

# Exercise Energy Expenditure Estimation Based on Acceleration Data Using the Linear Mixed Model

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## Abstract

*This paper introduces a novel algorithm for estimating energy expenditure during physical activity. The estimation is based on acceleration data measured from a wrist-worn accelerometer. Simultaneous measurements of acceleration and oxygen consumption using a biaxial accelerometer and a breath gas analyzer were made during four different activities: walking, running, Nordic walking and bicycling. A variance feature is used to compress the original acceleration signals. A linear mixed model is fitted to the data to estimate oxygen consumption based on the acceleration data. Lagged values of acceleration are used to take the delayed effect of physical activity on oxygen consumption into consideration. The algorithm also uses information on the height of the subjects. Oxygen consumption is estimated at 15-second intervals and energy expenditure is directly calculated from the oxygen consumption. Based on the experimental data gathered from 10 subjects, a new algorithm for estimating energy expenditure is suggested. It is shown that the method estimates energy expenditure very accurately. In walking, running and Nordic walking the model underestimates energy expenditure by 13, 2 and 9 percent, respectively, and in bicycling energy expenditure is overestimated by 7 percent. Thus, the new approach is a very promising method for estimating energy expenditure.*

## 1 Introduction

Daily physical activity is confirmed to have positive impacts on health [1]. Therefore, development of objective and reliable methods for accessing physical activity is very important. Energy expenditure caused by physical activity is commonly accepted as the standard reference of physical activity in humans [6]. Energy expenditure can be reliably measured from a person's oxygen consumption. However,

measurement of oxygen consumption requires the use of a breath gas analyzer (indirect calorimetry) and is therefore impractical and not feasible under free-living conditions.

Research on modelling physical activity in different activities based on acceleration data has expanded over the past two decades [3], [10]. Measurements done with body-mounted accelerometers are widely used in determining the frequency and intensity of movements during physical activity [2]. Estimation of energy expenditure based on acceleration measurements has become a widely discussed problem approached in various studies. However, widely accepted, precise and reliable methods for estimating physical activity based on acceleration data have not been found.

Placement and orientation of body-mounted accelerometers have been studied by several authors. Bouten *et al* [2] concluded that the low back, near the centre of gravity, is the optimal location for an accelerometer for estimating energy expenditure during level walking. Also others have used this location, *e.g.* [8], [9], [12]. However, Mathie *et al* [7] point out that waist-mounted accelerometers significantly underestimate activity concentrated in the upper body and the energy cost of walking on inclined surfaces. Therefore, in some studies additional acceleration sensors have been attached to other body parts [8].

In most of the previous studies, regression methods have been applied to accelerometer counts and oxygen consumption simultaneously measured to determine the relationship between the two measures and to define an equation to predict energy expenditure from acceleration [10]. The accelerometer counts are usually obtained by integrating the accelerometer signal [4].

In this study a novel method for estimating energy expenditure at 15-second intervals is suggested. Oxygen consumption during four different activities is modelled based on measurements from a biaxial accelerometer. The activities are walking, running, Nordic walking and bicycling. A linear mixed model is fitted to the data comprised of accel-

ation measurements and the heights of the subjects. Lagged values of acceleration are also used to take the delayed effect of physical activity on oxygen consumption into consideration. Energy expenditure is then directly calculated from estimated oxygen consumption. The linear mixed model was selected for use in this study because it offers the possibility to provide each of the subjects with an individual ground level of energy expenditure.

The accelerometer was placed on the subject's left wrist. This location was selected since it is an easy and comfortable location for the subject and does not disturb performance of the activity. To further reduce inconvenience to the subject, only one measurement device was used. In addition, this location is the most natural in that if estimated energy consumption is shown on the display of an activity monitor, the user can easily follow the reading from the wrist-worn monitor while performing the activity.

Unlike most of the previous studies, in this study a variance transformation of the acceleration signal is used instead of the acceleration counts. To match the sampling frequency of the acceleration measurements with the sampling frequency of measurements of oxygen consumption, the acceleration signal is compressed by calculating its variance at 15-second intervals. The variance feature is assumed to carry the most relevant information about the physical activity of the subject. Previously Hara *et al* [5] have presented a similar method that uses the standard deviation of the accelerometer signal to preprocess the raw signal to be used in estimating energy expenditure.

