

Occupancy Grid Mapping for Mobile Robot using Sensor Fusion

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Abstract- Sensor data fusion using more than one sensor such as sonar sensors fusion reduces uncertainties generated from a single sensor. To learn the environment using more than one sensor information, an accurate sensor model as well as a reasonable sensor fusion methodology is needed. In this work, the Moravec-Elfes sonar model for occupancy grid representation and the recursive Bayes update rule in sensor fusion is applied. The environment of the mobile robot may be highly uneven for that only one type of sensors are not enough. Hence to increase the sensor accuracy to a great extent, the information obtained from two sonar and two laser sensors are combined for identifying different shape of objects.

Index Terms- Occupancy grid, Bayesian inference, sonar and laser sensors, sensor fusion.

I. INTRODUCTION

It is basic requirement for achieving full autonomy in a mobile robot to sense the environment accurately. Sensor plays a fundamental role in the autonomy process of mobile robot. Various types of sensor such as sonar sensor, infrared sensor, laser sensor, vision sensor etc are used for environment mapping [1-8].

Each of the above mentioned sensors has its own drawbacks. The sonar sensor suffers from wide beam cone, specular reflection, cross talking etc [4, 8]. On the other hand lasers available in market are very costly and transparent to some material. Stereo vision systems are highly sensitive to changes in illumination and the algorithms that exist are computationally expensive [8, 11].

Due to defects produced in sensor it is clear that one sensor alone can never give satisfactory information for mapping of mobile robot's environment. Especially in the case of sonar this is quite difficult task due to some reasons like specular reflection, cross talk and wide beam cone which generates more uncertainty. In order to reduce uncertainty to a great extent fusion of sensors is a need indeed [1, 2, 4, 6, 12, and 17]. The main objective of a multi sensor system is to improve the capabilities of a single sonar system.

The recursive Bayes update rule has been used to update the map generated from sonar sensor reading. For updating the

occupancy grid [15], generated from sonar sensor information, readings are determined by taking the maximum of the reading in occupied area and minimum of the reading in empty area as prior reading for each cell of grid [1, 3, and 9]. The objective is to identify the different shape of the objects presented in the environment of the mobile robot. It is hard to measure the depth of the some objects in front of the robot using only sonar sensors. This paper represents the results showing reduced uncertainty after fusing sonar sensors reading with laser sensors.

Sensors used in this work, one is although expensive i.e. laser sensor but another one is very cheap i.e. sonar sensor. Both sensors compensate the disadvantage of each-other. Sonar sensor due to wide beam cone cannot detect exact shape of an object in some cases but laser is very useful there for identifying the shape of that object. Laser sensor also has some disadvantage as depending upon lighting of the surface and transparency in some cases but sonar sensor does not suffer with such conditions [11, 13].

II. SONAR MODEL

Elfes and Moravec [1], the researcher models the sonar beam as two probability density function, f_E and f_O . These function measure the confidence and uncertainty of an empty and occupied region in the cone beam of the sonar respectively. In this model the following is defined:

- r Range measurement.
- $P_{i,j}^O$ Probability of a particular cell being occupied.
- $P_{i,j}^E$ Probability of a particular cell being empty.
- r_{min} Minimum distance.
- ε Mean sonar deviation error.
- ω Width of the cone.
- S_s sonar sensor
- δ_r Distance between S_s to $C_{i,j}$.
- θ Angle between the main axis of sonar beam to the line $S_s C_{i,j}$.

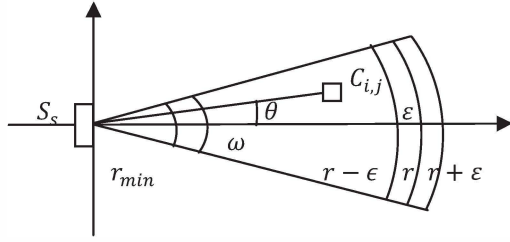


Fig.1. Field of view of the sonar sensor.

