A New Method For Indoor SLAM Based On Artificial Landmark

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Abstract: A mobile robot must be capable of localizing itself in unknown environments and constructing a map of the environments at the same time. Simultaneous localization and mapping (SLAM) is a challenging problem in indoor environments because GPS information isn't available. An algorithm is proposed in this paper for SLAM with vision sensors, which is designed by utilizing the artificial landmark MR code and integrating the FastSLAM algorithm, the method can decrease the time cost compared with particle filter and improve the accuracy of localization and mapping compared with natural landmarks. Experiments show the effectiveness and robustness of this algorithm.

Keywords: Mobile robot, artificial landmark, vision sensor, FastSLAM, localization.

1. INTRODUCTION

The problem of the Simultaneous localization and mapping ,which is also called as SLAM, is to build a environment map from a sequence of measured landmarks. it has been considered as a key prerequisite for truly autonomous robots[1,2]. in indoor environment, SLAM problem is more difficult to resolve because no GPS information is available. The dominant approach to this problem was introduced by Smith, Self, and Cheeseman [1], Which proposed the method using extended Kalman filter (EKF) for the estimation of the posterior distribution along with the positions of the landmarks. the method has gained widespread acceptance considering that the natural conditional independences of the SLAM problem [2, 3], FastSLAM [4] decomposes the problem into a localization problem and a set of landmark estimation problems, which is more effective compared with the other existing filter [5, 6]. While the data association is the key problem in FastSLAM because the natural landmark is difficult to be detected robustly [7, 8]. Compared with natural landmark, artificial landmark can be easier to be detected and recognized. in this paper ,we choose the artificial landmark MR code [9]as the key feature in FastSLAM implementation. the method can resolve the landmark obscure in FaslSLAM, so the accuracy of the localization and mapping has been improved greatly.

The paper is organized as follows. In section 2, we analysed the principle and the effectiveness of the artificial landmark MR code. in section 3, the integration of the landmark and FastSLAM is analysed. in section 4, the robot motion model and the landmark detection model are discussed for robot localization and mapping. Finally, the algorithm is verified in various experiments in section 5 and the conclusions are given in the last section.

2. THE ARTIFICIAL LANDMARK MR CODE

Some characters should be met in the design of an efficient landmark, which are detection, recognition and localization [10-12].

Considering that MR code has the ability to present distinct information and error correcting, we choose MR code as our artificial landmark. A prototype of MR code, which includes 8x8 units, is presented in Fig. (**1**). The MR code has some effective characteristics. Utilizing the computation of the cross ratio, the landmark pattern can keep invariant under different angles and illumination; the unit modules that contain the binary information encoded by binary BCH code, so MR code can provide amount of information and be recognized from the different environment robustly.

The MR landmark detection and recognition is implemented by four steps, which is shown briefly as follows.

1. Lines extraction. Edges are extracted by using the canny edge detector for the projective invariants calculation.

2. Invariants calculation. After the lines have been detected by the canny detector, the pairs of cross ratio invariants could be computed based on the landmark contour.

3. homography matrix Determination: Since the contour of the landmark is confirmed and the coordinates of the MR vertexes are determined. The homography matrix can be calculated based on the correspondences.

4. Code Reading and decoding. Utilizing the determined homography matrix, when a new image comes, which must have the same size as the MR code? the new image could be mapped to the MR code accurately based on the homography matrix, so the binary information included in MR code can be gained by matching the unit modules.

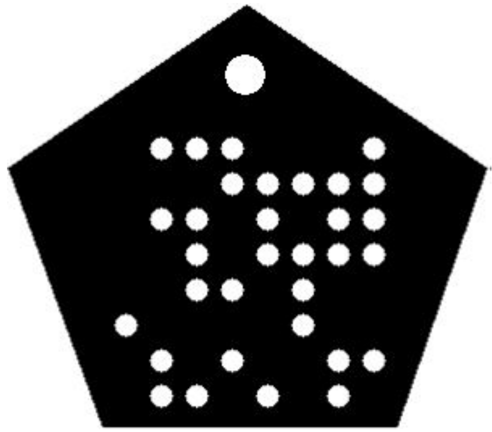

Fig. (1). A prototype of MR code.

