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Global Map Building and Navigation of Mobile Robot Based on Ultrasonic Sensor Data Fusion

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Abstract

In mobile robotics, ultrasonic sensors became standard devices for collision avoiding. Moreover, their applicability for map building and navigation has exploited in recent years. In this paper, as the preliminary step for developing a multi-purpose autonomous carrier mobile robot to transport trolleys or heavy goods and serve as robotic nursing assistant in hospital wards. The aim of this paper is to present the use of multi-sensor data fusion such as ultrasonic sensor, IR sensor for mobile robot to navigate, and presents an experimental mobile robot designed to operate autonomously within both indoor and outdoor environments.

The global map building based on multi-sensor data fusion is applied for recognition an obstacle free path from a starting position to a known goal region, and simultaneously build a map of straight line segment geometric primitives based on the application of the Hough transform from the actual and noisy sonar data. We will give an explanation for the robot system architecture designed and implemented in this study and a short review of existing techniques, Hough transform, since there exist several recent thorough books and review paper on this paper. Experimental results with a real Pioneer DX2 mobile robot will demonstrate the effectiveness of the discussed methods.

Key words : Intelligent space, multiple vision, tracking, mobile robot, covariance intersection

1. Introduction

Sensing of the environment and subsequent control is important feature of the navigation of an autonomous mobile robot. When a mobile robot navigates in an unknown or partially known environment, several types of sensors are commonly used for this purpose such as ultrasonic sensors, infrared sensors, laser range finders and vision systems for obstacle avoidance or path planning. Recently, it is increasing the use of vision system because it has inexpensive and is able to be fast real-time environmental recognition [1],[2]. In this paper we present a statistical method for dealing with the general problem of concurrent localization and map building. We furthermore address the problem of using occupancy grid maps for path planning in highly dynamic environments. The approaches have been tested extensively and several experimental results are given in the paper.

Probabilistic methods have been shown to be well suited for dealing with the uncertainties involved in this problem. The method is based on a variant of the EM algorithm, which is an efficient hill-climbing method for maximum likelihood estimation in high-dimensional spaces. In the context of mapping, EM iterates two alternating steps: a localization step, in which the robot is localized using a previously computed map, and a mapping step, which computes the most likely map based on the previous pose estimates. The resulting approach can be applied to different kinds of sensors and is general enough for topological and metric map building [3],[4]. A very popular approach to metric maps is occupancy grid maps, which were originally proposed in [5][6] and which since have been employed successfully in numerous mobile robot systems.

A mobile robot has many application fields because of its high workability. Especially, it is definitely necessary for the tasks that are difficult and dangerous for men to perform. There are many people who are interested in the mobile robot. However, most of them are aiming at successful navigation, that is, focusing on recognizing a location and reaching at a fixed destination safely.

This paper also implements sonar sensor-based on-line map building that is based on the application of the Hough Transform [7]. This approach builds a map of straight line geometric primitives which is then combined with the sensor fusion approach using local map data, resulting in an improved new method, allowing the system to make a more efficient use of collected sensory information for simultaneous and cooperative construction of a world model and learning to navigate to the goal.

2. Related Theories

2.1 Map Building and Object Classification

For many years, a lot of work has been invested in generating maps for mobile robots by ultrasonic sensors with or without classification of environment objects (Fig. 1).

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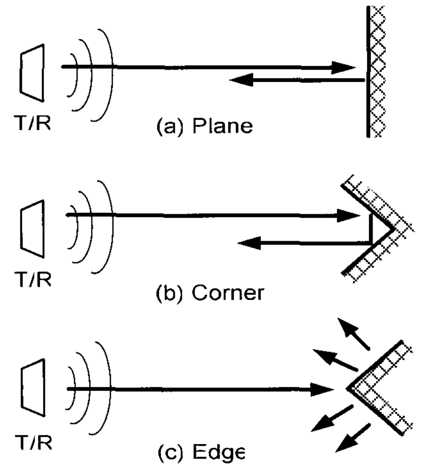


Fig. 1. Reflection behavior of a) planes, b) corners, and c) edges (according to[8]).

The main goal is still to find collision free paths for a given destination in an unknown environment. Generally, successful path planning strategies require sufficiently accurate information about the mobile robot's position. This is usually not satisfied by pure odometric measurement because of the accumulation of errors in the progress of robot's motion [9]. Therefore, pose tracking requires frequently recalibration. Additional information about the surroundings of the robot from sensor devices or offline prepared maps is needed. In the case of sensory generated maps, it is a question of precision and reduction of ambiguities to include information about echo causes and object shapes, respectively. In recent years, mainly two ways became apparent for map building and object classification purposes:

1) based on sensor arrays, capable of gathering information without sensor movement [10],[11] ;

2) based on a few sensors utilizing typical scanning movements (e.g., rotary scans) [1], [4].

