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Towards the Development of a Learning-Based Intention Classification Framework for Pushrim-Activated Power-Assisted Wheelchairs*

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Abstract— **There has been a growth in the design and use of power assist devices for manual wheelchairs (MWCs) to alleviate the physical load of MWC use. A pushrim-activated power-assisted wheel (PAPAW) is an example of a power assist device that replaces the conventional wheel of a MWC. Although the use of PAPAWs provides some benefits to MWC users, it can also cause difficulties in maneuvering the wheelchair. In this research, we examined the characteristics of wheelchair propulsion when using manual and powered wheels. We used the left and right wheels' angular velocity to calculate the linear and angular velocity of the wheelchair. Results of this analysis revealed that the powered wheel's controller is not optimally designed to reflect the intentions of a wheelchair user. To address some of the challenges with coordinating the pushes on PAPAWs, we proposed the design of a user-intention detection framework. We used the kinematic data of MWC experiments and tested six supervised learning algorithms to classify one of four movements: "not moving", "moving straight forward", "turning left", and "turning right". We found that all the classification algorithms determined the type of movement with high accuracy and low computation time. The proposed intention detection framework can be used in the design of learning-based controllers for PAPAWs that take into account the individualized characteristics of wheelchair users. Such a system may improve the experience of PAPAW users.**

I. Introduction

Manual wheelchairs (MWCs) are the most commonly used WMADs among the spinal cord injury (SCI) population. MWC users rely on their upper extremity strength to move themselves and the chair. MWCs are relatively lightweight, maneuverable, and portable, but are also physically demanding to use. Manual wheelchair (MWC) users are at high risk of upper extremity joint pain, joint degeneration, and fatigue [1]. Power wheelchairs (PWCs) are the second most commonly used WMADs among the SCI population. In these devices, batteries and electric motors provide all the required power to move the chair, allowing the users to easily navigate with minimal effort (e.g., use of joystick, touchpad, etc.). PWCs provide a less physically taxing alternative to MWCs. However, since PWCs are bulky and difficult to transport, users of these devices often face more environmental and social barriers. To address these secondary conditions, several power attachments have been developed to mitigate or eliminate the physical load of MWC use. Motorized front-end attachments, such as Firefly from Rio Mobility, transform a MWC to a powered tricycle by lifting the front casters [2]. 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 [3]. 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 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 stop or slow down, SmartDrive senses resistance and therefore provides more power to move forward. Pushrim-activated power-assisted wheels (PAPAWs) are another example of power attachments 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 [4]. 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 [5]); and/or (2) unexpected external disturbances (e.g., environmental and road conditions [6]). Accordingly, we believe that characterizing wheelchair users' intentions when interacting with the wheels is an essential step for successful, optimized PAPAW controller design.

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In this research, we performed two sets of experiments to examine the kinematic characteristics of manual and power-assisted pushrim-activated wheelchair propulsion. We used gyroscope data to calculate the linear and angular velocity of the wheelchair for different wheelchair movements and compared the propulsion performance by analyzing these velocities. Based on the findings of these experiments, we outlined some of the limitations of a PAPAW (Twion from Alber) controller. To address these limitations, we proposed the use of supervised learning algorithms to estimate the intention of MWC users by monitoring the kinematics of wheelchair motion. We tested six classification techniques to determine the user's intentions toward not moving, moving straight forward, turning left, or turning right.

II. Background

The wheelchair user's direct and continuous interaction with the left and right pushrim is required to initiate and maintain PAPAWs' motion. Here we review some of the control strategies that were developed for the collaborative interactions between the user and the powered wheels. In one study, a PAPAW controller was designed 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 [8]. Another PAPAW controller was designed to generate 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 [9]. In another research, a fuzzy algorithm that takes in the kinematics and kinetics characteristics of wheelchair propulsion (e.g., posture angle and angular velocity of the wheelchair, the input torque proportion and the sum of the input torque to the right and left wheels) was developed to provide the assist torque [10]. Researchers have also investigated the use of a two-dimensional assist torque 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 [11].

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 [8], 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 [12],[13]. 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 [14].

In this work, we used inertial measurement units (IMU) to measure the kinematic characteristics of manual and pushrim-activated power-assisted wheelchair movements. Moreover, we studied the use of supervised learning algorithms 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 may provide insight into the 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.

III. Methods

We performed two sets of experiments with an able-bodied subject with experience wheeling both a MWC and a pushrim-activated power-assisted wheelchair. In this section, we describe the experimental procedures as well as the techniques used to analyze the data.

