J. Biomed. Eng. Res : 301-309, 2006

A Generalized Calorie Estimation Algorithm Using 3-Axis Accelerometer

Jee Hyun Choi[1], Jeong-Whan Lee[2], and Kunsoo Shin[3]

[1]*National CRI Center for Calcium and Learning, Korea Institute of Science and Technology*
[2]*School of Biomedical Engineering, College of Biomedical & Life Science*
[3]*Interaction Lab, Samsung Advanced Institute of Technology*
(Received October 9, 2006. November 30, 2006)

Abstract

The main purpose of this study is to derive a regression equation that predicts the individual differences in activity energy expenditure (*AEE*) using accelerometer during different types of activity. Two subject groups were recruited separately in time: One is a homogeneous group of 94 healthy young adults with age ranged from 20 ~ 35 yrs. The other subject group has a broad spectrum of physical characteristics in terms of age and fat ratio. 226 adolescents and adults of age ranged from 12 ~ 57 yrs and fat ratio from 4.1 ~ 39.7% were in the second group. The wireless 3-axis accelerometers were developed and carefully fixed at the waist belt level. Simultaneously the total calorie expenditure was measured by gas analyzer. Each subject performed walking and running at speeds of 1.5, 3.0, 4.5, 6.0, 6.5, 7.5, and 8.5 km/hr. A generalized sensor-independent regression equation for *AEE* was derived. The regression equation was developed for walking and running. The regression coefficients were predicted as functions of physical factors - age, gender, height, and weight with multivariable regression analysis. The generalized calorie estimation equation predicts *AEE* with correlation coefficient of 0.96 and the average accuracy of the accumulated calorie was 89.6 ± 7.9%.

Key words : accelerometer, activity energy expenditure, calorie cost, multivariable regression analysis

I. INTRODUCTION

The energy balance of a human body is important to maintain a healthy life by preventing any diet related disease along with obesity. The energy balance is defined as a difference between intake calorie and calorie expenditure. About 70-85% of the calorie expenditure is burned to sustain a body's vital functions, such as the maintenance of body temperature, beating heart, and breathing[1]. When a person maintains his/her eating habits on a regular basis, the most critical parameter that governs the energy balance is the energy expenditure that is burned during physical activities. Therefore, a quantitative assessment of the activity energy expenditure (*AEE*) is noticed as one of the most important parameters guiding a healthy daily lifestyle.

One of the gold standards of measuring the energy expenditure is to measure arterial oxygen and carbon dioxide. It estimates calorie consumption by measuring the volumes of inspired and expired gas and extract the energy expenditure in real time on a breath-by-breath basis from the calculated consumed oxygen and expired carbon dioxide [2]. However, the application of gas analyzers to monitor daily life is limited since the environmental parameters such as air pressure, temperature, and gas concentrations must be calibrated before use and the gas mask must be sealed the mouth firmly prohibiting regular use. Over the past decades, the MEMS (micro-electro mechanical systems) technology developed rapidly and measuring the activity calorie consumption using accelerometer MEMS sensor has been validated and tested over the gas analyzer by showing the linear relationship between the integrated accelerometer signals and the calorie consumption [3-7]. The use of accelerometer provides a low-cost, small-sized, and convenient way of monitoring physical activity under free-living condition [8].

The up-to-date methods of evaluating *AEE* are in two folds: (i) classify the activity in MET (a unit of metabolic equivalent) cut-points according to the intensity of accelerometer counts and multiply the amount of time spent in activity and corresponding MET levels [9-12] and (ii) derive linear regression equations between accelerometer counts and energy expenditure assessed by doubly labeled water or gas analyzer [9,13-15]. It has been reported that accelerometer based calorimeter predicts *AEE* with an accuracy of 15 ~ 23% and correlation coefficient of 0.68 ~ 0.96 between *AEE* and accelerometer counts depending on the subject and experimental condition [4,16-18].

