Computer Vision-Based Door Detection for Accessibility of Unfamiliar Environments to Blind Persons

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Abstract. Doors are significant landmarks for indoor wayfinding and navigation to assist blind people accessing unfamiliar environments. Most camera-based door detection algorithms are limited to familiar environments where doors demonstrate known and similar appearance features. In this paper, we present a robust image-based door detection algorithm based on doors' general and stable features (edges and corners) instead of appearance features (color, texture, etc). A generic geometric door model is built to detect doors by combining edges and corners. Furthermore, additional geometric information is employed to distinguish doors from other objects with similar size and shape (e.g. bookshelf, cabinet, etc). The robustness and generalizability of the proposed detection algorithm are evaluated against a challenging database of doors collected from a variety of environments over a wide range of colors, textures, occlusions, illuminations, scale, and views.

1 Introduction

Independent travel is well known to present significant challenges for individuals with severe vision impairment, thereby reducing quality of life and compromising safety. There have been many efforts to study blind navigation and wayfinding with the ultimate goal of developing useful travel aids for blind people [5, 12], but very few have met with more than limited success. The most useful and accepted independent travel aids remain the Hoover white cane and the guide dog, both of which have been in use for many years. While GPS-guided electronic wayfinding aids show much promise in outdoor environments, there is still a lack of orientation and navigation aids to help people with severe vision impairment to independently find doors, rooms, elevators, stairs, bathrooms, and other building amenities in unfamiliar indoor environments.

In this paper, we develop a computer vision-based door detection method for assisting blind persons to access unfamiliar indoor environments. This method perhaps would be one module within a more complete computer-vision aid designed for blind persons that would mainly consist of a single camera and a computer. For example,

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visual information would be captured via a miniature camera mounted on the head via a cap or sunglasses (Figure 1), while image processing and speech output would be provided by a computer (with speech output via headphones or mini-speakers and updated in real-time). Our detection results from a large dataset of indoor images including door images and non-door images demonstrate that the proposed method is robust and generic to the changes of scales, view points, and occlusions in different buildings.

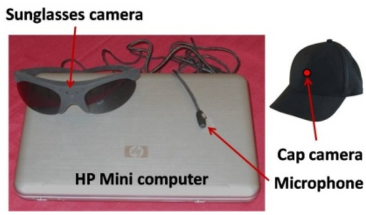

Fig. 1. Computer vision-based indoor navigation and wayfinding prototype system

2 State-of-the-Art

Door detection approaches have been developed for robot navigation. Some of these methods use laser range finders to establish range sensor models of the surrounding environment and to obtain the distance data to test door concavity [1, 7]. Stoeter *et al.* [13] employed sonar data to confirm or dismiss detection results from cameras. In [9], three cameras are employed to perform stereo vision for door detection. However, high-cost, high-power, and complexity in these systems make them inappropriate to work for visually impaired people. To reduce the cost and complexity of the device and its computational requirements, we use a single camera.

There are a few existing door detection algorithms using monocular visual information [3, 10, 11]. In [3] an AdaBoost classifier is trained to detect doors of similar appearance by combining the features of pairs of vertical lines, concavity, gap between the door and floor, color, texture, kick plate, and vanishing point. However, a perceptible gap below the floor and kick plate is not always present in different environments. Munoz-Salinas *et al.* [10] developed a doorframe model-based door detector by using Hough Transform to extract the edge segments and a fuzzy system to analyze the relationship between the segments. However, their algorithm cannot differentiate doors from large rectangular objects typically in indoor environments, such as bookshelves, cabinets, and cupboards. In [11], two classifiers were trained by using color and shape features. This algorithm was designed to detect the doors of the authors' office building, where all the doors have similar color. It would fail if the colors of the doors vary.

