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RESEARCH ARTICLE

Generalized Similarity Measure for Multisensor Information Fusion via Dempster-Shafer Evidence Theory

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ABSTRACT Dempster-Shafer evidence theory (DSET) stands out as a mathematical model for handling imperfect data, garnering significant interest across various domains. However, a notable limitation of DSET is Dempster's rule, which can lead to counterintuitive outcomes in cases of highly conflicting evidence. To mitigate this issue, this paper introduces a novel reinforced belief logarithmic similarity measure ($\mathcal{RBLSM}$), which assesses discrepancies between the evidences by incorporating both belief and plausibility functions. $\mathcal{RBLSM}$ exhibits several intriguing properties including boundedness, symmetry, and non-degeneracy, making it a robust tool for analysis. Furthermore, we develop a new multisensor information fusion method based on $\mathcal{RBLSM}$. The proposed method uniquely integrates credibility weight and information volume weight, offering a more comprehensive reflection the reliability of each evidence. The effectiveness and practicality of the proposed $\mathcal{RBLSM}$-based fusion method are demonstrated through its applications in target recognition and pattern classification scenarios.

INDEX TERMS Dempster-Shafer evidence theory, belief logarithmic similarity, information fusion, target recognition, pattern classification.

I. INTRODUCTION

Multisensor information fusion, a critical technique for leveraging varied levels of data for decision-making, has gained persistent focus and found applications across various fields like fault diagnosis [1], [2], [3], image processing [4], [5], target recognition [6], [7], [8] and pattern classification [9], [10], [11]. However, dealing with incomplete or uncertain data from multiple sensors poses a significant challenge in this area. To tackle this issue, several theories have been introduced, such as including fuzzy sets [12], [13], [14], intuitionistic fuzzy sets [15], [16], [17], Dempster-Shafer evidence theory [18], [19], [20], rough sets [21], [22] neutrosophic sets [23], [24], [25] and Z-number [26], [27]. These theories play a pivotal role in enhancing the effectiveness and accuracy of multisensor information fusion.

Dempster-Shafer evidence theory (DSET) [28], [29] is a versatile mathematical framework for managing uncertain and imprecise information, and it has found extensive applications across various fields [30], [31], [32], [33], [34], [35]. As an advancement of traditional probability theory, DSET uniquely quantifies uncertainty and imprecision by allocating a mass function to elements within a power set [36], [37]. Additionally, it introduces belief and plausibility functions, which act as the upper and lower probability bounds, offering a more nuanced representation of uncertainty and

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imprecision [38]. Importantly, Dempster's rule of combination, obeying both commutative and associative laws, provides an efficient approach for fusing information from multiple sensors. These qualities have made DSET a focal point of interest in the field.

While Dempster's rule is a cornerstone in Dempster-Shafer evidence theory (DSET), it encounters limitations in dealing with highly conflicting evidence, often leading to counter-intuitive outcomes [39]. Addressing this, researchers have explored two main strategies: modifying Dempster's rule of combination [40], [41], [42] and altering the evidence itself [43], [44], [45], [46]. The first type, despite its effectiveness in certain scenarios, sometimes compromises key properties of Dempster's rule, such as commutativity and associativity, and can lead to increased computational complexity as the discernment framework expands. Consequently, an increasing number of researchers are focusing on preprocessing the evidence prior to applying Dempster's rule. Notable contributions in this area include Murphy's average rule [43], which averages the belief masses from different pieces of evidence, and Deng et al.'s enhancement of this method using the Jousselme distance to measure differences between the evidences [44]. Other significant methods include Jiang's introduction of a novel correlation coefficient [45], Xiao's belief-based Jenson-Shannon divergence [46], and Zhao et al.'s subsequent divergence measures based on harmonic mean and square mean [47], [48]. Kaur and Srivastava [49] presented a new logarithmic function-based divergence for two pieces of evidence. Interestingly, there are also other ways to deal with the problem, see [50], [51], [52], and [53]. Despite these advancements, challenges persist, such as the tendency of some methods [46], [47], [48], [49] to oversimplify the complexity of evidence by treating multiple subsets as singletons, thereby overlooking the influence of varying subsets. This revealed a gap in the effective measurement of evidence for differences, which is also the motivation for this study. Furthermore, in the field of multi-sensor information fusion, most existing methods mainly rely on credibility weights to determine the importance of each evidence. These methods, while useful, may not be sufficient for some applications, suggesting the need for more comprehensive or alternative measures.

In this study, we first introduce a belief logarithmic similarity measure ($\mathcal{BLSM}$) to address scenarios involving single subsets. To enhance the difference in influence between different subsets, we subsequently propose the reinforced belief logarithmic similarity measure ($\mathcal{RBLSM}$). This measure is an integration of the belief and plausibility functions, which are recognized for encapsulating extensive informative content in DSET, thereby providing a more fine-grained assessment of differences between the evidences. A distinctive feature of $\mathcal{RBLSM}$ is its adaptability. In the case where the framework of discernment only consists of single subsets, $\mathcal{RBLSM}$ is reduced to $\mathcal{BLSM}$. Furthermore, we demonstrate that $\mathcal{RBLSM}$ embodies several advantageous properties, emphasizing its practicality and effectiveness. Furthermore, we propose a multi-sensor information fusion method within the DSET framework, which effectively exploits the advantages of $\mathcal{RBLSM}$ and provides an advanced solution for managing the complexities associated with multisensor information fusion.

A. CONTRIBUTION

- We propose a $\mathcal{RBLSM}$ based on the belief and plausibility functios to make it more suitable for measuring differences between the evidences.
- We demonstrate and analyze several appealing properties, including bounded, symmetry and non-degeneracy, which make it effective way to depict the differences between the evidences.
- We also provide a novel multisensor information fusion method based on $\mathcal{RBLSM}$ and belief entropy, which can be effectively applied to target recognition and pattern classification, verifying its efficiency and superiority.

B. PAPER OUTLINE

Section II briefly reviews the basics of DSET. In Section III, a new belief logarithmic similarity measure $\mathcal{BLSM}$ and a reinforced belief logarithm similarity measure $\mathcal{RBLSM}$ are proposed. Section IV provides a $\mathcal{RBLSM}$-based multi-sensor information fusion method. In Section V, we verify the superiority of the proposed method on two applications. Section VI makes the conclusion.

II. PRELIMINARIES

DSET [28], [29], as one of the most useful tools for dealing with uncertainty and imprecision, has a unique appeal in modeling imperfect knowledge. Here is a brief introduction to the basic concepts of DSET.

Definition 1 (Framework of Discernment): Let Ξ be the framework of discernment, which is represented by a finite set of elements that are exhaustive and mutually exclusive as follows:

$$\Xi = \{\mathcal{E}_1, \mathcal{E}_2, \cdots, \mathcal{E}_N\} \tag{1}$$

In DSET, the power-set of Ξ is depicted as 2^{Ξ}:

$$2^{\Xi} = \{\emptyset, \{\mathcal{E}_1\}, \{\mathcal{E}_2\}, \ldots, \{\mathcal{E}_N\}, \{\mathcal{E}_1, \mathcal{E}_2\}, \ldots, \Xi\} \tag{2}$$

where $\{\mathcal{E}_i\}$ and $\{\mathcal{E}_i, \mathcal{E}_j\}$ are the singleton and multiple subsets, and $\emptyset$ is an empty set.

Definition 2 (Mass Function): A mass function, commonly referred to as a basic belief assignment (BBA), is defined as a mapping $\mathbf{m}$: $2^{\Xi} \to [0, 1]$, adhering to the following conditions:

$$\begin{cases} \sum\limits_{\mathcal{E}_i \in 2^{\Xi}} m(\mathcal{E}_i) = 1 \\ m(\emptyset) = 0 \end{cases} \tag{3}$$

where $m(\mathcal{E}_i)$ denotes the mass of belief to $\mathcal{E}_i$.

Definition 3 (Belief and Plausibility Functions): For any focal element $\mathcal{E}_i$, the belief function $Bel(\mathcal{E}_i)$ and the plausibility function $Pl(\mathcal{E}_i)$ are defined as:

$$Bel(\mathcal{E}_i) = \sum_{\mathcal{E}_j \subseteq \mathcal{E}_i} m(\mathcal{E}_j) \tag{4}$$

$$Pl(\mathcal{E}_i) = \sum_{\mathcal{E}_j \cap \mathcal{E}_i \neq \emptyset} m(\mathcal{E}_j) \tag{5}$$

where $Bel(\mathcal{E}_i)$ and $Pl(\mathcal{E}_i)$ represent the lower and upper probability bounds of $\mathcal{E}_i$ respectively.

Definition 4 (Dempster's Rule): Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two distinct BBAs on Ξ, Dempster's rule is expressed as:

$$m(\mathcal{E}_i) = \begin{cases} 0, & \mathcal{E}_i = \emptyset \\ \dfrac{\sum\limits_{\mathcal{E}_j \cap \mathcal{E}_k = \mathcal{E}_i} m_1(\mathcal{E}_j) m_2(\mathcal{E}_k)}{1-K}, & \mathcal{E}_i \neq \emptyset \end{cases} \tag{6}$$

with

$$K = \sum_{\mathcal{E}_j \cap \mathcal{E}_k = \emptyset} m_1(\mathcal{E}_j) m_2(\mathcal{E}_k) \tag{7}$$

where K denotes the conflict coefficient between $\mathbf{m}_1$ and $\mathbf{m}_2$.

