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Novel mobile robot ufastslam based on unscented kalman filter

Lin Chang[1], Songhao Piao[2], Xiaokun Leng[2], Guo Li[2], Zhaoyi Pei[2]

Abstract. This paper proposes a novel UFastSLAM (Unscented Fast Simultaneous Localization and Mapping) based on UKF (Unscented Kalman Filter). A novel proposal distribution which integrates current observation is proposed, wherein the particles sampled from the proposal distribution based on Unscented Transform is driven to move to the high probability region of posterior distribution. The landmarks in map are updated with UKF to avoid the problem of linearization related to non-Gaussian and nonlinear state estimations caused by Extended Kalman Filter. A group of sigma points in UKF are used to approximate system statistical properties, in which sigma points are calculated based on nonlinear equation instead of linear one, for the proposed UFastSLAM has many superior advantages as compared to the traditional one. Finally the metric map based on UFastSLAM is built and the superior performances of the proposed method are shown in experiments.

Key words. mobile robot, slam, kalman filter, unscented transform.

1. Introduction

Many researchers have studied the creations of measure maps of robots based on the distance sensors (sonar, laser rangefinder, etc.) and proposed some practical methods of map creation [1]. Unfortunately, the position of the robots was assumed to be determined accurately on the map creation process in these methods. In fact, a large deviation occurred in the global environment when creating map for there is a large accumulative error when using odometer to locate [2]. One method to solve this problem is to make the robot self position based on the created maps when creating the current map, which is call SLAM (Simultaneous Localization and Mapping) of mobile robot [3]. Many scholars believe that SLAM is the key technology to realize the real autonomous mobile robot for its important values in both theory reasoning and practical application [4]. At the same time, Kalman Filter has been widely used in the academic research and practical application. Salvatore in the paper [5]

[1]Workshop 1 - Harbin Institute of Technology, Harbin; e-mail: changlin@lejurobot.com
[2]Workshop 2 - Harbin Institute of Technology, Harbin, Harbin; e-mail: piaosh@hit.edu.cn

proposed the employment of differential evolution to offline optimize the covariance matrices of a new reducing delaying-state Kalman-Filter-based algorithm and the stator-flux linkage components were estimated, in the stationary reference frame, to realize the sensorless control of induction motors. Szabat in the paper [6] dealt with the application of adaptive control structure for the torsional vibration suppression in the driving system with an elastic coupling. The proportional-integral speed controller and gain factors of two additional feedback loops, from the shaft torque to the load side speed, are tuned online according to the changeable load side inertia.

In recent years, many progresses are made in SLAM, in which most methods are based on EKF (Extended Kalman Filter) [7-10]. The time complexity and the space complexity of these methods is $O(N^2)$, respectively, where N stands for the signpost amount(s) of map. As the data amount from the laser range finder increases rapidly, the SLAM based on EKF will be hard to fit the map creation in the global environment. Recently, Montemerlo et al., based on the particle filter, proposed a SLAM algorithm called FastSLAM (fast SLAM) . Its time complexity is $O(N\log K)$, where N is the amount(s) of particles, K is the signpost amount(s) of map. Now this method has attracted more attention. Currently, the particles with new positions in FastSLAM particle filter are abstracted from the proposal distribution-movement model $p(s_t|s_{t-1},u_{t-1})$. s_t is the state of robot at time t, including the coordinate (x_t,y_t) and direction angle θ_t of robot position, which are illustrated in the original paper. The model means the probability distribution of transformation from the state $s_{t-1}$to s_t when $u_{t-1}$is input. It is shown that most of the convergence properties proved by Dissanayake *et al.* in the paper can be generalized to the practical nonlinear SLAM problems. In 2007, Huang investigated the convergence properties and consistency of EKF based on SLAM . Bailey proposed an analysis of the extended Kalman filter formulation of SLAM, and showed that the algorithm produced the very optimistic estimations once the “true” uncertainty in vehicle heading exceeded a limit . Since the performance of the EKF depends on correcting a priori knowledge of process and sensor/measurement noise covariance matrices (Q and R, respectively), Chatterjee in the paper proposed the development of a new neurofuzzy based on the adaptive Kalman filtering algorithm for SLAM of mobile robots or vehicles, which attempts to estimate the elements of the R matrix of EKF algorithm, at each sampling instant when a “measurement update” step is carried out. In 2009, Holmes in the paper proposed a Square Root Unscented Kalman Filter (SRUKF) for performing the video-rate visual SLAM using a single camera, and showed that the same results as the UKF within the machine accuracy are provided in SRUKF and it can be reposed with the complexity $O(N^2)$ for the state estimation in the visual SLAM.

