A Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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ABSTRACT The improvement in recognition accuracy of a multi-sensor system is inseparable from the sensors' dynamic reliability, especially in the case of highly conflicting information. Recent research on multi-sensor system has shown that a difficult problem for the system designer is to figure out what factors are crucial in determining the reliability of the sensor. However, the acquisition of sensor reliability is affected by multi-factors in practical applications. In this paper, a novel method for sensor dynamic reliability evaluation based on evidence theory and belief entropy has been developed, aimed at obtaining a reasonable reliability parameter. Through experimental analysis and practical applications, the results indicate that sensor weight distribution and information entropy value could be used as efficient elements for higher recognition rate to improve the robustness and recognition rate of the multi-sensor system.

INDEX TERMS Sensor reliability, belief entropy, evidence theory, target recognition, evidence credibility weight, Deng entropy.

I. INTRODUCTION

Multi-sensor information fusion [1]–[3] technology began to develop since the last century, and it has attracted much attention for its usability in the real world. By using computer technology for helping analyze multi-sensor or multi-source information automatically, information processing can complete the required decisions and make estimations based on some specific criteria [4]. With the continuous development of multi-sensor information fusion technology, a variety of application algorithms have been established. For instance, cluster analysis [5], evidence theory [6], D-S algorithm [7], Z number [8], [9], R number theory [10], [11], D number theory [12]–[14] and fuzzy set [15] are considered as relatively comprehensive methods. Also, in recent years, a newly proposed information fusion method, known as computer intelligence method, contains the concept of gray predication [16], entropy [17], [18], pattern classification [19], and fuzzy set theory [20], [21]. Among these methods, traditional evidence theory has been applied widely to the fusion process. However, it is not fully adapted to the multi-sensor

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system evaluation. As far as the traditional processing method is concerned, it is customary to assume that the reliability of multiple sensors is consistent and most of the attention is drawn on to the step of data fusion. However, in reality, sensor systems may have uncertainty [22] due to sensor accuracy, engine fault [23], [24], or external environment, and so on [25], [26], which might reduce the accuracy of identifying targets. This situation is more serious when only using a single sensor for the coupling and deficiencies of information. Therefore, collective multi-sensor systems tend to be more reliable. For instance, a multi-sensor system which is composed of acoustic sensor, pressure sensor and temperature sensor is superior in identifying the sea target, because each sensor in the system can independently analyze its own obtained data and give the probability of identifying the target. In this way, the recognition result containing sound, pressure and temperature (three indicators) will be better than the single sensor that only identify one indicator. Regardless of the type of sensor, ensuring its reliability is the first consideration. Therefore, in the process of information identification, maximizing the valid identification of sensor reliability is a very critical point. Methods like evidential reasoning [6], [27], [28], classifier fusion [29], [30],

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

IEEE *Access*

belief-rule-base [31], [32], etc. are helpful for making the decision of a multi-sensor system more convincing [33], even in the case of some highly conflicting situation.

Effective modification to information is critical for multi-sensor systems. So, considering the inconsistency of reliability between different sensors, the judgment of the information given by them should be modified correspondingly. Notably, highly reliable sensors should be given higher weight in decision making, while the data given by the sensors with low reliability tend to be modified to a greater extent. Thus, a practical sensor reliability assessment [34] needs to be performed before data fusion. Typically, the assessment is divided into two types based on whether there is accessible prior information [35] in a system. If the prior information is available in the system, which refers to the experience and historical data are derived in advance through the trial of obtaining the sample. In this way, the reliability of the sensor is evaluated based on previous training. For instance, using transferable belief model (TBM) [36], [37], Elouedi *et al.* [38] have developed a method by using a factor to minimize the distance [39] between pignistic probabilities, which are computed form the discounted belief functions [40] and the actual values of the data in a learning set. Then, sensor reliability is assessed by this factor. In order to gain a deeper insight into the process of sensor reliability evaluation, Guo *et al.* [41] improved Elouedi's work by combining two types of evaluation methods. One is known as a static evaluation method, whose static discount factor assigned to the sensor is based on a comparison between its original reading and the actual value of the data. So, the impact on the assessment is determined by extracting the information contained in the actual value of each target. The other is called dynamic evaluation method, the evidence is assessed through adaptive learning in real-time scenarios, but this kind of dynamic reliability is usually highly related to the dynamic performance of sensors. Yang *et al.* [42] used a RIMER method which existing knowledge-base structures are first examined, and knowledge representation schemes under uncertainty are then briefly analyzed.

However, in a real application [43], it is not necessarily achievable to require a multi-sensor system to have a sufficient amount of prior information to determine the accuracy of the sensor. So, the crucial part locates at obtaining the dynamic reliability of each sensor when there is no prior information provided in the system. Just as explained by Guo *et al.*, the dynamic reliability of a sensor is often evaluated based on evidence distance measurements [44], conflict measurements [45], [46], and some other induced dissimilarity measures [47]. Among these methods, the principle of subordinating to the majority [48] is widely used. Mainly, the reliability of sensors depends on their relationship with each other. That is to say; the more compatible a sensor is with other sensors in the system, the more reliable it is. There are several reliability assessment methods [49] based on this principle now. For instance, Schubert [50] introduced the concept of falsity degree as one of the considerations to evaluate

the reliability of data source. Feng *et al.* [51] built a new BRB model with attribute reliability (BRB-r) based on the statistical method which introduces a new calculation method of matching degree. Klein and Colot [52] proposed the calculation of dissent degree between each sensor in the system based on the Jousselme's [53] distance measure, which uses the distance between a BPA (basic probability assignment) and the average BPA to depict the sensor reliability. By combining the first two methods above, Yang *et al.* [40] used the falsity degree given by Schubert to define the divergence metric [54] when estimating the reliability of evidence sources. As we all know, distance as a parameter measures the difference between BPAs effectively, while the conflict coefficient is used to reveal the divergence degree between two belief functions in the process of supporting the target. Namely, the distance and conflict coefficient decrease as the similarity of the two BPAs increases. According to this, Liu *et al.* [55] introduced these two types of dissimilarity into a new measurement method based on Hamacher T-conorm fusion rule. Therefore, its progressive performance is that when measuring the reliability of the information given by the sensor, it considers both the external situation of the difference with other information sources and its inherent reliability factors [56] at the same time.

It is not difficult to find that the existing methods mainly measure the reliability of the sensor by the similarity [57] or dissimilarity between BPAs. Besides, the supporting degree and similarity between two BPAs tend to be explained as the same concept. However, there is still a significant difference between the two. The definition of similarity is symmetric, while the idea of supporting degree is asymmetric. For such a reason, Song *et al.* [58] proposed a method of asymmetric supporting degree measurement for BPAs, and re-improved the technique of evaluating sensor reliability by combining evidence theory and the framework of intuitionistic fuzzy sets (IFSs) [59].

Although Song et al.'s method is able to measure the reliability of each sensor to a certain extent in the system, and effectively identify the target, some defects still need to be improved. In this method, when there is an interference [60] in the multi-sensor system, for example, when the data of a sensor appears to be significantly different, the recognition result is often greatly affected by the influence of the sensor. Therefore, only considering the similarity between BPAs to determine the reliability of the sensor is not comprehensive, due to the lack of judgment on the validity of data [61] itself. For a system, the overall consideration is necessary. Feng *et al.* [51] integrate the attribute reliability into a whole BRB-r model. In this essay, from the perspective of the information itself, its uncertainty [62], [63] and credibility weight [64] are two significant factors which influence the reliability of the sensor. To further improve the accuracy of sensor reliability measurement and the recognition effect, a new method is proposed by combining the concept of belief entropy [65] and evidence credibility weight (CW) based on Song et al.'s method to measure the reliability of the sensor.

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J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

The remaining parts of this paper are arranged as follows. In Section II, we briefly introduce the basic definition of evidence theory, dynamic sensor reliability, Deng entropy and evidence credibility weight. In Section III, a newly proposed method is given based on the previous concept mentioned. In Section IV, two numerical examples are shown to apply this method. An application about dynamic target recognition is presented in Section V. The conclusion of this paper is put forward in Section VI.

II. PRELIMINARIES

This section introduces some basic information about D-S evidence theory, sensor dynamic reliability evaluation and belief entropy.