Corresponding Author : Jeong-Whan Lee
Konkuk University, 322 Danwol-dong,
Chungju-si, Chungcheongbuk-do, South Korea 380-701
Tel : +82-43-840-3798 / FAX : +82-43-851-0620
E-mail : jwlee95@kku.ac.kr

Table 1. Subject characteristics in inhomogeneous group.

group ID	No. of subjects	gender	Age (yr)			Fat ratio (%)		
			mean ± STD	min	max	mean ± STD	min	max
1	31	male	18.1 ± 0.9	16	19	14.7 ± 3.6	10.3	23.7
2	30	female	17.6 ± 2.6	12	22	24.9 ± 3.3	17.3	31.2
3	15	male	30.3 ± 3.4	24	37	27.5 ± 4.1	23.7	35.6
4	14	female	29.4 ± 4.9	24	40	30.4 ± 5.3	28.6	39.7
5	16	male	47.5 ± 6.6	33	57	26.6 ± 2.1	25	33.1
6	16	female	44.8 ± 4.2	41	53	32.1 ± 1.8	29.7	36.6
7	31	male	45.7 ± 4.4	40	53	18.6 ± 4	9.2	24.7
8	33	female	44.2 ± 6.3	41	51	25.8 ± 3.2	15	29.4
9	24	male	30.0 ± 3.6	23	36	16.4 ± 5.1	7.8	23.9
10	16	female	29.3 ± 5.1	22	38	21 ± 5.7	4.1	28.3

* Mean ± STD,

The calorie tracking procedure using these methods is easily achievable but different threshold values or regression lines need to be derived for different set of exercise or subject. In addition, the calorie estimation criteria are relying on the accelerometer count which is a sensor specific feature. Considering the distribution of sensitivity even within the same model of accelerometer, the count does not guarantee to measure exactly the same physical motion and hence *AEE* based on the count has the intrinsic source of error. In this paper, we applied an accelerometer signal that is normalized to gravitational constant, g to present sensor independent calorie estimation algorithm. In addition, we applied multivariate regression analysis on the regression coefficients with respect to physical factors of the subject such as gender, age, height, and mass in order to reduce the individual differences by predicting regression line from the physical characteristics. We also report the result of separating the activity types in predicting activity induced calorie cost.

II. METHODS

A. Subjects

Two subject groups were carefully selected so that the one represents homogeneous group and the other does inhomogeneous one. The subject in the homogeneous group were 94 healthy young volunteers (46 females and 48 males, mean age = 24.3 ± 4.0 yrs, mean body weight = 62.2 ± 12.6 kg, mean height = 167.0 ± 11.2 cm, fat-ratio = 21.0 ± 7.5%). Secondly, the inhomogeneous group was composed of 10 subgroups depending on age and obesity as described in table 1. The experiment periods were May to October in 2004 for the homogeneous group and March to June in 2005 for the inhomogeneous group. Both experiments were carried out indoor daytime. Each subject reported his/her age and height. The values of mass and fat ratio were measured by a body composition analyzer, Inbody 3.0 (Biospace, S.Korea). The obese group was classified by body mass index (BMI) higher 30 kg/m^2. The physical level of each subject was

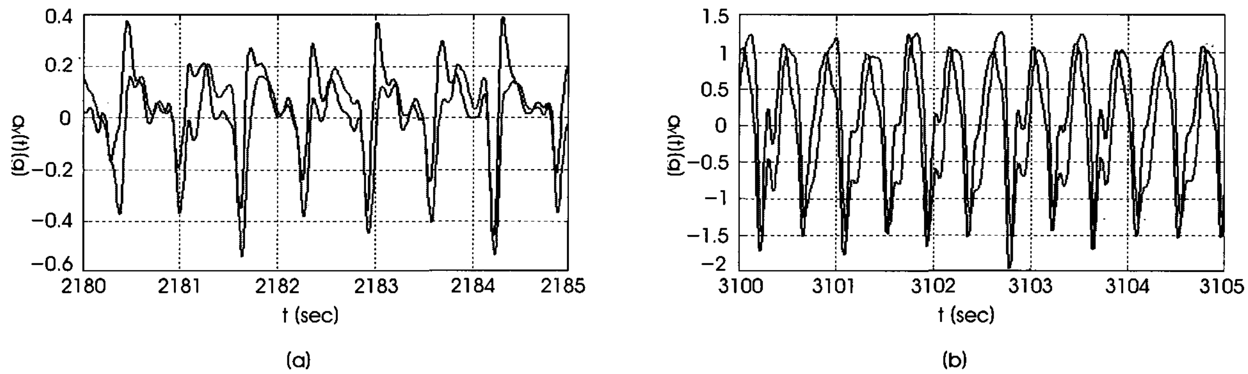

Fig. 1. Time series of vertical acceleration from two accelerometers, MSI (blue sold line) and ADXL311 (red dashed line) (a) during walking exercise (b) running exercise.

