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A Basic Consideration on Estimation of Robot Positions by Observing Unknown Environment

Keiji Gyohten, Koji Nagamura, Tsuyoshi Yoshikawa, Kazuhiko Sakamoto, Yoshiyuki Soma, Takashi Shimazaki and Tsuneo Kagawa

Department of Computer Science and Intelligent Systems, Faculty of Engineering, Oita University.

Abstract

This paper presents a method which reduces uncertainty of a position and a direction of an autonomous robot by observing environment with a camera. In the proposed method, the state of the robot is represented by a state vector obeying a probability distribution. The robot creates and renews an environment map by considering the information from the mounted camera. Moreover, the robot revises the probability distribution on its state by comparing the map and the information from the camera. This attempt at avoiding the inconsistency in the map reduces the uncertainty of the state of the robot. We present experimental results to show the possibility of this method.

1 Introduction

Controlling an autonomous robot is a subject to study attracting the interest of many researchers for these years. When using a state vector to represents a position and a direction of the robot, the system should grasp its true value correctly to make appropriate path planning. However, the state vector gradually deviates from expected values because small errors included in the actuating signals are heaped up as the robot is controlled successively.

This problem also has been coped with in many researches, where the uncertainty of state vector was often reduced using information obtained from a camera. One of the most interesting approaches represents the state vector statistically as a stochastic variable obeying a probability distribution[1][2]. In this method, the variance of the distribution can be narrowed effectively by comparing a given map and the information from the camera.

On the other hand, our research attempts to reduce the uncertainty of the state vector without a map given beforehand. This method creates and renews a map with the information from the camera through the process of moving the robot. This map consists of vertical edges of the obstacles which can be observed as the vertical edges in the images obtained successively. The locations of these edges are calculated on the basis of the stereo viewing which uses two images obtained at different positions on the path of the robot. The proposed method revises the probability distribution on the state vector by comparing the map and calculated edge locations. After that, each edge in the map is revised according to the newly obtained edge locations. The uncertainty of the state vector is reduced by this observation of the environment. We present some experimental results to show the possibility of the proposed method.

Address: 700 Dannoharu, Oita 870-1192 Japan.
E-mail: {gyohten, nagamura, yosikawa, kskaz, sowuch, simazaki, kagawa}@csis.oita-u.ac.jp

2 Uncertainty of state vector caused by movement

This research assumes a two-wheel-drive robot which has monocular vision with a camera as illustrated in Figure 1. Since each wheel is controlled independently, an actuating signal at time t can be denoted by $\boldsymbol{S}_t (= (s_{l(t)}, s_{r(t)})^T)$ where $s_{l(t)}$ and $s_{r(t)}$ represent the amount of rotation of left and right wheels, respectively. The state of the robot at time t is also denoted by $\boldsymbol{X}_t (= (R_{x(t)}, R_{z(t)}, R_{\theta(t)})^T)$. $R_{x(t)}$ and $R_{z(t)}$ represent the coordinates of the position where the robot exists as shown in Figure 2. $R_{\theta(t)}$ represents the direction of the robot. Now we calculate the error of the state vector $\boldsymbol{X}_t$, which ensues from the movement of the robot.

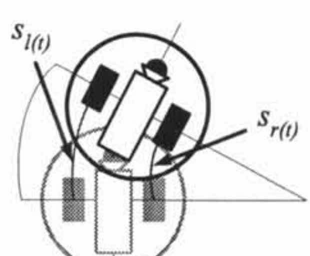

Figure 1: Structure of the robot.

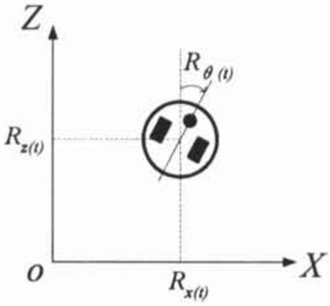

Figure 2: State of the robot.

The state of the robot at time t can be deduced theoretically from the information at time t-1, that is, the state vector $\boldsymbol{X}_{t-1}$ and the actuating signal $\boldsymbol{S}_{t-1}$ as follows:

$$\boldsymbol{X}_t = \boldsymbol{F}(\boldsymbol{X}_{t-1}, \boldsymbol{S}_{t-1}). \tag{1}$$

Here we assume that the values of the state vector and the actuating signal follow normal distribution. Using Taylor expansion to transform this function to a linear equation, a variance-covariance matrix of $\boldsymbol{X}_t$ can be derived as follows:

$$\Lambda_{X(t)} = \boldsymbol{J}_X \Lambda_{X(t-1)} \boldsymbol{J}_X^T + \boldsymbol{J}_S \Lambda_{S(t-1)} \boldsymbol{J}_S^T. \tag{2}$$

$\Lambda_{S(t-1)}$ is a variance-covariance matrix of $\boldsymbol{S}_{t-1}$, which should be given empirically from the structural property of the robot. $\boldsymbol{J}_X$ and $\boldsymbol{J}_S$ are Jacobians of $\boldsymbol{F}$ with respect to $\boldsymbol{X}_{t-1}$ and $\boldsymbol{S}_{t-1}$, respectively. This variance-covariance matrix shows the error of the state vector $\boldsymbol{X}_t$.

