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Automated Door Detection with a 3D-Sensor

Sebastian Meyer zu Borgsen, Matthias Schöpfer, Leon Ziegler, Sven Wachsmuth
CITEC - Center of Excellence Cognitive Interaction Technology
Bielefeld University
Bielefeld, 33615 Germany
Email: {semeyerz,mschoepf,lziegler,swachsmu}@techfak.uni-bielefeld.de

***Abstract*—Service robots share the living space of humans. Thus, they should have a similar concept of the environment without having everything labeled beforehand. The detection of closed doors is challenging because they appear with different materials, designs and can even include glass inlays. At the same time their detection is vital in any kind of navigation tasks in domestic environments. A typical 2D object recognition algorithm may not be able to handle the large optical variety of doors. Improvements of low-cost infrared 3D-sensors enable robots to perceive their environment as spatial structure. Therefore we propose a novel door detection algorithm that employs basic structural knowledge about doors and enables to extract parts of doors from point clouds based on constraint region growing. These parts get weighted with Gaussian probabilities and are combined to create an overall probability measure. To show the validity of our approach, a realistic dataset of different doors from different angles and distances was acquired.**

I. Introduction

Mobile robots are expected to orient themselves in new or changed environments. For this purpose, various Simultaneous Location And Mapping techniques (SLAM) [7], [15], [18] can be used. The detection of doors is an important aspect in order to enable the robot to autonomously explore its complete domicile. This paper describes how mobile robots can be given the capability to autonomously detect closed doors as important parts of such environments. In combination with established mapping algorithms, it is possible to consider these as functional elements in navigation tests.

A. Related Work

Generally, doors are a challenge for object recognition approaches that rely on the extraction of texture-based image descriptors, color histograms or uniform color regions. As doors usually do not have so much visual features, these classic approaches [1], [2], [11], [13], [19]–[21] often fail or do not generalize well. Even for depth sensors, doors are generally difficult because they may contain glass elements or are equipped with metallic handles that typically cause undefined measurements.

Therefore, several approaches have been explored so far for specificly recognizing doors and dealing with the problem of autonomously opening them [3], [4], [6], [8], [10], [17]. However, most make very specific assumptions about the environment and positions of the robot in order to perform them successfully. Kingbeil et al. [10] concentrate on the handle recognition by the 2d-sliding window approach and assume that the robot has already navigated towards a door. Sturm et al. [8] as well as Anguelov et al. [4] use motion properties learn or use articulation models of doors. However, this requires that the robot has already seen the door opening. Aude et al. [6] as well as Andreopoulos and Tsotsos [3] use 2D image edges in order to detect a door frame of a known size. The idea of concentrating on the door frame is similar to our approach but makes more assumptions about its width, clean background, and color contrast. M. Quigley et al. [14] combine some of the 2D image techniques with information from a laser line scan to improve detection rates. The main problem with line scans is the long times required to scan a scene which makes them hard to use on moving robots. Rusu et al. [17] propose a laser-based perception for door and handle identification. A dense point cloud is generated by a tilting laser sensor. Candidate door planes are pruned by different criteria. While this strategy works well for solid doors, we are also looking for doors with glass elements by utilizing a more sophisticated strategy for extracting the door planes. N. Kwak et al. [12] combine a lot of algorithms to enable a humanoid robot to open doors. However the robot needs a reference image of a door to open it, which means that a lot of preparation is needed to enable the robot to deal with a new environment. Creating a map of possible doors with 2D laser scans was also introduced by [4]. This might again work quiet well on open doors or doors that have frames with a high depth, but on closed doors the accuracy will suffer.

II. 3D Perception of Doors

A. Primesense

PrimeSense®3D depth sensors use structured light to determine the depth at a given point. An infrared projector casts a special pattern on the environment which cannot be seen by the human eye. This pattern is perceived by a CMOS chip and directly processed in the device. Various algorithms are used to triangulate and extract the 3D data from the sensed pattern. The depth information can be easily achieved via USB. These sensors were mainly constructed for person tracking in front of the Microsoft®XBOX. As they perform decently at a low price and are compact and light, they became a standard sensor in robotics. [9] shows some technical information which helped to tune the door detection algorithm. In addition the Poster [5] gives some more detail of the PrimeSense performance over longer distances.

