Robust Door Detection in Unfamiliar Environments by Combining Edge and Corner Features

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Abstract

Camera-based indoor navigation and wayfinding can assist blind people to independently access unfamiliar buildings. In indoor environments, doors are significant landmarks and door detection plays important roles for navigation and wayfinding. Most existing algorithms of door detection are limited to work for familiar environments with restricted features without taking account of the diversity and variance of doors in different environments. In this paper, we present an image-based door detection algorithm that utilizes the general and stable features of doors - edges and corners. Furthermore, we develop a general geometric model to characterize the door shape by combining edge and corner features without a training process. To validate the robustness and generalizability of our method, we collected a large dataset of door images from a variety of environments. The proposed algorithm achieves 91.7% true positive rate with a low false positive rate of 2.9%. The results demonstrate that our door detection method is generic and robust to different environments with variations of color, texture, occlusions, illumination, scales, and viewpoints.

1. Introduction

The World Health Organization (WHO) estimates that there were 161 million visually impaired people around the world in 2002, about 2.6% of the total population. Among this figure, 124 million (about 2%) had low vision and 37 million (about 0.6%) were blind. For the visually impaired people, independently accessing unfamiliar environments presents significant challenges, thereby reducing quality of life and compromising safety. While GPS-guided navigation has demonstrated much promise in outdoor environments, there is still a lack of orientation and navigation aids to assist people with severe vision impairment to independently find rooms, elevators, and other building amenities. In unfamiliar indoor environments, doors are significant landmarks for the navigation. Indoor environments are structured by artificial objects with specific size, shape, and location. Among these well-regulated objects, doors play an important role in providing transition points between separated spaces and the entrance and exit information, which can be further used for autonomous navigation and self-localization [14]. Therefore, the capability of efficient and reliable door detection method will benefit many autonomous and mobile applications including indoor navigation and wayfinding for visually impaired people.

1.1. Related Work

Wayfinding in unfamiliar indoor environments is a challenging task for the blind and low vision people. Several techniques have been proposed to assist the visually impaired people to find their way. Coughlan and Manduchi [5] propose a pie-shaped color pattern which can be used near a barcode or a text region. The color pattern can be easily and quickly detected because of its distinctive design. When the color pattern is detected, its nearby image area will be processed to read text or barcode which is able to provide location-specific information. Avoiding scanning the whole image to localize a text or barcode, this method makes the detection rate and detection result more desirable. In [13], Tjan *et al.* design a digital sign system for indoor navigation. A specially designed pattern printed on a retro-reflective sheet codes a 16-bit number, which corresponds to a specific meaning stored in a database to a specific building. However, the special designed signs must be installed in advance and are not available in every building, especially in the unfamiliar indoor environments. In highly structured man-made indoor environments, doors are frequently encountered and function as transitions between spaces. Furthermore, doors can be associated with semantic concepts. Therefore, doors can serve as landmarks for navigation, relative localization, and SLAM strategies [14].

There have been some efforts to detect doors by using different sensors, features, and training methods [1, 3-4, 7, 9-12]. Some approaches of door detection depend on 3D information including both visual data and distance data [1, 7, 9, 12]. Anguelov *et al.* [1] use laser range finder to establish range sensor model. Hensler *et al.* [7] apply laser range finder to obtain the distance data to test door concavity. In [12], sonars are used to confirm or dismiss door detection results from cameras. In [9], three cameras are employed to perform trinocular stereo. These methods suffer the disadvantages of high-cost, high-power, and complexity in the systems. Other door detection algorithms focus on using monocular visual information [3, 4, 10, 11]. Munoz-Salinas *et al.* apply fuzzy logic to develop a door model based on the membership degree of the vertical lines and horizontal lines [10]. Murillo *et al* [11] apply both appearance features and shape features (color histogram) to detect doors. Others apply multiple door features and training methods. Hensler *et al.* [7] combine multiple features such as color, door knob, door gap, doorframe, texture on bottom of a door, door width, and door concavity by an AdaBoost algorithm. In their system, the door knob model is defined as almost horizontal lines in left or right side of a door. This model is limited to a specific environment. Chen and Birchfield [3] also employ an AdaBoost algorithm to combine the features of pairs of vertical lines, concavity, gap between the door and floor, color, texture, kick plate, and vanishing point. However, a gap below the door and kick plate are not always present in different environments. In [4], two neural network based door classifiers are trained by using color and shape features respectively. Their algorithm is designed to detect the doors of the authors' office building, where all the doors have similar color. It would fail to detect doors with different colors. We observe that some features in previous work, such as kick plate and bottom gap, are not always present; and some other features, like color and texture, are not constant in different environments. Algorithms using these restricted features work for limited environments. Unlike existing work, we focus on developing robust and generic door detection algorithm to handle a variety of doors in unfamiliar environments by using a wearable camera which is connected to a mini-laptop or a PDA.

