TOWARDS MONITORING WHEELCHAIR PROPULSION IN NATURAL ENVIRONMENT USING WEARABLE SENSORS

by

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Due to lower limb paralysis, individuals with spinal cord injury (SCI) rely on their upper limbs for activities of daily living (ADLs) and wheelchair propulsion (WP). Previous research has found that specific biomechanical parameters of WP are associated with risk of UE pain and injury. However, the repetitiveness and quality of upper limb movements during WP are unclear. Recently, wearable sensors have been used to collect mobility characteristics of wheelchair users, but little research has looked into using them to monitor the quality of UE movements for WP in the natural environment. The purpose of this thesis was to develop and evaluate a WP monitoring device that can monitor wheelchair users' activities, and propulsion parameters in the natural environment.

This thesis is organized into three studies. The first study aims to develop activity classifiers that can distinguish WP episodes from a range of ADLs. Two classifying models were built using a Machine Learning (ML) technique. The model that yielded the highest accuracy showed an overall accuracy of 88.0%. Time spent on each activity was estimated based on the classifiers, and compared with the video observation. Percentage of difference between the criterion and estimated time ranged from 2.2% to 11.6%.

The second study aims to estimate temporal parameters of WP, including the stroke number (SN) and push frequency (PF), using wearable sensors. The estimated SN and PF were compared with the criterion measures using the mean absolute errors (MAE) and mean absolute

percentage of error (MAPE). Intraclass Correlation Coefficients were calculated to assess the agreement. The accelerometer placed on the upper arm yielded the highest accuracy with the MAPE of 8.0% for SN and 12.9% for PF.

The third study aims to estimate wheelchair propulsion forces. Propulsion forces were estimated from the accelerometer placed on the upper arm using a bagging regression technique. The estimated forces were compared with the criterion. Mean absolute errors (MAE), mean absolute percentage of error (MAPE), were calculated. The results showed an overall MAPE of 17.9%. Intraclass Correlation Coefficients and Bland-Altman plots were used to assess the agreement between the criterion and the estimated force.

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PREFACE

I would like to express my gratitude to the faculty and staff at University of Pittsburgh and those who have made this study a success. I would especially like to thank my academic advisor, Dr. Ding, for her support, mentoring and disposition at all times. I would also like to extend my appreciation to my committee members Dr. Cooper and Dr. Koontz for providing me with their assistance and time while serving on my thesis committee. I would like to thank all the students and staff at HERL especially Ray, Annemarie, and Stacy, for their valuable contribution to this work. Also I will like to thank the students who were part of this project: Sasa, Vijeta, and Lindsey who devoted their time to the study and helped me improve my mentoring skills. I would like to acknowledge that this research was supported by RERC SCI Research Center (#H133E070024). Last but not least, I would also like to thank my family that is my greatest inspiration and my source of energy. My dad for his strength and support at all time, my mom who is always cheering me up from heaven, my sisters: Lupita, Anita and Cecy for always being there whenever I needed them and Elmer for all his love, support and patience.

1.0 INTRODUCTION

Individuals with spinal cord injury (SCI) rely extensively on their upper limbs for activities of daily living (ADLs) [1]. Wheelchair propulsion is one of the major ADLs for 40.5% of individuals with SCI [2]. The upper limbs were not anatomically designed to perform such demanding activities. Therefore, upper extremity (UE) pain and injury is a common problem among manual wheelchair users (MWUs) with SCI [3-11]. According to previous studies UE pain may have very negative impact in the lifestyle of MWUS decreasing their independence and quality of life [9, 12-14]. Previous research has found that specific biomechanical parameters of wheelchair propulsion such as push frequency, magnitude of force, and pattern of the hand during the no propulsive part of the stroke to be associated with risk of UE pain and injury [15]. However, the repetitiveness and quality of upper limb movements for wheelchair propulsion that occur on a daily basis in the natural environment are unclear. This could be due to the lack of convenient monitoring devices that could be used in the community.

Most recently, wearable sensors have been increasingly used in monitoring ambulation, posture, and other ADLs among the able-bodied populations [16-19]. Wearable sensors have also been used to collect mobility characteristics of wheelchair users such as distance and speed travelled or to estimate physical activity related energy expenditure of MWUs [20-22]. Wearable technology can help to monitor MWUs activity and biomechanical parameters in their natural environment. This knowledge could help clinicians and researchers to better understand the etiology of upper extremity (UE) pain and injury. Furthermore, it could provide users valuable feedback on their propulsion performance. However, little research has looked into using wearable sensors to monitor the quality of upper limb movements for wheelchair propulsion in the natural environment.

This thesis presents an analysis on the performance of wearable sensors, (tri-axis accelerometers and a wheel rotation monitor (WRM) in monitoring the quality of upper limb movements for wheelchair propulsion. The overall goal is to develop a tool to monitor actual upper extremity usage in natural environments. This thesis consists of an introduction three studies and a conclusion. The first study evaluated the performance of three wearable sensors, (two-tri-axis accelerometers, and a wheel rotation monitor (WRM)) in detecting manual wheelchair users' activities. A Random Forest (RF) technique was used to build a classification model, which was able to discriminate between four wheelchair users' activities including: self-propulsion, being pushed, functional arm movement and rest. Results in this study may lead to further analysis on propulsion biomechanics such as stroke number, push frequency, and forces. This analysis was conducted in the second and third studies. The second study evaluated the performance of four wearable sensors, (two-tri-axis accelerometers, and a wheel rotation monitor (WRM)) in counting the number of strokes and push frequency. An algorithm was developed to count the number of strokes and calculate the push frequency. The arm accelerometer showed the lowest error between the estimated and the criterion stroke number and push frequency. Knowing that the arm accelerometer had the better performance in counting the number of strokes, the third study evaluated the performance of an accelerometer placed on the arm and a WRM attached to the wheelchair in predicting the forces during propulsion. A regression model based on a bagging technique was developed to estimate the wheelchair propulsion forces. Finally, the conclusion summarizes the findings of the three studies, their clinical applications and future work.

2.0 WHEELCHAIR ACTIVITY CLASSIFICATION USING WEARABLE SENSORS

2.1 INTRODUCTION

Due to lower limb paralysis, people with Spinal Cord Injury (SCI) rely extensively on their upper extremities for mobility and independence [1]. Therefore, it is not surprising that the incidence of UE pain among manual wheelchair users (MWUs) is high ranging from 49% to 78% [3-11]. UE pain and injury can have a severe impact in the lifestyle of manual wheelchair users, decreasing their functional abilities, independence, and quality of life [9, 12-14].

Monitoring daily activities performed by MWUs might contribute to understand the etiology of upper extremity pain and injury, and could also help to promote a healthy lifestyle among manual wheelchair users. Detection of wheelchair propulsion episodes may allow further analysis of upper limb repetitiveness for wheelchair propulsion such as stroke number, push frequency, and forces. Furthermore, monitoring the general activity level of MWUs may help develop targeted interventions that reduce sedentary lifestyle in this population, as well as understand the relation between physical activity patterns and secondary conditions such as coronary heart disease, diabetes, an overweight [23].

The use of wearable devices to monitor everyday activities has been widely studied in the ambulatory population [16, 18, 19, 24]. Studies have shown that wearable devices can be used to assess able-bodied individual's posture, gait, physical activity, as well as energy expenditure in the free-living environment [16-19]. However, only a limited number of studies have evaluated the use of wearable devices in detecting everyday activities among MWUs. Most of these studies have focused on monitoring gross mobility of wheelchair users by attaching a device to their wheelchairs [20-22]. A study conducted by Oyster et al. used a customized data-logging device to quantify wheelchair mobility and to assess the relationship between mobility and demographics, type wheelchair, and participation. A total of 132 persons with a spinal cord injury (SCI) were asked to use a customized data-logging device for 2 weeks. Distance traveled, average speed and average amount of time in the wheelchair were collected. Results showed that age was significantly related to average speed traveled per day. Whites were found to travel significantly further and accumulate more minutes per day compared with minorities. Participants who were employed traveled significantly further and for more minutes per day compared with those who were not employed. Findings indicate the efficacy of a customized data-logging device to track wheelchair mobility in community settings [25]. A study conducted by Sonenblum et al used a wheel-mounted bi-axial accelerometer to measure wheelchair movements, they found that the device was able to detect wheelchair movement with an accuracy 90% [26]. Although wheelchair movements are indicative of UE activities of manual wheelchair users, they cannot tell the exact amount of UE movements. A study conducted by Postman et al. used six accelerometers placed around the wrists, thighs, and along the sternum to detect wheelchair propulsion from a range of activities of daily living (ADL) among 10 manual wheelchair users. Results showed that the accelerometers were able to recognize wheelchair propulsion episodes with an overall accuracy of 92% [27]. Ambur et al. explored the use of a wrist-worn accelerometry-based device to classify four wheelchair propulsion patterns. The average classification accuracy was in the range of 60-90% depending on the surface type [28]. French et al. further expanded this work to classify wheelchair propulsion patterns, self–propulsion vs. external pushing, and surface type when three able-bodied individuals were tested in a laboratory setting. Results showed that the classifiers constructed were able to classify the three contexts with accuracies of up to 80-90% [29]. A study conducted by Ding et al. evaluated the performance of a tri-axis accelerometer placed on the dominant wrist and a wheelchair rotation monitor to classify wheelchair related activities among 27 wheelchair users. The results indicated that the two devices were able to classify the activities into three categories including self-propulsion, external pushing, and sedentary activities with an accuracy of 89.4-91.9% [30].

In this project, we aimed to assess the location and number of devices required for classifying wheelchair related activities in the free-living environment of wheelchair users using a Random Forest (RF) classification algorithm. Three devices were considered in this study including an accelerometer placed on the dominant upper arm, a wheel rotation monitor clipped to the wheel, and an accelerometer attached beneath the seat. The ability to detect and classify daily activities of MWUs such as wheelchair propulsion may allow to perform further analysis on propulsion biomechanics such as stroke number, push frequency, and forces. This knowledge might contribute to understand the etiology of UE pain and injury, and could also help to promote a healthy lifestyle among manual wheelchair users.

