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 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 [27]–[29], classifier fusion [30], [31], belief-rule-base [32], [33], etc. are helpful for making the decision of a
multi-sensor system more convincing [34], 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 [35] needs to be performed before data fusion. Typically, the assessment is divided into two types based on whether there is accessible prior information [36] 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) [37], [38], Elouedi et al. [39] have developed a method by using a factor to minimize the distance [40] between pignistic probabilities, which are computed form the discounted belief functions [41] 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. [42] 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. [43] 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 [44], 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 [45], conflict measurements [46], [47], and some other induced dissimilarity measures [48]. Among these methods, the principle of subordinating to the majority [49] 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 [50] based on this principle now. For instance, Schubert [51] introduced the concept of falsity degree as one of the considerations to evaluate the reliability of data source. Klein et al. [53] proposed a new BRB model with attribute reliability (BRB-r) based on the statistical method which introduces a new calculation method of matching degree. Thus, the calculation of dissent degree between each sensor in the system based on the Jousselme’s [54] 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. [41] used the falsity degree given by Schubert to define the divergence metric [55] 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. [56] 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 [57] at the same time.

It is not difficult to find that the existing methods mainly measure the reliability of the sensor by the similarity [58] 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. [59] 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) [60].

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 [61] 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 [62] itself. For a system, the overall consideration is necessary. Feng et al. [52] integrate the attribute reliability into a whole BRB-r model. In this essay, from the perspective of the information itself, its uncertainty [63], [64] and credibility weight [65] 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 [66] and evidence credibility weight (CW) based on Song et al.’s method to measure the reliability of the sensor.
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) [67], [68], marked as $\Theta$, including a limited number of propositions. Assume $\Theta = \{A_1, A_2, A_3, ..., A_n\}$, which $A_1, A_2, A_3, ..., A_n$ represent the basic events in probability theory and be regarded as basic elements.

1) Frame of discernment

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

\[
m(\phi) = 0
\]

\[
\sum_{i=1}^{n} m(A_i) = 1 \quad A \in \Theta
\]

$m$ is the basic probability assignment (BPA) [69], [70] on the frame, which $\phi$ 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

\[
Bel : 2^\Theta \rightarrow [0, 1]
\]

\[
Bel(A) = \sum_{B \subseteq A} m(B) \quad (\forall A \subset \Theta)
\]

$Bel$ is the belief function [71] on $\Theta$, representing the sum of the basic assignment functions corresponding to all subsets of $A$. Assume $Pls(A)$ is the plausibility function on frame $\Theta$, which represents the reliability of $A$ is not denied.

\[
Pls(A) = 1 - Bel(\bar{A}) = \sum_{B \supseteq \Theta} m(B) - \sum_{B \supseteq A} m(B) = \sum_{B \supseteq A} m(B)
\]

In fact, $[Bel(A), Pl(A)]$ indicates the unconfirmed interval [72] 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 $\Theta$, which $m_1$ and $m_2$ are the basic probability assignments (BPA) correspondingly during the evidence combination [73], [74]. Let the focal elements be $A_1, ..., A_k$ and $B_1, ..., B_r$, and according Dempster’s combination rule, the belief structure $m(C)$ is given by as follows:

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

where $K=\sum_{A \cap B \neq \phi} m_1(A) \cdot m_2(B)$

(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 $\lambda$, regarded as discounted coefficient [75], 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

\[
\{m^\lambda(A) = \lambda m(A), A \subset \Theta
\}

\[
m^\lambda(\Theta) = 1 - \lambda + m(\Theta)
\]

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 [40] [76]. Thus, Song et al. [59] 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 [77]–[79] provide a form for handling less rigorous information among the process of data fusion. Fuzzy set was firstly introduced by Zadeh in 1965 [80], and followed by Atanassov’s intuitionistic fuzzy set [81] as an expansion based on fuzzy set theory [82]. It simply gives an explanation 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.

