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Object Detection by an Autonomous Robot through Data Fusion

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***Abstract*— Wireless sensor network is an emerging technology that enables remote monitoring objects and environment. Object tracking is an important wireless sensor networks. Single sensor system cannot provide satisfactory accuracy or reliability as a result of which a system deploys multiple sensors in a particular scenario. To handle uncertain, incomplete and vague information, data fusion technique is applied to a measuring system to reduce effectively overall uncertainty and increase the accuracy. In data fusion Dempster-Shafer evidence theory is an efficient method. Here different bodies of evidences are combined by using Dempster's combination rule. This paper gives an approach to find the exact location of goal object through data acquisition and fusion by deploying multiple sensors. The work is concentrated on robot how to track the targets and obtain the target position effectively.**

***Keywords*— Mobile Robot, Dempster Shafer Evidence Theory, Data Fusion**

I. INTRODUCTION

The processing of incomplete, uncertain and vague information is required to get the best approximation. To deal with these factors different approaches like Bayesian probability theory, fuzzy logic and Dempster_Shafer Theory are there .The Bayesian theory requires complete prior knowledge of probability of evidences .As we don't have any prior knowledge we cannot use Bayesian Theory here. Fuzzy logic can be applied to combine evidences but fuzzy requires the complete knowledge of membership functions for fuzzy set which is not easy to obtain in real world application. We choose DS Theory because it supports the representation of both imprecise and uncertainty and it is able to deal with ignorance and missing information. Information fusion technique was introduced to get more accurate and integrated data to real world application. Multi-sensor system combines the information and gives more accurate and integrated data than a single sensor. Dempster_Shafer theory allows information integration by both belief and disbelief.

Information fusion is central to many computer systems that help users in decision making, forecasting, pattern recognition and diagnosis. A complicating factor in developing these decision support systems is the handling of the uncertainty resulting from imprecise, incomplete, vague and complementary information. The aim of the management of uncertainty in these systems is to get the best approximation. The main basic approaches to uncertain reasoning are certainty factors developed in expert systems, Bayesian probability theory, fuzzy logic and Dempster-Shafer (D-S) evidence theory[1-6].The Bayesian approach has a decision making theory, but it requires complete knowledge of combined conditional probabilities and specification of the prior knowledge of probability distribution proving that a piece of evidence is present. Besides, the main limitation of the Bayesian approach is that it cannot model imprecision. That is, the Bayesian probability theory cannot measure a body of evidence with an imprecision on probability measurement. The main advantage of the fuzzy fusion approach is that the evidence from multiple features can be combined using fuzzy logic operations, and uncertainty can be represented. The fuzzy set framework provides a lot of combination operators, which allows the user to adopt a fusion scheme and specify the data at hand. However, to our knowledge, the membership functions for the fuzzy set are not easy to obtain in real-world application systems.

There are three main reasons why the D-S evidence theory should be taken into account when it comes to information fusion. First of all, since the D-S evidence theory supports the representation of both imprecision and uncertainty, it is considered to be a more flexible and general approach than the traditional probability theory. Secondly, D-S offers the possibility of coming up with the probabilities of a collection of hypotheses, whereas a classical probability theory only deals with one single hypothesis. Finally, the major strength of the D-S theory is its ability to deal with ignorance and missing information. The most crucial rule of evidence combination in the D-S theory is called the Dempster's rule of combination. It has several interesting mathematical properties [3]. However, combination may yield illogical results when the collected bodies of evidences highly conflict with each other. The conflicting evidence has been one of the most important issues in D-S evidence theory [7]. Many methods have been proposed to solve this problem, but there has been no solution accepted universally so far. Information fusion technology not only eliminates redundancy but also obtains more accurate and integrated estimation than from any single source. Dempster-Shafer theory is a kind of reasoning algorithm based on evidence theory [3]. It was put forward by Dempster at first, and developed by Shafer, so it was called D-S evidence theory [1-2]. Data fusion is the process of combining data from several sources into a single unified description of a situation [7]. A system employs multiple sensors when the single sensor system cannot provide satisfactory accuracy or reliability [10, 11]. In real-time measuring system, most sensors have cross-sensitivity such that the measured variable is not usually affected or determined by only one parameter and it will change with the other parameters' change. To this problem, data fusion technique applied to a measuring system can reduce effectively overall uncertainty and increase the accuracy. It can also serve to increase reliability in the case of sensor error or failure [12, 13].