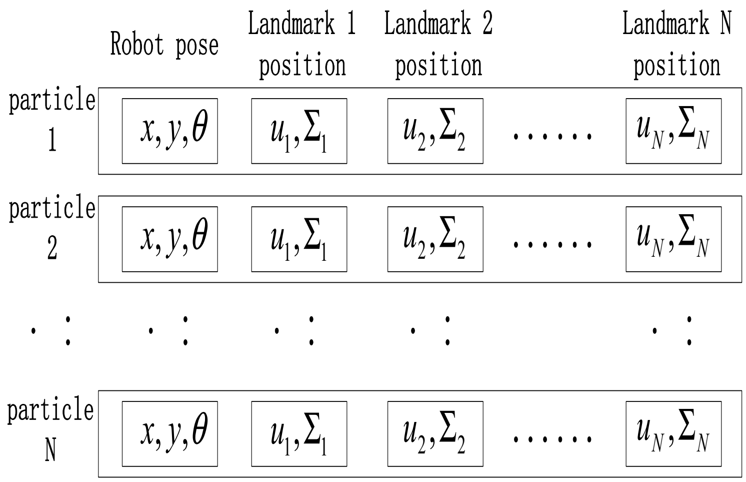

Fig. (2). The filter structure of FastSLAM, a total of M particles in filter and each particle owns distinct N EKF filters.

3. THE PROCESS OF SLAM INTEGRATING FASTSLAM AND ARTIFICIAL LANDMARKS

The Artificial landmark MR code has the accurate point correspondences, which is the key problem in FastSLAM implementation. this section is assumed that the point correspondences between MR code have been obtained, and then the FastSLAM analysis based on this is as follows.

The path estimation is implemented in The FastSLAM algorithm *by* using a modified particle filter [4], the filter could sample from the space efficiently and provides a good approximation of the posterior. pose estimation of the landmark are realized by Kalman filters, which uses distinct filters for different landmarks. Because the estimates of the landmark are relied on the estimation of the path, each particle has its distinct landmark estimates. so, for N particles and K landmarks, there would be KN Kalman filters.

So any particle in FastSLAM can be expressed as follows:

$$S_t^{[m]} = \{s_t^{[m]}, N_t^{[m]}, u_{1,t}^{[m]}, \Sigma_{1,t}^{[m]}, ..., u_{N_t^{[m]},t}^{[m]}, \Sigma_{N_t^{[m]},t}^{[m]}\} \tag{1}$$

This is assumed the each particle has $N_t^{[m]}$ characters in its correspondent map, among which $[m]$ is the sequence of the m-th particle and $s_t^{[m]}$ is its state estimates. $u_{N_t^{[m]},t}^{[m]}$, $\Sigma_{N_t^{[m]},t}^{[m]}$ are used to represent the average and the variance of the N-th landmark path. The set of the m-th particle at time t is noted as $S_t^{[m]}$。 filter is to cumpute the posteriori at time t from the previous time $t-1$. This is similiar to FastSLAM, which is to obtain the current state estimates S_t frome the previous state S_{t-1}. this can be shown as Fig. (**2**):

The algorithm includes three important steps, this is described as follows:

1．the state estimation and update

In the particle set S_t, each particle includes 的每个粒子 N EKF filters, the position of the n-th landmark at time *t* is obtained from time *t-1* based on bayes formula, this is expressed as follows:

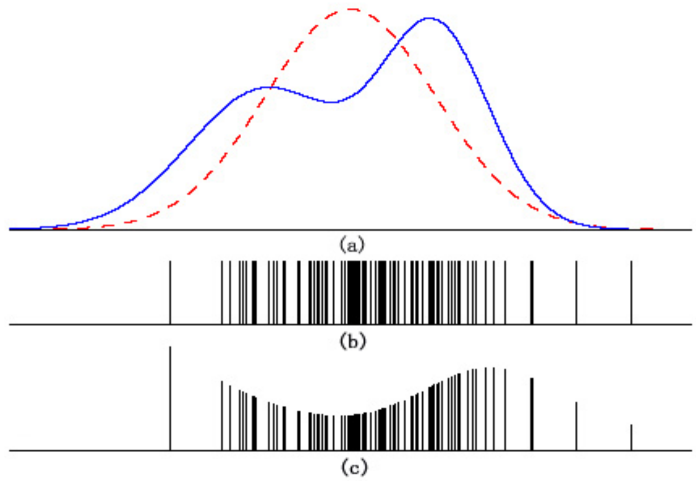

Fig. (3). The importance weight description: the dotted line in (**a**) represents suggestion distribution and the solid line represents actual distribution; (**b**) shows the sample from suggestion distribution while (**c**) shows the distribution of the sample after modification.

