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Research Article

An Improved Method for Multisensor High Conflict Data Fusion

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Dempster-Shafer evidence theory can effectively process imperfect information and is widely used in a data fusion system. However, classical Dempster-Shafer evidence theory involves counter-intuitive behaviors with the data of multisensor high conflict in target identification system. In order to solve this problem, an improved evidence combination method is proposed in this paper. By calculating the support degree and the belief entropy of each sensor, the proposed method combines conflict evidences. A new method is used to calculate support degree in this paper. At the same time, inspired by Deng entropy, the modified belief entropy is proposed by considering the scale of the frame of discernment (FOD) and the relative scale of the intersection between evidences with respect to FOD. Because of these two modifications, the effect has been improved in conflict data fusion. Several methods are compared and analyzed through examples. And the result suggests the proposed method can not only obtain reasonable and correct results but also have the highest fusion reliability in solving the problem of high conflict data fusion.

1. Introduction

The cooperative detection system with multisensor has been widely used in aerospace, medical rescue, environmental monitoring, national defense, and military fields. The communication, sensing, and processing ability of a single sensor is limited by various factors, and it is difficult to meet the needs of network applications. The cooperative detection system with a multisensor can solve the problems existing in the detection system with a single sensor, such as the longer positioning time, big position error, and discontinuous target track. However, the information obtained from different sensors may be uncertain, fuzzy, or even conflict, so the direct fusion of multisensor data may cause decision-making difficulties. Therefore, it is necessary to analyze and measure the effectiveness of data fusion. This paper focuses on multisensor high conflict data fusion.

Dempster-Shafer evidence theory [1–4] is a useful theory for modeling and processing with uncertainty information, which is regarded as an extension of Bayesian theory. It has the wide range of applications and has been extensively studied in many fields, such as decision-making [5, 6], risk evaluation [7, 8], and classification [9, 10]. Although D-S evidence theory is a useful mathematical theory for information fusion in real applications, the classical Dempster's rule of combination and the basic probability assignment (BPA) cannot handle conflict sensor data fusion directly, which may lead to counter-intuitive behaviors [11–13]. In order to deal with the impact of the high conflict, two main streams of methods have been proposed. The first class is to modify the classical Dempster's combination rule (DCR) [14]. In Yager's combination rule [15], the probability of conflicted evidences is completely distributed to the unknown proposition. Li et al. [16] thought that the evidence's conflicting probability is distributed to every proposition according to its average supported degree. Su et al. [17] introduce a new rule to combine dependent bodies of evidence based on the concept of joint belief distribution. The second class is to focus on the pretreatment for BPA. Tang et al. [18] proposed a weighted belief entropy based on Deng entropy to quantify the uncertainty of uncertain information. Lin et al. [19] used Euclidean distance to characterize the differences between different pieces of evidence. Zhang and Deng [20] proposed a method based on

DEMATEL that take the weight of each evidence into consideration. Although so many methods have been proposed, there is still space for making further progress.

It is necessary to quantify the uncertainty before further information processing. As an uncertainty measure of information volume in a system or process, Shannon entropy [21] plays a central role in information theory, but there are still some limitations for measuring the uncertainty of Dempster-Shafer evidence theory [22]. For measuring the uncertainty of Dempster-Shafer evidence theory, Shannon entropy cannot be applied because a mass function is a generalized probability [23]. Therefore, some other methods are proposed for measuring the uncertainty of Dempster-Shafer evidence theory such as Dubois and Prade's weighted Hartley entropy [24], Hohle's confusion measure [25], Klir and Ramer's discord [26], Klir and Parviz's strife [27], Deng entropy [28], Pan and Deng's entropy [29], Cui et al.'s entropy [30] and Li et al.'s entropy [31]. However, for some cases, these entropy theories cannot effectively measure the uncertainty of Dempster-Shafer evidence theory.

