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Evidence combination method in time domain based on reliability and importance

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Abstract: In order to achieve the information fusion in the time domain based on the evidence theory, an evidence combination method in the time domain based on reliability and importance is proposed according to the idea of evidence discount. Firstly, the distortion of the time-domain evidence is judged based on single exponential smoothing. The real-time reliability of the evidence at the adjacent time is obtained by the real-time reliability assessment method of the evidence based on the credibility decay model. Then, the relative importance of the evidence at the adjacent time is obtained by comprehensively considering improved conflict degree and uncertainty. Finally, based on the criterion of evidence discount and the Dempster's rule of combination, the evidence combination is carried out to achieve the sequential combination of time-domain evidence. The numerical simulation and analysis show that this method has fully embodied the dynamic characteristics of time-domain evidence combination, and it has strong processing ability for conflict information and anti-disturbing ability. The proposed method has good applicability to information fusion in the time domain.

Keywords: evidence theory, time-domain evidence combination, evidence discount, reliability, importance.

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1. Introduction

Since Dempster-Shafer evidence theory [1,2] was put forward and popularized, it has been widely used in the field of information fusion [3 – 7]. At present, the research of information fusion based on evidence theory is mainly focused on the spatial fusion of multi-sensor. However, due to the influence of the performance in itself and external environment disturbing, the information obtained at a certain moment by the sensors may distort. The results of spatial fusion may easily lead to mistakes in decision-making. For example, in a target identification system, a sensor may erroneously identify an enemy fighter that is close to us as still outside the safe distance of attack at a certain moment due to the serious range deception jamming. Then the distortion identification information at this moment may lead to making wrong decisions. In general, the information fusion in the time domain should be carried out based on the information at several moments. A scientific and perfect information fusion process shall be based on the temporal and spatial sequential fusion of multi-sensor. Because of the sequential and dynamic characteristics of information fusion in the time domain, the method for spatial information fusion is not necessarily applicable to the time domain. Therefore, it is necessary to propose an evidence combination method in time domain in line with the characteristics of time-domain information fusion.

The first problem that needs to be solved in evidence combination in the time domain is how to consider the influence of the time factor on fusion results. At present, there are few studies on the evidence combination method in the time domain. Hong et al. [8] proposed three spatial-temporal information fusion models based on the evidence theory, but no corresponding methods for evidence combination in the time domain have been given. Smets [9] introduced the evidence fusion in the time domain, but has not given a detailed description on the physical meaning and mathematical nature of temporal fusion. Song et al. [10,11] believed that the credibility of evidence will decrease over time, so a sequential combination method of the time-domain evidence based on the credibility decay model has been proposed. However, when calculating the reliability of evidence without considering the distortion of input evidence at some time and the evidence is distorted, the proposed evidence combination method in the time domain has poor anti-disturbing ability.

Another key issue in evidence combination in the time domain is how to deal with the conflict between time-domain evidences. In order to solve the combination problem of the high-conflict evidence, the current method for correcting evidence sources is mainly to assess the im-

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portance of evidence based on the similarity relation between evidences [6,12–15], that is, measure the importance of evidence according to the conflict degree between evidences in multiple evidence sources. If the conflict between a certain evidence and other evidences is larger, the evidence can be considered to be less supported by other evidences and the importance is lower. However, when there are only two evidences, regardless of the conflict of evidence information, both the importance of two evidences obtained by the method is 1. Therefore, the importance assessment method based on the similarity relation does not apply to the importance assessment of two evidences at the adjacent time in the time-domain evidence sequence.

Aiming at the problem that the existing time-domain evidence combination methods have not fully considered the influence of the time factor and have poor processing ability for conflict information, an evidence combination method in time domain based on reliability and importance is proposed according to the idea of evidence discount. Firstly, the single exponential smoothing is introduced to judge the distortion of the time-domain evidence. Then, the real-time reliability and relative importance of the evidence at the adjacent time in the time-domain evidence sequence have been obtained by respectively putting forward the real-time reliability assessment method of the evidence based on the credibility decay model and the relative importance assessment method of evidence considering improved conflict degree and uncertainty. Finally, based on the criterion of evidence discount and the Dempster's rule of combination, the evidence combination is carried out to achieve the sequential combination of the time-domain evidence. The evidence combination method in the time domain proposed in this paper has fully considered the influence of time factors on the results of the combination and has the strong dynamics. The proposed method also has the strong processing ability for the conflict evidence in the time-domain evidence sequence.

This paper is organized as follows. Section 2 briefly reviews the preliminaries Dempster-Shafer evidence theory and pignistic probability function. A relative importance assessment method of the evidence considering improved conflict degree and uncertainty is proposed in Section 3, which can be used to assess the relative importance of the time-domain evidence. In Section 4, an evidence combination method in the time domain based on reliability and importance is proposed. Numerical simulation is illustrated in Section 5 to show the efficiency of the proposed method. Finally, this paper is concluded in Section 6.