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

$$A = \{ (x, \mu_A(x)) | x \in U \}$$

(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:

$$A = \{ (x, \mu_A(x), \nu_A(x)) | x \in U \}$$

(9)

where $\mu_A(x)$ and $\nu_A(x)$ are the membership degree and non-membership degree of element $x$ to set $A$ respectively. In this way, the relation between sets and mass functions is changed easily. So, the corresponding supporting degree is expressed as follow:

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

(13)

The method of calculating the similarity between two IFSs is based on Euclidian distance [83]. In the framework of discernment $U = \{\theta_1, \theta_2, ..., \theta_n\}$, 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:

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

(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:

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

(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.

$$Total_{Sup}(m_j) = \sum_{i=1,i \neq j}^{N} Sup(m_i, m_j)$$

(16)

Considering the reliability of one sensor with the whole multi-sensors system [84], the reliability of each sensor is defined as follow:

$$R'(S_j) = \frac{Total_{Sup}(m_j)}{\sum_{j=1}^{N} Total_{Sup}(m_j)}$$

(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 $S_i(i = 1, 2, ..., N)$ is expressed by:

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

(18)

C. BELIEF ENTROPY

Entropy, a physics concept, is a description of the system status. In 1948, information entropy was firstly introduced by Shannon [85] 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:

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

where $N$ is the amount of basic states in an information system, $p_i$ represents the probability of state $i$ happens, and $\sum_{i=1}^{N} p_i = 1$.

2) Belief entropy

In order to measure the uncertainty degree [86], [87] of mass functions, a new uncertainty measure method called belief entropy [88], [89], 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.

$$E_d(m) = - \sum_{A \subseteq X} m(A) \log_2 \frac{m(A)}{2^{|A|} - 1}$$  \hspace{1cm} (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 [90].

**Example 2.3.2** 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

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

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

### 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 [91]–[93] of the error sensor and define the sensor credibility [84] 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 $\Theta = \{\theta_1, \theta_2, ..., \theta_j\}$ 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 $i$ ($i = 1, 2, ..., n$) assigns to an object set (each object set represents a possibility of identification result), and $O_p$ is the corresponding object set ($O_p \subset \Theta, 1 \leq p \leq 2^j - 1$). Let $t_i$ be the target identified by sensor $i$ and $m_i$ 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 $(S_i, \langle O_p \rangle) = 0$.

$$\begin{cases} 
\text{if } O_p = t_i, (S_i, \langle O_p \rangle) = 1 \\
\text{if } O_p \neq t_i, (S_i, \langle O_p \rangle) = 0 
\end{cases}$$  \hspace{1cm} (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:

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

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

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

$$Total_Tar(\langle O_p \rangle) = \sum_{i=1}^{n} ((S_i, \langle O_p \rangle))$$  \hspace{1cm} (23)

According to the $Total_Tar(\langle O_p \rangle)$ obtained by row $p$ ($1 \leq p \leq 2^j - 1$), 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:

$$STV_k = [(S_1, \langle O_k \rangle), (S_2, \langle O_k \rangle), ..., (S_n, \langle O_k \rangle)]$$  \hspace{1cm} (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:

$$\text{total_weight} = \begin{cases} 
\text{majority_weight} = \frac{\sum (S_i, \langle O_k \rangle)}{n} & \text{when } (S_i, \langle O_k \rangle) = 1 \\
\text{minority_weight} = 1 - \text{majority_weight} & \text{when } (S_i, \langle O_k \rangle) = 0 
\end{cases}$$  \hspace{1cm} (25)

$$\text{total_unit_weight} = \begin{cases} 
\text{majority_weight} = \frac{\sum m_i}{m_i} & \text{for } (S_i, \langle O_k \rangle) = 1 \\
\text{minority_weight} = \frac{\sum m_i}{m_i} & \text{for } (S_i, \langle O_k \rangle) = 0 
\end{cases}$$  \hspace{1cm} (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 two parts, assigned to \textit{majority_weight} and \textit{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 \(STV_{k}(k=1,2,...,2^{n}-1)\) in a multi-sensor system, the evidence credibility weight \((CW_i)\) of each sensor \(i\) \((i=1,2,...,n)\) in the corresponding \(STV_k\) is now defined by:

\[
CW_i = total\_unit\_weight \times m_i
\]

(27)

where \(m_i\) is the probability that sensor \(i\) \((i=1,2,...,n)\) 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 \(STV_k\):

\[
\overline{CW_i} = \frac{\sum_i^z CW_i}{z}
\]

(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:

\[
CW'_i = E_{di} \times \overline{CW_i}
\]

(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 \(S_1, S_2, ..., S_n\) into the corresponding BPAs form \(m_1, m_2, ..., m_n\) in the framework of Dempster-Shafer theory.

Step 2. Calculate the supporting degree.