The beam is divided in two regions:

- The free space area or empty probability region which is the part of the beam between the sensor and the range where the obstacle was detected. This includes cell $C_{i,j}$ inside the sonar beam. Each cell has an empty probability

$$P_{i,j}^e = E_r(\delta_r) \cdot E_a(\theta) \quad (1)$$

$E_r(\delta_r)$ is the estimation of the free space cell based on the range measurement from the sonar. The closer it is to the sensor the more likely it is to have a high estimation that the cell is empty.

$$E_r(\delta_r) = 1 - \left(\frac{\delta_r - r_{min}}{r - \epsilon - r_{min}} \right)^2 \quad \text{for } r_{min} \leq \delta_r \leq r - \epsilon \quad (2)$$

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

$E_a(\theta)$ is the estimation that the cell is free based on the angle of the cone beam. The closer it is to the main axis and to the sonar the more estimate that it is empty.

$$E_a(\theta) = 1 - \left(\frac{2\theta}{\omega} \right)^2 \quad \text{for } \frac{-\omega}{2} \leq \theta \leq \frac{\omega}{2} \quad (3)$$

$$E_a(\theta) = 0 \quad \text{otherwise}$$

- The occupied area or probability occupied region. This is the area where the obstacle was detected. In this region the uncertainty to the exact distance to the obstacle (ϵ) has to be taken into account. The probability of a cell being inside the occupied region is :-

$$P_{i,j}^o = O_r(\delta_r) \cdot O_a(\theta) \quad (4)$$

$O_r(\delta_r)$ is the estimation is based on the range reading . The closer the obstacle is to the sonar the higher the probability that the cell is occupied

$$O_r(\delta_r) = 1 - \left(\frac{\delta_r - r}{\epsilon} \right)^2 \quad \text{for } (r - \epsilon) \leq \delta_r \leq (r + \epsilon) \quad (5)$$

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

$O_a(\theta)$ is the estimation is based on the difference of the angle between the obstacle and the beam axis. The closer the obstacle is to the sonar the higher the probability that the cell is occupied.

$$O_a(\theta) = 1 - \left(\frac{2\theta}{\omega} \right)^2 \quad \text{for } \frac{-\omega}{2} \leq \theta \leq \frac{\omega}{2} \quad (6)$$

$$O_a(\theta) = 0 \quad \text{otherwise}$$

III. SENSOR FUSION FRAMEWORK

A. Bayesian Inference

Bayesian is a statically inference method in which observations are used to update or infer the probability that a hypothesis may be true. Bayesian inference is an approach to the statistics in which all forms of uncertainty are expressed in the form of probability.

If the event B_1, B_2, \dots, B_K constitute a partition in the sample space s , where $p(B_j \neq 0, \text{ for } j = 1, 2, 3, \dots, K)$. then for any even A in S such that $P(A) \neq 0$.

$$P(B_i|A) = \frac{P(B_i \cap A)}{\sum_{j=1}^K P(B_j \cap A)} = \frac{P(B_i)P(A|B_i)}{\sum_{j=1}^K P(B_j)P(A|B_j)} \quad (7)$$

For $i=1, 2, \dots, k$

- B_i is one of i mutually exclusive (disjoint) event to be estimated.
- A is the evidence event.
- $P(B_i)$ is the prior probability of the event B_i . It is prior in the sense that it does not take into account for any information about A .
- $P(B_i|A)$ is the conditional probability of B_i given A . It is also called the posterior probability because it is derived from or dependent upon the specified value of A
- $P(A|B_i)$ is the conditional probability of A given B_i
- $\sum_{j=1}^K P(B_j \cap A) = \sum_{j=1}^K P(B_j)P(A|B_j)$ is the total probability of A , and acts as a normalizing factor.

B. Recursive Bayes Update Rule

Bayes rule provides a way of computing a posteriori probability of a hypothesis being true giving supportive evidence [7,10] have successfully used bays rule to update the occupancy grid for multiple sensor readings (s_1, \dots, s_n). The (7) transformed to (8) and (9) to the occupancy grid framework for multiple sensor readings.

$$P_{i,j}^{o|s} = \frac{P_{i,j}^{s|o} P_{i,j}^o}{P_{i,j}^{s|o} P_{i,j}^o + (1 - P_{i,j}^{s|o})(1 - P_{i,j}^o)} \quad (8)$$

$$P_{i,j}^{e|s} = \frac{P_{i,j}^{s|e} P_{i,j}^e}{P_{i,j}^{s|e} P_{i,j}^e + (1 - P_{i,j}^{s|e})(1 - P_{i,j}^e)} \quad (9)$$