1.2. Approach Overview

In our image-based door detection algorithm, we take account of a variety of conditions including illumination and scale changes, deformation caused by perspective and occlusion, and variance of doors' color, texture and appearance. Furthermore, we build a geometric shape model of doorframe which contains two horizontal lines and two vertical lines between four corners. This geometric door shape model is the foundation to detect doors. In order to extract stable and reliable features of doors in various environments, we employ edge and corner features to model the geometric shape of doors. In our system, we first extract edges through Canny edge detector [2] and corners using the corner detector proposed by He and Yung [6]. Then, we establish a generic door model that contains 4 corners which are connected by edge lines of doorframe. Instead of detecting lines directly, we propose a matching process to combine corners and edges, which is able to avoid some disadvantages of existing line detection methods, such as, missing start and end points, sensitivity to parameters, and undesirable merging or splitting of lines. Doors in an image are detected when both corners and edges meet the geometric model and matching testing. Since our algorithm uses fundamental geometric shape information instead of features like color and texture, it can detect fully opened doors and glass doors. To evaluate the performance of the proposed algorithm, we collect a database from a wide variety of environments. The database is further categorized into three groups based on the complexity of background, changes of illumination, scale, and occlusion as: *Simple Category*, *Medium Category*, and *Complex Category*. Detection results corresponding to each category are presented.

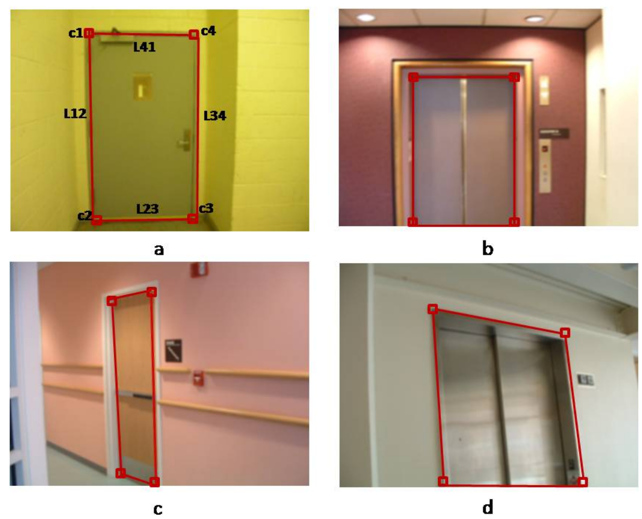

Figure 1. The geometric model of a door. (a) The ideal model. (b) The model with occlusion. (c) The model with perspective deformation. (d) The model with both perspective deformation and occlusion.

2. Proposed Method

2.1. General Geometric Door Model

The geometric model of a door in our algorithm consists of four corners and four lines of the doorframe as shown in Figure 1. Figure 1(a) depicts an ideal geometric door shape model. Figure 1(b) depicts the geometric model with occlusion. Figure 1(c) depicts the geometric model caused by perspective deformation. Figure 1(d) depicts the geometric model with both perspective deformation and occlusion. In the cases of Figure 1(a, c), four door corners are all visible. In the cases of Figure 1(b, d), two door corners are occluded. However, each occluded vertical line of the doorframe can still form a corner with the horizontal axis of the image. This geometric model makes the following assumptions:

1) At least two door corners of each doorframe are visible in an image.
2) Both vertical lines of each doorframe are visible in an image.
3) Vertical lines of doorframes are almost perpendicular to the horizontal axis of the image.
4) Doors in an image have at least a certain width and a certain length.

In practice, these conditions are easy to achieve. The proposed method is very robust to handle different situations without using any other assumptions. For example, the color of a door can be similar or different from that of a wall. The surface of a door can be textured or untextured. The material of a door can be wood, metal, or glass. The status of a door can be closed or fully opened. The upper horizontal line or the lower horizontal line of a doorframe can be occluded.

