# QUANTIFYING UPPER LIMB MOVEMENTS AMONG WHEELCHAIR USERS USING WHEELCHAIR PROPULSION MONITORING DEVICES

by

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Wheelchair users face the challenge of using their arms to mobilize their bodies instead of their legs—resulting in pain and injury. Development of tools to measure motions occurring during wheelchair propulsion presents the opportunity to study patterns and activities of wheelchair users to help prevent pain and injury. This study combined measurement tools including accelerometers and a wheel rotation data logger to collect data on activities performed by manual wheelchair users. Twenty-six participants with spinal cord injury completed lab visits of data collection. A model was created from lab data to classify data as propulsion, rest, activities of daily living (ADLs), or being pushed. The best percent accuracies of the classifying model for each activity are as follows: 84.5% for propulsion, 85.6% for rest, 84.6% for ADLs, and 79.9% for being pushed. When applied to data from a user's natural environment, this model can provide information on average time spent per day in each activity. With future work, the wheelchair propulsion monitoring devices of this study could quantify movement in manual wheelchair users' natural environments.

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## PREFACE

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# 1.0 INTRODUCTION

## 1.1 RATIONALE

Data from the National Spinal Cord Injury Statistical Center (2012) reports annual incidence of spinal cord injury (SCI) in the U.S. as approximately 12,000 new cases each year, excluding those who die at the scene of the accident.[1] These data report 270,000 persons with SCI in the U.S. in 2012.[1] Mobility aids, such as wheelchairs and scooters, are vital to persons with SCI. Of those U.S. residents with SCI using wheelchairs, 40.5% use manual wheelchairs.[1] Because the shoulder is not anatomically designed to propel the body through space like the hip is, people using manual wheelchairs frequently develop pain and injury. For manual wheelchair users, preventing upper extremity (UE) repetitive strain injuries is vital to maintain an independent life style. Studies on pain in manual wheelchair users found a 64-94% prevalence of UE pain.[2,3] Another study found 71% of respondents reported shoulder pain, 53% reported wrist pain, 43% reported hand pain, and 35% reported elbow pain. These pains were more likely associated with pressure reliefs, transfers, and wheelchair use than seven other functional activities.[4] Other studies of pathologies among people with SCI found 73% of participants had rotator cuff tears,[5] 72% had degenerative joint changes,[6] and 64% had carpal tunnel syndrome.[7,8]

For people with SCI to maintain quality of life, UE pain must be prevented because it limits mobility. UE pain among people with SCI who use manual wheelchairs is associated with overuse and incorrect use of their wheelchairs, as discussed in a Clinical Practice Guideline on the Preservation of Upper Limb Function Following Spinal Cord Injury.[9] Laboratory data on wheelchair propulsion have been used to study UE pain among people with SCI; however, data collected in a natural environment regarding activities of manual wheelchair users are lacking. The device used in this study can potentially collect such data.

This investigation identified whether a Wheelchair Propulsion Monitoring Device (WPMD) is able to determine specific UE motions of manual wheelchair users including propulsion, rest, being pushed, and Activities of Daily Living (ADLs). The WPMD includes 3-axis accelerometers (Shimmer Research™, Dublin, Ireland)[10] on the upper arm and underneath the seat and a wheel rotation data logger clipped to the wheel. The WPMD can be used in a natural environment of a manual wheelchair user to quantify and classify functional use of the UE; such information can be used to analyze quality of movement — a goal of both clinicians and researchers. Analyzing quality and quantity of movement are two important steps to understanding and addressing the pain and injury experienced by manual wheelchair users.

Overall, this study was a subsection of a larger study that aims to develop and validate accelerometry-based field measures for kinematic and kinetic performance of wheelchair propulsion in natural environments. To accomplish such goal, the larger study needs a device that can determine when manual wheelchair users are propelling their chairs in their home and community settings — the study of this thesis addresses this goal. A WPMD that can collect data to be classified as activities of manual wheelchair users can be used to examine propulsion parameters (stroke number, cadence, propulsion forces and moments) to provide insight on both quality and quantity of propulsion.

## 1.2 AIMS AND HYPOTHESES

This investigation used a WPMD, including two accelerometers and a wheel rotation data logger, to collect data from manual wheelchair users. Movement data on activities of manual wheelchair users obtained in the laboratory from this study were used to develop an activity classification model for classifying type of UE movements based on the WPMD.