Recently Rothney *et al* [8] have presented a similar approach for estimating min-by-min energy expenditure based on features extracted from accelerometer data and subject demographics. The data used in the study consisted of acceleration measurements from a biaxial sensor attached to the hip, whereas in our study a wrist-worn accelerometer is used. The tests were made in a room calorimeter during one day during which the subjects performed walking, jogging, exercise bicycling, sedentary activities and normal daily routines. Their method models energy expenditure using artificial neural networks. The results presented seem promising, but as only the mean error of energy expenditure during one day is given, it is difficult to evaluate the accuracy of the estimate for shorter periods. In addition, no details are given on the accuracy of estimation in different activities separately.

## 2 Methods

### 2.1 Experimental Protocol

The data were collected from ten healthy subjects (eight men and two women). The physical characteristics of the participants are shown in Table 1. Weight of the participants

was measured using a digital scale and it was documented to an accuracy of 1 kg. Height was measured in metres. Body mass index (BMI) was calculated by dividing the body mass (kg) of the subject by his/her height squared ( $m^2$ ).

The participants performed four different activities: *walking*, *running*, *Nordic walking* and *bicycling*. The activities were selected for this study because they constitute a considerable proportion of the incidental exercise performed in daily life; that is, the exercise we get doing daily activities. In addition, these activities are suitable for showing the functionality of the algorithm proposed in this study, since they differ in the amount of movement of different body parts. In walking, running and Nordic walking, both legs and arms perform a dynamic cyclic movement. In Nordic walking the movement of the arms is even greater and more intense than in walking and running. In bicycling, however, only the legs move and the arms are mostly immobile. The type of activity is of great concern since in this study the acceleration data are received from a wrist-worn accelerometer.

Each of the activities were performed for ten minutes. Before the test period the subjects performed a warm-up for five minutes in order to raise the level of oxygen consumption before the actual testing period. In the case of walking and running, warming-up consisted of walking, whereas for bicycling also the warm-up was performed by bicycling.

The test was performed by travelling back and forth along a predetermined route on flat ground. The distance travelled depended on the speed individually chosen by the participants. Midway through the testing period the subjects turned back into the direction they came from. By travelling in opposite directions the effects of circumstances caused by the environment, such as air resistance and minor inclination of the surface, were minimized.

Since oxygen consumption was used as a reference method to estimate energy expenditure in different activities, the load of the physical exercise was kept at an aerobic level during the entire test. Therefore, the subjects were asked to monitor their heart rate and keep it at least 20 beats/min below their maximum heart rate. Otherwise, since controlling the intensity of the exercise can disturb performance, the participants were advised to perform each of the activities at an intensity individually suitable for them. This makes the circumstances where the tests are made more realistic, but at the same time also complicates the modelling task.

Although all ten participants performed the four activities, the measurement data could not be received from all the activities due to technical problems with the accelerometer data logger. The bicycling data set contains measurements from nine subjects, the walking and Nordic walking data sets are comprised of seven tests and the running data set is comprised of measurements from six participants.

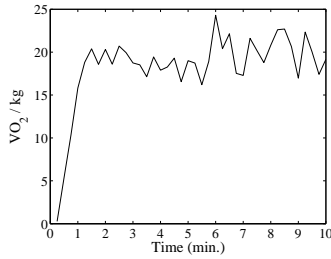
	Men (n=8)	Women (n=2)	All (n=10)
Age (years)	29.8 ± 4.7 (22-37)	24.5 ± 4.9 (21-28)	28.7 ± 4.9 (21-37)
Height (cm)	181 ± 5.6 (169-188)	164 ± 1.4 (163-165)	178 ± 8.8 (163-188)
Body mass (kg)	82.6 ± 13.1 (62-104)	56.5 ± 7.8 (51-62)	77.4 ± 16.2 (51-104)
BMI (kg/m <sup>2</sup> )	25.1 ± 3.4 (21.6-31.1)	21.0 ± 2.5 (19.2-22.8)	24.3 ± 3.5 (19.2-31.1)

**Table 1. Physical characteristics of the subjects (mean, standard deviation, range)**

## 2.2 Measurement of Energy Expenditure

Oxygen consumption  $\text{VO}_2$  (ml/min) of the subject was measured during the exercise using indirect calorimetry. Breath-by-breath data were collected using the Cosmed K4b<sup>2</sup> breath gas exchange measurement system (Cosmed K4b<sup>2</sup>, Rome, Italy). The K4B<sup>2</sup> is a light portable gas analyzer that uses a face mask.

