Journal of Computers Vol. 32 No. 5, 2021, pp. 257-270
doi:10.53106/199115992021103205022

Data Fusion for Target Recognition Based on Evidence Theory in IOT Environment

Xiaoning Bo[1*], Jin Wang[1], Guoqin Li[1], Yanli Tan[1], Yi Sui[2]

[1] Department of Electrical Engineering, Taiyuan Institute of Technology, No. 31 Xinlan Road, Taiyuan, Shanxi 030008, China
boxn@tit.edu.cn; wangj@tit.edu.cn; 18435149635@163.com; whytyl0310@126.com

[2] State Grid Co., Ltd, Taiyuan, Shanxi 030008, China
527588816@qq.com

Received 1 August 2021; Revised 1 September 2021; Accepted 8 October 2021

Abstract. Data fusion using evidence theory in IOT applications has been used extensively to recoginze targets because it offers the advantage of handling uncertainty. But the traditional Dempster's combination rule cannot deal with highly conflicting information because it often generates counter-intuitive results. In this paper, a new weighted evidence combination approach is proposed to solve this problem. First, two measures, i.e., an uncertainty measure of each evidence and a probabilistic-based dissimilarity measure between two evidences, are introduced to estimate the value of weight of each sensor. Then, when combining conflicting information, reasonable results can be produced by using weighted average of evidences and Dempster's combination rule. Our experimental results showed that the proposed method has better performance in performance than the existing methods.

Keywords: data fusion, evidence theory, uncertainty measure, dissimilarity measure

1 Introduction

In recent years, the Internet of Things (IOT) has attracted a great quantity of attention due to its advantages on interconnecting objects, people and other information sources together with intelligent services [1]. As one of important parts of an IOT system, the wireless sensor networks (WSNs), which is a typical distributed and self-organized network that usually consists of a large number of low-cost sensors nodes, can provide data acquisition for long–term environment monitoring [2]. Recently, with the increasing application of WSNs in detection and recognition, the data is generated, collected and analyzed at an unprecedented scale, and the volume of data is also explosively increasing when it is linked and fused with other data to make a reasonable decision [3]. On the other hand, sensor nodes are affected by various uncertain factors such as natural environment, human interference and sensor performance, so there is often a lot of uncertain information in the observed data [4]. In this case, the feasible data fusion method that can acquire the reliable combination result with uncertain data is an efficient strategy to capture the good recognition performance.

In IOT applications, data fusion is a technology that combines the data provided by several sources into a unified result [5]. It generates a comprehensive decision on monitoring the target based on the data provided by the sensor nodes [6]. In WSNs, a large number of sensor nodes are randomly deployed in the detection area to sense the observed targets. Because the data transmission energy and bandwidth of the network are very limited, each node needs to carry out local target recognition process according to the collected target attribute information, and send the obtained local decision information to the fusion center, which performs global fusion to form comprehensive decision-making judgment on target recognition. This process not only saves the energy and bandwidth consumption of communication

* Corresponding Author

transmission, but also improves the accuracy of final recognition and judgment through global fusion, which has a key practical value in engineering practice. Therefore, aiming at different local decisions provided by sensor nodes, how to acquire the feasible result of the trustworthy decision fusion with uncertain data is a huge challenge in IOT environment [1]. In such a case, a series of theories have been employed to deal with the problem of uncertainty, such as evidence theory [7], intuitionistic fuzzy sets [8], D numbers [9], Z-numbers [10], evidential reasoning [11], and so on [12-14].

The Dempster–Shafer evidence theory, also known as belief function theory of evidence theory, was firstly proposed by Dempster in 1967 [15], and then developed by Shafer in 1976 [16]. Compared with the classical probability theory, it provides an effective and flexible solution to handling the uncertainty without depending on prior information. Now the evidence theory is widely applied in sorts of fields, such as information fusion [17], decision making [18], supplier selection [19], fault diagnosis [20], reliability analysis [21], and so on [22]. Although Dempster's combination rule can combine the insular decisions reported by distinct sensor nodes, and produce the more accurate and comprehensive judgment and decision on the monitoring target, the counter-intuitive combined results may be obtained when synthesizing high conflict evidence. In order to address this problem, a lot of solutions have been proposed. Smets proposed an unnormalized combination rule [23]. Lefevre et al. came up with a generic framework which unify a number of classical combination rules [24]. In [25], a new combination rule is introduced based on the concept of joint belief distribution. Jing et al. brought up a novel basic belief assignment approach to preprocess the conflicting data before data fusion [26]. In [27], Xiao et al. put forward with the belief divergence measure to modify the conflicting data before data fusion. These solutions can be divided into two categories. The first kind is the method of modifying the combination rule, and the second kind is the method of modifying the bodies of evidence before data fusion.

In this paper, we focus on the second kind of methodology, which modifies the conflicting evidences before combination. A new weighted evidence combination method on the basis of belief entropy and dissimilarity measure is presented to deal with conflict in multi-sensor data fusion. The numerical example is provided to show the efficiency of our proposed method.

The rest of the paper is organized as follows. Section 2 introduces the basis of evidence theory. The proposed weighted evidence combination method is presented in Section 3. The numerical example is give in Section 4. Our conclusions are presented in Section 5

2 Preliminary Work

In this section, some basic concepts of evidence theory are briefly introduced below. The conflict management in in the course of the fusion process is also presented.

2.1 Basics of the Evidence Theory

The Dempster–Shafer evidence theory, as an uncertain reasoning theory, provides a flexible framework for dealing with data fusion problems. Some basic concepts of evidence theory are as follows.

