Contribution of Evidence-Similarity to Target Classification

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Abstract—**To resolve the target classification problem under the condition of interference, the paper presents a target classification method based on the evidence-similarity. Because the results of Dempster-Shafer Theory (DST) and Dezert-Smarandache Theory (DSmT) are used in different conflict condition. In the low conflict situation, the classification by DST has good effect, but the classification by DSmT introduces the focal element, which increase the amount of computation greatly. In the high conflict situation, DSmT can effectively tackle the problem that the contradiction focal element can not be fused in DST, and avoid the DST classification appearing counterintuitive conclusions. Therefore, the two kinds of classification theories are combined by the similarity of evidence in the paper. Experiment results show that the method can effectively improve the accuracy of the target classification under different conflict condition.**

Keywords--evidence-similarity; target classification; DST; PCR6

I. INTRODUCTION

Target classification is based on the target characteristics acquired by sensors. Dempster-Shafer Theory (DST) and Dezert-Smarandache Theory (DSmT) can achieve good classification results, and have advantages in the combination and measurement of uncertainty.

However, when the evidences acquired by multi-sensor system are in the high conflict situation, DST produces the counterintuitive conclusions [1-3]. DSmT can obtain a better result in the case that the evidences are dynamic and they are in high conflict. DSmT preserves the evidence of conflict as the focus element of data fusion, which will solve the evidences combination problem completely when the evidences are conflict. But the method is increased in the computation burden greatly, and the mainly focal element of the assignment function is very slow to converge. On condition that the reliability is reduced under the high conflict evidences, the fusion effect is not obvious [4][5].

In regard to the two methods mentioned have their limits, Scholars proposes a variety of improved methods, methods proposed in [6-8] compute the average reliability or the weighted average reliability to the basic reliability of the source of information firstly, and then a variety of fusion methods are used to calculate, but they did not take into account the correlation between sources of information.

Moreover, it makes no practical significance to think over the average source of information as the integration of information sources. Although the average in the process of integration eliminates the unfavorable effected to the results, it also abandoned the information contained in the conflict.

In fact, the two methods of DST and DSmT are highly complementary in essence. If the two are integrated and used in practice, it will improve the performance of the fusion system effectively in different conflict condition.

Due to these priorities, we present a new method for a target classification method by integrating the two methods. The state-of-the-art in target classification is based mostly either on similarity of evidence. By virtue of the concept of similarity of evidence, the similarity between the evidences is calculated, and then the DST fusion result and DSmT fusion result are integrated according to the similarity, together with an adaptive evidence fusion being done.

The rest part of this paper is as follows: Section II analyses the evidence theory and defines evidence-similarity. Section III proposes the target classification method based on evidence-similarity and explains fusion structure of the multi-sensor system. Section IV shows the experiment on the target classification method, and the conclusion of the research is given in Section V.

II. EVIDENCE THEORY ANALYSIS AND SIMILARITY OF EVIDENCE

A. Basic of DST

DST evidence theory is a theory based on a non-empty set Θ and function of basic reliability.

Suppose $\Theta = \{\theta_1, \theta_2, \cdots \theta_n\}$ is a finite set (called frame of discernment), which has n elements. The basic belief assignment (bba) in Θ defines a set function. $m(\bullet) : 2^{\Theta} \to [0,1]$, $m(\phi) = 0$ and $\sum\limits_{A \in 2^{\Theta}} m(A) = 1$.

$\forall A \in 2^{\Theta}, m(A)$ means the probability of the proposition A occurrence, which called A's basic reliability.

B. Basic of DSmT

1) General basic belief assignment(gbba)

Suppose the frame of discernment is $\Theta = \{\theta_1, \theta_2, \cdots \theta_n\}$. The general basic belief assignment defines a set function. $m(\bullet): D^{\Theta} \to [0,1]$, $m(\phi) = 0$ and $\sum_{A \in D^{\Theta}} m(A) = 1$.

$\forall A \in D^{\Theta}$, $m(A)$ denotes the probability of the proposition A occurs, which called the general basic reliability of A.

