Research on Positioning and Navigation Technology of Mobile Robot based on SLAM Algorithm

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Abstract: Mobile robot navigation is an important topic in the field of robotics research. In navigation technology, self-positioning is the basic function that robots should have, but the positioning problem is inseparable from the creation of environmental maps. If the robot's autonomous positioning and map creation are solved as a problem, it provides a good precondition for real self-navigation, namely Simultaneous Localization and Mapping (SLAM). The solution to the SLAM problem is one of the most noTable achievements in the robot field in the past decade, and has been applied in different fields such as outdoor, underwater and land. Faced with the complexity and dynamic characteristics of the real world, in order to improve the intelligence of mobile robots, the SLAM method with high adaptability, high robustness and high efficiency is a research hotspot in the field of robotics.

1. Modeling and Analysis of Mobile Robot Based on SLAM Algorithm

In the mobile robot positioning and navigation technology, the problem based on positioning and map construction can be described as: starting from the initial point in the unknown environment, the mobile robot uses its own sensor to sense the surrounding environment and uses the environmental information to locate the robot's own position. Further, based on the information acquired by the sensor, an incremental environment map is constructed, and the map is used to update its position. This process is similar to the form of "eggs and chickens". Therefore, the SLAM algorithm problem is a probability estimation problem that is transformed into the pose and observation information of the mobile robot. The model of SLAM is shown in Figure 1:

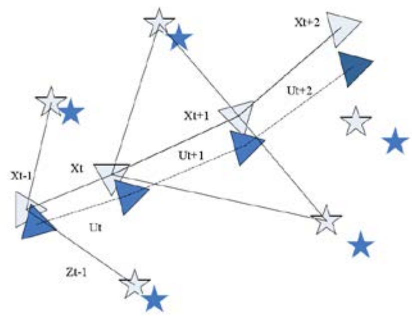

Figure 1 SLAM algorithm problem model

It represents the pose state vector X_t of the mobile robot at time t, and U_t represents the mobile robot input control vector, which Z_t represents the observation vector of the sensor at time t. The light triangle (△) represents the pose state of the real mobile robot, and the solid line between the pose states represents the true travel trajectory of the mobile robot. The dark triangle (▲) indicates the estimated pose state of the mobile robot, and the dotted line between the pose states indicates the estimated travel trajectory of the mobile robot. The light pentagram (☆) can be expressed as the real position information of the landmark points in the previously set sports environment, and the dark pentagram (★) can be expressed as the estimated position information of the landmark points.

The SLAM problem is actually a probability estimation problem. It is an "estimation"-"observation"-"correction" process. The main purpose is to estimate the distance between the observed information and the robot pose information and the actual observation information and the robot pose information. Close. The "estimation" means that the mobile robot estimates its own pose based on the encoder information or the steering gear information to achieve initial positioning of itself. "Observation" is the use of the sensors carried by the mobile robot to sense the surrounding environment, so as to obtain the required observation information. The "correction" is used by the mobile robot to calculate the posterior probability density by using the obtained observation information, thereby correcting the systematic error, and ensuring that the estimated observation information and the robot pose information and the real observation information are closer to the robot pose information.

You can set the pose of the mobile robot at the moment t as X_t , where $X_t = \{X_1, X_2, X_3\}$. If the mobile robot moves in an unknown two-dimensional environment, the pose of the robot consists of three parts, which are the coordinate points X_t, coordinate points and direction angles of the robot. In the SLAM algorithm, it is assumed that the external environment in which the robot is located has only N sTable landmark points, and the set of N landmark points is denoted by M, then the landmark position is represented as M= $[m_1 m_2 m_3 ..., \ m_n]^T$, and the landmark of each location is located as $i = 1,..., N$.

The pose of the robot follows the probability distribution and can be expressed as $p(X_t \mid u_t, X_{t-1})$, where $u = \{u_{1...} u_t\}$ the pose of the current moment of the mobile robot is only related to the control information of the mobile robot and the mobile robot at one moment t, regardless of other state quantities X_t. In order to realize the function of the mobile robot simultaneously positioning on the map construction, firstly, the mobile robot uses the sensor carried by itself to perceive the surrounding environment information, and sets the external environment with only N sTable landmark points, that is, obtains the landmark point information, and the observation information also follows a certain probability. Distribution, the observation of time, and can be described as $p(z_t \mid X_t, M)$. Therefore, z_t only relates to the landmark points observed at the current time and the robot pose at this moment, regardless of other state quantities.

