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Self-adaptive combination method for temporal evidence based on negotiation strategy

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Abstract In temporal information fusion, the information collected by sensors is obtained dynamically with the passage of time. Unlike the spatial information fusion, temporal fusion should be dynamic. Evidence theory has been applied to fuse temporal and spatial information; however, existing temporal fusion methods do not treat conflicting and non-conflicting evidence sources distinctively. Moreover, unlike spatial evidence sources, which are obtained simultaneously, temporal evidence sources cannot be evaluated simultaneously to obtain their degree of reliability. Thus, it is necessary to develop a method for temporal evidence combination. In this paper, a self-adaptive combination method for temporal evidence is proposed based on the negotiation strategy. In the proposed method, a set called an evidence set is constructed by the cumulative temporal fusion results of the previous moment, current moment, and future moment. The evidence set is evaluated as conflicting or non-conflicting according to the maximum power pignistic probability distance between each pair of evidence sources in the set. Then, temporal evidence sources are self-adaptively combined by different methods according to the degree of conflict. Numerical experiments were conducted to evaluate the performance of the proposed method. The results indicated that the proposed method is sufficiently effective and robust to support decision making.

Keywords information fusion, evidence theory, temporal fusion, self-adaptive combination, negotiation strategy

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1 Introduction

Most applications related to information fusion are likely to be affected by time. In other words, information fusion in the time domain must be considered when information fusion is applied to solve practical problems. For example, comprehensive target identification is affected by interference and sensor performance. Thus, the information obtained from the sensor at a single instant may be not accurate, and incomplete information may have to be fused from multiple time points to obtain reliable results. Therefore, comprehensive target identification based on multiple sensor platforms is a sequential recognition process involving information fusion in the space and time domains [1–6]. In the time domain, information is collected sequentially with the passage of time. Thus, the fusion of temporal information differs from the fusion of spatial information.

Since its inception [7,8], evidence theory has been widely used in a number of areas related to information fusion [9–13]. As an important tool for handling uncertain information, evidence theory can also be

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used in temporal information fusion [12–19]. Hong and Lynch [20] proposed three fusion models based on evidence theory: a centralized recursive fusion model, distributed recursive feedback-free fusion model, and distributed recursive feedback fusion model. These three models classify evidence sources into two types: spatial and temporal evidence.

Generally, spatial evidence sources are obtained from different sensors at the same time and are fused to obtain a spatial fusion result. In contrast, temporal evidence sources are collected from the same sensor at different time points. Temporal evidence fusion has both sequential and dynamic characteristics. As new data are collected, the cumulative temporal fusion result is updated [21]. In addition, any changes in the time intervals or evidence order may change the fusion result. Unlike temporal fusion, spatial fusion is independent of the fusion sequence and evidence order.

In evidence theory, Dempster's rule can be used to combine multiple evidence sources to obtain a fusion result and has been widely used in many areas. However, the fusion result obtained by Dempster's rule may be invalid when the degree of conflict between evidence sources is high. To solve this problem, researchers have considered the reliability of evidence in the fusion process to revise the original evidence sources prior to using Dempster's rule for evidence fusion. This approach can yield favorable results, and methods using this approach [22–27] can be used to combine highly conflicting spatial evidence sources. However, these methods are not suitable for temporal evidence combination because the reliability of evidence is largely determined by the degree of mutual support between evidence sources, which cannot be easily obtained for temporal evidence. In spatial evidence combination, there are often three or more spatial evidence sources, and the degree of their mutual support can be easily obtained through similarity or distance measurements. However, in temporal fusion, only two evidence sources are usually considered: the current moment and the cumulative fusion of past moments. Thus, we cannot obtain the reliability of temporal evidence by calculating the similarity or distance between the evidence sources.

The combination of temporal evidence has attracted considerable attention among researchers. Liu et al. [28] established a comprehensive identification model using the sequential fusion of spatiotemporal information to satisfy the requirements of a missile defense system. In temporal evidence fusion, Dempster's rule was used directly without accounting for the reliability of evidence sources. Wu et al. [29] proposed a hierarchical three-level information fusion structure to address the problem of spatiotemporal evidence fusion in multi-platform and multi-radar target identification processes. The reliability of the temporal evidence determined by spatial evidence gathered from sensors at each moment was taken into consideration. This method modifies the temporal evidence based on the discounting operation prior to using Dempster's rule. This method can obtain favourable results when two or more sensors participate in the fusion. However, if only a single sensor is considered, it is impossible to determine the reliability of the evidence, and invalid results may be produced. For the fusion of highly conflicting temporal evidence, we attempted to evaluate the relative reliability of temporal evidence based on the relation between evidence theory and intuitionistic fuzzy sets [21]. Together with real-time reliability obtained by the temporal evidence reliability attenuation model, a temporal evidence fusion method was developed based on composite reliability. This method provides a new approach to temporal evidence fusion; however, it may lead to an increased computational burden for evidence sources with a low degree of conflict. For spatiotemporal evidence fusion in fault diagnosis, Xu et al. [30] proposed a method that combines static evidence fusion and dynamic evidence updates. They adopted a dynamic update method based on the conditional linear combination in the temporal evidence fusion phase. They used temporal evidence information at the subsequent moment as a reference to obtain the updated composite weight of the cumulative temporal fusion result at the previous moment and the temporal evidence at the current moment. Temporal evidence fusion was implemented based on a conditional linear combination evidence update rule. This method can effectively improve the reliability of decision making for fault diagnosis. However, it is designed for evidence sources with a high degree of conflict, and its advantage is unclear for evidence with low conflict. Moreover, its calculation cost is high.

The above analysis indicates that various methods for temporal evidence combination have been developed and can achieve reasonable results in temporal information fusion. However, these methods are designed for conflicting evidence sources. If these methods are used to combine temporal evidence sources with a low degree of conflict, the process of evaluation and modification on evidence sources must be executed, which may lead to additional computational burden. Therefore, it is necessary to develop a temporal evidence combination method that can select different strategies for different evidence sources. This combination method should consist of three processes: determining the degree of conflict, combining conflicting evidence sources, and combining non-conflicting evidence sources. These requirements were our motivation to develop a new method for temporal evidence combination.

