천정부착 랜드마크 위치와 에지 화소의 이동벡터 정보에 의한 이동로봇 위치 인식

Mobile Robot Localization using Ceiling Landmark Positions and Edge Pixel Movement Vectors

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Abstract: A new indoor mobile robot localization method is presented. Robot recognizes well designed single color landmarks on the ceiling by vision system, as reference to compute its precise position. The proposed likelihood prediction based method enables the robot to estimate its position based only on the orientation of landmark.The use of single color landmarks helps to reduce the complexity of the landmark structure and makes it easily detectable. Edge based optical flow is further used to compensate for some landmark recognition error. This technique is applicable for navigation in an unlimited sized indoor space. Prediction scheme and localization algorithm are proposed, and edge based optical flow and data fusing are presented. Experimental results show that the proposed method provides accurate estimation of the robot position with a localization error within a range of 5 cm and directional error less than 4 degrees.

Keywords: mobile robot, localization system, low complexity landmark, optical flow

I. INTRODUCTION

High accuracy localization is a very important function to support mobile robot to complete a complex task in a known or unknown environment. Generally, most wheeled mobile robots used the dead reckoning method with lower complexity, but error accumulation was its drawback which was difficult to overcome and caused wheel slippage problem [1]. Ultrasonic sensors were widely used to overcome this problem [2-4]. Extended Kalman filtering with environment models [3-6], fuzzy fusion logic [7], or neural networks [8] were further used to improve the accuracy. But the efficiency relied on the amount of a priori knowledge about the environment, which resulted in complexity in system implementation and practical use.

More recently, visual landmarks are used. Camera recognizes the feature of natural or artificial landmarks to calculate the robot position. Ceiling lights as natural landmarks to navigate are used in [9] and 64 different landmarks, each with a unique feature, were designed in [10]. Through identifying different landmark, a mobile robot calculates its real position. But if the indoor space is very large, 64 different landmarks will be insufficient.

Another landmark based technology used RFID (Radio Frequency Identification). RFID readers read reference position information from the special distributed RFID tags [11-13], but the implementation cost is much higher.

Special coded color patches on the ceiling, named "cell-coded", which could be repeatedly used for an infinite area is proposed in [14]. But the path structure is still a little complex. In order to simplify the structure of patch, a likelihood prediction based method is presented in this paper, which also uses color patches as landmarks. Patch images are acquired by a camera facing the ceiling, mounted on the mobile robot. Based on image analysis, the robot can recognize the patches and estimates its position. In order to compensate for some landmark recognition error, edge based optical flow is used and resultant data is fused with landmark based data in real-time. Experimental results show that this system has high accuracy.

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II. LIKELIHOOD LANDMARK PREDICTION BASED LOCALIZATION

In a conventional vision based localization system, color patches as landmarks are arranged in a fixed pattern on the ceiling, as shown in Fig. 1, each dot representing a patch as a landmark. Each patch containing different information (ID and orientation) represents an absolute coordinate and the robot determines its position by identifying the nearest patch's information. However, patches with different IDs must have different features, such as different colors or different geometrical shapes. When more distinguishable IDs are needed, features used for patches become more complicated.

The "cell-coded" method [14], greatly simplifies the structure of patch, but still at least 3 colors should be used to create 9 different

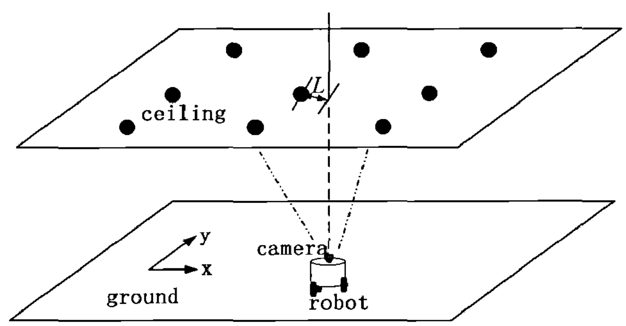


그림 1. 랜드마크를 이용한 위치계산 시스템.
Fig. 1. Vision landmark based localization system.

