Detection of Wheelchair Orientation in Human-Robot Interactions

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Abstract—**Autonomous mobile robots are being introduced in human-populated environments with increasing frequency, notably in hospitals and long-term care facilities. Ensuring safe and intuitive human robot interaction (HRI) is becoming a growing need, especially for pedestrians with mobility aids such as wheelchairs. The dynamics of wheelchair users differ from those of foot pedestrians, so accurate characterization of a wheelchair's location and orientation for state estimation is crucial. The 2D laser scanner is a well-suited sensor for accurate distance measurements with fast computation speeds, but the sparsity of its data is often a hindrance to effective object detection. Despite so, 2D range data from laser scanners is found to be effective in the detection and orientation estimation of wheelchairs, even in cluttered environments. The range data from the scanner is pre-processed by segmenting out objects using density-based clustering. A two-step classification algorithm first identifies wheelchair candidates from segmented objects with the random forest classifier, then estimates the wheelchair's orientation as one of six classes with a neural network. The models achieve 98% true positive rate for detection and 86% for orientation classification. The outcomes of this research can inform future works in building a real time wheelchair detection and state estimation for mobile robots.**

Keywords—mobile robots, pedestrian detection, human robot interaction

I. Introduction

Human-robot interaction is becoming commonplace as autonomous mobile robots are increasingly introduced in public settings. Mobile robots can be used for indoor or outdoor deliveries, wayfinding, and assistance for patients and clinicians in hospitals and rehabilitation centers [1-6]. In populated environments, the robot must be able to recognize human occupants in its surroundings and respond in appropriate ways to avoid confusion or causing injuries. Furthermore, to navigate safely and efficiently in settings like hospitals and care facilities, robots should be equipped with the ability to identify and path plan around pedestrians who use wheelchairs [6]. Wheelchair users account for a significant portion of the population at the estimated prevalence of 2.2% in the USA [7]. However, the detection of wheelchairs has received considerably less attention in research compared to the detection of upright walking pedestrians. Ensuring safe interaction between mobile robots and wheelchair users is critical, especially as the outside environment already poses higher injury inducing risks for people with mobility impairments [8].

In facilities where robots are used to guide patients and perform delivery tasks, wheelchair detection has been investigated using cameras [9-13] or 2D laser scanners [5], [14-16], both of which are common sensors equipped on mobile robots. Our work focuses on laser scanners as a lightweight alternative to richer image datasets, which generally require higher computation costs for processing and predictions. Laser scanners also provide highly accurate distance measurements within a large field-of-view. Laser-based methods tend to be more robust and perform well in close range and various lighting conditions, whereas cameras suffer from lens distortion and decreased image quality. However, due to the sparseness of the data, the informational content of laser scanners is comparatively lower than cameras.

In addition to detecting wheelchairs from laser scans, we are interested in estimating the orientation of the wheelchair, as wheelchair users exhibit unique movement characteristics when changing directions [6]. To our knowledge, no studies have attempted to estimate the angular orientation of a wheelchair in application to mobile robots. Knowledge of the orientation of a stationary or slow-moving wheelchair can benefit real time path planning without the need for temporal tracking, allowing the robot to mitigate any safety risks posed to the wheelchair user.

We experimentally demonstrate that 2D range data from a laser scanner can be used to identify manual wheelchairs and classify their orientation into one of six categories: back facing, front facing, left 45° angled, right 45° angled, left side facing, and right side facing. As a pre-processing step, we remove continuous lines of points that interfere with segmentation, then apply a density-based clustering algorithm to segment object clusters. Viable objects candidates are classified into wheelchairs or non-wheelchairs using a random forest classifier. Orientation estimation of the wheelchair object candidates is achieved using an artificial neural network (ANN). The proposed pipeline has high detection and orientation estimation accuracy, making it feasible for real time autonomous mobile robot path planning.

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II. Related Works

A. Wheelchair Detection

Pedestrian detection for mobile robots often makes use of 2D laser scanners, stereo cameras, RGBD cameras, or a fusion of several streams of data. Most research focuses on detecting distinct, often geometrical features of a human, such as the shapes of their legs, arms, torso, and head. For example, ambulatory pedestrians are associated with features like shape, size, and dynamic movements that enable the detection and tracking of individuals and groups. However, these characteristics are not inclusive of all types of pedestrians that the robot would encounter, such as wheelchair users who do not have the same gait patterns as upright walkers.