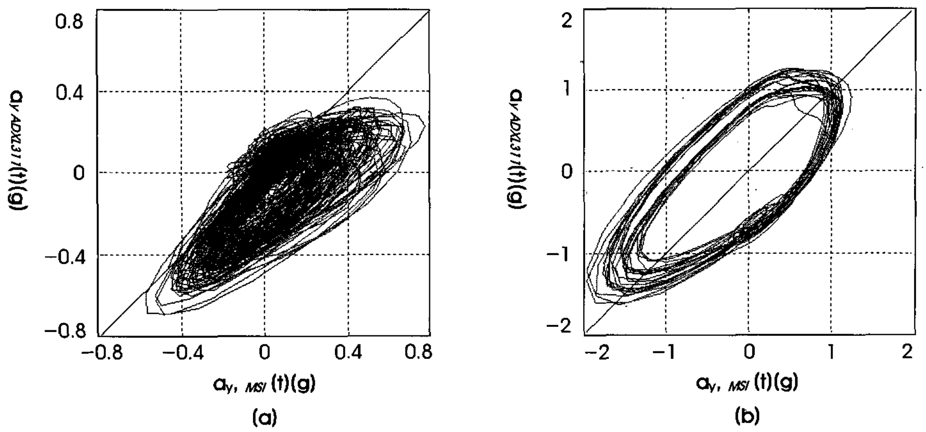

Fig. 2. Phase diagrams of two different accelerometer sensors. Horizontal axis is ay of MSI and vertical axis is ay of ADXL311 (a) during walking exercise (b) running exercise. The diagonal line of each Fig is the line of identity.

assessed by physical activity score (PAS) developed by NASA and Johnson Space Center. Each subject was required to fast for 4 hours and avoid extreme physical activity for 12 hours before the experiment. Alcohol, caffeine, and tobacco were prohibited on the day of experiment. All the subjects participated in the experiment provided a written informed consent form before beginning of experiments

B. Instrumentation

Accelerometer units with wireless communication function were built in-house. In the first experimental period (homogeneous group), four accelerometer units were positioned on both right and left sides of waist and thigh. In the second experimental period (inhomogeneous group), five accelerometer units were positioned on chest, waist, thigh, ankle, and wrist. In this study, only the waist position was analyzed. During the experiments, each accelerometer unit was carefully mounted so that x, y, and z axes are aligned to the anterior-posterior, vertical, and lateral directions of the body, respectively. The first accelerometer unit has one 3-axis (MSI 04-08-05) and two 2-axis (ADXL250 and ADXL311) accelerometer sensors in one unit. Two axes of biaxial accelerometer were aligned to the x and y-axis. MSI and ADXL311 are piezoelectric sensors, whereas ADXL250 is a piezoresistive sensor that detects the constant accelerometer such as gravity. The gains of the signal were amplified so that the dynamic ranges of the accelerometers are comparable to those of the human motion: ±8, ±4, and ±2*g* for MSI, ADXL250, and ADXL311, respectively. Based on the experimental results using three sensors, we applied Kionix (KXPA4 series) whose dynamic range of ±6*g* with three axes later for the inhomogeneous group to present lighter and power saving unit to the subjects. The data were transmitted to a laptop in real time wirelessly by the use of Bluetooth at a data sampling rate of 80 Hz. The dimension of the unit is 2.5 cm x 3 cm x1 cm weighting less than 50 gram.

Total energy expenditure (*TEE*) was determined by a continuous direct O_2/CO_2 gas analyzer (MetaMax, Cortex Biophysik GmbH, Leipzig, Germany). The oxygen and carbon dioxide concentrations in expired air were continuously measured. The value of each gas concentrations was transmitted wirelessly in real time to nearby computer with Metasoft software installed and averaged every 10sec. Pressure and temperature were calibrated prior to every subject and gas was calibrated every month.