The algorithm has a great impact on the calculation result and efficiency, such as [32–35]. In order to obtain better data fusion result when deal with high conflict data from multisensor, based on support degree and belief entropy, a new method of high conflict data fusion is introduced. The proposed method can avoid the influence of conflict evidence and improve the information validity of the fusion result by calculating the support degree and the belief entropy of each sensor. The credibility degree of every evidence is obtained by considering these two elements together. At the same time, this method can improve the performance of measuring belief entropy by considering the scale of the frame of discernment (FOD) and the influence of the intersection between evidences on uncertainty.

The remainder of this paper is organized as follows. In Section 2, some concepts about Dempster-Shafer evidence theory, Shannon entropy, and some uncertainty measures in Dempster-Shafer framework are briefly introduced. The improved Deng entropy is proposed in Section 3. The proposed method based on improved Deng entropy for multisensor data fusion is presented in Section 4. In Section 5, numerical examples are presented, as well as a comparative study between the new method and some other methods. Finally, we conclude this paper in Section 6.

2. Preliminary

In this section, some preliminaries are briefly introduced in this section, including Dempster-Shafer evidence theory [2–4], Shannon Entropy [21], Deng entropy [28], and some of existing uncertainty measures in Dempster-Shafer framework [24–27, 36, 37].

2.1. Dempster-Shafer Evidence Theory

Definition 1. Let Θ be a set of mutually exclusive and collectively exhaustive events, indicated by

$$\Theta = \{\theta_1, \theta_2, \cdots, \theta_i, \cdots, \theta_n\}. \tag{1}$$

Definition 2. A basic probability assignment (BPA) (also called mass function) is a mapping for elements in 2^{Θ} to the interval $[0, 1]$, formally defined by

$$m : 2^{\Theta} \longrightarrow [0, 1], \tag{2}$$

which satisfies the following conditions [1, 2]:

$$m(\varnothing) = 0, \sum_{A \subseteq \Theta} m(A) = 1, \tag{3}$$

where A is a subset of Θ; if $m(A) > 0$, the A in the FOD is called a focal element and the set of all the focal elements and their associated mass value is named Body of Evidence (BOE).

Definition 3. In Dempster-Shafer evidence theory, two BPAs are indicated by m_1 and m_2. Focal elements of m_1 and m_2 are described as A and B, respectively. They can be combined by Dempster's rule of combination as follows [1, 2]:

$$m(C) = m_1(A) \oplus m_2(B) = \frac{1}{K} \sum_{A \cap B = C} m_1(A) \cdot m_2(B), \tag{4}$$

where $C \neq \varnothing$ and K is a normalization constant, which represents the degree of conflict between m_1 and m_2, defined as follows [1, 2]:

$$K = \sum_{A \cap B \neq \varnothing} m_1(A) \cdot m_2(B) = 1 - \sum_{A \cap B = \varnothing} m_1(A) \cdot m_2(B). \tag{5}$$

2.2. Shannon Entropy. Shannon entropy [21] is the quantification of the expected value of the information in a message, which is first developed to measure the uncertainty of information volume in a system.

Definition 4. Information entropy is denoted as H; Shannon entropy is defined as follows [21]:

$$H = -\sum_{i=1}^{n} p_i \log_b p_i, \tag{6}$$

where n is the number of basic states and p_i is the probability of state i. The value of b is determined by the unit of information entropy, and the unit of information entropy is bit when $b = 2$.

2.3. Deng Entropy. Deng entropy [21] is proposed by Deng Yong, which is a generalization of Shannon entropy in Dempster-Shafer framework; if the information is modeled in the framework of a probability theory, Deng entropy can be degenerated to Shannon entropy.

Definition 5. Deng entropy, denoted as E_d, is defined as follows [21]:

$$E_d(m) = -\sum_{A \subseteq X} m(A) \log_2 \frac{m(A)}{2^{|A|} - 1}, \tag{7}$$

Table 1: Some of existing uncertainty measures in Dempster-Shafer framework.

