Application of Kalman filter on mobile robot self-localization

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Abstract: Self-localization is a fundamental requirement for the mobile robot. Robot usually contains a large number of different sensors, which provide the information of robot localization, and all the sensor information should be considered for the optimal location. Kalman filter is efficient to realize the information fusion. Used as an efficient sensor fusion algorithm, Kalman filter is an advanced filtering technique which can reduce errors of the position and orientation of the sensors. Kalman filter has been paied much attention to robot automation and solutions to solve uncertainties such as robot localization, navigation, following, tracking, motion control, estimation and prediction. The paper briefly describes Kalman filter theory, and establishes a simple mathematical model based on muti-sensor mobile robot. Meanwhile, Kalman filter is used in robot self-localization by simulations, and it is demonstrated by simulations that Kalman filter is effective.

Key words: Kalman filter; mobile robot; self-localization; target orientation

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0 Introduction

In recent years, robots are used to perform various complicated and hazardous tasks, especially in the fields of military, security and service. If mobile robots want to obtain a fast and collision-free access to the target location, it is necessary to know where it is. Traditional localization methods generally use electromagnetic navigation, sonar or laser range finder, GPS and other methods to obtain location information of the robot[1,2]. These methods are widely used, and can get satisfactory accuracy and reliability in the structured environment. With the in-depth research on the problem of robot localization, the uncertainty of the localization process is paid to more and more attention. when configuration environment map comes to match with environment model that is built based on sensor information, it may appear that an object matches with a number of objects due to the sensor error and uncertainty factors. In this case, generally we adopt the method based on probability to eliminate the ambiguity of matching. Among the methods based on probability, Markov localization[3], Kalman filter and Monte Carlo[4] are very representative and have been successfully applied.

Kalman filter is commonly used in the dynamic estimation. It is easy to achieve real-time optimal recursive filtering algorithm on the computer, suitable to handle multivariable systems, time-varying systems and non-stationary random process. It supports forecast and correction of the states in the past, present and future, particularly it is suitable for the situation that could not accurately model. And it has the advantages of a high prediction accuracy, a small amount of data storage and less computation time. Kalman filter has a wide range of applications in motion analysis. In this paper, we research the kalman filter method applied on the robot self-localization.

1 Kalman filter

Kalman filter[5] was first proposed by Kalman (R E Kalman) in 1960, and the filtering algorithm uses the signal extraction observations to estimate the desired signal. The concept of state space is introduced into state estimation theory. Kalman filter uses signal process as output of a linear system with white noise, uses the state equation to describe the relationship of input-output, and uses the system observation equation and the statistical characteristics of white noise as filter algorithm in the process of estimation.

Kalman filter is an optimal linear recursive estimation method[6], and uses linear state equation and observation equation to get a global optimal state estimation regardness of whether the data is accurate.

2 Basic theory of Kalman filter

The linear discrete time dynamic system is described by state equation and measurement equation[7], and they are as follows:

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$$\boldsymbol{X}_k = \boldsymbol{F}_k \boldsymbol{X}_{k-1} + \boldsymbol{G}_k w_k, \quad (1)$$

$$\boldsymbol{Z}_k = \boldsymbol{H}_k \boldsymbol{X}_{k-1} + v_k, \quad (2)$$

where $\boldsymbol{X}_k$ is the system state vector; $\boldsymbol{Z}_k$ is the system observed series; w_k is the system process noise series; v_k is the system measurement noise series; $\boldsymbol{F}_k$ is the system state transfer matrix; $\boldsymbol{H}_k$ is the system observation matrix; $\boldsymbol{G}_k$ is the system noise input function with covariance $\boldsymbol{Q}_k$[8]; and assuming that the random variables w_k and v_k represent the process and measurement noise respectively. They are assumed to be independent of each other. They are defined as

$$w_k \sim N(0, \boldsymbol{Q}_k), \quad (3)$$

$$v_k \sim N(0, \boldsymbol{R}_k), \quad (4)$$

where $\boldsymbol{Q}_k$ is the process noise covariance; $\boldsymbol{R}_k$ is measurement noise covariance.

