Door Detection in 3D Colored Laser Scans for Autonomous Indoor Navigation

B. Quintana, S. A. Prieto, A. Adán
3D Visual Computing and Robotics Lab
Universidad de Castilla-La Mancha.
Ciudad Real, Spain
{Blanca.Quintana, Samuel.Prieto, Antonio.Adan}@uclm.es

F. Bosché
School of Energy, Geoscience, Infrastructure and Society
Heriot-Watt University
Edinburgh, U.K.
f.n.bosche@hw.ac.uk

Abstract. *Door detection is becoming an increasingly important subject in relation to autonomous mobile robot navigation in indoor environments. This paper presents an original approach that recognizes open and closed doors in 3D laser scanned data. The proposed technique uses both the geometric (i.e. XYZ coordinates) and colour (i.e. RGB/HSV) information provided by a calibrated set of 3D laser scanner and a colour camera. In other words, our technique is developed under a 6D-space framework. The geometry/colour integration and other characteristics of our method make it robust under occlusion and efficient to slight changes in door colours resulting from varying lighting conditions experienced from different scanning locations. The approach is tested in both simulated and real scenes, yielding encouraging results.*

Keywords. ***Indoor spatial data model, 3D door positioning, 3D data processing, 3D building models.***

I.   INTRODUCTION

Door detection is a critical functionality that mobile robots must possess for their effective navigation (e.g. pass through doors) and manipulation (e.g. pushing half-open doors or grasping handles) in indoor environments. The work presented in this paper is part of a project to develop an autonomous mobile robot that carries out automatic digitization of indoor environments in furnished buildings. We deal with complex scenarios composed of several adjacent rooms, such as office floors or living apartments. The overall process to scan (and model) such environment goes as follows: the robot performs the complete scanning of an initial room. Then, the robot must find a door (open or closed), open it if necessary, and then locate itself under the doorframe to acquire the 'transition' scan to the next contiguous room (i.e. the first scan of the next room). Door detection is clearly a critical step in this process.

While the subject of door detection has been considered in previous research, this paper proposes a unique approach that: (1) provides the accurate size and the pose of the door in the 3D world-coordinate-system; (2) presents a general solution for open and closed doors; (3) can handle occlusion; and (4) uses both 3D geometry and colour for more robust detections and localisations. Such features are not always provided by existing door detection methods that have typically considered only one or two of those aspects.

II.   STATE OF THE ART

The ease to use and the low cost of artificial vision systems make very popular the use of 2D image-based approaches in the research field of door detection ([1]–[6]). One of the approaches able to deal with these kind of problems is that of Xiaodong Yang and Yingli Tian [1]. They define a 2D doorframe's model composed of two horizontal and two vertical lines between four corners. This model is matched with similar models detected in the image. Since the algorithm is based on geometrical features of doorframes, either open and closed doors, as well as glass doors, can be detected. Marwa M. Shalaby et al. [2] use a similar approach based on a similar 2D geometric model but they only show results with closed doors. Alexander Andreopoulos et al. [3] also make use of a similar edge and corner detection technique. The method recognizes the door, detects and localises the handle and the state of the door (open or closed). To detect and localise the handle, a learning algorithm is used that is trained with a dataset of 1,500 instances is used. Wei Chen et al. [4] propose a convolutional neural network deep learning approach trained with a very large dataset to detect doors. However, they do not mention nor demonstrate whether their approach is able to detect open or half-open doors. Soohwan Kim et al. [5] propose another door detection algorithm based on the detection of the handle, but that algorithm cannot be used to detect open doors. Finally, Rafiq Sekkal et al. [6] assume that the robot moves in a corridor, and so that the lines of the intersections of the walls, the floor and ceiling can be extracted along with the vanishing point in the scene to define a rough 3D model of the scene from the 2D image, and subsequently search for doors only on the wall plane. At that stage, the algorithm looks for two consecutive vertical lines in the wall and checks if the distance between them verifies some pre-defined values. According to the authors, this ad-hoc method is able to detect both open and closed doors – although arguably under non-negligible assumptions.

