A New Self-Adaptive Fusion Algorithm Based on DST and DSmT

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***Abstract*—A new self-adaptive fusion algorithm based on DST and DSmT is proposed. In the new algorithm, part of the conflicting information is normalized according to DST, while the other part is processed by DSmT. A controlling factor is used to control the quantity of information dealt by the two different methods adaptively, which is a new method avoiding setting for the threshold of conflict. The simulation results indicate that the new self-adaptive fusion algorithm based on DST and DSmT can deal with any conflicting situation with a good performance of convergence.**

***Keywords*—DST; DSmT; controlling factor; information fusion**

I. INTRODUCTION

Due to the complexity of modern battlefield, target identification is becoming more and more complex. It is difficult to give an accurate and credible identifying result only by one sensor. Therefore, target identification based on multi-source information is becoming a hot topic. Dempster-Shafer theory (DST) is an efficient method for uncertainty consequence ([1]). It is widely used in the domain of synthesize identification. However, DST can't give efficient fusion results when information from different sources becomes highly conflict. Many improvement are proposed, such as Yager's rule of combination ([2]), Murphy's rule of combination ([3]), Dengyong's rule of combination ([4]) etc. Dezert presented the Dezert-Smarandache theory (DSmT) ([5]), which can be considered as an extension of the classical DST. DSmT performs well in dealing with the fusion of uncertain, highly conflicting and imprecise sources. It can solve not only the static problems but also the complex dynamic fusion problems.

DST and DSmT have their own advantages and disadvantages for fusing the multi-source information. The advantages of DST mainly occur in the case of low degree of conflict, whereas it may give a bad fusion result which is absolutely contrary to the fact while the sources are in high degree of conflict. DSmT is more efficient in combining highly conflicting sources, but it offers convergence toward certainty slowly especially in low degree of conflict. So a new self-adaptive fusion algorithm is put forward in this paper.

II. REVIEW OF THE THEORY OF EVIDENCE

A. DST

DST was firstly proposed by Dempster in 1967 and extended by Shafer. The main idea will be reviewed as follows. Let $\Theta=\{\theta_1,\cdots,\theta_n\}$ be the frame of discernment of the fusion problem and all elements of Θ are exclusive. A basic belief assignment (BBA) $m:2^\Theta\rightarrow[0,1]$ is defined as

$$\begin{cases}\sum\limits_{A\in 2^\Theta} m(A)=1\\ m(\phi)=0\end{cases}\tag{1}$$

where 2^Θ is the power set of Θ and it includes all its subsets .

For two independent bodies of evidence whose BBAs are denoted by m_1 and m_2 respectively, the BBA of the combination of the two bodies is given by the following rule

$$m_{12}(X)=\begin{cases}\dfrac{\sum\limits_{A,B\in 2^\Theta,A\cap B=X} m_1(A)m_2(B)}{1-k},\forall X\in\Theta,X\neq\phi\\ 0,X=\phi\end{cases}\tag{2}$$

where $k=\sum\limits_{A\cap B=\phi} m_1(A)m_2(B)$ reflects the conflict degree of the two sources.

B. DSmT

DSmT, an extension of DST, was developed by Dezert and Smarandanche ([5]). DSmT differs from DST at that the elements of Θ could be overlapped. For simplicity, use D^Θ (Hyper-power set) to denote the set of all compositions built from elements of Θ with $\cup$ and $\cap$ operators. The generalized basic belief assignment (GBBA) $m:D^\Theta\rightarrow[0,1]$ is defined as

$$\begin{cases}\sum\limits_{A\in D^\Theta} m(A)=1\\ m(\phi)=0\end{cases}\tag{3}$$

Similarly, the classical combination rule for two independent bodies of evidence, whose GBBAs are m_1 and m_2 respectively, is given by

$$m_{M^f(\theta)}(X)=\begin{cases}\sum\limits_{A,B\in D^{\Theta},A\cap B=X} m_1(A)m_2(B),\forall X\in D^{\Theta},X\neq\phi\\ 0,X=\phi\end{cases}\quad(4)$$

It is remarked that DSmT keeps the conflicting information and doesn't need normalization.

The biggest difference between DST and DSmT can be intuitively described as follows. Let $\Theta=\{\theta_1,\theta_2\}$ be the frame of discernment (without any extra conditions). The DST deals with BBA $m(\cdot)\in[0,1]$ such that $m(\theta_1)+m(\theta_2)+m(\theta_1\cup\theta_2)=1$, while the DSmT deals with GBBA $m(\cdot)\in[0,1]$ such that $m(\theta_1)+m(\theta_2)+m(\theta_1\cup\theta_2)+m(\theta_1\cap\theta_2)=1$.

