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An Unsupervised Evidential Conflict Resolution Method for Data Fusion In IoT

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***Abstract*—Internet of Things (IoT) has gained substantial attention recently and plays a significant role in multiple real-world application deployments. A wide spectrum of such applications strongly depend on data fusion capabilities in the cloud from diverse information sources. In fact, various information sources often provide conflicting and contradictory for the same object, and thus it is important to fuse and resolve any possible information conflict before taking crucial decisions. For this reason, the primary aim of this paper is to provide a new evidential conflict resolution method that is able to automatically solve the problem of contradictory information provided by different sources in IoT applications. This method is based on the belief functions theory which is a powerful mathematical theory that can represent and manipulate various types if information imperfection. The performance of the proposed method was evaluated through simulation experiments. The results from these simulations demonstrated that our method outperforms the state-of-art methods in terms of effectiveness.**

I. Introduction

In RECENT years, the Internet of Things (IoT) has received considerable attention among academic researchers as well as industrial managers. The principal reason behind this consideration is the capabilities that IoT promises to offer. Indeed, IoT technology promises to revolutionize the way people live, work and interact with each other, by providing new opportunities to create a smarter world where all the abundant physical smart objects surrounding us can connect to the Internet and collaborate with one another so as to accomplish a common task with limited human intervention [1].

The greatest strength of the IoT paradigm is indisputably the high impact it has on people's everyday life. Its application covers various domains ranging from transportation, retail, healthcare, and defense to smart environments such as homes and cities [1]. All these applications rely on information pieces collected from many sensors of multiple types and reliability levels. These sensors collect, generate, and preserve a variety of information with diverse representations, scales, and quality. Bringing all the information pieces together opens opportunities to measure, understand and infer a robust and complete description of an environment or process of interest, and further makes it possible to provide intelligent services.

Data fusion plays a central part of IoT [2]. It combines information pieces collected from multiple sensors to achieve improved accuracy, enhanced precision, increased availability and more effective decision support than could be achieved by the use of a single sensor. Unfortunately, there are several issues involved in a sensory network that make the data fusion a difficult task. The majority of these issues arises from the quality of the information pieces to be fused and to the reliability degrees of the sensors providing them. In fact, information pieces produced by sensors are frequently dirty, which is mainly due to sensor failure, degradation or to its inherent limitation. Therefore, mechanisms to clean sensor information and improves the quality of decision-making are mandatory in IoT applications.

One way to overcome this problem is to eliminate the probable information conflict before the fusion procedure by considering the source reliability level. Consequently, all the information pieces to be merged should be corrected according to the reliability degree of the sources providing them. However, in many IoT applications, the information about the reliability of the sources is unavailable. In such situation, one should design an effective unsupervised method that is able to solve any probable information conflict and estimate the source reliability factors without having any training datasets. For this reason, we propose in this paper an unsupervised evidential conflict resolution method (U-ECRM) that overcome this problem. This method is based on the belief functions theory which has the merits of representing and handling various types of information imperfections.

The rest of this paper is structured as follows: Section 2 introduces the belief functions theory. Section 3 formulate the conflict resolution problem in IoT applications. Section 4 presents the main idea behind the proposed U-ECRM and details the proposed inference algorithm. The performances of the proposed method obtained from a synthetic dataset simulations are presented and discussed in Section 5. Finally, Section 6 concludes the paper.

II. Basics of Belief Functions Theory

In the Belief Functions Theory (BFT)[3], the Frame of Discernment (FoD) $\Theta = \{H_1, H_2, ..., H_N\}$ is a set of N mutually exclusive and exhaustive hypotheses. The power set of Θ, denoted by 2^Θ, contains all possible unions of the elements in Θ including Θ itself as well as the empty set.

