QUANTIFYING PHYSICAL ACTIVITY USING AN ACTIGRAPH IN MANUAL WHEELCHAIR USERS WITH SPINAL CORD INJURY

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INTRODUCTION

Manual wheelchair users (MWUs) with spinal cord injury (SCI) need to strike a balance between regular physical activity (PA) and the prevention of upper extremity injuries associated with PA. Regular PA is associated with increased cardiorespiratory fitness and muscular strength, and decreased deconditioning and pain (Glaser, Janssen, Suryaprasad, Gupta, & Mathews, 1996). On the other hand, overuse of upper extremities for wheelchair propulsion and transfers can lead to shoulder pain and carpal tunnel syndrome (Boninger, et al., 2005). To overcome this challenge, activity monitors can help MWUs attain an optimal PA level in a community setting (Hiremath & Ding, 2011; Warms & Belza, 2004; Washburn & Copay, 1999).

Past research has shown that sensor based activity monitors can quantify various types and levels of PAs in MWUs with SCI (Hiremath & Ding, 2011; Warms & Belza, 2004; Washburn & Copay, 1999). Washburn and Copay investigated the validity of uni-axial CSA accelerometers worn on both wrists, with respect to energy expenditure (EE) measured in 21 MWUs during wheelchair propulsion (Washburn & Copay, 1999). They reported significant correlations (0.52–0.66,$P<0.01$) between the activity counts/min from both the CSA accelerometers over three propulsion speeds. In another study, Warms and Belza evaluated the validity of the accelerometry-based Actiwatch to measure community living PA in 22 MWUs with SCI with respect to self-reported activity (Warms & Belza, 2004). The Pearson correlation between the activity counts and the self-reported activity varied from 0.30 to 0.77. In our previous study, we developed and evaluated new EE estimating models for the multi-sensor based SenseWear activity monitor in 24 MWUs with SCI during resting, wheelchair propulsion, arm-ergometry and deskwork activities (Hiremath & Ding, 2011). The results indicated that a general and four activity-specific models for SenseWear worn on the upper arm estimated EE with an error of 16.9-90.8% and 6.8-32.9% for various trials. In this study we extend earlier work (Hiremath & Ding, 2011; Warms & Belza, 2004; Washburn & Copay, 1999) by evaluating ActiGraph, a simple tri-axial accelerometer widely accessible to researchers and MWUs. Compared to the previous studies that limited their testing to wheelchair propulsion or small number of subjects, our project tested the ActiGraph activity monitor for multiple PAs and a larger number of MWUs (n=45).

The objective of this study was to develop and evaluate new EE prediction models for MWUs with SCI based on an ActiGraph activity monitor.

METHODOLOGY

Experimental Protocol

The Institutional Review Board at the University approved this study. Subjects were included in the study if they were between 18 and 60 years of age, used a manual wheelchair as a primary means of mobility, had an SCI, were at least six months post-injury, and could use an arm-ergometer to exercise. Subjects were excluded if they could not tolerate sitting for 4 hours, had active pelvic or thigh wounds, or failed to obtain their primary care physician's consent for the study. All subjects provided a written informed consent.

During the study's pre-activity session all subjects filled in a demographics questionnaire. In addition, we measured the subjects' weight, height, and skinfold measurements to estimate their fat percentage (Hiremath & Ding, 2011). During the activity session, subjects wore a portable metabolic cart K4b2 (COSMED srl, Rome, Italy) connected to a face mask, and an ActiGraph (ActiGraph, Fl, USA) on the right wrist. As most activity trials involved symmetric use of both hands, the ActiGraph's position was independent of the subject's dominant hand. The activity session started with a resting trial, followed by three activity routines: wheelchair propulsion, arm-ergometery, and desk work. The activity routines were counterbalanced and the trials within each activity routine were randomized to counter order effects. The resting session required the subjects to sit still in their wheelchairs for eight minutes while the devices collected data. The wheelchair propulsion activity included three trials, i.e., 0.89m/s (2mph) and 1.34m/s (3mph) on a dynamometer and 1.34m/s (3mph) on a tiled surface. The arm-ergometer exercise routine included three trials of 20 watts (W) resistance at 60 rotations per minute (rpm), 40W at 60rpm, and 40W at 90rpm. During the deskwork routine, subjects typed on a computer and read a book for four minutes each. Subjects performed each activity trial for a period of 8 minutes with a resting period of 5-10 minutes after each trial and a period of 30-40 minutes between activity routines.

