DSmT-based Generalized Fusion Machine for Information Fusion in Robot Map Building

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Abstract - ***Characteristics of uncertainty and imprecision, even imperfection is presented from knowledge acquisition in map reconstruction for autonomous mobile robots navigation. A method is presented for building grid map using sonar measurements. A generalized fusion machine including an ESMS (Evidence Supporting Measure of Similarity) information filter, a fusion operator based on DSmT (Dezert-Smarandache Theory) and a conflict redistributor based on PCR5 (Proportional Conflict Redistribution No.5) rule is proposed. It is applied to map-building of mobile robot with the help of self-localization method based on δ neighboring field appearance matching arithmetic. The general basic belief assignment (gbba) functions are also constructed according to sonar's uncertainty. An experiment using a Pioneer II mobile robot with 16 sonar detectors onboard is done in a small indoor environment, and a 2D Map is built online with our self-developing software platform. A comparison of the results of our new method for map reconstruction with respect to those obtained from classical ones is provided, and how the new tool proposed in this work outperforms other approaches is shown. This study provides aside an useful human-computer interface for a mobile robot exploring unknown environment, and for path planning and navigation. It also establishes a firm foundation for the deep study of information fusion theory.***

Keywords: Information fusion, Generalized fusion machine, DSmT, PCR5, Map-building.

1 Introduction

With the rapid development of intelligent mobile robots, their applications are more and more extensive. For example, robot rovers have been developed for planetary and space exploration, autonomous submersibles for submarines prospecting and surveying, mobile robots for automation purposes or for operation in hazardous mining environments, nuclear facilities and eliminating-explosion spot, and so on. All of these applications rest on the powerful and flexible perception systems, where the robot is able to interact coherently with its world, recovers robust and even gives a useful spatial description of its surroundings using sensory information. Therefore, map building under unknown environments has been one of the principal issues in the field of intelligent mobile robot. However, information acquired in map building presents characteristics of uncertainty, imprecision and even high conflict, especially in the course of building grid map using sonar sensors.

Up to now, there exists mainly three methods of map representation, i.e. grid, geometric paradigm and and topology. The grid map representation method is the most popular because of its simplification. Presently there are many methods based on different theories for grid-map building, such as Probability Theory [1], Fuzzy Theory [2], DST (Dempster-Shafer Theory) [3], Gray system Theory [4], DSmT [5, 6] and fusion machine[7]. We have already made a deep comparison among these methods in [7]. For example, DST takes a great deal of time in map-building, because the model of sonar is very conservative. Probability theory spends the least time in all methods, while the outline is very vague, and the precision of map is very limited. Maybe it is more fitting for the environment of large size. Fuzzy theory spends more time, moreover, the degree of vagueness is almost the same as the probability theory, whereas in a larger environment the precision of map building is very high. Gray system theory has a very high precision in small environment, which can deal with uncertainty effectively. Of course, it is also used to reconstruct a large environment, whereas the time taken might be a bit longer. DSmT and fusion machine not only work in crowded environment, but also in spacious one. However, their precision of map-building still needs to be improved when facing toward complex evidence sources. Therefore we propose herein a generalized fusion machine method based on our previous works. Due to the importance of mobile robot's correct pose in map-building, the self-localization method based on δ neighboring field appearance matching arithmetic is proposed to calibrate robot's pose.

This paper is organized as follows: In section 2, a DSmT-based generalized fusion machine is proposed, which includes ESMS information filter, DSmT[8] and PCR5[9] fusion rule. In section 3, we propose a model for representing the uncertainty of sonar information and a way to construct generalized basic belief assignments (gbba) associated with each sonar sensor onboard. In section 4, a new self-localization method based on δ neighboring field appearance matching arithmetic is proposed. In section 5, an experiment in a small indoor environment with a Pioneer II mobile robot is performed to show the advantage of our approach with respect to other ones. Concluding remarks are then given in section 6.

