Improved Evidence Theory Based on Partial Correction of Evidence Dissimilarity

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Abstract: Considering the difficulty of conflict evidences combination in target fusion recognition, a new improved approach based on partial correction of evidence dissimilarity is proposed from the perspective of evidence preprocessing. The proposed approach obtains judgment method of conflict evidences from the evidence dissimilarity and maximizes the support for non-conflicting evidences by use of the pretreatment of partial correction. By simulations, the results show that the proposed approach can combine the evidences with high conflict effectively and has better performance in recognition reliability, anti-interference and convergence speed.

1. Introduction

In the battlefield, when the radar network identifies the target, due to the influence of the radar precision or external interference, the target information obtained by different radars is uncertain and may conflict or even completely contradict. Conflict evidence cannot be completely avoided. The direct use of evidence theory to calculate conflict evidence will make incorrect decisions. Therefore, how to effectively integrate highly conflicting evidence is a very difficult issue. Aiming at improving the credibility and anti-interference ability of target recognition, this paper presents an improved approach based on the partial correction of evidence dissimilarity from the perspective of evidence preprocessing. The approach achieves better integration effect.

2. Evidence Theory and Its Present Situation

2.1 Evidence Theory Overview

Evidence theory, also known as Dempster-Shafer evidence theory[1-8], was put forward by the famous American scholar Dempster in 1967. The basic principle is summarized as follows.

Let Θ be a non-empty and finite set consisting of all possible values, and the elements of Θ are mutually incompatible, then Θ is the recognition frame. Θ= {θ1, θ2, …, θn}. Each element θi is called a primitive.

Let Θ be a recognition frame. Proposition A is a subset of Θ. When the function $m:2^{\Theta}\rightarrow[0,1]$ satisfies the following conditions:

1) $m(\phi)=0$

2) $\sum_{A\subset\Theta} m(A)=1$

Let m be the Basic Probability Assignment (BPA) function or mass function on the recognition frame Θ.

Let $m_1, m_2, \cdots, m_n$ be n mutually independent basic probability assignment functions on the same recognition frame Θ, and the combination rule of evidence theory is:

$$m(A)=\begin{cases}\dfrac{\sum\limits_{A_i\cap B_j\cap\cdots\cap Z_k=A} m_1(A_i)\cdot m_2(B_j)\cdots m_n(Z_k)}{1-K}, \\ 0, A=\phi\end{cases} \tag{1}$$

$$\forall A\subset\Theta, A\neq\phi$$

$$K=\sum_{A_i\cap B_j\cap\cdots\cap Z_k=\phi} m_1(A_i)\cdot m_2(B_j)\cdots m_n(Z_k)<1 \tag{2}$$

m(A) is the BPA of subset A after these n pieces of evidence are combined. K is the conflict factor. It is the BPA assigned to the empty set, which reflects the degree of evidence conflict.

2.2 Problems and Status Analysis

The use of evidence theory for highly conflicting evidence results in perverse results. In view of the above phenomenon, many improved methods have been proposed, which can be summarized into two categories: modifying evidence theory combination rules; preprocessing of evidence before the use of evidence theory, that is, modifying the original evidence.

The first kind of improvement method mainly studies how to assign the conflict, namely assignment of empty set, more reasonable. Scholars who support this type of method believe that the unreasonable result after combining highly conflicting evidence is due to the unreasonable normalization process in the combination rule. Therefore, they advocate the redistribution of the conflict[9]. For example, there are Smets[10], Yager[11], Sun Quan[12], Guo Huawei, Dubois , Prade[13,14] and Lefevre[15].

Scholars who support the second type of method consider the rules of evidence theory to be reasonable. Evidence theory combination rules are the extension of Bayes method, with a solid mathematical foundation. Blindly modifying the rules of evidence combination will undermine the good nature of the original rules, such as exchangeability and associativity. Therefore, in the fusion of highly conflicting evidence, the evidence should be preprocessed before using evidence combination rules. Representatives of such methods include the evidence averaging combination method proposed by Murphy[16]. Based on this idea, Deng Yong[17], Hu Changhua, Peng Ying[18], Liu Xiliang[19], Xiong Yanming[21] and others have adopted the method of evidence preprocessing to solve the problem of conflict evidence fusion.