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B. Point Cloud Library

The Point Cloud Library [16] is a framework for n-dimensional point clouds and 3D processing. This library includes a variety of state-of-the art algorithms for filtering, surface reconstruction and segmentation. We used the development version 1.7 as it provides normal based region growing, which is employed in the proposed algorithm.

C. Doors

Our implementation algorithm is optimized for the detection of single-leaf doors. Typically the dimensions of door leafs are standardized. DIN[1] 18101, for example defines door-widths of 610, 735, 860, 985 and 1110 [mm]. Door heights are standardized as 1985 and 2110 [mm] respectively. These specifications refer to the door leaf and will be used to increase the quality of detection. In addition to the door leaf, the handle set is used as a feature for the detection of a door. Unfortunately there is no general specification for handle sets. These can be round, straight or even any other graspable form, and with or without a keyhole.

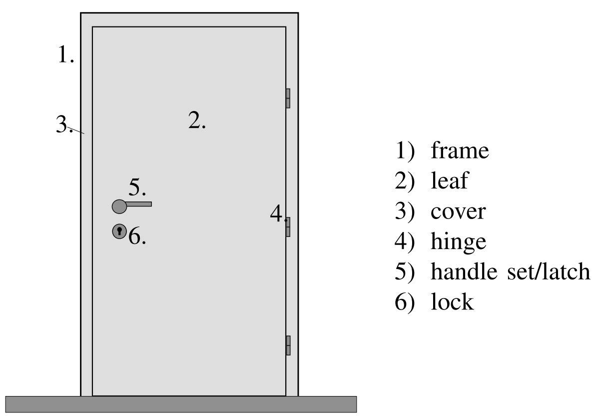


Fig. 1. Schematic figure of a door with labeling of different parts.

III. Detection Algorithm

A. Overview

The basic idea of this algorithm is to extract a set of typical door features from a 3D point cloud. This approach has the benefit of being able to rate various characteristics for an object being a door. Hence, in contrast to machine learning algorithms no training set is needed. We therefore obtained a training-set independent detection algorithm, as well as the ability to work in a new environment without any additional training time.

At first the algorithm partitions the sensed point cloud into sub clouds. These sub clouds are created with a region growing algorithm adopted from 2D image processing. Based on the plane normal of a group of clouds, this segmentation is a robust way of extracting connected planes. As most doors are connected planes, this is exactly what is needed. In addition to the door plane the algorithm tries to sense a door knob. Both of these features are measured and rated in a subsequent processing step.

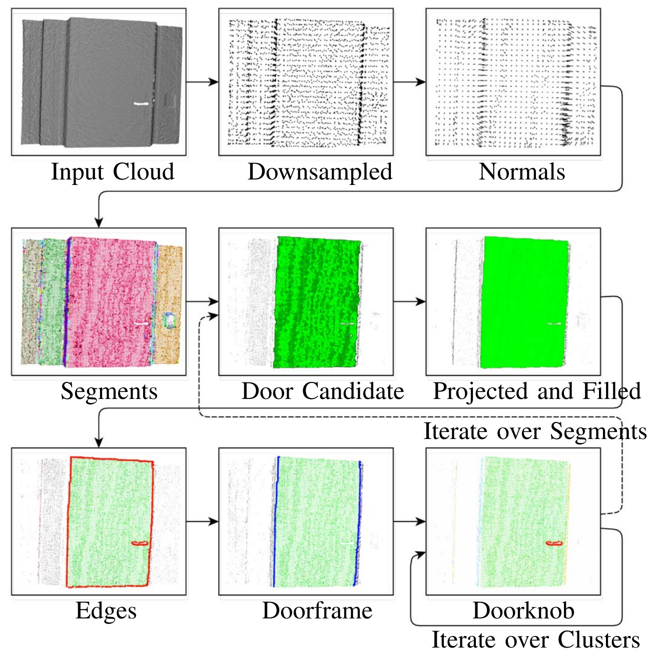


Fig. 2. This is a visualization of the nine processing steps for the door detection algorithm. The first three handle the preprocessing of the point cloud. The following steps are basically segmentation, feature generation and extraction. As last step the feature will be rated.