2) Analysis of the PCR series rules

J. Dezert and F. Smarandache have put forward six versions of the proportional conflict redistribution rules (PCR1 ~ PCR6) [2][9]. PCR1 only calculates the total mass of the conflict, and allocates to all non-empty set, but does not consider part of the conflict. PCR2 assigns the total mass of the conflict to non-empty set which is related with conflict by the sum of the column reliability quality, but does not considered part of the conflict either. PCR3 requires at least a non-empty set between the focal elements, and its column reliability assignment can not be zero. It redistributes the part of the conflict by the proportion of their respective non-empty set reliability quality in the total reliability quality. PCR4 is improved further based on PCR3; it distributes the part of the conflict to all collections related with the conflict, which is more accurate. PCR5 distributes the part of conflict to all sets which is related with the conflict. The distribution effect is the most precise but the calculation is the most complex. The latest PCR6 adopts the form that do a summation between the evidences, so the calculation of PCR6 is small in dealing with multi-evidence fusion. The method is fit for the real-time processing system [9]. Considering the factors of computational complexity, the accuracy of the results, system responding time and other parameters, this paper selects PCR6 fusion rule when the PCR rules are applied.

PCR6 rule separates parts of the conflict that the different data sources happen to the same assumption, which makes the distribution of the conflict become reasonable and accurate. The PCR6 rule used to deal with two evidences is defined as follows.

$\forall (X \neq \varphi) \in G^{\Theta}$ (G^{Θ} denotes the difference models)

$$m_{PCR6}(X) =$$
$$m_{12}(X) + \sum_{\substack{X_i \in G^{\Theta} \setminus \{X\} \\ c(X_i \cap X) = \varphi}} \left[\frac{m_1(X)^2 m_2(X_i)}{m_1(X) + m_2(X_i)} + \frac{m_2(X)^2 m_1(X_i)}{m_2(X) + m_1(X_i)} \right] \quad (1)$$

where $m_{12}(X) = \sum_{X_i \cap X_j = X, X_i, X_j \in G^{\Theta}} m_1(X_i) m_2(X_j) \cdot$

PCR6 rule has good performance in dealing with high conflict evidence. But the reliability of PCR6 rule is lower than Dempster combination rules due to the PCR6 rule referring to many focal elements in dealing with low conflict evidence. So PCR6 rule's performance is not as good as Dempster combination rules in dealing with low conflict evidence.

C. Evidence-Similarity

The correlation between the evidences determines the extent of evidence source supported by others. The similarity between the evidence is judged by the angle and distance in common. The angle selected as the similarity of the evidence is more reasonable than the distance. The distance in computing the similarity of the evidence overvalues the role of the cardinal, what leads to unreasonable result. According to the concept of the vector angle, Evidence-Similarity solves the problem. Therefore, Evidence-Similarity can show the comprehensive effect of the focal element between the two evidences and the basic belief assignment, which shows the difference between the evidences. Therefore, this paper proposes an approach named evidence-similarity based on the angle to analyze the similarity between evidences. Evidence-Similarity is based on the angel of two evidence vectors, and the length of the vector is not important. The similarity between two vectors is measured by the cosine. The definition is as follows.

Definition: suppose that the Θ is the frame of discernment with n independent propositions. $m_1, m_2 \cdots\cdots m_n$ is the gbba in Θ. Evidence-Similarity between m_1 and m_2 is expressed as

$$S_{12}(m_1, m_2) = \frac{\langle m_1, m_2 \rangle}{\sqrt{\|m_1\|^2 \bullet \|m_2\|^2}} \quad (2)$$

where $\|m\|^2 = \langle m, m \rangle$. $\langle m_1, m_2 \rangle$ is the inner product of the vector m_1 and m_2.

$$\langle m_1, m_2 \rangle = \sum_{i=1}^{D^{\Theta}} \sum_{j=1}^{D^{\Theta}} m_1(X_i) m_2(X_j) d(i, j), \ X_i, X_j \in D^{\Theta} \quad (3)$$

Put (3) in (2),
$$S_{12}(m_1, m_2) =$$

$$\frac{\sum_{i=1}^{D^{\Theta}} \sum_{j=1}^{D^{\Theta}} m_1(X_i) m_2(X_j) d(i, j)}{\sqrt{\{\sum_{i=1}^{D^{\Theta}} \sum_{j=1}^{D^{\Theta}} m_1(X_i) m_1(X_j) d(i, j)\} \bullet \{\sum_{i=1}^{D^{\Theta}} \sum_{j=1}^{D^{\Theta}} m_1(X_i) m_2(X_j)\} d(i, j)}} \quad (4)$$

where $d(i, j) = d(j, i) = \frac{|X_i \cap X_j|}{|X_i \cup X_j|} \ X_i, X_j \in D^{\Theta}$.

