Environment Mapping for Mobile Robots Navigation Using Sensor Fusion: A Dempster-Shafer Reasoning Theory Approach

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Abstract: One of the problems usually discussed in autonomous mobile robot navigation is how to build a map of the environment where the robot is navigating. In the case of indoor navigation, a suitable method to do this mapping is the fusion of the data that are gathered from the several sensors, which are mounted on the robot. Here, a mobile robot equipped just with range finding sensors has been supposed to do path planning autonomously. The environment map that is built by the robot has the same structure as an occupancy grids map, but with some differences and beneficial extensions. A new method has been proposed to fuse the ranges that are provided by the sensors. This method is based on the *Dempster 's Rule of Combination* in Dempster-Shafer theory of reasoning. Simulation results show that the new method results a map, which is safer for path planning, compared to the map deduced from the Bayesian fusion method.

Keywords: Autonomous Robots, Environment Modeling, Multi-source Data/Sensor Fusion, Mobile Robot Navigation, Occupancy Grids, Bayesian Fusion, Dempster-Shafer Reasoning Theory

1- Introduction

Because of the uncertainties existing in mobile robots applications, it is important that the robot attains a certain level of autonomy. The first and the most important requirement for a mobile robot to display autonomous behavior would be the ability of sensing its environment. Many research activities have been done to gain a map of the environment around a mobile robot that is navigating in it. Many of the researchers have preferred to use fuzzy logic and fuzzy rule-bases to forgive autonomy to a mobile robot (see [6,7,8]), even they have tried to build a real robot, which navigates reflexively based on hierarchical layers of fuzzy behaviors (see [11] for a real robot implementation named LiAS and [12] for our research on multi-agent fuzzy controller for boat navigation). Yet, it seems that using such reactive path planning methods, merely leads to the local navigation. It means that getting a high level of autonomy for a mobile robot needs some global information about the environment around it (see [10] for more discussion).

How to get the global information? The best answer is an artificial map of the environment. Such a map can be generated by many techniques e.g. images gotten from CCD cameras or distances measured by the range finder sensors (for example ultrasonic or laser range finders). In such cases, it is necessary to fuse the data gathered from several sensors.

There are many techniques to do sensor fusion for mobile robots and getting the map. Data fusion in a sense is a trial to simulate the human behavior while sensing the environment around him/herself ([2]).

In all of the sensor fusion methods, there is a common essential need to some conversion before fusion takes place. All the sensors must *speak with the same language.* It means that an *Internal Representation* is required. All the sensory measurements have to be converted to some values in the internal representation of the environment.

Elfes ([3]) introduced an *Occupancy Grids* framework to display a map of the environment in the applications of the mobile robot navigation. Mauris et.al. ([4]) introduced a fuzzy linguistic internal representation to aggregate the complementary sensory information. Elfes proposed to use probability values for generation of

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the map of the environment in occupancy grids framework. Fusion of the probability values was performed through applying *Bayesian Rule of Combination* in the probability theory, but this technique has its own difficulties. For example, the calculation of the conditional probabilities in each cell is not so easy. Van Dam in his research works ([9],[10]) has tried to calculate them using neural networks. Here, we have proposed a simple rule of combination in an occupancy grids framework. In this work, we are not engaged with probability values. Instead, we have some values, which are interpreted as some ***bpa*** (basic probability assignment) measure function values in a Dempster-Shafer reasoning bedside. In such an internal representation, the measure values are simply fused using the well-known *Dempster 's Rule of Combination.*

2- Dempster 's Rule of Combination: a brief review

The usage of evidential reasoning for fusion allows each sensor to contribute information at its own level of detail, e.g. one sensor may be able to provide information that can be used to distinguish individual objects, whereas the information from another sensor may only be able to distinguish classes of objects. The Bayesian approach, in contrast would not be able to fuse the information gathered from both sensors.

In Bayesian approach, all propositions for which there is no information, are assigned an equal *a priori* probability. When additional information from one sensor becomes available, and the number of unknown propositions is large relative to the number of known propositions, an intuitively unsatisfying result of the Bayesian approach is that the probability of known propositions become unstable.

In Dempster-Shafer approach, this is avoided by not assigning unknown propositions an *a priori* probability. Actually unknown propositions are assigned instead to "ignorance". This ignorance is reduced (i.e. probabilities are assigned to these propositions) only when supporting information becomes available.