2.2. Image Pre-processing

The proposed method is based on the detection of edges and corners of the original image. Before the detection of edges and corners, the original image is firstly down-sampled and then smoothed by Gaussian lowpass filters. This pre-process reduces the computational cost by down-sampling image size as well as eliminating the corners generated from noise and complex texture in the original image. In Figure 2(b-d), each black square corresponds to a detected corner. Figure 2(b) shows the detected corners in original image with the size of 640×480. Many corners are detected on the highly textured wall. After Gaussian smoothing, less corners are detected in the original image (Figure 2(c).) Figure 2(d) illustrates the corner detection results of the down-sampled image with the resolution of 320×240. Notice that most corners on the textured wall are not detected. In both Figure 2(c) and 2(d), key corners of the door frame are preserved. In our experiments, the Gaussian smoothing filter's size is 5×5, and its deviation sigma is 0.8. The numbers of detected corners under different conditions are presented in Table 1.

There is a tradeoff between the amount of detected corners and the accuracy of localization of corners. Images with lower resolution result in larger error of the localization of corners. Large errors of the localization of corners would cause more mistakes for testing door-corner candidates. Therefore, there is also a tradeoff between the accuracy of localization and the detection speed. In our experiment, we evaluate the proposed algorithm on images with resolution of 320×240 and 160×120.

Resolution	Gaussian smoothing	Amount of corners
640×480	No	205
	Yes	159
320×240	No	65
	Yes	61
160×120	No	35
	Yes	34

Table 2. Amounts of detected corners of Figure 2(a) under different conditions.

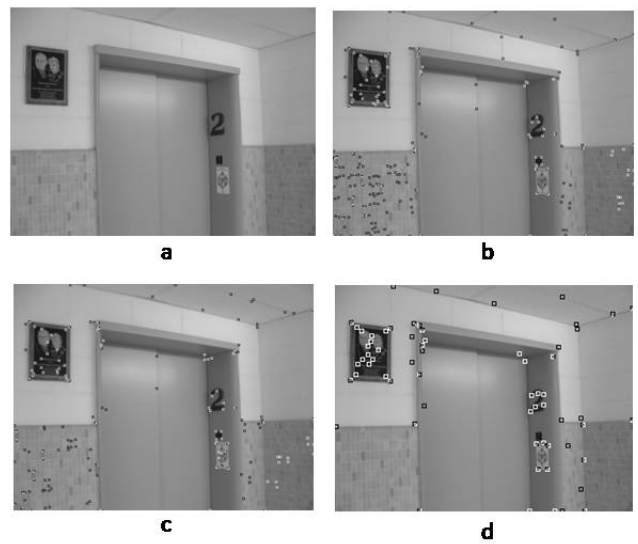

Figure 2. (a) Original image with resolution of 640×480. (b) Corner detection of the original image. (c) Corner detection of the original image after Gaussian smoothing. (d) Corner detection of down-sampled image with resolution of 320×240.

2.3. Edge and Corner Detection

The detection process begins with the Canny edge detector on the down-sampled and smoothed gray-level image to generate a binary edge map. In an edge map, if the endpoint of an edge nearly connects with another endpoint, the gap between the two endpoints is filled. In this way, contours, or more continuous edges, are extracted through the binary edge map. Then a corner detection method [6] is employed to extract corners from the contours based on curvature $K(u,\sigma)$:

$$K(u,\sigma) = \frac{X_u(u,\sigma)Y_{uu}(u,\sigma) - X_{uu}(u,\sigma)Y_u(u,\sigma)}{(X_u(u,\sigma)^2 + Y_u(u,\sigma)^2)^{1.5}} \quad (1)$$

where

$$X_u(u,\sigma) = x(u) \otimes g_u(u,\sigma) \quad X_{uu}(u,\sigma) = x(u) \otimes g_{uu}(u,\sigma)$$

$$Y_u(u,\sigma) = y(u) \otimes g_u(u,\sigma) \quad Y_{uu}(u,\sigma) = y(u) \otimes g_{uu}(u,\sigma)$$

$x(u)$ and $y(u)$ parameterize the curve Γ by the arc length u: $\Gamma(u) = (x(u), y(u))$. $g(u, \sigma)$ is the Gaussian kernel with the width of σ and $\otimes$ denotes the convolution operator.

