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Sonar Grid Map Building of Mobile Robots Based on DSmT

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Abstract: The research of self-location and map building among some entirely unknown environments is an important and popular subject of intelligent mobile robots. Someone compared it to the problem of chicken and egg. But the application of Sonar sensors with some advantages such as cheapness, simple-operation and convenient-disposal resulted in uncertain and imprecise knowledge acquired. Aimed to this, a new method of information fusion recently developed from Bayesian theory and Dempster-Shafer theory was applied and on the base of experiment, according to sonar's metrical characteristic, the general basic belief assignment functions were constructed for modeling of static environment. Finally, grid map of 3D building on-line for mobile robot was used to compare from the real environment by the experiment. By analyzing the result of comparison, the validity of this method was fully verified.

Key words: Uncertainty, DSmT, grid map, information fusion, mobile robots

INTRODUCTION

The study on the exploration of entirely unknown environment for intelligent mobile robots has being a difficult and popular subject for experts in robots' field for a long time[1,2]. Robots are unknown about the environment around themselves, that is, they has no any experienced knowledge about the environment such as size, shape, layout of the environment and also no any signs such as beacons, landmarks, let alone the determinate location about robot in the environment. Thus generally speaking, the relation between self-localization and map building for mobile robot is like a problem chicken and egg. This is because if mobile robot wants to build the map of the environment and then it must know the determinate position of its own among the environment; at the same time, if robot wants to know its own position and then it must have a referenced map of the environment. Though it is hard to answer this question, some intelligent sensors such as odometer, electronic compass, sonar detector, laser range finder and vision sensor are fixed on the mobile robot as if a person has perceptive organs.

How to manage and utilize this perceptive information acquired by organs, a new subject on information fusion will play an important role here. Presently as far as we know, experts have still not given a unified expression and just aiming to the practical field or system, proposed architecture of control such as hierarchical, concentrative, distributive and composite and then according to the different integrated hierarchy, compared the validity of all kinds of classical (probability) and intelligent (fuzzy, NN, rough theory, DST, etc.) arithmetic. As far as mobile robot is concerned, the popular arithmetic of self-localization in unknown environment relying on interoceptive sensors (odometer, electronic compass) and exteroceptive sensors (sonar detector, laser range finder and visual sensor) is Markov location[3] or Monte Carlo location[4], while the map of the environment is built by applying some arithmetic such as Probability theory, Fuzzy theory and NN. The information of environment may be expressed for grid map, geometrical feature or topological map, etc. Grid map is the most popular method of expression among these. In this paper, DSmT mentioned that has been proposed by Jean Dezert (French) and Florentin Smarandache (American)[5-7] based on Bayesian theory and DS theory[8] recently is a general, flexible and valid arithmetic of fusion. It is the largest advantage that it can deal with uncertain and imprecise information effectively, which supplies with a powerful tool to deal with uncertain information acquired by sonar detector in the course of building grid map[9,10].

THE REVIEW OF DSmT

DSmT is a new, general and flexible arithmetic of fusion, can solve the fusion problem of different tiers including data-tier, feature-tier and decision-tier and

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evennot only can dispose the static problem of fusion, but also can dispose the dynamic one. Especially, it has a prominent merit that it can deal with the uncertain and highly conflict information[5-7].

- Let $\Theta = \{\theta_1, \theta_2, ..., \theta_n\}$, here Θ is the frame of discernment, which includes n finite focal elements $\theta_i (i = 1,...n)$. Because the focal element is not precisely defined and separated so that no refinement of Θ in a new larger set Θ_{ref} of disjoint elementary hypotheses is possible.
- The hyper-power set D^{Θ} is defined as the set of all compositions built from elements of Θ with $\cup$ and $\cap$ (Θ generates D^{Θ} under operators $\cup$ and $\cap$) operators such that