$$p(\theta_{n_t} \mid s^t, z^t, u^t, n^t) = \eta p(z_t \mid \theta_{n_t}, s^t, z^{t-1}, u^t, n^t) \\ p(\theta_{n_t} \mid s^t, z^{t-1}, u^t, n^t) \tag{2}$$

Because the measurement z_t is dependent to s_t, u_t or n_t, so we can get:

$$p(\theta_{n_t} \mid s^t, z^t, u^t, n^t) \\ = \eta p(z_t \mid \theta_{n_t}, s_t, n_t) p(\theta_{n_t} \mid s^{t-1}, z^{t-1}, u^{t-1}, n^{t-1}) \tag{3}$$

3. the importance weight computation

The particles sampled from the motion model is computed as $p(s^t \mid z^{t-1}, u^t, n^{t-1})$, while the set of these particles is not according to the expected posterior $p(s^t \mid z^t, u^t, n^t)$, which is needed to modify. This process is called importance weight modification and this has been show as Fig. (**6**). Which means that particles is sample more in dense area.

The formula of the importance weight is as follows, because the importance weight is the ration of the suggestion distribution and the posterior distribution, so we can get:

$$w_t^{[m]} = \frac{target\ distribution}{proposal\ distribution} \\ = \frac{p(s^{t,[m]} \mid z^t, u^t, n^t)}{p(s^{t,[m]} \mid z^{t-1}, u^t, n^{t-1})} \tag{4}$$

According to the bayes formula:

$$w_t^{[m]} \overset{Bayes}{=} p(z_t \mid s^{t,[m]}, z^{t-1}, u^t, n^t) \\ \frac{p(s^{t,[m]} \mid z^{t-1}, u^t, n^t)}{p(s^{t,[m]} \mid z^{t-1}, u^t, n^{t-1})} \tag{5}$$

in the last formula, Neglecting the irrelevant terms refer to the newest detection z_t, the formula can be simplified as:

$$w_t^{[m]} \overset{Markov}{=} p(z_t \mid s^{t,[m]}, z^{t-1}, u^t, n^t) \\ \frac{p(s^{t,[m]} \mid z^{t-1}, u^t, n^{t-1})}{p(s^{t,[m]} \mid z^{t-1}, u^t, n^{t-1})} \\ = p(z_t \mid s^{t,[m]}, z^{t-1}, u^t, n^t) \tag{6}$$

Because the landmark is estimated based on t EKF, so the expectation of $p(z_t \mid s^{t,[m]}, z^{t-1}, u^t, n^t)$ is $\hat{z}_t$ and the variance is $Z_{n,t}$, the importance weight of the m -th particle at time *t* can be calculated as follows:

$$w_t^{[m]} = \frac{1}{\sqrt{|2\pi Z_{n_t,t}|}} \\ exp\{-\frac{1}{2}(z_t - \hat{z}_{n_t,t})^{\mathrm{T}} Z_{n_t,t}^{-1}(z_t - \hat{z}_{n_t,t})\} \tag{7}$$

Based on the distribution of the particle importance weight, we can deduced the localization of the robot and get the map simultaneously because each particle records relevant information.

In summary, the complete description of our method can be described as Table **1**.

Table 1 The flow of the algorithm.

$FastSLAM(S_{t-1}, z_t, R_t, u_t)$
$S_t = S_{aux} = \varnothing$;
◆**FOR** $m = 1$ **To** M // for all particles

