IMPLEMENTATION AND EVALUATION OF A PHYSICAL ACTIVITY AND ENERGY EXPENDITURE ALGORITHM IN A SENSIUM™-BASED BODY-WORN DEVICE

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Abstract: It is well known that sedentary life style lead to conditions such as obesity and diabetes. In recent years, there has been increasing interest in devices capable of measuring activity energy expenditure (AEE) and physical activity intensity (PAI) without disrupting the activities of daily living. In this paper we introduce a portable and light-weight device based on our Sensium^{TM} technology. Unlike existing commercially available devices, the latter can measure both AEE and PAI in a real-time basis and convey the resultant calculations wirelessly to a remote PC and/or sever. Such calculations are carried out by means of a mathematical model, which combines heart rate and accelerometer information to produce PAI and AEE estimations. The model was calibrated against a reference indirect calorimetry system. In particular, simulated annealing was used to adjust the model parameters so as to allow a closer match between the predicted and reference values. The resulting model was tested using a separate dataset with reference to indirect calorimetry. The 95% prediction interval and the Spearman's correlation coefficient (r) for PAI were found to be [-0.1307, 0.171] kJ/kg/min and 0.903 ($p<0.001$) respectively. In addition, the results revealed that there is agreement between Sensium^{TM} and a similar reference (validated) device.

1 INTRODUCTION

Sedentary individuals are more susceptible to a wide range of diseases. Different studies have made associations between the lack of physical activity, diabetes as well as obesity and heart conditions (Marchand et al., 1997).

Consequently, there has been substantial interest in affordable and portable devices to enable accurate estimations of Physical Activity (PA) on a routine basis. An example of such a device is the Actiheart®. It comprises a portable, light-weight device that measures activity energy expenditure using a group-calibrated set of equations. This mathematical approach is known as the Branch Equation Model (Brage et al., 2004). It has been validated against a number of well-established techniques, including direct and indirect calorimetry (Brage et al., 2005, Brage et al., 2004). The Actiheart® is mounted on the chest region of the subject, and data that is acquired from the subject is stored locally. Unfortunately, the Actiheart® is a data-logger that has to be removed from the subject to download the data for analysis. This restricts the possibility of continuous monitoring and feedback by medical experts in real-time, which is desirable in some clinical and sports contexts.

In contrast, the wireless device proposed here is capable of processing the acquired data and streaming it wirelessly in real-time to a base station. Thus, the results can be relayed to a central server that can be accessed by medical professionals, who can potentially provide information to subjects to allow changes to lifestyles at any time.

Therefore, the aim of this work was to adapt the branched equation model to our system, and evaluate its performance against two valid reference devices – an indirect calorimetry system and the Actiheart® when tested in normal individuals.

2 RELATED WORK

In 2004, Brage and colleagues developed and evaluated a method (Branched Equation Model - BEM) for measuring levels of PA and EE by

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combining accelerometry with HR monitoring, demonstrating improved estimation of these parameters when tested in 12 male normal subjects. The approach relies on a set of rules, regression equations and thresholds to estimate the PA or EE. Thus, these parameters are estimated by means of the selected piecewise function (i.e. one out of the four available in the branched model) which best suit to the level and intensity of the activity currently performed.

Later, the BEM approach was implemented in the ActiHeart® (CamNTech, Cambridge, UK). This device was shown to be reliable in estimating PA intensity reliably in several studies (Brage et al., 2005, Crouter et al., 2007), particularly for activities such as walking and running. However, one important drawback of this device is its inability to transmit data in real time. The latter has a negative impact on different aspects. First of all, the device may need to be applied to and removed from the patient several times until downloaded data reflects the adequacy of electrode placement. Secondly, the data logging capability is limited. For these reasons, this device is neither an option for long-term follow-up studies requiring several weeks or months; nor for a final product intended for continuous real-time feedback of physical activity and calorie expenditure.