Because of unknown echo direction inside the sound lobe, the sensor axis is often used as representation of the echo direction for each measurement. Rotary scans on different positions using this simple geometric interpretation leads to the typical regions of constant depth (RCDs) which can be used to build a map [2]. The different reflection behavior of different object types (Fig. 1) influences the length of RCDs. In combination with amplitude information, this can be used to distinguish planes, edges, and corners [3], [4].

The basic difference between convex and concave objects is the echo amplitude. To eliminate the distance dependency of the received signal, the damping losses in air and the amplitude reduction by the divergent soundwave are often compensated by time dependent receiver amplifiers. Typically, this compensation presupposes planes, and corners as reflectors. While they return the whole emitted sound energy (except from small damping losses on the objects surface), edges and convex vertices only return a small part of the energy because the reflected sound wave is dispersed by the object [Fig. 1(c) and [11]]. This effect increases with decreasing radius of curvature. Thus, concave and convex objects can be distinguished by their amplitude maximum and the length of RCDs from rotary scans while corners and planes can be distinguished by RCDs at different viewpoints.

2.2 Feature Extraction with Hough Transform

With the sonar model presented as Fig. 2, associating sonar returns to line segment geometric primitives may be stated as finding groups of sonar arcs all tangent to the same line.

Given the large amount of spurious data coming from moving people, specular reflections and sonar artifacts, the Hough Transform [7] seem very appropriate for the following reasons: 1) The location of line features can be easily described with two parameters, giving a 2D Hough space in which the voting process and the search for maxima can be done quite efficiently; 2) The sonar model presented can be used to restrict the votes generated by each sonar return to be located along the corresponding transformed sonar arc; 3) Since each sonar return emits a constant number of votes, the whole Hough process is linear with the number of returns processed; and 4) Being a voting scheme, it is intrinsically very robust against the presence of many spurious sonar returns.

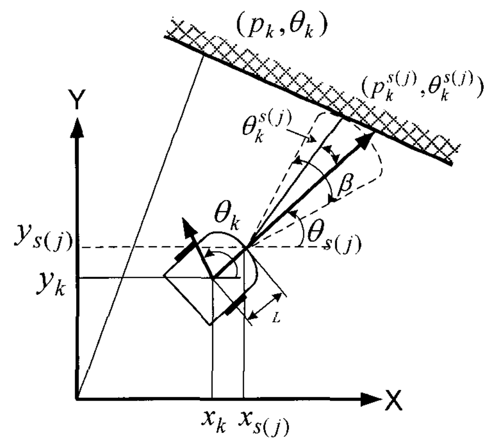


Fig. 2. Modeling of Sonar Ring.

If the location of the robot $S_k = (x_k, y_k, \theta_k)$ at time k is known, which can be obtained through the accumulation of encoder information. For more accuracy of the algorithm, we should consider the mounted position of each sonar sensor.

The value of each sonar sensor offsets robot heading is $22.5 \cdot j$ ($j = 0, \ldots, 15$), j is the sequence number of sonar, and Pioneer-DX mobile robot has 16 sonar sensors in all), which is invariable. Consequently, the $j-th$ sonar sensor position $(x_{s(j)}, y_{s(j)}, \theta_{s(j)})$ in the state space is given in (1)~(4):

$$\theta_{s(j)} = \theta_k - 22.5 \cdot j \quad (j = 0,\ldots,7) \tag{1}$$

$$\theta_{s(j)} = 360 - 22.5 \cdot j + \theta_k \quad (j = 8,\ldots,15) \tag{2}$$

$$x_{s(j)} = x_k + L \cdot \cos\theta_{s(j)} \tag{3}$$

$$y_{s(j)} = y_k + L \cdot \sin\theta_{s(j)} \tag{4}$$

Where L is the eccentric distance of sonar sensor, the value of (ρ_k, θ_k) can be given in (6), which is the position of the extracted line segment represented in a base reference for:

$$\theta_k = \theta_{s(j)} + \theta_k^{s(j)} \tag{5}$$

$$\rho_k = \rho_{s(j)} + x_{s(j)} \cos(\theta_k^{s(j)}) + y_{s(j)} \sin(\theta_k^{s(j)}) \tag{6}$$

One of the key issues of its practical implementation is choosing the parameters defining the Hough space and their quantization. In our implementation, we perform some prior filtering for removing noisy data. Two filtering operations on sonar data points are used. First the sonar returns obtained along short trajectories (around 2m), which above a certain limit, distance readings were not very reliable, and thus were rejected. A second filtering operation, Let Θ be a set of sonar data points. A point (ρ_k, θ_k) is rejected, if no other data point of Θ is found inside a circle of radius r and center at (ρ_k, θ_k).

