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An Improved Multisensor Data Fusion Method and Its Application in Fault Diagnosis

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ABSTRACT A multisensor system is used to improve the ability of monitoring and tracking accuracy of an engineering system since only one sensor is not enough, whereupon, faulty diagnosis, as a typical information fusion problem which is under multisensor environment, has attracted much attention in recent years. The evidence theory has been widely used to solve this problem. However, when there is a high level of conflict between the information gathered from different sensors, the counter-intuitive result could be obtained when using the classical Dempster's combination rule. To address this problem, an improved multisensor data fusion method is proposed to fuse the data collected from multisensors. Some numerical examples are illustrated to show that the proposed method is effective and feasible. Moreover, the fusion results using different methods are analyzed, which indicate the superiority and stronger application of the proposed method in the field of fault diagnosis.

INDEX TERMS Conflict evidence, Dempster's combination rule, belief entropy, Dempster-Shafer evidence theory, information theory.

I. INTRODUCTION

With the development of various defense, surveillance, and traffic control systems, higher and higher requirements are placed on sensors [1]–[3]. Especially in military applications, sensor systems are required to have greater reliability and flexibility. Traditional single sensor systems have been difficult to adapt to the needs of sensor performance. To this end, the research on multisensor systems is still in the process. At the same time, the information obtained from different sensors may be uncertain, fuzzy, or even conflict. Since so many scenarios need the fusion of multisensors information [4], [5], it is very important to make reasonable decision for the problems like how to cope with the uncertainty [6]–[8], how to handle the inconsistent information [9]–[11], as well as how to make a reasonable decision [12], [13]. In actual applications, even attributer eduction is required to deal with large and uncertain data which is linked to multiple relevant data sources [14]–[16].

However, due to the possibility of error in the sensor data which is likely to cause a great conflict between multisensors. Dempster-Shafer evidence theory plays a crucial role in dealing with the conflict information [17]. As introduced by Dempster [18] and then developed by Shafer *et al.* [19], it's widely applied to uncertainty modeling [20], [21], and so on. But until recently, existing methods can not deal with the conflict information accurately and effectively. In order to cope with the impact of the high conflict, two main streams of methods have been proposed, which are, modifying the classical Dempsters combination rule (DCR) [22] and focusing on the pretreatment for basic probability assignment (BPA) [23], [24]. Also, there are some other research aspects like how to fuse conflict evidences [25]–[27] and generate BPAs [28], [29]. The typical example using the first approach can be the method of Yager [30], which reallocated the conflict mass assignments to the unknown domain and proposed a modified DCR. It's likely that this method could increase the uncertainty of the fusion result. Jiang and Hu [31] extends Yager's soft likelihood function to combine the BPA. Sun *et al.* [32] introduced the valid coefficients in order to consider only partial conflicts. Li *et al.* [33] thought that each group of evidence can be treated equally so that the conflicts can be relocated by measuring weighted averaging support degree. By calculating the reliability of the evidence, Li and Gou [34] take the conflict distribution of the propositions in to consideration.

In the other category, Murphy [35] proposed an average approach that BPA is directly averaged, so that evidences of conflicts can be effectively dealt with. Murphy, however, did not take into account the correlation between the evidences. Tabassian *et al.* [36], who used a relabeling procedure to propose a classification method that combining ensemble learning with evidence theory. Chen *et al.* [37] preprocessed the classical DCR to obtain weighted evidences by calculating pignistic probability distance and evidence accuracy. Jiang *et al.* [38] used the information volume of the evidences as the discounting coefficients to weigh the credibility of the evidence. Lin *et al.* [39] importd Euclidean distance to characterize the differences between different evidences. Although so many methods have been proposed, there is still space for making further progress.

In this paper, based on the Euclidean distance and evidence entropy, a new method to combine conflict evidences that take into account the uncertainty of information - expressed by the belief entropy [40] - is introduced. The information obtained from different sensors were considered as the diagnosis evidences and the fault diagnosis system is considered as evidence fusion problem. By calculating the Euclidean distance and the evidence entropy of each sensor, two support degrees of each evidence are obtained. The weighted factors of every evidence are gained by considering these two elements together, with which we can get the modified BPA. In the end, the classic Dempster's combination rule is used to fuse the modified evidences.

The paper is organized as follows. The preliminaries basic concept of the evidence theory as well as the belief entropy are briefly introduced in Section 2. Section 3 presents a new method to deal with evidences that have high conflict degree. A counter-intuitive result of a classical DCR and an example in a complete different situation are illustrated in Section 4 to show the feasibility of the proposed method. In Section 5, numeric experiments are used to illustrate the performance of it and a fault diagnosis architecture of a distributed multisensor system is introduced. Then, a case of a rotating machine is used to manifest the effectiveness of this method. After that, a specific application is listed in Section 6 and finally, the conclusion is discussed.