Let Ω be a finite set called the frame of discernment, $\Omega = \{w_1, w_2, \ldots, w_i, \ldots, w_n\}$, the elements of which are exhaustive and mutually exclusive, and we denote its corresponding power set as 2^{Ω}. This power set represents the set of all possible subsets of Ω, indicated by:

$$2^{\Omega} = \{\phi, \{w_1\}, \ldots, \{w_n\}, \{w_1, w_2\}, \ldots, \{w_1, w_2, \ldots, w_i\}, \ldots, \Omega\}. \quad \textbf{(1)}$$

A Basic Belief Assignment (BBA), also known as a mass function, *m*, is a mapping $: 2^{\Omega} \rightarrow [0,1],$ such that $\Sigma_{A\in 2^{\Omega}} m(A) = 1, m(\phi) = 0.$ The focal element *A* is a subset of Ω, such that $m(A) > 0.$

If all focal elements are singleton elements, the corresponding mass function, *m*, defines a probability dis-tribution on Ω, and this *m* also is called a Bayesian BBA. In the theory of evidence, some specific BBAs are always used. A vacuous BBA is a BBA that satisfies $m(\Omega) = 1.$ A categorical BBA is a BBA that satisfies $m(A) = 1,$ where $A \neq \phi, A \neq \Omega$. A consonant BBA is a BBA in which the focal elements are included in each other.

Let m_1 and m_2 be two BBAs derived from independent sensors. The Dempster's combination rule is often applied for combining them, as follows:

$$m_{\oplus}(A) = m_1(B) \oplus m_2(C) = \begin{cases} 0, & B \cap C = \phi \\ \dfrac{\Sigma_{B \cap C = A,\, \forall B,\, C \subseteq \Omega} m_1(B) \times m_2(C)}{1 - \Sigma_{B \cap C = \phi,\, \forall B,\, C \subseteq \Omega} m_1(B) \times m_2(C)}, & B \cap C \neq \phi \end{cases}. \quad \textbf{(2)}$$

where $\Sigma_{B \cap C = \phi,\, \forall B,\, C \subseteq \Omega} m_1(B) \times m_2(C)$ is the mass of combined result committed to the empty set, denoted as $m_{\oplus}(\phi)$. The Dempster's combination rule is applicable only when $m_{\oplus}(\phi) \neq 1$.

In [23], the well-known pignistic probability function, *BetP*, which transfers the BBA into a subjective proba-bility distribution, is formally defined as follows:

$$BetP(w) = \Sigma_{w \in A,\, A \subseteq \Omega} \frac{1}{|A|} m(A). \quad \textbf{(3)}$$

where $m(\cdot)$ is the given BBA defined on Ω, and $|A|$ is the cardinality of focal element *A*. The transformation from BBA, *m*, to pignistic probability, *BetP*, is called the pignistic probability transformation. For an unknown target, the final decision based on decision fusion can be made according to the corresponding *BetP* of each singleton.

2.2 Conflict Management with Dempster's Combination Rule

Due to various uncertain factors, there is usually a large amount of inconsistent information between the observed data of various sensors. Therefore, the local decisions of different sensor nodes often conflict with each other, even completely contradictory. However, when Dempster's combination rules are used for multi-sensor decision fusion, the fusion of highly conflicting evidences may lead to a conclusion contrary to the facts. To solve this problem, Zadeh put forward a famous counterexample to verify the irrationality of Dempster's combination rule in dealing with high conflict evidences. This problem is indicated in Example 1.

Example 1: Assumes that two doctors, A and B, are diagnosing the same patient, and the patient's diseases may be meningitis (*M*), brain tumor (*BT*) and concussion (*C*). At this time, the identification framework of evidence is $\Omega = \{M, BT, C\}$. Doctor *A* thinks the patient's trust degree is 0.99 for meningitis and 0.01 for brain tumor, but doctor *B* thinks the patient's trust degree for brain tumor and concussion is 0.01 and 0.99 respectively. Although both doctors think that the patient has a small possibility of suffering from brain tumor, Doctor *A* agrees that the patient has meningitis, while Doctor *B* agrees that the patient has concussion, so their diagnosis results are almost completely conflicting. Table 1 shows the evidence constructed by their diagnosis results.

Table 1. Zadeh's counter example

Proposition / BBA	meningitis(M)	brain tumour(BT)	concussion(C)
m_A	0.99	0.01	0
M_B	0	0.01	0.99

After synthesizing the above diagnosis opinions by using Dempster's combination rule, the following conclusions can be obtained.

$$m(M) = 0, m(BT) = 1, m(C) = 0.$$

In Example 1, the results obtained by combining the two diagnostic opinions show that the patient's confidence in brain tumor is 1, and the confidence in the other two diseases is 0. Considering that both doctors think that the possibility of patients suffering from brain tumors is very low, the fusion result is obviously unreasonable. As an extreme example of high conflict evidence, this example can better reflect the problems of Dempster's combination rule in dealing with high conflict evidence. At this time, according to Dempster's combination formula, the global conflict *k* of these two evidences can be obtained as follows:

$$k = m_A(M)m_B(BT) + m_A(M)m_B(C) + m_A(BT)m_B(C) = 0.9999.$$

Through the global conflict $k = 0.9999$, it can be seen that there is basically a complete conflict between the two evidences. At the same time, for brain tumors, according to Dempster's combination rule, the belief degree of their mutual support for brain tumors after intersection is:

$$m_A(BT)m_B(BT) = 0.0001.$$

It can be seen that Dempster's combination rule assigns the global conflict k of two evidences to the proposition (brain tumor) that they support together, which leads to the fusion result contrary to common sense, that is, the possibility of brain tumor is $m(BT) = 1$.

In order to explain in detail the shortcomings of Dempster's combination rule when fusing conflicting evidences, the following will decompose its combination formula. The evidences m_1 and m_2 are assumed to be two mass functions defined on the same identification framework Ω, and they are fused by Dempster's combination rule. For $\forall A \subseteq \Omega, A \neq \phi$, the fused belief degree is:

$$m_1 \oplus m_2(A) = \frac{\Sigma_{B\cap C=A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)}{1-\Sigma_{B\cap C=\phi,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)}$$

$$= \sum_{B\cap C=A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C) + \frac{\Sigma_{B\cap C=A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)}{1-\Sigma_{B\cap C=\phi,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)} \times \sum_{B\cap C=\phi,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C).$$

$$= \Sigma_{B\cap C=A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C) + \frac{\Sigma_{B\cap C=A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)}{1-\Sigma_{B\cap C=\phi,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)} \times \Sigma_{B\cap C=\phi,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C). \quad \textbf{(4)}$$

In this, $\Sigma_{B\cap C=A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)$ is the product sum of the belief degrees of all intersecting supporting focal elements in these two evidences, but $\Sigma_{B\cap C\neq\phi A,\,\forall B,\,C\subseteq\Omega} m_1(B)\times m_2(C)$ is the product sum of the belief degrees of all conflicting focal elements in the two evidences, that is, global conflict k. Therefore, formula (4) reflects that Dempster's rule redistributes all conflicting information to the combined focal elements proportionally according to the belief degree of each combined focal element. In Example 1, only the proposition brain tumor (*BT*) after combination is the only focal element, so it gets all the conflicting information $k = 0.9999$, resulting in the fusion result which is contrary to common sense.