Excellent results have been obtained with data sets Θ, which coming from a number of consecutive sonar-ring scans. In order to keep the odometry errors small, lines are represented in a base reference, using parameters θ_k and ρ_k defining the line orientation and its distance to the origin (Fig. 2).

3. Sonar Data Fusion by Statistical Foundations

Data fusion is about deriving information about certain variables from observations of other variables. The application area is huge, see the special issue on data fusion in [12] for a recent overview. An edited collection of survey papers on data fusion in robotics and machine intelligent is given in [13]. Sensor fusion in general is discussed in [14].

From a statistical perspective, we have the following problem. Given two vector random variables X and Y, what does the observation $Y = y$ tell us about X? The complete answer is given by the so-called conditional probability density function,

$$p_{X|Y}(x \mid y) = \frac{p_{X|Y}(x,y)}{p_Y(y)} \tag{7}$$

Here $p_{X,Y}(x,y)$ is the joint probability density for X and Y, and $p_Y(y)$ is the probability density for Y. By using the dual assumption, namely that $X = x$ is given, we obtained the very useful Bayes rule

$$p_{X,Y}(x,y) = p_{X|Y}(x \mid y) p_Y(y) = p_{Y|X}(y \mid x) p_x(x) \tag{8}$$

$$p_{X,Y}(x,y) = \frac{p_{Y|X}(y \mid x) p_X(x)}{p_Y(y)} \tag{9}$$

which is the key formula in Bayesian and maximum likelihood estimation theory.

Different estimates of X can now be constructed from its distribution. The (conditional) minimal variance of X equals the conditional mean of X given $Y = y$,

$$\hat{x} = E[X \mid Y = y] = \int_{-\infty}^{\infty} x p_{X|Y}(x \mid y) dx \tag{10}$$

Another useful estimate is the maximum a posteriori estimate, which maximizes the function $p_{X|Y}(x \mid y)$. The rest is design and analysis issues, i.e. formulating the underlying model, specifying probability density functions and calculating equality/variance properties. The most used probability density function is the Gaussian one (the Normal distribution). The main reason is that the conditional density function also will be Gaussian, and analytic expressions of the minimal variance estimate can thus be obtained.

Let X and Y be jointly Gaussian, i.e. $Z = [X' \ Y']'$ is Gaussian with mean and covariance

$$m_z = \begin{bmatrix} \bar{x} \\ \bar{y} \end{bmatrix}, \Sigma_{zz} = \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{bmatrix} \tag{11}$$

Then X conditional on $Y = y$ has a Gaussian distribution with mean and covariance

$$m_{x|y} = \bar{x} + \Sigma_{xy} \Sigma_{yy}^{-1} (y - \bar{y}),$$

$$\Sigma_{x|y} = \Sigma_{xx} - \Sigma_{xy} \Sigma_{yy}^{-1} \Sigma_{yx} \tag{12}$$

Hence the conditional mean of X given $Y = y$, equals

$$\hat{x} = E[X \mid Y = y] = \bar{x} + \Sigma_{xy} \Sigma_{yy}^{-1} (y - \bar{y}) \tag{13}$$

Almost all practical estimators are special cases of the above result. The expression is called *the fundamental equations of linear estimation* in [15]. This reference also provides a very good introduction to estimation theory, in general, and tracking, in particular.

4. Robot and Experiment Environment

This proposed navigation method is applied for a mobile robot named as Pioneer-DX that has been developed in Laboratory for Intelligent Robot, DSU as shown in Fig. 3. We use a DC motor for each wheel, and use a ball-caster for an assistant wheel. Two encoders, a gyro-sensor (ENV-05D), an ultrasonic sensor and a vision sensor are used for the navigation control. The gyro sensor is used for recognizing the orientation of robot by measuring the rotational velocity; the ultrasonic sensor (Polaroid 6500) is used for recognizing environment, which is rotated by a step motor within 180 degrees; the CCD camera (Samsung SFA-410ED) is used for detecting obstacles. A Pentium 4, 2.45Ghz processor is used as a main controller and an 80C196KC microprocessor is used as a joint controller.

