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Mobile Robot Localization Based on Extended Kalman Filter*

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***Abstract* - The mobile robot localization methodologies in common use at present have been introduced. A localization algorithm based on Extended Kalman Filter (EKF) has been proposed on the basis of environment feature extraction and map building, which can reduce the error in the calculation of the robot's position and orientation. The method is that the mobile robot analyses and fuses the messages in surroundings from multiple sensors by EKF theory, which enables the robot to identify the surrounding objects clearly and guide itself successfully. The simulation and experimental results show that the proposed localization method is effective.**

Index Terms – Mobile robot, Localization, Extended kalman filter.

I. INTRODUCTION

In order to navigate safely and reliably, an autonomous mobile robot must be able to find its position simultaneously within its environment. To date, there have been many localization methods with respect to the work condition complexity, the category and number of the mounted sensors. All these methods of localization can be divided into two main categories: the relative and the absolute [1, 2]. Relative (local) localization consists of evaluating the position and the orientation through integration of information provided by diverse sensors. The integration is started from the initial position and is continuously updated in time. Absolute (global) localization is the technique which permits the robot to find its way directly in the domain of evolution of the mobile system. These methods usually rely on navigation beacons, active or passive landmarks, map matching or satellite-based signals like Global Positioning System (GPS).

Relative localization is also known as dead-reckoning (DR). Though its simplicity has made DR a widely used technique, we can not rely on it for long distances [4, 5]. The basic drawbacks are: **(1)** The kinematic model of the vehicle is never accurate (for example, we do not know the infinite precision of the distance between the wheel axes of the wheeled robot). **(2)** The sensor models also suffer from inaccuracies and can become very complicated (for example, use of exponential model for the gyroscope drift). **(3)** The sensor readings are corrupted by noise. **(4)** The motion of the vehicle involves external sources of error that are not observable by the sensors used (for example, slippage in the direction of motion or in the perpendicular direction). Due to the above reasons, there is error in the calculation of the robot's position and orientation which generally grows unbounded with time. There has been considerable ongoing research effort in robot localization and various methods have been explored by researchers in the past to address the position error problem [6, 7, 8]. The solution to this problem can be classified into two main groups: odometry error correction and environment or landmark observation [9, 10].

In our work, we integrate the advantages of "the relative localization" and "the absolute localization" and make them complementary, which will enable the mobile robot to localize itself more accurately. The mobile robot analyses and fuses the measurement information in the surroundings such as the sensory information from odometry, INS sensors (local) and information from the laser range finders. Then it will match the actual environment features (detected by these sensors) around the robot to the map known prior by the robot so as to localize the robot simultaneously and successfully.

We organize the rest of the paper as follows. Section II gives a brief description of the wheeled mobile robot's locomotion and odometry system. In section III, we define the environment feature extraction method which will be used in the posterior section. Section IV investigates the localization algorithm based on EKF theory. Section V gives the simulation and experimental results from this research work and finally in section VI, we make a conclusion of this research and list the directions of our future work.

II. THE LOCOMOTION AND ODOMETRY SYSTEM OF THE ROBOT

In the wheeled robot we have investigated, odometry is implemented by means of optical encoders which can monitor the wheel revolutions and steering angles of the robot wheels. Using simple geometric equations (kinematic model of the robot), the encoder data are then used to compute the momentary position of the vehicle relative to a known starting position. Fig. 1 shows the locomotion and odometry system which consists of drive wheels and separate encoder wheels to generate odometry measurements from optical shaft encoders. The system also has a laser range finder which can rotate vertically to the floor. Additionally, the robot's encoder wheels are made with O-rings contacting the floor so as to be as sharp-edged as practically possible to reduce wheelbase

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uncertainty, and are independently mounted on linear bearings to allow vertical motion, and hence minimize problems of wheel distortion and slippage. This design greatly improves the reliability of odometry measurements.

