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Position Estimation for Mobile Robot Using Sensor Fusion

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Abstract — *An accurate position estimation is essential for a mobile robot, especially under partially known environment. Dead Reckoning has been commonly used for position estimation. However this method has inherently problems because it also accumulate estimation errors. In this paper, we propose two methods to increase the accuracy of estimated positions using multiple sensors information. One method is a probabilistic approach using Bayes rule, and the other is a matching method applying least squared scheme. Both of these two approaches use features, such as corner points and edges of the object in the task environment instead of land-marks. It is shown that we will be able to estimate the position of mobile robot precisely, in which errors are not cumulated.*

1 Introduction

Robots must operate in an environment which is partially known or inherently uncertain. This uncertainty arises in the modeling, planning, and motion of mobile robot and objects. In industrial robotics and in most robotics research, there is a tendency to represent and solve the uncertainty for obtaining efficient operation by requiring any resulting errors to be small. Generally, the uncertainties are presented as a covariance of data errors. In this paper, we discuss about mobile robot motion uncertainty.

An accurate position estimation is essential for a mobile robot, especially under unknown environment. In the past dead reckoning method has been used. Dead reckoning method is to accumulate wheel's rotations as follows:

$$x(t+\tau) = x(t) + \tau v(t)cos(\theta) \quad (1)$$

$$y(t+\tau) = y(t) + \tau v(t)sin(\theta) \quad (2)$$

$$\theta(t+\tau) = \theta(t) + 2\tau u(t)/t \quad (3)$$

Here, $v(t)$ is a translation speed($v(t) = (v_r(t) + v_l(t))/2$), and $u(t)$ is a difference speed($u(t) = (v_r(t) - v_l(t))/2$) of left and right wheels. And, $v_r(t)$ and $v_l(t)$ are left wheel speed and right wheel's, respectively. The positioning errors are relative large and always accumulated, because this method is not good dealing with slipping motions of robot and sensor errors. Therefore, to prevent the error from being accumulated, many researchers has usually used the landmark. We, in this paper, propose new methods to estimate robot position without the landmark. This paper are composed of three parts. In the first part, two position estimation methods are discussed. One is a probabilistic approach, which is to choose a point with the highest possibility as robot position. The other one is to minimize position error using least square method. In section 3, a study for establishing an environment model to estimate the position under unknown environment has been presented. And, final section shows simulation results.

2 Position Estimation under Known Environment

The position of wheel-type mobile robot on the flat surface in the time step k can be presented as $P(x_k, y_k, \theta_k)$, relative to a global coordinate system. Here, θ_k is the robot's orientation. It is possible to calculate not only the position, but also the orientation using "dead reckoning method" which has been widely used. But it has several problems, such as large estimation errors and their accumulation effect. The major errors are generated due to slipping motions.

In this section, our aim is to investigate of an accurate and simple positioning method using data from ultrasonic sensors. At first, we assume that there are multiple ultra-sonic sensors on a mobile robot, and that there are two objects in known environment which is located at given positions (Fig.1).

In Fig.1, mobile robot equipped with eight ultra-sonic sensors and two encoders in two wheels. When an object is detected by sensor1, we can calculate the mobile robot position by changing a viewpoint, which means, assuming that the sensors are not placed on robot, but located on

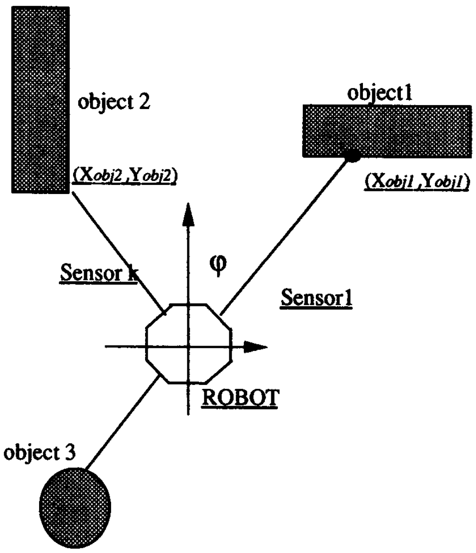

Figure 1: Sensing robot position

objects.

