Multi-ultrasonic sensor fusion for autonomous mobile robots

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ABSTRACT

Specular reflections from environments cause uncertainties to ultrasonic sensor range data. In this paper, we examine the application of evidential method for data integration using the specially designed sensor model to overcome the problem. Dempster's rule of combination is used to fuse the sensor data to obtain the map defined on a 2D evidence grid. The sensor model tries to reduce the uncertainties caused by specular reflections with a filtering factor. Experimental results have shown the usefulness of this method.

Keywords: Dempster-Shafer, mobile robot, sensor fusion, ultrasonic sensor, specular reflection

1. INTRODUCTION

The navigation of a multi-sensor based mobile robot requires a good representation of the environment. An autonomous mobile robot should be able to construct a map of its environment based on the sensory information. To build the map, sensory information from multiple sensors need to be combined to obtain the best view of the surroundings of the mobile robot. However, since there always exist various kinds of incompleteness and uncertainties in sensory information about the real world, the knowledge obtained is not good enough to help the mobile robot perform in an intelligent way. Ultrasonic sensors have been widely used in mobile robots applications as they can produce good range information based on the *time of the flight* (TOF) principle. This provides an easy and inexpensive way for the robot system to construct and maintain its map for localization, obstacle avoidance and other purposes during its navigation in unknown environments. Applications of ultrasonic sensors in autonomous mobile robots have been discussed by many researchers.[1,2,3,4,9,10] However, there are some fundamental drawbacks[12] which limit the usefulness of ultrasonic devices, of which the most significant one is the possibility of *specular reflections*[8] from the environment. As shown in Fig. 1b, the specular reflections occur when ultrasonic beam fails to return directly to the receiver since it will be bounced away from the target object. The incidence angle of the sonar signal

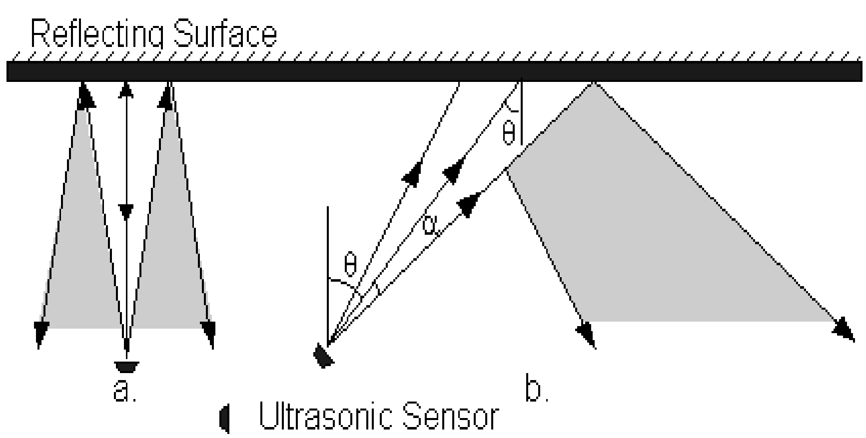

Figure 1. Example of the specular reflection, α is the half opening angle of sonar beam, θ is the incidence angle

and materials of the reflecting surfaces are decisive to the occurrence of *specular reflection*.[8,12] It happens frequently

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whenever the robot is moving in a small confined or narrow environment. The consequence of specular reflections is the longer range reading than the real distance from the ultrasonic sensor. False readings caused by specular reflections can be treated as uncertainties in sonar responses from the probabilistic view. The Bayesian updating formula[1] which projects the sensor responses on the evidence grid[13] has been widely used to express the uncertainties in sensory information about whether the area is *occupied* or *empty*. Dempster-Shafer's evidence theory has gained advantages over Bayesian for it being able to clearly distinguish the *ignorance* and the *contradiction*. In this paper, we present the method of using Dempster-Shafer's evidential method as the basic approach for sensory data fusion. We have applied the Dempster-Shafer's evidence method on the evidence grid using an appropriate ultrasonic sensor model in which a special filtering factor has been used to reduce unreliable ultrasonic readings corrupted by specular reflections from confined environments.