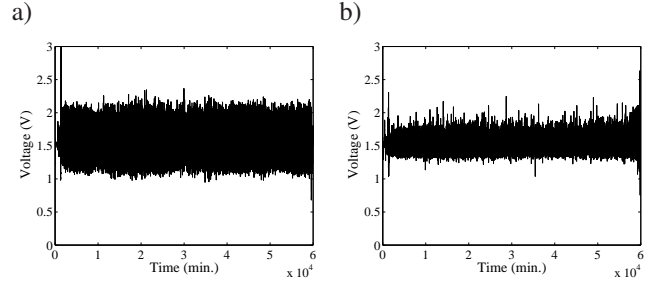
Before each test the oxygen analyzer was calibrated in the current air pressure, humidity and temperature. The concentration of expiration gases was measured at intervals of 15 seconds. The weight of the subject was taken into account in modelling by dividing the values of oxygen consumption by the weight of the subject. An example of an oxygen consumption measurement  $\text{VO}_2 / \text{kg}$  (ml/min/kg) is shown in Figure 1.



**Figure 1. Oxygen consumption (ml/min/kg)**

## 2.3 Measurement of Acceleration

The physical activity of the subject was measured using a biaxial accelerometer worn on the left wrist. The measuring device was composed of two 1-dimensional capacitive accelerometers (VTI Technologies) positioned perpendicular to each other. The sampling frequency of the accelerometer was 100 Hz. The signal values received from the accelerometer were recorded using separate data loggers. The unit of the signals was transformed to voltage (V) using a capacitance-to-voltage converter. The acceleration signals were preprocessed by replacing erroneous values falling outside the measurement range of the accelerometer (0-3 V) by the mean of the signal values. Examples of the acceleration measurements are shown in Figure 2.



**Figure 2. Measurement signals from the biaxial accelerometer. a) acceleration 1 b) acceleration 2**

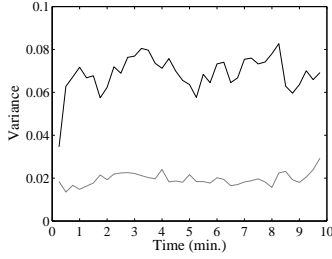
## 2.4 Data Preprocessing

Since the sampling frequency of the acceleration measurements (100 Hz) was higher than the sampling frequency of the measurements of expiration gases (1/15 Hz) the acceleration data were preprocessed to match the frequencies. The preprocessing consisted of transforming the original acceleration signals with a variance feature. The variance feature was calculated as the variance of the raw signal at intervals of 15 seconds. Signal variance at intervals of equal length was chosen as the way to represent the raw signal in a more compact form since it naturally describes the intensity of the acceleration signal, which was assumed to be essential in modelling energy expenditure. Examples of the variance-transformed acceleration signals are shown in Figure 3.

## 2.5 Linear Mixed Model

The oxygen consumption of the subject was modelled using the *linear mixed model*, which is a very flexible methodology well suited for modelling longitudinal data. This type of model was chosen to solve the estimation problem, since it is very suitable for modelling time series data containing repeated measures from several subjects. The repeated measurements are correlated with each other, which has to be taken into account in the modelling.

Classical statistics assumes that observations are independent and identically distributed. The linear mixed



**Figure 3. Variance-transformations of raw acceleration signals (1=black, 2=grey)**

model, however, assumes two sources of variation: subject-specific and population-specific. The vector of repeated measurements of each subject is assumed to follow a linear regression model where some of the regression parameters are common for all the subjects, whereas other parameters differ between subjects [11]. Therefore, the model offers the possibility to provide each of the subjects with an individual ground level of energy expenditure.

