Feasibility study of using classification techniques to detect manual wheelchair users’ intentions regarding the direction of motion

INTRODUCTION

Manual wheelchair (MWC) users are at high risk of upper extremity joint pain, joint degeneration, and fatigue. To address these secondary conditions, several power attachments have been developed to mitigate or eliminate the physical load of MWC propulsion. Motorized front-end attachments, such as Firefly from Rio Mobility, transform a MWC to a powered tricycle by lifting the front casters. The user can control the wheelchair’s speed by engaging a thumb or twist grip throttle while maneuvering the wheelchair by steering the front wheel. Controlling a MWC with a front-end attachment is intuitive and relatively easy for those with sufficient hand function. SmartDrive MX2+ from Permobil is an example of a rear-end attachment that connects to the wheelchair’s rear axle and can be controlled by thumb throttles or a wristband. The wristband has an embedded accelerometer to recognize predefined gestures and the user’s intention to start and stop the motion or maintain a constant speed. Although the control of SmartDrive is not taxing for more experienced users, it could be challenging and counter-intuitive for novice users. For example, if the user holds the rims to slow down, the SmartDrive senses resistance and therefore provides more power to move forward. Pushrim-activated power-assisted wheels (PAPAWs) are another example of power add-ons for MWCs. PAPAWs have built-in sensors to measure the user input at each stroke and use this information to provide the desired motor power to the wheels. PAPAW users can propel a wheelchair in the same way as propelling a MWC while exerting less effort.

Although PAPAWs and conventional manual wheels have very similar designs and user interfaces, PAPAW users have reported several difficulties with coordinating the pushes on each wheel to achieve a smooth ride [1]. The dynamics of wheelchair propulsion indicate that the applied forces on the left and right wheels, whether intended or not, determine the speed and direction of movement. Therefore, the abovementioned challenges of PAPAW control could be related to: (1) variances in users’ physical ability and propulsion habits (e.g., the user’s strength and/or temporal variability between the left and right sides [2]); and/or (2) unexpected external disturbances (e.g., environmental and road conditions [3]). Accordingly, we believe that characterizing wheelchair users’ intentions when interacting with the wheels is an essential step for successful PAPAW controller designs. In this paper, we propose the use of supervised learning algorithms to estimate the intention of MWC users by monitoring the kinetics of wheelchair motion. Linear and angular velocity of the wheelchair were computed from gyroscope data for different wheelchair movements. Five classification techniques were used to determine the user’s intentions toward moving straight forward, turning left, or turning right.

BACKGROUND

The wheelchair user’s direct and continuous interaction with the pushrims is required to initiate and maintain PAPAWs’ motion. Here we review some of the control strategies that were developed for this collaborative interaction between the user and the wheels. One strategy for PAPAW control was to amplify the user’s input force to the pushrims while considering a minimum threshold to compensate for side-to-side differences in the user’s input force [4]. Another method generated a balanced assist torque by considering the timing similarity between the user’s input torque to right and the left wheels and the ratio of these torques [5]. Another strategy used a fuzzy algorithm that takes in the posture angle and angular velocity of the wheelchair, the input torque proportion and sum of the input torque to the right and left wheels, to calculate the assist torque [6]. A two-dimensional assist torque was used to control the wheelchair’s straight and rotational motion by using the sum and difference of user input torque to the left and right pushrims, respectively [7].

Reported outcomes of the reviewed literature revealed that implementation of the proposed controllers in PAPAWs can improve user-wheelchair interaction by providing an intuitive sense of control to the users. However, all these controllers were designed based on a predefined model characteristic of a user-device interaction. Moreover, they used fixed thresholds to determine the intention of users for different wheelchair maneuvers. Therefore, the individual characteristics of users were disregarded. Although the development of learning-based controllers for PAPAWs was proposed in previous research [4], no studies have been published.

Inertial sensor-based measurements of wheelchair propulsion have been studied in previous research and were shown to provide reliable and high accuracy data to estimate the kinematics of wheelchair movements [8],[9]. In one study, data from multiple accelerometers and gyroscopes, which were attached to the wheelchair and the participant’s body, were used to observe the kinematics of wheelchair propulsion. Support vector machine (SVM) classifiers were then used to analyze the data and determine whether the wheelchair motion is a self-propelled or an attendant-propelled type [10].

In our work, we studied the use of supervised learning algorithms with inertial measurement unit (IMU) data to estimate wheelchair users’ intention regarding the direction of motion (e.g., moving straight, turning left, or turning...
right) when propelling a MWC. This information can provide insight into design of more efficient PAPAW controllers. We also sought a system that did not rely on pushrim force data in hopes of designing a simpler and cheaper system.

**METHOD**

We performed our experiments with an able-bodied subject with experience wheeling a MWC. We used an instrumented wheel (SmartWheel [11]) to measure the kinetics and kinematics of motion on the right side of a MWC. The other MWC wheel was modified for similar inertia characteristics to the SmartWheel. Force and kinematic data were collected at 240 Hz and transferred to a laptop via WiFi. Two smartphones, which had MATLAB android applications, were mounted at the center of each wheel. 3-Axis accelerometer and gyroscope data were collected at 10Hz and transferred to two separate laptops via WiFi. Accelerometer and gyroscope data were time-stamped and synchronized.