The mass function (*MF*) expresses the degree of belief committed to a subset $A \in 2^{\Theta}$ justified by the available information. The *MF* is defined as a mapping $m : 2^{\Theta} \to [0, 1]$ satisfying the following properties:

$$m_{1\oplus 2}(A) = \begin{cases} \frac{\sum_{\substack{B,C \in 2^{\Theta} \\ B \cap C = A}} m_1(B) * m_2(C)}{1 - \sum_{\substack{B,C \in 2^{\Theta} \\ B \cap C = \emptyset}} m_1(B) * m_2(C)} & A \in 2^{\Theta}, A \neq \emptyset \\ 0 & A = \emptyset \end{cases} \quad (1)$$

It is possible to have multiple *MF* on the same domain Θ that correspond to different experts' opinions. Dempster's Rule of combination [3] can aggregate these *mf*. This rule is defined as follows:

$$m_{1\oplus 2}(A) = \begin{cases} \frac{\sum_{B \cap C = A} m_1(B) * m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B) * m_2(C)} & \forall A \subseteq \Theta, A \neq \emptyset \\ 0 & if A \neq \emptyset \end{cases} \quad (2)$$

In BFT, a decision can be made by choosing the single hypothesis with the maximum pignistic probability [4] which is constructed from the *MF*. It is defined as follows:

$$BetP(A) = \sum_{B \subseteq \Theta, A \cap B \neq \emptyset} \frac{|A \cap B|}{|B|} m(B) \quad (3)$$

In the framework of BFT, a distance measure computes the dissimilarity between two pieces of evidence. Jousselme distance [5] has been widely used in this purpose. It is defined as follows:

$$d(m_1, m_2) = \sqrt{\frac{1}{2} (m_1 - m_2)^t \underline{\underline{D}} (m_1 - m_2)}$$
$$\underline{\underline{D}} = \begin{cases} 1 & if A = B \\ \frac{|A \cap B|}{|A \cup B|} & \forall A, B \in 2^{\Theta} \end{cases} \quad (4)$$

III. Problem formulation

Let us consider a set of M objects (variable) $O = \{o_1, o_1, ..., o_M\}$ where each variable $o_j \in O$ can takes its unique true value from the exhaustive and mutually exclusive FoD $\Omega_j = \{H_{1,j}, H_{2,j}, H_{3,j}, ..., H_{K_j,j}\}$. That is one and only one hypothesis $\hat{H}_j$ among the set of possible hypotheses Ω_j is the actual value of object o_j. Besides, we also consider the close world assumption, where the complete knowledge about the definition domain of each object o_j is known by everyone in the fusion system. Thus, the available information about the actual value of o_j is represented by a correct value mass function *CV−MF* m_j^{Ω} defined over the FoD Ω_j.

To determine the correct values of the objects $o_j \in O$, one can exploit the power of data fusion techniques by aggregating multiple pieces of information collected from several sources. To do so, let us now consider a set $S = \{s_1, s_2, s_3, \ldots, s_N\}$ of N cognitively independent sources, where each source s_i provides pieces of information describing its knowledge about the actual value of each object o_j. These pieces of information are encoded in the form of *MFs* $m_{i,j}^{\Omega}$ defined over the FoD Ω_j. The usage of BFT to model and manipulate the provided pieces of information allows a better exploration of all available information [3].

In addition to its expressiveness power, the BFT offers a promising tool to combine several pieces of evidence obtained from multiple sources. The principal aim of using the combination operator, such as Dempster's combination rule, is to reduce the epistemic uncertainty by acquiring and then merging several credible, yet possibly incomplete, evidence pieces delivered by various cognitively independent and equally reliable sources. Accordingly, this important operation can help the fusion system to determine the correct value among the set of all possible values, and thus leading the decision maker to make the best possible decision for a given task.

Unfortunately, sources are seldom of the same quality, and some of them frequently deliver wrong, biased and contradictory pieces of information for the same real-world object. As a consequence, combining these incorrect information pieces with the correct ones using Dempster's combination rule generally produces counter-intuitive results, which in turn can lead the fusion system to make misleading critical decisions. One possible solution to overcome this problem is to incorporate the reliability level of each source into the fusion task. In this way, the system can correct the quality of the provided information pieces according to their sources reliability level prior to combination and further usages. One of the most robust and effective ways to model the reliability level of the sources is to use our proposed Evidential Source Reliability Mass Function *ESR−MF*. In fact, unlike the traditional source reliability models, the *ESR−MF* exploits the power of BFT to model several possible types of the qualitative behavior of a given source. As a consequence, this model allows a more general modelization of the source attitude, and thus it can, along with the evidential correction mechanism, enhance the performance of the fusion system. In this regard, we suppose, in this paper, that the reliability level of each source s_i is encoded as an *ESR−MF* m_i^{Θ} defined over the FoD $\Theta = \{T, D, R\}$, where the meaning of T is that s_i has a trustworthy qualitative behavior, D means that s_i is defective and R represents the state where s_i is considered to have a random qualitative behavior.

