A Localization of Mobile Robot based on Ultra-sonic Sensor using Dynamic Obstacles

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Abstract

Localization is most important and necessary technology for mobile robot to work well. The robots need to recognize their position and pose in known environment as well as unknown environment. In the future, the robots will be human-friendly robots that are able to coexist with humans in dynamic space. The localization includes several restrictions which arise from dynamic obstacles-people, moving chair, and so on. It is desirable for a mobile robot to estimate his position using dynamic obstacles. In this paper, we propose the method for the localization of the mobile robot using a moving object. Throughout the computer simulation experiments, its performance is verified.

Keywords Mobile robot; Moving object; localization; position estimation;

1 Introduction

Localization of the mobile robot is one of the most important issues for successful autonomous navigation; therefore, a great number of localization methods have been proposed and developed so far[1][2].

The difficult problem that has a substantial impact on the localization of the mobile robot is the environment. The environments can be static or dynamics[3]. Static environments are environments where the only variable quantity state is the robot's pose. Put differently, only the robot moves in static environment. All other objects in the environments remain at the same location forever. Static environments have some nice mathematical properties that make them amenable to efficient probabilistic estimation. Dynamics environments possess objects other than the robot whose location or configuration changes over time. Specially, the changes persist over time. Examples of more persistent changes are people, and moving object such as furniture, chairs, and so forth. A good example of dynamic environments is shown in figure 1. Because of various uncertainties and limitation of sensor information for dynamic changes, localization in the dynamics environments is obviously more difficult than localization in the static ones. Therefore, there are two general methods for estimation of location under each environment. Under static environment, the localization of the mobile robot is based on landmark method using the wall, corner and door recognition. This method requires feature extraction of static obstacle or landmark. However, unfortunately, most real environments are dynamics with state changes occurring at a range of different speeds. Thus, for most real-world application, it is desirable that mobile robots are capable of exploring or moving within a dynamics environments[4].

This paper considers the situation where a mobile robot is moving an unstructured environment, there is only moving object. In this paper, we present a method for solving previous problem using ultrasonic sensor, which is able to measure the distance between the moving object and the mobile robot. The movements of object can be detected by sonar sensor, and then the position of the moving object is estimated. Using the distance data, the robot's position can be estimated.

This paper is organized as follows. Section 2 shows a kinematics modeling and position estimation of the mobile robot. In Section 3, the method that detects the moving object using ultrasonic sensor is described, the position correction technique with Kalman-filter is shown. In Section 4, the experiments environment and computer simulation results are shown to prove the validity of the proposed method. Finally, in Section 5, conclusion and further research topic are presented.

Fig. 1. The mobile robot in dynamic environments.

2 Robot Modeling

2.1 Kinematics modeling of a mobile robot

The modeling of a mobile robot is shown in fig. 2, where

x_R : the y-component of the mobile robot position;
y_R : the x-component of the mobile robot position;
θ_R : the orientation of the mobile robot;
v_L : the velocity of left wheel;
v_R : the velocity of right wheel;
v_1 : the linear velocity of the mobile robot;

v_2 : the angular velocity of the mobile robot;
l : the width of the mobile robot.

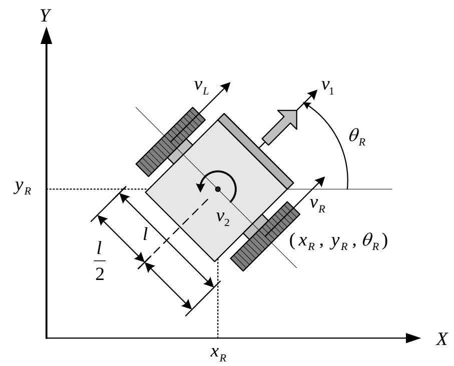

Fig. 2. Kinematics model of a mobile robot.