  (a) $\phi, \theta_1, \theta_2, \theta_3 \cdots \theta_n \in D^{\Theta}$

  (b) If $A, B \in D^{\Theta}$, then $A \cap B \in D^{\Theta}$ and $A \cup B \in D^{\Theta}$

  No other elements belong to D^{Θ}, except those obtained by using rules a) or b).
- General belief function and plausibility function
  Let $\Theta = \{\theta_1, \theta_2, ..., \theta_n\}$ is the general frame of discernment. For every evidential source S, let us define a set of map of $m(\cdot)$: $D^{\Theta} \in [0,1]$ associated to it (abandoning Shafer's model) by assuming here that the fuzzy/vague/relative nature of elements $\theta_i (i = 1,2,3,...n)$. can be non-exclusive, as well as no refinement of Θ into a new finer exclusive frame of discernment Θ_{ref} is possible. $m(\phi) = 0$ and $\sum_{A \in D^{\Theta}} m(A) = 1$, here m(A) is called A's generalized basic belief assignment (gbba). The general belief function and plausibility function are defined respectively in almost the same manner as within the DST, i.e.,

$$\mathrm{bel}(A) = \sum_{B \in D^{\Theta}, B \subseteq A} m(B) \qquad (1)$$

$$\mathrm{Pl}(A) = \sum_{B \cap A \neq \phi, B \in D^{\Theta}} m(B) \qquad (2)$$

- Classical (free) DSmT rule of combination
  Let $M^f(\Theta)$ is a free model of DSmT and then the classical (free) DSmT rule of combination for $k \geq 2$ sources is given as follows:

$$\begin{aligned} &\forall A \neq \phi \in D^{\Theta}, \\ &m_{M^f(\Theta)}(A) \cong [m_1 \oplus \cdots m_k](A) \\ &= \sum_{\substack{X_1, \cdots X_K \in D^{\Theta} \\ (X_1 \cap \cdots X_K) = A}} \prod_{i=1}^{k} m_i(X_i) \end{aligned} \qquad (3)$$

GRID MAP BUILDING BASED ON SONAR

Analysis on uncertainty of data acquired by sonar detector on pioneer II mobile robot: There are interoceptive sensors (odometer, electronic compass) and exteroceptive sensors (sonar detector, laser range finder and vision sensor) fixing on Pioneer II mobile robot shown in Fig. 1. The distribution of sonar detector on mobile robot is asymmetrical, which is shown in Fig. 2. Its working principle is shown in Fig. 3. Producing sheaves of cone-shaped wave and detecting the objects by receiving the reflected wave. Due to the restriction of sonar physical characteristic, metrical data behaves out uncertainty as follows:

- Beside its own error of making, the influence of external environment is also very great, for example, temperature, humidity, atmospheric pressure and so on.
- Because the sound wave spreads outwards in the form of loudspeaker and there exists a cone-shaped angle, we can't know the true position of object detected among the fan-shaped area, with the enlargement of distance between sonar and it.
- The use of lots of sonar detectors will result in interference each other. In the other side, for irregular object exists, when an angle of incidence is enough large, the sonar wave might be reflected out of the receiving range or might be received by other sonar detector.
- Because sonar detector utilizes the reflection principle of sound wave, if object absorbs very heavy sound wave, the sonar detector might be invalid.

The modeling for uncertainty of sonar in grid map: Sonar detectors scan grids of environment and acquire the information about position and appearance feature of object. At first, we get the metrical characteristic of sonar detector through the experiment. When the object is justly facing to sonar detector, the distance between object and sonar is measured which varies from 200 to 3000 mm^{-1} and measured value is list in Table 1. The deviation of result measured is not very great in the range of the distance from 200 to 3000 mm^{-1}, but with the increment of distance, whether mean deviation or mean square deviation has a tendency of enhancement. Especially when the distance is over 3000 mm^{-1} (here list nothing), the deviation of measurement is very great. Thus we let $R_{max} = 3000$ mm^{-1} (Table 1).