To overcome the limitations described above, we develop an image-based door detection algorithm by establishing a general geometric door model that utilizes the general and stable features of doors (i.e. edges and corners) without a training process. Furthermore, integrated with geometric information of lateral at similar horizontal coordinate, the proposed algorithm is able to distinguish doors from other objects with door-like shape and size. The detection results demonstrate that our door detection method is generic and robust to different environments with variations of color, texture, occlusions, illumination, scales, and viewpoints.

3 Methodology for Door Detection

3.1 Geometric Door Model

The ideal geometric model of a door consists of four 90° corners and four lines of the doorframe. However, due to perspective and occlusion, only part of a door is often captured by a wearable camera, and the corners may depart significantly from 90°. Figure 2 illustrates ideal and more realistic geometric door models including those under ideal conditions (a), and conditions with occlusion and perspective effects (b and c). Each geometric model includes four corners (red square) and four lines (red lines).

Our algorithm makes weak assumptions about doors in an image: 1) At least two corners of each doorframe are visible; 2) both vertical lines of each doorframe are visible; 3) vertical lines of doorframes are nearly perpendicular to the horizontal axis of the image; 4) doors in the image have at least a certain width and length. These requirements are very likely to met in most wearable camera images when a door is present in the field of view, and help make our door detection method more robust to variations of color, texture, occlusion, and door status (open or close). For example, the color of a door can be similar or different from that of a wall. The surface of a door can be with or without texture. The material of a door can be wood, metal, or glass. The status of a door can be closed or fully opened. The upper or lower part of a door can be occluded.

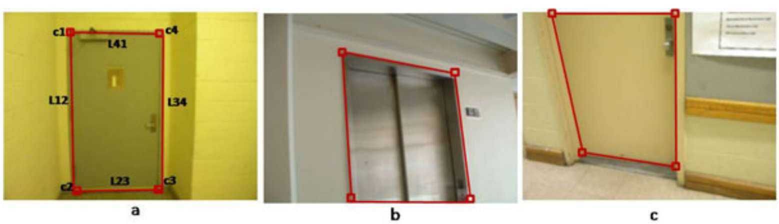

Fig. 2. The proposed geometric door model: (a) The ideal condition without occlusion or perspective effects. (b) The condition with lower part occluded and perspective effects. (c) The condition with upper part occluded and perspective effects.

3.2 Edges and Corners Detection

Edges and corners in images are relatively stable features to identify and are resistant to variations of scales, colors, viewpoints, and light changes. In order to develop a robust door detector to handle different environments, we combine both edge and corner features to characterize the geometric door shape model. In our system, we first apply Gaussian smoothing to reduce image noise. The smoothing process also eliminates the unnecessary corners for door detection. Then we extract edges through Canny edge detection [2] and create a binary edge map. Then corners are extracted through the edge map based on global and local curvature properties by the corner detector proposed by He and Yung [6]. Since the endpoint of an open contour is also considered as a corner by this method, four corners of a doorframe can be extracted by this corner detector regardless of occlusion (Figure 2(b, c)).

$$Siz_{ij} = \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{DI} \tag{1}$$

$$Dir_{ij} = tan^{-1}\frac{|x_i - x_j|}{|y_i - y_j|} \times \frac{180}{\pi} \tag{2}$$

As shown in Figure 2(a), C_1, C_2, C_3, and C_4 are four corners with coordinate of (x_i, y_i). L_{12} is the line connecting C_1 and C_2, similarly for L_{23}, L_{34}, and L_{41}. Suppose the length of the diagonal of an image is DI. The ratio between the length of L_{ij} and DI 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 in equation (1) and (2), respectively. Then, we use the geometric relationship of any four corners to establish door-corner candidates which satisfy the following rules:

1. A door in an image at least has a certain width and height. So, Siz_{12} and Siz_{34} should be within a certain range:
$$HeightThresL < Siz_{12}, Siz_{34} < HeightThresH$$
$$WidthThresL < Siz_{23}, Siz_{41} < WidthThresH$$
2. 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:
$$Dir_{23}, Dir_{41} < DirectionThres\mathrm{L}$$
3. Vertical lines of a door frame 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 of a door frame should parallel with each other:
$$|Dir_{12}-Dir_{34}| < ParallelThres$$
5. The ratio between height and width of a door frame should be within a range:
$$HWThresL < (Siz_{12}+Siz_{34}) / (Siz_{23}+Siz_{41}) < HWThresH$$

3.3 Door Model Matching by Combination of Edges and Corners

Door-corner candidates represent possible geometric models. The next step is to determine whether a door-corner candidate matches to a real door frame by combining the edge information. Most existing door systems employ Hough transforms [8] to detect straight lines. However, practical experiments demonstrate several disadvantages of this approach, such as missing start and end points, sensitivity to parameters, and unwanted merging or splitting of lines. A novel aspect of our algorithm is its use of the edge image as the reference map to match with the door-corner candidates, rather than directly detecting the lines. The proposed matching process can provide the information of start and end points. Besides, it is insensitive to the broken segments caused by small gaps. The concept of "*fill-ratio*" is the foundation for the matching process. In Figure 3(a), C_i and C_j are two corners. The gray area is a region formed by masks expanding from the straight line connecting C_i and C_j. In our algorithm implementation, the mask is a 7×7 window. The black line is the detected edge. The edge pixels in the gray region constitute the overlapping line. The "*fill-ratio*" of corner C_i and C_j in the edge map is defined as:

$$FR_{ij} = \frac{OverLap_{ij}}{Length_{ij}} \tag{3}$$

where $Length_{ij}$ is the length of L_{ij}, the straight line connecting corner C_i and C_j. $OverLap_{ij}$ is the length of the overlapping line.

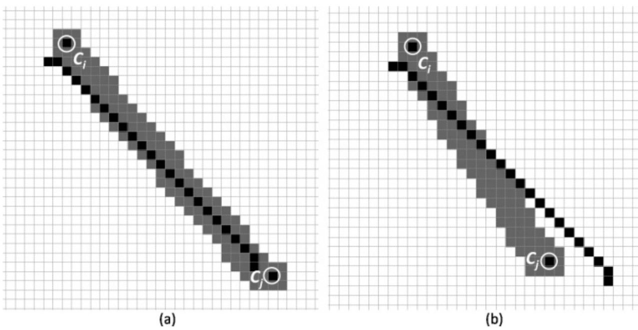

Fig. 3. Definition of "fill-ratio" for matching edges with two corners of a door-corner candidate. C_i and C_j: detected corners; black line: detected edges; gray area: matching mask; (a) an example with matching edge pixels $FR_{ij} = 0.96$; (b) an example without enough matching edge pixels $FR_{ij} = 0.54$.

The "fill-ratio" of two corners can also be understood as a measurement of the deviation between the straight line connecting the two corners and the reference edge. We first calculate four "fill-ratio" values: FR_{12}, FR_{23}, FR_{34}, and FR_{41} of each door-corner candidate. 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. To handle occlusions, the "fill-ratio" values of two corners that are both formed by two endpoints of open contours (see Figure 2(b, c)) are set to *FRThresH*. Sometimes, more than one door-corner candidate surrounding with a door frame matches 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.

