The Improvement of DS Evidence Theory and its Application in IR/MMW Target Recognition

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***Abstract*—ATR system has a broad application prospect in military, especially in the field of modern defense technology. When paradoxes are existence in ATR system due to adverse battlefield environment, integration cannot be effectively and reliably carried out only by traditional DS evidence theory. In this paper, A modified DS evidence theory is presented and applied in IR/MMW target recognition system to improve recognition rate. The improvement of DS evidence theory is realized by three steps. In order to ensure the consistency and reliability of different sources of evidence, it firstly introduces two impact factors as sensor priority and evidence credibility to realize the discount processing of evidences. Then, DS combination rule is modified to further enhance the accuracy of synthesis results through the global distribution of overall conflicts instead of the normalization step. Finally, it uses the compound decision making rule to get target recognition results. The application of the modified DS evidence theory in IR/MMW system is designed to deal with paradoxes caused by environmental uncertainty and imperfect knowledge, improve the target recognition rate, and ensure the reliability of target recognition system. Experiments are given to illustrate that the introduction of the modified DS evidence theory in IR/MMW system is better able to realize satisfactory target recognition performance through multi-sensor information fusion than any single-mode system.**

***Index Terms*—DS evidence theory, Target recognition, IR/MMW system, Multi-sensor information fusion.**

I. INTRODUCTION

AUTOMATIC target recognition system, namely the ATR system, has become an important part of the present and the future weapon system. For ATR systems in the modern warfare, with the growing complexity of battlefield environment, information that acquires from sensors is often incomplete, inaccurate, and has some degree of uncertainty and fuzziness, possibly is even contradictory. ATR system with single sensor has many limitations like weak anti-interference ability and low recognition reliability. Single-mode systems can't suit the demand of future battlefield because of their dependence on the observation environment. The complementarity and synergistic interaction of sensors can improve the ATR ability in dynamic scene. In consideration of defects and limitations of single-mode systems, IR/MMW fusion, as an inevitable trend of compound target recognition algorithm, can adopt others' strong points while overcoming its weak point, and make the system adapt to continued deterioration of battlefield environment and dynamical changes of objectives.

Uncertainty reasoning is the foundation of IR/MMW system, which can deal with incomplete, uncertain and unclear information that exists in IR/MMW system effectively. DS evidence theory, also known as Dempster-Shafer theory, is a common and wild used uncertainty reasoning [1], [2]. It has been widely used in many fields like expert system [3], [4], artificial intelligence [5], [6], fault diagnosis [7], [8], target recognition [9], [10], target tracking [11], decision making [12], and information fusion [13], etc. However, Wang found that traditional DS evidence theory cannot produce reasonable synthesis results in the case of paradoxes(because of the complexity of practical environment and probable conflicts of evidence sources) [14]. Therefore, DS evidence theory is improved primarily before its application in IR/MMW system.

Domestic and foreign researchers have done a lot of researches to solve paradoxes, which are mainly divided into two categories: the improved DS combination rules and the modified conflict evidences methods.

Some researchers think that unreasonable results are mainly caused by the normalization step of DS combination rule. Thus it optimizes the DS combination rule by giving evidence conflicts to certain subset with certain proportion, which is called the improved DS combination rule. In Smets's opinion, Θ is regarded as an incomplete set and conflicts are given to an unknown proposition [15]. This method solves paradoxes theoretically, but it actually increases the uncertainty of synthesis results by introducing an unknown proposition. Yager allotted conflicts directly to Θ [16]. However, it can only settle paradoxes efficiently with two evidence sources in system, and its too conservative to admit the useful information that exists in conflict evidences. On these basis, an improved method is proposed by dividing evidences into support evidences and conflict evidences, which solves the problem of unequal information quantity among evidences [17]. In addition, another algorithm proportionally allocates the conflicts to every focal element of conflict evidences through the introduction of a weight factor that is proportional to the conflicts [18]. In order to distinguish the local conflicts and global conflicts effectively, and make the system robust simultaneously, a new DS combination rule named absorptive method is put forward by allocating local conflicts directly to local propositions [19].

Other scholars consider that paradoxes are mainly caused by unreliable evidences. Therefore, it modifies evidences instead of changing the DS combination rule, which is called the modified conflict evidences method. Among them, an improved method is put forward by considering the average mean of evidences as a new evidence before evidences combination [20].

But it is obvious that the idea only averages the evidences without considering their differences. Takahiko came up with a method through calculating a new evidence by the weight sum of evidences instead of simple average [21]. In order to efficiently combine high conflict evidences, a novel method is proposed through the introduction of the distance function introduced by Lefevre, which can improve the reliability of system [21]. To manage conflict evidences, global conflicts are allocated in detail to several local conflicts, and a new method is presented based on number, reliability and relevance of evidence sources [23].

These two mainstream improved methods both solve paradoxes just on the sight of single angle without fully considering the differences among sensors and uncertainty of observation environment. In this paper, the novel algorithm firstly takes the consistency and reliability of evidence sources into consideration concurrently, thus introduces sensor priority and evidence credibility to realize discount processing of evidences. Then, it cancels the normalization step of DS combination rule to decrease the interference and unpredictability of observation environment and further enhance the reliability and rationality of synthesis results. Finally, it puts the synthesis results into decision making rule to get target recognition results. Experiment results demonstrate that the application of the novel method in IR/MMW system can improve the target recognition rate, ensure reliable operation of system, and enhance the battlefield adaptability, anti-jamming immunity, anti-stealth performance, and precision of target identification.

This paper is organized as follows. The foundation and discussions of traditional DS evidence theory are summarized in section II. Then, as the cores of this paper, section III highlights the modified DS evidence theory, and section IV provides the specific implement steps of its application in IR/MMW target recognition system. In section V, experiment results and analyses are shown to manifest the validity of the novel algorithm from the points of theory and application. And conclusions are presented in section VI at the end.

II. DS Evidence Theory

Researches were done for ATR system using DS evidence theory back in the 90s [24], [25]. The feasibility of applying DS evidence theory in ATR system has been testified in [26]. And in [27], it shows that compared with sugero's theory and possibility theory, the best performance in ATR system is achieved by DS evidence theory. Thus, DS evidence theory makes the system not only more powerful but also more robust [28].

A. Preliminaries

DS evidence theory firstly supposes the definition of a finite nonempty set of hypotheses as the frame of discernment (called FoD for short), which consists of N mutually exclusive and exhaustive hypotheses. The FoD is defined as follows:

$$\Theta = \{H_1, H_2, \cdots, H_N\} \tag{1}$$

where, N is the number of hypotheses in system, and H is a hypothesis of the FoD.