Pointing to the characteristics of sonar's measurement, we construct a model of uncertain

Table 1: Analysis on measurement of single sonar (mm)

Ture distance	200	600	1000	1400	1800	2200	2600	3000
Measured value	216	602	993	1396	1768	2210	2632	3024
	208	610	1009	1402	1776	2196	2585	3020
	209	595	1013	1391	1810	2221	2590	2991
	196	608	1003	1409	1795	2185	2621	3022
	204	592	992	1386	1809	2214	2616	3017
Mean	206	601	1002	1398	1792	2205	2609	3015
Mean deviation	6	1	2	-2	8	5	9	15
Mean square deviation	6.59	7.04	8.39	8.17	17.05	12.98	18.22	12.12

Fig. 1: Pioneer II mobile robot

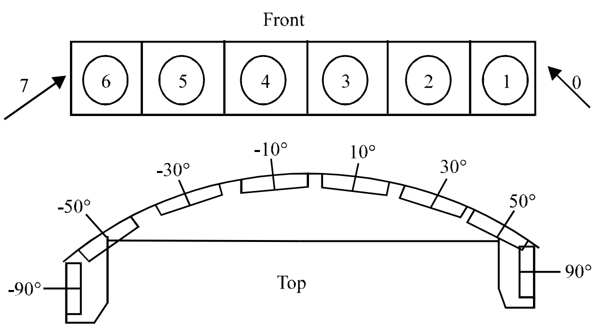

Fig. 2: Sketch of the layout of sonars

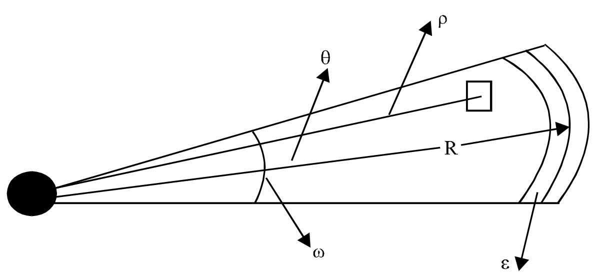

Fig. 3: Sketch of the principle of sonar

information acquired from grid map by sonar based on DsmT. Here we suppose there are two focal elements in system, that is, $\Theta = \{\theta_1, \theta_2\}$ and then we can get its hyper-power set $D^{\Theta} = \{\phi, \theta_1 \cap \theta_2, \theta_1, \theta_2, \theta_1 \cup \theta_2\}$. Every grid in environment is scanned $k \geq 2$ times, each of which is viewed as source of evidence. Then we may define a set of map aiming to every source of evidence and construct the general basic belief assignment