In this paper, we propose a self-adaptive fusion method for temporal evidence based on negotiation strategies. The proposed method uses temporal evidence at a subsequent moment as reference information. An evidence set is constructed by the previous cumulative temporal fusion result, current temporal evidence, and future temporal evidence. We use the power pignistic probability distance to analyze the degree of conflict in the evidence set. Based on a given criterion, we classify each evidence set as non-conflicting or conflicting. For non-conflicting evidence sources, Dempster's rule can be directly used to fuse the previous cumulative temporal fusion result with the current temporal evidence. For conflicting evidence sources, we evaluate the reliability of the previous cumulative temporal fusion result and the current temporal evidence, and then, revise the result using the discounting operation prior to fusing them by Dempster's rule.

The remainder of this paper is arranged as follows. Section 2 provides background knowledge on evidence theory, while Section 3 presents a method for determining the degree of conflict between basic probability assignments (BPAs). Section 4 discusses the self-adaptive combination rule for different evidence sets, while Section 5 presents numerical examples to illustrate the performance of the proposed method. Section 6 presents the conclusion of this paper.

2 Preliminaries

In this section, we present background knowledge on evidence theory. In evidence theory [7], a nonempty set Ω represents the frame of discernment, where the elements are exhaustive and mutually exclusive, and 2^{Ω} represents the power set of Ω.

Definition 1. Let Ω be the frame of discernment and A be a subset of Ω. $A \neq \emptyset$. The function $m : 2^{\Omega} \to [0, 1]$ is referred to as a BPA function on Ω if it satisfies the following conditions:

$$\begin{cases} m(\emptyset) = 0, \\ \displaystyle\sum_{A \subseteq \Omega} m(A) = 1. \end{cases} \tag{1}$$

For $\forall A \subseteq \Omega$, if $m(A) > 0$, A is referred to as the focus element of Ω, and $m(A)$ is the basic probability mass of A representing the degree of confidence of the evidence on A.

Definition 2 ([7])**.** Let m_1 and m_2 be two independent BPAs in the frame of discernment Ω. The result $m_{1\oplus 2}$ obtained by combining m_1 and m_2 using Dempster's rule of combination is

$$m_{1\oplus 2}(A) = \begin{cases} \dfrac{1}{1-k} \displaystyle\sum_{B \bigcap C = A} m_1(B) m_2(C), & A \neq \emptyset, \\ 0, & A = \emptyset, \end{cases} \tag{2}$$

where

$$k = \sum_{B \bigcap C = \emptyset} m_1(B) m_2(C) \tag{3}$$

denotes the conflict factor. When $k = 1$, the two evidence sources involved are in complete conflict and cannot be combined using Dempster's rule.

Definition 3. Let Ω be the frame of discernment. Assuming that the reliability of an evidence source is $1 - \alpha$, $(0 \leqslant \alpha \leqslant 1)$, and m is a BPA obtained from the evidence source, we can perform a discounting operation on m using the method proposed by Shafer [8]. The new BPA obtained after applying the discount is m^α:

$$\begin{cases} m^\alpha(A) = (1-\alpha)\cdot m(A), & \forall A \subset \Omega, \\ m^\alpha(\Omega) = (1-\alpha)\cdot m(\Omega) + \alpha, & A = \Omega, \end{cases} \tag{4}$$

where α is the discounting factor. $\alpha = 0$ indicates that the reliability of the evidence source is 1, which signifies that m is completely credible and remains unchanged by discounting. $\alpha = 1$ indicates that the reliability of the evidence source is 0, i.e., m is completely unreliable and may produce an empty BPA after discounting. An empty BPA discards the evidence owing to its unreliability.

3 Determining the degree of conflict in the evidence set

We use t to denote the current time point, $t-1$ to denote the previous time point, and $t+1$ to denote the subsequent time point. $m_{\oplus t-1}$ denotes the cumulative temporal fusion result at $t-1$, m_t represents the temporal evidence at moment t, and m_{t+1} denotes the temporal evidence obtained at time point $t+1$.

Temporal evidence fusion is the process of combining $m_{\oplus t-1}$ with m_t to obtain $m_{\oplus t}$. Prior to the fusion, it is necessary to determine whether $m_{\oplus t-1}$ and m_t are conflicting. If they are not conflicting, they can be combined in a simple way to obtain a valid fusion result. However, if they are conflicting, their reliability should be evaluated, and a preprocessing method should be performed to reduce the influence of unreliable evidence on the fusion result. At present, similarity and distance metrics are widely used to measure the degree of conflict in the evidence and evaluate the reliability of the evidence. The reliability of the evidence can be obtained based on the degree of the mutual support between more than three sources of evidence. However, these methods cannot be used for temporal evidence fusion, as only two evidence sources are involved in temporal fusion.

To solve the problems of conflict determination and reliability evaluation in the temporal evidence fusion process, we adopt the following negotiation strategy. In the fusion of $m_{\oplus t-1}$ and m_t, we introduce m_{t+1} as the reference evidence and form a temporal evidence set consisting of $m_{\oplus t-1}$, m_t, and m_{t+1}. We comprehensively analyze the information contained in the three pieces of temporal evidence to determine the conflict in the evidence set through negotiation. For conflicting evidence, we perform evaluation by negotiation for the reliability of $m_{\oplus t-1}$ and m_t. The negotiation strategy process includes two main parts. The first part is conflict determination. The maximum conflicting value between any two pieces of evidence in the evidence set is used to represent the conflict in the evidence set. The second part is reliability evaluation. Based on the mutual support between all pieces of evidence in the evidence set, we determine the reliability of $m_{\oplus t-1}$ and m_t.

The selection of conflict metrics is crucial. The conflict factor k in Dempster's rule is the earliest conflict measurement and can be applied for two or more evidence sources. Liu [31] demonstrated that a large value of k does not signify a large conflict in evidence through experiments with numerical examples. Other conflict metrics can only be applied to measuring the degree of conflict between two evidence sources. Jousselme and Maupin [32] provided a comprehensive survey and classification of these metrics. The representative metrics include distance [33] classified as a standard metric, pignistic probability distance [34] classified as a pseudo-metric, and angular similarity [24] classified as semi-pseudo-metric. New metric distances have emerged more recently. Yu et al. [25] proposed the support probability distance, while Bi et al. [26] proposed a new similarity metric combining the pignistic probability distance with the Tanimoto metric. Zhu et al. [35] proposed a power pignistic probability distance, which was proven to be a standard measure through mathematical derivation. The advantage of the power pignistic probability distance was also demonstrated by numerical examples.