In classic 2D laser scan classification studies, objects of interest are segmented from the scan using jump distances between points, such that a consecutive segment of points at the same distance from the sensor are considered as a single object. A common method for classifying the object cluster is using a boosted classifier on the object features, such as AdaBoost [14], [17-19] and random forest [20]. Arras et al. [17] achieved detection rate of over 90% for their human leg detectors using geometric features. Similarly, but using their novel generic distance invariant features, Weinrich et al.'s [14] GANDALF detector uses AdaBoost to detect people with wheelchairs and walkers, achieving 86% classification accuracy of the mobility device.

To improve performance over handcrafted classifiers, Beyer et al. [15] introduce the DROW detector, which applies unsupervised learning to 2D range data using a convolutional neural network (CNN). They classify people with mobility aids, outperforming GANDALF with higher precision and recall. In a follow up study [21], they extend their deep learning algorithm to include unaided people, relying on temporal data extracted from multiple frames to compensate for the sparseness of range data. More recently, Jia et al. [16] implements DR-SPAAM, an auto-regressive model with spatial attention that fuses information across scan frames with lower computation complexity than DROW. Zheng et al. [5] applies PointNet [22], a neural network for unordered point sets, to segmented laser scans. Also using deep learning, Vasquez et al. [9] and Kollmitz et al. [10] perform multi-class detection on people with mobility aids using image and depth data.

B. Orientation Estimation

Object orientation can be computed by either temporally tracking the object across multiple frames to estimate its direction of travel or classifying its orientation directly from a static frame of data. A combination of both methods is used by Ardiyanto et al. [23] for pedestrian tracking. Their algorithm directly predicts orientation when the object is static or slow moving. Similarly in this study, only information extracted from a single frame of data is used. This method does not rely on temporal information and guarantees performance when the wheelchair and robot are stationary.

As far as we are aware, the only wheelchair orientation estimation study using external sensors is performed by Yang et al. [24], who use single perspective geometry from a static camera to regress the orientation of a manual wheelchair. They model orientation as a continuous mathematical relationship with the elliptical shape of the wheel projected on the image plane. However, orientation cannot be modelled like this using range data, as geometrical features of the wheels are not as apparent in laser scans.

Estimating the orientation of upright humans is more prevalent. Glas et al. [25] uses a network of laser scanners to capture body contours, then fitting them with a parametric shape model to estimate their orientation. With a ubiquitous sensor network, they can construct the contours of the person in full. BačÍK et al. [26] uses CNNs on scans from a multi-layer LiDAR to estimate body orientation with an average error of 33.5°. However, no existing methods that estimate orientation using a standalone laser scanner were identified.

The remaining methods for human orientation estimation pertain to the usage of image data from cameras. Lewandowski et al. [27] estimates upper body orientation continuously from RGBD images to the accuracy of about 5°. Others, Ardiyanto et al. [23], Ji et al. [28], Weinrich et al. [29], and Rybok et al. [30], classify orientation into discrete categories rather than as a regression. Although the format of image data is vastly different from range data, we employ a multi-class approach like these studies. We discretize orientation into incremental classes and classification is performed to predict the closest aligning orientation class. Studies reported in [23], [29] achieved multi-class accuracy around 64% from images. Fusion between multi-view cameras was able to improve the accuracy to 87.8% in [30], but this is not applicable to mobile robots, which are restricted to a single perspective setup.

III. Methods

Fig. 1 shows an overview of the proposed pipeline for wheelchair detection and orientation estimation. Range data from the 2D laser scanner is pre-processed and segmented to identify object clusters. Object clusters are determined by the density of points rather than the jump distance between points, which benefits the sparser distribution of wheelchair clusters. Segmented objects are classified into wheelchairs or non-wheelchairs, then only the detected wheelchairs are passed into the orientation classifier to determine the closest aligning orientation class. Examples of segmented wheelchair clusters in each orientation are shown in the figure next to depictions of the birds-eye view of a wheelchair user.

A. Pre-Processing and Segmentation

A scan frame consists of an array of points representing the distance from the sensor where each laser beam is interrupted. From this, we can construct a planar birds-eye-view of the contours of objects present at the height of the sensor. Given that the nature of laser beams is that they cannot penetrate through solid materials, only the closest side of solid objects is visible on the scan, and the depth of the objects is unknown. Manual wheelchairs are unique in this aspect because they have empty spaces between the wheel spokes, allowing some laser beams to pass through to interrupt at the far side. This allows the data points to fill out a sparse contour of the outline of the wheelchair. This feature helps distinguish wheelchairs from other solid objects even when the density of data points is sparse.