(i) According each BPA \(m_i\), \((i=1,2,...,N)\), 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 \(A_i\) and \(A_j\), marked by \(A_k \cap A_i\).

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

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

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 \(R_{S_i}\) 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), \(Ed_{d1}, Ed_{d2}, ..., Ed_{dn}\) 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 \(\overline{CW_1}, \overline{CW_2}, ..., \overline{CW_n}\), then multiply them with the results in Step 4, \(Ed_{d1}, Ed_{d2}, ..., Ed_{dn}\). We can get the improved evidence credibility results \(CW'_1 = Ed_{d1} \times \overline{CW_1}, CW'_2 = Ed_{d2} \times \overline{CW_2}, ..., CW'_n = Ed_{dn} \times \overline{CW_n}\).

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 \((W'_i = CW'_i \times R_{S_i})\) and getting the absolute value of each \(W'_i\).

Based on the evidence discounting operation, the corresponding discounted BPAs are known as \(m_1^{W_1}, m_2^{W_1}, ..., m_n^{W_1}\).

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

According to D-S theory, get the data fusion results by combining the discounted BPAs \(m_1^{W_1}, m_2^{W_1}, ..., m_n^{W_1}\).

For brevity, the whole process of sensor data fusion is concluded through a flow chart shown in Fig.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 4.1** 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 $\theta_1, \theta_2$ and $\theta_3$. Now, the detecting situation is given by these three sensors based on the form of BPAs, where the data are from [59]:

<table>
<thead>
<tr>
<th>$\theta_1$</th>
<th>$\theta_2$</th>
<th>$\theta_3$</th>
<th>( \Theta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_1$</td>
<td>0.6</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>$m_2$</td>
<td>0.2</td>
<td>0.5</td>
<td>0.1</td>
</tr>
<tr>
<td>$m_3$</td>
<td>0.6</td>
<td>0.1</td>
<td>0.2</td>
</tr>
</tbody>
</table>

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

$A_1 = \{(\theta_1, 0.6, 0.3), (\theta_2, 0.1, 0.8), (\theta_3, 0.2, 0.7)\}$

$A_2 = \{(\theta_1, 0.2, 0.6), (\theta_2, 0.5, 0.3), (\theta_3, 0.1, 0.7)\}$

$A_3 = \{(\theta_1, 0.4, 0.3), (\theta_2, 0.1, 0.6), (\theta_3, 0.2, 0.5)\}$

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

$A_1 \cap A_2 = \{(\theta_1, 0.2, 0.6), (\theta_2, 0.1, 0.8), (\theta_3, 0.1, 0.7)\}$

$A_1 \cap A_3 = \{(\theta_1, 0.4, 0.3), (\theta_2, 0.1, 0.8), (\theta_3, 0.2, 0.7)\}$

$A_2 \cap A_3 = \{(\theta_1, 0.2, 0.6), (\theta_2, 0.1, 0.6), (\theta_3, 0.1, 0.7)\}$

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

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

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):

$$R^*_1 = \frac{1.7548}{1.7548 + 1.7209 + 1.8350} = 0.3304$$

$$R^*_2 = \frac{1.7548}{1.7548 + 1.7209 + 1.8350} = 0.3240$$

$$R^*_3 = \frac{1.7548}{1.7548 + 1.7209 + 1.8350} = 0.3455$$

And the corresponding absolute dynamic reliability of each sensor is:

$$R_1 = \frac{0.3304}{0.3304 + 0.3240 + 0.3455} = 0.9563$$

$$R_2 = \frac{0.3304}{0.3304 + 0.3240 + 0.3455} = 0.9378$$

$$R_3 = \frac{0.3304}{0.3304 + 0.3240 + 0.3455} = 1$$

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

$$E_{d_1} = -0.6 * log_2 0.6 - 0.1 * log_2 0.1 - 0.2 * log_2 0.2 - 0.1 * log_2 \frac{1}{0.7} = 1.8517$$

$$E_{d_2} = -0.2 * log_2 0.2 - 0.5 * log_2 0.5 - 0.1 * log_2 0.1 - 0.2 * log_2 \frac{0.3}{0.7} = 2.3224$$

$$E_{d_3} = -0.4 * log_2 0.4 - 0.1 * log_2 0.1 - 0.2 * log_2 0.2 - 0.3 * log_2 \frac{0.3}{0.7} = 2.6886$$