2 DSmT-based Generalized Fusion Machine (GFM)

2.1 General principle of GFM

The general principle of a Generalized Fusion Machine (GFM) consists in k sources of evidences (i.e. the inputs) after passing through the ESMS information filter providing basic belief assignments over a propositional space generated by elements of a frame of discernment Θ and set operators endowed with eventually a given set of integrity constraints which depend on the nature of elements of the frame. The set of gbba's must then be combined with an efficient fusion operator. Since in general the combination of uncertain information yields a degree of conflict, say K, between sources, this conflict must be managed by the fusion operator/machine. The way the conflict is managed is the key of the fusion step and makes the difference between the fusion machines. The fusion can be performed globally/optimally (when combining the sources in one derivation step alltogether) or sequentially (one source after another as in Fig.1). The sequential fusion processing (well adapted for temporal fusion) is natural and more simple than the global fusion but in general remains only suboptimal if the fusion rule chosen is not associative, which is the case for most of fusion rules, but Dempster's rule. In this paper, the sequential fusion based on the PCR5 rule[10] has been chosen because PCR5 has shown good performances in works where it has already been tested [7] and because the sequential fusion is much more simple to implement and to test. The PCR5 fusion rule formula for k sources is possible and has also been proposed but is much more difficult to implement and has not been tested yet. We present in more details the DSmT-based GFM in the following block scheme:

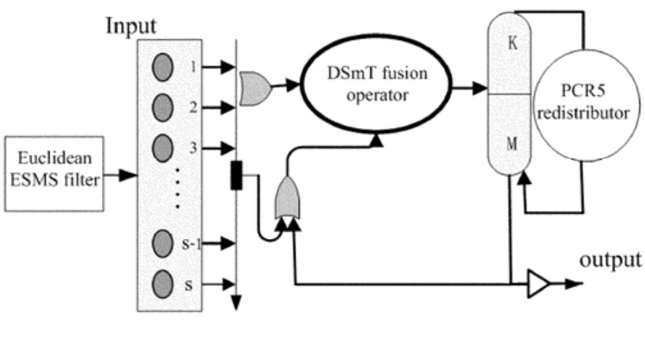

Figure 1: DSmT-based sequential GFM

2.2 Basis of DSmT

1) We denote $\Theta = \{\theta_1, \ldots, \theta_n\}$ the frame of the problem. The basic idea of DSmT is to consider all elements of Θ as not precisely defined and separated, so that no refinement of Θ into a new finer set Θ^{ref} of disjoint hypotheses is possible in general (at least in most of fusion problems involving vague elements expressed in natural language whose intrinsic nature is continuous), unless some integrity constraints are truly known and in such case they will be included in the DSm model of the frame. Shafer's model [11] assumes all θ_i, $i = 1, ..., n$ to be truly exclusive and appears only as a special case of DSm hybrid model in DSmT.

2) The *hyper-power set* D^Θ [8] is defined as the set of all propositions built from elements of the frame Θ with $\cap$ and $\cup$ operators such that:

   (a) $\emptyset, \theta_1, \ldots, \theta_n \in D^\Theta$.

   (b) If $A, B \in D^\Theta$, then $A \cap B$ and $A \cup B$ belong to D^Θ.

   (c) No other elements belong to D^Θ, except those obtained by using rules 1 or 2.

   When Shafer's model holds, D^Θ reduces to the classical power set 2^Θ. Without loss of generality, we denotes G^Θ the general set on which will be defined the basic belief assignments (or masses), i.e. $G^\Theta = 2^\Theta$ when DST is adopted or $G^\Theta = D^\Theta$ when DSmT is preferred instead, like in this work.

3) From a frame Θ, we define a general basic belief assignment (gbba) as a mapping $m_s(.) : G^\Theta \to [0, 1]$ associated to a given source, say s, of evidence as

$$m_s(\emptyset) = 0 \quad \text{and} \quad \sum_{A \in G^\Theta} m_s(A) = 1 \qquad (1)$$

   $m_s(A)$ is the gbba of A committed by the source s. The belief and plausibility of A are defined as:

$$\text{Bel}_s(A) \triangleq \sum_{\substack{B \subseteq A \\ B \in G^\Theta}} m_s(B) \text{ and } \text{Pl}_s(A) \triangleq \sum_{\substack{B \cap A \neq \emptyset \\ B \in G^\Theta}} m_s(B) \qquad (2)$$

4) When the free DSm model holds[1], the conjunctive consensus, called DSm classic rule (DSmC) of two gbba $m_1(.)$ and $m_2(.)$ is given $\forall C \in D^\Theta$ by [8]:

$$m_{DSmC}(C) = \sum_{\substack{A, B \in D^\Theta \\ A \cap B = C}} m_1(A) m_2(B) \qquad (3)$$

   D^Θ being closed under $\cup$ and $\cap$ operators, DSmC guarantees that $m_{DSmC}(.)$ is a proper gbba. DSmC is commutative and associative and can be used for the fusion of sources involving fuzzy concepts whenever the free-DSm model fits with the problem. It can be easily extended for the fusion of $k > 2$ independent sources as well - see also [8].