B. Preprocessing

Particularly for mobile platforms computational performance is always an important factor. With this regard, the detection steps should not exceed one or two seconds of computing time. For efficiency purposes reducing the number of points used in the point cloud has speed up potential on a typical personal computer. However, the given 300,000 points have to be reduced in a way that preserves most of the contained information. Hence, a voxel-grid-filter was used, which suits these requirements best as it reduces the point density to a given distance per coordinate axis. In this implementation a grid of cuboids is placed in the point cloud space. Each cuboid contains some of the 3D-points. These points are considered for calculating the centroid. The resulting centroid will be passed to the next calculation steps as input.

After reducing the cloud density, normal vectors will be calculated. For each of the points its euclidean local neighborhood is taken into account to generate the normals. Thereafter, a plane is fitted into this group of points. The group size has a significant influence on the detection quality and the overall performance. Large groups result in slow calculation and overly strong smoothing of the normals. If, on the other

[1]DIN - Deutsches Institut für Normung e.V. / German Institute for Standardization

hand, too small groups are chosen, the resulting normals might contain too much noise.

C. Segmentation and Analysis

Now, that the input data is prepared, the plane segmentation comes into place. The goal of the segmentation is to separate the door plane from the rest of the point cloud. This is achieved through a region growing algorithm based on the precalculated normals. The normal vectors are used to determine groups of points with similar normals. Normal based region growing proved to be the most stable way of detecting planes in point clouds. Other plane segmentation approaches (i.e. Random Sampling Consensus (RANSAC) with a plane model) often fail to separate doors if the leaf is just in the range of 1 - 2 [cm] above the door frame. Trying to fit a plane that minimizes the global error tends to select the wall including the door. The region growing starts with the calculation of the curvature of all points based on normal differences. In the next step a region seed is set to the point with the lowest curvature value, in order to get optimal results on large planes. That is an important key to detect the rather large door planes. Here all surface normals from the points in a given neighborhood get compared to the normal of the region seed. If the normal differs more than a given threshold, that normal gets selected as a new region seed. Otherwise this point gets the same label as the seed.

After every point has been assigned to a region, features like the number of points, height and width are determined. For this step the algorithm iterates over every detected region. At first regions with too few points are discarded from further processing. The remaining regions undergo two further processing stages. These are designed to close gaps resulting from erroneously pruned patches. These correction steps are started by creating a two dimensional convex hull around the segment. Some millimeter depth in each direction is added to get all points from the originally sensed point cloud back into the segment, e.g. the corner points. The second correction is done by projecting all the points into a perfect plane model generated by the RANSAC algorithm.

In the next step the frame dimensions are estimated by focusing on the border points of the region. To label all border points of a given segment, the normal vectors are once again taken into consideration. The algorithm finds two different types of border points: outer border points, which are meant to represent the door frame and inner border points around holes in the plane. Border points within the plane should mark the door knob. We use the normals in this step because they point away from the border. If a small neighborhood radius is used to determine the normal, the inner border points can easily be labeled. If the neighborhood is too large, holes are smoothed out of the plane. This however enables the algorithm to mark the outer border points as a possible part of the door frame. To ensure that these points belong to a straight door frame, two vertical straight lines are again fitted with RANSAC into the point cloud of outer border points. In the rating process these lines will be considered as the door frame to calculate the height and width of object in question.

D. Door Handle Detection

As the infrared 3D sensing is an optical method it has typical problems with reflective and dark materials. Such materials cause invalid measurements that prohibit the sensor to determine the depth of this object. Doorknobs and door handles often have reflective surfaces like metal or polished varnish. To overcome this sensing problem, the detection algorithm uses holes in the plane to find a door handle, instead of finding a handle itself. Either the plane has a hole from the handle because of the thrown shadow from the infrared projector or by the reflecting material of the handle. Since we are not always able to classify the 3D information of the latch, but always the contour of its shadow, we use it to analyze and rate the probability of the hole being produced by a door handle. Therefore the inlying border points are grouped with euclidean clustering to subsequently rate its size, shape and position.