2.2 METHODS

2.2.1 Study Participants

The Institutional Review Board at the University of Pittsburgh approved this study. A total of 26 manual wheelchair users with SCI volunteered and provided informed consent prior to their participation in the study. Subjects were identified through the IRB approved wheelchair user registries developed by the Human Engineering Research Laboratories (HERL) and the Department of Physical Medicine and Rehabilitation at the University of Pittsburgh. In addition, participants were recruited via flyers posted in local rehabilitation facilities and outpatient facilities. Subjects were included in the study if they 1) were 18 years of age or greater; 2) use a manual wheelchair as a primary means of mobility; 3) have a Spinal Cord Injury. Subjects were excluded if they were unable to tolerate sitting for 2 hours, and/or have upper limb pain that limits their mobility.

2.2.2 Instrumentation

Subjects were fitted with three monitoring devices as shown in Figure 1. The three monitoring devices included a custom wheel rotation monitor (WRM) attached to the wheelchair wheel and two off-the-shelf tri-axis accelerometers (Shimmer Research, Dublin) worn on the dominant upper arm, and underneath the wheelchair seat, respectively.

- The wheel rotation monitor (WRM) was developed at the HERL. It is a lightweight and self-contained device that can be easily attached to the wheelchair's wheel without any modifications to the wheelchair. It tracks the wheel rotation through three reed switches mounted 120° apart on the back of the printed circuit board and a magnet mounted at the bottom of a pendulum. As the wheel rotates and exceeds 120° of rotation, one of the reed switches is triggered, and date and time stamps are recorded. This information can be further processed to obtain the distance, speed, and time of movement [31]. The WRM has been used in previous studies to collect mobility characteristics of manual wheelchair users with different diagnoses [32-34].

- The tri-axis accelerometer (Shimmer Research, Dublin, Ireland) used in this study is a small low-power device that can record the motion data into a micro SD card. The upper arm accelerometer was sampled at 20Hz. and the accelerometer underneath the seat was sampled at 60 Hz.

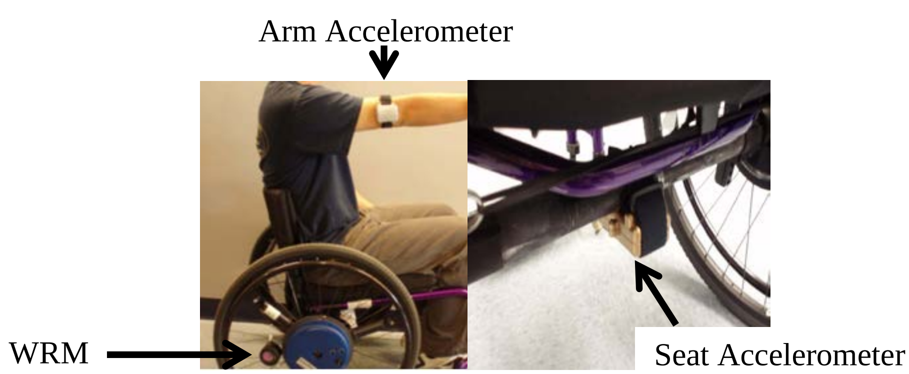

Figure 1**:** Instrumentation Setup

2.2.3 Experimental Protocol

Subjects were asked to pay two visits to HERL, each visit lasting about 2.5 hours. During the first visit, subjects completed a demographics survey. After subjects were fitted with the instrumentation described in the previous section, they were asked to propel their wheelchairs on two surfaces including a level surface of 33 meters and a sloped surface of 15 meters with a 3 degree incline. Participants propelled their wheelchairs on the level surface twice at three different speeds: self-selected, fast paced (approximately 1.75 m/s), and slow paced (approximately 0.59 m/s). The fast and slow paced speeds were regulated by asking the subjects to follow a power wheelchair with the preset speeds. Participants also propelled their wheelchairs up the sloped surface at a self-selected speed. After completing the propulsion trials participants were asked to complete a series of representative activities of daily living (ADLs): self-propulsion at a chosen pace on level and up slope surface, being pushed by someone else on level and up slope surface, and to simulate a series of daily activities, such as doing laundry, cooking, dressing, open doors. During the second visit, participants were asked to perform only the propulsion trials as detailed for the first visit. The purpose of the second visit was to collect additional propulsion information in order to have more data to build the model. All trials were videotaped using a hand-held digital video recorder.

2.2.4 Data Collection and Analysis

Videos recorded during the laboratory visits were used to label the different activities performed by the participants and served as a criterion measure for the classifying model. Two investigators watched and labeled the activities independently. Videos were re-examined when there was discrepancy. Labeled activities were then grouped into 4 categories including self-propulsion on level or sloped surfaces, being pushed on level or sloped surfaces, Functional Arm Movement (FAM) such as doing laundry, preparing food, dressing, opening doors, using a dishwasher, drinking water, cleaning hands, eating, opening drawers, and picking up things from the floor, and resting.

The wheelchair velocity data obtained from the wheel rotation monitor (WRM) and the tri-axial and resultant acceleration from the upper arm, and underneath the seat accelerometers were collected from both visits. A custom MATLAB® (Version 7.11.0 R2010b, The Mathworks, Inc. USA) program was written to label these data according to the video recordings, and to extract statistical features over windows of 10 seconds with 50% overlap. We experimentally compared window sizes of 5 second, 7 seconds, 10 seconds, and 12 seconds, and found that the 10-second window size produced the best classification performance. Feature extraction on sliding windows with 50% overlap has demonstrated to be beneficial [35]. The extracted features included: mean, standard deviation (SD), root mean square (RMS), mean absolute deviation (MAD), zero crossing (ZC), mean crossing (MC), magnitude, energy, entropy, correlation, number of peaks (NP), number of peaks multiplied by the MAD, and Wheelchair_Movement (WM). In order to assess the location and number of sensors that best classify wheelchair activities, two feature matrixes were fed into WEKA (Waikato Environment for Knowledge Analysis version 3.6.4 1999-2010) to develop activity classifiers using a Random Forest (RF) algorithm. RF trains an ensemble of individual decision trees, every tree is built using a random subset of samples and variables, after a large number of trees are generated, they vote for the most popular class [36]. Several studies have shown the advantages of RF classification technique over other classifying algorithms [37-39]. Data fed into WEKA to build the first model included features from the arm accelerometer, the WRM, and the accelerometer beneath the chair, this first matrix consisted of a total of 119 features and 12,280 instances or windows. For the second model, the data from the seat accelerometer was ignored. The second feature matrix consisted of 80 features and 12,280 instances or windows. Features were reduced using a correlation based feature selection (Cfs), this algorithm identifies and screens irrelevant, redundant, and noisy features and identifies relevant features as long as their relevance does not strongly depend on other features. The algorithm uses an heuristic search called Best First (BF) that allows backtracking this is, it moves through the search space by making local changes to the current feature subset, if the path being explored begins to look less promising, the best first search can back-track to a more promising previous subset and continue the search from there [40]. Reduced features for the first model included 5: Mean_velocity, correlation_x_Arm, correlation_y_Arm, mad_xyz_Arm, and mean_x_Seat. Reduced features for the second model included 4 features: mean_velocity, correlation_x_Arm, correlation_y_Arm, and mad_xyz_Arm. Both models were validated using Ten-fold cross-validation that takes the original sample (12,280 instances) and randomly divide the data in 10 subsamples of the same size. Of the 10 subsamples, a single subsample is left out for validation, and the remaining 9 subsamples are used as training data to build a model. This process is then repeated 10 times with each of the 10 subsamples used exactly once for validation. The 10 results from each iteration are then averaged to produce agreement measures [41]. Precision, Recall and F-Measure and a weighted average for each measure was calculated to assess the agreement between the predicted activity and the criterion activity from the videos. The estimated time for each activity category was compared with the criterion time based on video recordings. Mean absolute error (MAE) calculated as the average of the absolute differences between the estimated time and the video time, and mean absolute percentage of error (MAPE) calculated as the average ratio between the absolute difference and the video time.

2.3 RESULTS

A total of 26 participants were tested in the study. Their demographics are described in Table 1. Table 2 shows Precision, Recall and F-Measure for each activity category of the classification model built with the arm accelerometer, the seat accelerometer, and the WRM. Table 3 shows Precision, Recall and F-Measure for each activity category of the classification model built with the arm accelerometer, and the WRM. Table 4 and 5 shows mean absolute error, and mean absolute percentage of error between the criterion time and the estimated time for the model built with the arm accelerometer, the seat accelerometer, and the WRM. Table 6 and 7 shows mean absolute error, and mean absolute percentage of error between the criterion time and the estimated time from the model built with the arm accelerometer, and the WRM. Table 8 and 9 shows the classification confusion matrix for each model.

Table 1: Participant Demographics

Demographic variables	Mean ± SD
Sex	
Female	6
Male	20
Age (years)	40 ± 14
Weight (lb.)	159 ± 41
Manual Wheelchair Usage (years)	13 ± 8
Injury Level Range	
Paraplegia (T4 and below)	20
Tetraplegia (T3 and above)	6
Self-reported pain (WUSPI)	7 ± 10

Table 2: Agreement Measures based on Arm, Seat Accelerometers, and WRM

	Precision	Recall (TP)	F-Measure
Being Pushed	0.832	0.741	0.783
Propulsion	0.922	0.94	0.931
Functional Arm (FAM)	0.835	0.843	0.839
Rest	0.859	0.837	0.848
Overall	0.880	0.881	0.880

Table 3: Agreement Measures based on Arm Accelerometer and WRM

	Precision	Recall (TP)	F-Measure
Being Pushed	0.698	0.643	0.670
Propulsion	0.895	0.92	0.907
Functional Arm (FAM)	0.742	0.724	0.733
Rest	0.779	0.769	0.774
Overall	0.819	0.821	0.820

Table 4: Activity Time Comparison based on Arm, Seat Accelerometers, and WRM

	Criterion (sec)	Estimated (sec)	MAE (sec)	MAPE (%)
Being Pushed	237±4	211±	26±18	11.0±7.7
Propulsion	2516±3	2567±	55±41	2.2±1.6
FAM	1362±2	1375±	52±32	3.8±2.4
Rest	1445±3	1407±	40±32	2.8±2.2

Table 5: Speed Time Comparison based on Arm, Seat Accelerometers, and WRM

	Criterion (sec)	Estimated (sec)	MAE (sec)	MAPE (%)
Self-Selected	1250±2	1322±42	64±32	6±3
Slow-Pace	943±2	938±34	23±25	3±3
Fast-Pace	324±3	257±18	54±18	21±7

Table 6: Activity Time Comparison based on Arm Accelerometer and WRM

	Criterion (sec)	Estimated (sec)	MAE (sec)	MAPE (%)
Being Pushed	237±4	219±31	28±21	11.6±8.8
Propulsion	2516±3	2587±44	71±44	2.8±1.8
FAM	1362±2	1328±52	48±40	3.8±2.9
Rest	1445±3	1426±58	45±38	3.1±2.7

