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A New DS Combination Method for Dealing with Conflict Evidence Effectively

Jinfeng Pang, Yun Lin*, Yibing Li, Xiaochun Xu, Bin Li
College of Information and Communication Engineering
Harbin Engineering University, Harbin, China
linyun@hrbeu.edu.cn

Abstract

Evidence theory is an important method for uncertainty reasoning. Because evidence theory can well process uncertain information, imprecise information, fuzzy information, and information without prior knowledge, it is wildly used in information fusion, expert system, fuzzy recognition, and intelligent decision system. This paper depend on original evidence theory fusion algorithm, put forward a new algorithm to process conflict information efficiently, this algorithm change the basic probability assignment of evidences by changing its reliability, and then get the ultimate decision making result by doing a new combination. The simulation results show the effectiveness of this algorithm, and it can give a better decision making results in processing conflict evidences.

Keywords: *Information fusion; evidence theory; combination rules; cosine similarity coefficient*

1. Introduction

In recent years, with the wide application of sensors, the research of multi-sensor information fusion technology increasing rapidly. Combine uncertain multi-source information provided by multi-sensor not only can eliminate the contradictory information and the redundant information among evidences, but the complementary of information from multi-source will reduce the overall uncertainty, and then obtain a more accurate decision making result [1]. Evidence theory comes from multi-value map put forward by the Dempster in 1967, after this, Shafer perfected it, and establish a one to one correspondence relationship between proposition and set. By this way, he change the problem of uncertainty into the problem of the uncertainty of set, so formed a mathematical theory about evidence [2]. Evidence theory as a method of uncertainty reasoning method, it has been widely used in artificial intelligence, pattern recognition, multi-sensor information fusion fields.

Since the evidence theory has been proposed, its application range was expanding rapidly, and a lot of new and improved methods were put forward. As we all know, in practical applications, there are a lot of uncertain information, while in this case, the classical DS combination rule will give a results that inconsistent with the facts. So how to deal with conflicting information urgent issue that needed to be solve.

In this paper, we quote the cosine similarity coefficient, and calculate the credibility of the evidences, and then modify the basic probability assignment function, at last combine the new value by a new combination rule. The simulation results show that this method has good effectiveness and practicability.

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2. DS Combination Rule

In D-S combination rule[1,2], $\Theta = \{A_1, A_2, \cdots, A_n\}$ represents a mutually exclusive and exhaustive set of elements, E_1 and E_2 are two evidences, the corresponding basic probability assignment function are m_1 and m_2, the focal elements are A_i and A_j, so the D-S combination rules is

$$m(A) = \begin{cases} \frac{1}{1-k} \sum_{A_i \cap A_j = A} m_1(A_i) \cdot m_2(A_j) & A \neq \varnothing \\ 0 & A = \varnothing \end{cases} \tag{1}$$

Where k is the conflict coefficient between evidences

$$k = \sum_{A_i \cap A_j = \Phi} m_1(A_i) \cdot m_2(A_j) \tag{2}$$

And $\frac{1}{1-k}$ is called normalize coefficient.

From the formula we can see that, on the one hand, if $k = 1$, that is evidences have a high degree of conflict, the above formula doesn't applicable. On the other hand, if one of the evidences is $m_k(A_i) = 0$, there is no doubt that $m(A_i) = 0$.

There are two ways to improve the DS combination rule, one is change its combination rule, and the other is modify the basic probability assignment function.

3. Other Evidence Theory Algorithm

Many scholars have studied the problem of the fusion of the conflict evidences deeply, such as Yager [3], Murphy [4], SUN Quan [5], Jian Kang [6, 7], WEI Yong-chao [8, 9] and so on, they give us different solutions from different directions, next part will introduce some improved methods.

3.1. Yager

In order to deal with conflicting information, Yager proposed a new improved method. Yager take the conflict information as unknown information, and plus it to m(Θ)

$$m(\boldsymbol{A}) = \begin{cases} \sum_{\boldsymbol{A}_i \cap \boldsymbol{B}_j = \boldsymbol{A}} m_1(\boldsymbol{A}_i) m_2(\boldsymbol{B}_j) & \boldsymbol{A} \neq \boldsymbol{\Theta} \\ \sum_{\boldsymbol{A}_i \cap \boldsymbol{B}_j = \boldsymbol{\Theta}} m_1(\boldsymbol{A}_i) m_2(\boldsymbol{B}_j) + k & \boldsymbol{A} = \boldsymbol{\Theta} \end{cases} \tag{3}$$

He thought that, since we can't make a reasonable choice about conflict evidences, we should put them into unknown territory.