[1] i.e. all elements of Θ can be considered as partially overlapping because of their fuzzy intrinsic nature.

2.3 The PCR5 fusion rule

When integrity constraints are introduced in the model, one has to deal with the conflicting masses, i.e. all the masses that would become assigned to the empty set through DSmC rule. Many fusion rules (mostly based on Shafer's model) have been proposed [12] for managing the conflict. Among these rules, the Dempster's rule [11] redistributes the *total conflicting mass* over all propositions of 2^Θ through a simple normalization step. This rule has been the source of debates and criticisms because of its unexpected/counter-intuitive behavior in some cases. Many alternatives have then been proposed [12, 8] for overcoming this drawback. In DSmT, an extension of Dubois & Prade's rule [8] has been initially proposed for taking into account any integrity constraints in the model and also the possible dynamicity of the model and the frame. This rule, called DSmH (DSm Hybrid) rule, consists just in transferring the partial conflicts onto the partial ignorances[2]. Very recently however, DSmH rule has been advantageously replaced by the more sophisticated Proportional Conflict Redistribution rule no. 5 (PCR5) [10]. PCR5 rule actually does a better redistribution of the conflicting mass than Dempster's rule and even DSmH, since it goes backwards on the tracks of the conjunctive rule and it redistributes the partial conflicting masses only to the sets involved in the conflict and proportionally to their masses put in the conflict, considering the conjunctive normal form of the partial conflict. PCR5 is quasi-associative and preserves the neutral impact of the vacuous belief assignment. Since PCR5 is presented in details in [9] 9we just remind PCR5 rule for only two sources [3]: $m_{PCR5}(\emptyset) = 0$ and $\forall X \in G \setminus \{\emptyset\}$

$$m_{PCR5}(X) = m_{12}(X) + \sum_{\substack{Y \in G \setminus \{X\} \\ X \cap Y = \emptyset}} [\frac{m_1(X)^2 m_2(Y)}{m_1(X)+m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X)+m_1(Y)}] \quad (4)$$

where all propositions X, Y involved in the formula above are expressed in their canonical form, i.e. conjunctive normal form, also known as conjunction of disjunctions in Boolean algebra, which is unique, and where $m_{12}(X) = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2)$ corresponds to the conjunctive consensus on X between the two sources and where all denominators are different from zero. If a denominator is zero, that fraction is discarded.

2.4 Euclidean ESMS information filter

The information filter is used to select only a subset of sources, called consistent sources, to combine among all sources available at each time-step of the process. Such an idea is very general since it doesn't depend on the application neither on the fusion machine/rule itself (while the belief function framework is used). So the basic idea is to keep as feeding input of the fusion machine only sources coherent with respect to a pre-defined similarity measure. Inconsistent sources are discarded by the pre-processor and will not feed the fusion machine. In the sequel, the pre-processor is referred as the Evidence Support Measure of Similarity filter (ESMS filter for short) since the rejection of incoherent sources will be based on the filtering of Measure of Similarity based on Evidential information. We have proposed five ESMS functions including Euclidean ESMS function, Jousselme ESMS function, Ordered ESMS function, Pignistic ESMS function and Bhattacharyya ESMS function in our previous work[14]. Here the ESMS information filter based on Euclidean ESMS function[15] is proposed, which is defined as follows: Let $\Theta = \{\theta_1, \ldots, \theta_n\}$ $(n > 1)$, $m_1(\cdot)$ and $m_2(\cdot)$ in $\mathfrak{m}_{G^\Theta}$, X_i the i-th (generic) element of G^Θ and $|G^\Theta|$ the cardinality of G^Θ. The following simple Euclidean ESMS function can be used:

$$N_E(m_1, m_2) = 1 - \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{|G^\Theta|} (m_1(X_i) - m_2(X_i))^2} \quad (5)$$

of course, we also could choose some other ESMS functions aforementioned as the filter. In addition, the barycenter of belief masses considering the different evidence source is computed according to [15], in order to get a normal[4] source m_2.

