A Fusion Localization Algorithm Combining MCL with EKF

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Abstract: **The Monte Carlo algorithm uses a random and weighted sampling set to represent and estimate the possible and position distribution of the mobile robot. To improve the accuracy of localization, a new localization algorithm combining the original MCL (Monte Carlo Localization) with EKF (Extended Kalman Filter) is proposed in this paper. First, according to the initial set, the needed particles are collected in the space and the mean value of particles are calculated. Second, the best global features LG are extracted from the sensors' measurements. Finally, EKF is used to update the current state and covariance of the robot and exclude the useless particles. Simulations and experiments proved that the proposed algorithm is superior, for the localization particles distribute tightly around the moving robot with lower location error.**

Keywords*：*Monte Carlo Localization, Sampling, Extend Kalman Filter, Mobile robot.

I. INTRODUCTION

In the field of robotics, the predictions of a dynamic model of an autonomous robot are often updated by the values of the robot's sensors. This problem is often called "Localization", which can be formulated as a sampling problem [1]. Localization is an important part of autonomous motion of mobile robot, determining the exact position of the robot in an unknown environment [2]. Moreover, reducing location errors is a meaningful issue in the field of autonomous robotics.

According to available types of knowledge and the difficulties, localization problem can be divided into three sub-problems: position tracking, global localization and the kidnapped robot problem [3]. In the position tracking problem, it assumes that the robot knows its initial pose and can keep track of its movement, maintaining precise estimates of its pose in a known environment with relatively small noise. However, the global localization problem is more challenging. In this case, with no information of initial positions, the robot has to estimate the pose in the following process through control data and sensors data. To solve the initial localization problem, Hua proposed a guaranteed outlier minimal number estimator (OMNE) based on set inversion via interval analysis [4]. In addition, the kidnapped robot problem appears when a well-localized robot is teleported to some other place without being told. Robot kidnapping can be caused by many factors [5], which can be divided into two categories – real kidnapping and localization failures.

Among position tracking algorithms, EKF is one of the most popular approaches [6]. Due to the restrictive nature of the belief representation, the common EKF is inapplicable to the global localization problem. To overcome this limitation, the multi-hypothesis Kalman filter is proposed [7]. It represents beliefs using the mixture of Gaussian distributions, thus can proceed with multiple and distinct hypotheses. However, this approach inherits the Gaussian noise assumption from Kalman filter, therefore all practical implementations extract low-dimensional features from the sensor data, ignoring much more information.

MCL is one of most common approaches to deal with the global localization problem. MCL is based on a particle filter that represents the posterior belief by a set of weighted samples [8]. One disadvantage of MCL is the heavy computational burden. To obtain a reliable localization result, a certain number of particles will be needed. Actually, each particle can be seen as a pseudo-robot, which perceives the environment using a probabilistic measurement model. At each iteration, the virtual measurement takes large computational costs if there are hundreds of particles. In addition, not recovering from robot kidnapping is another disadvantage. If this pose happens to be incorrect, MCL is unable to recover from this global localization failure. Zhang proposed the augmented MCL algorithm to partly solve the kidnapped robot problem by adding random samples [9].

This paper will improve the location precision and reliability by combing EKF and MCL. The organization of the present paper is as follows. An overview of the research on robot localization is briefly introduced in Section 1. Section 2 mainly describes the basic concepts of the localization algorithm, including MCL, EKF. Section 3 proposes a new method to improve the sampling particles around the moving robot and increase

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the localization accuracy. Section 4 provides experimental results. Finally, main conclusions are discussed in Section 5.

II. MONTE CARLO LOCALIZATION

MCL is based on a particle filter, which represents the posterior belief by a set of of weighted samples distributed according to this posterior. As a consequence, the more intensive the region is populated by samples, the more likely the robot locates there:

$$S_t = \left\{ \left\langle s_t^{[n]}, \omega_t^{[n]} \right\rangle \right\}_{n=1,\dots,N} \qquad (1)$$

where each particle $s_t^{[n]}$ with $1 \le n \le N$ denotes a concrete instant of the robot's pose at time t. The number of particles N may be a fixed value or changing with some quantities related to the belief $bel(s_t)$. The $\omega_t^{[n]}$ is the non-negative numerical factor called importance factor.