III. TARGET CLASSIFICATION METHOD BASED ON EVIDENCE-SIMILARITY

A. Target Classification Method

For target classification of the multi-sensor system, the proposition is the kinds of target, and the evidence is the judgment result of the target's kinds which is obtained by the measurement and processing in the multi-sensor system. The evidences are used to construct the corresponding basic probability distribution function, what give all propositions (including the frame of discernment) reliability. The basic probability distribution function and the corresponding frame

of discernment are combined into a body of evidence. So each sensor is equivalent to a body of evidence. And the essence of multi-sensor data fusion is that a new body of evidence is complicated by the several of evidences using the fusion rules in the same frame of discernment. In other words, a total basic reliability is merged by the basic reliability of difference evidence with the fusion rules. The new evidence expresses the information obtained by the data fusion. And then make decisions based on the decision rules.

In case of low conflict situation, the effect of data fusion and classification by DST works well. The computation increases greatly because of the introduction of focal element's intersection by DSmT, which makes the efficiency of the classification is lower than DST. In case of high conflict situation, DSmT fusion and classification can effectively resolve the problem which the contradiction focal element can not be combined in DST, avoiding appearance of the counterintuitive conclusions due to the DST classification method. Therefore it is difficult to use a single classification method to fuse the evidences in the actual circumstances. The target classification method in the paper integrates the two results of the DST fusion method and the DSmT fusion method by the similarity of the evidences. DST fusion uses Dempster combination rules, and DSmT select PCR6 as the fusion rules. Figure 1 shows the flow chart of the multi-sensor target classification method based on evidence-similarity.

The steps of the target classification based on evidence-similarity are given as follows.

Step1: In the n sensors system at time t, all evidence gbba is got, and the evidence-similarity $S_n(\bullet)$ is computed by (4) combined with the fusion construction of the multi-sensor system.

Step2: According to the Dempster fusion rule, the evidence fusion result is $m_{DS}^n(\bullet)$ at time t;

Step3: According to the PCR6 fusion rule in DSmT, the evidence fusion result is $m_{PCR6}^n(\bullet)$ at time t;

Step4: On the basis of the evidence-similarity, combined with the fusion results of the two methods, the intersection synthetic result is as follows.

$$m^n(X) = S_n(\bullet) \times m_{PCR6}^n(\bullet) + [1 - S_n(\bullet)] \times m_{DS}^n(\bullet)$$

Step5: A cycle synthesis of the two fusion results by the new evidences is done at time t+1 to form a dynamic fusion. And the dynamic classification results are obtained in accordance with the decision rules.

B. Fusion structure of the multi-sensor system

In the multi-sensor data fusion system, the information sources increased lead to the data needed to be fused increasing largely. The method needs to calculate the similarity between two evidences. So the fusion computation method of multi-evidence in the paper adopts the structure of the evidence recursive.

The key point of the method is the combination between the Dempster fusion rule of DST theory and the PCR6 fusion rule of DSmT theory through the similarity of the evidences the fusion structure of multi-sensor system evidence is illustrated in Fig. 2. The belief assignment of two sensors is fused through Dempster fusion rule and PCR6 fusion rule respectively. Then according to the belief assignment of two sensors, evidence-similarity $S(\bullet)$ is computed. Integrating with the fusion results by Dempster fusion rule and PCR6 fusion rule, the target classification result $m^n(\bullet)$ is calculated.
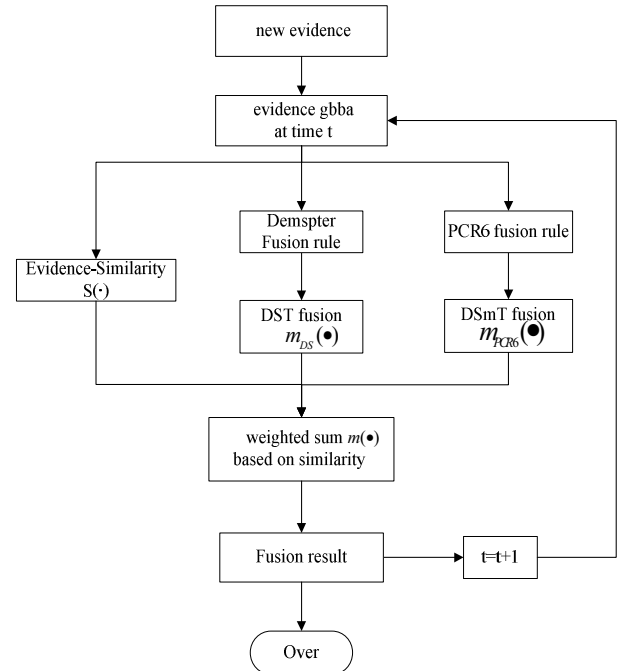

