

Environment Perception for a Mobile Robot Using Double Ultrasonic Sensors and a CCD Camera

Kai-Tai Song and Wen-Hui Tang

Abstract—To move efficiently in an unknown or uncertain environment, a mobile robot must use observations taken by various sensors to construct information for path planning and execution. A reasonably accurate representation of the external world would also be very useful for robot self-localization. One of the merits of applying multiple sensors to a mobile robot is the enhancement of environment recognition. In this paper, we propose to use sensory information combined from double ultrasonic sensors and a CCD camera. We developed an algorithm based on a dual-transducer design to eliminate errors resulting from the beam opening angle of ultrasonic sensors. An extended discrete Kalman filter (EDKF) was designed to fuse raw sensory data and to reduce the influence of specular reflection of ultrasonic type transducers, thereby providing a more reliable representation for environment perception. Computer simulation, as well as practical experimental results demonstrate that this sensory system can provide useful and comprehensive environment perception for intelligent robotics.

I. INTRODUCTION

ONE of the major problems in intelligent robotics concerns extracting and fusing data from multisensor systems to acquire more accurate information about the external environment and decrease the uncertainties that hinder manipulation [1]. Several methods have been reported that deal with this problem. Durrant-Whyte has developed a multi-Bayesian estimation technique for combining touch and stereo sensing [2], [3]. Tang and Lee proposed a generic framework that employs a sensor-independent, feature-based relational model to represent information acquired by various sensors [4]. In [5], a Kalman filter update equation was developed to obtain the correspondence of a line segment to a model, and this correspondence was then used to correct position estimation. In [6], an extended Kalman filter was used to manipulate image and spatial uncertainties. In our previous work, a neural-network-based system that combines the outputs of several ultrasonic sensors was proposed [7]. It appears that these methods were developed according to issues such as the types of sensors, the types of data to be processed, and the ways to describe the environment for the robot.

When a mobile robot travels in an unknown or partially known environment, it must use various sensors to understand the environment for obstacle avoidance or path planning [8]. Several types of sensors are commonly used for this purpose

such as ultrasonic sensors, infrared sensors, laser range finders and vision systems. These sensors are selected so as to accord with the goal of application, the specific constraints of the working environment, and the individual properties of the sensors themselves.

Ultrasonic sensors have been used widely in robotics for obstacle avoidance mainly due to their simplicity and relatively low cost. This type of external sensors are very good in distance measurement of the obstacles, but they also suffer from specular reflection and insufficient directional resolution due to their wide beam-opening-angle. This causes difficulties when use them for environment perception. On the other hand, CCD cameras are useful for getting information from the external environment. However, the computation load is huge to extract representations for environment perception. In this work, double ultrasonic sensors and a CCD camera were combined to provide a sensor system for a mobile robot. We used ultrasonic sensors for distance measurement and a vision system for object-boundary detection. These two types of data have their advantages and are very often used in robotic applications, but combining them provides even more useful information. This combined approach deserves further investigation. Furthermore, real transducers have their limitations and these limitations lead to uncertainties in the measurement that need to be dealt with. We tried to eliminate the error resulting from the beam opening angle of the ultrasonic sensors by using a dual-transducer design. The proposed sensor fusing algorithm also provides constraints that filter out unreliable data from the sensor readings. By applying a CCD camera, we are able to estimated the boundaries of objects more accurately than we had only used ultrasonic sensors alone. Moreover, extended discrete Kalman filters (EDKF) have been designed for raw sensor data fusion to obtain more reliable representation in environment perception procedures. The rest of this paper is organized as follows: Section II describes the design of our multisensor system. In Section III the environment perception procedure is explained. Our simulation and the experimental results of the sensor system for recognizing objects and walls are both described in Section IV. We conclude in Section V.

II. SENSOR SYSTEM DESIGN

The sensor system consists of a monochrome CCD camera and a pair of ultrasonic transducers. Fig. 1 is a picture of the developed sensor platform. All three transducers are mounted on an aluminum plate, which is supported on the shaft of a step motor. The step motor is controlled by a personal computer

Manuscript received February 8, 1995; revised November 28, 1995. This work was supported by the National Science Council of Taiwan, R.O.C., under grant NSC-83-0422-E-009-062.

K.-T. Song is with the Department of Control Engineering, National Chiao Tung University, Hsinchu 300, Taiwan, R.O.C.

W.-H. Tang is with the Industrial Technology Research Institute, Opto-Electronic & Systems Laboratories, Taiwan, R.O.C.

Publisher Item Identifier S 0278-0046(96)02370-2.

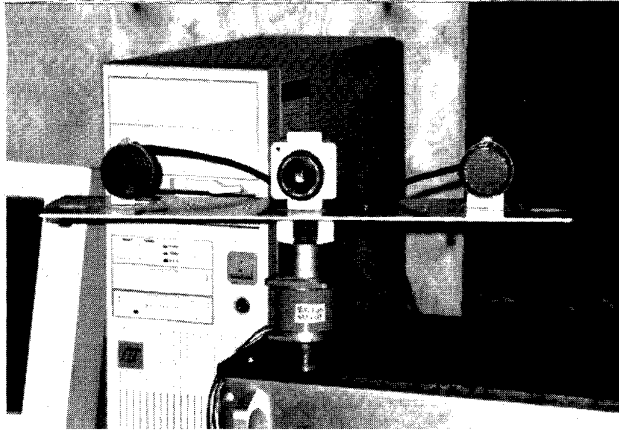


Fig. 1. A picture of the sensor platform.

