An Energy Expenditure Estimation Algorithm for a Wearable System

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Abstract - This paper presents an algorithm for physical activity classification and MET mapping regression model construction for a wide range of daily activities using a wearable system. The sensor system consists of several sensor modules that can be synchronized to record the accelerations of diverse motions/activities. During the measurement the accelerations of daily activities, three sensor modules are worn at the participant’s hand wrist, waist, and ankle, respectively. In addition, the participant’s chest is attached to an indirect calorimeter (Cosmed K4b²) to measure oxygen uptake to calculate actual metabolic equivalent (MET) during the experiments. The oxygen uptake for different activities is used to construct MET mapping regression models. Our experimental results show that the average classification accuracy of five categories of physical activities is 95.33%. The average error of MET estimation without and with activity classification is $-7.25 \times 10^{-15} \pm 1.16$ METs and $2.31 \times 10^{-4} \pm 0.71$ METs, respectively.

Keywords: Accelerometer, metabolic equivalent, neural networks, energy expenditure.

1 Introduction

Nowadays, many people suffer from physical inactivity due to lifestyle changes. This phenomenon not only increases the incidence of chronic illness to cause a burden of medical resources but also seriously affects living quality. Much literature [1], [2] has pointed out the importance of performing physical activities to prevent chronic illness. For example, having enough physical activities could reduce the incidence of certain diseases, such as coronary heart disease, apoplexy, high blood pressure, diabetes, breast cancer, etc. Hence, in the past years, it has been an important issue that to improve estimation accuracy. To name a few, Crouser et al. [18] wore a uniaxial Actical at wrist. When count value $\leq 10$, they set MET = 1, and when count value $> 10$, the coefficient of variation (CV) would be set as 13 to be the threshold value. If CV $\leq 13$, an exponential model is used to estimate walking and running activities, and the coefficient of determination (R2) and the standard error of the estimation (SEE) are 0.912 and 0.149 METs, respectively. Otherwise, a lifestyle/leisure time physical activity regression model was used with a CV > 13, and R2 = 0.884 and SEE=0.804. Klippel and Heil [9] used Actical mounted on hip to calculate counts, and further used different threshold count values to differentiate between four activity intensity levels, which were 1) $<50$, 2) $50 \leq$ counts $< 350$, 3) $350 \leq$ counts $< 1200$, and 4) $\geq 1200$. When the count value fell within level 1 and 2, the resulting METs were
set as 0.9 METs and 1.83 METs, respectively. When the
count value fell within level 3 and 4, two regression models
were developed to estimate METs for level 3 and 4,
respectively. The estimated results of level 3 and 4 were R² =
0.74 and SEE = 0.8 METs, and R² = 0.84 and SEE = 0.9
METs, respectively.

In this paper, a wearable system, an activity
classification algorithm, and multiple MET mapping
regression model were developed. The system consists of
several sensor modules that can be synchronized to record
motions/activities for physical activity classification with wide
range of activity intensities. The proposed physical activity
classification algorithm is composed of the procedures of
acceleration acquisition, signal preprocessing, and feature
generation. The acceleration signals of body motions are
measured by the wearable sensor modules. The features
extracted from the acceleration signals include count,
coefficient of variation, and the ratio of frequency’s
amplitudes. The features are sent to a probability neural
network (PNN) classifier for activity classification. After
using the PNN to classify five activity categories, the three
count values and personal parameters, height and weight, are
utilized to construct five MET mapping regression models to
estimate MET for the five activity categories, respectively.
The rest of this study is organized as follows. In Section 2, we
introduce the wearable system and the physical activity
estimation algorithm. The MET mapping regression model
construction are presented in Section 3. Then, in Section 4,
the experimental results effectively validated the proposed
approach. Finally, the conclusions are given in the last section.