In Dempster-Shafer evidential reasoning, the set θ termed the *Frame Of Discernment* (FOD) is composed of mutually exclusive and exhaustive propositions termed *singletons*. The level of detail represented by a singleton corresponds to the lowest level of information that is able to be discerned through the fusion of information from a group of sensors or other information sources, e.g. a knowledge base. Given n singletons, the power set of θ denoted by 2^{θ} contains 2^{n} elements and is composed of all the subsets of θ including itself, the empty set $\varnothing$, and each of the singletons. The elements of 2^{θ} are called *propositions* and each subset is composed of a disjunction of singletons. For each sensor S_i, the function:

$$m_i: \quad 2^{\theta} \rightarrow [0,1] \tag{1}$$

termed a *basic probability assignment* (bpa) maps a unit of probability mass or belief across the focal elements of S_i subject to the conditions:

$$\forall x \in 2^{\theta}; \quad 0 \le m_i(x) \le 1 \tag{2}$$

$$m_i(\varnothing) = 0 \tag{3}$$

$$\sum_{x \in 2^{\theta}} m_i(x) = 1 \tag{4}$$

Any probability mass that is not assigned to a proper subset of θ is included in $m_i(\theta)$ and represents the residual uncertainty of Si that is distributed in some unknown manner among its focal elements.

Dempster 's rule of combination is used to fuse the propositions X_1 and X_2 from the two sensors S_1 and S_2 by the following formulas:

$$m_{12}(X) = K \times \sum_{X_1 \cap X_2 = X} \left(m_1(X_1) \times m_2(X_2)\right) \tag{5}$$

$$K = \left(1 - \sum_{X_1 \cap X_2 = \varnothing} \left(m_1(X_1) \times m_2(X_2)\right)\right)^{-1} \tag{6}$$

Where X is a non-empty subset of 2^{θ} and m_{12} is the orthogonal sum of the two bpa 's. The denominator is a normalization factor that forces the new masses to sum to unity satisfying equ. (4).

There are many deep discussions about the meaning of measure functions and the *belief* and *plausibility* measures of the propositions. In some cases (such as the case study in this article) the two measurements take place in the same FOD. Then the formulas (5) and (6) can be used to combine them directly, but if they are not calculated and processed in the same FOD, they have to be transformed to a common FOD before using the Dempster 's rule (see [1] for more details).

3- Our Internal Representation for Map Building Using Measured Ranges

Oriollo et.al. ([5]) have proposed a suitable framework to do map building which has been utilized as the internal representation for map building in this research. Each measured range is interpreted as measure values for some of the cells in the occupancy grids framework. Indeed, they performed this conversion only for the ultrasonic range finders, while we formulate it for laser range finders also.

In this framework, when a sensor S gives a distance r from an obstacle near the robot, for all of the map cells existing in the view angle of the sensor, two values are generated. They are two measurement values for the cell C_j being *occupied* and *empty*, termed as $m_O(C_j)$ and $m_E(C_j)$.

Oriollo et. al. proposed to interpret these two values as two membership values for the cell being a member of two fuzzy sets, **O** as the set of *Occupied* cells and **E** as the set of *Empty* cells. Then they did sensor fusion in this internal representation merely by unifying the fuzzy sets gotten from each sensory measurement. They used the fuzzy union operators to do this.

The interesting matter here is applying "two" of measurement values for each cell. In a probabilistic framework there is only one probability value for each cell in the map, while in this framework each cell is associated with two measures. The sum of the two values is less than or equal to unity and the remainder can be interpreted as an *ignorance measure* for that cell. As it is observed in simulation results, this important difference is the basic reason of the advantages of the method that is proposed in this paper compared to the Bayesian method. To see how these measures are calculated from the sensory measured ranges, refer to [5].

4- The New Method

Assume that there is a map of the environment, which is to be improved. In this map, there are two values associated with each cell C:

- m_O as a degree of being occupied
- m_E as a degree of being empty

and we define a simple third value:

$$m_I = 1 - m_E - m_O \tag{7}$$

and interpret it as a measure for the existing *ignorance* about the state of the cell.

Also assume that a sensed range is given and after doing some processing, measure values m'_O and m'_E are generated for the same cell. Again, we can define:

$$m'_I = 1 - m'_E - m'_O \tag{8}$$

as a measure of the ignorance of the sensor about the cell C.

In a Dempster-Shafer reasoning theory approach, fortunately for all of the cells in the map, there is the same FOD. This common θ has two singletons only, named as:

$$x_1 \equiv \{C \textit{ is occupied}\} \tag{9}$$

and

$$x_2 \equiv \{C \textit{ is empty}\} \tag{10}$$

and there are four focal elements. The first one is the empty set. The next two are the singletons themselves with measure values:

$$m(x_1) = m_O \tag{11}$$

$$m(x_2) = m_E \tag{12}$$

and the last proposition is the *ignorance* with the measure value of:

$$\begin{aligned} m(x_1 \cup x_2) &= m_I \\ &= 1 - m_O - m_E \end{aligned} \tag{13}$$

Actually, the current knowledge is represented by the measure function **m** and the sensory knowledge is represented by the measure function **m'** values.

