VIBRATION-BASED TERRAIN CLASSIFICATION FOR ELECTRIC POWERED WHEELCHAIRS

Eric Coyle, Emmanuel G. Collins, Jr., Edmond DuPont, Dept. of Mechanical Engineering at FAMU-FSU Center for Intelligent Systems, Control and Robotics Tallahassee, FL 32310 coyleer, ecollins, edupont@eng.fsu.edu

Dan Ding, Hongwu Wang, Rory A. Cooper, Garrett Grindle Dept. of Rehabilitation Science and Tech. at Univ. of Pittsburgh Human Engineering Research Laboratory Pittsburgh, PA 15261 dad5, how11, rcooper, and ggg3@pitt.edu

ABSTRACT
Automated terrain classification for electric powered wheelchairs (EPWs) has two primary motivations. First, certain terrains (e.g., sand and gravel) make wheelchair mobility more difficult. To alleviate this problem the wheelchair control system can be manually tuned for maximum speeds and/or accelerations to help adapt to various terrains. Terrain classification can then be used to automate the switch from one control mode to another. Second, terrain classification can help yield a better understanding of the surfaces traversed by various groups of wheelchair users. This can provide the data needed to develop wheelchairs geared to specific groups of users. This paper presents an algorithm for vibration-based terrain classification on EPWs. This algorithm has been shown to be highly accurate in offline analysis of experimental data. Future work will stress online implementation and algorithm improvements.

KEY WORDS
Advanced Wheelchair Systems, Electric Powered Wheelchairs, Terrain Classification, Vibrations

1. Introduction
Based on the 2002 Survey of Income and Program Participation (SIPP) report there are over 11.8 million Americans over the age of 15 who require mobility assistance [1]. Among this population, 2.7 million require the use of manual or electric powered wheelchairs (EPWs). This should continue to increase over the next several years due to an aging U.S. population. The growing number of wheelchair users has created both need and demand for safer and more effective wheelchairs. Automated terrain classification can be used to aid the development of such wheelchairs in two primary ways.

First, wheelchair users encounter different environments and road conditions when driving outdoors. Incidence of loss of control and injury are far too frequent among EPW users [2]. Unstructured terrains can cause reduced speed control and loss of steering due to wheel slip or wheel sinkage. In drastic cases the user may become stranded and require personal assistance before the wheelchair can be used to resume regular activities. These problems can be alleviated or eliminated by tuning the vehicle control system for various terrains, similar to the way that the Land Rover LR3 Terrain Response System is used to adjust the control system of a Land Rover for four terrain groupings [3]. EPWs today are usually equipped with a programmable controller that allows the acceleration, deceleration, forward, reverse, and turning speeds to be adjusted for different driving conditions. This level of customization and adjustment may be adequate to meet the needs for highly skilled operators of EPWs in most circumstances. However, most people still have difficulty operating an EPW in some of the environments that they regularly encounter (e.g., grassy surface or snow/ice) [4]. Terrain classification can be used to automate the tuning of such parameters, allowing more wheelchair users to operate an EPW safely and effectively.

The second application of terrain classification for EPWs is to gain a better understanding of wheelchair usage and daily activities of wheelchair users in their natural environment. Currently, little is known about actual wheelchair usage and daily activities of wheelchair users with specific disabilities [5]. The current knowledge heavily relies on self-report methods such as diaries, logs, and recall surveys, which are subject to inaccuracy and recall bias [6]. A better understanding of the activities of impaired individuals could be obtained using a terrain classification system. This information can be used by wheelchair manufacturers to help tune wheelchairs for specific groups of users.