Experimental trials were designed to capture the characteristics of "bouts of wheelchair mobility" in actual activities of daily living, which are dominated by short and slow movements [12]. The participant was instructed to start the movement from rest and follow a predefined path at a self-selected speed. We performed 3 trials for each of the following sets of movements: (1) "straight": starting from rest, moving straight forward, and stopping 10 meters away from the starting point; (2) "left turn": starting from rest, moving straight forward for 5 meters, turning left at approximately a 90° angle, moving straight forward, and stopping 5 meters away from the turning point; and (3) "right turn": starting from rest, moving straight forward for 5 meters, turning right at approximately a 90° angle, moving straight forward, and stopping 5 meters away from the turning point. Navigating these three paths required bimanual coordination of the pushes on both wheels. All 9 trials were performed indoors and on a flat cement surface.

We calculated the linear and angular velocity of the wheelchair using gyroscope data from the left and right wheels. To validate the results, we compared the calculated linear velocity with the SmartWheel's measured speed (it's important to note that the SmartWheel's measured velocity is only valid for the straight motion of the wheelchair). Next, we used the calculated linear and angular velocity to compute the instantaneous radius of curvature. Finally, we calculated the linear and angular acceleration of the wheelchair using the Richardson extrapolation technique.

Five supervised learning algorithms, namely logistic regression, random forest, naive Bayes, extra trees, and artificial neural network, were implemented in Python. Features were selected from the measured and calculated kinematic data. The training data set included a combination of data from two trials of each movement sets. Data from the third trial of each movement set were used as the test set. We used different combinations of the kinematic data to classify 4 wheelchair movements as: "not moving", "moving straight forward", "turning left", or "turning right". To detect these phases, we defined the following rules: (1) the wheelchair is in a "not moving" phase if the magnitude of the linear velocity is less than 0.12 m/s [12]; (2) the user is intending to turn left if the angular velocity is greater than a certain positive threshold and is intending to turn right if the angular velocity is less than a certain negative threshold (the margins for the "turning left" and "turning right" movements were set after preliminary analysis of the "straight" movement trials); (3) the angular velocity condition for "turning left" and "turning right" movement needed to be valid for at least 1 second.

**RESULTS**

We calculated the linear and angular velocity of the wheelchair for all the trials; a summary of the results is presented in Table 1. The comparison between the SmartWheel linear velocity and the calculated linear velocity (using the gyroscope data) confirmed the validity of our calculations. The calculated linear and angular velocity of the wheelchair as well as the measured linear velocity by the SmartWheel, for one "right turn" trial, are shown in Figure 1. The average peak linear velocity of all the trials was 1.43±0.09 m/s, with the highest average peak velocity for the "straight" movement trials (positive sign indicates a forward motion). For all the "straight" trials, the magnitude of the angular velocity was greater than zero, but less than 0.4 rad/s, indicating the presence of side-to-side temporal and/or force asymmetry. On average, the magnitude of the angular velocity of the "straight" movement trials (0.30±0.08 rad/s) had the lowest value compared to the "left turn", and "right turn" trials (positive sign indicates a left turn). We analyzed our data set with five supervised classifiers; the classification accuracy of these algorithms is presented in Table 2. The test accuracy for all the algorithms was greater than 91%, and random forest had the best performance at 98.5% accuracy.
The aim of this research was to use classification techniques to estimate user intentions regarding the direction of motion when navigating a MWC. As discussed before, the kinematics of wheelchair motion is determined by input forces to the system. In the absence of external forces (e.g., gravitational forces on sloped surfaces) or disturbances (e.g., uneven surfaces), the kinematics of movement can be determined by the user input force on the pushrims. Moreover, under ideal conditions, where a MWC user is not experiencing considerable difficulties with wheeling (e.g., no joint pain or major upper extremity asymmetries), user intentions regarding the speed and direction of movement are directly reflected in the kinematics of wheelchair motion. To create this ideal condition, we performed our experiments with an able-bodied participant in an indoor environment with no external disturbances, and on a flat surface. Therefore, we can assume that the collected kinematic data are relevant indicators of the participant’s intentions.

The pattern of wheelchair propulsion that is shown in Figure 1 is consistent with the findings of previous literature [13]. This includes the gradual increase of the linear velocity during the start-up phase, periodic increase and decrease of the linear velocity during the push and recovery phase, respectively, and gradual decrease of the linear velocity before a complete stop.