III. PROPOSED SIMILARITY MEASURE

In DSET, accurately quantifying discrepancies or similarities between various pieces of evidence is crucial. However, identifying an effective method for this calculation remains an unresolved challenge in the field. To date, some methods have been developed to solve this issue, such as distance measure [54], [55], divergence measure [47], [49] and similarity measure [20], [50]. In this paper, we first attempt to propose a new belief logarithmic similarity measure ($\mathcal{BLSM}$) to solve the above issue. In parallel, we further define a reinforcement belief logarithmic similarity measure ($\mathcal{RBLSM}$) and demonstrate some interesting properties that $\mathcal{RBLSM}$ satisfies. Finally, we demonstrate the performance of $\mathcal{RBLSM}$ on some numerical examples. The details are described below.

A. A NEW BELIEF LOGARITHMIC SIMILARITY MEASURE

Definition 5 (Belief Logarithmic Similarity Measure): Let $\mathbf{m}_1$ and $\mathbf{m}_2$ be two independent BBAs on Ξ, the belief logarithmic similarity measure ($\mathcal{BLSM}$) between $\mathbf{m}_1$ and $\mathbf{m}_2$ is expressed as:

$$\mathcal{BLSM}(\mathbf{m}_1, \mathbf{m}_2) = \log_2 \left(2 - \sum_{\mathcal{E}_i \in 2^{\Xi}} \frac{|m_1(\mathcal{E}_i) - m_2(\mathcal{E}_i)|}{2} \right) \tag{8}$$

$\mathcal{BLSM}$ can use BBAs to gauge discrepancy among the evidences. However, its capability is somewhat limited, particularly in accurately discerning the influences of multiple subsets. To elucidate the limitations of $\mathcal{BLSM}$, we present a numerical example illustrating its shortcomings.

Example 1: Consider three BBAs $\mathbf{m}_1$, $\mathbf{m}_2$ and $\mathbf{m}_3$ in $\Xi = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}$:

$$\begin{aligned} \mathbf{m}_1 &: m_1(\{\mathcal{E}_1\}) = 0.6, \quad m_1(\{\mathcal{E}_2, \mathcal{E}_3\}) = 0.2, \\ &\quad m_1(\{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}) = 0.2 \\ \mathbf{m}_2 &: m_2(\{\mathcal{E}_1\}) = 0.2, \quad m_2(\{\mathcal{E}_2, \mathcal{E}_3\}) = 0.6, \\ &\quad m_2(\{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}) = 0.2 \\ \mathbf{m}_3 &: m_3(\{\mathcal{E}_1\}) = 0.2, \quad m_3(\{\mathcal{E}_2, \mathcal{E}_3\}) = 0.2, \\ &\quad m_3(\{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}) = 0.6 \end{aligned}$$

In DSET, a BBA can be characterized by Bel and Pl. Hence, these BBAs can be converted to Bel and Pl as follows:

$$\begin{aligned} \mathbf{m}_1 &: Bel_1(\{\mathcal{E}_1\}) = 0.6, \; Bel_1(\{\mathcal{E}_2\}) = 0, \; Bel_1(\{\mathcal{E}_3\}) = 0 \\ &\quad Pl_1(\{\mathcal{E}_1\}) = 0.8, \quad Pl_1(\{\mathcal{E}_2\}) = 0.4, \; Pl_1(\{\mathcal{E}_3\}) = 0.4 \\ \mathbf{m}_2 &: Bel_2(\{\mathcal{E}_1\}) = 0.2, \; Bel_2(\{\mathcal{E}_2\}) = 0, \; Bel_2(\{\mathcal{E}_3\}) = 0 \\ &\quad Pl_2(\{\mathcal{E}_1\}) = 0.4, \quad Pl_2(\{\mathcal{E}_2\}) = 0.8, \; Pl_2(\{\mathcal{E}_3\}) = 0.8 \\ \mathbf{m}_3 &: Bel_3(\{\mathcal{E}_1\}) = 0.2, \; Bel_3(\{\mathcal{E}_2\}) = 0, \; Bel_3(\{\mathcal{E}_3\}) = 0 \\ &\quad Pl_3(\{\mathcal{E}_1\}) = 0.8, \quad Pl_3(\{\mathcal{E}_2\}) = 0.8, \; Pl_3(\{\mathcal{E}_3\}) = 0.8 \end{aligned}$$

We can observe that $\mathbf{m}_1$ allocates a substantial belief mass to the proposition $\mathcal{E}_1$, whereas $\mathbf{m}_2$ assigns a larger belief mass to the proposition $\mathcal{E}_2, \mathcal{E}_3$ and $\mathbf{m}_3$ emphasizes the proposition $\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3$. Essentially, both $\mathbf{m}_2$ and $\mathbf{m}_3$ encapsulate the elements of uncertainty and imprecision in the information. Notably, there is a pronounced conflict between $\mathbf{m}_1$ and $\mathbf{m}_2$. Consequently, it is anticipated that the similarity between $\mathbf{m}_1$ and $\mathbf{m}_2$ would be lower compared to the similarity between either $\mathbf{m}_1$ and $\mathbf{m}_3$ or $\mathbf{m}_2$ and $\mathbf{m}_3$.

According to (8), the $\mathcal{BLSM}$ among $\mathbf{m}_1$, $\mathbf{m}_2$ and $\mathbf{m}_3$ are computed as follows:

$$\mathcal{BLSM}(\mathbf{m}_1, \mathbf{m}_2) = \mathcal{BLSM}(\mathbf{m}_1, \mathbf{m}_3) = \mathcal{BLSM}(\mathbf{m}_2, \mathbf{m}_3)$$

It becomes clear that the similarity between the BBAs remains uniform, a finding that deviates from our anticipations. This unexpected outcome arises because the original $\mathcal{BLSM}$ model only accounts for the influence of singleton subsets. Addressing this limitation, we introduce a reinforced $\mathcal{BLSM}$, designed to thoroughly incorporate the effects of both singleton and multiple subsets within BBAs. This refinement aims to provide a more accurate representation of similarities and discrepancies among BBAs, aligning more closely with theoretical expectations.

B. A REINFORCED BELIEF LOGARITHMIC SIMILARITY MEASURE

Definition 6 (Reinforced Belief Logarithmic Similarity Measure): Let $\mathbf{m}_1$ and $\mathbf{m}_2$ be two BBAs on Ξ, the reinforced belief logarithmic similarity measure ($\mathcal{RBLSM}$) between $\mathbf{m}_1$ and $\mathbf{m}_2$ is defined as:

$$\begin{aligned} &\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) \\ &= \log_2 \left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)|}{2} \right) \end{aligned} \tag{9}$$

where

$$\mathcal{BPL}_{\mathbf{m}}(\mathcal{E}_i) = \frac{Bel(\mathcal{E}_i) + Pl(\mathcal{E}_i)}{\sum\limits_{\mathcal{E}_i \in \Xi} Bel(\mathcal{E}_i) + Pl(\mathcal{E}_i)} \tag{10}$$

Remark 1: We can note that $\mathcal{BPL}_{\mathbf{m}}$ effectively converts BBA into a probability distribution by amalgamating Bel and Pl. The $\mathcal{RBLSM}$ introduced here is adept at capturing the interplay between singleton and multiple subsets. This capability ensures that the influence of multiple subsets, which might be overlooked by $\mathcal{BLSM}$, is duly considered and integrated into the analysis. Interestingly, $\mathcal{RBLSM}$ degenerates to $\mathcal{BLSM}$ when BBA contains only singleton subsets.

Remark 2: A higher value of $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)$ indicates a greater similarity between $\mathbf{m}_1$ and $\mathbf{m}_2$, *i.e.*, the disparity between $\mathbf{m}_1$ and $\mathbf{m}_2$ is comparatively smaller. Conversely, a lower value of $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)$ signifies a lesser similarity between $\mathbf{m}_1$ and $\mathbf{m}_2$, implying a larger discrepancy between the two.

Property 1: The new $\mathcal{RBLSM}$ satisfies the following properties:

1) Bounded: $0 \le \mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) \le 1$.
2) Symmetry: $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) = \mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_1)$.
3) Non-degeneracy: $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) = 1$ if and only if $\mathbf{m}_1 = \mathbf{m}_2$.

Proof 1: For two BBAs $\mathbf{m}_1$ and $\mathbf{m}_2$ in Ξ, we have:

$$\begin{aligned}&\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)\\ &\quad = \log_2\left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)|}{2}\right)\end{aligned}$$

We can easily get $0 \le \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)|}{2} \le 1$, Clearly, the value of $\log_2(\mathcal{X})$, $\mathcal{X} \in [1, 2]$ is always positive and within [0, 1]. Thus, we obtain $0 \le \mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) \le 1$.

Proof 2: For two BBAs $\mathbf{m}_1$ and $\mathbf{m}_2$ in Ξ, we have:

$$\begin{aligned}&\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)\\ &\quad = \log_2\left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)|}{2}\right)\end{aligned}$$

and

$$\begin{aligned}&\mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_1)\\ &\quad = \log_2\left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i)|}{2}\right)\end{aligned}$$

Since $|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)| = |\mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i)|$, it is easy to obtain $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) = \mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_1)$.