2.5 Algorithm for realizing the GFM

The principle of GFM is summarized on Fig.2. Here are the main step of the algorithm for implementing teh GFM:

1) Initialization of the parameters: the number of evidence sources is set to zero, (i.e. one has initially no source, $s = 0$), so that the number of evidence sources in the filter window is $n = 0$.

2) Include[5] an evidence source $\hat{S}_s$ and then test if the number of sources s is less than 2. If $s \geq 2$, then go to next step, otherwise include/take into account another source of evidence $\hat{S}_2$.

3) Based on the barycenter of gbba of the front $n \leq 10$ evidence sources, the degrees of similarity are computed according to the formula (5), and compared with a prior tuned threshold. If it is larger than the threshold, then let $n = n + 1$. Otherwise, introduce a new evidence source $\hat{S}_{s+1}$.

4) If $n = 1$, the current source, say S, doesn't take part in the fusion. If $n = 2$, then the fusion step must apply between S and $\hat{S}_2$ with classical DSm rule (3), i.e. conjunctive consensus. We then use PCR5 rule to redistribute the remaining partial

[2] partial ignorance being the disjunction of elements involved in the partial conflicts.

[3] A general expression of PCR5 for an arbitrary number ($s > 2$) of sources can be found in [9].

[4] Here the normal source is changing over time depending on inputs provided by the sources of evidences feeding the filter

[5] here supposed that DSm model is considered, and general basic belief assignments are given

conflicts only to the sets involved in the corresponding partial conflicts. We get a new combined source affected with same index S. If $2 < n \leq 10$, after the current evidence source $\hat{S}_s$ is combined with the final evidence source produced last time, a new evidence source is obtained and assigned to S again. Whenever $n \leq 10$, go back to step 2), otherwise, the current evidence source $\hat{S}_s$ under test has been accepted by the ESMS filter and is assigned to $\hat{S}_{10}$. Let $\hat{S}_{i-1} = \hat{S}_i, i \in [2, \cdots, 10]$, and fuse $\hat{S}_{10}$ with the newly producing S[6].

5) Test whether to stop or not[7]: if no, then introduce a new evidence source $\hat{S}_{s+1}$, otherwise stop and exit.

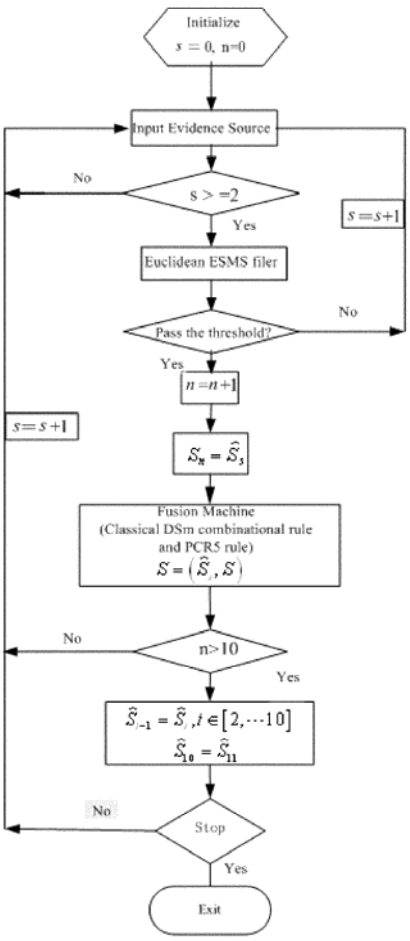

Figure 2: the procedure flow chart of DSmT-based generalized fusion machine

[6]In our study, A ESMS filter window can accommodate ten sources, if it is not full, the evidence source input can be stacked into the filter window, otherwise, the source input newly is stacked into the window and become the last one, at the same the fist one is abandoned.

