Statistical Approach to Range-Data Fusion and Interpretation

Petr Štěpán, Libor Přeučil
AI Division, Dept. of Control Engineering,
Faculty of Electrical Engineering,
Czech Technical University
Technická 2, CZ 166 27 Prague 6,
Czech Republic
E-mail: stepan, preucil@labe.felk.cvut.cz

Abstract

Making-use of multiple sensors is crucial for improvement of mobile robot navigation performance. The contribution introduces a problem of integrating noisy range-data by data fusion on signal/pixel level. This is performed for multiple sensors and different sensor positions into a common description of the environment. The following deals with grid models, which are used as a low-level representations of sonar range measurements as well as for data fusion process.

A short overview of used methods for the grid representation is shown and different fusion methods for various sonar models are discussed. Special attention is paid to the influence of sonar modeling on robustness of data integration process. The following deals with methods for improvement of fusion robustness. Novelty of the presented approach stands in a sonar model which is designed as dependent on measured distance. The other improvement is an optimal feature selection for doorway recognition. The designed methods are illustrated by examples and test runs on experimental mobile platform with sonar sensory system.

1. Introduction

An autonomous mobile robot has to be able to operate in an unstructured environment with a limited apriori information. To achieve this degree of independence, the robot system must understand of its surrounding. It needs a variety of sensors to measure the real world and mechanisms to extract meaningful information from the data.

The basic requirement for mobile robots is the ability to acquire and to handle information on the existence and localization of objects and empty space in the environment. This is important to compose information coming from multiple sensors and multiple robot position and to build a world map that reflects the measured information. Such a world model can serve as a basis for essential operations as path planning, obstacle avoidance, and position estimation.

There is number of approaches to inference under uncertainty, including the probability theory, Dempster-Shafer theory, and fuzzy sets [6]. We chose statistical approaches to sensor integration and data interpretation. The idea of the algorithm is based on certainty grid approach [1,2]. The main problems are to define a spatial interpretation model for each kind of sensor, to select a method for integration of the data gathered from multiple positions, and to select a decision-making method whether the cell is occupied, empty, or unknown.

The measured data strongly depend on the environment where the sonar is used. If the surrounding obstacles have smooth surfaces (specular reflections), the multiple reflections can be detected. That means that the measured distance is greater than the actual distance to the obstacle in question. This phenomenon has an essential influence on robustness of the whole algorithm. Hereunder we propose improvements that make possible to work properly even in such environment.

2. Using a Grid Map

The traditional approach to recovery of spatial information from range data is based on extraction of a geometric model directly from the sensor readings. The following selects an alternate approach that uses a grid map as a low level representation, avoiding early commitment to the geometric description. Therefore the following components of the data interpretation and integration processes are identified:

- *Spatial Interpretation Model*, developed for each kind of sensors. This model converts the measured distance

0-8186-7695-7/96 $5.00 © 1996 IEEE
Proceedings of EUROBOT '96

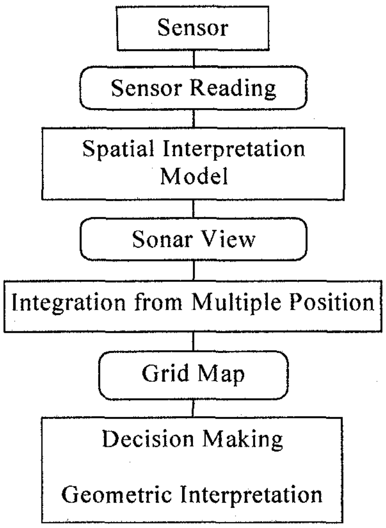

Fig. 1 Data Interpretation Process

in a given azimuth into numerical features like occupancy and emptiness probabilities for cells. This model is strongly dependent on sensor performance (hardware parameters).

- *Integration* of measurements from different positions. The probability values from Spatial Interpretation Model are integrated into a grid using integration method. The following methods are used:
  - Probability addition
  - Bayesian approach
- *Decision Making* is used whenever the cells must be explicitly labeled as *Occupied*, *Empty*, or *Unknown.*

The sonar map is built by evaluating the emptiness and occupancy probability distributions for each sonar range reading. The probabilities are projected onto a discrete grid, which is used to combine the single view with the sonar grid map. The position and orientation of the sonar sensors serves for coupling of the view with the map.