E. Rating

After the algorithm has determined all dimensions of the door leaf and the handle, these values have to be rated. The Confidence C states how reliably the object is considered a door. For each type of measured value $v_{measured}$, an ideal value v_{ideal} and a standard deviation v_{dev} is given. The ideal value is the mean or standard value for most doors. These are the parameters of the approach, but since their influence and meaning is quite straightforward, these parameters are easily tunable. As weighting function a modified version of the normal distribution is used.

$$v_{dist} = |v_{ideal} - v_{measured}|$$
$$C = e^{-\frac{1}{2}*(\frac{v_{dist}}{v_{dev}})^2}$$

Name	Description	Ideal value[1]	Var.[1]
dwith	mean door width	0,735;0,86;0,985	0,06
dheight	mean door height	1,9;cloud-height	0,10
kwidth	handle set width	0,11	0,08
kheight	handle set height	0,08	0,06
dfloor	handle set distance to floor	1,05	0,01
dframe	handle set distance to frame	0,02	0,04
heightDis	discrepancy of height left/right	0	0,04
widthDis	discrepancy of width bottom/top	0	0,03

TABLE I
MEASURES FOR THE RATING

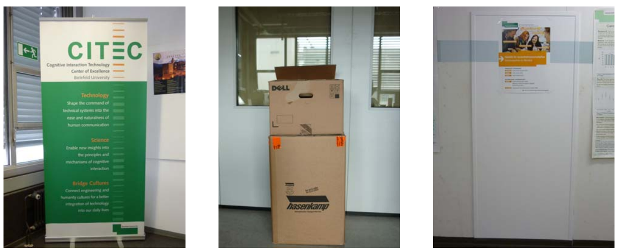
[1] Dimensions in meters.

Table I lists the eight parameters and their default values. The default leaf width and height are set accordingly to the previously mentioned DIN norm. If the camera cannot see the whole height of the door because of the low vertical aperture angle, the algorithm rates the leaf with the maximum visual height.

Some of these values might need adjustments according to the typical values for doors for the region where the algorithm is applied. If one of the values cannot be defined, the algorithm can be forced to ignore it by setting the variance to zero. All other values will be weighted uniformly for the final rating.

IV. Evaluation on Real-world Doors

We wanted to prove that the designed algorithm is able to detect real-world doors with high success rates while at the same time having a low number of false positives. Therefore we took an extensive set of doors from different kinds of rooms. A comprehensive figure of all doors in our test set shows figure 4. Doors with different colors, materials, a wide variety of handle sets and even with glass were presented to the algorithm. Fig. 7 shows an example of how well the algorithm performs even on doors with glass in the middle. The left part of Fig. 7 shows a picture of the door and right side shows the detection result. The green area shows where the algorithm was able to detect the door leaf. Even if the glass inlay is difficult to sense by the sensor, the optimization and correction steps of the algorithm reconstruct most of the door. Notice that the door frame is marked with a blue border. Even the metal door handle was detected and marked red.



(a) CITEC stand-up display (b) stacked cardboard boxes (c) walled door

Fig. 3. Pictures of non doors in the test set. Door like scenes were chosen to show its low false positive rate.

A. Set-Up

From every door in the test set we recorded a series of point clouds in 0.9, 1.4 and 2.2 [m] distance. For the two shorter distances we varied the angle for recording. The sensor was positioned with $-20°, +20°$ and head-on to simulate different approaching situations of a robot. Figure 5 gives an overview of the evaluation set-up. The vertical angle was fixed to $0°$ for all recordings. As a mounting we chose a 0.7 [m] high tripod to have a realistic height small to medium sized mobile robots. Due to sensor construction the lens has a distance to floor of .74 [m]. To reduce noise in the results, we took and analyzed six recordings from every point of reference.

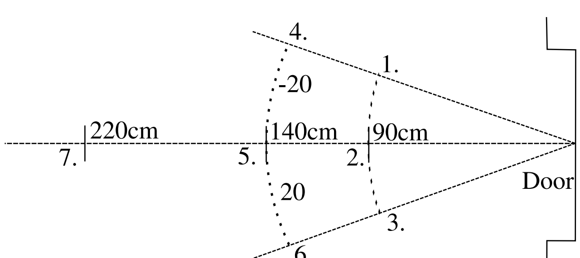


Fig. 5. Set-up drawing with reference points 1. to 7. Each door was recorded with three different distances and three angles.