2. Preliminaries

2.1 Dempster-Shafer evidence theory

Let Θ be a finite set of N mutually exclusive elements, then Θ is called the discriminant frame. The power set of Θ is defined as 2^{Θ}, which is the set of all subsets of Θ.

Definition 1 [1] Let Θ be the discriminant frame. If the function $m : 2^{\Theta} \rightarrow [0,1]$ satisfies the conditions $m(\varnothing) = 0$ and $\sum\limits_{A \subseteq \Theta} m(A) = 1$, then m is called the basic probability assignment (BPA) on Θ. The function m is also called the mass function. For each subset $A \subseteq \Theta$, $m(A)$ is called the basic probability mass (BPM) for A and it reflects the support degree of evidence to the proposition A. If $m(A) > 0$, then A is called a focal element. The union of all focal elements of the evidence is called the nucleus of evidence.

Definition 2 [2] Given a mass function m on the discriminant frame Θ. It is produced by a source of the evidence with a reliability of σ $(0 \leqslant \sigma \leqslant 1)$. Then according to Shafer's criterion of discount, m can be discounted as

$$m^{\sigma}(A) = \begin{cases} \sigma \times m(A), & A \subset \Theta \\ \sigma \times m(A) + 1 - \sigma, & A = \Theta \end{cases}. \tag{1}$$

Definition 3 [1] Let $m_1, m_2, \ldots, m_n$ be the independent mass functions on the discriminant frame Θ. According to Dempster's rule of combination, for each subset $A \subseteq \Theta$, the combined evidence can be obtained by

$$[m_1 \oplus m_2 \oplus \cdots \oplus m_n](A) = \\ \begin{cases} 0, & A = \varnothing \\ \dfrac{\sum\limits_{A_1 \cap A_2 \cap \cdots A_n = A} m_1(A_1) m_2(A_2) \cdots m_n(A_n)}{1 - k}, & A \neq \varnothing \end{cases} \tag{2}$$

where k is the conflict coefficient, which is defined as

$$k = \sum_{A_1 \cap A_2 \cap \cdots A_n = \varnothing} m_1(A_1) m_2(A_2) \cdots m_n(A_n). \tag{3}$$

2.2 Pignistic probability function

When applying the evidence theory to decision-making analysis, it is usually necessary to convert the mass function into a probability distribution on Θ and then make a decision. The pignistic probability conversion method proposed by Smets et al. [16] is based on the average allocation theory, which is widely used because of its small information loss during conversion.

Definition 4 Given a mass function m on the discriminant frame Θ. For each subset $A \subseteq \Theta$, the pignistic probability function $BetP_m : \Theta \rightarrow [0,1]$ is given by

$$BetP_m(A) = \sum_{B \subseteq \Theta} \frac{|A \cap B|}{|B|} \frac{m(B)}{1 - m(\varnothing)}, \quad m(\varnothing) \neq 1 \tag{4}$$

where $|\cdot|$ is the cardinality of a set.

3. Relative importance assessment of evidence considering improved conflict degree and uncertainty

In fact, the similarity relation is only one of the key factors to measure the importance of evidence, which reflects the importance of evidence from the external relation of evidence. The uncertainty is an important index to reflect the clarity of the evidence itself. It is another important factor to measure the importance of evidence for reflecting the importance of evidence from the inside of evidence [17,18]. Therefore, in order to make a comprehensive and objective assessment for the importance of evidence and satisfy the requirements of the importance assessment for time-domain evidence, a relative importance assessment method of evidence considering improved conflict degree and uncertainty is proposed in this section.

3.1 Determination of evidence weight based on improved conflict degree

The commonly-used index to measure evidence conflict degree at present is conflict coefficient and Jousselme distance, while the applications show that the illogical phenomenon may appear based on the method of conflict coefficient or Jousselme distance. However, there is a certain complementarity between the two. Therefore, a method for determination of evidence weight based on improved conflict degree is proposed in this section. Firstly, the improved conflict degree is comprehensively measured based on conflict coefficient and Jousselme distance. Then the weight of each evidence is determined according to the improved conflict degree between the evidence and the average evidence of all evidence sources.

Definition 5 [19] Assuming that there are two mass functions indicated by m_p and m_q on the discriminant frame Θ, the Jousselme distance between m_p and m_q is defined as

$$d_{BPA}(m_p, m_q) = \sqrt{\frac{1}{2}(\vec{m}_p - \vec{m}_q)^{\mathrm{T}} \underline{\underline{\boldsymbol{D}}}(\vec{m}_p - \vec{m}_q)} \quad (5)$$

where $\vec{m}_p, \vec{m}_q$ are the vector forms of m_p and m_q, $\underline{\underline{\boldsymbol{D}}}$ is the positive definite matrix of $2^N \times 2^N$, in which the element is given by