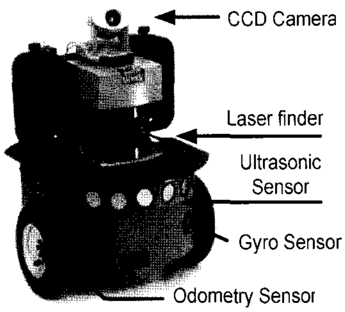


Fig. 3. Mobile Robot, Pioneer-DX

4.1. Building a local map

Building a robust and reliable avoid behavior has been found to require some kind of memory. Inspired by the work of Borenstein and Koren [5] we have implemented a grid based local map for the robot. So far this map has been updated using only the sonar data. At this early stage we have been using a ray-trace model for the sonar, which is justified by the motto, try simple first and supported by [10]. The results of these tests show that the avoid behavior is improved. Below (Fig. 4) is a sketch of the experimental environment. To show what the local maps look like, four samples of such maps are shown in Fig.s 5-7. The size of the cells in these maps were 20X20 mm and the number of cells were 200X200, giving a total size of 4X4m. Note that the coordinate system of the local maps are robot centered. The approximate location of the robot when the maps were saved is given in the sketch (Fig. 4) by the letters A-D.

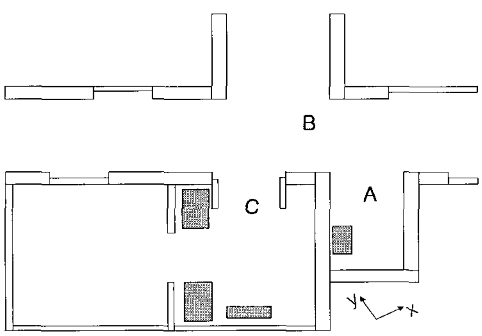


Fig. 4. Sketch of the Environment Around the Robot Lab.

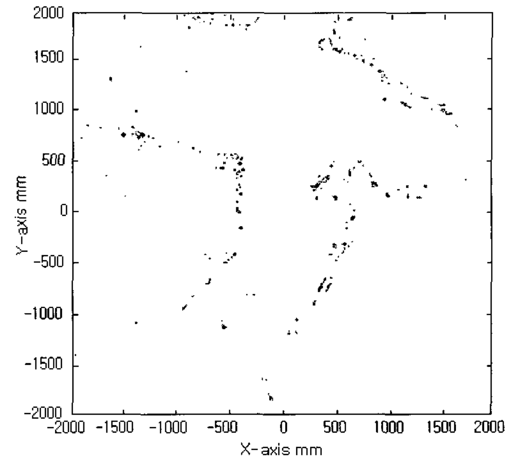


Fig. 5. Sonar based Local Map of the Corridor outside Room with Three Closed Wall and One Open. **A** in the Sketch.

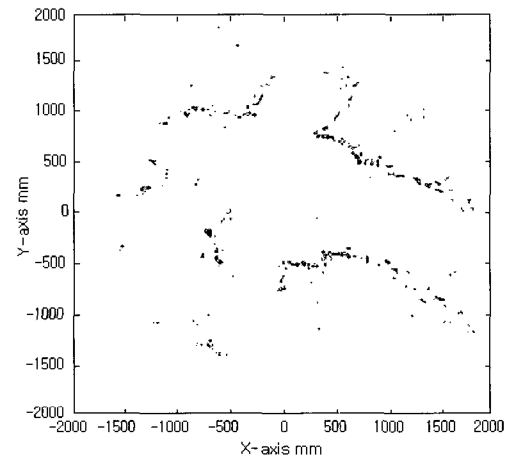


Fig. 6. Sonar Based Local Map of the Corridor beside Room. **B** in the Sketch.

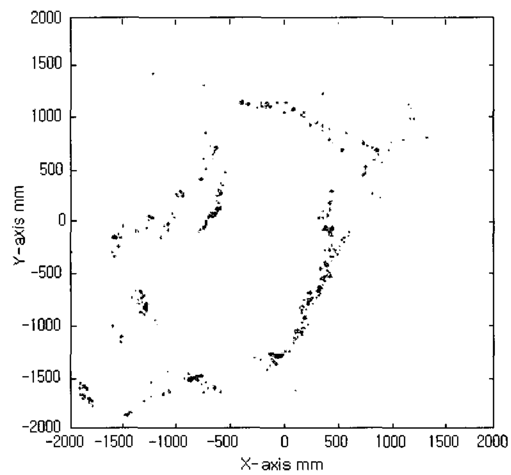


Fig. 7. Sonar based Local Map of the Door-passage into Room. **C** in the Sketch.