Each subject wore a wearable heart rate (HR) monitor (Polar Electro, Finland). The speed control of the treadmill was triggered by MetaMax software to assure the synchronization of the machines.

C. Experimental Protocol

Prior to the treadmill experiment, each subject was asked to lie down still in his/her supine position, but awake for 10 min in a dark and quiet room to measure both the resting metabolic rate (RMR) and rest HR. The speeds of the treadmill were 1.5, 3.0, 4.5, 6.0, 6.5, 7.5, and 8.5 *km/hr* and randomly arranged to avoid any cumulative effects of the exercise. The each exercise stage lasted 3 min and resting period was given for 2 min before performing the next stage. Each subject was instructed to walk at the speed lower than 6.0*km/hr* and run at the speed higher than 6.5*km/hr*. After full resting of the treadmill exercise, each subject performed the Balke protocol [1]. The HR recovery to resting HR was monitored to determine whether the subject recovered fully or not. The degree of the treadmill inclination was programmed to increase by 3 degree every 3 minutes. This Balke protocol was included in the experiments on homogeneous group only. In this publication, we use the data from Balke protocol only for the purpose of calculating VO_{2max}.

D. Calibration of Accelerometer

Typically, the output of accelerometers of the same model has some distribution of their performance and each accelerometer needs to be calibrated when the absolute value is needed like calorie estimation. The sensitivity of the accelerometer was calibrated in terms of voltage output corresponding to gravitational constant g (= 9.8 m/sec^2). AC and DC calibration system were built. The AC calibration system was depicted by Bouten et al [4]. The accelerometer was mounted onto a counterweight arm at a distance of 10 cm and the arm of the calibration system is positioned in the gravity direction. The rotation of the arm produces a sinusoidal signal with amplitude of g. The sensitivity of each axis was measured by putting the axis of interest in the rotational surface. By altering the rotational speed, the frequency response of the sensor was investigated. For piezoresistive accelerometer, DC calibration system was constructed using a test jig with horizontal level. Each accelerometer was mounted on the test setup in both positive and negative gravitational directions alternatively and the sensitivity was measured by finding the half of the difference between maximum and minimum voltage output. ADXL250 and KXPA4 sensors were calibrated with AC and DC calibration system twice to ascertain the consistent response of the piezoresistive accelerometer to both AC and DC.

E. Preprocess of Data

The unit of each accelerometer signals in volt was converted to g by normalizing the signal in V by the sensitivity in V/g of each axis that was determined by the calibration system. A symmetric digital low-pass filter was applied to the raw signal of each accelerometer (f_{pass} = 6.458 Hz, f_{stop} = 12.35 Hz, Butterworth IIR 13rd order) to remove any high frequency noise or moving artifacts. An integration of the vector magnitude of the accelerometer output at each axis over 1 sec time intervals was calculated to measure the physical activity of the human body such as

$$VM(t) = \int_{t}^{t+\tau} |a_x(s)|^2 + |a_y(s)|^2 + |a_z(s)^2| \, ds \qquad (1)$$

where $VM(t)$ is the vector magnitude referring the physical activity level measured by accelerometer, ax, ay, and az, represent the acceleration signals from x, y, and z axis, and is set to be 1 *sec.* At every 10 *sec*, *VM* were summed to be synchronized to the gas analyzer data.

TEE in kcal measured every 10 *sec* was subtracted by RMR in kcal/10 *sec* to evaluate the *AEE* in kcal/10 *sec*.

F. Multivariate Regression Analysis

Data of *AEE* and *VM* at each exercise stage were reduced to mean ± STD. In order to eliminate any transient effect, the first minute data of *AEE* and *VM* were removed. Regression analysis was used to measure the dependency of calorie on physical movement. Multivariate regression analysis was used to determine the relationship with gender, age, height, and mass on the regression coefficients, a and b in . Differences between groups of different age and fat ratio were analyzed by using the non-parametric one-way ANOVA analysis. The result of statistical analysis was summarized to deliver the regression coefficients as functions of physical factors at corresponding activity:

$$\begin{aligned} a_{activity} &= a_{activity}(gender, age, height, mass), \\ b_{activity} &= b_{activity}(gender, age, height, mass). \end{aligned} \qquad (2)$$

The regression was performed with 95% of confidence level.