For example, in pattern recognition system, there are a set of N mutually disjoint classes in the pattern space. Thus, the FoD should be defined as $\Theta = \{w_1, w_2, \cdots, w_N\}$, where w is a class in the pattern space.

Then, let us denote 2^Θ as the power set, which is composed with 2^N propositions of Θ.

$$\begin{aligned} 2^\Theta =& \{\varnothing, H_1, H_2, \cdots, H_N, \{H_1 \cup H_2\}, \\ & \{H_1 \cup H_3\}, \cdots, \{H_1 \cup H_2 \cup \cdots H_N\}\} \end{aligned} \tag{2}$$

where $\varnothing$ is the empty set, and any proposition in 2^Θ is a subset of Θ.

The basic probability assignment(called BPA for short) on 2^Θ, also called the basic belief assignment(called BBA for short), is a function $m : 2^\Theta \to [0, 1]$, which should satisfies the following conditions:

$$\begin{cases} m(\varnothing) = 0 \\ \sum\limits_{A \subseteq \Theta} m(A) = 1 \end{cases} \tag{3}$$

where, A is a proposition in 2^Θ which contains one or more hypotheses, and $m(A)$ represents the initial support degree for proposition A.

Due to the lack of further information, the BPA of proposition A cannot be subdivided into its proper subset. Any proposition A satisfying that $m(A) > 0 (A \subseteq \Theta)$ is called a focal element, and the set of all focal elements is called the core of BPA.

The belief function(called Bel for short) and plausibility function(called Pl for short) in 2^Θ is defined respectively as:

$$\begin{cases} Bel(A) = \sum\limits_{B \subseteq A} m(B) \\ Pl(A) = \sum\limits_{B \cap A \neq \Phi} m(B) \end{cases} \quad A, B \subseteq \Theta \tag{4}$$

where, A, B are both the propositions in 2^Θ.

It can be seen from formula(4) that the Bel of proposition A is interpreted as the minimum uncertainty value of A which constitutes a lower limit function on the probability of A, while its Pl is interpreted as the maximum uncertainty value of A which constitutes an upper limit function. And the relationship between $Bel(A)$ and $Pl(A)$ is defined as follows, which is shown in fig.1.

$$\begin{cases} Bel A \leq Pl(A) \\ Pl(A) = 1 - Bel(\bar{A}) \end{cases} \quad A \subseteq \Theta \tag{5}$$

where, $\bar{A}$ is the complement set of A.

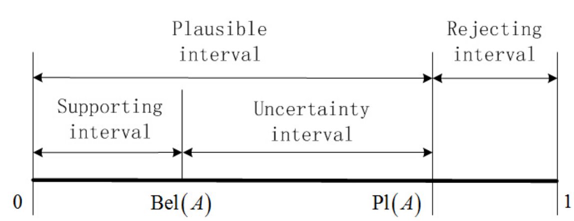


Fig. 1: The relationship diagram of $Bel(A)$ and $Pl(A)$

The interval $[Bel(A), Pl(A)]$ is named as the belief interval or uncertainty interval, which represents the uncertainty and imprecision of DS evidence theory. Suppose that $m_1, m_2, \cdots, m_N$ are N mutually independent $BPAs$ from N different sensors in the same FoD based on information detection. The DS combination rule, noted by $m = m_1 \oplus m_2 \oplus \cdots \oplus m_N$,is also called the orthogonal sum of evidences. Thus, the combination of $m_i, m_j (i, j = 1, 2, \cdots, N)$ can be defined as:

$$\begin{cases} m_{ij}(A) = \dfrac{1}{1-k} \displaystyle\sum_{A_i \cap A_j = A} m_i(A_i) \cdot m_j(A_j) \\ m(\varnothing) = 0 \qquad\qquad\qquad A \subseteq \Theta, A \neq \varnothing \end{cases} \tag{6}$$

where, k is called the total conflict factor, and it represents the total conflicts between evidence m_i and m_j:

$$k = \sum_{A_i \cap A_j = \varnothing} m_i(A_i) \cdot m_j(A_j) \tag{7}$$

k demonstrates the degree of conflicts between evidences, and $\frac{1}{1-k}$ is the normalization factor which ensures that the sum of $BPAs$ can be unit, and the BPA for null set is none. According to similar principle, we can calculate the corresponding $Bel(A)$ and $Pl(A)$.

Obviously, the DS combination rule satisfies both commutative law and associate law, which are shown separately as:

$$\begin{cases} m_1 \oplus m_2 = m_2 \oplus m_1 \\ (m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3) \end{cases} \tag{8}$$

B. Common paradoxes

Uncertainty of system can be categorized into four areas shown in [29]. Firstly, knowledge representation can be defined as confirmed, probable, possible, doubtful, and improbable to support the propositions, but the system cannot guarantee its objectivity. Secondly, Algorithms decide how the uncertainty model performs operations with information, which greatly affect uncertainty reduction. Thirdly, evidence representation usually depends on human experience, which has large invalidity. Lastly, the evidence sources are sensors that exist in environment with a variety of noises.

In this paper, due to the scarce knowledge of observation environment, the system may import a lot of interference and clutter. And the limitation of sensor precision will ulteriorly cause the uncertainty and imprecisely in DS reasoning. Thus, the paradox research is the premise to analyze the defects of DS evidence theory and realize its improvement.

The common paradoxes are divided into four classes: complete conflict paradox, 0 trust paradox (one ballot veto), 1 trust paradox and high conflict paradox.

1) Complete conflict paradox: Assuming that the FoD of system is $\Theta = \{A, B, C\}$, and there are two sources of evidence. The $BPAs$ are presented respectively as:

$$\begin{cases} m_1(A) = 1, m_1(B) = 0, m_1(C) = 0 \\ m_2(A) = 0, m_2(B) = 1, m_2(C) = 0 \end{cases} \tag{9}$$

According to formula(7), the total conflict factor k can be calculated as $k = 1$. It is apparent that evidences m_1, m_2 conflict completely, which causes the denominator of formula(6) becoming zero. Under such circumstances, DS combination rule is unable to synthesize. If there are two more sources of evidence, whose $BPAs$ are shown as:

$$\begin{cases} m_3(A) = 0.8, m_3(B) = 0.1, m_3(C) = 0.1 \\ m_4(A) = 0.8, m_4(B) = 0.1, m_4(C) = 0.1 \end{cases} \tag{10}$$

From intuitive judgment, the accurate synthesis results should drastically support proposition A because evidences m_1, m_3, m_4 all support proposition A with large $BPAs$. But DS combination rule cannot normally be used when $k = 1$. This kind of illogical situation is called complete conflict paradox.

