3	8.5	34.4	8.7	23	48
BMI (kg/m^2)	25.6	5.3	25.9	5.0	25.7	4.7	20.1	31.2
Activity level [1…5]	3.3	2.1	2.5	1.0	2.9	1.6	1	5

2.2 Activity Protocol

Each subject performed a standardized activity protocol. Sequence and duration of the activities are listed in Table 2. For the protocol we selected activities which occur typically at office workplaces. Furthermore, we considered to have at least two different intensity levels in each activity category. The protocol included office tasks during sitting (sitting quietly, typing, filing) and during standing (standing quietly, filing, sorting files in an office cabinet), walking at different speeds (4, 5 and 6 km/h) as well as going downstairs and upstairs (‘slow’ and ‘medium’ speed). In order to standardize the speed during walking and climbing stairs, subjects were accompanied by a person who set the pace with the aid of a clock and distance markers. The complete procedure took about 40 minutes.

Table 2. Activity protocol

Nr.	Activity	Duration [min]	Explanatory notes
1	Sitting 1	5	Sitting quietly
2	Sitting 2	3	Typing
3	Sitting 3	4	Filing
4	Standing 1	2	Standing quietly
5	Standing 2	4	Filing
6	Standing 3	2	Sorting files in a cabinet
7	Walking 1	3	4 km/h
8	Walking 2	3	5 km/h
9	Walking 3	3	6 km/h
10	Downstairs 1	1	Slow speed
11	Downstairs 2	1	Medium speed
12	Upstairs 1	1	Slow speed
13	Upstairs 2	1	Medium speed
Total duration (net)		33	
Total duration		**~40**	**(incl. change of location)**

2.3 Measurements

During the whole activity protocol, subjects were monitored simultaneously by the MetaMax 3B and the CUELA Activity System (see Fig. 1). Additionally, video recordings were conducted for documentation purposes.

Criterion Measure of EE (MetaMax 3B). Indirect calorimetry is considered the most accurate method for free-living assessment of physical activity EE [8] and is, therefore, adequate for application in calibration studies. In the present study, the portable indirect calorimeter MetaMax 3B (CORTEX Biophysik, Leipzig, Germany) was used for metabolic gas exchange analyses and subsequent determination of EE.

The portable MetaMax 3B operates with a volume sensor which is integrated into a mask as well as oxygen and carbon dioxide sensors which are integrated in a chest

Fig. 1. Measurement instrumentation during activity protocol

worn data logger (see Fig. 1). The system performs gas analysis via breath-by-breath method and yields different outcome measures of EE. In order to allow EE estimates to be independent of body size we use the metabolic equivalent (MET) as expression of EE. METs represent the ratio of working metabolic rate to the resting metabolic rate. One MET is defined as 1 kcal/kg/hour and is roughly equivalent to the energy cost of sitting quietly.

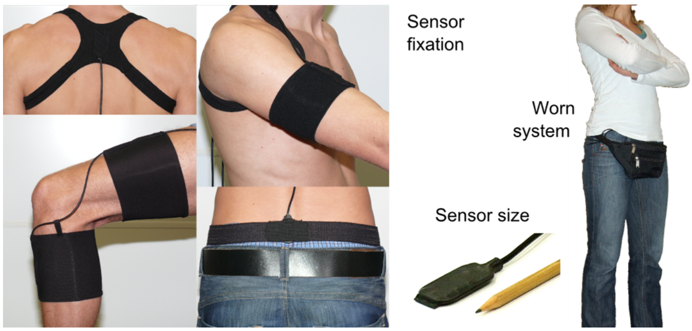

Fig. 2. Measurement setup of the CUELA Activity System

Quantification of PA (CUELA Activity System). The CUELA Activity System is developed by the Institute for Occupational Health and Safety of the German Social Accident Insurance (BGIA) in order to provide differentiated movement data [9]. The system operates with a total of seven miniaturized sensors, each consisting of a triaxial acceleration sensor and an uniaxial gyroscope. The sensors are attached to the back at level of thoracic spine and lumbar spine, both upper and lower legs and the upper arm of the dominant arm (see Fig. 2.). Elastic and breathable straps are used to fix the sensors under the clothing. Over the closing only a hip belt with the data logger is visible.