A mobile robot with differential driving mechanism has two wheels on the same axis, and each wheel is controlled by an independent motor. On the two dimensional $X-Y$ cartesian coordinates, position and orientation of the mobile robot is described by state vector as follow:

$$P_{robot} = [x_R \quad y_R \quad \theta_R]^T \tag{1}$$

The linear and angular velocities of the mobile robot can be described as follows:

$$v_1 = \frac{v_R + v_L}{2}, \tag{2}$$

$$v_2 = \frac{2(v_R - v_L)}{l}. \tag{3}$$

Now the kinematics model of the mobile robot can be represented as [5]

$$\dot{P}_{robot} = \begin{bmatrix} \cos\theta_R & 0 \\ \sin\theta_R & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \tag{4}$$

Kinematics analysis aims at the proper velocity assignment to each wheel to drive the mobile robot to a desired position and orientation.

2.2 Position propagation

In previous session, we studied that the states of the mobile robot with differential driving mechanism are changing according to the two wheel velocities.

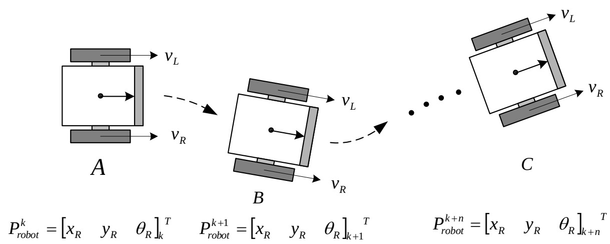

Fig. 3. Position propagation of the mobile robot.

In Fig. 3, when the mobile robot is moving from A where the robot is located on $P_{robot}^{k} = [x_R \quad y_R \quad \theta_R]_k^T$ at time = k to C where the position is on $P_{robot}^{k+n} = [x_R \quad y_R \quad \theta_R]_{k+n}^T$ at time = $k+n$. The state transition of the mobile robot can be described in terms of currents state and inputs as follows[ ]:

$$x_R^{k+1} = x_R^k + T\frac{v_R + v_R}{2}\cos\theta_R^k, \tag{5-a}$$

$$y_R^{k+1} = y_R^k + T\frac{v_R + v_R}{2}\sin\theta_R^k, \tag{5-b}$$

$$\theta_R^{k+1} = \theta_R^k + T\frac{v_R - v_R}{l}. \tag{5-c}$$

where T is the sampling period.

Note when the position of the mobile robot is estimated, state estimation error is included, and represented as follow:

$$\hat{P}_{robot}^{k+1} = f(P_{robot}^k, u(k)) + v(k), \tag{6}$$

where $u(k)$ is the current input, $v(k)$ denotes estimation error as a noise term. The estimation error is unexpected components, when position is calculated[6]. The error can be corrected by applying Kalman filtering technique in Section 3.

3 The Localization by Ultrasonic Sensor

3.1 Detecting moving object using sonar sensor

In this section, we describe the procedure of detecting a moving object through a distance obtained by ultrasonic sensor. When the object is moving, it can be detected by sonar sensor, and then distance information between the object and the robot is available to robot. The position of the mobile robot is updated. Fig. 4. show the coordinates of the moving object and the mobile robot with 12 ultrasonic sensors.

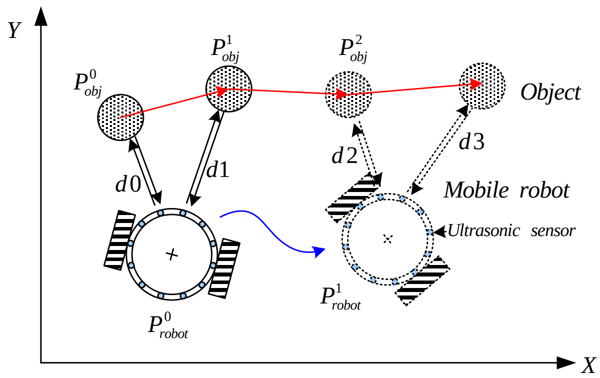

Fig. 4. The outline of motion of object and robot.

As shown fig. 4. the initial position of the object and mobile robot is precisely given as P_{obj}^0, P_{robot}^0, respectively. Also, the distance d between the object and the mobile robot is denoted.

There are three steps in procedure of detecting the moving object.