Name	Formula
Dubois & Prade's weighted Hartley entropy [24]	$I_{\mathrm{DP}}(m) = \sum_{A \subseteq X} m(A) \log_2 \lvert A \rvert$
Hohle's confusion measure [25]	$C_{\mathrm{H}}(m) = -\sum_{A \subseteq X} m(A) \log_2 Bel(A)$
Klir & Ramer's discord [26]	$D_{\mathrm{KR}}(m) = -\sum_{A \subseteq X} m(A) \log_2 \sum_{B \subseteq X} m(B) \frac{\lvert A \cap B \rvert}{\lvert B \rvert}$
Klir & Parviz's strife [27]	$E_{\mathrm{KR}}(m) = -\sum_{A \subseteq X} m(A) \log_2 \sum_{B \subseteq X} m(B) \frac{\lvert A \cap B \rvert}{\lvert A \rvert}$
Pan & Deng's entropy [29]	$P_{\mathrm{Bel}}(m) = -\sum_{A \subseteq 2^{\theta}} \frac{\mathrm{Bel}(A) + Pl(A)}{2} \log_2 \frac{\mathrm{Bel}(A) + Pl(A)}{2^{\lvert A \rvert} - 1}$
Cui et al.'s entropy [30]	$E(m) = -\sum_{A \subseteq X} m(A) \log_2 \left(\frac{m(A)}{2^{\lvert A \rvert} - 1} e^{\sum_{\substack{B \subseteq X \\ B \neq A}} (\lvert A \cap B \rvert)/\left(2^{\lvert X \rvert} - 1\right)} \right)$
Li et al.'s entropy [31]	$E_x(m) = -\sum_{A \subseteq \Theta} m(A) \log_2 \left(\frac{m(A)}{2^{\lvert A \rvert} - 1} e^{(\lvert A \rvert - 1)/\left(2^{\lvert X \rvert} - 1\right)} \right)$

Table 2: Comparison between the improved Deng Entropy and other methods with a variable proposition T.

Cases	Deng entropy	Cui et al.'s entropy	Wang et al.'s entropy	Weighted belief entropy	Improved Deng entropy
$T = 1$	2.6623	2.6622	2.5623	2.5180	2.5180
$T = 1, 2$	3.9303	3.9301	3.7703	3.7090	3.1461
$T = 1, 2, 3$	4.9082	4.908	4.6315	4.6100	4.5090
$T = 1, 2, 3, 4$	5.7878	5.7876	5.3945	5.4127	5.2204
$T = 1, 2, 3, 4, 5$	6.6256	6.6264	6.1156	6.1736	5.8899
$T = 1, 2, \cdots, 6$	7.4441	7.4438	6.8174	6.9151	6.1271
$T = 1, 2, \cdots, 7$	8.2352	8.2529	7.5666	7.6473	6.8496
$T = 1, 2, \cdots, 8$	9.0578	9.0574	8.3111	8.3749	7.3254
$T = 1, 2, \cdots, 9$	9.8600	9.8596	9.0534	9.1002	8.0411
$T = 1, 2, \cdots, 10$	10.6612	10.6607	9.7945	9.8244	8.7556
$T = 1, 2, \cdots, 11$	11.4617	11.4613	10.5351	10.5480	9.4696
$T = 1, 2, \cdots, 12$	12.2620	12.2615	11.2753	11.2714	10.183
$T = 1, 2, \cdots, 13$	13.0622	13.0616	12.0155	11.9946	10.897
$T = 1, 2, \cdots, 14$	13.8622	13.8616	12.7556	12.7177	11.610

where X is the FOD, focal elements of the mass function of X are described as A and B, and $\lvert A \rvert$ stands for the cardinality of A. Some uncertainty measures in Dempster-Shafer framework are shown in Table 1. But all of them are not entirely satisfactory. Deng entropy is proposed, which satisfies five axiomatic requirements: range, probabilistic consistency, set consistency, additivity, and subadditivity. Besides, Deng entropy can increase monotonously with the rise of the size of focal sets for mass functions in Dempster-Shafer framework.

