Energy expenditure estimation using accelerometry and heart rate for multiple sclerosis and healthy older adults

Validation against a mobile metabolic energy expenditure measurement system

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Abstract**—***Accurate estimation of Energy Expenditure (EE) in ambulatory settings provides greater insight into the underlying relation between different human physical activity and health. This paper describes the development and validation of energy expenditure estimation algorithms. A total of 4 healthy subjects and 3 suffering from multiple sclerosis were monitored using a gold-standard energy expenditure measurement system, a heart rate monitor and accelerometry. We demonstrated that greater improvements can be achieved by estimating energy expenditure during normal activities of daily living by combining both whole body acceleration estimates, vertical body acceleration estimates, body posture and heart rate data as part of a flex heart rate algorithm in subject specific models when compared to using accelerometry or heart rate data alone. This will allow more accurate EE estimation during normal activities of daily living.*

Keywords— Energy expenditure, heart rate, accelerometer, multiple sclerosis, elderly, ADL.

I. INTRODUCTION

The importance of physical activity and physical fitness is well accepted as a means to general physical and mental health. Many published studies exist establishing an inverse relationship between physical activity and morbidity and mortality from chronic diseases such as cardiovascular disease, hypertension, maturity onset diabetes, and colon cancer. Further studies have shown direct proportionality between physical activity and fitness with length of life.

Accurate estimation of Energy Expenditure (EE) in an ambulatory setting provides significant insight into determining the underlying relation between different types of human behavior related to physical activity and health.

The use of accelerometer based systems for the estimation of EE has received increasing attention in recent years. The portability and relatively low cost of these systems coupled with recent advances in signal processing has made their application to the problem of EE estimation very appealing, particularly for use in a free living environment where bulky, expensive systems such as indirect calorimeters are not practical. Thus in recent years accelerometers have been widely used in studies for the estimation of EE during physical activity [1]. To date a large number of commercial devices for the estimation of EE exist, these include: Actigraph GT3X+, PALtechnologies activPAL, McRoberts' Dynaport, the TriTrac R3D and Minisun's IDEEA among others. Within these commercial devices there are two main methods for energy expenditure. (1) an unit-less measure representative of whole body motion represented as *activity counts* is used to predict EE using a linear regression model or (2) a fixed EE value is associated with a particular type of activity identified.

A literature review performed by Murphy et al. 2009 [1] into commonly-used accelerometer based devices demonstrated their popularity but also noted that they do not capture the full energy cost of certain activities, such as walking while carrying a load, since acceleration patterns do not change under these conditions.

In the estimation of EE, Spurr et al. 1988 [2] observed that a nonlinear relationship exists between heart rate (HR) and EE during low intensity activities but above a certain HR threshold a strong correlation exists between HR and EE during higher intensity activities. This point of differentiation is known as the "flex-HR" and typically defined as the average of the highest resting HR value and the lowest exercising HR. Leonard et al. 2003 [3] and Leonard et al. 2012 [4] proposed that the flex-HR method has become a standard tool for measuring daily EE in free-living human populations. In fact, Rennie et al. 2001 [5] demonstrated that simply using the heart rate and basic anthropometric measures can produce results with a strong correlation.

However a drawback with relying on heart rate alone is that it can be affected by more than just activity (e.g. stimulus such as caffeine, stress). Thus the combination of inertial sensors and heart rate monitoring has the potential to account for more of the variables associated with EE estimation.

Recently Altini et al. 2012 [6] successfully demonstrated the efficacy of using both accelerometry and heart rate data to predict EE. Through incorporating the flex-HR method described above along with the detection of activity clusters as well as anthropometric data to the EE estimation improved by more than 19%.

A commercial system does exist that combines both heart rate data as well as accelerometry data to estimate EE. The CamNtech's Actiheart does produce an EE estimate, however as is the case with commercial EE estimation devices, details on the algorithms employed are not provided.