The basic MCL algorithm is depicted in Table 1, which calculates the particle set St recursively from the set St-1 with the latest control ut, measurement zt and the map m.

Table 1 The Basic MCL Algorithm

	Basic MCL Algorithm, adapted from ref.
1:	**Input:** S_{t-1}, u_t, z_t, m
2:	$\overline{S}_t = S_t = \varnothing$
3:	**For** n=1 to N **do**
4:	Generate a particle $s_t^{[n]} \sim p\left(s_t \middle| s_{t-1}^{[n]}, u_t, m\right)$
5:	Calculate an importance factor $\omega_t^{[n]} = p\left(z_t \middle| s_t^{[n]}, m\right)$
6:	Add $\left\langle s_t^{[n]}, \omega_t^{[n]} \right\rangle$ to $\overline{S}_t$
7:	**End for**
8:	Normalize ω_t
9:	**For** n=1 to N **do**
10:	Draw $s_t^{[n]}$ with importance factors $\omega_t^{[n]}$
11:	Add $s_t^{[n]}$ to S_t
12:	**End for**
13:	**Output:** S_t

In Table 1, Line 4 generates samples $s_t^{[n]}$ based on $s_{t-1}^{[n]}$, u_t and m, and the pair $\left(s_t^{[n]}, s_{t-1}^{[n]}\right)$ follows the product distribution,

$$p\left(s_t^{[n]} \middle| s_{t-1}^{[n]}, u_t, m\right) \times bel\left(s_{t-1}^{[n]}\right) \qquad (2)$$

In terms of the literature, the distribution is called the proposal distribution. Line 5 calculates the importance factor $\omega_t^{[n]}$ for each particle $s_t^{[n]}$. $\omega_t^{[n]}$ is used to correct the mismatch between the proposal distribution and the desired target distribution. $\omega_t^{[n]}$ is the probability of the measurement z_t under the hypothetical state $s_t^{[n]}$, which incorporates the measurement z_t into the particle set,

$$\omega_t^{[n]} = \frac{\eta p\left(z_t \middle| s_t^{[n]}\right) p\left(s_t^{[n]} \middle| s_{t-1}^{[n]}, u_t, m\right) bel\left(s_{t-1}^{[n]}\right)}{p\left(s_t^{[n]} \middle| s_{t-1}^{[n]}, u_t, m\right) \times bel\left(s_{t-1}^{[n]}\right)} = \eta p\left(z_t \middle| s_t^{[n]}\right) \qquad (3)$$

where the normalization η is a constant. To make the weighted particle set $\overline{S}_t$ distribute according to the posterior belief $bel(s_t)$, resampling is implemented by lines 9-12. After resampling, the particle set is distributed according to $bel(s_t)$.

III. Modified MCL

Usually, MCL algorithm uses a simple probability model of robot motion to predict robot's position and orientation distribution instead of using particle distribution. However, the less weight of noise will still occur in the process of rapid degradation of the phenomenon of particle. Due to many uncertain factors in the process of localization, this paper tries to use EKF to update the state of the initial particles. New update method is shown as follows. First, state $\hat{X}_t^-$ at time t is predicted. Then, the observation information is estimated by the information of the line L_G. Third, the Kalman gain is calculated and the state is updated according to the actual observation information $\hat{X}_t^-$. Last, particles X_t^i are gained from the sampling particles $\left(\hat{X}_t, P_t\right)$ and replace P_t with zero as the proposed distribution of next period.

The combined localization algorithm is implemented in three steps as illustrated in Fig.1.

Step1: collecting the useful messages from the sensors. The first step accepts the map m as the input. It outputs a measurement by EKF. Step2: calculating SER. Step3: Localization. The last accepts as input the particle set St-1. Step2 and 3 run online.