II. PRELIMINARIES

In this section, some preliminaries are briefly introduced.

A. DEMPSTER-SHAFER EVIDENCE THEORY

Several powerful methods including improved evidence theory [41]–[43], fuzzy aggregation operators [44], [45], D numbers [46]–[48], Z-number [49], [50], and entropy [51], [52] are proposed to handle uncertainty. Dempster-Shafer evidence theory (D-S theory), also referred to as the theory of belief functions, is proposed by Dempster [18] and developed later by Shafer *et al.* [19]. It has been widely used in the fields of uncertainty modeling [20], [21], decision making [53]–[56], fault diagnosis [57]–[60], information fusion [61]–[63], medical diagnosis [64], word sense disambiguation [65], complex network [66], multi-criteria decision-making [67] and so on. Some basic concepts in D-S theory are introduced.

A complete set of mutually incompatible basic propositions (assumptions) represents all possible events called the frame of discernment, indicated by:

$$X = \{\theta_1, \theta_2, \ldots, \theta_i, \ldots, \theta_{|X|}\} \tag{1}$$

The power set of X:

$$2^X = \{\phi, \{\theta_1\}, \ldots, \{\theta_{|X|}\}, \{\theta_1, \theta_2\}, \ldots, \{\theta_1, \theta_2, \ldots, \theta_i\}, \ldots, X\} \tag{2}$$

A subset of the recognition framework is called a proposition. The degree of trust assigned to each proposition is called basic probability distribution, that is, $m(A)$, which reflects the reliability of A.

Let function M be a map that satisfies the following conditions:

$$M : 2^X \to [0, 1] \tag{3}$$

- The result of the mass function of an impossible event is 0, that is:

$$m(\Phi) = 0 \tag{4}$$

- The sum of the basic probabilities of all elements in X is 1, that is:

$$\sum_{A \subseteq 2^X} m(A) = 1 \tag{5}$$

In D-S theory, a mass function is also called a basic probability assignment (BPA). BPA can be generated from different sensors based on the same focal discernment. Assume that two BPA are called m_1 and m_2, they can be combined using the Dempster's rule of combination:

$$m(A) = \begin{cases} \frac{1}{1-K} \sum\limits_{B \cap A = A} m_1(B) m_2(C), & A \neq \emptyset; \\ 0, & A = \emptyset. \end{cases} \tag{6}$$

where

$$K = \sum_{B \cap A = \emptyset} m_1(B) m_2(C) \tag{7}$$

The severity of the conflict: The larger the value of K, the greater the conflict between different evidences [68]. Note that the Dempster's rule of combination is only applicable to such two BPA which satisfy the condition $K < 1$.

B. BELIEF ENTROPY

The belief entropy, also called as Deng entropy [40]. It is the generalization of Shannnon entropy [69] that was first presented by Shannon for a random variable with communication theory. The belief entropy is used to measure the uncertainty degree of BPA that can be presented as follows:

$$E_d = -\sum_i m(F_i) log \frac{m(F_i)}{2^{|F_i|} - 1} \tag{8}$$

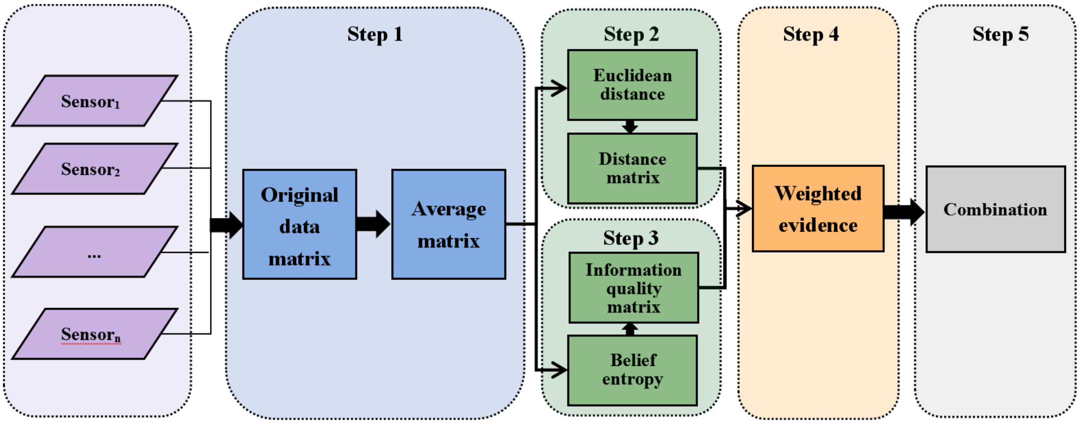

FIGURE 1. Flowchart of the proposed method.

where, F_i is a proposition in mass function m, and $|F_i|$ is the cardinality of F_i. We can easily see from the above definition that the belief entropy is similar with the classical Shannon entropy formally, whereas the belief for each proposition F_i is divided by a term $(2^{|F_i|} - 1)$ which represents the potential number of states in F_i (The empty set is not included). Specially, the entropy can definitely degenerate to the Shannon entropy if the belief is only assigned to single elements. That is:

$$E_d = -\sum_i m(F_i) log \frac{m(F_i)}{2^{|F_i|} - 1} = -\sum_i m(F_i) log m(F_i) \quad (9)$$

III. THE PROPOSED METHOD BASED ON THE BELIEF ENTROPY

A new proposed method is presented in this section which is also shown in Fig 1. The process steps are analyzed in detail.