Considering the performance of the power pignistic probability distance, we adopted it in this study to measure the degree of conflict in the evidence set. Several definitions related to the power pignistic probability distance are presented as follows.

Definition 4. Let Ω be the frame of discernment, A and B be subsets of Ω, $A \neq \emptyset$, and m be a BPA on Ω. The power-set-distribution pignistic probability function $\mathrm{PBet}P_m : 2^\Omega \to [0,1]$ corresponding to m

is defined as

$$\mathrm{PBet}P_m(B) = \sum_{A,B\subseteq\Omega} m(A)\frac{2^{|B\bigcap A|}-1}{2^{|A|}-1}, \tag{5}$$

where $|A|$ represents the cardinality of set A.

Based on the power-set-distribution pignistic probability function, we can construct the power pignistic probability as follows.

Definition 5. Let m_1 and m_2 be two independent BPAs on the frame of discernment Ω. $\mathrm{PBet}P_{m_1}$ and $\mathrm{PBet}P_{m_2}$ are their respective power-set-distribution pignistic probability functions. We define the power pignistic probability distance between m_1 and m_2 as

$$\mathrm{difPBet}P_{m_1}^{m_2} = \max_{A\subseteq\Omega}(|\mathrm{PBet}P_{m_1}(A) - \mathrm{PBet}P_{m_2}(A)|). \tag{6}$$

Influenced by the power-set-distribution pignistic probability function, the new distance works over the power set of Ω. Since the new distance is developed in the space containing more sets, it takes more information contained in the BPA. Based on the distance measure d_{PBet}, the temporal evidence set can be classified as non-conflicting or conflicting. It has been proven that the distance measure satisfies all the standard metric properties including non-negativity, symmetry, separability and triangle inequality [35].

Let Ω be the frame of discernment, $M = \{m_{\oplus t-1}, m_t, m_{t+1}\}$ be the temporal evidence set on Ω, $\max(d_{\mathrm{PBet}})$ denote the maximum value of d_{PBet} between evidence pairs in the evidence set, and μ denote the threshold. If $\max(d_{\mathrm{PBet}}) \leqslant \mu$, M is a non-conflicting evidence set. If $\max(d_{\mathrm{PBet}}) > \mu$, M is a conflicting evidence set.

It has been demonstrated that the choice of threshold μ is critical for the classification result. In application, μ should be determined according to the actual situation. Various methods, such as data-driven learning and expert consultation, can be used. In this study, we set the threshold as suggested by Liu [31], which is analyzed in detail as follows.

For the case in which there are only two pieces of evidence, Liu [31] constructed a binary metric using the conflict factor k and the pignistic probability distance d_{Bet}, and set two thresholds for both. Four cases are considered according to different values to decide whether to use Dempster's rule. If only d_{Bet} and its threshold ε_1 are considered, these four cases are simplified into two cases. If $d_{\mathrm{Bet}} \leqslant \varepsilon_1$, Dempster's rule of combination can be used. If $d_{\mathrm{Bet}} > \varepsilon_1$, Dempster's rule of combination can be used with caution. d_{PBet} is an improvement over d_{Bet}. Both of d_{Bet} and d_{PBet} quantify the dissimilarity between the two pieces of evidence; thus, the threshold ε_1 for d_{Bet} can be used when setting the threshold μ for d_{PBet}. Liu [31] suggested that ε_1 is set to 0.3, and we use the same value for μ. In addition, we do not use Dempster's rule when $d_{\mathrm{PBet}} > \mu$ to reduce the risk of decision making and the complexity of the algorithm.

4 Self-adaptive combination method

After the classification of the evidence set via the negotiation strategy, we must determine the combination rule for different types of evidence sources. Dempster's rule can be used to combine non-conflicting evidence sources and evidence sources with a low degree of conflict. Specifically, if $M = \{m_{\oplus t-1}, m_t, m_{t+1}\}$ is a non-conflicting evidence set, $m_{\oplus t-1}$, m_t, and m_{t+1} reach consensus or obtain a high degree of agreement, Dempster's rule can be used directly to fuse $m_{\oplus t-1}$ and m_t.

If M is classified as a conflicting evidence set, $m_{\oplus t-1}$, m_t, and m_{t+1} do not reach consensus or have a low degree of agreement. We must use information containing three temporal evidence sources $m_{\oplus t-1}, m_t$, and m_{t+1} to negotiate and evaluate the reliability of $m_{\oplus t-1}$ and m_t. In this process, three evidence sources are used to evaluate the reliability of two evidence sources. This is implemented by reassigning the reliability of m_{t+1} to $m_{\oplus t-1}$ and m_t according to their degrees of similarity with m_{t+1}, which can be expressed as follows:

$$\mathrm{Crd}'(m_{\oplus t-1}) = \mathrm{Crd}(m_{\oplus t-1}) + \mathrm{Crd}(m_{t+1}) \times \frac{\mathrm{Sim}(m_{\oplus t-1}, m_{t+1})}{\mathrm{Sim}(m_{\oplus t-1}, m_{t+1}) + \mathrm{Sim}(m_t, m_{t+1})}, \tag{7}$$

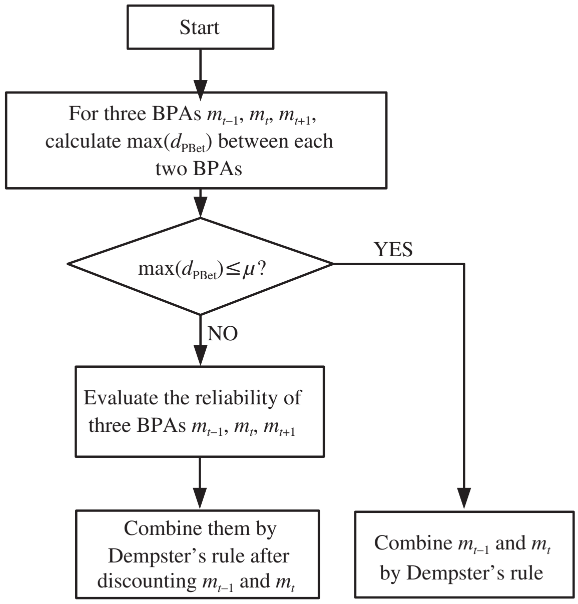

Figure 1 Flow chart of the adaptive fusion method for temporal evidence based on the negotiation strategy.