Proof 3: For two same BBAs $\mathbf{m}_1$ and $\mathbf{m}_2$ in Ξ, i.e. $\mathbf{m}_1 = \mathbf{m}_2$. Thus, we have:

$$\begin{aligned}&\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)\\ &\quad = \log_2\left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)|}{2}\right)\\ &\quad = \log_2\left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i)|}{2}\right)\\ &\quad = 1\end{aligned}$$

Conversely, assume that $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) = 1$, we thus have:

$$\log_2\left(2 - \sum_{\mathcal{E}_i \in \Xi} \frac{|\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)|}{2}\right) = 1$$

Hence, we can conclude $\sum_{\mathcal{E}_i \in \Xi} |\mathcal{BPL}_{\mathbf{m}_1}(\mathcal{E}_i) - \mathcal{BPL}_{\mathbf{m}_2}(\mathcal{E}_i)| = 0$, which also means that $\mathbf{m}_1 = \mathbf{m}_2$.

Example 2: Recall *Example 1*, the proposed similarity measure $\mathcal{RBLSM}$ among $\mathbf{m}_1$, $\mathbf{m}_2$ and $\mathbf{m}_3$ are computed as follows:

$$\begin{aligned}
\mathbf{m}_1 : \ & \mathcal{BPL}_{\mathbf{m}_1}(\{\mathcal{E}_1\}) = \frac{0.6 + 0.8}{0.6 + 0.8 + 0.4 + 0.4} = 0.6364\\
& \mathcal{BPL}_{\mathbf{m}_1}(\{\mathcal{E}_2\}) = \frac{0.4}{0.6 + 0.8 + 0.4 + 0.4} = 0.1818\\
& \mathcal{BPL}_{\mathbf{m}_1}(\{\mathcal{E}_3\}) = \frac{0.4}{0.6 + 0.8 + 0.4 + 0.4} = 0.1818\\
\mathbf{m}_2 : \ & \mathcal{BPL}_{\mathbf{m}_2}(\{\mathcal{E}_1\}) = \frac{0.2 + 0.4}{0.2 + 0.4 + 0.8 + 0.8} = 0.2727\\
& \mathcal{BPL}_{\mathbf{m}_2}(\{\mathcal{E}_2\}) = \frac{0.8}{0.2 + 0.4 + 0.8 + 0.8} = 0.3636\\
& \mathcal{BPL}_{\mathbf{m}_2}(\{\mathcal{E}_3\}) = \frac{0.8}{0.2 + 0.4 + 0.8 + 0.8} = 0.3636\\
\mathbf{m}_3 : \ & \mathcal{BPL}_{\mathbf{m}_3}(\{\mathcal{E}_1\}) = \frac{0.2 + 0.8}{0.2 + 0.8 + 0.8 + 0.8} = 0.3846\\
& \mathcal{BPL}_{\mathbf{m}_3}(\{\mathcal{E}_2\}) = \frac{0.8}{0.2 + 0.8 + 0.8 + 0.8} = 0.3077\\
& \mathcal{BPL}_{\mathbf{m}_3}(\{\mathcal{E}_3\}) = \frac{0.8}{0.2 + 0.8 + 0.8 + 0.8} = 0.3077
\end{aligned}$$

$\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)$, $RBLSM(\mathbf{m}_1, \mathbf{m}_3)$, and $\mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_3)$ as shown in the equation at the bottom of the next page. Hence, we can find that $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) \le \mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_3) \le \mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_3)$, which is consistent with our expectation.

Example 3: Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two BBAs on $\Xi = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3, \mathcal{E}_4, \mathcal{E}_5\}$.

$$\begin{aligned}
\mathbf{m}_1 : \ & m_1(\{\mathcal{E}_1\}) = 0.25, \ \ m_1(\{\mathcal{E}_2\}) = 0.15, \ \ m_1(\{\mathcal{E}_4\}) = 0.35\\
& m_1(\{\mathcal{E}_1, \mathcal{E}_3\}) = 0.05, \ \ m_1(\{\mathcal{E}_2, \mathcal{E}_3, \mathcal{E}_4, \mathcal{E}_5\}) = 0.20\\
\mathbf{m}_2 : \ & m_2(\{\mathcal{E}_1\}) = 0.25, \ \ m_2(\{\mathcal{E}_2\}) = 0.15, \ \ m_2(\{\mathcal{E}_4\}) = 0.35\\
& m_2(\{\mathcal{E}_1, \mathcal{E}_3\}) = 0.05, \ \ m_2(\{\mathcal{E}_2, \mathcal{E}_3, \mathcal{E}_4, \mathcal{E}_5\}) = 0.20
\end{aligned}$$

Clearly, $\mathbf{m}_1$ and $\mathbf{m}_2$ are the same, and the elements in each subset are the same. we find that $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) = 1$, illustrating that $\mathcal{RBLSM}$ is proficient in accurately measuring the similarity between identical BBAs. Furthermore, this particular example also showcases the non-degeneracy property of $\mathcal{RBLSM}$.

Example 4: Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two BBAs on $\Xi = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3, \mathcal{E}_4\}$.

$$\begin{aligned}
\mathbf{m}_1 :\ & m_1(\{\mathcal{E}_1\}) = 0.55,\ \ m_1(\{\mathcal{E}_2\}) = 0.10,\\
& m_1(\{\mathcal{E}_1, \mathcal{E}_3\}) = 0.20,\ \ m_1(\{\mathcal{E}_2, \mathcal{E}_4\}) = 0.05,\\
& m_1(\{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_4\}) = 0.10\\
\mathbf{m}_2 :\ & m_2(\{\mathcal{E}_1\}) = 0.10,\ \ m_2(\{\mathcal{E}_2\}) = 0.45,\\
& m_2(\{\mathcal{E}_1, \mathcal{E}_3\}) = 0.10,\ \ m_2(\{\mathcal{E}_2, \mathcal{E}_4\}) = 0.05,\\
& m_2(\{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_4\}) = 0.20
\end{aligned}$$

$\mathbf{m}_1$ has the greatest mass of belief for proposition $\mathcal{E}_1$, while $\mathbf{m}_2$ has a greater mass of belief for proposition $\mathcal{E}_2$, which indicates that there is a large discrepancy between $\mathbf{m}_1$ and $\mathbf{m}_2$. According to (9), we have $\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2) = 0.6211$ and $\mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_1) = 0.6211$. Therefore, we verify the property of symmetry.

Example 5: Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two BBAs on $\Xi = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}$.

$$\begin{aligned}
\mathbf{m}_1 :\ & m_1(\{\mathcal{E}_1\}) = \alpha,\quad m_1(\{\mathcal{E}_2\}) = \beta,\\
& m_1(\{\mathcal{E}_3\}) = 1 - \alpha - \beta\\
\mathbf{m}_2 :\ & m_2(\{\mathcal{E}_1\}) = 0.7,\quad m_2(\{\mathcal{E}_2\}) = 0.3
\end{aligned}$$

Given the constraints $0 \le \alpha, \beta \le 1$ and $0 \le \alpha + \beta \le 1$, the behavior of $\mathcal{RBLSM}$ can be observed in FIGURE 1. For instance, when $\alpha = 0.7$ and $\beta = 0.3$, the calculations result in $m_1(\{\mathcal{E}_1\}) = 0.7$ and $m_1(\{\mathcal{E}_2\}) = 0.3$, leading to $\mathbf{m}_1 = \mathbf{m}_2$. In this situation, the $\mathcal{RBLSM}$ achieves its maximum belief mass of 1, indicating complete similarity. Conversely, when $\alpha = 0$ and $\beta = 0$, we find $m_1(\{\mathcal{E}_1\}) = 0$, $m_1(\{\mathcal{E}_2\}) = 0$ and $m_1(\{\mathcal{E}_3\}) = 1$. This configuration results in $\mathbf{m}_1$ and $\mathbf{m}_2$ being completely at odds, with $\mathcal{RBLSM}$ reaching its minimum belief mass of 0, reflecting total dissimilarity. Moreover, regardless of the variations in α and β, $\mathcal{RBLSM}$ consistently maintains values within the range of [0,1]. This observation further validates the bounded property of $\mathcal{RBLSM}$.

Example 6: Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two BBAs on $\Xi = \{\mathcal{E}_1, \mathcal{E}_2\}$.

$$\begin{aligned}
\mathbf{m}_1 :\ & m_1(\{\mathcal{E}_1\}) = \alpha,\quad m_1(\{\mathcal{E}_2\}) = \beta,\\
& m_1(\{\mathcal{E}_1, \mathcal{E}_2\}) = 1 - \alpha - \beta\\
\mathbf{m}_2 :\ & m_2(\{\mathcal{E}_1\}) = \beta,\quad m_2(\{\mathcal{E}_2\}) = \alpha,\\
& m_2(\{\mathcal{E}_1, \mathcal{E}_2\}) = 1 - \alpha - \beta
\end{aligned}$$

where $0 \le \alpha, \beta \le 1$, and $0 \le \alpha + \beta \le 1$.

