Predicting physical activity intensity using raw acceleration signals in manual wheelchair users with spinal cord injury

[1,2]Yousif Shwetar,[1,3]Zijian Huang, [1,3]Akhila Veerubhotla, [1-3]Dan Ding

[1]*Human Engineering Research Laboratories, Department of Veterans Affairs,* [2]*Department of Bioengineering, Swanson School of Engineering, University of Pittsburgh,* [3]*Department of Rehabilitation and Science Technology, University of Pittsburgh*

INTRODUCTION

Life Expectancy of individuals with Spinal Cord Injuries (SCI) has increased with 43% of those who experience their injuries from ages 25 to 34 years living for another 40 years [1]. Yet, SCIs result in lowered levels of mobility, primarily requiring these individuals to rely on a wheelchair for daily mobility [2]. Despite the use of a manual wheelchair for physical activity (PA), this population of manual wheelchair users (MWUs) has lesser accessibility and fewer opportunities to engage in PA in comparison to the general population [3]. These issues lead to an increased prevalence of many chronic diseases associated with physical inactivity, including cardiovascular disease, diabetes, cancer, hypertension, obesity, depression, and osteoporosis [4].

Activity monitors have been widely utilized to track and promote changes in PA, with ActiGraph activity monitors (ActiGraph, LLC., Pensacola, FL, USA) being the most extensively studied device used to track PA in research settings [5, 6]. The ActiGraph devices are capable of collecting raw acceleration signals at a set frequency, as well as producing a proprietary variable called 'count' for each accelerometer axis. These 'count' recordings from all 3 axes are used to obtain a vector magnitude value, being vector magnitude count (VMC), which is often utilized as in predictive algorithms for physical activity intensity and energy expenditure in many research manuscripts. For example, several research groups including Learmonth [7], McCracken [8], and Veerubhotla [9] developed VMC-based thresholds for classifying physical activities performed by MWUs into sedentary behavior, light-weight intensity, and moderate-to-vigorous PA (MVPA) intensity. Yet, as VMC can only be obtained through ActiGraph devices and its associated software that costs $1700 [10], the applicability of these algorithms is restricted. Meanwhile, there are many other commercial wearables devices that are just as capable of recording raw acceleration signals but offered at an affordable price without requiring specialized software. Therefore, it is important to develop predictive algorithms for physical activity intensity based on raw accelerometer signals instead of proprietary 'counts'. In addition, translating raw accelerometer data sampled at a higher frequency (e.g., 30Hz) in an entire second or minute into a single 'count' may eliminate the rich features in the accelerometer signals that could potentially help improve the accuracy of PA estimation.

The purpose of this study is to develop a physical activity intensity classification model based on raw accelerometer signals for MWUs with SCI. A study protocol that encapsulates a series of ADLs with varying intensities was used to develop and cross-validate the model.

METHODS

This study was conducted at two sites including the Human Engineering Research Laboratories (HERL) in Pittsburgh, PA and the James J. Peters VA Medical Center in Bronx, NY. Approval for this study was granted by the US Department of Veterans Affairs' Central Institutional Review Board. The inclusion criteria are 1) between the ages of 18 and 65; 2) having an SCI at least one-year post injury and medically stable, and 3) using a manual wheelchair as their primary means of mobility for at least 40 hours/week.

Study Protocol

Participants were asked to avoid taking part in any MVPA the night before testing, along with ingesting any caffeine or food on the day of testing. Individuals first gave informed consent and completed a demographics questionnaire. Individuals were then instructed to lay in supine position while their height was measured using a tape measure. Weight was measured while individuals were in their wheelchair, on a wheelchair weight scale (Detecto, Webb City, MO, US). This weight was then subtracted by the weight of the wheelchair alone. For the activity protocol, individuals were asked to first rest in a seated position for 30 minutes, and then rest in supine position for 20 minutes. This was then followed by a randomly selected array of ADLs including: resting while sitting in a wheelchair; propulsion at self-selected slow, normal, and fast pace on flat tiled surface; propulsion up/down a slope; watching TV; working on a computer; practicing shooting a basketball; sweeping/vacuuming the floor; loading and unloading a dishwasher; weight lifting; TheraBand exercises; arm ergometry exercise at a self-selected slow and fast pace; folding laundry; and being pushed in their wheelchair. Each activity was performed for 10 minutes with a minimum break of 3 minutes between each activity.