$$\mathrm{Crd}'(m_t) = \mathrm{Crd}(m_t) + \mathrm{Crd}(m_{t+1}) \times \frac{\mathrm{Sim}(m_t, m_{t+1})}{\mathrm{Sim}(m_{\oplus t-1}, m_{t+1}) + \mathrm{Sim}(m_t, m_{t+1})}. \tag{8}$$

Then, we use the discounting operation to revise the original evidence $m_{\oplus t-1}$ and m_t. Finally, the revised evidence sources are combined by Dempster's rule.

Because the proposed method can select different combination rules according to the degree of conflict in the evidence set, it is called a negotiation-based self-adaptive method for temporal evidence. Figure 1 illustrates the process of this method.

Figure 1 illustrates that m_{t+1} is used only as reference information to negotiate with $m_{\oplus t-1}$ and m_t to determine the degree of conflict in the evidence set and to evaluate the reliability of $m_{\oplus t-1}$ and m_t. m_{t+1} does not directly participate in the fusion. By considering the reliability of $m_{\oplus t-1}$ and m_t in the fusion process, the reliability of the decision can be improved. This negotiation strategy leads to a delay in decision making, as the sensor provides the decision result for t when obtaining the data at time $t+1$. Similarly, the decision result of $t+1$ is obtained when the sensor obtains the evidence for $t+2$.

If the evidence set M is classified as a conflicting set, we use the discounting operation to modify the original evidence sources. Figure 2 illustrates the process of combining conflicting evidence sources.

In Figure 2, the large green dashed box contains the information required for temporal evidence fusion and outputs the cumulative temporal fusion result $m_{\oplus t}$ at time t. The detailed process of evaluating the reliability of the evidence is described as follows.

Step 1: Calculate d_{PBet} between each pair of $m_{\oplus t-1}$, m_t, and m_{t+1}. The corresponding similarity metric is $\mathrm{Sim} = 1 - d_{\mathrm{PBet}}$.

Step 2: Calculate the degree of support Sup of $m_{\oplus t-1}$, m_t, and m_{t+1} according to the following formulas: $\mathrm{Sup}(m_{\oplus t-1}) = \mathrm{Sim}(m_{\oplus t-1}, m_t) + \mathrm{Sim}(m_{\oplus t-1}, m_{t+1})$, $\mathrm{Sup}(m_t) = \mathrm{Sim}(m_t, m_{\oplus t-1}) + \mathrm{Sim}(m_t, m_{t+1})$, and $\mathrm{Sup}(m_{t+1}) = \mathrm{Sim}(m_{t+1}, m_{\oplus t-1}) + \mathrm{Sim}(m_{t+1}, m_t)$.

Step 3: Calculate the degree of belief $\mathrm{Crd}(m_i)$ for m_i ($i = \oplus t-1, t, t+1$), which is defined as $\mathrm{Crd}(m_i) = \frac{\mathrm{Sup}(m_i)}{\sum \mathrm{Sup}(m_i)}$ where $\sum \mathrm{Crd}(m_i) = 1$. The degree of belief $\mathrm{Crd}(m_i)$ reflects the relative importance of evidence m_i.

Step 4: Because m_{t+1} provides only the reference information in the fusion process and does not participate in the fusion, the credibility of m_{t+1} should be distributed to $m_{\oplus t-1}$ and m_t proportionally in the fusion of $m_{\oplus t-1}$ and m_t. After the distribution, the new degree of belief of $m_{\oplus t-1}$ and m_t is $\mathrm{Crd}'(m_{\oplus t-1}) = \mathrm{Crd}(m_{\oplus t-1}) + \mathrm{Crd}(m_{t+1}) \times \frac{\mathrm{Sim}(m_{\oplus t-1}, m_{t+1})}{\mathrm{Sim}(m_{\oplus t-1}, m_{t+1}) + \mathrm{Sim}(m_t, m_{t+1})}$ and $\mathrm{Crd}'(m_t) = \mathrm{Crd}(m_t) + \mathrm{Crd}(m_{t+1}) \times \frac{\mathrm{Sim}(m_t, m_{t+1})}{\mathrm{Sim}(m_{\oplus t-1}, m_{t+1}) + \mathrm{Sim}(m_t, m_{t+1})}$.

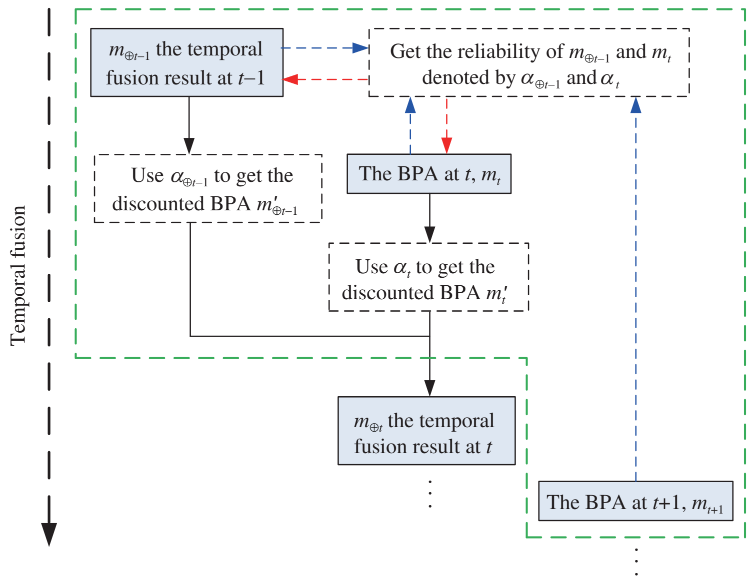

Figure 2 (Color online) Temporal evidence fusion structure in conflicting situations.