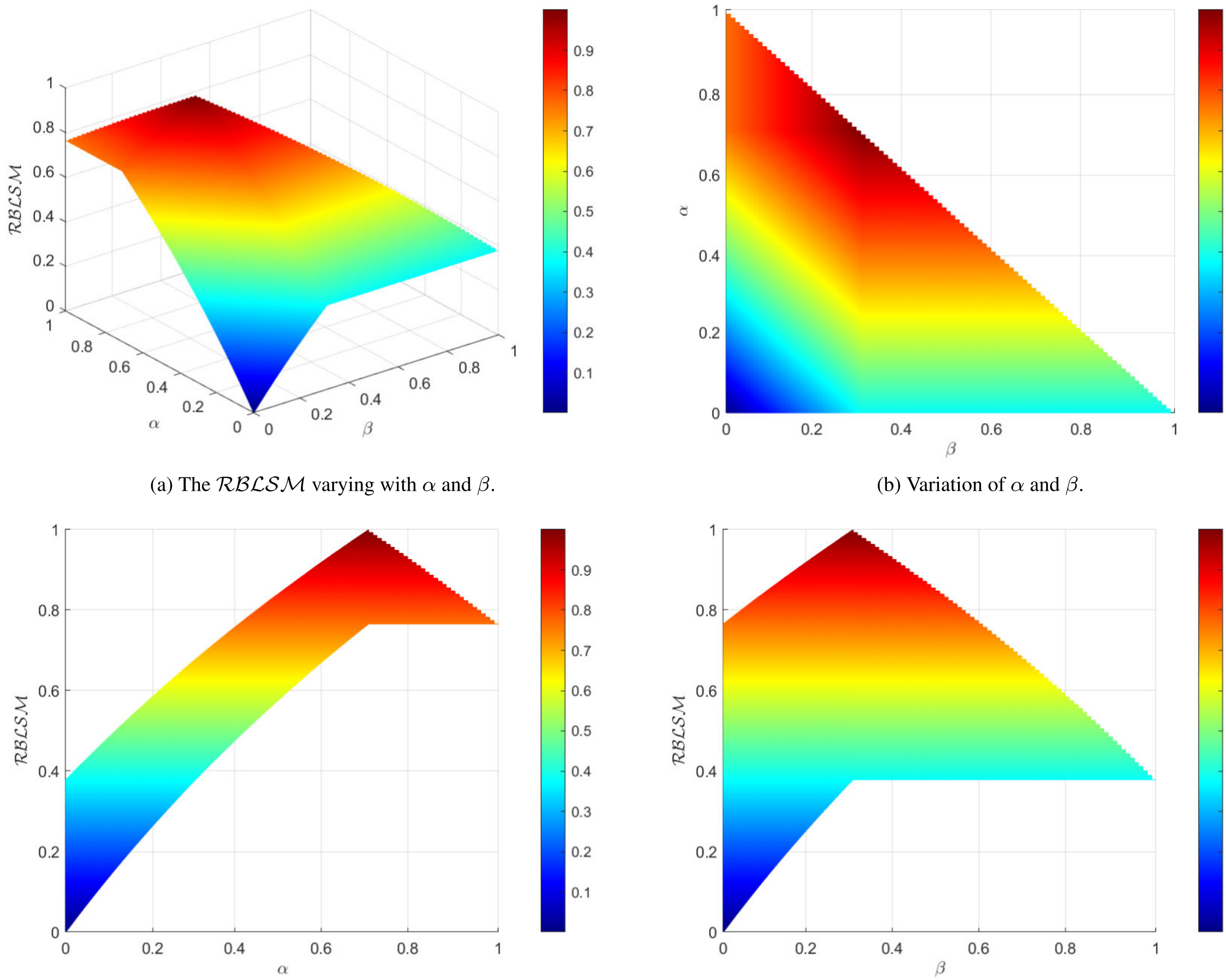
As depicted in FIGURE 2, when $\alpha = \beta$, it leads to $\mathbf{m}_1 = \mathbf{m}_2$. In this scenario, $\mathcal{RBLSM}$ attains its maximum value of 1, indicating a perfect similarity. On the other hand, when $\alpha = 1$ and $\beta = 1$, which is not possible within the specified constraints but hypothetically, it would mean that $\mathbf{m}_1$ and $\mathbf{m}_2$ are entirely conflicting. Under these conditions, $\mathcal{RBLSM}$ would reach its minimum value of 0, representing total dissimilarity. Moreover, regardless of the variations in α and β, $\mathcal{RBLSM}$ consistently maintains values within the range of [0,1]. This further confirms its property of boundedness. Examples 5 and 6 in the paper illustrate the ability of $\mathcal{RBLSM}$ to effectively measure the similarities between different subsets of BBAs, showcasing its versatility and effectiveness in handling diverse belief assignments.

Example 7: Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two BBAs on $\Xi = \{\mathcal{E}_1, \mathcal{E}_2\}$.

$$\begin{aligned}
\mathbf{m}_1 :\ & m_1(\{\mathcal{E}_1\}) = \alpha,\quad m_1(\{\mathcal{E}_2\}) = 1 - \alpha\\
\mathbf{m}_2 :\ & m_2(\{\mathcal{E}_2\}) = 1
\end{aligned}$$

In *Example 7*, $\mathbf{m}_1$ m1 and $\mathbf{m}_2$ contain only singleton subsets $\{\mathcal{E}_1\}$ and $\{\mathcal{E}_2\}$. FIGURE 3 shows the $\mathcal{BLSM}$ and $\mathcal{RBLSM}$ between $\mathbf{m}_1$ and $\mathbf{m}_2$. We can find that the results of $\mathcal{BLSM}$ and $\mathcal{RBLSM}$ are always the same under

$$\begin{aligned}
&\mathcal{RBLSM}(\mathbf{m}_1, \mathbf{m}_2)\\
&\quad = \log_2\left(2 - \frac{|0.6364 - 0.2727| + |0.1818 - 0.3636| + |0.1818 - 0.3636|}{2}\right)\\
&\quad = 0.7105\\
&RBLSM(\mathbf{m}_1, \mathbf{m}_3)\\
&\quad = \log_2\left(2 - \frac{|0.6364 - 0.3846| + |0.1818 - 0.3077| + |0.1818 - 0.3077|}{2}\right)\\
&\quad = 0.8059\\
&\mathcal{RBLSM}(\mathbf{m}_2, \mathbf{m}_3)\\
&\quad = \log_2\left(2 - \frac{|0.2727 - 0.3846| + |0.3636 - 0.3077| + |0.3636 - 0.3077|}{2}\right)\\
&\quad = 0.9169
\end{aligned}$$



(a) The $\mathcal{RBLSM}$ varying with α and β.

(b) Variation of α and β.

(c) The $\mathcal{RBLSM}$ varying with α.

(d) The $\mathcal{RBLSM}$ varying with β.

FIGURE 1. The results of $\mathcal{RBLSM}$ varying with α and β in *Example 5*.

different α. This is also consistent with our previous analysis that $\mathcal{RBLSM}$ degenerates into $\mathcal{BLSM}$ when BBA contains only singleton subsets.

Example 8: Suppose that $\mathbf{m}_1$ and $\mathbf{m}_2$ are two BBAs on $\Xi = \{\mathcal{E}_1, \mathcal{E}_2\}$.

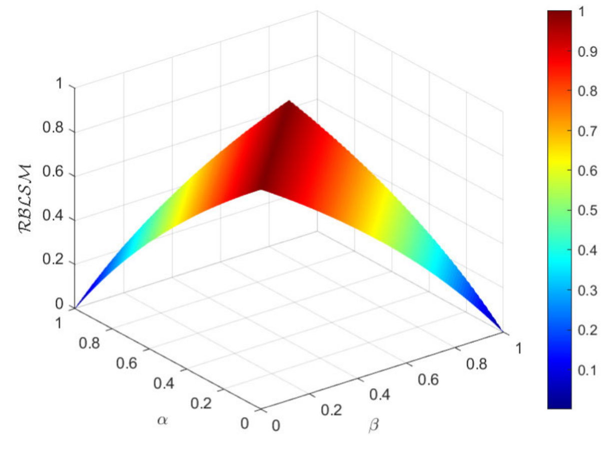
$$\mathbf{m}_1 : \; m_1(\{\mathcal{E}_1\}) = \alpha, \quad m_1(\{\mathcal{E}_1, \mathcal{E}_2\}) = 1 - \alpha$$
$$\mathbf{m}_2 : \; m_2(\{\mathcal{E}_2\}) = 1$$

In *Example 8*, $\mathbf{m}_1$ contains not only singleton subset $\{\mathcal{E}_1\}$ but also multiple subset $\{\mathcal{E}_1, \mathcal{E}_2\}$. FIGURE 4 displays Xiao's measure [46] and Kaur et al.'s measure [49][1] and the $\mathcal{BLSM}$ and $\mathcal{RBLSM}$ between m_1 and m_2. We can see that changes with α do not change the results of Xiao's measure, Kaur et al.'s measure and $\mathcal{BLSM}$ because they do not take into account the effect of multiple subsets when measuring similarities between BBAs. For comparison, the increase in α corresponds to the decrease in $\mathcal{RBLSM}$, which is reasonable. Therefore, $\mathcal{RBLSM}$ is in a better position to distinguish similarities between different subsets of BBAs.