$$D(A,B) = \frac{|A \cap B|}{|A \cup B|}, \quad A, B \in 2^{\Theta}. \quad (6)$$

If θ is an assumption on Θ, the maximum support assumption of evidence m is $\arg\max\limits_{\theta\in\Theta}(BetP_m(\theta))$. Let k_{pq} and d_{pq} respectively represent the conflict coefficient and Jousselme distance between evidence m_p and m_q, then the improved conflict degree cf_{pq} between evidence m_p and m_q can be obtained by

$$cf_{pq} = \begin{cases} 0, \quad \forall\theta \in 2^{\Theta}; m_p(\theta) = m_q(\theta) \\ 1, \quad (\cup A_p) \cap (\cup B_q) = \varnothing; \\ \qquad m_p(A_p) > 0, m_q(B_q) > 0 \\ \sqrt{\dfrac{k_{pq} + d_{pq}}{2}}, \quad (\cup(\arg\max\limits_{\theta\in\Theta}(BetP_{m_p}(\theta))))\cap \\ \qquad (\cup(\arg\max\limits_{\theta\in\Theta}(BetP_{m_q}(\theta)))) = \varnothing \\ \dfrac{k_{pq} + d_{pq}}{2}, \quad \text{otherwise} \end{cases} \quad (7)$$

where k_{pq} can be calculated by (3). The meaning of (7) is as follows. The improved conflict degree is a real number between 0 and 1. When two evidences are completely identical, the improved conflict degree is the minimum value of 0. When two evidences have no common focal element, the improved conflict degree is the maximum value of 1. When there is no common element between the sets made up by the maximum support assumptions of two evidences, the improved conflict degree is bigger and let it be $\sqrt{\dfrac{k_{pq} + d_{pq}}{2}}$. When there is a common element between the sets made up by the maximum support assumptions of two evidences, the improved conflict degree is smaller and let it be $\dfrac{k_{pq} + d_{pq}}{2}$.

In order to determine the improved conflict degree between each evidence and the average evidence of all evidence sources, firstly, the average evidence of all evidence sources shall be constructed. Considering that the subset greatly supported by the majority of evidence on Θ is also greatly supported by the average evidence, therefore, the mean m_0 can be calculated for all evidence as a representation of the majority opinion. Assuming that there are n evidences m_i $(i = 1, 2, \dots, n)$ to be combined, the average evidence m_0 is

$$m_0(A) = \frac{\sum\limits_{i=1}^{n} m_i(A)}{n}, \quad \forall A \subseteq \Theta. \quad (8)$$

After determining the average evidence m_0 of all evidence sources, the improved conflict degree cf_{i0} between evidence m_i and m_0 can be calculated by (3) to (7). The bigger cf_{i0} is, the less consistent the evidence m_i with the majority opinion is and the smaller the weight is. On the contrary, the greater the weight is. Thus, the evidence weight based on improved conflict degree is

$$\omega_i^c = \frac{1 - cf_{i0}}{\sum\limits_{i=1}^{n}(1 - cf_{i0})}. \quad (9)$$

3.2 Determination of evidence weight based on uncertainty

In the last decades, various uncertainty measures [20] in Dempster-Shafer evidence theory have been proposed, such as aggregated uncertainty (AU) [21], total uncertainty (TU) [22] and ambiguity measure (AM) [23]. However, all of them are not entirely satisfactory. Deng [24] proposed a new uncertainty measure method named as Deng entropy and proved that the method can measure the uncertainty of evidence more accurately than the existing methods. Therefore, the uncertainty measure method from Deng [24] is referenced to propose a determination method of evidence weight based on uncertainty.

Definition 6 Given a mass function m on the discriminant frame Θ. The Deng entropy of m is defined as

$$E_d(m) = -\sum_{A\subseteq\Theta} m(A)\log_2 \frac{m(A)}{2^{|A|}-1}. \tag{10}$$

Let $E_d(m_i)$ be the Deng entropy of evidence m_i, then the weight of m_i is given by

$$\beta_i = \exp(-\frac{E_d(m_i)}{\sum_{i=1}^{n} E_d(m_i)}). \tag{11}$$

After the normalization for β_i, the obtained evidence weight based on uncertainty is

$$\omega_i^u = \frac{\beta_i}{\sum_{i=1}^{n}\beta_i}. \tag{12}$$

3.3 Relative importance assessment of evidence

Most of the existing methods for evidence importance assessment have only considered one factor between the consistency between evidence or the uncertainty in the evidence itself. In fact, these two factors have a great influence on the combination results. Only when a certain evidence is true, reliable and orderly, can it be given a higher importance. Therefore, on the basis of respectively determining the evidence weight based on improved conflict degree and the evidence weight based on uncertainty, the importance of evidence is determined as follows:

$$\omega_i = \eta\omega_i^c + (1-\eta)\omega_i^u \tag{13}$$

where ω_i^c is the evidence weight considering improved conflict degree, ω_i^u is the evidence weight considering uncertainty, η $(0 \leqslant \eta \leqslant 1)$ is the compromise coefficient and $\eta = 0.5$ is taken in this paper.

