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Construction of Robot System Based on Kalman Filter

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Abstract

This paper introduces a construction method of mobile robot system based on Kalman filter. The system uses inertial measurement unit (IMU), vision sensor and odometer sensor as the main sources of positioning data, and realizes data fusion and filtering through Kalman filtering algorithm. The control module processes the sensor input and generates the robot motion control instructions. Kalman filter algorithm plays a key role in this module, providing accurate posture and position information of the robot. The experimental results show that the system has high positioning accuracy and robustness in indoor environment. Compared with traditional methods, it can deal with sensor noise and environmental changes more effectively, and improve the positioning accuracy and stability of mobile robots. This mobile robot system based on Kalman filter provides reliable technical support for automation applications.

Keywords

Construction, Robot System, Kalman Filter.

1. Research status and significance

With the wide application of mobile robot in automation, intelligent transportation, warehousing and logistics, the research on its positioning and navigation technology has attracted much attention. The positioning system of mobile robot based on Kalman filter is one of the hot spots in current research, and many important progress has been made.

Firstly, as a classical state estimation method, Kalman filter has been widely used in mobile robot positioning because of its effective suppression of sensor noise and good adaptability to system dynamic changes. Many studies have improved the accuracy and robustness of robot positioning by introducing different types of sensor data, such as IMU, GPS, visual sensors, etc., combined with Kalman filter algorithm for data fusion.

Secondly, the positioning accuracy of mobile robot directly affects its task execution effect and safety. The positioning system based on Kalman filter can effectively deal with sensor noise and environmental changes, and provide more reliable attitude and position information for robots. This is very important for key functions such as autonomous navigation, obstacle avoidance and path planning.

In addition, the mobile robot positioning system based on Kalman filter has good real-time performance and computational efficiency, and is suitable for various application scenarios in complex environments. For example, in indoor navigation, warehousing and logistics, intelligent inspection and other fields, this system can achieve high-precision positioning and reliable path planning, and improve work efficiency and safety.

Generally speaking, the mobile robot positioning system based on Kalman filter has important research significance and practical application value. Through in-depth research and optimization of the system, the positioning accuracy and robustness of mobile robots can be further improved, and the development and application of intelligent robot technology in various fields can be promoted. At the same time, it also provides reliable technical support for future automation and intelligent production and service, and helps to build a more intelligent and efficient industrial and social environment.

2. System design

1.Sensor selection

Inertial measurement unit (IMU) is used to obtain the acceleration and angular velocity information of the robot and provide the motion state of the robot.

Visual sensor: used to obtain visual information of the environment, such as feature points, edges, etc., for visual positioning.

Odometer sensor: It is used to measure the rotation of robot wheels and provide information on the distance and direction of movement.

2. Data fusion

The data obtained by the above sensors are fused to form comprehensive robot attitude and position information.

Kalman filter algorithm is used to effectively fuse and filter the data of different sensors to reduce noise and improve accuracy.

3. Control module

Receiving the fused attitude and position information, and generating the motion control instruction of the robot.

This module realizes the precise control of the robot through the accurate robot state provided by Kalman filtering algorithm.

4. Execution module

The command generated by the control module is converted into the actual movement of the robot.

According to the instruction, the robot execution module controls the rotation of the wheel and the steering of the steering gear, so that the robot can travel according to the predetermined path.

5. Real-time update

The system needs to update the sensor data in real time, and make state estimation and control instruction generation according to the latest data.

The advantage of Kalman filter algorithm is that it can continuously estimate the state and transmit it through Bluetooth to continuously track and adjust the robot state.

6. Experimental verification

The designed system is deployed to the mobile robot, and the positioning and navigation experiments are carried out in the indoor environment.

By comparing the experimental results, the differences between the system based on Kalman filter and the traditional method in positioning accuracy and stability are evaluated.

The advantage of this design idea lies in the fusion of multi-sensor data by using Kalman filter algorithm, which improves the positioning accuracy and robustness of mobile robot system. At the same time, the real-time update of the system and the efficient control module enable the robot to navigate and perform tasks stably in complex environment. Through the experimental verification, the feasibility and effectiveness of the system in practical application can be verified, which provides a reliable technical basis for autonomous navigation and intelligent application of mobile robots.