3. The Proposed Uncertainty Measure

A new method is presented in this section. In the framework of Dempster-Shafer evidence theory, the uncertain information can be modeled not only as a mass function but also as the source of uncertainty and the number of elements in the FOD. Deng entropy does not consider the cardinality of the FOD and the influence of the intersection between evidences on the uncertainty in BPA. In order to address more available information in the evidence, the improved Deng entropy is proposed.

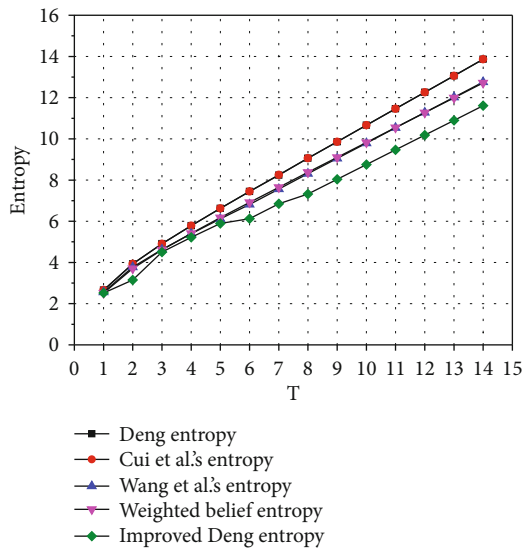

Figure 1: Comparison between the improved Deng Entropy and other methods.

3.1. Improved Deng Entropy

Definition 6. Improved Deng entropy, denoted as E_{Id}, is defined as follows:

$$E_{Id} = -\sum_{A \subseteq X} m(A) \log_2 \frac{m(A)}{2^{|A|} - 1} e^{\left(\left(\sum_{\substack{B \subseteq X \\ B \neq A}} |A \cap B| \right) / |X| \right)}, \tag{8}$$

where X is a FOD, $|X|$ is the number of elements in X, A is the focal element of the mass function, $|A|$ is the cardinality of the A, and $|A \cap B|$ is the cardinality of the intersection of A and B. Compared with Deng entropy, Hohle's confusion measure [25], Pan and Deng's entropy [29], the improved Deng entropy addresses more information in BOE, including the scale of FOD, denoted as $|X|$, and the relative scale of the intersection between evidences with respect to FOD, denoted as $|A \cap B|/|X|$. What is more, by involving the scale of FOD in the improved Deng entropy, the difference among different BOEs can be effectively quantified even if the same BPA is assigned to different FODs. Cui et al.'s entropy [30] and Li et al.'s entropy [31] consider the scale of FOD and the intersection between evidences. However, when the scale of FOD is large, the influence factor of the number of conditions for the intersection between evidences will be greatly reduced for the measurement of the uncertainty of the evidence.

3.2. Numerical Example. In order to show the rationality and the merit of the proposed belief entropy, recall the example in [28].

Example 7. Given a frame of discernment X with 15 elements which are denoted as element 1, element 2, etc.,

$$m(\{3,4,5\}) = 0.05, m(\{6\}) = 0.05, m(T) = 0.8, m(X) = 0.1, \tag{9}$$

where T is a variable change subset and the number of the element of T is changed from element 1 to element 14. Table 2 lists various Deng entropies, Cui et al.'s entropies [30], Wang et al.'s entropy [38], weighted belief entropy [18] and improved Deng entropies when T changes, which is also graphically shown in Figure 1.

From Table 2 and Figure 1, the results show that the improved Deng entropy is smaller than Wang et al.'s entropy, weighted belief entropy, Deng entropy, and Cui et al.'s entropy. This is because more information in the BOE is taken into consideration. That is to say, improved Deng entropy has less information loss than other uncertainty methods, so the uncertain degree of information is reduced.

In Figure 1, the entropy of m increases almost linearly with the rise of the size of subset T, measured by using other different uncertainty measures. But T and $\{3,4,5\}$ begin to have intersection when $T = \{1,2,3\}$, $T = \{1,2,3,4\}$, and $T = \{1,2,3,4,5\}$; the uncertain degree of information would increase, which means the uncertainty degree of mass function m should grow faster; only improved Deng entropy can show that the proposed improved Deng entropy takes advantage of more valuable information in BOE, which ensures it to be more reasonable for uncertainty measures in Dempster-Shafer framework.

