Detection of Wheelchair User Activities Using Wearable Sensors

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Abstract. Wearable sensors are increasingly used to monitor and quantify physical activity types and levels in a real-life environment. In this project we studied the activity classification in manual wheelchair users using wearable sensors. Twenty-seven subjects performed a series of representative activities of daily living in a semi-structured setting with a wheelchair propulsion monitoring device (WPMD) attached to their upper limb and their wheelchair. The WPMD included a wheel rotation datalogger that collected wheelchair movements and an eWatch that collected tri-axial acceleration on the wrist. Features were extracted from the sensors and fed into four machine learning algorithms to classify the activities into three and four categories. The results indicated that these algorithms were able to classify these activities into three categories including self propulsion, external pushing, and sedentary activity with an accuracy of 89.4-91.9%.

Keywords: Activity monitors, wearable sensors, activity classification, wheelchair users, rehabilitation.

1 Introduction

Manual wheelchair users rely extensively on their upper limbs for mobility and activities of daily living. The long-term reliance on the upper limbs for performing daily activities has been associated with the prevalence of overuse-related musculoskeletal injuries and reports of pain [1-4]. The Consortium for Spinal Cord Medicine published a Clinical Practice Guideline on Preservation of Upper Extremity Function Following Spinal Cord Injury [5]. The Guideline recommends reducing the frequency of repetitive upper limb tasks, minimizing forces required to complete tasks, and minimizing extremes of wrist and shoulder motions [5]. However, such information is usually collected in laboratory or clinical settings. The functional amount of use and the repetitiveness of upper limb activities that occur on a daily basis in manual wheelchair users are unclear.

Recent advances in miniature sensor technology have led to the development of wearable devices that use acceleration, audio, video, and other sensors to recognize user activity in a free-living environment. While much has been published on

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developing instrumentation and recognition software to monitor activities in the ambulatory population [6-8], only a few studies have evaluated wearable devices in detecting activities among manual wheelchair users [9-15]. Washburn and Copay evaluated an accelerometry-based wearable device and found significant correlations ($r=0.52$-0.66, $p <0.01$) between the activity counts from the device worn on the wrist and the energy expenditure during wheelchair propulsion [9]. Warms et al. found low to moderate correlations ($r=0.30$-0.77, $p<0.01$) between the activity counts from an Actiwatch wrist-worn device and self-reported activity [10]. Tolerico et al. used a wheel rotation datalogger to collect gross mobility characteristics of manual wheelchair users in two real-life settings including the National Veterans Wheelchair Games (NVWGs) and the subjects' residential setting [11]. They found that manual wheelchair users travelled a distance of 6745.3±1937.9 meters per day at a speed of 1.0±0.2 meters/second in the NVWGs, and a distance of 2457.0±1195.7 meters per day at a speed of 0.8±0.2 meters/second when returning to their homes. However, it was not clear if the wheelchair movements were due to self-propulsion or being pushed by others. French et al. used a wrist worn tri-axial accelerometer called eWatch to classify wheelchair propulsion patterns and were able to achieve an accuracy of 60-90% in three subjects without any disability [12]. They were also able to classify self-propulsion and external pushing using one eWatch on the wrist and another eWatch on the frame of the wheelchair with an accuracy of 80-85%. Postma et al. used a wearable monitoring system containing six accelerometers to detect wheelchair propulsion from a mixed set of activities of daily living among 10 subjects with SCI [14]. The accelerometers were attached by medical tapes to each wrist, each thigh, and over the sternum and a data recorder connecting the six accelerometers was carried in a belt around the waist. The results indicated that wheelchair propulsion could be detected with an overall accuracy of 92%. A subsequent study by the same group of researchers showed that using this wearable monitoring system did not influence the amount of daily wheelchair propulsion [15]. Furthermore, subjects in the study reported burdens with wearing this wearable system.

This study combined the eWatch and the wheel rotation datalogger to form a wheelchair propulsion monitoring device (WPMD) to capture and categorize wheelchair related activities. A primary objective of this study was to evaluate the performance of the WPMD in detecting and classifying different types of activities performed by manual wheelchair users. Knowing the upper limb usage for wheelchair propulsion and other activities of daily living in real-life environments will contributes to our understanding of the etiology of upper limb injuries and pain among this population.

2 Method

2.1 Subjects

The Institutional Review Board at the University of Pittsburgh and the Department of Veteran Affairs (VA) Pittsburgh Healthcare System approved the study protocol before initiation. The study was conducted at the 29th National Veterans Wheelchair Games (NVWGs) held in Spokane, WA, USA in 2009. Subjects were recruited recruitment through a booth located at the NVWGs and flyers that were posted around the facilities during the event. Participants in the NVWGs who were interested in the study were informed of the study aim, protocol, and the eligibility criteria. Subjects were recruited based on the inclusion criteria that they were between 18 and 70 years of age, used a manual wheelchair as their primary means of mobility, and were able to provide written informed consent. Subjects were excluded if they were unable to tolerate performing activities for 2 hours, which was the estimated length of the study.