(we used a PC-AT/486) and rotates at 1.8° per step. The two ultrasonic transducers, products of Polaroid Corp., have emission frequencies of 56 kHz [9]. The distance between them is 30 cm. To avoid the possible interference from the emission and echo waves, we fired each of the ultrasonic transducers in turn. The CCD camera, with a resolution of $512 \times 512 \times 8$ was fixed on the rotation center. An image processing board MVP-AT from MATROX was interfaced with the control computer and the software was developed using Microsoft C.

A. Limitations of Ultrasonic Sensors

The basic principle of distance measurement using ultrasonic sensor is to record the time difference between the emission of the transmission wave and the reception of the returned echo. The sensors used in this work are adopted from Polaroid Ultrasonic Ranging Units, which have a range of about 0.30 m to 10 m. However, due to the wide beam opening angle of the ultrasonic transducers, a measurement error will occur if the emitted wave is not perpendicular to the measured object. As shown in Fig. 2, the distance between the sensor and a flat wall should be $\overline{OA}$. But we will detect the distance $\overline{OA'}$, because the first returned echo will detect this point. The position measured in this case is then given by $\hat{A}$. Therefore, there is a difference between the location of the perceived wall and the location of the actual wall. This error caused by beam opening angle affects the accuracy of environment perception. We found that the beam opening angle of the sensors we used is about 22° . On the hand hand, the optimal angle between the line of emission and the surface of the measured object is 90° . If the incident angle is too large, then the sensor will not receive the rebounding signal. For the Polaroid transducers, it has been reported that the maximum angle of incidence α is about 25° [10]. If a larger amplification gain is designed for the receiver circuit, or if a rougher surface is hit by the wave, then the angle of incidence of the reflective signals will increase. However, if the incident angle exceeds the maximum value α , the echo may be received after many times of specular reflections. The detected data will then be erroneous. Therefore, ultrasonic sensors can easily measure the

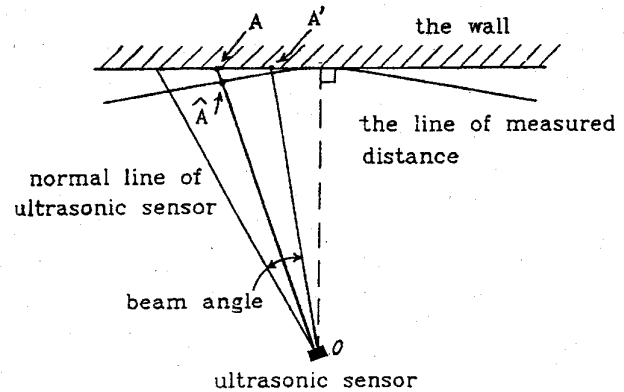


Fig. 2. The influence of the beam opening angle when scanning a wall with an ultrasonic sensor.

distance to an object, but they have poor angular resolution due to the beam opening angle and the reflective phenomenon. Moreover, it is difficult to obtain the precise boundaries of objects when ultrasonic sensors are used alone.

B. The Design of the Double Ultrasonic Sensor System

We noticed that the measurement error due to the beam opening angle is not a random error. When this error occurs, it will be difficult to obtain acceptable estimation results of the position of objects or walls even using methods such as EDKF or least squares. To eliminate this systematic error, we designed a sensor platform using two ultrasonic transducers placed in parallel. A sensor data fusion method is developed to estimate the distance using these two raw sensor readings. This method takes into account the beam opening angle and the geometric relations using two transducers. In our previous work, an artificial neural network as well as a mathematical model was designed to fuse two ultrasonic sensor data [7]. Fig. 3 depicts two conditions for calculating the fused estimation of the wall distance using two transducers. In the figure

$$\phi = \tan^{-1} \left(\frac{|d_1 - d_2|}{s_d} \right).$$

For situation 1: $\phi \leq \frac{\beta}{2}$

$$\psi = \sin^{-1} \left(\frac{|d_1 - d_2|}{s_d} \right) \quad (1)$$

$$\hat{d} = \frac{d_1 + d_2}{2 \cos \psi} \quad (2)$$

For situation 2: $\phi > \frac{\beta}{2}$

$$\hat{d} = \frac{s_d(d_1 + d_2) \cos \frac{\beta}{2}}{2(s_d - |d_1 - d_2| \sin \frac{\beta}{2})} \quad (3)$$

where

- $\hat{d}$ the estimated distance;
- d_1 the measured distance from the transducer S_1 ;
- d_2 the measured distance from the transducer S_2 ;

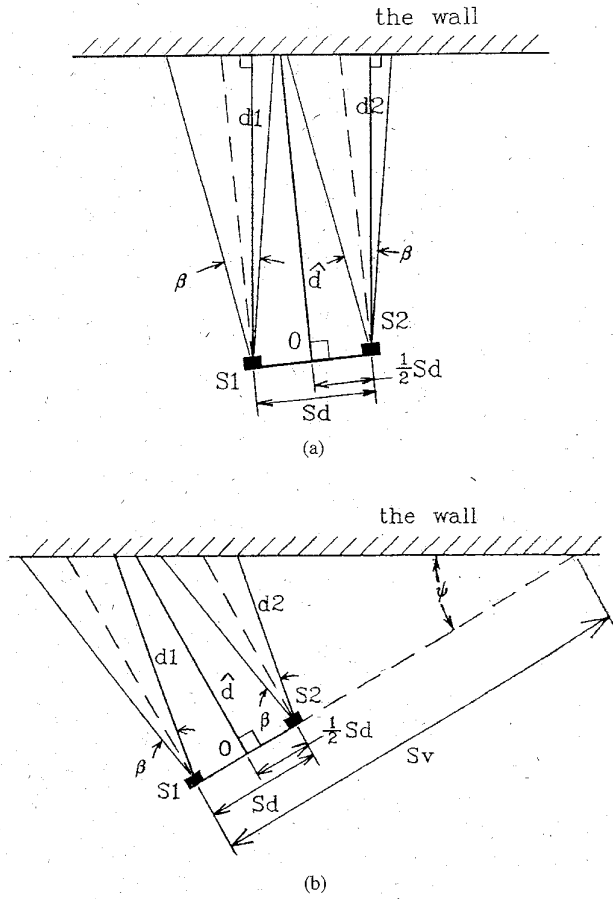


Fig. 3. Scanning a wall with double ultrasonic sensors. (a) When $\phi \leq \frac{\pi}{2}$. (b) When $\phi > \frac{\pi}{2}$.

s_d the distance between S_1 and S_2 ;
 β the beam opening angle.