4. The Proposed Conflict Data Fusion Method Based on Improved Deng Entropy

A new method for conflict data fusion is presented in this section which is also shown in Figure 2. First, calculate first weighted factor based on the support degree and the second weighted factor based on the improved Deng entropy. The two weighted factors measure the evidence from different angles. The first weighted factor focuses on the conflict of each evidence to reduce the influence of conflict. And the second weighted factor measures uncertain degree of information. Then, the two weighted factors are used to calculate the credibility degree of each BOE. After that, we use the credibility degree to modify the evidence. Finally, data fusion can be obtained by calculating Dempster's rule of combination. The process steps are analyzed in detail.

Step 1. Calculate the first weighted factor of each BOE. In the proposed method, the conflict among different evidences transformed and measured firstly. Suppose an evidence set in the same focal discernment: $M = \{m_i \mid i = 1, 2, \cdots, n\}$ with $\{F_1, F_2, \cdots, F_n\}$; the conflict k_{ij} between m_i and m_j is

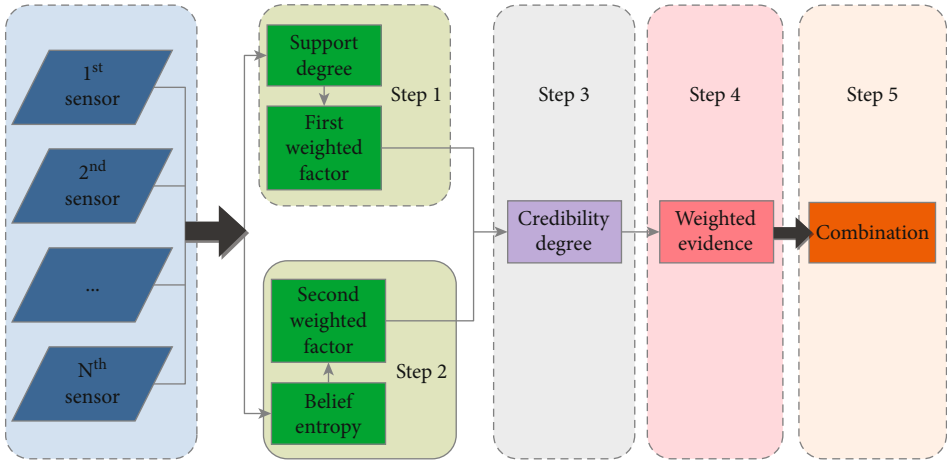

Figure 2: Flowchart of the proposed method.

measured as follows:

$$k_{ij} = \sum_{\substack{A_i \in F_i \\ A_j \in F_j \\ A_i \cap A_j = \varnothing}} m_i(A_i) \cdot m_j(A_j) = 1 - \sum_{\substack{A_i \in F_i \\ A_j \in F_j \\ A_i \cap A_j \neq \varnothing}} m_i(A_i) \cdot m_j(A_j). \tag{10}$$

As we all know, the greater the conflict of an evidence with others, the smaller the support degree of the evidence. Based on this common scene, the support degree is proposed.

Definition 8. The support degree of m_i is defined as

$$\varepsilon_i = e^{-k_i}, \qquad k_i = \frac{1}{n(n-1)/2} \sum_{i \neq j} k_{ij}, \quad n > 2, \tag{11}$$

where k_i is the conflict of evidence m_i with all other evidences. And then, the weight of the evidence m_i can be denoted as

$$w_1(m_i) = \frac{\varepsilon_i}{\sum_{i=1}^{n} \varepsilon_i}. \tag{12}$$

Step 2. Calculate the second weighted factor of each BOE. In the proposed method, the belief entropy of different evidences was transformed by the improved Deng entropy. According to Equation (8), the second weighted factor is calculated and shown as follows:

$$w_2(m_i) = \frac{E_{Id}(m_i)}{\sum_{i=1}^{n} E_{Id}(m_i)}. \tag{13}$$

Step 3. Calculate the credibility degree of each BOE. The credibility degree of the evidence m_i is proposed as follows:

$$\mathrm{Crd}(m_i) = \frac{w_1(m_i) w_2(m_i)}{\sum_{i=1}^{n} w_1(m_i) w_2(m_i)}. \tag{14}$$

$\mathrm{Crd}(m_i)$ is the final weight of the evidence m_i which appears satisfying $\sum_{i=1}^{n} \mathrm{Crd}(m_i) = 1$.