2) 0 trust paradox: Assuming that FoD of the system is $\Theta = \{A, B, C\}$, and four $BPAs$ of evidences are:

$$\begin{cases} m_1(A) = 0.5, m_1(B) = 0.2, m_1(C) = 0.3 \\ m_2(A) = 0, \quad m_2(B) = 0.9, m_2(C) = 0.1 \\ m_3(A) = 0.5, m_3(B) = 0.2, m_3(C) = 0.3 \\ m_4(A) = 0.5, m_4(B) = 0.2, m_4(C) = 0.3 \end{cases} \tag{11}$$

The total conflict factor can be calculated as $k = 0.99$ in the same way as shown before. Applying formula(7), the synthesis results are:

$$m(A) = 0, m(B) = 0.727, m(C) = 0.273 \tag{12}$$

It can be checked that because the evidence m_2 totally denies proposition A, the BPA for proposition A in the synthesis results will always be zero no matter how strongly evidences m_1, m_3, m_4 support proposition A. That is, DS combination rule has the disadvantage of one ballot veto.

3) 1 trust paradox: Assuming that the FoD of system is $\Theta = \{A, B, C\}$, and there are four evidences. The $BPAs$ are:

$$\begin{cases} m_1(A) = 0.9, m_1(B) = 0.1, m_1(C) = 0 \\ m_2(A) = 0, \quad m_2(B) = 0.1, m_2(C) = 0.9 \\ m_3(A) = 0.1, m_3(B) = 0.15, m_3(C) = 0.75 \\ m_4(A) = 0.1, m_4(B) = 0.15, m_4(C) = 0.75 \end{cases} \tag{13}$$

The total conflict factor can be calculated as $k = 0.9998$ and the synthesis results are:

$$m(A) = 0, m(B) = 1, m(C) = 0 \tag{14}$$

Although all sources of evidence give proposition B small $BPAs$, the synthesis results completely believe proposition B is the correct proposition, which is perverse in practical application.

4) High conflict paradox: Assuming that the FoD of system is $\Theta = \{A, B, C, D, E\}$, and there are five evidences. The $BPAs$ and synthesis results are respectively presented in formula(15) and formula(16).

The total conflict factor can be calculated as $k = 0.9999$. It can be proved in the similar way that precise synthesis results should support proposition A as evidences m_1, m_3, m_4, m_5 all give proposition A large $BPAs$. But high conflicts among evidences actually lead to error reasoning that shown in formula(16).

$$\begin{cases} m_1(A)=0.7, m_1(B)=0.1, m_1(C)=0.1, m_1(D)=0, \quad m_1(E)=0.1 \\ m_2(A)=0, \quad m_2(B)=0.5, m_2(C)=0.2, m_2(D)=0.1, m_2(E)=0.2 \\ m_3(A)=0.6, m_3(B)=0.1, m_3(C)=0.15, m_3(D)=0, \quad m_3(E)=0.15 \\ m_4(A)=0.55, m_4(B)=0.1, m_4(C)=0.1, m_4(D)=0.15, m_4(E)=0.1 \\ m_5(A)=0.6, m_5(B)=0.1, m_5(C)=0.2, m_5(D)=0, \quad m_5(E)=0.1 \end{cases} \tag{15}$$

$$m(A)=0, m(B)=0.3571, m(C)=0.4286, m(D)=0, m(E)=0.2143 \tag{16}$$

C. Relationship among Bayesian theory, DS evidence theory and DSmT reasoning

Relative to probability theory and Bayesian theory, DS evidence theory can settle imprecise information in the absence of priori knowledge and can be viewed as a generalization of probability theory. It can be seen in the previous section that DS evidence theory cannot handle the information with paradoxes. In order to overcome the problem, Jean Dezert and Florentin Smarandache put forward the DSmT reasoning which can combine uncertain, imprecise and contradictory information [30]. DSmT reasoning is an extension of traditional DS evidence theory, and it is widely applied in edge detection in color images [31], aircraft recognition [32] and remote sensing image classification [33],etc.

In 2003, Jean Dezert presents the hyper power set notation as D^{Θ} for DSmT. It retains the contradictory focal elements, while greatly increases the total number of focal elements. Examples are given as follows to show the increasing calculational complexity of DSmT compared with DS evidence theory.

1) $\Theta=\{\}$*(empty):* $2^{\Theta}=\{\varnothing\}$, $D^{\Theta}=\{\varnothing\}$.

2) $\Theta=\{H_1\}$*:* $2^{\Theta}=\{\varnothing, H_1\}$, $D^{\Theta}=\{\varnothing, H_1\}$.

3) $\Theta=\{H_1,H_2\}$*:* $2^{\Theta}=\{\varnothing,H_1,H_2,H_1\cup H_2\}$, $D^{\Theta}=\{\varnothing,H_1,H_2,H_1\cup H_2,H_1\cap H_2\}$.

4) $\Theta=\{H_1,H_2,H_3\}$*:* $2^{\Theta}=\{\varnothing,H_1,H_2,H_3,H_1\cup H_2,H_1\cup H_3,H_2\cup H_3,H_1\cup H_2\cup H_3\}$, $D^{\Theta}=\{\varnothing,H_1,H_2,H_3,H_1\cup H_2,H_1\cup H_3,H_2\cup H_3,H_1\cap H_2,H_1\cap H_3,H_2\cap H_3,H_1\cup H_2\cup H_3,H_1\cap H_2\cap H_3,(H_1\cup H_2)\cap H_3,(H_1\cup H_3)\cap H_2,(H_2\cup H_3)\cap H_1,(H_1\cap H_2)\cup H_3,(H_1\cap H_3)\cup H_2,(H_2\cap H_3)\cup H_1,(H_1\cup H_2)\cap(H_1\cap H_3)\cap(H_2\cup H_3)\}$.

From these discussions, it's obvious that DS evidence theory is an extension of Bayesian theory, and DSmT reasoning is view as a general flexible approach for managing uncertainty and conflicts for a wide class of fusion problems where the information to combine is modeled as a finite set of belief functions provided by different independent sources [34], [35]. And these three algorithms are used in the similar applications. It's easy to check that with the increasing number of FoD, the gap on the calculational amount between DS evidence theory and DSmT reasoning becomes larger. Thus, considering DSmT's large computational requirements, this paper uses DS evidence theory as the uncertain reasoning method in the IR/MMW target recognition system, which can not only ensure the identify speed of system, but also build the basis for DSmT's application implementation.

D. Comparison between two mainstream improved methods and PCR5

In the DSmT reasoning's FoD, the proportional conflict redistribution 5 (called $PCR5$ for short) is used generally to combine the $BPAs$ [34]. $PCR5$ transfers the conflict mass only to the elements involved in the conflict and proportionally to their individual masses, which is similar to the way that assign local conflicts directly to local propositions [19]. As $PCR5$ can be used in DS evidence theory as well, we take two mainstream improved methods to give a simple comparison.

