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Collaborative Fusion for Distributed Target Classification Using Evidence Theory in IOT Environment

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ABSTRACT As an efficient strategy, collaborative fusion can promote the classification performance while decreasing data transmission energy consumption and bandwidth requirements. In practice, the appropriate reliability assessment plays an essential rule in the fusion process. In this paper, we mainly concentrate on the classification problem of distributed target in Internet of Things scenarios, and an effective collaborative fusion method in terms of internal reliability and relative reliability evaluation is proposed. The inner reliability reveals the potential classes of the target in accordance with the local hard decision made by distinct sensor. The relative reliability reflects the credibility of the soft decision represented by belief function. These two reliability measures are complementary with each other. In our proposed fusion method, the inner reliability is applied to transfer the local hard decision into rational soft decision, and the relative reliability is utilized to decrease the influence of conflicting soft decisions by making full use of the evidential discounting operation. The discounted soft decisions are related to the combination rule of Dempster–Shafer for the final target classification. Results of experiment show that compared with the traditional fusion method, this method has the better fusion performance.

INDEX TERMS Data fusion, inner reliability, relative reliability, evidential reasoning.

I. INTRODUCTION

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 the most important part of an IOT system, the wireless sensor network (WSN) collects the information from the monitoring target and send it to the sink node [2]. Recently, the data is generated, collected and analyzed at an unprecedented scale as the increasing application of WSNs in detection and classification, and the volume of data is also explosively increasing when it is linked and fused with other data to make a class decision [3]. On the other hand, the power and bandwidth of wireless nodes are strictly limited, so it is unreasonable to upload original data to sink nodes [4]. In this case, proper data fusion is an effective strategy to obtain good classification performance. In IOT applications, data fusion is the technique of combing data provided by multiple data sources into a uniform result [5], [6]. In the meanwhile, it makes a comprehensive determination on monitoring the objectives according to data provided by the sensor nodes [7]. In a target classification system in terms of data fusion, local decisions are created by independent sensor nodes, and the fusion center connects these local decisions, making the final decision more rational according to the appropriate computing strategy [5]. Data fusion provides a flexible solution to make the classification result closer to the truth. In the wireless sensor network, the appropriate fusion scheme is adopted to reduce the amount of data required to be transmitted to the fusion center, and reduce energy consumption and communication bandwidth significantly. At present, data fusion has been extensively employed in military, medical, disaster search, and security surveillance applications and other complicated applications [8]. In these applications, the sensor nodes deployed in the monitoring area are vulnerable to the complicated physical surroundings and electronic jamming [9], and the information obtained by sensors nodes is always uncertain and imprecise [10], [11]. As a result, the method of acquiring the feasible result of the trustworthy data fusion with unreliable data is a huge challenge of WSNs in IOT applications [12].

In distributed target classification systems with data fusion, sensors are deployed in the specified region to collect the attribute knowledge of the monitoring target. The classifier of each sensor carries out the classification work according to the collected data. The classification result of each sensor is considered as a local decision. All sensors then upload their local decisions to the fusion center, which makes final decisions based on complementary local decisions [13]. Compared with single-sensor target classification, multi-sensor data fusion usually has higher classification accuracy [14]. When it comes to the limitations of the energy and the computation ability of the nodes, the classifier with low cost and simple process is employed by each sensor. As a consequence, the reasonable fusion scheme plays a critical rule in the process of data fusion [15]. The diverse approaches have been proposed to combine the ensemble decisions of various classifiers for the sake of acquiring good fusion results. Generally speaking, existing methodologies can be roughly composed of two categories: hard decision (HD) fusion [16] and soft decision (SD) fusion [17]. In HD strategies, the local decision of the classifier is only a label value. The fusion center combines these local decisions into a comprehensive one based some combination rules, such as the weighted sum [18], the max-log fusion [19], or the simple majority voting method [20]. In SD strategies, the local decisions are usually offered by soft membership measures, such as probability value, fuzzy memberships, or belief function, and the fusion operation is usually carried out in accordance with some data fusion methods, containing Bayesian combination [21], Fuzzy logic [22] as well as evidential reasoning mechanism [23]. In most cases, the HD fusion has great advantage based on uncomplicated implementation, but it usually provides lower fusion accuracy than the SD fusion. The soft classification result can provide more useful information than a hard label, and hence the SD fusion is expected to make the fused decision closer to the truth [14]. In this paper, we adopt the latter strategy as our basics for distributed target classification, and employ the evidential reasoning technology to cope with the data fusion problem of WSNs in IOT environment.

