A Pilot Study on BSN-based Ubiquitous Energy Expenditure Monitoring

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Abstract—This paper presented a wearable body sensor network (BSN) that could be potentially employed for dynamic body energy expenditure monitoring. Three compact BSN nodes were deployed at wrist, abdomen and ankle, respectively. Acceleration signals from the multiple body sites were used to calculate a whole body weighted acceleration value. Preliminary results indicated that the standard deviation of the whole body value was smaller than that from any individual body site. There was a strong linear correlation between the whole body weighted acceleration value and the speed, but this correlation was highly subject-dependant. The pilot study presented the first several steps towards a pervasive approach for body energy expenditure monitoring.

***Keywords- pilot; BSN;* energy expenditure*;* ubiquitous**

Ⅰ. INTRODUCTION

Body sensor networks (BSN) has shown a great deal of promises in promoting healthy living styles against obesity and other chronic diseases [1]. Obesity primarily results from overeating and inactivity, subjects with hyperkinesis have 2-4 times higher risks of suffering from myocardial infarction than that with moderate exercise [2]. In another side, previous research also indicated that sports anemia is contributed to endurance exercise [3], and many people have suffered or even died from overloaded physical exercises. Therefore it is essential to schedule physical exercises rationally. One of the key technical challenges is to monitor subject's energy expenditures (EE) in a dynamic and non-intrusive basis.

There are several well-established approaches for body EE measurements. The doubly labeled water method often serves as a golden-standard for validating the EE estimations obtained by other methods [4]. However, this method is not suitable for home-based dynamic monitoring and also the cost is prohibitively high. Calorimeters such as k4b2 from Cosmed and Oxylog from Metamax were primarily designed to measure gas exchange on the true breath during different activities. However these systems are not pervasive. Besides, pedometers and heart rate monitors have limited measurement accuracies for EE measurements [5, 6]. Indirect methods such as diet records [7] and activity questionnaires [8] are relatively unreliable due to factors such as recall bias.

Although extensive acquisition of biomechanical and biochemical information is available in almost all clinical settings, the configuration is not suitable for home-based pervasive sensing. Accelerator sensor, however, has received significant attentions in the pervasive sensing agenda due to its compact size, low power consumption and easily integrated within a wearable BSN node. In this paper an acceleration-based multi-node solution for body EE estimations was proposed and the pilot studies were carried on to validate our method.

Ⅱ. METHOD

As shown in Fig. 1, three body sites, i.e. wrist, abdomen and ankle were selected for body acceleration detections during physical exercises. The rationales are: (1) in terms of the mechanical architecture a human body is primarily divided to three parts: upper limbs, trunk, and lower limbs, whose percentage in weight of the body is approximately 10%, 60%, and 30%, respectively; (2) it was investigated that an accelerometer worn on wrist was capable of measuring arm-dominant activities, mostly sedentary activities during daily life [9], furthermore sensors in this setup could be seamlessly integrated within a watch; (3) abdomen close to the center of body mass is a popular place to measure body trunk acceleration that represents the movements of the body mass [10]; (4) acceleration signals from ankle highly correlate with different types and intensities of walking and running activities, the most frequent activities during daily life [11].

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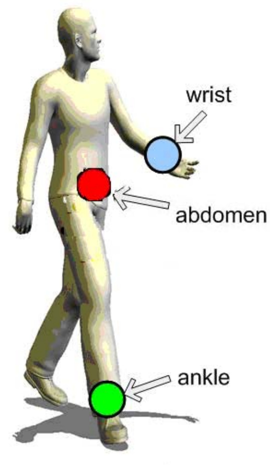
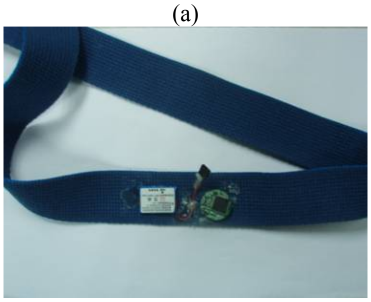


Fig.1 Different sites for on-body acceleration signal detections.

The hardware platform for wireless acceleration signal detections was consisted of three BSN node boards and a base station board [12]. The BSN node board integrated a digital 3-D accelerometer sensor (SCA3000 from VTI), a low-power microprocessor (MSP430 from TI), a radio transceiver (nRF905 from Nordic), a memory IC, a power regulator, and some affiliated discrete components. The BSN node board is 23-millimeter in diameter (Fig. 2) so it could be worn on almost any part of the body. During experiments the acceleration signals were transferred wireless to the base station board that connected with a PC via a serial port.

(a)



(b)

Fig.2 BSN node boards were assembled with (a) a wristband and (b) a textile strip so that the node board could be easily immobilized on-body.

There were three node boards for on-body acceleration measurements so totally there are nine acceleration signal channels. The whole body EE was estimated by calculating the weighted sum ($w_{body\ part}$) of all the individual acceleration signals ($A_{body\ part}$).

Acceleration signals from all channels were acquired at a sampling rate of 10 Sps. Acceleration of a moving object is consisted of two parts, its own gravity and the acceleration caused by human movements, which were called static accelerations and dynamic accelerations, respectively. It is the latter that was concerned in our experiments. Therefore a high pass filter (-3dB bandwidth 1 Hz) was employed to eliminate the static portions. The acceleration signal Ai was defined as:

$$\Delta A_i = [(X_{i+1}-X_i)^2+(Y_{i+1}-Y_i)^2+(Z_{i+1}-Z_i)^2]^{1/2}$$

$$A_{body\ part} = \sum \Delta A_i \text{ over one minute}$$

The whole body weighted acceleration value A_{whole} was calculated as

$$A_{whole} = w_{wrist} * A_{wrist} + w_{abdomen} * A_{abdomen} + w_{ankle} * A_{ankle}.$$

The weighting coefficients ($w_{body\ part}$) were based on the percentages of the weight in body, i.e. 0.1, 0.6 and 0.3 for wrist, abdomen and ankle, respectively.