The $PCR5$ rule in DS evidence theory is defined as follows (Assuming that there are two evidences):

$$m(A)=\sum_{A_1\cap A_2=A} m_1(A_1)\cdot m_2(A_2)+\Delta(A,2^{\Theta}) \tag{17}$$

where, $\Delta(A,2^{\Theta})=\sum\limits_{A_3\cap A=\varnothing}[\frac{m_1(A)^2\cdot m_2(A_3)}{m_1(A)+m_2(A_3)}+\frac{m_2(A)^2\cdot m_1(A_3)}{m_2(A)+m_1(A_3)}]$, and $A_1,A_2,A_3\subseteq 2^{\Theta}$.

The general description of the improved DS combination rules which presents in section I can be shown as:

$$m(A)=\sum_{A_1\cap A_2=A} m_1(A_1)\cdot m_2(A_2)+\Delta(A,\Theta) \tag{18}$$

where, $\Delta(A,\Theta)$ depends on the specific algorithm, and $A_1,A_2\subseteq\Theta$. In $Yager$ [16] and Sun [17], $\Delta_{Yager}(A,\Theta)=k$, if $A=\Theta$, otherwise, it becomes zero, and $\Delta_{Sun}(A,\Theta)=k\cdot e^{-k}\cdot(\frac{m1_(A)+m_2(A)}{2})$ when system has two evidence sources.

According to formula(17)(18), it's easy to see that the improved part changes from $\Delta(A,\Theta)$ in DS evidence theory to $\Delta(A,2^{\Theta})$ in $PCR5$, which demonstrates that $PCR5$ rule can get higher combination precision with extra and larger computational complexity.

In addition, the general description of the modified conflict evidences methods expressed in section I is shown as (Assuming that there are n evidences):

$$m(A)=\sum_{A_i\subseteq\Theta} m_i(A_i)\cdot w_i(A_i) \tag{19}$$

where, $w_i(A_i)$ denotes the weighted factor that assigns to $m_i(A_i)$. In $Murphy$ [20] and $Deng$ [22], $w_{i-Murphy}(A_i)=\frac{1}{n}$, where n is the evidence number, and $w_{i-Deng}(A_i)$ represents evidence credibility that got from the introduction of Euclidean distance.

Through comparison between $PCR5$ and the modified conflict evidences method in formula(17)(19), it is easy to verify that different from $PCR5$ rule, this kind of approach takes the ambient noises into consideration and handles conflicts from the perspective of evidence credibility, which is more proximate to actual applications.

From above mentioned, $PCR5$ rule in DS evidence theory can be classified into the improved DS combination rules with better validity and larger computational complexity, and the modified conflict evidences methods take factors like environmental noises, sensors precision into account, which have better ability of practical applications relative to $PCR5$ rule. Thus, in order to get accurate, effective and fast target recognition performance in IR/MMW system, this paper chooses to combine two mainstream improved methods and proposes the modified DS evidence theory that presented in next section.

III. The modified DS evidence theory

The modified DS evidence theory proposed in this paper is designed to deal with the paradoxes caused by environmental uncertainty and imperfect knowledge, and make it more suitable for IR/MMW target recognition system. It imitates the human brain's information reception processing and integration processing to realize information fusion in IR/MMW system. It firstly accurately assigns sensor priority through classifying evidences from different sources by their type and precision, and calculates evidence credibility of each evidence through introduction of Minkowski distance, then modifies DS combination rule to avoid probable paradoxes caused by the normalization step, and at last, uses decision making rule to produce reliable synthesis results.

A. Discount processing of evidences

The discount processing of evidences is composed of two parts. One is the definition of source priority for distinguishing the differences of data obtained from different sensors according to their types and precisions, and the other is the introduction of evidence credibility for analyses of different reliability of data from different sensors in consideration of weather and observation environment. The discount processing of evidences can decrease the conflicts caused by environmental uncertainty and differences among sensors, which is the precondition of DS combination rule.

1) Sensor priority: Suppose that there are M sensors with N different types in IR/MMW system, we regard the data received from different sensors as the sources of evidence, whose number is also M and type is N. Because the system has N types of sensors, sensor priorities are also quantized into N levels. According to the differences of sensor types and precisions, the sensor priority can be defined to represent the dominance and importance of different sensors under certain identification mission. And for a particular environment of target recognition, sensor priorities of different sensors differ, and satisfy that $pr(m_i) \in [0,1] (i = 1, 2, \cdots, N)$.

This paper only assigns sensor priority by considering sensor types and precisions to meet real-time demand of system, readers can take more factors into account by analogy. As sensor priorities are deemed to be the priori knowledge, assignment of evidence priorities depends on practical application. An example will make it clear: If there are five sensors in IR/MMW system with three same precision active IRs and two same precision passive $MMWs$, then, these three active IRs must have the same sensor priorities, and two passive $MMWs$ also have the same sensor priorities. The concrete value of sensor priority should be set by artificial operators based on system requirements. If system requires high spatial resolution and strong penetrating power, $MMWs$ have obvious superiority and their sensor priorities should be higher than that of IRs, such as assignment as $pr(m_{IRs}) = 0.9, pr(m_{MMRs}) = 0.4$. On the contrary, if system demands great night work ability, sensor priorities of IRs will be much higher than that of $MMWs$.

2) Evidence credibility: Sensor priority takes inequality and inconsistence caused by different types and precisions of sensors into account, but uncertainty caused by factors like weather, observation environment and missile-target distance is still the obstacle of obtaining accurate synthesis results. In order to relieve uncertainty and imperfect among evidences, evidence credibility is put forward to evaluate the reliability of different sensors before evidence combines.

Primarily, Minkowski distance is introduced as a distance function between two evidences. Assumption that there are N evidence sources, and $m_i, m_j (i, j = 1, 2, \cdots, N)$ are two $BPAs$ of mutually exclusive and exhaustive FoD:$\Theta = \{A_1, A_2, \cdots, A_M\}$, which are respectively shown as:

$$\begin{cases} m_i(A_1) = p_1, m_i(A_2) = p_2, \cdots, m_i(A_M) = p_M \\ m_j(A_1) = q_1, m_j(A_2) = q_2, \cdots, m_j(A_M) = q_M \end{cases} \tag{20}$$

Minkowski distance is a distance measurement in European space, and it is an extension of Euclidean distance and Manhattan distance. According to the introduction of Minkowski distance, the distance function of m_i, m_j can be calculated as:

$$d_{ij} = d(m_i, m_j) = (\sum_{l=1}^{M} |p_l - q_l|^m)^{\frac{1}{m}} \tag{21}$$

where, m is a variable parameter. By definition, Minkowski distance will degrade into Manhattan distance when $m = 1$, Euclidean distance when $m = 2$, and Chebyshev distance when $m \to \infty$. In this paper, m is unified to be 2 for the experimental convenience in Section V .