Ⅲ. RESULT AND DISCUSSION

A. Sensor Issues

In order to examine whether this sensor difference influences in estimating *AEE* or not, we evaluated the statistical significance of the sensor difference on VM. Nonparametric one-way ANOVA test (Kruskalwallis test) was performed on the *VM* values of MSI and ADXL311 sensors during exercise. For walking at the speeds of 1.5~6.0*km/hr*, there is no statistical difference found on the values of *VM* from two accelerometers. However, in case of running at speeds of 6.5~8.5*km/hr*, statistically significant difference was found between MSI and ADXL311. MSI does not show full measure during running

Table 2. Difference in terms of VM obtained from MSI and ADXL311 accelerometers.

Activity type	Walking				Running		
Speed (*km/hr*)	1.5	3.0	4.5	6.0	6.5	7.5	8.5
Difference in means of VM (%)	4.78	3.52	2.87	2.02	−7.99	−8.81	−8.22
p-value	0.014	0.120	0.089	0.362	0.000	0.000	0.000

* Difference in means of VM is defined by $(VM_{MSI} - VM_{ADXL311})/VM_{MSI} \times 100$ in %-

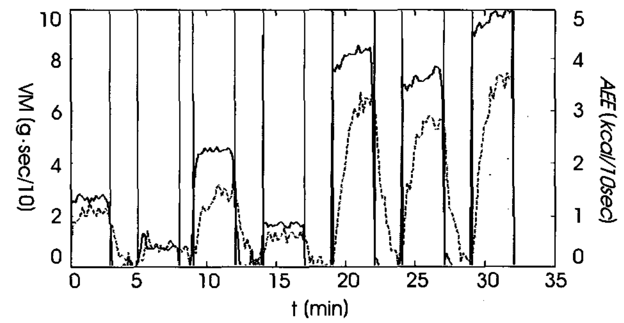

Fig. 3. Accelerometer output, *VM* (blue solid line) and energy expenditure for physical activity, *AEE* (red dashed line) during walking and running on treadmill. The vertical line indicates the start or end of each exercise stage.

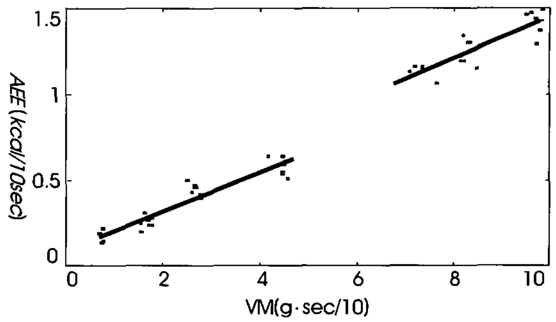

Fig. 4. Vector magnitude of accelerometer output (*VM*) versus activity calorie expenditure during physical activity (*AEE*) performed in treadmill walking and running. The solid lines are regression lines.

stage. Table 2 shows the difference in means of *VM* and p-values for the ANOVA test. The difference in means is defined as $(VM_{MSI} - VM_{ADXL311}) / VM_{MSI} \times 100$ in %.

After frequency response test using AC calibration system, we built an accelerometer unit with KXPA4 of which behaviors at different frequency are consistent and the dynamic range is ±6g.

B. Measure of Physical Activity

Fig. 3. illustrates a typical example of the activity and calorie changes during a treadmill exercise obtained from a healthy subject (male, 21 yrs old). The calorie consumption rate due to the activity increases at the start of the exercise until it reaches planar state. Our observation showed that this planar state lasts longer than several minutes in most of the subjects. However, the rate moves in any direction after the planar state depending on subject. In order to build an accurate min-by-min calorie estimation algorithm, we assumed the value at the planar state as *AEE* in Fig. 3. For the same subject, the linear relationship between *VM* and *AEE* was shown in Fig. 4. The regression lines were obtained for walking and running separately ($R^2 = 0.95$ and 0.87 for walking and running, respectively). In the case of this subject, the proportional rates of the regression line were 0.118 and 0.1242 and the y-intercepts 0.0946 and 0.2122 for walking and running, correspondingly.