A. Experiment 1: Manual Wheelchair Propulsion

An instrumented wheel (SmartWheel [15]) was used to measure the 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. One smartphone with a MATLAB android application was mounted at the center of each wheel. The mounting location is shown in Fig. 1 (left). 3-Axis gyroscope data were collected at 10Hz and transferred to two separate laptops via WIFI. 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 [16]. 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. A schematic of the three pre-defined paths is shown in Fig 2. Navigating these three paths required bimanual coordination of the pushes on both wheels. All 9 trials were performed indoors and on a flat concrete surface.

The linear and angular velocity of the wheelchair was calculated using the angular velocity of the left and right wheels. To validate the results, the calculated linear velocity was resampled and compared 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). We used the normalized root mean square error (NRMSE) measure to compare the similarity between the two curves for the "straight" movement sets only.

Figure 1. Location of the smartphone on the wheel (left); Location of the smartphone at the back of the seat (right)

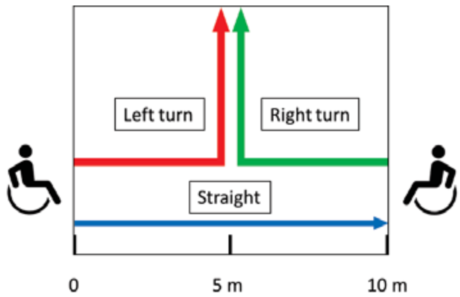

Figure 2. The predefined paths for the three movement sets: "Straight", "Left turn", "Right turn"

B. Experiment 2: Power-Assisted Wheelchair Propulsion

In this experiment, we replaced the manual wheels with the Twion powered wheels [17]. Similar to the previous experiment, one smartphone with a MATLAB android application was mounted at the center of each wheel. Another smartphone was mounted on the wheelchair frame at the backrest. The mounting location is shown in Fig. 1 (right). The gyroscope data from the three smartphones were measured and transferred to laptops similar to experiment 1. These data were collected from the same user while performing the same pushing maneuvers as experiment 1. To validate the results, we compared the calculated angular velocity with the measurements of the wheelchair frame's gyroscope. NRMSE was used to compare the similarity between the measured and calculated angular velocity for all the movement sets.

C. Measurement Analysis

The gyroscope measurements were filtered using a low-pass second order Butterworth filter with a cut off frequency of 4 Hz [18]. These data were then used to calculate the linear and angular velocity of the wheelchair. The linear and angular velocities represented the straight and rotational characteristics of the wheelchair motion, respectively. When performing a "straight" movement trial, it is ideal to have zero angular velocity throughout the motion. Deviations from this ideal pattern are not desirable and affect the quality of the ride. We used the root mean square (RMS) of the wheelchair's angular velocity to quantitatively evaluate these deviations. Lower RMS values are associated with smoother rides.

To address some of the limitations of a PAPAW controller, we proposed the use of supervised learning algorithms to effectively determine the user's intentions when propelling a wheelchair. To classify user intentions, we implemented six supervised learning algorithms in Python, namely logistic regression, random forest, naive Bayes, extra trees, and artificial neural network. Features were selected from the measured and calculated kinematic data of experiment 1 and included: linear and angular velocity of the wheelchair, linear and angular acceleration of the wheelchair (calculated using a 5-point backward numerical differentiation scheme), and the radius of curvature of the wheelchair's trajectory. 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 [16]; (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.

IV. Results

In experiment 1, the comparison between the measured linear velocity of the SmartWheel and the calculated linear velocity (using the wheels' gyroscope data) confirmed the validity of our calculations. The average NRMSE between the two data sets was less than 2.3%. In experiment 2, the comparison between the measured angular velocity of the wheelchair (using the seat's gyroscope data) and calculated angular velocity (using the wheels' gyroscope data) confirmed the validity of these calculations. The average NRMSE between the two data sets was less than 4.9%.

One example of a "straight" movement trial from experiment 1 is shown in Fig. 3. In this figure, the cyclic pattern of the linear velocity profile represents the push and recovery phases during wheelchair propulsion. Another example from a "left turn" trial in experiment 2 is shown in Fig. 4. In this figure, the region of the graph with high angular velocities (between $t \approx 4$ sec and $t \approx 6$ sec) indicates the 90°-turning phase of the "left turn" movement. Regions with low angular velocities are associated with the moving-straight-forward phase of the "left turn" movement where the user attempted to wheel on a straight path.

