Monitoring Daily Energy Expenditure using a 3-Axis Accelerometer with a Low-Power Microprocessor

Yoshihiro Kawahara, Nanami Ryu, Tohru Asami

Graduate School of Information Science and Technology
The University of Tokyo
7-3-1 Hongo Bunkyo-ku, Tokyo, Japan
{kawahara, nanami, asami} AT akg.t.u-tokyo.ac.jp

Abstract Recent mobile phones are capable of monitoring a user’s contextual information because they are equipped with computational, communication, and sensing abilities, and because people carry them continuously. This paper describes software that accurately monitors energy expenditure using a mobile phone handset equipped with a 3-axis accelerometer. This approach differs from other attempts because it detects non-exercise activity thermogenesis (NEAT) as well as active exercise (walking and running) regardless of the sensor position on the body. All the signal-processing tasks are implemented by the low-power 8-bit PIC microcontroller. Total power consumption is almost as much as that of the stand-by power consumption of mobile phones. Evaluation results indicate that this technology can monitor energy expenditure as accurately as a medical calorie meter.

1 Introduction

Metabolic syndrome is a risk factor for cardiovascular disease that is receiving much clinical attention [1]. The dominant underlying developmental features of metabolic syndrome are abdominal obesity and insulin resistance. More than 50 million Americans are estimated to have metabolic syndrome. First-line treatment involves healthy lifestyle changes. The most important action is to balance dietary intake and calories burned. However, it can be difficult for people to monitor their level of physical activity. Therefore, a practical activity-monitoring platform based on mobile and sensing technologies would be very useful.

1.1 Related Works

True total energy expenditure is very difficult to measure, and nearly all techniques use approximations. Measurement of metabolic carbon dioxide production (by Douglas bags and DLW) is accepted as the gold standard.
for medical research [2]. However, these techniques are awkward to use in daily life [3]. Other user-friendly approaches attempt to infer energy expenditure through the use of sensors. Pedometers only measure footfalls and are not accurate when used for activities that do not involve footfalls. Heart rate is affected by stress, medication, disease, and other physiological factors, and its correlation to energy expenditure is only accurate within a narrow range of moderate intensity exercise. Furthermore, due to individual variations, individual calibration is required. Some attempts have been made to combine heart rate and accelerometry using a technique called Flex-HR. Many current systems for continuously measuring heart rate and motion can be uncomfortable to wear for long periods of time because specific placement of a chest strap (such as the Polar chest strap [4]) or leg strap (such as the Dynastream system [5]) is required. The Sensewear [3] is an unobtrusive armband monitoring device, which utilizes a heat flux sensor, galvanic skin response (GSR) sensor, skin temperature sensor, near-body temperature sensor, and a two-axis accelerometer to gather data related to energy expenditure. The sensor readings are mapped to calorie consumption based on proprietary software algorithms. However, this device must be worn on the upper arm for 24 hours/day and can disrupt sleeping and interfere with clothing.

1.2 Challenges of Calorie Estimation Using a Mobile Phone

Mobile phones are an attractive device for monitoring human activities because people carry them frequently and the devices are capable of communication, computational, and sensing abilities. Some mobile phones are currently equipped with a 3-axis accelerometer as the user interface [6]. In this study, this accelerometer was exploited to monitor the user’s activities and then estimate calorie consumption based on the METS conversion method. Although this approach appeared straightforward, several technical challenges needed to be overcome to make the device practical.

1.2.1 Posture inference with a single accelerometer

Sensor capabilities are more limited on mobile phones compared to dedicated medical calorie meters. Although heat flux and GSR sensors play important roles in estimating calories, an accelerometer is the only sensor device likely to be included on a mobile phone. Location information given by GPS is often too rough for estimating non-exercise activities. Therefore, a user’s posture must be inferred using only an accelerometer.

1.2.2 Support for multiple sensor positions on the body

People carry mobile phones at different places on the body. One survey of mobile phone use indicated that 77.6% of respondents always put their
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mobile phones in a bag, pants pocket, or chest pocket, while 13.2% of people change the mobile phone position from day to day [7]. Therefore, a context inference method needs to adapt to at least those three positions and must be able to detect a change in position.

1.2.3 Energy efficient computation

Energy use is an important characteristic of mobile devices because users do not want to recharge the battery so frequently. Ancillary applications are not allowed to consume much energy in a mobile phone. Previous studies have extracted approximately 600 features from a set of sensors and classified them with Hidden Markov Models [8]. However this approach is not applicable to mobile phones because it requires a large amount of computation resources and memory. Therefore, we introduce a minimized computation algorithm and a simpler decision tree classifier to extend battery life.

The remainder of this paper presents solutions to the technical requirements. The energy-efficient posture inference scheme is addressed first using a 3-axis accelerometer, which can infer posture with one accelerometer with an 8-bit low-power PIC microprocessor. Next, the method that can estimate calories consumed from both exercise and non-exercise activity thermogenesis is described. Finally, performance of this approach is compared to existing calorie meters, followed by a summary of the contributions of this method and directions for future work.