Thus, the distance matrix is defined as :

$$DM = \begin{bmatrix} 0 & d_{12} & \cdots & d_{1N} \\ d_{21} & 0 & \cdots & d_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1} & d_{N2} & \cdots & 0 \end{bmatrix} \tag{22}$$

Then, the similarity function between two evidences is introduced as:

$$s_{ij} = s(m_i, m_j) = 1 - d_{ij} \tag{23}$$

It is obvious that the similarity function between two evidences will increase as the distance function decreases.

The similarity matrix of evidences is defined in the same way as shown before.

$$SM = \begin{bmatrix} 1 & s_{12} & \cdots & s_{1N} \\ s_{21} & 1 & \cdots & s_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ s_{N1} & s_{N2} & \cdots & 1 \end{bmatrix} \tag{24}$$

Further, the support measurement and credibility of evidence m_i are calculated separately as:

$$sup(m_i) = \sum_{j=1, j\neq i}^{N} s(m_i, m_j) \tag{25}$$

$$crd(m_i) = \frac{sup(m_i)}{\sum_{i=1}^{N} sup(m_i)} \tag{26}$$

It can be seen from formula(26) that, the credibility of evidences satisfies that $crd(m_i) \in [0,1]$ and $\sum_{i=1}^{N} crd(m_i) = 1$. The support measurement represents the similarity degree between certain evidence and other evidences, and credibility reflects the normalized support degree of certain evidence. It is clear that the support measurement and credibility of evidences will both increase when similarity function between certain evidence and other evidences increases.

3) Discount processing: Take sensor priority and evidence credibility for discount processing before evidences combine can enhance the consistency of sensors and reduce conflicts among evidences. The discount processing is defined as:

$$\begin{cases} m'(A) = \sum_{i=1}^{N} m_i(A) \cdot pr(m_i) \cdot crd(m_i) \\ m'(\varnothing) = 0 \qquad\qquad \forall A \subseteq \Theta, A \neq \varnothing \end{cases} \tag{27}$$

Because of $pr(m_i) \in [0,1]$ and $crd(m_i) \in [0,1]$, the discounted evidence satisfies that $\sum_{A\subseteq\Theta} m'(A) \leq 1$. To ensure the normalization of synthesis results, the discounted evidence should be normalized before evidences combine, which is defined as follows:

$$m''(A) = \frac{m'(A)}{\sum_{A\subseteq\Theta} m'(A)} \qquad A \subseteq \Theta \tag{28}$$

B. Improvement of DS combination rule

In the DS combination rule, paradoxes are mainly caused by incomplete FoD and the normalization step under the hypothesis of reliable evidences. In this section, paradoxes are only caused by the normalization step through assuming a complete FoD. Evidence conflicts have been greatly reduced by the discount processing with the introduction of sensor priority and evidence credibility. Under this circumstance, traditional DS combination rule can simply deal with common conflicts. However, conflicts caused by imperfect knowledge are still an urgent problem. In order to handle four common paradoxes described in section II, DS combination rule is improved correspondingly. The improvement of DS combination rule proportionally assigns global conflicts to propositions based on the discounted evidence instead of blindly negating information that hides in conflict evidences, which enhances the reliability and rationality of synthesis results.

The improved DS combination rule is defined as:

$$\begin{cases} m(A) = \sum_{A_1 \cap A_2 = A} m''(A_1) \cdot m''(A_2) + k \cdot m''(A) \\ m(\varnothing) = 0 \qquad\qquad \forall A \subseteq \Theta, A \neq \varnothing \end{cases} \tag{29}$$

Here needs to further explain one point. The reason why it adopts to assign global conflicts to all propositions instead of assigning local conflicts directly to local propositions is that: without discount processing, local assignment method is more rational than global assignment, but in current situation with discount processing, evidence conflicts have been drastically decreased. Global assignment method will lead to better convergence and less computation.

C. Decision making rule

In DS evidence theory, two common decision making rules are maximum belief function and maximum plausibility function method. But it's obvious that both of them are too simple to obtain accurate and satisfactory recognition results in IR/MMW system. Therefore, a compound decision making rule is applied. Assumption that the FoD is $\Theta = \{A_1, A_2, \cdots, A_M\}$, that is, M targets are existent in target recognition system. If the synthesis results satisfy:

$$\begin{aligned} &\begin{cases} m(A_1) = \max\{m(A_i), A_i \subseteq \Theta\} \\ m(A_2) = \max\{m(A_j), A_j \subseteq \Theta, A_j \neq A_1\} \end{cases} \\ &\begin{cases} m(A_1) - m(A_2) \geq \varepsilon_1 \\ m(\Theta) \geq \varepsilon_2 \\ m(A_1) \geq m(\Theta) \end{cases} \end{aligned} \tag{30}$$

the recognition result will be target A_1, where ε_1 and ε_2 are preset threshold values.

IV. Application in IR/MMW target recognition

As section in the previous chapter gives specific evolution thread of the novel algorithm, this section will present the implementation steps of its application in IR/MMW system. Combining different features of IRs and $MMWs$ in target recognition system, the modified DS evidence theory is applied as a decision making fusion method. Fig.2 shows the flow diagram of IR/MMW system (take an example of 2 IRs and 2 $MMWs$ corresponding to experiments in section V).

Specific implement steps of the application in IR/MMW system for target recognition are summarized as follows:

Step 1: Collect information of IRs and $MMWs$ as evidences and assume that all sensors have the same FoD, obtain $BPAs$ from all sensors through data acquisition and preprocessing. This step establishes a platform for information fusion.

Step 2: Utilize the modified DS evidence theory to combine evidences and make synthesis decision.

Step 3: Output the decision results as the recognition results.

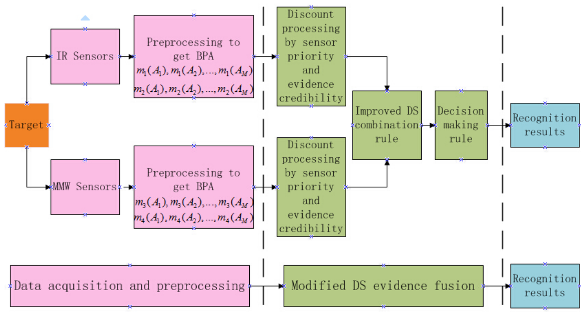


Fig. 2: The flow diagram of IR/MMW system

V. Experiment results and analyses

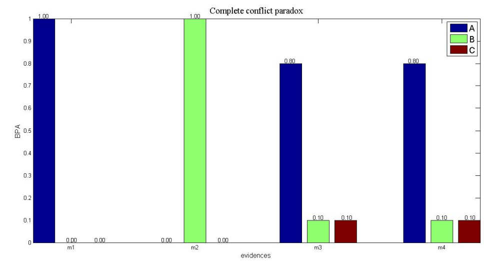
In this section, we give two experiments. One is the comparison of performance between the modified algorithm and several existent methods, which proves its validity and reliability theoretically. The other is its application in IR/MMW system, which demonstrates its feasibility in practice.