If the local map is extended to a size that can hold much more information the figure below (Fig. 8) show a possible result. It can be clearly seen that most of the features of the environment (corners, wall, etc) are accurately mapped. The intention of the local map is not to be this large, but rather to have a size more like the once shown above. The global map is updated based on the local map, i.e., the sensor data is not directly used in the global map.

4.2 Global Map Generation

The classified local structure can be regarded as a state and a state transition is caused by a turning action. The final step is to construct a global map representation by a graph of which nodes and arcs correspond to states and state-transition probabilities in terms of turning actions. Once we have such a graph representation, we can easily apply the conventional path planning or reinforcement learning methods on it. From the above argument, the unit of turning angle should be 30 degrees which corresponds to the angle between two sonar sensors next to each other. Actually, we construct the action space consists of $\pm 30^0$, $\pm 60^0$, $\pm 90^0$ turns, and totally we have 7 actions including no turns.

The state transition probability is obtained by the Maximum Likelihood Estimation (MLE) method. Let $Pr(s_i, a_p, s_j)$ be the state transition probability that the world will transit to the next state s_j from the current state-action pair (s_i, a_p) :

$$Pr(s_i, a_k, s_j) = \frac{times(s_i, a_k, s_j)}{\sum_{t=1}^{N} times(s_i, a_k, s_t)}, \tag{14}$$

where, $times(s_i, a_k, s_j)$ denotes the number of observations of the state s_j after execution of the action a_k at the state s_i. N denotes the number of all states. After memorizing the history of these transitions $times(s_i, a_k, s_j)$ to some extent during the learning process, we estimate the state transition probabilities.

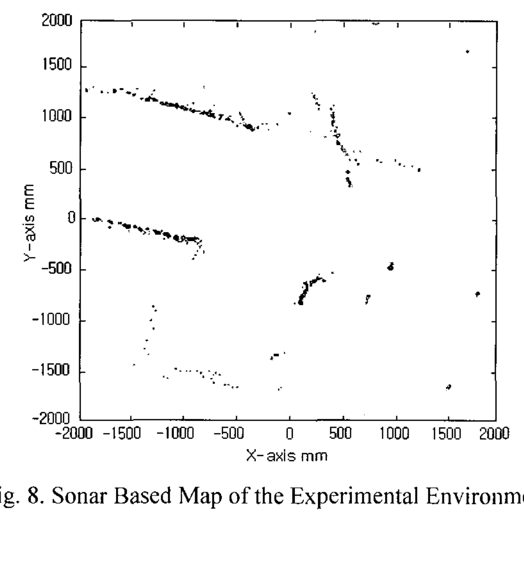
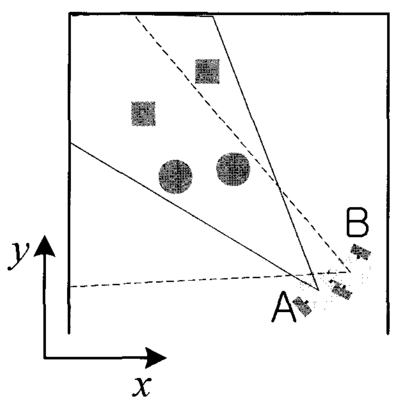


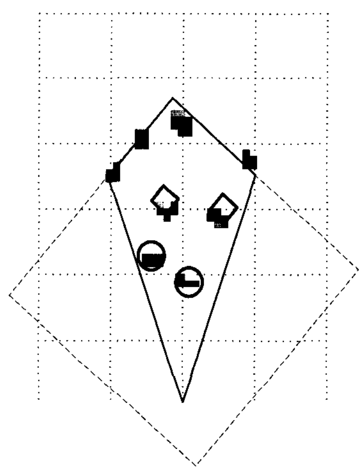
Fig. 8. Sonar Based Map of the Experimental Environment.