3 Constraints to state vector derived from visual observation

In this section, we show a way of limiting the range of the state vector to decrease its error obtained in Section 2. This method restricts the range of the state vector by observing the environment with monocular camera mounted on the robot. After describing generating an environment map by matching vertical edges obtained from the successive images, we refer to the way of limiting the state vector by minimizing inconsistency in the map.

This method is based on the premise that the location of each vertical edge in the images can be calculated with a stereo-matching method, which has been studied by many researchers. Since the main purpose of our research is to examine the effect of the environment observation to the probability distribution of the robot position, it is better to be able to handle the results of the environment observation manually. For this reason, our research assumes that the edge detection from images and the matching edges are operated manually.

The locations of the edges, which can be calculated from the images obtained at time t-1 and t as shown in Figure 3, are denoted by $\boldsymbol{M}_{t(i)}$ $(i = 1, \ldots, N_t)$. N_t is the number of the edges whose existence was confirmed till time t. $\boldsymbol{M}_{t(i)}$ is a two-dimensional vector whose components are X and Z coordinates. The map records and revises the average location of each observed edge as shown in Figure 4. The average location of i-th edge is denoted by $\boldsymbol{M}_{t(i)}^{map}$.

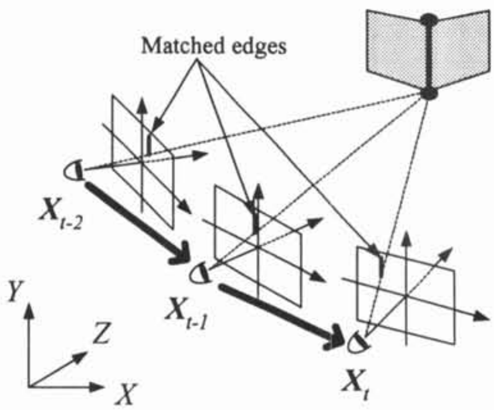

Figure 3: Stereo viewing of vertical edges.

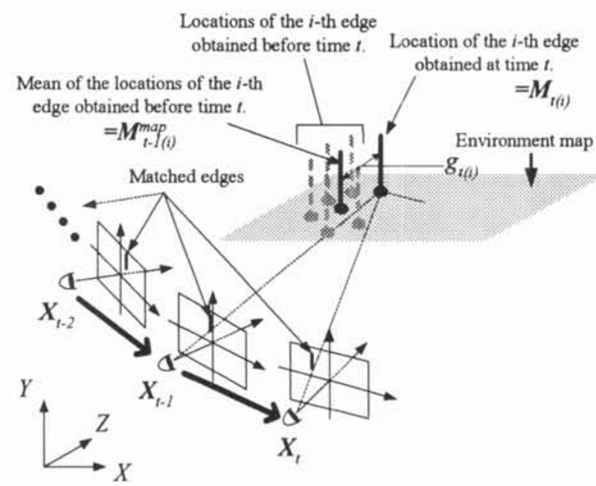

Figure 4: Generation of the environment map.

Apparently, locations of edges recorded in the map and those observed at time t are discrepant. This is because actual states of the robot are different from the assumed ones which are used to calculate locations of the edges at each time. This difference is caused by the error of the state vector ensuing from the movement of the robot. The proposed method attempts to decrease this error by minimizing the discrepancy of the locations of the edges. In this method, the gap between $\boldsymbol{M}_{t-1(i)}^{map}$ and $\boldsymbol{M}_{t(i)}$ is calculated with

$$g_{t(i)} = \left\| \boldsymbol{M}_{t(i)} - \boldsymbol{M}_{t-1(i)}^{map} \right\| \tag{3}$$

which is the Euclidean distance between $\boldsymbol{M}_{t-1(i)}^{map}$ and $\boldsymbol{M}_{t(i)}$. $g_{t(i)}$ is a function of $R_{x(t)}$, $R_{z(t)}$, $R_{\theta(t)}$, $R_{x(t-1)}$, $R_{z(t-1)}$ and $R_{\theta(t-1)}$. After using Taylor expansion to transform this function to a linear equation, we use the following conditions to minimize the total of squares of $g_{t(i)}$:

$$\frac{\partial}{\partial R_{x(t)}}\sum_{i=1}^{N_t} g_{t(i)}^2 = 0$$
$$\frac{\partial}{\partial R_{z(t)}}\sum_{i=1}^{N_t} g_{t(i)}^2 = 0 \qquad (4)$$
$$\frac{\partial}{\partial R_{\theta(t)}}\sum_{i=1}^{N_t} g_{t(i)}^2 = 0$$

