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Context-based Object Recognition for Door Detection

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Abstract— **This paper proposes a new method to detect doors using context-based object recognition. Particularly, in order to improve the efficiency of object recognition, we utilize robotic context such as the robot's viewpoint and the average height of doorknobs. The robotic context is used to make a region of interest in a captured image which reduces both the computational time and false-postive rate in the object recognition process. In addition, we employ shape features for object recognition which makes our method more robust to appearance changes than others using texture features like SIFTs and SURFs. We implemented a door detection system on a mobile robot with a stereo camera and demonstrated in corridor environments. Here, two types of doorknobs are tested: straight (door-handle) and round (door-knob) ones. The experimental results show that our method works successfully with different kinds of doorknobs in real environments.**

I. INTRODUCTION

One of the main features of intelligent robots is *mobility*. That is why navigation and exploration of mobile robots has been actively researched so far [1], [2], [3]. Particulary, range sensors such as laser range finders and infra-red scanners are usually used for mobile robots to navigate autonomously and to explore unknown environments. This is because the range data is one of the most important information to understand spaces, for example, whether some area is empty or occupied.

Recently, many researches [4], [5], [6], [7] have applied cameras for mobile robot navigation and exploration due to the richness of visual information. Local invariant features such as SIFTs [8] and SURFs [9] extracted from captured scenes are used as visual landmarks. Also, humans are detected by cameras to avoid during navigation or to follow for human augmented mapping [10].

In the meantime, there have been many researches to detect doors for indoor navigation and exploration. This is because doors play an important role even for the human's cognitive map [11]. A door is thought of as a gate to a new space, and thus, it can be considered as a starting or ending point of exploration. Moreover, since doors both separate spaces and connect rooms in indoor environments, they can be used for space recognition and path generation.

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In this paper, we propose a new method to detect doors using context-based object recognition. Particularly, we utilize robotic context such as the robot's viewpoint and the average height of doorknobs to enhace the efficiency of object recognition. Robotic context is appled in the pre-processing step of object recognition to speed up the process and to reduce the false-positive rate by restriciting the search space in the captured image.

For object recognition, we employ shape features to make our door detection system to be more robust to appearance changes than previous approaches using texture features like SIFTs and SURFs. To the best knowledge of the authors, it is the first try to apply both robotic context and shape-based object recognition to detect doors.

We implemented our door detection system on a mobile robot and demonstrated in a real environment. The experimental results show that our method works successfully with two types of doorknobs(straight and round types) in indoor environments.

The remainder of this paper is organized as follows. In section 2, related works of door detection and object recognition will be summarized. In section 3, we describe our robot system and office environments as well as the demonstration scenarios. We will give an brief overview of our approach in section 4. In section 5 and 6, we will explain more details about how we detect doors using robotic context and shape-based object recognition. The experimental results will be shown in section 7 and finally, we conclude this paper with future works in section 8.

II. RELATED WORKS

A. Door Detection

The approaches of door detection can be divided into two categories: range sensor-based and vision-based ones.

1) Range Sensor-based Door Detection: Anguelov et al. [12] defined two classes of objects: walls and doors. They modeled a wall with a set of segments along a straight line from laser scans and recognized doors with their motion. For example, a door is open at one time and closed at another.

On the other hand, Tapus et al. [13] modeled four types of spaces(corridor, X-crossing, T-crossing, and L-intersection) and five types of door models(closed door, right/left partially opened door, opened door, and no door) with line segments. They implemented a map building system which utilizes probability distributions and detects doors and corridors for topological map building.

Recently, Mozos et al. [14] classified each position of a mobile robot into corridor, room, or doorway. They applied the AdaBoost algorithm to boost simple geometric classifiers

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with range data into a strong one. Instead of detecting doors directly, their system detected a change from corridor to room while following a user and informed it to him or her.

However, range sensor-based door detection approaches usually assume opened doors or should observe several times to detect the motion of doors.