Based on Eq.(21) to Eq.(23), the object sets are assigned respectively (\(O_1 = \{\theta_1\}, O_2 = \{\theta_2\}, O_3 = \{\theta_3\}, O_7 = \{\Theta\}\)), 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:

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

$$\Rightarrow \begin{pmatrix}
Total_{Tar}(\theta_1) \\
Total_{Tar}(\theta_2) \\
Total_{Tar}(\theta_3)
\end{pmatrix} \Rightarrow \begin{pmatrix}
0 \\
0 \\
0
\end{pmatrix}$$

Obviously, the maximum value of Total_{Tar}(\theta_1) 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 = \begin{pmatrix}1 & 0 & 1\end{pmatrix}, which the corresponding weight distribution is that \(S_1\) and \(S_3\) share a weight of \(\frac{3}{4}\) while \(S_2\) gets \(\frac{1}{4}\). Then, follow the Eq.(28), the evidence credibility weight (CW) is assigned to each sensor like this:

$$CW_1 = \frac{2}{0.6 + 0.4} \times 0.6 = 0.4$$
Get the coefficients of improved evidence credibility weight as a measurement of this information detecting system.

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

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

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

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

\[
W_1 = \frac{W_1'}{\sum W_i'} = \frac{0.7083}{0.7187} = 0.9855 \\
W_2 = \frac{W_2'}{\sum W_i'} = \frac{0.7187}{0.7187} = 1 \\
W_3 = \frac{W_3'}{\sum W_i'} = \frac{0.7170}{0.7187} = 0.9975
\]

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

\[
m_{W1}^1(\{\theta_1\}) = 0.5913 \\
m_{W1}^1(\{\theta_2\}) = 0.1971 \\
m_{W2}^2(\{\theta_1\}) = 0.2 \\
m_{W2}^2(\{\theta_2\}) = 0.1 \\
m_{W3}^3(\{\theta_1\}) = 0.3990 \\
m_{W3}^3(\{\theta_2\}) = 0.1995 \\
m_{W3}^3(\{\theta_\Theta\}) = 0.3017
\]

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

\[
m(\{\theta_1\}) = 0.6575 \\
m(\{\theta_2\}) = 0.1816 \\
m(\{\theta_3\}) = 0.1373 \\
m(\{\theta_\Theta\}) = 0.0235
\]

The following table shows the difference by comparing this modified method and the original dynamic reliability sensor method given by Song et al. [59] when the disturbance is not strong in a system.

**TABLE 2. Result comparsion**

<table>
<thead>
<tr>
<th></th>
<th>(\theta_1)</th>
<th>(\theta_2)</th>
<th>(\theta_3)</th>
<th>(\Theta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Song et al.’s method in [59]</td>
<td>0.646</td>
<td>0.178</td>
<td>0.144</td>
<td>0.032</td>
</tr>
<tr>
<td>proposed method</td>
<td>0.658</td>
<td>0.182</td>
<td>0.137</td>
<td>0.024</td>
</tr>
</tbody>
</table>

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 4.2** 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 BPs [59] 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 [59].

<table>
<thead>
<tr>
<th></th>
<th>(m_1)</th>
<th>(m_2)</th>
<th>(m_3)</th>
<th>(m_4)</th>
<th>(m_5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>({\theta_1})</td>
<td>0.8</td>
<td>0.4</td>
<td>0</td>
<td>0.3</td>
<td>0.45</td>
</tr>
<tr>
<td>({\theta_2})</td>
<td>0.1</td>
<td>0.2</td>
<td>0.95</td>
<td>0.2</td>
<td>0.1</td>
</tr>
<tr>
<td>({\theta_3})</td>
<td>0</td>
<td>0.1</td>
<td>0.05</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>({\theta_1, \theta_2})</td>
<td>0</td>
<td>0.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>({\theta_2, \theta_3})</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.15</td>
</tr>
<tr>
<td>(\Theta)</td>
<td>0.1</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
<td>0.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(W_1)</th>
<th>(W_2)</th>
<th>(W_3)</th>
<th>(W_4)</th>
<th>(W_5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>({\theta_1})</td>
<td>0.5913</td>
<td>0.1971</td>
<td>0.2</td>
<td>0.1</td>
<td>0.3990</td>
</tr>
<tr>
<td>({\theta_2})</td>
<td>0.2</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1995</td>
</tr>
<tr>
<td>({\theta_3})</td>
<td>0.0783</td>
<td>0.7187</td>
<td>0.1816</td>
<td>0.1373</td>
<td>0.3017</td>
</tr>
</tbody>
</table>