In general, a linear mixed model is of the form

$$\begin{aligned}
 Y_i &= X_i\beta + Z_ib_i + \varepsilon_i, \\
 b_i &\sim NID(0, D), \\
 \varepsilon_i &\sim NID(0, \Sigma_i), \quad 1 \leq i \leq N,
 \end{aligned}$$

where  $N$  is the number of subjects,  $Y_i$  is the  $n_i$ -dimensional response vector for subject  $i$ ,  $X_i$  and  $Z_i$  are  $(n_i \times p)$  and  $(n_i \times q)$  dimensional fixed matrices of known covariates,  $\beta$  is a  $p$ -dimensional unknown fixed-effects parameter vector,  $b_i$  is the  $q$ -dimensional vector of random effects, and  $\varepsilon$  is an  $n_i$ -dimensional vector containing the error components.  $D$  is a general symmetric  $(q \times q)$  covariance matrix and  $\Sigma_i$  is a  $(n_i \times n_i)$  covariance matrix that has the property that the set of unknown parameters in  $\Sigma_i$  do not depend upon  $i$ . [11]

### 2.5.1 Implementation of the Model

A model structure that models both between-subject and within-subject variance was selected. An overall intercept term was fitted to model the average level of oxygen consumption, and subject-specific intercepts to model the individual ground level of each of the subjects. This is the so-called *random-intercepts model* [11], where the regression coefficients are the same for each subject.

When the model is applied to measurements outside the data set used to train it, no information on the subject-specific intercepts is available. Therefore, when the oxygen consumption of a subject outside the training set is estimated, only the overall intercept term and the fixed regression structure is used. This will be an important property in the future, when the model is applied to measure-

ments outside the data set used in this study and no oxygen consumption measurements specifying the correct subject-specific level are available.

The covariance structure  $\Sigma_i$  for the error components  $\varepsilon_i$  was specified to be first-order autoregressive (AR(1)). The maximum likelihood estimation method was used to estimate the covariance parameters.

Oxygen consumption was set as the response variable in the model. The explanatory variables include the two variance-transformed acceleration signals, the height of the subjects as well as a logarithmic transformation of the height and the product of the two acceleration values. In addition to the acceleration measurements made simultaneously to the oxygen consumption measurements, lagged values of acceleration were also used. Five preceding measurements of the variance-transformed acceleration were used. Since the variance feature consisted of signal variance calculated at intervals of 15 seconds, this means the influence of acceleration from 90 seconds preceding the oxygen consumption measurement were taken into account. The model was fitted using the SAS MIXED procedure (SAS Release 9.1.3.).

### 2.5.2 Model Specification

For each of the four activities, the linear mixed model described above was fitted to the data. From the data set available, the measurements of one of the subjects were excluded to be used in testing the model. The measurement data from the rest of the participants were used to select the model structure and train the model.

The model was first fitted using all the explanatory variables. After that, the optimal model structure for each of the activities was selected on the grounds of both the significance of the effects in the model and the fit statistics of the model. The significance of the effects was considered the primary criterion for model selection. The less significant effects (at a significance level of 0.1) were excluded from the model one by one. The  $-2 \log$  likelihood ratio of the model was also monitored and taken into account. Elimination of the effects was stopped if it would have had a notable negative influence on the model's performance. Therefore, some of the models also contain effects with a  $p$ -value slightly larger than 0.1. The performance of the model in the test set was not taken into consideration in model selection. This way the final model structure for each of the activities was selected.

## 3 Results

The person whose measurements were set aside to be used as a test set was a 22-year-old male, weight 86 kg and height 1.81 m. The measurements of the same person were

used in the testing of all the activities. The measurements of this subject were chosen to be used as test data since his measurements in all the activities were available. Moreover, a male test subject was selected because the proportion of females in the data was low. The measurements of the subject comprising the test set in walking are used as examples of the measurement signals in Figures 1-3. The data set used to train the model consisted of the measurements of all the other participants.