II. PRINCIPLE OF DS THEORY

In this section, the basic concepts of the D-S evidence theory are reviewed and the related functions are defined first. The Dempster-Shafer evidence theory was originally developed by Dempster, who concerned about the lower and upper probabilities, and later Shafer made his contribution by offering belief functions to model uncertain knowledge on the basis of mathematical foundations [3]. The confidence of the observed event can be quantified by the function defined in the theory of evidence. In the subsection below, we define the terminology of the D-S evidence theory and the notation to be used in this paper.

Consider Θ as the set of all objects, Hence Θ= $\{\theta1, \theta2, \theta3, \theta4, \ldots\ldots, \theta n\}$. The key feature of D-S Theory is the basic probability assignment i.e. bpa (m).

2^Θ denotes the power set of Θ, Hence m: $2^\Theta \rightarrow [0,1]$

For every element A, m is defined such that m(A) falls in an interval [0,1].

$$\mathbf{m(ø)=0,} \tag{1}$$

$$\textstyle\sum_{A \in 2^\Theta} m(A) = 1, \tag{2}$$

where ø is the empty set.

The mass of the null (ø) set is defined as zero in the Dempster-Shafer framework when it is under the closed-world assumption. For any $A \in 2^\Theta$, the quantity $m(A)$ represents a measure of belief that is committed exactly to A . The element A of 2^Θ such that $m(A)$ is greater than zero is called the focal element of *m*. The body of evidence is the set of all focal elements, and is expressed as:

$$(\wp, \mathbf{m})=\{[A, m(A)]; A \in 2^\Theta \text{ and } m(A) > 0\}. \tag{3}$$

Specially, $m(\Theta)$ =1 and $m(A) = 0$, $A \neq \Theta$ represent the global ignorance (total uncertainty) since the weight of evidence is not identified among the hypotheses.

The D-S evidence theory supports the representation of both imprecision and uncertainty by taking two functions called belief (*Bel*) and plausibility (*Pls*), which are both derived from the mass function m.

$$\mathbf{Bel:}\ 2^\Theta \rightarrow [0,1] \tag{4}$$

$$\mathbf{Pls:}\ 2^\Theta \rightarrow [0,1] \tag{5}$$

are defined on 2^Θ such that

$$\mathbf{Bel}\ (\emptyset) = 0, \tag{6}$$

$$\mathbf{Bel}(A) = \textstyle\sum_{B \subseteq A} m(B)\ , \qquad \forall A \subseteq \Theta, A \neq \emptyset, \tag{7}$$

$$\mathbf{Pls}(\emptyset) = 0, \tag{8}$$

$$\mathbf{Pls}(A) = \textstyle\sum_{B \cap A \neq \emptyset} m(B)\ , \qquad \forall A \subseteq \Theta, A \neq \emptyset, \tag{9}$$

Bel(A) measures the total belief that the hypothesis *A* is true. The plausibility Pls (A) can be viewed as the total amount of belief that could be potentially placed in *A*. Clearly, the two functions have the following properties:

$$\mathbf{Bel(\Theta)=1,} \tag{10}$$

$$\mathbf{Pls(\Theta)=1,} \tag{11}$$

$$\mathbf{Bel(A) \leq Pls(A)} \quad \forall A \subseteq \Theta, \tag{12}$$

$$\mathbf{Pls(A)= 1\text{-}Bel(\bar{A})} \quad \forall A \subseteq \Theta, \tag{13}$$

$$\mathbf{Bel(A) + Bel(\bar{A}) \leq 1} \quad \forall A \subseteq \Theta, \tag{14}$$

where $\bar{A}$ is the complementary hypothesis of A , $A \cup \bar{A} = \Theta$ and $A \cap \bar{A} = \varphi$. To be more specific, the belief value that belongs to neither A nor $\bar{A}$ is the degree of ignorance. The belief and plausibility function are sometimes referred to as the lower bound and upper bound on the probability of a subset, respectively [1], such that:

$$\mathbf{Bel(A) \leq Prob(A) \leq Pls(A).} \tag{15}$$

Thus, [Bel(A), Pls(A)] is called the "belief interval" and its length can be interpreted as the imprecision about the uncertainty value of *A* . In case of probability theory, using a single value (probability) in [0, 1] to represent uncertainty about an event, the imprecision about the uncertainty measurement is assumed to be null.

Shafer has shown that the evidence of any one of the three functions *m*, Bel, Pls is sufficient to derive the other two [3]. The mass function *A* can be reconverted from the corresponding belief function by

$$\mathbf{m(A)}= \textstyle\sum_{B \subseteq A} (-1)^{|A-B|}\ \mathrm{Bel}(B),\ \forall A \subseteq \Theta \tag{16}$$

where A − B denotes the cardinality number of the set (A−B).