Table **1**. contd…

to choose the m -th from set S_{t-1}

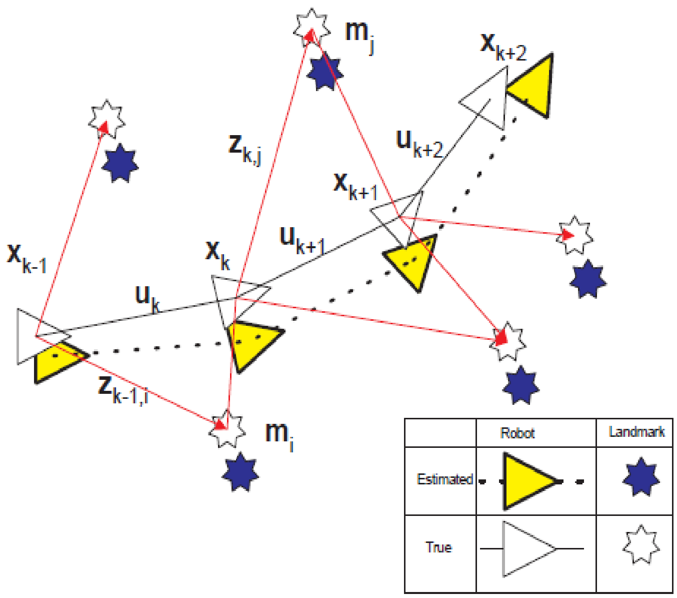

Fig. (4). SLAM problem description.

$\{s_{t-1}^{[m]}, N_{t-1}^{[m]}, u_{1,t-1}^{[m]}, \Sigma_{1,t-1}^{[m]}, ..., u_{N_t^{[m]},t-1}^{[m]}, \Sigma_{N_t^{[m]},t-1}^{[m]}\}$;

to predict the pose of the current particle based on $s_t^{[m]} \sim p(s_t \mid s_{t-1}^{[m]}, u_t)$;

◆**FOR** $n = 1$ **To** $N_{t-1}^{[m]}$ //a total of $N_t^{[m]}$ characters

$G_{\theta,n} = \nabla_{\theta_n} g(\theta_n, s_t)|_{\theta_n = u_{n,t-1}^{[i]}; s_t = s_t^{[i]}}$;

//measurement prediction

$\hat{z}_{n,t} = g(s_t^{[m]}, u_{n,t-1}^{[m]})$ $Z_{n,t} = G_{\theta,n}\Sigma_{n,t-1}^{[m]}G_{\theta,n}^T + R_t$;

// R_t represents measurement model noise

$p_{n,t}^{[m]} = |2\pi Z_{n,t}|^{-\frac{1}{2}} exp\{-\frac{1}{2}(z_t - \hat{z}_{n,t})^T Z_{n,t}^{-1}(z_t - \hat{z}_{n,t}$

◆**END FOR**

$p_{N_{t-1}^{[m]}+1,t}^{[m]} = p_0$;

//based on $\hat{n}_t = arg\,max_n\, p_{n,t}^{[m]}$,to choose $\hat{n}_t$ as the current landmark note;

◆**IF** $\hat{n}_t = N_{t-1}^{[m]} + 1$ //if it is a new landmark

$N_t^{[m]} = N_{t-1}^{[m]} + 1$;

$u_{\hat{n}_t,t}^{[m]} = g^{-1}(s_t^{[m]}, \hat{z}_{n,t})$;

$\Sigma_{\hat{n}_t,t}^{[m]} = (G_{\theta,\hat{n}_t}^T R^{-1} G_{\theta,\hat{n}_t})^{-1}$;

◆**ELSE** //if it is a known landmark, state update by EKF

$N_t^{[m]} = N_{t-1}^{[m]}$;

$K_{\hat{n}_t,t} = \Sigma_{\hat{n}_t,t-1} G_{\theta,\hat{n}_t}^T Z_{\hat{n}_t,t}^{-1}$;

$u_{\hat{n}_t,t}^{[m]} = u_{\hat{n}_t,t-1}^{[m]} + K_{\hat{n}_t,t}(z_t - \hat{z}_{n,t})$;

$\Sigma_{\hat{n}_t,t} = (I - K_{\hat{n}_t,t} G_{\theta,\hat{n}_t})\Sigma_{\hat{n}_t,t-1}^{[m]}$;

◆**END IF**

◆**FOR** $n = 1$ **To** $N_t^{[m]}$ //for the landmark that haven't been measured

◆**IF** $n \neq \hat{n}_t$

$u_{\theta_n,t}^{[m]} = u_{\theta_n,t-1}^{[m]}$;

$\Sigma_{\theta_n,t} = \Sigma_{\theta_n,t-1}$;

◆**END IF**

◆**END FOR**

$w_t^{[m]} = p_{\hat{n}_t,t}^{[m]}$;

// put the weighted particle $\{s_t^{[m]}, N_t^{[m]}, u_{1,t}^{[m]}, \Sigma_{1,t}^{[m]}, ..., u_{N_t^{[m]},t}^{[m]}, \Sigma_{N_t^{[m]},t}^{[m]}, w_t^{[m]}\}$ to the particle set S_{aux};

