Indoor Mobile Robot Localization Using Probabilistic Multi-Sensor Fusion

Ren C. Luo, Fellow, IEEE, Chun Chi Lai
Department of Electrical Engineering National Chung Cheng University
168, University Rd., Ming-Hsiung, Chia-Yi, Taiwan. 621
luo@ia.ee.ccu.edu.tw, cclai@ia.ee.ccu.edu.tw

Abstract—This paper presents a probability fusion methodology with a decision rule for a feature extraction of indoor environment. Two range sensors with complementary property are equipped on a mobile service robot. One is a servo sonar ring composed by Poloroid 6500 ultrasonic rangers and the other is a Hokuyo infrared range-finder. For a real indoor environment is usually composed of different objects with variant material characteristics such as sound absorbed or light refraction. Theses may cause the sensor measurement failure to imperil the localization estimation procedure of an indoor service robot. Thus, multi-sensor fusion with a decision methodology is necessary for feasibility and reliability while service mobile robot is working in a compound indoor environment.

I. INTRODUCTION

The feature extraction from environment is a base towards to map building or map association of SLAM. Because of uncertainty in the origins of sensor measurements, it is difficult to determine the correspondence between measured data and features of the scene being observed. In many applications, multiple sensors are equipped to provide the system with useful information concerning some features of interest in the robot’s environment. Multi-sensor fusion and integration refers to the synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information. The integration or fusion of redundant information can reduce overall uncertainty and thus serve to increase the accuracy with which the features are perceived by the system.

For indoor service robot applications, the ultrasonic range sensors are extensively employed on the mobile robot for navigation and localization [1]. The primary motivation is their low cost, small size and convenient calculation for Time of Flight (TOF). But these common pulse-types ultrasonic range sensors [2] present some limited angular resolution, i.e. the low azimuth resolution and wide beam pattern are drawbacks for these ultrasonic range sensors. Using a better sensor device would automatically solve the sonar drawbacks, such as the laser range system [3] which provides high resolution both in distance and azimuth. Howe ever, in more complex environment such as showcase or glass obstacle, the laser range system does not work properly, but the sonar sensor usually has effective measurement for these objects. Obviously, when these different sensors are measuring the same percepct, the complementary property can assist to reject the false negatives and improve the measurement precision. Thus, multi-sensor fusion is necessary to integrate the measurement results from complementary sensors and extract the relevant information, even the similar sensor types in different sensing from distributed sensors also can be exploited to provide plentiful data for more accuracy inference.

In SLAM algorithm, the robot localization model is presented and assumes that the robot has sensors capable of uniquely identifying each landmark, i.e. that the feature of environment such as corners, vertexes and planes are recognized in real application for robot SLAM problem. In the paper we focus on the feature extraction of environment. We use laser and sonar to approximate a polygon by applying a Hough transform. Finally, a decision is applying for feature identification. Section II presents related works about ranger sensors on our “Security Warrior” service robot platform. In Section III, ranger sensor measurement model is addressed. Section IV presents feature level extraction method by Hough Transform. Section V discusses the symbol level fusion for a sensing decision. Section VI shows the experimental results. Finally, Section VII presents brief concluding comment.

II. RELATED WORKS

A. Intelligent Service Mobile Robot “Security Warrior”

The Intelligent mobile robot platform “Security Warrior” [22] is constructed for providing service and security task. The diameter is 50cm, and height is 170cm. The major system

![Fig.1. System architecture of intelligent security robot](image-url)
components are shown in Fig.1. The system structure of the Security Warrior contains six subsystems including remote supervising, motion, vision, sensory, robot arms and power estimation subsystems. For achieving the security jobs of the robot, a central control unit called intelligent kernel is essential to handle the cooperation between all the subsystems. Each subsystem is running as an independent agent. The intelligent kernel coordinates with the agents by inter-process communication (IPC). Two kinds of IPC including internetworking socket and share memory are implemented for the communication.

B. Polaroid Servo Sonar Ring

There are sixteen Polaroid 6500 ultrasonic range sensors distributed around the Security Warrior as a sonar ring for environment exploration. The firing rate and sequence of the sonar ring are controlled by an embedded controller as shown in Fig.2. The configuration of multiple ultrasonic range sensors will influence the performance of environment sensing. There are mainly two ways to configure ultrasonic range sensor for local map building and landmark classification application:

1) Sensor array configuration: Gathering information without sensor movement [4], [5], [6].
2) Servo scanning configuration: (e.g. rotary scanning) [1], [4], [7].

