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Physical Activity Classification utilizing Activity Monitors in Manual Wheelchair Users with SCI

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Summary
Classification of physical activities (PA) in manual wheelchair users (MWU) can provide important feedback regarding their activity levels and actual upper extremity usage in a natural environment. This project evaluated PA classification in sixteen MWU with Spinal Cord Injury (SCI) using a SenseWear® (SW) activity monitor (AM) worn on the MWUs' upper arm. SW was used to collect multi-sensor data during resting, wheelchair propulsion, arm-ergometer exercises and deskwork. Leave-one-subject-out (LOSO) cross-validation process for four wheelchair related activities yielded an accuracy of 90.5%, 89.5%, 85.0% and 76.8% for Support Vector Machines, k-Nearest Neighbors, Naïve Bayes and Decision Trees, respectively. The high accuracy classification suggests that AMs can be used in MWU with SCI to classify PA.

Keywords: Manual wheelchair users, Accelerometer, Machine learning, Classification

Background

Manual wheelchair users lack activity monitors (AMs) that can assist in regular self-monitoring of physical activities (PA) in a free-living environment. Activity monitors have the potential to provide feedback regarding PA levels and energy expenditure (EE) in manual wheelchair users (MWU), thus assisting them to follow a healthy lifestyle. Availability of AMs is crucial in MWU as they face special challenges in maintaining an active and healthy lifestyle due to mobility and physiological limitations. Polzien et al. showed that continuous use of technology-based AMs during a weight loss program had a significant impact on altering the PA behavior [1]. Similarly, many other studies indicated that pedometers and AMs can be used in ambulatory populations without disabilities to measure PA and predict daily EE [2, 3]. However, these pedometers or AMs cannot be used unaltered by MWU as there are biomechanical differences between MWU and ambulatory population when performing activities of daily living.

One way to make AMs available for MWU is to adapt them to measure PA by capturing and quantifying upper-extremity movements during activities of daily living [4]. The sensor information obtained by the AMs can be used to identify the type, the intensity and the duration of PA improving the accuracy of PA measurement in MWU. Our previous research showed that a single regression equation cannot capture PA accurately, therefore we aim to assess PA in a two step process [5]. The process we have adopted involves the identification of specific wheelchair related activities, followed by the application of activity specific regression equations to estimate PA levels and EE [6]. This study focuses on the identification of wheelchair related activities in people with spinal cord injury (SCI), a large segment of MWU.

Previous research by French et al. showed that machine learning algorithms can be used to classify different wheelchair propulsion patterns on carpet and tile surface in persons without disabilities [7]. A primary objective of this study was to evaluate the performance of different machine learning algorithms to classify PA using the multi-sensor data collected by SW during resting, wheelchair propulsion, arm-ergometer exercises, and deskwork in MWU with SCI.

Methodology

<u>Experimental Protocol</u>: The study was approved by the Institutional Review Board at the University of Pittsburgh and the VA Pittsburgh Healthcare System. Subjects were recruited based on the following inclusion criteria: that they were between 18 and 60 years of age, use 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 written informed consent prior to their participation in the study. As part of the pre-activity session the

subjects answered a questionnaire and provided weight, height and skinfold measurements at biceps, triceps, subscapular and suprailiac. The average value of skinfold measurements was used to estimate the body fat percentage of the subjects. During the activity session the subjects participated in resting and three activities, including wheelchair propulsion, arm-ergometer exercises, and desk work. The three activities were counterbalanced and the trials within each activity were randomized to counter order effects.

All subjects wore a SW AM on their upper right arm while performing the activities. The subjects performed each activity trial for a maximum period of 8 minutes (min) with a resting period of 5 to 10 min each trial and a period of 30 to 40 min between each activity. During the propulsion activity the subjects propelled their wheelchairs for two trials of 2 miles per hour (mph) and 3mph on a stationary dynamometer (dyno), and a trial of 3mph on a flat tiled floor. The propulsion speed was regulated by observing a feedback monitor in front of the subjects on the dynamometer and following a power wheelchair with fixed speed on the tiled floor. The arm-ergometer exercises included three trials of 20 watts resistance (W) at 60 rotations per minute (rpm), 40W at 60rpm, and 40W at 90rpm. The arm-ergometer device offered a fixed resistance with a speed feedback. During the desk work activity session the subjects typed on a computer and read a book, spending four min for each sub-activity.

<u>Instrumentation and Data Collection</u>: The weight, height and skin fold measurements were measured using a Befour MX490D wheelchair scale (Befour, Inc. WI, USA), Stanley® Tape Rule (The Stanley Works, CT, USA) and Lange® skinfold caliper (Beta Technology, CA, USA), respectively. SW AM was used to collect transverse and longitudinal axis accelerations sampled at 8Hz, galvanic skin response (GSR) and skin (STEMP) and near body temperatures (NTEMP) sampled at 1 min. GSR and temperature sensors were sampled at a lower sampling frequency to ensure that SW could be used to collect data for a duration of three hours. Previous research in ambulatory population without disabilities demonstrated good performance of SW in predicting activities and EE [1, 2, 6]. The investigator of the study annotated the start and end of each activity trial by pushing the annotate button present on the SW. The raw multi-sensor data from SW was retrieved and analyzed using InnerView Research software 7.0 (Bodymedia Inc., USA). After downloading the data to a computer the annotation intervals were appropriately marked for analysis.