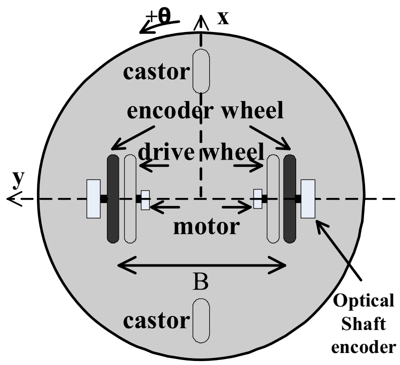

Fig.1 The locomotion and odometry system of the robot

III. Environment Feature Extraction

Almost all the existing localization methods depend on matching the actual environment features (detected by sensors) around the robot to the map known prior by the robot [11]. This map may be a static predetermined one, or a history one generated by the robot while moving. The type of environmental features to be observed by the robot depends on what kind of mapping method to be used, i.e. Geometric or Topological mapping. In the case of Topological map, the map is built using such features as walls, doors, hallways, etc. Conversely, in Geometric mapping method, the map is only described by the certainty of an obstacle occupying a grid cell, i.e. the map is independent and ignorant of the type of features surrounding the robot. Therefore, the features to be observed by the robot can be anything. Corners and straight lines are most commonly used.

A. Detecting Corners Around the Robot

In this work we choose Geometric mapping method and use corners in the environment to localize the robot. Generally, corners are regarded as discontinuity in the straight lines, and intersection of two straight lines with different gradients. In most indoor environments, the difference in gradients of these two intersecting lines is generally about 90 degrees. Fig. 2 shows an example of corners observed by the robot.

It should be noted that not all the discontinuity are corners, some could be table legs, people, wire trunking on walls or chairs. These kinds of discontinuity are undesirable, as they are usually not reflected in the map. To avoid this mistake, the following criteria have to be met in order for an observation to be considered as a corner:

a. Only the discontinuity between long straight lines would be considered. The length of the straight lines depends on the environment as well as the resolution and accuracy of the sensors used to observe the surrounding.

b. Discontinuity between two same straight lines (i.e. the line equations of both straight lines are the same or very close) would not be considered as corners. These discontinuities are usually noise or simply a small gap between cabinets. (Point g in Fig. 2 illustrates this condition)

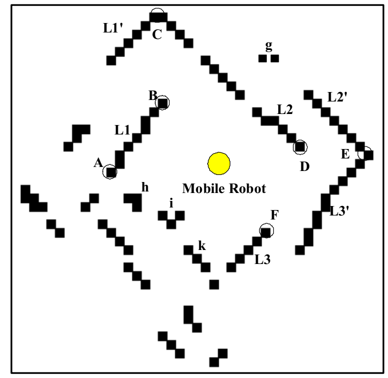

Fig.2 Points that are circled are corners observed

c. When a discontinuity occurs between two different straight lines (for example L1 and L1', L2 and L2', and L3 and L3' in Fig. 2), the point nearer to the robot is considered as a corner; while the point further away is treated to be unknown. This is due to the fact that the "real" corner belonging to the further straight line (represented by L1', L2' and L3' in Fig. 2) might not be within the line of sight of the robot's sensors. Point B, D and F in Fig. 2 illustrate this condition.

d. Note that Point A in Fig. 2 does not fit the previous condition, as the discontinuity does not occur between two straight lines. A straight line that is discontinued with the subsequent points further away from the robot (same concept as the previous condition) and does not form another straight line can be perceived as the end of a straight line, thus a corner too.

B. Detecting Continuous Straight Lines in the Environment

Consider the general planar surface shown in Fig. 3 and the corresponding sensed data points which would result from a perfect 2D line of sight laser sensor. Application of the Sine and Cosine Rules to the two triangles OAB and OBC in Fig. 3, and using the fact that the three points A, B and C all lie in a vertical plane (assuming all the laser range finder scans a horizontal plane), it is possible to show the relationship between successive range readings l_i, when the laser beam is incident upon a planar surface (or wall). This is given by:

$$l_{i+2} = \frac{l_i l_{i+1}}{(2 l_i \cos\theta) - l_{i+1}}$$

Where θ is the constant angle (in bearing) between successive samples of the sensor as it rotates about its vertical axis. We suppose that this formulation is valid for a perfect sensing device, in actual implementation an uncertainty of about $\pm 5mm$ is considered.