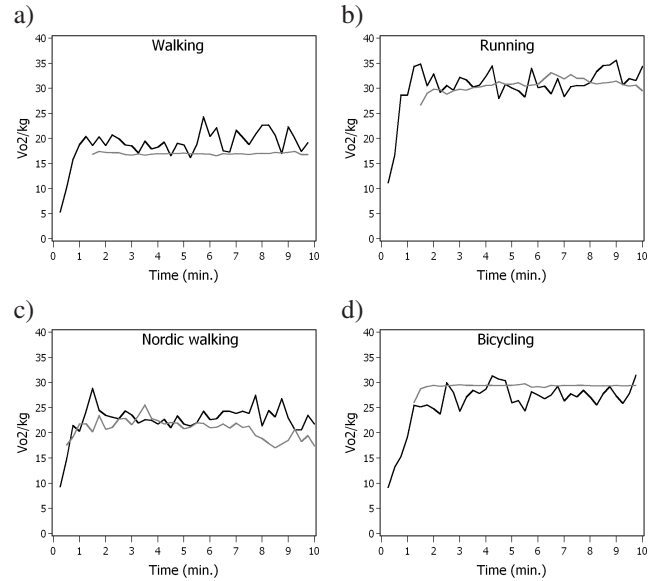
The modelling results for the test data in the four activities (walking, running, Nordic walking and bicycling) are shown in Figures 4 a) - d). The black line in the figures represents the true oxygen consumption measured using indirect calorimetry. The grey line is estimated oxygen consumption given by the linear mixed model. The fact that the estimated curve starts later than the measured oxygen consumption curve results from the use of lagged effects in the model.

It can be seen from Figures 4 a) - d) that the model estimates the level of oxygen consumption of the person used in testing the model very accurately. The line representing estimated oxygen consumption (grey) finds the correct level of oxygen consumption but does not follow the measured oxygen consumption curve (black) strictly. However, this is not even necessary in practise. More important for all practical purposes is to find the correct level of oxygen consumption.

The energy expenditure of a person is calculated from estimated oxygen consumption. The metabolic equivalent (MET) is a widely used unit for energy expenditure. It represents the energy cost of physical activity as multiples of resting metabolic rate. One MET corresponds to an oxygen consumption of 3.5 ml/kg/min. Thus, estimated oxygen consumption ( $VO_2 / \text{kg}$ ) is converted to METs by dividing by 3.5. Average energy expenditure during the exercise estimated on the basis of acceleration data using the linear mixed model and average energy expenditure calculated from oxygen consumption measured using indirect calorimetry are compared in Table 2. The method presented in this study gives a good estimate of the energy expenditure. In walking, running and Nordic walking, the model underestimates the average energy expenditure by 13, 2 and 9 percent, respectively, and in bicycling the average energy expenditure is overestimated by 7 percent.

## 4 Discussion

This paper examined estimation of energy expenditure based on acceleration data. A novel method using a linear mixed model to estimate oxygen consumption based on measurements from a biaxial accelerometer was introduced. The method estimates energy expenditure at 15-second intervals. The results presented in the preceding chapter show



**Figure 4. Measured (black) and estimated (grey) oxygen consumption. a) Walking b) Running c) Nordic walking d) Bicycling**

	True	Pred.	Error
Walking	4.7	4.1	13 %
Running	7.6	7.5	2 %
Nordic walking	6.3	5.7	9 %
Bicycling	6.8	7.3	7 %

**Table 2. Measured and estimated energy expenditure in METs and the prediction error in four activities**

the usefulness of the new approach.

As also Rothney *et al* [8] mention, one of the biggest challenges in modelling energy expenditure based on accelerometer data is the large deviation between subjects. Because of different personal characteristics, the same metabolic costs may not result from identical accelerations. The advantage of the linear mixed model is that it models both between-subject and within-subject variance. Therefore, an individual ground level of energy expenditure can be assigned to each of the subjects in the training set. This compensates for the differences between individuals. Another benefit of the method presented is that it utilizes lagged values of acceleration. This is important because of the delayed effect of physical exercise on energy expenditure.

Another strength of the linear mixed model is that it is easy to implement since no metaparameters controlling the

model structure need to be selected. Training of the model is computationally less complex than, for example, the artificial neural network used by Rothney *et al* [8]. Implementation of the method in a wearable activity monitor is also straightforward.

