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REAL-TIME MODEL-BASED ELECTRICAL POWERED WHEELCHAIR CONTROL

Hongwu Wang^{1,2}, Benjamin Salatin^{1,2}, Garrett G. Grindle^{1,2}, Dan Ding^{1,2,3}, and Rory A. Cooper^{1,2,3}

¹Human Engineering Research Laboratories, VA Pittsburgh Healthcare System

²Department of Rehabilitation Science and Technology, University of Pittsburgh

³Department of Bioengineering, University of Pittsburgh

Abstract

The purpose of this study was to evaluate the effects of three different control methods on driving speed variation and wheel-slip of an electric-powered wheelchair (EPW). A kinematic model as well as 3-D dynamic model was developed to control the velocity and traction of the wheelchair. A smart wheelchair platform was designed and built with a computerized controller and encoders to record wheel speeds and to detect the slip. A model based, a proportional-integral-derivative (PID) and an open-loop controller were applied with the EPW driving on four different surfaces at three specified speeds. The speed errors, variation, rise time, settling time and slip coefficient were calculated and compared for a speed step-response input. Experimental results showed that model based control performed best on all surfaces across the speeds.

Keywords

Electric-powered wheelchair; 3-D dynamic model; model based control; PID; medical rehabilitation

I. INTRODUCTION

Over 200,000 people in the United States use electric-powered wheelchairs (EPWs) as their primary means of mobility [1,2]. EPWs provide functional mobility for people with both lower and upper extremity impairments. Great advances have been made in the design of electric powered wheelchairs over the past 20 years, yet the control algorithms for these wheelchairs have improved comparatively little since the early 1980's. Electric-powered wheelchair driving could become safer, more effective in a broader array of environments, and functional for more people with the application of advanced control systems [3,4].

Control systems research has achieved broad application in other areas, such as telecommunications, robotics, automation, and medicine. The simple proportional-integral (PI) controller used on most EPWs today for velocity control does not perform well when subjected to disturbances, sensor uncertainties and load variation [5,6]. In addition, wheelchair users may

Corresponding Author: Rory A. Cooper, PhD, Human Engineering Research Laboratories (151R-1), VA Pittsburgh Healthcare System, 7180 Highland Dr., Pittsburgh, PA 15206, Phone: 412-365-4850, Fax: 412-365-4858, rcooper+@pitt.edu.

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encounter different environments and road conditions when driving indoors or outdoors. Incidence of loss of control and injury are far too frequent among EPW users [3], [5]. A substantial fraction of EPW accidents can be directly attributed to the control system and design features of EPWs [3–6]. Persons with severe and complex disabilities might find it difficult to steer an EPW in a confined environment or under adverse conditions such as slippery or uneven terrain or obstacles. Sometimes, even experienced users may lose control of their chairs under such driving conditions. Especially problematic are the actions of negotiating a slope-transition and crossing the threshold of a doorway. These complex actions require hand-eye coordination and fine motor control that for some individuals with high-level spinal cord injury, multiple sclerosis or brain injury that may be exceedingly challenging. For some of these people, learning how to safely and effectively use an EPW can take hours or weeks. Fehr et al reported that 18%–26% of their patients that used a manual wheelchair could not safely operate an EPW. Their study concluded that no independent mobility options for these patients existed at the time of assessment [7]. Furthermore, a report using data from the United States emergency departments stated that in 2003 over 100,000 wheelchairs related accidents were treated with 65–80 percent of the accidents being tips and falls [8].