**Step 1:** Five intuitionistic fuzzy sets in \(\Theta = \{\theta_1, \theta_2, \theta_3\}\) generated by above five BPs are expressed as follow:

\[
\begin{align*}
\theta_1: & (1.0, 0.8, 0.1), (0.8, 0.1, 0.0), (0.0, 0.9, 0.1), (0.9, 0.0, 0.0) \\
\theta_2: & (0.4, 0.6, 0.0), (0.6, 0.0, 0.0), (0.0, 0.0, 0.0) \\
\theta_3: & (0.3, 0.7, 0.0), (0.7, 0.0, 0.0) \\
\end{align*}
\]

**Step 2:** Construct the similarity degree matrix (SDM) based on Eq.(14).

\[
SDM = \begin{bmatrix}
1 & S_{\Theta}(\theta_1, \theta_2) & S_{\Theta}(\theta_1, \theta_3) & S_{\Theta}(\theta_1, \Theta) \\
S_{\Theta}(\theta_2, \theta_1) & 1 & S_{\Theta}(\theta_2, \theta_3) & S_{\Theta}(\theta_2, \Theta) \\
S_{\Theta}(\theta_3, \theta_1) & S_{\Theta}(\theta_3, \theta_2) & 1 & S_{\Theta}(\theta_3, \Theta) \\
S_{\Theta}(\Theta, \theta_1) & S_{\Theta}(\Theta, \theta_2) & S_{\Theta}(\Theta, \theta_3) & 1 \\
\end{bmatrix}
\]

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

\[
R_{S_1} = 0.8125 \\
R_{S_2} = 1 \\
R_{S_3} = 0.7535 \\
R_{S_4} = 0.7854 \\
R_{S_5} = 0.8631
\]

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

\[
E_{d1} = 1.2027 \\
E_{d2} = 2.3219 \\
E_{d3} = 0.2864 \\
E_{d4} = 2.6233 \\
E_{d5} = 2.8622
\]

**Step 5:** Since all four sensors determine the target as \(\theta_1\) 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.)
dynamic reliability obtained by still room for improvement in recognition accuracy. reflect the changing trend in the fusion process, and there is reduced to some extent. However, this method does not proposed an average synthesis rule. By averaging the Dempster’s rule. To deal with the problem, Murphy in a highly conflicting situation when applying the classical system has been dramatically affected after the fusion is not ideal (only slightly higher than the dynamic reliability of each sensor as the discounted generating the discounted BPAs based on directly using coefficient of BPAs. Although the final recognition result the influence generated in the whole decision result is very value and importance degree of the sensor \( S \). 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.

\[
\begin{align*}
CW_1 &= \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.8 = 0.3280 \\
CW_2 &= \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.4 = 0.1641 \\
CW_3 &= \frac{0.2}{0.2 + 0.3 + 0.2} \times 0.95 = 0.2 \\
CW_4 &= \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.3 = 0.1230 \\
CW_5 &= \frac{0.8}{0.8 + 0.4 + 0.3 + 0.45} \times 0.45 = 0.1846
\end{align*}
\]

Step 6: Get the improved evidence credibility weight result based on Eq.(29).
\[
\begin{align*}
CW_1' &= 0.3947 \\
CW_2' &= 0.3810 \\
CW_3' &= 0.0572 \\
CW_4' &= 0.3228 \\
CW_5' &= 0.5284
\end{align*}
\]

Step 7: According to the previous definition, the final modified dynamic reliability factors are obtained as:
\[
\begin{align*}
W_1 &= 0.3955 \\
W_2 &= 0.9399 \\
W_3 &= 0.0873 \\
W_4 &= 0.8340 \\
W_5 &= 1
\end{align*}
\]

Step 8: Calculate the discounted BPAs and get the result through data fusion.
\[
\begin{align*}
m(\{\theta_1\}) &= 0.7538 \\
m(\{\theta_2\}) &= 0.1568 \\
m(\{\theta_3\}) &= 0.0255 \\
m(\{\theta_1, \theta_2\}) &= 0.0374 \\
m(\{\theta_1, \theta_3\}) &= 0.0088 \\
m(\{\theta_2, \theta_3\}) &= 0.0176
\end{align*}
\]

From the result, it is clear that the recognition result of the multi-sensor system is \( \theta_1 \), 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.