If the shape of the proposal distribution is similar to that one of actual posterior distribution, the particles from the proposal distribution can stand for the posterior distribution greatly after it is compensated through using weighted function to compensate . But due to the proposal distribution does not consider the current sensing information, if the posterior distribution is located in a narrow region of the proposal distribution, the corresponding sampling amounts in the large area of the weight function value is few. At this time the probability distribution of sampling has a big difference with the actual posterior distribution, leading to spread of particle filter . This is the so-called loss problem of the particle filter.

Another problem of particle filter is the premature problem, which is also called the degeneracy problem-after some generations of iteration, most particles weights tend to be zero, and only a few of particles have effect on the estimation of system state. Although this phenomenon could be avoided through sampling in a certain extent, those particles with big weight will be copied for several times, the small ones would be ignored. So it would be possible to ignore the good particles and the particles would concentrate in a small area. If the robots make the global localization in the self-similar environment, the posture assumptions of robots are necessary to be traced for a long time . The premature problem will cause the wrong positioning.

In the traditional FastSLAM, a large amount of particles are usually needed. Since each particle corresponds to a signposts map, if the amount of particles is too large, the burdens on both computation and storage would be increased greatly, and the update of every signposts map would be restricted by the limitation of EKF for it uses EKF. In this paper, combining with Polar Coordinates Scan Matching method [, we use UKF to replace EKF to design a new kind of proposal distribution. The particles are sampled through UT (Unscented Transform) with the current sensing information to make particles move towards to the high probability area of the posterior distribution . So the distribution of particles can be similar to the posterior one greatly.

Kim in the paper provided a robust new algorithm based on the scaled unscented transformation called UFastSLAM. It overcomes the important drawbacks of the previous frameworks by directly using nonlinear relations. This approach improves the filter consistency and state estimation accuracy, and requires fewer particles than the FastSLAM approach. The simulation results in the large-scale environments and the experimental results with a benchmark dataset are presented, demonstrating the superiority of the UFastSLAM algorithm.

FastSLAM is improved and a new UFastSLAM is proposed in this article, in which a new proposal distribution is proposed with the current perception information. The particles are sampled on the proposal distribution through UT to drive the particles to move to the high probability region of posterior distribution. So the high accuracy of state estimation is obtained through fewer particles. At the same time, UKF is used in the signpost updating to avoid the problem of linearizing the non linear equation in EKF of FastSLAM. A group of well chosen sigma points are used to represent the statistical characteristics of system. The sigma points are calculated through nonlinear equation, so it is unnecessary to linearize the nonlinear equation. Compared to the paper [26], the laser distance sensor is used in our method. So there is little noise in the perception data and the data is more reliable. As the result, the perception deflection is fewer. At the same time, the current perception data is carefully dealt with when sampled, so it is impossible to be premature and degenerative for the re-sampled particle and the better result is obtained.

A group of well-chosen weighted sampling points (sigma points) in UKF is used to express the statistics characteristics of system. These Sigma points are counted according to the true nonlinear equation instead of making them linear. Based on

UKF, we propose a new UFastSLAM method. Comparing to the traditional method, it has the following advantages: (1) It combines the current sensory information with the proposal distribution, where the particles from the proposal distribution are approximated to the posterior distribution, and the loss problem of particle filters are solved in a certain extent. (2) The more accurate nonlinear model is used, where the nonlinear equation is not necessary to be transformed into the linear one. And it can realize the tracking of more targets and more assumptions by the chosen Sigma points, while Kalman Filter has only one single assumption, and EKF needs to transform the nonlinear equation into the linear one. (3) It can be more accurate to estimate the average and covariance of system state with the precision of the second-order Taylor expansion. (4)Comparing to the traditional method, its robustness is stronger and its efficiency is higher.

2. SLAM description

The basic idea of SLAM is that the map creation and the robot localization are carried out simultaneously, where the created map is used to adjust the estimating error of robot posture based on the moving model to increase the localization precision, while the reliable robot posture is used to create the map with higher precision.