According to the above analysis, it can be seen that the unreasonable way of dealing with conflict information is the main reason for the fusion conclusion which is contrary to common sense. In view of this, many scholars have done a lot of research on the combination method of high conflict evidence, at the same time, it also puts forward a series of improved ideas and solutions. These improved schemes can be divided into two categories, the method of improving the rules of evidence combination and the method of modifying the evidence before fusion. The method of improving evidence combination rule thinks that Dempster's combination rule has its own problems, and the wrong way of conflict information distribution is the fundamental reason that leads to the unreasonable fusion results. Therefore, it is necessary to modify the distribution mode of conflict information to obtain the fusion results which are consistent with the facts. However, before data fusion, the method of revising the evidence holds that Dempster's combination rule is no problem, and the irrational combined results come from unreliable evidence sources. When there is great inconsistency between evidences, all evidences should be preprocessed according to the reliability of each piece of evidence, and then the preprocessed evidences should be fused by Dempster's combination rule, so as to reduce the influence of highly conflicting evidences in the combination process and improve the rationality of the final conclusion. These two kinds of solutions solve the problem of effective multi-source data fusion under high conflict from different angles. However, the current methods of modifying evidence combination rules usually destroy the excellent mathematical characteristics of Dempster's combination rule, which will produce a heavy computational burden in the case of a large amount of evidence. In addition, from the philosophical point of view, when using y method to solve the problem of model x and getting the conclusion z which is against common sense, we cannot simply think that y method is wrong. The unreasonable conclusion is probably caused by the problem x of the model. Therefore, this paper considers that the complex improved combination rule method is not suitable for multi-sensor decision information fusion. Next, we will focus on the methods of modifying the evidence.

3 A New Weighted Evidence Combination Method

Generally, the method of modifying the evidence first obtains the credibility of each piece of evidence according to the degree of inconsistency or conflict between the evidences, and the credibility reflects the reliability of the data source. The higher the credibility of the evidence is, the more favorable it is for decision-making, and the greater the weight of the evidence in the fusion process should be. The lower the credibility of the evidence, the more unfavorable it is to the decision-making, and the smaller the weight that should be given to the evidence. Then, all the evidence is preprocessed by using the weight coefficient of evidence, and the preprocessing of evidence can effectively reduce the influence of high conflicting evidence on the synthesis result. At last, Dempster's combination rule is used to fuse the preprocessed evidence globally, and the final decision is obtained. This method keeps the good characteristics that Dempster's combination rule satisfies the law of association and exchange, and can flexibly and efficiently fuse multiple pieces of evidence one by one, while the fusion order will not affect the final conclusion. It has been widely used in engineering practice.

3.1 Existing Conflict Measures

In the method of modifying the evidence before fusion, the weight of evidence plays a vital role, and a reasonable weight measurement method can fundamentally solve the problem that the combined result is contrary to common sense. Generally speaking, if the conflict between a piece of evidence and most other evidence is smaller, the corresponding weight of this evidence value should be larger. However, if a piece of evidence conflicts with most other evidence, its corresponding weight should be smaller. In recent years, many scholars have done a lot of research on the conflict between evidences, and put forward corresponding calculation methods. This section will analyze the most commonly used measurement methods of Jousselme's distance and cosine distance.

With the wide application of evidence theory, the research of the distance between two pieces of evidence has attracted more and more attention, and a number of distance measures are proposed and analyzed. Among these measures of evidence distance, the most commonly used is Jousselme's distance in various evidence theory applications.

Let evidence m_1 and m_2 is on the same frame of discernment Ω, and the Jousselme's distance between them is defined as:

$$d_J(m_1, m_2) = \sqrt{\frac{1}{2}(m_1, m_2)^T D(m_1, m_2)}.. \quad \textbf{(5)}$$

D is a $2^{|\Omega|} \times 2^{|\Omega|}$ matrix, the elements in D can be expressed as $D_{ij} = \frac{|A_i \cap B_j|}{|A_i \cap B_j|}, A_i, B_j \in 2^{\Omega}$, $d_J(m_1, m_2) \in [0,1]$. Generally speaking, the greater the value of d_J the greater the inconsistency between evidences.

Jousselme's distance d_J is a typical measure of inconsistency between evidences. d_J introduced the idea of vector space, regarded evidence as vectors, and obtained the inconsistency between different evidences by calculating the distance between vectors.

Example 2: Let evidence m_1 and m_2 to identify two independent evidences on same frame of discernment $\Omega = \{A, B, C\}$, their mass functions are expressed as:

$$m_1(A) = 0.4, m_1(B) = 0.2, m_1(A, B) = 0.1, m_1(A, B, C) = 0.3,$$
$$m_2(A) = 0.5, m_2(B) = 0.2, m_2(A, B) = 0.1, m_2(A, B, C) = 0.2.$$

According to equation (5), the Jousselme's distance between m_1 and m_2 is calculated as follows:

$$d_J(m_1, m_2) = \sqrt{\frac{1}{2}(-0.1\ \ 0\ \ 0\ \ 0.1)\begin{pmatrix} 1 & 0 & \frac{1}{2} & \frac{1}{3} \\ 0 & 1 & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{2} & \frac{1}{2} & 1 & \frac{2}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{2}{3} & 1 \end{pmatrix}\begin{pmatrix} -0.1 \\ 0 \\ 0 \\ 0.1 \end{pmatrix}} = 0.1125.$$

Example 2 reflects the calculation process of Jousselme's distance. In addition, the difference between the basic belief assignments m_1 and m_2 is very small, and the calculation result using Jousselme's distance is $d_J(m_1, m_2) = 0.1125$. The value of d_J is basically consistent with the facts, which can well represent the inconsistency between evidences.