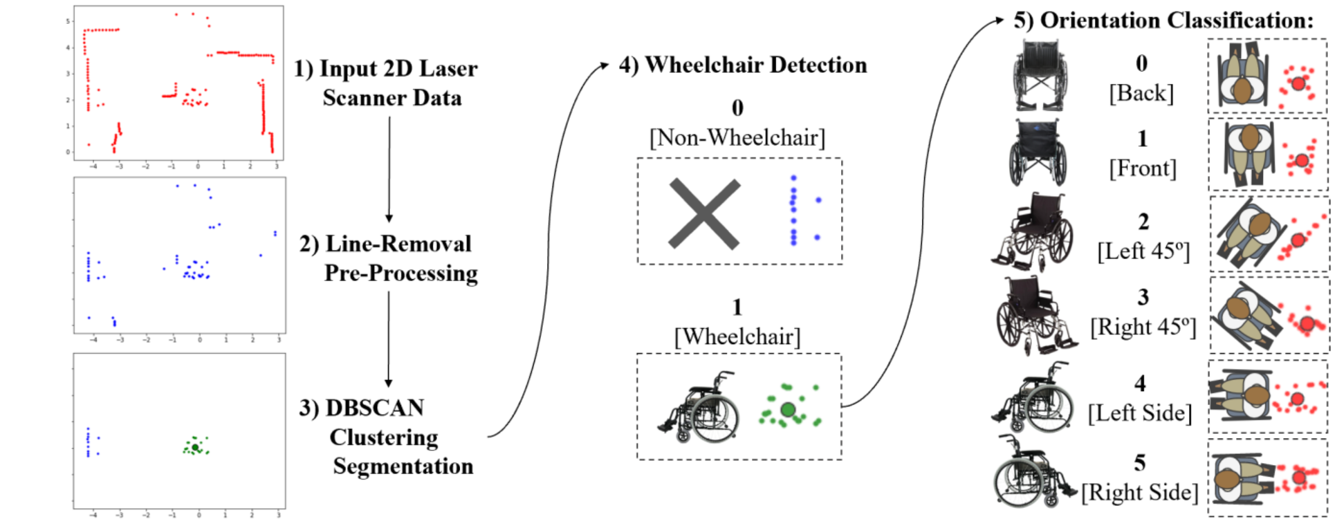


Fig. 1. Overview of the wheelchair orientation estimation algorithm: 1) scan frame of the 2D range data, 2) post-processed data with straight lines removed, 3) DBSCAN segmented, 4) classification on non-wheelchair and wheelchair clusters, and 5) samples of wheelchairs clusters in all orientation classes

Traditionally, jump distance between points is used as a threshold for segmentation. However, since wheelchairs do not produce interruptions at the same distance in consecutive segments of points, a more thoughtful method is required to segment out wheelchairs as distinct clusters. Through experimentation, it was determined that a density-based clustering algorithm is effective for this application. However, the presence of continuous and dense lines (produced by solid surfaces like walls) interferes with the segmentation of sparser objects, like wheelchairs. Hence, a line removing algorithm is implemented to eliminate consecutive segments of points that fit the parametric equation of a line with a residual error less than a hand-tuned threshold.

DBSCAN, a density-based clustering algorithm that also eliminates outliers, is applied to the remaining points. The DBSCAN parameters ε, which controls the maximum inclusivity distance between a point and its closest cluster, and η, which specifies the minimum number of points in a cluster, are optimized for the dataset used. The segmentation of wheelchairs is prioritized such that the outer contours of the clusters are well preserved. Confirmed with visual inspection, nearly all wheelchairs were segmented out with little or no loss to the integrity of their shapes.

B. Wheelchair Detection Model

After segmentation, the list of labelled objects is passed into a binary classifier that separates wheelchairs from non-wheelchairs without accounting for orientation. To standardize the size of the inputs, the coordinates of the points are mapped to a 100x100 pixel image. The scale of projection is determined by the size of the largest object, so that all objects retain their relative sizes after conversion. While it is possible to further extract features from the objects based on their dimensions, geometries, densities, and distributions, it was not attempted in this study since using the images directly achieved good outcomes.