The map stores information which has been extracted and integrated from past measurements in order to allow the integration with other readings. The internal structure of the map depends on the used integration method.

2.1 Probability Addition

The sonar map is a two-dimensional array of cells corresponding to a horizontal grid imposed on the mapped area. The grid has M×N cells, each of Δ×Δ size. At the fusion process end each cell contains its status (unknown, empty, or occupied). During the integration process each cell contains two values: emptiness probability p_E and occupancy probability p_O. The probabilities are real numbers from interval (0, 1), where the both are initialized to 0 at the beginning. The probabilities are integrated using probability addition formula:

$$p_E = p_E + r_E - p_E * r_E$$
$$p_O = p_O + r_O - p_O * r_O$$

where r_E is probability that the cell is empty during actual reading, r_O is probability that the cell is occupied during actual reading

The final state of a cell is given by comparison of the relative strengths of the emptiness to the occupancy values.

It is important to note that p_E and p_O are permanently rising values (for each p_E, $r_E \in (0,1)$ is $p_E \geq p_E + r_E - p_E * r_E$). Therefore, the both p_E and p_O may be equal to 1 after certain number of integration steps. This can be solved in many ways:

- By multiply old probabilities by a constant
- By multiply old probabilities by a function depending on robot position

Each probability value (a particular cell) within the grid is multiplied by a chosen constant before integration in the former case. The latter uses function f(d), where d stands for a distance from the cell to current position of the robot. As a function f(d) has been chosen Gausian distribution function $f(d) = 1 - \frac{1}{\sqrt{2\pi\sigma^2}} e^{-d^2/2\sigma^2}$. To decrease computational complexity of the f(d) some simplifying approximation can be used as well.

2.2 Bayesian Approach

For a given sensor, a probabilistic sensor model can be derived in the form of a conditional distribution P(sensor reading R | world is in state S). The state S of the world is described by the set of states of all cells in the map. A map containing n^2 cells, each having two possible states, would requrie to specify 2^{n^2} conditional probabilities for each reading. To avoid such combinatorial explosion, it can be assumed that the states of cells are mutually independent discrete random variables. The state of the map is determined by state estimation of each cell individually.

The integration method can be derived from the Bayesian theorem:

$$P(s_i|e) = \frac{P(e|s_i)P(s_i)}{\sum_j P(e|s_j)P(s_j)}$$

where s_i is one of n disjoint states which are estimated, e is the relevant evidence, $P(s_i)$ denotes the apriori probability of the system being in state s_i. The $P(e|s_i)$ defines the probability that the evidence e would be present, given that the system is in state s_i. The $P(s_i|e)$ stands for the needed probability that the system is in state s_i when evidence e.

In our case, the evidence is given by a sonar range reading R and we need to determine the probabilities of P(Oc|R) and P(Em|R). As an additional simplifying assumption that P(R|Oc) = 1-P(R|Em) and P(Oc) = 1-P(Em). The Bayesian theorem changes into:

$$P(Oc|R) = \frac{P(R|Oc)P(Oc)}{P(R|Oc)P(Oc) + (1-P(R|Oc))(1-P(Oc))}$$

Making assumption that P(Oc) = 1-P(Em), each cell contains only one probability value P(Oc). This value is initiated to 0.5 (represents unknown state). Values below 0.5 mean empty cells. Values greater than 0.5 mean occupied cells, respectively. The value P(R|Oc) is computed from the sonar model mentioned below.

As in the previous method if the P(Oc) is equal to 0 or 1 the new measurement cannot influence this value. Therefore a similar method of multiplication by a constant or function can be applied:. Suppose m is a multiplicative value (constant or function value) used by the previous method, then the modified probability is:

$$P(Oc)_{new} = P(Oc)_{old} * m + 0.5*(1 - m)$$

3. Sonar Modeling

The sonar model is a way to transform sensory reading into probability values. Range reading is interpreted as making an assertion about two volumes: one is probably empty and the other one is probably occupied. The sonar beam is modeled by two probability functions f_E, f_O, defined for these volumes.

