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Localization of Wheeled Mobile Robot Based on Extended Kalman Filtering

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ABSTRACT: A mobile robot localization method which combines relative positioning with absolute orientation is presented. The code salver and gyroscope are used for relative positioning, and the laser radar is used to detect absolute orientation. In this paper, we established environmental map, multi-sensor information fusion model, sensors and robot motion model. The Extended Kalman Filtering (EKF) is adopted as multi-sensor data fusion technology to realize the precise localization of wheeled mobile robot.

Keywords: Wheeled mobile robot, Positioning, Multi-sensor, EKF.

1 INTRODUCTION

With the development of technology, mobile robot technologies have made tremendous process. However, nowadays, people have put forward higher demand of mobile robots for both functions and performances due to the increasing complex environments and tasks; therefore, traditional robots are now evolving to intelligent robots. Intelligentization of robot poses new challenges to robot navigation. As the foundation of robot navigation, localization of mobile robot has received great attention. Because of its simple structure, high efficiency and controllability, wheeled mobile robot is widely used and researched as an important branch of mobile robot. Wheeled robot localization technology has become a hotspot in robot researches.

No single sensor can guarantee the accuracy, reliability and abundance of information because of its limited resources; therefore, robot cannot locate itself precisely based on only one sensor. Multi-sensor inputs can solve the problem of insufficient data with redundant and supplemental information. Through fusing information from multiple sensors properly, robot can obtain its accurate geographic information. This technology has become a new research direction in systems with sensors.

In this paper, we put forward a positioning method based on EKF with feature extraction function. Odometer, gyro, laser radar are adopted as the main sensors to combine relative positioning with absolute orientation. A model of robot motion is proposed by fusing odometer and gyro data. We establish the robot location observation model with environmental features obtained from laser radar to locate the robot. By combining location observation model and motion model, and then tracing environmental features with EKF, we realize precise localization of wheeled mobile robot.

2 SYSTEM PRINCIPLES

Figure 1 is the diagram of robot positioning system with EKF. The diagram shows that it is a recursive procedure. Location prediction or motion update is the first stage. We obtain odometer and gyro data by applying Gaussian error motion model to their measured value directly. Through fusing these data, we generate predicted location. We then search environmental map based on the predicted value to find predicted observation location that match this information, that is, to predict environmental features and their location information of the laser radar. During the procedure, robot compares predicted value with real value from the laser radar to find the best matching value. At last, we fuse information from the best matching vale with EKF to update prediction confidence, thus obtaining the best predicted value of robot location.

In this paper, we experiment on differential driving wheeled robot. Code salvers are installed on the wheels as odometer. They and gyro are used to estimate robot location information. Location errors increase over time because of measurement errors of the two types of sensors. External sensor laser radar that is installed on the robot is the key element to eliminate these errors. Laser radar continually matches external conditions with environmental map to obtain absolute location information. With this information, the robot can correct its location errors to overcome the increasing cumulative errors, thus realizing long-time precise location.

3 SENSOR MODEL

3.1 *Odometer Model*

As an effective relative positioning sensor, odometer has been widely used in the field of wheeled mobile robot. It estimates the changes of attitude by detecting