C. Individual Differences

In order to explore the degree of individual difference among people and how to normalize any individual difference, we investigated the regression coefficients within homogeneous group with similar physical attributes (Fig. 5). Even subject group with similar physical factors has broad distribution of regression coefficients as shown in table 3. The values of a and b are the regression coefficients of $AEE(kcal/10\sec) =$

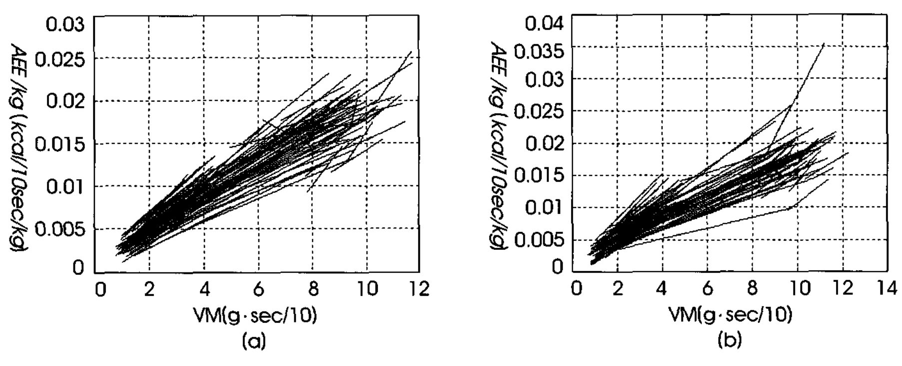

Fig. 5. Regression lines of AEE plotted against VM for (a) male (N = 48) and (b) female subject (N = 46) group within homogenous subject set (20-30 yrs) during treadmill walking/running.

Table 3. Regression coefficients in homogeneous group

Gender	Male		Female	
Activity	Walk	Run	Walk	Run
a	0.169 ± 0.035	0.164 ± 0.148	0.131 ± 0.031	0.056 ± 0.379
b	0.012 ± 0.059	−0.226 ± 1.399	0.028 ± 0.063	−0.071 ± 1.538

* *a* and *b* are regression coefficients for $AEE(kcal/10\sec) = a \times VM(g \cdot \sec) + b$

Table 4. Combination of physical factors as variables for multivariate regression analysis. Circle(O) indicates the corresponding physical factor was included in the variable set for the test and the cross () indicates not included.

Test set	Gender	Age	Height	Mass	Fat %	BMI	PAS	Rest HR	VO2max
1	O	O	O	O	O	O	O	'	'
2	O	O	O	O	'	'	'	'	'
3	O	'	O	O	'	'	'	'	'
4	O	'	'	'	'	O	'	'	'
5	O	'	O	'	'	'	'	'	'
6	O	'	'	O	'	'	'	'	'
7	O	'	'	'	O	'	'	'	'
8	O	O	O	O	O	O	O	O	O
9	O	'	'	'	'	'	'	O	'
10	O	'	'	'	'	'	'	O	O

* BMI stands for body mass index and PAS does physical activity scale.

$a \times VM(g \cdot \sec) + b$. As the standard deviation values of each regression coefficients show the individual variances appear to be significant even within the subject group with similar physical factors.

Fig. 6 show the box plots of the regression coefficients for walking/running depending on different subject groups. The middle, lower, and upper lines correspond to the median, lower quartile, and upper quartile values, respectively. The p-value inside of each plot is the returned value of ANOVA test for the coefficients. In both cases of walking and running, the p-values were smaller than 0.05 presenting that the calorie based on accelerometer depends on physical characteristics of the subject statistically significantly.

D. Activity Calorie Estimation Derived by Multivariate Regression Analysis

From each subject, gender, age, height, mass, fat ratio, BMI (body mass index), PAS (physical activity score), rest HR, and VO_{2max} were used as independent variables (predictors) of physical factors, where the dependent variables (responses) are the regression coefficients, *a* and *b* in the calorie estimation equation. 10 combinations of the dependent variables were designed as illustrated in Table 4. The multiple linear regressions using least squares were performed on the