We configure a servo motor for sonar rapid scanning and in 0.5° degree. The key feature for robot motion planning and localization is the sensor model, which provides the ability to predict and understand sensor information. With the sensor model, the robot cannot only determine whether a geometric beacon is detectable or not, but also obtain probabilistic information about the quality of the beacons. We will focus on the Polaroid ultrasonic and URG rangefinder, due to its popularity in the mobile robot community. For Polaroid transducer, the pressure amplitude of the acoustic beam has the shape of a Bessel function, but most of the actual implementations assume Gaussian distributions. Because of unknown echo orientation from an obstacle, the transducer’s azimuth is often used as representation for each measurement. Rotating the transducer on different orientation leads to the regions of constant depth (RCD). A region of constant depth is a connected set of returns with range difference less that ±δr. The definition of RCD can described as follow. A return, whose range difference with each of its adjacent returns, is greater than ±δr. For each RCD, let θ1 to be the angle of the right-most return of the RCD, and similarly, θ2 to be the angle of the left-most return of the RCD. ϑm is the orientation of the RCD, which is simply the mean of θ1 and θ2: ϑm = (θ1 + θ2)/2 as shown in Fig.3 [8].

C. Hokuyo Laser Ranger

The Hokuyo infrared range-finder [9] contains a light source is infrared laser of wavelength 785nm and scan area is 240° semicircles with maximum radius 4000mm. Each pitch angle is about 0.36° and sensor outputs the distance measured at every point (683 steps). Fig.4 shows the row scope of URG-04LX infrared range-finder. The principle of distance measurement is based on calculation of the phase difference. Table I summarizes the manufacturer’s specification of the URG-04LX.

<table>
<thead>
<tr>
<th>Detection Area: 240°</th>
<th>Non-radiated area: 120°</th>
<th>Max. Distance: 4000mm</th>
</tr>
</thead>
</table>

**TABLE I**

<table>
<thead>
<tr>
<th>Items</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (W D H)</td>
<td>50x50x70 mm</td>
</tr>
<tr>
<td>Total Weight</td>
<td>160 g</td>
</tr>
<tr>
<td>Resolution of Direction Angle</td>
<td>0.36°</td>
</tr>
<tr>
<td>Scanning Range</td>
<td>240°</td>
</tr>
<tr>
<td>Range of distance</td>
<td>20-4000mm</td>
</tr>
<tr>
<td>Interface Method</td>
<td>RS-232C, USB</td>
</tr>
<tr>
<td>Response Time</td>
<td>100msec/scan</td>
</tr>
<tr>
<td>Power Source</td>
<td>5V DC</td>
</tr>
</tbody>
</table>

III. RANGE SENSOR MEASUREMENT MODEL
A. Reflection Angle versus Sonar Bearing

According to the widely used Polaroid ultrasonic range sensors, when the sound lobe encounters an obstacle, it causes a significant echo response as a measurement value. The echo response must be a part of the sound lobe and the reflection point has to lie on the lobe. It can be simplified to the opening angle of the cone. So it is reasonable for a uniform distribution of the reflection point from the origin to the target, i.e., the reflection point will be anywhere along the arc of a sonar cone. A single sonar cone of a mobile robot is illustrated in Fig. 5. The angle $\phi_s$ is an actual reflection angle from a plane target, and a nominal distance $s_r$ is measured by a sonar sensor towards a global bearing angle $s$. Since the uniform distribution is assumed for a sonar cone, the detection model can be described as a conditional probability in Equation (1).

$$P(\alpha_s | \phi_s) = \begin{cases} \frac{1}{\beta}, & \phi_s - \frac{\beta}{2} \leq \alpha_s \leq \phi_s + \frac{\beta}{2} \\ 0, & \text{otherwise} \end{cases}$$ (1)

Other researchers [10] also use a uniform distribution model or Gaussian model as well. Certainly, this means that we cannot assume the reflection point lies along the sensor centerline with bearing angle $\alpha_s$, unless the sensor reading is quite small.

B. Sonar Range Measurement with Uncertainty

The stochastic specific sonar range sensor models which are actually used for the experimental component in previous researches [11]. The variation of range uncertainty with distance of a sonar sensor is shown in Fig. 6. The uncertainty measurement value $r_s$ is estimated by a Gaussian distribution. For the convenient, we assume the sonar range sensor is characterized by Gaussian with a variance $\sigma_{r_s}^2$. In this case, the range measurement model of a sonar sensor can be represented in a conditional probability form as below:

$$P(r_s | \phi_s) = \frac{1}{\sqrt{2\pi}\sigma_{r_s}^2}\exp\left[-\frac{1}{2\sigma_{r_s}^2}(r_s - r_{st})^2\right]$$ (2)

Where the sonar sensor whose range measurement value $r_s$ and the actual distance $r_{st}$ of reflection are corrupted by Gaussian distribution with variance $\sigma_{r_{st}}^2$.