Dempster-Shafer evidence theory, also referred as evidential reasoning or belief function theory, has been testified to be an effective method to deal with uncertain and inaccurate data [24], and it has been widely applied in sorts of applications, for example, state estimation [9], target recognition [7], data classification [25], and information fusion [4], and etc. In an evidential reasoning framework, the insular decisions reported by distinct sensor nodes are expressed as several pieces of evidence, and the combined decision can be produced by proper evidence combination rules [26]. Nevertheless, in reality, the performance of data fusion in terms of evidence theory is restricted in two important aspects. First, it is complex to find rational basic belief assignment (BBA) construction strategy. Second, it's a thorny problem to combine the BBAs in a feasible manner. Thus, quite a few methods have been proposed and discussed about the fusion of multi-classifier. In [27], a combination approach for multi-class classifier employing evidence theory was introduced, and the evidence was estimated by minimizing the mean squared error between the combined result and the truth of the training data set. In [28], the evidence was constructed based on the overall performance of classifiers, and a two-step combination scheme was developed. In [14], the concept of contextual reliability on the basis of inner reliability and relative reliability concepts was proposed. The inner reliability reveals the difference between the output value and the truth value for the different elements within each soft classification result, and the relative reliability characterizes the conflicting information among the classification results provided by various classifiers. The inner reliability and relative reliability can capture different aspects of the classification reliability, and employing both of them can efficiently improve the global classification performance. In our previous works, a simple and effective data fusion method based on evidential reasoning was introduced in [7]. Each sensor node only requires to send its hard decision and reliability to the fusion center and build the soft decision of each sensor according to the output confusion matrix in the fusion center. In this manner, the bandwidth demand for data transmission can be greatly reduced. Nevertheless, the evaluation of reliability degrees in the hard classification result is not always regarded as adequate, and it does not specifically reveal the reliability degree of each element (class) within the soft classification result. Meanwhile, relative reliability that can be used to properly reduce the bad impact of conflicting information among the classifiers is not taken into consideration in the fusion process.

As a result, we propose a new weighted data fusion method with reasonable reliability evaluation based on evidence theory in this work. This method utilizes the relative distance between the object and the sample set of each class to measure the inner reliability degrees of the different classes within the soft decision. A refined relative reliability evaluation in terms of the dissimilarity between different local soft decisions is also introduced to address the influence of conflicting information for the sake of promoting the global classification accuracy. Subsequently, the proposed combination method is tested on randomly generated data sets and vehicle classification data sets, and compared with other classical methods.

The remainder of this article is organized as follows. Section 2 fundamentally introduces the basis of evidence theory. The proposed weighted data fusion approach with evidential reasoning is presented in Section 3. Section 4 offers the experimental results to prove the performance of our method. Conclusions are finally summarized in Section 5.

II. PRELIMINARY WORK

In this part, we show several fundamental concepts that are commonly utilized in evidence theory. Generally, the data fusion based on evidential reasoning framework includes three phase: mass construction, BBA combination, and discounting operation.

A. MASS CONSTRUCTION

Dempster-Shafer evidence theory introduced by Shafer is also known as evidential reasoning. In this theory, the frame of discernment is defined as a finite set, whose elements are exhaustive and mutually exclusive, and it can be denoted by $\Omega = \{w_1, w_2, \ldots, w_i, \ldots, w_n\}$. The power set of Ω is denoted by 2^Ω, representing a set that identifies all probable subsets of the framework. For instance, if $\Omega = \{w_1, w_2, w_3\}$, then $2^\Omega = \{\phi, \{w_1\}, \{w_2\}, \{w_3\}, \{w_1, w_2\}, \{w_1, w_3\}, \{w_2, w_3\}, \Omega\}$. In a target classification system, the singleton element represents an individual class, and the compound element stands for the partial ignorance among several singleton classes in 2^Ω. When it comes to a monitoring target X, we can allocate X into any singleton element and compound element in 2^Ω with different basic belief assignments (BBAs). A BBA is also identified as a mass function, which is a mapping $m : 2^\Omega \to [0, 1]$, and it satisfies the following condition:

$$\sum\nolimits_{A\in 2^\Omega} m(A) = 1, \quad \text{and } m(\phi) = 0 \tag{1}$$

where A is the subset of 2^Ω, and the function $m(A)$ is utilized to compute the mass of belief of the class A. If $m(A) > 0$, the subset A can be referred to as the focal element of a mass function. The mass values of diverse focal elements containing singleton elements and compound elements can reasonably characterize the imprecise observation reported by each sensor on the object X.

In evidence theory, given a mass function m, the corresponding belief function $Bel(\cdot)$, plausibility function $Pl(\cdot)$ and pignistic probability function $BetP(\cdot)$ are defined as follows, respectively:

$$Bel(B) = \sum\nolimits_{A\subseteq B} m(A) \tag{2}$$

$$Pl(B) = \sum\nolimits_{A\cap B\neq\emptyset} m(A) \tag{3}$$

$$BetP(w) = \sum\nolimits_{w\in A, A\subseteq\Omega} \frac{1}{|A|} m(A) \tag{4}$$

where $|A|$ is the cardinality of focal element A. All three of these functions can be used to support decision making on classes of unknown monitoring objects on the basis of their corresponding values. For instance, the decision can be made by selecting the class label with maximum $BetP$.

In reality, the quantity of $Bel(A)$ can be taken into account minimum support degree of class A of the evidence, while quantity of $Pl(A)$ can be considered as the maximum support degree of class A of the evidence. Quantity of $BetP(A)$ offers a compromised support degree of class A of the evidence. The relationship among these three measures satisfies the following condition:

$$Bel(A) \leq BetP(A) \leq Pl(A), \quad \forall A \subseteq \Omega. \tag{5}$$

Generally speaking, there is no unified solution to solve the problem of large-scale construction. Any algorithm that satisfies the equation 1-4 can be used as a mass construction method.

