PREDICTING ENERGY EXPENDITURE OF MANUAL WHEELCHAIR USERS USING A WEARABLE DEVICE

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INTRODUCTION

Regular physical activity (PA) in manual wheelchair users (MWUs) with spinal cord injury (SCI) is associated with positive health benefits, such as increased cardiorespiratory fitness and muscular strength, and decreased deconditioning and pain (1). However, studies by Washburn et al. and Fernhall et al. have shown that only 13-16% of persons with SCI reported regular PA and the majority reported virtually no regular PA (2, 3).

One of the strategies to promote regular PA is to obtain an accurate estimate of everyday PA, which could increase MWUs' awareness of their activity levels and promote PA adherence (2-5). Currently, activity monitors (AMs) are extensively used in the ambulatory population to measure accurate PA in terms of energy expenditure (EE) on a daily basis (6). However, our previous study in 13 MWUs with SCI has found that these AMs do not work well for MWUs who extensively rely on their upper limbs for day-to-day activities (4). The EE estimated by the SenseWear Armband (SW) (BodyMedia Inc., PA, USA) and RT3 AMs (StayHealthy Inc., CA, USA) were significantly higher (17.8-131.4%) and lower (21.4-53.3%), respectively compared to the criterion EE in MWUs with SCI (4). On the other hand, our previous study has shown that EE from the SW explained 56% of variance in the criterion EE (4). In addition, several studies have developed individualized heart rate models that can predict EE in MWUs (5, 7). A limitation of this method is that it requires subjects to perform a range of PAs with different intensities to develop individualized prediction equations. To our knowledge, no study has been performed to investigate if the current AMs can be modified to provide an accurate EE prediction for MWUs with SCI.

The objective of this study was to develop and evaluate new EE prediction models for MWUs with SCI based on the commercially available SenseWear Armband.

METHODOLOGY

Experimental Protocol

A total of 24 MWUs with SCI participated in the study. The study was approved by the Institutional Review Board at the University of Pittsburgh and the VA Pittsburgh Healthcare System. Subjects were included if they were between 18 and 60 years, used a manual wheelchair as a primary means of mobility, have a SCI of T1 or below, were at least six months post-injury, and were able to use an arm-ergometer for exercise. Subjects were excluded if they were unable to tolerate sitting for 4 hours, had active pelvic or thigh wounds, or failed to obtain their primary care physician's consent to participate in the study. All subjects provided a written informed consent to participate in the study.

The protocol started with a pre-activity session where subjects answered a demographics questionnaire. In addition, their weight, height and skinfolds at biceps, triceps, subscapular and suprailiac were measured.

During the activity session, subjects wore a portable metabolic cart K4b2 (COSMED srl, Rome, Italy) connected to a face mask, a Polar heart rate monitor on their chest, and a SW on the upper right arm on triceps muscles. The SW consists of a three-axis accelerometer, a skin temperature sensor, a Galvanic Skin Response sensor, and a near body temperature sensor. The SW analysis software (InnerView Research Software 7.0) uses sensor data, height, weight, age, gender, dominant hand, and smoking status of the subjects to estimate the EE. The activity session consisted of resting and three activity routines including wheelchair propulsion, arm-ergometer exercise, and desk work. During the resting session, subjects were required to be seated quietly in their wheelchairs for a period of eight minutes while the metabolic cart and the SW were used to collect EE. The propulsion routine included three trials, i.e., 0.89m/s (2mph) and 1.34m/s (3mph) on a computer controlled dynamometer and 1.34m/s (3mph) on a flat tiled surface. The resistance offered by the dynamometer simulated propelling on a slope of 2°. The arm-ergometer exercise included three trials of 20 watts (W) resistance at 60 rotations per minute (rpm), 40W at 60rpm, and 40W at 90rpm. During the desk work routine, subjects typed on a computer and read a book. Subjects were asked to perform each activity trial for 8 minutes with a resting period of 5 to 10 minutes between each trial and a period of 30 to 40 minutes between each activity routine. The activity routines, except for resting, were counterbalanced and the trials within each activity routine were randomized to counter order effects.

<u>Instrumentation and Data Collection</u>

To ensure accuracy of the data collection, the K4b2 was calibrated for every subject and synchronized with the SW. The data collected from the K4b2 were EE in kcal/min. The data collected from the SW included the mean absolute deviation in longitudinal and transverse accelerations (LMAD and TMAD), and the average longitudinal (LAVG), transverse (TAVG), and resultant accelerations (RAVG) at 16Hz, and skin temperature (STEMP), galvanic skin response (GSR), near-body temperature (NTEMP), and EE in kcal/min at each minute.

<u>Data Analysis</u>

The data analysis software written in MATLAB® (Version 7.6 R2008a, The Mathworks Inc. MA, USA) processed and analyzed data from the K4b2 and the SW. To determine steady-state conditions, EE data in kcal/min for each of the activity trials were obtained by averaging breath-by-breath measures over 30 second periods, and EE values having coefficients of variation of less than 10% computed over windows of at least 1 minute was averaged and used in the later analysis.