By adopting such a dual-transducer system and applying the above equations, the measurement error caused by beam opening angle can be eliminated. Based on this structure, we developed a sensor system for environment perception using EDKF.

C. Constraints for Raw Sensor Data

The raw data d_1 and d_2 from the individual ultrasonic transducers contain other measurement errors that are also due to the above mentioned limitations of ultrasonic sensors. We found the following three constraints very useful to filter out unreliable data. They were derived according to the geometric relations of our dual-transducer design and properties of the ultrasonic sensors. We then applied the EDKF algorithm to fuse the residual data. As a result, we were able to estimate the parameters with better accuracy. The three constraints are given as follows:

- 1) $0.30(\text{m}) < d_1, d_2 < 10.00(\text{m})$;
- 2) $|d_1 - d_2| \sin(\frac{\beta}{2}) < s_d$;
- 3) $\tan^{-1}(\frac{|d_1 - d_2|}{s_d}) < \theta_f$.

Constraint 1 comes from the range of the Polaroid transducers. Constraint 2 is obtained by checking the denominator of (3). If d_1 and d_2 represent actual conditions, then they must satisfy this constraint. This is, however, only a necessary condition. Constraint 3 filters out the data caused by multi-reflection. The value of θ_f (about 25°) is related to the surface roughness of the object material.

D. Data Fusion by EDKF

For sake of simplicity, we started our design with rectangular-shaped objects and a walled environment. The goal was to determine the locations and shapes of the objects as accurately as possible. In the raw data obtained from measuring a wall, for instance, some unreliable data can be filtered out by the above constraints. The remaining information is then fused into a line representation, in which further reduction of the uncertainties is desirable. In this work, we represent the environment as a collection of line segments in a 2-D plane and then use the line equation $px + qy = 1$ and its two end points to describe objects. The EDKF technique is used to fuse the data and estimate the parameters required in the representation. In the following, we introduce equations that are used in discrete Kalman filters. Then we show how the formulas used in our method were derived.

In this application, we use the following system equations for a discrete-time system

$$x(k+1) = x(k) \quad (4)$$

$$y(k) = C(k)x(k) + w(k) \quad (5)$$

where $x(k)$ is the state vector, $y(k)$ is the output vector, $C(k)$ is the output matrix, and $w(k)$ is the measurement noise. The filter equations are reduced to the following

$$\hat{x}(k) = \hat{x}(k-1) + K(k)[y(k) - C(k)\hat{x}(k-1)] \quad (6)$$

$$K(k) = \tilde{P}(k-1)C^T(k)[C(k)\tilde{P}(k-1)C^T(k) + R(k)]^{-1} \quad (7)$$

$$\tilde{P}(k) = [I - K(k)C(k)]\tilde{P}(k-1) \quad (8)$$

where $R(k) = E[w(k)w^T(k)]$, $w(k)$ is the Gaussian noise, $\hat{x}(k)$ is the estimate of $x(k)$, $K(k)$ is the Kalman gain matrix, and $\tilde{P}(k)$ is the state covariance matrix. For a nonlinear system, filter equations are obtained through linearization. Let the nonlinear system be expressed as

$$f(a, b) = 0 \quad (9)$$

where a is the state vector or unknown parameter and b is the observable vector. Taking Taylor expansion of (9) at (a^*, b^*) and transfer it into the recursive form. Let $(a^*, b^*) = (\hat{a}(k-1), \hat{b}(k))$. We obtain the following expressions

$$y(k) = C(k)a(k) + w(k) \quad (10)$$

$$y(k) = -f(\hat{a}(k-1), \hat{b}(k)) + \frac{\partial f}{\partial a} \bigg|_{(\hat{a}(k-1), \hat{b}(k))} \hat{a}(k-1) \quad (11)$$

$$C(k) = \frac{\partial f}{\partial a} \bigg|_{(\hat{a}(k-1), \hat{b}(k))} \quad (12)$$

$$w(k) = \frac{\partial f}{\partial b} \bigg|_{(\hat{a}(k-1), \hat{b}(k))} (b(k) - \hat{b}(k)) \quad (13)$$

Using (6), (7), and (8), we obtain

$$\hat{a}(k) = \hat{a}(k-1) + K(k)[y(k) - C(k)\hat{a}(k-1)] \quad (14)$$

$$K(k) = \tilde{P}(k-1)C^T(k)[C(k)\tilde{P}(k-1)C^T(k) + R(k)]^{-1} \quad (15)$$

$$\tilde{P}(k) = [I - K(k)C(k)]\tilde{P}(k-1) \quad (16)$$

where

$$\Lambda(k) = [(b(k) - \hat{b}(k))(b(k) - \hat{b}(k))^T] \quad (17)$$

$$R(k) = \left[\frac{\partial f}{\partial b} \bigg|_{(\hat{a}(k-1), \hat{b}(k))} \right] \Lambda(k) \left[\frac{\partial f}{\partial b} \bigg|_{(\hat{a}(k-1), \hat{b}(k))} \right]^T \quad (18)$$