Image based methods are sometimes inefficient and often produce large numbers of false positives due to other objects in the wall (e.g. windows or paintings) or furniture near the walls (e.g. radiators). To achieve higher precision and reliability, some approaches use 3D sensors and process point clouds, sometimes together with 2D images, to recognize doors ([7]–[16]). Goron et al. [7] obtain point clouds from a LRF (Laser

Range Finder) and extract the planes corresponding to closed doors by applying RANSAC (Random Sample Consensus). That technique is not very robust because it is based on the strong assumption that doors do not lie in the wall planes, which is often not true. By using an RGB-D camera, Sebastian Meyer et al. [8] segment the original point cloud into planar patches using a region-growing algorithm based on point normal vectors. A door is detected if and only if the dimensions of the detected plane match pre-defined 'standard' dimensions and the door plane contains a handle. This approach is optimized to detect single-leaf closed doors. Karthik Mahesh et al. [9] originally propose an approach focused on detecting open doors. They obtain 3D information by means of a stereo camera rig. After extracting vertical planes in the 3D data by means of RANSAC, doors are searched with gaps in the wall plane 3D data (i.e. regions in the wall without sensed data). An approach proposed by Ting Han Yuan et al. [10] is able to recognize open or half-open doors. They use the depth information from an RGB-D camera to obtain the depth information of a wall. The door's opening angle is calculated through the shape of the gap inside the door, which assumes that the sensor is placed in front of the door. In a similar way, Matthew Derry and Brenna Argall [11] use a depth sensor to identify gaps in wall planes to infer the detection of open doors. And DaWei Dai et al. [12] use the same idea with the same sensor (an RGB-D camera) on board a mobile robot. Beside detecting the door, they detect the relative position between the door frame and the robot. This information is afterwards used for navigation of the robot through the door. Adiwahono et al. [14] propose a different approach. From 2D laser scan perspective, assuming the door is not flushed entirely with the wall, a door candidate is detected as a cluster of points forming a relatively straight line of specified length. Then, the robot approaches each candidate door and scans it with an RGB-D camera. The handle detection process is performed by matching (by means of an ICP algorithm) the segmented door point cloud with a door handle mesh model. Díaz-Vilariño et al. [15] carry out the extraction of closed doors by applying the Generalized Hough Transform on wall orthoimages extracted from coloured point clouds acquired with a laser scanning system. This method, which focuses on the detection of rectangles, is only able to detect closed doors. In the framework of the Darpa Robotic Challenge, Banerjee et al. [16] develop an approach enabling an Atlas robot to not only detect but also open doors. First, consecutive pairs of vertical lines at a specific distance are detected in a 2D image of the scene (using the Canny edge detector). Then, the lines are recalculated in a 3D space with the help of the RANSAC algorithm. If there is a flat surface between each pair of lines, they recognize this as a door. The handle detection is carried out by means of colour segmentation, on the assumption that it has a different colour than the door.

III. DOOR DETECTION CONTEXT

As was mentioned in Section I, door detection is one of many tasks that our robotic system carries out to extract 3D geometric models of indoors. The robot, which carries a 3D laser scanner, navigates autonomously with the help of a local positioning system and the outputs of a Next-Best-Scan (NBS)

module. The NBS module calculates the coordinates of the next best position of the robot for a new scan. That algorithm has been designed according with the final objective of the scan session: to collect as much data as possible from the visible 'structural elements' (SEs) of the building (ceiling, floor and walls). When the system considers that a room is completely scanned, the door detection algorithm is executed to enable the robot to detect and access any other room to be scanned. An important area of application of the proposed robotic system is the production of as-is or as-built semantic 3D models of interiors, commonly referred to as-is/as-built 3D Building Information Models (BIMs) [17]. Robust door detection and localisation would constitute an important contribution to the field of automated production of complete as-is/as-built BIMs.

In our approach, a simplified semantic 3D model of the scene and a labelled voxel space made of 20×20×20cm voxels is obtained before the robot moves to a contiguous room. Details of the voxel space and NBS algorithm can be found in [18]. This means that the essential parts of the architectural elements of the scene (i.e. SEs) are recognized and available in the world coordinate system, and it is possible to focus door detection within the data associated to the modelled walls. Specifically, the inputs of our door detection algorithm are: the vertical planar patch that delimitates the wall; the set of voxels intersecting the planar patch, labelled as Occupied, Occluded or Opening; and the coloured 3D points associated to these voxels (i.e. the patch).

IV. DETECTION OF OPEN DOORS

A. Detecting Voxels Corresponding to Wall Openings

Our NBS algorithm runs in a discretized voxel space that is setup for the scanning of each new room. When the NBS algorithm is executed from a particular position of the scanner, the current voxel space, together with its respective labels, is updated. We detect the ceiling, floor and walls (SEs) in this discretized space, and each voxel in the voxel space is then automatically labelled with one of the following labels:

- Occupied voxels can have either of the following three labels:

 * *Clutter*: The voxel contains points that do not belong to any SE;

 * *Occupied-Structure:* The voxel contains points belonging to a SE;

 * *Outlier*: the voxel contains points outside the detected room boundary.

- Non-occupied voxels can have either of the following three labels:

 * *Occluded-clutter*: The voxel has never been visible (i.e. has always occluded by an occupied voxel) and does not belong to a SE.