We compare the performances of neural networks and ensemble methods for classification. CNNs are used by [9-10], [15] for wheelchair detection using range data or RGBD data. CNNs convolve over an image and extracts information from pixel neighborhoods, making them ideal for image classification. However, since the input objects in this study are not complex like real images, a simpler artificial neural network ($ANN^{Detection}$) is included for comparison. Two ensemble machine learning algorithms are used as well. Random forest (RF) used in [17], is a fast classifier that combines the predictions of multiple individual decision trees to limit model overfitting. The AdaBoost (AB) classifier is used in laser-based object classification [14], [17-19], [31-32]. Hyperparameters of the classifiers, such as the number of layers and neurons in the neural networks, are experimentally tuned on the dataset collected. All four classifiers and their parameters are listed in Tab. 1.

K-fold cross-validation is implemented in the model training stage to reduce overfitting. This splits the data into a one-part validation set and K–1 part training set. The models are each trained K=4 times on all the data. A test set comprising of 10% of the input data is set aside from the training set.

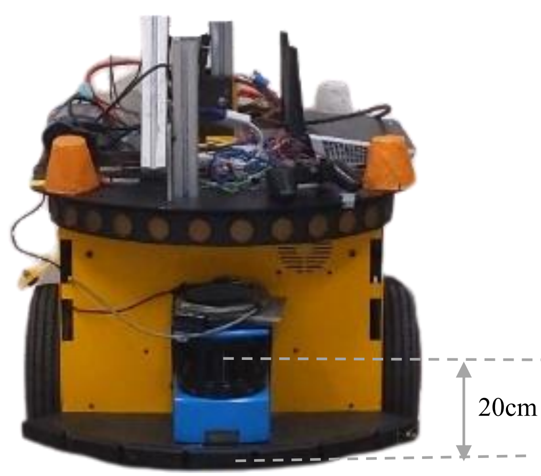


Fig. 2. PowerBot platform with mounted 2D laser scanner

TABLE I. WHEELCHAIR DETECTION AND ORIENTATION ESTIMATION CLASSIFIERS PARAMETERS

Stage	Classifier	Parameters
Wheelchair detection	ANN ^{Detection}	Two hidden layers of 500 and 50 neurons with ReLU activation
	CNN	Two hidden layers of 36 and 24 neurons with 3x3 kernel and ReLU activation.
	Random Forest	300 decision trees with no max-depth
	AdaBoost	300 decision trees with max-depth of 1
Orientation estimation	ANN ^{Orientation}	Hidden layer of 200 neurons with ReLU activation and L2 regularization

C. *Orientation Estimation Model*

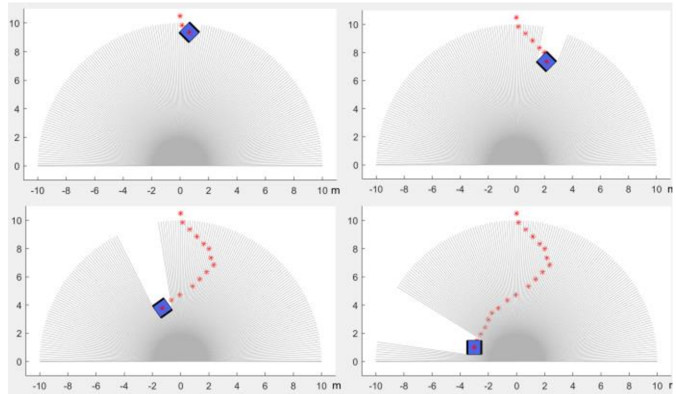
Wheelchair orientations are discretized into six classes: back facing, front facing, left 45° angled, right 45° angled, left side facing, and right side facing. The two back facing 45° angled orientations are excluded due to a lack of data. Orientations that mirrored each other (e.g., left/right and front/back) are purposefully differentiated from one another because knowing the direction is essential for trajectory estimation. Another neural network (ANN ^{Orientation}) is used with *softmax* at the output to achieve multi-class results. The network parameters also listed in Tab. 1. To prevent overfitting to the training data, L2-regularization is applied. The model is trained with K-fold cross-validation and evaluated on a 15% testing set.