2.2 Experimental Protocol

Signed informed consent was obtained from all subjects before the start of data collection. Subjects were asked to complete a brief demographic survey. In addition, the WPMD consisting of a wheel rotation datalogger and an eWatch was attached to the subject's wheelchair and wrist. The wheel rotation datalogger was self-contained, lightweight, and can be easily attached to the spokes of a manual wheelchair with zip-ties. It was developed at the Human Engineering Research Laboratories (HERL), University of Pittsburgh to monitor mobility characteristics of manual wheelchair users in real-world environments. It measures the rotation of the wheelchair wheel through the use of three reed switches mounted 120 degrees apart on the back of the printed circuit board and a magnet mounted at the bottom of a pendulum [11]. The eWatch was developed at the Human Computer Interaction Institute, Carnegie Mellon University. The eWatch consists of a tri-axial accelerometer that can sense three-axes of acceleration at user controllable sampling rate. In this study, the eWatch was worn on the subject's dominant wrist and sampled at a frequency of 20Hz. The wheel rotation datalogger and the eWatch were synchronized by setting their clocks to the same reference.

Subjects followed an activity protocol to perform a variety of activities of daily living (ADLs). The ADLs included resting, propelling their wheelchair over different surfaces and terrains, being pushed by an investigator, typing on a computer, reading, doing laundry, folding clothes, preparing meals, and transferring between their wheelchair and a chair. The wheelchair propulsion trials included propelling on a low-profile carpet for a distance of 20 meters, and propelling eighteen trials up and down a ramp of 3.7 meters in length. The ramp was a wooden platform with fixtures to adjust the surface type, the slope angles, and cross slope angles to simulate various types of real-world terrains. Each subject were asked to perform eighteen trials along the ramp when it was configured to three types of surfaces (i.e., wood, blind guide, and Teflon drizzled with soapy water) at three different cross slope angles (i.e., 0°, 1°, and 2°) and two different slope angles (i.e., 0° and 5°). The three surfaces simulated the smooth, rough, and slippery road conditions. The wheelchair population trials and other ADLs were mixed in terms of the sequence. Subjects were asked to perform these activities in their own manner at their own pace. Subjects performed only those activities that they were able to perform. Two investigators followed the subjects throughout the protocol and used a stopwatch to annotate the start and finish times of each activity.

2.3 Data Collection and Analysis

The data from the wheel rotation datalogger and the eWatch were downloaded using their specific software, respectively. A custom MATLAB® (The Mathworks, Inc., USA) program was written to extract features based on the wheelchair velocity, and the tri-axial and resultant accelerations at the wrist. The extracted features include the mean, standard deviation, root mean square (RMS), mean absolute deviation (MAD), zero crossings (ZCR), mean crossings (MCR), fluctuations in amplitude, energy, and entropy. Features were calculated using the 50% overlapping sliding windows of 10 seconds. MATLABArsenal, which includes SVMLight and Weka softwares, was used to classify the activities based on the extracted features [16]. The annotated data were used as the reference. The activities were classified into three and four categories. The four categories included self-propulsion, external pushing, sedentary upper limb activity, and non-activity. The three categories included self-propulsion, external pushing, and sedentary activity which combined the sedentary upper limb activity and non-activity. The classifiers used were Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Naïve Bayes (NB), and Decision Tress (C4.5). The performance of each classifier was analyzed by a leave-one-subject-out (LOSO) cross-validation approach.

3 Results

A total of 27 subjects participated in the study. Due to device malfunction, two subjects had missing data and were not included in the data analysis. Data of 25 subjects including 19 males and 6 females with an average age of 49.4±10.5 years were analyzed in this study. Nineteen subjects had spinal cord injury with injury levels ranging from C4 to L5, three subjects had multiple sclerosis, and the remaining three subjects had lower extremity amputation. The average duration since the onset of disability in the subjects was 14.3±9.8 years.

All the subjects were able to complete the protocol. Table 1 shows the classification performance of four classifiers. In addition to using a full set of features based on the wheelchair velocity, and the tri-axial and resultant accelerations at the wrist, we also selected a reduced feature set using the Best First search method and Correlation-based Feature Selection (CFS) algorithm [17]. The CFS algorithm uses an evaluation heuristic that examines the usefulness of individual features along with the level of inter-correlation among the feature. The reduced feature set included the RMS and zero crossing in the x-axis acceleration, mean crossing in the y-axis acceleration, mean and mean crossing in the resultant acceleration, and mean velocity from the wheel rotation datalogger. All the classifiers were able to classify three categories of activities with higher accuracies than when classifying four categories. The performances of these classifiers were not significantly influenced by the reduced number of features.

Table 1. Performance of four classifiers based on the LOSO cross-validation (%)

Activity Category	All Features (45)				Reduced Features (6)			
	SVM	KNN	NB	C4.5	SVM	KNN	NB	C4.5
3	89.4	91.5	89.7	90.5	91.9	91.4	91.2	91.7
4	80.6	75.3	76.8	73.1	75.6	73.0	74.1	76.0

Table 2 shows the classification accuracy for each activity category (out of three activity categories) based on the LOSO cross validation on the reduced feature set. Table 3 shows the confusion matrix for the decision tree C4.5 classifier using the LOSO cross validation for the three activity categories on the reduced feature set. Table 4 shows the classification accuracy for each activity category (out of four activity categories) based on the LOSO cross validation on the reduced feature set. Table 5 shows the confusion matrix for the decision tree C4.5 classifier using the LOSO cross validation for the four activity categories on the reduced feature set.