The issue of terrain classification has already been considered in the field of mobile robotics. Current detection techniques in this field are largely based on vision and terrain dependent vehicle responses. Although promising research is being conducted in the vision community using cameras and laser range finders [7], [8], [9], at this time visual detection does not seem to be cost effective for use with wheelchairs. However, response-based methods require relatively inexpensive sensor equipment and can be highly accurate as well. Vibration-based terrain classification was originally suggested in
discrete number of frequencies \( \omega \). Transform (FFT). This results in a frequency response at a frequency domain signals can improve accuracy and computation time as well as account for small variations in speed [11], [13], [15]. The difference in these results is that [11] uses a vote-based classifier, while [13] and [15] use Probabilistic Neural Networks (PNNs) to classify the terrain. These findings and techniques form a good basis for creating a unique terrain classification algorithm for EPWs.

This paper presents a vibration-based terrain classification algorithm for EPWs. The algorithm is based on techniques originally developed for mobile robotics, but has been specialized to suit terrain classification for EPWs. Although, it is expected that future improvements to the algorithm will be necessary for online implementation, the fundamental efficacy of the algorithm is proven here through experimental results.

The classification algorithm uses frequency response feature extraction, as in [12], which yields easily distinguished terrain signatures. Principal Component Analysis (PCA) feature selection, as in [11], [13], [15], is then used to improve accuracy and save computation time. However, unlike previous research, classification is performed in two stages. The first stage classifies whether the terrain is from an indoor or outdoor environment and the second stage determines the exact terrain encountered. The merits of this two stage classifier will be described in detail in the subsequent section.

2. Algorithm Overview

This terrain detection algorithm is based on several terrain classification techniques used on autonomous ground vehicles (AGVs) [11], [12], [13], [15] with specific improvements for classification with EPWs. Since AGVs have shown distinct terrain signatures in output frequency responses [12], it is believed that any vehicle, including an electric powered wheelchair, should also show distinct terrain signatures. An unrestrained wheelchair can vibrate in six independent directions and thus has six degrees of freedom. However, due to sensor availability and cost, this paper focuses on only three of these degrees of freedom, the \( x \), \( y \), and \( z \) accelerations, corresponding to the axes shown in Fig. 2. This algorithm conducts feature extraction on vibration output signals using a Fast Fourier Transform (FFT). This results in a frequency response at a discrete number of frequencies \( \{ \omega_1, \omega_2, \ldots, \omega_p \} \) between zero and half the sampling frequency, where \( \omega_p \) is the sampling frequency and \( p \) is the number of samples taken.

The number of frequencies will increase if the sampling rate or traversal time is increased. However, increasing the sampling rate will also widen the defined frequency range. A \( 3p \) dimensional feature vector \( \mathbf{n} \), is then defined by

\[
\mathbf{n} = \begin{bmatrix} \hat{v}(j\omega_1)_{[1:3]} & \hat{v}(j\omega_p)_{[1:3]} & \hat{x}(j\omega_p)_{[1:3]} \end{bmatrix}.
\]

Although, frequency response magnitudes show terrain signatures, the use of these magnitudes as classification features could result in a high dimensional feature space, particularly when using a large number of training vectors or a fast sampling rate. A high dimensional feature space ultimately requires more computation time to analyze.

Due to its dimension reduction capabilities and fast online implementation, Principal Component Analysis (PCA) is used to perform feature extraction and selection as in [15]. Consider the training matrix \( T \), defined by

\[
T = [\mathbf{n}_1 \; \mathbf{n}_2 \; \cdots \; \mathbf{n}_m]
\]

and the singular value decomposition,

\[
T - \bar{T} = U \Sigma V',
\]

where \( U \) and \( V \) are orthogonal matrices, \( \bar{T} = [\bar{i}_1 \; \bar{i}_2 \; \cdots \; \bar{i}_k] \) with \( \bar{i}_k = (\mathbf{n}_1 + \mathbf{n}_2 + \cdots + \mathbf{n}_m) / m \) and the column vectors \( u_i \) of matrix \( U \) are the eigenvectors that form an orthogonal basis for the unbiased training data \( T - \bar{T} \). Any feature vector \( \mathbf{n}_i \) can be projected onto the eigenspace spanned by \( k \) eigenvectors by

\[
a_k = U_i^T \mathbf{n}_i,
\]

where \( a_k \) is the new feature vector of dimension \( k \), which will be used for classification purposes. The eigenvectors \( u_i \) through \( u_k \), represent a percentage of the energy in the diagonal-like matrix \( \Sigma \). The appropriate energy percentage for classification is determined experimentally.

