

Color Landmark Based Self-Localization for Indoor Mobile Robots

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Abstract

We present a simple artificial landmark model and a robust tracking algorithm for the navigation of indoor mobile robots. The landmark model is designed to have a three-dimensional structure consisting of a multi-colored planar pattern. A stochastic algorithm based on Condensation [1] tracks the landmark model robustly using the color distribution of the pattern. A new self-localization algorithm computes the location of robot with the tracked single landmark. Experimental results show that the proposed landmark model is effective. Through extensive navigation experiments in a cluttered indoor environment, we demonstrate the feasibility of the single view based self-localization in real-time.

1. Introduction

One of the most important tasks for autonomous mobile robot is the estimation of its current location with respect to its surroundings. To estimate its location, simply we can guess dead reckoning. But its actual position and orientation gradually differs from that it commanded to hold. This effect is mainly caused by the slip of wheels.

To solve this problem, recently many vision-based self-localization methods using artificial or natural landmarks have been proposed [2-6]. Natural landmark is proper for both indoor and outdoor environments. Generally, natural landmarks are selected in the natural scene considering their geometrical or photometrical features and mobile robots recognize the characteristics of the landmarks [4], [7-8]. Omni-directional or panoramic images of the environments have been used for image matching based localization [9-10]. However it is a formidable task to extract landmarks reliably in complex environments.

On the other hand, artificial landmark is a very simple and powerful tool for self-localization in indoor environments. Landmarks based on barcode or specific shape patterns have been proposed recently. For

example, Briggs *et al* [3] use self-similar gray pattern landmarks to navigation and localization aids. But methods that use peculiar contour or edge information highly depend on the low-level processing results which are influenced by noise and defocus phenomenon in an image.

For a mobile robot working in indoor environments, we propose a simple artificial landmark model and a practical localization algorithm that uses a single landmark in a single image, which runs in real time.

2. Landmark model

Fig. 1. shows the appearance of the proposed landmark. The color pattern is composed of two vertically neighboring color patches. The color pattern makes the angle of 45° with respect to two supporting planes at the right angle. The two supporting planes intersect and forms a line as shown in Fig. 1. The relative position of the line with respect to the color pattern varies as a function of camera orientation.

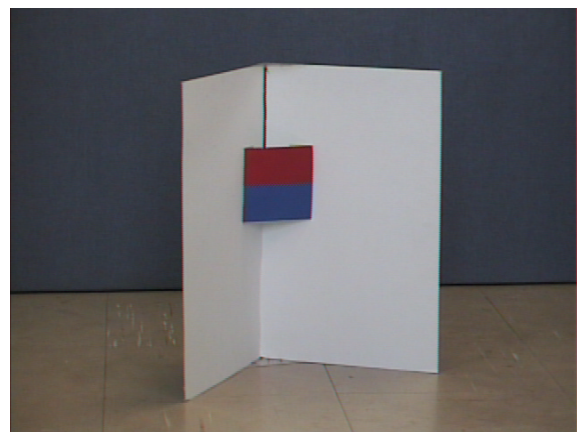


Fig. 1. Structure of landmark

The brightness variation caused by the illuminant change is reduced by the use of the chromaticity color space :

$$[r \ b] = \left[\frac{R}{R+G+B} \quad \frac{B}{R+G+B} \right] \quad (1)$$

To make each landmark distinguishable from the other, multiple colors having maximum distance in the chromaticity color space are selected for each landmark.

3. Landmark detection and tracking

3.1 Condensation (Conditional Density Propagation) algorithm

Condensation is a sampling-based tracking method, which produces the posterior probability density $p(\mathbf{x}_k | Z^k)$ with the local density of a set of N random samples $S_k = \{s_k^i, i=1..N\}$. Here, $Z^k = \{z_k, i=1..k\}$ is measurement and \mathbf{x}_k is state. The goal is to recursively compute at each time step k the set of samples S_k that is drawn from $p(\mathbf{x}_k | Z^k)$.

In the prediction phase, each particle s_{k-1}^i is applied to the motion model by sampling from the density $p(\mathbf{x}_k | s_{k-1}^i)$. As a result, a new set S'_k is obtained that approximates the predictive density $p(\mathbf{x}_k | Z^{k-1})$. In the update phase, the measurement z_k is found first, according to the measurement model. Then the samples in S'_k are weighted by $p_k^i = p(z_k | s_k'^i)$. We then obtain S_k by resampling from the weighted set. The number of resampling is determined in proportion to the weight scale. Alternating these two phases, tracking effect is produced.