However, under certain circumstances, using Jousselme's distance will also lead to a conclusion contrary to the facts. Especially when two pieces of evidence to be fused conflict completely, Jousselme's distance cannot accurately describe the difference between them.

Example 3: Let evidence m_1 and m_2 to identify two independent evidences on same frame of discernment $\Omega = \{A, B, C, D, E, F\}$, their mass functions are expressed as:

$$m_1(A) = m_1(B) = m_1(C) = \frac{1}{3},$$
$$m_2(D) = m_2(E) = m_2(F) = \frac{1}{3}.$$

In Example 3, evidences m_1 and m_2 do not have any common supporting focal element, and they are completely in conflict, so the value of d_J between them should be the maximum value of 1. However, according to equation (5), $d_J(m_1, m_2) = 0.577$ is actually calculated at this time, that is, if there is a complete conflict between the evidences, the calculated result of Jousselme's distance is not large enough to reflect the difference between them well.

Considering the shortage of Jousselme's distance in certain circumstances, cosine distance with less computation was proposed to measure the inconsistency between evidences based on vector metric and cosine theory.

Assume that evidence m_1 and m_2 are two evidences on the same recognition frame $\Omega = \{w_1, w_2, ..., w_n\}$ and the cosine distance between them is given as:

$$ConfDegree(m_1, m_2) = 1 - \frac{< BetP_{m_1}, BetP_{m2} >}{| BetP_{m_1} | \times | BetP_{m2} |}. \quad \textbf{(6)}$$

$BetP_{m_i}$ is an n-dimensional probability vector, $| BetP_{m_1} |$ is the length of the vector $BetP_{m_1}$, $< BetP_{m_1}, BetP_{m2} >$ is the inner product of $BetP_{m_1}$ and $BetP_{m_2}$.

Compared with Jousselme's distance, cosine distance is a more effective distance measure. In Example 3 using cosine distance calculation m_1 and m_2 can get $ConfDegree(m_1, m_2) = 1$, it shows that cosine distance is better than Jousselme's distance in distinguishing evidence of complete conflict. However, although cosine distance can obtain a better performance, it could not effectively describe the difference between uniform Bayesian mass function and empty mass function.

Example 4: Let evidence m_1 and m_2 to identify two independent evidences on same frame of discernment $\Omega = \{A, B\}$, m_1 is a uniform Bayesian mass function and m_2 is an empty mass function. Their mass functions are expressed as:

$$m_1(A) = \frac{1}{2}, m_1(B) = \frac{1}{2}, m_1(\Omega) = 0,$$
$$m_2(A) = 0, m_2(B) = 0, m_2(\Omega) = 11$$

After using pignisic probability transformation, evidence m_1 and m_2 have the same probability vector $BetP_{m_1}$ and $BetP_{m2}$:

$$BetP_{m_1}(A) = BetP_{m_1}(B) = \frac{1}{2},$$
$$BetP_{m2}(A) = BetP_{m_2}(B) = \frac{1}{2}.$$

At this time, the equation (6) can be used to get $ConfDegree(m_1, m_2) = 0$. This shows that there is no difference between evidence m_1 and m_2 at all. However, evidence m_1 indicates that proposition A and B have the same possibility, while m_2 cannot distinguish the possibility difference between proposition A and B at all. Therefore, evidence m_2 is more uncertain than m_1, and cosine distance *ConfDegree* cannot reflect this difference in uncertainty

By analyzing the typical conflict measurement methods, it can be seen that the commonly used conflict calculation methods will fail in specific usage scenarios. Although many improved measurement methods have been put forward by scholars at home and abroad, there is no uniform standard for conflict operation at present. At the same time, the degree of conflict between evidences directly affects the distribution of evidence weights, and reasonable evidence weights play a vital role in the fusion of highly conflicting evidences. Therefore, it is necessary to further analyze the characterization of evidence conflict and design an effective method to generate evidence weight.

3.2 The Proposed Method

In [28], Liu gave a generalized definition of conflict between evidences, which was widely supported by many scholars. This definition indicates that the conflict between two pieces of evidence can be qualitatively explained as one piece of evidence strongly supports proposition A, while the other piece of evidence strongly supports another proposition B, and propositions A and B are incompatible with each other.

It can be seen from the above definition that the conflict between evidences is essentially the inconsistency between propositions supported by evidences, that is, the inconsistency between main focal elements supported by evidences. When the main focal elements supported by two evidences are incompatible with each other, the two evidences are considered to be in conflict with each other. This definition is completely in line with people's intuitive judgment, so the conflict between evidences can be quantified according to this definition.

At the same time, in evidence theory, the main focal element of evidence can be either a single element focal element formed by a single element in the recognition framework or a composite focal element characterized by a collection of multiple single element focal elements. In the task of target recogintion, a single element focal element represents that the target belongs to a corresponding single class, and a compound focal element means that the target may belong to some single classes, but its specific class cannot be accurately judged. However, in IOT environment, it is generally considered that the observed objects can only belong to a specific single class. Therefore, for sensor local soft decision-making with composite focal elements, it is necessary to use pignisic probability function to transform the mass assignment of composite focal elements to single element focal elements, and then quantify the inconsistency between sensor local decisions based on the definition of conflict between evidences. In [29], the authors came up with a probabilistic-based dissimilarity measure, which is consistent with our above analysis. This measure only takes into account the difference between the main focal elements supported by each piece of evidence, but does not consider the difference between the other focal elements of the evidences. Therefore, it has less computational burden and is more suitable for computing at sensor nodes with limited energy.