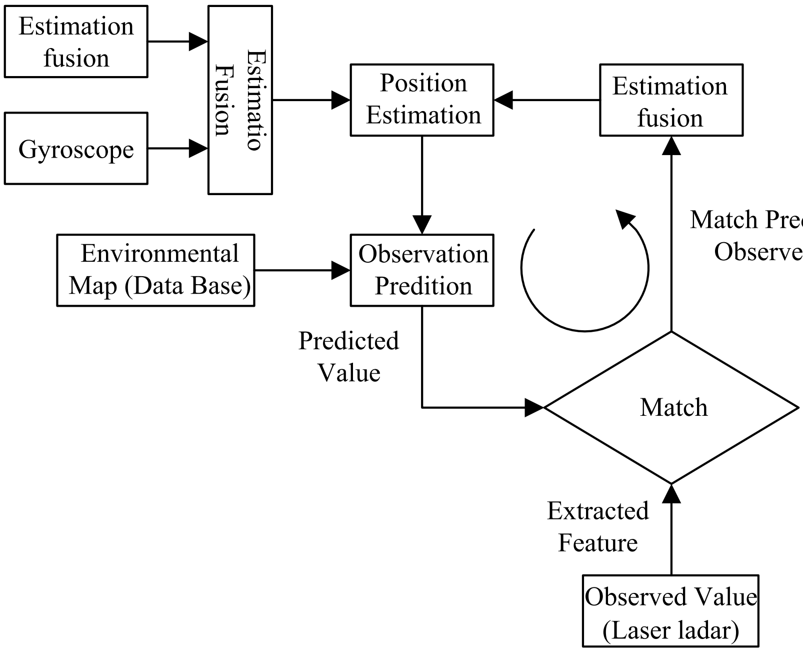

Figure 1. System diagram

radian changes in a certain time, via the code salvers installed on driving wheels. Generally speaking, attitude of mobile robot can be represented by the following vector:

$$p = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad (1)$$

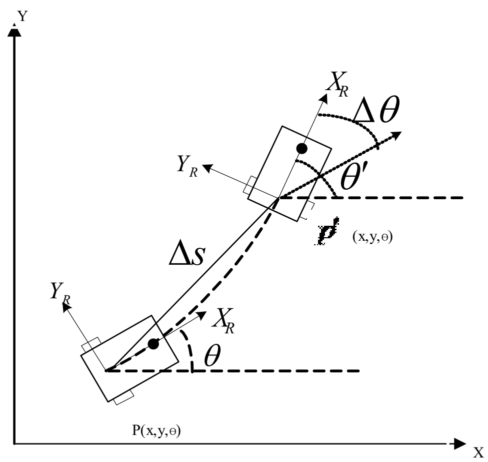

Figure 2. Motion model of the differential driving robot

Figure 2 shows the motion model of the differential driving robot. In a short period of sampling time Δt, the robot moves from position p to p', and the changes of attitude can be estimated by the integration of return value from code salvers. Mobile robot path can be represented by straight lines; therefore, the variation of position (Δx, Δy, $\Delta\theta$) from p to p' is:

$$\Delta x = \Delta s \cos(\theta + \Delta\theta / 2) \quad (2)$$

$$\Delta y = \Delta s \sin(\theta + \Delta\theta / 2) \quad (3)$$

$$\Delta\theta = \frac{\Delta s_r - \Delta s_l}{b} \quad (4)$$

$$\Delta s = \frac{\Delta s_r + \Delta s_l}{2} \quad (5)$$

Where, Δs_r and Δs_l represent moving distance of left and right wheels respectively; b represents distance between the two driving wheels. Therefore, the updated position p' is:

$$p' = \begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = p + \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta\theta \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta s \cos(\theta + \Delta\theta / 2) \\ \Delta s \sin(\theta + \Delta\theta / 2) \\ \Delta\theta \end{bmatrix} \quad (6)$$

Expression (6) is the basic equation of updated position value from odometer. In increment vector (Δs_r , Δs_l), there exist errors introduced by uncertain integral errors and the approximate motion model. For this reason, we must establish error model of position p' . The covariance matrix $\sum p'$ of odometer's estimated position is determined by the following expression:

$$\sum p' = \nabla_p f \sum p \nabla_p f^T + \nabla_{\Delta_{rl}} f \sum \Delta \nabla_{\Delta_{rl}} f^T \qquad (7)$$

We assume that the initial covariance matrix $\sum p$ is known, and then the covariance matrix of motion increment (Δs_r , Δs_l) is:

$$\sum \Delta = \begin{bmatrix} k_r|\Delta s_r| & 0 \\ 0 & k_l|\Delta s_l| \end{bmatrix} \qquad (8)$$

Where, k_r and k_l are error constants, which represent the uncertain parameters between driving motors, wheels and ground. Specific value of k_r and k_l should be determined by experiments.