In the D-S evidence theory, one of the main difficulties is how to initialize the mass function *mi* of bodies of evidences. There is no general answer to the key problem of mass definition [14-15]. Generally, the mass values are assigned by experts or depend on the application. In many application systems, the most widely used mass functions are derived from the probabilities, or from the neighbourhood information according to a distance [16]. In addition, some other methods based on likelihood functions or the use of neighbourhood information, have been proposed [17].

The procedure for aggregating multiple evidences from different sources defined on the same frame of discernment by means of the previously defined mass functions is an important issue in the D-S theory. This can be seen as a problem of information fusion. Two bodies of evidence m_1 and m_2 with focal elements $A_1, \ldots, A_i$ and $B_1, \ldots, B_j$, respectively, can be combined to yield a new mass function *m* by a combination rule. The D-S evidence theory provides a method to compute the orthogonal sum $m = m_1 \oplus m_2$ of two bodies of evidence, according to the Dempster's combination rule [1], by

$$\mathbf{m}(\emptyset) = 0,$$

$$m(A) = \frac{\sum_{A_i \cap B_j = A} m_1(A_i) m_2(B_j)}{1-K}, \forall A \subseteq \Theta, \tag{17}$$

(7)

where K= $\sum_{A_i \cap B_j = \emptyset} m_1(A_i) m_2(B_j)$ and K<1. (8)

All the bodies of evidences are independent. The variable K means the mass would be assigned to an empty set after combination. Thus, K can be taken as a normalization factor (division by $1-K$), K is known as conflict because it measures the degrees of conflict between the different bodies of evidences. When the K value is taken into account for the combination of different sources, if the K value is high, the conflict will be strong among the sources, and so combination would make no sense.

III. SYSTEM OVERVIEW

In our system we have used one robot with two sensors to track the object and a monitor to record the data for future calculation. Robot contains following modules: sensor module, microcontroller module and motor module. The sensor module is having ultrasonic sensor and IR sensor. The microcontroller module is further having programming module and navigation module. The programming module is used for location tracking. The navigation module is used to find the optimal path using DS Theory.

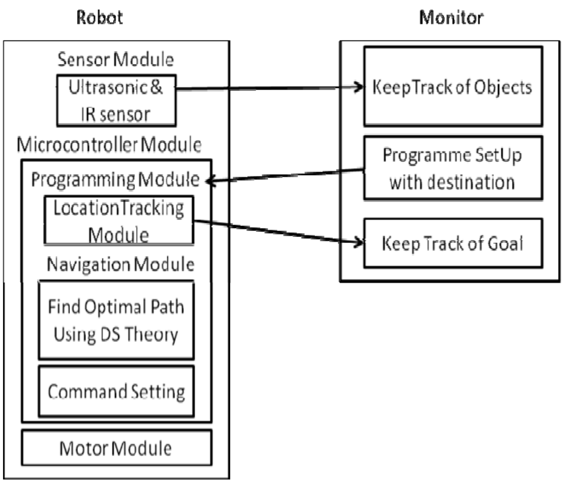

Fig. 1 Object Detection System Architecture

A. Work Flow of Robot Movement

1. Robot starts emitting beacon signals to track the object.
2. When an Object is detected then it decides whether it is detected by the left or the right sensor .If it is detected by the left sensor then it stops the right wheel and if it is detected by right sensor then it stops the left wheel and takes the turn accordingly.
3. After detecting the object; it sends the location of the object to the monitor.
4. Once the location is identified, the rate of selection, rejection and recognition is calculated .The rate of error for detecting the Object is determined using the DS Theory. Using these data the actual position of the object is calculated.
5. The above calculated information is passed to the monitor and then it is decided that whether the object is the target object or not. If not then it again go on detecting another object. This process goes on until the target object is detected.

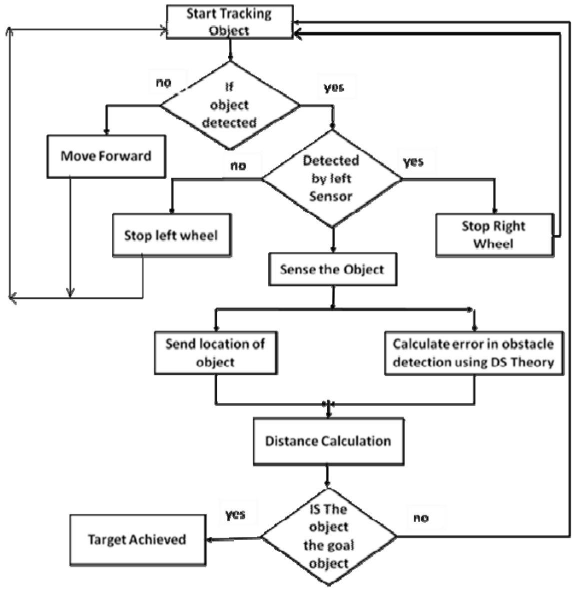

Fig. 2 Workflow of Robot Movement

B. Robot Movement Algorithm for Object Detection

To detect an object, the robot has to search optimal path using the algorithm given below.

