Research on Simultaneous Location and Mapping Algorithm of Intelligent vehicle Based on Improved Particle Filter Resampling

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Abstract
For the estimation problem that the Simultaneous Location and Mapping algorithm used in Intelligent vehicle suffers from sample impoverishment, a Multi-threshold differential evolutionary particle resampling method is proposed. The method adopts different particle updating strategies according to different thresholds of effective particle numbers. Particle diversity will be rapidly improved by differential evolution when particle degradation is severe. When the particle degradation is light, the system resampling method is directly used to copy the large weight particles and eliminate the small weight particles. By adopting different particle regeneration strategies for particles with different degrees of degradation, the problem of particle degradation and depletion in the process of state estimation can be effectively solved. Simulation experiments show that the root mean square error of the improved algorithm pose is reduced by 2.592m compared with the traditional algorithm. The road sign estimation root mean square error is also reduced by 2.428m compared with the traditional algorithm. Experiments show that the multi-threshold differential particle filter resampling method can effectively improve the particle diversity and ensure the state estimation accuracy of the vehicle.

Keywords: Particle filter, simultaneous location and mapping, multi-threshold, resampling, differential evolution

1. Introduction
Simultaneous Location and Mapping (SLAM) is the premise for Intelligent vehicle to complete other complex tasks. Accurate positioning requires accurate map construction. While, the construction of accurate maps requires the accurate positioning of vehicles\[9\]. Therefore, the realization of high-precision positioning and map construction has attracted many researchers’ attention.

Aiming at the problem that the simultaneous location and mapping algorithm of Intelligent vehicle, the vehicle pose and environmental roadmap are estimated mainly by probability method. Extended Kalman filtering and particle filtering are the main directions for solving SLAM problems. The extended Kalman filter algorithm mainly solves the weak linear Gaussian system, and the particle filter algorithm can solve the problem of the nonlinear non-Gaussian system. Particle Filtering originated from Monte Carlo Thoughts. Therefore, the traditional SLAM algorithm uses the Rao-Blackwellised particle filter method to estimate the vehicle’s own pose and environmental roadmap. However, the particle filter algorithm will suffer from sample impoverishment during the loop iteration. Doucet\[2\] theoretically proved the inevitability of particle degradation in this algorithm. Therefore, Gorden et al.\[3\] introduced a resampling step in the filtering process. However, the resampling process leads to a new problem of reduced particle diversity, which also could not improve the accuracy of state estimation. Many scholars have studied the strategy of resampling.

In order to solve the problem of particle diversity reduction, a multi-threshold differential evolution resampling particle filter SLAM method is proposed. According to the different states of the particles, different particle update strategies are adopted to ensure the accuracy of the state estimation.

2. Application of Intelligent vehicle particle filter SLAM algorithm
The basic particle filtering SLAM algorithm is described as follows. When the current position of the vehicle is known, the positional state of the vehicle at the next moment is predicted by the motion model and the observation model of the vehicle. At the same time, the predicted position of the vehicle is corrected by the observation information of the laser radar or the depth.
camera. Assume that the state vector of the vehicle in\( t \) is\( x_{t|t} = [x_1, x_2, ..., x_n] \). The observation vector of the surrounding environment information is\( y_{t|t} = [y_1, y_2, ..., y_l] \). The vehicle’s control vector is\( u_{t|t} = [u_1, u_2, ..., u_k] \), and the road signs is\( M = [m_1, m_2, ..., m_k] \). Then the simultaneous location and mapping algorithm of the vehicle can be regarded as the problem of solving the posterior probability density distribution. According to independence conditions based on SLAM environmental road signs. The road sign of the vehicle\( t + 1 \) moment and the position state of the vehicle can be expressed as a joint posterior probability.

\[
P(x_{t+1|t}, m|y_{t+1|t}, u_{t+1}) = P(m|x_{t+1|t}, y_{t+1|t})P(x_{t+1|t}, y_{t+1|t}, u_{t+1})
\]

The joint posterior probability of the above formula adopted Rao-Blackwellized transform method. Decompose the simultaneous positioning and map construction process into vehicle state estimation and environmental road sign estimation. In the SLAM algorithm, the extended Kalman filter is used to estimate the environment map, and the particle filter is used to estimate the position of the vehicle. Each particle represents a possibility for vehicle position and environmental road signs. It approximates the real vehicle state through a large collection of particles. The detailed algorithm steps are described as follows.

Step 1: Particle Importance Sampling. Using the realistic importance probability density as the recommended distribution of sampling could reflect the actual state of the vehicle realistically. In the basic SLAM algorithm, the observation information of the lidar and the odometer are selected as the importance suggestions. Suppose that the set of particles sampled at time \( t \) is \( N = [x_1^t, x_2^t, ..., x_n^t] \).