Two Jacobi matrixes can be calculated from expression (6):

$$F_P = \nabla_P f = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} & \frac{\partial f}{\partial \theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\Delta s \sin(\theta + \Delta\theta/2) \\ 0 & 1 & \Delta s \cos(\theta + \Delta\theta/2) \\ 0 & 0 & 1 \end{bmatrix} \qquad (9)$$

$$F_{\Delta_{rl}} = \nabla_{\Delta_{rl}} = \begin{bmatrix} \frac{1}{2}\cos(\theta + \frac{\Delta\theta}{2}) - \frac{\Delta s}{2b}\sin(\theta + \frac{\Delta\theta}{2}) & \frac{1}{2}\cos(\theta + \frac{\Delta\theta}{2}) + \frac{\Delta s}{2b}\sin(\theta + \frac{\Delta\theta}{2}) \\ \frac{1}{2}\sin(\theta + \frac{\Delta\theta}{2}) + \frac{\Delta s}{2b}\cos(\theta + \frac{\Delta\theta}{2}) & \frac{1}{2}\sin(\theta + \frac{\Delta\theta}{2}) - \frac{\Delta s}{2b}\cos(\theta + \frac{\Delta\theta}{2}) \\ \frac{1}{b} & -\frac{1}{b} \end{bmatrix} \qquad (10)$$

After analyzing the procedure and error model of odometer, we can use them as robot motion model. Along with the certain control input *u(k)*, we can predict robot location and its uncertainty. Two parameters p' and $\sum p'$ represent confidence status, which can be assumed that they obey Gaussian distribution.

3.2 *Gyro Model*

Gyro is a kind of inertial device and is used to measure its carrier's angular velocity and rotation angle. The variation of position angle is calculated through integration of gyro's output. Therefore, a reference direction is needed for gyro to accumulate its angular variation. At a certain time T_S , the following expression represents updated attitude angle:

$$\theta' = \theta + \Delta\theta = \theta + \int_0^{T_S} \omega_i d_t \qquad (11)$$

Where, θ represents initial attitude angle, ω_i represents angular velocity output of gyro.

There are two types of gyro errors; scale error and offset error. Scale error is introduced by the proportional relationship between the input and output of gyro, which belongs to regular drift error. Offset error is introduced by external environment, which means that gyro generates limited nonzero output even with no input. This type of error belongs to random drift error, and the main reasons are large-scale temperature variations and noise. In this paper, we assume that the measured values of gyro obey Gaussian white noise distribution. We determine model parameters by establishing fitting error model with zero input, and then determine variance Q(K).

3.3 *Laser Radar Model*

Laser radar is also called laser ranger, which has the same principles with ultrasonic ranger, and it belongs to active ranger instrument. It can scan surrounding environment on its scanning plain based on a given resolution, thus obtaining distance information ρ and scanning angular information θ of the measuring points in the environment. These points can reflect basic features of the environment. The features extracted from laser radar are linear features. The measured numbers of laser radar at a single point are greater than estimated numbers of linear feature parameters. Due to measuring errors of sensors, extraction of features needs certain optimizing algorithm to minimize differences between estimated values and measured values.

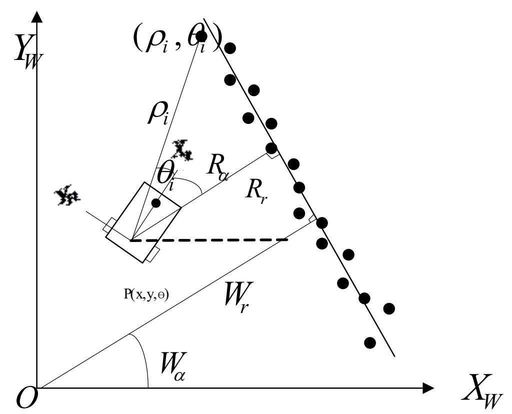

Figure 3. The least square estimation line and environment coordinate [W] to robot local coordinate [R]