The corner detection method first calculates the absolute value of curvature for each point on a contour. Points with local maximum curvature are selected as initial corner candidates. Then, adaptive curvature thresholds and angles of corner candidates are used to eliminate round corners and false corners due to noise and trivial details. By balancing the global relationship between neighboring features and local curvature properties, this corner detector can localize corners accurately. Furthermore, in our algorithm, the endpoint of an open contour is also considered as a corner. More details about the corner detection method can be found in paper [6].

In our proposed geometric model, each occluded vertical doorframe corresponds to an open contour. Accordingly, the endpoint of the open contour corresponds to the corner formed by the occluded vertical doorframe and the horizontal axis of an image. Therefore, regardless of occlusion, four door corners can be extracted. Figure 3(a) illustrates the endpoints of two open contours. In Figure 3(b), two vertical lines of doorframe intersect with the horizontal axis of the image. Two points of intersection detected as corners in Figure 3(b) correspond to the two endpoints of open contours in Figure 3(a).

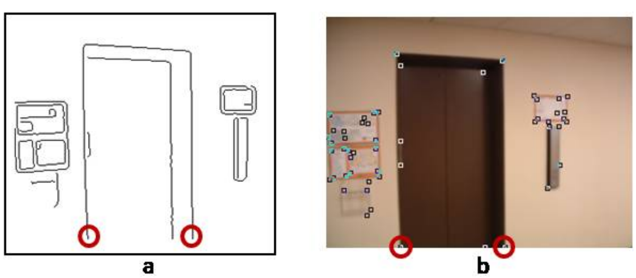

Figure 3. Detected corners for occluded vertical lines of a doorframe. (a) Two endpoint samples of open contours in the edge map. (b) Two endpoints correspond to two corners formed by occluded vertical lines and the horizontal axis of the image.

2.4. Door-Corner Candidates Grouping

The geometric model of a door consists of 4 corners. So, the maximum number of 4-corner groups is the combination of the amount of detected corners chooses four. In practice, this maximum is always very large. In order to reduce the number of 4-corner groups, we can use the relative geometric relationship of four corners to eliminate a part of groups, which would largely reduce the number of 4-corner groups.

As shown in Figure 1(a), the door model contains 4 corners C_1, C_2, C_3, and C_4. The coordinate of corner C_i is (x_i, y_i). L_{12} is the line connecting C_1 and C_2, L_{23} is the line connecting C_2 and C_3, L_{34} is the line connecting C_3 and C_4, and L_{41} is the line connecting C_4 and C_1. According to the 3rd and 4th assumptions of the proposed geometric door shape model in Section 2.1, the lengths and directions of L_{12}, L_{23}, L_{34}, and L_{41} can be used to obtain door-corner candidacy of each 4-corner group.

The ratio between the length of L_{ij} and the length of the diagonal of an image is measured by the variable Siz_{ij}. The direction of L_{ij} corresponding to the horizontal axis of an image is measured by the variable Dir_{ij}. Siz_{ij} and Dir_{ij} are defined by equation (2) and equation (3), respectively.

$$Siz_{ij} = \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{DI} \qquad (2)$$

$$Dir_{ij} = tan^{-1}\frac{|x_i - x_j|}{|y_i - y_j|} \times \frac{180}{\pi} \qquad (3)$$

where DI is the length of the diagonal of an image. For images with the size of 320×240, DI is 400. Siz_{ij} is within the range of [0, 1] and Dir_{ij} is within the range of [0, 90].

For each 4-corner group, if any of the following geometric requirements is not satisfied, this 4-corner group would be eliminated without further processing.

1) According to the 4th assumption, a door in an image at least has a certain width and height. So, Siz_{ij} should be within a certain range:
$$HeightThresL < Siz_{12}, Siz_{34} < HeightThresH$$
$$WidthThresL < Siz_{23}, Siz_{41} < WidthThresH$$
2) Ideally, L_{23} and L_{41} should parallel with the horizontal axis of an image. Due to perspective deformation, L_{23} and L_{41} could form a certain angle with the horizontal axis. But, Dir_{23} and Dir_{41} should not be too large:
$$Dir_{23}, Dir_{41} < DirectionThresL$$
3) According to the 3rd assumption, vertical lines are almost perpendicular to the horizontal axis of the image. So, Dir_{12} and Dir_{34} should be large enough:
$$Dir_{12}, Dir_{34} > DirectionThresH$$
4) Vertical lines should parallel with each other:
$$|Dir_{12} - Dir_{34}| < ParallelThres$$
5) If none of the four corners is generated from the endpoints of open contours, the ratio between the height and the width of a door frame should be within a range:
$$RatioThresL < (Siz_{12} + Siz_{34}) / (Siz_{23} + Siz_{41}) < RatioThresH$$

In our system, we set $HeightThresL=0.5$ and $HeightThresH=0.9$; $WidthThresL=0.1$ and $WidthThresH=0.8$; $DirectionThresL=35$ and $DirectionThresH=80$; $ParallelThres=6$; $RatioThresL=2.0$ and $RatioThresH=3.0$. The 4-corner groups that satisfy the above rules are marked as door-corner candidates, which will be tested by the following matching procedure.