B. BBA COMBINATION

In a multiple sensor data fusion system, the output of each sensor can be recognized as an evidence described by a BBA. Provided that there are two distinct sources of evidence denoted by m_1 and m_2 over 2^Ω, the well-known Dempster-Shafer (DS) combination rule can be utilized to combine them in the following manner:

$$\begin{aligned} &m_\oplus(A) \\ &= m_1(B) \oplus m_2(C) \\ &= \begin{cases} 0, & B\cap C = \phi; \\ \dfrac{\sum_{B\cap C=A,\forall B,C\subseteq\Omega} m_1(B) \times m_2(C)}{1 - \sum_{B\cap C=\phi,\forall B,C\subseteq\Omega} m_1(B) \times m_2(C)}, & B\cap C \neq \phi, \end{cases} \end{aligned} \tag{6}$$

where $\sum_{B\cap C=\phi,\forall B,C\subseteq\Omega} m_1(B) \times m_2(C) < 1$ characterizes the whole conflicting mass between m_1 and m_2, and by standardizing the steps, all focus elements are proportionally reassigned.

DS rule is commutative and associative, and it could be employed for combining multiple BBAs by sequentially. Assume that there are K pieces of evidences, we can use (6) to combine them as follows:

$$m = m_1 \oplus m_2 \oplus \cdots \oplus m_K \tag{7}$$

Additionally, the values of focal elements of m can be calculated by:

$$\begin{aligned} m(A) &= k \sum_{X_1\cap X_2\cap\cdots\cap X_K=A} \prod_{i=1}^{K} m_i(X_i) \\ k^{-1} &= 1 - \sum_{X_1\cap X_2\cap\cdots\cap X_K=\phi} \prod_{i=1}^{K} m_i(X_i) \\ &= \sum_{X_1\cap X_2\cap\cdots\cap X_K\neq\phi} \prod_{i=1}^{K} m_i(X_i) \end{aligned} \tag{8}$$

Nevertheless, DS combination rule often offers a poor performance due to counter-intuitive combined results in some conflicting cases. Thus, a series of alternative combination methods are proposed for this problem, such as Smets's unnormalized combination rule, the disjunctive combination rule, and Yager's combination rule [29], [30], etc. Unfortunately, these modified methods are less attractive for the reason that they are not associative and complicated to implement. In the next part, another solution named as discounting operation will be introduced to decrease negative influence on conflicting information in the course of the fusion process with classical DS combination rule.

C. DISCOUNTING OPERATION

In the course of the combination of multiple outputs represented by BBAs from different sensors, conflicting information sometimes may occur among the BBAs, and it often results in negative impact on the fusion process when the DS combination rule is employed. The Shafer's discounting method was introduced in [31] for the sake of reducing the influence of conflict. On the basis of the opinions from Shafer, the evidence is not completely reliable. The reliability (weight) factor α of a BBA can capture the degree of conflict between this BBA and other BBAs. If a BBA has a lower reliability than others, the influence of this BBA should be reduced in the fusion process.

Considering a BBA denoted by $m(\cdot)$ on the frame of discernment Ω, and its corresponding reliability (weight) factor $\alpha \in [0, 1]$, the discounting operation of this BBA can be implemented by:

$$\begin{cases} m^{\alpha}(A) = \alpha m(A), & A \neq \Omega \\ m^{\alpha}(\Omega) = \alpha m(\Omega) + (1-\alpha), & A = \Omega. \end{cases} \tag{9}$$

Based on reliability factor α, the mass value of each focal element in $m(\cdot)$ is proportionally redistributed to the total ignorance element Ω, which has no impact in the fusion process. By using the discount operation, the effect of unreliable evidence is reduced, and the rational final combination results can be obtained by using the classic DS combination rule. Thus, equation (6) is modified by:

$$(m_1^{\alpha_1} \oplus m_2^{\alpha_2})(A) = \begin{cases} 0, & A=\phi \\ \dfrac{1}{1-k} \displaystyle\sum_{B\cap C=A, \forall B,C\subseteq\Omega} m_1^{\alpha_1}(B)\times m_2^{\alpha_2}(C), & A\in 2^{\Omega}/\phi. \end{cases} \tag{10}$$

where

$$k = \sum_{B\cap C=\phi, \forall B,C\subseteq\Omega} m_1^{\alpha_1}(B) \times m_2^{\alpha_2}(C). \tag{11}$$

III. MULTIPLE SENSOR DATA FUSION BASED ON EVIDENTIAL REASONING

A. SYSTEM MODEL

In multiple sensor data fusion system, each sensor is independently deployed in the monitoring area, and there is no correlation between their observations. We assume that all potential classes are known in our system, thus the frame of discernment utilized in evidential reasoning can be exclusive and exhaustive. The system model is showed in Figure 1. Provided that there are $s = \{s_1, s_2, \cdots, s_n\}$ sensors deployed in the sensors network, all the local classifiers of sensor nodes will be well trained, and their training output confusion matrices will be saved in the fusion center. Any appropriate classifiers can be employed for this multi-class target recognition task, and we don't take into consideration how to understand the process of classification. For a target with $\Omega = \{w_1, w_2, \ldots, w_c\}$ potential classes, the n sensors carry out classification operations independently on the basis of their observations $x = \{x_1, x_2, \cdots x_n\}$. After classification processes of these sensors, the corresponding hard decisions $u = \{u_1, u_2, \cdots, u_n\}$, in which $u_i \subset \Omega\,(1 \leq i \leq n)$ and the reliability degrees of the decisions $r = \{r_1, r_2, \cdots r_n\}$ are generated by the classifiers of sensors in terms of their real-time observations. Subsequently, each sensor sends its local hard decision and corresponding reliability degree to fusion center. The global data fusion is conducted in the fusion center, and the final decision can be made directly on the basis of the final combined result. There exist several standard decision-making methods using the different criteria [32]. The pessimistic decision is made by choosing the class with maximum belief $Bel(\cdot)$. The optimistic decision makes up of selecting the class with maximum plausibility $Pl(\cdot)$. The middle decision is made by selecting the class with maximum pignistic probability $BetP(\cdot)$. In our classification system, the class with maximum BBA in the global combined result also has the maximum belief $Bel(\cdot)$, maximum plausibility $Pl(\cdot)$ and maximum pignistic probability $BetP(\cdot)$ due to the particular structure of BBA. As a result, our decision can be determined by selecting the class with maximum BBA, which is of a small computation burden in the global combined result.