(a) Steel Sheet (b) Wooden (c) Plain White (d) Small Wooden (e) With Paper (f) Small Knob (g) White Sheet (h) Glazed Inside (i) Glazed Outside (j) Plain Grey (k) Small Handle Set (l) White Wood

Fig. 4. Overview of the whole test set containing doors with different surfaces, sizes and handle sets. Some doors open in direction of the robot, some away from it.

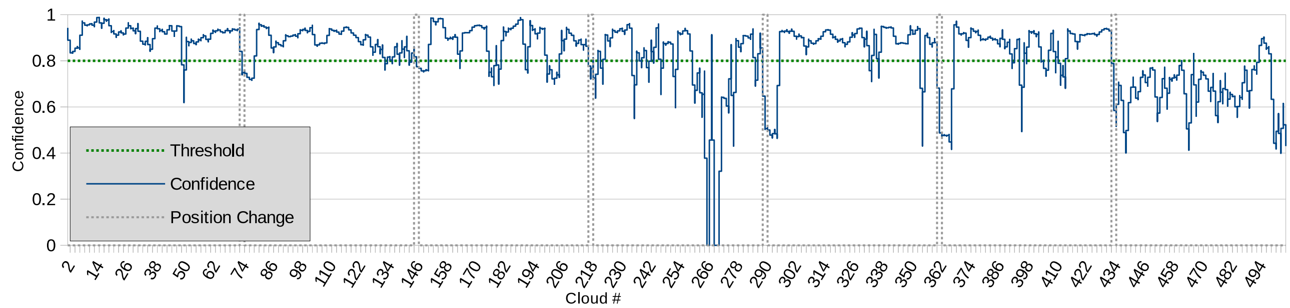
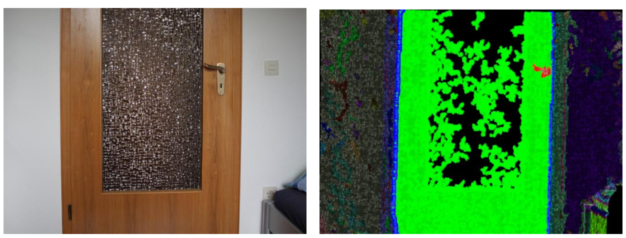


Fig. 6. Reached confidence for each sample presented to the algorithm. The threshold marks the point where no false-positives appeared. The gray dashed line marks the position changes (Fig. 5) that take place after each of the twelve doors is analyzed six times.



(a) Door Photograph (b) Door Detected

Fig. 7. Comparison between a Door as Photograph and in the Detector.

B. General Performance

The test set consists of a variety of twelve doors of different rooms. Some doors have knobs while others are opened by handles. (Fig. 4). This resulted in a total of 504 point clouds for the positive test set. All those point clouds were processed in a batch process. For the negative test set we recorded point clouds, in the same way as the doors, from scenes that have a lot of features in common with doors. These consisted of a bricked doorway, a stack of cardboards and a standing banner and can be seen in Fig. 3. Hence, the negative test set contained 126 examples.

The analysis of a point cloud took on average $0.94[s]$ of computation time. Recordings from shorter distances contain fewer points than clouds from further distances, which is caused by the voxel-grid for density reduction. As fewer points mean less computation effort, the recordings from 0.9 [m] took only half a second whereas the recordings from 2 [m] took about two seconds. These benchmarks were created with an off-the-shelf PC with Intel®Core^{TM}i7-2600K @3.4GHz, 16GB DDR3 RAM, Nvidia GTX460 graphics card and OCZ Vertex 3 240GB SSD. All tests were run on Linux x64 3.4. The implementation was compiled with GCC4.7.1 and CFLAGS $-march = native\ -O3$.

The reached confidence for each sample is plotted in figure 6. If we take a threshold at a confidence rate of at least 80% the algorithm detects 356 of 504 recorded doors. A threshold of 80% was chosen because false positives could not be determined below that rate. This equates to a success rate of 72%. Figure 8 shows how the confidence threshold selection relates to the classification rate. To calculate these graphs the true positives TP, true negatives TN, false positives FP and false negatives FN were determined. Sensitivity (or true positive rate) is $TPR = TP/(TP+FN)$, specificity (or true negative rate) is $SPC = TN/(FP+TN)$ and precision (or positive predictive value) is calculated with $PPV = TP/(TP+FP)$

In Table II, a more detailed analysis of the success rates from the different angles and position is given.