The following statements are defined

- The relevant evidence of true parameter B_i is given by $P_{i,j}^o$ and $P_{i,j}^e$, meaning that they are the prior probabilities of the cell $C_{i,j}$ being occupied or empty they are taken from the existing map.
- The conditional probability $P(A_i|B_i)$ is given by $P_{i,j}^{slo}$ and $P_{i,j}^{sle}$, which are the conditional probabilities that a sensor reading will exit given the state of the cell $C_{i,j}$, being occupied or empty. This conditional probability is given by the probabilistic sensor model.
- The conditional probability $P(B_i|A)$ is given by $P_{i,j}^{ols}$ and $P_{i,j}^{els}$, which is the conditional probability that a cell is occupied based on the past sensor readings it is the new estimate.

A new sensor readings introduces additional information about about the state of the cell $C_{i,j}$. This information is done by sensor model $P_{i,j}^{slo}$ and it is combined with the most recent probability estimate stored in the cell. This combination is done by the recursive bays rule $P_{i,j}^{ols}$ based on the current set of readings to give a new estimate $P_{i,j}^{ols}$. It is worth noting that when initializing the map an equal probability to each cell C_{ij} must be assigned. In other words the initial map cell prior probabilities are $P_{i,j}^o = P_{i,j}^e = 0.5$.

C. Fusion of sensors with two occupancy grids

Fusion of two or more occupancy grid is carried out by constructing occupancy grid for each sensor as a local grid map of individual sensor and these grids are used to build up the resulting grid. Each cell in both grids is evaluated before fusing the overlapped area of both the grids. In this sense, three rules are applied to obtain the resulting probability for each grid.

- If a cell $C_{i,j}$ in the source grid has higher probability of representing occupied space then a pre defined threshold T_0 , then the probability of the resulting cell being occupied is said to 1.
- A single cell $C_{i,j}$ is evaluated in the interval $\{1/2, T_0\}$.
- If the value that represents occupancy from a single cell does not fall in the former two rules the value in the cell is keep it.

D. Evaluation criterion for a single cell $C_{i,j}$

Let $C_{i,j}$ be a single cell in one of the source grids to be evaluated and $P_{i,j}^{os}$ the probability of a single cell being occupied based on the sensor reading s , so that

$$P_{i,j}^{os} = 1 \quad \text{for } P_{i,j}^{os} > T_0 \quad (10)$$

$$P_{i,j}^{os} = \frac{P_{i,j}^{os} + T_0 - 1}{2 \cdot T_0 - 1} \quad \text{for } P_{i,j}^{os} \in \{1/2, T_0\}$$

$$P_{i,j}^{os} \quad \text{otherwise}$$

The computed values are then applied in Bayes 'rule to obtain probabilities in the resulting grid:

$$P_{i,j}^{0s_1, s_2} = \frac{P_{i,j}^{s_1} P_{i,j}^{s_2}}{P_{i,j}^{s_1} P_{i,j}^{s_2} + (1 - P_{i,j}^{s_1})(1 - P_{i,j}^{s_2})} \quad (11)$$

Where $P_{i,j}^{s_1}$ is the modified probability of occupancy from the sonar sensor 1 and $P_{i,j}^{s_2}$ is the modified probability of occupancy from the sonar sensor 2. $P_{i,j}^{0s_1, s_2}$ is the probability of occupancy after data fusion.

The fusion of two sensors in two different grids has the advantage of not affecting the data between the two representations. A single grid is suitable for fusion of data from single sensor. Two separate grids are required for mapping the area in front of the robot furnished by each sensor. The final fusion takes place on another part of the computer memory in different grid. It is used for data fusion process and is not used for integration of range from individual sensor[10].