Instrumentation

Individuals were equipped with a COSMED K4b^2 portable metabolic cart (COSMED Inc, Rome, Italy), that measures oxygen uptake (VO_2) and carbon dioxide output (VCO_2). Individuals were also equipped with an ActiGraph GT9X Link on the dominant wrist, recording raw acceleration data at 30 Hz. Raw signal data was obtained from the ActiGraph ActiLife software (v6.11.9).

Data Preprocessing

All data that did not constitute activity data was removed. If either data for the K4b^2 or the ActiGraph was not available for a minute due to device malfunctioning, data for both devices was removed. Only steady-state data for each activity trial was obtained in the final dataset. Steady-state is defined as VO_2 and VCO_2 measured by the K4b^2 having changed less than 10% for 5 continuous minutes [11]. If this wasn't available for an activity, a minimum of 3 minutes was attempted [12], or the data was removed [12].

All data was organized into different PA intensity categories, being the metabolic equivalent of task (METs), defined as the average VO_2, in units of ml kg^{-1} min^{-1}, divided by 2.7 ml kg^{-1} min^{-1} [13]. This served as the criterion for PA intensity, with values below 1.5 as resting, those in-between 1.5 and 3.0 as light-intensity, and those above 3.0 as MVPA.

Data Modeling & Validation

A signal processing method, i.e., discrete wavelet transforms (DWT), was utilized to obtain potential predictors. DWT is able to capture significant features from natural signals and present them as a subset of DWT coefficients in a much smaller form than the original signal, essentially compressing the data. Since data sampled from the ActiGraph device is at 30 Hz, a single minute contains 1800 values. This approach is able to capture all the raw signal values and compress them into a smaller subset of feature rich coefficients.

Twelve total potential predictors were obtained using DWT on raw signal x-axis, y-axis, z-axis, and vector magnitude data. Using Daubechies 2 mother wavelet, raw signal data was sampled through two levels of decomposition. Euclidean norm was then applied to the first and second levels of resolution of the detail coefficients along with the approximation coefficient of the second level, giving a total of 12 predictors.

A random forest trees classification model (RFTM) was developed to classify sedentary activity, light-intensity PA, and MVPA using the 12 predictors. A 5-fold cross validation process was used for model validation, where 80% of the data was used to develop the model and the remaining 20% of data was used to validate the model in each fold. The data was stratified based on intensity levels to ensure the same intensity distribution in the model development and validation datasets. The cross-validation was also used to select the number of trees (starting at 10 trees with a 10-tree interval until 100 trees) for the RFTM that yields the best average accuracy. The number of trees that yielded the best accuracy was used as the final model. The sensitivity, specificity, and overall classification accuracy for the model was calculated for each fold. Also, a confusion matrix summing the values of all 5 models on all 5 validation sets was calculated.

Table 1: Demographic Data

Variables	Mean (SD), n (%)
Age (Years)	40 (13)
Weight (Kg)	83 (21)
Height (in)	69 (4)
Gender	
Male	26 (81%)
Female	6 (19%)
Body Mass Index	
BMI ≤ 25	13 (41%)
25 < BMI < 30	11 (34%)
30 ≤ BMI	8 (25%)
Time as MWU (Years)	9 (8)
Lesion Level	
Cervical	2 (6%)
Thoracic	26 (82%)
Lumbar	2 (6%)
Not Reported	2 (6%)
Lesion Type	
Complete	18 (56%)
Incomplete	8 (25%)
Not Reported	6 (19%)

RESULTS

A total of 32 participants were recruited and tested in this study. There were a total of 2,165 steady-state minutes of activity data. Of this data, 487 minutes (23%) were classified as sedentary behavior, 895 minutes (41%) being light-intensity PA, and 783 minutes (36%) being MVPA based on the criterion measure. Across these participants, the total steady-state activity minutes obtained ranged from 18 to 96 minutes with an average of 69 ± 20 minutes from each participant. Additional demographic information can be found in Table 1.