Consider a point P = (x,y) belonging to the volume swept by the sonar beam, the following can be defined:

R Range measurement returned by the sonar sensor
ε Maximum sonar measurement error
ω Sensor beam width
S S(x,y) sonar position
δ Distance from P to S
θ Angle between the axis of the beam and P from S

3.1 Quadratic Model

The model exploits two regions where the f_E or f_O are greater than 0. The empty region includes points satisfying: $\delta < R-\varepsilon$ and $|\theta| < \frac{\omega}{2}$, the occupied region contains points matching: $R-\varepsilon < \delta < R+\varepsilon$ and $|\theta| < \frac{\omega}{2}$ given in [2]:

$$f_E(\delta, \theta) = E_r(\delta) * An(\theta)$$
$$f_O(\delta, \theta) = O_r(\delta) * An(\theta)$$

$$E_r(\delta) = 1 - \left(\frac{\delta}{R-\varepsilon}\right)^2 \quad \text{for } \delta \in [0, R-\varepsilon]$$
$$E_r(\delta) = 0 \quad \text{otherwise}$$

$$O_r(\delta) = 1 - \left(\frac{\delta - R}{\varepsilon}\right)^2 \quad \text{for } \delta \in [R-\varepsilon, R+\varepsilon]$$
$$O_r(\delta) = 0 \quad \text{otherwise}$$
$$An(\theta) = 1 - \left(\frac{2*\theta}{\omega}\right)^2 \quad \text{for } \theta \in \left[-\frac{\omega}{2}, \frac{\omega}{2}\right]$$
$$An(\theta) = 0 \quad \text{otherwise}$$

probability distributions of the sonar sensor returning a range reading R. The plane defines the "unknown level", the values above the plane represent occupancy probabilities, and the values below represent the emptiness probabilities.

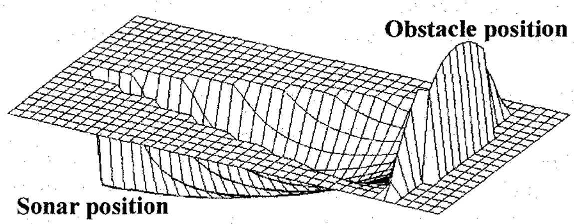

Fig. 2 Quadratic Probability Sonar Model

3.2 Exponential Model

The choice of a proper probability model has crucial influence on the fusion algorithm robustness. The leading idea is that the amount of information inserted into grid for near echoes is smaller than for more distant echoes. This fact differs the measured values by their quality in the following way. One bad and far measurement can destroy previously obtained information from many correct near measurements. This in fact spoils practical applicability of the presented function. Therefore, functions that keep the amount of information constant for every measured distance are designed. That means: $\iint f_E(\delta,\theta)d\delta d\theta \le c_1$ and $\iint f_O(\delta,\theta)d\delta d\theta \le c_2$, where the c_1 and c_2 are constants. Then only a change of the function E_r and O_r can suffice:

$$E_r(\delta)=\frac{e^{-\delta}-e^{\varepsilon-R}}{1-e^{\varepsilon-R}} \text{ or } E_{rs}(\delta)=e^{-\delta} \quad \text{for } \delta\in [0, R-\varepsilon]$$

$$E_r(\delta)=0 \quad \text{otherwise}$$

$$O_r(\delta)=\left(\frac{1}{R+1}\right)*\left(1-\left(\frac{\delta-R}{\varepsilon}\right)^2\right) \quad \text{for } \delta\in [R-\varepsilon, R+\varepsilon]$$

$$O_r(\delta)=0 \quad \text{otherwise}$$

Where the E_{rs} is simplified version of the E_r function defined above. These functions set up bounds for the amount of information inserted by one measurement. As bad measurements are typically spread over many cells, they can easily be removed by a correct measurement. The influence on robustness of the whole algorithm is demonstrated by test runs.