Let m_i^{Θ} represents the *ESR−MF* of s_i. This *MF* can be defined as a mapping function $m_i^{\Theta} : 2^{\Theta} \to [0, 1]$, such that:

$$\begin{cases} m_i^{\Theta}(A) \in [0, 1], & \forall A \in 2^{\Theta} \\ m_i^{\Theta}(\varnothing) = 0 \\ m_i^{\Theta}(T) + m_i^{\Theta}(D) + m_i^{\Theta}(R) + m_i^{\Theta}(T, D, R) = 1 \end{cases} \quad (5)$$

The support mass assigned to each subset of the FoD Θ_i have the following meaning: $m_i^{\Theta}(T)$ represents the support degree that s_i is trustworthy. $m_i^{\Theta}(D)$ represents the support degree that s_i is defective. $m_i^{\Theta}(R)$ represents the support degree that s_i has a random behavior. $m_i^{\Theta}(T, D, R)$ encodes the percentage of uncertainty about the behavior of s_i.

It is important to note that one of the possible ways to estimate the value of the *ESR−MF* is to focus the evaluation on the past contributions of the source. This can be achieved by evaluating the set of historical information pieces provided by the source with the actual values contained in the training dataset. In this way, it is possible to ascertain the historical behavior of the source, which in turn can be exploited to estimate its future behavior. This later can be used to correct the source's newly provided information pieces, and thus avoiding information conflict problems with the other sources. However, in many situations the *ESR−MF* of the sources are unknown a priori, and often training datasets are also unavailable. Therefore, the crucial problem that needs to be addressed is how to obtain the correct value of each object and to estimate the sources reliability level when there is no prior training dataset.

IV. THE PROPOSED UNSUPERVISED EVIDENTIAL METHOD

Due to the fact that the considered problem does not contain any prior knowledge other than the information pieces that is delivered by a set of sources, a robust method that is able to resolve the probable information conflict between the diverse sources without any supervision needs to be developed, where both the *ESR−MFs* and the *ESR−MFs* can only be estimated based on the provided pieces of information. To do so, the *ESR−MF* estimation and *CV−MF* determination steps are tightly related through the following two principles:

1) First, the sources that often deliver correct information pieces will be assigned higher trustworthiness degrees, the sources that mainly provide incorrect pieces of information will be regarded as defective and the ones that give a combination of correct and incorrect information pieces will be considered as random. At the same time, the estimated qualitative behavior of sources that supply more relevant information pieces will be considered as more certain than the ones that provide fewer pertinent information pieces.
2) Second, the information piece that is supported by trustworthy sources will be regarded as correct. Conversely, the information piece that is mostly supported by defective sources will be considered as wrong, and its complement is regarded as correct. On opposition to the two previous cases, the information pieces given by random or uncertain sources will be ignored and their support will not be taken into consideration.

This idea presents a chicken-and-egg dilemma. An unsupervised evidential conflict resolution method (U-ECRM) can solve this task by operating iteratively to simultaneously estimate the *ESR−MFs* and to determine the *CV−MFs* by following the above principles.

Following the previously principle, our proposed method is designed to jointly estimate source reliability and to determine the correct values. The flowchart of the inference algorithm is depicted in Figure 1. The basic core of the U-ECRM is an iterative algorithm, which starts with an initial setting of some parameters and then iteratively conducts the source weight update and truth update steps until a stopping condition is satisfied. Finally, a decision making step on the correct values of the considered objects is performed.