When robots move through an unknown environment, setting the position at time $tass_t = [x_t, y_t, \theta_t]^{\mathrm{T}}$, where, s_t is the state at time t, x_t, y_t, θ_t are coordinates of x, y and the direction angle at time t, respectively. Set M as the observed map, where$m_k$represents the signpost$k$, $k_t \in \{1, ..., N\}$ stands for the signpost index number with perception at time$t$. The complete state of the system can be expressed as$x_t = [s_{1:t}, \mathrm{M}]^{\mathrm{T}}$, where $s_{1:t} = s_1, s_2, ..., s_t$ stands for the robot moving path from 1 to time t. Also, u_{t-1}stands for the moving control information from $t-1$to time$t$, and z_t stands for the robot current perception information. Graphical model of SLAM is shown as Fig.1, robots move from the position s_0 by the control command sequence. With the movement of robots, the nearby signposts are perceived. At time t=1, signpost m_1 is perceived and the measure data z_1(including the distance and direction) is obtained, at time t=2, the signpost m_2 is perceived, and at time t=3, signpost m_1 is perceived once more. Now formed map is: M=$\{m_1$,m_2,$m_n\}$. The input information of SLAM is the signpost observed information $z_{1:t}$and the moving control information $u_{0:t-1}$.

The purpose of SLAM is to estimate the robot moving path $s_{1:t}$and themap M according to the input information. The probabilistic description form can be expressed as:

$p(s_{1:t}, \mathrm{M}|z_{1:t}, u_{0:t}, k_{1:t}) = p(\mathrm{x}_t|z_{1:t}, u_{0:t-1}, k_{1:t})$

According to Bayesian rules, we can get:

$Bel(\mathrm{x}_t) = p(\mathrm{x}_t|z_{1:t}, u_{0:t-1}, k_{1:t})$

$= \eta p(z_t|s_t, m_{k_t}, k_t)$

$\bullet \int p(s_t|s_{t-1}, u_{t-1}) p(s_{1:t-1}, \mathrm{M}|z_{1:t-1}, u_{0:t-2}, k_{1:t-1}) ds_{1:t-1}$

$= \eta p(z_t|s_t, m_{k_t}, k_t) \int p(s_t|s_{t-1}, u_{t-1}) Bel(\mathrm{x}_{t-1}) ds_{1:t-1}$

Where $Bel\ (\cdot)$is the function of Bayesian, and η is a standard constant. According

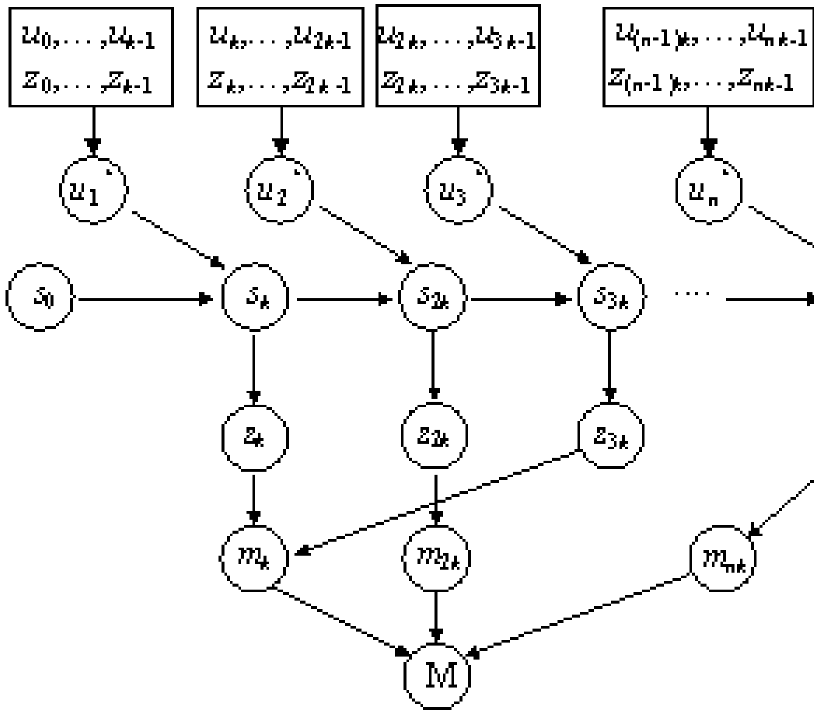

Fig. 1. Graphical model of SLAM problem

to the given distribution $p(z_t|s_t, m_{k_t}, k_t)$and$p(s_t|s_{t-1}, u_{t-1})$, the above formula can recursively estimate the posteriori probability distribution for both the map and path, where the sensing model and moving model are represented respectively as the following.