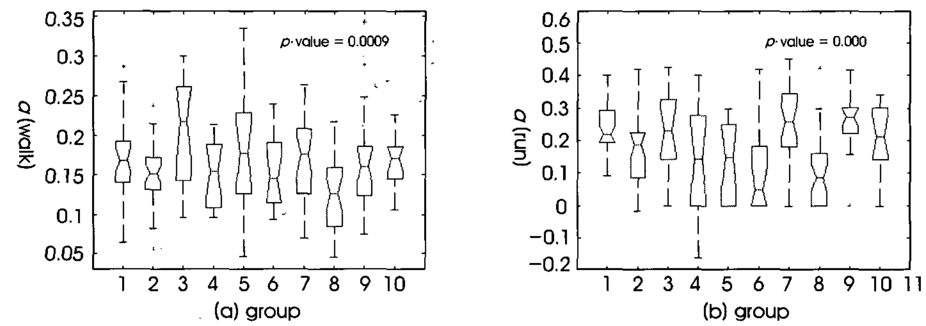

Fig. 6. Measured a, proportional coefficient in the calorie equation for (a) walking and (b) running activity grouped by subject. p-value smaller than 0.05 in both cases indicates that the regression equation of calorie is statistically significantly different depending on the subject's physical characteristics.

Table 5. Result of multivariate statistical analysis in 95% confident level

Test Set	p-value				R-square			
	Walk		Run		Walk		Run	
	a	b	a	b	a	b	a	b
1	0.00	0.17	0.34	0.89	0.47	0.10	0.09	0.03
2	0.00	0.19	0.09	0.65	0.46	0.05	0.08	0.02
3	0.00	0.14	0.04	0.46	0.46	0.04	0.08	0.02
4	0.00	0.11	0.01	0.29	0.38	0.02	0.06	0.01
5	0.00	0.15	0.01	0.28	0.31	0.02	0.08	0.02
6	0.00	0.11	0.01	0.29	0.46	0.02	0.06	0.01
7	0.00	0.04	0.00	0.19	0.08	0.04	0.02	0.01
8	0.00	0.27	0.40	0.92	0.47	0.11	0.11	0.05
9	0.00	0.16	0.00	0.22	0.12	0.02	0.09	0.02
10	0.00	0.33	0.02	0.48	0.14	0.03	0.09	0.02

Table 6. Relative error in % calculated by $(AEE_{measured} - AEE_{predicted})/AEE_{measured} \times 100$. *AEE* was summed during walking, running, and whole period of measurement.

Group	Subjects				1st Regression			2nd Regression		
	N	Gender	Age	Obesity	Walk	Run	Total	Walk	Run	Total
1	31	male	10~19	normal	18.8	11.6	12.8	16.8	10.8	11.4
2	30	female			15.5	13.4	12.8	13.5	19	15.8
3	15	male	20~39	obese	12.6	13.5	10.6	18.2	12.7	16
4	14	female			21.0	13.4	12.2	15.6	7.7	5.4
5	16	male	40~59	obese	21.0	11.5	14.4	10.0	9.6	6.2
6	16	female			16.4	14.0	14.2	16.3	10.1	9.5
7	31	male	40~59	normal	14.8	8.5	9.7	13.5	7.8	7.1
8	33	female			15.6	15.4	13.7	11.8	14.6	10.3
9	72	male	20~39	normal	14.7	10.9	10.5	12.3	11.2	8.7
10	62	female			16.6	13.7	13.3	12.5	15.1	12.2

Table 7. Relative error in % calculated by $(AEE_{measured} - AEE_{predicted}^{calibrated})/AEE_{measured} \times 100$. The *AEE* was predicted after calibration of individual *VM* with respect to gas analyzer data.

Group	Subjects				After calibration	
	N	Gender	Age	Obesity	Error (%)	R-square
1	31	male	10~19	normal	1.11	0.98
2	30	female			0.74	0.96
3	15	male	20~39	obese	0.46	0.98
4	14	female			0.67	0.97
5	16	male	40~60	obese	0.52	0.98
6	16	female			0.15	0.97
7	31	male	40~60	normal	0.50	0.98
8	33	female			0.52	0.97
9	72	male	20~40	normal	1.10	0.94
10	62	female			1.04	0.95