3.4 Distinguishing Doors from Large Convex Objects

Depth information is a significant reference for indoor object recognition. However, a single camera cannot provide depth information. Existing monocular camera-based door detection methods cannot differentiate doors from large object objects with door-like shape and size, such as bookshelves and cabinets. Although the use of a laser range finder, sonar, or binocular/trinocular camera can solve this problem, it suffers high-cost and high-complexity of the detecting system, which is unsuitable for the wearable indoor navigation aid we envision. Here we propose a novel and simple algorithm by combining lateral information of the detected door to obtain the relative depth information, which would be further used to distinguish doors from other door-like objects. As shown in Figure 4, the concave and convex objects demonstrate the laterals in different positions with respect to the frame. In Figure 4(a), the elevator door, a concave object relative to the wall, demonstrates its lateral (C_1-C_2-C_5-C_6) located *inside* of the frame's (C_1-C_2). In Figure 4(b), the bookshelf, a convex object relative to the wall, demonstrates its lateral (C_4-C_3-C_5-C_6) located *outside and adjacent to* the frame (C_3-C_4). The observation is true under different perspective scenarios. Such differences are used to infer the relative depth information of an indoor object to distinguish doors from other door-like objects (e.g. bookshelves, cabinets, etc.)

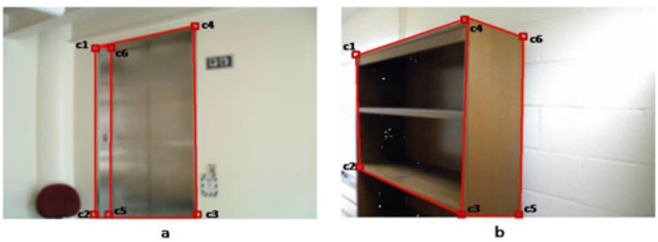

Fig. 4. Laterals of concave and convex objects. (a) A concave object demonstrate its lateral (C_1-C_2-C_5-C_6) located inside of the frame. (b) A convex object demonstrates its lateral (C_4-C_3-C_5-C_6) located outside the frame.

4 Experimental Results

To validate the robustness and generalizability of our method, we collected a database which contains 203 images of 210 doors from a wide variety of environments. The database includes doors with different colors and texture, elevators, open doors, glass doors, bookshelves, and doors captured with different viewpoints, light changes, and occlusions. Furthermore, based on the complexity of backgrounds, intensity of deformation and occlusion, as well as the changes of illuminations and scale, we categorize the doors into three groups: *Simple*, *Medium*, and *Complex*. The resolution of images used in our experiments is 320×240. The proposed algorithm achieves accuracy at detection rate of 91.9% with a false positive detection rate of 2.9%. The detail true positive detection results for each category are presented in Table 1. Figure 5 shows some examples of the detected doors from different environments. The first row shows the "*Simple*" examples with simple background. However, it includes a wide variety of conditions of different illuminations and occlusions. The second row shows the "*Medium*" examples with somewhat more complicated background. In some cases, there are multiple doors in a single image. The third row illustrates the "*Complex*" examples with very complex background. This category also includes glass doors and open doors.

Table 1. Door detection results for groups of "*Simple*", "*Medium*", and "*Complex*"

Data Category	Number of Images	Number of Doors	True Positive Rate	False Positive Rate
Simple	58	58	98.3%	1.7%
Medium	91	94	91.5%	1.1%
Complex	50	58	86.2%	6.9%
Total	**203**	**210**	**91.9%**	**2.9%**

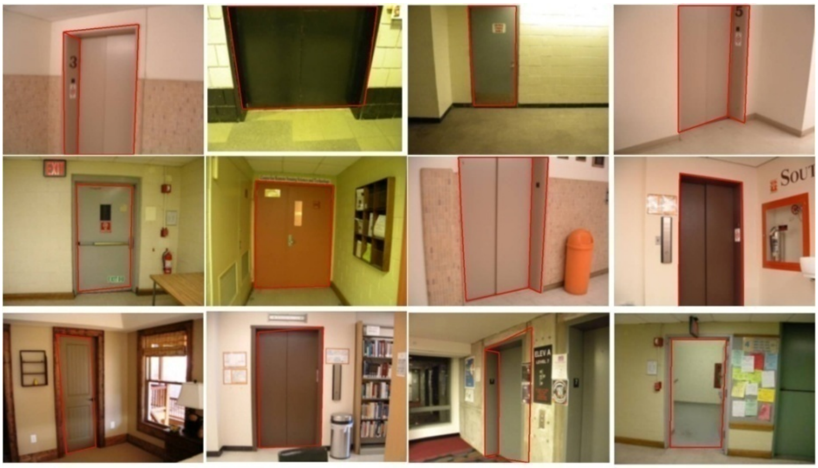

Fig. 5. Examples of successfully detected doors in different environments. The first row shows the "*Simple"* examples with simple background but include illumination variations and occlusions. The second row shows the "*Medium*" examples with more complicated background. The third row illustrates the "*Complex*" examples with very complex background include glass doors and open doors.