IDs. To further simplify the structure, likelihood prediction based localization is proposed, which uses single color only.

1. Prediction scheme

As the robot moves continuously, its trace is a continuous curve. So if the observer captures the robot continuously, the observed positions of robot at two consecutive time instants *t-1* and *t* are close enough (distance ≈ 0). Similarly, the position in image center, observed by camera on the robot, is also continuous. Considering that the processing time is not zero in practice, these positions observed by camera are a series of discrete points on the trace. But if the image processing speed is high enough, or the robot moving speed is not high, every two neighboring points are still very close. Based on this idea, we can predict every captured patch's position and further compute robot's position.

Patches are distributed in a grid as shown in Fig. 1 and the distance between each neighboring patches is *d*. Each patch contains direction information only. At any time instant, the relative position of robot and landmark can be easily estimated. Assume Fig. 2 shows one possible patch location in current image. "*x-y*" is the real coordinate system and "*x'-y'* " is the image coordinate system. Since our patch contains its orientation information, patch's orientation in the image can be easily calculated as the angle θ_1, the direction of the patch relative to the image center is θ_2, and the real distance from the image center to the patch center can be calculated as *L*. Then the robot's current position and orientation can be expressed by the following equation.

$$\begin{cases}(x_r, y_r) = (X_i + L\cos(\theta_2 - \theta_1 - \pi/2), Y_i + L\sin(\theta_2 - \theta_1 - \pi/2)) \\ \theta_r = \pi/2 + \theta_1\end{cases} \quad (1)$$

where, (x_r, y_r) and θ_r represent robot's current position and orientation respectively.

Suppose at time t_{i-1}, robot's position is R_{i-1} and its captured patch is P_5 as shown in Fig. 3(b) where all solid circles represent patches and stars represent the robot. At time t_i, the relative position of robot and captured patch is as indicated in Fig. 3(a). As the patch contains direction information, we can compute their relative position based on equation (1). As long as image processing speed is high enough, current captured patch at time t_i, must be one of the

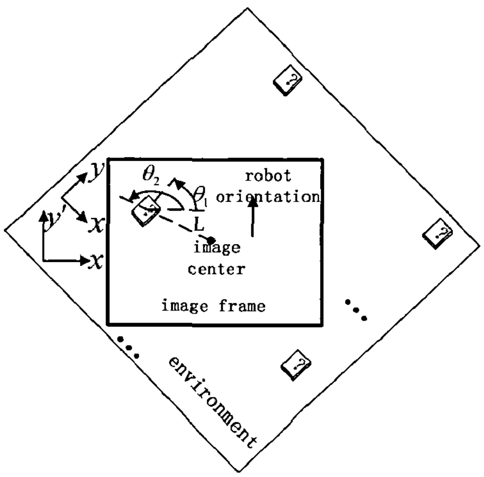
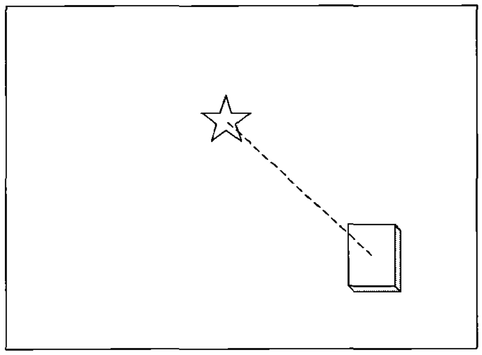
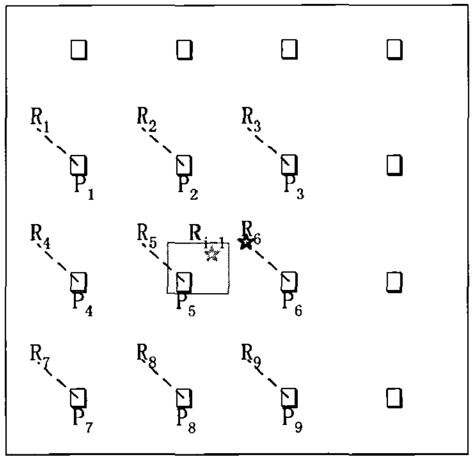


그림 2. 영상에서의 랜드마크의 배치.

