

Estimation of activity energy expenditure based on activity classification using multi-site triaxial accelerometry

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A wireless networked multi-site triaxial accelerometry system has been devised to estimate activity energy expenditure during daily life. A notable feature of the devised system is the utilisation of activity classification based on multi-site acceleration signals. During performance evaluation tests on a single subject, the proposed method showed higher correlation (adjusted $R^2 = 0.952$) and smaller estimation deviation (0.76 kcal/min) than two methods without activity classification (multi-site case: adjusted $R^2 = 0.924$, estimation deviation = 0.892 kcal/min and single-site case: adjusted $R^2 = 0.855$, estimation deviation = 1.18 kcal/min).

Introduction: Accelerometry-based activity energy expenditure (AEE) assessment has been widely used for its convenience, portability and reasonable accuracy. However, the performance of this method is known to be highly dependent on hardware setups, such as, place of attachment, type (uni-, bi- or triaxial accelerometer), and the number of acceleration sensors, and on the estimation algorithm used.

Owing to the high cost and difficulties of synchronising multi-site acceleration sensors, most efforts in hardware development have focused on achieving better accuracy based on single-site measurements. However, there is some debate over the optimal hardware setup required to provide a high correlation with actual AEE [1]. Regarding the estimation algorithm, some studies have tried to increase system performance given hardware setups (usually single-site accelerometry) by optimising a regression model that relates accelerometry results to actual AEE. For example, a number of studies have reported that the use of two optimised regression models could significantly enhance estimation accuracies for single-site measurements [2, 3].

However, to date the use of multi-site measurements, the categorisation of activity into different classes and the application of an additional regression factor in combination has not been attempted, though this would be expected to increase the accuracy of AEE estimation. As triaxial acceleration chips and solutions for local wireless network are available at affordable prices, we considered it worthwhile to try to define an optimal configuration and estimation algorithm in terms of maximising estimation accuracy. Therefore, in this Letter we propose a possible optimal configuration involving a multi-site triaxial accelerometer system and a new AEE estimation algorithm based on activity classification. We have also evaluated the performance of this configuration against multi-site and single-site systems without activity classification.

Decisions on placement, type and number of accelerometers: Considering three major segments and the right-left symmetry of the human body, acceleration sensors were placed on the right wrist, right ankle and waist. Accelerometers worn on upper extremities (wrist and arm) can properly measure arm-dominant activities and sedentary activities indoors [4]. Accelerometry signals from the lower extremities are highly correlated with type and speed of walking and running activities, which are the most frequent activities outdoors [5], and the waist is a popular place to measure body acceleration, because acceleration at the waist, which is close to the body's centre of mass is highly correlated with whole body movement [6].

Signal processing and estimation algorithm: We used the integral of absolute value of accelerometer output (IAA), which has been reported to be more accurate than the integral of magnitude of acceleration vector (IAV) [7]. Their definitions are as follows:

$$IAA \simeq \sum |Ax_i(n)| + \sum |Ay_i(n)| + \sum |Az_i(n)| \quad (1)$$

$$IAV \simeq \sum \sqrt{|Ax_i(n)|^2 + |Ay_i(n)|^2 + |Az_i(n)|^2} \quad (2)$$

where $Ax_i(n)$, $Ay_i(n)$, and $Az_i(n)$ represent i th sampled acceleration at every 0.01 s over the given time period for the x , y and z axes, respectively.

Calculated IAA values were then converted to estimated activity energy expenditure using a linear regression equation based on reference

data obtained using a standard method. Activity during a given period was automatically classified into two categories, i.e. arm-dominant and leg-dominant activities, according to the ratio of wrist to ankle acceleration signal amplitudes. This ratio was incorporated into the regression analysis as an additional factor.

The performances of different hardware setups and estimation algorithms was compared using the adjusted R^2 regression model; deviations in estimation (D) and estimation variation (V) were defined as follows:

$$V = (D_1 - D_2)/D_1 \quad \text{with} \quad D_1 = |y_i - \hat{y}_{i1}|, D_2 = |y_i - \hat{y}_{i2}|$$

where the y_i are the i th reference AEEs measured by a standard method, and \hat{y}_{i1} and \hat{y}_{i2} are the estimated AEEs for the corresponding period using different regression models (1) and (2).

Developed system description: Fig. 1 shows a functional block diagram of the developed system. A three axis low-g micromachined accelerometer (MMA7260Q, Freescale, USA), which has three $\pm 6g$ resolution analogue outputs, was selected as an acceleration sensor. Three sensor modules placed at different body locations were wirelessly networked using a 2.4 GHz RF transceiver (nRF24L01, Nordic, USA) to provide wearability and mobility. All measured acceleration signals in each module were filtered at 0.3–19 Hz, sampled at 100 Hz, and then converted to acceleration values using (1). Values acquired by ankle and waist modules were transmitted to the wrist module every second. The wrist module has an LCD as a user interface (UI) and a memory interface (1G SD card, SanDisk, USA) for logging seven days of acceleration data. Each module has a real-time clock IC chip (S-35190A, Seiko Instruments Inc., Japan) to ensure module synchronisation. An MSP430FG437 (Texas Instruments, USA) was selected as a micro control unit (MCU) because of its low power consumption, internal LCD driver, and 12-bit analogue-to-digital converter. Each module is powered by a single 1.5 V AAA-type battery.