2. FRAMEWORK OF SENSOR FUSION

2.1. Evidence Grid

The evidence grid[13] is a framework to integrate multi-sensory information. It is a 2D representation of the real world of the autonomous mobile robot. The Bayesian formula or Dempster's rule of combination can then be easily applied to combine different sources of sensory information[1,13]obtained from the sensor model. Through the sensor fusion algorithm, each cell in the evidence grid is assigned certain values representing its state of either being *occupied* or being *empty*. Bayesian theory has its limitation in assigning probabilities only to singletons. Such as in our case, for a cell which is either *occupied* or *empty*, the probabilities for these two *contradictions* must satisfy $p(\{occupied\}) + p(\{empty\}) = 1$. This means it will not be able to treat the evidence for the world as *ignorance*, where a cell can have equal evidence for being *occupied* and being *empty*. Dempster-Shafer's evidence theory has advantages over Bayesian theory in this aspect since it is able to provide evidence for both singletons and subsets so it can clearly distinguish between *ignorance* and *contradiction*.

2.2. Review of Dempster-Shafer's Evidence Theory

In applying the Dempster-Shafer's evidence theory,[5,6,7] a sensor is a source of evidence about a set of propositions of interest, called the *focal elements*. The set of *focal elements* that can be observed by a sensor is the *frame of discernment* (FOD), denoted as θ. In our case, the frame of discernment contains two propositions,

$$\theta = \{occupied, empty\} \tag{1}$$

We can transfer the *belief* of these propositions to evidence by mass distribution of any element in the *power set* of θ, denoted as 2^θ,

$$2^\theta = \{\{occupied\}, \{empty\}, \{unknown\}\} \tag{2}$$

In Equation(2), $\{unknown\} = \{occupied\} \cup \{empty\}$. Different sources of evidence are combined into a total amount of evidence through the Dempster's rule of combination.[6,7] In our case, the *new* evidence $m_n(C)$ is updated by the two evidence sources, m_s from *sensors* and m_o from the *old* existing evidence. $m_n(C)$ is called the *orthogonal sum* of m_s and m_o that is calculated as:

$$m_n(C) = (m_s \oplus m_o)(C) = \frac{\Sigma_{A \cap B = C; C \neq \phi} m_s(A) m_o(B)}{1 - \Sigma_{A \cap B = \phi} m_s(A) m_o(B)} \tag{3}$$

where $A, B, C \subseteq \theta$. For example, when $C = \{occupied\}$, we use *occ* to represent *occupied*, *emp* for *empty* and *unk* for *unknown*, so $m_n(\{occ\})$ is calculated as,

$$m_n(\{occ\}) = \frac{m_o(\{occ\})m_s(\{occ\}) + m_o(\{occ\})m_s(\{unk\}) + m_o(\{unk\})m_s(\{occ\})}{1 - m_o(\{occ\})m_s(\{emp\}) - m_o(\{emp\})m_s(\{occ\})} \tag{4}$$

2.3. Sensor Model

The evidence is obtained by projecting the raw ultrasonic sensor responses onto the evidence grid through the sensor model. The sonar model is a function of the angle and the sonar range reading as shown in Fig. 2. The model converts the range information into probability values. As shown in Fig.2, the model is given in Equation (5) $\sim$ Equation (10)[1,8]

