Classifying intensity of activity using ActiGraph monitor in wheelchair users

Akhila Veerubhotla, MS[1,2] Kalai Tsang, BS [1,2] Khara James, MS [1,2] and Dan Ding, PhD[1,2]

[1]*Department of Rehabilitation Sciences and Technology, School of Health and Rehabilitation Sciences, University of Pittsburgh, PA.,* [2]*Human Engineering Research Laboratories, Department of Veteran Affairs Pittsburgh Healthcare System, Pittsburgh, PA*

INTRODUCTION

Wheelchair users as a group are considered to be sedentary and among the least fit individuals. [1] It is well known that sedentary lifestyle adversely impacts health. [2-4] To promote health, research has focused on physical exercise interventions to increase physical activity (PA) or decrease sedentary time throughout the day. [5] There are also multiple PA guidelines that recommend the intensity and duration of PA for people with spinal cord injury (SCI) who often rely on wheelchairs for mobility. [6] Traditionally, self-report surveys are often used as surveillance tools to track habitual PA in the community, but they are limited by burdens of recall, lack of responses, and inaccuracy. [7] With the proliferation and cost reduction of wearable devices, accelerometer-based sensors are increasingly used for users to track their own PA behaviors and for researchers to examine the association of PA behaviors and health indicators.

Much research in ambulatory population has examined the ability of accelerometer-based sensors such as ActiGraph monitors (ActiGraph, Inc., FL, USA) to estimate PA intensity. [8-10] There are well-recognized cut-off points in accelerometer counts for ambulatory population to estimate their time spent in sedentary, lightweight, and moderate-to-vigorous intensities of PA (MVPA) over any period of time. [9] The accuracy of such estimation is often dependent on the population, sensor placement, and activities that were used to derive the cut-off points. [2,9,11] Thus, these cut-off points cannot be simply applied to manual wheelchair users (MWUs) because they were derived with sensors worn at hip/waist to capture primarily lower limb movements such as walking and running.

Research involving MWUs often asks participants to wear the sensors around the wrist to capture their upper limb movements for wheelchair propulsion and other activities of daily living (ADLs). [2,11] Studies have shown that accelerometer counts from ActiGraph sensors correlated with self-reported activity intensity by wheelchair users, and with energy expenditure during wheelchair propulsion activities. [2,4,11] Only one research study attempted to derive cut-off points in accelerometer counts for intensity estimation for MWUs, and showed the cut-off points based on wheelchair propulsion trials on a computer-controlled treadmill. [11] In this paper, we examine the ability of ActiGraph GT9X Link (ActiGraph, Inc., FL, USA) to estimate activity intensity for MWUs based on a variety of lifestyle activities and exercises.

METHODS

This study was approved by the US Department of Veterans Affairs Central Institutional Review Board. Individuals were invited to participate if they 1) had a spinal cord injury (SCI), 2) were between 18 and 65 years, 3) used a manual wheelchair as their primary means of mobility (≥40 hours/week), 4) were at least one-year post injury, and 5) were medically stable.

After informed consent, participants completed a demographics questionnaire. Their height and weight were measured. Participants rested in a supine position for 20 minutes and then performed a series of ADLs in random order. Activities included: resting while sitting in a wheelchair; propulsion at self-selected slow, normal, and fast pace; propulsion on a slope; watching TV; working on a computer; playing basketball; sweeping the floor; loading and unloading a dishwasher; weight lifting; TheraBand exercises; arm ergometry at a self-selected slow and fast pace; folding laundry; and being pushed in their wheelchair. Participants performed each activity for 10 minutes, followed by a 3-minute break. All activities were video recorded.