3.2 Measurement model

In the proposed tracking method, the sample of Condensation is designed as shown in Fig. 2. The sample is composed of a pair of points spaced vertically. The state has three parameters, two for the center location of the point pair and one for the distance between the point pair.

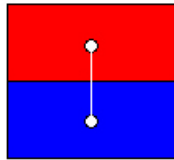


Fig. 2. Designed sample for Condensation algorithm

The measurement value of the sample is the product of two color similarity at each paired point. Each color similarity is set inversely proportional to the distance between the color of the point and the color of the stored model in chromatic color space. Pairing two colors makes the tracking system much more robust to clutter.

3.3 Landmark detection and tracking

When there is no prior information about the position of landmark, we do not know the current position of the robot and which landmark model exists in the scene. So, mobile robot has to detect and recognize the landmark by comparing the probabilities of each landmark model iteratively.

For example, at the initial stage we uniformly spread the samples on the whole image. Then, before the posterior PDF $p(\mathbf{x}_k | Z^k)$ is close to unimodal, in other words, before the samples gather into a small region, the stage remains at the detection period. In this period, the motion model is not applied. But in the proposed method, the transition from detection to tracking is automatic and seamless.

After the landmark position is determined, we control a pan-tilt camera unit to place the landmark in the center of the image. Pan-tilt control is processed with an independent thread.

After the detection of landmark, we predict the position of the landmark in the next frame based on the position in the current frame. We also use the factored sampling scheme for tracking. Samples propagate toward the accurate landmark location in every frame.

4. Self-localization

In this section, we propose an algorithm that allows the robot to verify its absolute position with a view of a single landmark in one image. Based on the assumption that an indoor mobile robot navigates on a flat floor we only seek for robot's two-dimensional location and direction with respect to the landmark.

For the localization of mobile robot using the proposed artificial landmark, we assume that the locations of landmarks in the 2-D floor map are given. Therefore, only with the position of robot with respect to the landmark, we can determine the absolute position of the robot. We also assume that the vertical positions of landmarks are set to the robot's eye level.

Many previous approaches for the localization have employed geometric triangulation using the relations among more than three landmarks [2]. But the limitation of camera viewing angle often makes it difficult to acquire more than two landmarks at a time with one camera. This problem can be solved using an Omni-directional camera. But the size of landmarks in the image become smaller, then detection, tracking and identification of landmark become difficult and the resolution of landmark becomes lower.

In the proposed method, because the depth change of landmark itself is much smaller than the distance between camera and landmark, we assume an affine camera model which has the characteristic that the parallelism in 3-dimensional space is preserved to projected image space.

4.1 Calculation of orientation

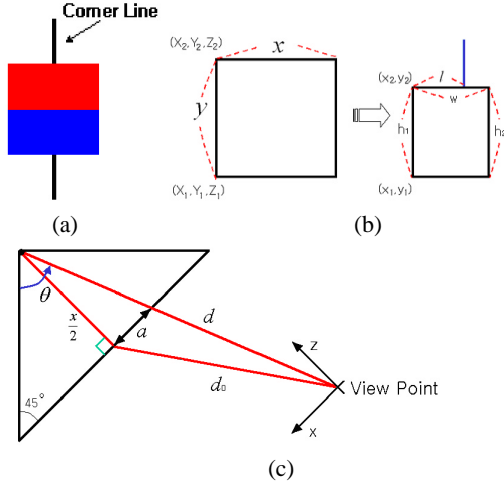


Fig. 3. Landmark model : (a) Front view (b) Real size and the size of the projected rectangle on the image (c) Top view

We set the direction of the robot q seen from the landmark as in Fig. 3. This angle is calculated with the position of junction between the corner line and the color pattern in the image. Assuming an affine camera, the length ratio between parallel lines is invariant [11]. Approximate the angle as

$$q = \frac{p}{4} + \tan^{-1} \frac{a}{x/2} \approx \frac{p}{4} + \tan^{-1} \frac{l-w/2}{w/2} \quad (2)$$

Fig. 4. shows the resulting angle error due to the affine camera assumption. When we use a square color pattern with one side length of 10cm, a maximum error of 0.8° occurs at 1m distance. The error diminishes as the distance gets larger because the landmark model satisfies the ideal affine camera model.