In the relative importance assessment of evidence, the relative importance of the evidence that has the highest importance is usually given as 1. Therefore, after normalization, the obtained relative importance of evidence by considering improved conflict degree and uncertainty is

$$I_i = \frac{\omega_i}{\max\limits_{1\leqslant i\leqslant n}(\omega_i)}, \quad i = 1, 2, \ldots, n. \tag{14}$$

4. Evidence combination method in time domain based on reliability and importance

In an information fusion system, the decision information at a certain moment depends not only on the information input in the system at that time, but also shall be closely related to the decision information at last time. Therefore, in order to achieve the recursive combination of conflict evidence in time sequence, an evidence combination method in time domain based on reliability and importance is proposed according to the idea of evidence discount and the non-feedback fusion model of recursive distribution in spatial-temporal information [8], which is shown in Fig. 1.

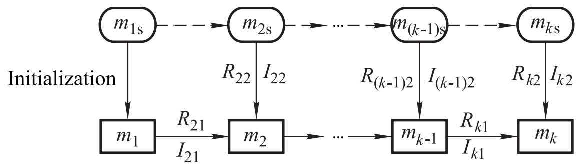

Fig. 1 The sequential combination procedure of time-domain evidence based on reliability and importance

In Fig. 1, m_{ts} $(t = 1, 2, \ldots, k)$ is the spatial fusion evidence of multiple sensors at moment t, which is also an input evidence of the sequential combination of time-domain evidence. m_t is the accumulative fusion evidence at moment t. R_{t1} and R_{t2} are respectively the real-time reliability of m_{t-1} and m_{ts} at moment t. I_{t1} and I_{t2} are respectively the relative importance of m_{t-1} and m_{ts}. The dotted arrow denotes distortion judgment of evidence. The solid arrow denotes the evidence discount and combination. Without loss of generality, the evidence combination in time domain at moment k is taken as an example to be analyzed in this paper.

4.1 Distortion judgment of evidence based on single exponential smoothing

Generally, in the evidence information of the time sequence, the BPM of a certain subset on the discriminant frame shall fluctuate around a certain average level at any moment. However, due to the existence of fault, noise disturbing and other various internal and external reasons, the output information of a sensor at some moment may distort. During time-domain evidence combination, the input evidence at that moment may have the phenomenon where the trend of evidence change is inconsistent with the previous input evidence. Therefore, a distortion judgment method of evidence based on single exponential smoothing is proposed in this section. Firstly, the input evidence at present is predicted with single exponential smoothing. Then the distortion of input evidence is judged according to the improved conflict degree between the input evidence at present and the predicted evidence.

Let $m_{1\mathrm{s}}, m_{2\mathrm{s}}, \dots, m_{(k-1)\mathrm{s}}$ be the input evidence at each previous moment. For $A_j \subseteq \Theta$ $(j = 1, 2, \dots, 2^N)$, the predicted value $\widehat{y}_{k\mathrm{s}}(A_j)$ of BPM at present is

$$\begin{cases} \widehat{y}_{k\mathrm{s}}(A_j) = \alpha_j \times m_{(k-1)\mathrm{s}}(A_j) + (1-\alpha_j) \times \widehat{y}_{(k-1)\mathrm{s}}(A_j) \\ \widehat{y}_{1\mathrm{s}}(A_j) = [m_{1\mathrm{s}}(A_j) + m_{2\mathrm{s}}(A_j)]/2 \end{cases} \tag{15}$$

where $m_{(k-1)\mathrm{s}}(A_j)$ is the actual value of BPM at moment $k-1$, $\widehat{y}_{(k-1)\mathrm{s}}(A_j)$ is the predicted value of BPM at moment $k-1$, α_j $(0 < \alpha_j < 1)$ is the smoothing factor.

In general, the mean-square error is used to measure the prediction accuracy of single exponential smoothing. The mean-square error of the predicted value at each moment is

$$MSE_j = \frac{\sum\limits_{t=1}^{k-1} [m_{t\mathrm{s}}(A_j) - \widehat{y}_{t\mathrm{s}}(A_j)]^2}{k-1}. \tag{16}$$

The most important problem is to reasonably determine the smoothing factor α_j while predicting by single exponential smoothing. The method commonly used at present is to select several representative parameters for prediction, and the principle with minimum mean-square error is used to determine the value of α_j. The parameters selected in this paper is $\{0.1, 0.3, 0.5, 0.7, 0.9\}$.