Some research has been conducted on simulation and control of EPWs. Brown et al. [9] applied optimal control theory to the design and development of a control system for an EPW. They developed a PID controller with self-adaptive gains. The controller did not consider robustness in terms of external disturbance rejection. Shung et al. [10] described a computer model of an EPW and its motor control circuitry. In their later work [11], they presented an EPW velocity feedback controller based on the rear wheel drive EPW model and motor control circuitry developed in [10]. A computer simulation study showed that the velocity controller made the EPW easier to drive under varying surface conditions. No driving experiments were reported to verify the practical use of the proposed controller. Another issue identified by EPW user's is wheel slip, which frequently occurs when driving over low-traction terrain, deformable terrain, steep hills, or during collisions with obstacles, and can frequently result in wheelchair loss of control or immobilization. The wheelchair should quickly detect the stalled state in order to let the user or control-system take appropriate action, such as planning an alternate route away from the low-traction terrain region or implementing a traction control algorithm [12]. For most automobiles, wheel slip can be accurately estimated through the use of encoders by comparing the speed of driven wheels to that of the coasting wheels [13]; however this does not apply for all-wheel drive vehicles or those without redundant encoders such as most EPWs. Ding and Cooper reviewed the past researches on EPW and stated that “control algorithms for these [EPW] wheelchairs have not improved substantially since the early 1980s.”[5]

The goal of this research is to provide EPW users expanded independent mobility that is safe, to eventually provide more people independent mobility. The controller for this study is based on the Versalogic EBX-12 COBRA industrial single board computer installed with VxWorks 6.3 real time operating system that replaces the Original Equipment Manufacturer (OEM) control electronics on an EPW as well as wheel encoders and inertia sensors to provide the researcher with control of the driving algorithms and the ability to read state data. The system is semiautonomous, which takes advantage of the intelligence of the wheelchair user by allowing the user to plan the general route while taking over lower level functions such as speed and anti-slip control. [14] This paper describes the evaluation of three different control methods on driving speed variation and wheel-slip of an electric-powered wheelchair (EPW): A 3D hybrid advanced control system (3D-HACS) based on the model of EPW that includes robust velocity control (RVC) and robust traction control (RTC) to reject external disturbances and compensate for parameter and sensor variations, PID control and open loop control.

II. DEVELOPMENT OF A 3-D HYBRID ADVANCED CONTROL SYSTEM

Our initial findings using a robust-velocity control (RVC) algorithm based on a 2D EPW model are described in [15,16]. The simulation results showed that the RVC suppressed disturbances better than a PI controller. In this study, we further refined the previous EPW dynamic model by considering EPW motion in 3D on inclined surfaces with cross-slopes, Fig. 1. We have incorporated a tri-axial gyroscope for providing real time feedback of the incline and cross-slope angles.

A. Robust Velocity Control

(a). Modeling the EPW—An EPW is a coupled electro-mechanical system in which two independent electrical motors produce torque to cause rotation the two rear drive wheels. Figure 1 shows the coordinate systems. The wheelchair is composed of a rigid platform and non-deforming wheels, and it moves on inclines of varying slope and cross-slope. Our 3D models is based upon the coordinate system illustrated in figure 2, $x'y'z'$ are fixed to the earth, xyz describe the wheelchair with the z axis perpendicular to the earth. The coordinate axes, $x''y''z''$ are affixed to the wheelchair with z axis perpendicular to the slope surface. Referring to figure 2, the following relations can be obtained among angles in these three coordinate systems.

$$\sin \gamma = \sin \alpha \cdot \cos \theta - \sin \beta \cdot \sin \theta \quad (1)$$

$$\sin \phi = \sin \alpha \cdot \sin \theta + \sin \beta \cdot \cos \theta \quad (2)$$

We define the traction force provided by the drive wheels as F_L, F_R which are dependent upon the torque the motors provide to each wheel.