2 Posture Inference Using 3-axis Accelerometer

Previous work proposed a user posture inference scheme using a 3-axis accelerometer for a mobile phone handset [11]. In this paper, the posture inference scheme was extended and optimized for implementation on a resource-limited microprocessor. The basic algorithms are reviewed and the optimized numerical calculation method is described.

2.1 Posture Inference

The inference method is divided into three steps. The first step involves pre-processing, during which the relevant feature values are extracted from the acceleration data. The second step is sensor position inference. The system infers where the mobile phone is placed to select the correct posture inference scheme. The last step is user posture inference (classification). The system recognizes the user’s posture using an algorithm based on the sensor position (Figure 1).

Many mobile devices, including mobile phones, digital cameras, laptop computers, game controllers (such as the Nintendo Wii), and pedometers,
are equipped with a MEMS-based 3-axis accelerometer. It can capture acceleration data at 10 to 100 Hz with 10-bit resolution and +/- 2G dynamic ranges. Our algorithm can operate with this type of off-the-shelf accelerometer.

2.1.1 Pre-Processing

The system calculates the variance for the last $N_v$ samples, the average of each axis for the last $N_a$ samples, the maximum value of the fast Fourier transform (FFT) power spectrum for continuous $N_f$ samples, and the change in angle of the sensor device. The sensor angle is calculated by detecting the gravity vector.

2.1.2 Sensor Position Inference

The sensor position is inferred based on the following features.

- When a user does not wear the sensor device, the variance is nearly 0.
- Given a well-calibrated sensor, the direction of gravity can be calculated when a user is standing or moving gently. This allows the sensor to determine vertical and horizontal directions.
- When the sensor device is in a pants pocket, the sensor angle fluctuates widely during walking.
- When the sensor device is in a chest pocket, the sensor data shows a unique change when the user leans forward in the chair.

2.1.3 Classification

When the orientation and position of the sensor has been determined by previous operation, the system selects a relevant algorithm to infer the user’s posture. First, two general rules are described. These rules are used regardless of device position. The variance value is used to determine whether the user is moving. The maximum value of the FFT power spectrum is used to determine the activity state (running, walking, and the pace of running or walking). Second, two specific rules are described based on the sensor device position. When the sensor device is in a pants pocket, a change in sensor angle can estimate sitting motion. When the device is in a chest pocket, sensor angle is helpful for estimating forward leaning, backward leaning, or side leaning.

All the rules are described in a decision tree that can be easily implemented in resource-limited devices.
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2.2 Reducing Computational Overhead for Low-power 8-bit Microprocessors

Many modern mobile phone platforms offer SDK to allow users and 3rd party developers to implement applications on the device. However, application processors on mobile phones are high-performance and typically consume greater than 100 mW. Therefore it may drain the batteries within several hours. Different from “kill-time” gaming applications, which are used for a limited time, a calorie meter application has to remain running for a full day.

Therefore, energy consumption must be reduced by 1/5 to 1/10. The most effective approach is to reduce computational complexity and introduce a dedicated low-power processor.

We implemented our algorithm on the PAVENET module, which was developed as a wireless sensor network device at the University of Tokyo. The PAVENET module consumes 30 mW at most when the MPU and the wireless interface are in use. It is composed of a PIC 18 microprocessor, wireless interface (Bluetooth[9] and/or IEEE 802.15.4[10]), and I/O interfaces to connect external sensor devices. Users can run software written by C language on the original hard real-time operating system named PAVNET OS.

Due to its low-power design, however, the available data memory is only 4 Kbytes and the MPU clock is 20 MHz. No floating-point coprocessor is on board. Therefore, some ingenuity is required for implementation.

Our preliminary experiments indicated that inference accuracy can be maximized when acceleration data is sampled at 20 Hz. This means feature extraction data need to be calculated and classification executed every 50 msec. However, FFT calculation during feature extraction requires

\[ (8 \text{ sine calculation}) \times (8 \text{ multiplication}) \times (4 \text{ addition}) \times (\frac{1}{2} \times N_f \text{ log}_2 N_f) \]

calculation \((N_f=64)\). Although a laptop computer can complete this cal-
calculation within 10 msec, a PIC microprocessor requires more than 3 sec for this feature extraction. A monitoring interval of 3 sec is too long for this classification algorithm because it can lose important triggers such as a change in posture and change in sensor position. The FFT calculation is the most significant bottleneck in this scheme, but it supplies important information because it indicates walking or running pace. Therefore, computation time was reduced by modifying trigonometric function and excluding floating-point operations. First, a generic trigonometric function provided by a math library is not needed because the sine values used for FFT are always the same as long as $N_f$ is fixed. Instead, a trigonometric function table is used when a sine value is necessary. Moreover, the floating-point operation was eliminated and replaced by integer values. The numbers after the decimal point were multiplied by a fixed coefficient and divided before used.