Table 7: Speed Time Comparison based on Arm Accelerometer and WRM

	Criterion (sec)	Estimated (sec)	MAE (sec)	MAPE (%)
Self-Selected	1250±2	1335±31	69±32	7±3
Slow-Pace	943±2	923±30	25±21	3±3
Fast-Pace	324±3	258±16	53±17	20±6

Table 8: Confusion Matrix based on Arm, Seat Accelerometers, and WRM

	Estimated	BP	SP	FAM	Rest
Criterion	Being Pushed	351	75	9	39
	Propulsion	46	4731	127	128
	FAM	14	185	2295	229
	Rest	11	143	318	2418

Table 9: Confusion Matrix based on Arm Accelerometer, and WRM

	Estimated	BP	SP	FAM	Rest
Criterion	Being Pushed	305	85	22	62
	Propulsion	75	4629	193	135
	FAM	30	289	1971	433
	Rest	27	171	470	2222

2.4 DISCUSSION

This study provides insight into the usage of wearable devices to classify activities of manual wheelchair users. Results showed that a classification model built with the combination of three sensors' data, yielded better accuracies than the model built only with two sensors. As shown in table 2 and 3 the overall precision difference between the two models was of 6.0 percentage points. These results suggested that the seat accelerometer data contributed to improve activity classification. Previous studies have shown that the combination of multiple accelerometers aid in better recognition and classification of activities [35]. Both models were able to classify four activity categories including self-propulsion, functional arm movement, being pushed, and rest with overall accuracies of 88.0% and 82.0% respectively. These results are slightly lower to the results by Potsma et al, who used six accelerometers to distinguish wheelchair propulsion and hand biking from other ADLs among 10 MWUs, achieving an overall accuracy of 92% in detecting wheelchair propulsion and hand biking [27]. The differences between Postman et al, study and the present study are that they excluded all activity data that lasted less than 5 seconds, considered both wheelchair propulsion and hand biking as one activity, and used 6 wired connected accelerometers. Using a wearable monitoring system consisting of 6 wired connected accelerometers might limited participant's mobility, and it may limits its use in natural environments. Results in this study suggested that wireless wearable sensors could be a more convenient solution for monitoring activities of MWUs in their natural environment.

Regarding accuracy within the four activity categories, self-propulsion and rest were consistently classified with higher accuracies, this could be due to the very distinguishable features of each activity such as high resultant acceleration and speed for wheelchair propulsion in contrast with low resultant acceleration and low or none speed for rest. The activity category that showed the lowest accuracies was being pushed; this could be due to the small number of samples included in the model (474 instances), not allowing the classification model to correctly discriminate this activity. These results are consistent with those reported by Ding et al, who evaluated the used an eWatch attached to participant's wrist a WRM to detect four activities categories. Results showed that the activity category with the highest accuracy was self-propulsion and the activity category with the lowest accuracy was being pushed [30]. However, the percentage of accuracies (self-propulsion: 87.6%, being pushed: 76.2%, sedentary activity: 56.8% and non-activity 79.9%) were lower than the accuracies presented in this study. These higher accuracies could suggest that the upper arm is a better location than the wrist to detect MWUs activities.

When comparing accuracies from each activity category, self-propulsion accuracies for both models were higher than those reported by French et al, where 3 non-wheelchair users were tested with a eWatch (tri-axial accelerometer) placed on the wrist and a WRM attached to the wheelchair frame. Results showed accuracies of 74% for self-propulsion and 86% for external pushing [42] .This difference in accuracy could be due to the type of classification technique French et al used. They evaluated two different classification techniques: K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). The KNN algorithm is an instance-based representation that uses the instances themselves to represent what is learned, rather than inferring a rule or decision tree. In the KNN algorithm each instance is compared with existing ones using a distance metric, and the closest existing instance is used to assign the class to the new one. The SVM algorithm is a combination of linear modeling and instance-based learning. It selects a small number of boundary instances from each class and builds a linear function that separates them as widely as possible [43]. The Random Forest (RF) algorithm trains an ensemble of individual decision trees, every tree is built using a random subset of samples and variables, after a large number of trees are generated, they vote for the most popular class. This technique allows to have significant improvements in classification accuracy generated by an ensemble of decision trees [36]. Several studies have shown the advantages of RF classification technique over other classifying algorithms [37-39].

Both models were able to classify activities, with high precision percentages, as well as high recall percentages. Precision is defined as a measure of the proportion between the total number of instances that were correctly classified and all the instances classified in an activity. It is calculated as $P = \frac{tp}{tp+fp}$ where *tp* is true positive, and *fp* is false positive Recall is define as a measure of proportion between the total numbers of instances that were correctly classified from all the true instances in an activity. It is calculated as $R = \frac{tp}{tp+fn}$ where *fn* is false negative. The F-Measure is a measure of the overall performance and it combines precision and recall into a single measure. It is calculated as $F = \frac{2PR}{R+P}$ [44]. The activity with the highest F-Measure was self-propulsion with a value of 93.1 for the first model and 90.7 for the second model. These results showed that wearable sensors could discriminate propulsion episodes from other ADLs with high accuracy. Being able to detect self-propulsion from other activities may be able to help researches deeply investigate propulsion biomechanics measures such as stroke number, push frequency and forces.

As shown in table 8 and 9 FAM is sometimes confused with rest. This could be related to the variety of activities grouped into this category, and the different way people perform these activities. For example some activities such as programming the machines (dishwasher, washing machine, dryer machine), eating, may require very little arm movement, and not wheelchair movement at all thus resulting in conditions similar to a rest category. In addition, some participants were moving their arms while being at rest. Another activities that were sometimes confused were being pushed and self-propulsion. This confusion could be because some participants moved their arms while being pushed, thus generating accelerations and wheelchair movement similar to those of propulsion.

The largest difference between the estimated and criterion time was found during the being pushed activity with a MAPE of 11.0% for the first model and 11.6% for the second model. The second, largest difference in time was FAM with 3.5% for the first model and 3.8% for the second model. On the other hand, the smallest difference between the estimated and the criterion was found during the self-propulsion activity with only 2.2% and 3.1 % MAPE. Regarding accuracies based on speed results showed that the largest difference between the estimated and criterion time was found during the fast-pace trials with a MAPE of 21.0% for the first model and 20.0% for the second model. The smallest difference was found during the slow-pace trials with only 3.0 % MAPE for both models. These results suggest that wearable sensor could be a viable option for monitoring time spent on different manual wheelchair activities in their natural environment. This information can provide clinical professionals and researchers with an indication of manual wheelchair user activity levels. It can also provide a tool to increase manual wheelchair users' awareness of their own activity levels, promoting regular physical activity.

One limitation of the study was the small number of samples for the being pushed category. This category only had a total of 474 instances compared with the other activities that had around 4000 instances. A second limitation was that sometimes participants used their non-dominant hand to perform some ADLs; in these cases we were not able to collect acceleration data. A third limitation was that participants pushed their chairs only on smooth surfaces the protocol did not include rough surfaces, this may limit the ability to perfectly mimic wheelchair propulsion over natural surfaces. Finally no data was collected for overhead activities and transfers which are common activities among MWUs. Future work could try to balance the different activities, to have equal data from each activity avoiding imbalance among the activities, include different surface roughness and overhead activities to better simulate real life conditions.

2.5 CONCLUSION

Results in this study suggest that the use of two tri-axis accelerometers and a WRM could be a viable option to accurately detect manual wheelchair user activities such as self-propulsion, being pushed, functional arm movement and rest. Detecting activity of manual wheelchair users in the natural environment, could contribute to better understand the etiology of UE pain and contribute to the preservation of upper limb functions among manual wheelchair users with SCI. This study could result in a potential tool that can monitor the actual activity levels among manual wheelchair users, and may help researchers and clinicians to quantify the quality of UE movement and monitor the effectiveness of interventions in the natural environment.

3.0 TEMPORAL PARAMETERS ESTIMATION FOR WHEELCHAIR PROPULSION USING WEARABLE SENSORS

3.1 INTRODUCTION

According to the 2010 Survey of Income and Program Participation (SIPP), about 3.6 million people aged 15 years and older in the US use a wheelchair [45]. Most of these individuals use a manual wheelchair for mobility. Manual wheelchair users often rely on their upper extremity (UE) for almost all activities of daily living (ADLs). Some of their daily activities such as wheelchair propulsion and transfers require high forces and repetitiveness of UE movements. Therefore, it is not surprising that the incidence of UE pain and injury among manual wheelchair users is high, ranging from 49% to 78% [3-11].

Given the negative impact that UE pain and injury may have in the lifestyle and quality of life of manual wheelchair users [9, 12-14], the Consortium for Spinal Cord medicine published the monograph, *Preservation of Upper Extremity Function Following Spinal Cord Injury: A Clinical Practice Guideline for Health Care Professionals,* where it provides concise ergonomic and equipment recommendations based on the review of published evidence [46]. 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. It also makes recommendations on wheelchair propulsion techniques such as reducing the number of strokes and push frequency.

Temporal parameters of wheelchair propulsion such as the number of strokes and push frequency have been quantified in laboratory settings using motion capture systems and Smart^{Wheels}, a force sensing wheel that can replace the wheelchair wheel to collect propulsion parameters [5, 47-49]. Unfortunately, due to the cost and intricate settings, these valuable tools are not appropriate for assessing UE movement in the home and community environment. Therefore, the repetitiveness of UE movement for wheelchair propulsion out of clinical settings is unclear. With the recent advancement of sensors and miniature technologies, accelerometers emerge as a possible solution for monitoring wheelchair propulsion parameters in the natural environment, contributing to the understanding and prevention of UE pain and injury in manual wheelchair users.

Previous studies have used accelerometers and other sensors to track gross mobility of wheelchair users. A pilot study conducted by Kumar et al. used a customized data-logging device to determine driving characteristics including distance, speed, and driving time of 19 power wheelchair soccer players [32]. A similar study conducted by Coulter et al. used two tri-axial accelerometers placed on the wheels of a wheelchair to estimate gross mobility of 14 manual wheelchair users with SCI. The results showed that the accelerometers were able to recognize wheelchair propulsion episodes with an overall accuracy of 92% [27]. A study conducted by Gendle et al. investigated the revolutions, duration, and direction of movements. They found the activity counts from the accelerometer were significantly different between light and moderate effort indicated by the heart rates [20]. Other researchers have evaluated the performance of accelerometers in detecting manual wheelchair user activities. A study conducted by Postman et al. used six accelerometers placed on different parts of the body to detect wheelchair propulsion episodes from a range of ADLs among 10 MWUs. Results showed that the accelerometers were able to recognize wheelchair propulsion episodes with an overall accuracy of 92% [21]. Although gross mobility, activities and its intensity of manual wheelchair users is, to some extent indicative of their UE movements, it cannot tell the exact amount and repetitiveness of UE movements for wheelchair propulsion.