[7]In our experiment, judge whether mobile robot stops receiving sonar's data

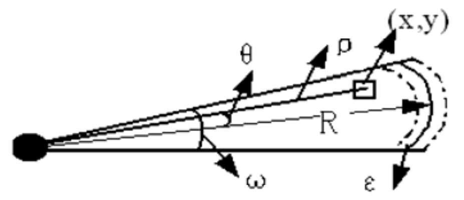

Figure 3: sketch of the principle of sonar

3 Construction of gbba for sonar

In this section we mainly discuss sonar sensor, which is used to build map in unknown environment. We are interested in modeling the uncertainty of sonar information and by the construction of gbba to combine from sonar measurement. The working principle of sonar, shown on Fig. 3, is: producing sheaves of cone-shaped wave, and detecting the objects by receiving the reflected wave. Pointing to the characteristics of sonar's measurement, we construct a model of uncertain information acquired from grid map using sonar based on DSmT. We suppose there are only two hypotheses in the frame committed to each cell of the grid map, that is, $\Theta = \{\theta_1, \theta_2\}$, where θ_1 means *grid cell is empty*, θ_2 means *grid cell is occupied*. The hyper-power set of Θ is then defined as $D^\Theta = \{\emptyset, \theta_1, \theta_2, \theta_1 \cap \theta_2, \theta_1 \cup \theta_2\}$. Every grid cell 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 gbba as follows: $m(\theta_1)$ represents the belief mass for grid-unoccupancy (emptiness), while $m(\theta_2)$ represents the belief mass for grid-occupancy; $m(\theta_1 \cap \theta_2)$ corresponds to the belief mass for holding grid-unoccupancy and occupancy simultaneous (conflict) and $m(\theta_1 \cup \theta_2)$ the belief mass for grid-ignorance due to the restriction of knowledge and experience presently[8], it reflects the degree of ignorance of grid-unoccupancy or occupancy. The gbba $m(.) : D^\Theta \rightarrow [0, 1]$ is then constructed according to the formulas (6)-(9) taking into account the physical characteristics of sonar sensors, i.e.

$$m(\theta_1) = E(\rho)E(\theta) = \tag{6}$$
$$\begin{cases} (1 - (\rho/(R - 2\epsilon))^2) \cdot (1 - \lambda/2) \text{ if } \begin{cases} R_{min} \leq \rho \leq R - 2\epsilon \\ 0 \leq \theta \leq \omega/2 \end{cases} \\ 0 \quad \text{otherwise} \end{cases}$$

$$m(\theta_2) = O(\rho)O(\theta) = \tag{7}$$
$$\begin{cases} e^{-3\rho_v(\rho - R)^2}\lambda \quad \text{if } \begin{cases} R_{min} \leq \rho \leq R + 2\epsilon \\ 0 \leq \theta \leq \omega/2 \end{cases} \\ 0 \quad \text{otherwise} \end{cases}$$

[8]Here referring to the gbba for these grids still not scanned presently.

$$m(\theta_1 \cap \theta_2) = \tag{8}$$
$$\begin{cases} [1-[\frac{2(\rho-R+\epsilon)}{R}]^2] & \text{if } \begin{cases} R_{min} \le \rho \le R+\epsilon \\ 0 \le \theta \le \omega/2 \end{cases} \\ 0 \quad \text{otherwise} \end{cases}$$

$$m(\theta_1 \cup \theta_2) = \tag{9}$$
$$\begin{cases} \tanh(2(\rho-R)) \cdot (1-\lambda/2) & \text{if } \begin{cases} R \le \rho \le R+2\epsilon \\ 0 \le \theta \le \omega/2 \end{cases} \\ 0 \quad \text{otherwise} \end{cases}$$

where $\lambda = E(\theta) = O(\theta)$ is given by (see [1] for justification)

$$\lambda = \begin{cases} 1-(2\theta/\omega)^2 & \text{if} \quad 0 \le |\theta| \le \omega/2 \\ 0 \quad \text{otherwise} \end{cases} \tag{10}$$

where $E(\theta) = 1-\lambda, O(\theta) = \lambda, E(\rho) = (1-(\rho/(R-2\epsilon))^2), O(\rho) = \exp(-3\rho_\nu(\rho-R)^2)$. ρ_ν in (7) is defined as the adjusting function of environment (here we don't consider it, and let $\rho_\nu = 1$).

4 Self-localization of the robot

In unknown environment, if we don't consider the small accumulative error and metrical error, then the coordinate of whole object outline in the environment detected by laser range finder on mobile robot will be consistent completely with the real one in global coordinate system. In reality, this is impossible because of inaccurate robot's pose. So the robot's pose must be calibrated. In this research, a new self-localization method based on δ Neighboring Field Appearance Matching (δ-NFAM) method is proposed and used to help mobile robot build map. Though it is very important, it isn't the keystone in this paper. Therefore, it is only briefly introduced here.