The results of this work showed that all the proposed algorithms estimated the 4 pre-defined classes with high accuracy on a level, smooth surface. After analyzing the performance of the classification algorithms, we realized that the misidentified data points were at the transitions between the “moving straight forward”, “turning left”, and “turning right” classes. This is justifiable because in reality there is no exact and clear transition moment between straight and turning movements. Although the current performance of these classification algorithms is

### Table 1. Wheelchair’s linear and angular velocity for all the trials

<table>
<thead>
<tr>
<th>Trial set</th>
<th>Angular velocity (rad/s)</th>
<th>Linear velocity (m/s)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peak positive direction</td>
<td>Peak negative direction</td>
<td>Peak positive direction</td>
</tr>
<tr>
<td>Straight forward trial 1</td>
<td>0.35</td>
<td>0.39</td>
<td>1.52</td>
</tr>
<tr>
<td>Straight forward trial 2</td>
<td>0.36</td>
<td>0.36</td>
<td>1.43</td>
</tr>
<tr>
<td>Straight forward trial 3</td>
<td>0.16</td>
<td>0.21</td>
<td>1.62</td>
</tr>
<tr>
<td>Left turn: trial 1</td>
<td>1.11</td>
<td>0.34</td>
<td>1.26</td>
</tr>
<tr>
<td>Left turn: trial 2</td>
<td>1.12</td>
<td>0.39</td>
<td>1.33</td>
</tr>
<tr>
<td>Left turn: trial 3</td>
<td>1.23</td>
<td>0.23</td>
<td>1.39</td>
</tr>
<tr>
<td>Right turn: trial 1</td>
<td>0.51</td>
<td>1.38</td>
<td>1.49</td>
</tr>
<tr>
<td>Right turn: trial 2</td>
<td>0.26</td>
<td>1.24</td>
<td>1.39</td>
</tr>
<tr>
<td>Right turn: trial 3</td>
<td>0.24</td>
<td>1.27</td>
<td>1.47</td>
</tr>
</tbody>
</table>

### Table 2. Training and test accuracy of the classifiers

<table>
<thead>
<tr>
<th>Type of classifier</th>
<th>Training accuracy</th>
<th>Test accuracy</th>
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<tr>
<td>Logistic regression</td>
<td>0.944</td>
<td>0.963</td>
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<tr>
<td>Random forest</td>
<td>0.991</td>
<td>0.985</td>
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<tr>
<td>Naive Bayes</td>
<td>0.897</td>
<td>0.916</td>
</tr>
<tr>
<td>Extra trees</td>
<td>0.995</td>
<td>0.974</td>
</tr>
<tr>
<td>Artificial neural network</td>
<td>0.952</td>
<td>0.971</td>
</tr>
</tbody>
</table>

**Figure 1. Kinematics of a “right turn” movement**

DISCUSSION

The aim of this research was to use classification techniques to estimate user intentions regarding the direction of motion when navigating a MWC. As discussed before, the kinematics of wheelchair motion is determined by input forces to the system. In the absence of external forces (e.g., gravitational forces on sloped surfaces) or disturbances (e.g., uneven surfaces), the kinematics of movement can be determined by the user input force on the pushrims. Moreover, under ideal conditions, where a MWC user is not experiencing considerable difficulties with wheeling (e.g., no joint pain or major upper extremity asymmetries), user intentions regarding the speed and direction of movement are directly reflected in the kinematics of wheelchair motion. To create this ideal condition, we performed our experiments with an able-bodied participant in an indoor environment with no external disturbances, and on a flat surface. Therefore, we can assume that the collected kinematic data are relevant indicators of the participant’s intentions.

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acceptable, introducing some complementary rules for the transition points could further improve the classification accuracy.

As discussed before, the previously designed PAPAW controllers have fixed control rules and no adaptation capabilities (e.g., to the user characteristics or intentions). We believe that the proposed intention detection framework in this work may provide the capability for self-calibrated controllers that result in the generation of adaptive context-aware power assist control for PAPAW users. The current dynamic user intention detection strategy has a run time of less than 25 microseconds and can be used in the future development of personalized learning-based real-time controllers for PAPAWs.

This work provides a preliminary foundation for the future development of more comprehensive intention detection frameworks. To address the limitation of the current technique, we need to monitor and analyze the environmental conditions (e.g., road inclination, type of surface) and their effects on the estimation process. Moreover, direct measurements of the user input force on pushrims can provide a more realistic indication of the user’s intention. Finally, more data should be collected (e.g., from expert wheelchair users when performing real-life activities, including more types of movements, and for longer periods of time), processed (e.g., using appropriate filters and sensor fusion techniques), and analyzed (e.g., using dimensionality reduction methods to identify the optimal number and type of sensors needed to detect the user intentions).

CONCLUSION

We used kinematics of wheelchair movement and learning-based algorithms to develop an intention detection technique for MWC users. The motivation for this work was to overcome the shortcomings of the existing control strategies for PAPAWs that rely on fixed calibration parameters that are usually chosen based on the average biomechanical characteristics of wheelchair propulsion. Preliminary results of this work confirmed the high accuracy performance of the proposed classification algorithms. Future studies will be focused on the analysis of more realistic wheelchair propulsion conditions to verify the validity of the classification techniques.

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REFERENCES