C. Conditional Probability Distribution of Sonar

From previous assumptions and conditions for a reflection point that a distance measurement value $r_s$ with an opening angle $\beta$ is considering. We combine these conditions in a Joint Probability Distribution Function as below:

$$P(Z|G) = \begin{cases} \frac{1}{\beta} N(r_{st}, \sigma_{r_{st}}), & \phi_{st} - \frac{\beta}{2} \leq \alpha_s \leq \phi_{st} + \frac{\beta}{2} \\ \min r_s \leq \max r_s, & \text{otherwise} \end{cases}$$ (3)

$Z$ is sonar measurement data $(r_s, \alpha_s)$ and $G$ is the actual plane reflection with parameter $(r_{st}, \phi_{st})$. Fig. 7 shows the joint conditional probability distribution of sonar response toward a wall.

D. Maximum Likelihood Estimation of Sonar Scanning

We consider the maximum likelihood approach to fuse the observations of servo sonar scanning. Maximum likelihood method has a number of attractive attributes. The major is good
convergence properties as the number of samples increases and is simpler than alternate estimation methods. The configuration of multiple ultrasonic range sensors will influence the performance of environment sensing. For the maximum utility and capability of our mobile robot, we fit a DC Servo Motor for scanning as shown in Fig.8. When rotary scanning from 0° to 45°, it will finish a circular measurement in twice data acquisition in a circular azimuth.

Let a set $D$ of observations from sonar drawn independently. From the probability density $p(Z \mid G)$ in (3), we can estimate the unknown parameter vector $P$. Suppose that $D$ contains $n$ observations, $Z_1…Z_n$ in each regions of constant depth (RCD). Then, since the samples were drawn independently, we have:

$$p(D \mid G) = \prod_{k=1}^{n} p(Z_k \mid G)$$  \hspace{1cm} (4)

$p(D \mid G)$ is the likelihood of $G$ with respect to the set of observations. The maximum likelihood estimate of $G$ is, by definition, the value $\hat{G}$ that maximizes $p(D \mid G)$. Intuitively, this estimate corresponds to the value of $G$ that in some sense best agrees with or supports the actually observed samples.

$$L(G) = \ln p(D \mid G) = \sum_{k=1}^{n} p(Z_k \mid G)$$  \hspace{1cm} (5)

$$\hat{G} = \arg \max_{G} L(G)$$ \hspace{1cm} (6)

$$\nabla_G L = \sum_{k=1}^{n} \nabla_G \ln p(Z_k \mid G) = 0$$ \hspace{1cm} (7)

Where $\nabla_G$ is gradient operator. Let $L(G)$ as the log-likelihood log-function in (5). We can then write our solution formally as the argument $\hat{G}$ that maximizes the log likelihood, i.e., (6). Thus, a set of necessary conditions for the maximum likelihood estimate for $G$ can be obtained from the set of equations (7).

IV. FEATURE EXTRACTION

A. Hough Transformation

The Hough transform is a methodology which can be used to identify features of a particular shape within an image data. Because the desired features are specified in some parametric form, so the Hough transform is most commonly used for the detection of regular curves such as lines, circles, ellipses, etc [15]. The original transformation equation, based on slope-intercept parameterization of a line, was improved by Duda and Hart [21] through the normal parameterization:

$$x \cos \phi + y \sin \phi = \delta$$ \hspace{1cm} (8)

$\delta$ is the norm from origin and $\phi$ is the orientation of with respect to the X-axis (See Fig.9. (a) and (b))

![Fig.9. (a) Parametric description of a straight line (b) Hough transform plane](image)

B. End Points of a line segment

The laser ranger which can cover a large field of view up to It can be proved mathematically that the maximum width of the butterfly wings for every accumulator cell is defined by the coordinates of the end points of the longest line that can be placed within the image corresponding to that cell. Based on this assertion, for an arbitrary line segment described by end: points $(x_1, y_1)$ and $(x_2, y_2)$ two sets of simultaneous equations can be set up using any two columns of $\phi$ ($\phi$ and $\phi_r$) in the parameter space. The coordinates of the line segment end points $(x_1, y_1)$ and $(x_2, y_2)$ can be obtained by simultaneously solving equations in (9) from Fig.10.