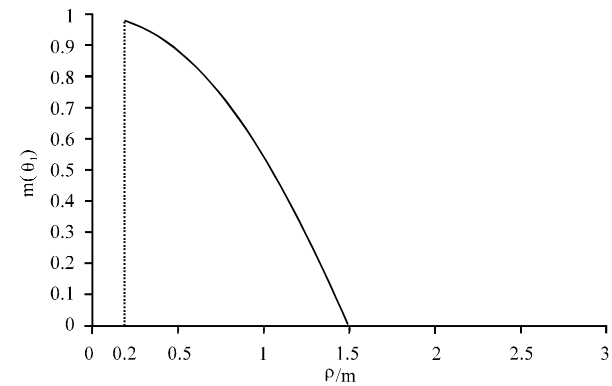

Fig. 4: The relation between ρ and emptiness of gbbaf

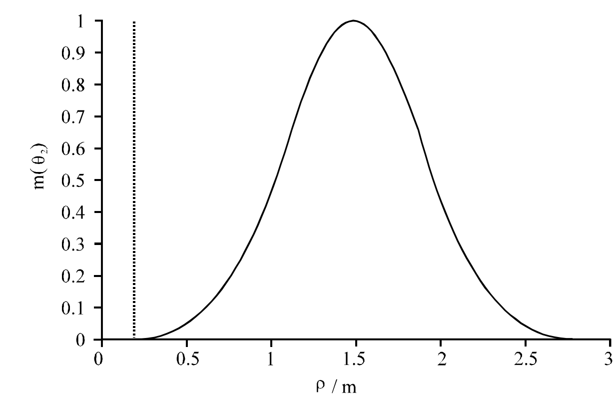

Fig. 5: The relation between ρ and occupancy of gbbaf

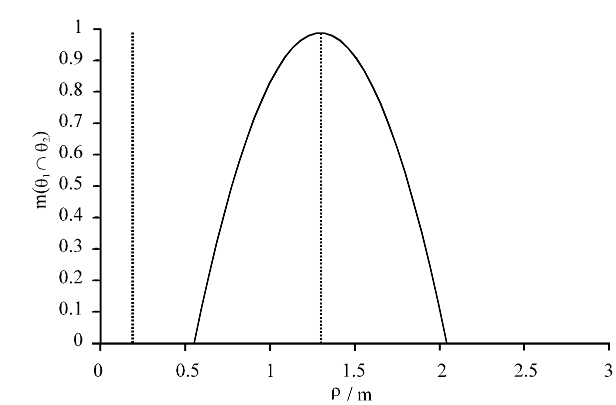

Fig. 6: The relation between ρ and conflict of gbbaf

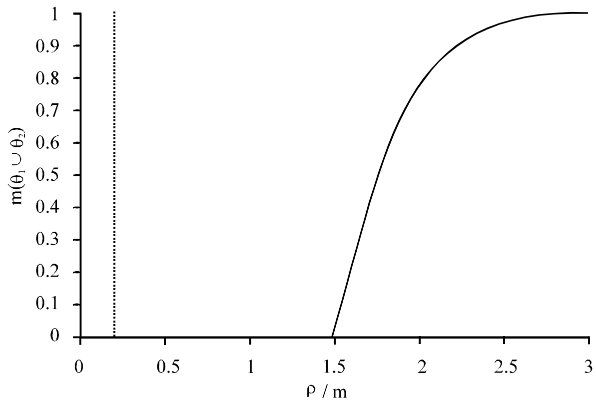

Fig. 7: The relation between ρ and ignorance of gbbaf

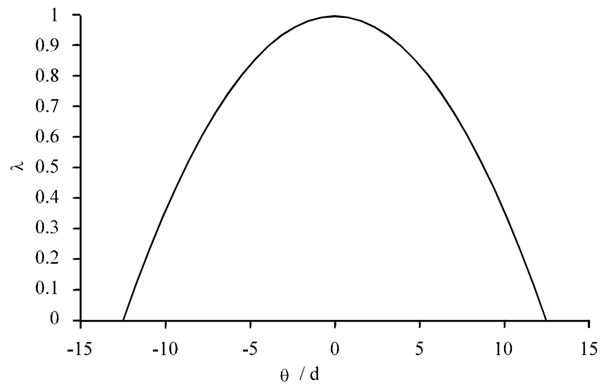

Fig. 8: The relation between ρ and λ

functions (gbbaf) as follows: $m(\theta_1)$ is defined as the gbbaf for grid-unoccupied (empty); $m(\theta_2)$ is defined as the gbbaf for grid-occupied; $m(\theta_1 \cap \theta_2)$ is defined as the gbbaf for holding grid-unoccupied and occupied simultaneous (conflict). $m(\theta_1 \cup \theta_2)$ is defined as the gbbaf for grid-ignorance due to the restriction of knowledge and experience presently(here referring to the gbbaf for these grids still not scanned presently), it reflects the degree of ignorance of grid-unoccupied or occupied.

The gbbaf of a set of map $m(\cdot)$: $D^{\Theta} \rightarrow [0,1]$ is constructed by authors such as the formulae 4-7 according to sonar physical characteristics. Here formula 9 comes from Elfes and Moravaec[9].