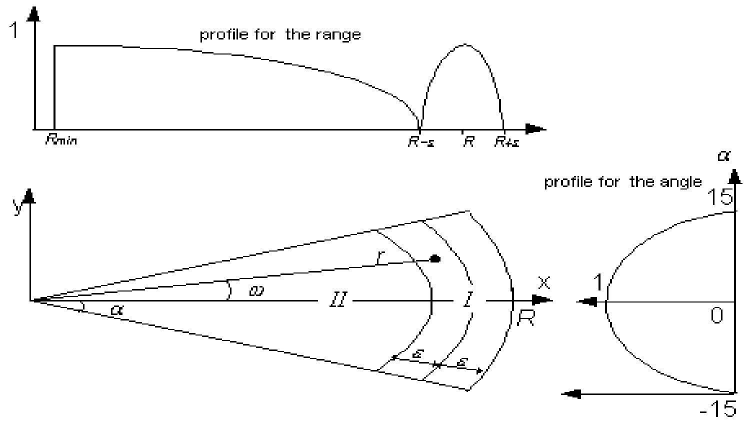

Figure 2. The profile of the ultrasonic sensor model.

Region I, where $R - \epsilon < r < R + \epsilon$:

$$m(\{occupied\}) = \frac{(\frac{\alpha-\omega}{\alpha})^2 + (\frac{\epsilon-|R-r|}{\epsilon})^2}{2} \tag{5}$$

$$m(\{empty\}) = 0.00 \tag{6}$$

$$m(\{unknown\}) = 1.00 - m(\{occupied\}) \tag{7}$$

Region II, where $R_{min} < r < R - \epsilon$:

$$m(\{occupied\}) = 0.00 \tag{8}$$

$$m(\{empty\}) = \frac{(\frac{\alpha-\omega}{\alpha})^2 + (\frac{R-\epsilon-r}{R-\epsilon})^2}{2} \tag{9}$$

$$m(\{unknown\}) = 1.00 - m(\{empty\}) \tag{10}$$

where R is the range response from the ultrasonic sensor, (r, ω) is the coordinate of a point inside the sonar cone. ϵ is the range error and it distributes the evidence in Region I. α is the half open beam angle of sonar cone.

3. DEALING WITH SPECULAR REFLECTIONS

The sensor model as represented in Equation (5) $\sim$ Equation (10) is effective in converting range information of ultrasonic sensors but is helpless in dealing with the specular reflection problem which is especially obvious in confined environments. To reduce unreliable readings caused by specular reflections in ultrasonic sensory responses, we have applied a specially designed filtering factor the *range confidence factor* (RCF). The idea of RCF was first introduced in Ref. 7. However, in Ref. 7, the sensor fusion strategy with RCF applied to the sensor model was based on the Bayesian probability theory, while in this paper, we investigate the effects of RCF in using Dempster-Shafer's evidence method for multi-ultrasonic sensor integration. The RCF used in our case is given in the following equation,[8]
when $R > R_{max}$:

$$RCF = RCF_{min} = \frac{R_{th}}{R_{th} + 1} \tag{11}$$

when R □ R_{max}:

$$RCF = \frac{\left(\frac{R_{max}-R}{R_{max}}\right)^{\tau} + R_{th}}{1 + R_{th}} \tag{12}$$

where R is the sonar response and RCF is determined by three parameters, τ, R_{th} and R_{max}. τ is used to reflect the sensitivity of the sensor to the reflected specular signal.[8] Nevertheless, we can use τ to reflect environment