- *Step 1*
  Suppose an evidence set in the same focal discernment: $M = \{m_i | i = 1, 2, \ldots, n\}$ with $\{F_1, F_2, \ldots, F_N\}$. The average value $m_a(F_k)$ was described as follows:

$$m_a(F_k) = \frac{1}{n} \sum_{i=1}^{n} m_i(F_k), \quad k = 1, 2, \ldots, N \quad (10)$$

  which satisfy:

$$\begin{cases} m_a(F_k) \in [0, 1] \\ \sum_{k=1}^{N} m_a(F_k) = 1 \end{cases}$$

- Step 2
  In this step, we calculate the Euclidean distance between the original BPA and the average BPA that denoted as $d(m_i, m_a)$ which can be described as follows:

$$d(m_i, m_a) = \sqrt{\sum_{k=1}^{N} [m_i(F_k) - m_a(F_k)]^2}, \; i = 1, 2, \ldots, n. \quad (11)$$

When the goal is to calculate the distance between n-dimensional vectors, distance vector is shown as follows:

$$D = \begin{bmatrix} d(m_1, m_a) \\ d(m_2, m_a) \\ \ldots \\ d(m_n, m_a) \end{bmatrix}$$

As we all know, the greater the distance between the two vectors, the smaller the similarities between them. Based on this common scene and the distance between two BPA that we have just given, the similarities are defined as follows:

$$S_{ia} = e^{-d(m_i, m_a)}, \quad i = 1, 2, \ldots, n. \quad (12)$$

Similarly, for the situation of n-dimensional vectors, the similarity degree vector can be defined:

$$S = \begin{bmatrix} S_{1a} \\ S_{2a} \\ \ldots \\ S_{na} \end{bmatrix}$$

And then one of the support degree of the evidence m_i is defined as:

$$Sup(m_i) = \frac{S_{ia}}{\sum_{k=1}^{n} S_{ka}} \quad (13)$$

- Step 3
  In this step, the belief entropy of the BPA is shown:

$$E_d(m_i) = -\sum_i m(F_i) log \frac{m(F_i)}{2^{|F_i|} - 1} \quad (14)$$

the second weighted factor:

$$I_q(m_i) = \frac{E_d(m_i)}{\sum_{k=1}^{n} E_d(m_k)} \quad (15)$$

- Step 4
After that, we use the belief entropy to modify the weight and to normalize the results:

$$Crd(m_i) = \frac{Sup(m_i) \times I_q(m_i)}{\sum_{k=1}^{n} Sup(m_k) \times I_q(m_k)} \tag{16}$$

It can be easily seen that $\sum_{i=1}^{n} Crd(m_i) = 1$, thus, the credibility degree is actually a weight of the i-th evidence. Then, the modified evidence can be shown as follows:

$$m'(F_k) = \sum_{i=1}^{n} w_i m_i(F_k), \quad k = 1, 2, \ldots, N. \tag{17}$$

As can be seen, the credibility degree of an evidence would be higher and has more effect on the final combination result if the evidence is supported by other evidences or have a higher belief entropy and vice versa.
- Step 5
In the end, we use the classical DCR to combine the modified BPA:

$$m(F) = \begin{cases} \dfrac{\sum_{\cap F_k = F} \prod_{i=1}^{n} m_i'(F_k)}{1 - \sum_{\cap F_k = \varnothing} \prod_{i=1}^{n} m_i'(F_k)}, \\ \quad F \neq \varnothing \quad \forall F_k \subseteq \Theta \\ 0, \quad F = \varnothing \end{cases} \tag{18}$$

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

IV. EXAMPLES

Example 1: Suppose a frame discrimination of a faulty diagnosis system is $\Theta = \{F_1, F_2, F_3\}$, *The BPA is shown as* m_1 *and* m_2. *The BPA from two sensors are shown in Table 1.*

TABLE 1. BPA from two different sensors.

Evidence	F_1	F_2	F_3
m_1	0.99	0.01	0
m_2	0	0.01	0.99

As we can see in the Table 1, the support degree of F_1 is 0.99 whereas from the second sensor is 0. On the contrary, the support degree of F_3 is 0 from the first sensor whereas it is 0.99 form the second sensor. They are obviously conflicting. At the same time, the support degree of F_2 from both of them are 0.01 which can almost be considered to be impossible. Nevertheless, when the classic method was used to combine them, the fusion result is: $m(F_1) = 0$, $m(F_2) = 1$, $m(F_3) = 0$ and $m(\Theta) = 0$.