Step 5: Calculate the reliability of $m_{\oplus t-1}$ and m_t, revise $m_{\oplus t-1}$ and m_t with the discounting method, and fuse them using Dempster's rule to produce the final result: $\alpha_{\oplus t-1} = \frac{\mathrm{Crd}'(m_{\oplus t-1})}{\max[\mathrm{Crd}'(m_{\oplus t-1}),\mathrm{Crd}'(m_t)]}$ and $\alpha_t = \frac{\mathrm{Crd}'(m_t)}{\max[\mathrm{Crd}'(m_{\oplus t-1}),\mathrm{Crd}'(m_t)]}$.

5 Numerical example and analysis

In this section, we describe two simulation experiments conducted to validate the performance of the proposed self-adaptive temporal evidence fusion method. In Example 1, the temporal evidence contained evidence of interference. We compared the fusion result obtained by our method with the fusion result obtained by Dempster's rule to analyze the anti-interference capability of the two methods. It has been claimed that temporal evidence combination based on the composite reliability factor (TEC-CRF) has high anti-interference ability [21]. In Example 2, we took the data used in [21] to perform a comparison with the TEC-CRF method.

Example 1. In a ballistic target comprehensive identification system, a photoelectric sensor detected the same target and made a soft decision of its type at six intervals: $t_1 = 1$ s, $t_2 = 3$ s, $t_3 = 5$ s, $t_4 = 7$ s, $t_5 = 9$ s, and $t_6 = 11$ s. The target was one of three types: warhead, decoy, or debris. Thus, the frame of discernment was $\Omega = \{A$ (Warhead), B (Decoy), C (Debris)$\}$. The true type of the known target was A (Warhead). The evidence sources obtained by the photoelectric sensor in chronological order were m_1, m_2, m_3, m_4, m_5, and m_6. Owing to the complex battlefield environment, the sensor failed at a certain point; thus, the data obtained at that moment contained interference. We considered three cases: this interference was present at $t_1 = 1$ s (starting time), $t_3 = 5$ s (near the middle), and $t_5 = 9$ s (near the end), represented as Case 1, Case 2, and Case 3, respectively.

We calculated the results by Dempster's rule and our method at each time for the three cases and analyzed the anti-interference ability of the two methods.

(1) When evidence of interference was obtained at $t_1 = 1$ s (starting time), six BPAs were collected as presented in Table 1. These six BPAs were combined by Dempster's rule and our method. Table 2 presents the output of the fusion result at each moment.

Table 2 demonstrates that at moment $t_1 = 1$ s, m_1 was the only temporal evidence, and it was not necessary to perform fusion. m_1 can be regarded as the cumulative temporal fusion result $m_{\oplus 1}$ at that moment. Because m_1 contained interference, B obtained the maximum belief degree 0.8 in $m_{\oplus 1}$, which may not have been reliable. At time $t_2 = 3$ s, the maximum belief degree was $m_2(A) = 0.5$. Dempster's

Table 1 BPA functions obtained from the information of photoelectric sensors (the interference appeared at $t_1 = 1$ s)

		A	B	C	AB
$t_1 = 1$ s	m_1	0.1	0.8	0.1	0
$t_2 = 3$ s	m_2	0.5	0.2	0	0.3
$t_3 = 5$ s	m_3	0.6	0	0.1	0.3
$t_4 = 7$ s	m_4	0.6	0.3	0.1	0
$t_5 = 9$ s	m_5	0.7	0.1	0.2	0
$t_6 = 11$ s	m_6	0.6	0.2	0.1	0.1

Table 2 Fusion results of Dempster's rule and the proposed method (the interference appeared at $t_1 = 1$ s)

	Dempster's rule	The proposed method
$t_1 = 1$ s	$m_{\oplus 1}(A) = 0.1$, $m_{\oplus 1}(B) = 0.8$, $m_{\oplus 1}(C) = 0.1$	$m_{\oplus 1}(A) = 0.1$, $m_{\oplus 1}(B) = 0.8$, $m_{\oplus 1}(C) = 0.1$
$t_2 = 3$ s	$m_{\oplus 2}(A) = 0.1667$, $m_{\oplus 2}(B) = 0.8333$	$m_{\oplus 2}(A) = 0.3919$, $m_{\oplus 2}(B) = 0.4054$, $m_{\oplus 2}(AB) = 0.2027$
$t_3 = 5$ s	$m_{\oplus 3}(A) = 0.3751$, $m_{\oplus 3}(B) = 0.6249$	$m_{\oplus 3}(A) = 0.7156$, $m_{\oplus 3}(B) = 0.1751$, $m_{\oplus 3}(C) = 0.0054$, $m_{\oplus 3}(AB) = 0.1039$
$t_4 = 7$ s	$m_{\oplus 4}(A) = 0.5456$, $m_{\oplus 4}(B) = 0.4544$	$m_{\oplus 4}(A) = 0.8537$, $m_{\oplus 4}(B) = 0.1453$, $m_{\oplus 4}(C) = 0.0009$
$t_5 = 9$ s	$m_{\oplus 5}(A) = 0.8937$, $m_{\oplus 5}(B) = 0.1063$	$m_{\oplus 5}(A) = 0.9760$, $m_{\oplus 5}(B) = 0.0237$, $m_{\oplus 5}(C) = 0.0003$
$t_6 = 11$ s	$m_{\oplus 6}(A) = 0.9515$, $m_{\oplus 6}(B) = 0.0485$	—

Table 3 BPA functions obtained from the information of photoelectric sensors (the interference appeared at $t_3 = 5$ s)

		A	B	C	AB
$t_1 = 1$ s	m_1	0.6	0	0.1	0.3
$t_2 = 3$ s	m_2	0.5	0.2	0	0.3
$t_3 = 5$ s	m_3	0.1	0.8	0.1	0
$t_4 = 7$ s	m_4	0.6	0.3	0.1	0
$t_5 = 9$ s	m_5	0.7	0.1	0.2	0
$t_6 = 11$ s	m_6	0.6	0.2	0.1	0.1

rule only considered the information contained in $m_{\oplus 1}$ and m_2 during the fusion, and $m_{\oplus 1}(B) = 0.8$ was much greater than $m_2(A) = 0.5$. Thus, the cumulative temporal fusion result at this moment still assigned a larger belief degree to B and only a small belief degree to A, expressed as $m_{\oplus 2}(A) = 0.1667, m_{\oplus 2}(B) = 0.8333$. This indicates that the fusion result obtained using Dempster's rule was significantly affected by the interference.