 * *Occluded-structure*: The voxel has never been visible and belongs to a SE.

* *Empty*: The non-occupied voxel has been visible (i.e. was not occluded by an occupied voxel from the current or any previous scanner position), and does not belong to a SE.

* *Opening:* The non-occupied voxel has been visible, and belongs to a SE.

Figure 1 shows an example of labelled space.
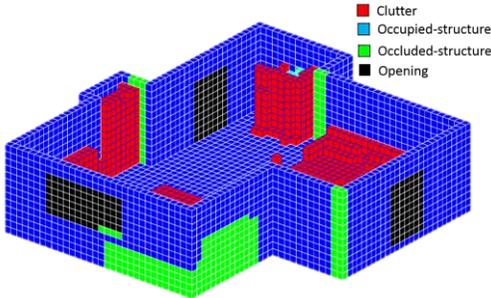
Figure 1. Illustration of a 3D voxel space and labels.

B. Recognition and positioning of open doors

The detection of doors is focused on the wall areas (wall planar patches and associated voxels and 3D points). The voxel labelling helps us delimitate roughly the position of openings in walls. These openings are then further processed to recognise open doors (among other types of openings). If the wall does not contain *Opening* voxels, the system jumps directly to the closed door recognition step (see Section V).

To localise wall openings with precision in the 3D space, we consider not only the voxels, but also the set S of all the scanned points associated to them. By means of a RANSAC algorithm, the rectangular patch R that fits S is first calculated. After that, S and the centroids of the *Opening* voxels are projected onto R. Thus, R can be converted into a 2D image I that contains *centroids*, *data* and *no-data*. Note that a *no-data* pixel could come from an occlusion or from an opening (i.e. door or window) in the wall. Figure 2 b) gives an example of image I.

Assuming rectangular doors, which is a reasonable hypothesis, the first stage of the proposed open door detection approach consists in extracting a set of candidate rectangles in I. To do this, we extract the horizontal and vertical lines in the image I with a lateral histogram technique, and consider all rectangles formed by the intersections of pairs of vertical lines with pairs of horizontal lines (see Figure 2 c)). This set of rectangles is reduced after imposing certain size restrictions. Then, the *centroids* are clustered by means of a region growing algorithm. For each cluster, the best candidate rectangle is found as follows. Among the rectangles that contain the highest number of centroids (could be several of them) we choose the one with the smallest area. This enables the identification of the most likely opening for each cluster of centroid. Finally, only the rectangles with their lower side at the level of the floor are kept as door candidates. Figures 2 d) and 2 e) show the clusters of centroids and the detected openings.

After carrying out this procedure for all the clusters, the chosen rectangles in the image I are converted into vertical polygons on the wall plane, and thus all openings, including the doors, are positioned in the 3D world coordinate system.
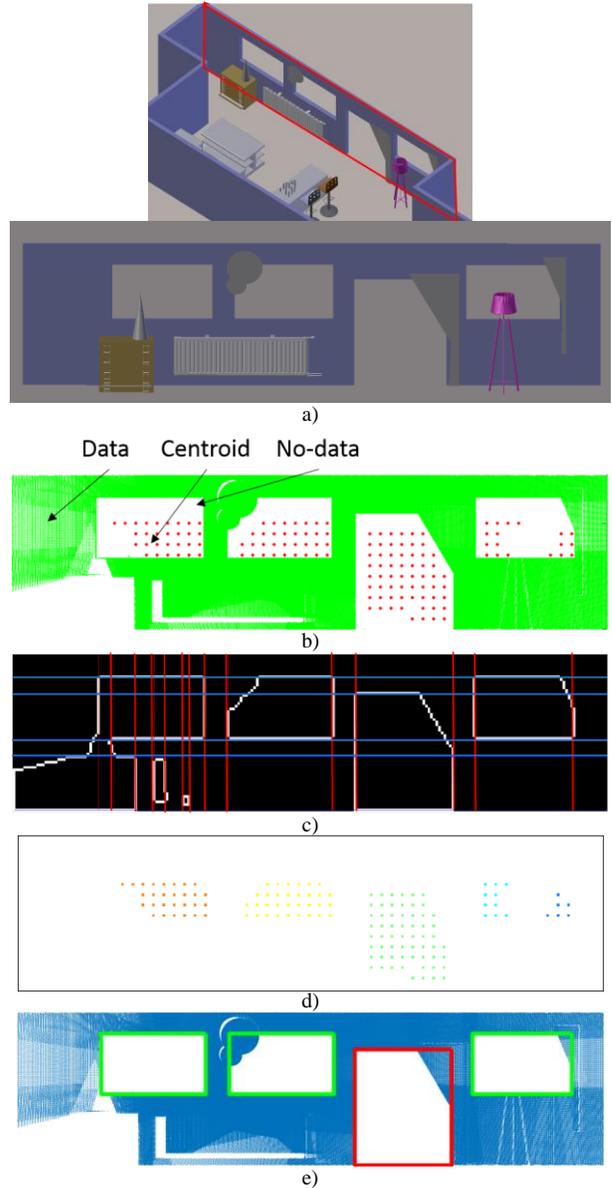