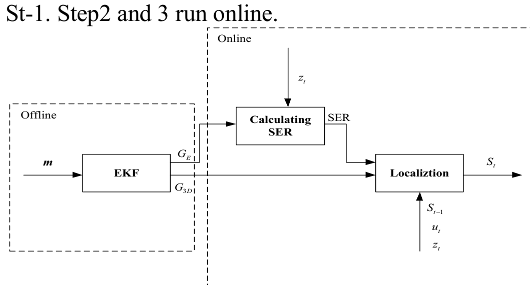


Fig.1 The process of the combined algorithm

In this paper, the fiber optic gyro is used as an internal sensor to measure the direction of the robot. The mean value of the angle θ_{t-1}^D and the mean value θ_{t-1}^G are substituted for $\Delta\theta_{t-1}$ by

$$X_t = f\left(X_{t-1}, U_{t-1}\right) + w_{t-1} = \begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix} = \begin{bmatrix} x_{t-1} + \Delta D_{t-1}\cos\left(\theta_{t-1} + \Delta\theta_{t-1}\right) \\ y_{t-1} + \Delta D_{t-1}\sin\left(\theta_{t-1} + \Delta\theta_{t-1}\right) \\ \theta_{t-1} + \Delta\theta_{t-1} \end{bmatrix} + w_{t-1} \qquad (4)$$

$$\Delta\theta_{t-1} = \frac{\Delta\theta_{t-1}^D + \Delta\theta_{t-1}^G}{2} \qquad (5)$$

The nonlinear function of the mileage meter model $f\left(X_{t-1},U_{t-1}\right)$ is Taylor expansion, which is as follows,

$$\nabla f_X=\begin{bmatrix}\frac{\partial x_t}{\partial x_{t-1}} & \frac{\partial x_t}{\partial y_{t-1}} & \frac{\partial x_t}{\partial \theta_{t-1}}\\ \frac{\partial y_t}{\partial x_{t-1}} & \frac{\partial y_t}{\partial y_{t-1}} & \frac{\partial y_t}{\partial \theta_{t-1}}\\ \frac{\partial \theta_t}{\partial x_{t-1}} & \frac{\partial \theta_t}{\partial y_{t-1}} & \frac{\partial \theta_t}{\partial \theta_{t-1}}\end{bmatrix}=\begin{bmatrix}1 & 0 & -\Delta D\sin\left(\theta_{t-1}+\Delta\theta_{t-1}\right)\\ 0 & 1 & \Delta D\cos\left(\theta_{t-1}+\Delta\theta_{t-1}\right)\\ 0 & 0 & 1\end{bmatrix} \quad (6)$$

In the update period, the actual distance values s of the laser is used. In this paper, the UTM-30LX laser can get a number of 181 part data per cycle. According to $p\left(s_t|X_t\right)$, by multiplying the probability of the ray observation, the observation probability of a single sweep in the position can be obtained by

$$\text{C}\; P\left(\rho_t|X_t^i\right)=\prod_{k=1}^{181}P\left(\rho_t^k|X_t^i\right) \quad (7)$$

ombined with the following models, it should be normalized to meet $\lambda_g+\lambda_d=1$.

$$\begin{aligned}P\left(\rho_t^k|X_t^i\right)&=\lambda_g P_g+\lambda_d P_d\\ &=\lambda_g\left(\sigma\sqrt{2\pi}\right)^{-1}\exp\left(\frac{-\left(x-\mu\right)^2}{2\sigma^2}\right)+\lambda_d P_d=\delta\left(\rho_t^k-\infty\right)\end{aligned} \quad (8)$$

In order to increase the accuracy, a modified algorithm combining MCL with EKF is proposed, which is shown in fig.2. The matching failure criteria is set as follows:

$$W<\eta W_{th} \quad (9)$$

where W is the sum weight, W_{th} is the threshold value and η is the coefficient.