2 Wearable System and Its Energy
Expenditure Estimation Algorithm

In this study, the wearable system developed by our
research lab consists of a user-specified number of sensor
modules that can be synchronized by computer application
software. The module consists of the following major
components: an accelerometer (LIS3L02AQ3), a
microcontroller (STM32F103C8), a micro SD card, and a
battery. The LIS3L02AQ3 possesses a user selectable full
scale of ±2g and ±6g, and is able to measure accelerations
over the bandwidth of 1.5 KHz for all axes. The
accelerometer’s sensitivity is set to ±6g in this study. The
microcontroller collects the analog signals generated from the
accelerometer and transforms the signals to digital ones via an
internal 12 bits A/D converter. The digital sampling rate (fs)
of the microcontroller is 10 Hz. The overall power
consumption of the hardware device is 25–28 mA at 4.2 V. In
our experiment, we recruited 13 students between 20 to 30
years old (9 males and 4 females, and their average body mass
index (BMI) 22.37 ± 2.79 kg/m²), and each participant were
asked to wear the wearable system to perform the predefined
activities. The subjects were nonsmokers and were free of
both diseases and medications known to change their
metabolic rates. The wearable system includes three
accelerometer-based portable activity recorders and indirect
calorimeter used to collect accelerations and oxygen
consumption, respectively.

![Fig. 1. A participant wears K4b² and the wearable physical activity sensor system. (a) The front view of the participant. (b) The back view of the participant.](image)

2.1 Indirect Calorimeter

Each participant wore a portable indirect calorimeter
system (Cosmed K4b², Rome, Italy) as Fig. 1 for the duration
of performing each activity and resting time. The Cosmed
K4b² which weighs 1.5 kg, including the battery and a
specially designed harness was worn on participants’ chest by
a chest harness. Also, a flexible face mask was placed over the
participants’ mouth and nose using a nylon mesh hairnet and
Velcro straps to secure. This mask was attached to a
flowmeter which is a bidirectional digital turbine and an
optoelectronic reader. A disposable gel seal placed between
the participant and the face mask was used to prevent air leaks
from the face mask. According to the manufacturer’s
guidelines, the Cosmed K4b² oxygen analyzer and carbon
dioxide analyzer were calibrated before performing each test.
The calibration process had four steps: room air calibration,
reference gas calibration, delay calibration, and turbine
calibration. First, the room air calibration was automatically
run to update the CO₂ analyzer baseline and the O₂ analyzer
gain so that they coincided with atmospheric values. We then
performed a reference gas calibration using 15.93% oxygen
and 4.92% carbon dioxide. After that, the delay calibration
was performed in order to adjust for the lag time between the
expiratory flow measurement and the gas analysis. The final
step was the turbine calibration that set the flowmeter with a
3.00-L syringe (Hans-Rudolph) to guarantee accurate volume
measurements. After completing the calibration process, we
entered the ambient humidity determined by a hygrometer into
the Cosmed K4b². In addition, we also entered participants’
physical characteristics (age, height, weight, and gender) into
the Cosmed K4b². After finishing the test, we downloaded all
data stored in the memory of the portable Cosmed K4b² to a
PC.
2.2 Experimental Procedures

All participants were asked to complete fourteen activities including various lifestyle activities and conditioning exercises that were divided into five categories:

1) Category 1 (static): lying quietly, standing quietly, sitting quietly, and doing computer work by sitting.
2) Category 2 (home activities): sweeping and mopping.
3) Category 3 (walking stairs): walking upstairs and downstairs.
4) Category 4 (ambulation): walking at 3 and 4 mph, and running at 6 and 7 mph on a treadmill (SportArt 6310), respectively.
5) Category 5 (bicycling): riding an indoor bicycle trainer (SportArt C5150) at 50 and 100 watts.

Before performing the required activities, each participant was instructed to wear three sensor modules as Fig. 1 fixed on the hand wrist, the waist, and the ankle, respectively. The participants all performed each activity for 6 min, and took a rest between activities for at least 5 min to ensure their heart rates were below 100 bpm. We only extracted acceleration and oxygen consumption measurements from the 3rd to the 6th minute for analysis. We segmented the acceleration data into non-overlapping windows of 1 min in length and extracted important features from each window.