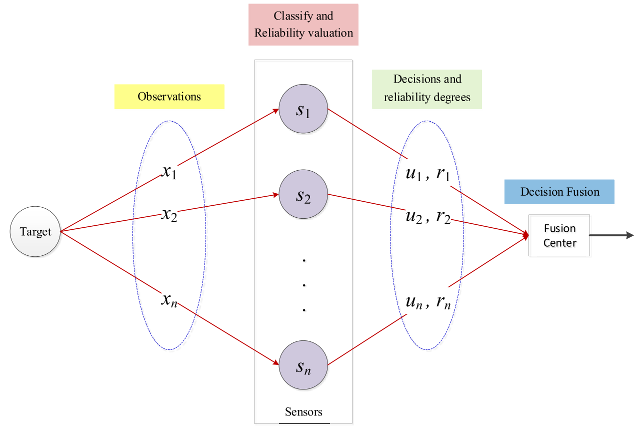

FIGURE 1. System model of the data fusion method for target classification.

B. DATA FUSION METHOD BASED ON CONFUSION MATRIX

In our previous work, a simple data fusion method based on confusion matrix was proposed [7]. This method consists of two main steps: (1) the determination of the local soft decision of each senor, and (2) the combination of different local soft decisions using equation (8). In this part, these two steps are briefly introduced, and the improved version of this method will be introduced in the next part.

For a sensor s_i $(1 \leq i \leq n)$, denote its training set as $\Gamma_i = \left\{\left(y_1^i, w_1\right), \cdots \left(y_c^i, w_c\right)\right\}$, when receiving a new observation x_i, the local classification operation is carried out, and the local hard decision u_i can be produced by the classifier of sensor s_i. Let $d_{i,j}$ denote the distance between x_i and training sample set $y_j (1 \leq j \leq c)$. We assume that the local hard decision is $u_i = w_k$ $(1 \leq k \leq c)$, and its corresponding distance is $d_{i,k}$. The relative distance between $d_{i,j}$ and $d_{i,k}$ can be calculated by:

$$\nabla d_{i,j} = \frac{d_{i,j}}{d_{i,k}}, \quad 1 \leq j \leq c, j \neq k \tag{12}$$

When this relative distance $\nabla d_{i,j}$ is large, it is certain that the target does not belong to w_j. When the value of $\nabla d_{i,j}$ is small, the class of this target should be w_j. Thus, this relative distance is applied to evaluate the reliability degree of decision u_i as follows:

$$r_i = \min_{1 \leq j \leq c} \left\{\lambda \left(1 - \exp\left(-\beta \nabla d_{i,j}^2\right)\right)\right\} \tag{13}$$

After that, the sensor s_i sends its determination u_i and the corresponding reliability degree r_i to the fusion center. In accordance with the decision u_i and confusion matrix of sensor s_i, we can obtain the corresponding condition probability vector $\mathrm{p}_i = \{p_i\left(u_i|w_1\right), \cdots, p_i\left(u_i|w_c\right)\}$, in which $p_i\left(u_i|w_k\right)$ $(1 \leq i, k \leq c)$ is the conditional probability of class w_k when the local decision is u_i. This probability vector characterizes the overall performance of sensor s_i. In our system, the confusion matrix of the classifier of each sensor is kept in the fusion center. When the local decision is uploaded to the fusion center, the conditional probability vector can be obtained directly from the confusion matrix.

With the probability $p_i\left(u_i|w_k\right)$ and reliability degree r_i, a BBA $m_{i,k}\left(u_i|w_k\right)$ on the frame of discernment $\Omega = \{w_1, w_2, \ldots, w_c\}$ can be calculated by:

$$\begin{aligned} m_{i,k}\left(u_i|w_k\right) &= r_i p_i\left(u_i|w_k\right) \\ m_{i,k}\left(u_i|\Omega\right) &= 1 - r_i p_i\left(u_i|w_k\right) \end{aligned} \tag{14}$$

By using the obtained BBAs $\left\{m_{i,1}, \cdots m_{i,c}\right\}$, the hard decision u_i can be transferred into a soft decision denoted by m_i, which is calculated as follows:

$$m_i\left(w_k\right) = \oplus_{k=1}^{c} m_{i,k}\left(u_i|w_k\right) \tag{15}$$

where $\oplus$ denotes the DS combination operation.

After the m_i construction process, we can acquire a set of BBAs $\mathrm{M} = \{m_1, \cdots, m_c\}$ from $\mathrm{s} = \{s_1, s_2, \cdots, s_n\}$ sensors. Equation (8) is employed to compute the global combined result, and the final decision is determined by selecting the class with maximum mass value in the global combined result.