Equations (10) through (18) make up the EDKF algorithm. In the following, we derive the formulas for line parameters. Suppose a vertical flat wall is projected on the horizontal plane and is represented by $px + qy = 1$. Here, we use the local coordinate system of the mobile robot. So, the sensor platform rotates about z -axis. This relation is depicted in Fig. 4. In the figure, θ is the angle between the line of emission and the x -axis. Let

$$a = \begin{bmatrix} p \\ q \end{bmatrix} \quad b = \begin{bmatrix} d_1 \\ d_2 \\ \theta \end{bmatrix}$$

$$x = \hat{d} \cos \theta \quad (19)$$

$$y = \hat{d} \sin \theta. \quad (20)$$

Taking (19) and (20) into $px + qy = 1$, we obtain

$$\Rightarrow p\hat{d} \cos \theta + q\hat{d} \sin \theta = 1. \quad (21)$$

Applying the result of Section II-B to (21), for situation 1: $\phi \leq \frac{\beta}{2}$

$$\begin{aligned} \psi &= \sin^{-1} \left(\frac{|d_1 - d_2|}{s_d} \right) \\ \hat{d} &= \frac{d_1 + d_2}{2 \cos \psi} \quad \text{taking into (21)} \\ \Rightarrow f(a, b) &= p \frac{d_1 + d_2}{2 \cos \psi} \cos \theta + q \frac{d_1 + d_2}{2 \cos \psi} \sin \theta - 1 = 0 \quad (22) \end{aligned}$$

for situation 2: $\phi > \frac{\beta}{2}$

$$\hat{d} = \frac{s_d(d_1 + d_2) \cos \frac{\beta}{2}}{2(s_d - |d_1 - d_2| \sin \frac{\beta}{2})} \quad \text{taking this expression into (21)}$$

$$\begin{aligned} \Rightarrow f(a, b) &= p \frac{s_d(d_1 + d_2) \cos \frac{\beta}{2}}{2(s_d - |d_1 - d_2| \sin \frac{\beta}{2})} \cos \theta \\ &+ q \frac{s_d(d_1 + d_2) \cos \frac{\beta}{2}}{2(s_d - |d_1 - d_2| \sin \frac{\beta}{2})} \sin \theta - 1 = 0. \quad (23) \end{aligned}$$

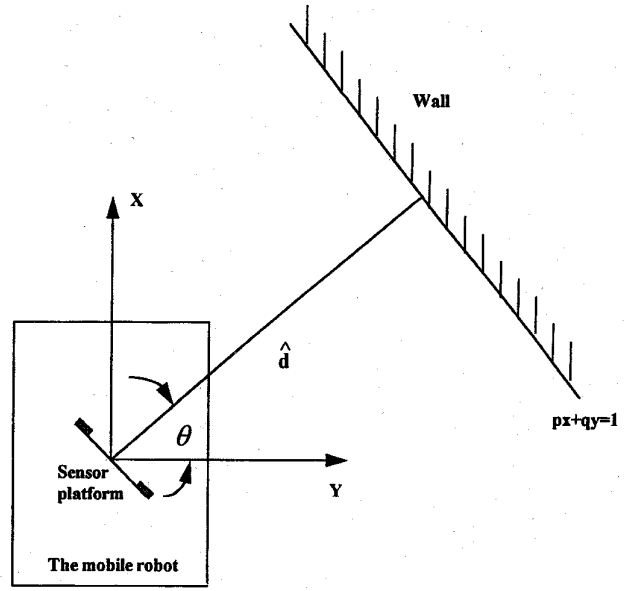


Fig. 4. The coordinate system of the mobile robot.

Both (22) and (23) are static system equations for parameter estimation. Therefore we can apply (10) through (18) to solve them and obtain optimal estimations of p and q .

E. Estimating Boundaries with a CCD Camera

We represented a line segment with the line equation $px + qy = 1$ and its two end points. The method for estimate of parameters p and q has been carried out as shown above. However, due to the limitations of the ultrasonic sensors, the boundaries of objects or walls are difficult to obtain using this type of sensor alone. Employing a CCD camera provides useful information that compensates for this shortcoming. Most boundaries can be treated as vertical edges, so we can apply a CCD camera to get image data and to extract the edges so as to determine the location of the boundaries with greater accuracy. The method of estimating the boundaries is summarized as follows.

- 1) Estimate the position of the vertical edges in the image. (In this process, an active window is first selected to simplify the image processing calculation.) Then apply sharpening and binarization with dynamic threshold in the selected window to detect the vertical edges.
- 2) Find the direction of the boundaries by matching the vertical lines from two consecutive images.
- 3) Obtain the boundaries of the measured object or wall. Because not all the detected vertical edges will be the boundaries that needed to be recognized, we developed an algorithm to isolate the desired boundaries [11].