The COSMED K4b2 (COSMED, srl., Rome, Italy) portable metabolic cart was used to measure breath-by-breath oxygen consumption (VO_2) during activities. Data from the K4b2 was downloaded using its software. For each activity, VO_2 values (ml/kg/min) were averaged for each minute and divided by the resting metabolic equivalent of 2.7 ml/kg/min to obtain the Metabolic Equivalent of Task (MET) for the minute, which served as the criterion measure of PA intensity. [12] MET values ≤ 1.5 are classified as sedentary behavior, 1.5-3 METs are classified as light intensity, and ≥ 3 METs are classified as moderate to vigorous intensity. The ActiGraph GT9X Link sensor worn at the dominant wrist was used to track PA as shown in Figure 1. It is a tri-axial accelerometer whose vector magnitude (VM) of acceleration is converted to activity counts called VM counts using the company's proprietary software. VM count data from the ActiGraph GT9X Link was downloaded in 60-sec epochs using the ActiLife software version v6.11.9. Both the K4b2 and ActiGraph Link were calibrated following standard procedures and time-synchronized. [13,14]

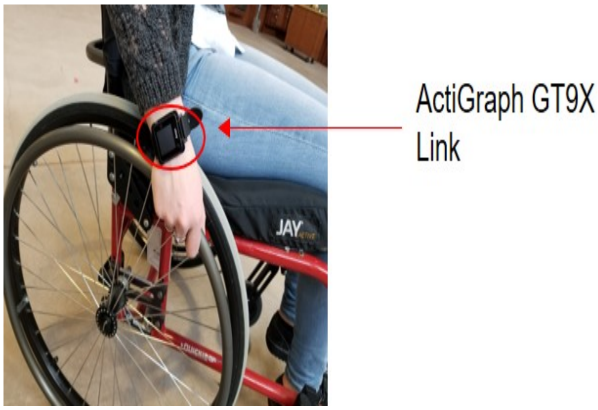

Figure 1: ActiGraph Link GT9X sensor worn on the dominant wrist

K4b2 and ActiGraph Link data during breaks were identified from video recordings and removed from the analysis. To obtain cut-off points for intensity estimation, an iterative process was utilized. For each iteration, we randomly divided the participants into two groups with 85% of participants in the model development group and 15% in the accuracy testing group. For the model development group, only steady-state data was used to build the prediction model. Steady-state was defined as less than 10% difference in the amount of oxygen (VO_2) inhaled and carbon dioxide (VCO_2) exhaled within a minute for four consecutive minutes. Steady-state data were then averaged for each activity for each participant. The averaged VM counts for different activities were correlated with criterion MET values. A linear regression equation was fit to predict MET values from the VM counts and the cut-off points for sedentary, light, and MVPA intensities were determined. The R^2 statistic and root mean square error (RMSE) were obtained to evaluate the model. The derived cut-off points were then applied to participants in the accuracy testing group. The estimated METs were compared to the criterion measure, and the total number and percentage of misclassified minutes were then calculated. This bootstrapping-alike process was iterated until all possible combinations of participants were tried in the model development group. The final equation to predict METs was formulated by averaging all iterations. R^2 statistic and RMSE were also calculated by averaging values over all iterations.

RESULTS

A total of 16 participants were recruited and completed the study. A total of 120 iterations were performed to accommodate all possible combinations of participants in the model development group (n = 14) and accuracy testing group (n = 2). Out of the total 16 participants, two had an injury level at C6 or above (both with incomplete injury), and the remaining were below T1 (11 with complete injury while 3 did not report). They had an average age of 42$\pm$ 14 years (range: 22-62 years), average weight of 203$\pm$ 47 pounds (range: 130-302 pounds) and an average height of 69$\pm$ 3 inches (range: 65-73 inches).

A strong, positive correlation (r=0.77) was observed between the VM counts per minute (CPM) and the MET values. The linear equation to predict MET was obtained as:

$$MET = 1.13+(0.00015) *CPM$$

The cut-off points between sedentary and light intensity was 2,433 CPM, and between light and moderate intensity was 12,467 CPM. The average R^2 statistic for all iterated models was 0.66 (p<0.001), indicating that 66% of the variance in the METs was explained by the VM count alone. The RMSE was 0.67. An average accuracy of 81% (with standard deviation of 5.8% across 120 iterations) was seen for classifying activities into different intensities. The total number and percent of misclassified minutes over 120 iterations is shown in the contingency table in Figure 2.