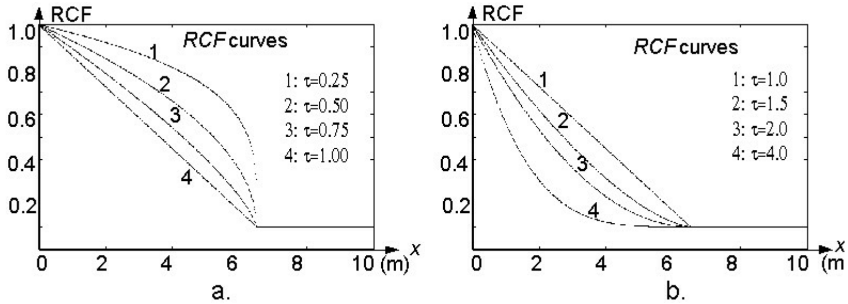

Figure 3. The range confidence factor. $R_{max} = 6.5m$

characteristics such as the confined space or the feature of reflective surfaces . In Fig. 3a, with $\tau < 1$, RCF decreases more slowly than it does in Fig. 3b where $\tau > 1$ until RCF reaches the RCF_{min}. So, the more τ is below 1, the less sensitive RCF will be to the range value that is less than R_{max}. RCF_{min} is the lowest RCF value thresholded by R_{th}. R_{max} sets the maximum range detection of sonar, for example, R_{max} can be set as the maximum diagonal length of the environment. As shown in Fig. 3, RCF will be restricted to RCF_{min} when the range detection reaches R_{max}. Therefore, responses affected by specular reflections will produce much less evidence from the sonar model, which consequently avoids accumulating evidence for unreliable sensory information caused by specular reflections. The RCF is applied by simply multiplying it with Equation (5) and Equation (9) as:

$$m(\{occupied\}) = RCF \times \frac{(\frac{\alpha-\omega}{\alpha})^2 + (\frac{\epsilon-|R-r|}{\epsilon})^2}{2} \tag{13}$$

$$m(\{empty\}) = RCF \times \frac{(\frac{\alpha-\omega}{\alpha})^2 + (\frac{R-\epsilon-r}{R-\epsilon})^2}{2} \tag{14}$$

The RCF is actually a filtering factor which adjusts the evidence for cells. What really work in RCF are the three values in Equation (12): τ, R_{th} and R_{max}. They are chosen based on heuristic understandings or experimental results.

4. EXPERIMENTS

4.1. Implementation

We have tested the effects of applying RCF to sensor model with Dempster-Shafer's evidence method for the multi-sensor fusion in a confined environment in our laboratory. The overview of the environment is given in Fig. 4. Materials of reflecting surfaces are those that most commonly used in normal laboratory walls. Raw sensor data

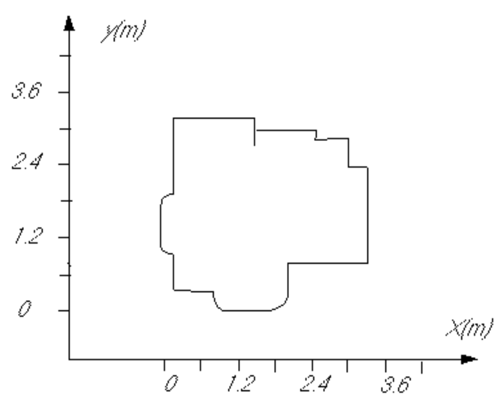

Figure 4. A typical confined environment

were collected by the Nomad Super Scout II robot platform at different locations. The robot has a sonar ring of 16 Polaroid ultrasonic sensor modules, as shown in Fig. 5.

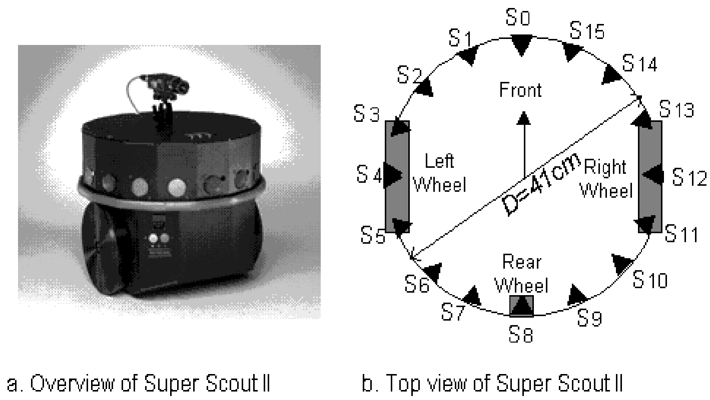

Figure 5. The Nomad Super Scout II mobile robot platform

4.2. Experimental Results

Fig. 6 $\sim$ Fig. 10 present all experimental results of fused evidence for *occupied* cells on the 2D evidence grid. In all figures, * represents $m(occ) > 0.8$ while $\cdot$ represents $m(occ) > 0.5$. Fig. 6 shows the noisy evidence grid when the RCF was not applied. Uncertainties in this figure are obvious and are particularly pronounced in areas near corners and arcs. However, when the RCF was used to modify the sensor data, these uncertainties were reduced dramatically as shown in Fig. 7 $\sim$ Fig. 10. These results also show how different selections of the three parameters in Equation (12) could bring different effects.