A. D-S EVIDENCE THEORY

Dempster-Shafer evidence theory is an expansion of traditional probability theory. It establishes an one-to-one correspondence between propositions and sets. The discourse domain of D-S theory is referred to the frame of discernment (FOD) [66], [67], marked as Θ, including a limited number of propositions. Assume $\Theta = \{A_1, A_2, A_3, \ldots, A_n\}$, which A_1, $A_2, A_3, \ldots, A_n$ represent the basic events in probability theory and be regarded as basic elements.

1) FRAME OF DISCERNMENT

Let $\Theta = \{A_1, A_2, A_3, \ldots, A_n\}$ be the frame of discernment. If set function m: $2^\Theta \to [0, 1]$ $(2^\Theta$ is the power set of $\Theta)$, which meets:

$$m(\phi) = 0 \tag{1}$$

$$\sum_{i=1}^{n} m(A_i) = 1 \quad A \in \Theta \tag{2}$$

m is the basic probability assignment (BPA) [68], [69] on the frame, which ϕ is an empty set, for $A \in \Theta$, $m(A)$ is the value of basic probability assignment. When $m(A) \neq 0$, A is the focal element assigned to the belief function.

2) BELIEF AND PLAUSIBILITY FUNCTION

$$Bel : 2^\Theta \to [0, 1] \tag{3}$$

$$Bel(A) = \sum_{B \subset A} m(B) \quad (\forall A \subset \Theta) \tag{4}$$

Bel is the belief function [70] on Θ, representing the sum of the basic assignment functions corresponding to all subsets of A. Assume $Pls(A)$ is the plausibility function on frame Θ, which represents the reliability of A is not denied.

$$Pls(A) = 1 - Bel(\bar{A}) = \sum_{B \subseteq \Theta} m(B) - \sum_{B \subseteq \bar{A}} m(B) = \sum_{B \cap A \neq \phi} m(B) \tag{5}$$

In fact, *[Bel(A), Pl(A)]* indicates the unconfirmed interval [71] of proposition A, and *[0, Bel(A)]* shows the interval of supporting evidence.

3) DEMPSTER'S COMBINATION RULE

Assume Bel_1 and Bel_2 are the two belief functions on a same discernment frame Θ, which m_1 and m_2 are the basic probability assignments (BPA) correspondingly during the evidence combination [72], [73]. Let the focal elements be : $A_1, \ldots, A_k$ and $B_1, \ldots, B_r$, and according Dempster's combination rule, the belief structure $m(C)$ is given by as follows:

$$m_1 \bigoplus m_2(C) = \frac{1}{K} \sum_{A \cap B = C} m_1(A) \cdot m_2(B)$$

$$\text{where } K = \sum_{A \cap B \neq \phi} m_1(A) \cdot m_2(B) = 1 - \sum_{A \cap B = \phi} m_1(A) \cdot m_2(B) \tag{6}$$

B. SENSOR DYNAMIC RELIABILITY

1) DISCOUNTED BPAs GENERATION PRINCIPLE

In real application, the reliable level of evidence source is different when it is affected by varying environments. So, a known reliability degree λ, regarded as discounted coefficient [74], is assigned to the definition of associated BPA to get discounted evidence. The common method for discounting operation is introduced by Shafer, and given by

$$\begin{cases} m^\lambda(A) = \lambda m(A), A \subset \Theta \\ m^\lambda(\Omega) = 1 - \lambda + \lambda mm(\Theta) \end{cases} \tag{7}$$

where $\lambda \in [0,1]$, and indicates the reliability degree of the evidence source. To be specific, $\lambda = 0$ represents the evidence source is totally unreliable. On the contrary, $\lambda = 1$ remains the percentages originally, showing that the evidence source is fully trusted in this circumstance.

However, this kind of discounted coefficient is applied on the condition of fixed and singular disturbance. For a multi-sensor system, the disturbance or outside influence is unstable and dynamical, which requires the sensors to make corresponding decision. So, it might cause conflictive results when only taking discounted evidence as a method to deal with the multi-sensor system [39], [75]. Thus, Song *et al.* [58] put forward a new method for data fusion in dynamic situation based on fuzzy set.

2) INTUITIONISTIC FUZZY SET

In data fusion field, information from identification framework is not rigorous sometimes. Based on this feature, fuzzy collections [76]–[78] provide a form for handling less rigorous information among the process of data fusion. Fuzzy set was firstly introduced by Zadeh in 1965 [79], and followed by Atanassov's intuitionistic fuzzy set [80] as an expansion based on fuzzy set theory [81]. It simply gives an explaination in an intuitive way. Traditionally, the concept of an exact set is that an object either belongs to this set or not. But for a fuzzy set, the object is not defined simply by "belong" or "not belong" to this set. According to this idea, a few definitions about this are as follow.

Assume a domain U is defined by a group of elements, $U = \{x_1, x_2, \ldots, x_n\}$. If there is a mapping form U to the

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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closed interval [0,1], then a fuzzy set A of U is determined, and U_A is referred as the membership function of fuzzy set A.

$$A = \{\langle x, \mu_A(x)\rangle \,|x \in U\} \qquad (8)$$

where $\mu_A(x)$ is the degree to which the element x belongs to the fuzzy set A in the domain U, and is simply referred to as the membership degree of x to A. For $\mu_A(x) \rightarrow 1$ represents the membership degree is high, and $\mu_A(x) \rightarrow 0$ means the membership degree is low.

Specifically, an Atanassov's intuitionistic fuzzy set (IFS) is an expansion based on fuzzy set, and given by:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle \,|x \in U\} \qquad (9)$$
$$0 \le \mu_A(x) + \nu_A(x) \le 1 \qquad (10)$$

Besides, $\pi_A(x)$ is introduced to define the vagueness of element x to set A:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \qquad (11)$$

3) BASIC FUZZY SET OPERATION

Assume there are two intuitionistic fuzzy sets A and B, $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle \,|x \in U\}$, $B = \{\langle x, \mu_B(x), \nu_B(x)\rangle \,|x \in U\}$, basic fuzzy sets operation definitions are given as follow:

$$A \cap B = \{< x, min(\mu_A(x), \mu_B(x)), max(\nu_A(x), \nu_B(x)) >\}$$
$$A \cup B = \{< x, max(\mu_A(x), \mu_B(x)), min(\nu_A(x), \nu_B(x)) >\}$$

4) CONVERSION BETWEEN BPAs AND FUZZY SETS

In evidence theory, confidence interval *[Bel(θ), Pl(θ)]* depict the uncertainty about θ. In this way, BPA is transformed to an IFS form on a known discernment $\Theta = \{\theta_1, \theta_2, \dots, \theta_n\}$. The related IFS is given by:

$$
\begin{aligned}
A &= \{\langle \theta, \mu_A(\theta), \nu_A(\theta)\rangle \,|\theta \in \Theta\} \\
&= \{\langle \theta_1, Bel(\theta_1), 1-Pl(\theta_1)\rangle, \dots, \langle \theta_n, Bel(\theta_n), 1-Pl(\theta_n)\rangle\}
\end{aligned}
$$
$$(12)$$

5) SUPPORTING DEGREE BETWEEN BPAs

To define the relationship between two BPAs, the concept of supporting degree is introduced as a symmetric measurement for implying the similarity and distance [55] between two BPAs. Using *Sup*, *Sim* and *Dis* to represent the supporting degree, similarity and distance between two BPAs, following relations have been defined:

$$Sup(m_1, m_2) \propto Sim(m_1, m_2)$$
$$Sup(m_1, m_2) \propto 1 - Dis(m_1, m_2)$$

Specifically, the higher the similarity between m_1 and the intersection of them, the more m_1 supports m_2.