To establish a SLAM algorithm problem model for mobile robots, we should first establish a mathematical model for each module.

Type, the detailed analysis and elaboration of the established motion model and observation model, the establishment of each model

Whether it is accurate or not directly affects the quality of the SLAM system. Therefore, the establishment of the model is crucial for the SLAM system.

In the positioning of the mobile robot, three coordinate systems OXY need to be established $O_1X_1Y_1$, which are the global coordinate system $O_2X_2Y_2$, the local coordinate system of the mobile robot, and the local coordinate system of the sensor. The origin of all coordinate systems is at the initial position of the robot, and the origin of the coordinates of the local coordinate system of the body is located at the geometric center of the robot body.

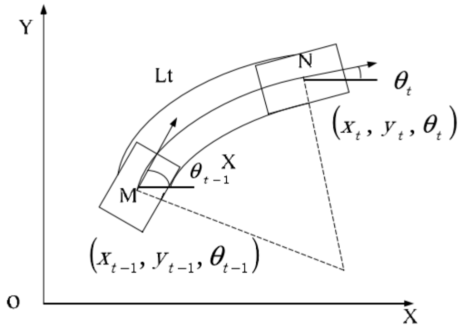

Figure 2 Schematic diagram of the mathematical model of the robot

$$X(t)=(x(t),\ y(t),\ \theta(t))$$

$$\begin{bmatrix} x(t) \\ y(t) \\ \theta(t) \end{bmatrix} = \begin{bmatrix} x(t-1)+\triangle d\cos(\theta(t-1)+\varphi)+\omega(t-1) \\ y(t-1)+\triangle d\sin(\theta(t-1)+\varphi)+\omega(t-1) \\ \theta(t-1)+\varphi MOD2\pi+\omega(t-1) \end{bmatrix}$$

Where: The position $(x(t),\ y(t))$ of the mobile robot in the global map is the angle $\theta(t)$ between the position of the mobile robot and the positive direction of the X-axis.

The SLAM problem is to find the posterior probability density of the vector. According to the Bayesian formula: $p(x(t),\ M|=(t),\ u(t))$ $= p(=(t)|x(t),M\int p(x(t)|u(t),\ x(t-1))\bullet p(x(t-1),M|=(t-1),\ u(t-1))dx(t-1)$

The SLAM problem can be decomposed into a solution process of the motion model and the observation model. The robot motion model $p(x(t)|u(t),x(t-1))$ can be represented by $x(t+1)=f(x(t))+w(t)$, and is the process noise vector. The robot observation model can be represented by $p(=(t)|x(t),M)$.

2. Mobile robot EKT-SALM algorithm based on time-varying adjustment factor

Under the uncertain or erroneous noise statistics, the standard EKF-SLAM has a slow convergence rate, a poor state estimation accuracy, and a large amount of calculation. It can be known from the innovation theory that when the motion state of the robot is simple, the filter gain can be reduced. Reduce the noise error. When the robot's motion state is complex, the filter gain can be increased to increase the filter bandwidth and increase the estimation accuracy. Therefore, the time-varying adjustment factor introduced in this paper can increase or decrease the filter gain according to the size of the new interest weight value, thus improving the state estimation accuracy.

Step 1: Filter initializes the initial position of the given robot x. And the initial variance, given the observed noise vector and the process noise vector, set the initial heading angle of the robot. Given the location of the landmark and the location of the landmark.

Step2: Pose prediction

Set the robot pose state vector to a total of N, the system state vector is expressed as $x(t)=[x(t)^T,M(t)^t]^T$ the introduction of the time-varying adjustment factor adjusts the covariance of the state prediction error, so that the strong tracking filter satisfies the orthogonal condition, that is, the residual sequence remains orthogonal, thus The purpose of the filter gain matrix is reached.

$$p(t)=u(t+1)f(t)p(t-1)f^T(t)+Q(t)$$

$$\lambda(t)=\begin{Bmatrix} \lambda_0,\lambda_0\geq 1 \\ 1,\lambda_0\leq 1 \end{Bmatrix}$$

$$\lambda_0=tr\,N(t)/M(t)$$

$$N(t)=\delta(t)-h(t)Q(t)h^T(t)-\phi R(t)$$

$$M(t)=h(t)f(t)p(t-1)f^T(t)h^T(t)$$

Where: $tr0$ the trace of the matrix, the covariance of the process noise $Q(t)$, and R(t) is the covariance of the measured noise, which ϕ is the weakening factor.