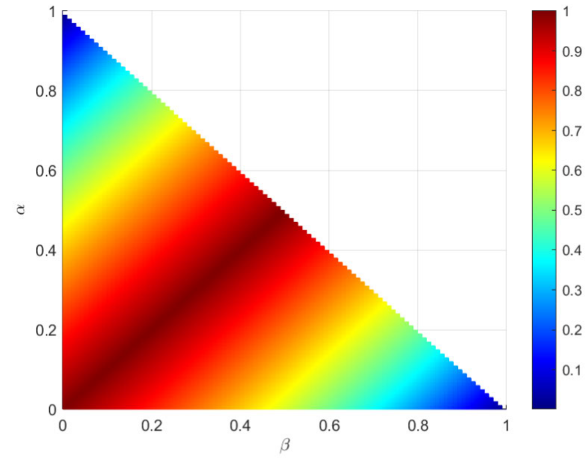
[1]Here, both measures are converted into similarity measures based on the original divergence.

IV. $\mathcal{RBLSM}$-BASED MULTISENSOR INFORMATION FUSION METHOD

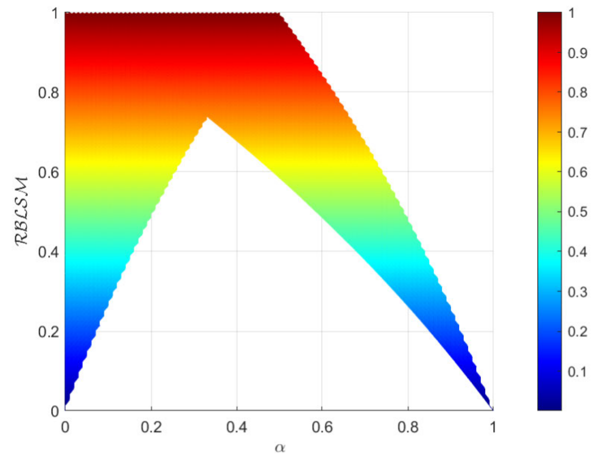
This section introduces an new multisensor information fusion method, ingeniously integrating $\mathcal{RBLSM}$ with a belief entropy concept. The method unfolds in a three-stage process. Initially, $\mathcal{RBLSM}$ is employed for assigning a credibility weight to each evidence. The key principle here is that the more an evidence agrees with others, the higher its credibility weight. Subsequently, the belief entropy is leveraged to quantify the information volume weight of each evidence. This measure encapsulates the richness or the informational content inherent in the evidence. Finally, a comprehensive weight is derived by integrating the previously calculated credibility and information volume



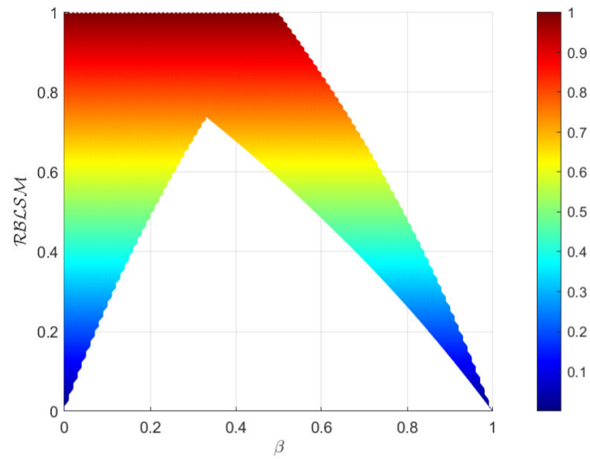
(a) The $\mathcal{RBLSM}$ varying with α and β.



(b) Variation of α and β.



(c) The $\mathcal{RBLSM}$ varying with α.



(d) The $\mathcal{RBLSM}$ varying with β.

FIGURE 2. The results of $\mathcal{RBLSM}$ varying with α and β in *Example 6*.

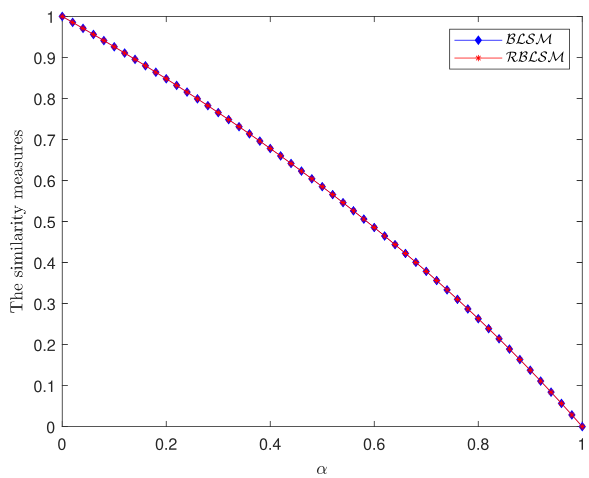


FIGURE 3. The results of $\mathcal{BLSM}$ and $\mathcal{RBLSM}$ varying with α in *Example 7*.

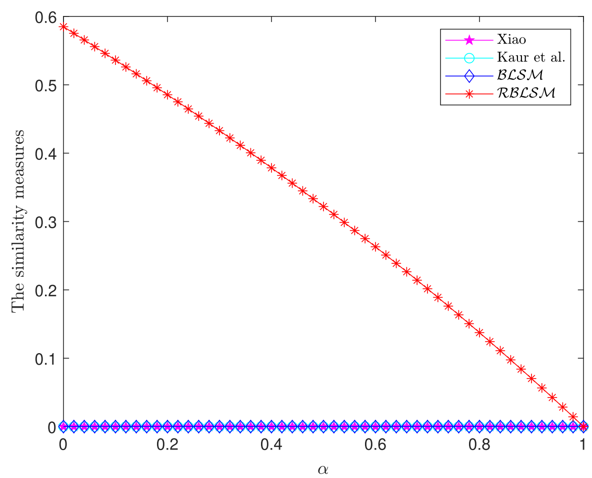


FIGURE 4. The results of various similarity measures varying with α in *Example 8*.

weights. This weight acts as a modifier for each evidence, fine-tuning them before they undergo fusion through the application of Dempster's rule. The flowchart of the proposed method is displayed in FIGURE 5.

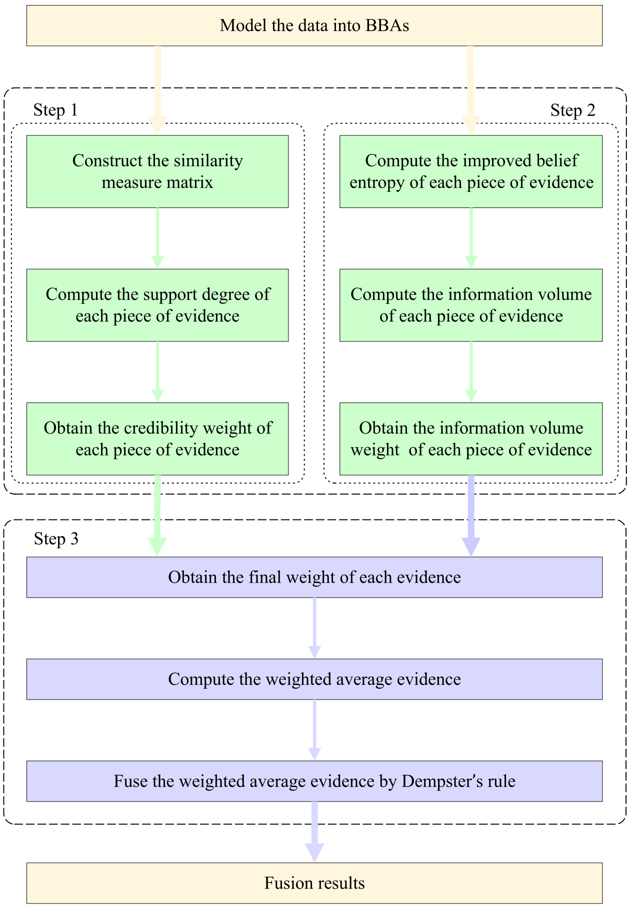


FIGURE 5. The flowchart of the proposed method.

Step 1: Obtaining credibility weights

Consider n distinct evidences, denoted as $\mathbf{m}_k(k = 1, \cdots, n)$, each defined within the framework $\Xi = \{\mathcal{E}_1, \cdots, \mathcal{E}_N\}$.

Step 1.1: Employ Eq. (9) to compute the similarity between the evidence $\mathbf{m}_k$ and $\mathbf{m}_l$ $(k, l = 1, \cdots, n)$, represented as $\mathcal{RBLSM}(\mathbf{m}_k, \mathbf{m}_l)$. This leads to the formation of a similarity matrix $\mathscr{SM}_{n\times n}$, which captures the pairwise similarities among all the evidences.

$$\mathscr{SM}_{n\times n} = \begin{bmatrix} 1 & \mathcal{RBLSM}_{12} & \ldots & \mathcal{RBLSM}_{1n} \\ \mathcal{RBLSM}_{21} & 1 & \ldots & \mathcal{RBLSM}_{2n} \\ \vdots & & \ddots & \vdots \\ \mathcal{RBLSM}_{n1} & \mathcal{RBLSM}_{n2} & \ldots & 1 \end{bmatrix} \tag{11}$$

Step 1.2: Calculate the support degree $\mathscr{SD}(\mathbf{m}_k)$ of $\mathbf{m}_k$ as:

$$\mathscr{SD}(\mathbf{m}_k) = \sum_{l=1, l\neq k}^{n} \mathcal{RBLSM}(\mathbf{m}_k, \mathbf{m}_l) \tag{12}$$

TABLE 1. BBAs modeled from sensors in case 1.