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Minimumpath (G, s,u)
Suppose the Graph contains N1, N2, ............N Objects.
Then assign bpa( basic probability assignment) to each Object
Determine the accuracy of detecting each Object
Initialise StartNode ←ø
Select SourceNode ←S
PathList← PathList U StartNode
While
do SelectNode← Minimum cost
          for each Node  v ∈Adj[u]
              AdjacentList← Adj[u]
              d[u]  ←∞
              EstimateDistance(u)
                    x← Distance of u(with accuracy)
                    if (x< d[u])
                              then d[u] ← x
                                        Pop (AdjacentList)
                                        EstimateDistance (v)
          SelectNode ←Node with minimum d[u]
          PathList ← S U SelectNode
if(GoalNode∉PathList)
          then return fail
PathList←PathList U GoalNode
SelectNode←SelectNode
while
          do PathList← PathList U SelectNode.ParentNode
          if(SelectNode.ParentNode=StartNode)
                    then return PathList
          SelectNode←SelectNode.ParentNode
```

IV DEVELOPMENT ENVIRONMENT AND RESULT

Our approach described above has been implemented and tested using a mobile robot equipped with ATmega32 microcontroller, 32 KB flash memory, LM324 motor controller and two wheels. The detailed hardware specification is described in Table 1. The robot is attached with two sensors out of which one is Ultra sonic and other is Infrared as shown in figure 3.

TABLE I
Hardware Specification

Type	Hardware Specification
Monitor	17 inch LCD screen
Microcontroller	Atmega 32
IR sensor	Can Detect within a range of 20m
UltraSonic Sensor	Can Detect within a range of 20m
Motor Controller	LM324
Flash Memory	32KB

Fig. 3 Ultrasonic Sensor and Infrared Sensor

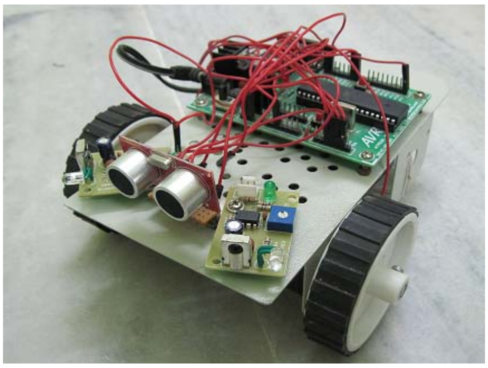

Fig. 4 Mobile Robot Deployed with Two Sensors

The sensors are deployed to detect various objects. The ultra sonic sensor used can detect the Object present within the range of 20 meters and the IR sensor used can detect the Object within the range of 20 meters. We have taken four Objects named ob_1, ob_2, ob_3 and ob_4. The sensors described above are deployed in an indoor environment to capture the location of the objects.

TABLE II: Percentage of Accuracy of Sensors in Locating the Objects

Sensors	Objects Detection			
	Ob_1	Ob_2	Ob_3	Ob_4
Ultrasonic	35	25	30	10
IR	15	10	65	10

Table II shows that the Ultra sonic sensor has the following recognition rate: 35% of accuracy for ob_1, 25% accuracy for ob_2, 30% accuracy for ob_3 and 10% accuracy for Ob_4. Similarly IR sensor has following recognition rate: 15% accuracy for ob_1, 10% accuracy for ob_2, 65% accuracy for ob_3 and 10% accuracy for ob_4. After getting the recognition rate, the rejection rate has been calculated and given in table III.

TABLE III: Rejection, Selection and Recognition Rate for Locating Objects

	Ob_1		Ob_2		Ob_3		Ob_4	
sensors	m (ob_1)	m $(\neg ob_1)$	m (ob_2)	m $(\neg ob_2)$	m (ob_3)	m $(\neg ob_3)$	m (ob_4)	m $(\neg ob_4)$