Specific Aim 1: Develop a model based on WPMD data that estimates time spent on four types of UE movement including: independent wheelchair propulsion, being pushed, resting, and UE movement for ADLs.

Hypothesis 1a: The model will be able to estimate the time spent on the four activities to be within 10% difference from the criterion measure by video recording.

## 1.3 BACKGROUND AND SIGNIFICANCE

Activity classification with activity monitors has been well documented in ambulatory populations but is lacking in manual wheelchair user populations.[11-15] In fact, accelerometers have been used in a number of studies to measure a person's posture, gait, running style, severity of tremor in some conditions, physical activity, and energy expenditure.[16-21] Despite the extensive investigation into quantifying motion of the ambulatory population, limited research exists for the population of manual wheelchair users. The studies that do exist focus on gross wheelchair motion (distance and speed); whereas the study of this thesis went further to classify more specific activities of manual wheelchair users.

Sonenblum et al (2012) used a wheel rotation data logger that measured time and distance to quantify bouts of mobility in everyday life of manual wheelchair users. Sonenblum et al (2012a) quantified distance and time of aggregated wheeling, but did not classify activity of manual wheelchair users as this thesis's study did.[22] In a separate study, Sonenblum et al (2012b) used a wheel-mounted accelerometer to study manual wheelchair movement by measuring distance wheeled and determining if the wheelchair was moving.[23] As seen in these previous studies, wheel rotation data loggers only provide gross motion of a wheelchair and are not adequate to assess movement quality and distinguish activity type because it is unclear whether the user is propelling or being pushed. The wheel rotation data logger used in the study of this thesis has been used in many previous studies to quantify wheelchair traveling information including distance and speed[24] and to collect mobility characteristics of manual wheelchair users.[25-28]

Activity classification of manual wheelchair users is important for investigations of pain, injury, and propulsion interventions. Researchers need to quantify motion occurring during propulsion by first classifying different activities of manual wheelchair users and then quantifying time spent in each activity. Activities classified in this study include propulsion, rest, being pushed, and ADLs. To classify activities of manual wheelchair users, accelerometers were used in this study to provide more specific measure of UE motion (arm) and wheelchair motion (seat) in addition to gross wheelchair motion detected by the wheel rotation data logger.

While work with accelerometers to classify activities of manual wheelchair is limited, a few studies are mentioned here; however, these studies lack aspects that the study of this thesis addressed. French et al. (2008) found 80-90% accuracy for classifying propulsion patterns with dual-axis wrist accelerometers on participants' wrists and wheelchair frames; however, this study only included 3 able-bodied individuals, which is not an adequate amount to validate the algorithm.[29] A separate study by Postma et al (2005) also found accelerometers to be valid detectors of wheelchair propulsion. Postma et al achieved 92% accuracy of detecting wheelchair propulsion; however, the use of six ADXL202 piezo-resistive accelerometers on different body parts is not practical to real-life situations.[30] Additional classification of activity by manual wheelchair user was performed by Ding et al (2008) with a tri-axis wrist-mounted accelerometer and a wheel rotation data logger, resulting with accuracies of 89.4-91.9%.[24] Ding et al did not include a wide variety of manual wheelchair user activities to classify, especially in regards to ADLs which are daily components of manual wheelchair users' lives.

In conclusion, activity classification by quantifying motion of manual wheelchair users is lacking. This study used a WPMD, including a wheel rotation data logger in addition to arm and seat accelerometers, to measure gross wheelchair motion, specific UE motion, and specific wheelchair motion. Quantifying and classifying activity of manual wheelchair users with the WPMD will assist future investigations of pain and injury.

# 2.0 METHODS

## 2.1 INSTRUMENTATION

The WPMD includes three devices: a wheel rotation data logger attached to the wheelchair wheel, a 3-axis accelerometer worn on the dominant upper arm, and a 3-axis accelerometer attached underneath the wheelchair seat. The WPMD monitors wheelchair movement as well as upper limb movement.