The linear and angular velocity of the wheelchair was calculated for all the trials; a summary of the results is presented in Fig. 5, Fig. 6, and Fig. 7. The average peak linear velocity in both experiments was the highest in the "straight" movement trials; 1.52±0.08 m/s and 1.65±0.09 m/s for manual and powered-wheels, respectively. For all the "straight" trials, the magnitude of the angular velocity was greater than zero, but less than 0.4 rad/s and 0.5 rad/s for the manual wheels and powered wheels, respectively. This indicates the presence of side-to-side temporal and/or force asymmetry. For the "left turn" and "right turn" trials, the maximum angular velocity was the highest during the turning phase. In the "left turn" trials, the average maximum angular velocity (CCW direction) was 1.15±0.04 rad/s and 1.34±0.20 rad/s for the manual and powered wheels, respectively. In the "right turn" trials, the average maximum angular velocity (CW direction) was 1.30±0.08 rad/s and 1.15±0.06 rad/s for

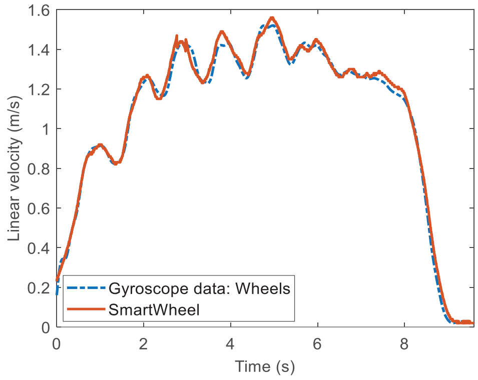

Figure 3. Validation of the gyroscope measurements: Experiment 1

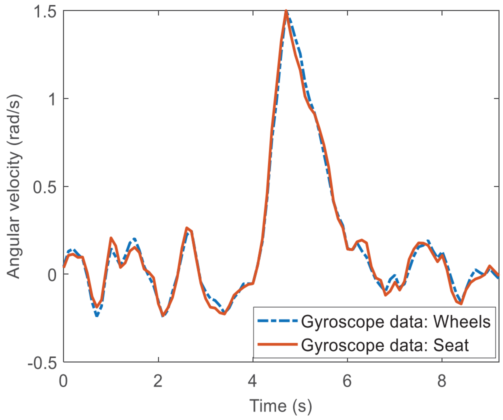

Figure 4. Validation of the gyroscope measurements: Experiment 2

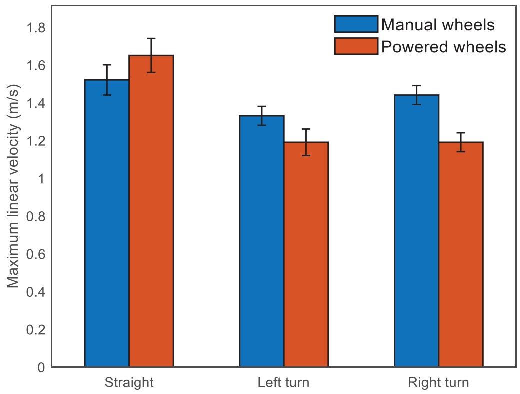

Figure 5. Peak linear velocity

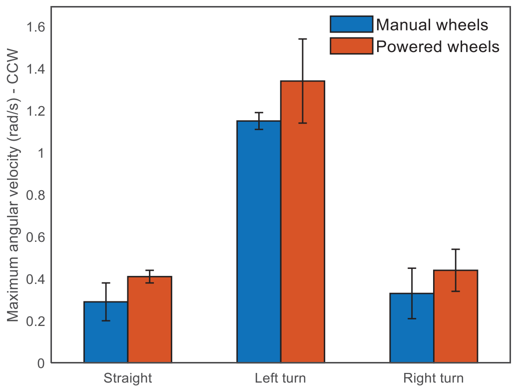

Figure 6. Peak angular velocity (CCW)

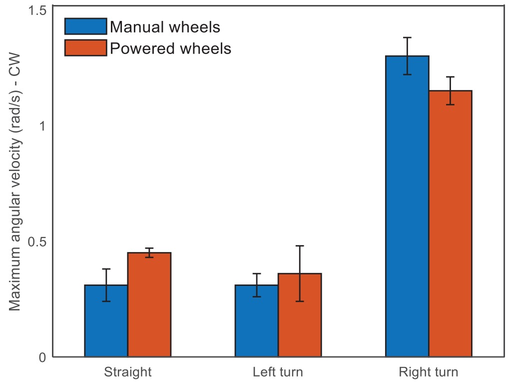

Figure 7. Peak angular velocity (CW)

the manual and powered wheels, respectively. Further analyses of the kinematic data revealed that:

- For the "straight" trials, the average linear velocity of the wheelchair was higher when using PAPAWs (1.06±0.16 m/s) compared to manual wheels (0.98±0.14 m/s).
- For the "left turn" and "right turn" trials, the average linear velocity of the wheelchair was higher when using manual wheels (0.85±0.04 m/s) compared to PAPAWs (0.76±0.06 m/s).
- For the "straight" trials, the variation in the angular velocity was higher when using PAPAWs (RMS = 0.2) compared to manual wheels (RMS = 0.1).
- For the "left turn" and "right turn" trials, the average magnitude of the angular velocity of the wheelchair was higher when using PAPAWs (0.83±0.02 rad/s) compared to manual wheels (0.81±0.06 rad/s).