IV. EXPERIMENTS

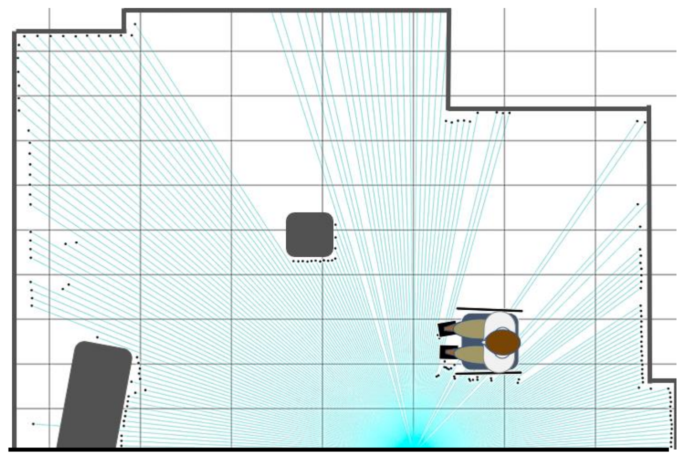
The experiment data was collected with a ROS-based PowerBot mobile robot platform, shown in Fig. 2. The PowerBot has a SICK LMS200 laser scanning sensor mounted to its base, which has a horizontal field-of-view of 180° at an angular resolution of 1° and a scanning frequency of 9 Hz. The scanner is optimized for indoor applications with a limit of 10-meter optimal operational range, but the wheelchair should be within 4 meters of the sensor to preserve shape details. An additional challenge working with planar data is finding the height of the scanning plane that would return the most feature rich data. Heights of 23 cm and 40 cm were used by Weinrich et al. [14], but their choice is based on features specific to human legs. The default height of the lower ledge of the PowerBot platform was used, which is 20 cm above the ground.

The experiment required a manual wheelchair to move through the field-of-view of the laser scanner. Data was captured for various wheelchair orientations and movements, including travelling in the direction towards the sensor, diagonal to the sensor, and fully orthogonal to the sensor. Fig. 3a depicts a MATLAB visualization of a wheelchair passing through the scanning field of the laser sensor. The red dots mark the center of the wheelchair as it travels along its path. Although the shown trajectory combines a compound of movements, which is emulative of real-world scenarios, this study simplifies the trajectory to single DOF movements for the ease of labelling. Fig. 3b shows a frame of the range data collected in the experiment, overlaid with a depiction of the room contour, objects, and the wheelchair user.

Two indoor spaces were identified for data collection. Both environments were spacious and relatively uncluttered to allow free movement, but not without a lack of props like tables, chairs, and boxes. A standard manual wheelchair operated by a human was used. In total, fourteen locations for the wheelchair were strategically chosen at different distances and radial positions with respect to the PowerBot and sensor. Some positions were selected near walls or other objects to test if the algorithm can segment out the wheelchair in less ideal environments. The locations were recorded such that segmented object clusters can be automatically labelled as wheelchairs if their centroid coincides with the pre-set coordinates. The ground truth dataset was constructed this way, and later verified by visual inspection. Data was recorded using *rosbag* then transferred offline for analysis.



(a) Simulated path of a wheelchair through the laser sensor field



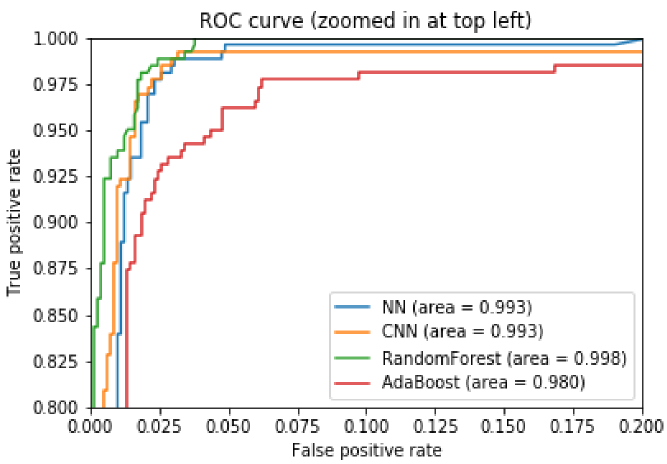
(b) Diagram of the room objects and wheelchair overlaid on range data from the laser sensor