Figure 2. a) Structural element in a 3D scene with occlusion. b) Image I with labels *data*, *centroid* and *no-data*. c) Vertical and horizontal lines detected in I. d) Clusters of centroids in different colours. e) Openings (door and windows) detected.

V. RECOGNITION AND POSITIONING OF CLOSED DOORS

Although the voxel space yields essential information to detect open doors, it is not helpful to detect closed doors that are typically co-planar with the wall plane and so appear as *Occupied* voxels like the rest of the wall. To detect closed doors, we develop a 4D (Colour+Depth) detection approach that is able to deal with a wide variety of cases, including with not entirely uniform colours. Note that, to achieve a complete

model of the scene, the system collects data (points+colour) from different positions. However, the lighting conditions may vary a bit from one position to the next so that colour artefact (boundaries) are often observed in the integrated point clouds, leading to non-uniform colours for the various walls.

The approach makes only few assumptions that we argue are true in a large majority of cases:

1. The walls are flat (this assumption is actually made at the SE recognition and modelling stage).

2. The wall has a fairly homogeneous colour, but with some variations possibly resulting from the phenomenon described above.

3. Doors are defined by rectangles with vertical and horizontal sides (same assumption as for the open door case).

The input to the proposed algorithm is the wall plane calculated through RANSAC (as discussed in Section IV) and all the coloured 3D points associated to the plane. The algorithm is divided in two steps: segmentation of the visible areas of the wall and door detection.

A. Segmentation of the visible areas of the wall

Using the input data, we first create an RGB-D orthoimage J_{CD} of the wall where each pixel has an RGB colour and the orthogonal distance to the wall plane. The segmentation of the visible areas of the wall is then achieved as follows (with illustration in Figure 3).

First, small square patches (5×5 pixels) are sampled in J_{CD} using a 20×20 grid (rows × columns). For each patch, the distribution of the RGB-D pixel values {$\mathbf{v}$} is analysed, and the patches for which the standard deviation in any of the four components is higher than a threshold (in our case 0.20) are discarded. The process ensures that only the patches that are *coherent* both in the colour domain and in the depth (e.g. the patch is not located on the edge of frame), are retained (see Figure 3 b)).

Each *coherent* square patch m is then represented by the mean value of the RGB-D values of its 25 pixels $\bar{v}_m$, and an adaptive k-means algorithm is then employed to group the sample patches $\{\bar{v}_m\}$ into k clusters, where k is calculated by the algorithm itself (see Figure 3 c)). The consistency within each cluster is then enhanced by removing any sample patch that has a silhouette value δ higher than a reasonable threshold ($|\delta|>0.7$). The silhouette value for a member of a cluster is a measure of how similar that member is to all the other members in the cluster, in comparison to members in the other clusters. The silhouette value ranges from -1 to +1 (see Figure 3 d)).

Finally, we identify the set of pixels of J_{CD} associated with the the i-th cluster $\{\bar{v}_m\}_{i,\,i=1...k}$ by means of an exclusive thresholding matching technique imposed on all the four components. Figure 3 e) shows the final results in three binary images that represent the pixels (in white) associated to each segment. The wall area is then selected as the cluster that

contains the largest number of pixels located at the border of the image.

a)

b)

c)

d)