From Figure 3, we can derive the force balance equations:

$$F_L + F_R - \mu(F_3 + F_4 + F_5 + F_6) - F_x = M \cdot \dot{v}_x \quad (3)$$

$$F_1 + F_2 - \mu(F_3 + F_4 + F_5 + F_6) + F_y = M \cdot \dot{v}_y \quad (4)$$

$$F_3 + F_4 + F_5 + F_6 - F_z = M \cdot \dot{v}_z = 0 \quad (5)$$

Where

$$\dot{v}_x = \frac{\dot{v}_R + \dot{v}_L}{2} - \frac{l \cdot (v_R^2 - v_L^2)}{W^2} \quad (6)$$

$$\dot{v}_y = \frac{(\dot{v}_R - \dot{v}_L) \cdot l}{W} + \frac{(v_R^2 - v_L^2)}{2 \cdot W} \quad (7)$$

$$F_x = \frac{M \cdot g \cdot \tan \gamma}{1 + \tan^2 \gamma + \tan^2 \beta} \quad (8)$$

$$F_y = \frac{M \cdot g \cdot \tan \beta}{1 + \tan^2 \gamma + \tan^2 \beta} \quad (9)$$

$$F_z = \frac{1}{1 + \tan^2 \gamma + \tan^2 \beta} \quad (10)$$

Moment balance about the center of mass of the system in figure 3 yields the equations:

$$(F_R - F_L) \cdot \frac{W}{2} - (F1 + F2) \cdot l = \frac{I_z \cdot \pi \cdot \dot{\omega}_z}{180} \quad (11)$$

$$(F3 + F5) \cdot \frac{W}{2} + (F1 + F2) \cdot H - (F4 + F6) \cdot \frac{W}{2} = 0 \quad (12)$$

$$(F5 + F6) \cdot (L - l) + (F_R + F_L) \cdot H - (F3 + F4) \cdot l = 0 \quad (13)$$

Where H is the height of center of mass (m), l is the distance that the center of mass is forward of rear axle (m), I_z is moment of inertia about Z'' axis ($\text{kg} \cdot \text{m}^2$), L is the EPW length measured from front axle to rear axle (m), M is total mass of EPW and driver (kg), W is width of EPW measured between rear wheel footprints (m), μ is the friction coefficient of the surface of the slope, F_X, F_Y, F_Z are x'', y'', Z'' component of total weight (N), F_R, F_L are the traction force provided by the motor (N), $F1-F6$ are other forces acting on front or rear wheels (N), v_x, v_y are x'', y'' component of velocity of center of mass (m/s), v_R, v_L are right/left wheel velocity (m/s), ω_z is EPW angular velocity about Z'' axis (degree/s).

From equation (3) through equation (13), it can be found that

$$\dot{v}_R = \frac{A+B}{2} \quad (14)$$

$$\dot{v}_L = \frac{A-B}{2} \quad (15)$$

$$\omega_z = \frac{d\theta}{dt} = \frac{180 \cdot (v_R - v_L)}{\pi \cdot W} \quad (16)$$

Where A and B are given by:

$$A = \frac{2(F_L + F_R - \mu F_Z - F_X)}{M} + \frac{2 \cdot l \cdot (v_R - v_L)^2}{W^2} \quad (17)$$

$$B = \frac{\frac{2 \cdot (F_Y - \mu F_Z) \cdot l + (F_R - F_L) \cdot W}{2 \cdot M \cdot l} - \frac{v_R^2 - v_L^2}{2 \cdot W}}{\frac{l}{W} + \frac{I_Z}{M \cdot l \cdot W}} \quad (18)$$

Applying Euler's method, we find that

$$v_R(k) = \frac{(A + B) \cdot \Delta t}{2} + v_R(k - 1) \quad (19)$$

$$v_L(k) = \frac{(A - B) \cdot \Delta t}{2} + v_L(k - 1) \quad (20)$$

$$\theta(k) = \frac{180 \cdot (v_R - v_L) \cdot \Delta t}{\pi \cdot W} + \theta(k - 1) \quad (21)$$

(b). Model based robust velocity control system—The models described above are essential parts of simulation models to control the motion of the wheelchair. However, no matter how detailed the analysis, these models will have uncertain parameters, such as the coefficient of rolling resistance, coefficient of friction and surface of the terrains.