Fig. 2. Possible patch location in the image.



(a) Relative position of current robot and captured patch



(b) Robot position in the whole map.

그림 3. 랜드마크 예측.

Fig. 3. Patch position prediction.

9 neighboring patches surrounding patch P_5 (including itself), that is one of patch $P_1,\ldots,P_9$.

It implies that there are 9 candidate patches and one of them could be the current captured patch. And according to Fig. 3(a), as the robot's position relative to current patch is known, there are also 9 candidate positions $R_1,\ldots,R9$ of the robot currently. Our scheme is to select the most likely one. As explained earlier, robot's most likely current position is R_6, the one closest to that at time t_{i-1} (position R_{i-1}), and the most likely patch is P_6.

2. Localization algorithm

Let (X_{i-1}, Y_{i-1}) and (X_i, Y_i) indicate captured patches' position at time t_{i-1} and t_i. Then (X_i, Y_i) must be one of

$$\left\{\begin{matrix}(X_i, Y_i) \middle| (X_i, Y_i) = (X_{i-1} + k_1 d, Y_{i-1} + k_2 d), \\ k_1, k_2 \in \{-1, 0, 1\}\end{matrix}\right\} \quad (2)$$

which has 9 candidate coordinates. If (x_{pi}, y_{pi}) indicate 9 candidate coordinates of robot at time t_i then from equation (1) and (2), the likely robot position can be calculated as equation (3).

$$(x_{pi}, y_{pi}) = (X_i, Y_i) + L \cdot (\cos(\theta_2 - \theta_1 - \pi/2), \sin(\theta_2 - \theta_1 - \pi/2)) \quad (3)$$

So the most likely position (x_i, y_i) of the robot at time *i* can be computed from equation (4)

$$(x_i, y_i) = \min\left|(x_{pi}, y_{pi}) - (x_{i-1}, y_{i-1})\right| \quad (4)$$

Substituting equation (2) and (3) into (4), we get

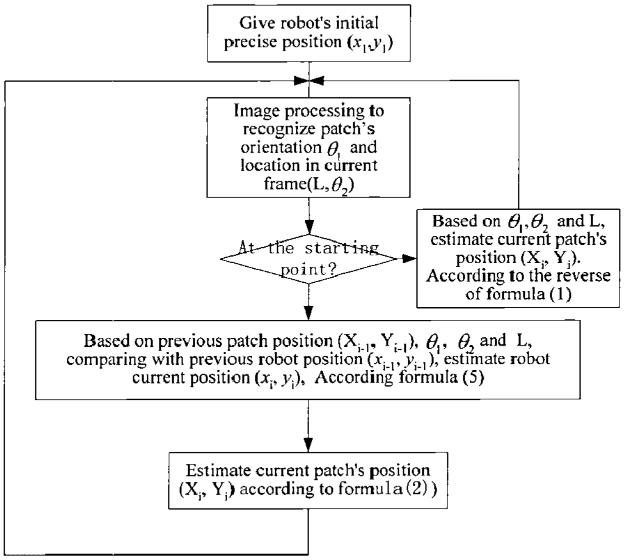


그림 4. 예측기반 위치계산 알고리즘의 순서도.