Angle \ Distance	0.9	1.4	2.2	sum
$-20°$	0.99	0.61	-	0.80
0°	0.86	0.87	0.111	0.62
20°	0.74	0.78	-	0.76
	0.889	0.755	0.111	0.738

TABLE II
DETECTION RATE BY DISTANCE AND ANGLE.

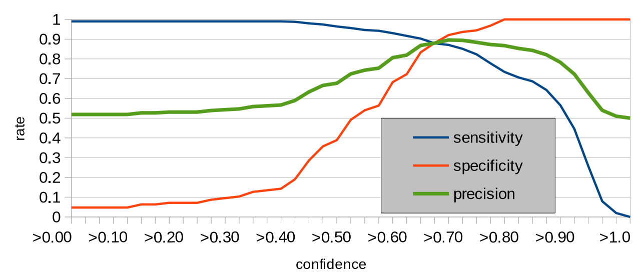


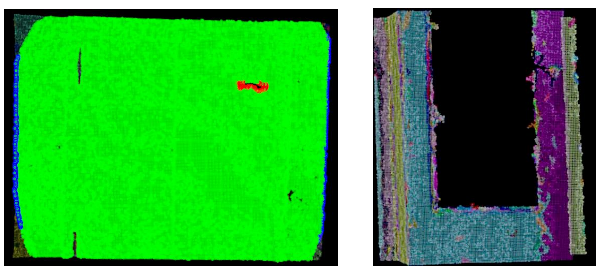
Fig. 8. Precision, sensitivity and specificity for different confidence values

While at 20° the results for 1.40 [m] and 0.9 [m] defer only very little, at $-20°$ the difference is significant. This is mostly caused by the door frame which covers the handle set of the door in some cases. In addition, Table II shows some variation for the distance of 0.9 [m]. While $-20°$ reaches almost 100% in that distance, the classification rate for the positive angle is considerably lower. Two of the twelve doors in the test set were not segmented correctly. One of them was reflecting the Infrared almost completely, therefore only a very bad 3D-sensing could be obtained from certain angles. The other one had its handle set covered by its door frame.

C. Result Analysis

Figure 9 illustrates some of the problems with the PrimeSense sensor. Sometimes the depth resolution is not good enough to resolve the transition from the door leaf to the door frame. For example, Fig. 9(a) shows a rendered door with a really flat sheet steel leaf. In this case the algorithm cannot be sure whether it detected a door or not. The confidence for a door in this image gets high values for the handle set, but the sensed sheet gets rated low for its high width and rounded corners.

In Fig. 9(b) a rendering result from the same door as stated in figure 7 is shown. In this case, no door leaf was detectable. Through the higher distance to the door, the additional introduced sensor noise made it impossible for the algorithm to detect this door. A reason for this is the missing connection between the right and left side of the door. The glass element in the middle of the door literally splits the door into two parts. If the connection between those parts becomes too small the region growing becomes unable to smooth the normals out.

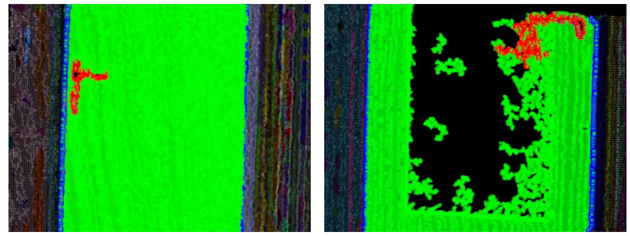


(a) Fire Door (b) Glazed Door

Fig. 9. Failed segmentation due to a not detectable frame on flat steel sheet doors 9(a) and noncontinuous door leaf, which may result in a split of the leaf 9(b).

The algorithm takes great emphasis to optimize the point clouds such that the detection of fully mirroring materials as door handles becomes possible. Figure 10(a) shows how the algorithm perfectly outlines the handle set of this door which is coated with chrome. In the depth image of the PrimeSense sensor it is only a dark spot because of the reflections. When, however, the door has an additional glass inlet the separation of the handle set becomes impossible for the algorithm as can be seen in Fig. 10(b).