C. Self-adaptive fusion algorithm based on DST and DSmT

Although DST behaves well while fusing sources are in low degree of conflict, it may give a fusion result that absolutely contrary to the fact while two sources are in high degree of conflict. Luckily, DSmT is capable of fusing the highly conflicting sources. A natural idea comes out that a self-adaptive fusion algorithm based on DST and DSmT could be used to obtain better performance in a way of simple combination, that is, if the degree of conflict is less than a given threshold, Dempster-Shafer combination rule can be used, otherwise DSm combination rule will be selected.

The limitation of applying the above idea in practice is that a threshold of conflict should be set in advance. It is very difficult to determine a suitable value for the conflicting threshold since different systems have different degrees of conflict, and an experiential value is usually used instead the true one by experimenting time after time. The risk lies that once the threshold is not suitable, fusion results will be bad.

To solve the above problem, this paper proposed a new self-adaptive algorithm based on DST and DSmT, which avoids setting for the conflicting threshold in advance.

III. A New Self-adaptive Fusion Algorithm

Note that the key difficulty lies in how to process the conflicting information. Before introducing the new self-adaptive fusion algorithm, we will review the existing methods and explain why we adopt such an algorithm.

According to DST, conflicting pieces of information between two bodies of evidence are eliminated by making normalization. Yager ([2]) distributed the conflicting information to the union of all elements, and viewed the conflict as unreliable and ignored it. Smets ([8]) distributed the conflicting information to empty set. He pointed out that all the sources of evidence are reliable but the frame of discernment is not complete and the actual result may lie out of the frame. The limitation of DST method is that it cannot deal with the cases of high degree conflicts.

On the contrary, DSmT keeps the conflicting information useful and redistributes the conflicting information according to some principles while fusing. It is capable of coping with the cases of high degree conflicts, but it offers slow convergence for the result.

To absorb the advantages of DST and DSmT, the new algorithm will treat the conflicting information in a combination way, that is, part of the conflicting information will be distributed to the nonempty set averagely and the other will be redistributed by other principles. A controlling factor will be proposed to decide the mass of conflicting information to be normalized or not.

A. Evaluation of conflict between bodies of evidence

Definition 1 (Conflict)[6]. A conflict between two beliefs in DS theory can be interpreted qualitatively as one source strongly supports one hypothesis and the other strongly supports another hypothesis, and the two hypotheses are not compatible.

It is well known that, the key problem of designing self-adaptive fusion algorithm based on DST and DSmT is how to compute the conflict between two bodies of evidence. Next we will show that the existing measures, including the conflict coefficient used in DST and DSmT and the degree of similarity, are not suitable to act as a eligible measure for conflicting information, although the former has long been taken as a fact in the Dempster–Shafer theory community. We also propose a new measure to fill in this gap.

Example 1. Let Θ be a frame of discernment with n hypotheses $\{\theta_1,\cdots,\theta_n\}$. Assume m_1 and m_2 are two BBAs offered by two distinct sources which are defined as

$$m_1(\theta_i)=1/n,\quad m_2(\theta_i)=1/n,\quad i=1,2,\cdots,n$$

Obviously, the two BBAs are totally consistent with each other. So there shouldn't exist conflict. Firstly, compute the conflict coefficient and get $k=1-1/n$, where n is the number of hypotheses in frame of discernment. Secondly, It can be found out that along with the increase of n, k will increase and approach to 1, as shown in the relationship between k and n is shown as Fig.1. If k is taken as a measurement of the degree of conflict, the two bodies of evidence are in high degree of conflict when n is larger than 5. It is surely contrary to the fact.