$p(z_t|s_t, m_{k_t}, k_t) = g(s_t, m_{k_t}) + \varepsilon_t, \quad \varepsilon_t \sim N(0, R_t)$

$p(s_t|s_{t-1}, u_{t-1}) = h(s_{t-1}, u_{t-1}) + \delta_t, \ \delta_t \sim N(0, P_t)$

Where $g(\cdot)$and $h(\cdot)$are functions of the perception model and motion model respectively, $\delta_t$and$\varepsilon_t$satisfy the normal distribution$N(\cdot)$. Formula gives the iterative form of SLAM problem, which is the core of SLAM problem. To realize SLAM is to solve this formula. For SLAM, it is really difficult to get the analytical form of $Bel(\mathrm{x}_t)$, so the n weighted particles similar with$Bel(\mathrm{x}_t) = \{x_t^{(i)}, w_t^{(i)}\}_{i=1,\ldots,n}$ are used in PF (Particle filter). Where$w_t^{(i)}$is the weight of particle i in time t. But since there are large amounts of signposts on the map of system state, it is impossible to solve it through PF directly. Therefore, it is needed to resolve the SLAM problem first. Since the relativity between signposts is caused by the uncertain robot positions. If the positions of robots are completely certain, the signposts are irrelevant, and the formula can be resolved as follows according to Rao-Blackwellized Particle filter:

$p(s_{1:t}, \mathrm{M}|z_{1:t}, u_{0:t-1}, k_{1:t})$
$= p(\mathrm{M}|s_{1:t}, z_{1:t}, u_{0:t-1}, k_{1:t}) \bullet p(s_{1:t}|z_{1:t}, u_{0:t-1}, k_{1:t})$
$= p(s_{1:t}|z_{1:t}, u_{0:t-1}, k_{1:t}) \bullet \prod_{k=1}^{K} p(m_k|s_{1:t}, z_{1:t}, k_{1:t})$

Where $k$stands for the signpost number of the map, namely SLAM can be resolved into $k+1$estimate problems, one of which is estimating the robot path $s_{1:t}$and other k are the signpost position in the estimating environment.

A set including n particles $\psi_t = \left\{\chi_t^{(i)} i = 1, ..., n\right\}$ is used to represent the posterior probability of system state $p\left(s_{1:t}, \mathrm{M}|z_{1:t,}u_{0:t-1,}k_{1:t}\right)$in FastSLAM, where every particle is ${\chi_t}^{(i)}=\{{\mathrm{x}_t}^{(i)},{w_t}^{(i)}\}_{i=1,...,n,}$, the state of particles ${\mathrm{x}_t}^{(i)}=[{s_{1:t}}^{(i)},\mathrm{M}^{(i)}]^T$, ${s_{1:t}}^{(i)}$ is the moving path of the particle i, and $\mathrm{M}^{(i)}$ is the created map according to the moving path ${s_{1:t}}^{(i)}$ .The corresponding robot position which each particle represents for is completely certain, therefore the formula can be ensured to be correct. The traditional FastSLAM is divided into following steps:

(1)Sampling robot's new posture;
(2)Counting the weight of particles;
(3)Update of signpost posture;
(4)Sampling once more.

3. UFastSLAM

3.1. Unscented Transform

Unscented Transform is a new method of computing random variable statistic characteristics of nonlinear transform. It is built from the idea as: estimating a Gaussian distribution is easier than estimating a random nonlinear function transform. Suppose the mean of n_x dimension random variable x is$\bar{x}$, the variance is P_{xx}, and random variable y is the nonlinear function of x: $y = g(x)$ In order to estimate the mean$\bar{y}$and variance $P_{yy}$of random variable y, UT chooses a group of random sampling x_i according to a specific and certain algorithm. The mean and variable of this group of random sampling x_i is$\bar{x}$and P_{xx}. when the nonlinear transform $g(.)$ is applied to each sampling, a group of sampling y_i after transforming is obtained. This group of sampling represents the statistic characteristics of random variable y greatly. The specific steps of transform are as follows:

(1) A group of random sampling points $_i$??$\{\chi_i,w_i\}$ is computed according to the following equations:

$\chi_0 = \bar{x},$
$w_0 = \kappa/(n_x + \kappa), \;\; i = 0$
$\chi_i = \bar{x} + (\sqrt{(n_x + \kappa)P_{xx}})_i,$
$w_i = 1/2(n_x + \kappa) \;\; i = 1, ..., n_x$
$\chi_i = \bar{x} - (\sqrt{(n_x + \kappa)P_{xx}})_i,$
$w_i = 1/2(n_x + \kappa) \;\; i = n_x + 1, ..., 2n_x$

Where κ is the scale parameter, and$(\sqrt{(n_x + \kappa)P_{xx}})_i$ is the column i of the square root matrix of$(n_x + \kappa)P_{xx}$, and w_i is the weight of the i sampling point χ_i, satisfying$\sum_{i=0}^{2n_x} w_i = 1$,

(2) According to the nonlinear function $g(.)$, the sampling y_i of the random variable y is computed:

$y_i = g(\chi_i) \qquad i = 0, ..., 2n_x$

(3) The mean $\bar{y}$ and variance P_{yy} of random variable y are computed as follow:

$\bar{y} = \sum_{i=0}^{2n_x} w_i y_i, \quad P_{yy} = \sum_{i=0}^{2n_x} w_i (y_i - \bar{y})(y_i - \bar{y})^T$

To any nonlinear function $g(.)$, the precision of above estimation of mean and covariance could be the second order Taylor expansion in Unscented Transform, without linearizing the nonlinear equation, and the error produced can be controlled by scale parameter κ . Comparing with EKF, three methods are considered: the first one is the similar posterior distribution of Montemerlo method to the 5000 sampling from Gaussian priori distribution after the random nonlinear transform. And the second one is EKF method, approximating the posterior distribution of the random variable by make the nonlinear function linearization. Obviously, the error of the posterior mean and variance after approximating is large. Only 5 sigma points to approximate the posterior distribution are enough in the above UT introduced.

3.2. UFastSLAM Based on Unscented Kalman Filter

Because of the above advantages of UT in solving nonlinear and non-Gaussian problems, when the maps of indoor environment are created, considering the complexity of the environment, UT is taken into FastSLAM to make the reliable approximation of posterior distribution for robot postures with the scanning match method of laser original data points, which overcomes the loss problem in the traditional particles method, and takes sampling once more by effective self-adaption. So the amount of particles is decreased greatly and a good approximating posterior distribution by only a few of particles is met. Besides, in this paper, the laser position is taken as a signpost based on the scanning match method, the related laser data is saves into the map, and a new kind of signpost creation and update method are proposed to make the map produced reliable and effective.

3.2.1. Take sample of new positions based on UT and scanning match method The current perception information z_t is taken into the traditional proposal distribution $p(s_t/s_{1:t-1}{}^{(i)},\ u_{1:t-1},\ z_t)$ to make the particles sampled from the priori distribution move towards the posterior high probability area. The traditional method approaching to this probability is to use the Gaussian approximation produced by EKF:

$p(s_t|s_{1:t-1}^{(i)}, u_{1:t-1}, z_t) \sim N(s_t, \bar{s}_t, P_{s_t})$

in EKF, the first order Taylor expansion of the mean $\bar{s}_t$ is used to approximate with the nonlinear perception function $z_t = g(\mathrm{M},\ s_t)$:

$z_t = g(\mathrm{M}, s_t) \sim g(\mathrm{M}, \bar{s}_t) + \Delta_{s_t} g'(\mathrm{M}, \bar{s}_t)$

So the mean and variance of the perception variable z_t respectively are:

$\bar{z}_t = g(\mathrm{M}, \bar{s}_t), \quad P_{z_t} = g'(\mathrm{M}, \bar{s}_t)^T P_{s_t} g'(\mathrm{M}, \bar{s}_t)$

In this paper, UT is used to compute the mean $\bar{z}_t$ and variance P_{z_t} of the perception variable z_t, so the precision could be the second order Taylor expansion. Setting L as the dimension of s_t , it can be divided into the following steps:

(1)Produce 2L+I Sigma points $_i$ $\{\chi_i, w_i\}$
$\chi_0 = \bar{s}_t, \quad \chi_i = \bar{s}_t + (\sqrt{(L+\lambda)P_{s_t}})_i, \quad i = 1, ..., L$
$\chi_i = \bar{s}_t - (\sqrt{(L+\lambda)P_{s_t}})_i, \quad i = L+1, ..., 2L$
$w_0^m = \lambda/(L+\lambda), \quad w_0^c = w_0^m + (1-\alpha^2+\beta)$
$w_i^m = w_i^c = 1/2(L+\lambda),$
$\lambda = \alpha^2(L+\gamma) - L, \quad i = 1, ..., 2L$
Where γ is a scale parameter to control the distance of Sigma points between mean$\bar{s}_t$, α is a positive scale parameter to control the high effect produced by the nonlinear function $g(.)$, β is a weight parameter to control the sigma point 0, and α=0??β=0 and γ=2 are usually the optimal values. Note that when computing the mean and the variance, respectively, the corresponding weights of sigma point 0 are ${w_0}^m$ and ${w_0}^c$.