3.2. SUN Quan Combination Rule

The basic probability assignment function are $m_1, m_2, \cdots, m_n$, and the evidence set is $\boldsymbol{F}_1, \boldsymbol{F}_2, \cdots, \boldsymbol{F}_n$, so the conflict between $\boldsymbol{F}_i$ and $\boldsymbol{F}_j$ is

$$k_{ij} = \sum_{\substack{\boldsymbol{A}_i \cap \boldsymbol{A}_j = \varnothing \\ \boldsymbol{A}_i \in \boldsymbol{F}_i, \boldsymbol{A}_j \in \boldsymbol{F}_j}} m_1(\boldsymbol{A}_i) m_2(\boldsymbol{A}_j) \tag{4}$$

Then, define ε is the credibility of evidence

$$\varepsilon = e^{-\tilde{k}} \tag{5}$$

Where

$$\tilde{k} = \frac{1}{n(n-1)/2} \sum_{i<j} k_{ij} \tag{6}$$

$\tilde{k}$ reflects the degree of conflict between two evidence. So the SUN Quan combination rule[5] is

$$m(\boldsymbol{A}) = \begin{cases} p(\boldsymbol{A}) + k \cdot \varepsilon \cdot q(\boldsymbol{A}) & \boldsymbol{A} \neq \boldsymbol{\Theta} \\ p(\boldsymbol{A}) + k \cdot \varepsilon \cdot q(\boldsymbol{A}) + k(1-\varepsilon) & \boldsymbol{A} = \boldsymbol{\Theta} \end{cases} \tag{7}$$

Where

$$p(\boldsymbol{A}) = \sum_{\substack{\boldsymbol{A}_i \subset \boldsymbol{\Theta} \\ \cap \boldsymbol{A}_i = \boldsymbol{A}}} m_1(\boldsymbol{A}_1) \cdots m_n(\boldsymbol{A}_n) \tag{8}$$

$$q(\boldsymbol{A}) = \frac{1}{n} \sum_{i=1}^{n} m_1(\boldsymbol{A}) \tag{9}$$

$$\varepsilon = e^{-\tilde{k}} \tag{10}$$

$$\tilde{k} = \frac{1}{n(n-1)/2} \sum_{i<j} k_{ij} \tag{11}$$

$$k_{ij} = \sum_{\substack{\boldsymbol{A}_i \cap \boldsymbol{A}_j = \varnothing \\ \boldsymbol{A}_i \in \boldsymbol{F}_i, \boldsymbol{A}_j \in \boldsymbol{F}_j}} m_1(\boldsymbol{A}_i) m_2(\boldsymbol{A}_j) \tag{12}$$

The credibility of evidence is defined by himself, so this concept has great subjectivity, also he didn’t give us a clear physical meaning.

3.3. Murphy Method

Murphy method doesn’t change the combination rule and just change the model. He analyzes some improved methods, and proposed evidences average algorithm[4]. The specific algorithms are introduced as follows. First, average the basic probability assignment, and then, combine them by the combination rule. This method can deal

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with conflict evidence effectively, also this method converges fast, but Murphy method has its disadvantage, he doesn't take the relationship among evidences into consideration, and he averages the multi-source information.

3.4. Pearson Correlation Coefficient

Pearson correlation, also known as product-moment correlation is a linear correlation proposed by Pearson of British statistician in the 20th century[9].

Suppose there are two variables X , Y , and the Pearson correlation coefficient can be calculated by the following formula

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E((X-\mu_X)(Y-\mu_Y))}{\sigma_X \sigma_Y} \tag{13}$$

Where

$$\begin{aligned} \mu_X &= E(X) \\ \sigma_X^2 &= E(X^2) - E^2(X) \end{aligned} \tag{14}$$

And then the weight of evidence is defined as

$$\omega_i = \sum_{j=1, j\neq i}^{n} \rho(E_i, E_j) / \max_{1\leq i\leq n}(\delta(E_i)) \tag{15}$$

4. Cosine Similarity Coefficient

The cosine similarity coefficient is one of the most commonly used algorithms in the calculation of similarity[8].