Knowing the repetitiveness of UE movements for wheelchair propulsion that occur on a daily basis could be important for understanding and preventing UE pain and injury. However research looking into using wearable sensors to directly estimate temporal parameters of wheelchair propulsion is limited. A study conducted by Hiremath et al. estimated temporal parameters of wheelchair propulsion including push frequency, propulsion time, and recovery time based on hand acceleration collected via a motion analysis system among 29 manual wheelchair users. Results showed high intraclass correlation between the estimated and criterion measures [50]. A study conducted by Turner et al. investigated the use of an accelerometer placed beneath the chair and a wheel-mounted magnet to detect wheelchair propulsion parameters including the number of strokes, push frequency, distance, and speed. Ten manual wheelchair users were asked to propel their wheelchair on indoor and outdoor surfaces. Estimated parameters were compared with criterion values obtained from OptiPush wheels. Results showed the average percentage of errors were -1.0% for the number of strokes and -1.7% for push frequency [51].

The purpose of this study is to assess the validity of a tri-axis accelerometer placed at three locations (i.e. wrist, upper arm, and underneath the wheelchair seat) in estimating temporal parameters of wheelchair propulsion including the number of strokes and push frequency. The information obtained can guide appropriate use of accelerometers for monitoring UE movements for wheelchair propulsion in the natural environment.

3.2 METHODS

3.2.1 Study Participants

The Institutional Review Board at the University of Pittsburgh approved this study. A total of 26 manual wheelchair users with SCI volunteered and provided informed consent prior to their participation in the study. Subjects were identified through the IRB approved wheelchair user registries developed by the Human Engineering Research Laboratories (HERL) and the Department of Physical Medicine and Rehabilitation at the University of Pittsburgh. In addition, participants were recruited via flyers posted in local rehabilitation facilities and outpatient facilities. Subjects were included in the study if they: 1) were 18 years of age or greater; 2) use a manual wheelchair as a primary means of mobility; 3) have a Spinal Cord Injury. Subjects were excluded if they were unable to tolerate sitting for 2 hours, and/or have upper limb pain that limits their mobility.

3.2.2 Instrumentation

Subjects were fitted with four monitoring devices and a Smart^{Wheel} (Three Rivers Holdings Inc., Mesa, AZ). The four monitoring devices included a custom wheel rotation monitor (WRM) attached to the wheelchair wheel and three off-the-shelf tri-axis accelerometers (Shimmer

Research, Dublin) worn on the dominant upper arm, dominant wrist, and underneath the wheelchair seat, respectively.

- The wheel rotation monitor (WRM) was developed at the HERL. It is a lightweight and self-contained device that can be easily attached to the wheelchair's wheel without any modifications to the wheelchair. It tracks the wheel rotation through three reed switches mounted 120° apart on the back of the printed circuit board and a magnet mounted at the bottom of a pendulum. As the wheel rotates and exceeds 120° of rotation, one of the reed switches is triggered, and a date and time stamp is recorded. This information can be further processed to obtain the distance, speed, and time of movement [31]. The WRM has been used in previous studies to collect mobility characteristics of manual wheelchair users with different diagnoses [32-34].
- The tri-axis accelerometer (Shimmer Research, Dublin, Ireland) used in this study is a small low-power device that can record the motion data into a micro SD card. The two upper arm accelerometers were sampled at 20Hz and the accelerometer underneath the seat was sampled at 60 Hz.
- The Smart^{Wheel} (Three Rivers Holdings Inc., Mesa, AZ) is a 3-D force and torque-sensing wheel that measures push forces, push smoothness, push frequency, speed, and push length in every push cycle. It is sampled at 240 Hz. Subjects' wheelchair wheels were replaced with a Smart^{Wheel} at the dominant side and a dummy wheel at the other side to balance the weight of the Smart^{Wheel}. The use of Smart^{Wheel} did not change the camber or the axle position.

3.2.3 Experimental Protocol

Subjects were asked to pay two visits to HERL with each visit lasting about 2.5 hours. During the first visit, subjects completed a demographics survey and the Wheelchair Users Shoulder Pain Index Questionnaire (WUSPI). The WUSPI questionnaire measures shoulder pain based on 15 questions using a 10 cm visual analogue scale, resulting in a total score from 0 (no pain) to 150 (extreme pain) [52]. After subjects were fitted with the instrumentation described in the previous section, they were asked to propel their wheelchairs on two surfaces including a level surface of 33 meters and a sloped surface of 15 meters with 3 degrees of incline. Participants propelled their wheelchairs on the level surface twice at three different speeds: self-selected, fast paced (approximately 1.75 m/s), and slow paced (approximately 0.59 m/s). The fast and slow paced speeds were regulated by asking the subjects to follow a power wheelchair with the preset speeds. Participants also propelled their wheelchairs up the sloped surface at a self-selected speed. All trials were videotaped using a hand-held digital video recorder.

During the second visit, participants were first asked to perform the propulsion trials as detailed for the first visit. Participants were then asked to complete a training session where they watched a multimedia instructional program (MMP) on a laptop computer that aimed to teach appropriate propulsion techniques. The MMP was developed by a previous study based on propulsion biomechanics literature and the Clinical Practice Guideline, which emphasized reducing push frequency and increasing push angle [53]. Examples of good and bad techniques were provided. After subjects practiced the propulsion techniques following the video training, they were asked to perform the same propulsion trials. This visit allows us to assess if the accelerometers were capable to capture propulsion changes due to training.

3.2.4 Data Collection and Analysis

Videos recorded during the two visits served as the criterion measure of the stroke number. Two investigators independently counted the stroke number for each propulsion trial, and video footages were re-examined when there was a discrepancy between the two investigators. The criterion push frequency was directly obtained from the Smart$^{\text{Wheel}}$.

Acceleration signals collected by the accelerometers on the wrist, upper arm, and underneath the seat were filtered using an 8th-order Butterworth low-pass filter with a cutoff frequency defined by the fundamental frequency calculated based on each propulsion trial. For the arm and wrist accelerometers, the resultant accelerations (the vector sum of three directions) were used to obtain the stroke number. For the seat accelerometer, only the longitudinal component (parallel to the propulsion direction) was used. An algorithm was developed to extract the stroke number for each propulsion trial. The algorithm first calculated a threshold defined as the mean acceleration plus 0.5 standard deviation over each trial. The stroke number was then counted as the number of acceleration peaks over the established threshold. Push frequency was calculated as the mean propulsion time between each stroke divided by one. Figure 2 shows a visual example of the stroke number and push frequency estimation. Custom MATLAB® (Version 7.11.0 R2010b, The Mathworks, Inc. USA) programs were used to process the acceleration signals.

The estimated stroke number and push frequency from the three accelerometers were compared with the criterion by calculating the mean absolute errors (MAE) calculated as the average of the absolute difference between the estimated and the criterion, and mean absolute percentage errors (MAPE) calculated as the average ratio between the absolute difference and the criterion. $MAE = \frac{1}{n}\sum_{i=1}^{n} /Ei - Ci / and \; MAPE = \frac{1}{n}\sum_{i=1}^{n} /(Ei - Ci)/Ci /$ where Ei is the estimated measure and Ci is the criterion measure. In addition, the Intraclass correlation coefficients ICC(3, 1) were used to assess their agreements. Bland-Altman plots were performed to provide a visual analysis of their agreements. Each point on the Bland and Altman plot represents the mean (x-axis) and the difference (y-axis) of the criterion and estimated values for each propulsion trial. We used all the propulsion trials during the first and the second visit to access the agreement [54].

To assess the validity of the accelerometers in capturing changes after training Intraclass Correlation Coefficients were calculated between the changes in the estimated parameters and the changes in the criterion parameters. Bland-Altman plots were also performed to assess their agreements. Independent sample t-test was performed to evaluate significant differences before and after training. All statistical analysis was performed using SPSS software (ver. 18.0, SPSS Inc., Chicago, IL, USA).

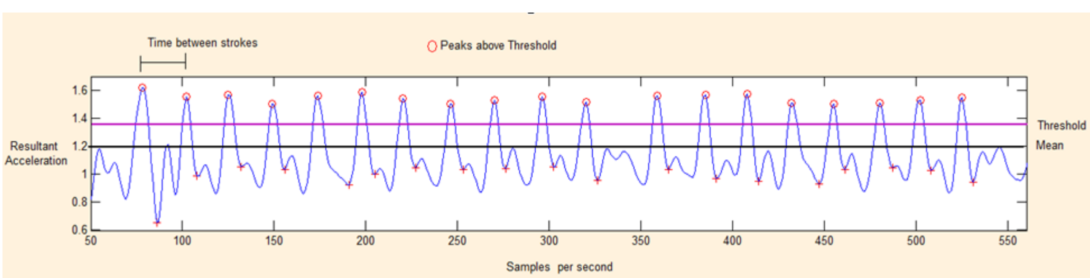

Figure 2: Visual Example for Stroke Number and Push Frequency Estimation

3.3 RESULTS

The demographics of the participants are described in Table 1. Table 10 and 11 show the mean and standard deviation (SD) of the criterion and estimated temporal parameters. Table 12 shows the mean absolute error (MAE) and the mean absolute percentage of error (MAPE) between the criterion and estimated stroke number from each accelerometer. Table 13 shows the MAE and MAPE between the criterion and estimated push frequency from each accelerometer. Table 14 shows the ICC (3, 1) between the criterion and estimated temporal parameters for each accelerometer. Table 15 shows the criterion and estimated SN before and after training and p-values. Table 16 shows the criterion and estimated PF before and after training p-values Table 17 shows ICC between the changes in the criterion measures after training and those in the estimated measures. All variables were calculated for the level surface trials (LS), the sloped surface trials (SS), and all trials combined (OA). Figure 3 and 4 show the Bland-Altman plots between the criterion and estimated stroke number (SN) and push frequency (PF) from each accelerometer, respectively.