Based on cross validation, the RFTM with 80 trees yielded the best average accuracy of 78% ± 2.4% across the five folds. Table 2 presents the sensitivity and specificity of classifying each intensity in each fold using mean, standard deviation, and range. Table 3 shows the confusion matrix detailing the correctly classified and incorrectly classified PA intensity minutes across all five folds.

DISCUSSION

In this study, we built an activity intensity classification model based on raw acceleration signals for MWUs with SCI. As no proprietary information is used for model development, the model could be potentially used by any device that records raw acceleration signals.

We used a machine learning approach to build a classification model where we applied signal processing techniques, specifically DWT on raw accelerometer values to produce potential features for the model. We chose the RFTM, a powerful ensemble learning algorithm, that combined multiple trees into one predictive model in order to decrease variance, bias and improve predictions.

Table 2: Model Performance across each fold of validation

	Sensitivity	Specificity
Sedentary	80% ± 6.0% (70% - 85%)	94% ± 2.4% (90% - 96%)
Light	75% ± 4.9% (68% - 80%)	81% ± 3.3% (76% - 84%)
MVPA	81% ± 3.9% (75% - 85%)	91% ± 1.2% (90% - 92%)

Table 3: Confusion matrix showing minutes spent at each intensity based on criterion and model estimation

		Estimated Minutes		
		Sedentary	**Light**	**MVPA**
Criterion Minutes	**Sedentary**	391	95	1
	Light	101	672	122
	MVPA	3	149	631

Based on the study results, the model yielded a good specificity (with good stability across each fold) for sedentary time and MVPA, indicating the model could perform reasonably well when it is used to classify minutes spent in these two intensities. However, the model lacked the ability to classify light-weight PA with a relatively low specificity. From the confusion matrix, it can also be seen that light-weight PA could be wrongly classified into either sedentary or MVPA category. We noticed that some light-intensity activity such as sweeping or folding laundry that involves consistent and large ranges of upper limb movements, may give higher raw acceleration values, leading to wrong classification into MVPA. While other light-intensity activities such as weight-lifting for some individuals was light-weight based on criterion METs, but were wrongly classified into sedentary category due to the infrequent upper limb movements. From the confusion matrix, there are also a portion of MVPA minutes that were wrongly classified into light-intensity. A trend we observed was that the model tended to incorrectly predict resistance-based activities. These typically contained METs values in the range of MVPA, however the lack of changes in raw signal data during these activities may have caused the predictors to record lower intensity values, leading to an increase in incorrectly classifying MVPA as light-intensity activity. With these observed trends, it might be possible to carefully devise features (or predictors) that can better capture the patterns of the movements in future work in order to further improve the prediction accuracy.

There are a few limitations in the study. First, although the study used the cross-validation approach, the study lacked a separate large testing dataset to validate the final classification model. Second, the number of subjects is relatively small and the activity minutes for each participant varied to a large degree, therefore, we split the datasets based on the number of minutes and an intensity-stratified method instead of based on the number of participants during cross validation. Thus, the model performance obtained may not accurately reflect the real-world applications. Finally, the RFTM model with 80 trees could be computationally costly and may not be appropriate for applications that need to provide real-time feedback to users. We plan to investigate other machine learning algorithms and investigate other potential features that may better capture the movement patterns.

CONCLUSION

A classification model to predict time in sedentary, light-intensity, and MVPA for MWUs with SCI was developed based on raw accelerometer signals and assessed using 5-fold cross-validation. Results from this study show that the model can potentially be used to predict sedentary and MVPA with moderate accuracy, however it should be used with caution when trying to measure time in light-intensity PA.

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