The wheel rotation data logger was developed at the Human Engineering Research Laboratories to monitor mobility of manual wheelchair users in natural environments. The wheel rotation data logger is self-contained, approximately 5 cm in diameter, and 3.8 cm in depth. The wheel rotation data logger is powered by a 1/6D wafer-cell lithium battery, with the ability to collect and store data for more than 3 months. No wheelchair modifications were required because the wheel rotation data logger easily attaches to spokes of a wheelchair. The wheel rotation data logger measures rotation with three reed switches. Each switch is mounted 120° apart on the back of the printed circuit board. A magnet is mounted at the bottom of a pendulum which maintains position as a result of gravity. With wheel rotation exceeding 120°, one reed switches is triggered, resulting in a date and time stamp which is then processed to obtain distance traveled, speed, time of movement, and number of stops.[27]

The accelerometer is a low-power inertial sensor platform that uses an onboard 3-axis accelerometer to record motion data. The accelerometer is about 3cm in width, 5 cm in length, 1.5cm in depth, and about 60 gm. Accelerometers used in this study contain a single tri-axial accelerometer and a power source to collect and store data for up to four days. Accelerometers were attached to the participant's dominant upper arm and underneath the wheelchair seat with elastic straps. Upper arm and wheelchair seat accelerometers were configured at 20 and 60 Hz, respectively.

## 2.2 PROTOCOL

### 2.2.1 Participants

A sample of 26 participants completed the study. Participants were identified through use of IRB approved registries developed by the Human Engineering Research Laboratories (VA IRB# 0212005) and UPMC Department of Physical Medicine and Rehabilitation (Pitt IRB # 0304069). All participants in these registries have provided informed consent to be contacted for future research studies. Registry coordinators received an IRB approved flyer to distribute to participants according to procedures approved in their respective IRB protocols. In addition, participants were recruited via flyers posted in local rehabilitation facilities and outpatient facilities. Participants were included if they 1) were 18 years of age or greater; 2) use a manual wheelchair as a primary means of mobility (80% or more of their time spent moving); 3) have a Spinal Cord Injury. Participants were excluded if they were unable to tolerate sitting for 2 hours, and/or have upper limb pain limiting mobility.

### 2.2.2 Testing

The study was divided into two visits for reasons pertaining to the larger study of which this study was a subsection. The larger study needed participants to return to their home with the WPMD to collect natural environment data for an average of two days. Each visit took about 2.5 hours, and was conducted at the Human Engineering Research Laboratories.

During visit one, participants completed an informed consent document, a demographics survey, and the Wheelchair User's Shoulder Pain Index (WUSPI). After completing required paperwork, accelerometers were attached to each participant's dominant arm and underneath the wheelchair seat (see Figures 1 and 2). Figure 1 includes an additional wrist accelerometer that was used for other protocol from the larger study of which this study was a subsection. A wheel rotation data logger was attached to each participant's wheel on his or her dominant side. Sampling frequencies of these devices can be found in Table 1.

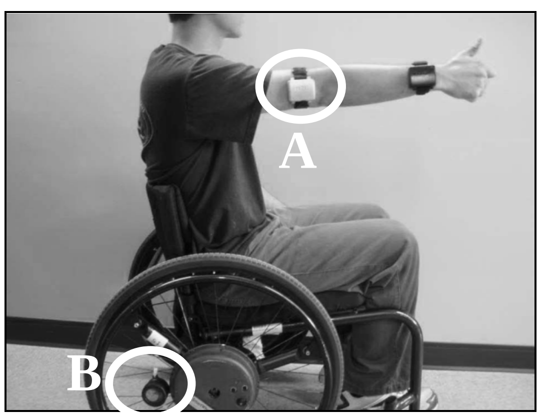


**Figure 1.** Arm(A) accelerometer and wheel rotation data logger (B)

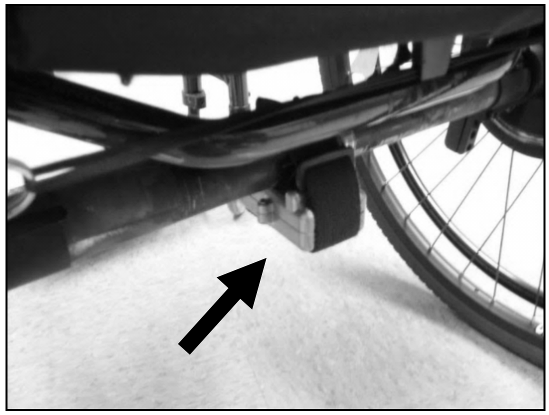

**Figure 2.** Seat accelerometer

**Table 1.** Devices' Sampling Frequencies

| **Device** | **Sampling Frequency** |
|---|---|
| Arm Accelerometer | 20Hz |
| Seat Accelerometer | 60Hz |