**V. CASE STUDY IN DYNAMIC TARGET RECOGNITION**

In some military or industrial applications, objects that need to be identified may change dynamically over time. 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 \( F \) 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 [59].

**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 the current time step is expressed as:

\[
\begin{align*}
\text{SDM} &\rightarrow \begin{bmatrix}
0.7538 & 0.1568 & 0.0255 \\
0.0374 & 0.0088 & 0.0176
\end{bmatrix}
\end{align*}
\]

Based on the original sensor dynamic reliability coefficient.

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 [59], 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 \( \theta_1 \), 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 \( \theta_1 \) and the supporting degree grows slowly even though the remaining sensors agree with the correct target \( \theta_1 \). 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.
each time nodes is obtained as:

\[
SDM_{t_1} = \left( \begin{array}{cc}
0.9654 & 0.9697 \\
0.9697 & 0.9909 \\
0.9764 & 0.9933 \\
1 & 1
\end{array} \right)
\]

\[
SDM_{t_2} = \left( \begin{array}{cc}
0.9407 & 0.8639 \\
0.8639 & 0.9232 \\
0.6946 & 0.8342 \\
1 & 1
\end{array} \right)
\]

\[
SDM_{t_3} = \left( \begin{array}{cc}
0.9325 & 0.8813 \\
0.9325 & 0.9558 \\
0.9442 & 0.9779 \\
1 & 1
\end{array} \right)
\]

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).

**TABLE 6. Values of the main parameters**

<table>
<thead>
<tr>
<th>Method</th>
<th>( t_1 )</th>
<th>( t_2 )</th>
<th>( t_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( R )</td>
<td>( E_d )</td>
<td>( CW )</td>
</tr>
<tr>
<td>( S_1 )</td>
<td>0.9926</td>
<td>2.0041</td>
<td>0.3498</td>
</tr>
<tr>
<td>( S_2 )</td>
<td>0.9990</td>
<td>2.2691</td>
<td>0.3182</td>
</tr>
<tr>
<td>( S_3 )</td>
<td>1</td>
<td>2.1678</td>
<td>0.3320</td>
</tr>
</tbody>
</table>

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

\[
W_{S_1}^{t_1} = 0.9646 \quad W_{S_1}^{t_2} = 1 \quad W_{S_1}^{t_3} = 0.9978
\]

\[
W_{S_2}^{t_1} = 0.3819 \quad W_{S_2}^{t_2} = 0.6461 \quad W_{S_2}^{t_3} = 1
\]

\[
W_{S_3}^{t_1} = 1 \quad W_{S_3}^{t_2} = 0.8741 \quad W_{S_3}^{t_3} = 0.6462
\]

By applying the obtained dynamic reliability parameters to the evidence discounting process, the discounted BPA is 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 \( \Theta \), the probability that the moving target \( Helicopter \) is recognized increases with

**TABLE 4. Combination results based on different methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>( m_1^1 )</th>
<th>( m_1^2 )</th>
<th>( m_1^3 )</th>
<th>( m_1^4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical Demesptre’s rule</td>
<td>( m({ \theta_1 })=0.8451 )</td>
<td>( m({ \theta_1 })=0.0000 )</td>
<td>( m({ \theta_1 })=0.0000 )</td>
<td>( m({ \theta_1 })=0.0000 )</td>
</tr>
<tr>
<td>Murphy’s rule [94]</td>
<td>( m({ \theta_1 })=0.4949 )</td>
<td>( m({ \theta_2 })=0.0000 )</td>
<td>( m({ \theta_3 })=0.0000 )</td>
<td>( m({ \theta_1 })=0.0000 )</td>
</tr>
<tr>
<td>Deng entropy’s rule</td>
<td>( m({ \theta_1 })=0.5261 )</td>
<td>( m({ \theta_2 })=0.0000 )</td>
<td>( m({ \theta_3 })=0.0000 )</td>
<td>( m({ \theta_4 })=0.0000 )</td>
</tr>
<tr>
<td>Song et al.’s method in [59]</td>
<td>( m({ \theta_1 })=0.8446 )</td>
<td>( m({ \theta_2 })=0.0000 )</td>
<td>( m({ \theta_3 })=0.0000 )</td>
<td>( m({ \theta_4 })=0.0000 )</td>
</tr>
<tr>
<td>Proposed method</td>
<td>( m({ \theta_1 })=0.6560 )</td>
<td>( m({ \theta_2 })=0.0000 )</td>
<td>( m({ \theta_3 })=0.0000 )</td>
<td>( m({ \theta_4 })=0.0000 )</td>
</tr>
</tbody>
</table>
enced parameters through asymmetric support, information applications, multi-factor-affected sensor reliability can be gradually approaches during this time period.