The result shows that F_2 will definitely happen while F_1 and F_3 will not happen, which is obviously not true. Therefore, when there is a conflict between evidences, the traditional fusion method is flawed.

Next, we calculate Example 1 in detail:

- Step 1
In this step, the average matrix is calculated.

$$m_a(F_1) = \frac{1}{2}\sum_{i=1}^{2} m_i(F_1) = \frac{1}{2}(0.99 + 0) = 0.495$$

$$m_a(F_2) = \frac{1}{2}\sum_{i=1}^{2} m_i(F_2) = \frac{1}{2}(0.01 + 0.01) = 0.01$$

$$m_a(F_3) = \frac{1}{2}\sum_{i=1}^{2} m_i(F_3) = \frac{1}{2}(0 + 0.99) = 0.495$$

- Step 2
The support degree is shown as:

$$\begin{aligned} d(m_1, m_a) &= |E_1 - E_a| = \sqrt{\sum_{k=1}^{3}[m_1(F_k) - m_a(F_k)]^2} \\ &= \sqrt{0.495^2 + 0^2 + 0.495^2} \\ &= 0.7 \end{aligned}$$

$$\begin{aligned} d(m_2, m_a) &= |E_2 - E_a| = \sqrt{\sum_{k=1}^{3}[m_2(F_k) - m_a(F_k)]^2} \\ &= \sqrt{0.495^2 + 0^2 + 0.495^2} \\ &= 0.7 \end{aligned}$$

$$S_{1a} = e^{-d(m_1, m_a)} = 0.4966$$

$$S_{2a} = e^{-d(m_2, m_a)} = 0.4966$$

$$Sup(m_1) = S_{1a} / \sum_{i=1}^{2} S_{ia} = 0.5$$

$$Sup(m_2) = S_{2a} / \sum_{i=1}^{2} S_{ia} = 0.5$$

- Step 3
Then the information quality is obtained:

$$\begin{aligned} E_d(m_1) &= -\sum_{i=1} m_1 log \frac{m_1}{2^{|m_1|} - 1} \\ &= -0.99 log \frac{0.99}{2^1 - 1} - 0.01 log \frac{0.01}{2^1 - 1} - 0 \\ &= 0.0560 \end{aligned}$$

$$\begin{aligned} E_d(m_2) &= -\sum_{i=1} m_2 log \frac{m_2}{2^{|m_2|} - 1} \\ &= 0 - 0.01 log \frac{0.01}{2^1 - 1} - 0.99 log \frac{0.99}{2^1 - 1} \\ &= 0.0560 \end{aligned}$$

$$I_q(m_1) = E_d(m_1) / \sum_{i=1}^{2} E_d(m_i) = 0.5$$

$$I_q(m_2) = E_d(m_2) / \sum_{i=1}^{2} E_d(m_i) = 0.5$$

- Step 4
  After that, the original BPA have been modified.

$$m'(F_1) = \sum_{i=1}^{2} w_i m_i(F_1) = 0.495$$
$$m'(F_2) = \sum_{i=1}^{2} w_i m_i(F_2) = 0.01$$
$$m'(F_2) = \sum_{i=1}^{2} w_i m_i(F_3) = 0.495$$

- Step 5
  Finally, the classical DCR is used to combine the modified BPA. The fusion result is: $m(F_1) = 0.4999$, $m(F_2) = 0.0002$ and $m(F_3) = 0.4999$ which shows that the F_1, F_3 is much more likely to occur than F_2. Obviously, this result is more reliable. Another numeric simulation that in a totally different situation still needs to be used for verifying the performance.

Now, the configuration is changed. The necessity of this situation is explained as follow:

Under normal conditions, the situation is considered ideal, that every sensor can give us the information we need. However, in reality, it is difficult to guarantee that there is no non-ideal situation, such as a failure of a sensor which could lead to the loss of information, etc. For instance, the data we obtained is no longer "$m(F_1) = 0.6, m(F_2) = 0.1, m(F_3) = 0.3$" but "$m(\{F_1\}) = 0.7, m(F_2, F_3) = 0.3$".

Given a frame of discernment X with seven elements, element F_1, F_2, and F_3 are on behalf of three different faults. Three mass functions are shown in Table 2.

TABLE 2. BPA from three different sensors.

Evidence	$\{F_1\}$	$\{F_2\}$	$\{F_3\}$	$\{F_1, F_2\}$	$\{F_2, F_3\}$	$\{F_1, F_3\}$	$\{F_1, F_2, F_3\}$
m_1	0.7	0.05	0.05	0.05	0.05	0.05	0.05
m_2	0.05	0.7	0.05	0.05	0.05	0.05	0.05
m_3	0.75	0.05	0	0.05	0.05	0.05	0.05

TABLE 3. Fusion results of Example 2.