III. OBJECT PERCEPTION FROM MULTIPLE SCANNING POSITIONS

The sensory information obtained from a single scanning at one particular position is generally limited to one highly localized area and incomplete. If we want to recognize the

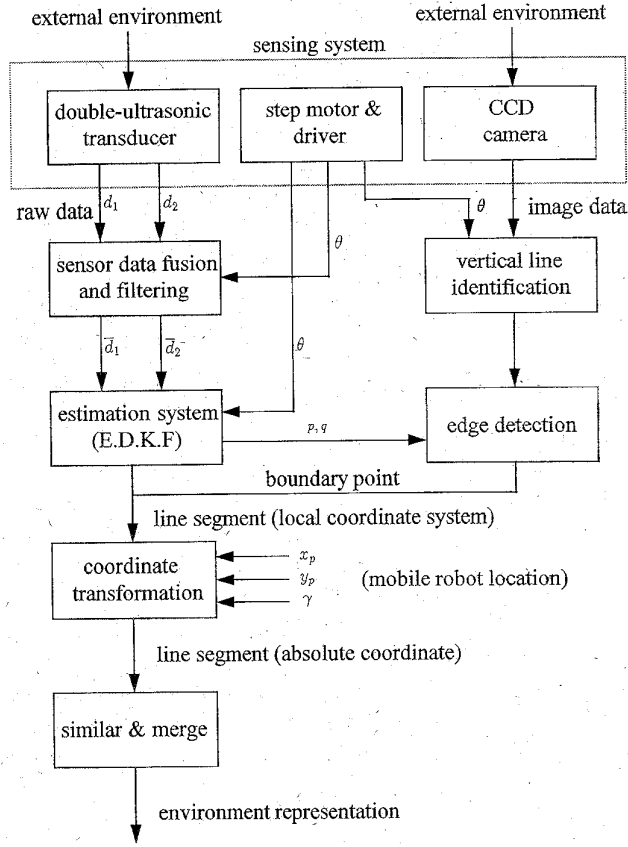


Fig. 5. The system diagram for environment perception.

complete environment and to build a reliable world model, a procedure has to be developed that fuses the information obtained by the sensory system at multiple scanning positions.

We propose an environment perception algorithm which allows us to do just that.

- 1) Obtain raw distance data d_1 and d_2 from two ultrasonic sensors and image data from a CCD camera through a 360° scanning with a $1.8^\circ/\text{step}$ at a fixed scanning position.
- 2) Filter and separate the data according to the constraints described in Section II-C.
- 3) Apply the EDKF and boundary estimation procedures to obtain the line segments.
- 4) Transform the description of the line segments from the robot coordinate system to the global coordinate system.
- 5) Repeat steps 1, 2, 3, and 4 at each scanning position.
- 6) Use *similar* and *merge* procedures to fuse the line segments that were obtained at the various scanning positions and, in this way, build a reliable representation.

Fig. 5 illustrates the structure of the whole sensor fusion system. Steps 4 and 6 will be described in the following two paragraphs.

When processing environment perception data, the parameters p and q , the end points and the covariance matrices of the line segments are all described in relation to local coordinate system of the mobile robot. These parameters must be pre-

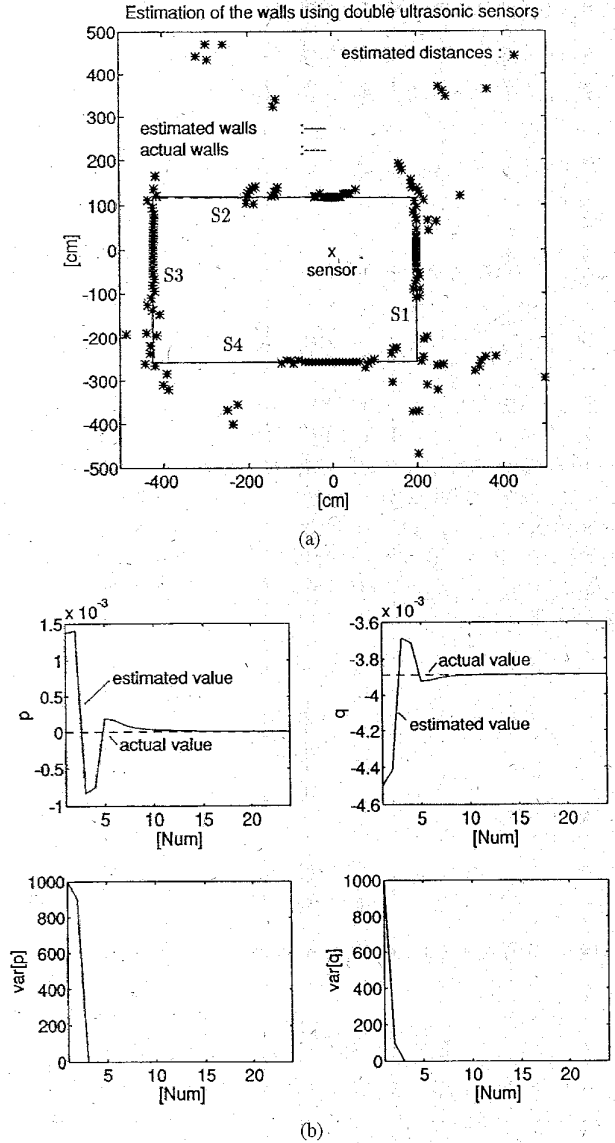


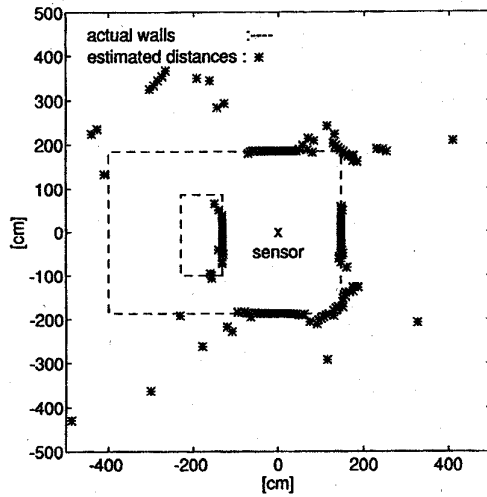
Fig. 6. Experimental results of double ultrasonic sensors when scanning a rectangular environment. (a) Fused sensory data and estimated walls. (b) Parameter estimation of wall S4.