EE estimation in a young healthy subject population, such as in [6], has been studied extensively. However, applying such estimation models to older subject groups or those who suffer from a particular chronic condition, which may hinder movement, needs to be investigated.

Multiple sclerosis (MS) is an immune-mediated disease characterized by inflammatory demyelination (CNS). This damage of the CNS structures leads to deficits of body functions, which, in turn, affect patient activities, such as walking, and normal activities of daily living (ADL). MS has a prevalence of 1 per 1,000 adults in the USA [7]. Due to the nature of this disease different levels of effort and thus energy are required for an affected and non-affected subject [8]. However little is known about the estimation of EE in this population group.

The aim of this study is thus to examine if combining both accelerometry and heart rate data, can more accurate estimates of energy expenditure be achieved when monitoring health middle aged and elderly subjects as well as subjects suffering from MS, using sensors located at the chest.

II. MATERIAL AND METHOD

A. *Trial set-up*

Movement kinematics, heart rate and energy expenditure data were recorded from 4 healthy middle aged subject and 3 subjects suffering from MS. The trial was carried out in collaboration with the Department of Education and Health Sciences and the Department of Electronic Engineering at the University of Limerick.

Ethical approval was granted by the University of Limerick research ethical committee. The 4 (3 F, 1 M) healthy subjects ranged in age from 53 to 64 years old (60±4.83yrs), height from 1.55m to 1.87m (1.68±0.15m), weight from 62kg to 91kg (73.25±12.53). The 3 (3 F, 0 M) MS subjects ranged in age from 35 to 63 years old (49±14.05yrs), height from 1.61m to 1.76m (1.69±0.08m), weight from 62kg to 77kg (67.33±8.39).

B. *Data acquisition*

Movement kinematics data was captured using the Shimmer [9] (www.shimmer-research.com) inertial sensors attached to the waist and left-underarm, held in place using elastic belts. Heart rate was acquired using a Polar chest strap (www.polar.com). Energy expenditure was obtained using the Oxycon Mobile Metabolic System[1] for EE measurement and was used as the gold standard to validate the signals. The monitoring set-up for this trial is detailed in Fig 1. Subjects were also video recorded during the complete trial to validate the activities. Tri-axial accelerometer data was obtained from Shimmer devices fitted on the left underarm and waist. The energy expenditure was sampled twice per minute and stored as metabolic equivalent of task METs (-) the heart rate (BPM) data were also sampled twice per minute.

C. *Protocol*

All subjects were asked to perform as standardised routine of various housework and lifestyle activities which include: (1) Resting (lying), (2) dressing, (3) Walking (figure of 8), (4) watching TV (sitting), (8) writing (sitting), (9) dusting upright, (10) Folding laundry (standing). The activities were performed in the order outlined to allow activities of higher intensity to be followed by activities of lower intensity with each activity lasting 10 minutes with the exception of the stair climbing task, which lasted 5 minutes. The complete protocol lasted 95 minutes.

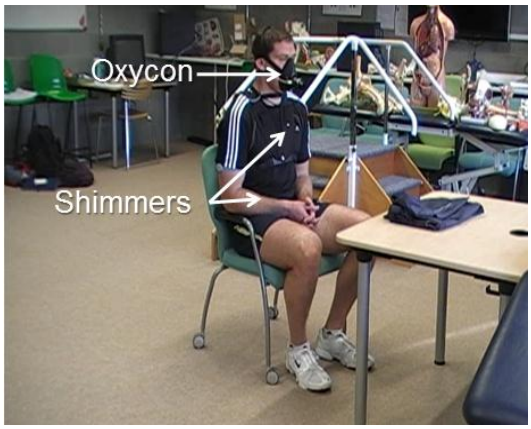

Fig 1 - Monitoring set-up. Subjects wore the Oxycon mobile system, the Shimmer inertial sensors, which include a tri-axial accelerometer at the left underarm and waist

D. *Features*

1) *Vertical acceleration estimate*

The tri-axial accelerometer data were converted to proper acceleration and 3-point median filtered. Estimates of vertical acceleration (m/s^2) and the gravity vector (g) were obtained through the method described by Bourke et al. [10] using a first order Butterworth filter with a cut-off of 0.85Hz. The mean of the vertical acceleration was taken using a non-overlapping 30 second window to make it directly comparable with energy expenditure and heart rate measurements.