Figure 2 shows *n* measuring points $x_i = (\rho_i, \theta_i)$ in the polar coordinates of robot sensors. We assume that the measuring errors of distance information ρ and scanning angle information θ are subjected to Gaussian probability density curve; average value is the measured value and variance is the independent constant σ_ρ and σ_θ. From these points, we can estimate an optimal line. Any given measuring point (ρ, θ) can be converted to Euclidean coordinates through two expressions: $x = \rho\cos\theta$; $y = \sin\theta$. A given straight line can be expressed by the following equation:

$$\rho\cos\theta\cos\alpha + \rho\sin\theta\sin\alpha - r = \rho\cos(\theta-\alpha) - r = 0 \tag{12}$$

The orthogonal distance between the line and a specific point $x_i = (\rho_i, \theta_i)$ is:

$$\rho_i \cos(\theta_i - \alpha) - r = d_i \tag{13}$$

Then we classify data which belong to the same line into one category, and use least squares fitting to generate a straight line. We calculate fitting straight line parameters α and r by the following expressions:

$$\alpha = \frac{1}{2}\arctan\left(\frac{\sum \rho_i^2 \sin 2\theta_i - \sum\sum \rho_i\rho_j \cos\theta_i \sin\theta_j}{\sum \rho_i^2 \cos 2\theta_i - \sum\sum \rho_i\rho_j (\cos\theta_i + \theta_j)}\right) \tag{14}$$

$$r = \sum \rho_i \cos(\theta_i - \alpha) \tag{15}$$

The uncertainty of laser radar measurement will amplify the uncertainty of extracted line. A and R represent random output variables α and r, the covariance matrix of system output is:

$$C_{AR} = \begin{bmatrix} \sigma_A^{\ 2} & \sigma_{AR} \\ \sigma_{AR} & \sigma_R^{\ 2} \end{bmatrix} = F_{\rho\theta} C_X F_{\rho\theta}^{\ T} \tag{16}$$

Where, C_X is a given $2n \times 2n$ input covariance matrix:

$$C_X = \begin{bmatrix} C_\rho & 0 \\ 0 & C_\alpha \end{bmatrix} = \begin{bmatrix} diag(\sigma_{\rho_i}^{\ 2}) & 0 \\ 0 & diag(\sigma_{\theta_i}^{\ 2}) \end{bmatrix} \tag{17}$$

and $F_{\rho\theta}$ is a Jacobi matrix:

$$F_{\rho\theta} = \begin{bmatrix} \frac{\partial\alpha}{\partial\rho_1} \frac{\partial\alpha}{\partial\rho_2} \cdots \frac{\partial\alpha}{\partial\rho_n} & \frac{\partial\alpha}{\partial\theta_1} \frac{\partial\alpha}{\partial\theta_2} \cdots \frac{\partial\alpha}{\partial\theta_n} \\ \frac{\partial r}{\partial\rho_1} \frac{\partial r}{\partial\rho_2} \cdots \frac{\partial r}{\partial\rho_n} & \frac{\partial r}{\partial\theta_1} \frac{\partial r}{\partial\theta_2} \cdots \frac{\partial r}{\partial\theta_n} \end{bmatrix} \tag{18}$$

Therefore, considering the laser radar data errors, we establish sensor model according to environmental features of the extracted line. For every line extracted from sensor data, there exists a pair of corresponding parameters (α , r) and error covariance matrix C_{AR}.

This covariance matrix is the observation error covariance $\sum_{R,i}$ in observation equation.

4 PREDICTION OF ENVIRONMENTAL FEATURES

In multi-sensor fusion, the most important thing is match between predicted environmental features and observed environmental features. Predicted robot position $\hat{p}(k \mid k)$ will generate expected feature $z_{t,i}$. In environmental map, the stored feature is linear feature, which is given as environmental coordinate parameters; whereas extracted linear feature is given as robot local coordinate. Therefore, we transform the predicted observation features in environmental coordinate [W] to robot local coordinate [R]. The following expression shows the transformation:

$$\hat{z}_i(k+1) = \begin{bmatrix} {}^W\alpha_{t,i} - {}^W\hat{\theta}(k+1/k) \\ {}^W r_{t,i} - ({}^W\hat{x}(k+1 \mid k)\cos({}^W\alpha_{t,i}) + {}^W\hat{y}(k+1 \mid k)\sin({}^W\alpha_{t,i})) \end{bmatrix} \tag{19}$$