Step 2: Calculation and normalization of weights. Each particle corresponding to a weight. The size of the weight represents the probability that the particle is close to the real state. According to the importance sampling principle, the weight of the \( n \)th particle sampled at time \( t \) can be expressed as follows.

\[
\omega_i^{(n)} = \frac{p(x_{t|t}^{(n)}|y_{t|t}, u_{t|t})}{q(x_{t|t}^{(n)}|y_{t|t}, u_{t|t})}
\]

Where \( q \) represents the suggested distribution of importance samples. Then weight normalize the particles.

\[
\bar{\omega}_i^{(n)} = \frac{\omega_i^{(n)}}{\sum_{i=1}^{n} \omega_i^{(n)}}
\]

Step 3: Particle Resampling. Firstly, calculate the effective particle number \( N_{eff} \) as a variable to weigh the degree of particle degradation. When the value of \( N_{eff} \) is less than the set threshold, the resampling operation is performed. The approximate formula for \( N_{eff} \) is expressed as follows.

\[
N_{eff} = \frac{1}{\sum_{i=1}^{n} (\omega_i^{(n)})^2}
\]

Step 4: Filtering and map update. The resampled particles are averaged to estimate the true state, and the environment map is updated incrementally.

3. IMPROVED RESAMPLING SLAM ALGORITHM

To solve the problem of particle depletion in SLAM algorithm. On the one hand, a better importance probability density function can be selected as the proposed distribution, and the particles can be directly sampled. It can accurately reflect the state of the vehicle; On the other hand, by improving the resampling method, the particles are moved to the high likelihood region, and the effective particle number is increased to increase the performance of the particle estimation. This paper starts with improving particle resampling, proposed a multi-threshold differential evolution particle resampling method. It was introduced into the SLAM algorithm.

3.1 Division of effective particle number threshold

The traditional particle filter resampling process usually sets the unique effective particle number as the condition for resampling. It can not adaptively resample operations based on the actual situation of particle degradation. When the value of \( N_{eff} \) is set too large, it is easy to cause excessive resampling, which accelerates the problem of particle depletion; If the value of \( N_{eff} \) is set too small. It also leads to the problem of low estimation accuracy. Therefore, this paper proposes a multi-threshold particle update method. It can perform different resampling operations at the right time during the overall operation of the particle filter algorithm. Multi-threshold division rules include the following.

(1) When the effective particle number is \( N_{eff} < 60\% \), it indicating that the particle is seriously degraded, the differential evolution resampling operation is performed on the particle, and the particle diversity is rapidly increased by the cross variation of the particle.
(2) When the effective particle number is 60%<\(N_{eff}\)<80%, the particle degradation problem is lighter. According to the traditional random resampling method, the large weight particles are duplicated, and the small weight particle process is eliminated to solve the particle degradation problem.

(3) When the effective particle number \(N_{eff}\) > 80%, the particles are basically not degraded, and no resampling operation is performed.

3.2 Differential evolution resampling

In the case of the effective particle number \(N_{eff}\) <60%, the differential evolution method is used to update the particles. The differential evolution algorithm uses a random heuristic search algorithm. The main idea of this algorithm is to continuously evolve, retain good individuals, eliminate inferior individuals, and finally guide the search to the optimal solution\[^4\]. The differential evolution algorithm operation mainly includes the process of mutation, intersection and selection. The differential evolution particle update steps are as follows.

(1) Population initialization. \(N\) particles are sampled according to the particle filter importance probability density function. These particles are used as initial populations, and the particles are encoded by real-number coding. Each individual is represented as:

\[x_{i,G}(i = 1, 2, ..., N)\]

Where \(i\) denotes the sequence of the particle, \(G\) denotes the algebra of evolution, and \(N\) denotes the number of populations.

(2) Population variation. According to formula (5), all particles in the population are mutated to generate new particles \(v_{i,G+1}\). Where \(r1, r2, r3\) is randomly generated particle numbers. They are different from each other. \(F \in [0,1]\) is the real factor of the variation. It controls the amount of deviation of new particles.

\[v_{i,G+1} = x_{i,G} + F(x_{2,G} - x_{3,G})\]  \hspace{1cm} (5)

(3) Population cross. The crossover operation is introduced according to the formula(6), while increasing the diversity of the interference parameter vector and generating new particles.

\[u_{i,G+1} = \begin{cases} v_{i,G+1}, & \text{if } rand(0,1) < CR \\ x_{i,G+1}, & \text{otherwise} \end{cases}\]  \hspace{1cm} (6)

Where \(CR\) is the crossover operator and \(rand(0,1)\) is a random number in the interval [0,1].