[1] Carefusion Netherlands, Houten, The Netherlands

2) Posture detection

A distinction between upright and lying was performed using the longitudinal accelerometer axis signal. Lying was determined using a threshold angle of greater than 60^0 from vertical.

3) Whole body acceleration estimate

An estimate of the whole body movement was obtained using the algorithm developed by Bouten et al. [11] where the inertial magnitude area (IMA_{tot}) was calculated using the norm of the band-pass filtered tri-axial accelerometer data integrated over a time window T.

4) Heart rate

The heart rate data sampled twice per minute and represented as BPM was used directly.

5) Flex heart rate algorithm

The flex HR threshold is calculated by taking the maximum HR while static and lying and the minimum HR while upright and dynamic. Distinguishing between lying and upright was performed using the method described in section D subsection 2). Distinguishing between static and dynamic activity was performed by thresholding the variance of the vertical accelerometer axis using a 5 second non-overlapping window with a threshold of 0.005. If the HR is above the flex HR both the heart rate and the accelerometer features are used to estimate the energy expenditure. If the HR is below the flex HR value only the accelerometer features are used.

E. The EE estimation algorithms

A total of six separate EE estimation algorithms are examined. These include; two separate accelerometer based algorithms, a separate heart rate algorithm and two algorithms that combine the accelerometer features, the heart rate and the flex heart rate algorithm.

Algorithm 1 uses only the IMA_{tot} whole body acceleration estimate developed by Bouten described in subsection 3), Algorithm 2 uses the vertical acceleration estimate, described in 1) and the vertical z-axis to indicate the posture angle. Algorithm 3 uses only the heart rate. Algorithm 4 combines algorithm 1 and the flex heart rate algorithm, Algorithm 5 combines algorithm 2 and the flex heart rate algorithm and Algorithm 6 combines Algorithms 1, 2 and the flex heart rate algorithm.

F. Data-analysis

A separate model for energy expenditure estimation was developed for each subject for all six algorithms. These were implemented using a linear regression model. The model requires a matrix, **X**, where each of the columns contains a feature, for every 30 seconds of activity, and a vector, $\boldsymbol{y}$, containing the 'gold–standard' energy expenditure recorded from the Oxycon Mobile Metabolic System. The set of weights, $\boldsymbol{w}$, are chosen to minimize the sum of squared errors between the estimate of EE, $\hat{\boldsymbol{y}}$, and the 'true' EE, $\boldsymbol{y}$, as in (1).

$$\hat{\boldsymbol{y}} = \boldsymbol{X}\boldsymbol{w} \tag{1}$$

The solution to this problem is given in (2).

$$\boldsymbol{w} = (\boldsymbol{X}^T \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{y} \tag{2}$$

This was repeated for each subject with each individual activity bout being separated into a 2/3 training set and 1/3 testing set.

III. RESULTS

A total of 11 hours and 5 minutes of EE data were recorded, from 4 healthy subjects and 3 suffering from MS. Subjects performed a series of low, medium and high intensity activities as described in section C. Data were analysed, with the 7 subject specific models for 6 different algorithms. Using the training data, a subject specific model was created for each algorithm as described previously. The test data were used with the developed models for the respective algorithms. Correlation coefficients and the percent error, calculated as the ratio between the root-mean-square-error to the peak-to-peak amplitude of the reference signal, were calculated to assess the relationship between the EE estimates and the measured EE and presented in TABLE I.