All statistical analysis was performed using SPSS software (ver. 15.0, SPSS Inc. Il., USA), with the statistical significance at an alpha level of 0.05. New EE prediction models were developed using the data from 20 subjects randomly selected from the 24 subjects using forward stepwise multiple regression. The remaining 4 subjects served as a validation group. In addition to a generalized prediction for all the activities, activity specific models were also developed, which consisted of four separate prediction equations for resting, deskwork, wheelchair propulsion, and arm-ergometry, respectively. The dependent variable was the EE in kcal/min measured from the K4b2. The independent variables included acceleration variables (i.e., LMAD, TMAD, LAVG, TAVG, and RVAG) and demographic variables (i.e., age and weight) which were significantly correlated (Pearson Correlations 0.25-0.77, $p<0.05$) with the criterion EE. Physiologic variables (i.e., STEMP, GSR, NTEMP) were not considered due to their weak correlations (Pearson correlations 0.0 7-0.54, $p>0.05$) with the criterion EE. Data from the activity trials within each activity routine were pooled and treated as independent observations. The resultant prediction equations were cross-validated with the data from the validation group by computing the absolute differences and absolute percentage errors between predicted and criterion EE.

RESULTS

Among the 24 subjects, there were 19 males and 5 females with a mean age of 41.4±11.4 years, weight of 82.4±25.1 kg, height of 178.0±9.4 cm, and body fat percentage of 28.0%±7.3%. The injury level varied from T3 to L4 with 11 of the 24 subjects having a complete injury. Self-reported PA indicated that 10 subjects performed regular PA; 8 performed occasional PA; and 6 performed no regular PA. All the 24 subjects completed the eight activity trials. Due to device malfunction of the K4b2, two trials including one 3mph propulsion trial on the tiled surface and one resting trial were discarded. In addition, three trials including one resting trial, one 2mph propulsion trial on dyno, and one deskwork trial that did not yield steady-state or near steady-state conditions were also discarded.

Table 1 shows the absolute difference and absolute percentage error between the criterion EE from the K4b2 and the estimated EE from the SW using manufacturer's equations.

Stepwise multiple linear regression analysis indicated that EE could be predicted by a few acceleration and demographic variables. Table 2 shows the results from the regression analysis for both the generalized model and the activity specific models. For each model, the significant predictors, the adjusted R-square, the standard error of the estimate (SEE) were reported. The final prediction equation for the generalized activity model is shown in equation 1. The final prediction equations for the activity specific models are shown in equations (2)-(5). Table 3 shows the validation results for both the generalized and activity specific models. In addition, the EE estimated by the general (Pearson correlation: 0.62, $p<0.05$) and activity specific EE prediction equations (Pearson correlation: 0.89, $p<0.05$) significantly correlated ($p<0.05$) with the criterion EE.

DISCUSSION

Availability of AMs that accurately estimate EE in MWUs with SCI can increase their PA awareness and promote regular PA. In this study, we have developed and evaluated new EE prediction models for MWUs with SCI based on SW AM.

The research showed that the SW AM using manufacturer's equations consistently overestimated EE with relatively small errors for light activities and large errors for wheelchair propulsion and arm ergometry. The results of this study (20.1-130.0% overestimation) are similar to our previous study (17.8-131.4%) which consisted of 13 MWU's with SCI (4).

The performance of the new general EE prediction equation significantly improved the EE prediction by SW for wheelchair propulsion and arm-ergometery compared to the default outputs. However, the EE prediction for the resting and deskwork using the new general EE prediction equation worsened. Better EE estimation during wheelchair propulsion and arm-ergometer exercise trials may be due to SW's ability to capture higher upper arm movement during these activities. The predictors of the generalized model include acceleration variables (LMAD and LAVG) and demographic variable (weight) indicating that the generalized model utilized upper extremity movements and demographic variables to estimate EE. The performance of the activity specific equations was better than the general EE prediction equation. In addition, the performance of activity specific equations compared to the manufacturer's equation for resting and deskwork were better and similar, respectively. The predictors for the activity-specific equations showed that weight was a single major contributor ($\beta=0.72$) toward EE during resting, while weight ($\beta=0.72$) and accelerometer variable (TAVG, $\beta=0.45$) contributed towards EE during deskwork. For the wheelchair propulsion and arm-ergometry trials LMAD was a significant predictor compared to the demographic variables (weight and age). Presence of accelerometer variables during deskwork, wheelchair propulsion and arm-ergometry indicates that SW AM can capture upper extremity movements that contribute towards overall EE. In addition, the variance explained by the estimated EE, using the activity specific equations, in the criterion EE was high (79%). On closer analysis, it was also found that the weight of one of the subjects (141.1kg) in the validation group lied outside the range of weights of the subjects (44.2kg-129.5kg) used for modeling. Removing this subject from the error analysis led to a better EE estimation using generalized (20.4-42.8%) and activity specific (6.4-18.9%) models.