Instrumentation and Data Collection

The K4b2 is an indirect calorimeter that measures the percentages of O_2 consumed and CO_2 released, in order to estimate breath-by-breath EE. We used the Cosmed software to retrieve the EE data from the K4b2. The ActiGraph GT3X consists of a tri-axial solid-state accelerometer sensor that detects ±3g ($g=9.8m/s^2$) of dynamic acceleration. In the next phase, the acceleration signal is processed with an analog band-pass filter to yield a range of +/-2.13g/sec at 0.75Hz. The filtered analog signals are sampled at 10Hz and converted to 256 distinct levels (8-bit digital values). Each level is considered as an activity count equivalent of 0.01664g/sec/count (ActiGraph, 2011). The sampling rate of the ActiGraph was set to 1Hz (a sample every second). We used the ActiLife analysis software to collect three axes activity counts data from the ActiGraph. For our analysis, instead of using activity counts from each individual axis, we used the resultant activity counts from all three axes as the local reference for the ActiGraph's accelerometer was limited only by the degrees of freedom at the wrist during wheelchair related activities (Boninger, et al., 2005). To ensure accuracy of the data collection, the K4b2 was calibrated for each subject and was time synchronized with the ActiGraph.

Data Analysis

We developed data analysis software in MATLAB® (The Mathworks Inc. MA, USA) to process and analyze data from the K4b2 and the ActiGraph. Steady-state conditions during the activity trials were determined by averaging breath-by-breath EE data in kcal/min over 30 second periods, and then identifying all EE values having coefficients of variation of less than 10% computed over windows of at least 1 minute. We used the average EE and the activity counts data per minute from the steady state conditions for later analysis. Further, we used the activity counts data per second to calculate statistical features including standard deviation, root mean square, mean absolute deviation, mean crossing rate and amplitude every minute.

All statistical analysis was performed using SPSS software (SPSS Inc. Il., USA), with the statistical significance at an alpha level of 0.05. Spearman's Rho correlations were calculated between the EE and the activity counts for each activity routine and all activities combined, as the data failed to meet the assumption of normality. New EE estimation models were developed using stepwise multiple regressions from 36 randomly selected subjects and validated in the remaining 9 subjects. The EE models developed consisted of a general model for all activities combined and four activity-specific models for each activity routine. The independent variables to estimate the EE included movement based variables (average and statistical features from activity counts) and demographic variables (age, weight, height, gender and completeness of injury). The new models were evaluated in the validation group (n=9) by computing the absolute differences and percentage errors between predicted and measured EE.

RESULTS

This study included a total of 45 MWUs (Males=37, Females=8) with SCI. Participants had a mean (SD) age of 40.2 (11.0) years, weight of 78.5 (21.9) kg, height of 178.2 (9.6) cm, and body fat percentage of 25.3 (7.7) %. The injury-level varied from C4 to L4 with 21 out of the 45 subjects having a complete injury. Self-reported PA indicated that 23 subjects performed regular PA, 13 performed occasional PA, and 9 performed no regular PA. All subjects completed the eight activity trials. Due to the malfunction of the K4b2, three trials from three subjects had to be discarded. In addition, five trials from four subjects that did not yield steady-state conditions were also discarded.

Table 1 shows the criterion EE and the activity counts for each trial and the Spearman Rho correlations between the EE and the activity counts for each routine. Significant correlations were found for wheelchair propulsion, arm-ergometry exercise and all activities combined. Figure 1 shows a near linear relationship between the activity counts and the EE. Table 2 shows the results from the regression analysis for both the general and the activity-specific EE estimation models with randomly selected 36 subjects. The general and the activity-specific models are shown in equations (1) and (2)-(5), respectively. Table 3 shows the validation results by the new models with the remaining 9 subjects. In addition, the EE estimated by general (Spearman's Rho: 0.88, $P<0.001$) and activity-specific (Spearman's Rho: 0.87, $P<0.001$) models significantly correlated with the criterion EE among the validation subject group.