Using the whole body acceleration estimate developed by Bouten et al. [11] in Algorithm 1, the average correlation coefficients and percentage errors were r=0.854±0.043, 11.8±1.05% and r=0.5800±0.279, 17.5±3.74% with healthy and MS subjects respectively. For Algorithm 2 a combination of the Vertical acceleration estimate and the vertical z-axis was used, the average correlation coefficients and percentage errors were r=0.8093±0.043, 13.1±0.98% and r=0.6102±0.2171, 17.3±3.06% for the healthy and MS subjects respectively.

Using the heart rate alone, in Algorithm 3, the average correlation coefficients and percentage errors were r=0.8211±0.031, 12.7±0.81% and r=0.7459±0.147, 14.8±3.55% for healthy and MS subjects respectively.

The flex heart rate was calculated as described earlier. The flex HR thresholds ranged between 64.5 bpm and 83.5 bpm for the healthy subject with a mean and standard deviation (SD) of 71.38±11.24 bpm and between 65 and 75 for the MS subjects with a mean and SD of 69.5±5.07 bpm. The flex HR values were using in Algorithms 4, 5 and 6.

Combining the Whole body acceleration estimate developed by Bouten et al. [11] in Algorithm 1 with the flex heart rate, for Algorithm 4, produced average correlation coefficients and percentage errors of r=0.9178±0.018, 8.9±0.83% and r=0.8466±0.018, 12.1±0.13% with healthy and MS subjects respectively. Combining the Vertical acceleration estimate and the vertical z-axis as in Algorithm 2 along with the Flex heart rate produced average correlation coefficients and percentage errors of r=0.9183±0.033, 8.7±1.34% and r=0.8486±0.026, 12.0±0.53% for the healthy and MS subjects respectively.

By combining algorithm 1, 2 and the Flex heart rate Algorithm 6 includes the whole body acceleration estimation, the vertical acceleration estimate, posture and heart rate data. Algorithm 6 thus produced average correlation coefficients and percentage errors of r=0.9226±0.021, 8.6±0.82% and r=0.8540±0.025, 11.8±0.41% for the healthy and MS subjects respectively.

TABLE I. CORRELATION COEFFICIENTS AND RMS PERCENTAGE ERROR FOR BOTH HEALTHY AND MS SUBJECTS FOR COMBINATIONS OF ACCELEROMETER AND HEART RATE FEATURES AND THE FLEX HR ALGORITHM.

Algorithm number	**1**		**2**		**3**		**4**		**5**		**6**	
Algorithm features	**IMA_{tot}**		**$\hat{a}_v$**		**HR**		**IMA_{tot} & Flex HR**		**$\hat{a}_v$ & Flex HR**		**$\hat{a}_v$, IMA_{tot} & Flex HR**	
	r	% error	r	% error	r	% error	r	% error	r	% error	r	% error
Healthy Subjects												
Subject 1	0.901	10.7	0.823	13.9	0.855	12.6	0.943	8.1	0.953	7.5	0.950	7.7
Subject 2	0.809	12.4	0.748	14.0	0.837	11.6	0.915	8.5	0.921	8.3	0.917	8.4
Subject 3	0.826	12.9	0.845	12.1	0.807	13.2	0.914	9.2	0.926	8.6	0.925	8.6
Subject 4	0.879	11.0	0.816	12.5	0.786	13.3	0.899	10.0	0.874	10.6	0.899	9.7
Mean (SD)	0.854 (0.043)	11.8 (1.05)	0.809 (0.043)	13.1 (0.98)	0.821 (0.031)	12.7 (0.81)	**0.918 (0.018)**	**8.9 (0.83)**	**0.918 (0.033)**	**8.7 (1.34)**	**0.923 (0.021)**	**8.6 (0.82)**
MS Subjects												
Subject 1	0.810	13.6	0.791	14.1	0.576	18.9	0.854	12.0	0.845	12.4	0.859	11.8
Subject 2	0.661	17.8	0.671	17.5	0.838	12.9	0.860	12.1	0.876	11.4	0.876	11.4
Subject 3	0.269	21.0	0.369	20.2	0.824	12.5	0.826	12.2	0.825	12.3	0.827	12.2
Mean (SD)	0.580 (0.279)	17.5 (3.74)	0.610 (0.2171)	17.3 (3.06)	0.746 (0.147)	14.8 (3.55)	**0.8466 (0.018)**	**12.1 (0.13)**	**0.8486 (0.026)**	**12.0 (0.53)**	**0.854 (0.025)**	**11.8 (0.41)**