sented in a global coordinate system so that the information detected by the sensory system at different positions may be integrated into a more complete representation. The transfer matrix can be expressed as follows

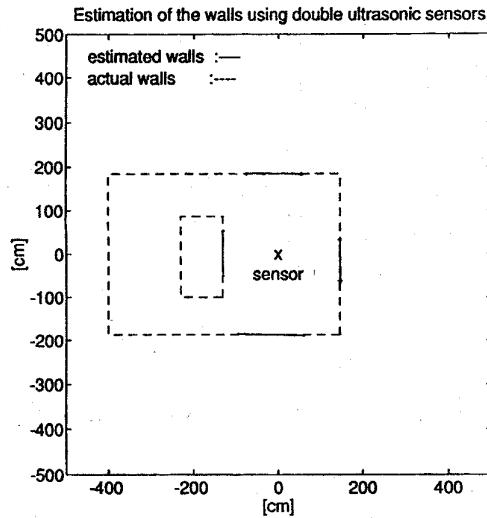
$$\begin{bmatrix} \cos \gamma & -\sin \gamma & 0 & x_p \\ \sin \gamma & \cos \gamma & 0 & y_p \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where γ is the heading angle of the robot in the global coordinate system. Let the detected wall be represented as equation $p_a x_a + q_a y_a = 1$ in the global coordinate system. Then according to coordinate transformation, we have

$$\begin{aligned} x_a &= x \cos \gamma - y \sin \gamma + x_p \\ y_a &= x \sin \gamma + y \cos \gamma + y_p \end{aligned}$$



(a)



(b)

Fig. 7. Experimental results of scanning a room with a rectangular table inside using only ultrasonic sensors. (a) Fused sensory data. (b) Estimated line segments using data from (a).

$$p_a = \frac{p \cos \gamma - q \sin \gamma}{1 + (p \cos \gamma - q \sin \gamma)x_p + (p \sin \gamma + q \cos \gamma)y_p}$$

$$q_a = \frac{p \sin \gamma + q \cos \gamma}{1 + (p \cos \gamma - q \sin \gamma)x_p + (p \sin \gamma + q \cos \gamma)y_p}$$

$$Pb_a = J \cdot Pb \cdot J^T$$

$$J = \begin{bmatrix} \frac{\partial p_a}{\partial p} & \frac{\partial p_a}{\partial q} \\ \frac{\partial q_a}{\partial p} & \frac{\partial q_a}{\partial q} \end{bmatrix}$$

where

- Pb_a the covariance matrix of the parameters p_a and q_a ;
- Pb the covariance matrix of the parameters p and q ;
- J the Jacobian matrix.

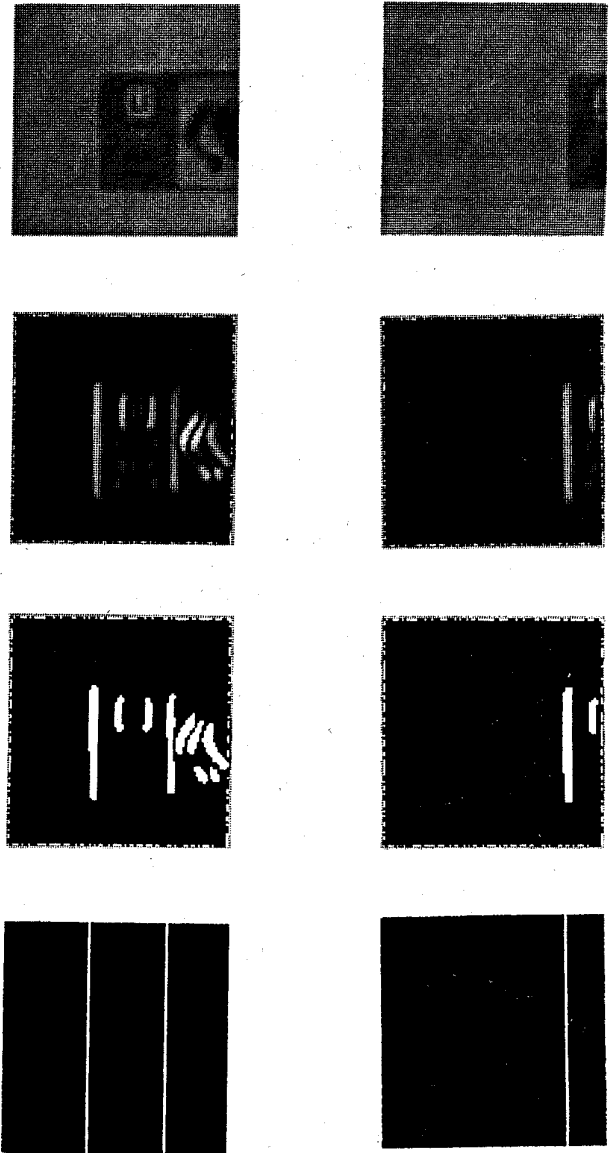


Fig. 8. Two experimental results of the vision system.

The function *similar* is used to judge if some of the line segments estimated at different scanning positions represent the single surface of an object

Let

$$u_i = \begin{bmatrix} p_{ai} \\ q_{ai} \end{bmatrix}$$

$$u_j = \begin{bmatrix} p_{aj} \\ q_{aj} \end{bmatrix}$$

- u_i, u_j the estimated line segments at different positions;
- Pb_{ai} the covariance matrix of u_i ;
- Pb_{aj} the covariance matrix of u_j .

The conditions of similarity can be summarized as follows.

- 1) The angle between u_i and u_j is less than θ_s .
- 2) The distance from each end of u_j to u_i is less than d_s .