3 SENSIUM PA-EE ESTIMATION

The approach adopted for PA-EE estimation can be explained from Figure 1 as follows:

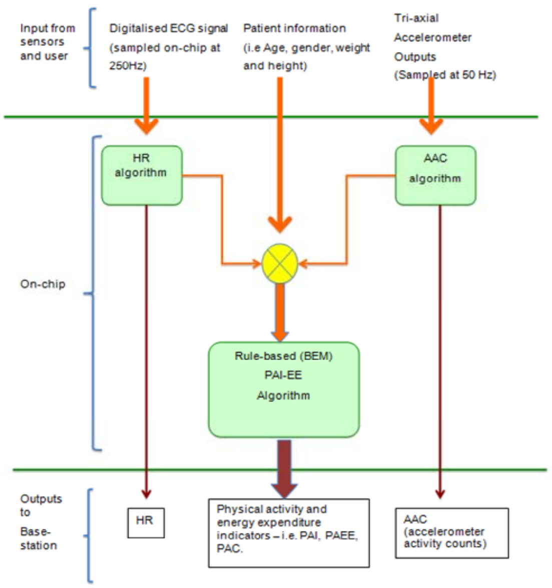

Figure 1: Block diagram of the Sensium™ PA-EE algorithm.

Raw ECG and tri-axial accelerometer data are collected by the Sensium™ body worn device at sampling frequencies of 250 and 50 Hz respectively, whereas patient information (i.e. age, gender, weight and height) is manually entered by the user into the system. The ECG and accelerometer data are fed to the HR and AAC modules in fixed epoch durations of 15 seconds.

The HR module was based on the Open Source ECG Algorithm (OSEA) (Hamilton and Tompkins, 1986, Pan and Tompkins, 1985). The authors of OSEA have reported high reliability and accuracy of OSEA when tested using ECG data from the MIT-BIH database. Nevertheless, a number of modifications were necessary to adapt the algorithm to the Sensium™. Firstly, the Sensium™ is positioned at a non-standard position (lower chest region, parallel to the Lead 1 position). Subsequently, the threshold that is used in QRS peak detection has been adjusted accordingly. Secondly, extra rules have been included to reject signals corrupted by motion artefacts. A preliminary evaluation indicated that these changes did not affect the efficacy of this algorithm. These results are available on request to the authors.

The AAC algorithm is based on previous work by Bouten and colleagues. Firstly, the signal is filtered using a Butterworth fourth-order band-pass filter (0.25-6Hz), designed for rejecting spurious noise without distorting the information corresponding to physical activities associated with the intended user population. Of particular interest, the upper limit of the filter bandwidth was chosen to attenuate high frequency disturbances occurring when the swinging foot impacts the ground during walking at initial contact. This frequency band is in the region of 15 Hz (Antonsson and Mann, 1985). After filtering, the accelerometer data corresponding to each axis is individually rectified and integrated over 15 seconds to obtain AAC.

In the final stage of the algorithm, the HR and AAC information are used to estimate the physical activity intensity. As discussed above, such estimation is possible by means of a rule-based algorithm that relies on a set of pre-defined thresholds, regression equations and weights, expressing the existing relationship between the duple HR/AAC and energy expenditure derived from oxygen consumption (VO2).

4 EXPERIMENTAL METHODS AND CALIBRATION

To calibrate the BEM, and to assess the reliability of this model, experiments were conducted to collect two separate datasets. In both experiments, the activities undertaken by the subjects include stepping exercises, cycling on a stationary bicycle, walking and running on a treadmill. These experiments have been approved by the Toumaz internal ethics committee.

In the calibration dataset, the accelerometer, ECG and VO2 data were simultaneously collected from 8 healthy participants (6 males and 2 females; age 26.11 ± 11.45 years old; weight 72.01 ± 9.35 Kg; and height 157.72 ± 59.47 cm) using the Sensium^{TM} and a indirect calorimeter (CPX-express, Medgraphics, USA). The indirect calorimeter automatically converts the VO2 data into normalised PAI units (cal/kg/min) using the widely accepted Weir formulation (Weir, 1949).

The calibrated Sensium™ algorithm was tested using a dataset collected from three systems: Sensium^{TM}, Actiheart®, and indirect calorimetry. The experimental subjects involve 6 additional healthy volunteers (1 female, 5 male), of weight 69.62 ± 11.25 Kg, height 174.95 ± 9.36 cm, and 26.67 ± 4.32 years old.