IV. DISCUSSION

We have assessed the use of both acceleration data harvested from accelerometers and heart rate data harvested using a chest strap for the estimation of EE during a scripted routine both separately and in different combinations. The outputs of the algorithms were validated and compared to EE recorded using the Oxycon Mobile Metabolic System which was used as the gold standard.

Through incorporating the heart rate data along with the accelerometer data into Algorithm 6 an improvement from r=0.85 to r=0.92 and from 11.8% to 8.6% error was observed for the health subject's test data and from r=0.0.6102 to r=0.854 and from 17.3% to 11.8% error for the MS subject's test data when compared to simply using the accelerometer alone. Comparing Algorithm 6 to using only the heart rate data demonstrated an improvement of r=0.8211 to 0.9226 and a percentage error reduction from 12.7 to 8.6 for health subjects and from r=0.7459 to 0.8540 and a percentage error reduction from 14.8 to 11.8 for MS subjects. Thus from these results it is clear to see that the combination of whole body acceleration estimation, vertical acceleration estimate, posture and heart rate as part of the flex heart rate algorithm (Algorithm 6) produces the lowest percentage error and highest correlation when compared to the gold-standard system and to all other algorithm combinations.

Algorithm 4 and 5 both incorporate the flex heart rate algorithm along with different accelerometer features. Marginal improvements can be seen between algorithms 4 and 5, and algorithm 6, with a percentage error improvement of <0.3%, and a correlation coefficient improvement of r<0.01 being observed between Algorithm 4 or 5 and Algorithm 6.

A sample of the output profile from Algorithm 6 compared to the Oxycon system is presented in Figure 2. The results thus demonstrate that by applying Algorithm 6, great accuracies can be achieved when estimating EE using both HR, as part of a flex heart rate algorithm and acceleration measurements in a subject specific model, even if the subjects have different physiological conditions. This does require that the model is trained for that subject using the Oxycon Mobile Metabolic System. Further research is required to estimate the long term accuracy of a model developed in this way.

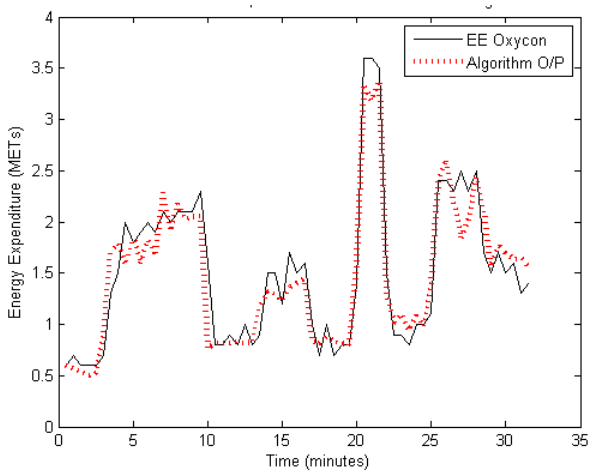

Figure 2 – A segment of algorithm 6 compared to the Oxycon output r=0.95 and error = 7.7%.

The accelerometry data was transformed into an estimate of vertical acceleration and used as one of only 3 inputs into Algorithms 2, 5 and 6. The motivation of using this signal is that many of the largest muscles in the human body are located

in the lower extremity, which include; the gluteus maximus, the quadriceps and the soleus. These muscles are used frequently for up and down movements such as sitting/lying to standing transitions, climbing stairs and walking. We hypothesise that including estimates of vertical acceleration into an EE model will produce greater EE estimates. This has been confirmed in this current data-set for both healthy and MS subjects even if only minor improvements were observed.