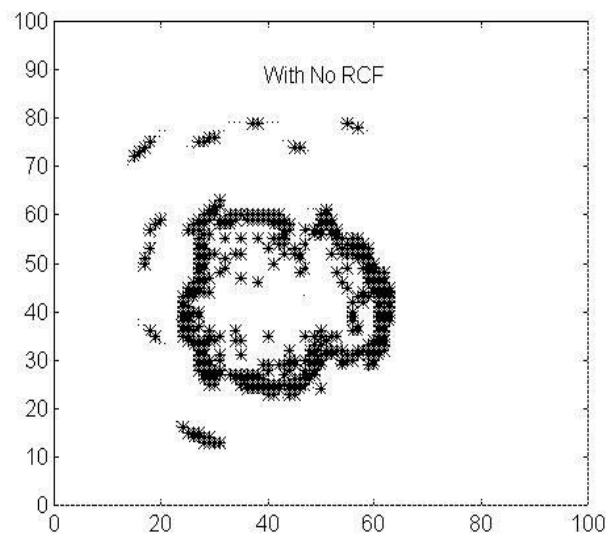

Figure 6. Evidence for being *occupied* without RCF

4.3. Discussions

As mentioned in the above, the use of RCF did work very well in reducing the unreliable responses as shown typically in Fig. 7. However we have also noticed that whether RCF can best perform depends highly on the values of the