e)
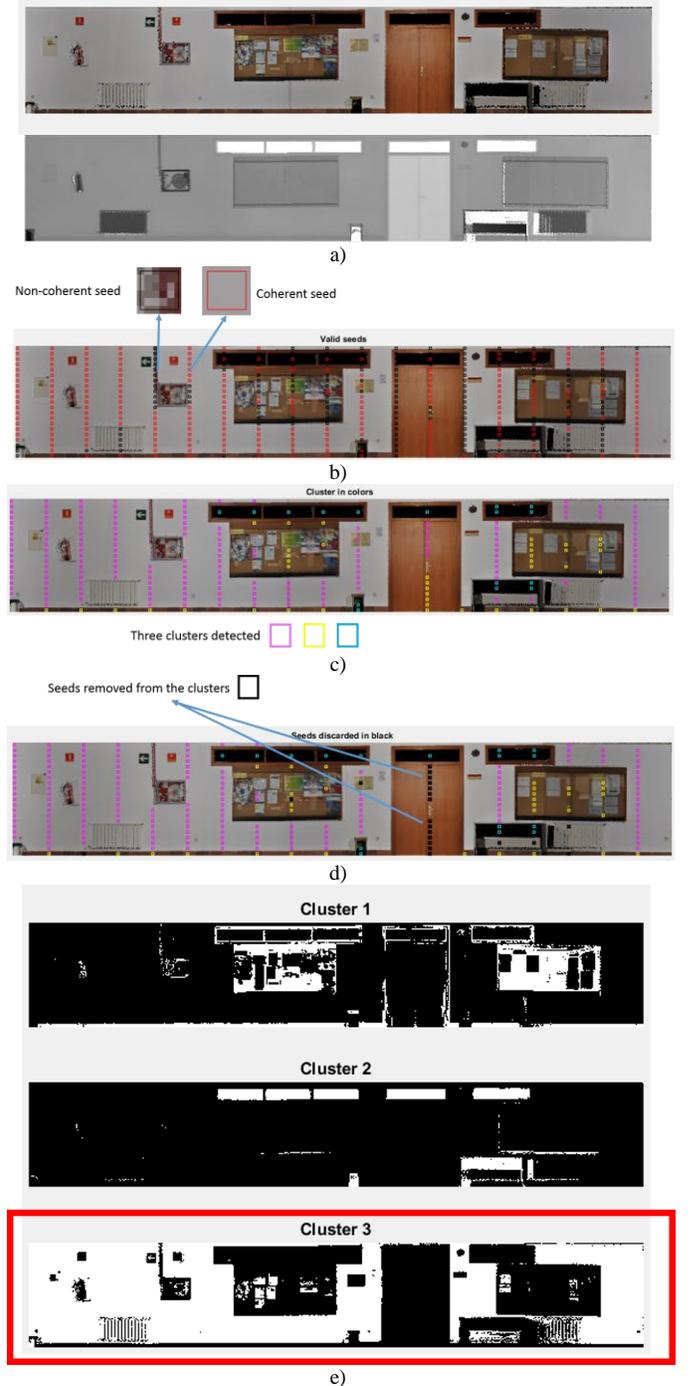
Figure 3. Wall's area detection. a) RGB image and depth image b) Searching valid small square patches (they are called seeds in the figure). c) Seed clusters. d) Removing inconsistent seeds from clusters. e) Segments and wall area identification (marked in red).

B. Door detection

Detection of closed doors can be a particularly challenging task when the door is partially occluded or when the wall contains a lot of objects in various colours. Such circumstances can be better handled in our colour-depth space.

We present an approach based on discontinuities in the 4D RGB-D space. In our proposal, both colour and depth components are processed separately, with the image J_{CD} decomposed into J_C (colour) and J_D (Depth), and the results recombined. For J_C a gradient operator is first applied to it that calculates the maximum change rate in the pixel (gradient) along the spectral dimensions [19]. This is followed by an image binarization process, using Otsu's global histogram threshold technique. Otsu's method chooses the threshold to minimize the intraclass variance of the black and white pixels. The result of this process is a binary image J'_C. For J_D (Depth), the Canny edge detector is first applied, generating a second binary image J'_D. J'_C and J'_D are finally combined (OR operator) to form a single gradient image J'_{CD}. Figure 4 illustrates this process.

White pixels in J'_{CD} represent discontinuities in the colour-depth space. This should enable the detection of door frames as discontinuities in the colour domain only, in the depth dimension only, or in both. For this, we detect straight lines in J'_{CD} (using the same approach as in Section IV). These lines contain the colour-depth discontinuities of the wall and, therefore, they contain parts of the contours of the hypothetical doors. The word '*part*' is used here because occlusions may exist (and are permitted in our framework).

Next, similarly to the case of open doors, we calculate all possible rectangles defined by two pairs of horizontal and vertical lines. Since we are looking for rectangles that delimitate doors, reasonable size restrictions are applied, and we also retain only the rectangles for which the lowest side lies at the bottom in image. This yields a highly reduced set of rectangles *{r}*.

Each rectangle of *{r}* is considered to correspond to an actual door (the door frame) if it fulfils the following conditions:

1. Colour and depth consistency. After applying an adaptive k-means clustering process over the colour and depth data contained in *r*, we establish that the dominant colour and the dominant depth must cover separately a certain percentage α_1 of the door area. The threshold has been set at $\alpha_1=55\%$.