Assume that evidence m_1 and m_2 to identify two independent evidences on same frame of discernment Ω. The dissimilarity measure between them is defined as follows:

$$Dis(m_1, m_2) = \begin{cases} 0, \ if \ argmaxBetP_{m_{1_{x\in\Omega}}}(x) \bigcap argmaxBetP_{m_{2_{x\in\Omega}}}(x) \neq \phi, \\ \frac{1}{2}\Sigma_{x\in X} \mid BetP_{m_1}(x) - BetP_{m_2}(x) \mid, \ otherwise. \end{cases} \quad \textbf{(7)}$$

X is a collection of main focal elements supported by evidence m_1 and m_2, $X = \{argmaxBetP_{m_{1x\in\Omega}}(x),$ $argmaxBetP_{m_{2x\in\Omega}}(x) \neq \phi\}$. When there is a main focal element supported by each other, it can be considered that these two evidences are consistent. Otherwise, these two Evidence are in conflict with each other, and the degree of dissimilarity between them can be calculated by equation (7).

Dissimilarity measure reflects the relationship and conflict between evidences to be fused, and the degree of conflict between evidences can be used to measure the degree of mutual support between evidences, which is one of the important factors to measure the weight of evidence. In [27], Xiao pointed out that another important factor associated with the value of weight is the information volume of the evidence. The greater the information volume of the evidence is, the more information the evidence contains. If the information volume of the evidence is great, this evidence will play a critical role in the final combination.

In evidence theory, the volume of uncertain information can be quantified by Deng entropy, which is an effective belief entropy to obtain the uncertain degree of BBA [30]. The definition of Deng entropy is presented as follows:

Let A_i be a proposition of the mass function m, $|A_i|$ is the cardinality of set A_i. Deng entropy E_d of set A_i can be defined as follows:

$$E_d = -\Sigma_i m(A_i)\log\frac{m(A_i)}{2^{|A_i|}-1}. \quad \textbf{(8)}$$

In particular, if all focal elements of mass function are singleton elements, the Deng entropy is degenerated as Shannon entropy:

$$E_d = -\Sigma_i m(A_i)\log\frac{m(A_i)}{2^{|A_i|}-1} = -\Sigma_i m(A_i)\log m(A_i). \quad \textbf{(9)}$$

Some numerical examples are given to illustrate the availability of Deng entropy.

Example 5: Assume the frame of discernment $\Omega = \{A, B, C\}$, for a mass function $m(A) = 0.3,$ $m(A,B) = 0.2, m(A,B,C) = 0.5$. The Deng entropy $E_d(m)$ can be calculated by:

$$E_d(m) = -0.3\times\log_2\frac{0.3}{2^1-1} - 0.2\times\log_2\frac{0.3}{2^2-1} - 0.5\times\log_2\frac{0.5}{2^3-1} = 3.2061.$$

Example 5 shows the detailed calculation process and calculation result of Deng entropy.

Example 6: Assume the frame of discernment $\Omega = \{A, B, C\}$, for a mass function $m(A) = m(B) =$ $m(C) = \frac{1}{3}$. The Shannon entropy $H(m)$ and Deng entropy $E_d(m)$ can be calculated by:

$$H(m) = -\frac{1}{3}\times\log_2\frac{1}{3} - \frac{1}{3}\times\log_2\frac{1}{3} - \frac{1}{3}\times\log_2\frac{1}{3} = 1.5850,$$
$$E_d(m) = -\frac{1}{3}\times\log_2\frac{1/3}{2^1-1} - \frac{1}{3}\times\log_2\frac{1/3}{2^2-1} - \frac{1}{3}\times\log_2\frac{1/3}{2^1-1} = 1.5850.$$

Example 6 shows that the Deng entropy equals Shannon entropy when the mass function is given as a probability distribution on Ω.

Based on the above analysis, this paper will comprehensively determine the weight coefficient of evidence through the belief entropy of evidence and the dissimilarity between evidences. The dissimilarity mainly reflects the degree of conflict between different evidences, and the degree of conflict between evidences can be used to measure the degree of mutual support between evidences. According to the thought that the minority is subordinate to the majority in group decision-making, if a piece of evidence conflicts with other evidence to a lesser extent, it can be considered that the evidence is supported by other evidence, and it should be given greater credibility. On the contrary, if a piece of evidence conflicts with other evidence to a great extent, it is considered that the evidence is not supported by other evidence, and it should be given less credibility. The credibility of evidence describes the relative importance of evidence in the fusion process. When there are n sensors deployed in the monitoring area to perform the target recognition task, the similarity between the local decisions m_i and m_j of the sensors can be expressed as:

$$Sim(m_i, m_j) = 1 - Dis(m_i, m_j). \tag{10}$$

The similarity between two evidences is also considered as the mutual support between them. Considering that n sensors have locally identified and judged the target, an $n \times n$ evidence similarity matrix can be obtained, namely:

$$S = \begin{bmatrix} 1 & Sim(m_1, m_2) & \cdots & Sim(m_1, m_n) \\ Sim(m_2, m_1) & 1 & \cdots & Sim(m_2, m_n) \\ \vdots & \vdots & \vdots & \vdots \\ Sim(m_n, m_1) & Sim(m_n, m_2) & \cdots & 1 \end{bmatrix} \tag{11}$$

In the matrix, the elements on the main diagonal represent the support degree of each piece of evidence, so their values are all 1. At the same time, according to equation (10), the similarity operation between evidences is a scalar operation, so the matrix is symmetric.

Evidence m_i is supported by other evidences can be expressed as:

$$Sup(m_1, m_2) = \sum_{j=1, j \neq i}^{n} Sup(m_i, m_j). \tag{12}$$

It is generally believed that the evidence with the greatest support is the most credible. The reliability of evidence m_i can be defined as:

$$Crd(m_i) = \frac{Sup(m_i)}{\sum_{j=1}^{n} Sup(m_j)}. \tag{13}$$

Credibility can reflect the relative reliability or importance of the source of evidence, so the credibility of evidence can be directly regarded as the weight of the corresponding evidence, and can also be used as an important factor to participate in the measurement of the weight of evidence. According to the analysis of conflict, the reasonable measurement method of evidence weight should also consider the information volume of the evidence. Therefore, belief entropy will be utilized to modify the credibility of evidence, so as to obtain the final weight coefficient which is more in line with the actual situation.