The sensor signals are stored on a flash card and subsequently imported into the associated analysis software on the PC. For the development of the EE prediction model the following analysis functions are relevant:

- The sensor data is used to determine body angles and postures. Via pattern recognition algorithms the software detects automatically which activity is performed at any given time. The identifiable activities are sitting, standing, lying, kneeling, crouching, walking, running, cycling and climbing upstairs and downstairs.
- The acceleration signals are used to determine PAI values according to the approach of the one-sensor devices. PAI for each body segment fitted by a sensor is calculated as follows: To cover all directions of movement the vector magnitude of the 3D acceleration vector (x, y, z) at time t is determined:

$$VM_{Segment_t} = \sqrt{x_t^2 + y_t^2 + z_t^2} \quad (1)$$

Subsequent high-pass filtering removes the constant signal portions, so that only the alternating portion – i.e., the signal representing actually movement – remains. To obtain the current movement intensity a moving root mean square is calculated for the high-pass filtered vector magnitudes (VMfilt) across T = 150 readings (equivalent to 3 s at the adopted sampling rate of 50 Hz):

$$PAI_{Segment_t} = \sqrt{\frac{1}{T}\int_{t-\frac{T}{2}}^{t+\frac{T}{2}} VMfilt_{Segment_t}{}^2(t)dt} \qquad (2)$$

The segment activities determined in this way are combined to calculate whole body PAI (PAI_{total}). According to the distribution of segment masses assumed in biomechanical models e.g. [13] the PAI values are merged using the following factors:

$$\begin{aligned} PAI_{total} = {} & 0.4 \cdot (0.5\ PAI_{thoracic\ spine} + 0.5 \cdot PAI_{lumbar\ spine}) \\ & + 2 \cdot 0.2 \cdot (0.65\ PAI_{upper\ leg} + 0.35 \cdot PAI_{lower\ leg}) \\ & + 0.2 \cdot PAI_{upper\ arm} \end{aligned} \qquad (3)$$

2.4 Data Analysis

In order to synchronize the data streams the MET values quantified by MetaMax 3B (MET_{MMX}) were imported into the CUELA software. For the accurate identification of the activities from the protocol the recorded videos were also synchronized with the measurement data.

The first part of developing an EE prediction model was to determine MET values according to the type of activity detected by CUELA. These METs are obtained from well-researched databases [1, 2]. As the CUELA System can only identify base activity categories like ‘sitting’ or ‘walking’ and not for example ‘sitting and sorting files’, we call them MET_{Basis}. Therefore, differences between measured and base METs are expected.

The second part of the model was then to examine these differences (MET_{Diff} = MET_{MMX} – MET_{Basis}) to correct the MET_{Basis} values appropriately. Following the assumption that differences are on the one hand due to the variety in movement intensity within one base activity category (i.e. identical MET_{Basis} value), scatter plots were drawn to analyze the relationship between MET_{Diff} and PAI_{total} at group level. On the other hand discrepancies may be caused by personal conditions; hence, differences between group and individual MET_{Diff}-PAI_{total} relationships were examined with respect to BMI, age, gender and activity level using scatter plots (all plots not shown).

Multiple regression analyses for the prediction of the MET_{Basis} correction were calculated. For this purpose activities from the protocol were investigated separately. The last 30 % of each activity interval were taken for examination, assuming that a steady state has been reached therein. PAI_{total} and MET_{Diff} were averaged for every activity. Regressions were calculated for each base activity category (sitting, standing, walking, walking downstairs and walking upstairs) whereas MET_{Diff} was the dependent variable and PAI_{total}, BMI, age, activity level and gender were the indepen-dent variables. For the analysis gender was dummy-coded (male = 1; female = 2) and the activity level were converted into scores according to Jurca et al. [3].