4. THE ROBOT MOTION MODEL AND DETECTION MODEL

To solve SLAM problem, the robot should set up the motion model and the measurement model. The principle has been shown if Fig. (**3**). When the robot moves, the distance that it has moved should be estimated, and the position of the landmark should be calculated simultaneously, so an effective motion model is necessary as well as measurement model. In Fig. (**3**), The yellow triangle is the estimated position of the robot and the white triangle is the its real position. The robot updates the estimated position when the new

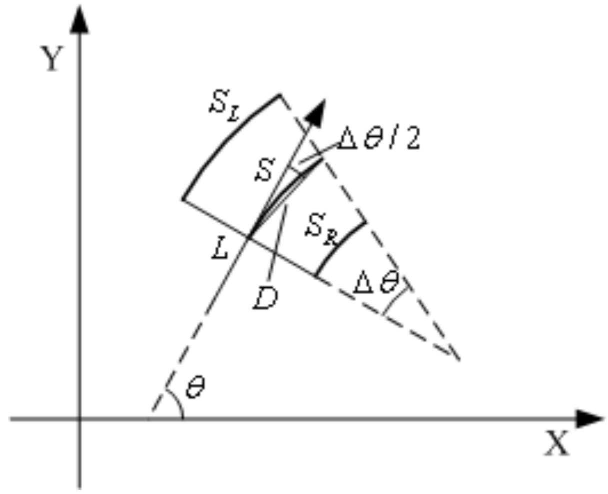

Fig. (5). The moving model of robot wheels.

landmark was found. While the position of the measured landmark is not accurate absolutely, an appropriate motion model and measurement model would be set which are described as follows.

To analyze the robot localization and mapping error, the robots moving model must be set up firstly. Because the robot that we used in this paper is a wheel robot, the model can be set as Fig. (**4**), among which SL is the distance that the left wheel moves and SR is the distance that the right wheel moves. $\Delta\theta$ is the wheel axis rotation angle and θ represents the intersection angle shown if Fig. (**5**).

Then the robot pose change between the current one and the last one can be estimated, among which $X_i(x_i, y_i, \theta_i)$ is the current robot pose and $X_{i-1}(x_{i-1}, y_{i-1}, \theta_{i-1})$ is the last one. so the relation between the robot rotation angle and the distance that the robot moves can be calculated as equation 8. The arc length, which is the distance the robot centre has moved, can be represented as equation 9, and And D can be calculated as equation 10:

$$\Delta\theta = (S_L - S_R)/L \tag{8}$$

$$S = (S_L + S_R)/2 \tag{9}$$

$$D/2 = S/\Delta\theta \times \sin(\Delta\theta/2) \tag{10}$$

Considering that the distance between S_L and S_R is very short, so we can get an assumption that:

$$\Delta\theta = 0 \tag{11}$$

$$\begin{aligned} \Delta x &= S \times \cos\theta \\ \Delta y &= S \times \sin\theta \end{aligned} \tag{12}$$

the current pose update can be described as the equation 13, Considering the noise, the formula of the pose can be changed as equation 14, Among which W_{i-1} is the ordinarily assumed gauss noise and its average and variance are described as equation 15:

$$X_i = X_{i-1} + (\Delta x, \Delta y, \Delta\theta) \tag{13}$$

$$X_i = F(X_{i-1}, S_{Li-1}, S_{Ri-1}) + W_i \tag{14}$$

$$\mathrm{E}[W_i] = 0,\ \mathrm{E}[W_i, W_i^{\mathrm{T}}] = Q_i \tag{15}$$

Covariance could be described as a diagonal matrix, and the diagonal entries are equation 16:

$$\begin{aligned} Q_{11} &= K_x \left|S\cos\theta\right|, \\ Q_{22} &= K_y \left|S\sin\theta\right|, \\ Q_{33} &= K_{S\theta}\left|S\right| + K_{\theta\theta}\left|\Delta\theta\right| \end{aligned} \tag{16}$$

Among which K_x and K_y are the robot drift coefficients along the axis X and the axis Y, similarly, $K_{S\theta}$ and $K_{\theta\theta}$ are the robot drift coefficients of angles. The values of the coefficients can represent the error.