The belief entropy of the evidence can be calculated by equation (8). In order to avoid assigning zero weight to the evidence, the information volume $IV(m_i)$ is exploited to measure the uncertain degree of the evidence m_i:

$$IV(m_i) = e^{E_d(m_i)}. \tag{14}$$

According to equation (15), the information volume $IV(m_i)$ is normalized, denoted as $\tilde{IV}(m_i)$:

$$\tilde{IV}(m_i) = \frac{IV(m_i)}{\sum_{j=1}^{n} \tilde{IV}(m_j)}. \tag{15}$$

Based on the normalized information volume $\tilde{IV}(m_i)$, the weight coefficient of the evidence m_i can be defined as follows:

$$w(m_i) = Crd(m_i) \times \tilde{IV}(m_i). \tag{16}$$

For evidences provided by sensor nodes, the weight $\tilde{w}(m_i)$ of evidence m_i can be obtained by equation (16), and all weights of evidences need to be normalized:

$$\tilde{w}(m_i) = \frac{w(m_i)}{\sum_{j=1}^{n} w(m_j)}. \tag{17}$$

Normalized weight $\tilde{w}(m_i)$ embodies the relative importance of evidence in the fusion process. With the weight $\tilde{w}(m_i)$, the weighted averaged mass function, denoted by MAE(m) is calculated as follows:

$$MAE(m_i) = \sum_{i=1}^{n} \tilde{w}(m_i) \times m_i. \tag{18}$$

When modifying evidences, according to the weight $\tilde{w}(m_i)$ of each evidence, the mass values of the corresponding focal elements of all evidences are weighted and summed, so as to obtain the new evidence MAE(m). The weighted average method greatly reduces the influence of high conflicting evidence, so the new evidence MAE(m) is considered to be authentic and reliable. The final fusion result can be obtained by applying Dempster's combination rule to MAE(m) for n-1 iterations. This method not only retains the excellent mathematical characteristics of Dempster's combination rule, but also fully considers the mutual relations between evidences and the information volume of evidence, which makes the combined result more reasonable and is conducive to making accurate decisions.

The flowchart of the proposed method is shown in Fig.1.

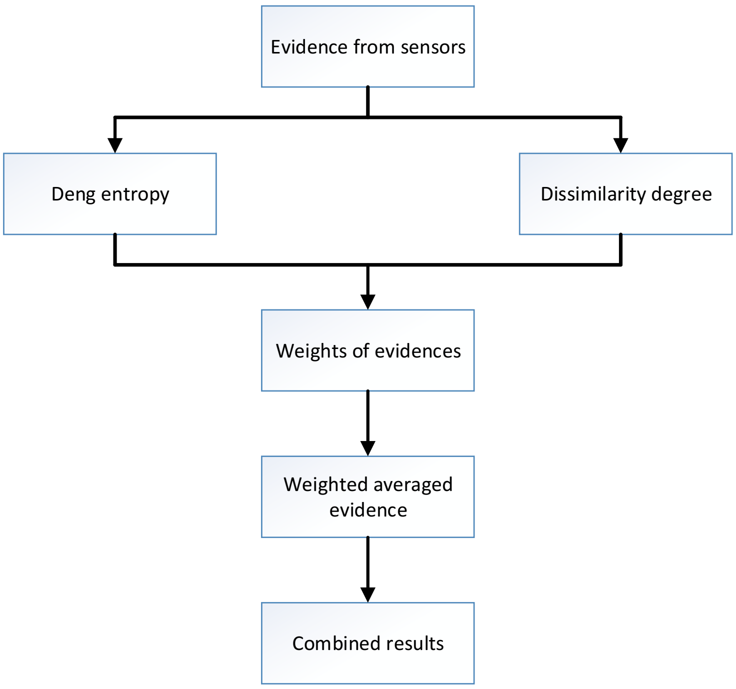

Fig. 1. The flowchart of the new method

4 Numerical Example

In this section, a target recognition experiment will be conducted to verify the effectiveness of the proposed weighted combination method in dealing with high conflict data. In this experiment, through a commonly used example of multi-sensor target recognition from [27], the proposed method is compared with other evidence combination methods based on the weighted average of evidences, including Murphy's simple average method [31], Deng et al.'s weighted average method based on Jousselme's distance [32], Zhang et al.'s weighted average method based on cosine distance [33], and Zhang et al.'s weighted average method based on dissimilarity and contradiction [29].

Example 7: Assume that in a target recognition system, a total of 5 sensor nodes participate in target observation, i.e., $S1$, $S2$, $S3$, $S4$, $S5$. They will upload the decision information to the fusion center after identifying and judging the observation data of the same target locally, and the fusion center will perform global fusion. At the same time, there may be three different categories of the measured target, so the recognition framework of this example is denoted as $\Omega = \{A, B, C\}$. Consider a target with a real category A is perceived by five sensors, and the evidence received by the fusion center, which is composed of local decisions of sensors, namely:

$$
\begin{aligned}
&S1: m_1(A) = 0.41, m_1(B) = 0.29, m_1(C) = 0.3,\\
&S2: m_2(A) = 0, m_2(B) = 0.9, m_2(C) = 0.1,\\
&S3: m_3(A) = 0.58, m_3(B) = 0.07, m_3(A, C) = 0.35,\\
&S4: m_4(A) = 0.55, m_4(B) = 0.1, m_4(A, C) = 0.35,\\
&S4: m_4(A) = 0.6, m_4(B) = 0.1, m_4(A, C) = 0.3.
\end{aligned}
$$

It can be seen from these five pieces of evidence that only the second piece of evidence thinks that the category of the target to be measured is B, and it is determined that it is not A. The remaining four pieces of evidence all think that the target belongs to A with the greatest possibility, and belongs to B and C with little possibility. This may be because the sensor $S2$ is interfered by the outside environment, which leads to a big conflict between the observed information obtained by it and the observed information of the other four sensors, and makes it make a wrong decision.

Considering that the calculation amount is too large when five local decisions are fused together, this section fuses these five pieces of evidence one by one. Table 2 shows the fusion results obtained by using different evidence combination methods respectively. At the same time, these methods all meet the exchange law and combination law, so the fusion order of evidence will not affect the final conclusions of these methods.