Fig. 4. Flow diagram of Likelihood Prediction based localization algorithm.

$$(x_i,y_i)=\min_{k_1,k_2\in\{-1,0,1\}}\left|\begin{array}{l}(X_{i-1}+k_1d,Y_{i-1}+k_2d)+\\ L\cdot(\sin(\theta_2-\theta_1),-\cos(\theta_2-\theta_1))-\\ (x_{i-1},y_{i-1})\end{array}\right| \qquad (5)$$

Once we obtain the values of k_1 and k_2 that satisfy equation (5), (X_i,Y_i) can also be computed and used for consecutive time $i+1$. So as long as the initial position is given at the very beginning, captured patch's position can be computed based on Fig. 2, and the robot's position can be computed at any time. Fig. 4 shows the flow diagram of proposed algorithm.

III. EDGE BASED OPTICAL FLOW TO COMPUTE ROBOT'S ROTATING ANGLE AND SHIFTING VECTOR

1. Edge based optical flow

Although we can design a special patch which is easily distinguished from the background and helps in the recognition of the patch's orientation, errors in patch recognition may occur due to change in intensity or the blurring of image. This leads to erroneous robot's position estimation. We use optical flow to compensate for the error.

When the robot moves or rotates, the image of the ceiling in the captured image also moves or rotates inversely. By comparing two successive image frames, optical flow algorithm can be used to find the moving vector of the ceiling in the image, whose inverse will approximate the robot's moving vector.

Generally, optical flow is based on the derivative of intensity. It estimates each point's optical flow based in some neighboring area so as to minimize the difference of all those point's optical flow [16]. But the optical flow at each point in the image is different and because of the intensity variations, the accuracy of the calculated optical flow is quite low. In our case, as the camera is always vertical to the ceiling, all the pixels have same linear and angular displacement. So, each pixel has the same moving vector, which is the global moving vector. We overlay the first frame in the second frame, and an optimal matching is found which minimizes the total

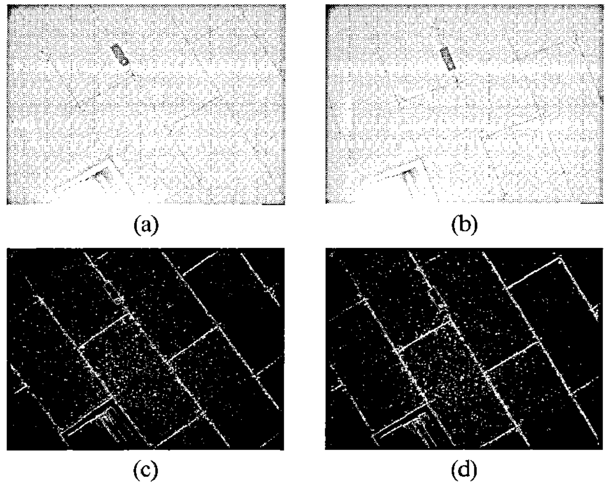


그림 5. 인접한 프레임과 에지 영상 (a-b) 2 개의인접 프레임 (c-d) 그림 (a)와 (b)의 에지 영상.

Fig. 5. Two consecutive frames and their edge images (a-b) two consecutive frames (c-d) edge images of image (a) and (b).

intensity differences of each pixel. Thus found moving vector will be the inverse of robot's moving vector, but the processing time is high.

In most cases, ceilings are not smooth and may contain some texture, straight lines, circles or some other objects .The edges of the ceiling can be extracted and as the edge of same position in ceiling will not change dramatically, the same position can be located in two consecutive images. Fig. 5 shows 2 consecutive frames and their edge image when the robot is in motion. It can be observed that, though there are some noises, the edges from the two images have a strong relationship. We can use the edge pixels in the first frame to search for a match in the second and this method will be computationally efficient.