C. Corners Matching

The corners recognition methods discussed above applies to the corners in the map as well. In order to achieve localization based on corners in the environment, it is important to match the observed corners to the predetermined corners correctly. Incorrect matching will result in disastrous errors in the localization of the robot.

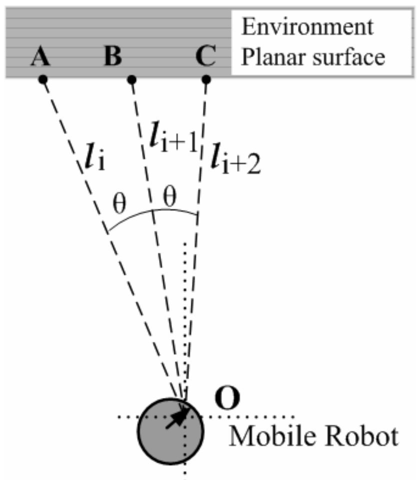

Fig.3 Successive laser range readings when scanning a planar surface

The corners matching method is similar to the detection method for corners in the actual environment. As discussed, the determination of corners depends on the straight lines detected from the environment. Therefore, it will be useful to associate a corner with a straight line. In Fig. 4, we will only consider corners A, B, C, D and E, which are within the sight of the robot laser sensor. Points a', b', c', d' and e' are corresponding corners in the predetermined map. For consistency, the corners are associated to the straight lines on their left whenever possible. Note that in the case of corner a', this is impossible, therefore the straight line l_1 is shared by corners a' and b'.

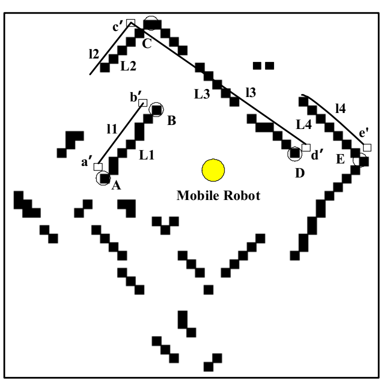

Fig.4 Matching corners detected to corners in predetermined map

The localization work here assumes that the robot is near to the predicted location based on the odometry. Thus, besides matching a corner (for example c') on the map to an observed corner (for example C) by the sensor in its vicinity, the matching procedure will also match the associated straight line and planar surface located by the laser sensor (l_2 and L_2 respectively). This straight line matching thus verifies that the corners matching between c' ad C is correct.

IV. Localization Using Extended Kalman Filter

Wheel slippage causes a drift in the mobile robot, which can be quite disastrous in mobile robot localization and navigation. To provide noise rejection and develop a model dependant estimation of position and orientation, an Extended Kalman Filter (EKF) is applied to the distance data of the mobile robot in our research. The EKF is a modification of the Linear Kalman Filter (LKF) and can handle nonlinear dynamics and nonlinear measurement equations [12]. The EKF is an optimal estimator that recursively combines noisy sensor data with a model of the system dynamics. Inputs to the EKF include distance measurements between the robot and the landmarks as well as the velocities of both tracks. The dynamics in this application are the kinematic relationships that express the change in position of the robot as a function of the track speeds. The EKF fuses this dead reckoning data with the other sensor measurements. The two inputs complement each other to produce an optimal estimate of the robot's position and orientation.