2.3 Performance of Posture Inference

These changes allowed a reduction in FFT computation time from about 3 sec to 74 msec. Total feature extraction procedure including FFT takes 78 msec. Thus, the total inference procedure (including feature extraction and classification) takes 80 msec. When the user’s posture is obtained every 200 msec, total power consumption of the PAVENET module (including operating system overhead and access to the sensor) was 14.3 mW. This power consumption is almost as much as that of the stand-by power consumption of mobile phones. If a typical Li-ion battery is used for mobile phones (3.7 V, 950 mAh), it lasts for 246 hours (10 days). Compared to previous results [11], there was a decrease in accuracy of the posture inference due to the difference in bit depth of the variables in this implementation. Table 1 shows the accuracy of inference with cur-
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<table>
<thead>
<tr>
<th>Location</th>
<th>Sitting</th>
<th>Standing</th>
<th>Walking</th>
<th>Running</th>
</tr>
</thead>
<tbody>
<tr>
<td>In Pants Pocket</td>
<td>80.7%</td>
<td>99.2%</td>
<td>92.5%</td>
<td>98.5%</td>
</tr>
<tr>
<td>In Bag</td>
<td>–</td>
<td>99.4%</td>
<td>96.9%</td>
<td>98.8%</td>
</tr>
<tr>
<td>In Chest Pocket</td>
<td>–</td>
<td>99.4%</td>
<td>95.0%</td>
<td>98.1%</td>
</tr>
</tbody>
</table>

Table 1: Accuracy of inference

rent implementation. We obtained data from more than 500 trials from four individuals. However, overall performance was accurate enough for a calorie monitoring application.

3 Calorie Estimation Based on METS

A unit of metabolic equivalent, or MET, is defined as the ratio of a person’s working metabolic rate relative to the resting metabolic rate. METS values correlate with oxygen requirements. Starting with 1, which is the least amount of activity (such as resting), the values increase with the amount of activity. For example, running at 9.7 km/h has a METS value of 10. Standard tables exist that provide METS values for a wide range of exercises and activities. A person’s calorie consumption can be easily calculated using this METS values given by equation 1.

\[ \text{Energy (kcal)} = 1.05 \times \text{METS} \times \text{Weight (kg)} \times \text{Exercise time (h)} \]  

METS values of different daily activities have been previously defined [12]. Here, the user’s inferred activities are matched with METS value to estimate total energy expenditure. Table 2 presents simplified METS values for each activity.

Our posture inference scheme can detect four contexts. When a user is sitting or standing, the corresponding METS value changes according to the activity the user is doing (e.g., cooking or sweeping). However, our posture inference algorithm cannot detect such detailed activities. Therefore a linear mapping of METS and variance of acceleration data was created based on observation. When the user is walking or running, the METS values changes according to the speed. Fortunately, the pace of the running or walking can be obtained from the dominant frequency of the acceleration sensor data. Thus, the speed of walking or running can be obtained by multiplying pace by the length of stride.

3.1 Evaluation

We performed a comparative evaluation with our system. Eight individuals were asked to conduct their usual daily activities, including desk work.
Table 2: METS values and user contexts

<table>
<thead>
<tr>
<th>Context</th>
<th>METS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sitting</td>
<td>1.0 – 2.0</td>
</tr>
<tr>
<td>Standing</td>
<td>1.2 – 2.3</td>
</tr>
<tr>
<td>Walking</td>
<td>$0.0272 \times \text{walking speed (m/min)} + 1.2$</td>
</tr>
<tr>
<td>Running</td>
<td>$0.093 \times \text{running speed (m/min)} - 4.7$</td>
</tr>
</tbody>
</table>

Figure 3: Estimated Energy Expenditure

(2 to 3 hours), walking (1 to 2 hours), and jogging for several minutes. The trial subjects consisted of two females and six males ranging from 20 to 30 years old. We choose 2 commercial activity monitors (SenseWear [3] and Polar [4]) for comparison.

Figure 3 shows the experimental results. The SenseWear is considered a reference device because it provides an accurate estimate of energy expenditure during simulated patterns of daily activity involving sitting, standing, and walking [11]. Mean estimated daily energy expenditure measured with our method was 5% lower than that measured with SenseWear. Despite this group difference, individual comparisons between our method and SenseWear were close (correlation of 0.90). In contrast, energy expenditure presented by Polar was 18% higher than that measured with SenseWear. As mentioned in section 1, monitoring tool based on heart rate requires careful calibration and is not suitable for monitoring energy expenditure when daily activity is dominant.
4 Conclusions

We developed a daily energy expenditure monitoring application using a 3-axis accelerometer on a mobile phone handset.

The results of this study indicate:

- The METS-based energy expenditure estimation scheme is as accurate as a medical calorie meter.

- The posture inference algorithm is accurate and practical enough to be used as an energy expenditure monitoring device using only one 3-axis accelerometer.

- All software was implemented on a low-power sensor network platform named PAVENET and was run by a mobile phone’s stand-by energy.

A limitation of this current posture inference scheme is that it does not support some fitness activities such as bicycling, tennis, and swimming. Although non-exercise activity thermogenesis is dominant in the life of an average person, another calorie meter may be needed to measure energy expenditure during some fitness exercises. Moreover, our test subjects were all healthy young adults. Currently, we are working on demonstrating the performance of our application for a wider range of people by implementing it on a commercial mobile phone.

References


Yoshihiro Kawahara, Nanami Ryu, Tohru Asami