4.1 Implementation of Our Proposed Method

Step 1: Calculate the dissimilarity between two evidence, and the dissimilarity matrix can be obtained as follows:

$$
Dis = \begin{bmatrix} 0 & 0.51 & 0 & 0 & 0 \\ 0.51 & 0 & 0.7925 & 0.7625 & 0.775 \\ 0 & 0.7925 & 0 & 0 & 0 \\ 0 & 0.7625 & 0 & 0 & 0 \\ 0 & 0.775 & 0 & 0 & 0 \end{bmatrix}.
$$

Step 2: Calculate the similarity matrix according to equation (10) and (11) as follows:

$$
S = \begin{bmatrix} 1 & 0.49 & 1 & 1 & 1 \\ 0.49 & 1 & 0.2075 & 0.2375 & 0.225 \\ 1 & 0.2075 & 1 & 1 & 1 \\ 1 & 0.2375 & 1 & 1 & 1 \\ 1 & 0.225 & 1 & 1 & 1 \end{bmatrix}.
$$

Step 3: Obtain the support degree of each evidence according to equation (12) as follows:

$$Sup(m_1) = 3.49, Sup(m_2) = 1.16, Sup(m_3) = 3.2075, Sup(m_4) = 3.2375, Sup(m_5) = 3.225.$$

Step4 : Determine the degree of credibility of each evidence according to equation (13) as follows:

$$Crd(m_1) = 0.2437, Crd(m_2) = 0.0810, Crd(m_3) = 0.2240, Crd(m_4) = 0.2261, Crd(m_5) = 0.2252.$$

Step 5: Calculate the Deng entropy of each evidence according to equation (8) as follows:

$$E_d(m_1) = 1.5664, E_d(m_2) = 0.4690, E_d(m_3) = 1.8092, E_d(m_4) = 1.8914, E_d(m_5) = 1.7710.$$

Step 6: Generate the information volume of each evidence according to equation (14) as follows:

$$IV(m_1) = 4.7894, IV(m_2) = 1.5984, IV(m_3) = 6.1056, IV(m_4) = 6.6286, IV(m_5) = 5.8767.$$

Step 7: Normalize the information volume of each evidence according to equation (15) as follows:

$$\tilde{IV}(m_1) = 0.1916, \tilde{IV}(m_2) = 0.0639, \tilde{IV}(m_3) = 0.2442, \tilde{IV}(m_4) = 0.2652, \tilde{IV}(m_5) = 0.2351.$$

Step 8: Estimate the weight coefficient of each evidence according to equation (16) as follows:

$$w(m_1) = 0.0467, w(m_2) = 0.0052, w(m_3) = 0.0547, w(m_4) = 0.06, w(m_5) = 0.0529.$$

Step 9: Normalize the weight coefficient of each evidence according to equation (17) as follows:

$$\tilde{w}(m_1) = 0.2128, \tilde{w}(m_2) = 0.0237, \tilde{w}(m_3) = 0.2492, \tilde{w}(m_4) = 0.2733, \tilde{w}(m_5) = 0.2410.$$

Step 10: Generate the weighted averaged mass function according to equation (18) as follows:

$$m(A) = 0.5267, m(B) = 0.1519, m(C) = 0.0662, m(A, C) = 0.2552.$$

Finally, the weighted averaged mass function is combined with Dempster's combination rule for 4 iterations, and the combined results are shown in Table 2.

Table 2. Combined results based on different combination methods

Method	$m(A)$	$m(B)$	$m(C)$	$m(A, C)$	Target
Dempster's rule	0	0.1422	0.8578	0	C
Murphy's method [31]	0.9620	0.0210	0.0138	0.0032	A
Deng et al.'s method [32]	0.9820	0.0039	0.0107	0.0034	A
Zhang et al.'s method [33]	0.9820	0.0034	0.0115	0.0032	A
Zhang et al.'s method [29]	0.9851	0.0010	0.0109	0.0030	A
Proposed method	0.9881	0.0003	0.0080	0.0036	A

4.2 Discussion

It can be seen from Table 2 that, under the influence of the decision information from sensor *S*2, the Dempster's combination rule produces counter-intuitive results and identify object *C* as the target, even if the other four pieces of evidence support target *A*. which is totally contrary to the facts. However, Murphy's method [31], Deng et al.'s method based on Jousselme's distance [32], Zhang et al.'s method based on cosine distance [33], the method in [29] based on dissimilarity and contradiction, and the proposed method all generate the reasonable combined results and accurately judge that the target is *A*. At the same time, among the combined results of these five improved methods, the proposed method gives the highest value to $m(A)$ (98.81%). This shows that when the conflicting evidence are fused, the proposed method is more efficient and beneficial to decision-making. The reason is that our method not only considers the dissimilarity between two evidences, but also fully discusses the information volume of each evidence. Although other methods also introduce the evidence distance and dissimilarity, the uncertainty measurement is not taken into full consideration. Through the above comparative analysis, it can be seen that our proposed method can effectively increase the reliable evidence's weight while decrease the unreliable evidence's weight, so that the negative effects of the conflicting evidences are released on the final combined results.

5 Conclusion

In IOT application of target recognition, there is usually a big conflict between the local decisions of sensor nodes due to various interferences. However, the traditional Dempster's combination rule may lead to a perverse conclusion when fusing high conflicting evidences, which makes the fusion center make a wrong judgment. To solve this problem, after analyzing the existing solutions, this paper proposes a new evidence weighted combination method. The method fully considers the dissimilarity between two evidences and the information volume of each evidence when weighing the weight of evidence. Through using the idea of evidence correction for reference, the influence of high conflict evidence in the fusion process is restrained by the weighted average method. The experimental results show that the proposed method can effectively improve the rationality of fusion results, which is beneficial for the fusion center to quickly and accurately identify and judge. In future study, the improvement will include the following two aspects: (1) finding a more accurate measure to quantify the uncertain degree of the evidence; (2) designing more effective combination methods to deal with uncertain and conflicting data in IOT environment.