BBAs	$\{\mathcal{E}_1\}$	$\{\mathcal{E}_2\}$	$\{\mathcal{E}_3\}$	Ξ
$\mathbb{S}_1$: $\mathbf{m}_1(\cdot)$	0.40	0.60	0.00	0.00
$\mathbb{S}_2$: $\mathbf{m}_2(\cdot)$	0.00	0.70	0.30	0.00
$\mathbb{S}_3$: $\mathbf{m}_3(\cdot)$	0.85	0.00	0.00	0.15
$\mathbb{S}_4$: $\mathbf{m}_4(\cdot)$	0.40	0.60	0.00	0.00
$\mathbb{S}_5$: $\mathbf{m}_5(\cdot)$	0.75	0.00	0.00	0.25

Step 1.3: Calculate the credibility weight $\mathscr{CW}(\mathbf{m}_k)$ of $\mathbf{m}_k$ as:

$$\mathscr{CW}(\mathbf{m}_k) = \frac{\mathscr{SD}(\mathbf{m}_k)}{\sum_{k=1}^{n} \mathscr{SD}(\mathbf{m}_k)} \tag{13}$$

Step 2: Obtaining information volume weights

Belief entropy, as proposed in [56], is commonly used to quantify the uncertainty inherent in each evidence. However, it has certain limitations. In our earlier research [39], we developed an enhanced version of belief entropy, which builds upon the original concept by incorporating both belief and plausibility functions. These functions are recognized for encompassing a broader spectrum of useful information, thereby offering a more comprehensive measure of uncertainty.

Step 2.1: Calculate the belief entropy $\mathscr{BE}(\mathbf{m}_k)$ for $\mathbf{m}_k$ as:

$$\begin{aligned} \mathscr{BE}(\mathbf{m}_k) = &\sum_{\mathcal{E}_i \in \Xi} \mathcal{BPL}_k(\mathcal{E}_i) \log_2 \left(\frac{1}{\mathcal{BPL}_k(\mathcal{E}_i)} \right) \\ &+ \sum_{\mathcal{E}_i \in 2^\Xi} m_k(\mathcal{E}_i) \log_2 \left(2^{|\mathcal{E}_i|} - 1 \right) \end{aligned} \tag{14}$$

Step 2.2: Calculate the information volume $\mathscr{IV}(\mathbf{m}_k)$ for $\mathbf{m}_k$ as:

$$\mathscr{IV}(\mathbf{m}_k) = \exp\left(\mathscr{BE}(\mathbf{m}_k)\right), \forall k = 1, \ldots, n \tag{15}$$

Step 2.3: Calculate the information volume weight $\mathscr{IVW}(\mathbf{m}_k)$ for $\mathbf{m}_k$ as:

$$\mathscr{IVW}(\mathbf{m}_k) = \frac{\mathscr{IV}(\mathbf{m}_k)}{\sum_{k=1}^{n} \mathscr{IV}(\mathbf{m}_k)} \tag{16}$$

Step 3: Obtaining final fusion results

Step 3.1: Calculate the comprehensive weight $\mathscr{W}(\mathbf{m}_k)$ for $\mathbf{m}_k$ as:

$$\mathscr{W}(\mathbf{m}_k) = \frac{\mathscr{CW}(\mathbf{m}_k) \times \mathscr{IV}(\mathbf{m}_k)}{\sum_{k=1}^{n} \mathscr{CW}(\mathbf{m}_k) \times \mathscr{IV}(\mathbf{m}_k)} \tag{17}$$

Step 3.2: Calculate the weighted average evidence $\bar{\mathbf{m}}_k$ as:

$$\bar{m}_k(\mathcal{E}_i) = \sum_{k=1}^{n} \mathscr{W}(\mathbf{m}_k) \times m_k(\mathcal{E}_i) \tag{18}$$

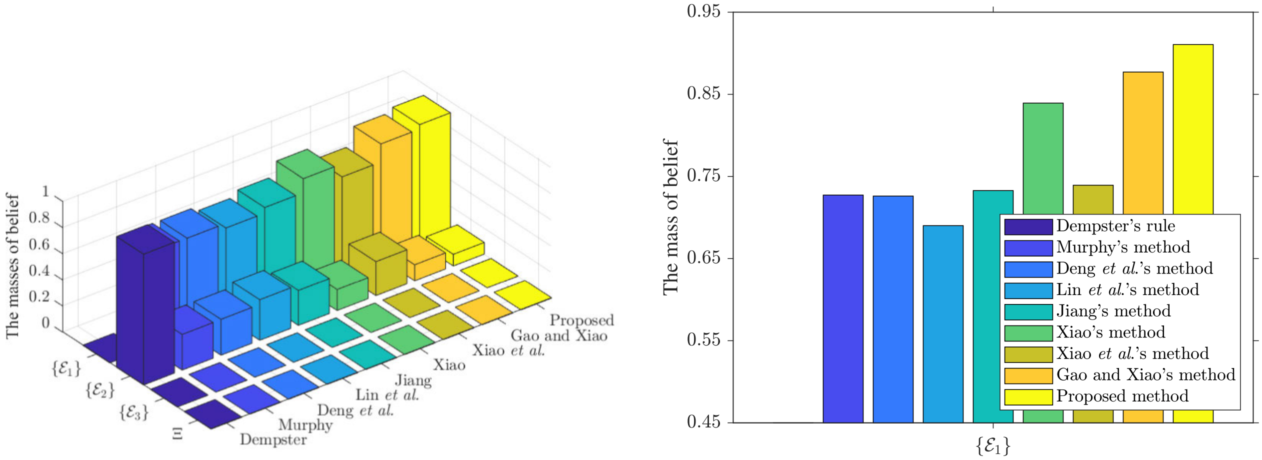
Step 3.3: Utilize Eq. (6) to fuse $\bar{\mathbf{m}}_k$ $n-1$ times.

TABLE 2. Fusion results of different methods in case 1.

Step	Result	$\mathbf{m}_1$	$\mathbf{m}_2$	$\mathbf{m}_3$	$\mathbf{m}_4$	$\mathbf{m}_5$
2	$\mathscr{SD}$	2.8293	1.8341	2.2387	2.8293	2.4198
3	$\mathscr{CW}$	0.2328	0.1509	0.1842	0.2328	0.1991
4	$\mathscr{BE}$	0.9710	0.8813	1.1437	0.9710	1.6883
5	$\mathscr{IV}$	2.6405	2.4140	3.1382	2.6405	5.4101
6	$\mathscr{IVW}$	0.1626	0.1486	0.1932	0.1626	0.3331
7	$\mathscr{W}$	0.1892	0.1121	0.1779	0.1892	0.3315

TABLE 3. Fusion results of different methods in case 1.

Methods	$\{\mathcal{E}_1\}$	$\{\mathcal{E}_2\}$	$\{\mathcal{E}_3\}$	Ξ
Dempster's rule [28]	0.0000	**1**	0.0000	0.0000
Murphy's method [43]	**0.7273**	0.2720	0.0007	0.0000
Deng *et al.*'s method [44]	**0.7261**	0.2736	0.0004	0.0000
Lin *et al.*'s method [1]	**0.6901**	0.3096	0.0003	0.0000
Jiang *et al.*'s method [45]	**0.7328**	0.2669	0.0003	0.0000
Xiao's method [46]	**0.8393**	0.1605	0.0002	0.0000
Xiao *et al.*'s method [2]	**0.7393**	0.2604	0.0002	0.0000
Gao and Xiao's method [31]	**0.8771**	0.1226	0.0002	0.0000
Proposed method	**0.9106**	0.0890	0.0003	0.0001



(a) The masses of belief with different methods.

(b) The masses of belief to $\{\mathcal{E}_1\}$ with different methods.

FIGURE 6. The fusion results of different methods.

V. APPLICATION IN MULTISENSOR INFORMATION FUSION

In this section, to validate the effectiveness of the proposed method, two distinct applications are employed as test cases.

A. CASE 1: TARGET RECOGNITION

- **Background statement.**

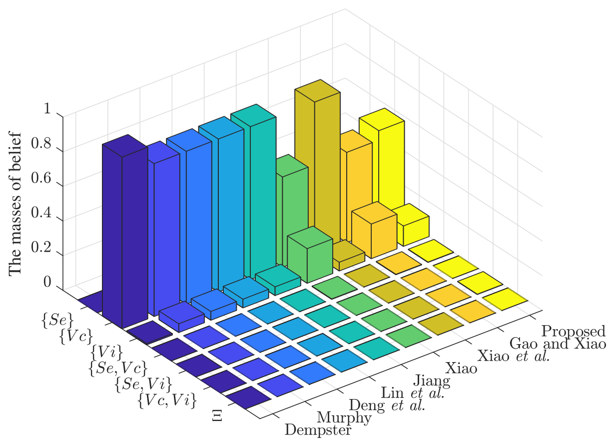
To compare the proposed method to other competitive methods, the target recognition case from [57] is employed. A total of five different sensors ($\mathbb{S}_1$, $\mathbb{S}_2$, $\mathbb{S}_3$, $\mathbb{S}_4$ and $\mathbb{S}_5$) are used to collect data and model as BBAs. The framework of discernment $\Xi = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3\}$ comprises three possible targets: ft $\{\mathcal{E}_1\}$, airliner, bomber $\{\mathcal{E}_2\}$ and fighter $\{\mathcal{E}_3\}$. The BBA of each sensor in TABLE 1 shows that only $\mathbf{m}_2$ strongly supports target $\{\mathcal{E}_2\}$, while all the others support target $\{\mathcal{E}_1\}$. Due to its highly conflicting with other pieces of evidence, $\mathbf{m}_2$ can be considered unreliable one.