4.1. The Cosine Similarity Coefficient

Assume the basic probability assignment function of E_i and E_j are $m_i = (m_i(a_1), m_i(a_2), \cdots, m_i(a_n))$ and $m_j = (m_j(a_1), m_j(a_2), \cdots, m_j(a_n))$, the cosine similarity coefficient between m_i and m_j is expressed by $\boldsymbol{C_{ij}}$, and $\boldsymbol{C_{ij}}$ should satisfy

$$\begin{aligned} &\textbf{(1)}\ \left|C_{ij}\right| \leq 1 \text{且}\ C_{ii} = 1; \\ &\textbf{(2)}\ C_{ij} = \pm 1 \Leftrightarrow m_i = m_j\ (C \neq 0); \\ &\textbf{(3)}\ C_{ij} = C_{ji}. \end{aligned} \tag{16}$$

If $\boldsymbol{C_{ij}}$ closer to 1, indicating that m_i and m_j are the greater similarity. The cosine similarity coefficient[11] of m_i and m_j is defined as

$$C_{ij} = \frac{\sum_{\alpha_p \cap \alpha_t = \alpha_k \neq \varnothing} m_i(\alpha_p) m_j(\alpha_t)}{\sqrt{\sum m_i^2(\alpha_p) \sum m_j^2(\alpha_t)}} \tag{17}$$

4.2. The Weights of Evidences

From C_{ij}, we can get the degree of m_i similarity with other evidences

$$D_i = \sum_{j=1, j \neq i}^{n} C_{ij} \tag{18}$$

So the weight of m_i is

$$\omega_i = D_i / \max_{1 \le i \le n} D_i \tag{19}$$

4.3. Reallocate the Basic Probability Assignment Function

From the formula (19), we will obtain the weight of every evidence, that is

$$m_k^{'}(\alpha_i) = \begin{cases} \omega_k m_k(\alpha_i) & \alpha_i \neq \Theta \\ 1 - \sum\limits_{\alpha_i \neq \varnothing} \omega_k m_k(\alpha_i) & \alpha_i = \Theta \end{cases} \tag{20}$$

4.4. Combination Rule

In this method, we make full use of conflict coefficient, so we introduce a new factor, we call it weighted factor. We can get weighted factor of every focal element by the followed calculation

$$f(\alpha_i) = \frac{\sum\limits_{k=1}^{K} m_k(\alpha_i)}{\sum\limits_{i=1}^{n} \sum\limits_{k=1}^{K} m_k(\alpha_i)} \tag{21}$$

The above formula represents the weight of each focal element, so the conflict trust of coefficient assigns to each focal element can be described as

$$\Delta(\alpha_i) = kf(\alpha_i) \tag{22}$$

So the new combination rule can be expressed as follows

$$\begin{cases} \tilde{m}(\alpha) = \sum\limits_{\substack{\alpha_i \cap \alpha_j \\ = \alpha}} m_1^{'}(\alpha_i) m_2^{'}(\alpha_j) + kf(\alpha) & \alpha \neq \varnothing, \Theta \\ \tilde{m}(\varnothing) = 0 \\ \tilde{m}(\Theta) = 1 - \sum\limits_{\alpha \in \Theta} \tilde{m}(\alpha) \end{cases} \tag{23}$$

The new combination rule make full use of conflict information, so it reduces the possibility of unknown information, and increases the probability of the targets.

5. Simulation and Analysis

The simulation data used in this paper are come from the literature[9].

We analyse the algorithm in two ways, the first is data are consistent with each other, the other is there has conflict information in data source, in this we can prove the feasibility and practicality of the method proposed in this paper.

And the simulation results are shown as Table 3 and Table 4.

Table 1. The Basic Probability Assignment Function

Evidences	Recognition Framework		
	a	*b*	*c*
m_1	0.9	0	0.1
m_2	0.88	0.01	0.11
m_3	0.5	0.2	0.3
m_4	0.98	0.01	0.01
m_5	0.9	0.05	0.05

Table 2. The Basic Probability Assignment Function with Conflict Information

Evidences	Recognition Framework		
	a	*b*	*c*
m_1	0.9	0	0.1
m_2	0	0.01	0.99
m_3	0.5	0.2	0.3
m_4	0.98	0.01	0.01
m_5	0.9	0.05	0.05

