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Multi-ultrasonic Sensor Fusion for Mobile Robots

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Abstract

To learn the environment using multi-sensory information, we need both an accurate sensor model and a reasonable sensor fusion methodology. Ultrasonic sensors provide good range information. However, uncertainties in ultrasonic sensors caused by the specular reflection from environments make them less attractive. We have used the Dempster-Shafer evidence method in sensor fusion with the specially designed sensor model. By applying a filtering factor to the sensor model, uncertainties in sonar responses can be successfully reduced. In this paper, we introduce a novel way of using the conflict value in Dempster-Shafer evidence theory in the sensor model. Through this new method, our robot would be able to modify its sensor model dynamically during its navigation. Experimental results have shown that the new method has improved the performance of the modified ultrasonic sensor model in dealing with specular reflections.

Keywords Ultrasonic Sensor, Multi-Sensor Fusion, Dempster-Shafer.

1 Introduction

One of the most important issues in the navigation of multi-sensor based mobile robots is the building of the environment map from sensory information. The mobile robot accumulates its understanding of its surroundings on the map which will be used to help the robot perform certain types of tasks, such as path planning and obstacle avoidance. Because ultrasonic sensors can provide good range information based on the *time of the flight*(TOF) principle for rather low expense, they have been widely used in mobile robots applications. Many researchers [4, 1, 7, 6, 5, 3] have discussed the use of ultrasonic sensors in autonomous mobile robots in details. However, there are also some fundamental drawbacks which limit the use of ultrasonic sensors [2], of which the most significant one is the possibility of *specular reflections* [8] from the environment. As shown in Fig. 1, the specular reflection occurs 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 and

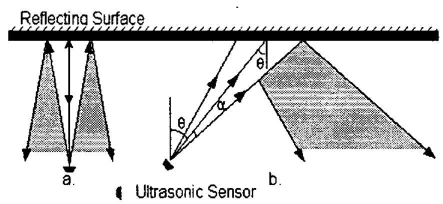

Figure 1: Example of the specular reflection

materials of the reflecting surfaces are decisive to the occurrence of *specular reflection* [8]. In Fig.1b, when incidence angle θ reaches to a certain value, called the *critical angle of specular reflection* [2], the ultrasonic sensor fails to receive the correct response from the object. It happens frequently whenever the robot is moving into confined or narrow environments. 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 [4] which projects the sensor responses on the evidence grid [9] has been widely used to express the uncertainties in sensory information about whether the area is *occupied* or *empty*. Dempster-Shafer evidence method has gained advantages over Bayesian for it being able to clearly distinguish between the *ignorance* and the *contradiction*. In this paper, we introduce a novel method to effectively reduce unreliable sensor responses caused by specular reflections. This method makes use of the conflict value in Dempster-Shafer evidence theory to modify the sensor model dynamically. Ultrasonic sensory information obtained through the new sensor model is integrated by the Dempster's rule of combination.

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2 Sensor Fusion Framework

2.1 Evidence Grid

The evidence grid [9] 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-Shafer evidence method can then be easily applied to combine different sources of sensory information [4, 9] obtained from the sensor model. Through the sensor fusion algorithm, each cell in the evidence grid is assigned to certain probability values representing its state of either being *occupied* or being *empty*. The limitation in Bayesian theory is that it assigns probabilities only to singletons. In the case for a cell on the evidence grid, probability values for the two *contradictions*, *occupied* and *empty*, must satisfy $p(occ) + p(emp) = 1$. This means Bayesian method will not be able to treat the evidence for the world as *ignorance* since a cell can have equal evidence for being *occupied* and being *empty*. Dempster-Shafer evidence theory has advantages over Bayesian theory because it is able to provide evidence to both singletons and subsets. Therefore it can clearly distinguish between *ignorance* and *contradiction*.