A typical exponential probability distribution is shown in the Fig. 3.

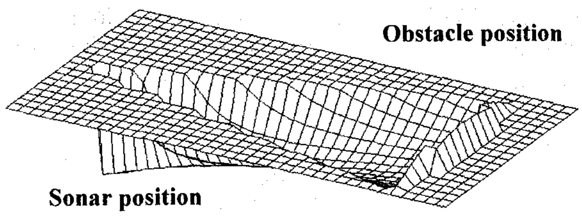

Fig. 3 Exponential Probability Sonar Model

4. Removal of Multiple Reflections

Multiple reflections belong to the major misfeeds of a sonar performance. If the sensor measures a distance with a multiple reflection, the result of this reading cannot be used. As the measured distance exceeds the actual distance of an obstacle, it can cause a collision. (Note, that data from one position are not sufficient for any king of recognition of multiple reflection.) The above mentioned exponential model can decrease influence of bad measurements, but not in general.

This problem can be approached by making-use of an assumption on minimal obstacle distance (from the sonar position). It is supposed that the obstacle surfaces are perpendicular with respect to the floor and every visible edge (junction of two obstacle surfaces) is detectable. Then the minimal measured distance defines a safe area where any obstacle cannot exist.. On condition that the sonar makes regularly spaced (in azimuth) and overlapped scans, the minimum of the obtained distances cannot be a multiple reflection. The sonar is desired to find the minimal distance to a nearest obstacle (obstacle surface and/or edge). Then a circle centered to sonar position and with a radius equal to the minimal distance is considered for free of obstacles.

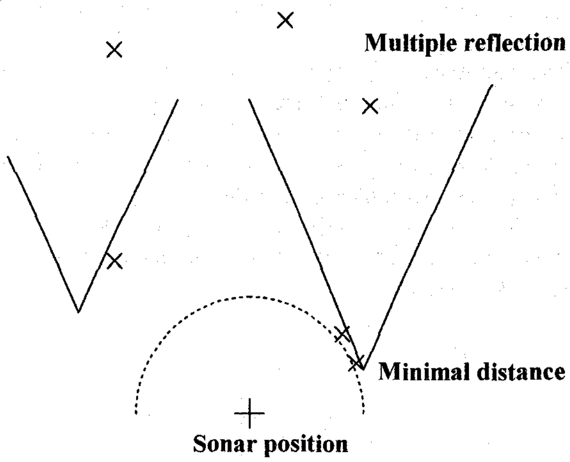

Fig. 4 Multiple Reflections

This can be used to suppress bad measurements. The feature of finding minimal distances has no influence on interpretation of occupied regions. Moreover, the minimal distance is used only to normalize the emptiness function E in order to restrict emptiness function to a safety circle area. Then, a new model having an emptiness probability dependent on the minimal distance can be defined:

$$E_r(\delta)=e^{-\frac{\delta}{M}} \quad \text{for } \delta\in [0, R-\varepsilon]$$

$$E_r(\delta)=0 \quad \text{otherwise}$$

Where M stands for the distance measured from the sonar current position. Such change minimizes influence of the emptiness function to outside of the safety circle.

The algorithm can be improved by taking the minimum only over a half of the scan. This is allowed, because the obstacle that produces multiple reflection (and which is assumed to be convex) occupies only one half of the space pane. In other words, the search is done only within an angle interval of (-90°, 90°) from each actual measurement (direction).

5. Doorway Detection

The previous section defines very safe sonar model, which detects every detectable obstacle. Unfortunately, such model leads to problems with recognition of doorways and similar passages in the environment. As it is not possible to recognize multiple reflections for the doorway case generally, a particular case has to be selected. Let's make an assumption that the robot moves roughly perpendicular to the obstacle surface (e.g. a wall with doorway).