When each participant performed each activity, oxygen consumption and accelerations were measured continuously throughout the routine by a Cosmed K4b2 and the sensor modules, respectively. We only extracted oxygen consumption and acceleration signals from the 3rd to the 6th min for analysis. We segmented the acceleration data into non-overlapping windows of 1 min in length and extracted important features from each window.

After introducing the experimental protocol, we used a probabilistic neural network (PNN) classifier is used for activity classification. Typically, a PNN consists of an input layer, a pattern layer, a summation layer, and a decision layer. In this paper, the output of the PNN is represented as the label of the desired outcome defined by users. For example, in our physical activity categories, the labels ‘1’, ‘2’, ‘3’, ‘4’, and ‘5’ are used to represent activity categories 1, 2, 3, 4, and 5, respectively.

With enough generated features, the PNN is guaranteed to converge to a Bayesian classifier, and thus it has a great potential for making classification decisions accurately and providing probability and reliability measures for each classification. In addition, the training procedure of PNNs only needs one epoch to adjust the weights and biases of the network architecture.

We now summarize the proposed physical activity classification algorithm in the following steps:

**Step 1:** Acquire the raw acceleration signals from three accelerometer-based sensor modules.

**Step 2:** Remove drift errors or offsets by calibration, and remove the gravity from the filtered accelerations by a high-pass filter. Finally, segment the acceleration data into non-overlapping windows of 1 min in length by windowing.

**Step 3:** Generate the time- and frequency-domain features from the preprocessed acceleration of each axis including count, CV, and the ratio of frequency amplitudes.

3 Construction of MET Regression Model

We developed MET mapping regression models for energy expenditure estimation. There are two MET mapping regression models developed including a single regression model without activity classification and multiple regression models with activity classification. The parameters of each model were the three counts, subject’s weight (WT), and subject’s height (HT) as shown in the following equation:

\[
MET_e = \sum_{i=1}^{n} (a_i \times \text{count}_{\text{wrist}}^i + b_i \times \text{count}_{\text{neck}}^i + c_i \times \text{count}_{\text{ankle}}^i) + d \times WT + e \times HT + f,
\]

where \( n \) is the power of the model, \( a_i, b_i, c_i, d, e \) are coefficients. \( MET_e \) calculated by oxygen consumption is the output of each model. Without activity classification, we utilized the least squares method to develop a single regression model in order to estimate the METs of five
physical activity categories. With activity classification, we still utilized the least square method to develop multiple regression models according to each activity category. For all regression models, we developed from the simple to polynomial mapping regression models. The mean and the standard deviation of estimation errors were utilized to evaluate whether the activity classification is conducive to MET estimation. The mean and the standard deviation of estimation errors can be calculated by the following equations (4) and (5), respectively.

\[
SSE = \sum_{i=1}^{n} (\text{MET}_a - \text{MET}_e)^2
\]

\[
\text{error} = \text{AEE}_r - \text{AEE}_e
\]

\[
\text{error}_\text{mean} = \frac{\sum_{i=1}^{n} \text{error}_i}{n}
\]

\[
\text{error}_\text{std} = \sqrt{\frac{\sum_{i=1}^{n} (\text{error}_i - \text{error}_\text{mean})^2}{n-1}}
\]

where \( n \) is the total number of the activities conducted by all participants. \( \text{AEE}_r \) is the actual MET during activities. \( \text{error} \) is the estimation errors of METs. \( \text{error}_\text{mean} \) is the mean of estimation errors. \( \text{error}_\text{std} \) is the standard deviation of estimation errors. The units of \( \text{AEE}_r, \text{error}, \text{error}_\text{mean}, \) and \( \text{error}_\text{std} \) are MET.

### 4 Experimental Results

The effectiveness of physical activity classification algorithm is evaluated by the experiments of five activity categories and the results of MET mapping regression models are evaluated by comparisons between without and with classification. The proposed classification algorithm includes acceleration acquisition, signal preprocessing, and feature generation. We employed the PNN as our classifier to classify five categories of physical activities. After physical activity classification, the MET mapping regression model of each activity category is developed to estimate activity energy expenditure. In this study, there were two MET mapping regression models developed including a single MET mapping regression model without classification and multiple MET mapping regression models with classification. The results of energy expenditure estimation of multiple MET mapping regression models with classification will compare with the results of without classification.