$$\begin{align*}
\delta_{i1}^A &= x_i \cos \phi_1 + y_1 \sin \phi_1 \\
\delta_{i2}^A &= x_i \cos \phi_1 + y_2 \sin \phi_1 \\
\delta_{i1}^B &= x_i \cos \phi_r + y_1 \sin \phi_r \\
\delta_{i2}^B &= x_i \cos \phi_r + y_2 \sin \phi_r
\end{align*}$$ \hspace{1cm} (9)
C. Line extraction

The laser ranger which can cover a large field of view up to 180° with high azimuth resolution in the range. But the sonar is poor in azimuth resolution. In servo configured, the sonar ring can scanning up to 45° and some valid reflection points around the robot can be found. Let $M_s$ is the set of reflection points with its respective directions of measurement from sonar target scanning around robot.

$$M_s = \{(r_{x1}, \phi_{x1}), (r_{x2}, \phi_{x2}), (r_{x3}, \phi_{x3}), \ldots, (r_{xm}, \phi_{xm})\}$$ (10)

Where $i \leq m$ and similar the laser target measurements are:

$$M_l = \{(r_{l1}, \phi_{l1}), (r_{l2}, \phi_{l2}), (r_{l3}, \phi_{l3}), \ldots, (r_{ln}, \phi_{ln})\}$$ (11)

Where $k \leq 180°$. For a Hough transform; each parameter $(\phi, \delta)$ represents the parameter of a possible line equation $\ell$ as shown in fig.10 (a). The probability confidence function $C(\phi, \delta)$ can express the existence of a line $\ell$ in the global map. The local maxima of $C(\phi, \delta)$ indicate the set of lines (walls) of the environment. The confidence function is updated by Bayesian rules [15], the confidence function can be expressed as below:

$$C(\phi, \delta) = P(\ell | \phi, \delta) = \alpha P(\ell) P(\phi, \delta)$$ (12)

Where:

- $i \in [1, m]$ on the measurement set $\mathcal{R}_s$,
- $P(\ell | \phi, \delta)$ is the posterior probability associated to a line $\ell$ that leads from the measurement set $\mathcal{R}_s$;
- $P(\ell)$ is the prior probability of the line model $\ell$ in HT plane (with the absence of any measured evidence);
- $P(\phi, \delta)$ is the likelihood that the if the measurement points

V. OPTIMAL DECISION FUSION

The fusion algorithm [11] assumes that $H_1, H_2, \ldots, H_n$ represent mutually exclusive and exhaustive hypotheses as follows:

$$H_i = \begin{cases} +1: & \text{a line segment present} \\ 0: & \text{unknown} \\ -1: & \text{line segment absent} \end{cases}$$ (13)

The weight is a function of the known probability of detection $P_D$ and the probability of false alarm $P_F$. Therefore, we can define the following function $S$:

$$W_i = \log\frac{P_D}{P_F}$$

$$S = \sum_{i=1}^{n} W_i H_i$$ (15)

Where $n$ is the number of sensor. We can define the threshold $\eta$. When $S \geq \eta$, the line segment is present, and the decision output is 1; when $S \leq -\eta$, the line segment is absent, and the decision output is -1; when $-\eta < S < \eta$, the feature is uncertainty, and the decision output is 0.

VI. FUSION RESULT

In order to evaluate the proposed methodology, we have plotted the measurements for laser and sonar toward a wall as shown in Fig.11 (a), (b). Fig.10(c) is the credence for a laser scanning and (d) is the credence summation of scanning ultrasonic sensors. Fig.10 (e) and (f) shows the Bayesian updating with each row measurement. Finally, Fig.10 (g) is the optimal fusion output for a sign +1 to indicate a line feature is identified in HT parametric space.
VII. CONCLUSION

We have presented a multi sensor fusion inference for Polaroid ultrasonic range sensors with HOKUYO URG-04XL laser ranger to extract a line segment for the feature association of an indoor mobile robot. We utilize a servo configuration (i.e. a rotatory ultrasonic sensor ring is equipped on the mobile robot) to align the data acquisition from laser raw scanning. The Bayesian estimation is to extract the wall feature in 2-D environment both on sonar and laser row data. Finally, an optimal decision classifier will indicate the high accuracy feature association. Preliminary experimental results indicate that the proposed methods can make effectively fuse decision for environment exploration or provide the most reliable feature extraction for mobile robot map building and map association.

REFERENCES