Compared with the classical naïve Bayes rule and weighted majority voting rule, this data fusion has better performance on classification accuracy [7]. But in the determination process of the local soft decision, the reliability degree r_i of hard decision u_i is represented by a single number, and this number plays the same role in the calculation operation of mass values of different focal elements according to equation (14) and (15). Moreover, the relative reliability that is utilized to properly decrease the negative impact of conflicting information among the classifiers is not taken into consideration in the global fusion process. Therefore, a refined inner reliability evaluation method that assigns different reliability degrees to different focal elements in the process of the determination of the local soft decision will be introduced, and a reasonable relative reliability measure will also be shown in the next part.

C. IMPROVED DATA FUSION

In WSNs, the classifier of sensor s_i conducts the classification operation and makes the local hard decision u_i when a new observation x_i is acquired. For decision u_i, we regard the vector $\mathrm{r}_i = \{r_i(u_i|w_1), \cdots, r_i(u_i|w_c)\}$ as its corresponding inner reliability degree vector, and the elements in this vector satisfies $0 < r_i(u_i|w_j) < 1$, $\sum_{j=1}^{c} r_i(u_i|w_j) = 1 (1 \leq i, j \leq c)$. This vector r_i can be evaluated in terms of the distance between the object and the sample set of each training class. For instance, when the object is close to the class w_j, inner reliability degree $r_i(u_i|w_j)$ should be large. In contrast, when the object is far away from the w_j, inner reliability degree $r_i(u_i|w_j)$ should be small. The value of $r_i(u_i|w_j) (1 \leq j \leq c)$ reflects the relative probability of the object potentially belonging to class w_j, when the local hard decision is u_i. Therefore, the inner reliability degree vector of hard decision u_i can be defined as:

$$r_i(u_i|w_j) = \frac{e^{-d(x_i, w_j)}}{\sum_{q=1}^{c} e^{-d(x_i, w_q)}} \tag{16}$$

where

$$d(x_i, w_j) = \frac{d_{i,j}}{\min_{1 \leq p \leq c} d_{i,p}} \tag{17}$$

Obviously, the value of $r_i(u_i|w_j)$ is limited to interval $(0, 1)$, and $d(x_i, w_j)$ is the relative distance of the object x_i to the class w_j with respect to the minimum distance to the all training classes. The distance $d_{i,j} (1 \leq j \leq c)$ can be calculated according to any appropriate distance definitions, for example, Euclidean distance, Cosine distance, Hamming distance, and etc. In the meanwhile, the selected samples in each class for distance computation can be the whole sample set, or the k nearest neighbors to the object. In this paper, we utilize Euclidean distance to calculate the inner reliability degree.

In our approach, the inner reliability degree vector $\mathrm{r}_i = \{r_i(u_i|w_1), \cdots, r_i(u_i|w_c)\}$ is different from the condition probability vector $\mathrm{p}_i = \{p_i\left(u_i|w_1\right), \cdots, p_i\left(u_i|w_c\right)\}$. The inner reliability degree reveals the relative probability of the object potentially belonging to each class when the local decision is u_i, and it is related to the object that requires to be classified. The condition probability vector reflects the overall classification performance of the classifier, and it is related with the classifier. The information provided by these two vectors is complementary. As a sequence, when both of them are taken into account, the refined local soft decision can be produced.

With the received pattern (u_i, r_i) from sensor s_i, the fusion center can obtain the corresponding the condition probability vector p_i directly according to confusion matrix. After that, a BBA $m_{i,k}\,(u_i|w_k)$ $(1 \leq k \leq c)$ on the frame of discernment $\Omega = \{w_1, w_2, \ldots, w_c\}$ can be computed by:

$$\begin{aligned} m_{i,k}\,(u_i|w_k) &= r_i\,(u_i|w_k) \times p_i\,(u_i|w_k) \\ m_{i,k}\,(u_i|\Omega) &= 1 - r_i\,(u_i|w_k) \times p_i\,(u_i|w_k) \end{aligned} \tag{18}$$

Because there are c elements in both the inner reliability degree vector and condition probability vector, we can obtain a set of BBAs $\{m_{i,1}, \cdots m_{i,c}\}$. For convenience, $p_i\,(u_i|w_k)$ and $r_i\,(u_i|w_k)$ are denoted by $p_{i,k}$ and $r_{i,k}$ for short. By combining BBAs $\{m_{i,1}, \cdots m_{i,c}\}$ by (8), the local soft decision can be calculated as follows:

$$\begin{aligned} m_i\,(w_k) &= \frac{1}{1-k_i}\frac{r_{i,k}p_{i,k}}{1-r_{i,k}p_{i,k}}\prod_{j=1}^{c}\left(1-r_{i,j}p_{i,j}\right) \\ m_i\,(\Omega) &= \frac{1}{1-k_i}\prod_{j=1}^{c}\left(1-r_{i,j}p_{i,j}\right) \end{aligned} \tag{19}$$

where

$$k_i = 1 - \left(\sum_{k=1}^{c}\frac{r_{i,k}p_{i,k}}{1-r_{i,k}p_{i,k}} + 1\right)\prod_{j=1}^{c}\left(1-r_{i,j}p_{i,j}\right) \tag{20}$$

After the determination of the local soft decision of $\mathrm{s} = \{s_1, s_2, \cdots, s_n\}$ sensors, we can obtain n pieces of BBAs, denoted by $\mathrm{M} = \{m_1, \cdots, m_c\}$.