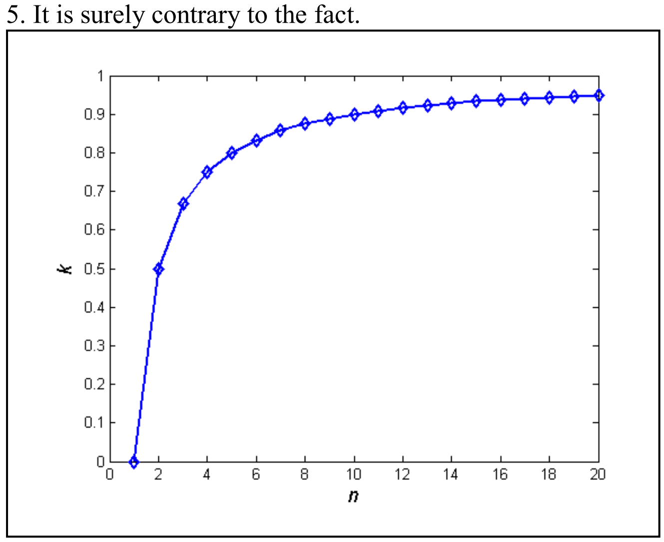

Fig.1. Relationship between k and n in example 1

Example 2. Let Θ be a frame of discernment with two hypotheses $\{\theta_1, \theta_2\}$. The BBAs offered by two sources are defined as

$$m_1(\theta_1) = p\,,\ m_1(\theta_2) = 1 - p$$

$$m_2(\theta_1) = 1 - p\,,\ m_2(\theta_2) = p$$

where $p \in [0,1]$. It is obvious that the two bodies of evidence are highly contradicted with each other. According to DST, the conflict coefficient can be calculated as $k = p^2 + (1-p)^2$. Fig 2 shows the relationship between k and p. As p changes from 0 to 1, k will decrease from 1 to 0.5 and then increase to 1 again, as shown in Fig 2. Note that k is low than 1 at most time especially while p is around 0.5. It can't reflect the conflict between two sources of evidence rightly.

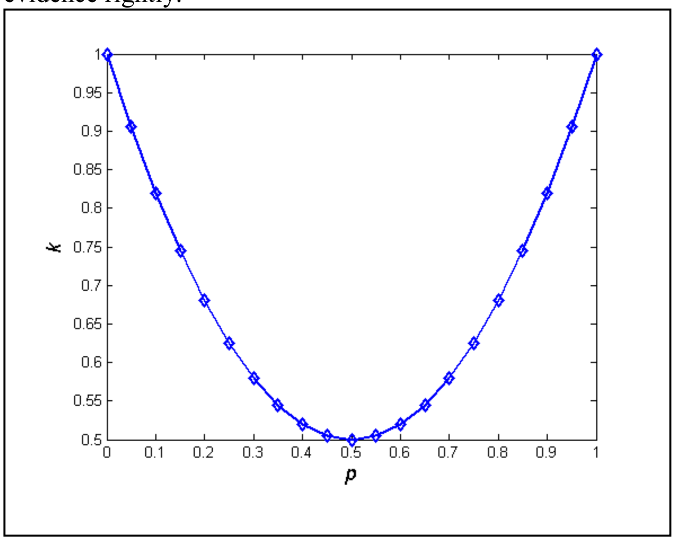

Fig.2. Relationship between k and n in example 2

From Example 1 and 2, we can see that the conflict coefficient k can't be used as a suitable measure of conflict.

To overcome the above shortage, some other evaluating methods of conflict are put forward, such as the degree of similarity. Since the similarity of two bodies of evidence can also reflect their conflict, it can be used as a candidate to reveal the conflict between two sources of evidence. Generally speaking, the larger the degree of similarity is, the smaller the conflict is.

Usually, the degree of similarity can be calculated by the distance between bodies of evidence. There are some kinds of distance being used in information fusion, such as the famous the Euclidean distance ([7]) proposed by Cuzzolin, the Bhattacharyya distance ([8]) given by Ristic and Smets. Both of them are defined in the frame of Dempster-Shafer theory. Nevertheless, neither of them can reflect the similarity of the subset of frame Θ. Besides, Tessem turned the belief function into the probability function by pignistic transformation and evaluated the distance between bodies of evidence in the level of pignistic ([9]). However, the distance defined in this way doesn't accord with the distance theory. No valuable distance can be used in practice until the coming out of Jousselme distance ([10]), which is the most widely used distance of evidence at present. The definition of Jousselme distance is given as follows.