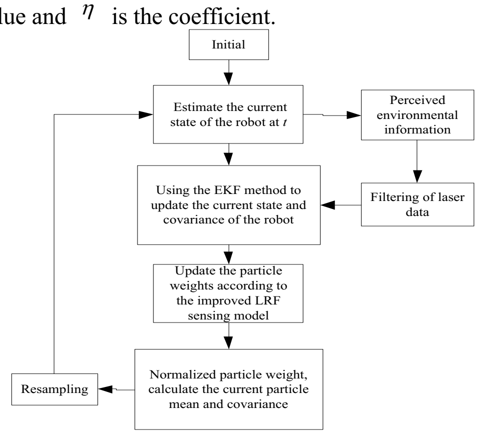


Fig.2 Flowchart of the modified MCL algorithm

The proposed EKF and MCL fusion localization algorithm is described as follows.

Initial: Set the initial states, orientation of the mobile robot, and the parameters needed in the initialization process. Then collect particles in the space according to equation 1.

Calculate the mean value of particles according to equation 2.

Combined with global map information, the best global features L_G are extracted from the sensor's sensing information according to equation 3. Using the EKF method to update the current state and covariance of the robot according to equation 4.

Filter the observation data of the sensor, and put forward the data of the dynamic obstacles. Then, update the weight of each particle in the sum of particles.

Calculate the sum of the weight of the particles, the matching of the sampling distribution and the sensing information of the laser range finder is tested, and only the criterion is established to match successfully according to equation 5 and 6.

Normalized particle weight, calculate the current particle mean and covariance according to equation 7.

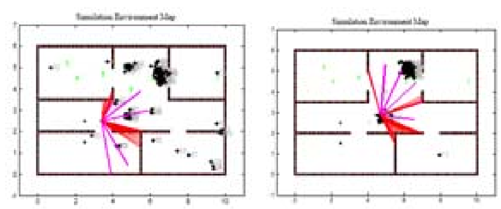
Based on the number of particles identified in step 5, the normalized particle set is calculated and compared with the boundary conditions according to equation 8.

Return to step 2.

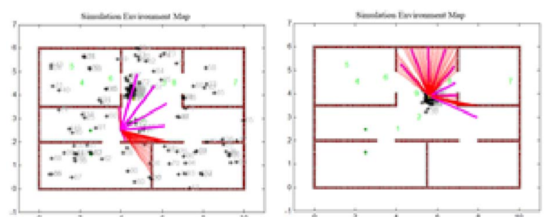
IV. Simulation and Experimental Results

In this section, detailed simulation and experiment are given to compare the differences between the proposed algorithm and the original MCL. This section uses MATLAB as the simulation platform.

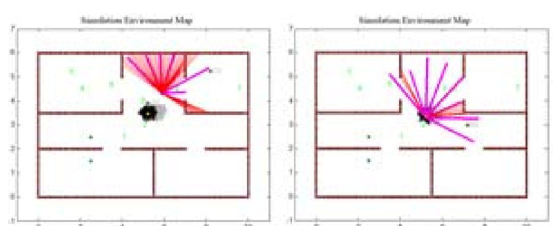
A.Simulation results



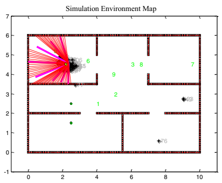
(a) Step=5 (a) Step=5



(b)Step=10 (b)Step=10

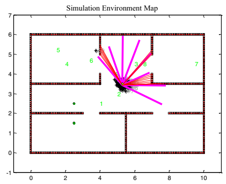


©Step=15 (c) Step=15



(d)Step=22

Fig 3. The original MCL



(d) Step=19

Fig 4. The modified MCL

In experiments, the initial position of the mobile robot is unknown, and the global positioning particles are initialized with 150 particles for uniform distribution. Fig. 3 and Fig. 4 show simulation results of the standard MCL algorithm and the proposed fusion algorithm with convergence and distribution, where the black dots represent particle locations. The process of fusion algorithm, respectively, listed in the iteration 5, 10, 15 times the status of the positioning. In the fifth iteration, comparing Fig. 3 (a) and Fig. 4 (a), it shows that the standard MCL algorithm still has a lot of particle distribution in the map, and the proposed algorithm is more concentrated. In the 10 times, standard MCL localization algorithm didn't locate successfully. In the 15th iteration, from Fig.3 (c) and Fig. 4 (c), standard MCL could not locate robot's real position, and this proposed algorithm outputs true position of the robot. It shows that the new algorithm uses less time to find its true positions. In addition, the proposed algorithm in the iterative 19 times can locate successfully. In addition, detailed location errors between the two algorithms are given in Fig.5, which shows that the modified MCL has the lower errors.