#### 4.1 Results of Physical Activity Classification

we utilized a leave-one-subject-out cross-validation method to validate the effectiveness of the PNN classifier. The neuron numbers and the computational time of the PNN classifier are shown in Table 1. In each repetition of the cross-validation process, the acceleration data collected from 12 participants randomly was used in the training procedure. Then, the acceleration data from the rest who was left out of the training procedure was used to test the classification performance. The procedure was repeated for all subjects. The average recognition accuracy was 95.33% in the cross-validation procedure. The best classification accuracy of static activity category was 100%, and the worst classification accuracy of walking stairs was 80.77%. From Table 2, the misclassification of walking stairs category focuses on walking upstairs. The main reason of false alarm is because the acceleration signals of walking upstairs and walking were more similar and thus resulted in more similarity in the extracted features.

<table>
<thead>
<tr>
<th>Numbers of input neuron</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numbers of hidden neuron</td>
<td>900</td>
</tr>
<tr>
<td>Numbers of output neuron</td>
<td>5</td>
</tr>
<tr>
<td>Computational time (sec.)</td>
<td>0.031</td>
</tr>
</tbody>
</table>

#### 4.2 Results of MET Estimation

In this study, there are two MET mapping regression models developed including single regression model without activity classification and multiple regression models with activity classification. Table 3 shows the comparisons of the mean and the standard deviation of MET estimation errors by the regression models developed with and without activity classification. Without activity classification, the results of the quartic regression model were the most accurate, where the standard deviation of estimation errors was 1.16 METs. With activity classification, all standard deviations of estimation errors of each power regression model were less than that of the regression models developed without activity classification. Thus, the results validated that the accuracy of MET estimation could be effectively enhanced by using multiple regression models developed with activity classification. The MET estimation errors of the single regression model and the multiple regression models are shown in Fig. 3(a) and (b), respectively.

Without activity classification, the single regression model seriously underestimated the bicycling activity with 2.05 METs less than the actual MET as shown in Table 4. It also overestimated walking stairs activity with 0.67 METs more the actual MET. The results showed that the single regression model could not provide accurate activity MET estimation. On the contrary, constructing multiple regression models supplemented with the activity classifier to estimate METs could decrease the errors of estimation the two activity categories to 0.16 METs and 0.21 METs, respectively, and thus effectively improved the estimation accuracy.

The average AEE estimation values for each category and activity with and without activity classification are shown in Figs. 3 and 4, respectively. Without activity classification, although the single regression model could give a close estimation for light-intensity activities, such as static and home activities, and vigorous-intensity activities, such as running, an estimation error higher than 0.5 METs would occur for six activities including walking upstairs and downstairs, walking (3mph and 4mph), and riding an indoor bicycle trainer (50 watts and 100 watts). Among all, walking upstairs had the most serious estimation error with 1.84 METs in average.
Table 2 Confusion matrix of each activity of physical activity classification for all subjects

<table>
<thead>
<tr>
<th>Activity categories</th>
<th>Activities</th>
<th>Recognized</th>
<th>Static</th>
<th>Home activities</th>
<th>Walking Stairs</th>
<th>Ambulation</th>
<th>Bicycling</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static</td>
<td>Standing</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>Sitting</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>Lying</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>Desk working</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td>Home activities</td>
<td>Sweeping</td>
<td>0</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>Mopping</td>
<td>1</td>
<td>51</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>98.08</td>
</tr>
<tr>
<td>Walking Stairs</td>
<td>Walking upstairs</td>
<td>0</td>
<td>0</td>
<td>35</td>
<td>17</td>
<td>0</td>
<td>0</td>
<td>67.31</td>
</tr>
<tr>
<td></td>
<td>Walking downstairs</td>
<td>0</td>
<td>0</td>
<td>49</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>94.23</td>
</tr>
<tr>
<td>Ambulation</td>
<td>Walking 3mph</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>51</td>
<td>0</td>
<td>0</td>
<td>98.08</td>
</tr>
<tr>
<td></td>
<td>Walking 4mph</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>Running 6mph</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>44</td>
<td>0</td>
<td>0</td>
<td>84.62</td>
</tr>
<tr>
<td></td>
<td>Running 7mph</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>100.00</td>
</tr>
<tr>
<td>Bicycling</td>
<td>bicycling 50 Watts</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>48</td>
<td>0</td>
<td>92.31</td>
</tr>
<tr>
<td></td>
<td>bicycling 100 Watts</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>52</td>
<td>0</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 3 Means and standard deviations of MET estimation errors by different power of regression models