A. Mathematical Model of the Mobile Robot

The wheeled robot starts from an uncertain position, and acquires the environment characteristic values relative to the environment. It can use these measurement values to build up and maintain the localization map incrementally. Therefore, it can obtain the real position of itself simultaneously. The mathematical model of the mobile robot system describes how the robot's position $x(k)$ changes with time in response to the control input and noise disturbance. It can be described as following:

$$X = [x_v, x_1] \tag{1}$$

$$x_v = (x, y, \theta) \tag{2}$$

$$x_1 = (x_1, y_1, ..., x_n, y_n) \tag{3}$$

In the formula, x_v and x_1 stands for the robot state and the landmark separately. Since the landmark is static, the kinetic model of the system can be extended as:

$$x_v(k+1) = f(x_v(k)), x_1(k+1) = x_1(k) \tag{4}$$

Both the distance and orientation information measured by the sensors are relative to the robot itself, therefore the observation equation is the function of the robot state and the landmark:

$$z_r^i = h_r(X) = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{5}$$

$$z_\beta^i = h_\beta(X) = a\tan(\frac{y - y_i}{x - x_i}) - \gamma \tag{6}$$

After we have obtained the sensor observation model, we can carry out the estimation of the robot position according to the classical Kalman filter theory after establishing the system state equation and observation equation required by kalman filter. Unfortunately, we have to use EKF in the robot position estimation because the system's equation in our research doesn't have a constant coefficient.

B. Localization Algorithm Based on EKF

As an intermediate result, the EKF will compute the difference between the predicted and observed measurements, which is called innovation. In our implementation, we use the innovation to reject inaccurate distance measurements. With knowledge of the models required for the computation of the Kalman gain, explanation of the localization procedure will become very easy [13, 14]. Fig. 5 briefly describes the cyclic localization procedure during the localization procedure. The algorithm consists of such steps as position prediction, observation, measurement prediction, matching and estimation. In the EKF localization algorithm, we describe the localization system's posterior value as a multidimensional Gaussian parameter. The mean value describes the mostly possible state of the robot and the landmark. The covariance matrix manifests the correlation of all the state variables. We now proceed to discuss each of these steps in detail.

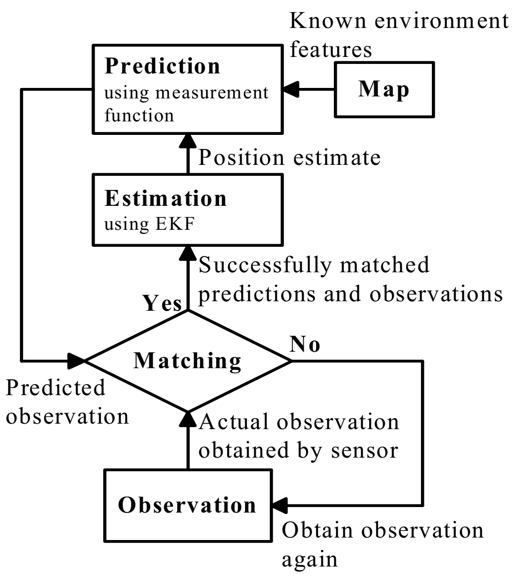

Fig.5 Localization algorithm based on EKF

Step 1 Initialization

Initialize the general state vector $\hat{x}_0$ and aberration covariance matrix p_0 of the mobile robot.

$$\hat{x}_0 = [x_0, y_0, \theta_0]^T \tag{7}$$

$$P_0 = \xi_0 \xi_0^T \tag{8}$$

Step 2 Position Prediction

The robot position prediction can be calculated by (9), and the associated state covariance $P(k+1\mid k)$ is obtained by (10).

$$\hat{x}(k+1\mid k) = f(x(k), u(k)) \tag{9}$$

$$P(k+1\mid k) = \nabla f P(k\mid k) \nabla f^T + Q(k) \tag{10}$$

Step 3 Observation/Measurement Prediction

The observation of the corners in the environment is obtained by the laser range-finder:

$$z(k+1) = [z_r^i, z_\beta^i]^T \tag{11}$$

Using the predicted robot position $\hat{x}(k+1\mid k)$ and the current map with known corners position we can generate the predicted observation.