Adjust the covariance matrix online λ by using the time-varying adjustment factor to adjust the filter gain matrix. The covariance is described as follows:

$$p(t+1)=u(t+1)f(t)p(t)f^T(t)+Q(t)$$

According to the state estimation at t time, the motion model, and the observation model $t+1$, the

X and P of the time are estimated, that is, the pose of the robot is predicted based on the motion model $p(x(t)\,|\,x(t-1),\ u(t))$, and the pose of the robot $x(t)$ at the time is expressed.

$$x(t+1) = f(x(t), \lambda(t))$$

$$x(t+1) = \sum_{i=0}^{i=N} \omega_i x(t)$$

$$z(t+1) = h(x(t), \lambda(t))$$

$$z(t+1) = \sum_{i=0}^{i=N} \omega_i z(t)$$

$$p(t+1) = f(t)p(t)f^T(t) + Q(t)$$

$$p(t+1) = \lambda(t)$$

Medium: $f(t)$ is the time state transition matrix, which $h(t)$ is the observation matrix. The covariance matrix for the system process noise $Q(t)$.

Step3: Feature value update

According to the mean and variance of each feature in the map of the observation information particle, if the road sign is not observed by the robot at time t, it is not updated, that is, the variance and mean of the feature remain unchanged, if the feature When the value is observed, its eigenvalue is updated.

$$K(t) = \lambda(t)K'(t)$$

$$p(t+1) = p(t) - K(t+1) \times S(t+1) \times K^T(t+1)$$

$$K(t) = p(t)p^{-1}(t)$$

$$x(t+1) = x(t) + K(t)[z(t+1) - z(t)]$$

$$p(t+1) = p(t) - K(t)p(t)K^T(t)$$

Where: $K^{'}(t)$ to increase the filter gain before the time-varying adjustment factor, $K(t+1)$ is the Kalmar filter gain at the moment $t+1$.

Step4: Data Association

The observed features are associated with the predicted features or new feature points are generated.

Steps: Vector augmentation

Use the environmental characteristics observed by the sensor, including old features and new features, old features used to update the state

Predicted values, new features are used for initialization and added to the state vector.

3. Artificial robot based optimization of mobile robot FastSLAM algorithm

The SLAM algorithm problem can be described as the mobile robot in the unknown environment, through its own sensor to sense its position, starting from the starting point, using the sensor to perceive the environmental information, incrementally constructing the map, and using the built The map locates the robot. This process is similar to the form of "eggs and chickens." Mobile robot positioning requires the construction of accurate environmental maps, and the construction of environmental maps also requires precise positioning. The probability description form of the SLAM algorithm problem is as follows

$$p(x_{0t}, m_t \,|\, z_{0t}, u_{1:t})$$

The mobile robot poses $x_{0:t}$ from 0 to the time; it represents the map information observed by the mobile robot at the time; and the motion control information $z_{0:t}, u_{1:t}$ of the mobile robot from the time of the 0th to the time and the movement control information of the mobile robot from the 1st time to the time.

The essence of FastSLAM is to transform the SLAM problem into two parts: mobile robot pose estimation and environmental road sign estimation. Particle filter is used to estimate the pose of the robot. Extended Kalman filter is used to estimate the landmarks to reduce the calculation of FastSLAM algorithm $s_i^i = \{x_i^i, \ m_t, \ \omega_i^i\},$.

$$p(x_{0:t}, m_t \mid z_{0:t}, u_{1:t}) = p(x_{0:t} \mid z_{0:t}, u_{1:t}) \prod_{k=1}^{K} p(m_{t,k} \mid x_{0:t}, z_{0:t}, u_{1:t})$$

For robot path estimation $p(x_{0:t}, m_t \mid z_{0:t}, u_{1:t})$, estimate for the map $\prod_{k=1}^{k} p(m_{t:\,k} \mid x_{0:t}, z_{0:t}, u_{1:t})$. Which $m_{t:k}$ represents the position of the first road sign in the time map (=1, 2...K).

Li Xiaolei et al. conducted long-term observations and studies on various activities of real fish in the actual ocean, and in 2002 proposed the Artificial Fish Swarm Algorithm (AFSA).

AFSA mimics the many behaviors of real fish in the ocean (such as the foraging, gathering, following, and random behavior of real fish). This algorithm has the characteristics of low initial value, globality, and simplicity. At present, it is widely used in the fields of neural network training, pattern classification, fuzzy system control, function optimization, and optimization scheduling.