Classification via derived cut-off points (columns); Classification via criterion (rows)

	Sedentary	Light	MVPA
Sedentary	814 (93.4 %)	57 (6.5 %)	1 (0.1 %)
Light	44 (4.7 %)	740 (79.6 %)	146 (15.7 %)
MVPA	6 (1 %)	196 (33.2 %)	389 (65.8 %)

Figure 2: Contingency table showing total number of minutes (and percentages) spent in sedentary, light and MVPA intensities by all participants.

DISCUSSION

This ongoing study derived cut-off points in VM counts for MWUs to estimate PA intensity based on a range of ADLs. It was found that the wrist-worn ActiGraph sensor was able to quantify sedentary behavior with a high accuracy of 93.4% as shown in Figure 2. A growing body of evidence in the general population indicates that sedentary behavior is associated with increased morbidity—particularly cardiovascular and diabetic—and mortality, independent of PA. [5,15] However, there is a lack of knowledge and research on sedentary behaviors in MWUs. [5] The preliminary findings of this study showed that the ActiGraph sensor has the potential to track sedentary behaviors (e.g., total time, number of sedentary bouts, and number of breaks etc.) in MWUs and support future research that examines the adverse health effect of sedentary lifestyles and the effectiveness of interventions aiming at breaking sedentary time in this population.

Our results also showed the ActiGraph sensor was able to classify light and moderate-to-vigorous activity intensities with reasonable accuracies. About 80% of the lightweight activities were correctly classified, while some (15.7%) were wrongly classified as MVPA. For example, sweeping floors as a lightweight activity was wrongly classified into moderate intensity, because it involved a great amount of wrist movements, but not physical exertion. About 66% of MVPA minutes were correctly classified, while the rest were wrongly classified into light-weight category. Most of the misclassifications were from resistance-based activities such as propulsion up a slope, weight lifting, and TheraBand exercises where the physical exertion was not proportional to the upper limb movements. Since ActiGraph sensor only recorded wrist movements, the VM counts were relatively low during these high resistance activities, even though participants expended more energy.

The total minutes of PA tested in this study comprised of 37% of sedentary, 39% of light and 24% of MVPA. There were three resistance-based activities which accounted for about 43% of total MVPA minutes. The distribution of sedentary, light and MVPA minutes in this protocol may be different from that in the community where sedentary behavior typically constitutes the majority of the daily time. Thus, this result from this study should be viewed with caution, especially when an individual engages in many resistance-based activities.

Nonetheless, the study is still ongoing and with more participants tested in the study, we can further refine the algorithm and evaluate the generalizability of the derived cut-off points. Previous studies have used individualized calibrated heart rate to estimate activity intensity, however, this approach involves additional testing procedures and accurate heart rate measurements with chest sensors. [16,17] In addition, heart rate in people with SCI are affected by many factors such as injury levels and medications. We have collected the heart rate data in this study via a wrist-worn device and a chest-worn device, respectively, and plan to examine the extent to which the heart rate information from each device could help improve intensity estimation accuracy especially for MVPA in future work.

CONCLUSIONS

In this study, cut-off points were derived for sedentary, light, and MVPA activities for MWUs with SCI using ActiGraph Link based on a number of ADLs. The preliminary findings showed that the derived cut-off points in accelerometer counts could be used to estimate time spent in different intensities of PA in the community for this group of individuals with reasonable accuracy.

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REFERENCES

[1] ANDREW, J. (2017). Physiology of Exercise in Spinal Cord Injury. SPRINGER-VERLAG NEW YORK.