Evidence	$m_{1,2}$	$m_{1,2,3}$
$m(F_1)$	0.4579	0.8381
$m(F_2)$	0.4579	0.1431
$m(F_3)$	0.0399	0.0114
$m(F_1, F_2)$	0.0133	0.0023
$m(F_1, F_3)$	0.0133	0.0023
$m(F_2, F_3)$	0.0133	0.0023
$m(F_1, F_2, F_3)$	0.0044	0.0005

From the Table 3, we can clearly see that despite the huge conflicts in the data, when combining all of Sensor1, Sensor 2, and Sensor 3, the support degree of F_1 is the highest, that is to say, the right judgment was made. Therefore, the proposed new method is feasible.

V. EXPERIMENT

In this section, by comparing with the existing methods, the better applicability and accuracy of the proposed method is shown.

Example 2: Again, we assumed a frame discrimination of a faulty gnosis system is $\Theta = \{F_1, F_2, F_3\}$ and the BPA is shown in Table 4.

TABLE 4. BPA from five different sensors.

Evidence	F_1	F_2	F_3	Θ
m_1	0.70	0.15	0.15	0
m_2	0.40	0.20	0.40	0
m_3	0.65	0.35	0	0
m_4	0.75	0	0.25	0
m_5	0	0.20	0.80	0

As we can see in the Table 4, Sensors 1, 2, 3, 4 support the fault F_1 whereas Sensor 5 has a different result that it supports the fault F_3 with which there is no other sensor support. Moreover, it's unlikely that the fault F_1 would happen as well, which shows clearly that there is a high level of conflict among these information. From the above analysis, we can draw the conclusion that $m(F_2)$ and $m(F_3)$ should be much lower than $m(F_1)$ with DCR. Different fusion results are shown in Table 5 and the combination result of $m_{1,2,3,4,5}$ are shown in Fig 2. The detailed analysis is as follows.

TABLE 5. Combination results.

Rules		$m_{1,2}$	$m_{1,2,3}$	$m_{1,2,3,4}$	$m_{1,2,3,4,5}$
DS [70]	$m(F_1)$	0.7568	0.9455	1	NaN
	$m(F_2)$	0.0811	0.0545	0	NaN
	$m(F_3)$	0.1621	0	0	NaN
	$m(\Theta)$	0	0	0	NaN
Yager [30]	$m(F_1)$	0.2800	0.1820	0.1365	0
	$m(F_2)$	0.0300	0.0105	0	0
	$m(F_3)$	0.0600	0	0	0
	$m(\Theta)$	0.6300	0.8075	0.8635	1
Li *et al.* [33]	$m(F_1)$	0.6265	0.6531	0.6762	0.5000
	$m(F_2)$	0.1403	0.1989	0.1511	0.1800
	$m(F_3)$	0.2332	0.1480	0.1727	0.3200
	$m(\Theta)$	0	0	0	0
Sun *et al.* [32]	$m(F_1)$	0.4645	0.4412	0.4457	0.2594
	$m(F_2)$	0.0887	0.1142	0.0866	0.0934
	$m(F_3)$	0.1523	0.0814	0.0989	0.1660
	$m(\Theta)$	0.2945	0.3632	0.3688	0.4812
Li and Gou [34]	$m(F_1)$	0.6265	0.6475	0.6669	0.5445
	$m(F_2)$	0.1403	0.2036	0.1553	0.1757
	$m(F_3)$	0.2332	0.1489	0.1778	0.2798
	$m(\Theta)$	0	0	0	0
Deng *et al.* [71]	$m(F_1)$	0.6265	0.6475	0.6669	0.5445
	$m(F_2)$	0.1403	0.2036	0.1553	0.1757
	$m(F_3)$	0.2332	0.1489	0.1778	0.2798
	$m(\Theta)$	0	0	0	0
Jiang *et al.* [38]	$m(F_1)$	0.8540	0.9639	0.9942	0.9384
	$m(F_2)$	0.0290	0.0244	0.0019	0.0020
	$m(F_3)$	0.1170	0.0116	0.0039	0.0596
	$m(\Theta)$	0	0	0	0
Lin *et al.* [39]	$m(F_1)$	0.7401	0.9190	0.9854	0.9443
	$m(F_2)$	0.0749	0.0556	0.0054	0.0040
	$m(F_3)$	0.1850	0.0245	0.0093	0.0517
	$m(\Theta)$	0	0	0	0
Proposed method	$m(F_1)$	0.7084	0.9020	0.9764	0.9495
	$m(F_2)$	0.0793	0.0528	0.0074	0.0045
	$m(F_3)$	0.2123	0.0452	0.0162	0.0465
	$m(\Theta)$	0	0	0	0