Through the above calculation, the predicted values of BPM of all subsets on the discriminant frame at present can be determined. After the normalization for them, the obtained predicted value $\widehat{m}_{k\mathrm{s}}$ of input evidence at present is

$$\widehat{m}_{k\mathrm{s}}(A_j) = \frac{\widehat{y}_{k\mathrm{s}}(A_j)}{\sum\limits_{j=1}^{2^N} \widehat{y}_{k\mathrm{s}}(A_j)}, \quad A_j \subseteq \Theta. \tag{17}$$

Assuming that the input evidence at present is $m_{k\mathrm{s}}$, then the improved conflict degree $cf_{k\mathrm{s}}$ between evidence $m_{k\mathrm{s}}$ and $\widehat{m}_{k\mathrm{s}}$ can be calculated by (3) to (7). Set the conflict threshold δ $(0 \leqslant \delta \leqslant 1)$, if $cf_{k\mathrm{s}} > \delta$ is satisfied, it is determined that $m_{k\mathrm{s}}$ distorts. Otherwise, $m_{k\mathrm{s}}$ is not distorted.

4.2 Real-time reliability assessment of evidence based on credibility decay model

During time-domain evidence combination, it is usually necessary to consider the influence of the time factor on combination results. Song et al. [10,11] has considered the effect of evidence credibility decay during the research on sequential combination of time-domain evidence. This opens up a new way to study time-domain evidence combination, but the shortcomings are that the distortion of input evidence has not been considered. When the input evidence distorts, the combination results obtained by the above methods are often easily to lead to mistakes in decision-making. Therefore, on the basis of the distortion judgment method of evidence based on single exponential smoothing, a real-time reliability assessment method of evidence based on the credibility decay model is proposed in this section.

Definition 7 [10] Credibility decay model. Let m_i be the evidence produced at moment t_i, its dynamic credibility at moment t_j $(t_j > t_i)$ is defined as

$$R_{ij} = \mathrm{e}^{-\lambda(t_j - t_i)} \tag{18}$$

where λ $(\lambda > 0)$ is the credibility decay factor. In order to reduce information loss, generally let λ be $0 < \lambda < \ln 2$.

Generally, as time goes on, the output information of sensors will be more and more accurate. Therefore, during the sequential combination of time-domain evidence, the influence of $m_{k\mathrm{s}}$ on fusion results is greater, so a higher reliability shall be given to it. While the influence of m_{k-1} on fusion results is smaller, so a lower reliability shall be given to it. However, if $m_{k\mathrm{s}}$ distorts because the sensors are disturbed or due to other reasons, and if a higher reliability is still given to $m_{k\mathrm{s}}$ at this time, while a lower reliability is given to m_{k-1} at the same time, the information fusion system will be interfered and even make wrong decisions. Therefore, the reliability of time-domain evidence shall be assessed according to whether the input evidence is distorted.

Let R_{k1} and R_{k2} respectively represent the real-time reliability of m_{k-1} and $m_{k\mathrm{s}}$ at moment k. Their value can be determined according to the results of distortion judgment of $m_{k\mathrm{s}}$:

$$[R_{k1}, R_{k2}] = \begin{cases} [\mathrm{e}^{-\lambda(t_k - t_{k-1})}, 1], & cf_{k\mathrm{s}} \leqslant \delta \\ [1, \mathrm{e}^{-\lambda(t_k - t_{k-1})}], & cf_{k\mathrm{s}} > \delta \end{cases}. \tag{19}$$

After determining the real-time reliability R_{k1} and R_{k2}, the evidence m_{k-1} and $m_{k\mathrm{s}}$ can be discounted according to the Shafer's criterion of discount, and the evidences after discounting are respectively

$$m_{k-1}^{R_{k1}}(A) = \begin{cases} R_{k1} \times m_{k-1}(A), & A \subset \Theta \\ R_{k1} \times m_{k-1}(A) + 1 - R_{k1}, \\ \quad A = \Theta \end{cases} \tag{20}$$

$$m_{k\mathrm{s}}^{R_{k2}}(A) = \begin{cases} R_{k2} \times m_{k\mathrm{s}}(A), & A \subset \Theta \\ R_{k2} \times m_{k\mathrm{s}}(A) + 1 - R_{k2}, \\ \quad A = \Theta \end{cases}. \tag{21}$$

4.3 Relative importance assessment and combination of evidence

The key to time-domain evidence combination is to handle the conflict between m_{k-1} and m_{ks} reasonably. The real-time reliability assessment method of evidence based on the credibility decay model has only considered the timeliness of time-domain evidence itself, but has not fully considered the intrinsic relation between m_{k-1} and m_{ks}. Therefore, the reliability assessment result is not comprehensivey enough. In order to further improve the conflict information processing ability of the time-domain evidence combination method, based on the relative importance assessment method of evidence considering improved conflict degree and uncertainty proposed in Section 3, the importance of two evidences at the adjacent time in time-domain evidence sequence shall be assessed in this section.