A. Parameters initialization

For the iterative methods, some parameters must be initialized in order to start the algorithms. In our U-ECRM, the *CV−MFs* are chosen to be the set of parameter to be initialized. Various techniques can be used to choose the initial value of these parameters. However, since the iterative methods are generally sensitive to arbitrary initializations, we prefer to use one of the majority opinion combination rules to infer the first guess of each *CV−MF*. For instance, in the current setting, each set of the provided information pieces about a particular object is combined by Murphy combination rule [6] in order to get a first value for the correct. This rule first applies a simple arithmetic averaging method, then the obtained averaged *MF* is combined with itself N-1 times by Dempster's combination rule.

B. Evidential source reliability mass function estimation

To estimate the *ESR−MF* m_i^{Θ} of each s_i, two series of input parameter are needed: the provided *MF* $m_{i,j}^{\Omega}$ about the actual value of each object o_j, and the objects' previously computed *CV−MFs* $m_{j\in\{1,2,\ldots,M\}}^{\Omega,*}$. Since these two series of parameters are available in this step of computation, the *ESR−MFs* $m_{i\in\{1,2,\ldots,N\}}^{\Theta}$ can be computed. For each source, we start by evaluating the correctness degree of each of the *MFs* that is provided by this source with respect to the computed *CV−MFs* of the considered objects. This evaluation step yields a set of evidence correctness mass functions *EC−MFs* $m_{i,j}^{\Psi}$, which represent how correct and relevant the source's information pieces are. The *EC−MF* $m_{i,j}^{\Psi}$ is defined over the FoD $\Psi_{i,j} = \{C, \bar{C}\}$ where C represents the hypothesis that the provided information $m_{i,j}^{\Omega}$ is correct, whereas $\bar{C}$ represents the hypothesis that the provided information $m_{i,j}^{\Omega}$ is incorrect.

Given $m_{i,j}^{\Omega}$, the *EC−MF* $m_{i,j}^{\Psi}$ can be computed by comparing $m_{i,j}^{\Omega}$ with the *CV−MF* $m_j^{\Omega,*}$. This comparison can be made by equation 6.

$$\begin{cases} m_{i,j}^{\Psi}(C) = \sum\limits_{B\in 2^{\Omega}} m_j^{\Omega}(B) \left(\sum\limits_{B\cap A=B} f(|A|) m_{i,j}^{\Omega}(A) \right) \\ m_{i,j}^{\Psi}(\bar{C}) = \sum\limits_{B\in 2^{\Omega}} m_j^{\Omega}(B) \left(\sum\limits_{B\cap A=\varnothing} m_{i,j}^{\Omega}(A) \right) \\ m_{i,j}^{\Psi}(C,\bar{C}) = 1 - \left(m_{i,j}^{\Psi}(C) + m_{i,j}^{\Psi}(\bar{C}) \right) \end{cases} \tag{6}$$

where f is a function which distributes the imprecision of s_i between the support degree that that the given evidence is correct $m_{i,j}^{\Psi}(C)$ and the support degree that the provided information is irrelevant $m_{i,j}^{\Psi}(C,\bar{C})$. This function can be defined as follows:

$$f(|A|) = \frac{|\Omega_j| - |A|}{|\Omega_j| - 1} \tag{7}$$

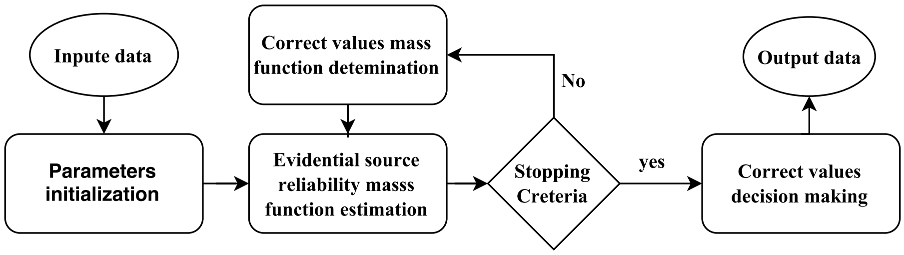

Figure 1. Flowchart of the unsupervised evidential conflict resolution method.