2. Door frame occlusion. $\alpha_2\%$ of the length of each side of *r* must be supported by discontinuity information, i.e. white pixels in J'_{CD}. The threshold has been set at $\alpha_2=70\%$. Therefore 30% of occlusion is permitted.

3. Location consistency. The area enclosed by *r* does not intersect the wall area identified in the process described in Section V.A, with an allowance of $\alpha_3=3\%$.

4. *r* is not contained within any other rectangle that verifies conditions 1, 2 and 3.

Parameters α_1, α_2 and α_3 have been defined empirically from experiments with over 40 synthetic cases, with up to 50% of occlusion. Figure 5 illustrates the outputs for each step of the second part of the door detection algorithm. In this case, only one door is (correctly) found.
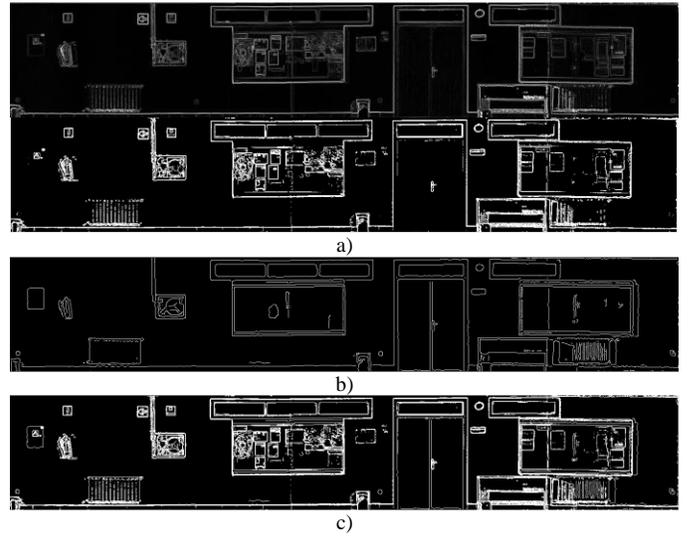
Figure 4. Generating the combined discontinuity image. a) J_C gradient image and J'_C. b) J'_D. c) Integrated J'_{CD}.
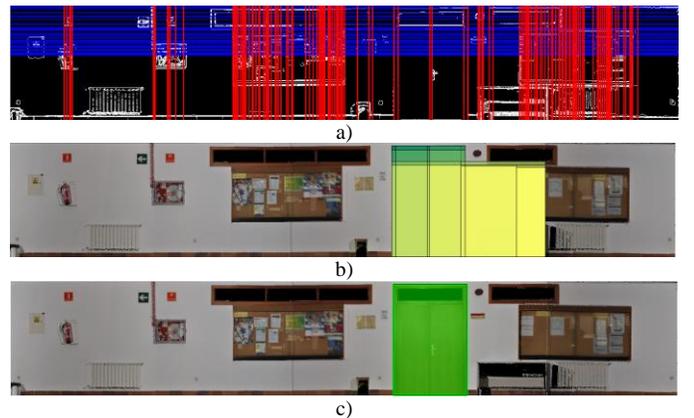

Figure 5. Door detection example. a) Horizontal and vertical lines detected in J'_{CD}. b) Set of rectangles *{r}*. The candidate rectangles are superimposed in the image in different colours. c) Rectangle that encloses the door in green.

VI. EXPERIMENTAL WORK

A. Testing the door detection algorithm in simulated scenes

Several simulated experiments in complex scenarios have been carried out. The scene has been developed with the software Blender and simulated scans generated using its add-on Blensor [20]. This tool allows the simulation of real scanning with a 3D laser scanner similar to ours, the Riegl VZ-400. We present here the results in the multi-room environment shown in Figure 6 a). Since the ground truth is available in simulated scenarios, a precise evaluation of the results is possible.

The scenario is composed of 5 adjacent rooms interconnected by 6 doors and with a total of 9 windows. The size of the simulated scenario is 27m × 21 m. The structure consists of 66 walls, 5 ceilings and 5 rooms. Clutter and occlusion are introduced through furniture and other objects (curtains, signs, paintings, ...). The mean occlusion in walls is 14%.

The proposed method detects all doors, as shown in Figure 6 b) where the recognized doors (in red) are superimposed to the ground truth ones (in blue). It can be seen, in some cases, a slight difference between the associated rectangles. Therefore, a quantitative evaluation is necessary to measure the positioning accuracy.


a) b)
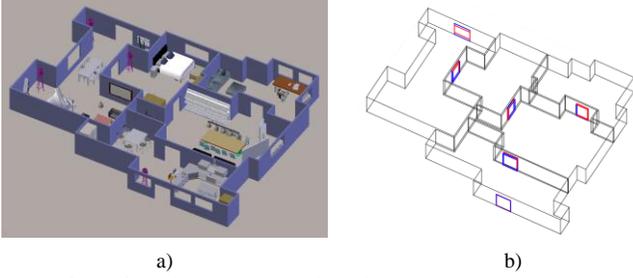
Figure 6. a) 3D synthetic model in which the method has been tested. b) Door detection results. Rectangles of the ground truth are in blue and calculated rectangles are in red.