Where, ρ_v in formula 5 is defined as environment adjusting variable, that is, the fewer the object is in environment, the greater the variable ρ_v is and makes the function of $m(\theta_2)$ more sensitive. The analysis on the characteristics of gbbaf are shown in Fig. 4-8.

$$m(\theta_1) = E(\rho).E(\theta) = \begin{cases} \left(1-(\rho/R)^2\right)\cdot\lambda & \begin{cases} R_{min} \le \rho \le R \le R_{max}, \\ 0 \le \theta \le \omega/2 \end{cases} \\ 0 & \text{other} \end{cases} \tag{4}$$

$$m(\theta_2) = O(\rho).O(\theta) = \begin{cases} \exp\left(-3\rho_v(\rho-R)^2\right)\cdot\lambda & \begin{cases} R_{min} \le \rho \le R+\varepsilon \le R_{max}, \\ 0 \le \theta \le \omega/2 \end{cases} \\ 0 & \text{other} \end{cases} \tag{5}$$

$$m(\theta_1 \cap \theta_2) = \begin{cases} \left(1-\left(2(\rho-(R-2\varepsilon))/R\right)^2\right)\cdot\lambda & \begin{cases} R_{min} \le \rho \le R \le R_{max}, \\ 0 \le \theta \le \omega/2 \end{cases} \\ 0 & \text{other} \end{cases} \tag{6}$$

$$m(\theta_1 \cup \theta_2) = \begin{cases} \tanh\left(2(\rho-R)\right)\cdot\lambda & \begin{cases} R \le \rho \le R_{max}, \\ 0 \le \theta \le \omega/2 \end{cases} \\ 0 & \text{other} \end{cases} \tag{7}$$

here,

$$\lambda = E(\theta) = O(\theta) = \begin{cases} 1-(2\theta/\omega)^2 & 0 \le |\theta| \le \omega/2 \\ 0 & \text{other} \end{cases} \tag{8}$$

$m(\theta_1)$ has a falling tendency with the addition of distance between grid and sonar and has the maximum at R_{min} and zero at R (Fig. 4). From the point of view of working principle of sonar, the more the distance between them approaches the measured value, the more that grid might be occupied. Thus the probability that grid indicates empty is very low, of course the gbbaf of grid-unoccupied is given low value.

$m(\theta_2)$ takes on the distribution of gaussian function with the addition of distance between them, has the maximum at R, which answers for the characteristic of sonar acquiring information (Fig. 5).

$m(\theta_1 \cap \theta_2)$ takes on the distribution of parabola function with the addition of distance between them (Fig. 6). In fact, when $m(\theta_1)$ equals $m(\theta_2)$, $m(\theta_1 \cap \theta_2)$ has the maximum there. But it is v ery difficult and unnecessary to find the point of intersection of the two functions. Generally, we let the position of R-2ε replace the point of intersection. Experience indicates that its approximate value is more rational.

$m(\theta_1 \cap \theta_2)$ takes on the distribution of hyperbola function with the addition of distance between them and zero at R(Fig. 7). This function reflects well the ignorance of grid information at $R \le \rho \le R_{max}$.

The relation between θ and λ is reflected in Fig. 8, where the more the position of grid approaches central axis, the greater λ becomes, that is, the greater the contribution to belief assignment is. Otherwise, the lower it is.

In short, the general basic belief assignment functions (gbbaf) that we construct accord entirely with the characteristic of sonar acquiring information. This supplies with a theoretic foundation for dealing with uncertain information in grid map building.

RESULT AND DISCUSSION

we suppose the environment (size: 5×5m) partitioned 2500 discrete even rectangular grids (50×50). Objects are in rectangular grid map shown as Fig. 9. Mobile robot cruises there and gets 82 points of localization for acquiring information. In order to improve the precision of fusion and weed out those under-proof data, let mobile robot acquire information from three different directions for every point of localization. DSmT arithmetic adopts the method of the restrained spreading to reduce the complexity of computer[11], which only calculates the value of gbbaf of grids scanned by sonar and builds the map on-line according to the rule of combination given in formula 3. At last, 3D map is built for the global environment shown in Fig. 10.