Figure 3. Simulated and real range data collected with the wheelchair

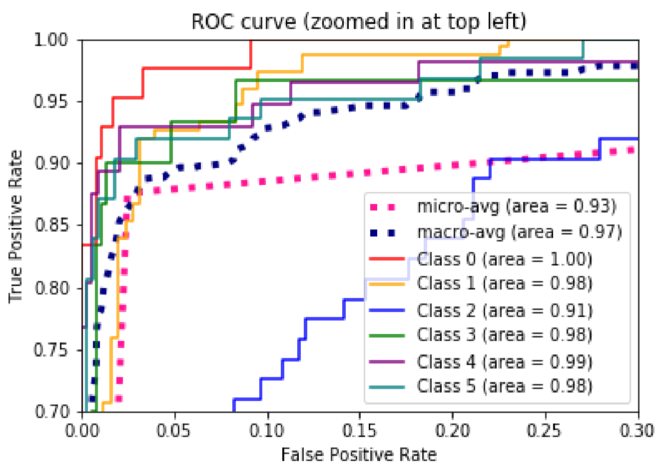
V. RESULTS

A. *Wheelchair Detection*

Fifty trial comprising 10 to 200 data frames each were conducted, yielding 10,818 labelled objects. About 25% (2694) are wheelchairs and 75% (8124) are miscellaneous objects, furniture, wall segments, or columns. Tab. 2 shows the computation time, training accuracy, and test accuracy from the four classifiers (ANN ^{Detection}, CNN, RF, and AB). Fig. 4a shows each classifier's ROC curves, which represents the discrimination threshold of the algorithm.



a) ROC curves of the evaluated wheelchair detection classifiers.



b) ROC curves of orientation classification by class

Fig. 4. ROC curves of detection and orientation estimation models

The ANN $^{\text{Detection}}$, CNN, and random forest achieved similar accuracies, whereas AdaBoost performed significantly worse. In terms of runtime, random forest outperformed the others, with CNN being the slowest. Random forest also saw the most consistent training and testing accuracy, which means that the model performs well on generalized data outside the training set. This is not surprising as random forest is a proven classifier for large datasets with high dimensionality and is not prone to model overfitting.

Tab. 3 shows the confusion matrix, precision, recall, and weighted F1-score of the random forest, where [0] represents non-wheelchair and [1] represents wheelchair. The rows represent the ground truth, and the columns represent the predicted class. The weighted F1-score was computed with the micro-averaging method, which accounts for the contribution from each class according to sample size, giving a useful metric for imbalanced datasets. The true positive rate of wheelchair detection using random forest is 98.1%. However, the precision for wheelchair is noticeably lower than non-wheelchair, which indicates that the false positive rate of the classifier is also high, so some non-wheelchair objects will be passed into the orientation classifier. Although not desirable, the impact of this is better than having a high false negative rate, which would result in more missed wheelchairs.

TABLE II. WHEELCHAIR DETECTION AND ORIENTATION ESTIMATION CLASSIFIERS PERFORMANCE

Classifier	Time/Sample	Training Accuracy	Testing Accuracy
ANN $^{\text{Detection}}$	750 µs	99.14 ± 1.0%	97.50%
CNN	64 ms	99.16 ± 0.74%	97.60%
RF	160 µs	98.10 ± 0.29%	98.10%
AB	1.8 ms	96.58 ± 0.38%	96.02%
ANN $^{\text{Orientation}}$	970 µs	89.0 ± 2.2%	87.6%

TABLE III. CONFUSION MATRIX, PRECISION, RECALL, AND F1-SCORE FOR WHEELCHAIR DETECTION WITH RF

	0	**1**	**Precision**
0	98.2%	1.8%	0.99
1	1.9%	98.1%	0.94
Recall	0.98	0.98	**$F1_w$:** 0.98

TABLE IV. WHEELCHAIR ORIENTATION CLASS DISTRIBUTION

Class #	*0*	*1*	*2*	*3*	*4*	*5*
Class Name	Back	Front	Left 45°	Right 45°	Left Side	Right Side
#	308	960	446	293	338	329
%	11.5%	35.9%	16.7%	10.9%	12.6%	12.3%