2.2 Dempster's Rule of Combination

Dempster's rule of combination has been used as our sensor fusion strategy, as given in Equation (1) [10],

$$m_n(C) = \frac{1}{1-\kappa} \sum_{A \cap B = C; C \neq \phi} m_s(A) m_o(B) \quad (1)$$

where 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. The term κ in Equation (1) measures the extent of conflict between the different sources of evidence. κ is defined as,

$$\kappa = \sum_{A \cap B = \phi} m_s(A) m_o(B) \quad (2)$$

$A, B, C \subseteq \theta$, θ={*occupied, empty*} is the set of *focal elements* that can be observed by a sensor. θ is called as the *frame of discernment* (FOD). A, B, C are also elements of the power set of θ denoted as 2^θ,

$$2^\theta = \{\{occupied\}, \{empty\}, \{unknown\}\} \quad (3)$$

where $\{unknown\} = \{empty\} \cup \{occupied\}$. For example, when $C = \{unknown\}$, if we use u to represent *unknown*, o to represent *occupied* and e to represent *empty*, then Equation (4) shows how $m_n(\{unknown\})$ is calculated,

$$m_n(\{unknown\}) = m_n(\{u\}) = \frac{m_o(\{u\}) m_s(\{u\})}{1 - m_o(\{o\}) m_s(\{e\}) - m_o(\{e\}) m_s(\{o\})} \quad (4)$$

For the same example in Equation (4), κ is calculated as,

$$\kappa = m_o(\{o\}) m_s(\{e\}) + m_o(\{e\}) m_s(\{o\}) \quad (5)$$

2.3 Sensor Model

The evidence is obtained by projecting the raw ultrasonic sensor responses onto the 2D evidence grid through sensor model. The sonar model is a function as shown in Fig. 2, which converts the range information into probability values to represent uncertainties in sonar responses. According to Fig. 2, the sensor model is given in Equation (6) $\sim$ Equation (11),

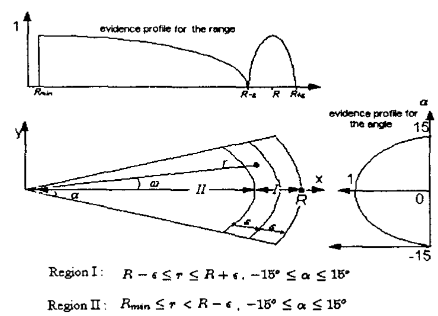


Figure 2: Sensor model profile.

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

$$\begin{aligned} m(\{occupied\}) &= \frac{(\frac{\alpha-\omega}{\alpha})^2 + (\frac{\epsilon-|R-r|}{\epsilon})^2}{2} && (6) \\ m(\{empty\}) &= 0.00 && (7) \\ m(\{unknown\}) &= 1.00 - m(\{occupied\}) && (8) \end{aligned}$$

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

$$\begin{aligned} m(\{occupied\}) &= 0.00 && (9) \\ m(\{empty\}) &= \frac{(\frac{\alpha-\omega}{\alpha})^2 + (\frac{R-\epsilon-r}{R-\epsilon})^2}{2} && (10) \\ m(\{unknown\}) &= 1.00 - m(\{empty\}) && (11) \end{aligned}$$

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, which is normally 15^o for standard Polaroid ranging module.

3 Dealing with Specular Reflections

3.1 Range Confidence Factor

The sensor model in Equation (6) $\sim$ Equation (11) is effective in converting range information of ultrasonic sensors. However,the model is helpless in

dealing with the specular reflection problem which is especially obvious in confined environments because it treats the unreliable readings as reliable or correct ones. To deal with this problem, we have applied *range confidence factor* (RCF), which was first introduced in [8]. Definition of RCF has been given in Equation (12) and Equation (13),
when $R > R_{max}$:

$$RCF = RCF_{min} = \frac{R_{th}}{R_{th}+1} \qquad (12)$$

when $R \leq R_{max}$:

$$RCF = \frac{(\frac{R_{max}-R}{R_{max}})^{\tau} + R_{th}}{1+R_{th}} \qquad (13)$$

R is the sonar response. τ is used to reflect the sensitivity of the sensor to the reflected specular signal. RCF_{min} is the lowest RCF value thresholded by R_{th}. R_{max} sets the maximum range detection of sonar [8, 11]. The RCF is actually a filtering factor which adjusts the evidence obtained from ultrasonic sensors.