In the process of door-candidates grouping, the proposed geometric door shape model has fully considered conditions of occlusion. In [3], the robot camera closed to the ground often misses the top of a door. So, their model only handles the conditions that the lintel of a door is occluded. In [7], the camera properly tilted up always captures the top bar of a door. So, their system is restricted to detect doors with top part. Our algorithm can handle both occlusion conditions. This is very important for blind users. Figure 4 illustrates the detected door under two occlusion conditions of the same door.

Figure 4. Door detection results under different occlusion conditions. Left: Door detection result with the bottom part occlusion. Right: Door detection result with the top part occlusion.

2.5. Matching Combining Edges and Corners

Each door-corner candidate represents an abstract geometric model of 4 corners of a doorframe. Next step is to detect if a door-corner candidate matches to the real door frame in an image by combining edge information. The line L_{ij} connecting corners C_i and C_j can be used as the reference for the matching process. Many existing systems employ Hough transform [8] to detect straight lines. However, practical experiments demonstrate several disadvantages of this approach. First, Hough transform can only provide line direction and position without the start and end points. Thus, it fails to localize the start and end points of a line or to determine the length of a line. Second, this method is sensitive to the choice of parameters, which results in the undesirable splitting of lines or the undesirable merging of lines. Other line detection methods also suffer the broken segments caused by small gaps, like door hinges or knobs. In order to avoid the pitfalls of existing line detection methods, we combine the edge images and door-corner candidates for the door detection.

Our algorithm uses the edge image as the reference map to match with the door-corner candidates, instead of directly detecting the lines. This method can provide the information of start and end points. In addition, it is insensitive to the choice of parameters and robust to broken segments caused by small gaps. Before describing the matching process, we first introduce the concept of "*fill-ratio*". In Figure 5(a), the red dots and green lines correspond to corners of a door-corner candidate and the detected edges, respectively. The red line L_{12} in Figure 5(b) is the line connecting corner C_1 and C_2, similarly for L_{34}. In Figure 5(c), the red regions R_{12} and R_{34} are the masks expanding from L_{12} and L_{34}. In Figure 5(d), the lines with yellow color are the overlapped parts of the green edges in Figure 5(a) with the masks (i.e. the red regions in Figure 5(c).) In another point of view, the "*fill-ratio*" of two corners can be used to measure the deviation between the imaginary line connecting two corners and the reference edge in the edge map. The "*fill-ratio*" of corner C_i and C_j in an edge map is defined as:

$$FR_{ij} = \frac{OverLap_{ij}}{Length_{ij}} \tag{4}$$

where $Length_{ij}$ is the length of L_{ij}, and $OverLap_{ij}$ is the length of the overlapped part, the edges falling in the region formed by masks expanding from the line connecting two corners.