$$Sup(m_1, m_2) \propto Sim(m_1, m_1 \cap m_2)$$

As mentioned above, BPA is transformed under the framework of IFS. In this way, the relation between sets and mass functions is changed easily. So, the corresponding supporting degree is expressed as follow :

$$Sup(m_1, m_2) = Sup(A_1, A_2) = Sim(A_1, A_1 \cap A_2) \quad (13)$$

The method of calculating the similarity between two IFSs is based on Euclidian distance [82]. In the framework of discernment $U = \{\theta_1, \theta_2, \dots, \theta_n\}$, let two intuitionistic fuzzy sets $A = \{\langle \theta, \mu_A(\theta), \nu_A(\theta)\rangle \,|\theta \in U\}$, $B = \{\langle \theta, \mu_B(\theta), \nu_B(\theta)\rangle \,|\theta \in U\}$, the similarity between A and B is:

$$S_E(A, B) = 1 - \frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{(\mu_A(\theta_i)-\mu_B(\theta_i))^2+(\nu_A(\theta_i)-\nu_B(\theta_i))^2}{2}}$$
$$(14)$$

6) DYNAMIC RELIABILITY OF MULTI-SENSORS

For a multi-sensor system, its dynamic reliability is calculated by constructing a supporting degree matrix (SDM). The SDM is defined as:

$$SDM = \begin{pmatrix} Sup(m_1, m_1) & Sup(m_1, m_2) & \dots & Sup(m_1, m_N) \\ Sup(m_2, m_1) & Sup(m_1, m_2) & \dots & Sup(m_2, m_N) \\ \vdots & \vdots & \vdots & \\ Sup(m_N, m_1) & Sup(m_N, m_2) & \dots & Sup(m_N, m_N) \end{pmatrix}$$
$$(15)$$

From each column, the elements represents the supporting degree which m_j obtained from other sensors. So, calculate the total supporting degree of m_j by adding up all the other elements column by column.

$$Total\_Sup(m_j) = \sum_{i=1, i\neq j}^{N} Sup(m_i, m_j) \qquad (16)$$

Considering the reliability of one sensor with the whole multi-sensors system [83], the reliability of each sensor is defined as follow:

$$R'(S_j) = \frac{Total\_Sup(m_j)}{\sum_{j=1}^{N} Total\_Sup(m_j)} \qquad (17)$$

For a multi-sensors system, the sensor with the highest reliability is given priority as a primary sensor. So the absolute dynamic reliability of sensor $S_i(i = 1, 2, \dots, N)$ is expressed by:

$$R(S_i) = \frac{R'(S_j)}{max_{j=1,2,\dots,N}R'(S_j)} \qquad (18)$$

C. BELIEF ENTROPY

Entropy, a physics concept, is a description of the system status. In 1948, information entropy was firstly introduced by Shannon [84] to measure the amount of information which a system contains. In some extent, it implys the uncertainty level of a system.

1) INFORMATION ENTROPY

The classic Shannon entropy equation is given as follow:

$$H = -\sum_{i=1}^{N} p_i log_b \, p_i \qquad (19)$$

where N is the amount of basic states in an information system, p_i represents the probability of state i happens,

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J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

$\sum_1^N p_i = 1$, b indicates the base of algorithm, and the unit of information entropy is bit when b equals to 2.

2) BELIEF ENTROPY

In order to measure the uncertainty degree [85], [86] of mass functions, a new uncertainty measure method called belief entropy [87], [88], known as Deng entropy, was introduced particularly.

Assume there is a mass function m defining on the frame of discernment X, and A is the focal element of function m, the cardinality of A is $|A|$. The following definition is used to measure the uncertainty of a mass function.

$$E_d(m) = -\sum_{A \subseteq X} m(A) log_2 \frac{m(A)}{2^{|A|} - 1} \quad (20)$$

Both Shannon entropy and Deng entropy are capable to use in evidence theory for measuring the uncertainty level of mass functions, but Deng entropy has higher precision. An example is given as follow [89].

Example 1: There exists a frame of discernment $X = \{a, b, c\}$, for a mass function $m(a) = m(b, c) = 1/2$, the Shannon entropy H and Deng entropy E_d are

$$H(m) = -\frac{1}{2} \times log_2 \frac{1}{2} - \frac{1}{2} \times log_2 \frac{1}{2} = 1$$

$$E_d(m) = -\frac{1}{2} \times log_2 \frac{1}{2} - \frac{1}{2} \times log_2 \frac{\frac{1}{2}}{2^2 - 1} = 1.79$$

III. THE PROPOSED METHOD

A. EVIDENCE CREDIBILITY WEIGHT

In real application, not all the sensors can detect the target successfully. When one sensor among the system contains obvious disturbance information, it is essential to reduce the weight [90]–[92] of the error sensor and define the sensor credibility [83] correctly. A new concept called evidence credibility weight for assigning weight to a multi-sensor system is introduced as follow.

Convert the objects we need to identify in real application into corresponding elements in the evidence theory framework. Let $\Theta = \{\theta_1, \theta_2, \ldots, \theta_j\}$ be a discernment framework, which corresponds to 2^j types of possibilities about recognition result. For a multi-sensor system, $m_i(O_p)$ represents the probability which sensor i ($i = 1, 2, \ldots, n$) assigns to an object set (each object set represents a possibility of identification result), and O_p is the corresponding object set ($O_p \subset \Theta, 1 \leqslant p \leqslant 2^j - 1$). Let t_i be the target identified by sensor i and m_{t_i} is the probability which sensor i assign to the target (maximum value of BPAs in each sensor). $(S_i, \langle O_p \rangle)$ is the recognition result of sensor i towards object set O_p, which $(S_i, \langle O_p \rangle) = 1$ shows that O_p is the target identified by sensor i, otherwise $(S_i, \langle O_p \rangle) = 0$.

$$\begin{cases} if \ O_p = t_i, \ (S_i, \langle O_p \rangle) = 1 \\ if \ O_p \neq t_i, \ (S_i, \langle O_p \rangle) = 0 \end{cases} \quad (21)$$

In short, the object set with the highest probability is considered as the target we need to find, and we denoted it as $(S_i, \langle O_p \rangle) = 1$ to express the support from one sensor.

Since the identification framework of each sensor in the system is the same, in order to show the analysis of the global information of all the sensors, put every possible situation in a matrix. For a n-sensor system (n represents the number of sensors), the target identification matrix (TIM) is defined as:

$$TIM = \begin{pmatrix} (S_1, \langle O_1 \rangle) & (S_2, \langle O_1 \rangle) & \ldots & (S_n, \langle O_1 \rangle) \\ (S_1, \langle O_2 \rangle) & (S_2, \langle O_2 \rangle) & \ldots & (S_n, \langle O_2 \rangle) \\ \vdots & \vdots & \vdots & \\ (S_1, \langle O_p \rangle) & (S_2, \langle O_p \rangle) & \ldots & (S_n, \langle O_p \rangle) \\ \vdots & \vdots & \vdots & \\ (S_1, \langle O_{2^j-1} \rangle) & (S_2, \langle O_{2^j-1} \rangle) & \ldots & (S_n, \langle O_{2^j-1} \rangle) \end{pmatrix} \quad (22)$$

where the object set $O_{p(1 \leqslant p \leqslant 2^j - 1)} \subset \Theta$, p represents the serial row number in the target identification matrix (TIM).

From each row, the elements represent the target recognition detected by sensor i ($i = 1, 2, \ldots, n$). So, obtain the total recognition result of object set O_p ($1 \leqslant p \leqslant 2^j - 1$) by adding up all the elements row by row and the sum represents the number of sensors which support the object set.

$$Total\_Tar(\langle O_p \rangle) = \sum_{i=1}^n ((S_i, \langle O_p \rangle)) \quad (23)$$

According to the $Total\_Tar(\langle O_p \rangle)$ obtained by row p ($1 \leqslant p \leqslant 2^j - 1$), the row which has the maximum of $Total\_Tar(\langle O_p \rangle)$ should be extracted as the sensor target vector (STV). STV_k is defined by:

$$STV_k = [(S_1, \langle O_k \rangle), (S_2, \langle O_k \rangle), \ldots, (S_n, \langle O_k \rangle)]$$
$$(k = arg \max_{1 \leq p \leq 2^j-1} \{Total\_Tar(\langle O_p \rangle)\}) \quad (24)$$

where arg represents extracting the subscript of the row in which the object set belongs to.