TABLE 4. BBAs modeled from sensors in case 2.

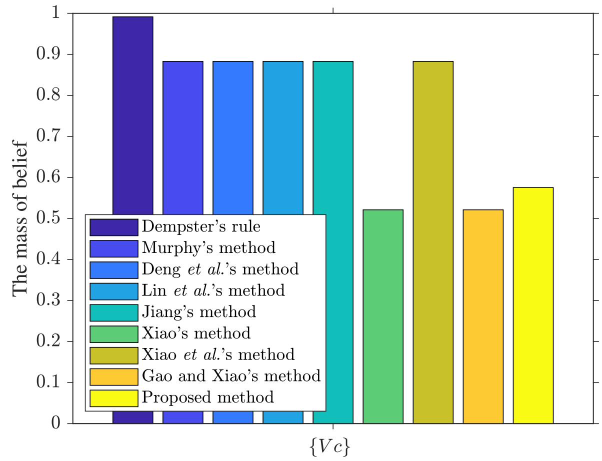
BBAs	$SL_{\mathbf{m}_1}$	$SW_{\mathbf{m}_2}$	$PL_{\mathbf{m}_3}$	$PW_{\mathbf{m}_4}$
$\{Se\}$	0.3337	0.0000	0.6699	0.6996
$\{Vc\}$	0.3165	0.9900	0.2374	0.2120
$\{Vi\}$	0.2816	0.0100	0.0884	0.0658
$\{Se, Vc\}$	0.0307	0.0000	0.0000	0.0000
$\{Se, Vi\}$	0.0052	0.0000	0.0000	0.0000
$\{Vc, Vi\}$	0.0272	0.0000	0.0043	0.0226
Ξ	0.0052	0.0000	0.0000	0.0000

TABLE 5. Fusion results of different methods in case 2.

Methods	Classes	$SL_{\mathbf{m}_1}, SW_{\mathbf{m}_2}$	$SL_{\mathbf{m}_1}, SW_{\mathbf{m}_2}, PL_{\mathbf{m}_3}$	$SL_{\mathbf{m}_1}, SW_{\mathbf{m}_2}, PL_{\mathbf{m}_3}, PW_{\mathbf{m}_4}$
Dempster's rule [28]	$\{Se\}$	0.0000	0.0000	0.0000
	$\{Vc\}$	**0.9916**	**0.9968**	**0.9988**
	$\{Vi\}$	0.0084	0.0032	0.0012
	$\{Se, Vc\}$	0.0000	0.0000	0.0000
	$\{Se, Vi\}$	0.0000	0.0000	0.0000
	$\{Vc, Vi\}$	0.0000	0.0000	0.0000
	Ξ	0.0000	0.0000	0.0000
Murphy's method [43]	$\{Se\}$	0.0655	0.2112	0.4422
	$\{Vc\}$	**0.8828**	**0.7749**	**0.5546**
	$\{Vi\}$	0.0505	0.0139	0.0032
	$\{Se, Vc\}$	6×10^{-4}	8×10^{-6}	8×10^{-8}
	$\{Se, Vi\}$	4×10^{-5}	2×10^{-7}	5×10^{-10}
	$\{Vc, Vi\}$	5×10^{-4}	9×10^{-6}	6×10^{-7}
	Ξ	1×10^{-5}	3×10^{-8}	3×10^{-11}
Deng *et al.*'s method [44]	$\{Se\}$	0.0655	0.3219	**0.7301**
	$\{Vc\}$	**0.8828**	**0.6534**	0.2652
	$\{Vi\}$	0.0505	0.0247	0.0047
	$\{Se, Vc\}$	6×10^{-4}	2×10^{-5}	1×10^{-7}
	$\{Se, Vi\}$	4×10^{-5}	4×10^{-7}	7×10^{-10}
	$\{Vc, Vi\}$	5×10^{-4}	2×10^{-5}	9×10^{-7}
	Ξ	1×10^{-5}	5×10^{-8}	5×10^{-11}
Lin *et al.*'s method [1]	$\{Se\}$	0.0655	0.2701	**0.6137**
	$\{Vc\}$	**0.8828**	**0.7080**	0.3811
	$\{Vi\}$	0.0505	0.0219	0.0053
	$\{Se, Vc\}$	6×10^{-4}	2×10^{-5}	2×10^{-7}
	$\{Se, Vi\}$	4×10^{-5}	3×10^{-7}	1×10^{-9}
	$\{Vc, Vi\}$	5×10^{-4}	2×10^{-5}	2×10^{-7}
	Ξ	1×10^{-5}	5×10^{-8}	7×10^{-11}
Jiang's method [45]	$\{Se\}$	0.0655	0.2914	**0.6828**
	$\{Vc\}$	**0.8828**	**0.6844**	0.3119
	$\{Vi\}$	0.0505	0.0241	0.0053
	$\{Se, Vc\}$	6×10^{-4}	2×10^{-5}	1×10^{-7}
	$\{Se, Vi\}$	4×10^{-5}	4×10^{-7}	9×10^{-10}
	$\{Vc, Vi\}$	5×10^{-4}	2×10^{-5}	10×10^{-7}
	Ξ	1×10^{-5}	5×10^{-8}	6×10^{-11}
Xiao's method [46]	$\{Se\}$	0.2740	**0.5395**	**0.8191**
	$\{Vc\}$	**0.5212**	0.3619	0.1583
	$\{Vi\}$	0.2001	0.0984	0.0226
	$\{Se, Vc\}$	0.0025	1×10^{-4}	1×10^{-6}
	$\{Se, Vi\}$	2×10^{-4}	2×10^{-6}	10×10^{-9}
	$\{Vc, Vi\}$	0.0020	9×10^{-5}	3×10^{-6}
	Ξ	5×10^{-5}	3×10^{-7}	6×10^{-10}
Xiao *et al.*'s method [2]	$\{Se\}$	0.0655	0.3896	**0.8277**
	$\{Vc\}$	**0.8828**	**0.5760**	0.1668
	$\{Vi\}$	0.0505	0.0344	0.0054
	$\{Se, Vc\}$	6×10^{-4}	3×10^{-5}	1×10^{-7}
	$\{Se, Vi\}$	4×10^{-5}	6×10^{-7}	9×10^{-10}
	$\{Vc, Vi\}$	5×10^{-4}	3×10^{-5}	1×10^{-6}
	Ξ	1×10^{-5}	8×10^{-8}	6×10^{-11}
Gao and Xiao's method [31]	$\{Se\}$	0.2740	**0.5340**	**0.8160**
	$\{Vc\}$	**0.5212**	0.3646	0.1606
	$\{Vi\}$	0.2001	0.1013	0.0234
	$\{Se, Vc\}$	0.0025	1×10^{-4}	2×10^{-6}
	$\{Se, Vi\}$	2×10^{-4}	2×10^{-6}	1×10^{-8}
	$\{Vc, Vi\}$	0.0020	9×10^{-5}	3×10^{-6}
	Ξ	5×10^{-5}	3×10^{-7}	6×10^{-10}
Proposed method	$\{Se\}$	0.2426	**0.5685**	**0.8480**
	$\{Vc\}$	**0.5754**	0.3605	0.1392
	$\{Vi\}$	0.1778	0.0710	0.0128
	$\{Se, Vc\}$	0.0022	6×10^{-5}	6×10^{-7}
	$\{Se, Vi\}$	1×10^{-4}	1×10^{-6}	4×10^{-9}
	$\{Vc, Vi\}$	0.0018	6×10^{-5}	2×10^{-6}
	Ξ	5×10^{-5}	2×10^{-7}	3×10^{-10}

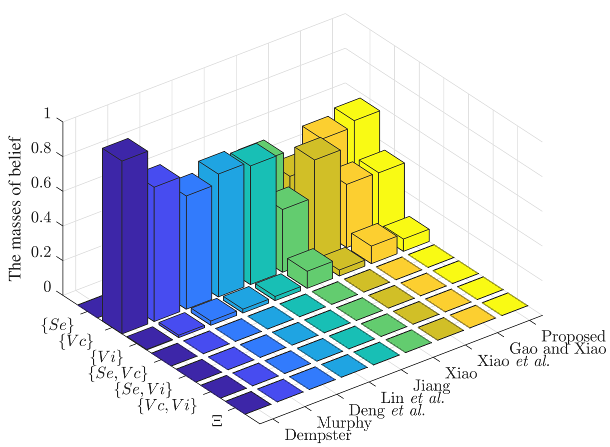


(a) The masses of belief with different methods.

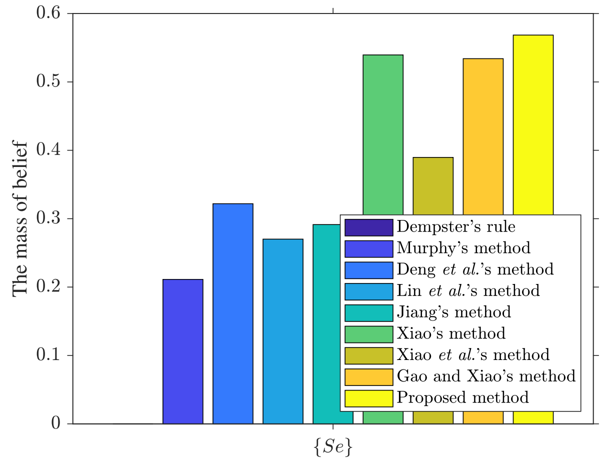


(b) The masses of belief to $\{Vc\}$ with different methods.