Table 3. The Simulation Results of Normal Data

Methods	Decision-making Results			
	Two sets of evidences	*Three sets of evidences*	*Four sets of evidences*	*Five sets of evidences*
DS	$m(a)$=0.9863 $m(b)$=0 $m(c)$=0.0137 $m(\Theta)$=0 k=0.1970	$m(a)$ = 0.9917 $m(b)$ =0 $m(c)$ =0.0083 $m(\Theta)$=0 k=0.6007	$m(a)$= 0.9999 $m(b)$= 0 $m(c)$= 0.0001 $m(\Theta)$=0 k=0.6119	$m(a)$=1 $m(b)$=0 $m(c)$=0 $m(\Theta)$=0 k=0.6507
Yager	$m(a)$= 0.7920 $m(b)$=0 $m(c)$= 0.0110 m(Θ)=0.1970 k=0.1970	$m(a)$= 0.3960 $m(b)$=0 $m(c)$= 0.0033 m(Θ)=0.6007 k=0.6007	$m(a)$= 0.3881 $m(b)$=0 $m(c)$=0 m(Θ)=0.6119 k=0.6119	$m(a)$= 0.3493 $m(b)$=0 $m(c)$=0 m(Θ)=0.6507 k=0.6507
SUN Quan	$m(a)$= 0.9360 $m(b)$= 0.0008 $m(c)$= 0.0280 m(Θ)=0.0352 k=0.1970	$m(a)$= 0.5278 $m(b)$= 0.0121 $m(c)$= 0.0328 m(Θ)=0.4273 k=0.6007	$m(a)$= 0.4555 $m(b)$= 0.0046 $m(c)$= 0.0108 m(Θ)=0.5291 k=0.6119	$m(a)$= 0.3754 $m(b)$= 0.0017 $m(c)$= 0.0036 m(Θ)=0.6193 k=0.6507
Murphy	$m(a)$=0 .9863 $m(b)$=0	$m(a)$= 0.9447 $m(b)$= 0.0080	$m(a)$= 0.9709 $m(b)$= 0.0044	$m(a)$= 0.9775 $m(b)$= 0.0041

Methods	Decision-making Results			
	Two sets of evidences	*Three sets of evidences*	*Four sets of evidences*	*Five sets of evidences*
	m(c)=0.0137 m(Θ)=0 k=0.1970	m(c)= 0.0473 m(Θ)=0 k=0.6007	m(c)= 0.0247 m(Θ)=0 k=0.6119	m(c)= 0.0184 m(Θ)=0 k=0.6507
KL Distance	m(a)= 0.9673 m(b)= 0.0010 m(c)= 0.0317 m(Θ)=0 k=0.1970	m(a)= 0.5365 m(b)= 0.0246 m(c)= 0.0825 m(Θ)=0.3564 k=0.9303	m(a)= 0.5236 m(b)= 0.0165 m(c)= 0.0606 m(Θ)=0.3993 k=0.9697	m(a)= 0.5799 m(b)= 0.0216 m(c)= 0.0561 m(Θ)=0.3423 k=0.9773
Pearson	m(a)= 0.9673 m(b)= 0.0010 m(c)= 0.0317 m(Θ)=0 k=0.1970	m(a)= 0.8498 m(b)= 0.0419 m(c)= 0.1055 m(Θ)=0.0028 k=0.6063	m(a)= 0.8803 m(b)= 0.0336 m(c)= 0.0802 m(Θ)=0.0059 k=0.6263	m(a)= 0.8840 m(b)= 0.0351 m(c)= 0.0747 m(Θ)=0.0062 k=0.6667
This Paper	m(a)= 0.9863 m(b)= 0.0010 m(c)= 0.0137 m(Θ)=0 k=0.1970	m(a)= 0.8493 m(b)= 0.0422 m(c)= 0.1085 m(Θ)=0 k=0.6324	m(a)= 0.8829 m(b)= 0.0339 m(c)= 0.0833 m(Θ)=0 k=0.6619	m(a)= 0.8880 m(b)= 0.0353 m(c)= 0.0767 m(Θ)=0 k=0.6980