The following method has been developed for an extremely sparse data gathered by equipped ultrasonic transducers spaced regularly at 18° apart. The following choice of features for data description has been motivated by [5]. In the particular case following attributes were defined in order to recognize a doorway making-use of 5 measured values. This sparse measurements cover 72 degrees of horizon:

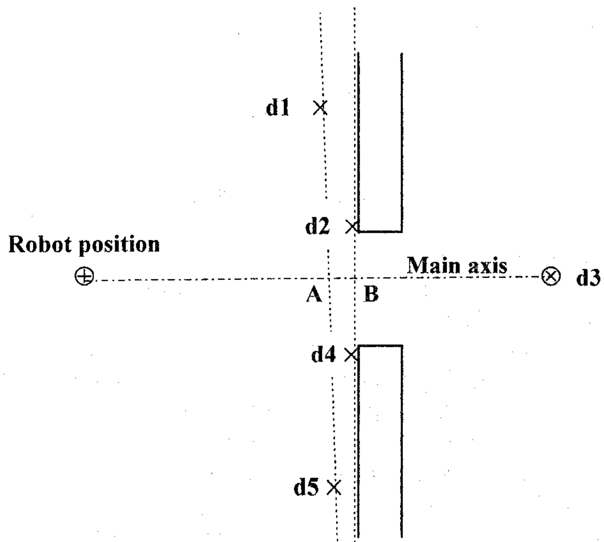

Fig. 5 Attribute definition for doorway recognition

The distance measurements are marked d1 through d5 and it is aimed to decide whether the measurement d3 is inside the doorway or not. Therefore, it can be supposed that the dorway occures when:

$$d3 > \max(d1, d2, d4, d5)$$

The chosen features for recognition are:

- α - angle of line d2,d4 and main axis
- β - angle of line d1,d5 and main axis
- d - distance between A and B, where A is an intersection of the line d1d5 with the main axis B is an intersection of the line d2d4 with the main axis

The doorway is detected if only an if $|\alpha-90°| <$ max_angle, $|\beta-\alpha| <$ max_angle, and $|d| <$ max_dist. These threshold constants can be obtained via training data incorporating normal wall (diffuse reflectivity, no multiple reflections), smooth wall (specular reflectivity, produces multiple reflections), and normal walls with door in it.

The method has been tested on a mobile robot and the obtained results are presented below.

Let's assume that a set of measurements (a sparse scan) is recognized as a doorway. Then the minimal distance (safety circle) overtaken from the previous model is not applied within the area of doorway. This change enables doorway recognition from greater distance than without.

6. Test Results

The methods have been tested on an experimental mobile platform equipped with 20 Polaroid™ ultrasonic transducers [3] spaced at 18° apart. The used range finder system provides the main lobe width of about 30 degrees and a useful measuring range of 0.20 to 7.0 meters. The sonars are fired sequentialy. To decrease scaning time an interlaced mode of firing is required. Even scans trig even transducers on the ring, the odd scans trig odd transducers. This firing schema speeds up the scanning rate twice and ensures still relatively homogenous coverage of the space. The size of grid cells was 0.1×0.1 meter.

The following introduces typical behavior of the sonar in a room with specular walls. The robot has moved by the wall and scanned the environment from 15 different positions. The measured data are shown in the Fig.6 (crosses). Measurements with a multiple reflection can be noticed as well.

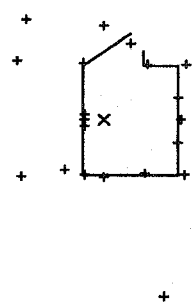

Fig. 6 Room reflections from smooth surfaces

The fusion results of the previous measurements via improved certainty grids are presented in the Fig. 7 and Fig. 8. The white cells are showing empty regions, gray cells are unknown areas, and black ones stand for occupied regions. All examples use the Bayesian integration method.

Comparing the previous figures it can be seen that multiple reflections break the walls and set some cells behind the walls to "empty". The Fig.8 shows that the "emptiness" behind the walls is decreased to minimum and the walls are not broken through.