Participants then completed a propulsion course, an ADL course, and finished with the propulsion course again. The propulsion course contained a level surface (33 meters) and a 1:12 sloped surface (13 meters) and was completed at three different speeds: self-selected, slow (approximately 0.59m/s), and fast (approximately 1.75m/s). Slow and fast speeds were controlled by requiring participants to follow a power chair operated by an investigator. The ADL course was comprised of activities including: putting on and taking off a jacket, opening a door, doing laundry, and preparing a meal. This ADL course also had a portion in which the participant pushed and was pushed in his or her wheelchair along the propulsion course.

During visit two, participants were set up with same devices from lab visit one. Participants completed the propulsion course twice during this second visit with a rest period in between, during which participants watched an instructional video on propulsion for protocol of the larger study.

With completion of both visits, each participant propelled for a total of 24 level-surface trials at self-selected speed, low speed, and fast speed, and 12 sloped-surface trials at a self-selected speed. Additionally, each participant completed one ADL trial and was pushed for two level-surface trials and two sloped-surface trials.

## 2.3 DATA COLLECTION

Acceleration data collected were saved in the accelerometer's memory. All acceleration data were converted to g forces (m/s) using Shimmer software and were later processed using a MATLAB® algorithm. Data collected from the wheel rotation data logger were saved and converted using data logger software. These data were later processed with a MATLAB® algorithm to obtain distance and speed. Accelerometers and the wheel rotation data logger were synchronized based from a central computer time.

Videos from laboratory trials were used as a reference for data analysis. Participants' movements were labeled as 1 of 13 activities based from video (see Table 2, Activity Labels). Two research assistants labeled activities based from video to double check for errors. Incomplete rest differed from complete rest by including movements of participants in which they were stationary in their chairs but had slight upper extremity motion. Examples of incomplete rest include when participants adjusted clothing and when participants used hands for gestures during normal conversation.

**Table 2.** Activity Labels

| Activity | Re-assignment |
|---|---|
| Level Propulsion | Propulsion |
| Up-Slope Propulsion | Propulsion |
| Down-Slope Propulsion | Propulsion |
| Being pushed on a level surface | Being Pushed |
| Being pushed up a slope | Being Pushed |
| Being pushed down a slope | Being Pushed |
| Turn | Propulsion |
| Complete Rest | Rest |
| Incomplete Rest | Rest |
| Dressing | ADL |
| Meal Preparation | ADL |
| Opening a door | ADL |
| Doing Laundry | ADL |

Start times of WPMD (accelerometers and wheel rotation data logger) for each visit were plotted and visually synchronized so data could be analyzed and compared. Figure 3 shows an example of synchronized data. Next a research assistant used a MATLAB® (Version 7.11.0 R2010b, The Mathworks, Inc. USA) algorithm to label data with corresponding activities from video recording of each visit. The algorithm segmented data into windows with 50% overlap, then each window was assigned the majority activity. The algorithm then re-assigned activities into 1 of 4 groups: self-propulsion, being pushed, rest, and ADLs (See Table 2 for re-assignment classifications). Statistical features calculated for each window include: mean, standard deviation, root mean square, mean absolute deviation, zero crossing, mean crossing, magnitude, energy, entropy and correlation to resultant. These features were calculated for x, y, z and resultant axis from accelerometers and for velocity from the wheel rotation data logger. Different size windows were used to see the effect number of samples had on model accuracy; five, 10, and 30 second windows were used. Different window sizes produced different numbers of sample data to create the model with; the larger the window the fewer samples. Five second windows produced 32,944 samples, 10 second windows produced 15,851 samples, and 30 second windows produced 5,338 samples. In addition to creating the model with different window sizes, the model was also created both with and without seat accelerometer data to see the effect on accuracy.

