개선된 UKF 를 기반의 다종 로봇 SLAM
Multi-robot SLAM(Simultaneous Localization and Mapping) Based on Enhanced Unscented Kalman Filter

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Key words : UKF, SLAM, EKF, Multi-robot, Map fusion

1. Introduction

To achieve truly autonomous robot, the robot must be able to localize itself in an exploring environment. If we don't have an available map, the robot should build the map and perform its localization at the same time. Many methods can be used to solve this problem effectively [1]. However, in practical, we always need robot to implement SLAM in a large or complicated environment. It will spend so much time if only one robot is made to implement this task. Thus, we have to make multi-robot to implement one task. When the robots are working, each robot solves only one SLAM problem, and then fuse their maps to a common map.

To solve the multi robot SLAM, we have many methods which almost base on the EKF algorithm and assuming main robot [2,3]. When the robots meet, the additional robots' information is transformed to the main robot's frame. However, there are some duplicate landmarks in each robot's observation and many people choose to ignore the duplicate landmarks of additional robots [4]. However, if the additional robots' all landmarks are duplicate, we can not get a good performance. To solve this problem we will adopt a new strategy.

In this paper, we extended UKF method to solve the multi robot SLAM problem. We decompose the multi robot SLAM problem into two cases as the known initial poses case and unknown initial poses case. In the first case, we assume each robot knows its pose (position and angle). We can give the robots different controls to achieve a task, and build the common map at the same time. The second case introduces how to solve the problem if we don't know the robots' initial poses. This is an important case, because in practical we can not decide the initial poses of the robots.

2. Multi Robot SLAM with Known Initial Poses

We can easily extend the single robot problem to this case. At first, generate an augmented state vector with mean and covariance.

$$\mu_t^a = \begin{bmatrix} \mu_t^{R_1T} & \mu_t^{R_2T} & \mu^{mT} & \mu^{vT} & \mu^{zT} \end{bmatrix}^T \qquad (1)$$

$$\Sigma_t^a = \begin{bmatrix} \Sigma_t^{R_1 R_2 m} & 0 & 0 \\ 0 & \Sigma_t^v & 0 \\ 0 & 0 & \Sigma_t^z \end{bmatrix} \qquad (2)$$

Where μ^m is the map, μ^v is motion noise of all robots. μ^z is measurement noise of all robots. Σ is covariance of the state. Thereafter, we need generate sigma points which can be created as follows:

$$\chi_t^a = [\chi_{t,0}^a \quad \chi_{t,j}^a \quad \chi_{t,j+n}^a] \qquad (3)$$

The robots are propagated forward in time through the non-linear state equation to get the predicted means and covariances of all robots respectively.

When the measurement stage, there are two cases, the landmark is duplicate or independent. If the landmark is measured by only one robot, we let the robot update the map using the landmark. Else, let each robot that obtained the landmark update the map using the landmark in sequence. In the process, after each robot update the map, we should generate the sigma point again to let the next robot update the map using new map information.

3. Multi Robot SLAM with Unknown Initial Poses

In practical, knowing the initial poses may be impractical if the distance between robots is so long. Therefore, we exploit the notion of encounter to determine the relative pose of robots. We start mapping (*common map*) with only the first robot and each additional robot makes its own map. When each additional robot waits the first encounter with the main robot, incorporate data from the robot into the common map.

When two robots encounter, they can measure the distance and bearing from each other.

$$ {}^{i}z_j = \begin{bmatrix} {}^{i}\rho_m \\ {}^{i}\theta_j \end{bmatrix} + \begin{bmatrix} \varepsilon_\rho \\ \varepsilon_{{}^{i}\theta_j} \end{bmatrix} \tag{4} $$

Since the two distance measurements are independent, we can combine them.

$$ Z = \begin{bmatrix} \rho_m \\ {}^{1}\theta_2 \\ {}^{2}\theta_1 \end{bmatrix} + \begin{bmatrix} \varepsilon_\rho \\ \varepsilon_{{}^{1}\theta_2} \\ \varepsilon_{{}^{2}\theta_1} \end{bmatrix} \tag{5} $$

And then, generate the compound mean vector and covariance.

$$ \mu^a = \begin{bmatrix} {}^{G_1}\mu_{R_1} \\ {}^{G_2}\mu_{R_2} \\ \varepsilon \end{bmatrix} \qquad \Sigma^a = \begin{bmatrix} \Sigma_{R_1} & & \\ & \Sigma_{R_2} & \\ & & \Sigma_\varepsilon \end{bmatrix} \tag{6} $$

Where, ${}^{G1}\mu_{R1}$ is the robot1 description in frame one, and ε is noise value. And then, use unscented filet to perform the transformed equation (see [2] for details). At first, generate the sigma points. And then, compute each sigma points by transformed function. Thereafter, compute the mean and covariance.

In this case, we ignore the duplicate landmarks when transform additional robot information into robot1 frame. Finally, we can make the robots go on implementing multi robot SLAM and ignore all subsequent encounters between the robots.

4. Simulation

To verify the proposed algorithm, we let the robots perform the unknown initial poses case.

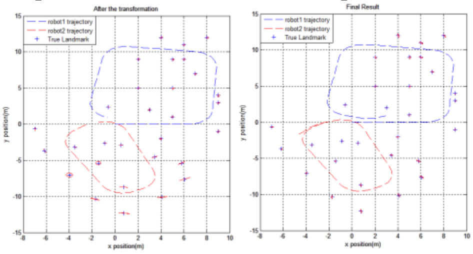

Fig. 1 After the transformation, the transformed landmarks will get bigger errors than the landmarks of robot1 (left picture), then let the robots go on performing the algorithm, we get the better result (right picture).

5. Conclusion

This paper has proposed an algorithm based unscented Kalman filter (UKF). We adopt a new strategy to solve the multi-robot SLAM problem. However, in unknown initial poses case we have to let the robots encounter to transform the mapping information. A future extension of this work will be to focus on reliable map-merging without encounter.

Reference

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