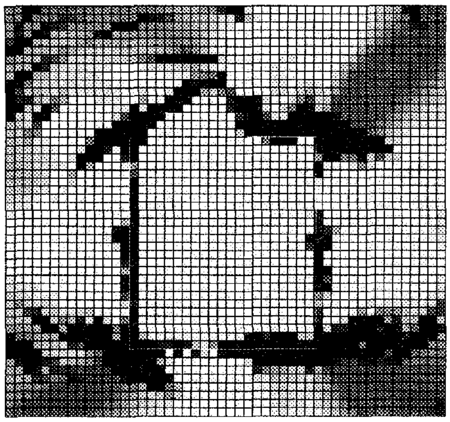

Fig. 7 Fusion with Quadratic Sonar Model

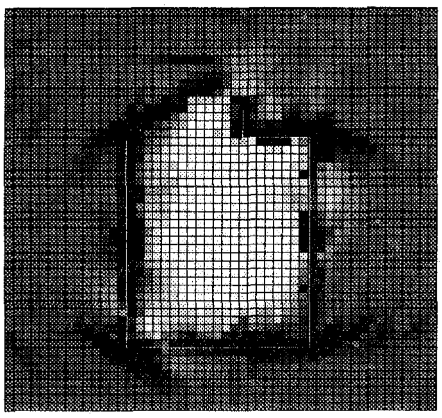

Fig. 8 Fusion with Exponential Sonar Model and removal of multiple reflections

Another example shown the in the Fig.9 illustrates results of the doorway detection. The robot (dark rectangle) is found in laboratory room containing obstacles (white rectangles) where two doorways were recognized (marked by D). Taking into account, that the input data are extremely sparse the achieved result of about 95% reliability of doorway detection can be considered for very good.

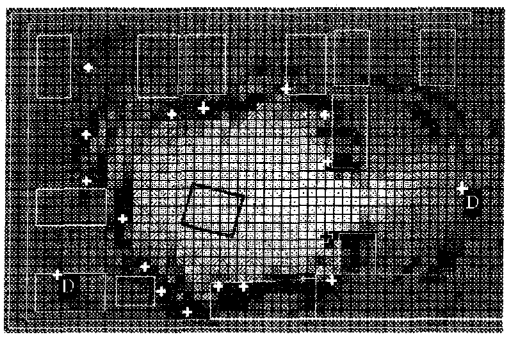

Fig. 9 Example of doorway recognition

The conducted experiments have shown that the presented methods and their improvements provide acceptable results towards fusion and interpretation of highly sparse and error-loaded range data (as sonars typically provide).

It has also been determined that the major influence on the final result of data fusion rises not from integration methods but from the sonar model itself. As for the final result a suitable sonar probabilistic model has been designed and improved by the "safety circle" and "doorway definition" heuristics.

For an integration method the Bayesian approach has been selected as the most perspective one for the further application.

Another advantage that brings the grid approach is speed of the method. It has been used the algorithm for scan line arc filling which improves speed of grid updating. The algorithm can be easily suited for real-time controls (e.g. local collision avoidance) - the grid (100x100 cells) updating 20 measurement takes about 0.2 second on a PC 486DX2/66 running in protected mode (what is basically less than needed for data collection).

Based on the achived results and performance the above introduced research has been targeted towards application of the grid maps in collision avoidance and local path planning.

Acknowledgment: This research has been carried out under support of the EC Copernicus'93 Joint Research Program, project no.5855 "Information Processing for Active CIM Subsystems"

References:

[1] Matthies L., Elfes A.: Integration of Sonar and Stereo Range Data Using a Grid-Based Representation, Proceedings of the IEEE International Conference on Robotics and Automation, 1988, p. 727-733

[2] Elfes A.: Sonar-Based Real-World Mapping and Navigation, IEEE Journal of Robotics and Automaton, June 1987, p.249-265

[3] Polaroid Corporation: Ultrasonic Range Finders, Polaroid Corporation, 1982

[4] Berger, J.O.: Statistical Decision Theory and Bayesian Analysis, Springer-Verlag, Berlin, 1985, Second Edition

[5] Young T.Y., Calvert T.W.: Classification Estimation and Pattern Recognition, Elsevier Publ. Comp., New York, 1974.

[6] Abidi M.A., Gondzales R.C. (Eds): Data Fusion Methods in Robotics and Machine Intelligence, Academic Press, 1992.