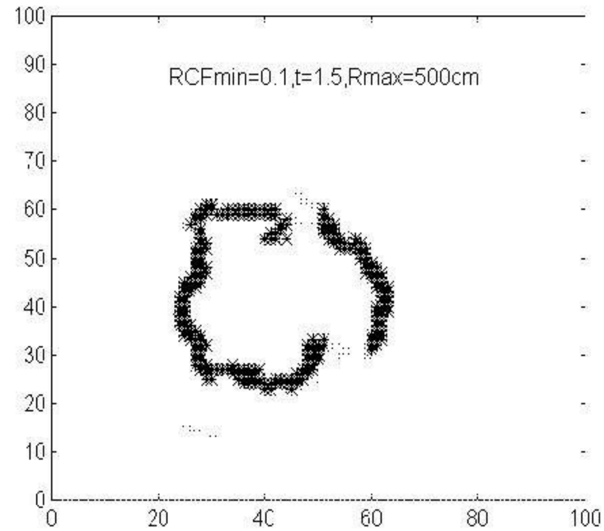

Figure 7. $RCF_{min} = 0.1, \tau = 1.5, R_{max} = 500cm$

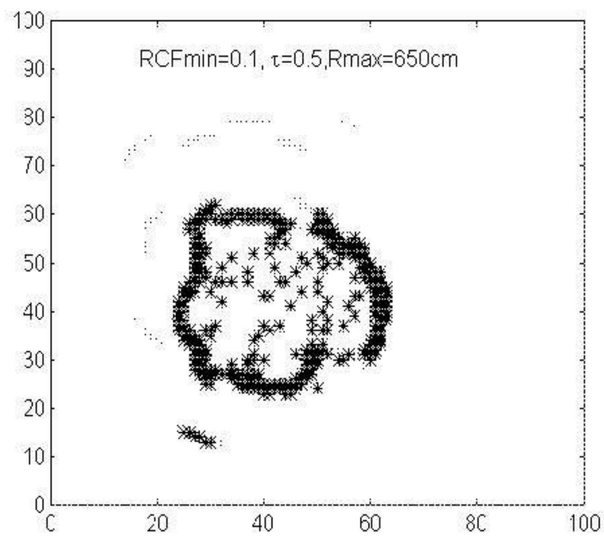

Figure 8. $RCF_{min} = 0.1, \tau = 0.5, R_{max} = 650cm$

three parameters in Equation (12). RCF acts as a filtering factor in reducing unreliable responses. The price to pay for this improvement is the decreased rate of evidence accumulation. This can be compensated by increasing the number of sets of sensor readings. The sharp difference between Fig. 8 and Fig. 10 are two extreme cases in our experiments. In Fig. 10, the sensor model was assigned the most conservative set of the three values while in Fig. 8 it was just the opposite case. Obviously the robot in Fig. 10 was much better in reducing unreliable responses than in Fig. 8. However as also shown in Fig. 10, a rather great amount of information has been lost as well. In our experiments, we have found the group of values used in Fig. 7 was most satisfactory. Therefore, to find an effective set of values for these three parameters is of great importance in RCF's performance in dealing with the specular reflection problem. The selection of the three parameters is very much a tried and error process.

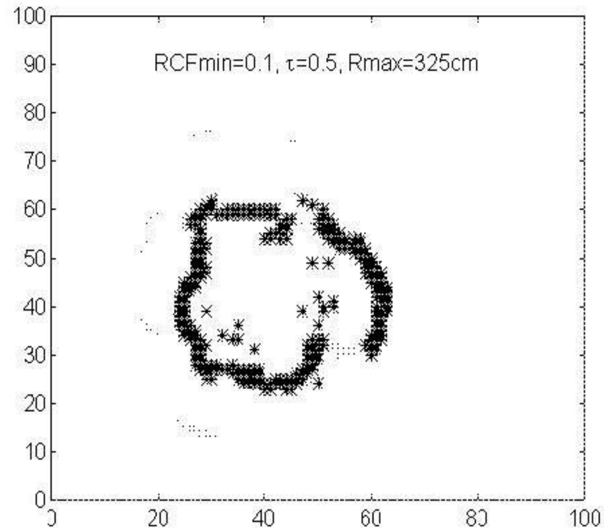

Figure 9. $RCF_{min} = 0.1, \tau = 0.5, R_{max} = 325cm$

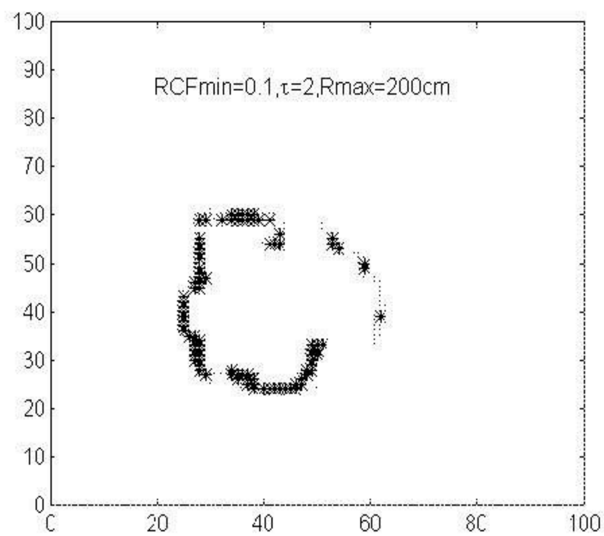

Figure 10. $RCF_{min} = 0.1, \tau = 2, R_{max} = 200cm$

5. CONCLUSIONS

In this paper, we have investigated the use of *the range confidence factor (RCF)* proposed in Ref. 7, in ultrasonic sensor model to reduce unreliable responses caused by specular reflections. Dempster-Shafer's evidence theory was used as the basis for multi-ultrasonic sensor fusion strategy on the evidence grid with the appropriate sensor model. Experimental results have confirmed the important role of RCF in reducing unreliable responses. Since the performance of RCF depends highly on the selection of the three values in Equation (12), further work is necessary on developing adaptive methods in sensor model for navigations in unknown environments.

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