The proposed method considered the information contained in $m_{\oplus 1}$, m_2, and m_3. Because the degree of agreement between m_2 and m_3 was high while their degree of agreement with $m_{\oplus 1}$ was low, the fusion of $m_{\oplus 1}$ and m_2 had to be revised by the discounting method according to their reliability. Thus, the degrees of reliability of B and A were nearly equal and less affected by the interference. At $t_3 = 5$ s, $t_4 = 7$ s, and $t_5 = 9$ s, m_3, m_4, and m_5 agreed strongly with m_2. Dempster's rule and our proposed method gradually increased the degree of belief on A. Our proposed method identified the target as A at $t_3 = 5$ s, exhibiting improved focus ability, while Dempster's rule was still significantly affected by the interference at $t_3 = 5$ s and identified the target category as B. Dempster's rule was unable to recognize the target as A until the moment $t_4 = 7$ s. The focusing performance was thus low. At time $t_6 = 11$ s, owing to the use of the negotiation strategy, our method was unable to yield a cumulative temporal fusion result at that moment owing to the absence of subsequent reference evidence.

(2) Table 3 presents the details of the six BPAs when the interference appeared at time $t_3 = 5$ s (near the middle). The positions of m_1 and m_3 in Table 1 are exchanged, while the positions of other BPAs remain unchanged. Temporal fusion on the six BPAs was performed by Dempster's rule and the proposed method. The fusion result output at each moment is presented in Table 4.

In Table 4, m_1 is the cumulative temporal fusion result $m_{\oplus 1}$ at $t_1 = 1$ s, which assigned a maximum degree of belief of 0.6 to A. At $t_2 = 3$ s, m_2 assigned the maximum belief degree 0.5 to A. At that moment, the degree of agreement between $m_{\oplus 1}$ and m_2 was high, and data with interference did not

Table 4 Fusion results of Dempster's rule and the proposed method (the interference appeared at $t_3 = 5$ s)

	Dempster's rule	The proposed method
$t_1 = 1$ s	$m_{\oplus 1}(A) = 0.6$, $m_{\oplus 1}(B) = 0.1$, $m_{\oplus 1}(AB) = 0.3$.	$m_{\oplus 1}(A) = 0.6$, $m_{\oplus 1}(B) = 0.1$, $m_{\oplus 1}(AB) = 0.3$
$t_2 = 3$ s	$m_{\oplus 2}(A) = 0.8077$, $m_{\oplus 2}(B) = 0.0769$, $m_{\oplus 2}(AB) = 0.1154$	$m_{\oplus 2}(A) = 0.7061$, $m_{\oplus 2}(B) = 0.0960$, $m_{\oplus 2}(AB) = 0.1440$
$t_3 = 5$ s	$m_{\oplus 3}(A) = 0.3751$, $m_{\oplus 3}(B) = 0.6249$	$m_{\oplus 3}(A) = 0.5759$, $m_{\oplus 3}(B) = 0.3404$, $m_{\oplus 3}(AB) = 0.0837$
$t_4 = 7$ s	$m_{\oplus 4}(A) = 0.5456$, $m_{\oplus 4}(B) = 0.4544$	$m_{\oplus 4}(A) = 0.7567$, $m_{\oplus 4}(B) = 0.2433$
$t_5 = 9$ s	$m_{\oplus 5}(A) = 0.8937$, $m_{\oplus 5}(B) = 0.1063$	$m_{\oplus 5}(A) = 0.9561$, $m_{\oplus 5}(B) = 0.0439$
$t_6 = 11$ s	$m_{\oplus 6}(A) = 0.9515$, $m_{\oplus 6}(B) = 0.0485$	—

Table 5 BPA functions obtained from information obtained by photoelectric sensors (the interference appeared at $t_5 = 9$ s)

		A	B	C	AB
$t_1 = 1$ s	m_1	0.7	0.1	0.2	0
$t_2 = 3$ s	m_2	0.5	0.2	0	0.3
$t_3 = 5$ s	m_3	0.6	0	0.1	0.3
$t_4 = 7$ s	m_4	0.6	0.3	0.1	0
$t_5 = 9$ s	m_5	0.1	0.8	0.1	0
$t_6 = 11$ s	m_6	0.6	0.2	0.1	0.1

Table 6 Fusion results of Dempster's rule and the proposed method (the interference appeared at $t_5 = 9$ s)

	Dempster's rule	The proposed method
$t_1 = 1$ s	$m_{\oplus 1}(A) = 0.7$, $m_{\oplus 1}(B) = 0.1$, $m_{\oplus 1}(C) = 0.2$	$m_{\oplus 1}(A) = 0.7$, $m_{\oplus 1}(B) = 0.1$, $m_{\oplus 1}(C) = 0.2$
$t_2 = 3$ s	$m_{\oplus 2}(A) = 0.9180$, $m_{\oplus 2}(B) = 0.0820$	$m_{\oplus 2}(A) = 0.9180$, $m_{\oplus 2}(B) = 0.0820$
$t_3 = 5$ s	$m_{\oplus 3}(A) = 0.9711$, $m_{\oplus 3}(B) = 0.0289$	$m_{\oplus 3}(A) = 0.9286$, $m_{\oplus 3}(B) = 0.0256$, $m_{\oplus 3}(C) = 0.0114$, $m_{\oplus 3}(AB) = 0.0343$
$t_4 = 7$ s	$m_{\oplus 4}(A) = 0.9853$, $m_{\oplus 4}(B) = 0.0147$	$m_{\oplus 4}(A) = 0.7638$, $m_{\oplus 4}(B) = 0.1798$, $m_{\oplus 4}(C) = 0.0563$
$t_5 = 9$ s	$m_{\oplus 5}(A) = 0.8937$, $m_{\oplus 5}(B) = 0.1063$	$m_{\oplus 5}(A) = 0.6628$, $m_{\oplus 5}(B) = 0.2884$, $m_{\oplus 5}(C) = 0.0489$
$t_6 = 11$ s	$m_{\oplus 6}(A) = 0.9515$,$m_{\oplus 6}(B) = 0.0485$	—