3 Results

Base MET values referring to the protocol are given in Table 3. During all performed activities differences between looked-up METs (MET_{Basis}) and measured METs (MET_{MMX}) were found. The mean differences over all subjects and intensity levels within one category are presented in Table 3. The absolute values of the mean differences were the lowest for sitting (0.32 METs) and the highest for climbing upstairs (2.09 METs), whereas the highest relative mean differences occurred during standing (61 %) and the lowest during walking (14 %).

Table 3. Differences between looked-up and measured METs

	MET_{Basis}	$MET_{Diff} = MET_{MMX} - MET_{Basis}$				
		Mean	SD	Mean in %	Min	Max
Sitting	1.0	0.32	0.25	31.64	-0.11	0.71
Standing	1.2	0.73	0.74	61.20	-0.25	2.12
Walking	3.5	0.49	0.70	14.04	-0.87	1.91
Downstairs	3.0	0.69	0.63	23.08	-0.76	1.74
Upstairs	8.0	-2.09	2.04	-26.07	-4.89	1.10

Values are in METs (1 MET = 1 kcal/kg/h), except for Mean in %; MET_{Basis}, looked-up base METs; MET_{MMX}, METs measured by MetaMax 3B.

MET_{Diff} values increased with raising intensity within one base activity category. Scatter plots (not shown) demonstrated strong linear relationships between these differences and PAI_{total}. Linear relationships were also found for the differences between group and individual MET_{Diff}-PAI_{total} relations and the personal characteristics. Multiple linear regression analyses with PAI_{total} (PAI), BMI, activity level (Act), age and gender (G) as predictors yielded the following correction terms for sitting, standing, walking and climbing stairs:

$$Corr_{Sitting} = 0.994 + 48.438 \cdot PAI - 0.032 \cdot BMI - 0.030 \cdot Act - 0.004 \cdot Age - 0.158 \cdot G \quad (4)$$

$$Corr_{Standing} = 1.513 + 31.416 \cdot PAI - 0.029 \cdot BMI - 0.032 \cdot Act - 0.009 \cdot Age - 0.370 \cdot G \quad (5)$$

$$Corr_{Walking} = -0.984 + 8.870 \cdot PAI - 0.03 \cdot BMI - 0.049 \cdot Act - 0.018 \cdot Age - 0.238 \cdot G \quad (6)$$

$$Corr_{Downstairs} = 1.266 + 4.786 \cdot PAI - 0.096 \cdot BMI - 0.310 \cdot Act + 0.006 \cdot Age + 0.228 \cdot G \quad (7)$$

$$Corr_{Upstairs} = 8.064 + 32.429 \cdot PAI - 0.206 \cdot BMI - 0.315 \cdot Act + 0.040 \cdot Age + 1.076 \cdot G \quad (8)$$

Standard error of estimate (SEE) and adjusted multiple determination coefficients (adj. R^2) of the correction models as well as the standardized coefficients (beta coefficients) of all predictors are given in Table 4. SEE was the lowest for the correction term for sitting (0.08 METs) and the highest for climbing upstairs (1.37 METs). Compared to the standard deviation of the respective dependent variables (see Table 3) all SEE values are considerably lower. The linear combinations of the adopted predictors explain between 83 and 90 % of the variance of the dependent variable during sitting, standing and walking and slightly more than half of the variance during walking upstairs and downstairs. The prediction models for MET_{Basis} correction were highly significant ($p \leq 0.001$) for sitting, standing and walking and significant for the stair climbing correction terms ($p \leq 0.05$).

In order to show the importance of each predictor within one model standardized beta coefficients are presented here. For all activity categories except for walking downstairs PAI_{total} has the clearly highest influence on the correction term. For walking downstairs the absolute beta coefficient of BMI is somewhat higher than the value for PAI_{total}. Except for age and sex during climbing stairs, the person related variables have a negative sign. Among these predictors BMI is of highest importance for sitting and climbing downstairs and upstairs. For standing gender shows the largest absolute beta and for walking the highest impact is found for age.
For all activities beta coefficients for PAI_{total} are significant. Further significant beta coefficients are found for BMI (for sitting and walking downstairs) and gender (only for sitting).