Helicopter time. (regarded as the process in which the moving target

TABLE 5. Sensor identification information represented by BPAs

<table>
<thead>
<tr>
<th></th>
<th>(m({A}))</th>
<th>(m({H}))</th>
<th>(m({F}))</th>
<th>(m({\Theta}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(S_1)</td>
<td>0.3666</td>
<td>0.8176</td>
<td>0.0003</td>
<td>0.3771</td>
</tr>
<tr>
<td>(m({A}))</td>
<td>0.4563</td>
<td>0.1185</td>
<td>0.1553</td>
<td>0.0586</td>
</tr>
<tr>
<td>(m({H}))</td>
<td>0.0268</td>
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<td></td>
</tr>
</tbody>
</table>

TABLE 7. Modified BPAs based on proposed method

<table>
<thead>
<tr>
<th></th>
<th>(m({A}))</th>
<th>(m({H}))</th>
<th>(m({F}))</th>
<th>(m({\Theta}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(S_1)</td>
<td>0.3536</td>
<td>0.3122</td>
<td>0.0001</td>
<td>0.3771</td>
</tr>
<tr>
<td>(m({A}))</td>
<td>0.4401</td>
<td>0.1143</td>
<td>0.0593</td>
<td>0.0920</td>
</tr>
<tr>
<td>(m({H}))</td>
<td>0.6285</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(m({\Theta}))</td>
<td>0.2652</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(m({A}))</td>
<td>0.2793</td>
<td>0.2403</td>
<td>0.0004</td>
<td>0.1402</td>
</tr>
<tr>
<td>(m({H}))</td>
<td>0.4331</td>
<td>0.2470</td>
<td>0.0002</td>
<td>0.7452</td>
</tr>
<tr>
<td>(m({\Theta}))</td>
<td>0.0302</td>
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</tbody>
</table>

TABLE 8. Fusion results based on different methods

<table>
<thead>
<tr>
<th></th>
<th>(m({A}))</th>
<th>(m({H}))</th>
<th>(m({\Theta}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deng entropy’s rule</td>
<td>0.3365</td>
<td>0.0150</td>
<td>0.0045</td>
</tr>
<tr>
<td>(m({A}))</td>
<td>0.6143</td>
<td>0.0195</td>
<td></td>
</tr>
<tr>
<td>(m({H}))</td>
<td>0.0010</td>
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</tr>
<tr>
<td>Song et al.’s method in [59]</td>
<td>0.2375</td>
<td>0.0323</td>
<td>0.0002</td>
</tr>
<tr>
<td>(m({A}))</td>
<td>0.6308</td>
<td>0.0315</td>
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</tr>
<tr>
<td>(m({H}))</td>
<td>0.0483</td>
<td></td>
<td></td>
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<tr>
<td>(m({\Theta}))</td>
<td>0.0002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed method</td>
<td>0.3771</td>
<td>0.0349</td>
<td>0.0003</td>
</tr>
<tr>
<td>(m({A}))</td>
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<td>0.0150</td>
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<td>(m({H}))</td>
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<tr>
<td>(m({\Theta}))</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(m({A}))</td>
<td>0.0840</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(m({H}))</td>
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<tr>
<td>(m({\Theta}))</td>
<td>0.0989</td>
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</tbody>
</table>

VI. CONCLUSIONS

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2019.2943353, IEEE Access
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 multifactor evaluation in practical applications.

REFERENCES


[9] Hamidreza Seiti and Ashkan Hafezalkotob. Developing the r-tOPSIS conflict data. In short, the findings lead us to believe that it is necessary to measure the sensor reliability based on multifactor evaluation in practical applications.

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[70] Zeng H. Gu and Dong Ling. Distance formulas capable of unifying euclidian space and probability space. 2018.


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