2) Vision-based Door Detection: Munoz-Salinas el al. [15] detected doors with their boundaries which consist of two vertical lines and one horizontal line. They extracted line segments from Canny edges using Hough Transform and recognized doors using a fuzzy system with length, direction and distances between two segments. However, since this approach only considers line segments and their relations, windows and bulletin boards are sometimes recognized as doors.

Chen and Birchfield [16] utilized a variety of features including color, texture, and intensity edges. They also introduced two geometric features: concavity and bottom-edge intensity profile. They applied the Adaboost algorithm to produce a strong classifier with weak classifiers based on these features. However, their algorithm is optimized to low viewpoints where doors and the ground are seen together, and restricted to detect closed doors only.

Our approach is very similar to that of Jauregi et al. [17]. They searched for lines and circles in captured images using Hough Transform. Lines and circles were corresponded to door blades and doorknobs, respectively. Then, they recognized a doorknob around the circle with SIFT features. But their approach only covers circular doorknobs and is not robust to various doorknob shapes because SIFT features are basically based on the texture of the object which varies dramatically with appearance changes. Another big difference between their approach and ours is that we integrate robotic context into object recognition to improve the performance.

B. Object Recognition

Object recognition can be divided into to approaches, shape-based and texture-based ones. The former extracts geometric information from images like contour segments and determines which object belongs to which category, while the latter applies appearance information and finds what the object looks like the most in the object database.

Some researches applied local appearance features [18], [19] or combined appearance and shape information [20], [21] to determine the category of the objects. But they have limitations on their applications because in general objects within the same category have similar shapes, but their colors and textures vary significantly.

Leordeanu et al. [22] proposed the category shape model based on shape information only. They extracted feature points along the object contours and designed a potential function of a pair of feature points. They applied Spectral Matching [23] for pair-wise feature matching. However, since they assume that the poses of objects in positive training images are almost same, their algorithm fails in recognizing objects of different poses.

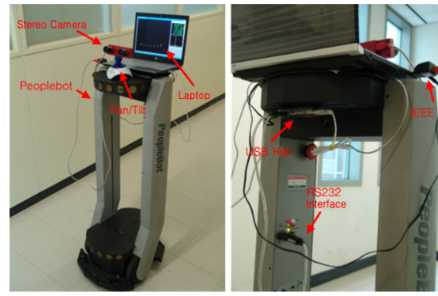

Fig. 1. Our Robot System

Fig. 2. Our Experimental Environment, Corridors

Kim et al. [24] suggested affine category shape model. They estimated 2D homography between training images and automatically transformed them to be aligned. Thus, their algorithm is robust to affine transformation as well as in-plane rotation and translation.

Recently, the significance of context in object recognition has been emphasized. This is because with context humans can quickly pay attention to a particular region of interest in natural scenes and recognize thousands of objects categories in cluttered scenes despite variability in pose, illumination changes and occlusions.

Torralba et al. [25] used the place information as contextual priors for object recognition. They were provided a strong prior for which objects are likely to appear in a given place as well as their expected size and position within the image. Thus, the place context reduced the need for brute force search in object recognition.

Hoiem et al. [26] provided a framework for placing local object detection in the context of the overall 3D scene by modeling the interdependence of objects, surface orientations, and camera viewpoint. For example, they extracted the ground surface from the camera view point and searched pedestrians on the ground using human-size windows scaled by the viewpoint.

III. ROBOT SYSTEM AND EXPERIMENTAL ENVIRONMENT

Fig. 1 shows our robot system which has a stereo camera on a pan/tilt unit. Note that in this paper, we only use a stereo camera without other sensors such as sonar and infrared sensors which are built in the robot.

The experimental environment is depicted in Fig. 2. It is a common office environment where doors are placed each side of the corridor.