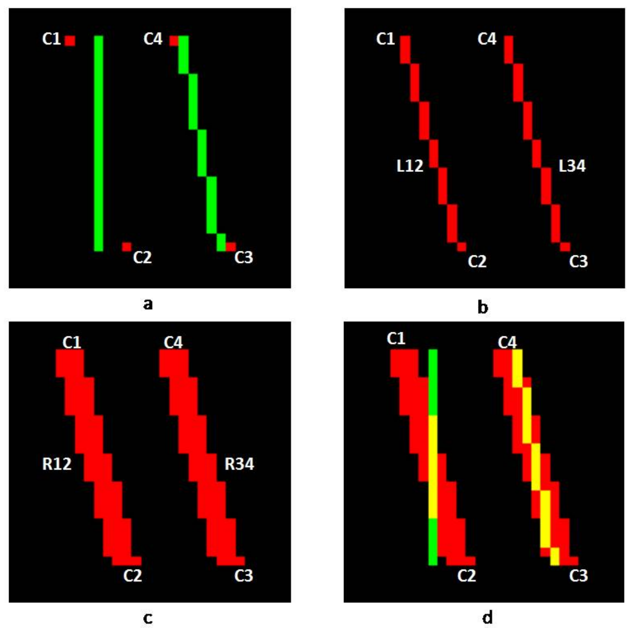

Figure 5. Definition of "*fill-ratio*": (a) Four red corners C_1, C_2, C_3, and C_4 and two green edges. (b) Two red lines L_{12} and L_{34} connecting corners C_1, C_2 and C_3, C_4. (c) Two red masks expanded from two red lines in (c). (d) Yellow lines are the overlapped part of green edges in (a) and red masks in (c). The "*fill-ratios*" for corners C_1, C_2 and C_3, C_4 in (a) are $FR_{12} = 0.5$ and $FR_{34} = 1$.

In order to detect whether a door-corner candidate matches to a real doorframe, we first calculate four "*fill-ratio*" values: FR_{12}, FR_{23}, FR_{34}, and FR_{41}. If the four "*fill- ratio*" values are larger than a threshold *FRThresL* and the average value of the four "*fill-ratio*" values is larger than *FRThresH*, then the door-corner candidate is determined to correspond to a real door in the image. In

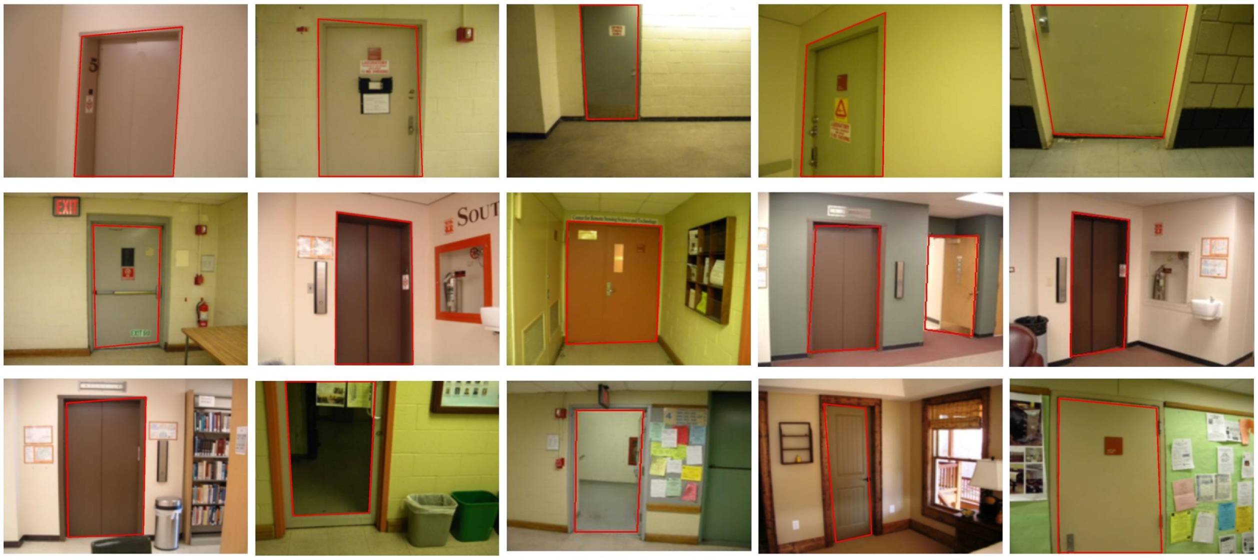

Figure 6. Examples of successfully detected doors. First row, second row and third row correspond to examples in categories of *Simple*, *Medium*, and *Complex*.

practice, we set *FRThresL* smaller than *FRThresH* for following reasons: 1) Relatively smaller value of *FRThresL* overcomes the broken edges caused by small gaps; 2) relatively larger value of *FRThresH* guarantees the accuracy of the matching results. To handle occlusions, the "*fill-ratio*" values of two corners that are both formed by two endpoints of open contours (see Figure 3) are set to *FRThresH*. Sometimes, more than one door-corner candidates surrounding with a door frame match with the edge map. In fact, they all represent the same door frame. So, if the overlapped area of two detected doors is large enough, the two detected doors would be merged as one door.