In order to validate the proposed wearable EE estimation method, two sets of *in-situ* experiments were carried on. (1) single-subject-multiple-speed experiment. One subject (25 year-old, 53kg) ran on a treadmill (PATL30806 from ICON) at four different speeds (2 km/h, 4 km/h, 6 km/h, and 8 km/h) for multiple times, each run lasted for five minutes. (2) multiple-subject-single-speed experiment. Four subjects (weighted 45 kg, 53kg, 70kg, and 85kg) ran at a fixed speed of 6 km/h for multiple times, each run lasted for five minutes.

III. RESULT

The BSN node boards that integrated the 3-D accelerometer sensors were found to be comfortably worn by all the subjects. The wireless link between the node boards and the base station was highly reliable.

Figure 3 compared the relative standard deviations from the wrist, abdomen, ankle and the whole body.

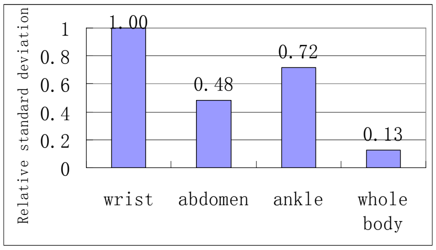
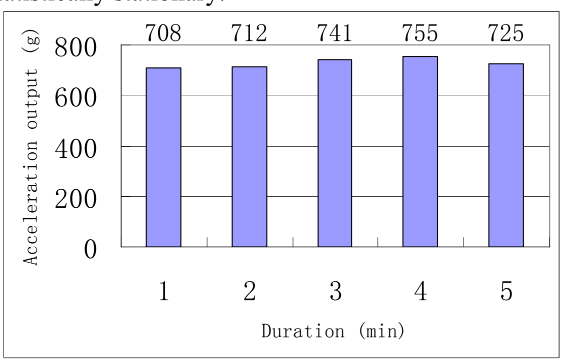


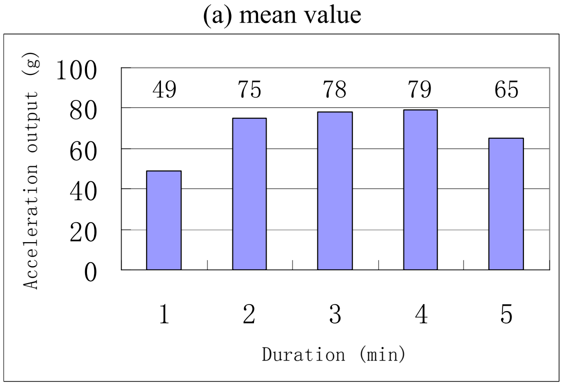
Fig.3 Relative standard deviations from different body sites of one subject. The results were averaged from five runs. The whole body value was calculated using the aforementioned Equations.

It was clearly indicated in Fig 3 that the standard deviation from the whole body weighted acceleration value A_{whole} was smaller than that from wrist, abdomen or ankle, suggesting the A_{whole} could lead to a more robust estimation for body EE measurements.

Fig. 4 illustrated the averaged mean value and standard deviation value over 1-minute time slot, which suggested that the whole body weighted acceleration value during the 5-minute test runs were statistically stationary.



(a) mean value



(b) standard deviation

Fig.4 The averaged (a) mean value and (b) standard deviation of the whole body EE estimations over 1-minute time-slot. The results were averaged from five runs.

Fig. 5 demonstrated the linear correlation between the whole body weighted acceleration value A_{whole} and the various speed ($\mathbf{R}^2$=0.9946), suggesting that the A_{whole} could be used to estimate the speed.

For experiment (2), the correlation co-efficiency between the body weights and the A_{whole} across different subjects was poor ($\mathbf{R}^2$=0.868), illustrated that whole body weighted acceleration value A_{whole} was highly subject-dependent. Therefore personalized calibrations were essential for the consequent EE estimations.

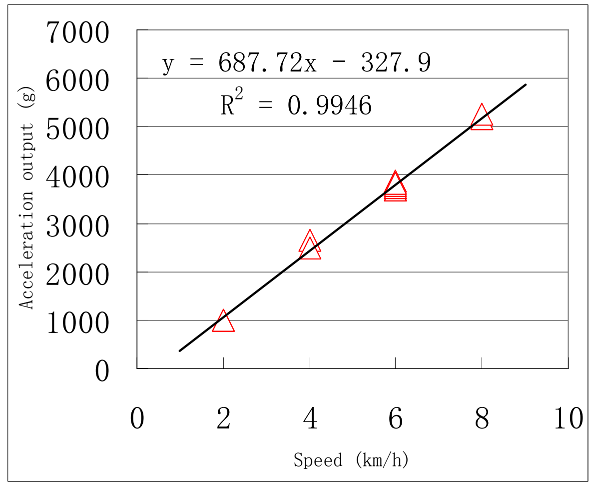


Fig.5 The correlation between the whole body weighted acceleration values A_{whole} and the different speeds for the same subject.

Ⅳ. CONCLUSION

In this paper, a feasibility study was conducted for examining a BSN-based approach for ubiquitous body energy expenditure monitoring. The pilot study concluded that the whole body weighted acceleration value that was calculated from wrist, abdomen and ankle acceleration signals enhanced the EE estimation robustness. In the future we will investigate a more advanced data fusion algorithm and compare our solution with the golden-standard method.

Ⅴ. ACKNOWLEDGEMENT

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