FIGURE 7. **The fusion results via $SL_{\mathbf{m}_1}$ and $SW_{\mathbf{m}_2}$ of different methods.**



(a) The masses of belief with different methods.



(b) The masses of belief to $\{Se\}$ with different methods.

FIGURE 8. **The fusion results via $SL_{\mathbf{m}_1}$, $SW_{\mathbf{m}_2}$ and $PL_{\mathbf{m}_3}$ of different methods.**

- **Fusion procedure.**

Step 1.1: The similarity matrix, denoted as $\mathscr{SM}$, is constructed using the following procedure:

$$\mathscr{SM} = \begin{bmatrix} 1 & 0.6781 & 0.5556 & 1 & 0.5956 \\ 0.6781 & 1 & 0.1884 & 0.6781 & 0.2895 \\ 0.5556 & 0.1884 & 1 & 0.5556 & 0.9391 \\ 1 & 0.6781 & 0.5556 & 1 & 0.5956 \\ 0.5956 & 0.2895 & 0.9391 & 0.5956 & 1 \end{bmatrix}$$

Steps 1.2 - 3.1: The $\mathscr{SD}$, $\mathscr{CW}$, $\mathscr{BE}$, $\mathscr{IV}$, $\mathscr{IVW}$ and $\mathscr{W}$ are calculated as shown in TABLE 2:

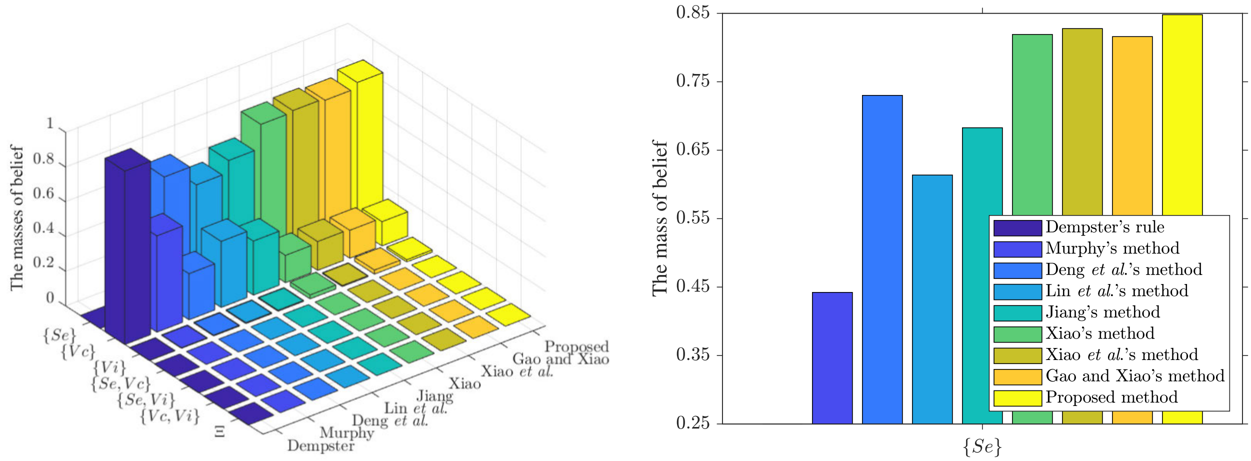
Step 3.2: The weighted average evidence $\bar{\mathbf{m}}$ is calculated as follows:

$$\bar{m}(\mathcal{E}_1) = 0.5513,\ \bar{m}(\mathcal{E}_2) = 0.3055,\ \bar{m}(\mathcal{E}_3) = 0.0336,$$
$$\bar{m}(\Xi) = 0.1096$$

Step 3.3: The final result $\mathscr{FR}$ is calculated as shown in TABLE 3.

- **Discussion.**

Table 3 clearly displays the fusion results obtained using various methods, including the traditional Dempster's rule and the newly proposed method, alongside other improved techniques. Notably, Dempster's rule demonstrates a pronounced bias towards $\mathcal{E}_2$, neglecting support for $\mathcal{E}_1$. This skew in results highlights a potential limitation of Dempster's rule in certain scenarios. In stark contrast, the proposed method exhibits a more balanced and accurate identification, successfully recognizing the target $\mathcal{E}_1$. This outcome aligns well with the results obtained from other improved fusion methods, indicating a more reliable and nuanced approach to information synthesis. Moreover, as illustrated in Figure 6, the proposed method not only correctly identifies the target but also shows a higher degree of support for $\mathcal{E}_1$ compared to other enhanced methods. This superior performance underscores the method's robustness and efficiency, particularly in decision-making scenarios where accurate target recognition is crucial. The findings suggest that the proposed method



(a) The masses of belief with different methods.

(b) The masses of belief to $\{Se\}$ with different methods.

FIGURE 9. The fusion results via SL_{m_1}, SW_{m_2}, PL_{m_3} and PW_{m_4} of different methods.

TABLE 6. Fusion results of different methods in case 2.

Methods	$\{Se\}$	$\{Vc\}$	$\{Vi\}$	$\{Se, Vc\}$	$\{Se, Vi\}$	$\{Vc, Vi\}$	Ξ
$\mathcal{RBLSM}$-based method	**0.7205**	0.2749	0.0046	1×10^{-7}	7×10^{-10}	9×10^{-7}	5×10^{-11}
Belief entropy-based method	**0.7768**	0.2102	0.0130	6×10^{-7}	4×10^{-9}	2×10^{-6}	3×10^{-10}
Proposed method	**0.8480**	0.1392	0.0128	6×10^{-7}	4×10^{-9}	2×10^{-6}	3×10^{-10}

could offer significant advantages in environments where discerning the correct target from multiple sensor inputs is essential.

B. CASE 2: PATTERN CLASSIFICATION

In an application focusing on pattern classification, the well-known Iris dataset from the UCI database is utilized. This dataset includes three distinct classes: Setosa $\{Se\}$, Versicolor $\{Vc\}$, Virginica $\{Vi\}$. Each sample in the dataset is characterized by four attributes: Sepal length (SL), Sepal width (SW), Petal length (PL), and Petal width (PW). As detailed in Table 4, the dataset information is represented through BBAs, with an added layer of complexity in the form of noise interference [58]. Compared to the other evidences, the second evidence seems to conflict with them.

TABLE 5 presents the fusion results obtained using various methods. Notably, Dempster's rule exhibits a strong inclination towards class $\{Vc\}$, entirely neglecting support for class $\{Se\}$. This outcome underscores potential limitations in Dempster's rule when faced with certain types of evidence configurations. Murphy's method also demonstrates shortcomings, indicating that a simplistic averaging of all the evidences may not suffice for accurate decision-making. This highlights the need for more nuanced approaches in handling evidence fusion. Interestingly, when the third evidence is introduced, Xiao's method [46], Gao and Xiao's method [31], and the proposed method manage to discern the correct result. Conversely, Deng et al.'s method [44], Lin et al.'s method [1], Jiang's method [45] and Xiao et al.'s method [2] continue to favor class Vc. This persistence is attributed to these methods focusing solely on the discrepancies between evidence pieces, while disregarding the actual information content within each evidence. FIGURE 7, 8, and 9 visualize the belief masses for classes $\{Vc\}$ and $\{Se\}$ across different methods. A notable observation is that the proposed method secures the highest belief mass as the number of BBAs increases. This enhancement in belief mass directly contributes to improved accuracy in decision-making, which is a testament to the effectiveness and superiority of the proposed method. Moreover, we compare the performance of the proposed method with the $\mathcal{RBLSM}$-based method and the belief entropy-based method in TABLE 6. As can be seen from TABLE 6, although each method can classify accurately, the proposed method (which takes into account both the credibility and information volume of the evidence) guarantees the highest belief value. The rationale is that similarity measure is used to measure the differences between evidences, while belief entropy quantifies the uncertainty for evidence. This shows that considering these two dimensions can significantly improve the effectiveness of the fusion results.

VI. CONCLUSION

This paper introduces a new reinforcement belief logarithmic similarity measure ($\mathcal{RBLSM}$), specifically crafted to assess the variances among the evidences. We demonstrate that $\mathcal{RBLSM}$ adheres to essential properties such as bounded, symmetry, and non-degeneracy. This adherence is further corroborated through a series of numerical examples, which effectively illustrate the robustness and reliability of $\mathcal{RBLSM}$. Building upon the foundation laid by $\mathcal{RBLSM}$, we develop a novel multisensor information fusion technique. The utility and practicality of this method are rigorously validated through two distinct application scenarios: target recognition and pattern classification. These applications highlight its adaptability to various contexts.

While the proposed method holds considerable potential for practical applications, it is currently limited to handling real numbers. In some scenarios, complex numbers are often used to represent richer information, which will limit the application of the proposed method. Consequently, in future work, expanding the proposed method to accommodate complex evidence theory is crucial and could greatly enhance its relevance and scope.

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