# Activity energy expenditure assessment system based on activity classification using multi-site triaxial accelerometers 

Kim, Dongwoo and Hee Chan Kim


#### Abstract

Wireless networked multisite triaxial accelerometry system was proposed to estimate activity energy expenditure during daily life. Proposed system used different estimation algorithms according to activity classification based on measured acceleration signals. The estimation results showed higher correlation $\left(\mathrm{R}^{2}=0.98\right)$ and smaller standard errors of estimation (SEE $=0.66 \mathbf{k c a l}$ ) than any other system in preceding reports.


## I. Introduction

Accelerometry-based activity energy expenditure (AEE) -assessment has been used widely for its convenience, portability and accuracy. However, performance of the accelerometry-based AEE estimation method varies according to the body part of measurement, types of accelerometer (uni-, bi- or tri-axial) and the total number of measurement axes. Many studies have tried to optimize these factors to increase the estimation accuracy without a consensus on the optimal experimental setup to get a high enough correlation with true AEE [1]. On the other hand, some statistical approaches attempted to increase the estimation performance by improving regression models which relate accelerometry results to activity energy expenditure. A few studies which used acceleration counts from waist only reported that separating human activities into two and applying different models could significantly enhance the estimation performance[2, 3]. But there is still much room for improvement by incorporating detailed information of more body segments' movements. In this paper, we present the design and evaluation of a new portable AEE estimation system using multi-site tri-axial accelerometers, which provides better performance than any other system in preceding reports.

## II. METHOD

## A. Decision of accelerometer placement

Three body points of wrist, ankle and waist were selected for acceleration measurement. An accelerometer worn on

[^0]wrist properly measures arm-dominant activities, mostly sedentary activities during daily life [4]. Also, this accelerometer can easily be installed inside of a watch-type monitoring device as a user interface (UI). Acceleration signals from ankle highly correlate with types and intensity of walking and running activities, the most frequent activities during daily life[5]. Waist close to the center of mass of body is a popular place to measure body trunk acceleration which represents the movement of body mass [6]. Three tri-axial accelerometers attached to each body point produce the total nine channels of acceleration signals.

Signal processing and estimation algorithm: Tri-axial acceleration signals from each body part were used to calculate integral of absolute value of accelerometer output (IAA), which was reported more accurate than integral of magnitude of acceleration vector (IAV)[7].

$$
\begin{aligned}
& I A A=\int|A x| d t+\int|A y| d t+\int|A z| d t \\
& I A V=\int \sqrt{|A x|^{2}+|A y|^{2}+|A z|^{2}} d t
\end{aligned}
$$

Calculated IAA values were converted to the representative acceleration value $\left(\operatorname{Arep}_{\mathrm{IAA}}\right)$ for a certain activity by calculating the weighted $\left(\mathrm{w}_{1}, \mathrm{w}_{2}, \mathrm{w}_{3}\right)$ sum of IAA value of each body part (IAA Wrist IAA Waist, IAA $_{\text {Ankle }}$ ).

The final AEE value was then estimated from Arep ${ }_{\text {IAA }}$ by regression equations, where three different regression models were compared. First regression model does not distinguish activity into different types and uses one regression equation. Second model separates the activities into two groups of an arm-work dominant activity (mopping and cleaning window) and a leg-work dominant activity (walking and running) and derives two regression equations. Last model halves each group in the second model further based on exercise intensity level (walking vs running and washing window vs mopping) to get the total four different regression equations. SEE and correlation value were evaluated for three regression models by SPSS program (SPSS Inc. USA).

## B. Developed system

Fig. 1 shows a block diagram of the developed tri-axial accelerometry system. A three axis low-g micro-machined accelerometer (MMA7260Q, Freescale, USA) was used as an acceleration sensor which provides analog outputs with $+/-6 \mathrm{~g}$ sensitivity. All the measured acceleration signals were band-pass filtered ( $0.3 \sim 19 \mathrm{~Hz}$ ) before A/D conversion at 100 Hz sample rate. Then the digital data measured at the ankle
and waist modules were transmitted to the wrist module at every second through a wireless network using a 2.4 GHz RF communication linkage (nRF42L01 ANT protocol, Nordic, USA) to provide wearability and mobility of the system. The wrist module has an LCD as a UI and a memory interface (1G SD card, SanDisk, USA) for logging total 7 day acceleration data. Each module has a real time clock (RTC) chip (S-35190A, Seiko Instruments Inc., Japan) for synchronization among the modules. A 16-bit ultra-low-power MCU (MSP430FG437, Texas Instruments, USA) was selected due to not only low power consumption, but also internal LCD driver for UI and analog to digital converter. The dimension of the developed system is $58 \times 79$ x 24 mm 3 and the wrist module weighs 103g while the ankle and waist modules 60 g . The system operates 5 days with a AAA-type $1,5 \mathrm{~V}$ battery.


Fig. 1 A block diagram of the developed tri-axial accelerometry system.