The measurement model can be described as Fig. (**6**) shows, the measurement of the i-th landmark can be described as equation 17, so the measurement model can be deduced as equation 18:

$$z_i(k) = \begin{bmatrix} x_{i|s}(k) & y_{i|s}(k) & \theta_{i|s}(k) \end{bmatrix}^T \tag{17}$$

$$\begin{aligned} z_i(k) &= \begin{bmatrix} x_{i|s}(k) \\ y_{i|s}(k) \\ \theta_{i|s}(k) \end{bmatrix} = h(X(k)) + v(k) \\ &= \begin{bmatrix} \cos(\theta_r(k)) & \sin(\theta_r(k)) & 0 \\ -\sin(\theta_r(k)) & \cos(\theta_r(k)) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_i - x_r(k) \\ y_i - y_r(k) \\ \theta_i - \theta_r(k) \end{bmatrix} + v(k) \end{aligned} \tag{18}$$

In equation 18, the measurement noise can be ordinarily assumed as gauss noise, among which the average is assumed to zero and covariance matrix is assumed as diagonal matrix.

Table 4. The error between the landmark position of real and estimated.

Measurement Value			Error		
X	Y	θ	ΔX	ΔY	$\Delta\theta$
212.6	-8.3	0.4	-4.2	8.3	0.4
-7.7	167.4	78.7	4.8	3.2	0.5
16.5	-378.8	234.9	-16.4	-19.7	-0.6
584.5	-24.7	[illegible]	6.8	20.5	0.5
41.3	623.9	5[illegible]	-35.5	-1.4	0.6
-567.9	12.4	178.5	-25.2	-8.9	1.2
43.7	-580.6	250.8	38.2	24.8	0.5

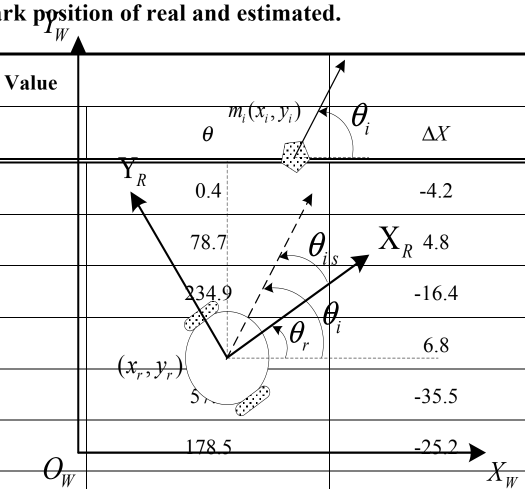

Fig. (6). The robot measurement model.

Table 5. Error statistic (cm).

FastSLAM Plus MR Code		MR Code	
Average	Distance	Average	Distance
3.2	150	8.5	150

Table 2. The inner parameter of calibration (mm).

Inner Parameter	kx		ky	
	Result	Variants	Result	Variants
camera	568.27	2.44	566.21	2.76

Table 3. The center of the camera (mm).

u0		v0	
RESULT	VARIANTS	Result	Variants
232.12	2.91	177.98	1.98

5. EXPERIMENTS AND ANALYSIS

Some various experiments have been implemented with a vision system is mounted on the center of the robot fixedly connected with PC, which is equipped with an INTEL- i5-3570S CPU and a RAM of 1G. for the accuracy of the localization and mapping, the camera should be precisely calibrated beforehand.

We implement the calibration using the zhang method and the result is shown as Table **2** and Table **3**. Among which Table **2** shows. The inner calibration parameter and Table **3** shows the center and the focus of camera.

Table **4** gives some results of the landmark detection error between the real position and the estimated. The data shows that within distance about 150cm the error is below 10cm and the error grows acutely in the distance about 400cm.the error can be decreased with the FastSLAM algorithm.

Integrating the FastSLAM and MR code, the error of localization and mapping is decreased quickly, we implement a statistic as Table **5** shows, the average error has been decreased from 8.5cm to 3.2cm at the average distance about 150mm.

CONCLUSION AND FUTURE WORK

FastSLAM algorithm is an efficient solution to SLAM problem, which utilizes a Rao-Blackwellized representation for the posterior and integrates particle filter and Kalman filter representations. Artificial landmark MR code can provide more accurate feature compared with natural landmark. In this paper, the integration of the two methods was presented and the experiments show its effectiveness.

Future work would seek more accurate artificial landmark or natural landmark.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

ACKNOWLEDGEMENTS

Declared none.

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Received: September 16, 2014 Revised: December 23, 2014 Accepted: December 31, 2014