According to the relative importance assessment method of evidence considering improved conflict degree and uncertainty, the relative importance I_{k1} and I_{k2} of $m_{k-1}^{R_{k1}}$ and $m_{ks}^{R_{k2}}$ can be obtained. Then the evidence $m_{k-1}^{R_{k1}}$ and $m_{ks}^{R_{k2}}$ can be discounted according to the Shafer's criterion of discount, and the evidences after discounting are respectively

$$m_{k-1}^{R_{k1},I_{k1}}(A)=\begin{cases} I_{k1}\times m_{k-1}^{R_{k1}}(A), & A\subset\Theta \\ I_{k1}\times m_{k-1}^{R_{k1}}(A)+1-I_{k1}, & \\ \quad A=\Theta & \end{cases} \tag{22}$$

$$m_{ks}^{R_{k2},I_{k2}}(A)=\begin{cases} I_{k2}\times m_{ks}^{R_{k2}}(A), & A\subset\Theta \\ I_{k2}\times m_{ks}^{R_{k2}}(A)+1-I_{k2}, & . \\ \quad A=\Theta & \end{cases} \tag{23}$$

Finally, the combination can be carried out with the Dempster's rule of combination to achieve the sequential combination of conflict evidence in time domain.

5. Numerical simulation

Assuming that the discriminant frame of a mid-course ballistic target integrated identification system is $\Theta = \{A,B,C\}$. Multiple sensors have identified the targeted category at six consecutive moments. The evidence after the spatial fusion of data provided by multi-sensor at each moment shall be the input evidence of sequential combination in time domain, as shown in Table 1.

Table 1 Input evidence of each moment

Moment/s	$m_s(A)$	$m_s(B)$	$m_s(C)$
$t_1=0$	0.60	0.10	0.30
$t_2=5$	0.65	0.15	0.20
$t_3=10$	0.60	0.20	0.20
$t_4=15$	0	0.85	0.15
$t_5=20$	0.55	0.20	0.25
$t_6=25$	0.60	0.15	0.25

To verify the efficiency of the proposed method in this paper, the input evidence of each moment shall be combined respectively by Dempster's rule, Song's method [10], Song's method [11], the proposed method without considering the uncertainty of evidence (WCUE) and the proposed method. The obtained cumulative fusion evidence of each moment is shown in Table 2. Give the conflict threshold $\delta = 0.5$ and the credibility decay factor $\lambda = 0.05$ in the numerical simulation.

5.1 Effectiveness of the proposed method

To facilitate intuitive analysis, the trends of pignistic probability distribution varies with moment when implementing time-domain evidence combination based on Dempster's rule, Song's method [10], Song's method [11], the proposed method WCUE and the proposed method are respectively shown in Fig. 2 – Fig. 6. The analysis on Table 2 and Fig. 2 – Fig. 6 reflects that when the sensors provide the normal data at moment $t_1 - t_3$, the proposed method, Dempster's rule, Song's method [10], Song's method [11] and the proposed method WCUE can make a correct decision at any moment. However, Dempster's rule has not considered the timeliness of time-domain evidence itself and merely combines the time-domain evidence in sequence, which has low credibility for fusion results. The proposed method, Song's method [10], Song's method [11] and the proposed method WCUE have taken the influence of the time factor into account while fusing. Compared with Song's method [11], the proposed method, Song's method [10] and the proposed method WCUE have a rapid rate of convergence and are more conductive to making a decision due to less uncertainty for fusion results. Therefore, the proposed method has fully embodied the dynamic characteristics of time-domain evidence combination, which can effectively handle the conflict information of time-domain evidence.

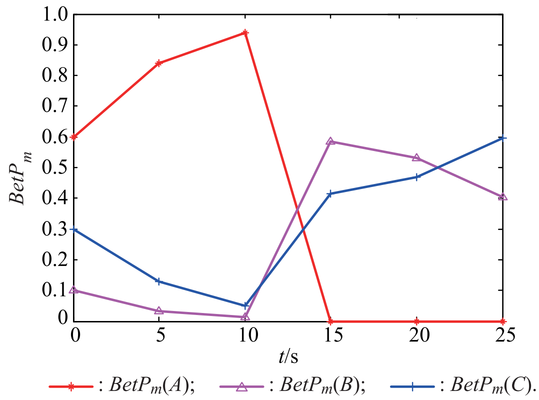

Fig. 2 Pignistic probability based on Dempster's rule

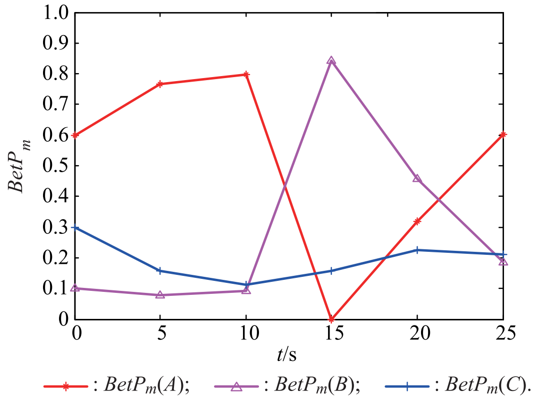

Fig. 3 Pignistic probability based on Song's method [10]