The models of open-loop and closed-loop control systems that can be utilized to control the velocity are shown in Figure 4 for each driving wheel of the wheelchair. Since the open-loop system is highly sensitive to these uncertainties and hence can yield poor velocity control, while the feedback system can dramatically reduce the effects of the model uncertainty. In the experimental test described in the following session, the closed-loop model based control system is employed as the RVC algorithm. The whole dynamic models of the chair and wheelchair-terrain interactions were described as above. In our study, a modified PID controller was adopted from [17] where the input to the derivative term of the PID is the reference signal instead of error signal.

For motor, the moment of inertia and viscous friction of the motor are assumed small enough compared with inertia and friction associated with the wheelchair thus could be ignored. The speed and current curve for the DC motor [18], which is of the form $\omega_w = -\eta I_m + b(V_m)$, where ω_w and I_m are respectively the angular velocity and current of the motor, when $\eta > 0$ such that the slope is negative, and $b(V_m)$ changes monotonically with the motor voltage V_m . The motor must be constrained such that $I < I_m$, where represents the maximum current allowable before the motor is in danger of overheating and burning out. The motor control could be treated as an electrical drive system for the motor. In this study the Advance Motion Control 50A8DDE motor controller had been utilized.

B. Traction Control

The wheel slip ζ is usually defined by a nonlinear function of the wheel velocity ω_w , wheel radius r_w , and the wheelchair velocity V as follows:

$$\zeta = \frac{\omega_w r_w - V}{\omega_w r_w} \quad (22)$$

The wheel slip ζ can be monitored via the above equation, which also functions as a switch between the RTC algorithm and RVC algorithm, i.e.

$$\text{Controller} = \begin{cases} \text{RTC}, & \zeta \geq \zeta_{\text{lim it}} \\ \text{RVC}, & \zeta < \zeta_{\text{lim it}} \end{cases}$$

These algorithms serve as the basis for our hybrid robust controller that was compared to open-loop and PID classical methods. In our research, the data from the caster encoder which is the caster velocity represents the velocity of the wheelchair, and from encoder data of the driving wheel we collect the wheel velocity. If a wheel slip was detected, there would be a difference between wheelchair velocity and wheel velocity. The threshold of slip coefficient $\zeta_{\text{lim it}}$ for whether the traction controller will be chosen based on the experimental results.

If a slip is detected, while the driving wheel velocity is bigger than wheelchair velocity, in order to get enough traction, the controller will slow down the driving wheel velocity until the wheelchair begins moving. In case that the wheelchair does not move before it completely stops, user input may be required to either turn the wheelchair or backup the wheelchair to exit from the slippery situation.

III. EXPERIMENTAL METHODS

A. Test Wheelchair

The controller hardware and sensors were mounted on a Golden Alante wheelchair frame. The core electronic systems were divided into high and low power components. The high current components consist of two 12V batteries, two 420W motors with brakes, two industrial amplifiers, a brake release circuit, a DC-DC converter, and fuses. The motors and batteries are original equipment retained from the Golden Alante EPW that was chosen as the base. The Alante base was chosen for its simplicity and ability to operate as a front wheel or rear wheel drive EPW. The power amplifiers used were the Advance Motion Control 50A8DDE, which are power rated for 25A continuous and 50A for 2 seconds and accept a 20–28V input. The output for the 50A8DDE is controlled by a pulse-width-modulation (PWM) signal and a digital direction pin. The joystick was from the wheelchair OEM from which two voltage outputs representing speed (vertical axis) and direction (horizontal axis) and are within 1 V to 4 V ranges, with 3.5 V representing the neutral position voltage. The sensors on the EPW employed in this study were three digital incremental encoders attached to both of the driving wheel and one of the casters as well as a six degree of freedom Micro-Electro-Mechanical Systems (MEMS) based inertia sensor amounted on the seat post of the EPW (Fig. 5) which provides the linear acceleration and angular velocity of the EPW. The data collected were recorded at 200 HZ on an onboard 32 Gb solid state hard drive. Control algorithms were written in C language implemented on a VxWorks Operating System.