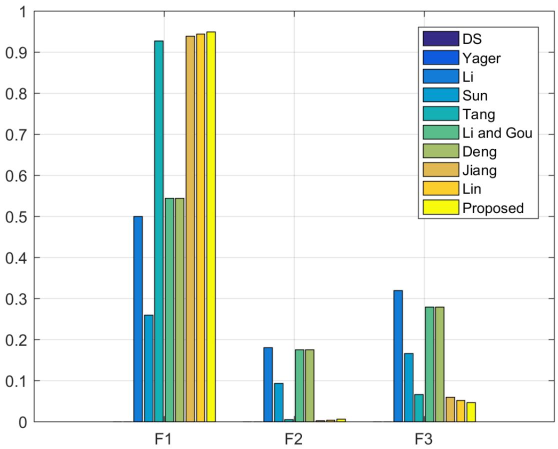

FIGURE 2. Combination result when fusing data from five sensors.

The classic DCR is unserviceable under this situation given that it can not obtain the fusion results when the fifth evidence of a high degree of conflict was involved. Yager's method removes the process of normalizing in the DCR and assigns the conflict to an unknown domain for which reason it is also unable to combine the high conflict evidences. Li *et al.* sets up a model to allocate the evidence conflict whereas Sun considered only partial conflicts between different evidence that could definitely lead to strong uncertainty. Li and Gou modified the model by distributing the conflict and as a result, the fusion result are relatively conservative. All in all, most methods have the same view that the second evidence has the greatest credibility and the fifth evidence is the least believable. It can be seen that the proposed method has a better performance when dealing with information with high degree of conflict that the fusion result of fault F_1 only has a slight decrease from 0.9764 to 0.9495 when combining the fifth evidence which is conflict with the first four pieces of evidences. The degree of decrease is minimal whereas the support degree of the correct result is still the highest.

VI. APPLICATION

A. THE APPLICATION I OF FAULT DIAGNOSIS

A new fault diagnosis architecture of a distributed multisensor system is introduced.

In order to improve the accuracy of the system, we use multisensor in the fault diagnosis system to get the system status. When the system is working, each sensor can continuously generate its own diagnostic evidence for different faults. After that, we use DCR to fuse all the evidences. And in the end, the decision rules make the final decision on the final state of the system. Now, the architecture of the system is presented.

To achieve the goals of the system, the system is divided into five levels. They are: Data level, Feature level, Evidence level, Fusion level, and Decision level.

At the Data level, the data are collected from different sensors and the frame of discernment could be built. At the Feature level, a number of faulty features that can monitor the state of the system would be extracted. At the Evidence level, BPA of different sensors will be generated based on the extracted features. At the Fusion level, different BPA will be combined, and finally, at the Decision level, a reasonable decision rule will be applied to get the final conclusion.

Next, a rotating machinery system [39] is used to verify the performance of the system. Before we go any further, there are four faulty types: "Imbalance", "Shaft crack", "Misalignment" and "Bearing loose" which are presented by F_1, F_2, F_3, and F_4. Namely, the frame of discernment is: $\Theta = \{F_1, F_2, F_3, F_4\}$.

Then, in Data level, the data from five sensor that can monitor the status of the system are collected and in Feature level, the fault features are: E_1 = "Wavelet energy spectrum entropy", E_2 = "Wavelet space spectral entropy", E_3 = "Wavelet energy spectrum entropy", and E_4 = "Power spectrum entropy".

The reference fault feature vector is: $R(F_i) = \{E_{i1}, E_{i2}, E_{i3}, E_{i4}\}(i = 1, 2, 3, 4)$, which is obtained from the training samples. In Evidence level, the distance between the reference and the measurement fault feature vector of five sensors which are presented as $M(F)^{(k)} = \{E_1', E_2', E_3', E_4'\}(k = 1, 2, \ldots, 5)$ is defined as follows:

$$d_{ki} = d_k(F_i) = \left[\sum_{k=1}^{5} |M(F)^{(i)} - R(F_i)|\right]^{\frac{1}{2}} \tag{19}$$

Since the greater the distance, the smaller the degree of the similarity. The similarity degree was presented using an inverse function to transform the distance function. Then, the BPA of sensor k could be obtained by normalize the similarity degree. In the end, in Decision level, assume that $\forall F_1, F_2 \subset \Theta$, satisfy:

$$\begin{cases} m(F_1) = max\{m(F_i), F_i \subset \Theta\} \\ m(F_2) = max\{m(F_i), F_i \subset \Theta, F_i \neq F_1\} \end{cases} \tag{20}$$

ε_1, ε_2 are two thresholds of decision and, F_1 would be the final decision only if they satisfy:

$$\begin{cases} m(F_1) - m(F_2) > \varepsilon_1 \\ m(\Theta) < \varepsilon_2 \\ m(F_1) > m(\Theta) \end{cases}$$

In this example, the reference features of four typical mechanical faults are shown in Table 6 according to data statistics in [72].