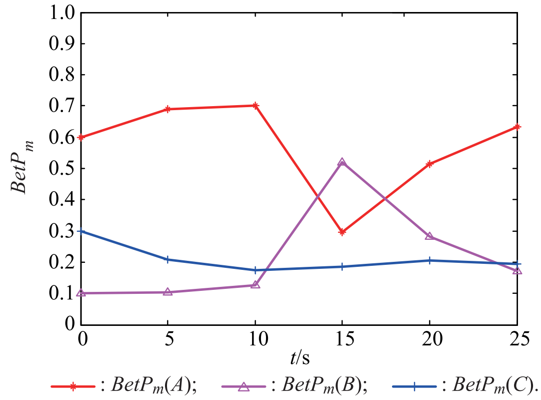

Fig. 4 Pignistic probability based on Song's method [11]

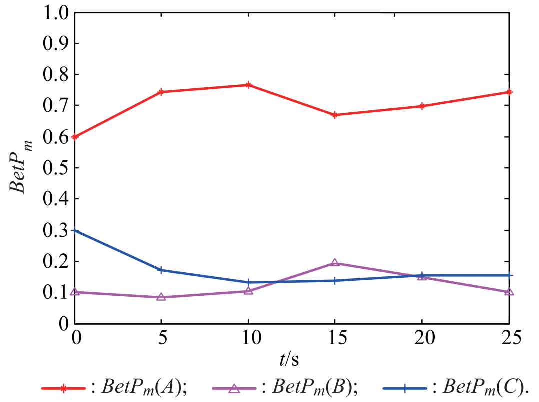

Fig. 5 Pignistic probability based on the proposed method WCUE

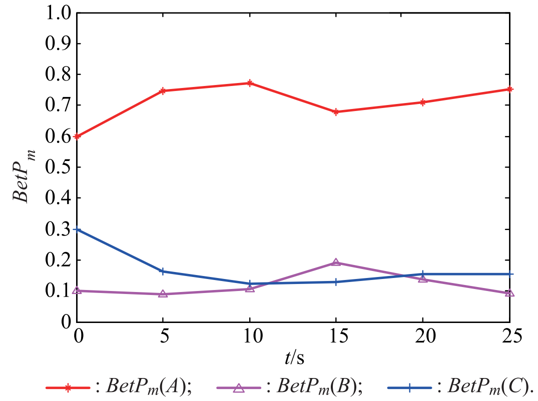

Fig. 6 Pignistic probability based on the proposed method

Table 2 Cumulative fusion evidence of each moment

Method	$t_2 = 5$ s	$t_3 = 10$ s	$t_4 = 15$ s	$t_5 = 20$ s	$t_6 = 25$ s
Dempster's rule	$m(A) = 0.838\,7$	$m(A) = 0.939\,8$	$m(A) = 0$	$m(A) = 0$	$m(A) = 0$
	$m(B) = 0.032\,3$	$m(B) = 0.012\,0$	$m(B) = 0.586\,2$	$m(B) = 0.531\,3$	$m(B) = 0.404\,8$
	$m(C) = 0.129\,0$	$m(C) = 0.048\,2$	$m(C) = 0.413\,8$	$m(C) = 0.468\,7$	$m(C) = 0.595\,2$
	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$
Song's method [10]	$m(A) = 0.767\,2$	$m(A) = 0.797\,4$	$m(A) = 0$	$m(A) = 0.317\,6$	$m(A) = 0.602\,3$
	$m(B) = 0.076\,9$	$m(B) = 0.091\,3$	$m(B) = 0.843\,3$	$m(B) = 0.458\,4$	$m(B) = 0.185\,8$
	$m(C) = 0.155\,9$	$m(C) = 0.111\,3$	$m(C) = 0.156\,7$	$m(C) = 0.224\,0$	$m(C) = 0.211\,9$
	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$
Song's method [11]	$m(A) = 0.665\,1$	$m(A) = 0.664\,2$	$m(A) = 0.246\,5$	$m(A) = 0.503\,2$	$m(A) = 0.610\,5$
	$m(B) = 0.077\,2$	$m(B) = 0.089\,1$	$m(B) = 0.471\,5$	$m(B) = 0.270\,2$	$m(B) = 0.148\,4$
	$m(C) = 0.182\,4$	$m(C) = 0.137\,0$	$m(C) = 0.135\,9$	$m(C) = 0.194\,5$	$m(C) = 0.172\,4$
	$m(\Theta) = 0.075\,3$	$m(\Theta) = 0.109\,7$	$m(\Theta) = 0.146\,1$	$m(\Theta) = 0.032\,1$	$m(\Theta) = 0.068\,7$
The proposed method WCUE	$m(A) = 0.737\,2$	$m(A) = 0.753\,2$	$m(A) = 0.658\,7$	$m(A) = 0.684\,8$	$m(A) = 0.732\,3$
	$m(B) = 0.077\,0$	$m(B) = 0.090\,6$	$m(B) = 0.182\,3$	$m(B) = 0.134\,9$	$m(B) = 0.089\,7$
	$m(C) = 0.163\,7$	$m(C) = 0.119\,4$	$m(C) = 0.126\,8$	$m(C) = 0.140\,2$	$m(C) = 0.141\,4$
	$m(\Theta) = 0.022\,1$	$m(\Theta) = 0.036\,8$	$m(\Theta) = 0.032\,2$	$m(\Theta) = 0.040\,1$	$m(\Theta) = 0.036\,6$
The proposed method	$m(A) = 0.746\,2$	$m(A) = 0.771\,0$	$m(A) = 0.679\,7$	$m(A) = 0.708\,4$	$m(A) = 0.753\,3$
	$m(B) = 0.090\,0$	$m(B) = 0.106\,0$	$m(B) = 0.191\,8$	$m(B) = 0.138\,2$	$m(B) = 0.090\,9$
	$m(C) = 0.163\,8$	$m(C) = 0.123\,0$	$m(C) = 0.128\,5$	$m(C) = 0.153\,4$	$m(C) = 0.155\,8$
	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$	$m(\Theta) = 0$