[2] Nightingale, T. E., Walhin, J. P., Thompson, D., & Bilzon, J. L. J. (2015). Influence of accelerometer type and placement on physical activity energy expenditure prediction in manual wheelchair users. PloS one, 10(5), e0126086.

[3] Warms, C. A., Whitney, J. D., & Belza, B. (2008). Measurement and description of physical activity in adult manual wheelchair users. Disability and health journal, 1(4), 236-244.

[4] Nightingale, T. E., Walhim, J. P., Thompson, D., & Bilzon, J. L. (2014). Predicting physical activity energy expenditure in manual wheelchair users. Medicine and science in sports and exercise, 46(9), 1849-1858.

[5] Nooijen, C. F., Stam, H. J., Sluis, T., Valent, L., Twisk, J., & van den Berg-Emons, R. J. (2017). A behavioral intervention promoting physical activity in people with subacute spinal cord injury: secondary effects on health, social participation and quality of life. Clinical rehabilitation, 31(6), 772-780.

[6] Ginis, K. M., Hicks, A. L., Latimer, A. E., Warburton, D. E. R., Bourne, C., Ditor, D. S., ... & Pomerleau, P. (2011). The development of evidence-informed physical activity guidelines for adults with spinal cord injury. Spinal cord, 49(11), 1088.

[7] Nightingale, T. E., Rouse, P. C., Thompson, D., & Bilzon, J. L. (2017). Measurement of physical activity and energy expenditure in wheelchair users: methods, considerations and future directions. Sports medicine-open, 3(1), 10.

[8] Trost, S. G., Loprinzi, P. D., Moore, R., & Pfeiffer, K. A. (2011). Comparison of accelerometer cut points for predicting activity intensity in youth. Medicine and science in sports and exercise, 43(7), 1360-1368.

[9] Freedson, P. S., Melanson, E., & Sirard, J. (1998). Calibration of the Computer Science and Applications, Inc. accelerometer. Medicine and science in sports and exercise, 30(5), 777-781.

[10] Aguilar-Farías, N., Brown, W. J., & Peeters, G. G. (2014). ActiGraph GT3X+ cut-points for identifying sedentary behaviour in older adults in free-living environments. Journal of Science and Medicine in Sport, 17(3), 293-299.

[11] Learmonth, Y. C., Kinnett-Hopkins, D., Rice, I. M., Dysterheft, J. L., & Motl, R. W. (2016). Accelerometer output and its association with energy expenditure during manual wheelchair propulsion. Spinal cord, 54(2), 110-114.

[12] Collins, E. G., Gater, D., Kiratli, J., Butler, J., Hanson, K., & Langbein, W. E. (2010). Energy cost of physical activities in persons with spinal cord injury. Medicine and science in sports and exercise, 42(4), 691-700.

[13] Sandroff, B. M., Motl, R. W., & Suh, Y. (2012). Accelerometer output and its association with energy expenditure in persons with multiple sclerosis. Journal of rehabilitation research and development, 49(3), 467.

[14] Pinnington, H. C., Wong, P., Tay, J., Green, D., & Dawson, B. (2001). The level of accuracy and agreement in measures of FEO2, FECO2 and VE between the Cosmed K4b2 portable, respiratory gas analysis system and a metabolic cart. Journal of Science and Medicine in Sport, 4(3), 324-335.

[15] de Rezende, L. F. M., Lopes, M. R., Rey-López, J. P., Matsudo, V. K. R., & do Carmo Luiz, O. (2014). Sedentary behavior and health outcomes: an overview of systematic reviews. PloS one, 9(8), e105620.

[16] Lee, M., Zhu, W., Hedrick, B., & Fernhall, B. (2010). Estimating MET values using the ratio of HR for persons with paraplegia. Medicine and science in sports and exercise, 42(5), 985-990.

[17] Coutinho, A. C., Neto, F. R., & Beraldo, P. S. (2014). Validity of heart rate indexes to assess wheeling efficiency in patients with spinal cord injuries. Spinal cord, 52(9), 677-68