Unlike previous terrain classification techniques, this algorithm is structured in two classification stages with separate PCA feature extraction and selection processes and PNN classifiers. This structure is presented in Fig. 1.

![Fig. 1. Algorithm Structure](image)

The first classification stage consists of determining if the test vector is from an indoor or outdoor terrain. This structure is based on the expectation that indoor terrain frequency responses will look similar to the frequency responses of outdoor terrains. The second stage, which determines the exact terrain of the feature vector, could then be trained to distinguish the terrain signatures of indoor terrains even when the differences in signature are subtle. However, in the future a more scientific grouping method will be used to group together terrains with similar magnitude frequency responses. The ability to
distinguish less significant differences in frequency response may be particularly important in determining changes in terrain conditions. For example, when compared to structured indoor surfaces wet and dry grass will likely show similar frequency responses. But when only comparing wet and dry grass, the distinction between the two surfaces will probably be more evident. Such distinctions are important due to increased slip on wet or frozen surfaces, which will require different EPW adjustments.

Additionally, multiple stages can be helpful when considering a large number of terrains. Some terrains may have a large amount of variability (such as grass, or gravel) where others are more structured (such as asphalt or indoor surfaces). Each stage can then be tuned to discern and classify based on features that are most important to the terrains included in the stage. The observed merits of this multi-stage structure will be discussed in Section 4.

The PNN classifier used in both stages of this algorithm, estimates probability density functions (PDFs) for each class using Parzen Window estimation [16]. From the PDFs the probability of a test vector belonging to each class can be determined. The test vector is then classified based on the Bayes decision rule, which assigns the test vector to the class with the highest associated probability.

3. Experimental Set-Up and Procedure

The Quickie® P200 EPW (Sunrise Medical) used in these experiments is shown in Fig. 2. The P200 was used because it is a popular brand/type and has solid tires reducing variability due to tire pressure. It weighs approximately 220 lbs, and was operated by a 160 lb non-disabled individual.

Using a tri-axial accelerometer and onboard notebook computer, the x, y, and z-accelerations were recorded at a frequency of 200 Hz. This differs from previous research that used linear and angular vibration signals [13], [15], [12] or only a single linear vibration [11]. The tri-axial accelerometer used in this experiment was attached to an aluminum plate and placed directly underneath the seat cushion. Two traversal speeds, 1 m/s and 2 m/s, were analyzed in the experiments. These speeds correspond to relatively slow and moderate driving speeds of wheelchair users. Speed was verified for each trial using a stopwatch over a known distance. Trials were considered acceptable when the time was within 0.1 s of the target time.

These experiments were conducted under eight different terrains which are shown in Fig. 3: tile, thick carpet, light carpet, concrete, asphalt, grass, curb-cuts (including road crossing), and gravel. These terrains represent many of the typical terrains encountered by wheelchair users. Although some of these terrains may not require different wheelchair control adjustments, classification of terrains such as different carpet surfaces at home and work may be important for determining the activeness of an individual. Six trials per terrain were collected while the EPW was driven in a straight line. Offline, the output signals were divided into one second time intervals, which were used to create the feature vectors. In terms of online implementation these one second segments correspond to sampling the terrain every second. In general, it would be helpful to record as much data as possible from a terrain before attempting to classify the terrain. However, the time delay in detecting the encountered terrain increases with the amount of data used for classification. It is expected that, if sampling fast enough, a significant amount of terrain data can be collected, while keeping the detection delay to a minimum. For this reason, one second time intervals were chosen.