Once the *EC−MFd* of all objects are obtained, the total true positive TP_i and the total false negative FN_i of s_i are calculated by means of equation 8 and equation 9 respectively.

$$TP_i = \sum_{j=1}^{M} m^{\Psi}_{i,j}\left(C\right) \tag{8}$$

$$FN_i = \sum_{j=1}^{M} m^{\Psi}_{i,j}\left(\bar{C}\right) \tag{9}$$

After computing the TP_i and FN_i of s_i, they are used along with an application-specific user-specified cautious parameter $C_{cautious}$ to estimate the qualitative behavior of the source by using equation 10 or equation 11 depending on the difference between TP_i and FN_i.

- **Case 1:** $TP_i \geq FN_i$**:**

$$\begin{cases} m^{\Theta}_i(T) &= \frac{TP_i - FN_i}{TP_i + FN_i + C_{cautious}} \\ m^{\Theta}_i(D) &= 0 \\ m^{\Theta}_i(R) &= \frac{2FN_i}{TP_i + FN_i + C_{cautious}} \\ m^{\Theta}_i(T,D,R) &= \frac{C_{cautious}}{TP_i + FN_i + C_{cautious}} \end{cases} \tag{10}$$

- **Case 2:** $TP_i \leq FN_i$**:**

$$\begin{cases} m^{\Theta}_i(T) &= 0 \\ m^{\Theta}_i(D) &= \frac{FN_i - TP_i}{TP_i + FN_i + C_{cautious}} \\ m^{\Theta}_i(R) &= \frac{2TP_i}{TP_i + FN_i + C_{cautious}} \\ m^{\Theta}_i(T,D,R) &= \frac{C_{cautious}}{TP_i + FN_i + C_{cautious}} \end{cases} \tag{11}$$

C. Correct value mass function determination

The *CV−MF* determination procedure aims at computing the set of all *CV−MFs* $m^{\Omega,*}_{j\in\{1,2,\ldots,M\}}$ given that the set of all sources' provided *MFs* $m^{\Omega}_{i\in\{1,2,\ldots,N\},j\in\{1,2,\ldots,M\}}$ and the estimated *ESR−MFs* $m^{\Theta}_{i\in\{1,2,\ldots,N\}}$ of all sources $s_{i\in\{1,2,\ldots,N\}}$ are available. For a given object o_j, this procedure begins by correcting the provided *MFs* $m^{\Omega}_{i\in\{1,2,\ldots,N\},j}$ according to their appropriate sources' *ESR−MFs* $m^{\Theta}_{i\in\{1,2,\ldots,N\}}$ by means of the evidential correction mechanism. This mechanism can take advantages of the information contained in the *ESR−MF* to correct the provided information pieces before further exploitation. It can be formally defined in equation 12.

Immediately after correcting all the provided information pieces, these obtained corrected *MFs* $m^{\Omega,*}_{i\in\{1,2,\ldots,N\},j}$ can be aggregated by Dempster's rule to produce the combined *CV−MF* $m^{\Omega,*}_j$. Note that the correction step and the aggregation step must be applied to all objects $o_j \in O$. Once done, the set of all *CV−MFs* $m^{\Omega,*}_{j\in\{1,2,\ldots,M\}}$ is returned as the output of this procedure, and can be used to either re-estimate the *ESR−MFs* or make decision about the correct values.

D. Correct values decision making

The main purpose of the U-ECRM is to resolve the probable evidence conflict between the sources by estimating and then incorporating the *ESR−MFs* into the fusion task. In the current problem, these decisions can be made from the obtained *CV−MFs* $m^{\Omega,*}_{j\in\{1,2,\ldots,M\}}$. To make reasonable decisions in the U-ECRM, the pignistic transformation $BetP_j$ of each *CV−MF* $m^{\Omega,*}_j$ is firstly constructed. Then, the decision can be made based on selecting the hypothesis $\hat{H}_j$ with the largest pignistic probability.