4.1 Calibration Process

In the calibration process, four piece-wise functions together with a set of thresholds and coefficients are required to determine PAI at low-moderate and moderate-high intensities using the BEM approach. These regression functions describe the relationships between the PAI and HR, as well as between PAI and AAC. Data from only treadmill activity was used to obtain the equations, as treadmill exercise is the best controlled part of the experiment.

First, the transition points between piece-wise functions were selected by means of visual inspection. Specifically, this was performed by manually adjusting the value of the transition point thresholds for both HR and AAC data; and then re-running the regression procedure repeatedly to generate the curves that best fit to the treadmill data. The resultant HR-PAI polynomials for low-moderate (PHL) and moderate-high PAI (PHH) are shown in (1) and (2).

$$PHL = -0.2475Hs + 0.0376Hs^2 \quad (1)$$

$$PHH = 1.1364Hs + 43.2588 \quad (2)$$

'Hs' corresponds to the HR above sleeping, and it was obtained by subtracting 10 bpm from the resting heart rate (RHR), as shown in (3). This is consistent with the procedure found in (CamNTech, 2009).

$$Hs = RHR - 10 \quad (3)$$

Likewise, the AAC-PAI expressions for low-moderate (PAL) and moderate-high (PAH) levels of activity are found using (4) and (5).

$$PAL = 0.167\ AAC \quad (4)$$

$$PAH = 0.0002832AAC^2 - 0.1921572AAC + 81.9311294 \quad (5)$$

Subsequently, the HR flex-points for low-moderate and moderate-high activity levels were determined by applying regression analysis over all the data points collected from different types of exercises except resting, since HR is not a reliable parameter for estimation of EE at low activity levels (Andre and Wolf, 2007). The heart rates (above sleeping) corresponding to 3.5 and 5.5 METs were then derived as initial HR flex-points. Likewise, the initial AAC flex-point between moderate and high levels of activity was found using regression, involving only the cycling data. This made possible the selection of a threshold value which was low enough to reject the majority of noise, but sufficiently high to account for the low ground-impact of some strenuous activities such as cycling, rowing and cross training.

The initial weights towards the AAC-PAI and the HR-PAI relationships were chosen from (Brage et al., 2004). Further refinement to the model is carried out by Simulated Annealing (Bertsimas and Tsitsiklis, 1993). Using this technique, the weights, and threshold values were adjusted to minimize the absolute error of the model. The optimized model is shown in Figure 2.

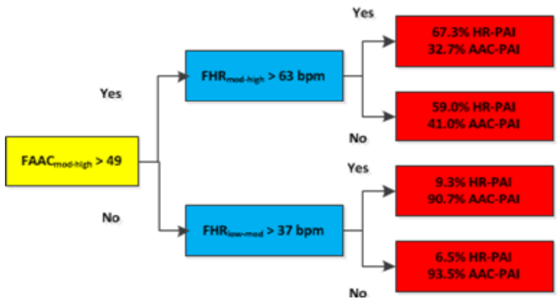

Figure 2: Branch equation model after the application of simulated annealing.

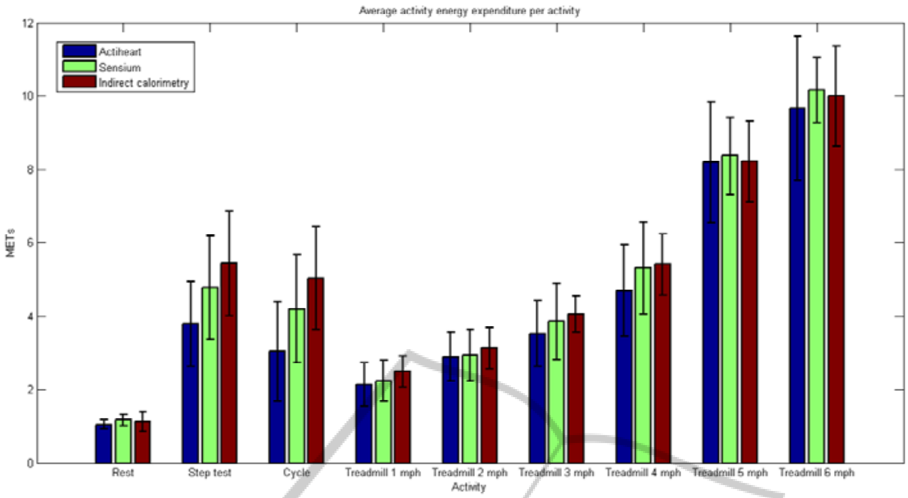

Figure 3: Activity energy expenditure results for different activity types, derived from Actiheart®, Sensium™, and indirect calorimetry.