Analysis of these preliminary results confirmed the findings of the previous research regarding the challenges in maintaining a smooth ride with PAPAWs. To potentially improve the performance of PAPAW controllers in a future implementation, we examined the use of supervised classification techniques to determine the intention of users when propelling a wheelchair. The classification accuracy of these algorithms is presented in Table I. The test accuracy for all the algorithms was greater than 90%, with random forest having the best performance at 98% accuracy. The classification errors were associated with the transition points between the *"moving straight forward"*, *"turning left"*, and *"turning right"* classes. The next step will be to use this accurate intention-classification algorithm to smooth out the desired path of a user's intended movement.

V. Discussion

The aim of this research was to examine and compare the kinematic characteristics of wheelchair propulsion when using manual and powered wheels in order to design a better PAPAW controller. The results of our experiments agreed with the findings of previous research, that is, using gyroscope data from two wheels is a reliable technique to examine the kinematics of wheelchair propulsion. Moreover,

TABLE I. TRAINING AND TEST ACCURACY OF THE CLASSIFIERS (EXPERIMENT 1)

Type of classifier	Training accuracy	Test accuracy
Logistic regression	0.94	0.96
Random forest	0.99	0.98
Naive Bayes	0.90	0.92
Extra trees	0.99	0.97
Artificial neural network (ANN)	0.95	0.97
Support vector machine (SVM)	0.96	0.93

the pattern of wheelchair propulsion that is shown in Fig. 3 was found to be consistent with the findings of previous literature [19]. 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. Analysis of the results revealed further insights regarding the wheeling characteristics that are discussed below.

By comparing the values of the angular velocity for the "straight" movement trials we concluded that: the MWC user had better control over the direction of motion and performed a smoother ride compared to the second experiment where she conducted the same activities with PAPAWs. Potential reasons for this are that small variations of the side-to-side user input to the pushrims are magnified when using PAPAWs. Also, the side-to-side variations are more apparent when moving with higher linear velocities.

When anticipating a turning movement, the user wheeled with lower linear velocities when using PAPAWs compared to manual wheels. One reason for this may be related to the fact that the user had better control over the direction of movement when wheeling at lower speeds (i.e. during preparation for a turn). However, this could be undesirable since the user has to be more cautious about the propulsion characteristics and may be inhibiting the natural propulsion pattern, as well as perhaps moving slower than desired.

We found that the average maximum angular velocity of the wheelchair is higher when turning with a PAPAW compared to a MWC. However, it's not clear whether this is according to the user's intentions or due to the poor performance of the PAPAW's controller and the wheelchair's lower stability (i.e., similar to the "straight" movement trials where using PAPAWs resulted in higher angular velocities and deviations from the straight path).

The abovementioned characteristics of the wheelchair propulsion provided further evidence regarding some of the shortcomings of PAPAW controllers. Some examples include: deviating from the desired direction of motion or occasionally moving at lower speeds to maintain stability when using PAPAWs. This indicated that to fully realize a shared control system with contributions from both a user and two motors, the user's intention needs to be considered and the system may need to be trained with the characteristics of each individual user.

We speculated that the characteristics of MWC propulsion can be used as baseline knowledge to design more efficient PAPAW controllers. To study the feasibility of this approach, we used 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 results of this study 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 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 classification framework in this work may provide the capability for self-calibrated controllers that results in the generation of adaptive context-aware power assist control for PAPAW users. The current dynamic user intention classification 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.

The main limitation of this preliminary research is the single subject used for both experiments. Moreover, the data were collected for limited durations and for simple activities under ideal conditions (e.g., no external disturbances). To address the limitation of the current research, 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). Despite these limitations, we believe that the findings of this study serve as preliminary evidence regarding the feasibility of designing learning-based controllers and provide a foundation for the future development of more comprehensive intention classification frameworks.

VI. CONCLUSION

We examined the kinematic features of manual and power-assisted pushrim-activated wheelchair propulsion and used these data to evaluate their performance. The comparison between the characteristics of manual and powered wheels further confirmed the limitations of PAPAW controllers. We aimed 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. We used kinematics of wheelchair movement and learning-based algorithms to develop an intention classification framework for wheelchair propulsion. Preliminary results of this work confirmed the high accuracy performance of the proposed classification algorithms. An accurate user intention-classification framework may be used to determine the user's intention toward a specific movement and thus smooth out unwanted deviations from their intended path. Future implementation of this framework in PAPAW controllers has the potential to enable an adaptive control through the adjustment of the wheelchair's linear and angular velocity. 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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