(2)According to the nonlinear function $g(.)$, the sampling$y_i$of the random variable y is computed as
$y_i = g(\chi_i), i = 0, \ldots, 2L$
(3) The mean$\bar{y}$and variance $P_{yy}$of random variable y is computed as
$\bar{y} = \sum_{i=0}^{2L} w_i^m y_i, \quad P_{yy} = \sum_{i=0}^{2L} w_i^c (y_i - \bar{y})(y_i - \bar{y})^T$
Next new position ${s_t}^{(i)}$ can be sampled to expand the robot paths ${s_{1:t}}^{(i)}$ according to the UT algorithm by absorbing the proposal distribution $p(s_t/{s_{t-1}}^{(i)}$, u_{t-1}, $z_t)$ from the current perception information z_t :

(1)The posture i of the priori random variable s_{t-1} is estimated to compute the particle amount of 2L+1 sigma points$\{\chi_{t-1}^{(i),(j)}, w_{t-1}^{(i),(j)}\}$ (i=1,...,N is the amount of particles, j=1,..,2L+1 is the amount of sigma points).

(2)The movement model prediction is applied. The model input information is divided into two kinds: based on the odometer reading data and based on the scanning match result. Since the odometer reading data translation$d_t^{(i)}$and deflection$\alpha_t^{(i)}$ are reliable in a short distance range, at this time the input information of the movement model$p(s_t^{(i)}|s_{t-1}^{(i)}, u_{t-1}^{(i)})isu_{t-1}^{(i)} = \{d_{t-1}^{(i)}, \alpha_{t-1}^{(i)}\}$. But as the increasing of the distance, the accumulation of the odometer reading data error increases. The laser scanning match method is used to adjust, in which the scanning match is computed every k steps, and the translation$d_t^{(i)}$and deflection$\alpha_t^{(i)}$relative to the past moment are estimated according to the perception information of the past $k-1$ steps and the odometer reading data of recent step k. Shown as Fig.1, the input information of the movement model is $u_{t-1}^{(i)} = \{d_{t-1}^{(i)}, \alpha_{t-1}^{(i)}\}$, and the prediction based on the movement model is:

$$BH_{Y_{t-1}-D} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\alpha D_{t0}) & -\sin(\alpha D_{t0}) \\ 0 & \sin(\alpha D_{t0}) & \cos(\alpha D_{t0}) \end{bmatrix}$$

Where the robot movement model$p(s_t^{(i)}|s_{t-1}^{(i)}, u_{t-1}^{(i)})$ is represented by$f(s_{t-1}^{(i)}, u_{t-1}^{(i)})$, $\chi_{t-1}^{(i),(j)} = [x_{t-1}^{(i),(j)}, y_{t-1}^{(i),(j)}, \theta_{t-1}^{(i),(j)}]^T$ stands for the position of the robot in particle i and sigma point j at time t-1. The movement model describes the robot position at time t-1 is$s_{t-1}^{(i)}$??with the condition that the input information is$u_t^{(i)}$, and the probability distribution of the robot position at time t. Usually take the following movement model:

$x_t = x_{t-1} + d_t \cos(\theta_{t-1} + \alpha_t),$
$y_t = y_{t-1} + d_t \sin(\theta_{t-1} + \alpha_t),$
$\theta_t = \theta_{t-1} + mod(\alpha_t, 2\pi)$
(3) Absorb the current perception information z_t:

$$(\alpha D_{t-1}, \beta D_{t-1}, \gamma D_{t-1}) = (\alpha D_{t_0}, \beta D_{t_0}, \gamma D_{t_0}) * \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\alpha D_{t-1}) & -\sin(\alpha D_{t-1}) \\ 0 & \sin(\alpha D_{t-1}) & \cos(\alpha D_{t-1}) \end{bmatrix}$$

(4)The robot's new posture ${s_t}^{(i)}$ is sampled, and the robot path ${s_{1:t}}^{(i)}$ is expanded:
$s_t^{(i)} \sim p(s_t | s_{1:t-1}^{(i)}, u_{1:t-1}, z_t) = N(s_t; \bar{s}_t^{(i)}, P_t^{(i)})$
$s_{1:t}^{(i)} = (s_{1:t-1}^{(i)}, s_t^{(i)})$

3.2.2. Geometry of the plate Thinking of the laser original data with much information of environment, in this paper the laser scanning positions are treated as the signposts instead of the traditional feature positions. At the same time of updating the signposts, the scanning data related to the laser scanning position is saved into the map. Once the distance that the robot moving to the nearest signpost is beyond a certain range (for example 80cm), a new signpost will be created. If the robot moving distance is short (for example 30cm and the rotation angle is less than 15?), the signpost will not be updated, for in a short time the odometer reading data is more reliable than the scanning match result.