The sample of subjects in the current study was limited, recruiting only 4 healthy subjects and 3 subjects suffering from MS. However a total of over 11 hours of data were recorded during this experiment and the final outcome was used to prove that a subject specific model using Algorithm 6 produces high coefficients of correlation when analysing the results from the test data sets.

A time delay does exist between the start of the onset of an activity and the change in HR. This was manually removed for each subject by aligning the change in HR and activity that exists when the stair climbing activity was performed. Further research will need to be performed to correctly characterise this time delay in order to develop a more robust real-time system.

V. CONCLUSION

In conclusion we have demonstrated that by combing whole body acceleration estimation, vertical acceleration estimation, posture and heart rate as part of the flex heart rate algorithm, greater estimates of EE can be obtained when a subject specific model is created for both healthy subjects and those suffering from MS. This will allow more accurate EE estimation monitoring during normal activities of daily living.

ACKNOWLEDGMENT

We wish to acknowledge both the eCAALYX AAL project and the REWIRE FP7 projects for their sponsorship of this research and to all of the subjects who gave so willingly of their time.

REFERENCES

[1] S. L. Murphy, “Review of physical activity measurement using accelerometers in older adults: considerations for research design and conduct.,” *Prev. Med. (Baltim).*, vol. 48, no. 2, pp. 108–14, Feb. 2009.

[2] G. Spurr and A. Prentice, “Energy expenditure from minute-by-minute heart-rate recording: comparison with indirect calorimetry.,” *Am. J. Clin. Nutr.*, vol. 48, no. 3, pp. 552–559, 1988.

[3] W. R. Leonard, “Measuring human energy expenditure: what have we learned from the flex-heart rate method?,” *Am. J. Hum. Biol.*, vol. 15, no. 4, pp. 479–89, 2003.

[4] W. R. Leonard, “Laboratory and field methods for measuring human energy expenditure.,” *Am. J. Hum. Biol.*, vol. 24, no. 3, pp. 372–84, 2012.

[5] K. Rennie and S. Hennings, “Estimating energy expenditure by heart-rate monitoring without individual calibration,” *Med. Sci. Sport. Exerc.*, vol. 33, no. 6, pp. 939–945, 2001.

[6] M. Altini, J. Penders, and O. Amft, “Energy expenditure estimation using wearable sensors: a new methodology for activity-specific models,” *Proc. Conf. Wirel. Heal.*, 2012.

[7] R. W. Motl and L. a Pilutti, “The benefits of exercise training in multiple sclerosis.,” *Nat. Rev. Neurol.*, vol. 8, no. 9, pp. 487–97, Sep. 2012.

[8] B. M. Sandroff, D. Dlugonski, M. Weikert, Y. Suh, S. Balantrapu, and R. W. Motl, “Physical activity and multiple sclerosis: new insights regarding inactivity.,” *Acta Neurol. Scand.*, vol. 126, no. 4, pp. 256–62, Oct. 2012.

[9] A. Burns, B. R. Greene, M. J. McGrath, T. J. O’Shea, B. Kuris, S. M. Ayer, F. Stroiescu, and V. Cionca, “SHIMMER™ – A Wireless Sensor Platform for Noninvasive Biomedical Research,” *IEEE Sens. J.*, vol. 10, no. 9, pp. 1527–1534, Sep. 2010.

[10] A. K. Bourke, K. O’Donovan, A. Clifford, G. ÓLaighin, and J. Nelson, “Optimum gravity vector and vertical acceleration estimation using a tri-axial accelerometer for falls and normal activities.,” in *Conference proceedings of the IEEE Engineering in Medicine and Biology Society.*, 2011, vol. 2011, pp. 7896–9.

[11] C. V Bouten, K. T. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, “A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity,” *IEEE Trans Biomed Eng*, vol. 44, no. 3, pp. 136–147, 1997.