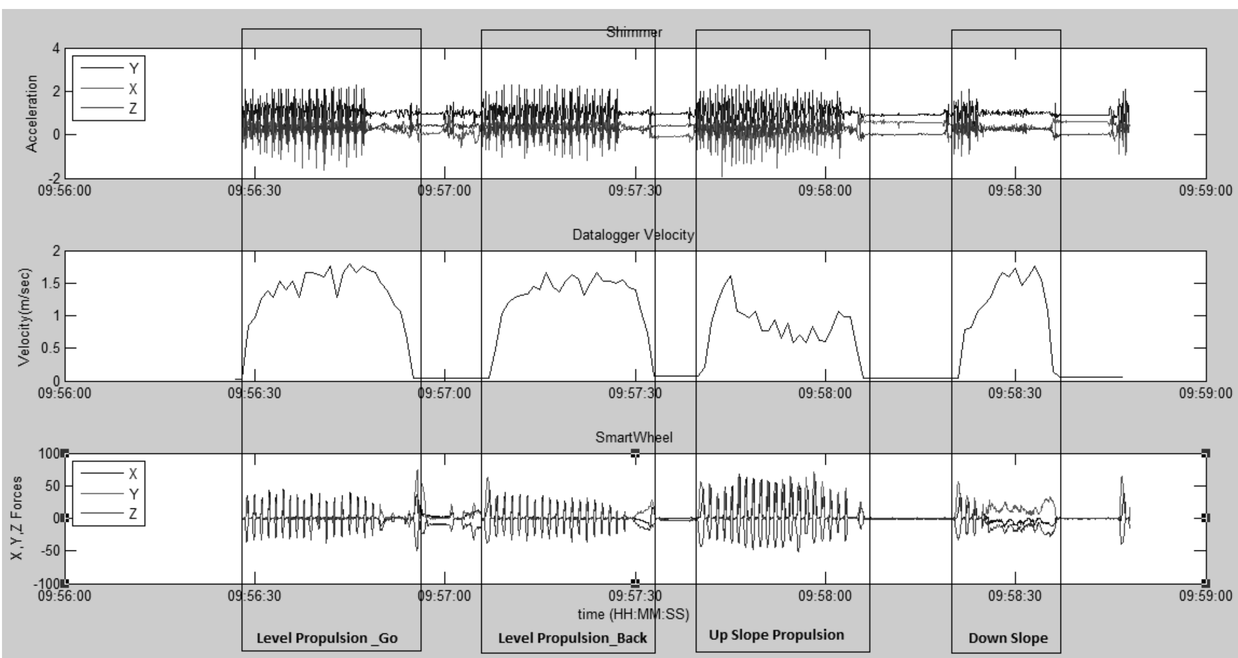


**Figure 3.** Plot Synchronization

# 3.0 DATA ANALYSIS

Features calculated for data labeled as 1 of 4 activities were organized into matrices and fed into WEKA (Waikato Environment for Knowledge Analysis version 3.6.4 1999-2010) to develop a classifying model using a decision tree method (Random Forest) with 10-fold cross validation. WEKA is a program that uses machine-learning algorithms to classify a data set. The data from the WPMD were organized as described in the data collection section, and then WEKA created a model based off of this data to classify future WPMD data as self-propulsion, being pushed, rest or ADLs based on labels of data collected from lab visits. WEKA uses algorithms to classify data based on variables provided. The 10-fold cross validation used to create the classifying model split the data into 10 sections, then used nine sections to create a model and the tenth section to determine the accuracy of the model. Each of the 10 sections was used once to validate the model; percent accuracies presented in this paper are averages of the 10 accuracies obtained for each validation run. An attribute selection option in WEKA was used to eliminate highly correlated variables from features matrices. Different selections of variables were used to see the effect on percent accuracy. See Table 3 for different combinations of variables used to create the model.