B. Software Algorithms

All control algorithms were embedded within the VxWorks real-time operating system. For open-loop control, no feedback was applied to the controller and the EPW actual speed was directly proportional to the joystick output. The control output frequency and sample frequency for data collection were set at 200HZ.

For PID control, the instantaneous wheels speeds were used as feedback to the controller which adjusted the error signal between the desired speed (set by the joystick) and the actual wheel speed to track the desired speed.

The model based controller was based on our 3-D EPW model. The physical parameters for the model were measured within the laboratory with the inertia of the EPW was measured using the method stated in [19]. The traction forces provided by the motor F_R , F_L were estimated from the current of the motor which was measured from sensors within the amplifiers. The anti-slip control algorithm compares the speeds of the driving wheels and the caster. The caster wheels are not powered, and therefore caster speed provides an estimate of the EPW velocity. Loss of traction, wheel slip, was defined as a difference in the angular velocity of the each drive wheel with respect to the caster of greater than 20%. When loss of traction was detected, the driving wheel speed was decreased until the wheel slip was within tolerances, and the EPW continued forward progress albeit possibly at a reduced speed.

C. Experimental Protocol

The experimental protocol consisted of driving the EPW with each of the control algorithms in-turn on five different surfaces which incorporated both indoor and outdoor environments (Fig. 6) and collecting data about the wheelchair speeds. A 2.44m Teflon sheet attached to an adjustable slope ramp with maximum 5° was used to simulate a slippery surface (e.g., ice, snow, wet grass). The initial set-up of the slope ramp is 3° . For each of the surfaces, in order to decrease the experimental error, the EPW was driven in the same manner for each trial. The control parameters were measured and recorded during each trial. The driving test was carried out using a step-response at three different desired speeds, fast 2 m/s, medium 1.5 m/s, and slow 1 m/s. All tests were conducted driving straight forwards, turns and reverse driving tests will require further development and are left for future studies. The order of testing the driving surfaces was randomly chosen; however, for each surface, the EPW was always driven with the fastest speed first, then medium and then slow speed. Also tests on the next surface were initiated after all the tests on the former surface were completed. The actual speeds of the two driving wheels and the caster were collected by encoders incorporated on the EPW. For PID and model based control, driving wheel encoder data were used as feedback to the controller. The caster encoder data were compared with the average of the driving wheel encoder data in the controller to detect the slip then initiate traction control if slip was detected. Data for each trial were analyzed using Matlab 7 (R14) and normalized to 10 seconds for comparison purposes.

In order to evaluate the performance of each control algorithm, the following variables were calculated and compared: rise time, settling time, speed error, speed variance and slip coefficient. Control algorithm performance was defined by lower errors and variances as well as faster response and shorter rise times. The rise-time was measured as the time it took for the wheelchair output speed to rise beyond 90% of the desired speed for the first time. The settling-time was recorded as the time from beginning to the time it took for the system to converge to its steady-state. The steady state here was the desired speed for PID and model based control and the stable speed for open loop control since with open loop control, the wheelchair could not be able to reach the desired speed. The system was considered to be steady state while changing of the velocity within 95% of the desired speed. This variable shows how fast the

wheelchair could settle down to the desired speed. The 10 second normalized root mean square error (NRMSE) between the desired speed and real speed recorded by the encoders was used as the speed-error. Variance of the error between desired speed and actual speed at steady-state was used for representing the speed-variance to examine “bucking” of the control on different surfaces at different speeds. EPW drivers are sensitive the “bucking” and will reject controllers with intolerable speed-variance. The difference between driving wheel speed and wheelchair speed (caster speed) normalized to the driving wheel speed was used to define the slip-coefficient to evaluate traction control.

IV. RESULTS

The parameters for the PID controller were chosen based on computer simulation results. During the experimental tests the PID parameters were: $K_i=0.8$, $K_p=1.5$ and $K_d=1.25$. Before the process of applying the model based control, physical parameters for the test EPW system were measured (see Table 1). The mass parameter in the table includes the EPW and the test-pilot (146 lb).