Due to the short length of the tested carpet terrains, the trials on these surfaces resulted in shorter time signals. Additionally, the time-signal from one trial was found to be corrupted and had to be discarded. In turn this resulted in fewer feature vectors on gravel, heavy and light carpet as shown in Table 1. It should be noted that the reduced number of feature vectors on gravel and carpeted surfaces is expected because they are typically shorter terrains.
As the speed increases, the EPW vibrates at faster rates, response magnitudes represent the terrain signatures. In either the underneath the tiles. Additionally, most of the terrains have higher magnitudes at low frequencies than any of the other terrains, possibly due to the grout lines magnitude peak between 70 and 80 Hz that is unseen by other terrains. It can also be seen that at 1 m/s tile has a magnitude above 0.5 m/s² in the frequency range [1, 7] Hz, but at 2 m/s grass has a magnitude above 0.5 m/s² in the frequency range [5, 20] Hz. These figures also show that when the EPW’s speed increases, more drastic EPW vibration occurs, resulting in frequency responses that have higher magnitudes than the frequency responses corresponding to slower speeds. These speed-dependent changes in terrain signatures are indicative of why direct comparison between responses at different speeds is difficult (i.e. classification based on vibration outputs is speed dependent).

Before attempting to classify the encountered terrain, appropriate values for the following algorithm parameters were determined: frequency range, PCA energy percentage and \( \sigma \), which is the spread of the radial density functions in the PNN classifier. Ideally these parameters could be determined using cross-validation. But due to the fairly small number of feature vectors recorded, the empirical parameters that yield the best classification results were used instead. However, this means that the algorithm may not have sufficient robustness to inconsistencies in each terrain. The use of more data will eliminate this uncertainty in future experiments. Table 2 shows the parameter values used for each speed and classification stage.

<table>
<thead>
<tr>
<th>Speed</th>
<th>Indoor/Outdoor</th>
<th>Low Freq.</th>
<th>High Freq.</th>
<th>Spread, ( \sigma )</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 m/s</td>
<td>In vs. Out</td>
<td>0</td>
<td>100</td>
<td>0.07</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>Indoor</td>
<td>0</td>
<td>100</td>
<td>0.04</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>Outdoor</td>
<td>0</td>
<td>100</td>
<td>0.16</td>
<td>90</td>
</tr>
<tr>
<td>2 m/s</td>
<td>In vs. Out</td>
<td>0</td>
<td>100</td>
<td>0.07</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Indoor</td>
<td>0</td>
<td>100</td>
<td>0.35</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td>Outdoor</td>
<td>0</td>
<td>100</td>
<td>0.23</td>
<td>64</td>
</tr>
</tbody>
</table>

In each stage the maximum frequency range of [0, 100] Hz is used. This is an indication that all the time-varying information recorded is necessary for classification. Thus, if the sampling frequency decreased, time vectors longer than one second will most likely be required. It should also be noted from Table 2 that at high speeds \( \sigma \) is larger than at slow speeds. The parameter \( \sigma \) can be viewed as determining the range of influence of the training features. Increasing and decreasing \( \sigma \) is analogous to increasing and decreasing the influence of each training vector on the estimation of the class PDFs. Thus, the required increase in \( \sigma \) at 2 m/s compared to 1 m/s shows that the variance within classes increases as the speed increases. This further supports the need to test and train vibration outputs at the same speed.

Classification results are shown in Fig. 6 and Fig. 7 corresponding to 1 m/s and 2 m/s respectively. The grey
bars in these figures represent the detected terrain. The first stage, which detects whether the terrain is indoors or outdoors, was found to be 100% accurate at 1 m/s and 97.5% accurate at 2 m/s. Overall, the algorithm was found to be 90% accurate in determining the exact terrain at both speeds. As a comparison, a single stage PCA-PNN classification process between these eight terrains could not exceed 87.5% classification accuracy at 1 m/s and 86.3% classification accuracy at 2 m/s. Additionally, at least 70% of the test vectors for each terrain were properly identified and half of the terrains at each speed were identified with 100% accuracy using a two-stage classification process. A single stage process alone was found to have more difficulty distinguishing between curb-cuts, concrete and asphalt (as low as 50% for concrete) as well as tile, heavy carpet and light carpet (as low as 60% for light carpet). Although vibrations for these surfaces are highly similar, distinguishing between these terrains may be necessary. For instance, detecting a curb-cut would indicate the EPW is in the process of crossing a road. During road crossings, the user should probably be given complete control of the EPW for safety reasons. Research is currently being conducted to determine a thorough list of terrains and surfaces that require unique control strategies or other wheelchair adjustments. This list will include appropriate groupings of the terrains considered in these experiments, as well as other relevant terrains such as mud and snow. The benefits of this two stage classification process beyond what has been shown here will not be fully understood until this list can be completed.