DISCUSSION

The availability of various accelerometer based activity monitors can aid MWUs to quantitatively measure their regular PA to meet an optimal quota of PA similar to the moderate PA recommendations made by Healthy People 2020 (U.S. Department of Health and Human Services, 2011).

The results indicated strong correlations (0.5-1.0) for all activities combined and wheelchair propulsion, and medium correlations (0.3-0.5) for arm-ergometry trials. Correlations for wheelchair propulsion trials (0.512,$P<0.05$) in this study were similar to Washburn et al.'s research (0.52,$P<0.01$) (Washburn & Copay, 1999). The high variation of the EE measured from the scatter plot (Figure 1) and the standard error of estimate (Table 2) for wheelchair propulsion compared to the other activities could be due to the different propulsion patterns (Boninger, et al., 2005).

The EE estimation errors for the general and activity-specific models were comparable (Table 3) for all trials except for deskwork, where the estimation error was much higher for the general model. As deskwork activity is associated with intermittent movements, which do not always reflect substantial increases in the EE, the general model may not estimate the EE accurately. In comparison with the SenseWear's EE estimation errors from our previous study (general model: 16.9-90.8%; activity-specific models: 6.8-32.9%), the current EE estimation errors for the ActiGraph had a smaller variation (general: 16.7-42.1%; activity-specific: 15.4- 25.0%) (Hiremath & Ding, 2011). The predictors of the general model included accelerometer based variables and weight similar to the SenseWear's models, which estimated the EE using mean absolute deviation and average acceleration in longitudinal direction and weight (Hiremath & Ding, 2011). The predictors of the activity-specific models indicated weight as a major predictor across all activities. In addition to weight, upper limb movement (activity counts) was chosen as an important predictor for PAs such as wheelchair propulsion and arm-ergometry. However, the activity-specific model developed for the deskwork routine failed to identify any movement based variables, probably due to small wrist movements associated with deskwork activity. These small movements may have led to the flooring effect of the activity counts which failed to explain the variability in the EE during deskwork (Tables 1 and 2).

This study's limitations included testing ActiGraph in MWUs with SCI and limited PAs. We tested the ActiGraph only in MWUs with SCI to minimize the impact of different types of disabilities on EE and activity count measurements. In the future, we hope to test the ActiGraph in persons with other disabilities and various PAs in natural settings. In conclusion, simple accelerometer-based activity monitors such as the ActiGraph can be used to quantify PAs in MWUs with SCI.

FIGURE AND TABLES

Table 1. The criterion EE from the K4b2 and the activity counts/min from the ActiGraph for each activity trial and the Spearman Rho correlations between the EE and activity counts for each routine.

Activity	Mean (SD)		Spearman Rho Correlation	
	EE in kcal/min	**Activity Count/min**	***Rho***	***P value***
Resting	1.12 (0.31)	1.81 (4.21)	0.029	0.856
2mph on dyno	3.35 (1.40)	152.11 (63.83)		
3mph on dyno	4.30 (1.81)	198.86 (69.29)	0.512*	<0.001
3mph on tile	2.86 (1.10)	118.70 (49.07)		
20W at 60rpm	3.11 (0.56)	310.87 (46.83)		
40W at 60rpm	4.35 (0.80)	307.34 (57.82)	0.408*	<0.001
40W at 90rpm	5.34 (1.06)	470.09 (88.86)		
Deskwork	1.32 (0.37)	8.14 (6.67)	0.212	0.167
All Activities	3.22 (1.72)	196.10 (159.74)	0.780*	<0.001

Table 2. General and activity-specific EE models' predictors and statistics for ActiGraph.