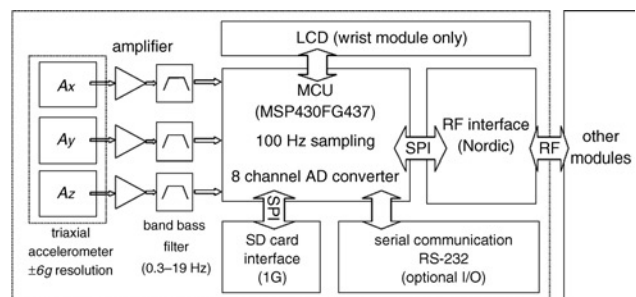


Fig. 1 Functional block diagram of developed accelerometry system

Experiments: Performance evaluation tests were performed for a single volunteer (176 cm, 68 kg, 30-year-old male) wearing the developed three accelerometer modules. All modules are $58 \times 79 \times 24$ mm in size; the wrist module weighs 103 g and the waist and ankle modules 60 g. At the same time, the volunteer also wore an indirect calorimetry system (K4B², COSMED, Italy) to obtain reference energy expenditure data from respiratory gas exchange volumes. The experimental protocol started with a 5 min rest in order to calculate resting metabolic energy expenditure. This was followed by 1 min exercise and 2–7 min resting periods. The rest periods depended on exercise intensity, which included walking (1–7 km/h) and running (5–12 km/h) as typical leg-dominant activities, and mopping and washing windows as representative arm-dominant activities. These exercises were conducted in a random manner.

Results: To verify the effect of multi-site measurements and the activity classification, we used two different regression models for multi-site measurements with and without activity classification and one for single-site measurements (Fig. 2). The regression coefficients, adjusted R^2 values and accuracies of these three models are given in Table 1. The single-site model, in which acceleration signals from the waist module were used, produced the largest estimation deviation (1.18 kcal/min) and the lowest adjusted R^2 value (0.852). The multi-site (waist, ankle and wrist) acceleration model improved this estimation accuracy by about 25% ($D = 0.892$ kcal/min, $V = 0.246$) and increased the adjusted R^2 value (0.924). However, the proposed multi-site and activity classification model resulted in a remarkable 35% improvement in

estimation deviation ($D = 0.763$ kcal/min, $V = 0.354$) over the single-site model and increased the highest adjusted R^2 value (0.956).

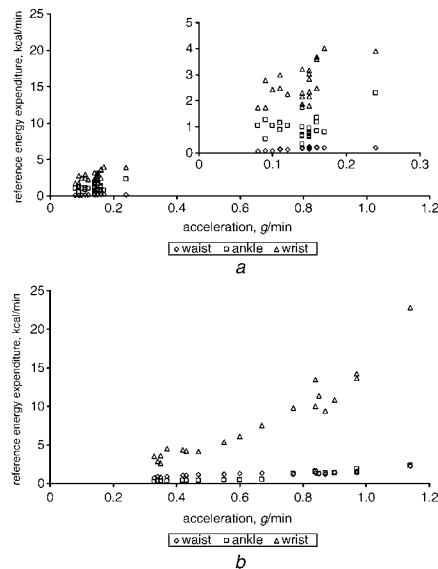


Fig. 2 Reference activity energy expenditure (AEE) measured by indirect calorimetry compared to integral of absolute value of accelerometer output (IAA) from waist, ankle and wrist modules
a Arm-dominant activity group
b Leg-dominant activity group

Table 1: Specific coefficients, p -values, adjusted R^2 s for two different models of multi-site acceleration measurement with and without activity classification and one single-site measurement model. Estimation accuracies of model are presented as estimated deviations (D). Adjusted R^2 changes and estimation variations (V) were calculated against single-site model

Model		Coefficients (p -value)	Adjusted R^2	Adj. R^2 change*** (p -value)	Estimation deviation (D)	Estimation variation*** (V)
Single-site	(constant)	0.212 (0.610)	0.855	N/A	1.183 (kcal/min)	N/A
	waist	13.310*				
Multi-site	(constant)	-1.742*	0.924	0.070 (<0.001)	0.892 (kcal/min)	0.246 (=24.6%)
	waist	5.429 (0.077)				
	ankle	3.160*				
	wrist	3.094*				
Multi-site with activity classification	(constant)	-0.965*	0.952	0.097 (<0.001)	0.763 (kcal/min)	0.354 (=35.4%)
	waist	6.469*				
	ankle	7.050*				
	wrist	1.586*				
	activity**	-5.080*				

* p -values are less than 0.05

**activity = 0 for arm-work dominant activities, 1 for leg-work dominant activities

***compared to single-site regression model

Conclusions: The devised multi-site (wrist, waist, and ankle) accelerometry system was implemented using a wireless body area network to estimate activity energy expenditure, and was found to provide improved accuracy without disturbing daily life. Another advantage of the multi-site measurement system is that it enables activities to be automatically classified, i.e. into arm-dominant and leg-dominant groups, and this classification process was found to increase further AEE estimation accuracy.

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