A. Experiment 1: Theoretical comparison between the modified algorithm and existent methods

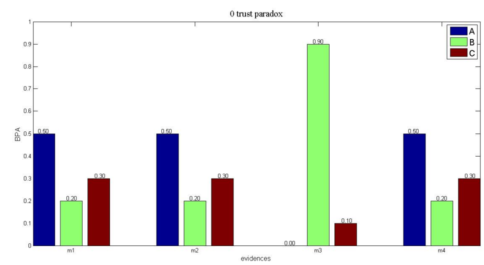
Take four paradoxes described in section II as examples to discuss the rationality and validity of the modified algorithm. The $BPAs$ of four common paradoxes presented in section II-B are shown in table I and fig.3.

TABLE I: $BPAs$ of four common paradoxes

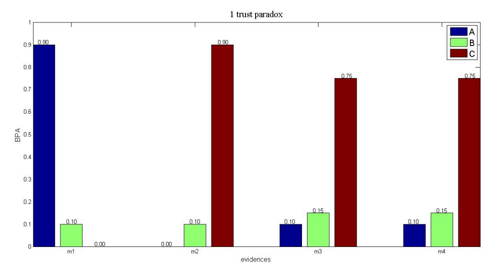
Paradoxes	Evidences	Propositions				
		A	B	C	D	E
Complete conflict paradox	m_1	1	0	0	\	\
	m_2	0	1	0	\	\
	m_3	0.8	0.1	0.1	\	\
	m_4	0.8	0.1	0.1	\	\
0 trust paradox	m_1	0.5	0.2	0.3	\	\
	m_2	0.5	0.2	0.3	\	\
	m_3	0	0.9	0.1	\	\
	m_4	0.5	0.2	0.3	\	\
1 trust paradox	m_1	0.9	0.1	0	\	\
	m_2	0	0.1	0.9	\	\
	m_3	0.1	0.15	0.75	\	\
	m_4	0.1	0.15	0.75	\	\
High conflict paradox	m_1	0.7	0.1	0.1	0	0.1
	m_2	0	0.5	0.2	0.1	0.2
	m_3	0.6	0.1	0.15	0	0.15
	m_4	0.55	0.1	0.1	0.15	0.1
	m_5	0.6	0.1	0.2	0	0.1



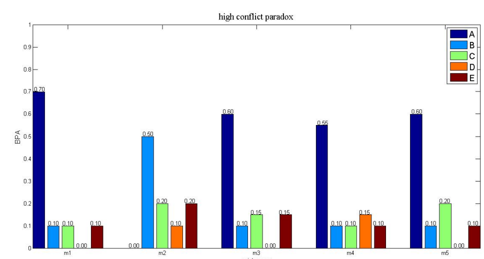
(a) BPA of complete conflict paradox



(b) BPA of 0 trust paradox



(c) BPA of 1 trust paradox



(d) BPA of high conflict paradox

Fig. 3: $BPAs$ of four common paradoxes

It can be seen from table I and fig.3 that evidences in IR/MMW system can be divided into consistent evidences and conflict evidences. Apparently, the relatively consistent evidences are m_1, m_3, m_4 in complete conflict paradox, m_1, m_2, m_4 in 0 trust paradox, m_2, m_3, m_4 in 1 trust paradox, and m_1, m_3, m_4, m_5 in high conflict paradox. Thus, accurate synthesis results should agree with these consistent evidences while away from conflict evidences.

It is evident that traditional DS combination rule is unable to manage all four paradoxes, so we choose four existent improved methods respectively proposed by Yager [16], Sun [17], Murphy [20] and Deng [22](called $Yager$, Sun, $Murphy$ and $Deng$ for short) for comprehensive analyses with the modified method(called $Modified$ for short). And the synthesis results are presented in table II and fig.4.

According to table II and fig.4, we make the following discussion.

1) In complete conflict paradox($k = 1$): m_1, m_3, m_4 are the relatively consistent evidences. $Yager$ gives Θ the whole belief as $m(\Theta) = 1$, which on the contrary, increases propositions' uncertainty. Sun only solves part of the conflicts as the BPA of propositions A, B, C match the $BPAs'$ proportion of these consistent evidences, but the BPA for Θ is still high as $m(\Theta) = 0.8589$, which still has high uncertainty. At the same time, $Murphy$, $Deng$ and $Modified$ can all get relatively rational results in complete conflict paradox.

TABLE II: Comparison of the synthesis results

Paradoxes	Methods	Propositions					
		A	B	C	D	E	Θ
Complete conflict paradox ($k = 1$)	$Yager$	0	0	0	\	\	1
	Sun	0.0917	0.0423	0.0071	\	\	0.8589
	$Murphy$	0.8204	0.1748	0.0048	\	\	0
	$Deng$	0.8166	0.1164	0.0670	\	\	0
	$Modified$	0.9242	0.0502	0.0256	\	\	0
0 trust paradox ($k = 0.99$)	$Yager$	0	0.7273	0.2727	\	\	0
	Sun	0.0525	0.0597	0.0377	\	\	0.8501
	$Murphy$	0.4091	0.4091	0.1818	\	\	0
	$Deng$	0.4318	0.2955	0.2727	\	\	0
	$Modified$	0.4679	0.2800	0.2521	\	\	0
1 trust paradox ($k = 0.9998$)	$Yager$	0	1	0	\	\	0
	Sun	0.0388	0.0179	0.0846	\	\	0.8587
	$Murphy$	0.1676	0.0346	0.7978	\	\	0
	$Deng$	0.1388	0.1318	0.7294	\	\	0
	$Modified$	0.0791	0.0743	0.8466	\	\	0
High conflict paradox ($k = 0.9999$)	$Yager$	0	0.3571	0.4286	0	0.2143	0
	Sun	0.0443	0.0163	0.0136	0.0045	0.0118	0.9094
	$Murphy$	0.7637	0.1031	0.0716	0.0080	0.0538	0
	$Deng$	0.5324	0.1521	0.1462	0.0451	0.1241	0
	$Modified$	0.6320	0.1227	0.1171	0.0316	0.0967	0

2) In 0 trust paradox: m_1, m_2, m_4 are the relatively consistent evidences. It's easy to check that the consistent evidences are the same, so the most valid algorithm should have the minimum difference between the synthesis results and the consistent evidences. As can be seen intuitively, $Yager$ presents totally wrong results, and $Modified$ is the most effective algorithm in this kind of paradox.