We have two scenarios to detect doors: active and passive ones. In the former, our robot is supposed to detect a doorwith vertical lines, to move close to it, and to verify

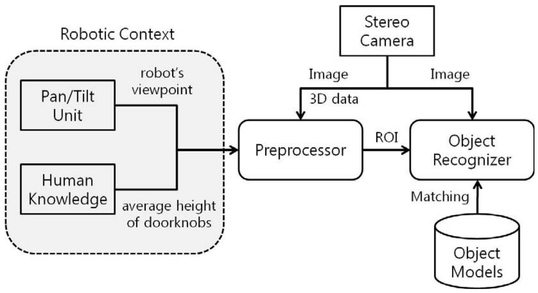

Fig. 3. Our Context-based Object Recognition Approach

it by recognizing a doorknob. Here, because a doorknob can exist on left- or right-hand side of the door, the robot needs to pan and tilt its head to search for the doorknob.

The latter scenario is almost the same except that active control of its wheels and head is excluded. The door detection is executed in parallel while the robot is moving, for example, wall following. Note that this paper is focused on the detection of doors, not tracking or motion control. So, the most of the algorithm will be explained based on passive door detection scenario.

IV. OVERVIEW OF OUR APPROACH

In this paper, we apply a context-based object recognition approach which utilizes prior knowledge of the situation or environments in the preprocessing step.

Fig. 3 shows the conceptual diagram of our context-based object recognition approach. Basically, we perform object recognition to detect a door, to be more specific, to detect a doorknob as a cue of a door. Also, in order to reduce the time complexity and false-positive rate we append a preprocessing step before the object recognizer. It removes worthless parts in the captured image and makes a focus on the potential doorknob region, so-called, a region of interest by using some robotic context such as the robot's viewpoint and the average height of doorknobs.

Here, note that the preprocessing step doesn't change anything of the captured image but makes a region of interest as an input to the object recognizer to improve the performance, and thus, nothing needs to be changed in the object recognition method.

Our approach is also thought of as a combination of top-down and bottom-up approaches since the preprocessing step exploits human's intelligence to guess where a doorknob is most likely to be located in the image, while the object recognizer manipulates pixels to recognize a doorknob. It is also considered as hypothesis generation and evaluation; a door hypothesis is built with robotic context and evaluated by doorknob recognition within the region of interest.

V. MAKING A REGION OF INTEREST USING ROBOTIC CONTEXT

In this section, we describe the preprocessor of our context-based object recognition approach. Again, the result of this process is a region of interest where a doorknob is thought to be located in images.

A. Detecting a Door with Vertical Lines

We assume that a door is composed with two parallel lines which is vertical to the ground, and it has a doorknob in a certain range of height close to one of the vertical lines.

Fig. 4 shows the procedure of detecting a door and making a region of interest using a stereo camera. First, we find canny edges from the original image. Then, before extracting vertical lines from the canny edges, we filter out those edges of which heights are out of a certain range. (in this paper, 80$\sim$100cm) Here, the robotic context of the current robot viewpoint and the average height of doorknobs is applied. Through this refinement, we can eliminate those vertical lines which belong to windows or frames higher than the threshold.

In order to extract vertical lines, we use a moving window to scan the refined edge image along the x axis and to build a histogram of edges. The width of the moving window is set wide enough to cover inclined vertical lines. (in this paper, 7 pixels) Instead of using a scanning window, you may apply Hough Transform to detect lines, but it requires another filtering procedure and parameter tuning.

If there is a local maximum in the edge histogram and its value is greater than a threshold (in this paper, 40 for 320$\times$240 images), we judge that there is a vertical line in that position. Here, we compute the distance between vertical lines to the robot and select the most closest one between 700mm to 1,000mm. This is because large doorknobs are advantageous to be recognized, but it looks distorted or cropped in a too close view. In Fig. 4.(d) candidate vertical lines at local minima are expressed with thin, bright blue vertical lines, the final one with a thick, red vertical line, and the threshold with a blue horizontal line.

Note that we detect a door with one vertical line since two vertical line are not seen in one image during wall following in the passive door detection scenario. In the active scenario, instead, we use two vertical lines and utilize another context, the average width of doors. Here, the procedure of finding vertical lines is the same except searching for pairs of vertical lines of which distance is in the range of the average door width.

B. Making a Region of Interest for a Doorknob

Once a vertical line of a door is detected, it is straightforward to make a region of interest where a doorknob is expected to place in the image. Here, we express a region of interest with a rectangle in this paper. So, the only thing to do is to set the x and y range of the box in the image coordinates.