The improved method of preprocessing the evidences is essentially giving the weight of evidence in different ways, and then applying the rule of evidence combination, in order to restrain the adverse impact of conflict evidence and improve the accuracy of the fusion result. To make evidence theory combine the highly conflicting evidence correctly, this paper follows the second kind of method and proposes an improved method based on partial correction of evidence dissimilarity. Among them, how to obtain a reasonable weight and how to give different weight of evidence are two very crucial issues.

3. Improved Approach Based on Partial Correction of Evidence Dissimilarity

3.1 The Evidence Dissimilarity

If a piece of evidence is more similar to the majority of the evidence, then the evidence is supported by other evidence to a higher degree, indicating a higher credibility and should be given a greater weight. Conversely, the evidence is very different and should be given a smaller weight. Therefore, based on the similarity or difference between the evidences, we should explore ways to obtain the weight of evidence. Reference [17] introduced Jousselme distance function to measure the similarity between the evidence.

Let Θ be a recognition frame, and m1 and m2 are two independent sets of BPA on the recognition frame. Then the Jousselme distance between m1 and m2 is expressed as:

$$d(m_1,m_2)=\sqrt{\frac{1}{2}(m_1-m_2)^T D(m_1-m_2)} \tag{3}$$

D is a positive definite matrix. For $\forall A, B \subseteq \Theta$, $D(A,B)$ is an element of D, which should be satisfied:

$$D(A,B)=\frac{|A\cap B|}{|A\cup B|} \tag{4}$$

$|A|$ represents the base of focal cell A. Jousselme distance measures only the distance difference between the evidence. In this paper, the cosine of the vector is introduced to measure the direction difference between the evidence.

Considering the two evidences m1 and m2 as two vectors, the cosine is:

$$\cos(m_1,m_2)=\frac{\langle m_1,m_2\rangle}{|m_1|\times|m_2|} \tag{5}$$

$\langle m_1,m_2\rangle$ represents the inner product of two vectors. $|m_1|$ and $|m_2|$ represent the modulus of the vector. The smaller the cosine between the two evidences, the greater the difference.

In order to better express the similarity or difference between the evidences and give the accurate weight to the evidences, the difference between the two evidences is composed of the distance difference and the direction difference. $d(m_1,m_2)$ is Jousselme distance between evidence. $\cos(m_1,m_2)$ is the cosine. The evidence dissimilarity between m1 and m2 is expressed as[22]:

$$\Delta(m_1,m_2)=d(m_1,m_2)\times(1-\cos(m_1,m_2)) \tag{6}$$

The smaller $\Delta(m_1,m_2)$ is, the smaller the difference between the two evidences is. The larger $\Delta(m_1,m_2)$ is, the greater the difference between the two evidences is.

3.2 Conflict Judgment

Let Θ be a recognition frame. $m_1,m_2,\cdots,m_n$ are n independent sets of BPA on the recognition frame, that is, n evidences of evidence theory. Δ_{ij} is the evidence dissimilarity between m_i and m_j. Then the evidence dissimilarity matrix is expressed as:

$$\Delta=\begin{bmatrix} 0 & \Delta_{12} & \cdots & \Delta_{1j} & \cdots & \Delta_{1n} \\ \vdots & \vdots & & \vdots & & \vdots \\ \Delta_{i1} & \Delta_{i2} & \cdots & \Delta_{ij} & \cdots & \Delta_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ \Delta_{n1} & \Delta_{n2} & \cdots & \Delta_{nj} & \cdots & 0 \end{bmatrix} \tag{7}$$

The average difference between evidence mi and other evidence is:

$$\bar{\Delta}_i=\frac{1}{n-1}\sum_{j=1,i\neq j}^{n}\Delta_{ij} \tag{8}$$

The average difference of n evidences obtained from $\bar{\Delta}_i$ is:

$$\bar{\Delta}=\frac{1}{n}\sum_{i=1}^{n}\bar{\Delta}_i \tag{9}$$

$\bar{\Delta}$ represents the difference of overall the evidence. The basic idea of conflict judgment is that if there is a high degree of conflict between one evidence and the other evidences, its average difference is relatively large. Compare $\bar{\Delta}_i$ of each evidence with $\bar{\Delta}$. For evidence mi, when $\bar{\Delta}_i\geq\bar{\Delta}$, it indicates that the evidence mi has great difference with other evidences, and mi is the conflicting evidence. When $\bar{\Delta}_i<\bar{\Delta}$, it indicates that the evidence mi has small difference with other evidences, mi is not the conflicting evidence. Thus, the judgment method of conflict evidence is obtained.