Definition 2 (Jousselme distance). Let Θ be a frame of discernment with n hypotheses. The BBAs offered by two sensors are denoted as m_1 and m_2. Distance between them can be defined as

$$Dis(m_1, m_2) = \sqrt{\frac{1}{2}(m_1 - m_2)^T D(m_1 - m_2)} \qquad (5)$$

where $D = \left(D_{ij}\right) = \left(\dfrac{|A_i \cap B_j|}{|A_i \cup B_j|}\right)$ is a $2^n \times 2^n$-dimensional matrix, and $|A|$ denotes the number of elements of A. It reflects the degree of similarity of the evidence. Formula (5) can be rewritten as

$$Dis(m_1, m_2) = \sqrt{\frac{1}{2}(\|m_1\|^2 + \|m_2\|^2 - 2 < m_1, m_2 >)}$$

where $\|m_i\|^2 = < m_i, m_i >$, $i = 1,2$, and

$$< m_1, m_2 > = \sum_{i=1}^{2^n} \sum_{j=1}^{2^n} m_1(A_i) m_2(B_j) \frac{|A_i \cap B_j|}{|A_i \cup B_j|}$$

is the product of two vectors.

Note that in the frame of discernment in DSmT, hypotheses could be overlapped potentially. Then a generalized Jousselme distance is defined as follows.

Definition 3 (generalized Jousselme distance). Let Θ be a fame of discernment in DSmT with n hypothesis. The two GBBAs offered by sensors are denoted as m_1 and m_2. Distance between them is defined as

$$Dis(m_1, m_2) = \sqrt{\frac{1}{2}(m_1 - m_2)^T D(m_1 - m_2)} \qquad (6)$$

where $D = \left(D_{ij}\right) = \left(\dfrac{|A_i \cap B_j|}{|A_i \cup B_j|}\right)$ is a $N \times N$-dimensional matrix, N is the number of elements in the power set of Θ, and $|A|$ denotes the DSm cardinality of A. Similarly, distance can be transformed as

$$Dis(m_1, m_2) = \sqrt{\frac{1}{2}(\|m_1\|^2 + \|m_2\|^2 - 2 < m_1, m_2 >)}\,,$$

where $\|m_i\|^2 = < m_i, m_i >$, $i = 1,2$, and

$$< m_1, m_2 > = \sum_{i=1}^{N} \sum_{j=1}^{N} m_1(A_i) m_2(B_j) \frac{|A_i \cap B_j|}{|A_i \cup B_j|}\,,$$

$\forall A \in D^\Theta$.

It is easy to see that $Dis(m_1,m_2)\in[0,1]$, and the degree of similarity can be defined as

$$Sim(m_1,m_2)=1-Dis(m_1,m_2) \tag{7}$$

Obviously, it has $Sim(m_1,m_2)\in[0,1]$.

In example 1, the Jousselme distance is always 0 no matter what the value of n be. In other words, the similarity between two bodies of evidence is always 1, it accords with the fact. In example 2, the Jousselme distance is computed as $Dis(m_1,m_2)=|1-2p|$. As p changes from 0 to 1, the Jousselme distance decreases from 1 to 0 and then increases to 1 again. It is also reasonable in intuition. However, one cannot determine the value of conflict between two bodies of evidence correctly just by the similarity. We will show this by the following Example 3.

Example 3. Let Θ be a frame of discernment with two hypotheses $\{\theta_1,\theta_2\}$. The two BBAs offered by sensors are defined as

$$m_1(\theta_1)=0.8,\ m_1(\theta_1\cup\theta_2)=0.2$$
$$m_2(\theta_1\cup\theta_2)=1$$

Simple calculation will yield $Dis(m_1,m_2)=0.5657$, and $Sim(m_1,m_2)=0.4343$. If the conflict is estimated by the degree of similarity, the two sources of evidence are in conflict. However, it is obvious that the second body of evidence is totally unknown. Thus one can't assert that they are in conflict. In other words, it is not credible to determine the degree of conflict only by on the degree of similarity.

In summary, neither conflict coefficient nor degree of similarity can be used as the quantitative measure of conflict alone. A natural idea comes out that one may make a judgment objectively by considering the two factors synthetically. Actually, many researchers followed this way. For example, Jiang ([12]) took the average of Joussleme distance and conflict coefficient as the new measure for conflict. Liu ([6]) made the dualistic array by conflict coefficient and the distance between betting commitments to analysis the conflict under different situations. Liu ([13]) used the geometric mean of conflict coefficient and distance between betting commitments as the measure of the conflict.

This paper also adopts the above idea. One will see in the following text that, in our new combination model there are two places where the degrees of conflict need to be estimated. On one side, the classical conflict coefficient is taken to measure the value of conflict. On the other side, the similarity between bodies of evidence is used as a controlling factor to distribute the conflicting information. See next for details.