Based on the sensor target vector (STV_k), the weight distribution of the n-sensor system is as follows:

$$total\_weight$$
$$\Rightarrow \begin{cases} majority\_weight = \frac{\sum (S_i, \langle O_k \rangle)}{n} \\ (when \ (S_i, \langle O_k \rangle) = 1) \\ minority\_weight = 1 - majority\_weight \\ (when \ (S_i, \langle O_k \rangle) = 0) \end{cases} \quad (25)$$

$$total\_unit\_weight$$
$$\Rightarrow \begin{cases} \frac{majority\_weight}{\sum m_{ti}} & (for \ (S_i, \langle O_k \rangle) = 1) \\ \frac{minority\_weight}{\sum m_{ti}} & (for \ (S_i, \langle O_k \rangle) = 0) \end{cases} \quad (26)$$

The overall weight is valued as a "1", and distinguish the sensors that are inconsistent with most sensor identification results by assigning the ratio. The system now is divided into

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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two parts, assigned to *majority_weight* and *minority_weight*, sensors among one part are subject to the majority (group of $(S_i, \langle O_k \rangle) = 1$)), while the rest sensors among the other part are not same with the major decision (group of $(S_i, \langle O_k \rangle) = 0$)), which is often regarded as disturbance information.

Considering the fact that the sensor might give the same highest probability to a collection of different objects (i.e., $(S_1, \langle \theta_1 \rangle) = 1$ and $(S_1, \langle \theta_2 \rangle) = 1$ when $m_1(\theta_1) = m_1(\theta_2) = 0.45$), there may be multiple STVs in the system. For each piece of $STV_{k(k=1,2,\ldots,2^j-1)}$ in a multi-sensor system, the evidence credibility weight (CW_i) of each sensor i ($i = 1, 2, \ldots, n$) in the corresponding STV_k is now defined by:

$$CW_i = total\_unit\_weight \times m_{t_i} \qquad (27)$$

where m_{t_i} is the probability that sensor i ($i = 1, 2, \ldots, n$) assigns to the target.

Finally, if there are z pieces of *STV* in the system and the weight of each sensor should be averaged according to STV_k:

$$\overline{CW_i} = \frac{\sum_1^z CW_i}{z} \qquad (28)$$

B. IMPROVED EVIDENCE CREDIBILITY WEIGHT

Evidence credibility weight determines each object in the system and derives evidence credibility for each sensor based on this. However, it is inaccurate to only use it as a measurement factor, because the overall situation of each BPA is not taken into account. Therefore, for each sensor, the corresponding entropy value combine with the evidence credibility weight to generate an improved coefficient. The improved evidence credibility weight not only considers the complete information read by the sensor vertically, but also comprehensively synthesizes the judgment result of each sensor for a specific object. The definition of improved evidence credibility weight for sensor i is:

$$CW_i' = E_{di} \times \overline{CW_i} \qquad (29)$$

C. THE PROPOSED SENSOR DYNAMIC RELIABILITY METHOD

In multi-sensors system, it is very important to know the reliability of each sensor. Otherwise, when the reliability value of each sensor is not effectively measured, the sensor that detects interference data might take the dominant position in the process of data fusion, which results in lower test accuracy. The previous method by Song et al. used dynamic sensor reliability factor as the discount coefficient in data fusion to imitate the changing decision-making process. However, in real application situation, the reliability of sensor is generated by a combination of several factors. So, a newly proposed method which uses Deng Entropy and evidence credibility weight of sensor based on dynamic sensor reliability is given in this essay.

Step 1. Model uncertain data from sensors to BPA.

In practical applications, the data detected by the sensor may be in various forms. Therefore, it is necessary to convert the outputs of the sensors $S_1, S_2, \ldots, S_n$ into the

corresponding BPAs form $m_1, m_2, \ldots, m_n$ in the framework of Dempster-Shafer theory.

Step 2. Calculate the supporting degree.

(i) According each BPA m_i, ($i = 1, 2, \ldots, N$), based on Eq.(4) and Eq.(5), try to get the belief and plausibility function of corresponding BPA.

(ii) By Eq.(9), transform them into IFSs form respectively.

(iii) Based on the principle of IFSs operation, get the intersection of two IFSs A_k and A_i, marked by $A_k \cap A_i$.

(iv) Use Eq.(14), calculate the similarity degree between two IFSs, $S_E(A_i, A_k \cap A_i)$.

(v) Then, the supporting degree of m_i agrees m_k is $Sup(m_i, m_k) = S_E(A_i, A_k \cap A_i)$.

Step 3. Calculate the dynamic reliability of each sensor.

In the multi-sensors system, Since the similarity degrees between each BPA with all the rest BPAs are obtained, the support degree matrix (SDM) is constructed naturally as Eq.(15). Then, use Eq.(17) and Eq.(18) to calculate the absolute dynamic reliability of each sensor R_{Si} in the system.

Step 4. Calculate the Deng entropy of each sensor.

Use Deng Entropy to indicate the information uncertainty of each sensor. Based on Eq.(20), $E_{d1}, E_{d2}, \ldots, E_{dn}$ is obtained respectively.

Step 5. Calculate the evidence credibility weight (CW) of each sensor.

According to Eq.(28), get the evidence credibility weight (CW) of each sensor $\overline{CW_1}, \overline{CW_2}, \ldots, \overline{CW_n}$, then multiply them with the results in Step 4, $E_{d1}, E_{d2}, \ldots, E_{dn}$. We can get the improved evidence credibility results $CW_1' = E_{d1} \times \overline{CW_1}, CW_2' = E_{d2} \times \overline{CW_2}, \ldots, CW_n' = E_{dn} \times \overline{CW_n}$.

Step 6. Get discounted BPAs from modified coefficient.

Generating a new modified dynamic reliability factor W_i by multiplying the results from Step 3 and Step 5 ($W_i' = CW_i' * R_{Si}$.) and getting the absolute value of each W_i'. Based on the evidence discounting operation, the corresponding discounted BPAs are known as $m_1^{W_i}, m_2^{W_i}, \ldots, m_n^{W_i}$.

Step 7. Data fusion based on D-S theory.

According to D-S theory, get the data fusion results by combining the discounted BPAs $m_1^{W_i}, m_2^{W_i}, \ldots, m_n^{W_i}$.

Model uncertain data from sensors to BPA

Calculate the supporting degree

Calculate the dynamic reliability of each sensor

Calculate the Deng entropy of each sensor

Calculate the evidence credibility weight of each sensor

Get discounted BPAs from improved coefficient
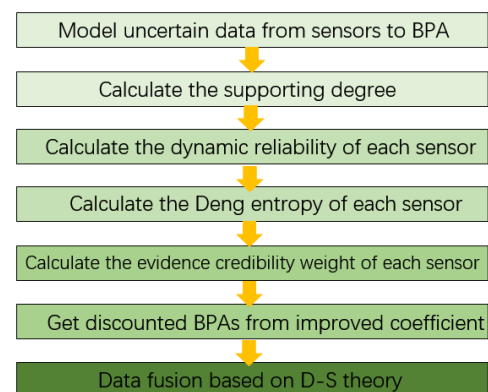
Data fusion based on D-S theory

FIGURE 1. The flow chart of sensor data fusion process.

For brevity, the whole process of sensor data fusion is concluded through a flow chart shown in Fig.1.

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J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

TABLE 1. Sensor reading.

	θ_1	θ_2	θ_3	Θ
m_1	0.6	0.1	0.2	0.1
m_2	0.2	0.5	0.1	0.2
m_3	0.6	0.1	0.2	0.1

IV. NUMERICAL EXAMPLE

In this section, the proposed method will be applied to the application of multi-sensors identification fusion process to show its effectiveness of detecting target compared with only using dynamic reliability evaluation. To begin with, a simple example is given to show the implementation of combining dynamic reliability evaluation with Deng entropy and Evidence credibility weight methods together and its application in data fusion.