Step 4. Calculate the weighted mass functions. After that, we use the weight to modify the evidence:

$$m_w(A) = \sum_{i=1}^{n} \mathrm{Crd}(m_i) m_i(A). \tag{15}$$

For each proposition A in the BOE, $m_w(A)$ is the final weighted mass function of each proposition, which is used for the final data fusion. As can be seen, the credibility degree of evidence would be higher and has more effect on the final combination result if the evidence is supported by other evidences or have a higher belief entropy and vice versa.

Step 5. Data fusion with Dempster's rule of combination. Finally, data fusion can be obtained by calculating Dempster's rule of combination with $(n-1)$ times:

$$m(A) = \left(\left(\left(m_w \oplus m_w\right)_1 \oplus m_w\right)_2 \oplus \cdots \oplus m_w\right)_{(n-1)}(A), \quad n > 2, \tag{16}$$

where $m(A)$ is the final fusion result.

The time complexity of the first step is $O(n^2)$, and the second, third, fourth, and fifth steps are $O(n)$. Therefore, the time complexity of the proposed method is $O(n^2)$.

5. Experiment

In this section, by comparing with the existing methods, the rationality and effectiveness of proposed multisensor data fusion method are shown.

Example 9 (see [39]). In a multisensory-based automatic target recognition system, suppose the real target is o_1. From five different sensors, the system has collected five bodies of evidence shown as Table 3.

(i) The first weighted factor is obtained:

$$k_{12} = \sum_{\substack{A_1 \in F_i \\ A_2 \in F_j \\ A_1 \cap A_2 = \varnothing}} m_1(A_1) \cdot m_2(A_2) = 0.709,$$

$$k_{13} = \sum_{\substack{A_1 \in F_i \\ A_3 \in F_j \\ A_1 \cap A_3 = \varnothing}} m_1(A_1) \cdot m_3(A_3) = 0.742,$$

$$k_{14} = \sum_{\substack{A_1 \in F_i \\ A_4 \in F_j \\ A_1 \cap A_4 = \varnothing}} m_1(A_1) \cdot m_4(A_4) = 0.746,$$

$$k_{15} = \sum_{\substack{A_1 \in F_i \\ A_5 \in F_j \\ A_1 \cap A_5 = \varnothing}} m_1(A_1) \cdot m_5(A_5) = 0.725,$$

$$k_{23} = \sum_{\substack{A_2 \in F_i \\ A_3 \in F_j \\ A_2 \cap A_3 = \varnothing}} m_2(A_2) \cdot m_3(A_3) = 0.937,$$

$$k_{24} = \sum_{\substack{A_2 \in F_i \\ A_4 \in F_j \\ A_2 \cap A_4 = \varnothing}} m_2(A_2) \cdot m_4(A_4) = 0.910,$$

$$k_{25} = \sum_{\substack{A_2 \in F_i \\ A_5 \in F_j \\ A_2 \cap A_5 = \varnothing}} m_2(A_2) \cdot m_5(A_5) = 0.910,$$

$$k_{34} = \sum_{\substack{A_3 \in F_i \\ A_4 \in F_j \\ A_3 \cap A_4 = \varnothing}} m_3(A_3) \cdot m_4(A_4) = 0.552,$$

$$k_{35} = \sum_{\substack{A_3 \in F_i \\ A_5 \in F_j \\ A_3 \cap A_5 = \varnothing}} m_3(A_3) \cdot m_5(A_5) = 0.540,$$