Updating the signposts means to realize the posterior estimation of $m_{k_t,t-1}^{(i)} = \{\mu_{k_t,t-1}^{(i)}, \Sigma_{k_t,t-1}^{(i)}\}$in the particle i and signpost k_t. The updated value $\{\mu_{k_t,t}^{(i)}, \Sigma_{k_t,t}^{(i)}\}$ and the new sampling position ${s_t}^{(i)}$ of robot are put into the temporary particles set $?_t$, and the update of signpost k_t depends on if it is perceived at time t. If matched, the posture is updated. If not, it means that it is not perceived, the posture remains unchanged. The update is as follows:

$$\begin{aligned} & p(m_{k_t,t}^{(i)} | z_t^{(i)}, s_t^{(i)}, k_t) \\ & = \frac{p(z_t^{(i)} | m_{k_t,t}^{(i)}, s_t^{(i)}, z_{1:t-1}^{(i)}, k_t) p(m_{k_t,t}^{(i)} | s_t^{(i)}, z_{1:t-1}^{(i)}, k_t)}{p(z_t^{(i)} | s_t^{(i)}, z_{1:t-1}^{(i)}, k_t)} \\ & = \eta \underbrace{p(z_t^{(i)} | m_{k_t,t}^{(i)}, s_t^{(i)}, z_{1:t-1}^{(i)}, k_t)}_{\sim N(z_t; g(m_{k_t,t}^{(i)}, s_t^{(i)}), R_t)} \underbrace{p(m_{k_t,t}^{(i)} | s_t^{(i)}, z_{1:t-1}^{(i)}, k_t)}_{\sim N(m_{k_t,t}^{(i)}; \mu_{k_t,t-1}^{(i)}, \Sigma_{k_t,t-1}^{(i)})} \end{aligned}$$

Where the probability$p(m_{k_t,t-1}^{(i)} | z_{t-1}^{(i)}, s_{t-1}^{(i)}, k_t)$at time t-1 is represented as Gaussian distribution$N(\mu_{k_t,t-1}^{(i)}, \Sigma_{k_t,t-1}^{(i)})$, and the new estimation at time t is also of Gaussian. It is needed to produce the Gaussian approximation of the perception model. We use UT method to approximate the nonlinear perception function$g(m_{k_t,t}^{(i)}, s_t^{(i)})$:

(1)Produce 2L+1 sigma points $(\xi_{k_t,t-1}^{(i),(j)}, w_{k_t,t-1}^{(i),(j)})$, j 0,..., $2L$:

$$LDn_{t-1} = (xD_{t-1}, yD_{t-1}, zD_{t-1}) = SDn_{t-1} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\delta_x) & -\sin(\delta_x) \\ 0 & \sin(\delta_x) & \cos(\delta_x) \end{bmatrix}$$

(2)The perception model is used to compute the mean and covariance of perception:

$A = -\{xD_{t_0}\sin(\gamma D_{t-1})[yD_{t0} \bullet \cos(\alpha D_{t-1}) + zD_{t0} \bullet \sin(\alpha D_{t-1})]\}\sin(\sigma_x)$

(3) According to this approximation, the position posterior of signpost $m_{k_t,t}^{(i)}$ is of Gaussian distribution, and the mean and variance update as the following rules:

$$D = \cos(\delta_x)\{-xD_{t0}\sin(\gamma D_{t-1}) + \cos(\gamma D_{t-1})[yD_{t0}\cos(\alpha D_{t-1}) + zD_{t0}\sin(\alpha D_{t-1})]\}$$

3.2.3. The computation of the particle weights The particles sampled from the proposal distribution can not approximate the posterior distribution well probably, and the difference between them needs to be measured by a kind of evaluation, so the weight coefficient is defined as follows:

$w_t^{(i)}$ = target distribution/proposal distribution

Where the target distribution is the posterior distribution$p(s_{1:t}^{(i)}|z_{1:t}, u_{1:t-1}, n_{1:t})$of approximating robot path of the particles sampled. Suppose the paths$s_{1:t-1}^{(i)}$ at the moment before is produced as the posterior distribution$p(s_{1:t-1}^{(i)}|z_{1:t-1}, u_{1:t-2}, n_{1:t-1})$.