The particle filter uses each particle to represent the pose estimation of the mobile robot. The particle weight indicates the confidence of the particle to the pose estimation of the robot, and optimizes the probability distribution of the predicted particle based on the motion input and observation information. The post-particle set estimated pose is expressed as an estimate of the pose of the robot. In this paper, the artificial fish swarm optimization algorithm is introduced into the particle filter, so that the particle set can be optimized before the particle weight is calculated, so that the predicted particle is closer to the prediction of the real system state distribution, so that the predicted pose of the robot is closer to the real. Mobile robot pose.

In order to determine the optimization degree of the optimized predicted particle set to the pose orientation of the mobile robot, the fitness function is introduced, and the fitness function expression is as follows:

$$f_{fitness} = \exp\{-sqrt[\frac{(z_t - z_{t\Pr ed}) \cdot R_k^{-1} \cdot (z_t - z_{t\Pr ed})^T}{c_3}]\}$$

In equation above, the covariance matrix characterizes R_k the observed noise of the mobile robot; and z_{tpred} characterizes the value of the landmark position predicted by the robot at the moment. The comprehensive predicted road sign position value can be obtained from the previously constructed map m_{t-1}, and its calculation function formula can be expressed as:

$$z_{tpred} = g(x_t^*, \ m_{t-1})$$

Using the above function, it can be judged that the artificial robot's posture and true pose after optimization of the artificial fish population are

No closer. Determine the position of the mobile robot after the artificial fish swarm algorithm is optimized by calculating the fitness function

The distance between the position of the pose and the true pose of the robot, that is, whether it is distributed in the attachment of the robot's true pose. Therefore, a threshold is introduced to determine the distance between the predicted value and the position of the real robot. When $f_{fitness} < \delta$, the predicted value of the robot can no longer accurately track the real position of the robot, and a certain degree has been generated between the two positions. deviation. When this happens, the artificial fish swarm algorithm is used to optimize the particle set to reduce the degree of bias. When $f_{fitness} \geq \delta$, it indicates that the predicted value of the particle set is very close to the true pose of the mobile robot, and the artificial fish swarm algorithm is optimized. The method proposed in this paper needs to optimize the artificial fish swarm for each particle in the estimated particle set, so that each particle in the particle set is estimated to be closer to the true pose of the mobile robot after being optimized by the artificial fish.

4. Conclusion

Instant positioning and map creation of mobile robots combines positioning and map creation to lay the foundation for robot navigation. Foreign scholars have done a lot of research work in this area. Based on the relevant literature in recent years, the following aspects will be the hotspots of future research. In recent years, the initiative to improve robots has received extensive attention in the field of robotics, and has been well applied in many aspects, such as active vision and active positioning. The robotic operating environment extends from a known structured environment to an unknown, unstructured environment. Expanding the application environment of SLAM: At present, SLAM is also limited to research and application in two-dimensional static environment, and the real environment is usually a dynamic three-dimensional environment. Emphasis on practical use in experimental research. The SLAM theory, method and technology that can predict high, adaptability, high robustness and high efficiency will be the research hotspots in the future.

References

[1] HAN Rui. Research on navigation algorithm of mobile robot based on SLAM in unknown environment [D]. Wuhan University of Technology, 2006.

[2] Tao Hui, Wu Huaiyu, Cheng Lei, et al. Research on Autonomous Navigation of Mobile Robot EKF-SLAM and FastSLAM Algorithm Based on Feature Map[J]. Journal of Beijing Union University, 2010, 24(2): 18-24.

[3] Tao Y, Liu Z, Peng Y. Global Translational Motion Estimation (GTME)[C]// International Conference on Life System Modeling and Simulation. Springer, Berlin, Heidelberg, 2007.

[4] Zhang Xin, Zhang Wei, Su Xiaoming. Mobile robot SLAM based on heuristic algorithm[J]. Journal of Chinese Inertial Technology, 2018, 26(1): 45-50.

[5] Liu Y P , Liu Z H , Ma S C . A Novel Secure Inter-Domain Routing for Identifier/Locator Split Network [J]. Applied Mechanics and Materials, 2013, 411-414:9.

[6] Zhang Chao, Liang Fang, etc. Low-temperature nano-precision electron beam etching and in-situ electrical transport properties measurement based on microchip-based transmission electron microscopy [J]. Acta Phys. Sin.. 2014, 63 (24).

[7] Dongqing Liu, Haifeng Chen, etc. Research progress on memristor and its resistance mechanism [J]. Acta Phys. Sin.. 2014, 63 (18).