3) In 1 trust paradox: m_2, m_3, m_4 are the relatively consistent evidences. $Yager$ and Sun cannot handle this paradox practically which can be proved in the similar way as shown in the discussion of complete conflict paradox. And $Murphy$, $Deng$ and $Modified$ can manage 1 trust paradox in different degrees.

4) In high conflict paradox: m_1, m_3, m_4, m_5 are the relatively consistent evidences. $Yager$ and Sun are logical theoretically but cannot be put into practice because of their increasing uncertainty. And $Murphy$, $Deng$ and $Modified$ all produce the relatively reasonable results in this kind of paradox.

It's verified that $Yager$ always produces wrong synthesis results under the condition of paradoxes, and it is unable to handle any kind of paradox. Sun allots most of conflicts directly to Θ, which just solves paradoxes theoretically. It is not suitable for practical application because of the increasing uncertainty of synthesis results. $Murphy$ averages all evidences without separating consistent evidences and conflict evidences. And it's clear that it cannot solve paradoxes fundamentally because evidences' contributions for the synthesis results are totally different, even it has advantage in low computation. Therefore, only $Deng$ and $Modified$ can generate relatively reasonable synthesis results for all these four common paradoxes.

There are two details need to be illustrated. On the one hand, Experiments here just discuss theoretical feasibility of the modified algorithm without considering its application, thus sensor priorities are all set to be 1. It represents that every sensor is equally suitable for the current demands of system. While in practical application, experiment results will be more effective and reliable with the introduction of sensor priority. On the other hand, in theoretical experiments, there is no need to prove the validity of decision making rule, so it only outputs the synthesis results without decision making. The advantages of sensor priority and decision making rule are demonstrated in the next experiment.

Then, the comparison of $Deng$ and $Modified$ is discussed here in detail. The evaluation criterion is composed of two part: the weight distance measurement(wd) between the synthesis result and original evidences, and the decrement(∇_{wd}) between $Deng$ and $Modified$, which are defined as:

$$\begin{cases} wd = \sum_{i=1}^{N} d(m_i, m) \cdot crd(m_i) \\ \nabla_{wd} = \dfrac{|wd_2 - wd_1|}{wd_1} \cdot 100\% \end{cases} \tag{31}$$

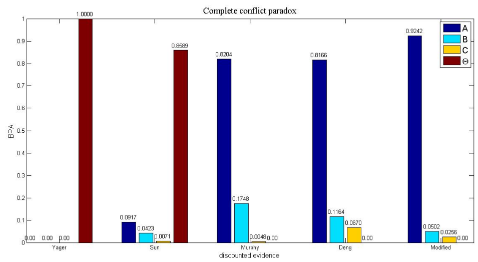
where, $m_i (i = 1, 2, \cdots, N)$, m respectively represents N original evidences and the synthesis result, and wd_1,wd_2 separately represents the weight distance measurement of $Deng$ and $Modified$.

In formula(31), we can see that when the synthesis result is consistent with original evidences, the weight distance measurement becomes small. It means that the smaller wd is, the more efficient this combination method is. The comparison is shown in table III.

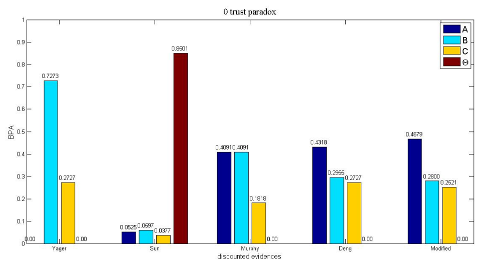
TABLE III: Comparison between $Deng$ and $Modified$

Paradoxes	Methods	wd	∇_{wd}
Complete conflict paradox	$Deng$	0.1064	11.69%
	$Modified$	0.0940	
0 trust paradox	$Deng$	0.1472	78.69%
	$Modified$	0.0314	
1 trust paradox	$Deng$	0.1275	20.37%
	$Modified$	0.1015	
Complete conflict paradox	$Deng$	0.1407	43.68%
	$Modified$	0.0793	

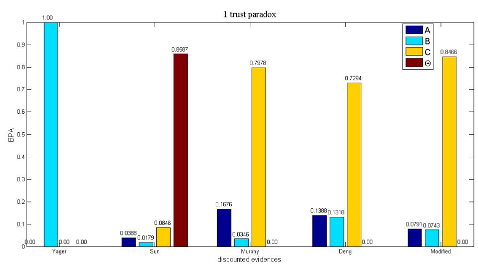
It can be seen from table III that wd of $Modified$ is far



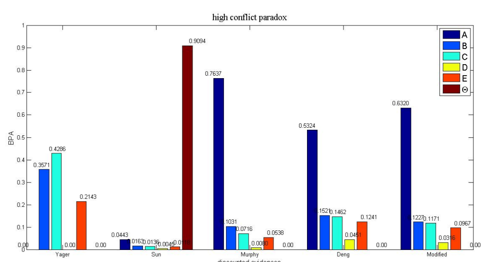
(a) Synthesis result of complete conflict paradox



(b) Synthesis result of 0 trust paradox



(c) Synthesis result of 1 trust paradox



(d) Synthesis result of high conflict paradox

Fig. 4: Comparison of the synthesis results

less than that of $Deng$. It demonstrates that: $Modified$ can solve all the four paradoxes better, the evidences processed by $Modified$ have better consistency and reliability, and the synthesis results produced by $Modified$ are more rational and valid. Therefore, Experiments here successfully certify theoretical rationality and feasibility of the modified DS evidence theory before its practical application.

B. Experiment 2: Practical experiment on application of IR/MMW system

To illustrate practical application of the modified method, three groups of data are set here for target recognition, including two ordinary data (data 1 and data 2) and one adverse data (data 3). According to the data acquisition and preprocessing method that described in [36], we extract the features of information from IRs and MMWs, and then use grey correlation classifier to get $BPAs$ as the input of the modified DS evidence fusion.

Experiment conditions: In IR/MMW system, Assume that the FoD is $\Theta = \{A_1, A_2, A_3\}$, where A_1, A_2, A_3 separately represents reconnaissance aircraft, bomber aircraft and fighters. IRs and $MMWs$ provide information about targets as evidences, and there are four evidence sources including $IR1$, $IR2$, $MMW1$ and $MMW2$. The sensor priorities are expressed as $pr(m_1), pr(m_2), pr(m_3), pr(m_4)$, and the preset threshold values in decision making rule are $\varepsilon_1 = 0.2, \varepsilon_2 = 0.25$.