appear. Dempster's rule only considered the information contained in $m_{\oplus 1}$ and m_2 during fusion. At that moment, the cumulative temporal evidence fusion result $m_{\oplus 2}$ assigned the maximum degree of belief of 0.8077 to A, which was valid. In our proposed method, the reliability of $m_{\oplus 1}$ and m_2 was added to the fusion process and obtained valid results. The focusing performance was similar to that of Dempster's rule. At $t_3 = 5$ s, because m_3 contained interference and Dempster's rule did not consider the reliability of the evidence, the fusion result was significantly affected, and the maximum degree of belief was assigned to B, leading to an valid result. Our method considered the reliability of the evidence and was affected less by the interference, and thus, still yielded valid results. Following the interference, Dempster's rule and our proposed method both assigned the maximum degree of belief to A at times $t_4 = 7$ s and $t_5 = 9$ s. However, our method exhibited improved focusing ability. At $t_6 = 11$ s, the use of a negotiation strategy prevented our method from yielding a cumulative temporal fusion result owing to the lack of subsequent reference evidence.

(3) Table 5 presents the details of the BPAs when the interference appeared at time $t_5 = 9$ s (near the end). The positions of m_1 and m_5 in Table 1 are exchanged, while the positions of the other BPAs remain unchanged. Temporal fusion of the six BPAs was performed using Dempster's rule and our method. The output of the fusion result at each moment is provided in Table 6.

Table 6 indicates that at moments $t_1 = 1$ s, $t_2 = 3$ s, $t_3 = 5$ s, and $t_4 = 7$ s, there was no interference, and Dempster's rule and the proposed method were thus both able to obtain reasonable cumulative fusion results. However, we note that the belief degree assigned to C was 0 from t_2 when Dempster's rule was used. This was caused by the "one-vote veto" property of Dempster's rule. Because our proposed method considers the evidence reliability and discounting operation when handling conflicting evidence sources, the belief degree assignment to A did not increase all times. However, this did not affect the decision making. At $t_5 = 9$ s, m_5 was affected by interference. Because Dempster's rule does not consider the

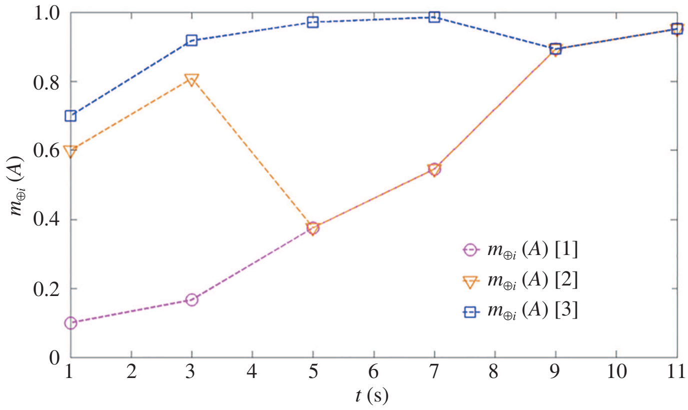

Figure 3 (Color online) Trends in the belief degree on A based on Dempster's rule in three cases.

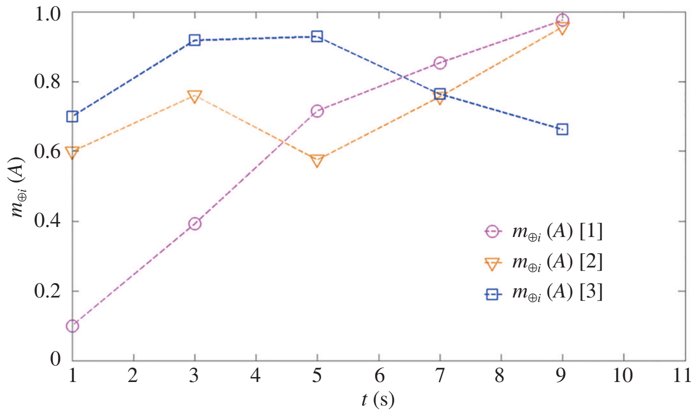

Figure 4 (Color online) Trends in the belief degree on A based on the proposed method in three cases.

reliability of evidence, the fusion result was influenced by interference, appearing as the decrease in the belief degree of A from 0.9853 to 0.8937. This was caused by the high agreement degree of earlier BPAs. In the proposed method, the reliability of the evidence at time $t_5 = 9$ s was considered. The belief degree assigned to A decreased while the belief degree assigned to B increased. However, $m_{\oplus 5}(A)$ was greater than $m_{\oplus 5}(B)$, which was helpful for decision making. At time $t_6 = 11$ s, the use of a negotiation strategy prevented the proposed method from yielding a cumulative temporal fusion result owing to the lack of subsequent data. Although Dempster's rule could also obtain reasonable results for decision making in this case, this did not indicate the anti-interference ability of Dempster's rule. Dempster's rule may fail if the BPA obtained from the interference assigns a belief degree of 0 to A, that is, $m_5(A) = 0$. In the special case of $m_5(A) = 0, m_{\oplus 5}(A)$ is 0 forever regardless of the information obtained after the interference.

The above analysis demonstrates that our proposed method has strong anti-interference ability regardless of when the interference appears. This is the result of the negotiation strategy for evaluating the reliability of the evidence. Dempster's rule does not consider the reliability of evidence; therefore, its anti-interference ability is relatively low with occasional invalid results.

(4) Next, we examine the effect of the time factor on the fusion results obtained by Dempster's rule and our proposed method.

It has been reported that temporal evidence fusion is dynamic [21]. Generally, any change in the fusion order of temporal evidence affects the final fusion result. Figures 3 and 4 display the trend in the belief degree on A obtained by Dempster's rule and the proposed method, respectively. Three cases in which the interference appeared at $t_1 = 1$ s, $t_3 = 5$ s, and $t_5 = 9$ s were considered. In the figures, the lines labeled [1], [2], and [3] represent three cases.