The modelling was based on variance of the accelerometer signals calculated at 15-second intervals. This feature was selected to present the raw signals in a form that enables their use in modelling, since it was assumed to carry most of the information relevant to estimating energy expenditure. In fact, the results presented in the previous chapter confirm this assumption to be correct. However, when using the variance feature calculated from an acceleration signal measured with a wrist-worn sensor, special attention needs to be given to the fact that, especially in real-life conditions, the subject may also perform some excess movements with his/her hand that are not typical to the activity in question. Such movements could be, for example, checking the time from a watch or stroking the forehead. Therefore, the model should be able to estimate the correct level of oxygen consumption despite such short periods of anomalous activities.

The approach presented in this paper can also be directly applied to other features that present the characteristics of the accelerometer signals. In addition, subject demographics other than the height of the subject, used in this study, could be used.

In this study the approach was applied to a data set containing measurements from ten minutes of exercise in four different activities. The data was collected from ten subjects, of which eight were male and two female. For the presented method to be further validated, it should be tested with larger data sets in terms of both the number of subjects and the length of the measurements.

At this point the results of this method have been compared with energy expenditure estimated using indirect calorimetry. In the future the approach should also be tested against other available methods.

## 5 Conclusions and Future Work

This paper introduced a novel approach for estimating energy expenditure during physical activity. The estimation was based on acceleration data measured from a biaxial accelerometer located on the subject's left wrist. A linear mixed model was used to estimate oxygen consumption based on the accelerometer data. The approach was applied to a data set gathered from 10 subjects during four different activities: walking, running, Nordic walking and bicycling. It was shown that oxygen consumption can be accurately estimated based on accelerometer data by using a linear mixed model.

The aim of this study was to preliminarily introduce the idea of using a linear mixed model to estimate energy ex-

penditure. The functionality of the approach was proven by applying the method to data gathered in circumstances resembling free-living conditions. However, for the functionality of the approach to be more generally shown, it should be applied to larger data sets. In addition, the method could also be applied to activities other than the ones examined in this study and to data sets containing successive measurements in different activities.

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## References

- [1] S. Blair, H. Kohl, N. Gordon, and R. Paffenbarger. How much physical activity is good for health? *Annu Rev Public Health*, 13:99–126, 1992.
- [2] C. Bouten, A. Sauren, M. Verduin, and J. Janssen. Effects of placement and orientation of body-fixed accelerometers on the assessment of energy expenditure during walking. *Med Biol Eng Comput*, 35(1):50–6, 1997.
- [3] C. Bouten, K. Westerterp, M. Verduin, and J. Janssen. Assessment of energy expenditure for physical activity using a triaxial accelerometer. *Med Sci Sports Exerc*, 26:1516–1523, 1994.
- [4] K. Chen and D. B. Jr. The technology of accelerometry-based activity monitors: Current and future. *Med Sci Sports Exerc*, 37(11 Suppl):S490–S500, 2005.
- [5] Y. Hara, M. Yoshida, and K. Minato. New evaluation method of the physical activity by an acceleration sensor. volume 2, pages 1712–1715, 17-21 Sept. 2003.
- [6] R. LaPorte and H. M. C. Caspersen. Assessment of physical activity in epidemiologic research: problems and prospects. *Public Health Rep*, 100(2):131–46, 1985.
- [7] M. Mathie, A. Coster, N. Lovell, and B. Celler. Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. *Physiological Measurement*, 25(2):R1–R20, 2004.
- [8] M. Rothney, M. Neumann, A. Beziat, and K. Chen. An artificial neural network model of energy expenditure using non-integrated acceleration signals. *J Appl Physiol*, 103:1419–1427, 2007.
- [9] P. Terrier, K. Aminian, and Y. Schutz. Can accelerometry accurately predict the energy cost of uphill/downhill walking? *Ergonomics*, 44(1):48–62, 2001.
- [10] R. Troiano. Translating accelerometer counts into energy expenditure: advancing the quest. *J Appl Physiol*, 100(4):1107–1108, 2006.
- [11] G. Verbeke and G. Molenberghs. *Linear Mixed Models for Longitudinal Data*. Springer, New York, 2000.
- [12] G. Welk, J. Schaben, and J. M. Jr. Reliability of accelerometry-based activity monitors: a generalizability study. *Med Sci Sports Exerc*, 36(9):1637–45, 2004.