3. Correlation calculation of Kalman filter system algorithm

The Kalman filter model assumes that the state of the system at time t evolves from the prior state at time t-1 according to the equation:

$$x_t = F_t x_{t-1} + B_t u_t + w_t$$

Xt is the state vector (such as position, speed and heading) containing the items of interest of the system at time t, ut is the vector containing any control input (steering angle, thrust setting and braking force), Ft is the state transition matrix, which affects the system state at time t by each system state parameter at time t (for example, the position and speed of t-1 will affect the position of time t, Bt is the control input matrix, It controls the influence of each input parameter in the vector ut on the state vector (for example, the influence of throttle setting on the system speed and position), and wt is a vector containing the process noise term of each parameter in the state vector. It is assumed that the process noise comes from zero-mean multivariate normal distribution, and the covariance is represented by covariance matrix Qt.

Zt is the measurement vector, Ht is the transformation matrix to map the state vector parameters to the measurement domain, and yt is the measurement vector sum view.

Error of inspection vector:

$$y_t = H_t x_t - z_t$$

The Kalman filtering algorithm involves two stages: prediction and metric update. The formula of standard Kalman filtering equation in the prediction stage is as follows:

$$P_{t|t-1} = F_t P_{t-1|t-1} F_t^T + Q_t$$

$$x_{t|t-1} = F_t x_{t-1|t-1} + B_t u_t$$

The measurement update formula is:

$$K_t = P_{t|t-1} H_t^T (H_t P_{t|t-1} H_t^T + R_t)^{-1}$$

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t (y_t - H_t \hat{x}_{t|t-1})$$

$$P_{t|t} = P_{t|t-1} - K_t H_t P_{t|t-1}$$

The use of Kalman filter mainly makes use of the key characteristics of normal distribution: the product of two normal distributions produces another normal distribution.

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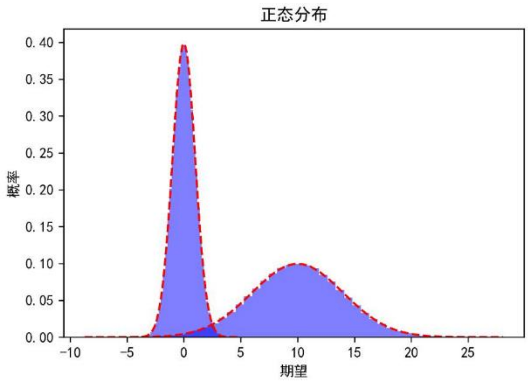

Figure 3.1 Initial Distribution

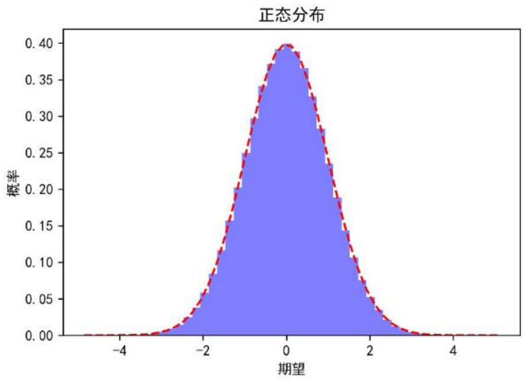

Figure 3.2 Initial and Predicted Distribution

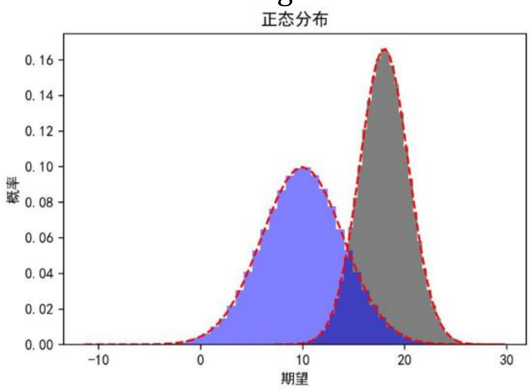

Figure 3.3 Predicted and Observed Distribution

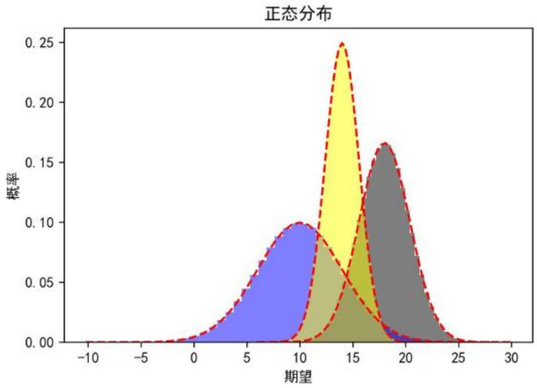

Figure 3.4 Predicted observation combined distribution

Formula (2.9) gives the predicted value of blue normal distribution and the observed value of gray normal distribution in Figure 2.4:

The information provided by the two normal distributions is fused by multiplying them, and the best current estimation of the system is given by the product of the two normal distributions in Formula (2.9):

$$y_1(\gamma;\mu_1;\sigma_1)=\frac{1}{\sqrt{2\Pi\sigma_1^2}}e^{-\frac{(\gamma-\mu_1)^2}{2\sigma_1^2}}$$

$$y_1(\gamma;\mu_2;\sigma_2)=\frac{1}{\sqrt{2\pi\sigma_2^2}}e^{-\frac{(\gamma-\mu_2)^2}{2\sigma_2^2}}$$

$$\begin{aligned} & y_r(\gamma;\mu_1;\sigma_1;\mu_2;\sigma_2) \\ & =\frac{1}{\sqrt{2\pi\sigma_1^2}}e^{-\frac{(\gamma-\mu_1)^2}{2\sigma_1^2}}\times\frac{1}{\sqrt{2\pi\sigma_2^2}}e^{-\frac{(\gamma-\mu_2)^2}{2\sigma_2^2}} \\ & =\frac{1}{2\pi\sqrt{\sigma_1^2\sigma_2^2}}e^{-(\frac{(\gamma-\mu_1)^2}{2\sigma_1^2}+\frac{(\gamma-\mu_2)^2}{2\sigma_2^2})} \end{aligned}$$

The quadratic term in this new function can be extended, μ γ is the weighted average of μ1 and μ2, σ γ is half of the harmonic average of σ1 and σ2, and the whole expression is rewritten in the form of normal distribution:

$$k = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}$$
$$\mu' = \mu_1 + k(\mu_2 - \mu_1)$$
$$\sigma'^2 = \sigma_0^2 - k\sigma_0^2$$

Equation (2.10) can be transformed into a high-dimensional matrix expression, where σ is the covariance matrix of normal distribution, μ is the average value of each dimension, and equation (2.15) can be obtained by substituting relevant data into equation (2.14), and k is the Kalman gain:

$$K = \Sigma_1(\Sigma_1 + \Sigma_2)^{-1}$$
$$\vec{\mu}' = \vec{\mu}_1 + K(\vec{\mu}_2 - \vec{\mu}_1)$$
$$\Sigma' = \Sigma_1 - K\Sigma_1$$

There are two distributions, the predicted distribution is (μ 1, σ 1) = (HKXK, HKPKHKT), and the observed value distribution of the sensor is (μ 2, σ 2) = (ZK, Rk). Now, these two distributions are brought into the formula (2.11) and the simplified formula (2.12) is obtained as follows:

$$x_k' = x_k + K'(z_k - H_k x_k)$$
$$P_k' = P_k - K' H_k P_k$$

$$K' = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1}$$

Next, look at two formulas of extended Kalman filter:

$$S = HP'H^T + R$$
$$K = P'H^T S^{-1}$$

According to the observation that Z is a 5x1 column vector containing coordinate positions x,y, and the state vector X' is a 5x1 column vector containing angular velocity information of position and velocity information, according to the formula y=z-Hx', it can be known that the dimension of the measurement matrix H is 2 rows and 5 columns, namely:

$$h(x) = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} H_{00} & H_{01} & H_{02} & H_{03} & H_{04} \\ H_{10} & H_{11} & H_{12} & H_{13} & H_{14} \end{bmatrix} \times \begin{bmatrix} x' \\ y' \\ v' \\ \theta' \\ \omega' \end{bmatrix} = H \times x'$$

Equation (2.24) shows that the transformation between the two sides of the equation is nonlinear, and there is no constant matrix H, which can make the two sides of the equation hold. The nonlinear function can be approximated by Taylor formula:

$$h(x) = h(x_0) + \frac{\dot{h}(x_0)}{1!}(x - x_0) + \frac{\ddot{h}(x_0)}{2!}(x - x_0)^2 + ..$$