3.2 Using the Conflict Value

We have found that RCF did work very well in reducing uncertainties caused by specular reflections in sensory information [11]. However we have also noticed that whether RCF can best perform depends highly on its parameters in Equation (13). Inappropriate selection of these parameters result in bad performance of RCF, which will cause the slowing-down of the evidence accumulation. However, to set parameters beforehand for RCF is obviously impractical as the mobile robot is to navigate in unknown environments. Considering this, we have modified our method using the term κ given in Equation (2). This value directly reflects how much the two different sources of evidence are in conflict with each other. Specular reflections cause much larger range readings than actual ones. This false reading will result in larger conflict values between the new evidence from the senor and the old existing evidence. Therefore, the conflict value can be treated as an indicator of the reliability of the ultrasonic sensor reading. Hence we can use the conflict value to help select the appropriate value for RCF. Based on this characteristic, the following factor denoted as Ω has been introduced to the sensor model. Ω is defined as,

$$\Omega = (\frac{1-\kappa}{1+\kappa})^2 \qquad (14)$$

The relationship between Ω and κ is shown in Fig. 3. The application of Ω in Equation (14) in the following equations will change the parameters of RCF accordingly to help the sensor model to extract sensory information more efficiently. For Equation (13), we modify the τ and R_{max} as,

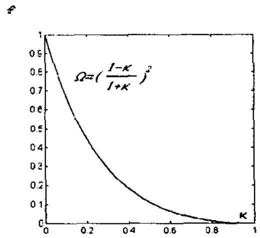


Figure 3: Relationship between Ω and κ

$$\tau' = \frac{1}{\Omega} = (\frac{1+\kappa}{1-\kappa})^2 \qquad (15)$$

$$R'_{max} = R_{max} \cdot \Omega = R_{max} \cdot (\frac{1-\kappa}{1+\kappa})^2 \qquad (16)$$

R_{max} then can be as the longest range reading of the ultrasonic sensor, which means there is no need for us to know the environmental information beforehand now. In our case, we have set it to 6.5m, which is the longest range reading reported by the ultrasonic sensing unit in the Nomad Super Scout II mobile robot. The modified RCF is denoted as RCF'. To decrease the area to be assigned the evidence for being *occupied* when specular reflections occur, Ω is also applied to adjust the ultrasonic sensor opening angle as,

$$\alpha' = \alpha \cdot \Omega = \alpha \cdot (\frac{1-\kappa}{1+\kappa})^2 \qquad (17)$$

With modifications introduced in the above equations, the sensor model will be automatically adjusted according to the change in the conflict value. Hence, to apply this method, Equation (6) $\sim$ Equation (10) should be rewritten as,

$$m(occupied) = RCF' \cdot \frac{(\frac{\alpha'-\omega}{\alpha'})^2 + (\frac{\epsilon-|R-r|}{\epsilon})^2}{2} \qquad (18)$$

$$m(empty) = RCF' \cdot \frac{(\frac{\alpha'-\omega}{\alpha'})^2 + (\frac{R-\epsilon-r}{R-\epsilon})^2}{2} \qquad (19)$$

4 Experiments

4.1 Implementation and Results

The method has been tested in a typical confined environment in our laboratory. The overview of this environment is given in Fig. 4. Raw sensor