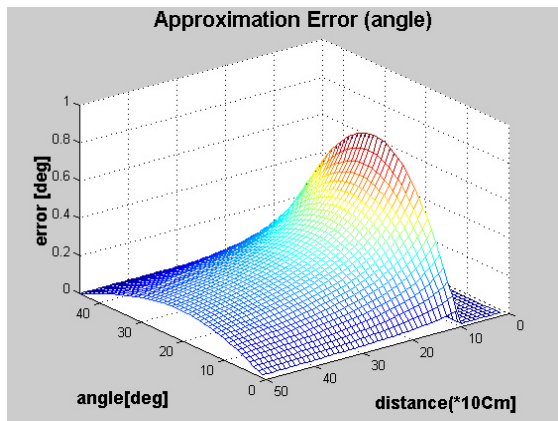


Fig. 4. Approximation error (angle)

4.2 Calculation of distance

4.2.1 The fixed focal length model

For two world corner points (X_1, Y_1, Z_1) and (X_2, Y_2, Z_2) , two corresponding image points (x_1, y_1) and (x_2, y_2) are

$$y_1 = f \frac{Y_1}{Z_1}, \quad y_2 = f \frac{Y_2}{Z_2} \quad (3)$$

where f is the focal length.

If the landmark is positioned vertically, $Z = Z_1 = Z_2$.

From (3)

$$y_2 - y_1 = h_1 = f \left(\frac{Y_2 - Y_1}{Z} \right) \quad (4)$$

From the assumption of affine camera model, we let the left and right height of color pattern in the image be the same. Therefore we have $h = h_1 = h_2$

By letting $k = f(Y_2 - Y_1)$

$$Z = \frac{k}{h} \quad (5)$$

From (5), the distance is inversely proportional to the height of color pattern in the image with a fixed k .

If the viewing direction is set to the color patch, we let $d_0 \approx Z$. Then, using the cosine rule we can finally calculate d in Fig. 3 (c) as

$$d = \frac{x}{2} \cos\left(q - \frac{p}{4}\right) + \sqrt{d_0^2 - \left(\frac{x}{2} \sin\left(q - \frac{p}{4}\right)\right)^2} \quad (6)$$

4.2.2 The variable focal length model

There are two deficiencies in the fixed focal length model. First, autonomous mobile robots are generally equipped with an auto-focus camera, for which k varies with the change of focal length. Then, we cannot calculate the distance Z only with h as in (5). Second, when the focal length is small or the distance between camera and landmark is large, the area covered by the landmark in the image is relatively small. With a smaller projected landmark in the image the localization accuracy will be seriously degraded.

To solve these problems, an auto-focus zoom camera can zoom-in the landmark so that its image size is being kept constant. The relationship between the distance and the image size of the landmark can be calibrated for a variety of zoom levels and distances. We don't need to consider the auto-focus problem separately because this

method reflects both the zoom and auto-focus at the same time. Fig. 5. shows the result of 3^d order curve fitting. The pixel heights of landmark in the acquired image are fitted for each zoom level (9 stages) and at each distance (10 stages, 30cm equal interval, 90cm-360cm).

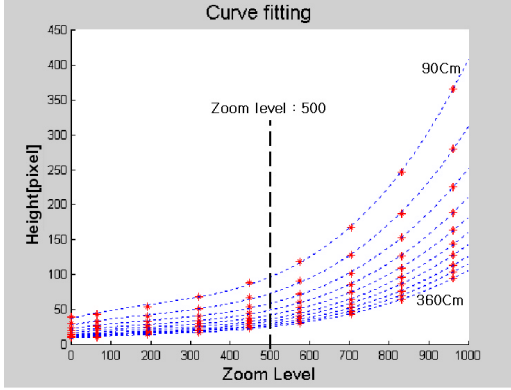


Fig. 5. Curve fitting result for various zoom levels

The steps to get the distance are

1. Conduct curve fitting for sampled distance and zoom level as in Fig. 5, then save the coefficient of the fitted curve. (off-line)
2. Using the curve equations acquired in step 1 find the pixel height for each sampled distance at given zoom level read from the encoder.
3. Conduct curve fitting with the sampled distance and acquired corresponding heights in step 2 as in Fig. 6, then find the distance with the fitted curve
4. Substitute the result from step 3 to Eq. (6) and find the distance from the reference corner.

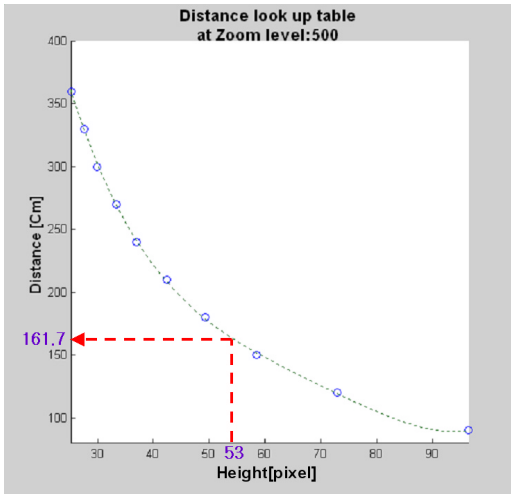


Fig. 6. Relation between distance and height of landmark in the image at a given zoom level

5. Experimental Results

As a test-bed for our approach we used the wheeled mobile robot KASIRI (KAist Simple Roaming Intelligence)-III shown in Fig. 7. KASIRI functioned for navigation in severely complex and cluttered environments such as laboratory. The pan-tilt-zoom camera (SONY EVI-D30) was used for localization. The size of color patch was set to 10cm*10cm. All tests have been conducted in real-time.