The Jacobi matrix ∇h_i is given by the following expression:

$$\nabla h_i = \begin{bmatrix} \frac{\partial\alpha_{t,i}}{\partial\hat{x}} & \frac{\partial\alpha_{t,i}}{\partial\hat{y}} & \frac{\partial\alpha_{t,i}}{\partial\hat{\theta}} \\ \frac{\partial r_{t,i}}{\partial\hat{x}} & \frac{\partial r_{t,i}}{\partial\hat{y}} & \frac{\partial r_{t,i}}{\partial\hat{\theta}} \end{bmatrix} = \begin{bmatrix} 0 & 0 & -1 \\ -\cos{}^W\alpha_{t,i} & -\sin{}^W\alpha_{t,i} & 0 \end{bmatrix} \tag{20}$$

From the predicted position of robot, we extract environmental features in robot local coordinate. According to EKF, the following observation equation can be obtained:

$$\hat{z}_i(k+1) = h_i(z_t \hat{p}(k+1/k)) + w_i(k) \tag{21}$$

Where, $w_i(k)$ represents observation errors of sensors.

5 EXPERIMENT

The experimental platform is an autonomous mobile robot, which is based on 32-bit ARM Cortex-M3 microcontroller LM3S8962 and coprocessor DSP. According to our model, the robot has installed internal sensor photoelectric encoder, gyro, and external environmental sensor laser radar. Laser radar is SICK LMS200, whose scanning scope ranges from 0° to 180°. It returns the distance information and angle information of the measured points.

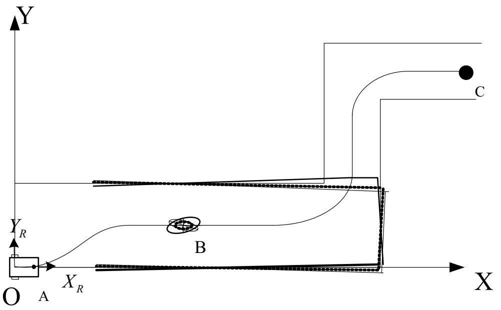

Figure 4. Robot path

As shown in Figure 4, the experiment is conducted in corridor. Point O is the origin of the environmental map, the robot is planned to move from original position A to terminal point C, approximately 20 meters. The robot's speed is 1m/s, sampling time is 0.5s, and estimated starting point $A(x, y, \theta)$ is (0, 0, 0). Practically, point A deviates from the origin to some extent to verify algorithm convergence. The robot use EKF to locate itself during the procedure. In point B, we give the predicted line (thin line), measured line (thick line) and updated estimated line (thick dash line) after data fusing. The prediction, measurement and latest estimation of robot location is uncertain, so the location of the robot is expressed as ellipse. The predicted and observed features of the robot are judged and matched through Mahalanobis Distance.

The robot use linear control algorithm to find the path tracking. Figure 5 shows the whole route. The robot reaches the destination as required; every location's mean-square deviation is about 2 centimeters, and heading angle is less than 0.5. The experimental results show that the sensor fusion system has improved robot navigation.

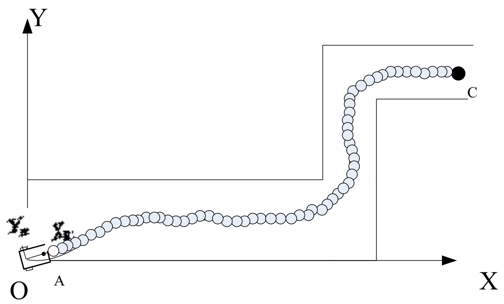

Figure 5. Actual robot path in experiment

6 CONCLUSION

In this paper, we overcome the disadvantages of the system error expression method of previous single sensor or multi-sensor system by adopting the Extended Kalman Filter as mobile robot localization method. When applied to actual robot navigation and location, the results show that the method can improve the precision and reliability of robot localization.

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