Table 4. Model fit statistics and standardized coefficients of the base MET correction terms

Correction term for	**SEE (METs)**	**Adj. R²**	**Standardized coefficients (beta)**				
			PAI_{total}	BMI	Act	Age	G
Sitting	0.08	0.90**	0.79**	-0.53**	-0.13	-0.15	-0.32*
Standing	0.30	0.83**	0.93**	-0.17	-0.05	-0.11	-0.26
Walking	0.24	0.88**	0.95**	-0.19	-0.06	-0.24	-0.17
Downstairs	0.44	0.51*	0.54*	-0.65*	-0.54	0.08	0.19
Upstairs	1.37	0.55*	0.83**	-0.43	-0.17	0.16	0.27

* $p \leq 0.05$; ** $p \leq 0.001$; Adj. R^2, adjusted multiple determination coefficient; SEE, standard error of estimate; PAI_{total}, whole body physical activity intensity; Act, activity level; G, gender.

4 Discussion

The presented approach for EE estimation by means of motion sensors combines the existing methods and addresses their problems at the same time: Using the automatic activity recognition of the CUELA Activity System, it was possible to develop a branched model with different EE prediction equations for the respective activity categories. This proceeding seems inevitable since precise prediction of EE with just one equation for all activities is not possible [10]. As the system can not detect all imaginable human activities, additional movements, for example during sitting or standing, are involved by regarding PAI values of different body regions. PAI of upper and lower legs and trunk as well as the dominant arm are integrated into whole body PAI. Thus, more differentiated information on movement intensity than just PAI measured at hip level is considered. Underestimations of the previous approaches referring to this might be solved. In addition, the integration of BMI, age, sex and activity level may possibly further reduce estimation errors.

The first part of the developed model (consulting look-up tables for EE determination) corresponds to the IDEEA approach. As expected, the looked-up METs (MET_{Basis}) differed from the measured METs (MET_{MMX}) during all performed activities. The discovered positive linear relationships between these differences (MET_{Diff}) and PAI_{total} reconfirmed the approach of estimating EE by PAI: growing energy demand due to increasing movement intensity can be predicted to a large extent by whole body PAI. In order to get a more precise prediction for correcting MET_{Base}, multiple regression analyses with supplementary consideration of personal characteristics were conducted. Regarding the small sample size typically a method for stepwise selection of variables would be suitable. Since we used predictors which are well known as EE determinants they were entered into the regression analyses via inclusion method.

Checking the model fit revealed statistical significance for each correction equation. Adjusted R^2 was lower for the models of walking downstairs and upstairs. This might be due to the experimental protocol: for climbing stairs only two different intensity levels were included and, therefore, less data points are provided for these activities.

With regard to the non standardized regression coefficients it can be stated that, the higher the relative differences between base METs and measured METs are, the larger the coefficients for PAI_{total} tend to be. Beta coefficients for PAI_{total} showed significance for all correction terms and, thus, prove the high importance of PAI on the variance in EE. Negative signs of the regression coefficients of the individual variables agree with known effects of personal characteristics on EE: the correction term is smaller, i.e. EE per kg body weight is lower, (1) for persons who have a higher BMI, (2) for physically more active persons, (3) for older persons and (4) for women. Solely for the climbing upstairs and downstairs correction terms the coefficients for sex and age are positive. However, these coefficients are each of very low impact on the whole equation. Considering the standardized coefficients for the personal characteristics only few of them were significant. This is likely caused by the small sample size and should be investigated again with more subjects.

Anyhow, it can be concluded that combining the information on type of activity, movement's intensity (PAI) and a person's characteristica may improve estimation of EE by motion sensors. By integrating the determined regression models into an EE prediction model linked to the CUELA Activity System, this device seems promising for accurate analysis of PA and EE for a broad range of applications, for example the activity assessment of computer workers in the context of quantification of inactivity and evaluation of PA promotion measures. Currently, we are analyzing data of a validation study, in which the resulting EE prediction model is tested against indirect calorimetry for an independent sample. Once being evaluated, the CUELA Activity System might overcome limitations of methods used to measure PA and EE. The system will, for instance, be more valid than questionnaires or one-sensor systems and more practicable than indirect calorimetry.

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