$$[X_k, Y_k]^T = \begin{bmatrix} X_{obj1} - l_1 \sin(\varphi_1 - \theta_k) \\ Y_{obj1} - l_1 \cos(\varphi_1 - \theta_k) \end{bmatrix} \quad (4)$$

Here, φ is an angle of sensor in robot coordinate. However, a value of θ_k, which is a rotation angle between robot coordinate and global coordinate, has not been known unfortunately. Therefore let's assume another situation that one of the other sensors is sensing another object simultaneously. This assumption is not so unreasonable because eight ultra-sonic sensors are placed on robot. Therefore, it is possible to obtain robot position data as shown in Eqs.(5):

$$[X_k, Y_k]^T = \begin{bmatrix} X_{obj2} - l_2 \sin(\varphi_i - \theta_k) \\ Y_{obj2} - l_2 \cos(\varphi_i - \theta_k) \end{bmatrix} \quad (5)$$

Thus, θ_k is calculated combining Eqs.(5) with Eqs.(4).

$$\theta_k = \arctan(\frac{(Y_{obj2} - Y_{obj1})\,\eta_1 - (X_{obj2} - X_{obj1})\,\zeta_1}{(Y_{obj2} - Y_{obj1})\,\eta_2 + (X_{obj2} - X_{obj1})\,\zeta_2} \quad (6)$$

Here, $\eta_1 = l_2 \sin(\varphi_2) - l_2 \sin(\varphi_1)$, $\eta_2 = l_1 \cos(\varphi_2) - l_1 \cos(\varphi_1)$, $\zeta_1 = l_2 \cos(\varphi_2) - l_1 \cos(\varphi_1)$, and $\zeta_2 = l_2 \sin(\varphi_2) - l_1 \sin(\varphi_1)$. Eqs.(6) has been established under a presupposition, which is for ultra-sonic sensors to be able to give the very accurate distance data. If it is not accurate, it may not be possible to combine Eqs.(4) with Eqs.(5), that is, $[X_k, Y_k]$ of Eqs.(4) are not coincide with $[X_k, Y_k]$ of Eqs.(5). In general, ultrasonic sensor is a common form of range sensors, but their resolution is very poor because of the large beam width (typically 15 or more degrees). Consequently, for solving the estimation problem with inaccurate range data, it requires to consider uncertainties of ultra-sonic sensor data.

2.1 Probabilistic Approach

To represent the inaccurate range data, consider an ultrasonic sensor in which the measurements are corrupted by Gaussian noise of zero mean and variance σ^2. The corresponding sensor p.d.f (probability density function) is given by

$$P_u(r|z,\theta) = \frac{1}{2\pi\sigma_r\sigma_\theta} exp\left[-\frac{1}{2}\left(\frac{(r-z)^2}{\sigma_r^2} + \frac{(\theta)^2}{\sigma_\theta^2}\right)\right] \quad (7)$$

Here, r is a measured distance, z is a real distance value. On the other hand, an environment around mobile robot is expressed as a tessellation of space into cells, where each cell stores a probabilistic estimate of its state, based on the measured distance data. A realization of the tessellated environment is obtained by estimating an occupied state of each cell from sensor data. Applying Bayes' theorem to the data, we determine the state of a cell [1].

$$P[s(C_i) = occ|r] = \frac{P[r|s(C_i) = occ]\,P[s(C_i) = occ]}{\Sigma P[r|s(C_i)]\,P[s(C_i)]} \quad (8)$$

Here, $P[r|s(C_i) = occ]$ can be determined using the above mentioned sensor model, $P[s(C_i) = occ]$ is a previous or initial state of the cell.

We change again our viewpoint: "The data are values of distance which were not measured from robot to objects, but were sensed from objects - as sensors are placed on objects."