B. New combination rule

Let $\Theta=\{\theta_1,\cdots,\theta_n\}$ be a discernment frame with n hypotheses. The hypotheses of the frame could be non-exclusive. D^Θ is the hyper-power set. The generalized basic belief assignment is defined as $m:D^\Theta\to[0,1]$ where

$$\begin{cases}\sum_{A\in D^\Theta} m(A)=1\\ m(\phi)=0\end{cases} \tag{8}$$

Let m_1 and m_2 be the GBBAs of two sensors which are independent with each other. The new combination rule can be defined as

$$m_{12}(X)=\frac{\sum_{\substack{A,B\in D^\Theta\\ A\cap B=X}} m_1(A)m_2(B)+P(X)}{1-k'},\forall X\in D^\Theta, X\neq\phi \tag{9}$$

where $k=\sum_{A,B\in D^\Theta, A\cap B=\phi} m_1(A)m_2(B)$ reflects the mass of conflict, $k'=\sigma k$ is the conflict that will be distributed to the all hypotheses averagely by normalizing. The rest $(1-\sigma)k$ will be redistributed by other rules. Here σ is a controlling factor. Denote the conflicting information that be distributed to hypothesis X by $P(X)$, and thus $\sum_{X\in D^\Theta} P(X)=(1-\sigma)k$.

It can be seen from formula (9) that, as σ changes, the fusion results will be different. When $\sigma=0$, all conflict information will be kept and distributed to the hypotheses which bring on the conflict, and then the new algorithm will degenerate to DSm combination rule. When $\sigma=1$, all conflict information will be distributed to all hypotheses averagely, and then the new algorithm will degenerate to DS combination rule. When $\sigma\in(0,1)$, part of the conflict will be kept as useful and the rest will be distributed averagely, then the new algorithm is the synthesis of DSm and DS combination rules.

The new algorithm uses the degree of similarity as the controlling factor to adjust the fusion result adaptively. Let s be the number of sources. If $s=2$, then $\sigma=Sim(m_1,m_2)$; if $s>2$, then $\sigma=\min\{Sim(m_i,m_j)\,|\,i,j=1,\cdots,s\}$.

While there are more than two sources to be fused, the new combination rule can be defined as

$$m(X)=\frac{\sum_{\cap A_i=X}\prod_{1\le j\le s} m_j(A_i)+P(X)}{1-k'},\forall X\in D^\Theta, X\neq\phi \tag{10}$$

where $k'=\sigma k$, $k=\sum_{\cap A_i=\phi}\prod_{1\le j\le s} m_j(A_i)$.

C. Conflict distribution rule

To copy with the complex constraints in real systems, Dezert proposed the hybrid DSm combination rule, which works properly even if in high degree of conflict. However, due to the big number of element in D^Θ, it cannot offer quick convergence and cost too much time for calculation. To achieve a better performance, some new distribution rules based on the DSm rule are put forward and are classified as PCR1~PCR6 according to distribution rules ([11]). It is remarked that PCR5 is thought to be the most precise in distribution and its combination rule is defined as

$$m(X) = \sum_{A \cap B = X} m_1(A)m_2(B) + \sum_{\substack{Y \in D^\Theta \\ X \cap Y = \phi}} \left[\frac{m_1^2(X)m_2(Y)}{m_1(X)+m_2(Y)} + \frac{m_2^2(X)m_1(Y)}{m_2(X)+m_1(Y)} \right] \quad (11)$$

where $X \in D^\Theta, X \neq \phi$.

According to PCR5, the conflicting information caused by X and Y will be distributed to themselves without considering of their union. In fact, the conflicting information is decompounded to two parts as $m_1(X)m_2(Y)$ and $m_2(X)m_1(Y)$, which will be distributed separately. Hypotheses X and Y will get the conflicting information in proportion to their basic belief assignments. Due to the high performance, PCR5 is widely used in real systems. As an upgraded version of PCR5, PCR6 is the latest rule which is used to fuse more bodies of evidence and has also been applied in real systems.