Analysis on the result of experiment as follows:

- High correctness rate of recognition. From Fig. 10, objects shown in Fig. 9 are basically identified out. Especially, the basic outline characteristic of objects is full sketched distinctly out. Though very few grid still exist mistake n expression, which influence is very small. This facilitates very much the development of Human-computer Interface for mobile robot exploring unknown, dangerous and sightless area.
- Low coupling. Though there are many objects in grid map, but there occurs no phenomenon of the apparently severed, but actually connected. Thus it supplies with a powerful evidence for self-localization, path planning and navigation of mobile robot.
- High validity of computer. The method blending DSmT arithmetic with restrained spreading is adopted and overcomes the shortcoming that the global grids in map must be reckoned once for sonar scanning every time and improves the validity of computer. In addition, though here we don't compare at length DSmT and DST, just from the point of view of complexity of computer, because DSmT's power set is smaller than that of DST, its amount of computer is very low[7].
- Because of the limitations of Sonar own characteristic, the method described in this paper can only discern the appearance outline characteristic of the object, if we want to describe the detail of the object, we need to adopt DSmT based on the discounting method[8,12,13,14] to merge the information of other sensors, such as laser, vision, etc.
- In this study we just apply classical model of DSmT to static environment. But aiming to dynamic environment such as moving object and walking person there, we must consider the hybrid model of DSmT[15].

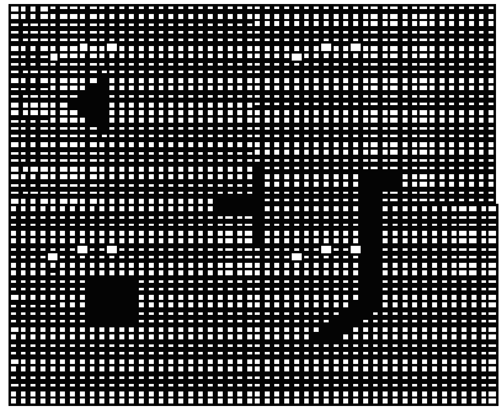

Fig. 9: The grid map of the original environment

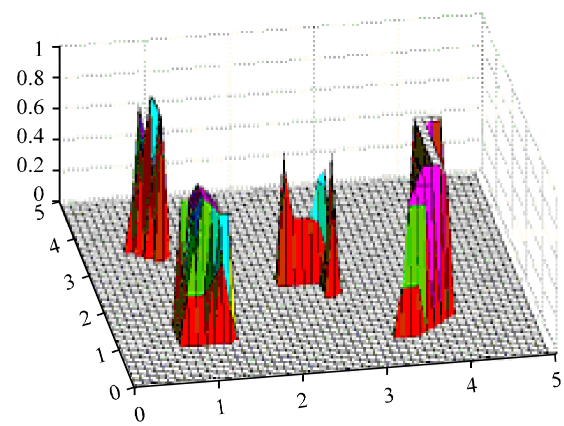

Fig. 10: The cubic figure of the fusion of the grid map

CONCLUSIONS

In this study classical DSmT algorithm is adopted and has solved the modeling problem of grid maps of the static environmental effectively, at the same time has sketched out the basic outline characteristic of the objects in real environment, which supplies with a powerful theoretic foundation for mobile robot's SLAM (Simultaneous localization and Mapping). This facilitates very much the development of Human-computer Interface for mobile robot exploring unknown, dangerous and sightless area. Moreover, we may apply DSmT based on the discounting method to merging unreliable sources information further. Pointing to dynamic environment, we start with hybrid model of DsmT and choose appropriate integration control structure to merge other sensor information. In short, this study also establishes a firm foundation for studying the localization and mapping of multi-mobile robots further.

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