There are several limitations of this study including small sample size, and limited PAs. The study also chose to test AM only in MWUs with paraplegia to minimize the impact of different types and levels of disabilities on EE measurements. In future, we hope to perform rigorous cross-validations and also include important demographics such as gender and injury to develop models.

In conclusion, the new activity specific EE equations significantly reduced prediction errors compared to the original output indicating that the SW with appropriate modifications could be used by MWUs with SCI to gauge their activity levels in terms of EE.

TABLES

Table 1 SW prediction errors using manufacture's equations

Activity Mean (SD)	EE (kcal/min)		SW Prediction Absolute Error	
	K4b2	***SW***	***Error***	***Percentage***
Resting	1.1 (0.3)	1.3 (0.3)	0.2 (0.2)	24.7 (19.4)
2mph on dyno	3.7 (1.5)	7.9 (4.2)	4.7 (3.8)	130.0 (96.1)
3mph on dyno	4.7 (2.1)	9.0 (4.3)	4.2 (3.9)	95.2 (71.7)
3mph on tile	2.9 (1.1)	6.1 (1.9)	3.2 (1.4)	114.8 (61.8)
20W at 60rpm	3.1 (0.5)	5.6 (1.9)	2.1 (1.1)	66.2 (34.8)
40W at 60rpm	4.4 (0.6)	6.2 (1.9)	1.6 (1.1)	38.2 (29.6)
40W at 90rpm	5.5 (1.0)	8.3 (3.2)	2.3 (1.5)	40.4 (24.1)
Deskwork	1.3 (0.4)	1.6 (0.3)	0.3 (0.1)	20.1 (14.0)

Table 2 Generalized and activity specific EE models' predictors and statistics for SW AM

Generalized Model	Predictors	LMAD (β=0.88, p<0.001), weight (β=0.24, p<0.001), LAVG (β=-0.25, p<0.001)
	Adjusted R^2	0.73
	SEE	0.97 kcal/min
	Significance	$F_{3,151}$=138.66, p<0.001
Resting Model	Predictors	Weight (β=0.72, p=0.001)
	Adjusted R^2	0.49
	SEE	0.20 kcal/min
	Significance	$F_{1,16}$=17.49, p=0.001
Wheelchair Propulsion Model	Predictors	LMAD (β=0.81, p<0.001), Weight (β=0.45, p<0.001), Age (β=0.15, p<=0.029)
	Adjusted R^2	0.82
	SEE	0.78 kcal/min
	Significance	$F_{3,54}$=55.09, p<0.001
Arm-Ergometer Exercise Model	Predictors	LMAD (β=0.63, p<0.001), Weight (β=0.30, p=0.001)
	Adjusted R^2	0.54
	SEE	0.82 kcal/min
	Significance	$F_{2,57}$=35.85, p<0.001
Deskwork Model	Predictors	Weight (β=0.72, p<0.001), TAVG (β=0.45, p=0.011)
	Adjusted R^2	0.57
	SEE	0.23 kcal/min
	Significance	$F_{2,16}$=12.83, p<0.001

Table 3 SW prediction errors using the new prediction models

Activity Mean (SD)	General Model Prediction		Activity Specific Model Prediction	
	Error	***%***	***Error***	***%***
Resting	0.8 (1.0)	79.9 (93.3)	0.2 (0.3)	22.6 (26.1)
2mph on dyno	0.8 (0.5)	26.9 (10.9)	0.6 (0.8)	20.6 (19.8)
3mph on dyno	0.8 (0.3)	21.2 (6.9)	0.4 (0.4)	10.4 (8.0)
3mph on tile	0.7 (0.3)	25.0 (7.7)	0.5 (0.4)	16.6 (16.3)
20W at 60rpm	1.0 (0.8)	33.9 (27.4)	1.0 (0.9)	32.9 (30.1)
40W at 60rpm	1.7 (0.4)	39.5 (6.8)	0.8 (1.0)	18.9 (10.1)
40W at 90rpm	0.9 (0.7)	16.9 (11.3)	0.4 (0.6)	6.8 (6.2)
Deskwork	1.0 (1.2)	90.8 (115.1)	0.2 (0.3)	20.8 (29.1)

EQUATIONS

$$EE_{general}=2.060+0.491*LMAD +0.020*weight-2.955*LAVG \quad (1)$$

$$EE_{resting}=0.405+0.009*weight \quad (2)$$

$$EE_{propulsion}=-0.640+0.441*LMAD +0.037*weight-0.027*Age \quad (3)$$

$$EE_{ergometry}= 1.705+0.352*LMAD +0.016*Weight \quad (4)$$

$$EE_{deskwork}=0.745+0.625*TAVG +0.011*weight \quad (5)$$

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