1) The x range of the region of interest: Actually, we already know the rough size of a doorknob from training images, and this is another prior knowledge. From the experience, we learned that the width of a doorknob is about 80 pixels in a 320$\times$240 image. Thus, the x range of the region of interest is,

$$x_v - 80 \leq x \leq x_v + 80, \quad (1)$$

where x_v denotes the x coordinate of the vertical line.

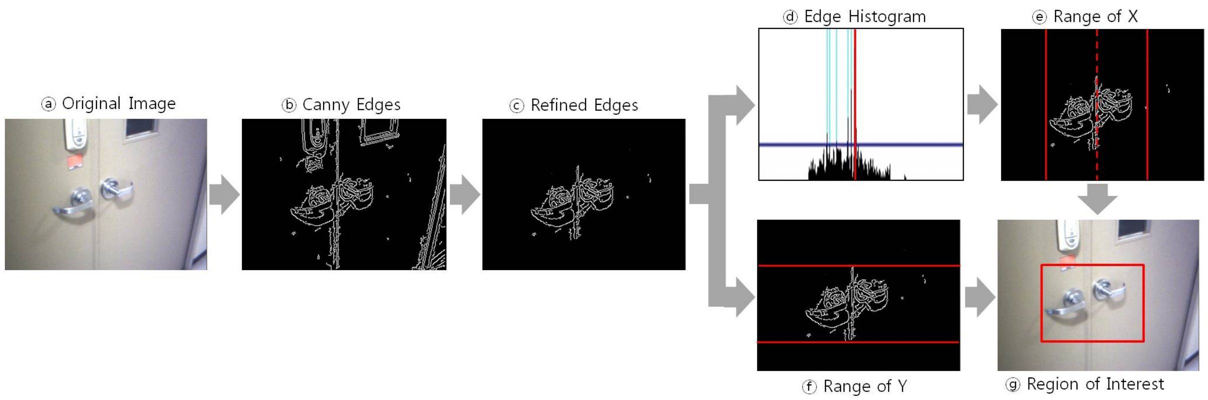

Fig. 4. The Procedure of Making a Region of Interest using Robotic Context

Fig. 4.(e) describes the x range of the region of interest, and the vertical line is expressed with a dash line in the middle of the range.

2) The y range of the region of interest: The cue of the y range of the region of interest comes from the refined edge image. Since we already refined canny edges with their heights, we take them as the boundary of the region of interest. Thus, the y range of the region of interest is,

$$y_{min} \leq y \leq y_{max}, \tag{2}$$

where y_{min} and y_{max} denote the minimum and maximum y values of refined edges.

Fig. 4.(f) shows the y range of the region of interest, and finally, the region of interest are built by combining the two ranges as shown in Fig. 4.(g).

VI. DOORKNOB RECOGNITION

Here, we briefly explain our category recognition method in our previous research [24].

A. Affine Category Shape Model

Our affine category shape model utilizes object shapes only. Feature points are extracted periodically along the object contour, and a graph of feature points are constructed. Each node represents each feature point of our affine category shape model which contains information about the position, normal vector, and curvature On the other hand, each edge between two nodes carries geometric information such as the distance between two node and relative direction.

Particularly, our affine category shape model is designed to be invariant to in-plane rotation and translate and robust to affine transformation. Thus, 2D homography is estimated between positive images while training and applied to them before extracting and updating feature points.

The training procedure of our affine category shape model is described in Fig. 5. Feature points extracted from each iteration are added to the initial affine category shape model and updated with a matching score. Through this loop, common features are remained in the model, and irrelevant ones are removed. Here, the position, normal vector, and curvature of each node is a probabilistic variable which has distributions over the positive images.