3.3 Partial Correction

In most current preprocessing methods, all evidence is given a corresponding weight, which can weaken the negative effects of conflicting evidence, but at the same time it reduces the trust of non-conflicting evidence. In this regard, this article adopts the method of partial correction, and only gives the weight to the conflicting evidence, without changing the trust to non-conflicting evidence.

This preprocessing method preserves the maximum support for non-conflicting evidence so that the fusion results achieve better convergence.

Based on the above average difference, the support for evidence mi is expressed as:

$$Sup(m_i) = \frac{\sum_{i=1}^{n} \overline{\Delta}_i - \overline{\Delta}_i}{\sum_{i=1}^{n} \overline{\Delta}_i}, i = 1, 2, \cdots, n \tag{10}$$

$Sup(m_i)$ reflects the extent to which mi is supported by other evidence. The greater the average difference between mi and other evidence, the less support it has. Use it to normalize the support degree to get the weight of evidence mi:

$$w_i = \frac{Sup(m_i)}{\sum_{i=1}^{n} Sup(m_i)} \tag{11}$$

Conflicting evidence is locked by the conflict judgment method above, and only conflicting evidence is corrected. The correction method is:

$$\begin{aligned} &m_i'(A_k) = w_i \bullet m_i(A_k) + (1 - w_i) \bullet \frac{1}{n} \sum_{i=1}^{n} m_i(A_k), \\ &\forall A_k \in \Theta \end{aligned} \tag{12}$$

wi is the weight of evidence mi. $m_i(A_k)$ is BPA of evidence mi about focal cell Ak.

It is verified：

$$\begin{aligned} \sum_{k=1}^{m} m_i'(A_k) &= w_i \bullet \sum_{k=1}^{m} m_i(A_k) + (1 - w_i) \bullet \frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{m} m_i(A_k) \\ &= w_i + (1 - w_i) \\ &= 1 \end{aligned} \tag{13}$$

Thus, the corrected evidence still satisfies that the sum of assignments of each focal cell is 1 in evidence. It indicates that corrected assignment of trust of each focal cell is still the basic probability assignment.

In summary, the partial correction process for different evidences is as follows:

$$\begin{cases} m_i'(A_k) = w_i \bullet m_i(A_k) + (1 - w_i) \bullet \frac{1}{n} \sum_{i=1}^{n} m_i(A_k), \overline{\Delta}_i > \overline{\Delta} \\ m_i'(A_k) = m_i(A_k), \overline{\Delta}_i \le \overline{\Delta} \end{cases} \tag{14}$$

Conflicting evidences are found through the judgment method of conflict evidence, and the weight of conflicting evidence is obtained by the evidence dissimilarity. Only give the corresponding weight to the conflicting evidence and keep the non-conflicting evidence. This results in a partial corrected BPA. Then we use the combination rule of evidence theory to fuse partial corrected evidence to get a reasonable fusion result.

The specific steps of the improved approach based on partial correction of evidence dissimilarity proposed in this paper are shown in Fig. 1.

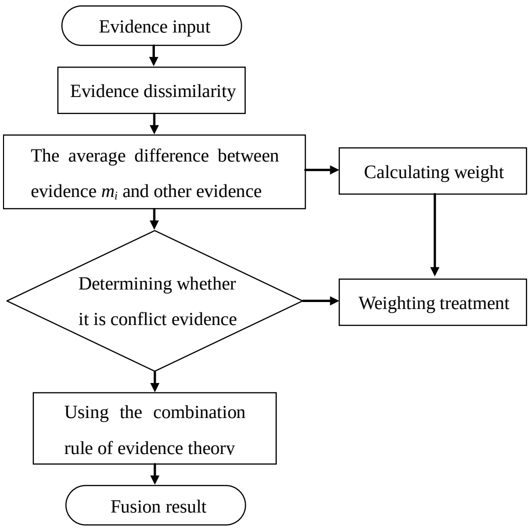

Fig.1 Processing of improved approach based on partial correction of evidence dissimilarity

4. Simulation Experiment

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To illustrate the advantages of the improved approach based on partial correction of evidence dissimilarity, the following simulation experiments are carried out. For the specific example of target recognition in [20], several typical evidence theory improvement approaches and the improved approach based on partial correction of evidence dissimilarity proposed in this paper are used.