Kalman filter is a typical Bayesian filter. It just needs the initial state value $\hat{\boldsymbol{X}}_0$, covariance matrix $\boldsymbol{P}_0$ and the observed value $\boldsymbol{Z}_k$, then uses Eq. (3) and Eq. (4) to calculate the time of system state estimation $\hat{\boldsymbol{X}}_k$. Specific steps are as follows[9].

Step 1: Using the priori state estimation $\hat{\boldsymbol{X}}_{k-1}^-$ and the covariance metrix $\boldsymbol{P}_{k-1}$ to predict the current state estimation $\hat{\boldsymbol{X}}_k^-$ and the covariance matrix $\boldsymbol{P}_k^-$ (the predicted values are marked by superscript "−") as follows:

$$\hat{\boldsymbol{X}}_k^- = \boldsymbol{F}_k \hat{\boldsymbol{X}}_{k-1}, \quad (5)$$

$$\boldsymbol{P}_k^- = \boldsymbol{F}_k \boldsymbol{P}_{k-1} \boldsymbol{F}_k^T + \boldsymbol{G}_k \boldsymbol{Q}_k \boldsymbol{G}_k^T. \quad (6)$$

Step 2: Using the predicted covariance matrix $\boldsymbol{P}_k^-$ and the measurement noise covariance $\boldsymbol{R}_k$ to compute the Kalman gain K_k.

$$K_k = \boldsymbol{P}_k^- \boldsymbol{H}_k^T (\boldsymbol{H}_k \boldsymbol{P}_k^- \boldsymbol{H}_k^T + \boldsymbol{R}_k)^{-1}. \quad (7)$$

Step 3: Using the predicted state estimation $\hat{\boldsymbol{X}}_k^-$ and the actual measurement $\boldsymbol{Z}_k$ to modify the state estimation $\hat{\boldsymbol{X}}_k$ of the system and their covariance matrix $\boldsymbol{P}_k$. They are

$$\hat{\boldsymbol{X}}_k = \boldsymbol{X}_k^- + K_k(\boldsymbol{Z}_k - \boldsymbol{H}_k \hat{\boldsymbol{X}}_k^-), \quad (8)$$

$$\boldsymbol{P}_k = (I - K_k \boldsymbol{H}_k) \boldsymbol{P}_k^-. \quad (9)$$

We can get two loops of Kalman filter from the steps, which are plus loop and filter loop. Meanwhile, after each time and measurement update pair, the process is repeated with the previous posteriori estimates to project (or predict) the new prioriestimates. The recursive nature is one of the very appealing features of Kalman filter, so the method is convenient for real-time processing, computer realization and time saving.

3 Model of mobile robot self-localization

Commonly, the classical Kalman filter used in robot localization requires a linear motion model. We assume that the mobile robot goes along a line with variable motion. Displacement s_k, velocity v_k, acceleration a_k, jerk j_k at the time t_k, their initial values are: $s_0 = 1$, $v_0 = 0.5$, $a_0 = 0.2$. To measure the position of the mobile robot, the measured value is $\boldsymbol{Z}_k = s_k + v_k$. Noise interference is zero-mean white noise.

The sampling period is T, and $T = 0.1$. Loop equation is

$$\begin{aligned} s_k &= s_{k-1} + v_{k-1} + a_{k-1}\frac{T^2}{2}, \\ v_k &= v_{k-1} + a_{k-1}T, \\ a_k &= a_{k-1} + j_{k-1}T. \end{aligned} \quad (10)$$

For motion tracking, the jerk j_k is a random quantity, so we can use white noise to describe it.

And $\boldsymbol{X}_k = [s_k \quad v_k \quad a_k]^T$.