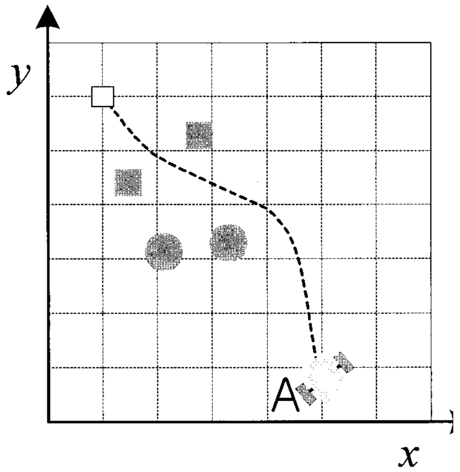
4.3 Autonomous Navigation used map-building

We executed the experiments that a mobile robot navigate to the goal point having the initial condition in figure 10 using MARCH mobile robot . We fixed initial point and goal point of the mobile robot to initial point (x:500cm, y:80cm, 120°) and goal point (x:100cm, y=600), and initial point (x:600cm, y:100cm, 150°) and goal point (x:100cm, y=600). The results is showed in figure 3(b) and 3(c). Probability method that we proposed navigation algorithm is used for map building and navigation. The fusion formula just means that estimates should be weighted together, with weights inversely proportional to their qualities/variances. It is easy to modify the fusion filter to handle correlated estimators. We have concentrated on quadratic norms, which follows from a Gaussian assumption. However, the sensor noise may have very different characteristics, including existence of so-called outliers.

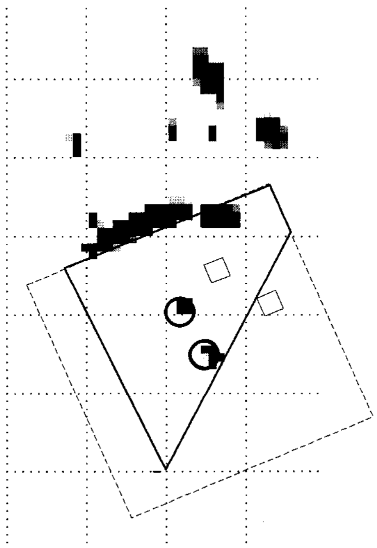


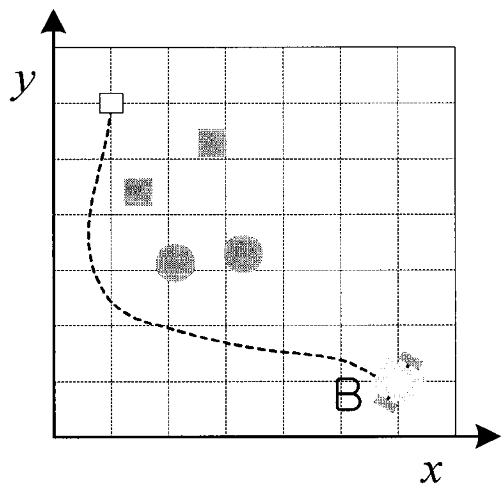
(a) Diagram of Navigation Environment





(b) Map Building and Navigation [**A**]: Initial Point (500,80,120°), Target Point (100,600)





(c) Map building and navigation [B]: Initial point (600,100,150°), Target point (100,600)

Fig. 9. Experimental Results of Map Building and Navigation.

Figure 10(b) showed that the map-building and navigation is completed successfully. In case of figure 10(c), mobile robot navigated using map information and finished safely, but map-building wasn't correct slightly. It results from the error of recogniton. Because image information from CCD camera based on 2D coordinate system isn't sufficient to compute compont in Z plane although obstacles is seperated each in real environment. However, through many experiments, information obtained from the proposed method was suffiicient to build a map and navigate a complete and reliable representation.

5. Conclusion

In this paper, we have presented two more or less orthogonal approaches for using sonar sensor and map-building by multi-sensor mobile robot to navigate within an indoor setting. Important regions of the robot workspace (locales) are represented using grid-based map collected during the exploration phase. From a scientific/academic perspective it is important to study very general issues and approaches, were the ultimate aim is full autonomy. However, the engineering perspective is the opposite, i.e. one wants to solve a specific problem, e.g. a sonar sensor based feedback control algorithm for going through narrow doorways. However, the main issue for such research is scalability, i.e. is the solution of more general interest and can it be extended to more complex situations.

For future works, it is straightforward to control robot locate a certain target with multi-sensor upon navigation. Also it will be interesting to have the robot to learn and map an unknown or pseudo-unknown environment.

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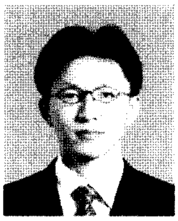

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