References

[1] Y. Zhang, Y. Liu, Z. Zhang, N. Zhao, Collaborative fusion for distributed target classification using evidence theory in IoT environment, IEEE Access 6(2018) 62314-62323.

[2] L. Tang, and Z. Lu, DS Evidence Theory-Based Energy Balanced Routing Algorithm for Network Lifetime Enhancement in WSN-Assisted IOT, Algorithms 13(6)(2020) 152.

[3] S. Smys, Energy-aware security routing protocol for WSN in big-data applications, Journal of ISMAC, 1(1)(2019) 38-55.

[4] A. Ali, S. Talpur, S. Narejo, Detecting Faulty Sensors by Analyzing the Uncertain Data Using Probabilistic Database, in: 3rd International Conference on Computing, Mathematics and Engineering Technologies, 2020.

[5] S. Kumar, and V. K. Chaurasiya, A multisensor data fusion strategy for path selection in Internet- of- Things oriented wireless sensor network (WSN), Concurrency and Computation: Practice and Experience 30(18)(2018) e4477.

[6] P. Jaiswal, Analysis of Decision Fusion Detection in Wireless Sensor Network, Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12(11)(2021) 3857-3867.

[7] C. Zhu, B. Qin, F. Xiao, Z. Cao, H. M. Pandey, A fuzzy preference-based Dempster-Shafer evidence theory for decision fusion, Information Sciences 570(2021) 306-322.

[8] Y. Xue, and Y. Deng, Decision making under measure-based granular uncertainty with intuitionistic fuzzy sets, Applied Intelligence (2021) 1-10.

[9] Y. Tian, X. Mi, L. Liu, and B. Kang, A new soft likelihood function based on d numbers in handling uncertain information, International Journal of Fuzzy Systems 22(7)(2020) 2333-2349.

[10] D. Qiao, K.-w. Shen, J.-q. Wang, T.-l. Wang, Multi-criteria PROMETHEE method based on possibility degree with Z-numbers under uncertain linguistic environment, Journal of Ambient Intelligence and humanized computing 11(5)(2020) 2187-2201.

[11] C. Fu, Q. Zhan, W. Liu, Evidential reasoning based ensemble classifier for uncertain imbalanced data, Information Sciences 578(2021) 378-400.

[12] P. Liu, and H. Yang, Three-way decisions with intuitionistic uncertain linguistic decision-theoretic rough sets based on generalized Maclaurin symmetric mean operators, International Journal of Fuzzy Systems 22(2)(2020) 653-667.

[13] J. Wang, Y. Mao, Z. Li, J. Gao, H. Liu, Robust fusion estimation for multisensor uncertain systems with state delay based on data-driven communication strategy, IEEE Access 8(2020) 151888-151897.

[14] D. Zhu, X. Cheng, L. Yang, Y. Chen, S. X. Yang, Information Fusion Fault Diagnosis Method for Deep-Sea Human Occupied Vehicle Thruster Based on Deep Belief Network, IEEE Transactions on Cybernetics 2021.

[15] A. Dempster, Upper and Lower Probabilities Induced by a Multivalued Mapping, Annals of Mathematical Statistics 38(2)(1967) 325-339.

[16] G. Shafer, A mathematical theory of evidence: Princeton university press, 1976.

[17] Z. Lin, and J. Xie, Research on improved evidence theory based on multi-sensor information fusion, Scientific Reports 11(1)(2021) 1-6.

[18] P. Liu, X. Zhang, W. Pedrycz, A consensus model for hesitant fuzzy linguistic group decision-making in the framework of dempster–shafer evidence theory, Knowledge-Based Systems 212(2021) 106559.

[19] P. Sureeyatanapas, N. Waleekhajornlert, S. Arunyanart, T. Niyamosoth, Resilient supplier selection in electronic components procurement: an integration of evidence theory and rule-based transformation into TOPSIS to tackle uncertain and incomplete information, Symmetry 12(7)(2020) 1109.

[20] H. Zhang, Y. Deng, Weighted belief function of sensor data fusion in engine fault diagnosis, Soft computing 24(3)(2020) 2329-2339.

[21] Z. Zhang, C. Jiang, Evidence-theory-based structural reliability analysis with epistemic uncertainty: a review, Structural and Multidisciplinary Optimization (2021) 1-19.

[22] X. Wang, Y. Song, Uncertainty measure in evidence theory with its applications, Applied Intelligence, 48(7)(2018) 1672-1688.

[23] P. Smets, The combination of evidence in the transferable belief model, IEEE Transactions on pattern analysis and machine intelligence 12(5)(1990) 447-458.

[24] E. Lefevre, O. Colot, P. Vannoorenberghe, Belief function combination and conflict management, Information fusion 3(2)(2002) 149-162.

[25] X. Su, L. Li, H. Qian, S. Mahadevan, Y. Deng, A new rule to combine dependent bodies of evidence, Soft Computing 23(20)(2019) 9793-9799.

[26] M. Jing, Y. Tang, A new base basic probability assignment approach for conflict data fusion in the evidence theory, Applied Intelligence 51(2)(2021) 1056-106.

[27] F. Xiao, Multi-sensor data fusion based on the belief divergence measure of evidences and the belief entropy, Information Fusion 46(2019) 23-32.

[28] W. Liu, Analyzing the degree of conflict among belief functions, Artificial intelligence 170(11)(2006) 909-924.

[29] Y. Zhang, Y. Liu, Z. Zhang, H.-C. Chao, J. Zhang, Q. Liu, A weighted evidence combination approach for target identification in wireless sensor networks, IEEE Access 5(2017) 21585-21596.

[30] Y. Deng, Deng entropy, Chaos, Solitons & Fractals 91(2016) 549-553.

[31] C. K. Murphy, Combining belief functions when evidence conflicts, Decision support systems 29(1)(2000) 1-9.

[32] D. Yong, S. Wenkang, Z. Zhenfu, L. Qi, Combining belief functions based on distance of evidence, Decision support systems 38(3)(2004) 489-493.

[33] Z. Zhang, T. Liu, D. Chen, W. Zhang, Novel algorithm for identifying and fusing conflicting data in wireless sensor networks, Sensors 14(6)(2014) 9562-9581.