Initially, the mobile robot and the object is kept stationary. When the object is moving, distance information at time k and k+1, respectively, generate the distance differences. When distance differences exceed the specified threshold value, thus, resulting in the detection of motion of the object.

Secondary, in case that a distance information is obtained by neighboring sensor due to movement of the object, the displacement and angular data with respect to measuring time, T_M of the object can be calculated as shown in fig. 5. And then, the current state of the moving object is estimated thought initial state and obtained information.

Finally, the mobile robot moves along a free path after estimation of the moving object is finished. The inverse method is used to estimate the position of the mobile robot. When the object is kept stationary and the mobile robot moves, the displacement and velocity with respect to the measuring time, T_M of the mobile robot can be obtained. The state vector of the mobile robot is estimated.

To obtained the sequential position estimation, we can use proposed step recursively. The outputs of step are chosen as the estimated state vector of the moving object and mobile robot.

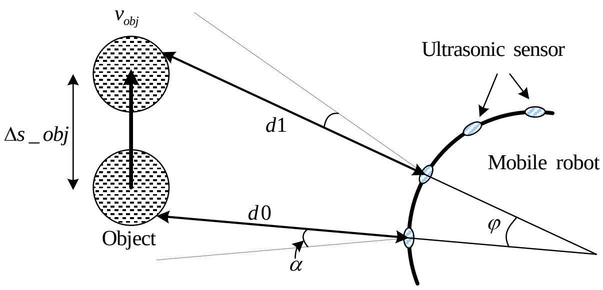

Fig. 5. The motion of object.

3.2 Correction using Kalman filter

The estimated position of the moving object includes some unexpected estimation error. This leads to failure in localization of the mobile robot. An Kalman filter[7] can be one of the good method to tackle this problem. To apply the state estimation of a moving object to the Kalman filter, eq.(7) and (8) of the state transition matrix are required. The Kalman filter minimizes the estimation error by modifying the state transition model based on the error between the estimated vectors and the measured vectors, with an appropriate filter gain. The state vector which consists of a position on the x-y plane, the direction, linear and angular velocity can be estimated using the measured vectors representing the position of the moving object[8].

$$x^k = \Phi^k x^{k-1} + w^{k-1} \tag{7}$$

$$z^k = H^k x^k + v^{k-1} \tag{8}$$

The Kalman filter is a recursive algorithm to determine $\hat{x}^k$, the optimal estimation value of state vector, x^k in a linear dynamic system. Kalman filtering is divided into the three steps of prediction, measurement, and correction.

In the prediction step, the next state vector $x_{(-)}^{K+1}$ and the covariance matrix of the estimated error $P_{(-)}^{k+1}$ are predicted. The symbol (-) means that the values don't correct through measurement. The covariance matrix of the estimated error is just like eq.(9).

$$P_{(-)}^{k+1} = E[(x^k - \hat{x}^k)(x^k - \hat{x}^k)^T] \tag{9}$$

The projected estimates of the covariance matrix of the estimated error and the state vector in the prediction step are represented as

$$\hat{x}^{k+1} = \Phi^k \hat{x}_{(+)}^k + w^k \tag{10}$$

$$P_{(-)}^{k+1} = P_{(+)}^k + Q^k \tag{11}$$

where Φ^k is the state transition matrix of $\hat{x}_{(-)}^{K+1}$, w^k is the model noise of the system, where Q^k is the covariance matrix of w^k.

The measurement step is represented as

$$z^k = H^k \hat{x}^k + v^k \tag{12}$$

where z^k is the measurement vector, H^k represents the relationship between the measurement and the state vector, and v^k is the measurement error.