Fig 7. Our test-bed, KASIRI. This robot is equipped with color pan-tilt-zoom camera

The landmark detection process in the initialization step is shown in Fig. 8. One landmark is placed in an indoor environment with complex background. The dotted points represent the samples.

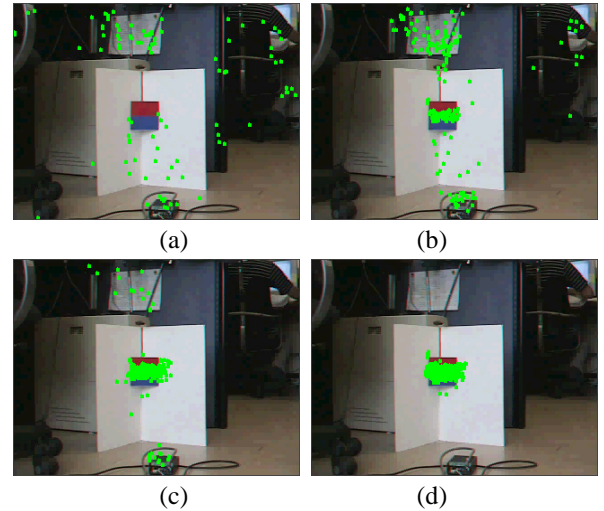


Fig. 8. Initial landmark detection

In Fig. 8 (a), the samples are scattered randomly over the entire image. Each sample has the probability representing the similarity to the landmark model. In the next step, the samples propagate toward the landmark according to the probability as the iteration proceeds. The final detection result is shown in Fig. 8 (d). All the samples gathered to the small region of landmark.

Fig. 9. shows results of robust landmark tracking after the detection stage, in which the circles indicate the center of detected landmark.

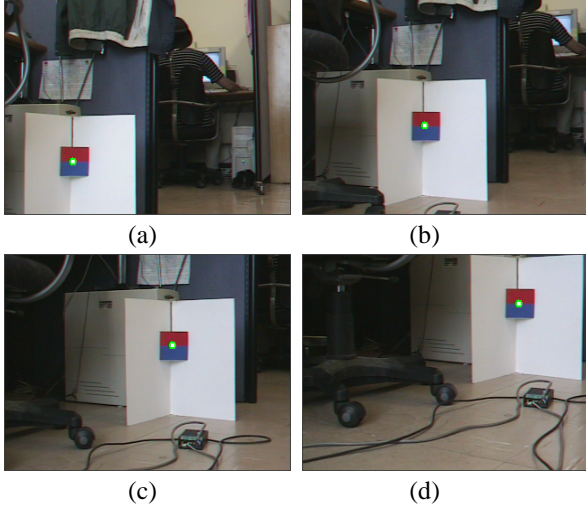


Fig. 9. Landmark tracking

Fig. 10. shows the result of landmark segmentation and detection of the vertical black line. In Fig. 10, we can observe that the assumption of affine camera is proper from the preservation of parallelism at various distances and viewing angles. To enhance the accuracy, we control the pan-tilt to locate the landmark at the center of the image where the affine camera model is most acceptable.

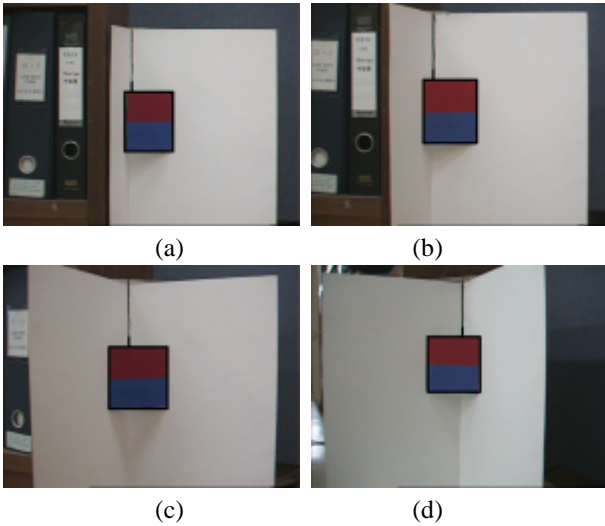


Fig. 10. Outlines of color pattern and junction point

Fig. 11. is the results of self-localization using the fixed focal length model (a) and the variable focal length model (b). Both of them show relatively accurate results. With the fixed focal length model, the average distance error is 9.8cm and with the variable focal length model showing an average distance error of

6.5cm. Also we can observe the error magnitude gets larger as the landmark grows distant in (a) because when the landmark is distant from the camera, a small measurement error such as one or two pixel error can introduce large error in proportion. But in (b), the distance between camera and landmark doesn't have much influence on the error magnitude.