5 Conclusion and Future Work

Our goal is to develop a computer vision-based door detection algorithm for navigation and wayfinding to help blind persons independently access unfamiliar indoor environments. In this paper we have proposed a geometric door model that contains only lines and corners of a doorframe. Unlike existing algorithms using the Hough Transform, we develop a new matching method which combines corners and edges. Since our method does not depend on color and other appearance features, it is very robust and can detect doors in unfamiliar environments with variations of color, texture, occlusions, illumination, scales, and viewpoints. This research has the following significant impact: (1) It significantly enriches the study of indoor object detection and leads to significant improvements over existing methods; (2) It provides new strategies and technologies for blind and visually impaired persons to access unfamiliar indoor environments; and (3) It can potentially benefit many other important areas including scene understanding, robot navigation, autonomous systems, etc.

Our future work will focus on detecting and recognizing more types of indoor objects and incorporating context information to improve indoor wayfinding for blind people. We will also address the significant human interface issues including auditory displays and spatial updating of object location, orientation, and distance. With real-time updates, blind users will be able to better use spatial memory to understand the surrounding environment.

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References

1. Anguelov, D., Koller, D., Parker, E., Thrun, S.: Detecting and modeling doors with mobile robots. In: Proceedings of the IEEE International Conference on Robotics and Automation (2004)
2. Canny, J.: A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI-8, 679–698 (1986)
3. Chen, Z., Birchfield, S.: Visual Detection of Lintel-Occluded Doors from a Single Image. In: IEEE Computer Society Workshop on Visual Localization for Mobile Platforms (2008)
4. Cicirelli, G., D'orazio, T., Distante, A.: Target recognition by components for mobile robot navigation. Journal of Experimental & Theoretical Artificial Intelligence 15(3) (July-September 2003)
5. Giudice, N., Legge, G.E.: Blind navigation and the role of technology. In: Helal, A.A., Mokhtari, M., Abdulrazak, B. (eds.) The engineering handbook of smart technology for aging, disability, and independence. Wiley, Hoboken (2008)
6. He, X., Yung, N.: Corner detector based on global and local curvature properties. Optical Engineering 47(5) (2008)
7. Hensler, J., Blaich, M., Bittel, O.: Real-time Door Detection Based on AdaBoost Learning Algorithm. In: International Conference on Research and Education in Robotics, Eurobot (2009)
8. Hough, P.V.C.: Method and means for recognizing complex patterns. U. S. Patent 3, 069 654 (1962)
9. Kim, D., Nevatia, R.: A method for recognition and localization of generic objects for indoor navigation. In: ARPA Image Understanding Workshop (1994)
10. Munoz-Salinas, R., Aguirre, E., Garcia-Silvente, M., Gonzalez, A.: 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. Murillo, A.C., Kosecka, J., Guerrero, J.J., Sagues, C.: Visual door detection integrating appearance and shape cues. Robotics and Autonomous Systems (2008)
12. National Research Council, Electronic travel aids: New directions for research. Working Group on Mobility Aids for the Visually Impaired and Blind, ed. C.o. Vision. National Academy Press, Washington (1986)
13. Stoeter, S.A., Mauff, F.L., Papanikolopoulos, N.P.: Realtime door detection in cluttered environments. In: Proceedings of the 15th IEEE International Symposium on Intelligent Control (2000)