Now doing the combination is very easy. The normalization factor is:

$$\begin{aligned} K &= \left(1 - m(x_1).m'(x_2) - m(x_2).m'(x_1)\right)^{-1} \\ &= \left(1 - m_O.m'_E - m_E.m'_O\right)^{-1} \end{aligned} \tag{14}$$

and the resulting measure values can be calculated easily based on the equation (5) as:

$$m''_O = K \times (m_O.m'_O + m_O.m'_I + m_I.m'_O) \quad (15)$$

$$m''_E = K \times (m_E.m'_E + m_E.m'_I + m_I.m'_E) \quad (16)$$

In the map building algorithm, at first, there is no information about the state of any of the cells in the map. So for each cell, the values of m_O and m_E are initialized to zero. After each sensing, these values are gradually improved using formulas (15) and (16). Thus, after sufficient iterations of sensing, while exploring the whole of the environment, the robot achieves an artificial map of the environment. This map can be used as an input to any graph search algorithm such as the well-known A* algorithm ([5]), to do the path planning and optimal-safe navigation in the environment.

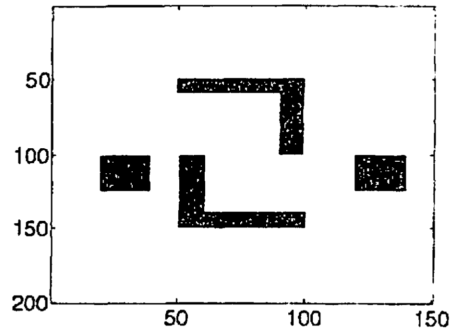
This map has advantages to the map gained through applying the Bayesian method, which will be discussed later.

5- Simulation Results

In the simulation work, a mobile robot with a cylindrical shape has been considered navigating in a rectangle room. The robot is assumed to have no knowledge about the size of the room and the location of the obstacles existing inside it. Also, the mobile robot is equipped merely with two rings of range finder sensors. One ring contains 8 ultrasonic range finders and the other contains 8 laser range finders. The robot must be able to create a map of the room, that contains the walls and all of the obstacles existing inside the room.

About the simulated room, its size is assumed to be in 15m X 20m. The occupancy grids framework has a cell size of 10cm X 10cm. Thus, there is a 150 X 200 pixels map to be generated in the memory of the robot. There are four obstacles with rectangular shapes inside the room. Two of them are L-shaped and the other two are simple rectangles. In figure(1) the room and the existing obstacles inside it, are shown.

To achieve a suitable comparative sense about the result, at first the Bayesian fusion method was applied to generate the map. Each range finder sensor gives the two values m_O and m_E for some



Figure(1) : ideal map of the room and the obstacles

of the cells existing in the view angle of the sensor. Refer to [5] for more study about how to gain these values from the measured ranges.

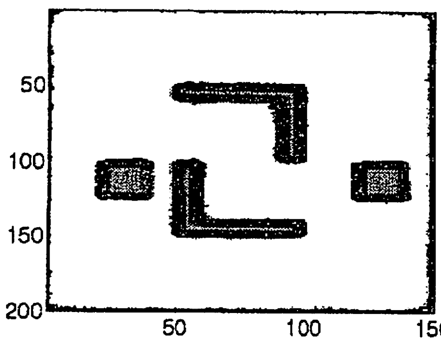
These values are converted to one probability value, using the suggestion formula:

$$P_{OCC} = (1 + m_O - m_E)/2 \quad (17)$$

The above conversion means that when the two measure values or masses are equal, the probability is $\frac{1}{2}$ showing no information and no useful judgment about the state of the cell. But based on the relative values of the masses, this probability increases or decreases over than $\frac{1}{2}$ or below it.

Applying Bayes rule of combination, these probabilities have been fused gradually and after 4500 sensing iterations the map in figure(2) is generated. In the sensing iterations, the robot moved in two time phases. At the first phase, it was forced around the obstacles and the walls manually. At the second phase, it moved randomly in the environment. In this random movement, the robot did not use the map to do path planning and obstacle avoidance. Just it avoided the obstacles by usage of the local navigation fuzzy rule-base technique described in [4]. In the mentioned two steps of the robot navigation, it revolves while navigating so that all of the cells in the map are covered in its sensors view.

The same navigation in 4500 sensing iterations was repeated in the second simulation, but Dempster 's rule of combination (15 and 16) was applied to improve the measure values. In figure (3) the resulting map is shown.