Table 10: Criterion and Estimated Stroke Number (SN)

	Video	Arm	Wrist	Seat
Level Surface (LS)	24.6 ± 4.1	24.6 ± 4.0	24.6 ± 4.6	25.0 ± 4.3
Sloped Surface (SS)	18.1 ± 1.1	17.2 ± 1.3	17.0 ± 1.4	17.7 ± 2.0
Overall (OA)	22.4 ± 3.6	22.2 ± 3.6	22.1 ± 4.0	22.6 ± 3.8

Table 11: Criterion and Estimated Push Frequency (PF)

	SMW	Arm	Wrist	Seat
Level Surface (LS)	0.95 ± 0.15	0.93 ± 0.09	0.94 ± 0.09	0.82 ± 0.19
Sloped Surface (SS)	1.06 ± 0.09	1.02 ± 0.04	1.03 ± 0.13	0.94 ± 0.22
Overall (OA)	0.98 ± 0.11	0.96 ± 0.06	0.98 ± 0.09	0.86 ± 0.18

Table 12: SN Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE)

	MAE			MAPE %		
	ARM	WRIST	SEAT	ARM	WRIST	SEAT
Level Surface (LS)	1.7 ± 1.5	2.4 ± 2.3	2.9 ± 3.5	7.7 ± 6.6	11.0±10.2	13.5 ± 16.4
Sloped Surface (SS)	1.5 ± 1.2	1.8 ± 1.3	2.4 ± 2.1	8.6 ± 7.0	10.3 ± 7.9	13.4 ± 11.8
Overall (OA)	1.6 ± 1.4	2.2 ± 2.1	2.7 ± 3.2	8.0 ± 7.1	10.8 ± 9.8	13.4 ± 15.6

Table 13: PF Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE)

	MAE			MAPE %		
	ARM	WRIST	SEAT	ARM	WRIST	SEAT
Level Surface (LS)	0.1 ± 0.1	0.2 ± 0.2	0.3 ± 0.2	16.1 ± 16.7	21.5 ± 21.4	25.4 ± 16.9
Sloped Surface (SS)	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2	6.4 ± 4.6	8.0 ± 6.1	21.8 ± 14.6
Overall (OA)	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2	12.9 ± 15.1	17.2 ± 19.3	24.2 ± 16.6

Table 14: SN and PF Intraclass Correlation Coefficient (ICC)

		ICC	95% CI	p-value
Stroke	ARM	0.994	.988~.997	<0.001
Number	WRIST	0.990	.980~.995	<0.001
	SEAT	0.984	.972~.991	<0.001
Push	ARM	0.916	.843~.953	<0.001
Frequency	WRIST	0.889	.802~.936	<0.001
	SEAT	0.690	.071~.868	<0.001

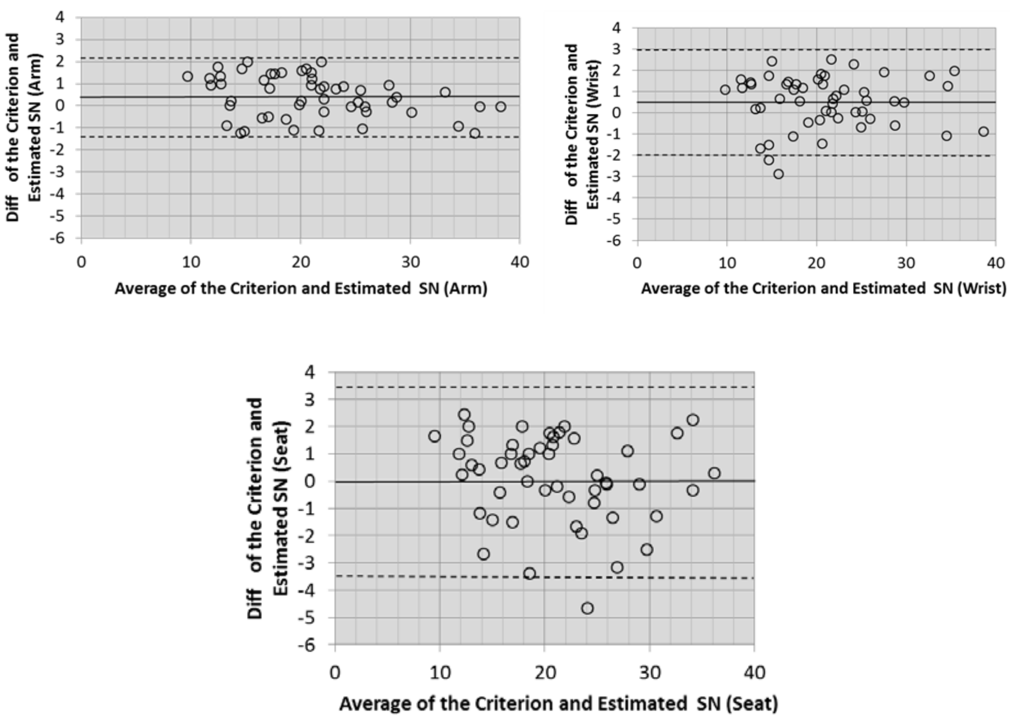

Figure 3: SN Bland-Altman Plots from the Arm, Wrist and Seat Accelerometers

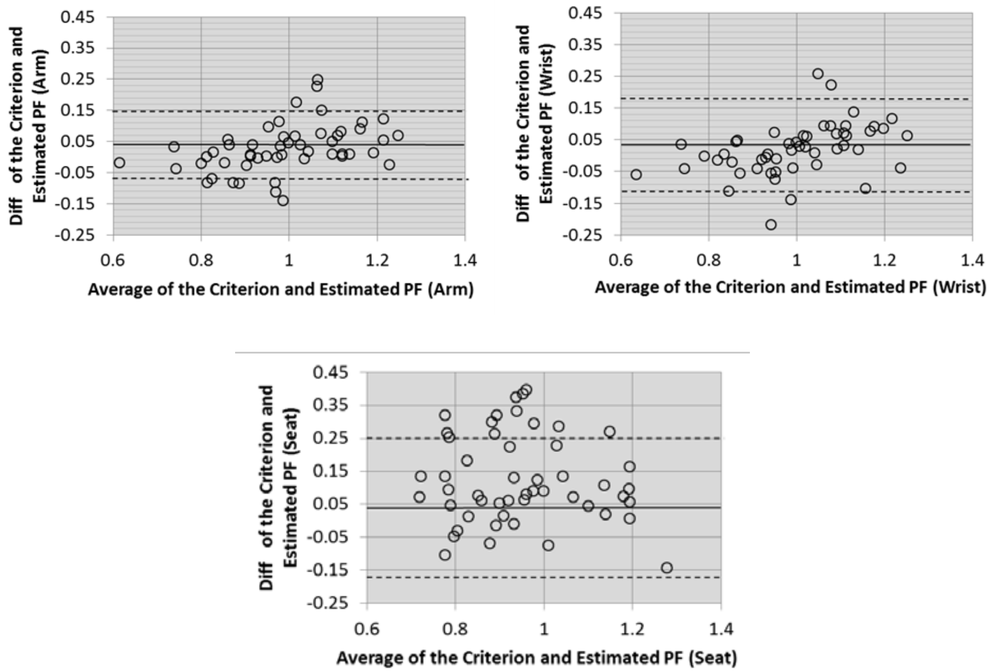

Figure 4: PF Bland-Altman Plots from the Arm, Wrist and Seat Accelerometer

Table 15: Criterion and Estimated SN before and after Training, Change and P-value

		Before		After		Change		
		Mean	STD	Mean	STD	Mean	STD	P-value
Video	LS	25.5	7.6	22.3	5.7	-3.2	0.96	0.093
	SS	18.2	6.2	16.7	4.4	-2.1	1.13	0.682
	OA	21.8	7.8	19.6	5.8	-2.6	1.02	0.163
Arm	LS	25.2	7.2	22.7	5.6	-2.5	0.94	0.170
	SS	17.1	5.9	15.8	4.8	-1.9	1.06	0.707
	OA	21.2	7.7	19.3	6.2	-2.2	0.98	0.268
Wrist	LS	25.0	7.0	23.2	5.7	-1.8	0.93	0.306
	SS	16.9	6.0	16.1	4.1	-1.4	1.08	0.930
	OA	20.9	7.7	19.7	6.1	-1.6	0.98	0.477
Seat	LS	26.3	8.9	25.2	6.4	-1.1	0.84	0.129
	SS	18.0	6.7	17.3	5.6	-0.7	1.06	0.663
	OA	22.1	8.9	21.3	6.8	-0.8	0.95	0.193

Table 16: Criterion and Estimated PF before and after Training, Change and P-value

		Before		After		Change		
		Mean	STD	Mean	STD	Mean	STD	P-value
SMW	LS	0.96	0.16	0.88	0.16	0.09	0.12	0.061
	SS	1.13	0.18	0.98	0.15	0.18	0.20	0.001
	OA	1.04	0.19	0.93	0.16	0.13	0.17	0.001
Arm	LS	0.94	0.14	0.89	0.13	0.05	0.13	0.197
	SS	1.05	0.14	0.95	0.13	0.14	0.19	0.007
	OA	1.00	0.15	0.92	0.14	0.09	0.17	0.007
Wrist	LS	0.93	0.11	0.90	0.12	0.03	0.09	0.327
	SS	1.08	0.19	0.98	0.14	0.13	0.21	0.024
	OA	1.00	0.17	0.94	0.13	0.08	0.17	0.022
Seat	LS	0.84	0.17	0.77	0.14	0.07	0.14	0.134
	SS	0.98	0.30	0.87	0.29	0.04	0.40	0.081
	OA	0.91	0.25	0.82	0.19	0.06	0.30	0.028

Table 17: SN and PF Intraclass Correlation Coefficient (ICC) before and after Training

		ICC	95% CI	p-value
Stroke Number	ARM	0.980	.964~.989	<0.001
	WRIST	0.969	.916~.986	<0.001
	SEAT	0.870	.773~.925	<0.001
Push Frequency	ARM	0.856	.684~.899	<0.001
	WRIST	0.822	.711~.923	<0.001
	SEAT	0.568	.248~.752	<0.001

3.4 DISCUSSION

This study provides insight into the usage of portable devices (e.g. tri-axis accelerometers) to track UE movements for wheelchair propulsion. The small discrepancies between the criterion and estimated parameters shown in Table 12 and 13 suggest that portable sensors have the potential to not only detect gross mobility levels of wheelchair users [20, 26, 27], but to quantify the quality of UE movements for wheelchair propulsion in terms of the repetitiveness. The developed algorithm showed to be robust in calculating number of strokes based on acceleration data being the arm accelerometer the one who yielded the best results. We anticipate that the algorithm could be applied to home collected data.