Table 2 shows the overall mean, standard deviation of speed errors, speed variance, rise time, settling time and slip coefficient. For both left and right wheels, speed errors of PID (left wheel: 1.46 ± 1.47 m/s; right wheel: 0.93 ± 1.03 m/s) and model based control (left wheel: 1.47 ± 1.38 m/s; right wheel: 0.69 ± 0.44 m/s) were much smaller than open loop control (left wheel: 2.56 ± 1.99 m/s; right wheel: 1.91 ± 1.58 m/s). As for the speed variance, model based control (left wheel: 1.35 ± 1.07 m/s; right wheel: 0.44 ± 0.28 m/s) was less than PID (left wheel: 1.47 ± 1.49 m/s; right wheel: 1.03 ± 0.93 m/s) control while PID control was less than open loop control (left wheel: 1.99 ± 1.77 m/s; right wheel: 1.58 ± 1.39 m/s). For the rise time, both PID (3.08 ± 2.09 second) and model based (2.92 ± 1.69 second) control were slightly longer than open loop control (2.15 ± 0.66 second), but the difference was less than 1 second. The settling time of PID (8.59 ± 5.91 second) and model based control (8.59 ± 5.26 second) were similar and less than half second longer than open loop control (8.08 ± 5.09 second). The slip-coefficient tracks the difference between the wheelchair speed and the driving wheels speed. Table 2 shows that model based control (0.04 ± 0.02) and PID control (0.06 ± 0.04) had smaller slip-coefficient values than open loop control (0.11 ± 0.04).

Figure 7 a–f shows representative plots of the desired speeds and real speeds at 1m/s and 2m/s for the three control algorithms on a grass surface. From Fig. 7, one can observe that PID and Model based Control methods track the desired speed better than open-loop control.

The slip coefficient of the wheelchair driving on 2m/s on grass surface is shown in figure 8, from which one can see that with model based control, the slip coefficient was smaller than PID and open-loop control, especially during the critical acceleration phase of the step-response.

Figure 9 a–e show box plots of the different variables between the three control methods categorized by speed. From figure 9 (a) and (b) one can see that for the same method, higher speeds induced larger errors and variances than the low speed. For the rise time and settling time, the faster the speed, less time was needed. The slip-coefficient, with open-loop and PID control, the faster the speed, the bigger the slip coefficient indicating greater slip was detected. However, with model based control, the slip coefficient was visibly lower at all desired speeds.

Figure 10 a–e show box plots of the different variables between three methods categorized by surface. From figure 10 (e) one can see that greater slip occurred for open-loop and PID control than model based control. When examining the model based controller, there was more slip on grass than any other surfaces. For the left and right wheel speed error (figure 10 a, and b), there was larger error on the Teflon surface than any other surface. For the rise time and settling

time (figure 10 c, and d), the tougher the surface (grass and slope), the more time was needed to obtain the desired speed and to reach a stable speed.

During the experimental tests, no slip could be seen by the investigators while observing the tests. However, our focus group participants reported having seen their wheels slip. Therefore, future studies should examine other surfaces or conditions. In order to test whether the anti-slip control method was effective, we put the Teflon on a ramp with 5° degrees slope on which the wheelchair was driven. The following figure 11 a–c show how the wheelchair performed during this scenario. From figure 11 (a) and (b) we observed that with open-loop and PID control, when slip happened, the two driving wheels kept spinning while the speed of the EPW was almost zero. In figure 11 (c), we could observe and recorded that the controller decreased the driving wheel speed in order to gain traction. However, Teflon surface length was insufficient to have the EPW fully reject slip, and regain the desired speed. Anti-slip control is an area where further work is needed to overcome slip more rapidly and effectively.