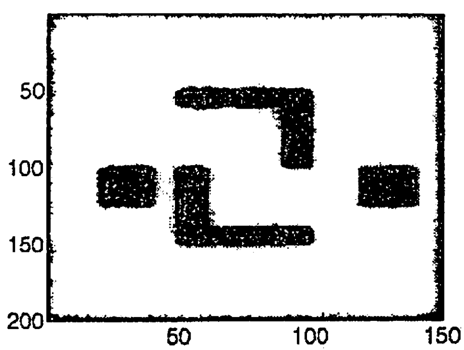


Figure(2) : Bayesian Map of the environment after 4500 sensing iterations.

As an occupancy mass for each cell the two masses were mixed by:

$$m_{OCC} = \max(1 - m_E, m_O) \qquad (18)$$

and the resulting value was considered as an occupancy mass of the cell to generate a map as the input to a path planning algorithm.



Figure(3) : Dempster-Shafer fusion resulting map of the environment after 4500 sensing iterations

Comparing the two maps shows that although the Bayesian map is cleaner and nearer to the ideal map, the map generated by Dempster fusion is safer. Mainly the dangerous areas in the Dempster 's map are more stressed and when this map is used for global navigation, the obstacles are more avoided.

Factly, the reason is based on the same discussion done briefly in section 2. In the Bayesian method, there is no modeling for *ignorance* while in the Dempster fusion approach it exists. In other words, uncertainty is modeled more exactly and more deeply in the proposed approach compared to the Bayesian approach.

To prove the truth of our claim some path planning simulation was done. A* algorithm ([5]) was applied to find the global optimum path from some start points to some goal (destination) points. 8 difficult paths were chosen. They are the passes termed as P1, P2, ... , P8 from points to points. In the following you see the chosen paths for navigation:

P1 : (20,20) -------- (120,180)
P2 : (20,180) -------- (120,20)
P3 : (20,20) -------- (80,80)
P4 : (120,180) -------- (80,80)
P5 : (20,180) -------- (80,80)
P6 : (120,20) -------- (80,80)
P7 : (80,20) -------- (80,80)
P8 : (80,180) -------- (80,80)

In figures (4) and (5) the results for the navigation using Bayesian and Dempster 's Fusion maps are shown respectively.

Figures (4) and (5) show the fact that: when the environment map generated by fusion using Dempster-Shafer reasoning theory is appied for navigation, the paths resulted by A* algorithm are safer and more suitable to navigate. In a sense, they are farther than the obstacles and meanwhile closer to the destination points.

6- Conclusion

In this paper, a new method of sensor fusion was proposed, which can be useful in the map building applications for mobile robots navigation. Although there are many research literature in this area and in the scope of using Dempster-Shafer reasoning theory, the idea of applying this theory in map building especially in occupancy grids framework is new.

In Dempster-Shafer reasoning theory, uncertainty is modeled by a more detailed and more complete representation, compared to the probabilistic reasoning theory. This important fact causes the generation of safer and more certain maps for mobile robot navigation. Simulation results show that when the map generated by the proposed method, is fed to A* navigation algorithm, the paths produced by the algorithm for the navigation are safer and the distances from the obstacles while navigating in the paths are farther compared to the case of the map generated by the Bayesian fusion.

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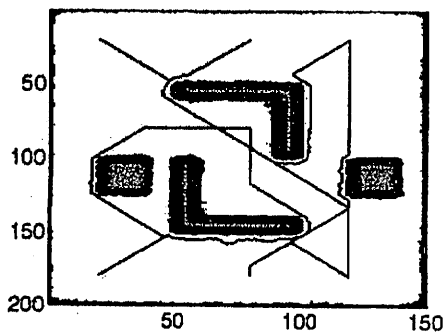
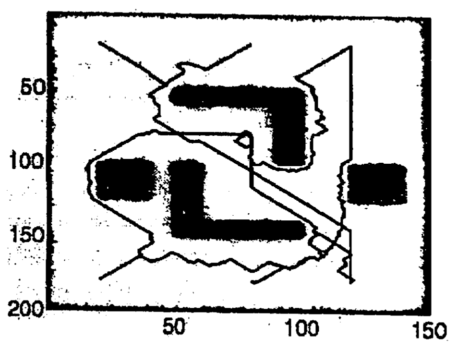


Figure(4) : Several navigation paths generated by A* path planning algorithm while the input map to the algorithm was the Bayesian map.



Figure(5) : Several navigation paths generated by A* path planning algorithm while the input map to the algorithm was the map generated by Dempster fusion.

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