Precision and *Recall* concepts have been used previously to evaluate pose and size estimation results. We similarly use these statistical measures to reflect the level of overlap between the areas of the ground truth and calculated rectangles. Let Q and G be the areas of a pair of query and ground-truth doors. The true-positive (t_p) value is calculated as the intersection of Q and G, whereas the false-positive (f_p) value is calculated as the area of Q that does not interest G. On the other hand, the area of G that does not intersect to Q is considered as the false-negative (f_n) value. Figure 7 a) illustrates these.

As a result, *Precision* is the fraction of the detected opening's surface that is really an opening (Equation (1)), whereas *Recall* is the fraction of the ground truth that is correctly recognized (Equation (2)).

A measurement that combines Precision and Recall is the harmonic mean of precision and recall, *F-measure* (F_β). This statistic is a kind of weighted average of the two values (Equation (3)).

$$Precision = \frac{t_p}{f_p + t_p} \qquad (1)$$

$$Recall = \frac{t_p}{f_n + t_p} \qquad (2)$$

$$F_\beta = (1+\beta^2)\frac{Precision.Recall}{\beta^2.Precision+Recall} \qquad (3)$$

A second set of performance measures evaluate the modelling error. We consider separately the error for each detected opening as the sum of f_p and f_n portions. Absolute and relative errors are in equations (4) and (5).

$$e_{abs} = f_p + f_n \qquad (4)$$

$$e_{rel} == \frac{f_p + f_n}{f_p + t_p} \qquad (5)$$

The positioning evaluation results for the simulated scene are as follows. The average values of Precision and Recall are 0.979 and 0.949 respectively. More details for all individual doors can be seen in Figure 7 b). Regarding the errors, the average values are e_{abs}=0.259 m^2 and e_{rel}=0.081. These values demonstrate the good performance of the algorithm.

To extend the analysis of the results, we calculated the weighted F_β for an interval β=[1/3, 3]. The result is shown in Figure 7 c). Note that F decreases as ß decreases. For the balanced value (ß=1), F_β=0.988.


a)

b) c)
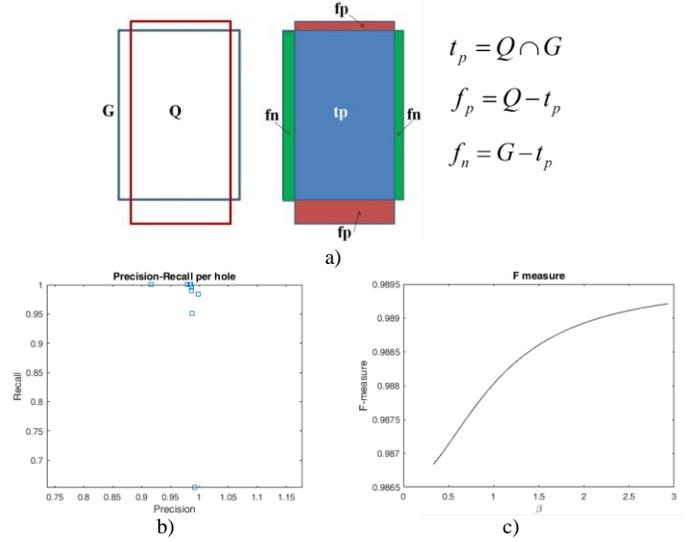
Figure 7. a) Definition of parameters t_p, f_p and f_n in openings b) *Precision* (X axis) and *Recall* (Y axis) results. c) Evolution of *F-measure* in the range β=[1/3, 3].

B. Detecting closed doors with a mobile platform

This section is devoted to showing the results of the closed-door detection algorithm integrated with our experimental platform.

We have implemented the autonomous scanning system in the platform MoPAD (Mobile Platform for Autonomous Digitization) composed of a mobile robot (Robotnik Guardian) equipped with a Riegl VZ-400 3D laser scanner and two Hokuyo URG-04LX-UG01, one at the back of the robot and one at the front, at the height of the Riegl VZ-400, as is shown in Figure 8. The experiment is carried out in the hall of the Computer Science School of Castilla La Mancha University. The size of the explored environment is 8m × 34m.