In terms of estimating the stroke number and push frequency, the arm accelerometer showed the highest accuracy among the three accelerometers, indicating that the upper arm could be a better location for detecting temporal parameters of wheelchair propulsion. The wrist accelerometer can be more sensitive to small UE movements, possibly leading to the increased error. The seat accelerometer showed the lowest accuracy with a MAPE of 13.4% for the stroke number and 24.2% for the push frequency. The estimation errors for the seat accelerometer were greater than the study by Turner et al. where they also placed an accelerometer beneath the wheelchair seat to estimate the stroke number and push frequency among 10 manual wheelchair users. Unfortunately, the data analysis results were not described in details. The study only reported an average percent error (i.e. -1.0% for stroke number and -1.7% for push frequency) instead of the MAPE averaged by each trial of each subject. An average percent error only indicates the estimation bias and may not be sufficient to show the estimation accuracy, as the positive and negative estimation errors from the trials may cancel each other, resulting in smaller overall errors [51].

Compared with the stroke number estimation, push frequency estimation was less accurate, which could be due to the estimation of the total cycle time comprised of push and recovery phases. The estimation algorithm based on the accelerometer signals was able to identify the push phase more accurately, but unable to accurately determine the end of recovery phases, possibly leading to the inaccuracy when estimating the cycle time.

Table 15 and 16 showed that subjects reduced their stroke number and push frequency after the propulsion training program, but there were only significant difference on the PF on the up-sloped surfaces. Despite the lack of significant difference after training, the ICC values (Table 17) shows that the accelerometers were able to capture such changes. The responsiveness of the accelerometer and its estimation algorithm for propulsion parameters makes it possible to track the effectiveness of training out of clinical settings, contributing to the preservation of upper limb functions in manual wheelchair users with SCI [55].

Considering the negative impact that UE pain and injuries can have on manual wheelchair users with SCI, it is important to monitor and understand how the use of upper limbs during wheelchair propulsion and other ADLs are related to such pain and injury. The Clinical Practice Guideline on the Preservation of Upper Limb Function Following Spinal Cord Injury stresses the importance of reducing the frequency of repetitive upper limb tasks [46]. This study could result in a potential tool that can monitor the actual usage of UE in terms of the repetitiveness during wheelchair propulsion in the natural environment, and provide clinical professionals and researchers with an indication of activity levels as well as propulsion skills of wheelchair users in their daily life. With the accelerometry technology getting cheaper and smaller, it is also possible to provide real-time feedback to wheelchair users about their upper limb use and repetitiveness, further contributing to the prevention of upper limb among this population.

The study has some limitations. Given that the sensor was placed on the dominant arm, we were not able to detect movement on the non-dominant arm. This could be important for those who propel their wheelchairs unevenly.

3.5 CONCLUSION

Results in this study suggest that the use of tri-axis accelerometers could be a viable option to accurately monitor temporal parameters of wheelchair propulsion in the natural environment of wheelchair users, especially when the accelerometer is worn on the upper arm. This study could result in a potential tool that can monitor the actual usage of upper limbs in terms of the repetitiveness and contribute to the preservation of upper limb functions among manual wheelchair users with SCI.

4.0 ESTIMATING WHEELCHAIR PROPULSION FORCE USING WEARABLE SENSORS

4.1 INTRODUCTION

Increased use of upper limbs to perform daily activities in manual wheelchair users (MWUs) has been associated with a high prevalence of upper extremity (UE) pain and injury. This prevalence seems to be related to the duration of the Spinal Cord Injury [4]. Recent literature has found a relation between push rim biomechanics and risk of injury to the upper extremity (UE). Specifically, increasing propulsion frequency and a higher rate of rise of total push rim forces have been correlated with increased UE injuries [56]. A study conducted by Boninger et al. among 60 people with SCI found that those who pushed with greater force had higher risk of developing nerve dysfunction [15]. Other studies have also found a correlation between higher propulsion forces and UE pain and injury [11, 46, 57].

UE pain can have a significant negative impact in the lifestyle of MWUs. Two of the most important impacts are on social participation and quality of life (QOL). UE pain may reduce a person's ability and motivation to participate socially. Furthermore, QOL can be impaired because of the distress of the pain, this pain may reduce the ability of being independent, and functional [8-10]. Therefore, it is very important to preserve upper limb function and prevent UE pain and injury. The consortium for spinal cord medicine developed a clinical practice guideline with several recommendations to preserve UE function after SCI. According to this guideline, forces experienced at the shoulder during wheelchair propulsion should be reduced [46].

Monitoring tools capable of assessing wheelchair propulsion biomechanics, specifically wheelchair propulsion forces, may play an important role in the preservation of UE function and prevention of pain. Nowadays, there are many monitoring tools and techniques that can be used to assess wheelchair propulsion forces. For example, a study conducted by Gil-Agudo et al, among 16 participants with SCI used four camcorders (Kinescan IBV) and a Smart^{Wheel} to analyze the change in shoulder joint forces during propulsion at two different speeds. The study found that shoulder joint forces and moments depended strongly on the propulsion speed, increasing in magnitude when speed increased [49]. Another study conducted by Dubowsky et al, used kinematic data from a motion analysis system, kinetic data from force-sensing push rims, and electromyography data from four upper-limb muscles for ten push strokes to determine the force during propulsion and its difference between able bodied persons and people with paraplegia. The study concluded that greater muscle energy results in a greater resultant force in the shoulder and elbow, placing people with paraplegia at risk of developing upper extremity injuries [58]. A study conducted by Lin et al, developed a two-dimensional energy model to predict wheelchair propulsion forces. Ten able-bodied participants and 10 manual wheelchair users were asked to propel their chairs, kinematic data of the upper extremity joints were obtained using a planar four-bar linkage analysis, and used as an input to build a two-dimensional energy model to detect hand-rim forces applied during wheelchair propulsion. Results demonstrated that predicted forces generally agreed with experimentally obtained forces in direction and magnitude for both inexperienced and experienced wheelchair users [59]. Many of the actual monitoring tools such as motion capture systems, sensing wheels, electromyography data, and energy models can only be used in clinical settings. With the recent advancement of sensors and miniature technologies, accelerometers and wearable sensors emerge as a possible solution for monitoring wheelchair propulsion forces. The performance of accelerometers and sensors such as customized data loggers have been studied in assessing different aspects of wheelchair propulsion, such as gross mobility, traveled distance, biomechanical parameters, energy expenditure, and activity classification [20, 21, 27, 32, 51, 60]. However, to the extent of our knowledge none of the previous studies have looked into the use of wearable sensors to estimate propulsion forces.

The purpose of this study is to assess the performance of a tri-axis accelerometer placed at the upper arm, and a WRM in estimating force applied during wheelchair propulsion. This information can provide a convenient solution for monitoring wheelchair propulsion force in the natural environment.

4.2 METHODS

4.2.1 Study Participants

The Institutional Review Board at the University of Pittsburgh approved this study. A total of 26 manual wheelchair users with SCI volunteered and provided informed consent prior to their participation in the study. Subjects were identified through the IRB approved wheelchair user registries developed by the Human Engineering Research Laboratories (HERL) and the

Department of Physical Medicine and Rehabilitation at the University of Pittsburgh. In addition, participants were recruited via flyers posted in local rehabilitation facilities and outpatient facilities. Subjects were included in the study if they: 1) were 18 years of age or greater; 2) use a manual wheelchair as a primary means of mobility; 3) have a Spinal Cord Injury. Subjects were excluded if they were unable to tolerate sitting for 2 hours, and/or have upper limb pain that limits their mobility.

4.2.2 Instrumentation

Subjects were fitted with monitoring devices and a Smart^{Wheel} (Three Rivers Holdings Inc., Mesa, AZ) 1. The monitoring devices included a custom wheel rotation monitor (WRM) attached to the wheelchair wheel and one off-the-shelf tri-axis accelerometer (Shimmer Research, Dublin) worn on the dominant upper arm.

- The wheel rotation monitor (WRM) was developed at the HERL. It is a lightweight and self-contained device that can be easily attached to the wheelchair's wheel without any modifications to the wheelchair. It tracks the wheel rotation through three reed switches mounted 120° apart on the back of the printed circuit board and a magnet mounted at the bottom of a pendulum. As the wheel rotates and exceeds 120° of rotation, one of the reed switches is triggered, and a date and time stamp is recorded. This information can be further processed to obtain the distance, speed, and time of movement [31]. The WRM has been used in previous studies to collect mobility characteristics of manual wheelchair users with different diagnoses [32-34].

- The tri-axis accelerometer (Shimmer Research, Dublin, Ireland) used in this study is a small low-power device that can record the motion data into a micro SD card. The upper arm accelerometer was sampled at 20Hz.
- The SmartWheel (Three Rivers Holdings Inc., Mesa, AZ) is a 3-D force and torque-sensing wheel that measures push forces, push smoothness, push frequency, speed, and push length in every push cycle. It is sampled at 240 Hz. Subjects' wheelchair wheels were replaced with a SmartWheel at the dominant side and a dummy wheel at the other side to balance the weight of the SmartWheel. The use of SmartWheel did not change the camber or the axle position.

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During the second visit, participants were first asked to perform the propulsion trials as detailed for the first visit. The purpose of the second visit was to collect additional propulsion information in order to have more data to build the model.