Ultra Sonic	0.35	0.65	0.25	0.75	0.3	0.7	0.1	0.9
IR	0.15	0.85	0.1	0.9	0.7	0.35	0.1	0.9

It can be seen from the above table that; the rejection rate of Ultra sonic sensor for ob_1 is 0.65, for ob_2 is 0.75, for ob_3 is 0.30 and for ob_4 is 0.90. Similarly rejection rate of IR sensor for ob_1 is 0.85, for ob_2 is 0.90, for ob_3 is 0.35 and for ob_4 is 0.90.

Once we have calculated the rejection rate**.** Then the Dempster- Shafer combination rule is applied to get a standard accuracy for a particular object. For a sample from the test data, based on the recognition, substitution and rejection rates (RSR) the bpa used for m(i) and m(¬i) has been shown. Since the rejection rate is zero for all the classes, and therefore m(Θ) = 0, this value is not shown in the table IV**.**

TABLE IV: Dempster's Combination

(Ultra)m$_1$ / **(IR)m$_2$**	{ob_1} 0.35	{ob_2} 0.25	{ob_3} 0.30	{ob_4} 0.10
{ob_1} 0.15	{ob_1} 0.0525	{ø} 0.0375	{ø} 0.045	{ø} 0.015
{ob_2} 0.10	{ø} 0.035	{ob_2} 0.025	{ø} 0.03	{ø} 0.01
{ob_3} 0.65	{ø} 0.2275	{ø} 0.1625	{ob_3} 0.195	{ø} 0.065
{ob_4} 0.10	{ø} 0.035	{ø} 0.025	{ø} 0.03	{ob_4} 0.01

Using orthogonal summation the K value can be calculated as:

K=0.0375+0.045+0.015+0.035+0.03+0.01+0.2275+0.1625 +0.065+0.035+0.025+0.03=0.7175

According to Equation (17) the combined belief result for identifying different objects can be calculated as follows:

To detect the ob_1 the combined belief is:
$m(ob_1) = m1(ob_1)*m2(ob_1) /(1\text{-}K) = (0.35*0.15) /(1\text{-}0.7175) = 0.0525/(1\text{-}0.7175) = 0.0525/0.2825= 0.19$

Similarly to detect the ob_2 combined belief is:
$m(ob_2) = m1(ob_2)*m2(ob_2) / (1\text{-}K) = (0.25*0.10) / (1\text{-}0.7175) = 0.025 / (1\text{-}0.7175) = 0.025/0.2825 = 0.09$

Similarly to detect the ob_3 combined belief is:
$m(ob_3)=m_1(ob_3)*m_2(ob_3)/(1\text{-}K) = (0.30*0.65) /(1\text{-}0.7175) = 0.025/(1\text{-}0.7175) = 0.195/0.2825 = 0.69$

Similarly to detect the ob_4 combined belief is:
$m(ob_4)=m_1(ob_4)*m_2(ob_4)/(1\text{-}K) = (0.10*0.10) / (1\text{-}0.7175) = 0.01/(1\text{-}0.7175) = 0.01/0.2825=0.04$

After applying the DS Theory the combined belief of ob1, ob2, ob3 and ob4 are obtained as 0.19, 0.09, 0.69 and 0.04. Fig 5 shows the combined belief of Ultrasonic and IR sensor towards ob1, ob2, ob3 and ob4. The green color in the graph shows the belief of IR sensor, blue color shows the belief of ultrasonic sensor and finally red color shows the combined belief.

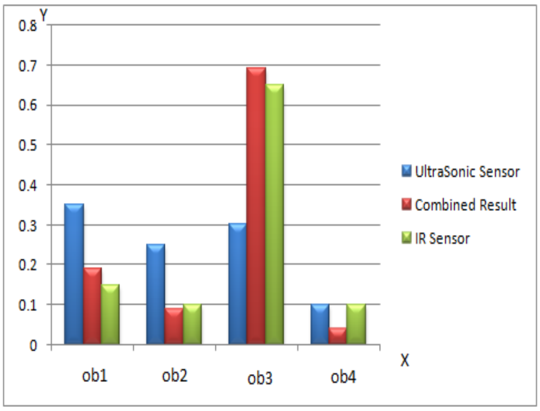

Fig. 5 Comparison Result for Accuracy Detected by Ultrasonic and IR Sensor

V.CONCLUSION

The D-S evidence theory is a useful method for dealing with uncertainty problems in multi-sensor data fusion.This paper has presented an approach for object detection in multi-sensor environment. We have designed a robot using multi-sensor system and detected the object and calculated the accuracy of detecting the object by applying DS Theory. With the help of this accuracy we have developed an algorithm to find the minimum path to locate the goal object.

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