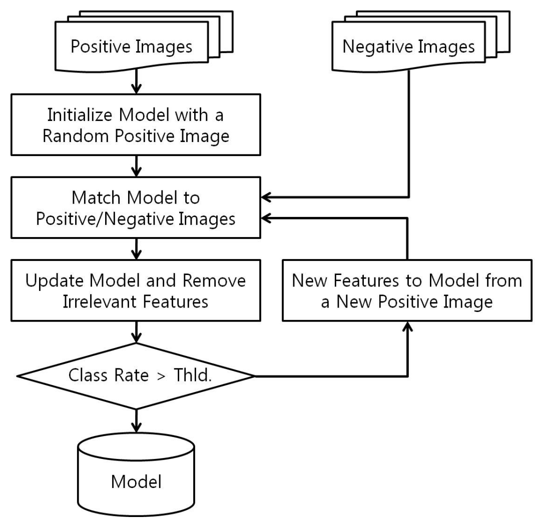

Fig. 5. Training Procedure of Affine Category Shape Model

B. Robust Feature Matching

Now, we define the matching score between two pairs of feature points according to the geometric relation. Here, we only utilize the relative geometric relation and thus, it is invariant to in-plane rotation and translation and robust to affine transformation.

The relative geometric relation, e_{ij} between two feature points, i and j, is defined as

$$e_{ij} = [\theta_{ij} \quad \sigma_{ij} \quad \sigma_{ji} \quad d_{ij} \quad \kappa_i \quad \kappa_j]^T, \tag{3}$$

where $\theta_{ij} = |\theta_i - \theta j|$ and κ_i and κ_j are the curvatures of the feature i and j. And θ_i, θ_j, σ_{ij}, σ_{ji}, and d_{ij} are described in Fig. 6

The matching score, E is defined as

$$E = \sum_{ia;jb} x_{ia} x_{jb} G_{ia;jb}, \tag{4}$$

where x denotes the indication vector of which ith element is 1 if the feature i in the model matches with the feature a in the image, or 0, otherwise.

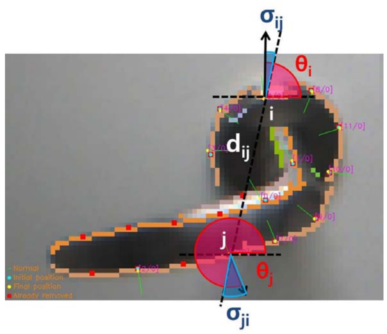

Fig. 6. Parameters for Relative Geometric Relation

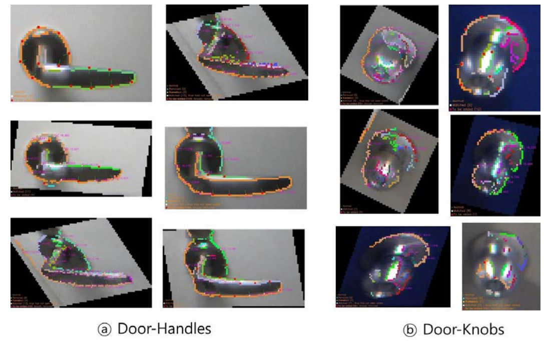

Fig. 7. Two types of doorknobs learned from training images: (a) door-handles and (b) door-knobs

Here, the potential function $G_{ia;jb}$ is defined as

$$G_{ia;jb} = v_{ij}\frac{1}{1 + exp(-\rho w^T g_{ij}(a, b))}, \quad (5)$$

where v_{ij} represents the reliability of the normal vector of the model node pair, (i, j), and ρ and w denotes the penalty coefficient and the weighting vector, respectively.

Finally, the geometric transformation between two pairs of features, $g_{ij}(a, b)$ is defined as

$$g_{ij}(a, b) = [1 \quad \gamma \quad |\epsilon(1)| \cdots \ |\epsilon(6)|]^T, \quad (6)$$

where $\gamma = \frac{max(d_{ij},d_{ab})+c}{min(d_{ij},d_{ab})+c}$ and $\epsilon = e_{ij} - e_{ab}$.

Therefore, the solution vector, x^* which representsa matching between two features can be calculated by Maximum likelihood as

$$x^* = argmax(x^T Gx), \quad (7)$$

where $G = G_{ia;jb}$ and $x = x_{ia}$.