However, it is difficult to determine that the measured data are distance between robot and the coresponding object. If we assume that the robot's position and orientation will change very small during one sample time, robot's near position can be assumed as output of dead reckoning. We then be able to decide at where object is being detected. Because each measured data from ultrasonic sensors has uncertainty value which is defined by error covariance, an occupied state of each cell around mobile robot is estimated as an occupied probability by applying the above equation Eqs.(8) to data of each sensor. We choose a point or cell, which has the highest

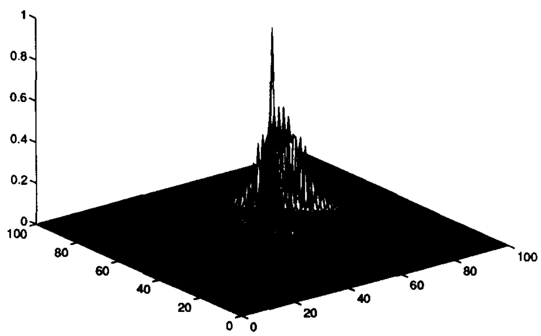

Figure 2: An example of robot existence probability

probability of cells, as robot's current position. Consequently, the more precise position are calculated by

$$[R_x, R_y]^T = \begin{bmatrix} \dfrac{\int_{s \in x} X P[s(C_i)=occ|r_1,\ldots,r_n]dx}{\iint_{s \in x,y} P[s(C_i)=occ|r_1,\ldots,r_n]dxdy} \\ \dfrac{\int_{s \in y} Y P[s(C_i)=occ|r_1,\ldots,r_n]dy}{\iint_{s \in x,y} P[s(C_i)=occ|r_1,\ldots,r_n]dxdy} \end{bmatrix} \quad (9)$$

As an example, the obtained probability of each cell is represented as shown in Fig.2.

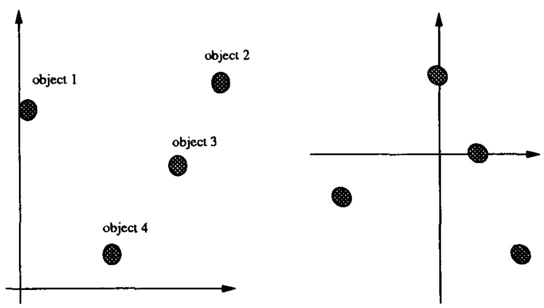

Figure 3: object pattern (a)in real world,(b)in robot view

In 2-D world, the objects detected by the sensors can be viewed from world coordinate system and mobil robot moving coordinate system as shown in Fig.3(a) and 3(b).

2.2 Position Estimation using Least Squares Method

To estimate a robot position, we match the two object patterns using least square method [10. 11]. Let $X = \{x_1, x_2, \cdots, x_n\}$ and $Y = \{y_1, y_2, \cdots, y_n\}$ be corresponding object patterns in 2-dimensional space. That is, X and Y are sets of object positions on Fig.3(a) and Fig.3(b), respectively. To match X and Y, minimize the following equation.

$$F(R,t) = \frac{1}{n}\sum_{i=1}^{n} \|y_i - (Rx_i + t)\|^2 \quad (10)$$

Here, R is a 2×2 rotation matrix, and t is a 2×1 translation vector. The optimum transformations are determined uniquely as follows:

$$R = USV^T, \qquad t = \mu_y - R\mu_x \quad (11)$$

where UDV^T is a singular value decomposition of XY^T ($UU^T = VV^T = I, D = diag(d_i), d_1 \geq d_2 \geq 0$), $\mu_x = \frac{1}{n}\sum_{i=1}^{n} x_i$,and $\mu_y = \frac{1}{n}\sum_{i=1}^{n} y_i$. And, S in Eqs.11 is chosen as

$$S = \begin{cases} I & \text{if } det(U)det(V) = 1 \\ diag(1,-1) & \text{if } det(U)det(V) = -1 \end{cases} \quad (12)$$

Consequently, a current position and orientation of mobile robot can be expressed optimally using t and R in Eqs.(11).

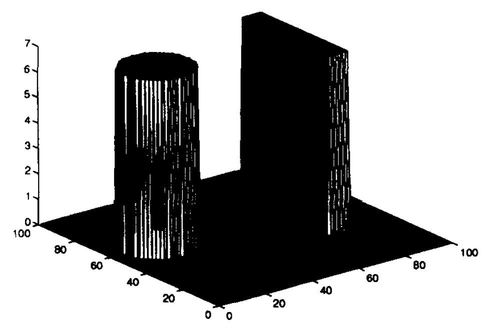

Figure 4: An Example of environment

3 Environment Model

To estimate robot position under unknown environment using data from ultra-sonic sensors, it is necessary to establish environment probability model with information from sensors. The mathematic model of the sensors is given in Eqs.7. And, an environment represented as a tessellation of space into cells, where each cell stores a probabilistic estimate of its state. A realization of the tessellated environment is obtained by estimating an occupied state of each cell from sensor data. To determine