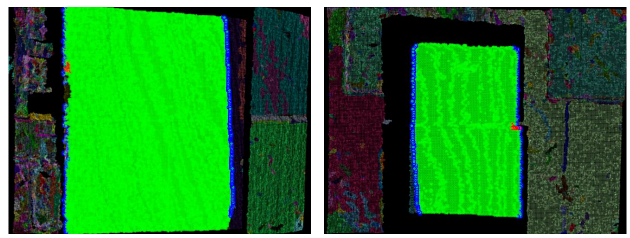
We did not only want to proof that the algorithm is able to detect doors but to also show that the false positives are sparse on real world examples as well. The non-door examples were chosen because of the high similarity to doors. With the chosen minimum confidence rate of 80% non of these test cases was labeled as a door. Figure 11 shows two of the non-door examples. The first one is a stand-up display with door like dimensions. In this case there was only some sensor noise on the left side responsible for a confidence of about 70%. Nevertheless, it was low enough to stay a non-door object. The second example shows two stacked cardboard boxes which have a lot in common with a door. The dimensions fit really well and even the gap between the boxes can be distinguished



(a) Reflections on Handle Set (b) Inseparable Handle Set

Fig. 10. In some cases the handle detection may fail. In case the part around the handle set is mirroring in gets assigned to the handle. If the door leaf has noncontinuous parts around the door they get assigned to the handle set as well.

as a handle set. Still our algorithm is able to not label this object as a door.



(a) Sensor Noise at Border (b) Gap between Boxes

Fig. 11. In scenes with door like objects like stacked boxes or a stand-up display, the algorithm remains able to distinguish between a real door.

V. Conclusion and Future Work

A. Conclusion

This paper discusses a new approach for detecting doors in new environments. As basis a 3D sensor is used. As the resulting depth image contains some noise, a lot of mathematical methods had to be used for the preprocessing as well as the actual detection. The normal based 3D region growing adopted from classical image processing provided a reliable way of segmenting door leafs from the environment of the robot. This important step leads to feature extraction like the frame of the door as well as searching for holes in the 3D point cloud of the door leaf. A heuristic method for classifying and rating handle sets on these holes was implemented to enable reliable detection even of handle sets made out of optically reflective materials.

As this algorithm was designed for mobile robots processing speed was another important criterion. Through optimization, like early pruning of regions that unlikely being a door and reduction of cloud density to a minimum, the algorithm is able to process a given scene on off-the-shelf hardware in about one second.

To achieve representative results in a first evaluation of the algorithm we recorded a set of point clouds of DIN-normed doors. The evaluation was targeted to be as realistic as possible. 630 scenes from different angles and distances were recorded to simulate a drive by situation with a mobile robot. In addition to the doors a smaller set of objects with similarities of doors were recorded in order to create a negative set. This evaluation showed a correct classification rate of up to 90%. In distances of over 2 meters the depth image of the used sensor degraded quickly and thus the classification rate suffered.

B. Future Work and Improvements

The classification rate of this algorithm scales very well with sensing quality. A sensor with higher depth resolution and less distortion could greatly improve the results without any additional implementation work. This would lead to a higher number of points to process and to longer computation time. To overcome this problem faster hardware or better use of the existing hardware through usage of graphic processors instead of general purpose CPUs could fasten the processing of point clouds. Especially the normal vector computation benefits a lot of parallelization on GPUs.

In addition to this 3D based algorithm a color image could be used to support the predictions. The more information considered the better the possible result. In particular if the distance to the door is significantly above 2.2 [m], the spatial resolution of the PrimeSense sensor will not be sufficient. In this case a 2D based prediction will improve the overall door detection rate. Another useful case for supporting the 3D detection with a 2D image shows 9(a). Those doors with nearly no detectable 3D frame can not be segmented by the region growing but by simple 2D edge detection.

As the algorithm has a lot of parameters for cloud densities and rating for the confidence features a combination with a machine learning algorithm should also be taken into consideration. Especially the standardized measurements (i.e. door width, door height), are already close to optimal, but other parameters, especially those concerned with the handle set, are more difficult to tune by hand and might benefit from an autonomous learning procedure. Eventually this could also lead into an increasing detection rate if the algorithm adopts its parameters to typical doors in its actual environment.

The most pressing work will be the full integration in a mobile robot, including the autonomous opening of closed doors. Also, with the information about its current position, the robot will be able to add the sensed doors to its map.

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