linear model of $y = \vec{c_1} \cdot \vec{x} + c_2$, where y represents a and b and $\vec{x}$ is a vector of physical factors, i.e. $\vec{x} = (\geq nder, age\ height, mass)$. Table 5 shows the results of the analysis on 10 different sets of independent variables. p-value smaller than 0.05 indicates that the test set reliably predicts the regression coefficient at the 95% confident level. The y-intercept b does not show any statistically significant dependency on the physical values. The predicted values of a were plotted against a values measured from the homogeneous group of 94 subjects in Fig. 7(a). In the same subject group, the activity calorie, AEE estimated with this predicted coefficients were plotted against the measured AEE (Fig. 7(b)). Although the test sets including fat ratio and PAS gave us better result, we have used only gender, age, height, mass, and BMI for independent parameters since these values are relatively easy to obtain from the users. The correlation coefficient between the measured and predicted *AEE* is 0.92 and the average error of the estimated calorie accumulated during whole period of exercise was 10.5%with respect to the measured accumulated calorie for this subject group.

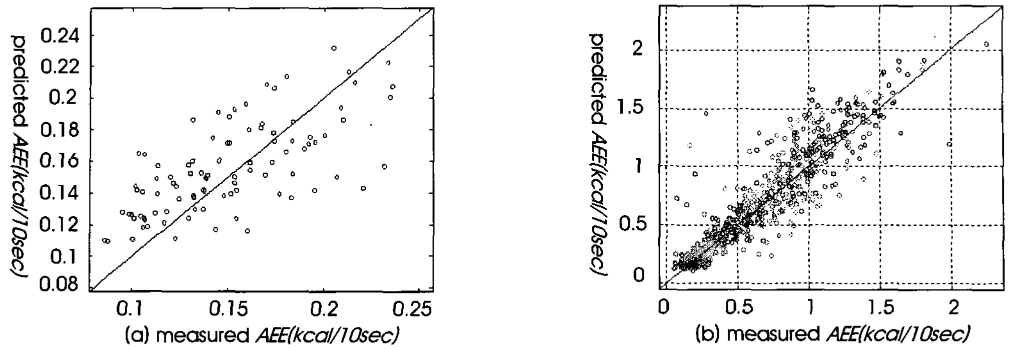

Fig. 7. (a) Predicted regression coefficient, a based on subject's physical factors *versus* measured regression coefficient, *a* obtained from the relationship of *VM* from accelerometer and *AEE* from gas analyzer.
(b) predicted *AEE* plotted against measured *AEE*.

Including the inhomogeneous groups, the multivariate regr ession analysis was attempted in two ways: (i) performing the regression analysis on the whole subject group (N = 320), (ii) performing the regression analysis separately on each subject subgroup grouped by gender, age, and fat ratio. Theerrors of the predicted *AEE* were calculated and summarized in Table 6. The results show that the regression line at each subject subgroup shows better results than a single regression line of the whole subject groups. By applying the regression equations derived by the 2nd analysis, the prediction error of accumulated activity calorie for whole period of exercise was 10.4%. Normally, male is predicted with higher accuracy than female: the error was 9.3% for male and 11.6% for female.

E. Upper Limit of Accuracy

In order to find the upper limit of the accuracy in the activity calorie estimation using single-point tri-axial accelerometer, we applied the linear regression line of each subject that was obtained from the relationship between measured *AEE* and measured *VM* in order to predict *AEE*. This process corresponds to personal calibration of accelerometer signals using gas analyzer. As the result appeared in Table 7 shows when we have a calibrated data of *VM* with respect to *AEE* measured by golden standard such as gas analyzer, the accuracy level is very high over 98%. However, the calibration with gas analyzer prior to the usage of the accelerometer-based calorimeter is practically difficult to carry out for general user. It would be a key to find any calibration method in free living condition to increase the accuracy of calorie estimation using an accelerometer dramatically.

Ⅳ. CONCLUSION

In this study, we have developed a generalized equation to predict energy expenditure in *kcal* per 10 seconds from the vector magnitude of integrated amplitudes using a tri-axial accelerometer sensor. This equation is applied to adolescent and adults, and reduces the individual variation by finding regression coefficients as functions of physical factors as results of multivariate regression analysis. However, the calibration with gas analyzer prior to the usage of the accelerometer-based calorimeter is practically difficult to carry out for general user. It would be a key to find any calibration method in free living condition to increase the accuracy of calorie estimation using an accelerometer dramatically.

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