There are four radars in the radar network to detect and recognize an air target, which is one of the civil aircraft, the bomber or the fighter. Therefore, the recognition frame of evidence theory is: $\Theta = \{A = \text{bomber}, B = \text{civil aircraft}, C = \text{fighter}\}$. The target data of each radar are processed and BPA is obtained. The evidence is as follows:

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

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

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

$m_4 : m_4(A) = 0.8, m_4(B) = 0.1, m_4(C) = 0.1$

According to the above improvement approach, the average difference between each evidence and other evidence is obtained from the evidence dissimilarity.

$\bar{\Delta}_1=0.1394, \bar{\Delta}_2=0.5537, \bar{\Delta}_3=0.1978, \bar{\Delta}_4=0.2431$

The weight of different evidence is calculated by (11).

$w_1=0.2923, w_2=0.1706, w_3=0.2752, w_4=0.2619$

According to the judgment method of conflict evidence, it is reasonable to judge only m2 as conflict evidence and other non-conflict evidence. According to the (12), the pretreatment of partial correction is used to process the conflict evidence. The combination rule of evidence theory is applied to preprocessed evidence. The fusion results of several typical approaches and the improved approach proposed in this paper are shown in Table 1.

Table 1.Comparison of Fusion Results

Approaches	$m_1 \oplus m_2$	$m_1 \oplus m_2 \oplus m_3$	$m_1 \oplus m_2 \oplus m_3 \oplus m_4$
Dempster	$m(A)=0, m(B)=0.8571$ $m(C)=0.1429, m(\Theta)=0$	$m(A)=0, m(B)=0.6667$ $m(C)=0.3333, m(\Theta)=0$	$m(A)=0, m(B)=0.6667$ $m(C)=0.3333, m(\Theta)=0$
Yager[11]	$m(A)=0, m(B)=0.18$ $m(C)=0.03, m(\Theta)=0.79$	$m(A)=0, m(B)=0.018$ $m(C)=0.009, m(\Theta)=0.973$	$m(A)=0, m(B)=0.0018$ $m(C)=0.0009, m(\Theta)=0.9973$
Murphy[16]	$m(A)=0.1543, m(B)=0.7469$ $m(C)=0.0988, m(\Theta)=0$	$m(A)=0.3912, m(B)=0.5079$ $m(C)=0.1088, m(\Theta)=0$	$m(A)=0.7996, m(B)=0.1752$ $m(C)=0.0251, m(\Theta)=0$
Sun Quan[12]	$m(A)=0.1331, m(B)=0.4727$ $m(C)=0.1364, m(\Theta)=0.2578$	$m(A)=0.2448, m(B)=0.2851$ $m(C)=0.1648, m(\Theta)=0.3053$	$m(A)=0.3341, m(B)=0.2304$ $m(C)=0.1416, m(\Theta)=0.2939$
Hu Chang-hua[20]	$m(A)=0.2627, m(B)=0.4590$ $m(C)=0.2088, m(\Theta)=0.0695$	$m(A)=0.5938, m(B)=0.1575$ $m(C)=0.2487, m(\Theta)=0$	$m(A)=0.8240, m(B)=0.0682$ $m(C)=0.1078, m(\Theta)=0$
This paper approach	$m(A)=0.1316, m(B)=0.7632$ $m(C)=0.1053, m(\Theta)=0$	$m(A)=0.7431, m(B)=0.0947$ $m(C)=0.1622, m(\Theta)=0$	$m(A)=0.9743, m(B)=0.0087$ $m(C)=0.0170, m(\Theta)=0$

As shown in Table 1, the Dempster method cannot get the correct fusion result for conflict evidence. The Yager method assigns the conflict parts to the complete set and it cannot make effective recognition. Murphy method and Sun Quan method can get the correct fusion results. But the convergence rate is slower, until the fourth evidence is fused to get the correct result. There is a risk in the case of less evidence. Hu Changhua method can make the right decision when they combine the third evidence, and the effect is better.

From the fusion results, the BPA of the recognition result A in the improved approach proposed in this paper is higher than other approaches. This approach reduces the recognition error rate, has more credibility, and makes effective recognition when the third evidence is fused. The reason is analyzed: this approach use the pretreatment of partial correction. While weakening the interference of conflict evidence to the result, the pretreatment method retains the trust of non-conflict evidence to the maximum extent. And the weight coefficient makes use of the original information of the evidence, which is more reasonable, so that the fusion result achieves better convergence effect.