**Table 3.** Attribute Selection

| |
|---|
| Arm Accelerometer and Data Logger |
| 12 Variables |
| Mean (x axis, arm accelerometer– g) |
| Mean absolute deviation (x axis, arm accelerometer– g) |
| Correlation (x axis, arm accelerometer– g) |
| Correlation (y axis, arm accelerometer– g) |
| Mean absolute deviation (z axis, arm accelerometer– g) |
| Standard deviation (xyz axis, arm accelerometer– g) |
| Mean absolute deviation (xyz axis, arm accelerometer– g) |
| Mean crossing (xyz axis, arm accelerometer– g) |
| Entropy (xyz axis, arm accelerometer– g) |
| Mean (velocity– m/s) |
| Root mean squared (velocity– m/s) |
| Mean absolute deviation (velocity– m/s) |
| 10 Variables |
| Exclude mean crossing and entropy for all data |
| 7 Variables |
| Exclude mean crossing and entropy for all data<br>Exclude root mean squared and mean absolute deviation for velocity |
| Arm Accelerometer, Seat Accelerometer, and Data Logger |
| 16 Variables |
| Mean (x axis, arm accelerometer– g) |
| Correlation (x axis, arm accelerometer– g) |
| Correlation (y axis, arm accelerometer– g) |
| Mean absolute deviation (z axis, arm accelerometer– g) |
| Standard deviation (xyz axis, arm accelerometer– g) |
| Mean absolute deviation (xyz axis, arm accelerometer– g) |
| Mean crossing (xyz axis, arm accelerometer– g) |
| Entropy (xyz axis, arm accelerometer– g) |
| Mean (x axis, seat accelerometer– g) |
| Mean absolute deviation (x axis, seat accelerometer– g) |
| Mean absolute deviation (z axis, seat accelerometer– g) |
| Mean absolute deviation (xyz axis, seat accelerometer– g) |
| Entropy (xyz axis, seat accelerometer– g) |
| Mean (velocity– m/s) |
| Root mean squared (velocity– m/s) |
| Mean absolute deviation (velocity– m/s) |
| 13 Variables |
| Exclude mean crossing and entropy for all data |
| 12 Variables |
| Exclude mean crossing and entropy for all data<br>Exclude root mean squared and mean absolute deviation for velocity |

Random Forest is a decision tree machine learning algorithm requiring data that can be described by features. To predict class label, this algorithm uses a logical set of decisions summarized by a tree. A small tree with low error achieves effectiveness. A decision tree algorithm was used because relationships between collected data and corresponding labels are nonlinear and have complex relationships since the labels were based on activity that was unique to each participant.[32] Other studies investigating activity recognition also used a decision tree algorithm because of its balance between accuracy and complexity.[33-35] Additional studies investigating wheelchair activity cite use of Random Forest, further supporting this study's use of the algorithm for activity classification.[24, 36]

# 4.0 RESULTS

## 4.1 PARTICIPANTS

Twenty-six participants including six females and 20 males with SCI and an average age of 40±14 years were tested. Participants have been using a manual wheelchair 12.62±8.11 years and all participants use their wheelchairs over six hours a day. More details regarding demographic information of participants can be found in Table 4. No participants experienced adverse events from participation in this study. The participants in this study reported average pain levels of 5.13 based on the WUSPI (0 being no pain, 150 being extreme pain).

**Table 4.** Participants' Demographics

| Characteristic | |
|---|---|
| Male gender – no. (%) | 20 (77) |
| Age – yr. | 40±14 |
| Weight – lb. | 159.12±40.71 |
| Ethnic Origin – no. (%) | |
| *Caucasian* | 20 (77) |
| *African-American* | 4 (15) |
| *Asian-American* | 2 (8) |
| SCI Level – no. (%) | |
| *Cervical* | 6 (23) |
| *Thoracic* | 15 (58) |
| *Thoracic – Lumbar* | 2 (8) |
| *Lumbar* | 2 (8) |
| *Cauda Equina* | 1 (4) |
| Wheelchair Type – no. (%) | |
| *Depot* | 8 (31) |
| *Light Weight* | 7 (27) |
| *Ultra-Light* | 10 (38) |
| *Power Assist* | 1 (4) |
| Years spent using wheelchair | 12.62±8.11 |

## 4.2 DATA

Table 5 compares percent accuracies for different window lengths, different variables, and different device combinations. For the 26 participants, the classifying model based on Random Forest Tree Decision algorithm had best percent accuracy using 16 variables of data from arm accelerometer, seat accelerometer, and wheel rotation data logger split into 10 second windows. Figure 4 is a confusion matrix of this model, illustrating how the model classified and misclassified windows of recorded data.