In practice, if *FRThresL* or *FRThresH* is too large, the false positive rate will be low, but the true positive rate will also decrease; if *FRThresL* or *FRThresH* is too small, the true positive rate will be high, but the false positive rate will increase too. In order to reduce the false positive rate and increase the detection rate simultaneously, we initialize *FRThresL* and *FRThresH* by two relative low values. Then, the detection result is checked: if only one door-corner candidate is matched, then it is the detection result; if more than one door-corner candidate is matched, then *FRThresL* and *FRThresH* with relatively high values are used to re-match the matched door-corner candidates. In our experiments, the increased thresholds are effective to eliminate the spurious detection results.

In our system, *FRThresL=0.6* and *FRThresH*=0.85 in the first matching process. They are set to 0.87 and 0.90, respectively in the re-matching process.

3. Experimental Results and Analysis

To test the performance of the algorithm, a database of 193 images containing total 204 doors was collected from a wide variety of environments. The database includes doors with different colors and texture, elevators, open doors, glass doors, and doors captured under different viewpoints, light changes, and occlusions. The database will be released to public. For images with resolution of 320×240, the algorithm achieves 91.7% true positive rate with a false positive rate of 2.9%. Furthermore, we also test the detection results for images with the size of 160×120 in the same database. The true positive rate and false positive rate for images with the resolution of 160×120 is 87.3% and 14.2%, respectively. In order to analyze the effects of image backgrounds to the experimental results, we further categorize this database into three groups based on the complexity of background, as well as the intensity of deformation and occlusion, changes of illumination and scale: 55 images as *Simple Category*, 90 images as *Medium Category*, and 48 images as *Complex Category*.

Figure 6 demonstrates some examples of successful detection results for images with the resolution of 320×240 in each category. The first row is the examples of *Simple Category* with relatively clear background. However, this category includes a wide variety of conditions of different perspective deformation, illuminations and occlusions. The second row demonstrates the examples of *Medium Category* with more complicated background. In some cases, there are multiple doors in a single image. The third row illustrates the examples of *Complex Category* with very complex background. This category also includes glass doors and open doors. To investigate the effects of image resolution, we evaluate the proposed method at resolutions of both 320×240 and 160×120 in the three categories (Tables 2 and Table 3).

Data Category	Number of Images	Number of Doors	True Positive Rate	False Positive Rate
Simple	55	55	98.2%	1.8%
Medium	90	93	91.4%	1.1%
Complex	48	56	85.7%	7.1%
Total	193	204	91.7%	2.9%

Table 2. Detection results for *Simple Category*, *Medium Category*, and *Complex Category* images with the resolution of 320×240.

Data Category	Number of Images	Number of Doors	True Positive Rate	False Positive Rate
Simple	55	55	96.4%	3.6%
Medium	90	93	88.2%	15.1%
Complex	48	56	76.8%	23.2%
Total	193	204	87.3%	14.2%

Table 3. Detection results for *Simple Category*, *Medium Category*, and *Complex Category* images with the resolution of 160×120.

Table 2 displays the detection results at resolution of 320×240. We observe that from *Simple Category* to *Complex Category*, the true positive rates decrease from 98.2% to 85.7%, and the false positive rates increase from 1.8% to 7.1%. The false positive rate of *Medium Category* is a little smaller than that of *Simple Category*, which, we think, is caused by the volume differences between categories of *Simple* and *Medium*. From *Simple Category* to *Complex Category*, the backgrounds are more complex, which would result in more corners. So, the probability of detection spurious doors also augments. That is the reason why the trend for false positive rate increases. The failure of detection of key corners of a door is the main reason for the decline of true positive rate. Besides, in some images of *Medium Category* and *Complex Category*, there is more than one door in a single image. Sometimes, it fails to detect all of the doors appeared in one image due to the size constraint or occlusion of key corners. However, in the application of wayfinding and navigation, the blind people are interested in detecting the most closed doors. So, we are more concern about the closed doors, rather than detecting all the doors appearing in an image. Figure 7 displays two samples of errors in the detection results of images with the size of 320×240. In the left image, it fails to detect other doors whose key corners or edges are occluded. In the right one, a false positive occurs because of the lateral wall.

The tendencies of true positive rate and false positive rate from *Simple Category* to *Complex Categories* in Table 3 are similar to that in Table 2. However, compared with the detection results in Table 2, the true positive rates of each category are lower, especially for *Complex Category*; and the false positive rates are higher, especially for *Medium Category* and *Complex Category*. Because of down-sampling in the images with size of 160×120, the deviation between the line connecting two corners and the reference edge decreases. Therefore, the probability of detecting spurious doors would increase. That is the reason why the false positive rates in Table 3 are higher. Although images of 160×120 can highly decrease the computational cost, considering the accuracy of detection result, we recommend the resolution of 320×240 in practical applications.