5. Conclusion

Aiming at the problems existing in the application of evidence theory, this paper proposes an improved approach based on partial correction of evidence dissimilarity. Firstly, a judgment method of conflict evidence is proposed by using the evidence dissimilarity. Secondly, the pretreatment method of partial correction is adopted, which only gives weight to conflict evidence without changing the trust in non-conflict evidence. Finally, the combination rule of evidence theory is applied to preprocessed evidence, so that the fusion results can achieve better convergence effect. The experimental results show that the improved approach proposed in this paper can solve the problems of evidence theory and accurately fuse the evidences with high conflict. It has the advantages of high reliability, fast convergence speed and strong anti- interference ability. It is suitable for radar network target fusion recognition and provides ideas and methods for other decision-making problems.

References

[1] Xu Yan-ke, Liang Xiao-geng, Jia Xiao-hong. Information fusion based on fuzzy evidence theory and its application in target recognition[J]. Journal of Harbin Institute of Technology, 2012, 44(3): 107-111.

[2] Zhang Zhi, Yang Qing-hai. Target recognition method based on BP neural networks and improved D-S evidence theory[J]. Computer Applications and Software, 2018, 35(03):151-156.

[3] Han De-qiang, Yang Yi, Han Chong-zhao. Advances in DS evidence theory and related discussions[J]. Control and Decision, 2014, 29(1): 1-11.

[4] Bi Wen-hao, Zhang An, Li Chong. Weighted evidence combination method based on new evidence conflict measurement approach[J]. Control and Decision, 2016, 31(1): 73-78.

[5] An Chun-lian, Huang Jing, Wu Yao-yun. A Multi-Source Information Fusion Model Based on Evidence Theory[J]. Electronic Information Warfare Technology, 2017, 32(01):23-26.

[6] Dempster A P. Upper and lower probabilities induced by a multi-valued mapping[J]. Annual Math Statist, 1967, 38(4): 325 -339.

[7] Shafer G. A mathematical theory of evidence[M]. Princeton: Princeton University Press, 1976.

[8] Jia Yu-ping. Target recognition fusion based on belief function theory[D]. Changsha: National University of Defense Technology, 2009.

[9] Han Feng, Yang Wan-hai, Yuan Xiao-guang. A efficient approach for conflict evidence combination[J]. Electronics Optics & Control, 2010, 17(4): 5-8.

[10] Smets P. The combination of evidence in the transferable belief model[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1990, 12(5): 447-458.

[11] Yager R R. On the dempster-shafer framework and new combination rules[J]. Information Sciences, 1987, 41(2): 93–137.

[12] Sun Quan, Ye Xiu-qing, Gu Wei-kang. A New Combination Rules of Evidence Theory[J]. Acta Electronica Sinica, 2000, 28(8): 117-119.

[13] Dubois D, Prade H. Representation and combination of uncertainty with belief functions and possibility measures[J]. Computational Intelligence, 1988, 4(3): 244-264.

[14] Dubois D, Prade H. A set-theoretic view of belief functions[M]. Springer Berlin Heidelberg, 2008.

[15] Lefevre E, Colot O, Vannoorenberghe P. Belief function combination and conflict management[J]. Information Fusion, 2002, 3(2): 149-162.

[16] Murphy C K. Combining belief functions when evidence conflicts[J]. Decision Support Systems, 2000, 29(99): 1-9.

[17] Deng Yong, Shi Wen-kang, Zhu Zhen-fu. Efficient combination approach of conflict evidence[J]. Journal Infrared Millimeter and Waves, 2004, 23(1): 27-32.

[18] Peng Ying, Shen Huai-rong, Ma Yong-yi. A New Fusion Method for Conflicting Evidence[J]. Acta Armamentarii, 2011, 32(1): 78-84.

[19] Liu Xi-liang, Chen Gui-ming, Li Fang-xi, Zhang Qian. Approach of conflict evidence judgment and combination based on clustering analysis[J]. Infrared and Laser Engineering, 2013, 42(10): 2853-2857.

[20] Hu Chang-hua, Si Xiao-sheng, Zhou Zhi-jie, Wang Peng. An Improved D-S Algorithm Under the New measure Criteria of Evidence Conflict[J]. Acta Electronica Sinica, 2009, 37(7): 1578-1583.