In the final correction step, the state vector and the estimate error are corrected to a new value based on the measurement value of the measurement step. The formula is represented as

$$K^k = P_{(-)}^k (H^k)^T [H^k P_{(-)}^k (H^k)^T + R^k]^{-1} \tag{13}$$

$$\hat{x}_{(+)}^k = \hat{x}_{(-)}^k + K^k [z^k - H^k \hat{x}_{(-)}^k] \tag{14}$$

$$P_{(-)}^k = [I - K^k H^k] P_{(-)}^k \tag{15}$$

where R^k is the covariance matrix of the measurement noise, and K^k represents the Kalman gain. The optimal filter gain K^k minimizes the estimate errors by the covariance matrix of the estimate error $P_{(-)}^k$, the measurement matrix H^k, and the covariance matrix of measurement noise R^k in eq.(20). Next time, the estimate of the state vector $\hat{x}_{(+)}^k$ from the measurement z^k is expressed as eq.(21). The Kalman gain functions as the weighting between the measurement and the estimate value when the state vector x^k is corrected. In the end, as in eq.(22), the covariance matrix of the estimated error is corrected.

4 Simulation Experiments

4.1 Experimental environment

The proposed approach is implemented on computer simulation program. The experimental parameters 1 for computer simulation are listed in Table.

Let assume some conditions for finding the position of moving object and localization of the mobile robot.

1) The maximum velocity of the mobile robot is faster than that of moving object.
2) There is no interference between other ultrasonic sensors
3) The initial position of the robot and object is given.
4) The path of the robot and object is piecewise continuously differential.

Table 1. Simulation parameter

Parameter list	Value
Size(diameter) of Robot	0.5 m
Size(diameter) of object	0.15 m
Number of ultrasonic sensor	12
Maximum detecting range of ultrasonic sensor	3 (m)
Directivity of ultrasonic sensor	10 (deg)

4.2 Experimental results and discussions

The initial position of the moving object and the mobile robot was set as (0.5, 3, 0^o) and (1, 2, 10 ^{o}), respectively. Fig. 6. shows the path of the moving object and the mobile robot.

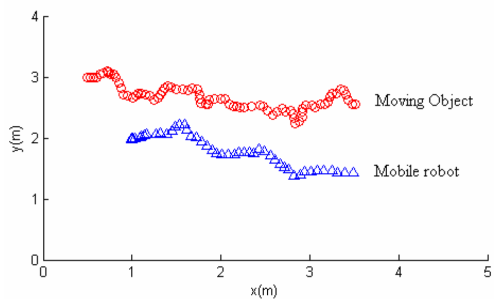

Fig. 6. The path of the moving object and robot.

The estimated state vector of the mobile robot by only dead-reckoning method with uncertainty is shown in fig. 7. And in fig. 8, reduced error with proposed algorithm is shown.

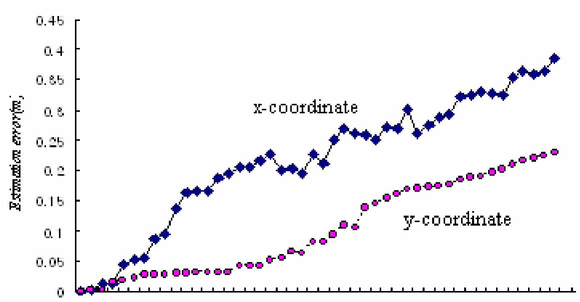

Fig. 7. Position estimation error of the mobile robot using only dead-reckoning method.

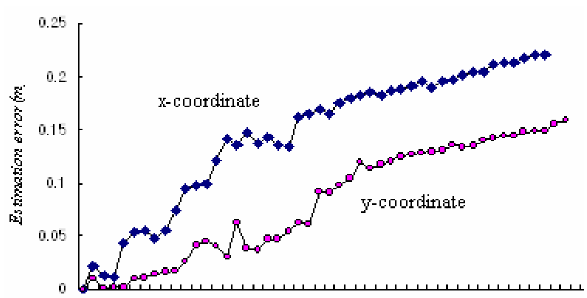

Fig. 8. Position estimation error of the mobile robot using moving object

5 Conclusions

In this paper, an state estimation method for a mobile robot with ultrasonic sensor was proposed using the moving object. The estimated errors is reduced using Kalman filter. It was demonstrated that localization of the mobile robot on computer simulation.

The localization is one of the fundamental functions for intelligent mobile robot. The mobile robot has to handle various dynamic uncertainties for localization robustly. In further research, proposed method will be verified throughout the real experiments with a robot system. And the effective localization of the mobile robot will be needed to improve the estimation accuracy.

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