A. EXAMPLE AND PROCEDURES

Example 2: In a multi-sensors recognition system, there are three sensors known as S_1 (acoustic sensor), S_2 (pressure sensor) and S_3 (infrared sensor) to detect the identification of targets. In the framework of discernment $\Theta = \{\theta_1, \theta_2, \theta_3\}$, which stands for three types of different targets θ_1, θ_2 and θ_3. Now, the detecting situation is given by these three sensors based on the form of BPAs, where the data are from [58]:

Then try to transform the expressions form BPA form to intuitionistic fuzzy sets in $\Theta = \{\theta_1, \theta_2, \theta_3\}$.

$$A_1 = \{\langle \theta_1, 0.6, 0.3 \rangle, \langle \theta_2, 0.1, 0.8 \rangle, \langle \theta_3, 0.2, 0.7 \rangle\}$$
$$A_2 = \{\langle \theta_1, 0.2, 0.6 \rangle, \langle \theta_2, 0.5, 0.3 \rangle, \langle \theta_3, 0.1, 0.7 \rangle\}$$
$$A_3 = \{\langle \theta_1, 0.4, 0.3 \rangle, \langle \theta_2, 0.1, 0.6 \rangle, \langle \theta_3, 0.2, 0.5 \rangle\}$$

According the IFS operation, the following intersection results are easily obtained.

$$A_1 \cap A_2 = \{\langle \theta_1, 0.2, 0.6 \rangle, \langle \theta_2, 0.1, 0.8 \rangle, \langle \theta_3, 0.1, 0.7 \rangle\}$$
$$A_1 \cap A_3 = \{\langle \theta_1, 0.4, 0.3 \rangle, \langle \theta_2, 0.1, 0.8 \rangle, \langle \theta_3, 0.2, 0.7 \rangle\}$$
$$A_2 \cap A_3 = \{\langle \theta_1, 0.2, 0.6 \rangle, \langle \theta_2, 0.1, 0.6 \rangle, \langle \theta_3, 0.1, 0.7 \rangle\}$$

Now, based on the definition given in Eq.(14), a supporting degree matrix (SDM) is shown as follows:

$$SDM = \begin{pmatrix} 1 & S_E(A_1, A_1 \cap A_2) & S_E(A_1, A_1 \cap A_3) \\ S_E(A_2, A_2 \cap A_1) & 1 & S_E(A_2, A_2 \cap A_3) \\ S_E(A_3, A_3 \cap A_1) & S_E(A_3, A_3 \cap A_2) & 1 \end{pmatrix}$$

By using the definition of calculating the similarity between two IFSs, the SDM result is :

$$SDM = \begin{pmatrix} 1 & 0.8586 & 0.9529 \\ 0.8491 & 1 & 0.8821 \\ 0.9057 & 0.8623 & 1 \end{pmatrix}$$

Based on Eq.(16), the total supporting degree of each sensor is calculated column by column:

$$Total\_Sup(m_1) = 0.8491 + 0.9057 = 1.7548$$
$$Total\_Sup(m_2) = 0.8586 + 0.8623 = 1.7209$$
$$Total\_Sup(m_3) = 0.9529 + 0.8821 = 1.8350$$

So, the relative dynamic reliability of each sensor is derived through Eq.(17):

$$R'_{S_1} = \frac{1.7548}{1.7548 + 1.7209 + 1.8350} = 0.3304$$
$$R'_{S_2} = \frac{1.7209}{1.7548 + 1.7209 + 1.8350} = 0.3240$$
$$R'_{S_3} = \frac{1.8350}{1.7548 + 1.7209 + 1.8350} = 0.3455$$

And the corresponding absolute dynamic reliability of each sensor is:

$$R_{S_1} = \frac{0.3304}{0.3455} = 0.9563$$
$$R_{S_2} = \frac{0.9378}{0.3455} = 0.9378$$
$$R_{S_3} = \frac{0.3455}{0.3455} = 1$$

Use the definition of Deng entropy, calculate the uncertainty level of each sensor:

$$E_{d1} = -0.6 * log_2\, 0.6 - 0.1 * log_2\, 0.1 - 0.2 * log_2\, 0.2$$
$$-0.1 * log_2 \frac{0.1}{2^3 - 1} = 1.8517$$
$$E_{d2} = -0.2 * log_2\, 0.2 - 0.5 * log_2\, 0.5 - 0.1 * log_2\, 0.1$$
$$-0.2 * log_2 \frac{0.2}{2^3 - 1} = 2.3224$$
$$E_{d3} = -0.4 * log_2\, 0.4 - 0.1 * log_2\, 0.1 - 0.2 * log_2\, 0.2$$
$$-0.3 * log_2 \frac{0.3}{2^3 - 1} = 2.6886$$

Based on Eq.(21) to Eq.(23), the object sets are assigned respectively $(O_1 = \langle \theta_1 \rangle, O_2 = \langle \theta_2 \rangle, O_3 = \langle \theta_3 \rangle, O_7 = \langle \Theta \rangle$, the remaining O_4, O_5, O_6 are not detected by the sensor system in this example). Then, the target identification matrix (TIM) of this three-sensor system is generated as:

$$TIM = \begin{pmatrix} (S_1, \langle O_1 \rangle) & (S_2, \langle O_1 \rangle) & (S_3, \langle O_1 \rangle) \\ (S_1, \langle O_2 \rangle) & (S_2, \langle O_2 \rangle) & (S_3, \langle O_2 \rangle) \\ (S_1, \langle O_3 \rangle) & (S_2, \langle O_3 \rangle) & (S_3, \langle O_3 \rangle) \\ (S_1, \langle O_7 \rangle) & (S_2, \langle O_7 \rangle) & (S_3, \langle O_7 \rangle) \end{pmatrix} = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$$\Rightarrow \begin{bmatrix} Total\_Tar(\langle \theta_1 \rangle) \\ Total\_Tar(\langle \theta_2 \rangle) \\ Total\_Tar(\langle \theta_3 \rangle) \\ Total\_Tar(\langle \Theta \rangle) \end{bmatrix} \Rightarrow \begin{bmatrix} 2 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

Obviously, the maximum value of $Total\_Tar(\langle \theta_1 \rangle)$ is unique in this multi-sensor system, which generates one piece of STV ($z = 1$ in Eq.(28)) and $k = 1$. Therefore, the sensor target vector of this system is $STV_1 = [1\ 0\ 1]$, which the corresponding weight distribution is that S_1 and S_3 share a weight of $\frac{2}{3}$ while S_2 gets $\frac{1}{3}$. Then, follow the Eq.(28), the evidence credibility weight (CW) is assigned to each sensor like this:

$$\overline{CW_1} = \frac{\frac{2}{3}}{0.6 + 0.4} \times 0.6 = 0.4$$

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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TABLE 2. Result comparsion.

	θ_1	θ_2	θ_3	Θ
Song et al.'s method in [59]	0.646	0.178	0.144	0.032
proposed method	0.658	0.182	0.137	0.024

TABLE 3. Five BPAs detected by sensors.

	m_1	m_2	m_3	m_4	m_5
$\{\theta_1\}$	0.8	0.4	0	0.3	0.45
$\{\theta_2\}$	0.1	0.2	0.95	0.2	0.1
$\{\theta_3\}$	0	0.1	0.05	0.25	0
$\{\theta_1, \theta_2\}$	0	0.3	0	0.2	0
$\{\theta_2, \theta_3\}$	0	0	0	0	0.15
$\{\Theta\}$	0.1	0	0	0.05	0.3

$$\overline{CW_2} = \frac{\frac{1}{3}}{0.2} \times 0.2 = 0.33$$

$$\overline{CW_3} = \frac{\frac{2}{3}}{0.6 + 0.4} \times 0.4 = 0.27$$

Get the coefficients of improved evidence credibility weight as a measurement of this information detecting system.

$$CW_1' = E_{d1} \times \overline{CW_1} = 1.8517 \times 0.4 = 0.7407$$
$$CW_2' = E_{d2} \times \overline{CW_2} = 2.3224 \times 0.33 = 0.7664$$
$$CW_3' = E_{d3} \times \overline{CW_3} = 2.6886 \times 0.27 = 0.7170$$

Combine the coefficients with the absolute dynamic reliability above, modified dynamic sensor factors are obtained.

$$W_1' = R_{S1} \times CW_1' = 0.9563 \times 0.7407 = 0.7083$$
$$W_2' = R_{S2} \times CW_2' = 0.9378 \times 0.7664 = 0.7187$$
$$W_3' = R_{S3} \times CW_3' = \quad 1 \quad \times 0.7170 = 0.7170$$

Finally, normalize the above modified dynamic reliability factors and get the absolute value of each sensor.