TABLE 6. Reference fault feature.

Fault types	E_1	E_2	E_3	E_4
F_1	43.5828	30.8859	10.6806	53.7343
F_2	74.3605	72.1393	17.8107	74.1857
F_3	63.9286	58.6064	21.7660	67.5529
F_4	49.8858	46.8183	14.4998	52.6699

TABLE 7. Fault feature of five sensors.

Sensors	E_1	E_2	E_3	E_4
S_1	66.2913	57.3129	22.8701	65.0923
S_2	62.3361	55.3618	22.8297	66.1382
S_3	73.4274	69.8329	16.5621	72.5824
S_4	65.8638	61.5325	24.2016	69.2899
S_5	51.4154	48.3248	15.4123	50.3624

TABLE 8. BPA of different sensors.

Evidence	F_1	F_2	F_3	F_4
m_1	0.1469	0.2057	0.4660	0.1813
m_2	0.1521	0.1935	0.4631	0.1914
m_3	0.1278	0.5008	0.2221	0.1493
m_4	0.1459	0.2396	0.4395	0.1750
m_5	0.2068	0.1399	0.1755	0.4777

Now, the fault F_3 happens. Five sensors will get a number of data and the fault features extracted from five sensors in Feature level are shown in Table 7.

Using the calculation model above, we can obtain the BPA from which we can see the conflict clearly that all Sensors 1, 2, and 4 manifest that the fault is F_3 whereas Sensor 3 and Sensor 5 indicated that it is F_2 and F_4 respectively. The BPA is listed in Table 8.

In the following Table 9, the calculation using both classic DCR and our method to combine these BPA are shown.

TABLE 9. Fusion result.

Rules	Results	F_1	F_2	F_3	F_4
DS	$m_{1,2}$	0.0714	0.1273	0.6902	0.1110
Lin *et al.*		0.0715	0.1274	0.6903	0.1111
Proposed		0.0715	0.1274	0.6900	0.1110
DS	$m_{1,2,3}$	0.0376	0.2626	0.6315	0.0683
Lin *et al.*		0.0315	0.2675	0.6431	0.0579
Proposed		0.0314	0.2594	0.6490	0.0578
DS	$m_{1,2,3,4}$	0.0153	0.1758	0.7755	0.0334
Lin *et al.*		0.0125	0.1692	0.7906	0.0276
Proposed		0.0126	0.1643	0.8026	0.0278
DS	$m_{1,2,3,4,5}$	0.0176	0.1368	0.7570	0.0886
Lin *et al.*		0.0109	0.1258	0.7874	0.0759
Proposed		0.0108	0.1204	0.7941	0.0747

Set $\varepsilon_1 = \varepsilon_2 = 0.1$, according to the results shown in Table 9, both of these two methods support the Fault F_3. Admittedly, there was a slight drop in the support degree of F_3 when the BPA from the first three sensors was fused due to conflicting information from the Sensor 3. Finally, when combining the BPA from Sensors 1 to 5, the result is still Fault F_3. Hence,we have confidence to conclude that the fault diagnosis system can make a right decision. And specially, the optimality of our method can be seen in Fig 3 as it always have a higher support degree for the right answer.

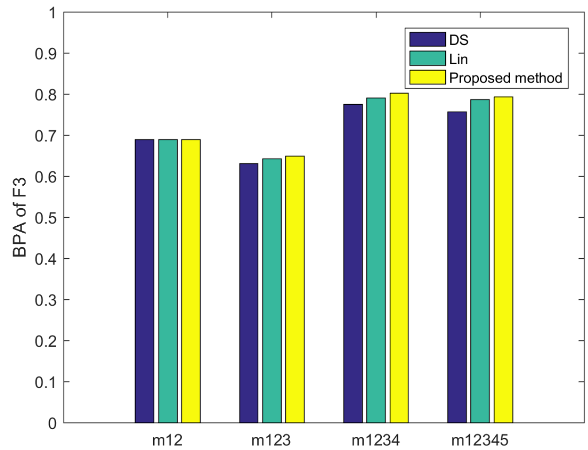

FIGURE 3. Combination result when confuse data from five sensors.

B. THE APPLICATION II OF FAULT DIAGNOSIS

In order to further illustrate the efficiency of the new method, a data set recorded from the real situation [73] is shown to consolidate the conclusion. An engineering application of fault diagnosis of a motor rotor is carried out. Several sensors are used to measure the vibration acceleration of the motor rotor within minor intervals to obtain 9 evidences. A total of 20 samples collected from each sensor within a period of time make up a data set.

Using the method in [74] to generate the BPA from the data set provided in [73] which is shown in Table 10. After that, the proposed method is used to modify the BPA. The modified BPA and the fusion results using different methods are shown in Table 12.

From the final BPA after combining, it is clear that the test sample is classified into F_2 class which coincides with

TABLE 10. The BPA generated form the data set.