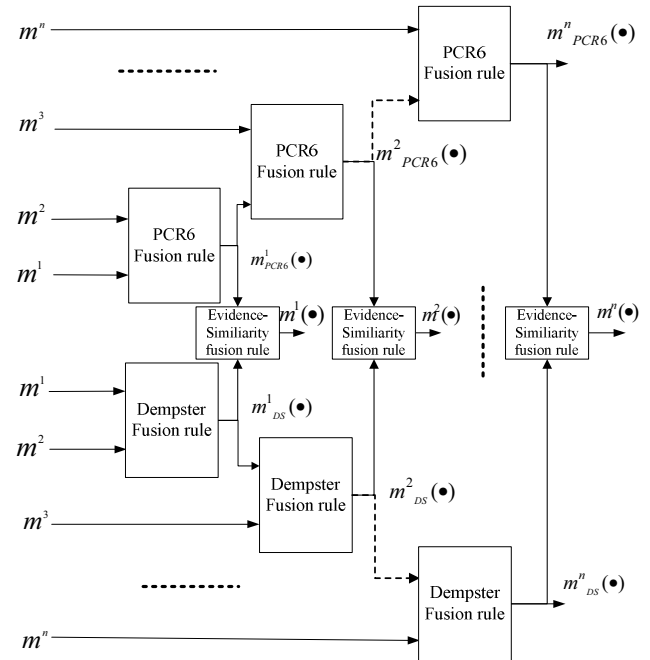Fig.1.Flow chart of the target classification method

Fig.2. Fusion structure of multi-sensor system

Because the fusion structure of multi-sensor system uses the recursive structure, according to (4), the evidence-similarity $S_{12}(X)$ between m_1 and m_2 in gbba is calculated. Under the rules of the PCR6 fusion rule in DSmT theory, the fusion result of m_1 and m_2 is $m^1_{PCR6}(\bullet)$. When the m_3 is in, the new evidence-similarity is shown as follows.

$$S_{13}(m^1_{PCR6}(\bullet),m_3) = \frac{\left\langle m^1_{PCR6}(\bullet),m_3 \right\rangle}{\sqrt{\left\| m^1_{PCR6}(\bullet) \right\|^2 \bullet \left\| m_3 \right\|^2}} \quad (5)$$

Simultaneously, on the basis of the recursive structure, the evidence-similarity between m_n and m_{n+1} is $S_{1n}(m^{n-2}_{PCR6}(\bullet),m_n)$.

IV. EXPERIMENT ON THE TARGET CLASSIFICATION METHOD

In order to verify the availability of the method proposed in the paper, the kinds of vehicle category used in the experiment are car, bus and unknown. Five sensors are placed in different positions of the road to get vehicle information. The five sensors include a sound sensor, a magnetic sensor and three vibration sensors. In addition, the corresponding gbba of the five sensors are m1, m2, m3, m4 and m5. In the experiment, the targets may be car(C), bus(B) and unknown(N). So the Θ ={C, B, N}, and target classification probability are m(C), m(B) and m(N).

The experiments are conducted on a straight road that is 2-kilometer long and 12-meter wide. The surface of the road is reinforced concrete. The sensor is properly installed to ensure that its sensitive axis is parallel with the directions of moving vehicles. The vehicles pass the sensor within a distance of three meters to ensure that the vehicles are in the detection range of the sensor. The sensor signal is sampled at the frequency of 2000Hz. The structure of the detection system and the sensor installation diagram are shown in Fig. 3 and Fig. 4, respectively.
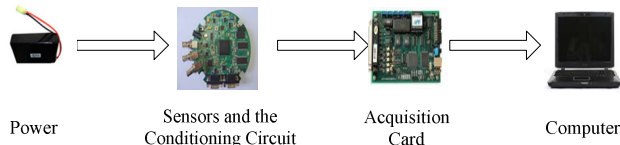

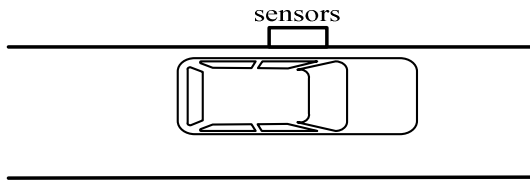Fig. 3 Structure of the detection system

Fig. 4 Sensor installation diagram

In order to show the effect of the method, the classification results by Dempster fusion rule, PCR6 fusion rule and evidence-similarity fusion rule are compared in the condition of low and high conflict respectively.