$$k_{45} = \sum_{\substack{A_4 \in F_i \\ A_5 \in F_j \\ A_4 \cap A_5 = \varnothing}} m_4(A_4) \cdot m_5(A_5) = 0.555,$$

$$\varepsilon_1 = e^{-(k_{12}+k_{13}+k_{14}+k_{15})} = 0.053858,$$

$$\varepsilon_2 = e^{-(k_{12}+k_{23}+k_{24}+k_{25})} = 0.031242,$$

$$\varepsilon_3 = e^{-(k_{13}+k_{23}+k_{34}+k_{35})} = 0.062637,$$

$$\varepsilon_4 = e^{-(k_{14}+k_{24}+k_{34}+k_{45})} = 0.063165,$$

$$\varepsilon_5 = e^{-(k_{15}+k_{25}+k_{35}+k_{45})} = 0.065219,$$

$$w_1(m_1) = \frac{\varepsilon_1}{\sum_{i=1}^{n} \varepsilon_i} = 0.195,$$

$$w_1(m_2) = \frac{\varepsilon_2}{\sum_{i=1}^{n} \varepsilon_i} = 0.113, w_1(m_3) = \frac{\varepsilon_3}{\sum_{i=1}^{n} \varepsilon_i} = 0.227,$$

$$w_1(m_4) = \frac{\varepsilon_4}{\sum_{i=1}^{n} \varepsilon_i} = 0.229, w_1(m_5) = \frac{\varepsilon_5}{\sum_{i=1}^{n} \varepsilon_i} = 0.236. \tag{17}$$

According to Table 3, the collection of the evidence m_2 is different from other evidences, which may be caused by many factors such as atrocious weather, enemy's jammer, or the flaws of the sensor itself. The weight of "Bad" evidence m_2 should be the smallest. As can be seen from Table 4, the 2nd sensor has the smallest $w_1(0.113)$ compared with other sensors, which proves that the algorithm proposed in this paper is correct.

(ii) The second weighted factor is calculated as follows, and the calculation results are shown in Table 5.

$$E_{\mathrm{Id}}(m_1) = -\sum_{A \subseteq X} m_1(A) \log_2 \frac{m_1(A)}{2^{|A|}-1} e^{\left(\sum_{\substack{B \subseteq X \\ B \neq A}} |A \cap B|\right) / |X|} = 1.0807,$$

$$E_{\mathrm{Id}}(m_2) = -\sum_{A \subseteq X} m_2(A) \log_2 \frac{m_2(A)}{2^{|A|}-1} e^{\left(\sum_{\substack{B \subseteq X \\ B \neq A}} |A \cap B|\right) / |X|} = 0.4209,$$

$$E_{\mathrm{Id}}(m_3) = -\sum_{A \subseteq X} m_3(A) \log_2 \frac{m_3(A)}{2^{|A|}-1} e^{\left(\sum_{\substack{B \subseteq X \\ B \neq A}} |A \cap B|\right) / |X|} = 1.1937,$$

Table 3: Basic probability assignment of artificial data.

Sensor	BPA			
	m_{o_1}	m_{o_2}	m_{o_3}	m_{o_1,o_3}
1st sensor: $m_1(\cdot)$	0.41	0.29	0.3	0
2nd sensor: $m_2(\cdot)$	0	0.9	0.1	0
3rd sensor: $m_3(\cdot)$	0.58	0.07	0	0.35
4th sensor: $m_4(\cdot)$	0.55	0.1	0	0.35
5th sensor: $m_5(\cdot)$	0.6	0.1	0	0.3

Table 4: The first weighted factor of each BOE.

Sensor	1st sensor	2nd sensor	3rd sensor	4th sensor	5th sensor
w_1	0.195	0.113	0.227	0.229	0.236

Table 5: The second weighted factor of each BOE.

Sensor	1st sensor	2nd sensor	3rd sensor	4th sensor	5th sensor
w_2	0.2086	0.0813	0.2305	0.2491	0.2305

Table 6: Credibility degree of each BOE.