4.2.4 Data Collection and Analysis

Kinetics data was collected from the SMART^{Wheel} (SMW). A custom MATLAB® (Version 7.11.0 R2010b, The Mathworks, Inc USA) program was used to process the data and calculate the resultant force defined as the vector sum of the three forces components (Fx, Fy, Fz), the mean peak resultant force was calculated over windows of 10 second. The mean peak resultant force from each window was used as a criterion for the regression model. Using a MATLAB custom program data from the wheel rotation monitor (WRM) was converted to wheel speed. A set of statistical measures was calculated over 10-second windows for the x, y, z, and resultant acceleration of the arm accelerometer. These statistical measures included: mean, standard deviation (SD), root mean square (RMS), mean absolute deviation (MAD), zero crossing (ZC), mean crossing (MC), magnitude, energy, entropy, correlation, and number of peaks (NP), number of peaks multiplied by the MAD. We experimentally compared the performance of the regression technique including the arm and seat accelerometer and only including the arm accelerometer. The difference in MAPE between the first and the second was only of 0.03 percentage points. Therefore we decided to use only the arm accelerometer to estimate the propulsion forces. The calculated statistical measures together with the participants' demographics such as age, gender, level of injury, weight and years of experience using a wheelchair, the type of surface, and velocity were used to build a feature matrix with a total of 120 features that was fed into the Waikato Environment for Knowledge Analysis (WEKA version 3.6 1999-2012). To build the regression model features were reduced using a correlation based feature selection (Cfs) algorithm that identified and screens irrelevant, redundant, and noisy features and identifies relevant features as long as their relevance does not strongly depend on other features. The algorithm uses an heuristic search called Subset Size Forward Selection that performs an internal cross-validation in order to determine the optimal subset size [40]. Reduce features included: entropy_z_Arm, Peaks_z_Arm, std_xyz_Arm, Weight, Age, and type of surface. A revised leave one subject out (LOSO) cross validation method where all the data from the 25 participants and half of the data from the validation subject were used as training data to build the model and the other half of the data from the validation subject was used as testing data to evaluate the model. This cross-validation process is repeated 26 times with each participant serving as the validation subject once. A Bagging Regression Technique was used to estimate the propulsion forces. This technique is an aggregated technique that grows multiple decision trees and then averages the judgments of the individual trees. It reduces the variance associated with prediction, and thereby improve the prediction process [44]. Several studies have found Bagging Regression Technique to have substantial improvement in prediction over conventional regression techniques [61, 62]. Mean absolute error (MAE), and mean absolute percentage of error (MAPE) were calculated between the criterion and the estimated force for each model.

4.3 RESULTS

Participant's demographic characteristics are described in Table 1. Table 18 shows the mean and standard deviation (SD) of the criterion and estimated force for each type of surface. Table 19 shows MAE and MAPE between the criterion and estimated force for each type of surface. Table 20 shows the Intraclass Correlation Coefficient between the criterion and estimated force for each type of surface. All variables were calculated for the level surface trials (LS), the sloped surface trials (SS), and all trials combined (OA). Figure 5 show the Bland-Altman plots between the criterion and estimated force calculated for the level surface, and slope surfaces. Table 21 shows the criterion and estimated force, the Mean Absolute Error (MAE) and the Mean Absolute Percentage of Error MAPE (%) and WUSPI scores per subject. Results were calculated for both the level surfaces, and slope surfaces.

Table 18: Criterion and Estimated Force (N)

	Criterion (N)		Estimated (N)	
Level Surface	33.4	±17.1	33.3	±14.1
Sloped Surface	49.2	±21.6	47.6	±19.3
Overall	37.7	±19.7	37.2	±16.9

Table 19: Force Mean Absolute Error (MAE) Mean Absolute Percentage Error (MAPE)

	MAE (N)		MAPE (%)	
Level Surface	5.27	±5.38	18.1	±20.5
Up Slope	7.65	±6.29	17.4	±16.0
Overall	5.92	±5.73	17.9	±19.4

Table 20: Force Intraclass Correlation Coefficient

	ICC	95% CI	p-value
Level Surface	0.944	.880~.994	<0.001
Up Slope	0.967	.929~.985	<0.001
Overall	0.958	.927~.975	<0.001

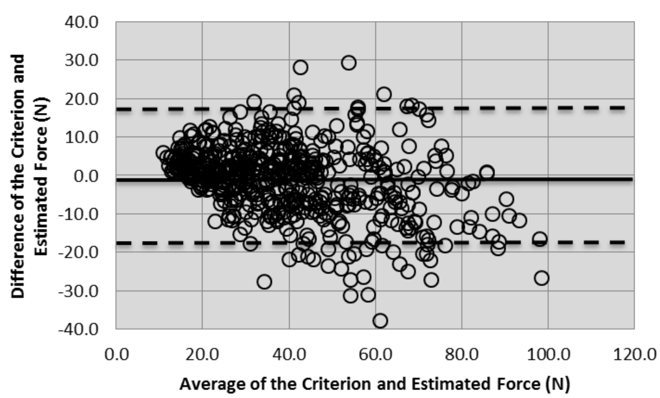

Figure 5: Force Bland-Altman Plot

Table 21: Criterion and Estimated Force (N), MAE (N) and MAPE (%) and Pain Level

	Criterion (N)		Estimated (N)		MAE (N)		MAPE (%)		WUSPI SCORE
1	51.3	±16.0	46.6	±13.9	7.4	±4.2	13.0	±8.7	6.0
2	53.1	±11.3	55.2	±8.8	5.6	±4.8	11.6	±6.8	9.5
3	69.3	±14.5	62.6	±8.4	6.8	±6.6	9.9	±27.0	0.0
4	27.2	±9.6	29.0	±5.6	7.4	±2.6	31.9	±6.1	27.5
5	39.5	±8.7	37.3	±9.5	3.6	±3.2	9.0	±15.3	2.5
6	20.6	±11.5	22.9	±4.3	3.2	±4.3	17.4	±10.4	1.0
7	60.0	±23.5	61.7	±16.6	4.9	±6.7	9.5	±8.8	14.4
8	67.0	±12.8	62.8	±8.1	10.2	±4.6	15.2	±28.2	0.0
9	27.9	±18.3	29.1	±14.7	5.9	±4.7	27.0	±8.3	0.0
10	37.8	±10.3	36.4	±9.8	4.2	±6.0	10.4	±28.7	2.3
11	27.2	±14.0	27.8	±8.9	5.3	±6.0	20.4	±11.6	0.6
12	29.8	±12.1	27.2	±19.0	7.2	±10.	21.2	±37.7	0.0
13	32.7	±18.4	47.5	±11.4	15.6	±6.1	47.8	±8.3	3.2
14	37.4	±10.9	33.8	±7.9	7.5	±3.5	18.7	±13.7	4.4
15	31.3	±10.0	29.7	±8.6	3.5	±6.3	12.1	±20.5	0.0
16	25.9	±12.0	25.9	±9.9	4.9	±2.8	19.2	±10.3	0.0
17	31.9	±9.7	33.6	±6.5	3.5	±4.1	12.5	±15.3	0.0
18	25.7	±14.3	26.0	±7.3	5.0	±4.7	20.4	±19.6	2.3
19	31.9	±19.8	31.9	±20.3	8.5	±6.6	30.5	±8.7	3.0
20	62.9	±7.2	62.0	±5.0	7.1	±2.4	10.7	±10.4	20.8
21	23.3	±8.8	23.0	±4.9	2.5	±3.3	11.6	±18.8	0.0
22	23.4	±13.8	22.0	±10.7	4.6	±4.3	22.3	±25.3	0.0
23	29.3	±11.8	30.4	±8.5	5.9	±5.4	25.0	±9.4	54.6
24	49.1	±15.6	47.1	±8.9	6.2	±7.7	12.1	±37.0	0.0
25	36.1	±9.4	33.3	±4.4	7.9	±4.2	26.9	±10.4	23.5
26	26.6	±19.7	25.7	±16.9	4.5	±5.7	15.6	±19.4	25.0

4.4 DISCUSSION

This study provides insights into the usage of portable devices (e.g. tri-axis accelerometer and a WRM) to estimate wheelchair propulsion force. The MAPE between the criterion and estimated force shown in table 19 suggest that portable sensors have the potential to estimate wheelchair propulsion force with an overall MAPE of 17.9%. As shown in table 18 mean peak forces during the sloped surfaces are higher than the force during the level surface, this results are similar to those of Cowan et al, who examined the impact of surface type, wheelchair weight, and rear axle position on 53 ambulatory older adults with minimal wheelchair experience. Results showed that participants used the highest forces on the ramped condition [63]. The need of applying higher forces during a sloped or ramp surfaces may help to reduce the error between the criterion and the estimated. Participant need to make full contact on the push rim to keep going up providing a clearer criterion force. As shown in table 19, the overall MAPE for the up-sloped surfaces was lower than for the level surfaces. Regarding the overall MAE, results showed that the regression models were able to predict forces with an absolute error of 5.9 N. A case study conducted by Rice et al, on a manual wheelchair user who received propulsion training for three months found that Mean Peak Resultant Force decreased by 14.9 N after training [64]. Results in this study suggested that wearable sensors could be capable of detecting force changes after an intervention under similar conditions of those from Rice et al.

In terms of the performance of the regression model per subject the MAPE per subject, Table 23 shows that some participants had higher MAPE. This could be because some of them pushed on the wheel instead of on the instrumented hand rim which was designed to sense the propulsion forces. Analyzing the videos recordings we confirmed that participant 4, 9, 13, 23, and 25 were pushing on the wheels. A second cause for having a MAPE over the average could be a poor grasping. Participants 19, and 22 who had a high spinal cord injury had a poor grasping. Considering these limitations and omitting these subjects from the analysis the overall MAPE will decrease to 15.1%. Regarding the relation between the individual level of pain and the performance of the regression model per subject results showed a weak positive correlation with a correlation coefficient r= 0.1863. These results suggest that the perceived level of pain is not highly correlated with the performance of the regression model. However, when we analyzed the data subject by subject we see that participants with WUSPI scores above the average showed also a MAPE above the average.

When looking into the predictors of the regression models, (Appendix A) we noted that the body weight was a predictor in all models. This result is similar to the results found in a study conducted by Boninger et al, among 34 manual wheelchair users with paraplegia, they found that subject's weight was related to push rim forces and median nerve function [65]. The average number of predictors among the different regression models was 6 features. None of the 26 models' predictors included any feature related with the velocity. This could be because even though the velocity has a correlation coefficient r = of 0.204 there were other attributes with higher correlations, for example the standard deviation of the arm resultant acceleration showed a higher correlation with a correlation coefficient of r = 0.479, another attribute that was highly correlated with the criterion measures was the number of peaks from the z acceleration component with a correlation coefficient of r= 0.417.

Developing a system for measuring propulsion forces is complex [66]. Previous studies have tried to measure push rim forces using inverse dynamic models [67], external devices such as sensing push rims and smart wheels [11, 68]. Despite the ample research in understanding forces applied during propulsion, few studies have evaluated the performance of wearable sensors, like accelerometers, to estimate the force during propulsion. This study has shown that accelerometers have the potential to estimate propulsion force with an average error of 17.9%.