5. Real-Time Implementation Challenges

To determine the fundamental feasibility of vibration-based terrain classification for EPWs offline analysis is sufficient, but online implementation will be necessary to use terrain classification for any automated transitions in EPW control. Due to this fact, the algorithm's computation time was also considered. This algorithm was written and implemented offline using non-optimized MATLAB code. Yet the algorithm still seems fast enough for online implementation. On average it takes 0.0122 sec at 1 m/s and 0.0107 sec at 2 m/s to process and classify a single test vector using a 2 GHz Intel Core Duo Processor. Classification at 2 m/s is faster than 1 m/s due to lower dimensioned feature spaces caused by smaller PCA energy percentages. Online implementation will be performed using C, which is expected to reduce the computation time. Additionally, the algorithm may benefit from a sliding horizon approach for determining the feature vector. This could allow the detected terrain to be updated faster than once per second and consequently allow for faster transitions between control system settings. How quickly the feature vector is updated using a sliding horizon would be based on the computation time as well as the delay between detecting the terrain and updating the EPW control system.

As a human operated vehicle, typical EPW operation will not occur at a constant speed. Additionally, since wheelchair users are expected to carry both personal items and consumer products during typical use of their wheelchair, EPW loads are expected to vary as well. Since this algorithm relied on testing and training at the same speed and load, in theory this could require the classification algorithm to be trained at a large number of speeds and load conditions. In turn, this could require many training experiments. However, EPWs typically operate only within a small speed range, meaning the required number of training speeds should be significantly reduced. This small speed range should also reduce the affects of acceleration and deceleration since neither can occur at high magnitude for a long period of time. If the change in load is relatively small, the EPW vibrations may remain relatively unchanged. However, if the affects of loads or speed are too significant to be handled by additional training as proposed in [20], several algorithm improvements may be considered, including Terrain Input Classification [21], or an Eigenspace Manifold approach [22].

As previously mentioned, the algorithm presented in this paper relies solely on the three linear acceleration measurements. However, allowing the EPW to turn and accelerate/decelerate more freely will decrease the effectiveness of using the x and y accelerations to create classification features. This is due to the fact that these
measurements can be heavily influenced by these maneuvers. However, due to rigid body kinematics, it can be shown that when the accelerometers are placed away from the center of rotation, parts of the recorded measurements are in fact a result of the wheelchair’s angular motion. Thus, when driving at a constant speed, without turning much of the observed x and y acceleration could be due to changes in pitch and roll angles. This means that the pitch and roll rates could serve as suitable feature replacements for the x and y accelerations.

6. Conclusion

The growing population of wheelchair users has increased the need for safe and adaptive wheelchairs. One such adaptation method is to improve wheelchair performance on unstructured or uncertain terrains. By correctly identifying terrains, wheelchairs will be able to automatically make changes in the control system that adapt to the changing road conditions and thus provide improved mobility without compromising user control. This paper presents vibration-based terrain classification results on an electric powered wheelchair using terrain classification principles from mobile robotics. This algorithm was shown to be highly effective in classifying eight different terrains at two different speeds.

The focus of current research is to implement this algorithm online, using additional training data and a more appropriate set of grouped terrains. Future research will address how to handle changes in mass that can occur due to imposed loads or fluctuations in user weight in addition to fluctuations in EPW speed. The final goal is to implement terrain-dependent wheelchair adjustments alongside terrain classification.

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References