For each captured image I_i, edge detection is performed and the corresponding binary edge image EI_i, is obtained. If the whole edge image EI_{i-1} is matched in the edge image EI_i, the time consumption is same as that using original image, as we have to compute the differences at every pixel position. Though matching the edge pixels in the first frame only will lose some pixels for comparison with the second frame, it is still acceptable as the lost pixels account for less than 1% of the total edge pixels. The edge pixels of edge image EI_i are extracted into a 2 dimensional array E_i. Elements in each row of E_i indicate coordinates of one edge point. Fig. 6 shows the structure of array E_i. $E_i(j,1)$ and $E_i(j,2)$ represent the x and y coordinates of j^{th} edge point in image EI_i. As the origin of image EI_i is assumed at the top left and the y axis pointing downwards, the transformed coordinate of the edge points after

x_1	y_1
x_2	y_2
⋮	⋮
x_j	x_j
⋮	⋮

그림 6. 에지 점의 열.

Fig. 6. Edge points array.

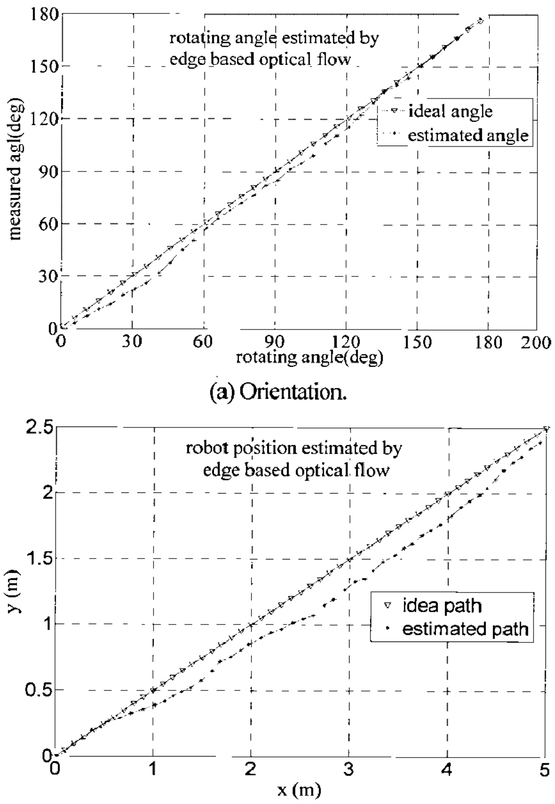
rotating the image EI_i through angle θ and shifting it with vector $\vec{V}$, can be found by

$$E_{\substack{i\\ \theta,V}} = \left| \left(\left(E_i - I \cdot \begin{pmatrix} w & 0 \\ 0 & h \end{pmatrix} \right) \cdot \begin{pmatrix} \cos\theta \\ \sin\theta \end{pmatrix} + I \cdot \begin{pmatrix} w & 0 \\ 0 & h \end{pmatrix} + I \cdot \begin{pmatrix} V_x & 0 \\ 0 & V_y \end{pmatrix} \right) \right| \tag{6}$$

where, I is a 2 dimensional array with the same size as E_i, and each element is assigned value 1, w and h are the image width and height respectively and, V_x and V_y are the x and y elements of $\vec{V}$.

$$\vec{V} = (V_x, V_y) \tag{7}$$

As the robots rotation during two consecutive sampling periods will not be large, the rotating range can be fixed within (θ_l, θ_h). Similarly, the x and y elements of $\vec{V}$ can be fixed within (V_{xl}, V_{xh}) and (V_{yl}, V_{yh}). If $EI_{\substack{i\\ \theta,V}}$ is the changed image of EI_i, and as all edge point coordinates are saved in array $E_{\substack{i\\ \theta,V}}$ we only need to check whether all these coordinate points correspond to edge pixels at the same locations in image EI_{i+1} or not. If each corresponding point in image EI_{i+1} is an edge point whose value is 1, there is no error. Otherwise, that point does not match. Equation (8) can be used to evaluate the total matching grade and select the most suitable rotating angle θ and shifting vector $\vec{V}$.



(a) Orientation.

(b) Position.

그림 7. 에지 기반화소 이동벡터를 사용한 로봇의 방향과 위치 계산.