Data 1: Target recognition for A_1: Assumption that there are a lot of smoke, fog and cloud in observation environment(actual battlefield). And system requires high spatial resolution and strong penetrating power. Under these conditions, $MMWs$ have obvious advantage over IRs. As prior knowledge, sensor priorities are set as $pr(m_1) = pr(m_2) = 0.53, pr(m_3) = pr(m_4) = 0.85$.

Data 2: Target recognition for A_2: Assumption that target recognition mission is marched in the night and system requires great night work ability and strong concealment. It is obvious that IRs have obvious advantage over $MMWs$ on this situation. As prior knowledge, sensor priorities are set as $pr(m_1) = pr(m_2) = 0.86, pr(m_3) = pr(m_4) = 0.45$.

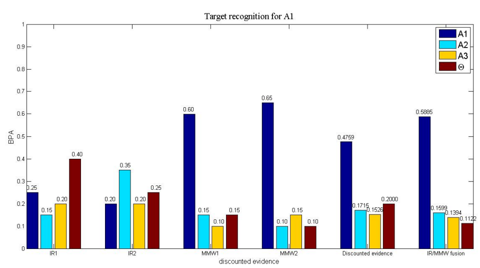
Data 3: Target recognition for A_3: Assumption that observation environment is abominable due to environmental clutter and artificial interference. Single-mode system won't produce correct recognition results. In order to ensure the reliability of target recognition, IR/MMW system is inevitable trend. If system requires wide range of search and interception, $MMWs$ have obvious advantage over IRs. As prior knowledge, sensor priorities are set as $pr(m_1) = 0.40, pr(m_2) = 0.35, pr(m_3) = 0.60, pr(m_4) = 0.65$.

According to above data, the recognition results of IR/MMW system are presented in table IV and fig.5.

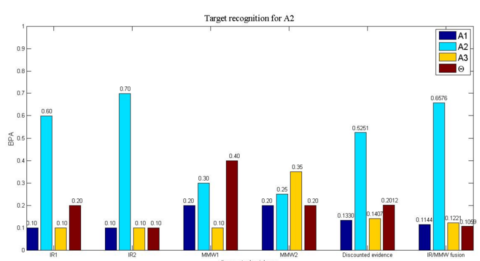
It can be seen from table IV and fig.5 that in target recognition of A_1, system is led mainly by $MMWs$ with complement by IRs according to their sensor priorities. In the single-mode systems, $MMWs$ can identify objective correctly, while IRs can't. And IR/MMW fusion can not only identify real objective, but also enhance the accuracy of recognition results by greatly increasing the BPA of real target. In similar principle when identifying A_2, the syncretic recognition results verify rationality and validity of the modified DS evidence theory in IR/MMW system. Experiment results of data 3 show that all sensor priorities are low because of poor observation environment, and only $MMW2$ in single-mode systems can identify real objective but with large BPA for Θ. It demonstrates that large uncertainty are existed in this single-mode's recognition results. However, under that experimental condition, recognition results in fusion system significantly decrease uncertainty of system to facilitate decision making. In addition, the modified algorithm in IR/MMW system can still accurately identify objective even two or three of sensors are unable to identify real objective, and greatly increase reliability

TABLE IV: Recognition results of IR/MMW system

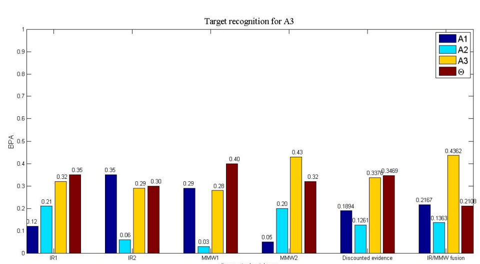
Targets	Sensors		$m_i(A_j), i=1,2,3,4, A_j \subseteq \Theta$				Recognition results
	Sensor Type	Sensor Priority	A_1	A_2	A_3	Θ	
A_1	$IR1$	0.53	0.25	0.15	0.20	0.40	Θ
	$IR2$	0.53	0.20	0.35	0.20	0.25	A_2
	$MMW1$	0.85	0.60	0.15	0.10	0.15	A_1
	$MMW2$	0.85	0.65	0.10	0.15	0.10	A_1
	Discounted evidence		0.4759	0.1715	0.1526	0.2000	A_1
	IR/MMW fusion		0.5885	0.1599	0.1394	0.1122	A_1
A_2	$IR1$	0.86	0.10	0.60	0.10	0.20	A_2
	$IR2$	0.86	0.10	0.70	0.10	0.10	A_2
	$MMW1$	0.45	0.20	0.30	0.10	0.40	Θ
	$MMW2$	0.45	0.20	0.25	0.35	0.20	A_3
	Discounted evidence		0.1330	0.5251	0.1407	0.2012	A_2
	IR/MMW fusion		0.1144	0.6576	0.1221	0.1059	A_2
A_3	$IR1$	0.40	0.12	0.21	0.32	0.35	Θ
	$IR2$	0.35	0.35	0.06	0.29	0.30	A_1
	$MMW1$	0.60	0.29	0.03	0.28	0.40	Θ
	$MMW2$	0.65	0.05	0.20	0.43	0.32	A_3
	Discounted evidence		0.1894	0.1261	0.3376	0.3469	Θ
	IR/MMW fusion		0.2167	0.1363	0.4362	0.2108	A_3



(a) Target recognition for A_1



(b) Target recognition for A_2



(c) Target recognition for A_3

Fig. 5: Recognition results of IR/MMW system

of IR/MMW system.

Through above analyses, application of the modified DS evidence theory in IR/MMW system can efficiently fuse multi-sensor information, accurately identify objective, and improve recognition rate and system reliability. It directly proves validity and rationality of the modified algorithm and adaptability and flexibility of the system.

VI. Conclusion

This paper proposes a modified DS evidence theory method for target recognition in IR/MMW system. With the discount processing and modified DS combination rule, the novel algorithm theoretically solves paradoxes caused by inconsistency and inequality of evidences, reduces the negative effects caused by complex environmental factors, improves effectiveness and accuracy of the synthesis results. And the introduction of the compound decision making rule further ensure to produce satisfactory recognition results. Experiment results and analyses demonstrate that application of the modified algorithm as an information fusion method in IR/MMW system can enhance recognition rate of system, improve the accuracy and anti-jamming immunity of guidance system. Thus, it greatly enhances the operational performance of weapon system under various environmental condition, and realizes the all-weather operations. That is, it has great engineering application value.

In the further study, there is two technical researches that needs to study. With the increasing number of sensors, there will be a huge computation burden for system along with great recognition performance. And The application of DSmT in target recognition system should be studied to realize the uncertainty reasoning better. Therefore, this method should be simplified and optimized.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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