Based on the revised LOSO cross validation method results suggested that incorporating to the model the propulsion data from a new participant, could increase the accuracy in estimating the propulsion forces. This suggests that a personal calibration consisting on collecting propulsion data from an unknown participant and adding this data to the model may enable it to predict propulsion forces with higher accuracies. We envision that this calibration would need to be done at a clinical setting in order to use the SamrtWheel as the criterion measure. With the accelerometers and wearable sensors technology getting cheaper and smaller, it is also possible to provide real-time feedback to wheelchair users about their upper limb use. According to the Clinical Practice guideline on the preservation of upper extremities after SCI, a reduction in the force applied during propulsion, may reduce the risk of developing UE pain and injury [46]. This study is a first step toward the development of a device capable of monitoring propulsion force in natural environments. This knowledge could contribute to the preservation of upper limb functions among MWUs with SCI.

The study has several limitations the first one is related to the Smart$^{\text{Wheel}}$ and the dummy wheel. Although these two wheels had the same size, and dimensions, the weights were slightly different, which might cause some turning tendency. The imbalance of pushing may affect the force direction and might also change the way people push their chairs. Another limitation is that even though we advised participants to use the push rim to push their chairs, none all of them did it this way, and some pushed on the wheel instead of the instrumented hand rim which was designed to sense the propulsion forces. Future studies should consider using Smart$^{\text{Wheels}}$ on both sides and require participants to push on the push rim.

4.5 CONCLUSION

Results in this study suggest that the use tri-axis accelerometer could be a viable option to monitor propulsion force in not only clinical settings but also in the natural environment. This study could result in a potential tool that can monitor the actual usage of upper limbs in terms of propulsion force and contribute to the preservation of upper limb functions among manual wheelchair users with SCI.

5.0 CONCLUSION AND FUTURE WORK

Results in this thesis suggest that wearable sensors could be a viable option to monitor UE quality of MWUs in their natural environment. It has been shown that a combination of accelerometers and a WRM could classify activities of manual wheelchair users, provide data to understand the repetitiveness of UE movement counting the number of strokes and push frequency, and estimate the force during propulsion in the natural environment. This knowledge could contribute to a better understanding of the etiology of UE pain and may also contribute to the preservation of upper limb functions among manual wheelchair users with SCI. Furthermore, it may help researchers and clinicians to quantify the quality of UE movement and monitor the effectiveness of interventions in the natural environment.

Regarding the activity classification model, results showed that a classification model built with the combination of three sensors, (Arm accelerometer, seat accelerometer, and WRM), yielded better accuracies than the model built only with two sensors (Arm accelerometer and the WRM). Both models were able to classify four activity categories including self-propulsion, functional arm movement, being pushed, and rest with overall accuracies of 88.0% and 82.0% respectively. Self-propulsion and rest were consistently classified with higher accuracies. The activity category that showed the lowest accuracies was being pushed; this could be due to the small samples of being pushed included in the model. When comparing the estimated time spent on each activity with the criterion time from the video, mean absolute percentage of error were low ranging from 2.2% to 11.6%. These results suggest that wearable sensors could be used to monitor time spent on different manual wheelchair users' activities in the natural environment. This information can provide clinical professionals and researchers with an indication of manual wheelchair user activity levels. It can also provide a tool to increase manual wheelchair users' awareness of their own activity levels, promoting regular physical activity.

Knowing the repetitiveness of UE movement, specifically the number stroke and push frequency could be an important factor in preventing UE pain and injury. Results of the stroke number and push frequency estimation presented in Chapter 3 suggest that portable sensors have the potential to quantify the quality of UE movements for wheelchair propulsion in terms of the repetitiveness. The responsiveness of the accelerometer and its estimation algorithm for propulsion parameters makes it possible to track the effectiveness of training out of clinical settings, contributing to the preservation of upper limb functions in manual wheelchair users with SCI. With the accelerometry technology getting cheaper and smaller, it is also possible to provide real-time feedback to wheelchair users about their upper limb use and repetitiveness, further contributing to the prevention of upper limb pain and injury among this population.

People who push with greater force have higher risk of developing nerve dysfunction and UE pain. Therefore, forces experienced at the shoulder during wheelchair propulsion should be reduced [15]. Results presented in Chapter 4 suggest that portable sensors have the potential to estimate wheelchair propulsion force with an overall MAPE of 17.9%. Regarding the overall MAE, results showed that regression models based on a bagging technique were able to predict forces with an absolute error of 5.9 N. suggesting that this regression technique could be capable of detecting changes after an intervention. The revised LOSO validation showed that by adding some propulsion data of a new participant to the regression model; it could estimate propulsion forces with higher accuracies. This study is a first step toward the development of a device capable of monitoring propulsion force in natural environments.

Results in this thesis may have different clinical applications. Result in chapter 2 suggests that accelerometers have the ability to monitoring general activity levels of MWUs by distinguishing different activities. This knowledge may help clinicians to promote healthy lifestyles among MWUs, and may also help them to develop targeted interventions, and to better understand the relationship between physical activity patterns and secondary conditions such as heart disease, diabetes, and overweight among MWUs. In addition, this knowledge may also help end-users to be aware of their physical activity levels, and may help to decrease sedentary lifestyles among. Results in chapter 3 and 4 suggest that accelerometers have the capability to monitor the quality of UE movement. This knowledge may help clinicians to monitor actual usage of UE in terms of the repetitiveness out of clinical settings, in MWU's natural environment. It may help clinicians to have an indication of the users' propulsion skills. This knowledge may help clinicians to justify wheelchair choices. For example, a clinician ask a MWU to use wearable sensors, and data con be collected to prove whether a user propels more using an specific type of wheelchair for instance a light weight manual wheelchair versus a standard wheelchair. Having an objective measure of the quality of UE movement has potential to impact insurance policies, such as those restricting wheelchair upgrades and renewals. It may also help clinicians to find the perfect wheelchair settings, and fit for each client. In addition, a wearable monitoring tool for MWUs can provide users a real time feedback about their upper limb use and repetitiveness movements that may help them to prevent pain and injury.

Future work could take advantage of the advancement in miniature sensor and wireless technologies. Accelerometers could be integrated with gyroscopes which could provide more detail information about UE movement. Commonly used technology such as Smartphones could be used to collect, store and transmit information that could provide feedback to end-users. Furthermore, information could be transmitted to clinicians who could monitor wheelchair propulsion skills and the effectiveness of training. Results in this thesis suggested that models and algorithms developed could be applied to community collected data. This information could help to understand the etiology of UE pain, and could contribute to the preservation of UEs.

APPENDIX

REDUCED FEATURES

Table 22: Models Reduced Features per Subject

M1	entropy_z_Arm	M2	entropy_z_Arm	M3	entropy_z_Arm	M4	entropy_z_Arm	M5	entropy_z_Arm	M6	entropy_z_Arm
M1	Peaks_z_Arm	M2	Peaks_z_Arm	M3	Peaks_z_Arm	M4	Peaks_z_Arm	M5	Peaks_z_Arm	M6	Peaks_z_Arm
M1	std_xyz_Arm	M2	std_xyz_Arm	M3	std_xyz_Arm	M4	std_xyz_Arm	M5	std_xyz_Arm	M6	std_xyz_Arm
M1	Weight	M2	Weight	M3	Weight	M4	Weight	M5	Weight	M6	Weight
M1	TypeSurface	M2	TypeSurface	M3	TypeSurface	M4	TypeSurface	M5	TypeSurface	M6	TypeSurface
M1	Age	M2	Age	M3	Age	M4	Age	M5	Age	M6	Age
M7	entropy_z_Arm	M8	entropy_z_Arm	M9	entropy_z_Arm	M10	entropy_z_Arm	M11	entropy_z_Arm	M12	entropy_z_Arm
M7	Peaks_z_Arm	M8	Peaks_z_Arm	M9	Peaks_z_Arm	M10	Peaks_z_Arm	M11	Peaks_z_Arm	M12	Peaks_z_Arm
M7	std_xyz_Arm	M8	std_xyz_Arm	M9	std_xyz_Arm	M10	std_xyz_Arm	M11	std_xyz_Arm	M12	std_xyz_Arm
M7	Weight	M8	Weight	M9	Weight	M10	Weight	M11	Weight	M12	Weight
M7	TypeSurface	M8	Age	M9	TypeSurface	M10	TypeSurface	M11	TypeSurface	M12	TypeSurface
M7	Age	M8	TypeSurface	M9	Age	M10	Age	M11	Age	M12	Age
M13	entropy_z_Arm	M14	entropy_z_Arm	M15	entropy_z_Arm	M16	std_z_Arm	M17	entropy_z_Arm	M18	entropy_z_Arm
M13	Peaks_z_Arm	M14	Peaks_z_Arm	M15	Peaks_z_Arm	M16	entropy_z_Arm	M17	Peaks_z_Arm	M18	Peaks_z_Arm
M13	std_xyz_Arm	M14	std_xyz_Arm	M15	std_xyz_Arm	M16	std_xyz_Arm	M17	std_xyz_Arm	M18	std_xyz_Arm
M13	Weight	M14	Weight	M15	Weight	M16	Weight	M17	Weight	M18	Weight
M13	TypeSurface	M14	TypeSurface	M15	TypeSurface	M16	TypeSurface	M17	TypeSurface	M18	Years of experience
M13	Age	M14	Age	M15	Age	M16	Age	M17	Age	M18	TypeSurface
										M18	Age
M19	entropy_z_Arm	M20	mean_x_Arm	M21	entropy_z_Arm	M22	entropy_z_Arm	M23	mean_x_Arm	M24	entropy_z_Arm
M19	Peaks_z_Arm	M20	Peaks_z_Arm	M21	Peaks_z_Arm	M22	Peaks_z_Arm	M23	entropy_z_Arm	M24	Peaks_z_Arm
M19	std_xyz_Arm	M20	std_xyz_Arm	M21	std_xyz_Arm	M22	std_xyz_Arm	M23	Peaks_z_Arm	M24	std_xyz_Arm
M19	Weight	M20	Weight	M21	Weight	M22	Weight	M23	std_xyz_Arm	M24	Weight
M19	TypeSurface	M20	TypeSurface	M21	Age	M22	Years of experier	M23	Weight	M24	TypeSurface
M19	Age	M20	Age	M21	TypeSurface	M22	TypeSurface	M23	TypeSurface	M24	Age
						M22	Age	M23	Age		
M25	entropy_z_Arm	M26	entropy_z_Arm								
M25	Peaks_z_Arm	M26	Peaks_z_Arm								
M25	std_xyz_Arm	M26	std_xyz_Arm								
M25	Weight	M26	Weight								
M25	TypeSurface	M26	TypeSurface								
M25	Age	M26	Age								

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