Fig. 7. Robot's orientation and position estimated by edge based optical flow.

$$(\theta, V) = \max_{\substack{\theta_l \le \theta \le \theta_h,\\ V_{xl} \le V_x \le V_{xh}, V_{yl} \le V_y \le V_{yh}}} \sum_j \left| EI_{i+1}\left(E_{\substack{i\\ \theta,V}}(j,1),\ E_{\substack{i\\ \theta,V}}(j,2) \right) \right| \tag{8}$$

2. Result of edge based optical flow to estimate robot's rotating angle and shifting vector

At any time $i+1$, we can estimate the rotating angle θ and shifting vector $\vec{V}$ of ceiling in image from equation (8). So the inverse of θ and $\vec{V}$ is the robot's rotating angle θ' and shifting vector $\vec{V}'$.

$$(\theta', \vec{V}') = (-\theta, -p \cdot \vec{V}) \tag{9}$$

$\vec{V}'$ is multiplied by a scaling factor p, which specifies the real-world distance between two adjacent pixels.

Fig. 7 shows the localization result when using edge based optical flow. Fig. 7(a) shows robot's orientation when rotating the robot around the center of camera from 0 degree to 180 degree. Fig. 7(b) shows estimated robot's position when moving the robot along a straight line from (0,0) to (5m ,2.5m). From the result, we see that the algorithm works effectively but the errors are accumulated.

IV. DATA FUSION

Because of change in image intensity or image blurring, exact landmarks recognition may not be possible and big error will be introduced in the localization of the robot. Though edge based optical flow can work under varied circumstances small error will be accumulated. Fusing these two kinds of data can help overcome either of their shortcomings.

Let the estimated robot position by landmark based algorithm and edge based optical flow at any time instant be (x_i, y_i) and (x_i', y_i') respectively. If there is no recognition error of landmark, then these 2 points are close to each other and the position from the landmark based method (x_i, y_i) is considered as the current robot position. If

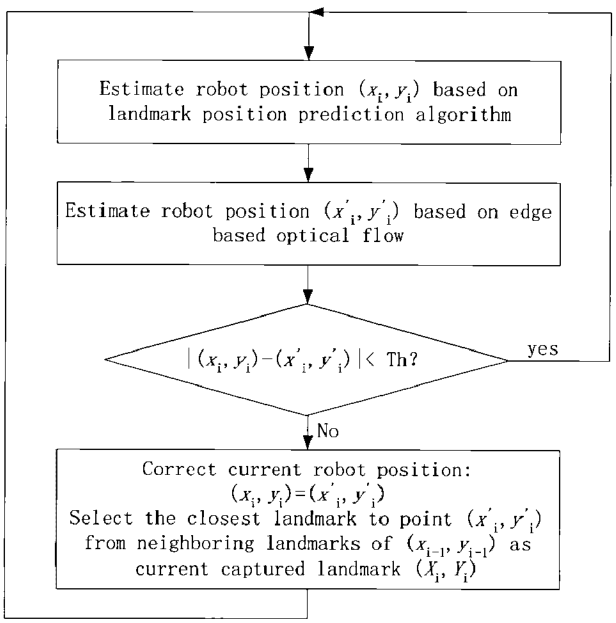


그림 8. 정보 융합 순서도.

Fig. 8. Flow diagram of data fusing.

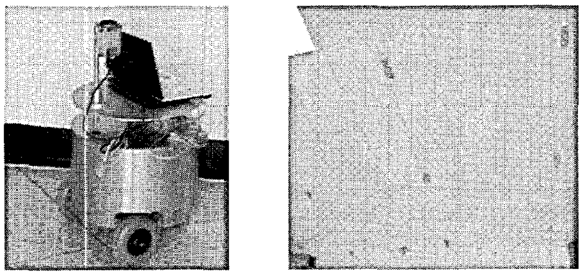
(x_i,y_i) and (x_i',y_i') are not close to each other, then error is assumed and (x_i',y_i') is chosen as the current robot position. From the neighborhood of previously identified landmark (X_{i-1},Y_{i-1}), another landmark closest to the current robot position (x_i',y_i') is chosen as the reference landmark (X_i,Y_i). Now using equation (2) and (5) the next captured landmark position (X_{i+1},Y_{i+1}) and robot position (x_{i+1},y_{i+1}) can be estimated.