State equations are

$$\boldsymbol{X}_k = \boldsymbol{F}\boldsymbol{X}_{k-1} + \boldsymbol{G} j_{k-1}, \quad (11)$$

$$\boldsymbol{F} = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \ \boldsymbol{G} = \begin{bmatrix} 0 \\ 0 \\ T \end{bmatrix}. \quad (12)$$

Measurement equation is

$$\boldsymbol{Z}_k = [1 \quad 0 \quad 0] \begin{bmatrix} s_k \\ v_k \\ a_k \end{bmatrix} + v_k. \quad (13)$$

So $\boldsymbol{H} = [1 \quad 0 \quad 0]$.

When we select the initial state values $\boldsymbol{X}_0$ and $\boldsymbol{P}_0$, due to the stability of the system affected by the initial values, so $\hat{\boldsymbol{X}}_0 = E\boldsymbol{X}_0$, $\boldsymbol{P}_0 = \mathrm{var}\boldsymbol{X}_0$, Kalman filter is unbiased estimator from the beginning, and the estimated variance matrix is the minimum. But in the actual case, the initial true values of the system are difficult to be obtained, so they are assumed values usually. Assuming principles are: under the circumstances of the values of $\boldsymbol{P}_0$, $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$ can not be accurately acquired, we use larger values as conservative values as much as possible. It can prevent the actual estimation error variance divergence by using the conservative values[10]. Therefore, the model assumes that we have already known the range of the values.

The initial values are estimated as

$$\hat{\boldsymbol{X}}_0 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \ \boldsymbol{P}_0 = \begin{bmatrix} 10 & 0 & 0 \\ 0 & 10 & 0 \\ 0 & 0 & 10 \end{bmatrix}. \quad (14)$$

4 Simulation

Kalman filter is simulated by MATLAB. Line of true position represents the ideal curve of the position of the moving target varied with time in Fig.1. And line of measurement position represents the actual curve, and line of KF position represents the predicted values. Based on the predictive values of the target position we can get the current position by Kalman filter. The simulation results of the homing bomb show that the position got by Kalman filter is very closed to the actual position, and errors decrease with time prolonged.

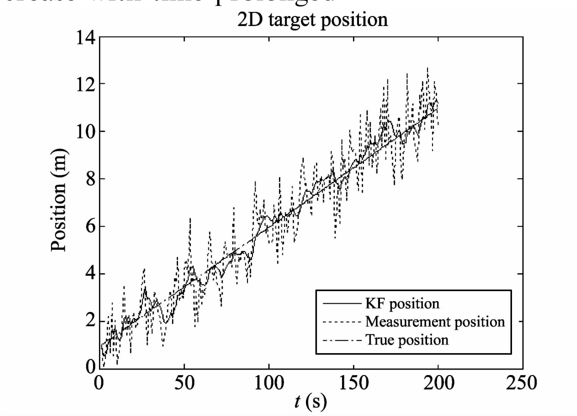

Fig.1 Figure of target position estimation varied with time

5 Conclusion

In this paper, we discuss that Kalman filter is used to estimate states and the initial values in the case of noise linear motion model. Compared with other positioning methods, Kalman filter has strong robusticity, which is useful for decision-making and cooperation of Robot. Moreover, the key advantage of Kalman filter algorithm is its effectiveness, and the recursive characteristic of Kalman filter algorithm makes that its data processing needs not mass data storage and compute. So it has been widely used in the field of mobile robot self-localization.

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卡尔曼滤波器在移动机器人自主定位中的应用

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摘　要： 自主定位是移动机器人的基本性能，但移动机器人最优的定位信息需要综合考虑所携带的各类传感器数据，故如何有效融合这些数据是自主定位的难点。卡尔曼滤波器是实现不同信息融合的工具，可有效减少定位过程中机器人的位置和角度误差，因此在机器人定位、导航、后跟踪、运动控制、评估、预测等方面得到了广泛应用。本文阐述了卡尔曼滤波器的基本原理，建立了一个基于多传感器移动机器人的简易数学模型，并通过仿真实现了目标定位的基本功能，结果验证了卡尔曼滤波器自主定位移动机器人的可行性。

关键词： 卡尔曼滤波器；移动机器人；自主定位；目标定向

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