The above formula can be obtained through the linear approximation of nonlinear perception function g in the perception z_t, and the mean$\bar{z}_t^{(i)}$and the varianceQ_t (the formula 21) are obtained directly by UT in this paper, so the weight of the particle i is similar to:

$C = xD_{t0}\cos(\gamma D_{t-1}) + \sin(\gamma D_{t-1})[yD_{t0}\cos(\alpha D_{t-1}) + zD_{t0}\sin(\alpha D_{t-1})]$

3.2.4. Self-adaptive re-sampling Re-sampling can have a great effect on the performance of particle filter. Not only the low weight particles are replaced by the high weight particles, but also only those limited and necessary particles are allowed to approximate the posterior at the same time. So when there are lots of differences between propose distribution and posterior distribution, it is very important to take sample again. But sampling again may also ignored some high weight particles in the particles set, and the worst result may lead the filter diverged. For this, we define an effective value N_{eff}, self-adaption sampling again according to the effective value:

$N_{eff} = 1/\sum_{i=1}^{n}(w^{(i)})^2$

It is the effect of the approximate posterior of current particle set, which is used to decide whether to sample again or not.

4. Experiment

The pseudocodes of key part in the proposed arithmetic are described as follow:

Initialize parameters α,β,λ, $S_t = \emptyset, S'_t = \emptyset$;
for all particles
Sample s_{t-1};
Computing the mean $\bar{s}_{t-1}$and variance $P_{s_{t-1}}$;
Produce $2L$+1 sigma points $\xi^i_{t-1}\{\chi^i_{t-1}, w^i_{t-1}\}$;
Estimation the new points$\{\chi^{(i)}_{t|t-1}, w^{(i)}_{t|t-1}\}$
according to the motion model;
Absorb the current perception information z_t;
Upate the sigma points$\{\chi^i_t, w^i_t\}$;
Sample new $s^{(i)}_t$, and expand the robot paths$s^{(i)}_{1:t}$;
Use the perception model to compute the mean $\bar{z}_t$
and covariance Q_{z_t};
Computing the importance weights w^i_t;
Upate S'_t;
End for
Adapt resampling from S'_t;
Update S_t;

We use the Pioneer3-DX indoor capacity moving robots of company ActiveMedia. The senor robots have includes the odometer, the collision senor, the laser telemeter, the sonar senor and CCD camera. The odometer can estimate the translation distance and rotation angle of the robots, but it is easily influenced by the robot wheels slipping. The robot experiment environment for creating the map is the indoor office environment. The rooms are connected by the doors and corridor. The robot can move free, and the doors are all opened to keep the robot going across free. Shown as Fig.2, the dotted line in the figure stands for the robot moving path. The robot starts from the starting point S, and goes back to the finishing point E after going across every room. The robot completes the creating experiment of the measure map. The details of the creating process are shown as Fig.3. The black cloud around in the figure stands for the laser scanning data, and the red round entity stands for the robot, and the curve behind the robot stands for the robot moving path. The final created measure map is shown as Fig.4. At the same time, we use the traditional FastSLAM method to create the measure map as well. And from the created measure map we can see that the one using the method of this article is basically the same as the environment model, so it can describe the environment well. And the one using the traditional FastSLAM method, because the error of the robot positions is too large, leads many redundancy laser scanning points. So it can not correspond to the actual environment well.

The specific performance comparison of UFastSLAM and FastSLAM is shown as Fig.5. From the figure we can see that although the man signposts is few, because of the increasing of time caused by unscented transform, as the increase of the signposts numbers, the Sigma points gained by unscented transform will decrease greatly the needed time for the algorithm running and the needed save memory. The algorithm in this article can convergence faster, and the traditional algorithm need a large number of particles to gain a high positioning accuracy, and the positioning accuracy is easily influenced by the number of particles. But the algorithm used in this article can reach a higher accuracy by taking only a few particles. When the number of particles reaches a certain number, the positioning accuracy will not be influenced by the number of particles.

Fig. 2. Experiment environment

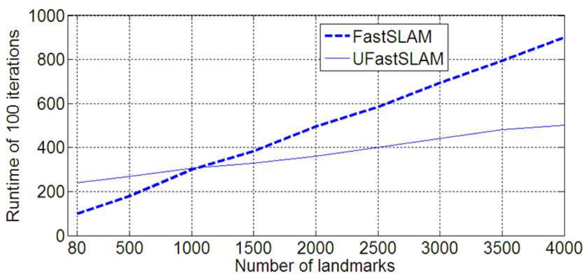

Fig. 3. Performance comparison of UFastSLAM with FastSLAM

5. Conclusion

A novel UFastSLAM based on UKF is proposed, in which the novel proposal distribution that integrates the current observation is proposed to drive the particles sampled from the proposal distribution based on UT to move towards the high density area of posterior distribution, so the fairly high precision state estimation with fewer particles could be obtained. A group of sigma point is used to approximate the system statistical properties, and Sigma points are calculated based on the nonlinear equation instead of linearizing the equation, so it has the superior performance over EKF in both the theory and the real application. Compared to the traditional FastSLAM, UFastSLAM has many superior performances.

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