Table 4. The Simulation Results of Conflict Information

Methods	Decision-making Results			
	Two sets of evidences	*Three sets of evidences*	*Four sets of evidences*	*Five sets of evidences*
DS	m(a)=0 m(b)=0 m(c)=1 m(Θ)=0 k=0.9010	m(a) = 0 m(b) =0 m(c) =1 m(Θ)=0 k=0.9703	m(a)= 0 m(b)= 0 m(c)= 1 m(Θ)=0 k=0.9997	m(a)=0 m(b)=0 m(c)=0 m(Θ)=0 k=1.0000
Yager	m(a)= 0.7920 m(b)=0 m(c)= 0.0110 m(Θ)=0.1970 k=0.1970	m(a)= 0.3960 m(b)=0 m(c)= 0.0033 m(Θ)=0.6007 k=0.6007	m(a)= 0.3881 m(b)=0 m(c)=0 m(Θ)=0.6119 k=0.6119	m(a)= 0.3493 m(b)=0 m(c)=0 m(Θ)=0.6507 k=0.6507
SUN Quan	m(a)= 0.1647 m(b)= 0.0018 m(c)= 0.2984 m(Θ)=0.535 k=0.9010	m(a)= 0.0542 m(b)= 0.0081 m(c)= 0.0836 m(Θ)=0.8541 k=0.9703	m(a)= 0.0142 m(b)= 0.0013 m(c)= 0.0087 m(Θ)=0.9758 k=0.9997	m(a)= 0.0027 m(b)= 0.0002 m(c)= 0.0012 m(Θ)=0.9959 k=1.0000
Murphy	m(a)=0 .9863 m(b)=0 m(c)=0.0137 m(Θ)=0 k=0.1970	m(a)= 0.9447 m(b)= 0.0080 m(c)= 0.0473 m(Θ)=0 k=0.6007	m(a)= 0.9709 m(b)= 0.0044 m(c)= 0.0247 m(Θ)=0 k=0.6119	m(a)= 0.9775 m(b)= 0.0041 m(c)= 0.0184 m(Θ)=0 k=0.6507
KL	m(a)= 0.4055 m(b)= 0.0045	m(a)= 0.3502 m(b)= 0.0677	m(a)= 0.4446 m(b)= 0.0523	m(a)= 0.5249 m(b)= 0.0502

Methods	Decision-making Results			
	Two sets of evidences	*Three sets of evidences*	*Four sets of evidences*	*Five sets of evidences*
Distance	$m(c)$= 0.5900 m(Θ)=0 k=0.9010	$m(c)$= 0.2851 m(Θ)=0.2971 k=0.9912	$m(c)$= 0.1754 m(Θ)=0.3277 k=1.0000	$m(c)$= 0.1366 m(Θ)=0.2882 k=1.0000
Pearson	$m(a)$= 0.4055 $m(b)$= 0.0045 $m(c)$= 0.5900 $m(\Theta)$=0 k=0.9010	$m(a)$= 0.4271 $m(b)$= 0.0670 $m(c)$= 0.2052 $m(\Theta)$=0.3007 k=0.9944	$m(a)$= 0.5550 $m(b)$= 0.0521 $m(c)$= 0.0895 $m(\Theta)$=0.3034 k=1.0000	$m(a)$= 0.6262 $m(b)$= 0.0509 $m(c)$= 0.0565 $m(\Theta)$=0.2664 k=1.0000
This Paper	$m(a)$= 0.4055 $m(b)$= 0.0045 $m(c)$= 0.5900 $m(\Theta)$=0 k=0.9010	$m(a)$= 0.5251 $m(b)$= 0.0936 $m(c)$= 0.3813 $m(\Theta)$=0 k=0.9905	$m(a)$= 0.7065 $m(b)$= 0.0697 $m(c)$= 0.2238 $m(\Theta)$=0 k=0.9999	$m(a)$= 0.7721 $m(b)$= 0.0634 $m(c)$= 0.1645 $m(\Theta)$=0 k=1.0000

From the result, although DS method has a good result in deal with normal data, it can't give a right result when there has conflict information; because SUN Quan treat conflict information as unknown data, it increases the value of unknown item, we can see this phenomenon from the result, and this decision-making results are not reasonable; the Yager has the same problem with SUN Quan; Murphy combination results are good than others, but its principle is too simple to identify by people; Pearson correlation coefficient is better than the methods mentioned above because of he take the relationship among evidences into consideration, he calculate the credibility of the evidence by Pearson correlation coefficient. The method proposed in this paper gives the best result, this method not only take the credibility of the evidence into account, but also it makes full use of conflict coefficient, and the results show that the algorithm improves the possibility of the recognition target, and reduces the probability of unknown information.

6. Conclusion

With the rapidly development of multi-sensor applications, multi-sensor information fusion technology has been widely studied, especially in the research of uncertain information, incomplete information and conflicting information. In this paper, we improve the original algorithms from both two ways, through the simulation analysis, we prove that this method can deal with conflicting information smoothly.

In the research of evidence theory, there has a problem that hasn't solved. For the combination result of evidence theory there hasn't a standard evaluation criteria, we just by compared with other methods or by a personal subjective view. First, the result should satisfy people's logic. Second, the certainty should be increased after combination. Now, what we are concern about is how to improve the algorithm, change the combination formula or modify the basic probability assignment function, while we need a standard evaluation criteria to judge whether our algorithm is reasonable.

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