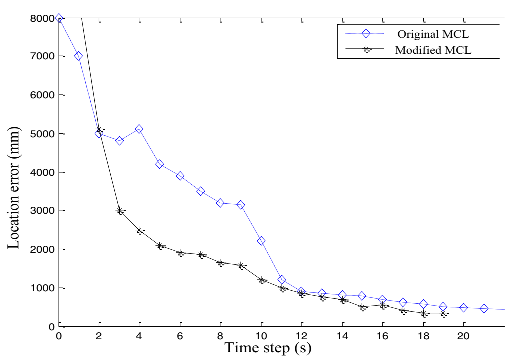


Fig 5. Location Error

B. Experimental results

The experiment is performed on the Turtlebot robot which is shown in Figure 5(a). It is equipped with a Kinect and a UTM-30LX to measure the environment. The programs is written in C++ on Robot Operation System, running on laptop CPU Core i5-2430 2.4 GHz. Figure 5(b) shows the experimental environment, and the robot need to move from the first point to the last point.

(a)Turtlebot (b) Experimental Environment

Fig. 6 Experimental Setting

Firstly, by using ROS system a new 2D grid map was created. In the created map, the initial pose of the robot is given. Figure 7 is the 2D grid map created in this paper, the green dots represent the location of particle of the algorithm, if green particles tightly around the TurtleBot, it means that positioning effect is very good. If particle orientation and TurtleBot deviation are very powerful, the positioning effect is not good.

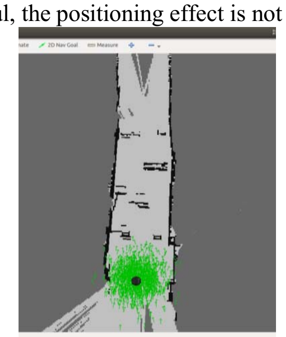
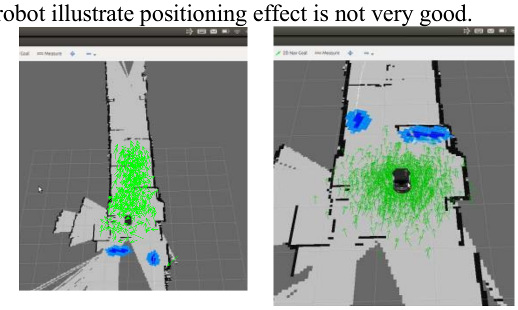


Fig. 7 Map of the experiment environment

Figure 8 shows is MCL positioning algorithm and the fusion algorithm in locating the particle distribution, Figure 8(a) representation is the traditional MCL algorithm in locating the particle distribution and Figure 8(b) for the fusion location algorithm of particle distribution, comparison can be found, this fusion algorithm in locating particles tightly around the around the TurtleBot, and original MCL localization algorithm in the positioning of location of particle distribution throughout the map and not tightly around the mobile robot illustrate positioning effect is not very good.



(a) original MCL (b) modified MCL

Fig.8 Localization particles between different algorithms

V. Conclusions

In this paper, a new fusion localization algorithm is proposed to improve the accuracy of location for the mobile robots. The resulting system runs on a platform based on TurtleBot. The synthesis results showed few hardware resources consumption, which demonstrates the suitability of the proposed architecture. Moreover, the accuracy of the location is improved by combing MCL and EKF. The simulation results also prove that the proposed localization algorithm improve the motion estimation accuracy compared with existing methods. The future work would address to the issue of the fusion algorithm in the multi-robot localization problem.

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