General Model	Predictors	Act_Counts(β=0.554,P<0.001) weight(β=0.293,P<0.001) Mean_crossing_rate(β=0.262,P<0.001)
	Adjusted R^2	0.613
	Standard Error of Estimate (SEE)	1.07 kcal/min
	Significance	$F_{3,278}$=149.073,P<0.001
Resting Model	Predictors	Weight(β=0.403,P=0.018)
	Adjusted R^2	0.136
	SEE	0.284 kcal/min
	Significance	$F_{1,32}$=6.205,P =0.018
Wheelchair Propulsion Model	Predictors	Act_counts(β=0.424,P<0.001), Weight(β=0.432,P<0.001)
	Adjusted R^2	0.423
	SEE	1.257 kcal/min
	Significance	$F_{2,103}$=39.424,P<0.001
Arm-Ergometer Exercise Model	Predictors	Act_counts(β=0.476,P<0.001) Weight(β=0.360,P<0.001)
	Adjusted R^2	0.363
	SEE	0.970 kcal/min
	Significance	$F_{2,103}$=30.920,P<0.001
Deskwork Model	Predictors	Weight (β=0.389, P=0.019)
	Adjusted R^2	0.126
	SEE	0.350 kcal/min
	Significance	$F_{2,34}$=6.050,P=0.019

Table 3. Absolute prediction errors for ActiGraph using the new prediction models in the validation group.

Activity Mean (SD)	General Model Prediction		Activity-specific Model Prediction	
	Error	***%***	***Error***	***%***
Resting	0.31 (0.45)	26.75 (25.69)	0.24 (0.30)	22.00 (12.25)
2mph on dyno	0.53 (0.58)	17.42 (13.22)	0.57 (0.50)	17.56 (9.22)
3mph on dyno	0.88 (0.99)	17.88 (12.64)	0.65 (0.75)	15.37 (11.20)
3mph on tile	0.48 (0.67)	20.28 (24.14)	0.56 (0.52)	23.80 (23.70)
20W at 60rpm	0.65 (0.68)	19.78 (14.37)	0.82 (0.72)	25.02 (14.74)
40W at 60rpm	1.06 (0.99)	19.64 (14.14)	0.95 (1.00)	17.32 (15.03)
40W at 90rpm	0.87 (1.14)	16.70 (15.20)	0.92 (0.98)	16.30 (11.19)
Deskwork	0.55 (0.50)	42.11 (32.30)	0.25 (0.29)	22.11 (15.22)

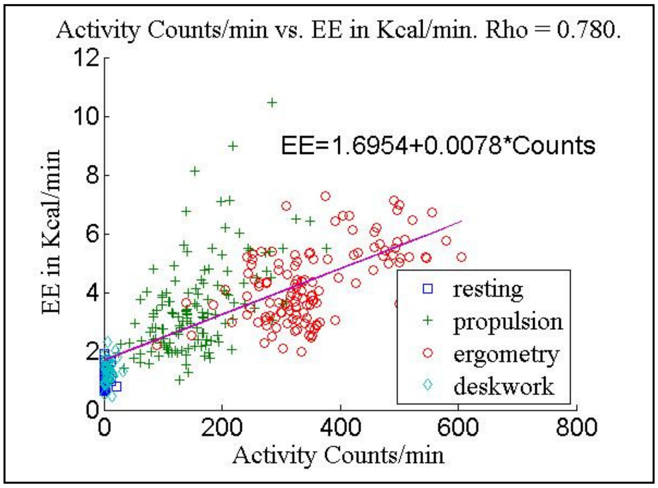

Figure 1: Scatter plot of activity counts from ActiGraph versus EE from K4b2.

EQUATIONS

$EE_{general}$ = -0.631+0.006*Act_counts+0.023*Weight +0.047*Mean_cross_rate……………….(1)

$EE_{resting}$ = 0.680+0.006*Weight…………………….....(2)

$EE_{propulsion}$ = -0.644+0.011*Act_counts+0.032*Weight...(3)

$EE_{ergometry}$ = 0.543+0.006*Act_counts +.020*Weight….(4)

$EE_{deskwork}$ = 0.815+0.007*Weight……………………...(5)

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