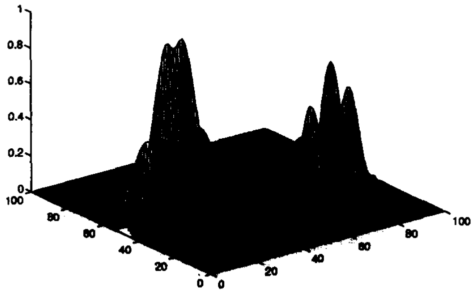

Figure 5: Environment probability

the state of a cell, we start by applying Bayes' theorem with the data, as shown in Eqs.8. As an example of an environment model shown in Fig. 4, we can obtain its probability model as shown in Fig. 5.

3.1 Environment Probability Model by Visual Sensor

Assume that mobile robot working at indoor environment obstacle, objects are located on flat floor, and visual sensor is feasible to see the entire object. As an example of the probability map obtained from visual sensor data, Fig. 6 shows an environment probability model generated , when cubic object of Fig.4 is detected completely, however cylindrical object is detected only partially.

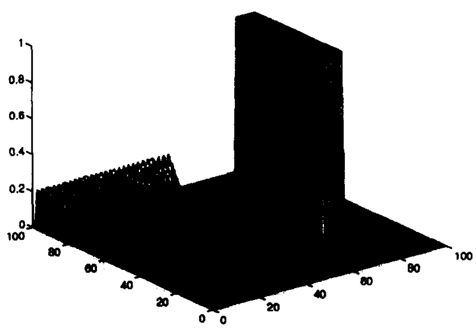

Figure 6: An example of probability map from visual sensor data

3.2 Combination of Two Map using Dempster-Shafer Rule

Each map has been expressed as the occupied probability of cells, that is, denoted as $P[s(ci) = occ]$. D-S rule (Dempster-Shafer rule) is applied for combining two maps and increasing the reliability as follows.

$$P\left[s\left(C_i\right) = occ\right] = \frac{P_v\left[s\left(C_i\right) = occ\right] P_u\left[s\left(C_i\right) = occ\right]}{1 - \chi_s} \tag{13}$$

Here, $\chi_s = P_u\left(1 - P_v\right) + P_v\left(1 - P_u\right)$, P_v and P_u are probability in visual sensor map and ultra-sonic sensor map, respectively. As an example, Fig. 5 combines with Fig. 6 become fused information as shown in Fig. 7. With the above combined Map (Fig. 7), robot positions can be estimated using the least square method or probability method.

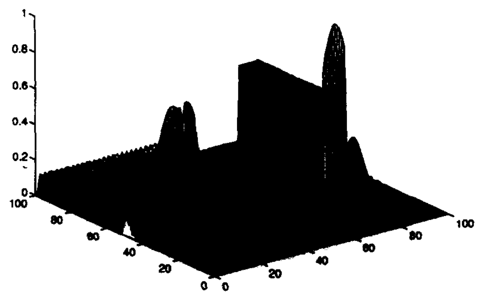

Figure 7: An example of the map combination

4 Simulation Results

The proposed methods are tested on an environment as shown in Fig.8. The mobile robot move from origin point to final place through intermediate points, P1 and P2. Here, origin point is (0,0), final goal is (85.85), and intermediate points are P1(15,15) and P2(85,15), where the units of numbers are 0.1 meter. At first, we tested dead-reckoning method on this environment. The results are shown in Fig.9. Here, the solid line is the actual position and the dotted line represents the estimated position by dead-reckoning method.

Fig.9 shows that the position error to be updated is large and especially, position errors are affected by the orientation error seriously.