Our algorithm also adopts the PCR5 for conflict distribution, and then the item $P(X)$ in formula (9) could be rewritten as:

$$P(X) = (1-\sigma) \sum_{\substack{Y \in D^\Theta \\ X \cap Y = \phi}} \left[\frac{m_1^2(X)m_2(Y)}{m_1(X)+m_2(Y)} + \frac{m_2^2(X)m_1(Y)}{m_2(X)+m_1(Y)} \right] \quad (12)$$

If there are more than two sources, they can be combined one by one according to PCR5. In addition, they can also be combined according to PCR6, and the item $P(X)$ in formula (9) could be rewritten as

$$P(X) = (1-\sigma) \left\{ \sum_{i=1}^{s} m_i^2(X) \sum_{\bigcap_{k=1}^{s-1} Y_{\sigma_i(k)} \cap X = \phi} \left[\frac{\prod_{j=1}^{s-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)})}{m_i(X) + \sum_{j=1}^{s-1} m_{\sigma_i(j)}(Y_{\sigma_i(j)})} \right] \right\} \quad (13)$$

where $\sigma_i(j) = \begin{cases} j, j < i \\ j+1, j \geq i \end{cases}$.

D. Realization of the new algorithm

Let $\Theta = \{\theta_1, \cdots, \theta_n\}$ be a frame of discernment with n hypotheses. $m_1(A_i)$ and $m_2(B_j)$ are the basic belief functions of two sources which are independent with each other, where $\sum_{A_i \in D^\Theta} m_1(A_i) = 1$, $\sum_{B_j \in D^\Theta} m_2(B_j) = 1$. The new self-adaptive fusion algorithm based on DST and DSmT can be described as following four steps. Here we use $m(X)$ to denote the fusion result.

Step1. $\forall X \in D^\Theta, X \neq \phi$, set $m(X) = 0$ and $k = 0$. Compute $Dis(m_1, m_2)$, $Sim(m_1, m_2)$, and $\sigma = Sim(m_1, m_2)$.

Step2. $\forall i, j = 1, 2, \cdots$, compute $m_1(A_i)m_2(B_j)$. If $A_i \cap B_j \neq \phi$, then renew $m(A_i \cap B_j)$ with $m(A_i \cap B_j) + m_1(A_i)m_2(B_j)$, else renew k with $k + m_1(A_i)m_2(B_j)$, renew $m(A_i)$ with $m(A_i) + (1-\sigma)m_1^2(A_i)m_2(B_j)/(m_1(A_i)+m_2(B_j))$, and renew $m(B_j)$ with $m(B_j) + (1-\sigma)m_1(A_i)m_2^2(B_j)/(m_1(A_i)+m_2(B_j))$;

Step3. If all of $m_1(A_i)m_2(B_j)$ have been computed, go to step4; otherwise, go to step 2;

Step4. $\forall X \in D^\Theta$, if $X = \phi$, $m(X) = 0$; otherwise, $m(X) = m(X)/(1-\sigma k)$.

IV. NUMERICAL EXAMPLE

Suppose five sensors are used to detect targets which are independent with each other. Let $\Theta = \{A, B, C\}$ be the frame of discernment. Elements in Θ are exclusive.

Example 1 (no conflicting evidence): The basic belief assignments offered by five sensors are given as follows.

Evidence 1: $m_1(A) = 0.5, m_1(B) = 0.2, m_1(C) = 0.3$;

Evidence 2: $m_2(A) = 0.6, m_2(B) = 0.2, m_2(C) = 0.2$;

Evidence 3: $m_3(A) = 0.55, m_3(B) = 0.1, m_3(C) = 0.35$;

Evidence 4: $m_4(A) = 0.55, m_4(B) = 0.1, m_4(C) = 0.35$;

Evidence 5: $m_5(A) = 0.55, m_5(B) = 0.1, m_5(C) = 0.35$;

It is easy to see that all bodies of evidence support the identity A and they are in low degree of conflict. Fusion results offered by different combination rules are given in table 1.

Example 2 (one conflicting body of evidence): The basic belief assignments offered by five sensors are given as follows.

Evidence 1: $m_1(A) = 0.5, m_1(B) = 0.2, m_1(C) = 0.3$;

Evidence 2: $m_2(A) = 0, m_2(B) = 0.9, m_2(C) = 0.1$;

Evidence 3: $m_3(A) = 0.55, m_3(B) = 0.1, m_3(C) = 0.35$;

Evidence 4: $m_4(A) = 0.55, m_4(B) = 0.1, m_4(C) = 0.35$;

Evidence 5: $m_5(A) = 0.55, m_5(B) = 0.1, m_5(C) = 0.35$;

It is obviously that most bodies of evidence support the identity A but the second body of evidence supports the identity B. In other words, they are in high degree of conflict. Fusion results offered by different combination rules are given in table 2.

Example 3 (two conflicting bodies of evidence): The basic belief assignments offered by five sensors are given as follows.