Considering that the local combination results provided by different sensors on the same object may cause major conflicts, we propose a new method of relative reliability measurement to detect the unreliable BBAs. For the reason that the conflicting information often offers negative influence in the fusion process, the classical discounting operation will be conducted before the global combination for the sake of reducing the impact of unreliable evidence.

In this work, we propose that the relative reliability of the sensor is correlated with uncertainty and dissimilarity [5]. The uncertainty measure is used to quantify the quality of each piece of evidence, and the dissimilarity measure references the idea of mutual conflict between two pieces of evidence.

In the framework of evidential reasoning, many researchers propose a series of methods to measure the conflict between BBAs, such as the famous Jousselme's evidential distance d_j [33], MaxDiff distance [34], and the Deng entropy function [35]. The efficiency of these approaches has been proved in a series of literatures [23]. Therefore, we employ the Jousselme's distance to measure the dissimilarity between two BBAs, and use Deng entropy function to quantify the quality of a BBA directly.

Assume there are two BBAs m_1 and m_2 generated by two independent sensors on the frame of discernment Ω. The corresponding Jousselme's distance d_J between them can be formally defined as follows:

$$d_J\,(m_1, m_2) = \sqrt{\frac{1}{2}(m_1 - m_2)^T D\,(m_1 - m_2)}, \tag{21}$$

where D is a $2^{|\Omega|} \times 2^{|\Omega|}$ positively defined matrix, whose elements are calculated as follows:

$$D_{ij} = \frac{\left|A_i \cap B_j\right|}{\left|A_i \cup B_j\right|}, A_i, B_j \in 2^{\Omega} \tag{22}$$

This distance satisfies all requirements (non-negativity, non-degeneracy, symmetry, and triangle inequality) of a strict distance metric, and it is a widely accepted metric to measure the dissimilarity between two BBAs.

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

$$E_d = -\sum_i m\,(A_i) \log \frac{m\,(A_i)}{2^{|A_i|} - 1}. \tag{23}$$

Deng entropy is the generalization of Shannon entropy. It offers a significant way to measure and handle the uncertainty in the belief function theory.

In the multi-class pattern recognition application, the relative reliability degree of each sensor is calculated by the fusion of the uncertainty and contradiction measures in the fusion center [5]. The value of d_J expresses the degree of conflict between two pieces of evidences. We presume that the more one source contradicts other sources, the less reliable it becomes. When n sensors are deployed in the monitoring area, the dissimilarity between two sensors can be calculated by (21). The greater the dissimilarity between two sensors, the smaller the similarity between them. Thus, the similarity measure can be obtain by:

$$Sim\left(m_i, m_j\right) = 1 - d_J\,(m_1, m_2)\,, \tag{24}$$

where $Sim\left(m_i, m_j\right)$ denotes the degree of similarity between m_i and m_j.

Then, the support degree of the m_i is defined as

$$Sup\,(m_i) = \sum_{j=1, j\neq i}^{n} Sim(m_i, m_j). \tag{25}$$

Subsequently, the credibility of the BBA, m_i, can be given by:

$$Crd\,(m_i) = \frac{Sup(m_i)}{\sum_{j=1}^{n} Sup(m_j)}. \tag{26}$$

Provided that a BBA m_i has relatively high credibility degree determined by (26), we take into account that it should be more credible when it has more information volume than the others. Thus, this BBA m_i can obtain a larger relative reliability degree due to its good quality. Based on this idea, the credibility measure of a BBA can be modified as follows:

$$Crd^{\alpha}\,(m_i) = Crd\,(m_i) \times Q\,(m_i)\,. \tag{27}$$

where

$$Q(m_i) = e^{E_d^{\alpha}(m_i)} \tag{28}$$

$$E_d^{\alpha}(m_i) = \frac{E_d(m_i)}{\sum_{i=1}^{n} E_d(m_i)} \tag{29}$$

If the output of a sensor m_i is considered quite credible, it usually has a large reliability degree. Thus, the relative reliability of m_i can be defined based on the uncertainty and the dissimilarity is defined as:

$$\alpha_i = \frac{Crd^{\alpha}(m_i)}{\max_{1 \le j \le n} Crd^{\alpha}(m_j)} \tag{30}$$

Since the relative reliability $\alpha_i\,(1 \le i \le n)$ reflects the whole credibility of the elements in local soft decision represented by m_i, Shafer's discounting operation, denoted by (9),will be used to discount all local soft decisions $\mathrm{M} = \{m_1, \cdots, m_c\}$. The discounted BBAs can be combined by (10). The final decision is to select the largest class of BBA in the global composite result.

It's generally considered that the appropriate reliability evaluation method can promote the classification performance in a multi-class target classification task. Moreover, in WSNs, the data gained by sensors nodes are always conflicting and imprecise. The relative reliability and inner reliability measures can efficiently show and cope with such conflicting and imprecise data, and make the classification result closer to the truth. In our proposed multiple sensor data fusion system based evidential reasoning, we assume that all sensors have sufficient calculations to perform local classification and internal reliability evaluation operations. The communication channel is regarded as an error-free channel, and the information of sensors will be sent to the fusion center without distortion. Table 1 supplies the pseudocode of the proposed data fusion method.

TABLE 1. Pseudocode of the proposed data fusion method.