In the second stage, we apply dead-reckoning until robot about to arrive at the point P2 and then, the pro-

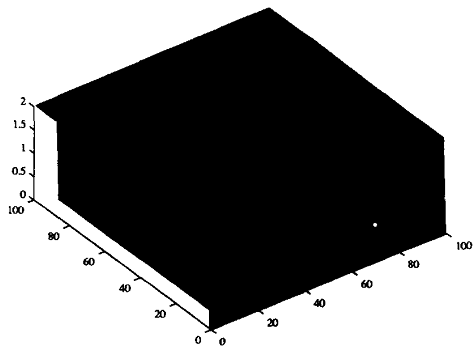

Figure 8: Simulation environment

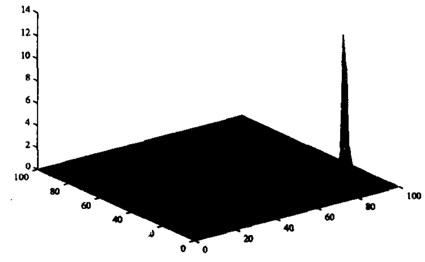

Figure 10: Robot position probability map

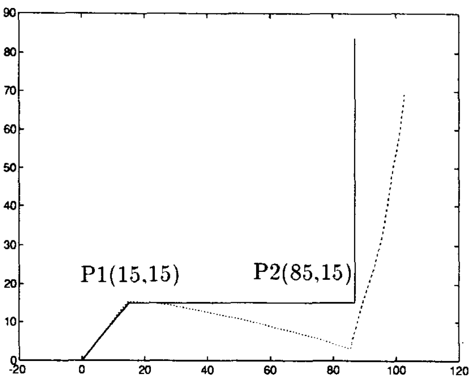

Figure 9: Positioning by dead-reckoning method

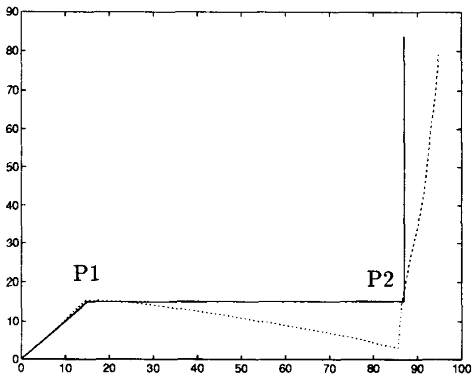

Figure 11: Positioning by probability method

posed probabilistic method is used at P2 for robot positioning. This is due to the fact that the robot will be able to apply probabilistic method after detecting environment features such as corner points. After sensing edges and corner point, we can establish a probability map as shown in Fig.10. While the coordinates of P2 is (85,15), this probabilistic method estimates the coordinates as (85,13.34).

Fig.11 shows that the errors are not updated at P2 and the positional errors are reduced.

Under the above situation, our least square method is applied at P2. The results is better than the probabilistic approach, for example, the estimated coordinates is (85,14.03). As shown in Fig.12, our approaches are applicable to estimate under unknown environment. Firstly, establish a probability map of environment using our method described in section three, and make a decision for detecting obstacles or objects. And then, apply our methods for positioning mobile robot. At initial time, the positioning is very poor. However, the environment map is being updated, so that it becomes very close to real world. Therefore, the estimation method we proposed are in real value.

5 Conclusion

We have proposed and simulated the robot positioning methods, which errors are not accumulated and not so large. Also, by detecting features of real world and using them instead of land-marks, we showed that the proposed methods can estimate the position of mobile robot precisely. However, our least square method needs the assumption that the measured points are matched with points in a given model as one-to-one correspondence and that the every points in the model are be-

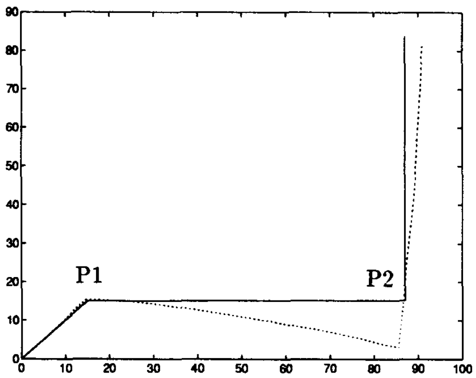

Figure 12: Least square under known environment

ing measured simultaneously. Of course, the matching problem can be solved using a small window and processing data only within that window. The probabilistic approach has not such matching problem, but it needs high computing power.

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