$\dot{F}$	$\{F_1\}$	$\{F_2\}$	$\{F_3\}$	$\{F_1, F_2\}$	$\{F_1, F_2, F_3\}$
E_1	0	0.6931	0.0003	0.1316	0.1750
E_2	0	0.5362	0.0009	0.0612	0.4018
E_3	0	0.1995	0.0003	0.0117	0.7885
E_4	0	0.5280	0	0	0.4720
E_5	0	0.7258	0	0	0.2742
E_6	0	0.7136	0	0	0.2864
E_7	0.3108	0.3868	0	0.1005	0.2020
E_8	0.2646	0.3933	0	0.2513	0.0907
E_9	0.2405	0.3594	0	0.2050	0.1950

TABLE 11. Accuracy.

Fault types	Test times	Proposed method's Accuracy
F_1	100	100%
F_2	100	100%
F_3	100	100%

TABLE 12. Fusion result of the BPA generated from the data set recorded from the real situation.

Evidences	method	$m_{1,2}$	$m_{1,2,3}$	$m_{1,2,3,4}$	$m_{1,\ldots,5}$	$m_{1,\ldots,6}$	$m_{1,\ldots,7}$	$m_{1,\ldots,8}$	$m_{1,\ldots,9}$
$m(\{F_1\})$	DS	0	0	0	0	0	0	0	0
	Lin *et al.*	0.0860	0.0640	0.0424	0.0263	0.0156	0.0090	0.0051	0.0028
	Proposed	0.0417	0.0200	0.0085	0.0034	0.0013	0.0005	0.0002	0.0001
$m(\{F_2\})$	DS	0.8577	0.8861	0.9463	0.9853	0.9958	0.9964	0.9970	0.9973
	Lin *et al.*	0.7418	0.8594	0.9235	0.9586	0.9776	0.9879	0.9934	0.9962
	Proposed	**0.8853**	**0.9594**	**0.9858**	**0.9950**	**0.9983**	**0.9994**	**0.9998**	**0.9999**
$m(\{F_3\})$	DS	0.0003	0.0002	0.0001	0	0	0	0	0
	Lin *et al.*	0.0001	0.0001	0	0	0	0	0	0
	Proposed	0.0003	0.0001	0	0	0	0	0	0
$m(\{F_1, F_1\})$	DS	0.0717	0.0582	0.0275	0.0075	0.0022	0.0012	0.0008	0.0004
	Lin *et al.*	0.0652	0.0390	0.0209	0.0104	0.0050	0.0023	0.0011	0.0005
	Proposed	0.0289	0.0109	0.0036	0.0011	0.0003	0.0001	0	0
$m(\{F_1, F_2, F_3\})$	DS	0.0704	0.0555	0.0262	0.0072	0.0021	0.0006	0.0001	0
	Lin *et al.*	0.1068	0.0374	0.0131	0.0046	0.0016	0.0005	0.0002	0.0001
	Proposed	0.0438	0.0096	0.0021	0.0005	0.0001	0	0	0

the reality. Moreover, the simulation results show that the model improves the support degree of the right result to 99.99% which also always have the highest support degree of the correct result.

To further evaluate the proposed method, different samples that are random selected from F_1, F_2 and F_3 were tested as test sets 100 times, respectively, to generate the BPA. And the accuracy of the method on the data set diagnosis is presented in Table 11. It can be seen that by using the proposed mentioned, the overall recognition rate of the three categories is 100%. That is, in each of the 100 diagnostic trials, the fault diagnosis result were correct. Therefore, we have confidence to say that the proposed method is accurate and effective to deal with multiple fault diagnosis problems. The calculation formula of accuracy is as follows:

$$A = \frac{N_{correct}}{N_{test}} \tag{21}$$

where N_{test} is the total number of tests and $N_{correct}$ is the number of tests whose diagnosis results are correct.

VII. CONCLUSION

Multisensor system is widely used in many fields on account of only one sensor is not adequate to meet the needs of modern society. Yet the information collected from all the sensors may be uncertain, fuzzy or even conflict. Therefore, the modeling of multisensor information fusion system is indispensable. The main contribution of this paper is that a new method is proposed to be used in a faulty diagnosis modeling. The new proposed method takes the belief entropy in to account so that it could provide a promising way to make an accurate determination. Furthermore, numerical example in different situations have been proposed to prove that it is effective and superior. Moreover, a practical application was given to prove the feasible of the proposed method. In the future work, our work should focus on adapting the method to more complex environments and improving its accuracy.

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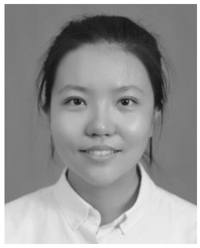

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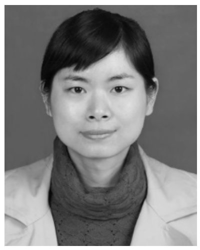

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