The scene is composed of 29 structural elements with 18 doors. In that experiment, the robot is manually moved to each room and the doors of the room are then closed. Our scan planning algorithm calculates the successive positions of the scanner. The overall point cloud is processed, with all the structure elements extracted. Each wall element together with its associated datapoints (with colour) are stored, and the door detection algorithm is executed.

The door recognition algorithm succeeded in 100% of the doors (18/18). Figure 8 illustrates examples of walls and detected doors, some of them are occluded. Figure 9 shows the

results in two doors co-planar to the wall and with a very similar colour.

The pose evaluation was carried out after obtaining the ground truth manually. The results in terms of Precision, Recall, absolute and relative errors are reported in Table 1. In general, it can be stated that the method yields encouraging results. Very high averages are reported, which demonstrates the precision in the estimations of the size and position of the detected doors.

TABLE I.   EXPERIMENTAL RESULTS

Wall	Precision	Recall	Abs. Error (m^2)	Rel. Error
#1	0,9930	0,9957	0,0375	0,0113
#2	1,0000	0,9888	0,0376	0,0114
#3	1,0000	0,9917	0,0370	0,0084
#4	1,0000	0,9849	0,0570	0,0153
#5	1,0000	0,8771	0,4052	0,1402
#5	1,0000	0,8604	0,4660	0,1623
#6	0,9897	0,9951	0,0301	0,0151
#7	0,9938	0,9918	0,0562	0,0144
#8	0,9912	0,9949	0,0309	0,0139
#8	1,0000	0,9760	0,0527	0,0245
#9	1,0000	0,9818	0,0624	0,0185
#9	0,9587	0,9959	0,1321	0,0453
#9	0,9853	1,0000	0,0241	0,0147
#10	1,0000	0,9815	0,0430	0,0188
#10	1,0000	0,9581	0,0961	0,0437
#11	1,0000	0,9863	0,0316	0,0138
#11	1,0000	0,9863	0,0315	0,0139
#12	0,9945	0,9952	0,0388	0,0103
Mean	**0,9948**	**0,9745**	**0,0928**	**0,0331**
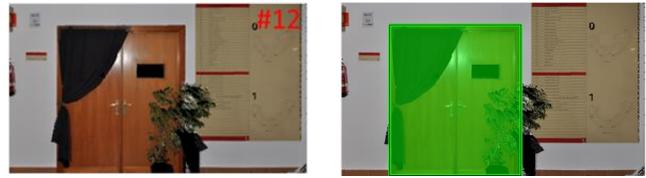
Figure 8. a) MoPAD and examples of detected doors. Walls 10 and 12 with 38.3% and 38.8% of occlusion

a)   b)
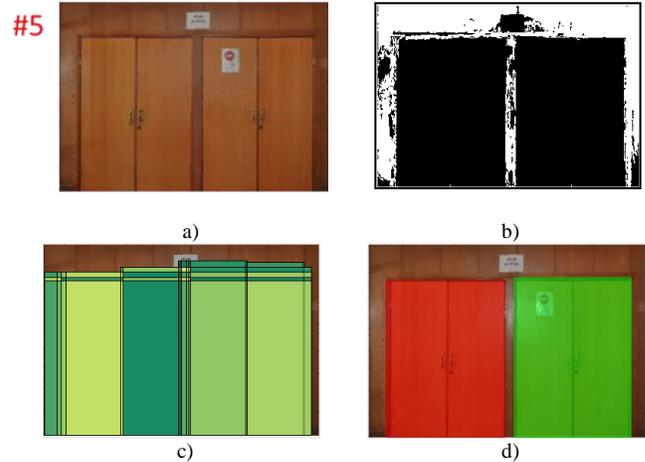
c)   d)
Figure 9. a) Complex case: wall co-planar door and wall with similar colour. b) Wall area identification. c) Candidate rectangles superimposed in different colours. d) Rectangles that encloses the doors in red and green.

CONCLUSIONS

We proposed a novel approach for the detection of doors that are either closed or open in coloured 3D laser scanned point clouds. The detection of open doors is based on the detection of rectangular point cloud data gaps in the wall planes, while the detection of closed doors is based on the detection of the actual wall area and subsequently the processing of the rectangular areas not corresponding to the wall. Overall, the unique approach proposed in this paper: (1) provides the accurate size and the pose of the door in the 3D world-coordinate-system; (2) provides a general solution for open and closed doors; (3) can handle occlusion; and (4) uses both 3D geometry and colour for more robust detections and localisations. Its robustness and performance have been shown and validated experimentally using a simulated dataset (providing exact ground truth) and a challenging real-life dataset. The approach works in very challenging cases where doors are closed, are co-planar to the wall, and have a very similar colour to it. Future work will focus on addressing more complex cases.

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