Figure 3 demonstrates that after the interference appeared at $t_3 = 5$ s (Case 2), the cumulative temporal fusions of Cases 1 and 2 were identical. At time $t_5 = 9$ s (Case 3), after the interference appeared, the

Table 7 Spatial fusion results at different times

		A	B	C
$t_1 = 5$ s	m_1	0.9509	0.0189	0.0302
$t_2 = 8$ s	m_2	0.2322	0.1299	0.6379
$t_3 = 16$ s	m_3	0.4425	0.0993	0.4582
$t_4 = 23$ s	m_4	0.1951	0.0920	0.7129
$t_5 = 26$ s	m_5	0.2546	0.1956	0.5498

Table 8 Fusion results obtained using temporal evidence combination based on composite reliability factor (TEC-CRF) and proposed method

	Dempster's rule	The proposed method
$t_1 = 5$ s	$m_{\oplus 1}(A) = 0.9509$, $m_{\oplus 1}(B) = 0.0189$, $m_{\oplus 1}(BC) = 0.0302$	$m_{\oplus 1}(A) = 0.9509$, $m_{\oplus 1}(AB) = 0.0189$, $m_{\oplus 1}(BC) = 0.0302$
$t_2 = 8$ s	$m_{\oplus 2}(A) = 0.5427$, $m_{\oplus 2}(B) = 0.0751$, $m_{\oplus 2}(C) = 0.3822$	$m_{\oplus 2}(A) = 0.4629$, $m_{\oplus 2}(B) = 0.0892$, $m_{\oplus 2}(C) = 0.4480$
$t_3 = 16$ s	$m_{\oplus 3}(A) = 0.4300$, $m_{\oplus 3}(B) = 0.0558$, $m_{\oplus 3}(C) = 0.3441$, $m_{\oplus 3}(ABC) = 0.1701$	$m_{\oplus 3}(A) = 0.4889$, $m_{\oplus 3}(B) = 0.0211$, $m_{\oplus 3}(C) = 0.4900$
$t_4 = 23$ s	$m_{\oplus 4}(A) = 0.2854$, $m_{\oplus 4}(B) = 0.0510$, $m_{\oplus 4}(C) = 0.4868$, $m_{\oplus 4}(ABC) = 0.1768$	$m_{\oplus 4}(A) = 0.2136$, $m_{\oplus 4}(B) = 0.0043$, $m_{\oplus 4}(C) = 0.7821$
$t_5 = 26$ s	$m_{\oplus 5}(A) = 0.2321$, $m_{\oplus 5}(B) = 0.1158$, $m_{\oplus 5}(C) = 0.6521$	—

cumulative temporal fusions of Cases 1–3 were the same. In fact, in these three cases, from the beginning to the time when the interference appeared, all the temporal evidence participating in the fusion was identical; however, the fusion order was different. The characteristics reflected by Dempster's rule in the fusion of temporal evidence were identical to those in the fusion of spatial evidence. However, this does not reflect the influence of time factors on the cumulative results of temporal fusion. In addition, the dynamic characteristics of temporal evidence fusion cannot be reflected. Figure 4 reveals that the cumulative temporal fusion results of the three cases obtained using our method were always different. This behavior reflects the influence of time factors on temporal evidence fusion, which is consistent with the dynamic characteristics of temporal evidence fusion.

Example 2. A comprehensive ballistic target identification system fused information based on the recursive centralized spatiotemporal evidence fusion model. Information from multiple sensors was fused to obtain spatial fusion results at each moment. Then, the aggregated information at each time point was fused temporally. In the identification task, the frame of discernment $\Omega = \{A, B, C\}$ could be obtained by the attributes of the target to be identified. The system's spatial fusion results were m_1, m_2, m_3, m_4, and m_5 for the target at times $t_1 = 5$ s, $t_2 = 8$ s, $t_3 = 16$ s, $t_4 = 23$ s, and $t_5 = 26$ s, respectively. Temporal fusions were implemented based on five BPAs. The details are presented in Table 7.

Owing to the superior anti-interference ability of the TEC-CRF method proposed in [2], for comparison, we used it to handle conflicting information in temporal evidence. Table 8 presents the fusion results using the TEC-CRF method and our proposed method.

Table 7 reveals that only m_1 assigned the maximum degree of belief to A, while the other four evidence sources all assigned the maximum degree of belief to C. Therefore, m_1 can be regarded as interference, and a rational cumulative temporal fusion result should assign the maximum degree of belief to C. Table 8 indicates that both the TEC-CRF method and our method had strong anti-interference ability, gradually reducing the influence of interference, and yielding rational results. Compared with the TEC-CRF method, our proposed method was able to recover more quickly from the interference. This was reflected by the reduced speed of the belief degree on A. Thus, the proposed method could identify the correct target category more quickly, which was beneficial to decision making. At $t_4 = 23$ s, the target could be classified as C. Owing to the negotiation strategy, our method could not yield cumulative temporal fusion results at time $t_5 = 26$ s without reference information.

6 Conclusion

Temporal evidence fusion is sequential, real-time, and dynamic. In the temporal evidence fusion approach, the cumulative temporal fusion result for the current moment can be obtained by fusing the cumulative temporal fusion result of the previous moment and the temporal evidence of the current moment. As there are only two pieces of evidence, it is impossible to determine which is more reliable. This makes it difficult to incorporate the reliability of evidence into the fusion process.

In this paper, a negotiation strategy is introduced to temporal fusion, and a self-adaptive fusion method for temporal evidence is proposed. In this method, temporal evidence at a future moment is used as a reference to form an evidence set together with the cumulative temporal fusion result at the previous moment and temporal evidence at the current moment. Based on the maximum power pignistic probability distance between each pair of evidence in the evidence set, the evidence set is classified as non-conflicting or conflicting. For non-conflicting cases, Dempster's rule is used to fuse the cumulative temporal fusion results at the previous moment and the current temporal evidence. For conflicting cases, after obtaining the reliability of the evidence, the discounting operation is used to revise the evidence prior to fusion using Dempster's rule. Numerical examples demonstrate that our method has strong anti-interference ability and better focusing performance than current alternatives. Moreover, the proposed method aids decision making by decreasing the risk of arbitrary decisions.

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