$$W_1 = \frac{W_1'}{W_2'} = \frac{0.7083}{0.7187} = 0.9855 \quad W_2 = \frac{W_2'}{W_2'} = \frac{0.7187}{0.7187} = 1$$

$$W_3 = \frac{W_3'}{W_2'} = \frac{0.7170}{0.7187} = 0.9975$$

Based on the modified dynamic reliability factor, changing original BPAs by using discounted operation are:

$$m_1^{W1}(\{\theta_1\}) = 0.5913 \quad m_1^{W1}(\{\theta_2\}) = 0.0986$$
$$m_1^{W1}(\{\theta_3\}) = 0.1971 \quad m_1^{W1}(\{\Theta\}) = 0.1130$$
$$m_2^{W2}(\{\theta_1\}) = 0.2 \quad m_2^{W2}(\{\theta_2\}) = 0.5$$
$$m_2^{W2}(\{\theta_3\}) = 0.1 \quad m_2^{W2}(\{\Theta\}) = 0.2$$
$$m_3^{W3}(\{\theta_1\}) = 0.3990 \quad m_3^{W3}(\{\theta_2\}) = 0.0998$$
$$m_3^{W3}(\{\theta_3\}) = 0.1995 \quad m_3^{W3}(\{\Theta\}) = 0.3017$$

Finish the data fusion process by Dempster-Shafer rule, the final result is:

$$m(\{\theta_1\}) = 0.6575 \quad m(\{\theta_2\}) = 0.1816$$
$$m(\{\theta_3\}) = 0.1373 \quad m(\{\Theta\}) = 0.0235$$

The following table shows the difference by comparing this modified method and the original dynamic reliability sensor method given by Song *et al.* [58] when the disturbance is not strong in a system.

It can be seen from Table 2 that when the number of sensors in the system is not enough, the conflict data cannot be completely judged, so the reliability of the three sensors is relatively close, and the accuracy of the recognition target is slightly improved.

Example 3: A group of sensors $(S_1, S_2, S_3, S_4, S_5)$ are used to detect sea target in a multi-sensor information system, which are considered as acoustic sensor, photosensitive sensor, thermal sensor and speed sensor, position sensor respectively. Five normalized BPAs [58] are the details provided by these five sensors over the frame of discernment $\Theta = \{\theta_1, \theta_2, \theta_3\}$ as shown in Table 3, where the data are from [58].

It is obvious from the table that the data monitored by sensor S_3 is significantly different from other sensors, Sensor S_3 gives most of the decision results to θ_2, while the remaining sensors believe that the target should be θ_1. Therefore, the dynamic reliability parameter of sensor S_3 should be small to reduce the adverse effect on the data fusion process. The main process of calculating the modified dynamic sensor factors is shown below.

Step1: Five intuitionistic fuzzy sets in $\Theta = \{\theta_1, \theta_2, \theta_3\}$ generated by above five BPAs are expressed as follow:

$$A_1 = \{ \ < \theta_1, 0.8, 0.1 >, < \theta_2, 0.1, 0.8 >, < \theta_3, 0, 0.9 >,$$
$$< \{\theta_1, \theta_2\}, 0, 0.9 >, < \{\theta_2, \theta_3\}, 0, 0.9 > \}$$
$$A_2 = \{ \ < \theta_1, 0.4, 0.6 >, < \theta_2, 0.2, 0.8 >, < \theta_3, 0.1, 0.9 >,$$
$$< \{\theta_1, \theta_2\}, 0.3, 0.7 >, < \{\theta_2, \theta_3\}, 0, 1 > \}$$
$$A_3 = \{ \ < \theta_1, 0, 1 >, < \theta_2, 0.95, 0.05 >, < \theta_3, 0.05, 0.95 >,$$
$$< \{\theta_1, \theta_2\}, 0, 1 >, < \{\theta_2, \theta_3\}, 0, 1 > \}$$
$$A_4 = \{ < \theta_1, 0.3, 0.65 >, < \theta_2, 0.2, 0.75 >, < \theta_3, 0.25, 0.7 >,$$
$$< \{\theta_1, \theta_2\}, 0.2, 0.75 >, < \{\theta_2, \theta_3\}, 0, 1 > \}$$
$$A_5 = \{ \ < \theta_1, 0.45, 0.25 >, < \theta_2, 0.1, 0.6 >, < \theta_3, 0, 1 >,$$
$$< \{\theta_1, \theta_2\}, 0, 1 >, < \{\theta_2, \theta_3\}, 0.15, 0.55 > \}$$

Step 2: Construct the similarity degree matrix (SDM) based on Eq.(14), SDM, as shown at the top of the next page.

Step 3: Calculate the corresponding dynamic reliability of each sensor, and the factors are given as follow:

$$R_{S_1} = 0.8125 \quad R_{S_2} = 1 \ R_{S_3} = 0.7535$$
$$R_{S_4} = 0.7854 \quad R_{S_5} 0.8631$$

Step 4: Get the Deng entropy value of each sensor.

$$E_{d1} = 1.2027 \quad E_{d2} = 2.3219 \ E_{d3} = 0.2864$$
$$E_{d4} = 2.6233 \quad E_{d5} = 2.8622$$

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J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

$$SDM = \begin{pmatrix} 1 & S_E(A_1, A_1 \cap A_2) & S_E(A_1, A_1 \cap A_3) & S_E(A_1, A_1 \cap A_4) & S_E(A_1, A_1 \cap A_5) \\ S_E(A_2, A_2 \cap A_1) & 1 & S_E(A_2, A_2 \cap A_3) & S_E(A_2, A_2 \cap A_4) & S_E(A_2, A_2 \cap A_5) \\ S_E(A_3, A_3 \cap A_1) & S_E(A_3, A_3 \cap A_2) & 1 & S_E(A_3, A_3 \cap A_4) & S_E(A_3, A_3 \cap A_5) \\ S_E(A_4, A_4 \cap A_1) & S_E(A_4, A_4 \cap A_2) & S_E(A_4, A_4 \cap A_3) & 1 & S_E(A_4, A_4 \cap A_5) \\ S_E(A_5, A_5 \cap A_1) & S_E(A_5, A_5 \cap A_2) & S_E(A_5, A_5 \cap A_3) & S_E(A_5, A_5 \cap A_4) & 1 \end{pmatrix}$$

Step 5: Since all four sensors determine the target as θ_1 while the S_3 sensor gives a different result, the sensor target vector is $STV_1 = [1\ 1\ 0\ 1\ 1]$, and the evidence credibility weight (CW) of each sensor is assigned like this: (the S_3 sensor is assigned to 0.2, while the remaining four sensors share a weight of 0.8.)

$$\overline{CW_1} = \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.8 = 0.3280$$

$$\overline{CW_2} = \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.4 = 0.1641$$

$$\overline{CW_3} = \frac{0.2}{0.95} \times 0.95 = 0.2$$

$$\overline{CW_4} = \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.3 = 0.1230$$

$$\overline{CW_5} = \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.45 = 0.1846$$

Step 6: Get the improved evidence credibility weight result based on Eq.(29).

$$CW_1' = 0.3947 \quad CW_2' = 0.3810 \quad CW_3' = 0.0572$$
$$CW_4' = 0.3228 \quad CW_5' = 0.5284$$

Step 7: According to the previous definition, the final modified dynamic reliability factors are obtained as:

$$W_1 = 0.3955 \quad W_2 = 0.9399 \quad W_3 = 0.0873$$
$$W_4 = 0.8340 \quad W_5 = 1$$

Step 8: Calculate the discounted BPAs and get the result through data fusion.

$$m(\{\theta_1\}) = 0.7538 \quad m(\{\theta_2\}) = 0.1568$$
$$m(\{\theta_3\}) = 0.0255$$
$$m(\{\theta_1, \theta_2\}) = 0.0374 \quad m(\{\theta_2, \theta_3\}) = 0.0088$$
$$m(\{\Theta\}) = 0.0176$$

From the result, it is clear that the recognition result of the multi-sensor system is θ_1, and since the information entropy value and importance degree of the sensor S_3 are both low, the influence generated in the whole decision result is very small after fusion.