Ignoring the higher-order terms above the second degree, we can get an approximate linearized equation, which is used to replace the nonlinear function h(x) and extend the nonlinear function to multiple dimensions, that is, to find the partial derivatives of each variable, that is:

$$h(x) \approx h(x_0) + \frac{\partial h(x_0)}{\partial x}(x - x_0)$$

The extended Kalman filter linearizes the nonlinear motion by Taylor formula, and discards the high-order derivative. As long as the low-order derivative is used, the curve motion can be approximated as a linear motion.

$$\begin{aligned}
&X' = A \times X_{t-1} + u \\
&P = F \times P \times F^T \\
&Z = [x_t, y_t] \\
&y = Z^T - (H \times X') \\
&S = H \times P \times H^T + R \\
&K = P \times H^T \times S^{-1} \\
&X_t = X' + (K \times y) \\
&P = (I - (K \times H) \times P)
\end{aligned}$$

It is known that the observed value of the moving target is (xt, yt). Although there is noise, the velocity vt can be obtained by using the current observed value and the previous observed value (xt-1, yt-1). The specific formula is as follows:

$$v_t = \frac{\sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}}{dt}$$

In this way, the speed of each step of the moving target can be obtained, and at the same time, the facing direction θt can also be obtained by xt, yt, xt-1 and yt-1:

$$\theta_t = \arctan(x_t - x_{t-1}, y_t - y_{t-1})$$

For the specific application of the extended Kalman filter positioning method, firstly, a noisy (x,y) coordinate is obtained by observing the value. Then the position of the next step is predicted by the extended Kalman filter method, and the moving target moves one step to obtain the current coordinates of the target body with noise. An error is obtained by comparing the current position of the moving target with the predicted position. When the error is less than 0.02v(v is the speed of the moving target), it is determined that the prediction is consistent with the position of the moving target.

4. Conclusion and prospect:

The positioning system of mobile robot based on Kalman filter has been designed and expounded in detail in this paper. By fusing the data of inertial measurement unit (IMU), vision sensor and odometer sensor, and combining with the application of Kalman filter algorithm, we design a mobile robot system that can provide high-precision positioning and robustness. The experimental results verify the positioning accuracy and stability of the system in indoor environment. Compared with traditional methods, the system based on Kalman filter can deal with sensor noise and environmental changes more effectively, and improve the positioning accuracy and stability of the mobile robot.

To sum up, the mobile robot positioning system based on Kalman filter is of great significance in modern automation and intelligent applications. Future research and application will further

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promote the development of mobile robot technology and bring more convenience and benefits to human society.

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References

[1] A New Algorithm for Estimating Bias Correction and Extended Kalman Filtering [J] Deng Bing; Sun Zhengbo; He Qing. Journal of Xi'an University of Electronic Science and Technology, 2018 (03)

[2] The principle and application of Kalman filtering [M] Huang Xiaoping;; Wang Yan. Electronic Industry Press. 2015

[3] Vehicle Driving State Estimation Based on Kalman Filter [A] Wu Zhicheng; Lin Qinghua; Yang Lin; Zhao Yuzhuang; Ren Hongbin. Proceedings of the Annual Meeting of the Chinese Society of Automotive Engineers in 2020 (3)

[4] An Active Target Estimation Algorithm Based on Iterative Dual Expansion Kalman Filter [J] Lu Yu; Zhang Hua. Journal of China Academy of Electronic Science, 2019 (09)

[5] The basic principle and application of Kalman filtering [J] Peng Dingcong. Software Guide, 2009 (11)

[6] The Application of Information Fusion Technology Based on Extended Kalman Filter in Vehicle State Estimation [J] Zong Changfu; Pan Zhao; Hu Dan; Zheng Hongyu; Xu Ying; Dong Yiliang. Journal of Mechanical Engineering, 2009 (10)

[7] Research on the Application of Extended Kalman Filter in Target Tracking [J] Zhang Aimin. Information Technology, 2013 (10)

[8] A Mobile Robot Extended Kalman Filter Localization Algorithm and Simulation [J] Zhang Qian. Journal of Guangdong Second Normal University, 2017 (05)

[9] An Improved Extended Kalman Filter [J] Li Zhiguo; Li Xuming; Wang Yunfeng. Modern Electronic Technology, 2016 (02)