Due to the limitation of detecting range of laser range finder, it only detects a part of the whole environment. In our research the main idea about self-localization of mobile robot with δ-NFAM method is a Step-by-Step mode. That is, when mobile robot moves a step, its pose can be calibrated with the old referenced appearance and gets a new pose. According to the new pose calibrate some features of outline newly detected and choose some of them as the new reference appearance, and so on. The main idea of the δ-NFAM method is to search the best pose of mobile robot in a small rectangle field ($2\delta_x \times 2\delta_y$) around the robot as shown on Fig.4. we adopt still the grid representation, that is, the whole map is divided into many enough small rectangle lattices/cells having same size. Supposed that there are many virtual mobile robot poses such as (x', y', θ') on Fig.4, which are chosen by ergodicity (i.e. from the $x-\delta_x$ to $x+\delta_x$, from $y-\delta_y$ to $y+\delta_y$, from $\theta-\delta_\theta$ to $\theta+\delta_\theta$ in terms of small step length), the virtual perceptive feature appearance is

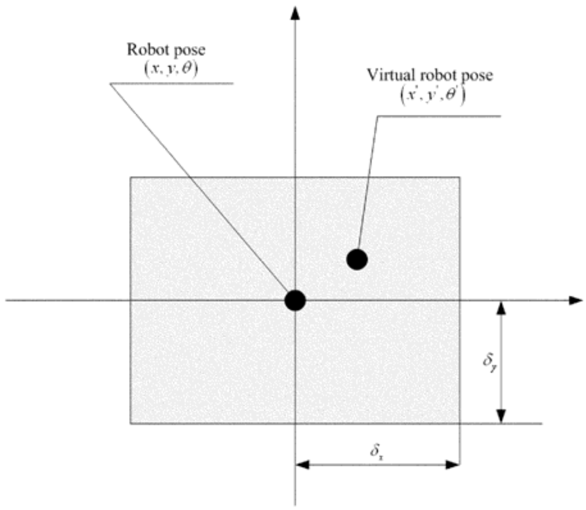

Figure 4: principle of the δ-NFAM method

compared from the referenced appearance. Because all referenced feature appearances are discretized and represented by grids, when giving a virtual pose, we can compute the coincidence number between the current virtual perceptive feature grid and the referenced one. When an ergodic process is completed, we can find the most possible pose of mobile robot corresponding to the maximum coincidence number. Then we replace the current pose according to odometer with the virtual pose. At the same time, we also can calibrate other features newly obtained and take some of them as new referenced feature in historical list. Thus this completes the self-localization process. here are the main advantages of the δ-NFAM method we propose:

1) The computation burden is low, especially for experiment in indoor environment since the ground is usually very flat and smooth so that the accumulating errors on x and y axis remain very small. In such case, one may only consider the search of the most possible pose from $\theta-\delta_\theta$ to $\theta+\delta_\theta$. In a more complex environment, one needs to expand the search scope and the computation burden will increase a bit.

2) It has very high precision of self-localization. Moreover, this method is very robust, especially with respect to the self-localization method based on fast-Hough transform. This has been tested and validated in our experiments both in real and simulated environments.

3) It is very simple and easy to implement because it has no complex arithmetic. Of course, we also are applying the arithmetic with sonar information to self-localization, in order to solve the SLAM (Self-Localization And Mapping) problem more effectively. However, it is more difficult due to the uncertainty of sonar information.

5 Experiment

The experiment is performed to run Pioneer II mobile robot carrying 16 sonar detectors and laser range finder in our (indoor) laboratory environment as shown on Fig. 5. The environment's size is $4550mm \times 3750mm$ and the grid map method is adopted. The environment is divided into 91×75 rectangular cells having same size. The robot starts to move from the location (1 m, 0.6 m), which faces towards 0 degree. We take the corner of left bottom as the global coordinate origin of the map. Objects/obstacles in rectangular grid map are sketched on Fig. 6. Of course, all of these steps can be done on our intelligent perception and fusion system (shown in Fig. 7) developed with our software Toolbox developed under C++ 6.0 and OpenGL severs as a client end, which can connect the server end (also developed by ourselves, which connects the mobile robot). When the robot moves in the environment, the server end collects much information (i.e. the location of robot, sensors measurements, velocity, etc) from the mobile robot and its sensors onboard. Through the protocol of TCP/IP, the client end can get any information from the server end and fuse them. Since our environment is small,the robot moves less time or a short distance. Then one only considers the self-localization method based on δ-NFAM method with the search from $\theta - \delta_\theta$ to $\theta + \delta_\theta$[9]. In order to reduce the computation burden, the restricted spreading arithmetic has been chosen. The flow chart of this procedure for this experiment is given on Fig.8. Its main steps are the following ones:

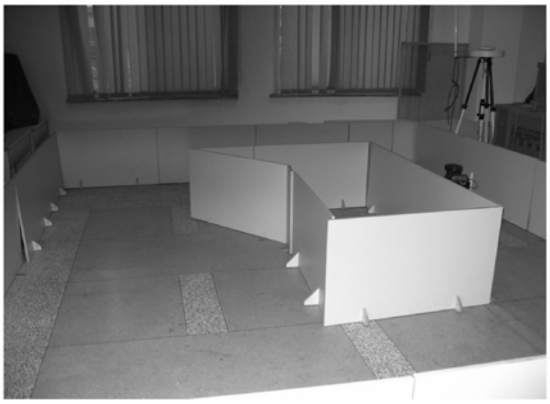

Figure 5: the real experimental environment.

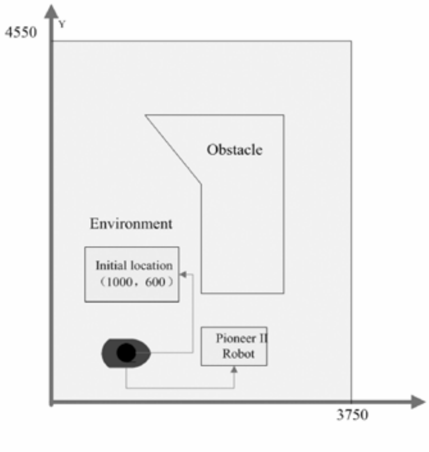

Figure 6: global coordinate system for the experiment.

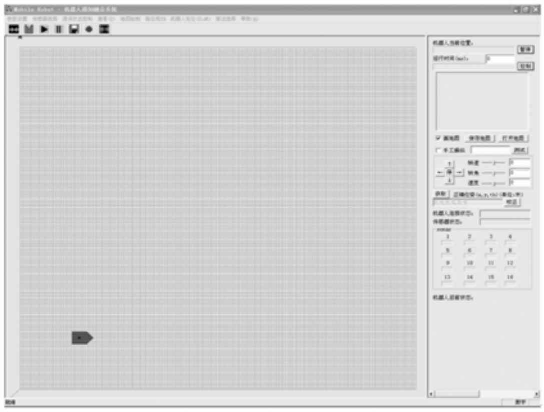

Figure 7: the intelligent perception and fusion system

1) Initialize the parameters of the robot (i.e. initial location, moving velocity, etc.).

2) Acquire 16 sonar measurements, laser reading, and robot's location from odometer, when the robot is running in the environment. We can calibrate the robot's pose with our new self-localization method proposed in the section 4. Here we set the first timer, of which interval is 100 ms.

3) Compute gbba of the fan-form area detected by each sonar sensor according to the formulas (6)$\sim$(10).

4) Apply the DSmT-based GFM, that is, adopt Euclidean information filter to choose basic consistent evidence source according to the formula (5). Then combine the consistent evidence sources with DSm rule (3) and compute gbbas after combination, and then redistribute partial conflict factor to the gbbas of sets involved in the partial conflict with the PCR5 rule (4) as explained in section 2.5.

5) Compute the total belief of cell occupancy $bel(\theta_2)$ of some grids according to (2), after saving them into the map matrix, and go to next step.

6) Update the map of the environment (here we set the second timer, of which interval is 100 ms). Generally speaking, more the times of scanning map are, more accurate the final map reconstructed is. At the same time, also test whether robot stops receiving the detecting data: if yes, then stop fusion and exit, otherwise, go back to step 2).

[9]One has taken $\delta_\theta = 5^o$ in our experiment.