- 3) The distance from each end of u_i to u_j is less than d_s .
- 4) When the projection of u_i on u_j is not inside u_j , the distance between the two nearest ends of u_i and u_j is less than d_p .

The selection of the values of θ_s and d_s is related to the uncertainty of the line segments. The selection of the value of d_p is related to the minimum width the mobile robot can pass through. If u_i and u_j satisfy the above conditions, we can merge the two line segments to estimate a new line segment. To do this, we used the *merge* function to merge two line segments into a new line segment, thus increasing the reliability of the estimation. Merging also reduces the amount of data in the representation. We also adopted the discrete Kalman filtering technique for merging the line segments. The DKF algorithm for merge is given as follows:

$$\begin{aligned}
 K &= Pb_{ai}[Pb_{ai} + Pb_{aj}]^{-1} \\
 Pb_a &= Pb_{ai} - K \cdot Pb_{ai} \\
 u &= u_i + K[u_j - u_i]
 \end{aligned}$$

where

- u_i, u_j the estimated line segments at different positions;
- Pb_{ai} the covariance matrix of u_i ;
- Pb_{aj} the covariance matrix of u_j ;
- K Kalman matrix;
- u a new estimate vector;
- Pb_a the covariance matrix of u .

IV. EXPERIMENTAL RESULTS

We evaluated the algorithm by conducting several practical experiments. The setup of the sensor system has been described in Section II. The test environment was a rectangular-shaped walled space.

A. Double Ultrasonic Sensor Fusion

In a practical test of the double ultrasonic sensor system, we used a rectangular shaped flat-wall environment constructed from three wooden plates and a cement wall. The purpose was to check the environment perception capacity of the dual-transducer ultrasonic sensor system. We placed the sensor platform inside the space and made a 360° scanning of it by rotating the step motor with $1.8^\circ/\text{step}$. The experimental results of using EDKF to fuse the data and estimate the locations of the walls is shown in Fig. 6(a). The processing of parameter estimation for one of the four wall-surfaces is shown in Fig. 6(b). We observe from the experiment that the reflective phenomenon is highly detrimental to measurement. If this error is not filtered out by the constraints, then the accuracy of the estimation will be degraded. Hence the constraints are helpful for increasing the accuracy of estimation.

B. CCD Sensor Fusion for Boundary Estimation

If we only use the double ultrasonic sensors to detect objects in the environment, it is difficult to determine the ends of an object or a flat wall. For instance, Fig. 7(a) shows

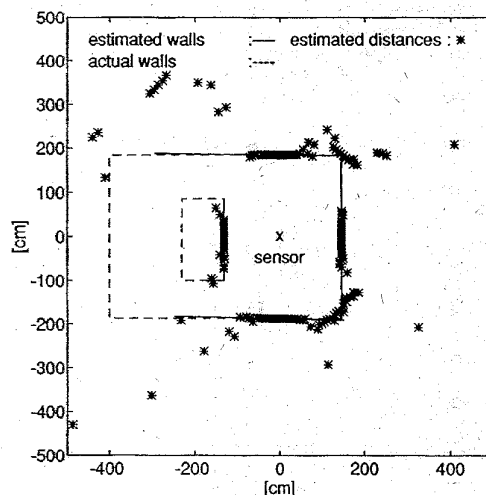


Fig. 9. Perception results obtained by combining the CCD camera and the double ultrasonic sensors.

double ultrasonic sensor scanning of an closed walled space in which there was a rectangular table. Fig. 7(b) shows the estimated line segments of the environment from the data of Fig. 7(a). Clearly, there is not enough information to determine the positions of the boundaries of the table and the wall. To improve the accuracy of the estimation, data from the CCD camera was added to detect the vertical edges in the active window. Fig. 8 depicts the test results of the image processing. When we used the vision system to estimate the edges, we obtained the boundaries of the object and walls satisfactorily, as shown in Fig. 9. Moreover, when using this setup, information obtained at fewer scanning positions was sufficient to build a complete and reliable representation.

C. Simulation of Environment Reconstruction

In order to test the merge procedure without requiring a real mobile robot, we carried out a simulation on the reconstruction of a representation of the environment. In this simulation, the maximum incident angle of the ultrasonic transducers was set to 25° . Over this range, the sensor data would be discarded. We also assumed that accurate recognition of the boundaries of the objects or walls was possible, for instance, when using the vision system. The sensor system scanned the environment 360° around with every step 1.8° . There were 7 scanning positions in this simulation. The result of the environment perception at point 1 is shown in Fig. 10(a). Through gradual merging, point by point, the reconstructed representation approaches the actual environment. Fig. 10(b) depicts the merging result at point 4. In the figures, the solid lines represent the shape detected and the symbol $\times$ represents the scanning positions of the sensor platform (which is installed on the mobile robot).

V. CONCLUSION

A sensor system has been designed and constructed for environment perception of a mobile robot. We combined a pair of ultrasonic sensors with a CCD camera to provide more