Evidence 1: $m_1(A) = 0.5, m_1(B) = 0.2, m_1(C) = 0.3$;

Evidence 2: $m_2(A) = 0, m_2(B) = 0.9, m_2(C) = 0.1$;

Evidence 3: $m_3(A) = 0.3, m_3(B) = 0.6, m_3(C) = 0.1$;

Evidence 4: $m_4(A) = 0.55, m_4(B) = 0.1, m_4(C) = 0.35$;

Evidence 5: $m_5(A) = 0.55, m_5(B) = 0.1, m_5(C) = 0.35$;

As in example 2, most bodies of evidence support the identity A, but there are two bodies of evidence support the identity B. They are also in high degree of conflict. Fusion results offered by different combination rules are given in table 3.

TABLE 1. FUSION RESULTS OF EXAMPLE 1

Fusion algorithm	Element of D^{Θ}	m_1m_2	$m_1m_2m_3$	$m_1m_2m_3m_4$	$m_1m_2m_3m_4m_5$
DST	A	0.75	0.8684	0.9213	0.9503
	B	0.1	0.0211	0.0041	0.0007
	C	0.15	0.1105	0.0746	0.049
PCR5	A	0.6529	0.7087	0.7373	0.7506
	B	0.1426	0.0602	0.0281	0.0201
	C	0.2045	0.2311	0.2346	0.2293
New self-adaptive combination rule	A	0.7289	0.8235	0.8598	0.8755
	B	0.1092	0.0303	0.0113	0.008
	C	0.1619	0.1462	0.1289	0.1165

TABLE 2. FUSION RESULTS OF EXAMPLE 2

Fusion algorithm	Element of D^{Θ}	m_1m_2	$m_1m_2m_3$	$m_1m_2m_3m_4$	$m_1m_2m_3m_4m_5$
DST	A	0	0	0	0
	B	0.8571	0.6316	0.3288	0.1228
	C	0.1429	0.3684	0.6712	0.8772
PCR5	A	0.2024	0.37	0.5101	0.6154
	B	0.6851	0.4482	0.258	0.1247
	C	0.1125	0.1818	0.2319	0.2599
New self-adaptive combination rule	A	0.1797	0.3727	0.5724	0.7366
	B	0.7044	0.4441	0.2068	0.0610
	C	0.1159	0.1832	0.2208	0.2024

TABLE 3. FUSION RESULTS OF EXAMPLE 3

Fusion algorithm	Element of D^{Θ}	m_1m_2	$m_1m_2m_3$	$m_1m_2m_3m_4$	$m_1m_2m_3m_4m_5$
DST	A	0	0	0	0
	B	0.8571	0.9730	0.9114	0.7461
	C	0.1429	0.0270	0.0886	0.2539
PCR5	A	0.2024	0.1920	0.3413	0.4827
	B	0.6851	0.7615	0.5116	0.3068
	C	0.1125	0.0465	0.1471	0.2105
New self-adaptive combination rule	A	0.1797	0.1246	0.2962	0.4904
	B	0.7044	0.8467	0.5791	0.3222
	C	0.1159	0.0287	0.1247	0.1874

Table 1 shows us that, DST is very suitable for fusing bodies of evidence in low degree of conflict. However, because PCR5 keeps the conflicting focal elements, the support degree of A is just 0.7506 when fusing the fifth body of evidence. It has been shown in Fig.3 that the degree of A offered by PCR5 is much less than the value offered by DST (0.9503). When applying the new self-adaptive algorithm, the support degree of A is 0.8755, which achieves a great improvement for that of PCR5. In other words, the new algorithm can fuse the sources of evidence in low degree of conflict well.

It can be seen from table 2 that, due to the high degree of conflict, the mass of A in fusion results by applying the DST rule is always 0. Obviously, it is illogical in real world. By using the PCR5 rule, one can make the right decision. However, we can see from Fig.4 that PCR5 rule could only offer slow convergence, while the new self-adaptive fusion algorithm not only overcomes the shortage of DST whose fusion result is illogical but also makes the right decision with quick convergence.

Table 3 gives the fusion results of example 3. Although there are two bodies of evidence which are in conflict with other evidence, our algorithm and PCR5 will give the right results. Besides, it can be seen from Fig.5 that, as the number of bodies of evidence increases, the new algorithm will get a better performance on convergence than PCR5. In conclusion, the new self-adaptive fusion algorithm is the best one among the three algorithms while dealing with high degree of conflict.