## III. EXPERIMENTS

Performance of the developed system was evaluated by a volunteer ( 30 -year-old male, $176 \mathrm{~cm}, 68 \mathrm{~kg}$ ) who worn the developed system as well as a portable telemetric gas analysis system (K4B ${ }^{2}$, COSMED, ITALY) to get reference data. Experiments protocol started with a 5-minute resting to measure the resting metabolic rate ( Kcal ) and then 1-minute activity followed by another 2~7 minutes resting until normal heart beat was recovered. The activity was randomly selected from walking ( $1 \sim 7 \mathrm{~km} / \mathrm{h}$ ), running ( $5 \sim 12 \mathrm{~km} / \mathrm{h}$ ), mopping and washing window as typical activities in daily life

## IV. Result

The correlation, a SEE, and optimized weight vectors are given in table 1 and also regression equations for each model were shown in Fig 2.

a) non-separation-based regression model

b) activity-group-based regression model

c) activity-based regression model

Activity-based regression model showed best result which has the smallest SEE (SEE $=0.66 \mathrm{kcal}$ ) and the highest correlation coefficient ( $\mathrm{R}^{2}=0.98$ ). And non-separated regression model showed worst result. Activity-based regression model enhanced the correlation and a SEE, compared to a singlesite waist-based triaxial accelerometer $\operatorname{system}\left(R^{2}=0.86\right.$, SEE $\left.=1.59 \mathrm{kcal}\right)$.

| Regression model | Optimized Weights |  |  | $\mathrm{R}^{2}$ | SEE |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | waist | ankle | wrist |  |  |  |
| Activity <br> based | walk | 1.00 | 0.00 | 0.00 |  |  |
|  | run | 0.26 | 0.74 | 0.00 | 0.98 | 0.66 |
|  | mop | 1.00 | 0.00 | 0.00 |  |  |
| Group <br> activity <br> based | leg <br> dominant | 0.00 | 0.62 | 0.38 |  | Arm <br> dominant |
|  | 0.88 | 0.00 | 0.12 | 0.97 | 0.79 |  |
| Non-separation based <br> multisite | 0.82 | 0.00 | 0.18 | 0.92 | 1.23 |  |
| Non-separation based <br> waist | 1.00 | 0.00 | 0.00 | 0.86 | 1.59 |  |
| Non-separation based <br> ankle | 0.00 | 1.00 | 0.00 | 0.85 | 2.00 |  |
| Non-separation based <br> wrist | 0.00 | 0.00 | 1.00 | 0.63 | 2.23 |  |

Table. 1 Correlation, standard errors of estimation (SEE) and optimized weight vectors for each of regression model

## V.Conclusion

The developed multisite accelerometer system has a merit that multisite accelerations could be used to classify activities. Also wireless network makes it possible that the user is not disturbed during daily activities and keeps monitoring of his activity energy expenditure by a watch-type wrist module. But considering the difficulty of implementation of activity classification algorithm, activity group-based (arm-dominant and leg-dominant group) regression model was the second possible solution, which can be implemented relatively with ease. This group-based algorithm also showed enhanced performance compared to a singlesite waist-based estimation.

## Acknowledgment

This work was supported by the Korea Science and Engineering Foundation (KOSEF) grant funded by the Korea government (MOST) (No. M10536060001-06N3606-00110)

## References

[1] S. G. Trost, K. L. McIver, and R. R. Pate, "Conducting accelerometer-based activity assessments in field-based research," Med Sci Sports Exerc, vol. 37, pp. S531-43, Nov 2005.
[2] K. Y. Chen and M. Sun, "Improving energy expenditure estimation by using a triaxial accelerometer," J Appl Physiol, vol. 83, pp. 2112-22, Dec 1997.
[3] S. E. Crouter, K. G. Clowers, and D. R. Bassett, Jr., "A novel method for using accelerometer data to predict energy expenditure," J Appl Physiol, vol. 100, pp. 1324-31, Apr 2006.
[4] A. M. Swartz, S. J. Strath, D. R. Bassett, Jr., W. L. O'Brien, G. A. King, and B. E. Ainsworth, "Estimation of energy expenditure using CSA accelerometers at hip and wrist sites," Med Sci Sports Exerc, vol. 32, pp. S450-6, Sep 2000.
[5] R. C. Foster, L. M. Lanningham-Foster, C. Manohar, S. K. McCrady, L. J. Nysse, K. R. Kaufman, D. J. Padgett, and J. A. Levine, "Precision and accuracy of an ankle-worn accelerometer-based pedometer in step counting and energy expenditure," Prev Med, vol. 41, pp. 778-83, Sep-Oct 2005.
[6] M. J. Mathie, A. C. Coster, N. H. Lovell, and B. G. Celler, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," Physiol

Meas, vol. 25, pp. R1-20, Apr 2004.
[7] C. V. Bouten, K. T. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity," IEEE Trans Biomed Eng, vol. 44, pp. 136-47, Mar 1997.


[^0]:    Manuscript received April 16, 2007. This work was supported by the Korea Science and Engineering Foundation (KOSEF) grant funded by the Korea government (MOST) (No. M10536060001-06N3606-00110)

    Kim, Dongwoo is with Interdisciplinary Program, Biomedical Engineering Major, Graduate School, Seoul National University, Seoul, Korea (email: indykide@melab.snu.ac.kr).

    Hee Chan Kim is with Department of Biomedical Engineering, College of Medicine and Institute of Medical and Biological Engineering, Medical Research Center, Seoul National University, Seoul, Korea (email: hckim@snu.ac.kr).