**Table 5.** Percent Accuracy

| Arm Accelerometer and Data Logger | | | |
|---|---|---|---|
| 12 Variables | | | |
| | **5 second window** | **10 second window** | **30 second window** |
| ADL | 78.8% | 81.0% | 65.8% |
| Being Pushed | 74.4% | 71.9% | 78.4% |
| Propulsion | 79.6% | 81.2% | 83.3% |
| Rest | 80.3% | 80.2% | 76.9% |
| 10 Variables | | | |
| ADL | 77.5% | 80.0% | 65.8% |
| Being Pushed | 71.6% | 71.8% | 78.0% |
| Propulsion | 79.5% | 80.8% | 81.9% |
| Rest | 80.1% | 80.2% | 76.9% |
| 7 Variables | | | |
| ADL | 73.5% | 78.9% | 66.0% |
| Being Pushed | 69.2% | 68.4% | 77.2% |
| Propulsion | 79.2% | 80.5% | 81.6% |
| Rest | 78.5% | 79.7% | 76.3% |
| Arm Accelerometer, Seat Accelerometer, and Data Logger | | | |
| 16 Variables | | | |
| | **5 second window** | **10 second window** | **30 second window** |
| ADL | 85.1% | 84.6% | 75.4% |
| Being Pushed | 80.0% | 79.9% | 80.1% |
| Propulsion | 83.9% | 84.5% | 87.3% |
| Rest | 85.3% | 85.6% | 82.8% |
| 13 Variables | | | |
| ADL | 84.0% | 84.3% | 73.4% |
| Being Pushed | 79.0% | 78.7% | 80.0% |
| Propulsion | 83.4% | 84.2% | 86.9% |
| Rest | 85.2% | 85.5% | 83.0% |
| 12 Variables | | | |
| ADL | 81.4% | 83.7% | 75.3% |
| Being Pushed | 81.6% | 78.2% | 79.3% |
| Propulsion | 83.7% | 83.8% | 84.8% |
| Rest | 84.8% | 84.6% | 81.0% |

| Predicted Activity based on Model | | | | | |
|---|---|---|---|---|---|
| ADL | Being pushed | Propulsion | Rest | | |
| 2160 | 4 | 105 | 254 | ADL | Criterion measure based on video |
| 13 | 428 | 81 | 79 | Being Pushed | |
| 157 | 50 | 5206 | 620 | Propulsion | |
| 222 | 54 | 769 | 5649 | Rest | |

**Figure 4.** Confusion Matrix

The total time participants spent in the four activities during lab visits was totaled based on the video recording. The model then quantified the time spent in the four activities for each participant. The percent error for total times are as follows: 2.3% error for time propelling, 0% error for time resting, 6.5% error for time performing ADLs, and 18.1% error for time being pushed. See Table 6 for average total times spent in each activity.

**Table 6.** Total Time Comparison: Model vs. Video

| | Average time participants spent in each activity during lab visits | | | |
|---|---|---|---|---|
| | Video | Model | Difference | Percent Error |
| Propulsion | 00:21:00 | 00:20:32 | 00:00:28 | 2.3% |
| Being Pushed | 00:02:11 | 00:01:47 | 00:00:24 | 18.1% |
| ADL | 00:09:06 | 00:08:30 | 00:00:36 | 6.5% |
| Rest | 00:22:00 | 00:22:00 | 00:00:00 | 0.0% |

# 5.0 DISCUSSION

Previous studies have attempted to use activity monitors to detect gross mobility levels in terms of traveling distance, speed,[37-40] and wheelchair propulsion episodes.[41] Performance accuracy results obtained in the decision tree Random Forest classifier for self-propulsion and external pushing of 84.5% and 79.9% respectively are similar to results by Ding et al (2008) with average accuracies of 88% and 71 % respectively.[24] The study presented in this thesis included a more extensive span of activities to collect data on (specifically ADLs) than Ding et al (2008). Another study on wheelchair activity classification, by Postma et al (2005), achieved accuracies of 87-92% for detecting wheelchair propulsion versus non-propulsion, as compared to this study's accuracies of 84.5% for propulsion and 85.6% for rest.[30] The study presented in this thesis had more participants than Postma et al (2005), expanding variety of data used to create the classifying model. French et al (2008) recognized propulsion patterns over a variety of surfaces with a wrist mounted accelerometer and found accuracies of 80-90%.[29] Unlike the study presented in this thesis, French et al (2008) did not classify activities of wheelchair users outside of propulsion. French et al. (2008) did another study on propulsion patterns with a virtual coach to classify self-propulsion and external pushing resulting with average accuracies of 80%.[36] This thesis's study had different devices than these other studies discussed above, including a seat accelerometer. As seen in Table 5, the percent accuracy of the classifying model improves with the use of data from the seat accelerometer. Although this study did not investigate transfers, the inclusion of the seat accelerometer in the WPMD provides the opportunity for future work to classify transfers as an activity. Additional protocol for the larger study required multiple visits which expanded the amount of data obtained to create the classifying model. Multiple visits also increased variety of data by including data from different days.