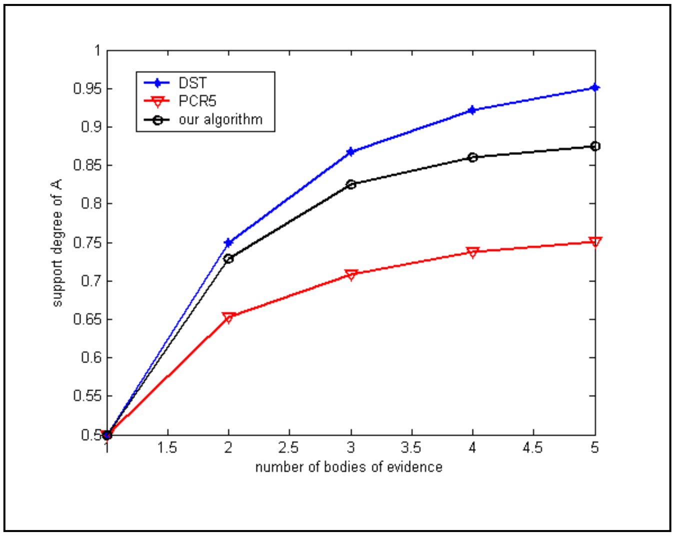

Fig.3. Support degree of A in Example 1

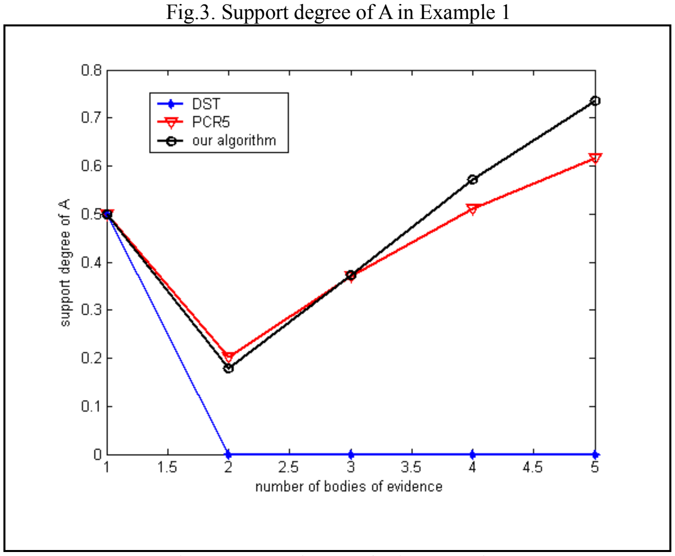

Fig.4. Support degree of A in Example 2

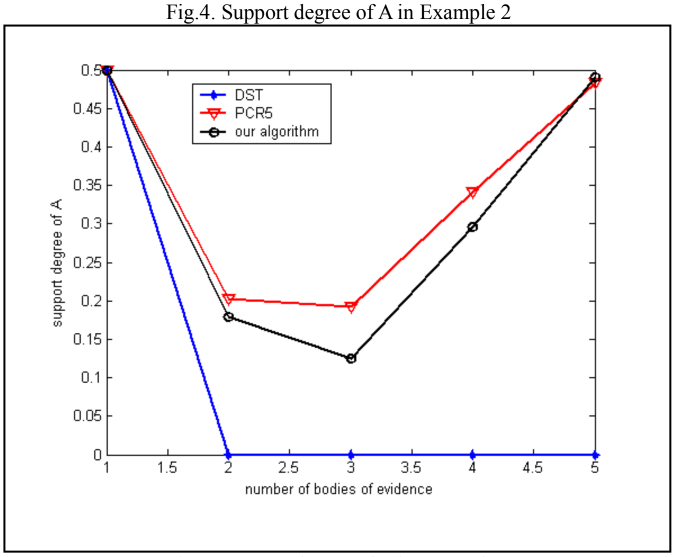

Fig.5. Support degree of A in Example 3

To sum up, the new self-adaptive algorithm can deal with high degree of conflict with a good performance on convergence.

V. CONCLUSION

Based on DST and DSmT, this paper proposes a new self-adaptive fusion algorithm. A controlling factor is introduced to avoid setting of the conflict threshold. Simulation results show that the new model can reach a preferable fusion result no matter the sources of evidence are in high degree of conflict or not. Furthermore, the new algorithm offers a quick convergence and it is more appropriate to be used in the real fusion system.

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