Figure 7. Some errors in detection results. Left: false negative error. Right: false positive error.

4. Conclusions and Future Work

In this paper, we have presented an image-based door detection algorithm. The geometric door shape model consisting of four corners and four lines of a doorframe is first established. In order to balance the detection accuracy and detection speed, we down-sample the original image with the size of 640×480 to the size of 320×240, and then smooth the resized image by a Gaussian lowpass filter. Then the corners and edges are extracted. Geometric relationships between the detected corners are used to group four corners as door-corner candidates. The door-corner candidates can handle different occlusion conditions. Finally the edge map is used to match with each door-corner candidate without performing line detection. Therefore, it is able to avoid some disadvantages of line detection algorithms. For instance, it can provide the endpoint information, and alleviate the unwanted splitting and merging errors. We evaluate our method on a large database collected from a wide variety of environments, the proposed algorithm achieves 91.7% detection rate with a low false positive rate of 2.9%. The results demonstrate the validity of our algorithm for door detection in unfamiliar environments for visually impaired people.

The future work will focus on increasing accuracy of door detection in the environments with complex background and distinguishing doors, elevators, and other objects with similar shape of doors (e.g. cabinets, bookshelves, etc). More generic features, such as the door knob, will be incorporated into our door detection method. We will also incorporate context information (sign and text) on/around the door and the proposed algorithm into the computer vision-based indoor navigation and wayfinding system.

Acknowledgement

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References

[1] D. Anguelov, D. Koller, E. Parker, and S. Thrun. Detecting and modeling doors with mobile robots. In Proceedings of the IEEE International Conference on Robotics and Automation, 2004.

[2] J. Canny. A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-8:679,698.

[3] Z. Chen and S. Birchfield. Visual Detection of Lintel-Occluded Doors from a Single Image. IEEE Computer Society Workshop on Visual Localization for Mobile Platforms *CVPR 2008*. Anchorage, Alaska, June 2008.

[4] G. Cicirelli, T. D'orazio, A. Distante. Target recognition by components for mobile robot navigation. Journal of Experimental & Theoretical Artificial Intelligence, Volume 15, Number 3, July-September 2003, pp. 281-297(17)

[5] J. Coughlan and R. Manduchi. Functional Assessment of a Camera Phone-Based Wayfinding System Operated by Blind and Visually Impaired Users. International Journal on Artificial Intelligence Tools. Vol. 18, No. 3, pp. 379–397. 2009.

[6] X.C. He and N.H.C. Yung. Corner detector based on global and local curvature properties. Optical Engineering, 47(5), pp: 057008, 2008.

[7] J. Hensler, M. Blaich, and O. Bittel. Real-time Door Detection Based on AdaBoost Learning Algorithm. International Conference on Research and Education in Robotics, Eurobot 2009.

[8] P. V. C. Hough. Method and means for recognizing complex patterns. U. S. Patent 3, 069 654, December 18, 1962.

[9] D. Kim and R. Nevatia. A method for recognition and localization of generic objects for indoor navigation. In ARPA Image Understanding Workshop, 1994.

[10] R. Munoz-Salinas, E. Aguirre, M. Garcia-Silvente, and A. Gonzalez. Door-detection using computer vision and fuzzy logic. In Proceedings of the 6th WSEAS International Conference on Mathematical Methods & Computational Techniques in Electrical Engineering, 2004.

[11] A. C. Murillo, J. Kosecka, J. J. Guerrero, and C. Sagues. Visual door detection integrating appearance and shape cues. Robotics and Autonomous Systems, 2008.

[12] S. A. Stoeter, F. L. Mauff, and N. P. Papanikolopoulos. Realtime door detection in cluttered environments. In Proceedings of the 15th IEEE International Symposium on Intelligent Control, 2000.

[13] B.S. Tjan, P.J. Beckmann, R. Roy, N. Giudice and G.E. Legge: Digital Sign System for Indoor Wayfinding for the Visually Impaired. IEEE Computer Society Workshop on Computer Vision Applications for the Visually Impaired *CVPR 2005*, San Diego, Califonia, June 2005.

[14] N. Tomatis, I. Nourbakhsh, and R. Siegwart. Hybrid simultaneous localization and map building: a natural integration of topological and metric. Robotics and Autonomous Systems, 44:3–14, 2003.