$$\hat{z}(k+1) = h(z(k+1\mid k), \hat{x}(k+1\mid k)) \tag{12}$$

The error between the actual measurement $z(k+1)$ and the predicted observation (without noise) based on our best estimate of the state is:

$$v(k+1) = z(k+1) - \hat{z}(k+1) \tag{13}$$

The innovation covariance is：

$$S(k+1) = \nabla h P(k+1\mid k) \nabla h^T + R(k+1) \tag{14}$$

Step 4 Matching

For each measurement, the uncertainty of the measurement value makes it necessary to validate whether it is matching or not. If the measurement result satisfies the following inequality, it is thought to be eligible, otherwise, it is not, and it will be abnegated.

$$v(k+1) S(k+1) v^T(k+1) \le G \tag{15}$$

Step 5 Estimation

Now we can compute the final state estimate at step k

$$\hat{x}(k+1\mid k+1) = \hat{x}(k+1\mid k) + W(k+1) v(k+1) \tag{16}$$

Where $W(k+1)$ is the Kalman gain:

$$W(k+1) = P(k+1\mid k) \nabla h^T S^{-1}(k+1) \tag{17}$$

The new state covariance matrix is:

$$\mathrm{P(k+1|k+1)=P(k+1|k)+W(k+1)S(k+1)W^T}(k+1) \tag{18}$$

Step 6 Return to Step 2 and implement step 2 to step 5 mentioned above recursively.

V. Simulation and Experiment

To assess the localization capability of the mobile robot, a simulation and a simple experiment have been carried out. In the simulation, we set its initial position marked out, and the mobile robot is made to move in a two by two metres square path from point S to point G. In order to be able to localize or verify the reported robot position, a prior knowledge of the environment is needed. We assumed that the first reported position is one that is perfect. A scan of the surrounding will then determine the global positions of some of the obstacles around the mobile robot. This initial obstacle information is therefore treated as one that is based on accurate positioning. Fig. 6 shows the simulation result of the localization algorithm based on EKF.

Fig.7 shows an experiment of the autonomous localization and navigation implemented in a real laboratory environment. The robot's task is to start from point A to arrive at the destination B so as to seek for the lamp. From fig. 7, we can see that the wheeled robot can localize itself by fusing the sensor information and map matching so as to avoid the obstacles successfully until it reaches point B (to find the lamp). This experiment proves the validity of the localization algorithm based on EKF theory.

VI. Conclusion

This paper presents the results from the ongoing research effort related to the localization based on EKF. One of the conclusions derived from this work is that the EKF provides the robot with position and orientation estimates reliably. It was also shown that the inclusion of sensor data fusion had considerable affect on the uncertainty of the estimates. The last conclusion shows that it is of great importance to integrate the absolute and the relative localization method in the mobile robot localization and navigation.

Within our goals in the near future is to define and use a more accurate kinematic model of the robot that will enable us to expand the estimation to the 3D space. We also plan to fuse extra information from sensors not used in the current implementation (such as the accelerometers). Finally we expect to use data from the real robot to tune the EKF appropriately.

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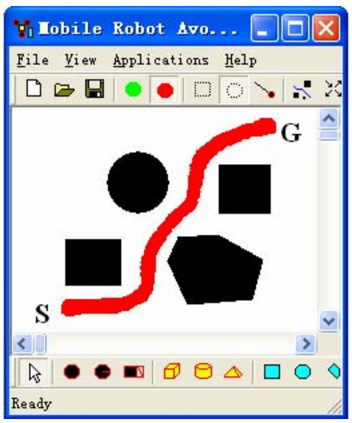

Fig.6 Simulation of the localization algorithm based on EKF

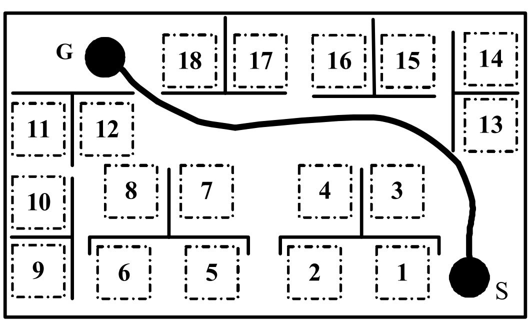

Fig.7 Autonomous moving in the Lab

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