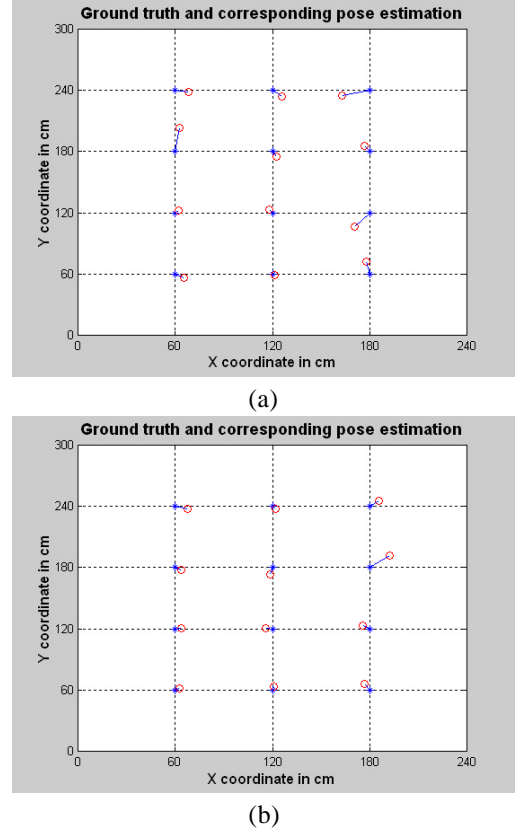


Fig. 11. The set of estimates obtained using the proposed method (a) Fixed focal length model (b) Variable focal length model

Fig. 12 shows the result of a navigation experiment using the proposed method. We set seven landmarks at the predetermined positions in laboratory and corridor then the robot estimated its position and corrected the direction of movement along the round path. Using a pan-tilt-zoom color camera and the variable focal length model, we overcome the degradation of resolution caused by the increase of distance.

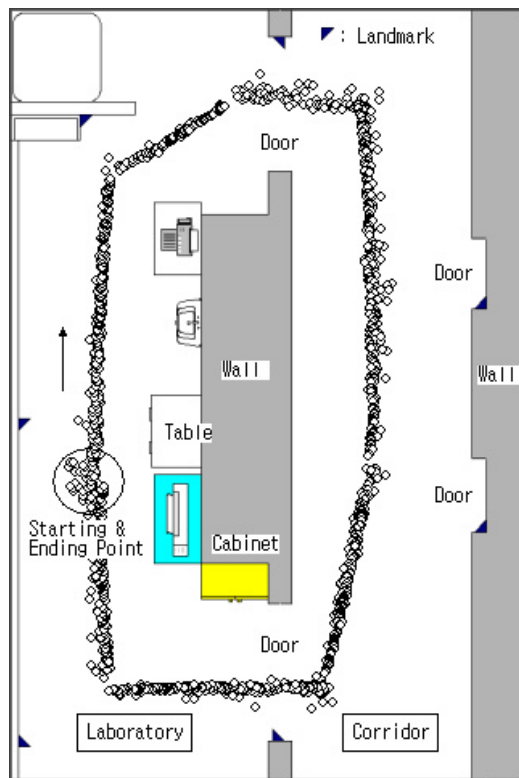


Fig. 12. Self-localization result using the proposed method (9.6m*6.4m)

6. Conclusion

In this paper we have proposed a simple artificial landmark model, which can be used for the self-localization of indoor mobile robots. Also an effective detection and tracking algorithm for this landmark is proposed.

A pair of color points neighboring each other has been used as a sample to represent the probability density in the Condensation algorithm. This has made the tracking system much more robust.

Under the assumption of affine camera, only with the information of a single landmark in a single image, we have presented a novel localization algorithm to estimate the absolute position accurately.

In the proposed method, the most deterministic factor is the accuracy of extracted length information in the given image resolution. Work is currently underway to enhance the localization performance using more robust and accurate line fitting. And we plan to apply this method to robot soccer game.

Acknowledgments

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