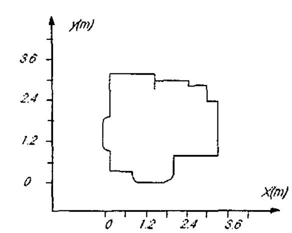
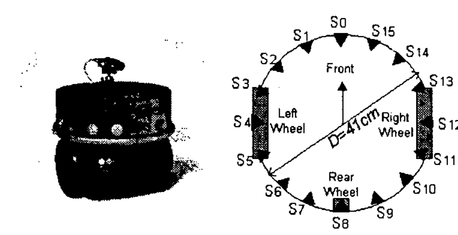


Figure 4: A typical confined environment

data 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. Fig. 5 gives an overview of Super Scout II and the layout of the 16 ultrasonic sensors. Fig. 6, Fig. 7 and Fig. 8 present all experimental results of fused evidence for *occupied* cells on the 2D evidence grids. In all figures, * represents $m(\{occ\}) \geq 0.8$ while + represents $m(\{occ\}) \geq 0.5$. Fig. 6 is the case when no RCF was used. Fig. 7 is the case when the RCF was applied with parameters selected beforehand. Fig. 8 shows the results when Ω was used.



a. Overview of Super Scout II b. Top view of Super Scout II

Figure 5: The overview of our Super Scout II

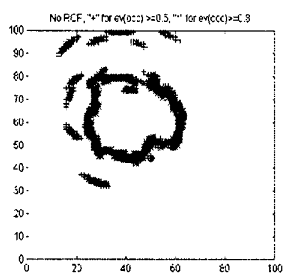


Figure 6: Before RCF was applied

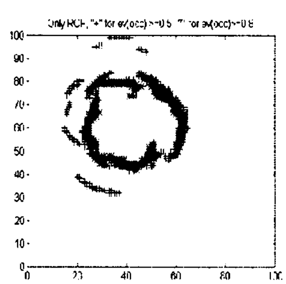


Figure 7: After RCF was applied

4.2 Discussions

Fig. 6 gives the results of the sensor model with RCF in our earlier work [11], in which we have found the selection of the three values in Equation (13) is a try and error process. We have carried a lot of experiments in an effort to find the best set of values for RCF. However, the requirement on the

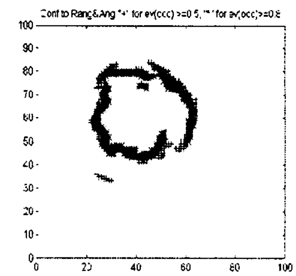


Figure 8: When Ω has been applied to RCF

selection of these parameters is not practical since the robot is to navigate in unknown environments. Therefore we have introduced the new method so that the sensor model would be able to adjust itself dynamically. Clearly, results of the new method shown in Fig. 7 is very effective in improving the accuracy of robot's knowledge about its environments. At the same time, it needs no environmental knowledge beforehand. In this method, the conflict value has been treated as an item representing the reliability of the sensor reading. When the conflict value is rather high, it means the new evidence from sensors is quite different from the existing evidence, which represents the understanding of the robot about its surroundings so far. Therefore, the high conflict shows most probably there has been a false reading from the ultrasonic sensor caused by specular reflections. To reduce uncertainties caused by specular reflections, conflict value has been used to adjust RCF in the modified sensor model. This is done by introducing a new item Ω given in Equation (14). Experimental results have confirmed the effectiveness of this novel way in using conflict value to reduce the uncertainties in sensory information caused by specular reflections from environments.

5 Conclusions

In this paper, we have presented the multi-sensor fusion strategy using Dempster-Shafer evidence theory. A new method has been introduced to modify the ultrasonic sensor model for more accurate sensory information. The novel way of using conflict value as an adjusting factor to the sensor model is reasonable in theoretical and practical sense. Experimental results have also proved the effectiveness of this new method in reducing the uncertainties in ultrasonic sensory information caused by specular reflections. However, so far our environment has contained no objects, so further work will be needed to test and expand this method to a variety of environments with obstacles inside.

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