Two experiments have been done. Table 1 is the basic probability assignment function at time t in high conflict situation in one experiment. The data of the 2nd sensor supports that the target is bus(B), and others support that the target is car(C). Table 2 is the basic probability assignment function at time t in low conflict situation in the other experiment. The data of all sensors support that the target is car(C). Table 3 and 4 are the comparison of the classification results in high and low conflict situations respectively.

TABLE I. BASIC PROBABILITY ASSIGNMENT FUNCTION OF THE CANDIDATE TARGET OBTAINED BY SENSORS (HIGH-CONFLICT EXAMPLE)

Target style	Evidence				
	m1	m2	m3	m4	m5
C	0.55	0	0.6	0.5	0.55
B	0.2	0.85	0.1	0.1	0.2
N	0.25	0.15	0.3	0.4	0.25

TABLE II. BASIC PROBABILITY ASSIGNMENT FUNCTION OF THE CANDIDATE TARGET OBTAINED BY SENSORS (LOW-CONFLICT EXAMPLE)

Target style	Evidence				
	m1	m2	m3	m4	m5
C	0.5	0.8	0.6	0.55	0.5
B	0.2	0	0.1	0.1	0.2
N	0.3	0.2	0.3	0.35	0.3

TABLE III. COMPARISON OF THE CLASSIFICATION RESULT IN HIGH CONFLICT

		m1～m2	m1～m3	m1～m4	m1～m5
Dempster Fusion rule	m(C)	0	0	0	0
	m(B)	0.8432	0.6058	0.3354	0.2561
	m(N)	0.1568	0.3942	0.6646	0.7439
PCR6 Fusion rule	m(C)	0.2238	0.3805	0.5206	0.5923
	m(B)	0.6855	0.4523	0.2342	0.1725
	m(N)	0.0907	0.1672	0.2452	0.2352
Evidence similarity fusion rule	m(C)	0.1255	0.3365	0.5745	0.7253
	m(B)	0.7503	0.4647	0.1933	0.0924
	m(N)	0.1242	0.1988	0.2322	0.1823

From the Table 3, in the high conflict situation, the result shows that Dempster fusion rule comes with the counterintuitive result, when the target is car, it is mistakenly classified to unknown(N). The second evidence m2 has the vote power, no amount of evidences supporting have been rejected. Dempster fusion rule can not handle with the high conflict evidence. PCR6 fusion rule can get reasonable result and exclude the impact of the "wrong" evidence, and the probability supporting the target is car is 0.5923. The probability of Evidence-Similarity fusion rule support that the target is car reaches 0.7253, which is higher than PCR6 fusion rule. So Evidence-Similarity fusion rule has good effect in the high conflict situation.

TABLE IV. COMPARISON OF THE CLASSIFICATION RESULT IN LOW CONFLICT

		m1～m2	m1～m3	m1～m4	m1～m5
Dempster Fusion rule	m(C)	0.9248	0.9505	0.9712	0.9839
	m(B)	0	0	0	0
	m(N)	0.0752	0.0495	0.0288	0.0161
PCR6 Fusion rule	m(C)	0.8514	0.8395	0.8115	0.7893
	m(B)	0.0451	0.0223	0.0214	0.0552
	m(N)	0.1035	0.1382	0.1671	0.1555
Evidence similarity fusion rule	m(C)	0.9354	0.9325	0.9486	0.9542
	m(B)	0.7503	0.4647	0.1933	0.0924
	m(N)	0.1242	0.1988	0.2322	0.1823

From the table 4, in the low conflict example, the effect of Dempster fusion rule is good. When the target is car, and the probability that Dempster fusion rule support the target is car reaches 0.9839, so it is fit for the low conflict situation. But the adding conflict focal elements in PCR6 fusion rule make the reliability decreased. And the probability for car(C) is only 0.7893. The probability of Evidence-Similarity fusion rule support that the target is car reaches 0.9542, which is lower 0.03 than Dempster fusion rule, and the effect is satisfactory.

The two examples show that Dempster fusion rules in dealing with high conflict situation and the PCR6 fusion rule in dealing with low conflict situation have obvious flaws, but the fusion rule based on evidence-similarity presented in the paper has good effect in handling with different levels of conflict.

V. CONCLUSION

The paper presents a target classification method based on the similarity of evidence. It makes the similarity of evidence as the weight of interactive synthetic of DST fusion result and DSmT fusion result. This method can not only get better classification effect under low conflict situation, but also can effectively resolve the classification problem in high conflict situation. Experimental results show that the method can achieve good target classification rate. The method was applied to classify vehicles in this paper. And its application can be extend to many other fields But this method needs to calculate the similarity of the evidence, which increases the amount of computation. This is what we need to study.

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