<table>
<thead>
<tr>
<th>The power of N of the models</th>
<th>MET errors of all activities (METs)</th>
<th>Without classification</th>
<th>With classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard deviation</td>
<td>Mean</td>
</tr>
<tr>
<td>1</td>
<td>1.11×10^{-15}</td>
<td>1.49</td>
<td>-1.58×10^{-16}</td>
</tr>
<tr>
<td>2</td>
<td>-3.71×10^{-15}</td>
<td>1.24</td>
<td>-2.65×10^{-17}</td>
</tr>
<tr>
<td>3</td>
<td>2.95×10^{-15}</td>
<td>1.20</td>
<td>3.55×10^{-15}</td>
</tr>
<tr>
<td>4</td>
<td>-7.25×10^{-15}</td>
<td>1.16</td>
<td>2.31×10^{-4}</td>
</tr>
<tr>
<td>5</td>
<td>3.3×10^{-3}</td>
<td>1.25</td>
<td>1.3×10^{-3}</td>
</tr>
</tbody>
</table>

Fig. 3 Estimation errors of all activity categories by the regression models: (a) Without classification. (b) With classification. The middle line represents the estimated mean value. The dashed lines represent margin of twice the standard deviation.
Table 4 Average estimation error of AEE for each activity category with and without activity classification using the classifier combing the quartic regression model.

<table>
<thead>
<tr>
<th>Activity categories</th>
<th>Without classification</th>
<th>With classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>Static</td>
<td>-0.47</td>
<td>0.38</td>
</tr>
<tr>
<td>Home activities</td>
<td>0.04</td>
<td>0.61</td>
</tr>
<tr>
<td>Walking Stairs</td>
<td>-0.67</td>
<td>2.23</td>
</tr>
<tr>
<td>Ambulation</td>
<td>-0.23</td>
<td>1.20</td>
</tr>
<tr>
<td>Bicycling</td>
<td>2.05</td>
<td>1.24</td>
</tr>
</tbody>
</table>

Fig. 3 Average MET estimation for each activity category with and without activity classification using the quartic regression model.

Fig. 4 Average MET estimation for each activity with and without activity classification using the quartic regression model.
However, combing the activity classifier to estimate METs could increase the estimation accuracy ranged from 0.31 METs to 1.23 METs for these six activities and basically maintained certain estimation accuracy for the rest. Thus, the above results verified that respectively conducting MET estimation according to different activity categories could improve the estimation accuracy of the system.

5 Conclusions

This paper presents algorithms for physical activity classification and MET mapping regression model construction using a wearable physical activity sensor system. The proposed activity classification algorithm composes of the procedures of acceleration acquisition, signal preprocessing, and feature generation. The algorithm is capable of translating time-series acceleration signals into important feature vectors. The algorithm first extracts the time- and frequency-domain features from the acceleration signals, and the features are sent to a trained probabilistic neural network (PNN) for classification. Finally, the count and the user’s characters such as height and weight are the features to construct MET mapping regression models to estimate activity energy expenditure. In our experiments, the average classification accuracy of five categories of physical activities for physical activity classification is 95.33%. The average error of MET estimation without and with activity classification is -7.25×10⁻² to 1.23 METs for these six activities and basically maintained certain estimation accuracy for the rest. Thus, the above results verified that respectively conducting MET estimation according to different activity categories could improve the estimation accuracy of the system.

6 References