Fig. 8 shows the data fusing algorithm where *Th* is a appropriately selected threshold which measures the proximity of points (x_i',y_i') and (x_i,y_i). If the points are not close enough, then equation (10) is used to reselect the current landmark position.

$$(X_i,Y_i)=\min_{k_1,k_2\in\{-1,0,1\}}\left|(X_{i-1}+k_1d,Y_{i-1}+k_2d)-(x_i',y_i')\right| \quad (10)$$

V. EXPERIMENT AND RESULT

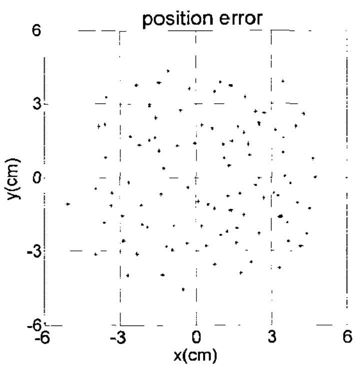
Fig. 9(a) shows the experimental setup of the robot with camera facing the ceiling. The robot diameter is 40cm. Fig. 9(b) shows the color patches on the ceiling. The distance between two adjacent patches is 1m and the patch size is 3cmx9cm.



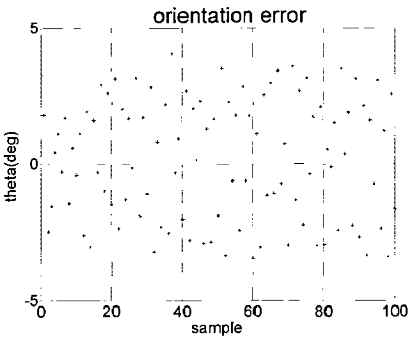
(a) Mobile robot used in the experiment (b) Color patches on the ceiling

그림 9. 실험 환경.

Fig. 9. Experimental setup.



(a) Position estimation error



(b) Orientation estimation error.

그림 10. 측정결과.

Fig. 10. Estimation error.

100 positions were tested with the robot moving in a straight line at a velocity of 0.1m/s. Complex trace has not been considered as it is related to control algorithm. Fig. 10 shows the measurement error for each sample where we can see that the estimation error is less than 5 cm and directional error is less than 4°.

VI. CONCLUSION

In this paper we presented a novel system for mobile robot localization. Simple patches with orientation information only were created on the ceiling as landmarks and the likelihood prediction based method used these patches as reference to find the current position and the moving direction of the robot. Edge based optical flow is further used to compensate for some landmark recognition error. Experimental results demonstrate that the proposed system provides accurate estimation of robot position where the evaluated localization error is within the range of 5 centimeters while the directional error is less than 4 degrees. This makes the proposed system reliable for practical applications.

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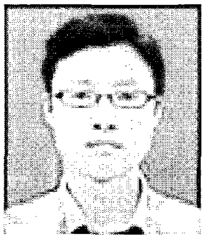

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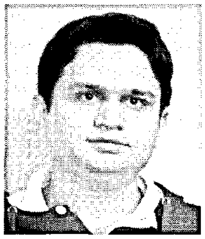

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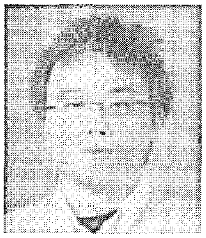

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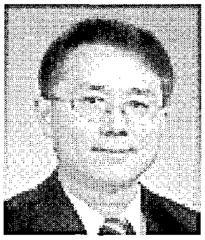

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