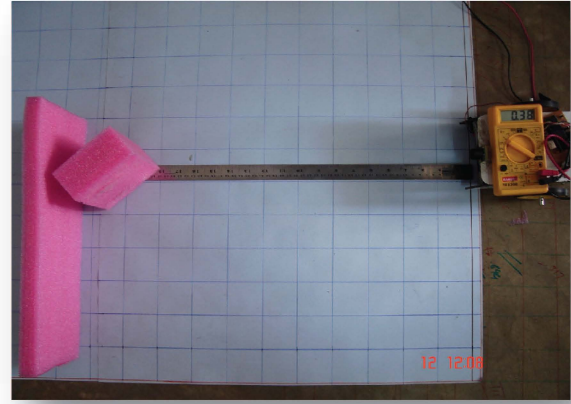


Fig.2. A mobile robot with sonar sensor (Robotics Lab, NIT Jalandhar).

IV. SENSOR FUSION RESULTS

Reference to Fig.3 to 8, the robot is positioned near the cell No.8 and 11. The position of sensor S_1 and sensor S_2 is shown in the Fig. in cell No. 8 and 11. Two laser sensor L_{S1} and L_{S2} are also placed over sonar sensors. Fig. 3, 5 and 7 shows the updated fused result using (8) and (9) in respect to sonar sensor S_1 and S_2 and Fig. 4, 6 and 8 shows their gray scale representation respectively. The real object in front of the sonar sensor is I shaped. The fused result shows the I shaped cell having maximum occupancy as shown in Fig.3 and 4.

In Fig.5 and 6, a L shaped object is shown. In this condition sonar sensor is more useful than laser to detect actual shape. In Fig.8 the advantage of combining laser sensors with sonar sensors can be easily investigated. The information obtained from sonar sensors shows I shaped object instead of C shaped object but because of laser sensors the actual shape can be estimated.

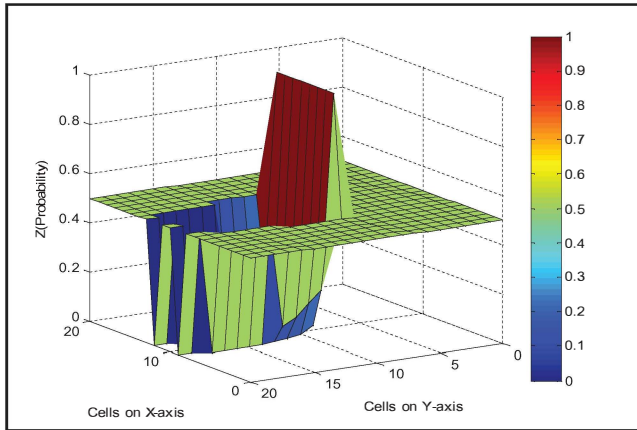


Fig.3. 3D View of Sensor Fusion of Two Sonar and Two Laser for I Shaped Object.

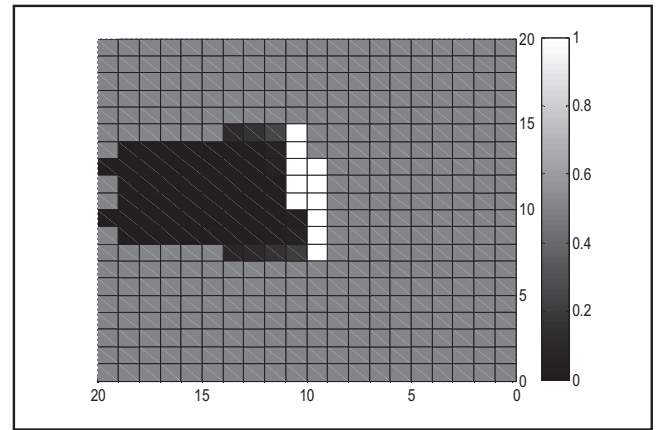


Fig.6. Gray Scale Representation of L Shaped Object.

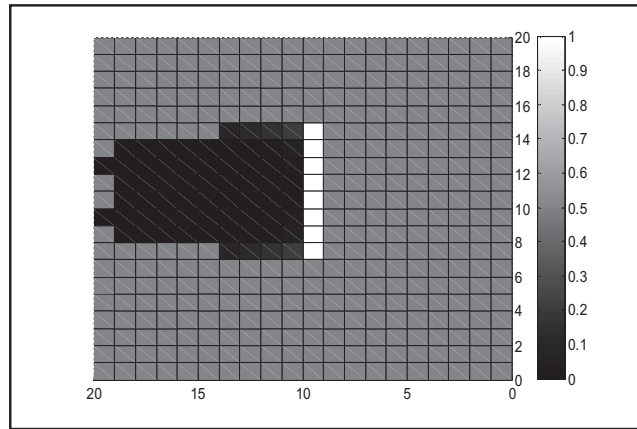


Fig.4. Gray Scale Representation of I Shaped Object.