Input: Observation data: $\mathrm{X} = \{x_1, x_2, \cdots x_n\}$

event n sensors detect the target **do**
  for each observation $x_i\,(1 \le i \le n)$ is captured by sensor s_i **do**
    recognize the target and make local decision u_i
    calculate the inner reliability degree vector $r_i(u_i \mid w_j)$ by (16)
    upload the decision and corresponding reliability degree (u_i, r_i) to fusion center
  end for each
end event

event fusion center receives uploading from sensors **do**
  for each received pattern (u_i, r_i) **do**
    calculate the BBAs of patterns by (18)
    calculate the local soft decision by (19)
    calculate the similarity between two BBAs by (24)
    calculate the support degree of each BBA by (25)
    calculate the credibility degree of each BBA by (26)
    modify the credibility degree of each BBA by (27)
    calculate the relative reliability of each BBA by (30)
    discount the BBAs with relative reliability by (9)
  end for each
  combine the discount BBAs by (10)
  choose the class with maximum BBA as the final decision
end event

IV. EXPERIMENT RESULTS

In this section, two experiments are carried out to evaluate our proposed data fusion method. The first one is implemented on artificial generated dataset. The sensor number and sample distribution are artificially changed in this experiment. Subsequently, the classification performance can be expressed with changing sensor number and sample distribution. The second experiment is applied to test the performance of the proposed weighted data fusion by using real sensor dataset. In these two experiments, take into account that the complexity of calculation, local decision is made for each sensor using two easy-to-implement classifiers, namely k-nearest neighbor (k-NN) and extreme learning machine (ELM). For performance comparison, three related data fusion methods, containing the Naïve Bayes fusion, the weighted majority voting, and the belief function on the basis of confusion matrix, have been evaluated in this paper. In the naïve Bayes, the fusion decision is made by selecting the class with maximum fusion statistic, as showed by:

$$l_d = \arg\max_{1 \le k \le c} \left\{ \prod_{i=1}^{n} p_{i,k} \right\} \tag{31}$$

In the weighted majority voting rule, decision $u_{i,k}$ is weighted by adjustment factor b_i, and the determination is made by:

$$l_d = \arg\max_{1 \le k \le c} \left\{ \sum_{i=1}^{n} b_i u_{i,k} \right\} \tag{32}$$

In the belief function method based on confusion matrix, the decision is made by [7]:

$$w_d = \arg\min_{1 \le k \le c} \left\{ \prod_{i=1}^{n} (1 - r_i p_{i,k}) \right\} \tag{33}$$

A. EXPERIMENT ON ARTIFICIAL GENERATED DATASET

The Gaussian random number generating function randomly generated data set is utilized in this experiment. The target class is designed to be five, and each example presumes two randomly generated attributes that follow diverse Gaussian distributions. As demonstrated in Table 2, α is a coefficient of variation of sensor data standard deviation. Obviously, this coefficient can influence the classification accuracies. Figure 2 provides an example of sample data.

Since the data set is randomly generated, we generate 1,500 examples and 500 examples respectively as the training data set and test data. There are 300 training samples and 100 test samples in each class. After training process, 1000 samples are randomly generated as new observations.

TABLE 2. Data generation parameters.

Label	μ_1	μ_2	σ
w_1	10	10	4α
w_2	20	10	4α
w_3	30	10	4α
w_4	15	20	5α
w_5	25	20	5α

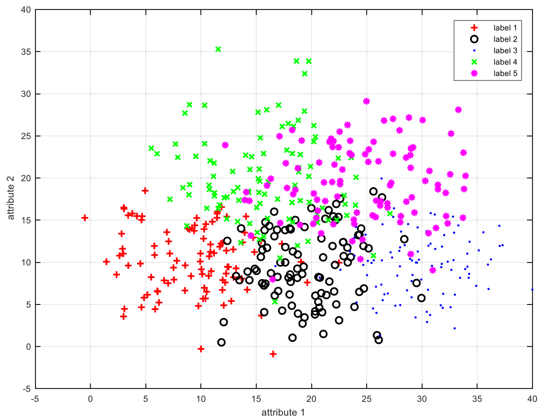

FIGURE 2. An example of randomly generated data with 100 samples per class tag.

The categories observed is randomly selected. The new observations are classified by using the classifier acquired in the training process. In this experiment, we use ELM classifier to make the local decision of sensor. The hidden neurons in ELM is 50, meanwhile, the activation function is ''radbas'' function.

The following four methods are utilized for performance comparison: the proposed weighted belief function fusion, the belief function fusion on the basis of confusion matrix, the naïve Bayes fusion, and the weighted majority voting method. We fix the sensor number as 5. This experiment is repeated 5 times to gain the average classification accuracy. The experiment results with different α values are shown in Figure 3.

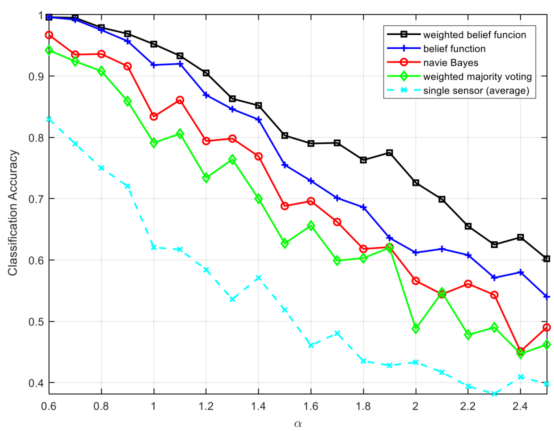

FIGURE 3. Average classification accuracy with changing α values.