(4) Population selection. Using the weight of the particle as the fitness function. Comparing the new particles generated by (6) with the original particles, and selecting the new generation of population particles for the state estimation. that is:

\[x_{i,G+1} = \begin{cases} u_{i,G+1}, & \text{if } f(u_{i,G+1}) > f(x_{i,G}) \\ x_{i,G}, & \text{otherwise} \end{cases}\]  \hspace{1cm} (7)

(5) End. Determine whether to perform the next generation iteration by calculating the effective particle number of the new particle. When the number of effective particles \(N_{eff}\) >80%, the differential evolution algorithm ends. Then normalize the new particle weights and estimate the vehicle state with the new particles; If \(N_{eff}\) <80%, go to the next iteration.

Through the above, The overall process of multi-threshold differential evolution resampling is shown in Figure 1.

4. SIMULATION EXPERIMENT AND ERROR ANALYSIS

4.1 Simulation Experiment

The simulation experiment was conducted by using the vehicle simulation dataset published by the University of Sydney\[^5\]. The experimental environment
is 200 meters long and 160 meters wide. The vehicle path is pre-set during the experiment. The vehicle has a line speed of 3m/s, a maximum steering angle of 30 degrees, and a wheelbase between wheels of 4m. The maximum observation distance of the sensor is 30m. In the case of 50 identical initial particles, the simulation experiments were carried out under the traditional algorithm and the improved resampling SLAM algorithm. Figure 2 is a comparison of simulation results. In the figure, the green "*" is the actual road sign for the environment, and the red "." is the estimated road sign. The solid red line is the actual path of the vehicle, and the solid blue line is the estimated path of the vehicle. It can be seen from figure 2(a) that the estimated path of the vehicle is greatly deviated from the actual path, and the difference between the landmarks is large, especially in the later stage of the algorithm, the deviation is getting larger and larger. The experiment shows that the traditional SLAM algorithm resampling process simply copies large weight particles and eliminates small weight particles, which causes the vehicle to lose a lot of useful information, which eventually leads to large deviation between its own positioning and map estimation. Figure 2(b) is a simulation result of the SLAM algorithm for improved resampling. It can be seen that the vehicle’s own pose estimation and environmental road sign estimation can achieve higher precision. When the vehicle runs one circle, the vehicle pose and the environmental road sign have less deviation.

4.2 Error Analysis

The effectiveness of the proposed algorithm is estimated by using the vehicle pose estimation x-direction error, y-direction error and environmental landmark error. Figure 3 is a comparison of the three kinds of errors between traditional algorithm and improved algorithm. It can be seen from Figure 3(a) and (b) that the vehicle pose estimation x coordinate error and y coordinate error of improved algorithm are lower than the traditional algorithm. It can be seen from figure 3(c) that the estimation error of the improved algorithm for the landmark is also significantly smaller than that of the traditional algorithm. The improved road sign estimate error curve is more gradual than the traditional algorithm.
In order to further analyze the performance of the improved algorithm, the positional root mean square error RMSE is used as the quantitative evaluation index. The estimation performance of the two algorithms is evaluated by comparing the root mean square error of vehicle and road sign between the traditional algorithm and the improved algorithm. Equation (8) shows the formula for calculating RMSE.

\[
RMSE_i(x_i, \hat{x}_i) = \frac{1}{MC} \sum_{i=1}^{MC} (\|x_i - \hat{x}_i\|_2)^2
\]

Where \( x_i \) is the actual position of the vehicle, \( \hat{x}_i \) is the estimated position of the vehicle, and MC is the number of simulations of the particle Monte Carlo. Table 1 compares the root mean square error of vehicle position and landmark estimation with traditional and improved algorithm. It can be seen that the positional root mean square error of the improved SLAM algorithm is reduced by 2.592m compared to the conventional algorithm. The road sign estimation error is reduced by 2.428m compared with the traditional algorithm. It is further proved that the multi-threshold differential evolution resampling SLAM method can effectively improve the particle diversity and improve the overall estimation accuracy of the algorithm.

<table>
<thead>
<tr>
<th>experiment</th>
<th>vehicle position NMSE/m</th>
<th>environmental road sign NMSE/m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional</td>
<td>5.603</td>
<td>4.952</td>
</tr>
<tr>
<td>improved</td>
<td>3.011</td>
<td>2.524</td>
</tr>
</tbody>
</table>

4.3 Conclusion

In this paper, a multi-threshold differential evolutionary particle filter SLAM method is proposed. During the running of the algorithm, different particle update strategies are adopted according to different thresholds of effective particles. Especially when the particle degradation is serious, the differential evolution particle regeneration method can effectively ensure the particle diversity. Simulation experiments show that the proposed method can effectively reduce the vehicle pose estimation error and landmark estimation error caused by particle degradation and sample depletion. Compared with the traditional algorithm, the improved algorithm vehicle pose and road sign error are reduced by at least 2m.

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Reference