E. Stopping condition

The iterative process in the proposed U-ECRM is carried out until the stopping criterion is satisfied. The stopping condition is defined with regard to the computed *CV−MFs* $m^{\Omega,*}_{j\in\{1,2,\ldots,M\}}$. In each iteration, we first compute the Jousselme distance between the computed *CV−MF* of the current iteration and the computed *CV−MF* of the previous iteration of each o_j. If the mean of all computed Jousselme distances of all objects is less than a small positive number ε, then the convergence criterion is satisfied.

V. Experimental evaluation

The performance evaluation of our U-ECRM is tested and compared with the baseline methods (majority voting, TruthFinder [7], 2-Estimate [8]) on samples of synthetic datasets generated by Waguih et al. synthetic datasets generator [9].

To evaluate the Precision rate of the proposed method, we chose the following configuration. We first defined the scale parameters by setting the number of objects to 1,000, and the number of possible values for each object to 4. We also chose the uniform distribution for the distribution of the distinct values per object. In addition, we configured the source coverage to follow the exponential distributions. More importantly, we selected 80-pessimistic distributions for the ground truth distribution. The main reason behind choosing these distributions for the generated synthetic dataset is their close similarity to real-world scenarios.

Based on the above setting, we generate 20 synthetic datasets for each experiment of a specific number of sources.

$$\begin{cases} m_{i,j}^{\Omega *}(A) = m_i^{\Theta}(T) m_{i,j}^{\Omega}(A) + m_i^{\Theta}(D) m_{i,j}^{\Omega}(\bar{A}) & \forall \mathrm{A} \in 2^{\Omega}/\Omega \\ m_{i,j}^{\Omega *}(\Omega) = m_{i,j}^{\Omega}(\Omega) + \left[m_i^{\Theta}(R) + m_i^{\Theta}(T, D, R)\right] \sum\limits_{\mathrm{A} \in 2^{\Omega}/\Omega} m_{i,j}^{\Omega}(A) & \end{cases} \tag{12}$$

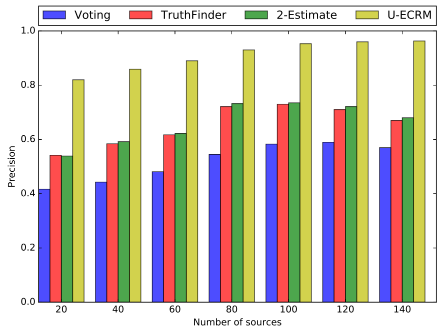

Figure 2. The precision of the conflict resolution methods on synthetic datasets with varying in the number of sources.

To reduce the randomness of the dataset generation process, the evaluation metric of each conflict resolution method is computed as the average of these 20 generated datasets.

Figure 2 is a bar chart that illustrates the precision rate of the considered conflict resolution methods on the generated synthetic datasets. It can be seen from this bar chart that the proposed U-ECRM overcomes the other methods in terms of precision rate. It can also be observed that adding more sources to the fusion task increases the precision rate of our proposed method and hence it improves the performance of the fusion task. This is a good property since the number of sources in real-world applications is generally large. However, this behavior is not observed with the other methods where their performance tends to degrade after the number of sources exceeds 100. This is to be expected because the distribution of the ground truth is 80-pessimistic. In other words, when the number of sources increases, the number of unreliable sources becomes higher and hence the influence of these sources will decrease the performance of the methods. On the other hand, the proposed U-ECRM benefits from this situation since it can identify the defective sources, and then it exploits this information to improve the performance of the fusion task.

VI. Conclusion

In this paper, we focused on the problem of resolving the information conflict between different sources in the case where the reliability factors of the sources are unknown because no training dataset is available to assess their values. To do so, we proposed in this paper an unsupervised evidential method that is able to simultaneously estimate the evidential source reliability mass functions and determining the correct value mass functions in the case where no training dataset is available. This method proceeds iteratively over the whole datasets, and thus it guarantees a general consensus between all the sources over the entire available information pieces. In this way, several data fusion problems in multiple IoT applications can be solved. The primary simulation experiments have shown that the proposed evidential method outperforms the state-of-art methods in terms of effectiveness.

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