As illustrated in Figure 3, the average classification accuracies of these fusion methods decline with different rates when the value of α increases from 0.6 to 2.5. Compared with the other three method, the average classification accuracy of our proposed weighted belief function fusion is reduced at the lowest rate, especially when α is larger than 1.5. It demonstrates the proposed method always has better performance rather than the others even with sparse and imprecise samples.

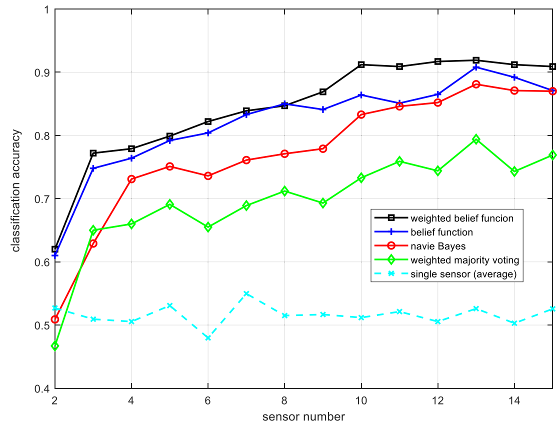

FIGURE 4. Average classification accuracy with changing sensor number.

As the number of sensors changes, the average classification accuracy is shown in Figure 4. In this experiment, the value of α is fixed as 1.5. The results illustrate that our weighted belief function fusion also has the better classification performance than the others when the number of sensor increases from 2 to 15.

B. EXPERIMENT ON VEHICLE CLASSIFICATION

In this experiment, we make full use of the collected sensor vehicle classification data set for vehicle monitoring applications by a distributed WSN in IOT environment. The 23 sensors are deployed on the road to record signals from passing vehicles. 11 sensors were chosen for vehicle classification. The acoustic and seismic signals captured by the sensor are used for classification missions, and the target vehicle may be an Assault Amphibian Vehicle (AAV) or a Dragon Wagon (DW).

The k-NN classifier and the ELM classifier are chosen to make local hard decision of each sensor. The value of k applied in k-NN classifier is set as 1. The hidden neurons in ELM is 50, meanwhile, the activation function is ''radbas'' function. We repeated the experiment 20 times to get the average classification accuracy. The classification performance comparison of fusion results is shown in Figure 5.

As observed from Figure 5, the proposed weighted belief function fusion has the best performance in these four methods. Our scheme can significantly promote the classification accuracy of k-NN classifier from 0.72 to 0.98. We also find out that the ELM classifier has a better performance than k-NN classifier when the sensor number is equal. Nevertheless, when the sensor number is 11, they can get almost the

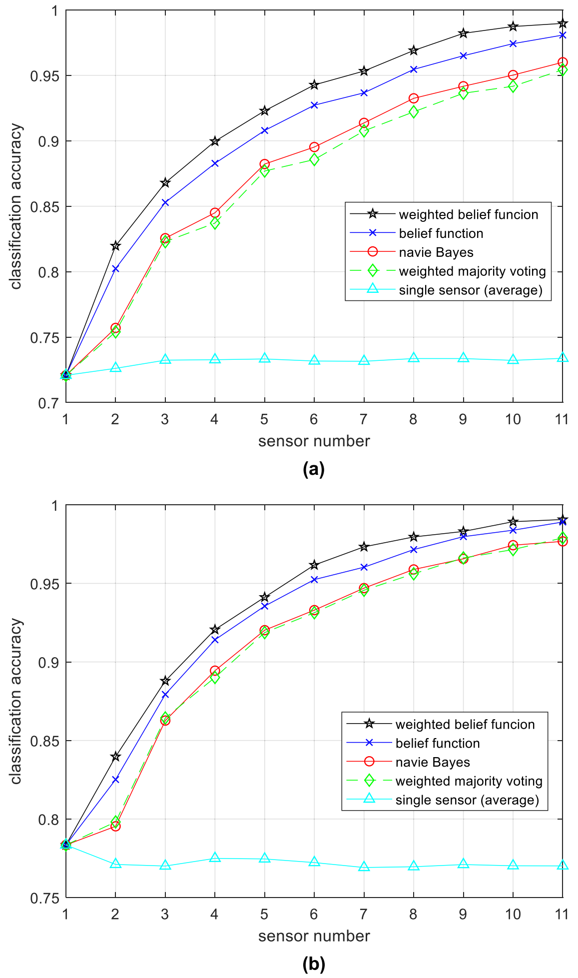

FIGURE 5. Average classification accuracy with changing sensor number. Classifier utilized in subplots (a, b) are *k*-NN and ELM, respectively.

same classification accuracy. It indicates that our proposed method can efficiently improve the fusion accuracy in the distributed target classification task.

V. CONCLUSION

In this paper, we study the distributed target classification problem in IOT applications, and propose an effective data fusion method on the basis of internal and relative reliability evaluation. In our proposed fusion method, the inner reliability is used to transfer the local hard decision made by distinct sensor into a rational soft decision represented by BBAs, and the relative reliability is employed to decrease the influence of conflicting soft decisions by utilizing classical shafer's discounting operation. The discounted soft decisions are combined with the DS combination rule. The final decision was to choose the top class in the BBA. Experimental results show that the fusion method can significantly enhance the classification accuracy of multi-pattern recognition. Our future work mainly involves the following two aspects: (1) finding a more efficient strategy to construct rational BBAs and improve the classification accuracy; (2) designing more trustworthy big data fusion methods to deal with the uncertain data in IOT environment.

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