VII. EXPERIMENTAL RESULTS

We implemented our door detection algorithm in our robot system and demonstrated in a real environment. In the corridors of our office environment, there are two types of doorknobs: straight and circular ones. We named the former *door-handle* and the latter *door-knob*. Even though our object detection algorithm is robust to the affine transform, we divided left and right door-handles due to the big shape difference. Thus, we trained three object classes for doorknob recognition: left/right door-handle and door-knob.

Fig. 7 shows door-handles and door-knobs and their contour features learned from training images. We took 6 images for each door model and trained them off-line.

TABLE I

RESULTS OF DOORKNOB RECOGNITION AND DOOR DETECTION

Type	Doorknob exists		No Doorknobs		Door Detection Rate
	True-Positive	False-Negative	False-Positive	True-Negative	
Handle	18/40 (45%)	22/40 (55%)	1/102 (0.09%)	101/102 (99.1%)	8/8 (100%)
Knob	42/73 (57.5%)	31/73 (42.5%)	5/189 (2.6%)	184/189 (97.4%)	9/9 (100%)

Table I summarizes the experimental results of doorknob recognition and door detection. There are 8 doors with door-handles and 9 doors with door-knobs in the experimental corridors. The number of images taken while the robot is following the wall is 142 for the door-handle type and 226 for the door-knob one., respectively.

In the case of door-handle, among 142 captured images 40 images have door-handles and 45% of them are well recognized(true-positive), while 102 images have no door-handles and one of them is recognized wrong(false-positive). Each door has evaluated several times with its captured images, and so, all 8 doors with door-handles are well recognized more than once. Therefore, the door detection rate for the door-handle type is 100%.

In the case of door-knob, on the other hand, among 262 images 73 images contain door-knobs and 57.5% of them are well recognized(true-positive), while 2.6% of 189 images without door-knobs are recognized wrong(false-positive). Similarly, all 9 doors with door-knobs are well recognized more than once and so, the door detection rate for the door-knob type is also 100%. It can be thought that if our door detection algorithm is integrated with a tracking module in the active door detection scenario, it is expected to execute more robustly.

Fig. 8 shows true-positive cases of doorknob recognition. Big and blue rectangles represent the regions of interest, and small and red boxes indicate the recognized doorknobs. The left images describes the result of object recognition for left hand-side door-handle, while the right ones for right hand-side door-handle.

Fig. 9 describes false-positive cases of doorknob recognition. False-positives occurred in those images which have complex objects such as instructions of fire extinguisher.

VIII. CONCLUSIONS AND FUTURE WORKS

In this paper, we proposed a new door detection method using context-based object recognition. Particularly, robotic context such as a robot's point of view and the average height of doorknobs is utilized as prior knowledge to enhance the performance of object recognition.

It is considered as a preprocessing process for object recognition which produces a region of interest. So, without

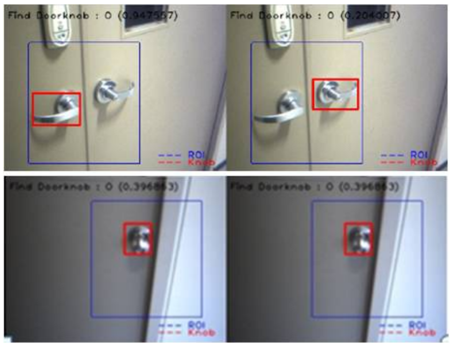

Fig. 8. Experimental Results: True-Positive (Up: door-handle, Down: doorknob

Fig. 9. Experimental Results: False-Positive (Up: door-handle, Down: doorknob

any modification we can improve the efficiency of object recognition (in this paper, doorknobs).

We implemented our method on a mobile robot and demonstrated in corridor environments. Experimental results show that our door detection system works efficiently and robustly with two types of doorknobs in real environments.

In this paper, we only focused on detecting doors rather than tracking, motion control, or map representation. And those are remained as future works. Moreover, it is necessary to integrate the range sensor-based approach with ours to improve the performance.

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