When the sensors are disturbed at moment t_4, Dempster's rule has fallen into the trouble of "one-vote veto" because it has not considered the real-time reliability and relative importance of evidence. Thereafter, regardless of the support degree of input evidence to A at each moment, the support degree to A is 0 in the final results, and the system can no longer return to normal. Song's method [10] mistakenly determines the identification results as B at moment t_4 and t_5 due to the lack of evidence distortion judgment mechanism and evidence relative importance assessment method, and the system returns to normal until moment t_6. Song's method [11] mistakenly determines the identification results as B at moment t_4 due to the lack of evidence distortion judgment mechanism. Although it can correctly identify A at moment t_5, the support degree to B is still greater, and the system returns to normal until moment t_6. Moreover, the fusion results of Song's method [11] have greater uncertainty than other four methods, which is not conductive to making a decision. Although the support degree to B at moment t_4 is increased relatively, the proposed method and the proposed method WCUE can still correctly identify A, and the system returns to normal until moment t_5. However, compared with the proposed method WCUE, the proposed method can assess the relative importance of evidence more comprehensively due to considering the uncertainty in the evidence itself. Therefore, the proposed method has rapid rate of convergence and is more conductive to making a decision due to less uncertainty for fusion results. As a result, compared with other four methods, the proposed method has stronger processing ability for conflict information of time-domain evidence, which is more conductive to making a correct decision in time.

5.2 Anti-disturbing ability of the proposed method

To carry out further comparison with Dempster's rule, Song's method [10], Song's method [11] and the proposed method WCUE, the variation of $BetP_m(A)$ at each moment in five methods shall be drawn, as shown in Fig. 7.

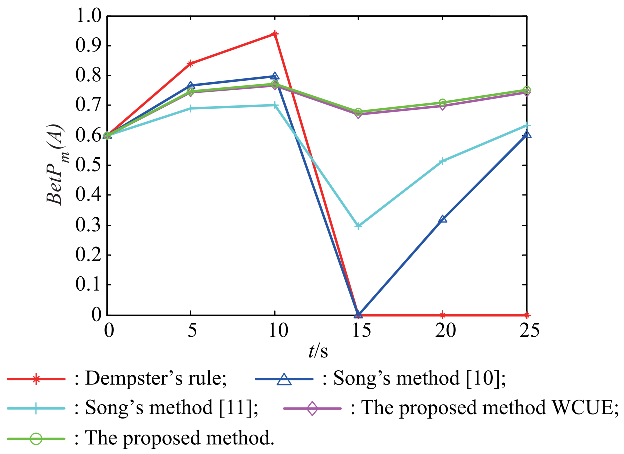

Fig. 7 Variation of $BetP_m(A)$ at each moment in five methods

It is obvious that when the sensors are disturbed at moment t_4, the fluctuation of $BetP_m(A)$ in the proposed method is smaller, which further shows that the proposed method can effectively handle the conflict information of time-domain evidence and has stronger anti-disturbing ability.

6. Conclusions

Evidence theory has been widely used in the field of spatial-temporal information fusion. To achieve the sequential combination of the time-domain evidence effectively, an evidence combination method in the time domain based on reliability and importance is proposed according to the idea of evidence discount in this paper. The numerical simulation and analysis show that the proposed method has fully taken the influence of the time factor into account and meets the dynamic characteristics of information fusion in the time domain. Furthermore, the proposed method can effectively handle the conflict information of the time-domain evidence and has the strong anti-disturbing ability, which is applicable to information fusion in the time domain.

What needs to be pointed out is that there are still many problems to be solved in time-domain evidence combination due to the complexity of information fusion, such as the determination of the time-domain evidence combination rule, the evaluation of combination results and other aspects, which are the emphases of our further research.

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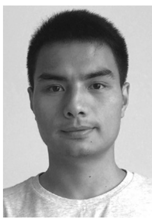
Biographies



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