From these equations, we can finally derive the following equation:

$$\boldsymbol{C}_t(\boldsymbol{X}_t - \overline{\boldsymbol{X}}_t) + \boldsymbol{C}_{t-1}(\boldsymbol{X}_{t-1} - \overline{\boldsymbol{X}}_{t-1}) + \boldsymbol{C}' = \boldsymbol{0} \qquad (5)$$

where $\overline{\boldsymbol{X}_t}$ and $\overline{\boldsymbol{X}_{t-1}}$ are the means of the normal distribution of the state vectors at time t and $t-1$. $\boldsymbol{C}_t$ and $\boldsymbol{C}_{t-1}$ are matrices of (3, 3)-type, which can be derived from partial differentials of $g_{t(i)}$. $\boldsymbol{C}'$ is a three-dimensional column vector, which also can be derived from the partial differentials of $g_{t(i)}$. We assume that this vector takes an ideal value, that is, a zero vector. Using the variance-covariance matrix of the state vector at time $t-1$, the newly obtained variance-covariance matrix of $\mathbf{X}_t$ can be calculated as follows:

$$\Lambda_{X(t)} = \boldsymbol{C}_t^{-1}\boldsymbol{C}_{t-1}\Lambda_{X(t-1)}\boldsymbol{C}_{t-1}^T(\boldsymbol{C}_t^{-1})^T \qquad (6)$$

To restrict the range of the state vector, this method selects the smaller variance-covariance matrix $\boldsymbol{\Lambda}_{X(t)}$ from Equations (2) or (6).

4 Experimental results

In order to examine the possibility of the proposed method, experiments were performed using a two-wheel-drive robot Rug Warrior with a wireless CCD camera. The value of variance-covariance matrix of the actuating signal used in these experiments was established empirically. Before these experiments, we calibrated the camera parameters which were used to calculate the locations of the vertical edges in the map. But since the used camera is very cheap and has a distorted lens, we could not determine their appropriate values over an entire image except the area near the center.

[Experiment 1]

This experiment checks that the proposed method can narrow the probability distribution of the state vector. Images used in this experiment were taken at the fixed positions as shown in Figure 5. Figure 6 is one of the used images, in which the black lines illustrate the vertical edges obtained manually. The locations of these edges are calculated based on the stereo viewing and recorded in the environment map. In this experiment, any operation of the robot is not performed. Instead of moving the robot, we put it at the positions A-E in Figure 5 and obtained images from the camera. From the coordinates of these positions and the obtained images, we calculated the variance-covariance matrices. Table 1 shows sizes of the 3-sigma ellipses calculated by Equations (2) and (6), at which value of the actuating signal $\boldsymbol{S}_t$ is obtained by the reverse calculation. The way of the calculation of these ellipses is described in [3]. Obviously, range of the state vector gets larger following the movement of the robot. Moreover, its size obtained by Equation (6) is smaller that that by Equation (2). This shows the possibility that the visual observation can reduce the uncertainty of the states of the robot.

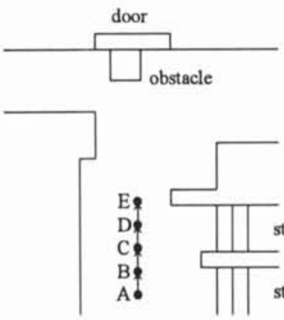

Figure 5: Environment in Experiment 1.

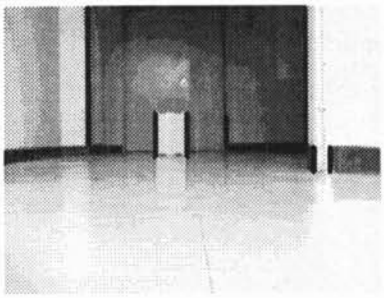

Figure 6: One of the used images in Experiment 1.

Table 1: Results in Experiment 1.

(a) Results with Equation (2).

(b) Results with Equation (6).