B. EXPERIMENT ANALYSIS

Table 4 shows the fusion results by using different methods. From Table 4, the problem with the classical Demster's is obvious. After the system adding the data of the sensor S_3, the recognition rate of θ_1 becomes 0, while θ_2 is near to 1. This situation is unreasonable for most sensors to assign

their recognition result to θ_1 and S_3 should be considered as interference. Therefore, a counter-intuitive result occurs in a highly conflicting situation when applying the classical Dempster's rule [45]. To deal with the problem, Murphy [93] proposed an average synthesis rule. By averaging the evidence before data fusion, the impact of conflict evidence is reduced to some extent. However, this method does not reflect the changing trend in the fusion process, and there is still room for improvement in recognition accuracy.

As can be seen from the previous calculation steps, the dynamic reliability obtained by S_3 is the lowest in the system. In Song et al.'s method [58], data fusion is performed by generating the discounted BPAs based on directly using the dynamic reliability of each sensor as the discounted coefficient of BPAs. Although the final recognition result of the system is θ_1, the recognition accuracy of the system is not ideal (only slightly higher than 50%). Apparently, the system has been dramatically affected after the fusion of S_3, resulting in the considerable reduction of supporting θ_1 and the supporting degree grows slowly even though the remaining sensors agree with the correct target θ_1.

The proposed method further introduces the concept of entropy value and evidence credibility weight as two factors based on the original sensor dynamic reliability coefficient. In principle, when a set of highly conflicting data appears in a multi-sensor system, the sensor which reads this set of data tends to allocate most of its support to a wrong recognition target, resulting in a low information entropy value (also considered as the confirmation of the wrong target is strong). However, when other sensors highly support the correct target, the corresponding information entropy value is also reduced. Therefore, it is not enough to rely on the information entropy value for helping authenticate the sensor reliability. Thus, the importance of each sensor should be predicted before data fusion by using the evidence credibility weight. Through dividing the multi-sensor identification system into two parts, most of the sensors with the same recognition target will dominate the decision-making process (given the most of the evidence credibility weight), and among them, the sensor which supports target the most will be assigned the highest weight ratio. Clearly, the actual fusion results that the integration of multiple factors enhances the robustness of the system and improves the accuracy of the recognition target.

V. CASE STUDY IN DYNAMIC TARGET RECOGNITION
In some military or industrial applications, objects that need to be identified may change dynamically over time.

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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TABLE 4. Combination results based on different methods.

	m_1^2	m_1^3	m_1^4	m_1^5
Classical Demspter's rule	$m(\{\theta_1\})=0.8451$	$m(\{\theta_1\})=0$	$m(\{\theta_1\})=0$	$m(\{\theta_1\})=0$
	$m(\{\theta_2\})=0.0986$	$m(\{\theta_2\})=0.9948$	$m(\{\theta_2\})=0.9965$	$m(\{\theta_2\})=0.9971$
	$m(\{\theta_3\})=0.0140$	$m(\{\theta_3\})=0.0052$	$m(\{\theta_3\})=0.0035$	$m(\{\theta_3\})=0.0029$
	$m(\{\theta_1,\theta_2\})=0.0423$			
Murphy's rule [94]	$m(\{\theta_1\})=0.4949$	$m(\{\theta_1\})=0.5482$	$m(\{\theta_1\})=0.5821$	$m(\{\theta_1\})=0.6082$
	$m(\{\theta_2\})=0.3930$	$m(\{\theta_2\})=0.4107$	$m(\{\theta_2\})=0.4031$	$m(\{\theta_2\})=0.3865$
	$m(\{\theta_3\})=0.0422$	$m(\{\theta_3\})=0.0183$	$m(\{\theta_3\})=0.0072$	$m(\{\theta_3\})=0.0027$
	$m(\{\theta_1,\theta_2\})=0.0461$	$m(\{\theta_1,\theta_2\})=0.0179$	$m(\{\theta_1,\theta_2\})=0.0064$	$m(\{\theta_1,\theta_2\})=0.0022$
	$m(\{\theta_2,\theta_3\})=0.0104$	$m(\{\theta_2,\theta_3\})=0.0029$	$m(\{\theta_2,\theta_3\})=0.0007$	$m(\{\theta_2,\theta_3\})=0.0002$
	$m(\{\Theta\})=0.0133$	$m(\{\Theta\})=0.0021$	$m(\{\Theta\})=0.0003$	$m(\{\Theta\})=0.0001$
Deng entropy's rule	$m(\{\theta_1\})=0.5261$	$m(\{\theta_1\})=0.5071$	$m(\{\theta_1\})=0.5847$	$m(\{\theta_1\})=0.6921$
	$m(\{\theta_2\})=0.1592$	$m(\{\theta_2\})=0.1890$	$m(\{\theta_2\})=0.2207$	$m(\{\theta_2\})=0.2128$
	$m(\{\theta_3\})=0.0678$	$m(\{\theta_3\})=0.0659$	$m(\{\theta_3\})=0.0562$	$m(\{\theta_3\})=0.0349$
	$m(\{\theta_1,\theta_2\})=0.2035$	$m(\{\theta_1,\theta_2\})=0.1962$	$m(\{\theta_1,\theta_2\})=0.1250$	$m(\{\theta_1,\theta_2\})=0.0518$
	$m(\{\Theta\})=0.0434$	$m(\{\Theta\})=0.0418$	$m(\{\Theta\})=0.0135$	$m(\{\Theta\})=0.0056$
Song et al.'s method in [59]	$m(\{\theta_1\})=0.8446$	$m(\{\theta_1\})=0.3729$	$m(\{\theta_1\})=0.4585$	$m(\{\theta_1\})=0.5760$
	$m(\{\theta_2\})=0.0986$	$m(\{\theta_2\})=0.5898$	$m(\{\theta_2\})=0.5174$	$m(\{\theta_2\})=0.4090$
	$m(\{\theta_3\})=0.0139$	$m(\{\theta_3\})=0.0118$	$m(\{\theta_3\})=0.0083$	$m(\{\theta_3\})=0.0065$
	$m(\{\theta_1,\theta_2\})=0.0418$	$m(\{\theta_1,\theta_2\})=0.0255$	$m(\{\theta_1,\theta_2\})=0.0158$	$m(\{\theta_1,\theta_2\})=0.0084$
	$m(\{\Theta\})=0.0011$			$m(\{\Theta\})=0.0001$
Proposed method	$m(\{\theta_1\})=0.6560$	$m(\{\theta_1\})=0.6363$	$m(\{\theta_1\})=0.6615$	$m(\{\theta_1\})=0.7538$
	$m(\{\theta_2\})=0.1233$	$m(\{\theta_2\})=0.1491$	$m(\{\theta_2\})=0.1610$	$m(\{\theta_2\})=0.1568$
	$m(\{\theta_3\})=0.0370$	$m(\{\theta_3\})=0.0364$	$m(\{\theta_3\})=0.0418$	$m(\{\theta_3\})=0.0255$
	$m(\{\theta_1,\theta_2\})=0.1109$	$m(\{\theta_1,\theta_2\})=0.1076$	$m(\{\theta_1,\theta_2\})=0.0921$	$m(\{\theta_1,\theta_2\})=0.0374$
	$m(\{\Theta\})=0.0728$	$m(\{\Theta\})=0.0706$	$m(\{\Theta\})=0.0435$	$m(\{\Theta\})=0.0176$

TABLE 5. Sensor identification information represented by BPAs.

	t_1	t_2	t_3
S_1	$m(\{A\})=0.3666$	$m(\{H\})=0.8176$	$m(\{H\})=0.6229$
	$m(\{H\})=0.4563$	$m(\{F\})=0.0003$	$m(\{\Theta\})=0.3771$
	$m(\{A,H\})=0.1185$	$m(\{A,H\})=0.1553$	
	$m(\{\Theta\})=0.0586$	$m(\{\Theta\})=0.0268$	
S_2	$m(\{A\})=0.2793$	$m(\{H\})=0.5658$	$m(\{H\})=0.7660$
	$m(\{H\})=0.4151$	$m(\{F\})=0.0009$	$m(\{\Theta\})=0.2340$
	$m(\{A,H\})=0.2652$	$m(\{A,H\})=0.0646$	
	$m(\{\Theta\})=0.0404$	$m(\{\Theta\})=0.3687$	
S_3	$m(\{A\})=0.2897$	$m(\{H\})=0.2403$	$m(\{H\})=0.8598$
	$m(\{H\})=0.4331$	$m(\{F\})=0.0004$	$m(\{\Theta\})=0.1402$
	$m(\{A,H\})=0.2470$	$m(\{A,H\})=0.0141$	
	$m(\{\Theta\})=0.0302$	$m(\{\Theta\})=0.7452$	

TABLE 6. Values of the main parameters.