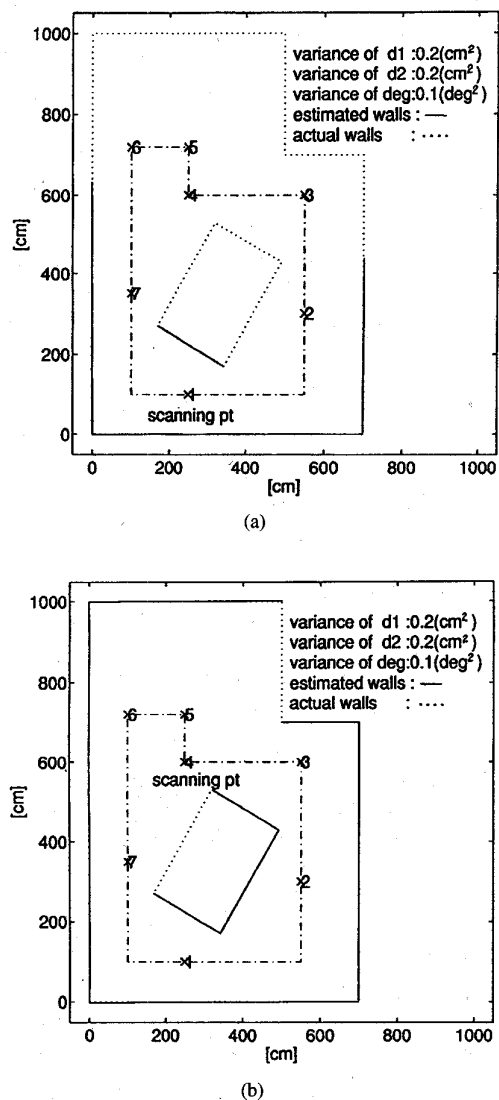


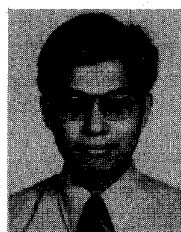
Fig. 10. Simulation results of merging sensory data from multiple scanning points. (a) Perception result after point 1. (b) Perception result after point 4.

reliable perception of rectangular-shaped objects. Algorithms for eliminating the measurement error resulting from the beam opening angle have been derived and tested using the double-transducer design. We used extended Kalman filtering techniques to successfully decrease the estimation uncertainties. The fusion of CCD image data into sonar ranging system further improves the boundary-determination of an object. Practical experiments show that the measurement errors that arise when conventional ultrasonic sensors are used alone can be reduced using this multisensor system. This study demonstrates an encouraging approach using geometric model and Kalman filters to integrate several sensors at different

levels. Further investigation will be continued to deal with multisensor perception of other shapes of objects and practical application of real mobile robot.

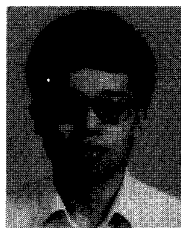
REFERENCES

- [1] R. C. Luo and M. G. Kay, "Multisensor integration and fusion in intelligent systems," *IEEE Trans. Syst., Man, Cybern.*, vol. 19, no. 5, pp. 901-931, 1989.
- [2] H. F. Durrant-Whyte, "Consistent integration and propagation of disparate sensor observations," *Int. J. Robot. Res.*, vol. 6, no. 3, pp. 3-24, 1987.
- [3] —, "Sensor models and multi-sensor integration," *Int. J. Robot. Res.*, vol. 7, no. 6, pp. 97-113, 1988.
- [4] Y. C. Tang and C. S. G. Lee, "A geometric feature relation graph formulation for consistent sensor fusion," in *Proc. IEEE 1990 Int. Conf. Syst., Man, Cybern.*, Los Angeles, CA, 1990, pp. 188-193.
- [5] J. L. Crowley, "World modeling and position estimation for a mobile robot using ultrasonic ranging," in *Proc. IEEE Int. Conf. Robot., Automat.*, 1989, pp. 674-680.
- [6] T. Skordas, P. Puget, R. Zigmann, and N. Ayache, "Building 3-D edge-lines tracked in an image sequence," in *Proc. Intell. Autonomous Systems-2*, Amsterdam, 1989, pp. 907-917.
- [7] K. T. Song and C. C. Chang, "Ultrasonic sensor data fusion for environment recognition," in *Proc. 1993 IEEE Int. Conf. Intell. Robots, Syst.*, Yokohama, 1993, pp. 384-390.
- [8] K. T. Song and J. C. Tai, "Fuzzy navigation of a mobile robot," in *Proc. of 1992 IEEE Int. Conf. Intell. Robots, Syst.*, Raleigh, 1992, pp. 621-627.
- [9] Polaroid Corp., Ultrasonic Ranging System—Polaroid Corp., Norwood, MA, USA, 1990.
- [10] J. Borenstein and Y. Koren, "Obstacle avoidance with ultrasonic sensors," *IEEE Trans. Robot. Automat.*, vol. 4, no. 2, pp. 213-218, 1988.
- [11] W.-H. Tang, "Design and implementation of a sensory system for environment recognition of robotic systems," Master thesis, National Chiao Tung University, Taiwan, (in Chinese), 1993.



Kai-Tai Song was born in Taipei, Taiwan, R.O.C., on March 22, 1957. He received the B.S. degree in power mechanical engineering from National Tsing Hua University in 1979 and the Ph.D. degree in applied sciences from the Katholieke Universiteit Leuven, Belgium, in 1989.

He was with the Chung Shan Institute of Science and Technology from 1981 to 1984. Since 1989 he has been with College of Electrical Engineering and Computer Science, National Chiao Tung University, Taiwan, where he is currently Associate Professor in the Department of Control Engineering. His research interests are in intelligent robotic system, sensing and perception, sensor integration in control system design, and intelligent control.



Wen-Hui Tang was born in Taipei, Taiwan, R.O.C., on March 15, 1964. He received the B.S. degree in mechanical engineering from Chung-Yuan Christian University, Taiwan, in 1986 and the M.S. degree in control engineering from National Chiao Tung University in 1993.

He was with the Aeronautical Research Laboratory, Chung Shan Institute of Science and Technology, from 1986 to 1990. Since 1993 he has been with the Opto-Electronic & Systems Laboratory, Industrial Technology Research Institute, Taiwan.

His research interests are in sensor technology and industrial automation.