Position		A	B	C	D	E
(a)	lateral direction	3.00	61.17	86.50	105.92	122.05
	front direction	3.00	16.00	17.80	32.71	43.25
(b)	lateral direction			19.60	54.19	60.86
	front direction			17.80	22.74	32.08

[Experiment 2]

In this experiment, we moved the robot in some directions in our laboratory and calculated the 3-sigma ellipses. Figure 7 is one of the used images in which the shaded lines are the vertical edges obtained manually. The results are shown in Table 2. Figure 8 illustrates some results in Table 2(a). The thick arrows show the actual positions and directions of the robot, while the ellipses represent the 3-sigma ellipses. It can be seen that the 3-sigma ellipses cover the actual state vectors. But their sizes get larger following the movement of the robot.

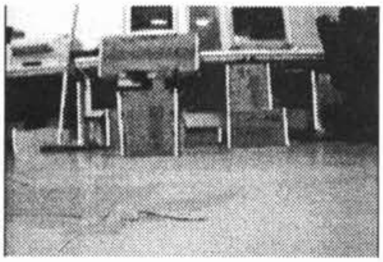

Figure 7: One of the used images in Experiment 2.

Table 2: Results in Experiment 2.
(a) Results only with Equation (2).
(b) Results with Equation (6).

	Time	0	1	2	3	4
(a)	lateral direction	3.00	19.79	59.18	109.04	161.58
	front direction	3.00	12.67	21.52	22.06	46.90
(b)	lateral direction			51.04	74.65	116.36
	front direction			16.23	15.30	11.67

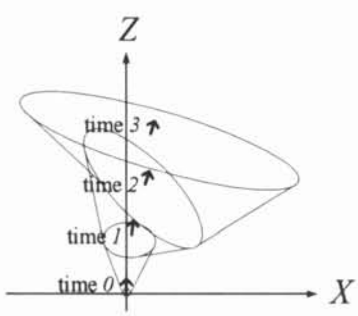

Figure 8: Shapes of the 3-sigma ellipses in Table 2(a).

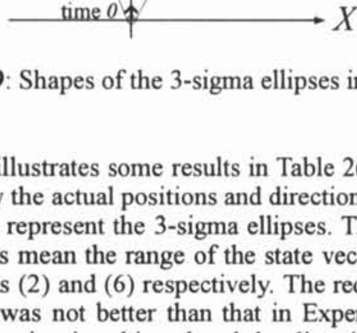

Figure 9: Shapes of the 3-sigma ellipses in Table 2(b).

Figure 9 illustrates some results in Table 2(b). The thick arrows show the actual positions and directions of the robot. The ellipses represent the 3-sigma ellipses. The dotted and solid ellipses mean the range of the state vector calculated by Equations (2) and (6) respectively. The reduction of the ellipse size was not better than that in Experiment 1. But the size reduction is achieved and the directions of the ellipses are modified appropriately at each position.

The unfavorable results in Experiment 2 would be caused by the following reasons. In Experiment 2, coordinates of the vertical edges were calculated erroneously and were recorded at wrong locations in the map. The unreliability of the map would lead to the failure in the size reduction of the 3-sigma ellipses. As previously stated, the camera used in these experiments has a lens distorted, especially at the rim. Therefore, when the vertical edges appear near the sides of the images, their locations in the map are calculated erroneously. This failure affected the size reduction of the range of the state vector calculated by Equation (6). To cope with this problem, more accurate camera model should be incorporated in this method. Another reason for the unfavorable results would be the gap between the calculated and actual positions of the robot. In Experiment 1, the mean of the state vector is let to be the fixed positions in Figure 5. On the other hand, the mean of the state vector is let to be the ideal value calculated with Equation (1) in Experiment 2. To avoid this problem, a way of calculating more accurate mean of the state vector, which is near the actual state of the robot, is required.

5 Conclusions

This paper presented an approach to reduce uncertainty of robot states by observing the environment. The proposed method can restrict the range of the state vector of the robot by resolving the inconsistency of the edge locations in a generated environment map.

The subjects for a future study are the following: 1) representing objects in the environment stochastically to make the description in the map have theoretical background, 2) advance in reducing the uncertainty of the state vector, for example, by considering the spatial relationships between the edges on a same plane.

References

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[2] I.Moon, J.Miura, Y.Yanaga and Y.Shirai: "Planning of Vision-Based Navigation for a Mobile Robot under Uncertainty," *Proc. 1997 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pp. 1202-1207 (1997).

[3] `http://www.robotics.im.hiroshima-cu.ac.jp/~kanbara/dpaper.ps.gz`