V. DISCUSSION

The data collected indicated that both the PID controller and model based controller decreased the error between the desired speed and actual speed of the wheelchair as compared to open-loop control over all test conditions (terrain and speeds). The results also showed that the model based control had smaller variances of error than PID control and open-loop control (Table 2 and figure 7) showing that the speed performance of the model based control is most consistent over different surfaces and speeds. The rise time and settling time for the model based control were close to PID and open-loop which indicates that the additional complexity of the model based control did not significantly sacrifice response time to decrease speed error and variance. Furthermore, the slip coefficient for model based control was smaller than PID and open-loop control demonstrating that model based control has greater sensitivity and better control when loss of traction may occur (table 2 and figure 8). Overall, model based control provided superior performance than PID and open-loop control.

Examining the performance of the wheelchair while driving at different speeds (figure 10 a–e and figure 9 (a) and (b)), it was observed that for each control algorithm higher speed had larger errors and variances than the low speed. This is understandable since under higher speed conditions, the distance traveled is longer between sampling periods for a fixed sampling rate. A more detailed model may improve the model based control at the fastest speed. Rise time and settling time were lower at the faster speeds. The slip coefficient, with open loop and PID control, the faster the speed the larger the slip coefficient indicating greater reduction in traction. However, with model based control, the slip coefficient was similar at different speeds because when slip exceeded the pre-defined threshold the algorithm decreased the driving wheel speed to increase the traction. Further investigation is needed to develop more effective and rapid means of implementing anti-slip control. However, one challenge is to avoid introducing unnecessary complexity and maintaining low-cost. Fortunately, sensor, computing, and memory costs continue to decline.

Focusing on the performance of the wheelchair while driving over different surfaces (figure 10 a–e) there was greater speed error on the low-friction surface (Teflon) than with the other surfaces for model based control. This was due to our anti-slip controller decreasing the driving wheel speed when slip was detected (figure 11), essentially trading-off speed for traction. The results of this study showed that our anti-slip control was ineffective if the wheelchair lost too much traction which requires further study. Future work on anti-slip control should examine control of wheel torque as well as speed to reduce slip. This may have the desired effect of reducing speed error and increase effectiveness over a wider variety of terrain (e.g., sand and gravel). From figure 10 (e), it can be seen that the slip coefficient is larger for open-loop and

PID control then model based control as a result of the anti-slip algorithm. For the model based controller, the slip coefficient was between the thresholds set in the algorithm resulting in higher values than for the other surfaces. A rapid method for detecting terrain may be helpful for setting terrain-specific slip coefficient control thresholds or even entirely different control approaches.

A potential approach to detecting EPW driving terrain, slip and immobilization is to add and analyze GPS measurements. However, nearby trees and buildings can cause signal loss and multi-path errors and changing satellites can cause position and velocity jumps [20], [21]. Additionally, GPS provides low frequency updates (e.g. typically near 1 Hz [22]) making GPS alone undesirable. Another approach could rely on methods for detecting robot immobilization using a signal-recognition approach. Offline, a support vector machine (SVM) classifier could be trained to recognize immobilized conditions within a feature space formed using an inertial measurement unit and optional wheel speed measurements. The trained SVM can then be used to quickly detect immobilization with little computation. Experimental results have shown the algorithm to quickly and accurately detect immobilization in various scenarios [23], [24].

The tougher surfaces (grass and slope) required more time to get the desired speed and stabilize at the desired speed. These surfaces induced more involuntary jostling of the test-pilot, which may have caused deviation from the model based control parameters. Incorporation of a more accurate human model within the algorithm may improve control. Further study should have both the human pilot and wheelchair in the 3-D model.

From table 2 and figure 8, figure 9 and figure 10, it can be observed that the left and right drive wheels did not perform the same during the experiments despite no tasks requiring turns. The EPW model assumed for simplicity that the two drive wheel motors of the EPW were symmetric. In practice, EPW do not use matched motors, and their parameters may vary notably resulting in differences between the speeds of the driving wheels, especially with open-loop control. Future studies may benefit from using matched motors or a model that does not assume symmetry during the further development and testing.