Table 2. Classification accuracy for three activity categories (%)

Activity Category	SVM	KNN	NB	C4.5
Self-Propulsion	85.5	84.1	88.1	86.0
External Pushing	64.2	71.0	64.8	74.6
Sedentary activity	96.0	95.3	93.9	94.9

Table 3. Confusion matrix when using C4.5 classifier for three activity categories (%)

	Detected SP	Detected EP	Detected SA
Annotated Self-Propulsion (SP)	86.0	1.6	12.4
Annotated External Pushing (EP)	7.5	74.6	17.9
Annotated Sedentary Activity (SA)	4.7	0.5	94.9

Table 4. Classification accuracy for four activity categories (%)

Activity Category	SVM	KNN	NB	C4.5
Self-Propulsion	88.5	86.2	89.5	87.6
External Pushing	66.8	71.3	68.7	76.2
Sedentary activity	46.7	48.8	33.0	56.8
Non Activity	86.1	79.1	89.4	79.9

Table 5. Confusion matrix when using C4.5 classifier for four activity categories (%)

	Detected SP	Detected EP	Detected SA	Detected NA
Annotated Self-Propulsion (SP)	87.6	1.7	7.6	3.2
Annotated External Pushing (EP)	9.8	76.2	6.2	7.8
Annotated Sedentary activity (SA)	11.3	0.8	56.8	31.1
Annotated Non Activity (NA)	2.4	0.4	17.3	79.9

4 Discussions

All the classifiers were able to classify three activities i.e., self-propulsion, being pushed, and sedentary activity with an accuracy of about 90% or higher (Table 1).

The performance is similar to the results by Postma et al., who used six accelerometer based sensors to detect wheelchair propulsion versus non-propulsion [14] and achieved the accuracy of 87-92%. Compared to attaching six accelerometer based sensors to the thighs, wrists and the sternum, the WPMD has only two sensors with one being attached to the wheelchair wheel and one acting as a wrist watch. Our solution is more practical for capturing activities performed in real-life environments. However, the WPMD was unable to detect any motion in the lower extremities and the trunk. It may also miss detecting the upper limb motion if subjects used their non-dominant arm rather the dominant arm where the eWatch was attached. In terms of data preprocessing, the previous study disregarded the data if a task lasted less than five seconds while the current study used all the data from the testing without trimming off data.

The results of the decision tree C4.5 classifier (Table 2 and Table 4) for self propulsion and external pushing (74-86%) are similar to the study by French et al where three non-wheelchair users were tested with an eWatch on the wrist and another eWatch on the wheelchair frame, and the classification accuracy of self-propulsion and external pushing ranged from 80-85% [12]. From the confusion matrices (Table 3 and Table 4), self-propulsion and non-activity category were usually detected with good accuracy. This could be due to the very distinguishable features such as high resultant acceleration with wheelchair movement for self-propulsion and very low resultant acceleration without wheelchair movement for non-activity, respectively. Self-propulsion was occasionally confused with sedentary activities, which can be attributed to the transitions between activities and inaccuracies in hand annotation where the annotator incorrectly assigned the activity type. For example, doing laundry was assigned as a sedentary upper limb activity, but may require subjects to move their wheelchairs. In some cases the classifiers predicted external pushing as self-propulsion, which could be due to the upper limb movements by the subjects while being pushed in their wheelchair. The low classification accuracy of sedentary upper limb activity and non-activity (Table 4) could also be also due to inaccuracies in hand annotation. For example, dialing a phone was assigned to sedentary upper limb activity, but there were moments where subjects may not move their upper limbs and wheelchairs, and stayed in non-activity state. Nonetheless, the high LOSO cross-validation accuracy for the three activity categories by all the classifiers on the reduced feature set suggested that these classifiers can be used in real-world applications where activities in manual wheelchair users need to be classified.

One limitation of the study was to use hand annotation rather than video recording as the reference method. With self-propulsion episodes being accurately detected out of a series of activities of daily living, the next step is to investigate the relationship between upper limb acceleration and important biomechanical variables in wheelchair propulsion such as propulsion frequency and forces. Such wearable devices may help researchers and clinicians to quantify propulsion performance and upper limb usage, and monitor the effectiveness of interventions targeting to improve propulsion skills among manual wheelchair users.

5 Conclusions

In this paper, we discussed using a portable WPMD comprised of a wheel rotation datalogger and an eWatch to monitor wheelchair related activities in a semi-structured setting among 27 manual wheelchair users. We showed that common machine learning algorithms can be used to classify wheelchair related activities into self-propulsion, external pushing, and sedentary activity with an accuracy of around 90% or higher. The results suggest that it is feasible to use the WPMD to quantify self-propulsion and other ADLs in real life environments. The information on upper limb usage in manual wheelchair users will help understand the etiology of upper limb injuries and pain among this population.

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