Sensor	1st sensor	2nd sensor	3rd sensor	4th sensor	5th sensor
Crd	0.192	0.042	0.244	0.268	0.254

Table 7: The weighted mass function of artificial data.

Sensor	$m_w(o_1)$	$m_w(o_2)$	$m_w(o_3)$	$m_w(o_4)$
m_w	0.52004	0.16276	0.0618	0.2554

Table 8: Fusion result with different method.

Methods	BPA			
	m_{o_1}	m_{o_2}	m_{o_3}	m_{o_1,o_3}
Dempster's rule	0	0.1442	0.8578	0
Deng et al.'s method [28]	0.9820	0.0039	0.0107	0.0034
Zhang et al.'s method [40]	0.9820	0.0033	0.0115	0.0032
Yuan et al.'s method [41]	0.9886	0.0002	0.0072	0.0039
Tang et al.'s method [18]	0.9895	0.0003	0.0057	0.0045
The proposed method	0.9904	0.0006	0.0033	0.0057

$$E_{\mathrm{Id}}(m_4) = -\sum_{A\subseteq X} m_4(A)\log_2 \frac{m_4(A)}{2^{|A|}-1} e^{\left(\sum_{\substack{B\subseteq X\\ B\neq A}} |A\cap B|\right)/|X|} = 1.2903,$$

$$E_{\mathrm{Id}}(m_5) = -\sum_{A\subseteq X} m_5(A)\log_2 \frac{m_5(A)}{2^{|A|}-1} e^{\left(\sum_{\substack{B\subseteq X\\ B\neq A}} |A\cap B|\right)/|X|} = 1.1939,$$

$$w_2(m_1) = \frac{E_{\mathrm{Id}}(m_1)}{\sum_{i=1}^{n} E_{\mathrm{Id}}(m_i)} = 0.2086,$$

$$w_2(m_2) = \frac{E_{\mathrm{Id}}(m_2)}{\sum_{i=1}^{n} E_{\mathrm{Id}}(m_i)} = 0.0813,$$

$$w_2(m_3) = \frac{E_{\mathrm{Id}}(m_3)}{\sum_{i=1}^{n} E_{\mathrm{Id}}(m_i)} = 0.2305,$$

$$w_2(m_4) = \frac{E_{\mathrm{Id}}(m_4)}{\sum_{i=1}^{n} E_{\mathrm{Id}}(m_i)} = 0.2491,$$

$$w_2(m_5) = \frac{E_{\mathrm{Id}}(m_5)}{\sum_{i=1}^{n} E_{\mathrm{Id}}(m_i)} = 0.2305. \quad (18)$$

(iii) Then the credibility degree of each BOE can be calculated with Equation (14), and the calculation results are shown in Table 6.

(iv) After that, the original BPAs have been modified, and the results are shown in Table 7.

(v) Finally, the classical DCR is used to combine the modified BPA, and the results are shown in Table 8.

The fusion results are presented and listed in Table 8. When conflicting evidence is collected, the classical Dempster's rule cannot reflect the actual distribution of beliefs. The experiment results with the methods in [18, 28, 40, 41] all get a high belief on target o_1; the proposed new method has the highest belief (0.9904) on the recognized target o_1. Therefore, the proposed method is accurate and effective to deal with conflict data from multisensor.

6. Conclusion

In order to obtain better data fusion result when dealing with high conflict data from a multisensor, a new method of high conflict data fusion is introduced. By considering the new method of calculating support degree and the modified belief entropy of every evidence, the proposed method can avoid the influence of high conflict evidence and improve the performance of measuring uncertain degree with BPA. The modified belief entropy considered the scale of the frame of discernment (FOD), and the relative scale of the intersection between evidences with respect to FOD has less information loss than other uncertainty methods. Numerical examples show that the new method can not only obtain reasonable and correct results but also have the highest fusion reliability in solving the problem of high conflict data fusion. The application of the proposed method is not studied in this work; a further study will be focused on the application in multisensor high conflict data fusion.

Data Availability

All data generated or analyzed during this study are included in this article and in the references that were cited at appropriate places within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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