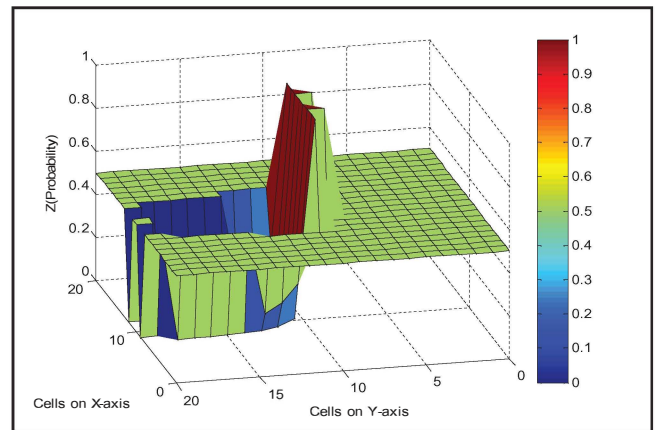


Fig.7. 3D View of Sensor Fusion of Two Sonar and Two Laser Sensors for C Shaped Object.

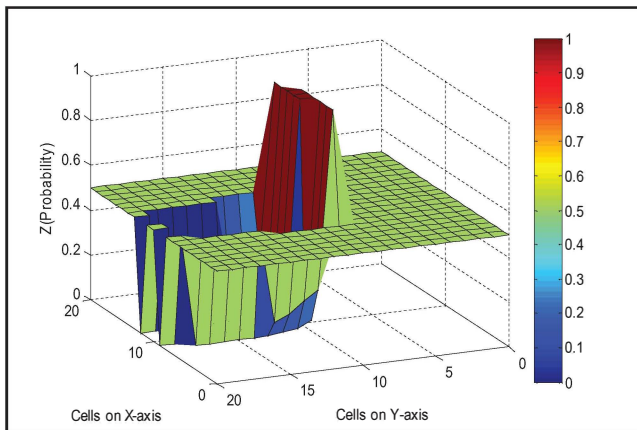


Fig.5. 3D View of Sensor Fusion of Two Sonar and Two Laser Sensors for LShaped Object.

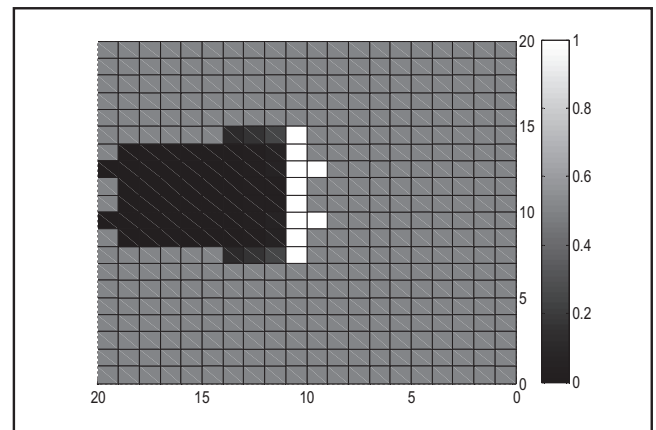


Fig.8. Gray Scale Representation of C Shaped Object.

V. CONCLUSION

From results of sensor fusion, it is clear that only sonar sensors cannot identify the actual shape of the objects due to wide beam cone in some issues. In this work, a laser sensor with each sonar sensor is mounted for identifying more accurate shape of an object. Results obtained in the previous section shows different maps for different type of objects and their gray scale representation. In Fig.7 and 8, C shaped object is shown. In this case if only sonar sensors are used they will give information same as I shaped object due to wide beam cone (30 degrees) of the sonar. But due to laser sensors, the difference in the mapping can be investigated easily.

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