Method	t_1			t_2			t_3		
	R	E_d	CW	R	E_d	CW	R	E_d	CW
S_1	0.9926	2.0041	0.3498	0.8701	1.1196	0.3940	1	2.0146	0.2771
S_2	0.9990	2.2691	0.3182	0.9931	2.3975	0.2727	0.9931	1.4418	0.3408
S_3	1	2.1678	0.3320	1	3.0160	0.3333	0.9653	0.9784	0.3821

In such a scenario, sensors are required to make some corresponding precautions accurately. However, the recognition result of a single sensor is often not comprehensive enough and is susceptible to external interference. Therefore, in order to improve the reliability of recognition, the system is often composed of multiple sensors. In the case of continuous time series, it is very important to ensure that multi-sensor effectively identify the target even under some certain interference.

A. PROBLEM DESCRIPTION

Suppose there are radar, infrared and visible light sensors at a military base detecting an unknown aerial target over a period of time. The target has three possible types which are *Airplane*, *Helicopter* and *Fighter* (denoted as *A*, *H* and

IEEE Access

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

TABLE 7. Modified BPAs based on proposed method.

	t_1	t_2	t_3
S_1	$m(\{A\})$=0.3536 $m(\{H\})$=0.4401 $m(\{A,H\})$=0.1143 $m(\{\Theta\})$=0.0920	$m(\{H\})$=0.3122 $m(\{F\})$=0.0001 $m(\{A,H\})$=0.0593 $m(\{\Theta\})$=0.6285	$m(\{H\})$=0.6229 $m(\{\Theta\})$=0.3771
S_2	$m(\{A\})$=0.2793 $m(\{H\})$=0.4151 $m(\{A,H\})$=0.2652 $m(\{\Theta\})$=0.0404	$m(\{H\})$=0.3656 $m(\{F\})$=0.0005 $m(\{A,H\})$=0.0417 $m(\{\Theta\})$=0.5922	$m(\{H\})$=0.6696 $m(\{\Theta\})$=0.3304
S_3	$m(\{A\})$=0.2891 $m(\{H\})$=0.4321 $m(\{A,H\})$=0.2465 $m(\{\Theta\})$=0.0323	$m(\{H\})$=0.2403 $m(\{F\})$=0.0004 $m(\{A,H\})$=0.0141 $m(\{\Theta\})$=0.7452	$m(\{H\})$=0.5556 $m(\{\Theta\})$=0.4444

TABLE 8. Fusion results based on different methods.

	t_1	t_2	t_3
Deng entropy's rule	$m(\{A\})$=0.3365 $m(\{H\})$=0.6143 $m(\{A,H\})$=0.0483 $m(\{\Theta\})$=0.0010	$m(\{A\})$=0.1355 $m(\{H\})$=0.8447 $m(\{A,H\})$=0.0195	$m(\{A\})$=0.0158 $m(\{H\})$=0.9818
Song et al.'s method in [59]	$m(\{A\})$=0.3375 $m(\{H\})$=0.6308 $m(\{A,H\})$=0.0315 $m(\{\Theta\})$=0.0002	$m(\{A\})$=0.0485 $m(\{H\})$=0.9470 $m(\{A,H\})$=0.0045	$m(\{A\})$=0.0484 $m(\{H\})$=0.9462
Proposed method	$m(\{A\})$=0.3771 $m(\{H\})$=0.6277 $m(\{A,H\})$=0.0349 $m(\{\Theta\})$=0.0003	$m(\{A\})$=0.1442 $m(\{H\})$=0.8408 $m(\{A,H\})$=0.0150	$m(\{A\})$=0.0092 $m(\{H\})$=0.9898

F respectively). By applying the framework of evidence theory to this practical problem, the discernment framework is expressed as $\Theta = \{A, H, F\}$. In order to correctly identify the type of target, three sensors in the system are applied to track and identify the target. The three sensors output corresponding identification information for a period of time. Table 5 shows the identification information read by these sensors for three consecutive time nodes, where the data are from [58] .

B. FUSION RESULT BASED ON PROPOSED METHOD

According to the previous proposed method, the main results of calculating the dynamic reliability of the sensors are shown as follow. The Supporting Degree Matrix (SDM) at each time nodes is obtained as:

$$SDM_{t_1} = \begin{pmatrix} 1 & 0.9654 & 0.9697 \\ 0.9697 & 1 & 0.9909 \\ 0.9764 & 0.9933 & 1 \end{pmatrix}$$

$$SDM_{t_2} = \begin{pmatrix} 1 & 0.9407 & 0.8639 \\ 0.8603 & 1 & 0.9232 \\ 0.6946 & 0.8342 & 1 \end{pmatrix}$$

$$SDM_{t_3} = \begin{pmatrix} 1 & 0.9325 & 0.8883 \\ 0.9663 & 1 & 0.9558 \\ 0.9442 & 0.9779 & 1 \end{pmatrix}$$

Then, the values of the main parameters in the calculation process is shown from the following Table 6 (R, E_d and CW

are denoted as absolute dynamic reliability, Deng entropy and evidence credibility weight respectively).

As a result, the corresponding dynamic reliability of sensors at three time nodes during this period is derived as:

$$W_{S_1}^{t_1} = 0.9646 \quad W_{S_2}^{t_1} = 1 \; W_{S_3}^{t_1} = 0.9978$$
$$W_{S_1}^{t_2} = 0.3819 \quad W_{S_2}^{t_2} = 0.6461 \; W_{S_3}^{t_2} = 1$$
$$W_{S_1}^{t_3} = 1 \quad W_{S_2}^{t_3} = 0.8741 \; W_{S_3}^{t_3} = 0.6462$$

By applying the obtained dynamic reliability parameters to the evidence discounting process, the discounted BPAs are shown in Table 7. Finally, we can get the fusion results of three sensors during this period and a comparison has been made in Table 8 by using different methods. Hence, for the subsequent time nodes, the sensor will make comprehensive decisions by combining the information given by the pre-order time point and its own time point.

C. DISCUSSIONS

As is shown from the raw data of Table 5, although there is a large difference in the recognition of S_3 at time t_2 when it assigns most of the probability to Θ, the probability that the moving target *Helicopter* is recognized increases with time. (regarded as the process in which the moving target *Helicopter* gradually approaches during this time period.)

According to Table 8, the result of the proposed method is consistent with other methods'. Besides, it reasonably

J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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shows the influence from sensor S_3 at time t_2, and the target is determined at the highest recognition rate at the final moment t_3. Therefore, in dynamic multi-sensor identification applications, multi-factor-affected sensor reliability can be reasonably calculated to deal with emergencies.

The key word "dynamic" in the identification process is mainly reflected in two aspects. First, for a single point in time, it instantaneously integrates the multifactorial influenced parameters through asymmetric support, information entropy, and sensor weight between BPAs to measure reliability. Secondly, for the continuous time period, each time point contains the information of the pre-order time point. Therefore, the proposed method for calculating the dynamic reliability of the multi-sensor is reasonable.

VI. CONCLUSION

Previous studies have attempted to link sensor reliability to a certain impact factor, but to some extent ignore the fact that the fusion process is a multi-factor decision-making situation. This paper has given an account of and the reasons for the importance of multi-factor-determined sensor reliability, aimed at determining what key factors have impact on the multi-sensor identification process. Since the information that the sensors need to process in practical applications is often unpredictable non-prior information, the advantage of using evidence theory to deal with uncertain information is obvious. Therefore, we leveraged the relationship between belief functions and intuitionistic fuzzy sets as the basis to calculate the supporting degree between BPAs under the framework of evidence theory. Satisfaction with recognition accuracy increased after the implementation of internal system factor (entropy value) and the external factor (sensor evidence credibility weight) in the evaluation process and there was an effective improvement when it comes to highly conflict data. In short, the findings lead us to believe that it is necessary to measure the sensor reliability based on multi-factor evaluation in practical applications.

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J. Weng, F. Xiao: Novel Sensor Dynamic Reliability Evaluation Method and Its Application in Multi-Sensor Information Fusion

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