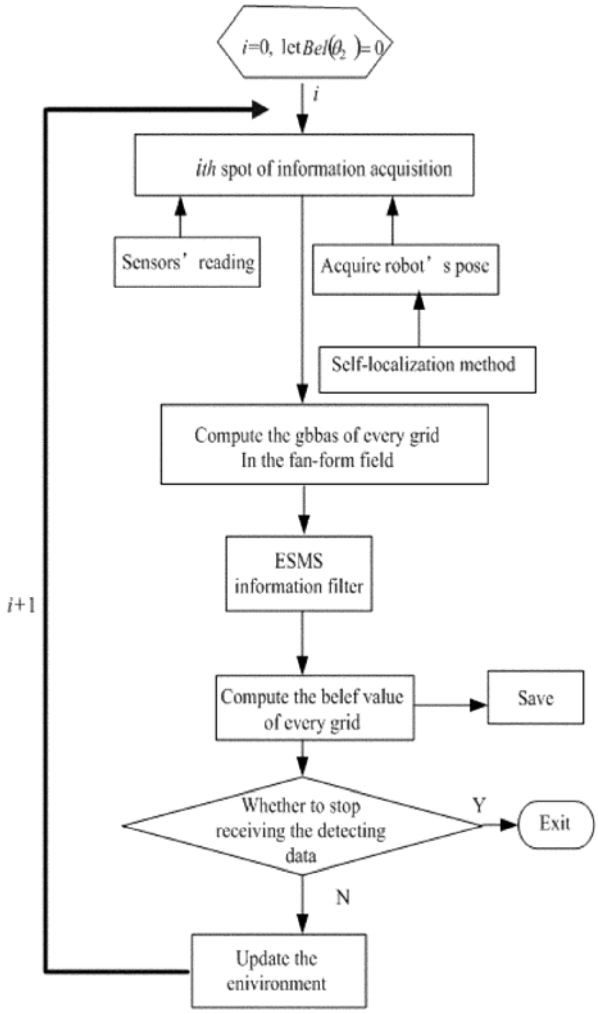

Figure 8: flow chart of map-building with GFM

The following results have been obtained from our experiment:

1) High accuracy: According to Fig.9, the map reconstructed is very similar to the original one, and the basic outline of obstacle in 2D space can be recognized distinctly. This method supplies with an approach to do some research on self-localization, path planning and navigation of mobile robot.

2) High efficiency of computation: The ESMS information filter coupled with DSm and PCR5 rule with the restricted spreading arithmetic, allows to reduce drastically the computation burden and to deal with highly conflicting information. At the same time, this also overcomes the shortcoming of computing all grids of every scanning period and greatly improves the computing efficiency.

3) High precision of map-building: The ESMS filter allows not to take into account in the fusion process the highly conflicting sources so that the *bad* information is not feeded to the fusion machine. Thus one avoids their disturbing influences and makes the fusion more precise.

4) As far as ESMS information filter is concerned, from the theoretic point of view, it seems as if more high the threshold is, better the fusion efficiency is. However, in fact, according to our experiment results, it isn't so. By analysis, we know that evidence source number becomes less and less, and even some useful ones are also filtered out with higher and higher threshold set, which explains this behavior.

To show the advantage of GFM, we have also compared it with two other methods: a DSmT-based Classical Fusion Machine (CFMW) using DSmC fusion rule With PCR5 rule and another DSmT-based Classical Fusion Machine (CFM) using DSmC fusion rule Without PCR5 rule. The following results were obtained:

1) From Figures 9, 10 and 11, one clearly sees that the effect of map-building based on GFM is better than the one obtained from CFMW and CFM. This is because GFM includes the ESMS information filter besides of PCR5 rule, its map-building effect is the best among three methods.

2) It seemed that GFM using ESMS information filter needs a bit more computation burden and time with respect to CFMW and CFM. But the extra time taken by GFM is not so much as CFMW and CFM since the ESMS information filters filter out some "bad" evidence sources, which won't take part in the next fusion step, and this actually saves computation burden and time.

3) GFM includes the ESMS information filter and consequently makes the method more robust, flexible and particularly efficient.

6 Conclusions

In this paper, one has applied successfully a new DSmT-based GFM for mobile robot's map-building in an unknown environment with the help of self-localization based on δ-NFAM method. Based on a belief model for sonar grid map, an experiment has been performed which clearly shows the advantage of this approach with respect to the methods based only on DSmC fusion rule (with or without ESMS filter) in our small laboratory environment. This study supplied with an approach for human-computer interface of mobile robot exploring unknown environment, path planning and navigation and so on, and also established a firm foundation for the deep study of information fusion theory.

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Figure 9: map building based on GFM

Figure 10: map building based on CFMW

Figure 11: map building based on CFM

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