Figure 4, a confusion matrix, illustrates how some lab data are misclassified. The classifying model predicted some data to be rest when the criterion measure was ADL. Rest and ADL activities both involve little chair motion; this is a possible source of misclassification. Additionally, when labeling activities based from video criterion, all movements occurring during ADLs were labeled as ADLs. For instance, if the subject took a rest between getting cooking materials and preparing a meal, it was still classified as ADL. Other errors of classification may stem from confusion due to data from downhill propulsion. Data from downhill propulsion were labeled as propulsion, despite the dramatic difference in upper extremity motion from uphill or level propulsion. This combination of wheel rotation and little upper extremity motion may contribute to model's incorrect classification of propulsion data as being pushed. Further error of the model may be related to the little data collected while participants were being pushed. As seen by Table 6, participants only spent an average of two minutes and 11 seconds being pushed. Future work should focus on more specific labeling of activities to improve classification accuracy.

This model can be important to researchers for data collection and to clinicians for analysis of motion in users' natural environments. First, the WPMD in the study successfully collected data on activities of manual wheelchair users in a laboratory. Quantifying data on such activities can help researchers study etiology of pain and injury and propulsion patterns. The pain levels of the participants in this study need to be considered when applying data from a different population. The model was not created based on data from participants with severe pain, and thus it may need modification before being generalized to this population. As previously discussed, overuse of manual wheelchairs is associated with pain and injury for users, but not a lot of data exists to define overuse. The WPMD can quantify data on propulsion to help make this definition. More importantly, the WPMD can be used in a user's natural environment. If a WPMD is used in clients' natural environments and their data are applied to this model, clinicians can produce an estimate for quantity of time spent in activities. This information is useful for implementing and monitoring any therapeutic home-programs in addition to defining overuse. Quantifying wheelchair use can also aid clinicians in justifying wheelchair choices. For example, a clinician can use a WPMD to prove whether a client propels more using a light weight manual wheelchair than using a standard chair. Quantified activity in a client's natural environment has potential to impact insurance policies, such as those restricting wheelchair upgrades and renewals.

A WPMD can also potentially evaluate quality of UE motions for propulsion and other ADLs. Such information could help healthcare professionals reduce UE pain experienced by people with SCI using manual wheelchairs. A Clinical Practice Guideline on the Preservation of Upper Limb Function Following Spinal Cord Injury mentions the importance of reducing frequency of repetitive upper limb tasks.[9] This study could result in a potential tool to monitor activity of manual wheelchair users and contribute to preservation of upper limb functions. If WPMD data in this study are found to be correlated with biomechanical data of wheelchair propulsion, the WPMD will become an integral tool for researchers to examine UE motions of wheelchair users in their natural environments. Once again, this will help with understanding etiology of UE pain and injury in this population.

As previously discussed, the study of this thesis is part of a larger study. By validating WPMD collection and classification of data on activities of manual wheelchair users, this study will assist the larger study in evaluating and quantifying activities in a natural environment. Additionally, another aspect of the larger study examined usefulness of a WPMD to count stroke number, which can help users adjust propulsion patterns to preserve upper limb function. Future work should focus on increasing classification accuracy of the model; more data could be collected from more participants to build a larger base for the model to use to make decisions.

# 6.0 CONCLUSION

This study has shown, when used together, accelerometers and a wheel rotation data logger can detect activities of wheelchair users including propulsion, being pushed, rest, and ADLs. Collecting data on these activities from 26 participants with spinal cord injury has added to the pool of information regarding manual wheelchair propulsion and has created a model to classify activities based off data. Data collected in manual wheelchair users' natural environments with accelerometers and wheel rotation data logger can be applied to the model created in this study to quantify and classify activity. The model has percent accuracies for classifying each activity as follows: 84.8% for propulsion, 85.8% for rest, 84.9% for ADLs, and 79.7% for being pushed.

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