<u>Data Analysis</u>: MATLAB® (The Mathworks, Inc., USA) software was used to extract features based on transverse, longitudinal and resultant acceleration data using the 50% overlapping sliding windows of length 10 seconds (s). The features extracted were mean, standard deviation (SD), root mean square (RMS), mean absolute deviation (MAD), zero crossings, mean crossings, fluctuations in amplitude, energy, entropy and correlation. The acceleration based features were combined with the mean values of GSR, STEMP and NTEMP to obtain 33 features for the PA classification. MATLABArsenal, SVMLight and Weka softwares were used to analyze and implement machine learning algorithms. Best first search method in Weka was also used to identify a key set of features that considerably contributed towards the PA classification. Supervised learning strategy, data annotated by an investigator was used to classify the PA into four activities. In addition the classification of PA was evaluated into three classes by combining resting and deskwork as sedentary activities. The classifiers used to evaluate PA classification were Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Naïve Bayes (NB) and Decision Tress (C4.5). The performances of the classifiers were analyzed by performing leave one subject out (LOSO) and tenfold (10-fold) cross-validation (CV).

Table 1. Classification performance in percentage (%)

CV	Class	33 Features				7 Key Features			
		SVM	KNN	NB	C4.5	SVM	KNN	NB	C4.5
LOSO	4	90.5	89.5	85.1	76.8	71.9	61.1	67.6	56.8
10-fold	4	89.8	88.9	84.4	79.1	69.7	59.6	66.5	60.4
LOSO	3	90.6	89.7	82.3	77.6	77.9	66.6	72.7	64.3
10-fold	3	89.5	89.1	82.4	79.9	76.5	65.1	72.5	63.5

Table 2. Physical activity classification in percentage (%)

	SVM	KNN	NB	C4.5
Activities	LOSO	LOSO	LOSO	LOSO
Resting	83.7	75.1	91.1	78.8
Propulsion	93.4	94.3	86.1	82.0
Arm-ergometry	91.8	91.4	89.6	76.5
Deskwork	86.2	85.6	65.3	61.6

Table 3. Confusion matrix for SVM using LOSO CV

Class	RE	PR	AE	DW
Resting [RE]	1368	1	1	264
Propulsion [PR]	2	4425	291	22
Arm-ergometry [AE]	0	352	4187	21
Deskwork [DW]	197	11	38	1539

Results

The participants were 12 males and 4 females with a mean age of 43.0±10.1 years, weight of 78.3±18.6 kg, height of 177.3±10.2 cm, and body fat percentage of 27.7%±6.9%. The choice of the 10s sliding window was based on preliminary research of PA classification using SVM and DT on acceleration based features using varying sliding window durations. The 10-fold CV classification results using SVM yielded an accuracy of 77.0% for 1s, 83.7% for 3s, 87.0% for 5s, 85.3% for 7s and 87.9% for 10s and the DT yielded an accuracy of 70.56% for 1s, 76.2% for 3s, 77.8% for 5s, 79.8% for 7s and 77.3% for 10s. Table 1 presents the classification performance for four different types of classifiers on the combined and key set of features. The best first search method provided seven features including: mean and RMS values in longitudinal direction; mean, RMS and entropy values in resultant direction; correlation between longitudinal and resultant directions and skin temperature. The results indicate that SVM with radial basis function (RBF) and KNN with distance type euclidean and 3 nearest neighbors were able to classify four PAs with accuracies of 89.4% and 88.3%, respectively. The results of LOSO CV using SVM classifier resulted in an accuracy of greater than 83.7% for four PAs (Tab. 2). A closer analysis of the confusion matrix of PA classification using SVM with LOSO CV indicates that misclassification is higher between resting and deskwork which are sedentary activities and wheelchair propulsion, and arm-ergometry exercises which involve voluntary use of upper extremities (Table 3).

Discussion and Conclusion

The high LOSO CV classification accuracy of 85% to 90% for SVM, KNN and NB suggests that machine learning algorithms can be used to classify PA using the multi-sensor data collected by SW during resting, wheelchair propulsion, arm-ergometer exercises, and deskwork in MWU with SCI (Table 1). In comparison to the study performed by French et al. who classified wheelchair propulsion patterns and surfaces in three persons without disability, this study showed similar classification accuracies in classifying four different types of PAs in sixteen MWU with SCI [7]. The LOSO CV classification dramatically reduced to a moderate accuracy of 57% to 72% for all classifiers for reduced feature set indicating that it may be useful to use all the features for PA classification. The outcome also indicates that the reduced features extracted from the transverse, longitudinal and resultant axis may not be sufficient to discriminate PA.

Additionally, the higher classification accuracy for propulsion and arm-ergometry using SVM and KNN indicates that these classifiers used the variation in the acceleration data during PA involving upper extremity movements (Table 2). Misclassification of PA within sedentary and exercise related activities suggests that there might have been time periods when participants interjected a minor activity within a major activity. One possible approach to increase the classification accuracy and reduce misclassification would be to add an AM on the trunk of MWU or on the wheel of manual wheelchairs to can assist with differentiating PA.

In the next stage, the study will estimate the computation cost of feature extraction and activity classification for the above mentioned classifiers on the AM platform and develop activity specific regression equations to estimate PA levels and energy expenditure. Also evaluate unsupervised learning on the feature data to identify intervals of other activities performed by study participants.

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