TABLE V. CONFUSION MATRIX, PRECISION, RECALL, AND F1 FOR ORIENTATION ESTIMATION WITH ANN $^{\text{ORIENTATION}}$

	0	**1**	**2**	**3**	**4**	**5**	**Precision**
0	***88%***	10%	2%	0%	0%	0%	0.93
1	0%	***96%***	4%	0%	0%	0%	0.88
2	5%	14%	***80%***	1%	0%	0%	0.75
3	0%	3%	3%	***77%***	3%	13%	0.82
4	0%	14%	4%	5%	***77%***	0%	0.96
5	0%	0%	10%	1%	0%	***89%***	0.93
Recall	0.88	0.96	0.79	0.77	0.79	0.89	**$F1_w$:** 0.88

The most comparable study [14], which uses range data for wheelchair detection, achieves a true positive rate of around 92%. However, it should be noted that their study detects humans, wheelchairs, and walkers, so the complexity of classification is higher. The laser scanner they use has a finer angular resolution at 0.5°, so they retain more object detail. They also recorded their data from a rehabilitation center, which contained twice the number of wheelchairs, which indicates that their results could be more robust to real-world conditions.

B. *Orientation Estimation*

Labelled wheelchair clusters, with Tab. 4 showing the distribution by class, are passed into the orientation classifier ANN $^{\text{Orientation}}$. The bottom row of Tab. 2 shows the runtime, training accuracy, and testing accuracy. Tab. 5 shows the precision and recall for each class, as well as the micro-averaged, weighted F1-score. Fig. 4b shows the ROC curves for each class and the micro- and macro-averaged curves. Front facing wheelchairs had the most samples, slightly unbalancing the dataset in its favor. The classifier also often predicted in favor of the front facing class, giving it the highest recall. The bias toward the class is also evidenced by the ROC curves. In contrast, the left and right 45° classes had the lowest precision and recall scores.

Compounding the results of the best performing classifier in the first step, the random forest, with the $ANN^{Orientation}$ gives the overall accuracy of 85.9% for predicting the orientation of a wheelchair. The implications of misclassifying orientation primarily affect wheelchair state estimation and trajectory prediction. Sporadic misclassifications can be tolerated through applying a Kalman filter to estimating the state (position, orientation, and velocity) of a moving wheelchair.

Our results are comparable to other orientation classification studies [23], [29-30] that discretized orientations into incremental classes, albeit using image data instead of laser. Ardiyanto et al. [23] use a monocular camera mounted to a moving robotic platform and split orientations into eight classes at 45° increments. They achieve an accuracy rate of 64% using random forest. Weinrich et al. [29] use a monocular camera and the same eight classes of orientation. Their support vector machine (SVM) model achieved 64% accuracy. Rybok et al. [30] use a multi-camera approach and divide orientation into twelve classes at 30° increments. They use a nearest mean classifier to predict orientation from each camera, then fuse the results using a Bayesian filter, achieving 87.8%.

C. Limitations

A major limitation of the classifier comes from the coarse discretization process. What orientation class does an *in-between* angle like 22° belong to? When labelling the data, all segmented wheelchair candidates were rounded to their closest orientation category. Thus, at orientation class boundaries (such as 22°), nearly identical data clusters would be present in both the front facing and 45° angled classes, introducing ambiguity in the ground truth. Misclassifications on *in-between* orientations should perhaps be weighed less heavily than misclassifications on more obvious orientations, or otherwise a regression approach can be considered. Overall, variations in the discretization bin sizes should be further explored to characterize the trade-off between the angular precision of the estimation and the accuracy of the orientation class prediction.

VI. Conclusions

This study presents a method for wheelchair detection and orientation estimation for mobile robotics, which creates a foundation for robust wheelchair state estimation. Using only 2D range data from a standalone laser scanning sensor mounted to a mobile robot, the experimental set-up can be easily recreated with other autonomous robots deployed in real-life settings. Follow-up works can include investigating the online performance of the algorithm in experiments with human participants.

As a pre-processing step for the inputs to the classification algorithm, we found it effective to use density-based clustering to segment out objects from the range data. Wheelchair candidate objects are identified using a random forest classifier, then passed into a multi-class orientation estimation neural network. Combining the two steps, the orientation classification achieves an accuracy of 86% at test time. The proposed model was tested with a physical mobile robot and it was verified that the algorithm performs well in cluttered environments that are reflective of real-world conditions. The outcomes of this research can inform future works in building a real-time wheelchair detection and trajectory prediction for mobile robots, a further step towards achieving safe and effective human-robot interactions for vulnerable pedestrian groups.

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