This control system experiments could be expanded to incorporate more driving scenarios. The results of this study may be dependent on the test EPW setup and test-pilot so further experimentation may be necessary to generalize the results to other EPW types. A wider variety of terrains should be tested such as different types of carpets, slippery surfaces and ramps. As more is learned about the challenges of driving an EPW, the information will be used to develop and refine our driving control algorithms with the goal of creating a higher level of safety and usability for all EPW users.

In future studies, models based on front- and middle- wheel drive wheelchairs including caster dynamics will be tested; the dynamics and performances of users will be included in the model to provide better feedback from the wheelchair users; the stability and safety of the users and wheelchairs should be considered during deciding the thresholds of control parameters; more sensors will be added and more effective control algorithms will be developed to improve the performance of EPWs. At the same time, we are working on to design a more compact, durable and economic affordable controller box which could be marketed and served as future controller.

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Figure 1.
Conceptual model of a wheelchair on an inclined surface with cross slope

Figure 2. wheelchair axis systems on a slope showing OAP as the slope surface, C represents the wheelchair, α (up/downhill slope of surface) and β (side slope of surface) associated with the surface, γ (slope along line of EPW motion) and ϕ (cross-slope to EPW motion) associated with the wheelchair, and the EPW direction θ

Figure 3.
Mathematical representatives of different views of a wheelchair on a slope

Figure 4.
Open-loop and closed-loop control systems for the model based control of a wheelchair

Figure 5.
the smart wheelchair platform used in this experiment

Figure 6.
Five different surfaces on which the experiment was conducted.

Fig. 7 a. Open loop control with slow speed

Fig. 7 b. Open loop control with high speed

Fig. 7 c. PID control with low speed

Fig. 7 d. PID control with low speed

Fig. 7 e. Model based control with low speed

Fig. 7 f. Model based control with high speed

Figure 7.

A example figure of two driving wheels and caster speeds with different controllers applied at low and high speeds on a grass surface.

Figure 8.
Slip coefficients of three controllers with the wheelchair driving on grass at 2 m/s.

Figure 9.
Wheelchair performances with three controllers at three different speeds.

Figure 10.
Wheelchair performances with three controllers on five different surfaces

Fig. 11 a. Slip measurement with Open loop

Fig. 11 b. Slip measurement with PID control

Fig. 11 c. Slip measurement with Model based control

Figure 11.

Slip measurements with three different controllers: open loop, PID and model based control

Physical parameters for the test EPW and test surface, where * means the parameters were found from other resources

Table 1

Constant Variables	Result
H (height of COM)	23.23(cm)
l (distance between COM and rear axle)	7.63(cm)
L (chair length between rear and front axle)	17.05(cm)
W (width of wheelchair between two rear footprints)	21.22(cm)
M (weight of wheelchair)	123.75(kg)
I_z (inertia of wheelchair to Z axis)	5.00(kg·m ²)
Surface Variables	Teflon Tile Asphalt Slope Grass
μ (friction coefficient)*	0.04 0.55 0.72 1.02 0.35
α (Up/downhill slope of road)	5° 3° 1° 11° 0°
β (Side slope of road)	0° 1.2° 0.7° 8° 0°
θ (Chair direction)	0° 0° 0° 0° 0°

Table 2

Test results of the mean, standard deviation and variance of the wheels speed NRMSE of all the three control methods

Method	Speed Error (Mean (Std)) (m/s)	Variance (m/s)	Settling Time (s)	Rise Time (s)	Slip Coefficient
Open Loop	Left: 2.56 (1.99)	1.99 (1.77)	8.08 (5.09)	2.15 (0.66)	0.11 (0.04)
	Right: 1.91 (1.58)	1.58 (1.39)			
PID	Left: 1.46 (1.47)	1.47 (1.49)	8.59 (5.91)	3.08 (2.69)	0.06 (0.04)
	Right: 0.93 (1.03)	1.03 (0.93)			
Model Based	Left: 1.47 (1.38)	1.35 (1.07)	8.59 (5.26)	2.92 (1.69)	0.04 (0.02)
	Right: 0.69 (0.44)	0.44 (0.28)			