4.2 Discussion

Inferential statistics using ANOVA (Analysis of Variance) was carried out on the experimental datasets. Table 1 shows the results. These results indicate that the differences between the Indirect Calorimetry, Actiheart, and Sensium measurements are statistically significant.

Table 1: ANOVA and t-test results from indirect calorimetry, Sensium™, and the Actiheart®.

F-test	**Mean sum of squares**	**p-value**
16.96	0.801	<0.001
t-test results from Sensium™ and Actiheart®		
Degrees of freedom	**95% CI (kJ/kg/min)**	**Difference of the means (kJ/kg/min)**
2209	[0.0170, 0.0234]	0.0202 (p<0.001)

The Bland-Altman plot corresponding to the Sensium^{TM} and indirect calorimetry (Figure 4) reflects a bias and the 95% PI of 0.0179 kJ/kg/min (0.26 MET) and [-0.134, 0.170] kJ/kg/min ([-1.922, 2.438] METs) respectively. These results indicate that the differences for the Sensium^{TM} and Actiheart®, with reference to indirect calorimetry, are similar. Also, by comparing the Actiheart® with the indirect calorimeter, the 95% PI was found to be [-0.170, 0.246] kJ/kg/min. This range is consistent with the a previous study done by (Brage et al., 2004). In addition, a two-tailed t-test was carried out between the Actiheart® and Sensium™, in order to confirm the similarity between these two devices. The results of this test are summarised in Table 1, and revealed statistically significant (although small) differences.

Finally, the results from the second experiment were grouped into different categories of activities, as shown in Figure 3. From the chart, it can be observed that the average activity expenditure for the Sensium^{TM} and Actiheart are similar for most of the activities. For the step test and cycling activities, the Sensium™ algorithm produced results closer to indirect calorimetry than the Actiheart®. Overall, the results from the Sensium^{TM} were found to be closer to the ones obtained from Indirect Calorimetry system. This can be expected as the Sensium^{TM} algorithm was calibrated with data obtained from this particular reference system.

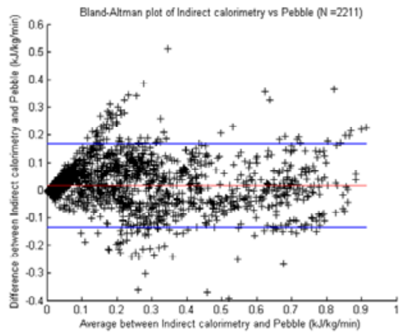

Figure 4: Bland-Altman plot of indirect calorimetry vs Sensium™.

5 CONCLUSIONS

This paper reported on the incorporation of an algorithm for estimation of physical activity intensity and energy expenditure as part of a wireless body-worn device. The algorithm was calibrated for a Sensium™ device, embedded with a triaxial accelerometer and ECG sensors.

The results for the evaluation of the algorithm revealed that statistically significant differences between indirect calorimetry, Actiheart, and the Sensium™. However, these differences were small and similar to those found in a separate study (Crouter et al., 2007). In addition, it was found that with reference to indirect calorimetry, the mean error for the Sensium™ was lower for certain activities, including the step test exercise and cycling on a stationary bicycle.

In this work, the authors found that the use of simulated annealing was successful in adapting the Branch Equation Model to the Sensium™ platform, indicating the generality of this model. Future work include the use of automatic activity classification, to reduce the errors caused by different activity types. Another limitation of this investigation is the limited scope of activities considered. Therefore, future directions will consider the inclusion of further and more representative activities of daily living and exercise.

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