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An Improved Radar Emitter Recognition Method Based on Dezert-Smarandache Theory*

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Abstract — The parameters of radar emitter are fast changing in the current complicated electromagnetic environment, and the radar emitter recognition rate which used single sensor method cannot satisfied. To solve the problem, an improved radar emitter recognition method based on Dezert-Smarandache theory is proposed, which can improve proportional conflict redistribution rule to solve fuzzy and conflicting information from radar emitter. Some examples are given to show the validity of the improved method.

Key words — Radar emitter, Proportional conflict redistribution rule, Fusion recognition, Dezert-smarandache theory.

I. Introduction

At present, the radar emitter recognition is mainly based on the single sensor, which has seriously affected the efficiency of emitter target recognition in the complex battlefield electromagnetic signal environment, and the use of multiple sensor data fusion technology has gradually become hot. In current war condition, a large number of complex system radar are applied to the war, which require all kinds of electronic reconnaissance equipment to quickly identify the type and threat level of radar. But this demand cannot be met, because radar with one sensor often provides a large amount of uncertain information, which makes it very difficult to identify the radar emitters quickly. Evidence reasoning theory is an important basic theoretical theory for information fusion. It is an essential tool for more objective target recognition from Dempster-Shafer (DS) theory to Dezert-Smarandache (DSm) theory[1−4]. Compared with the DS theorythe latter one provides a new idea for dealing with evidence combination problem when the evidence is conflicting. It can combine any type of independent information source with reliable function. Its biggest advantage is that it is able to deal with uncertain, imprecise and high conflicting information effectively, especially when the conflict is violent and there are some vague and imprecise factors. Ridding the limitations of DS theory, DSm theory can solve the matter about complicated static or dynamic fusion recognition.

A fusion recognition method of radar emitter based on DSm theory is proposed. The parameters of radar emitters are from different sensors, so the emitter parameters reliability degree is improved, it can also improve the recognition rate. Through the simulation, the novel method is correct and effective.

II. Procedures of Emitter Recognition Based on DSm Theory

Because of the DSm theory can deal with the imprecise, even the conflict evidence, so it can be used in the radar emitter recognition.

Fig.1 is the recognition flow figure based on DSm theory. The $m_1(.), m_2(.), \cdots, m_n(.)$ of figure are the BBA of N information sources. The $m(A)$ is the belief value of target recognitionwhich is obtained by combination rule of DSm theory. The steps of emitter recognition based on DSm theory are as follows:

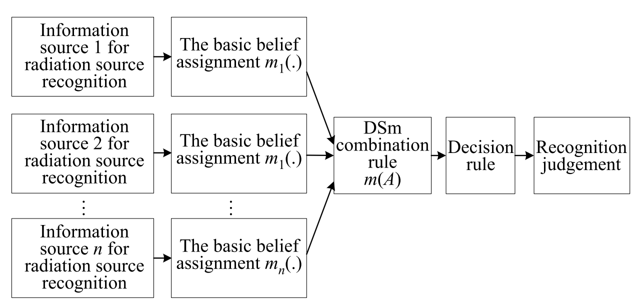

Fig. 1. Recognition flow figure based on DSm theory

Step 1 Define the discerment framework. Adding the possible proposition into the discerment framework.

Step 2 Obtain the basic belief assignment. In the DSm theory, how to obtain the basic belief assignment of various possible proposition according to the actual situation? Basic belief assignment shows the reasoning about target recognition hypothesis based on information source. This judgment

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is affected by various factors; different prior knowledge will constitute different basic belief assignment.

Step 3 Use suitable combination rule to fuse the basic belief assignment. Appropriate combination method should be adopted according to the features of unidentified objects and characteristics of information sources.

Step 4 Determine the judgment rule of target recognition. After getting the fusion result, right judgment rule should be employed based on the characteristics of emitter recognition.

III. Emitter Recognition Method Based on Improved PCR

DSm theory introduce the conflict focal element into the discerment framework, solving the problem of the evidence conflict paradox[5]. However, the reliability of the focal element is dispersed because of the adding of the conflict focal element. Although the result is correct, but it makes a great impact on the decision, that is, it effects the application of DSm theory in practice. Some improved evidence combination rules are proposed by Dezert and Smarandanche based on DSm theory, and the Proportional conflict redistribution (PCR) rule[6−11] is widely acknowledged as an effective combination rule. The PCR rule is not only an effective method for treatment of highly conflict evidence, but also can transfer the belief value of conflict focal element to other related elements, which has been recognized by the majority of experts and scholars in this field. The equation of PCR5 rule is clear; the results are reasonably combined and widely used. PCR5 rule will combine the conflict with evidence reliability which is conflicted with each other. When assigning the conflicts, the known evidence should be completely followed. This method can ensure the fairness of the combined results. The main problem of PCR rule is the conservative character of combination result. The result is completely obtained by machine decision. When making decisions, the commanders should study the data, and analyze the data according to their own experiences. This approach is more beneficial to the inference of event occur probability under the condition in which the information is uncertain or incomplete, and more conducive to make a scientific decision.

Based on this, this thesis puts forward an improved PCR rule. The following are the key points of the method: increasing the BBA obtained by high reliability sensor about radiation source characteristics, which means to increase the ratio between two reliabilities, increase the reliability of the big reliability, and reduce the assignment factors of the small reliability. Therefore, no longer get the distribution proportion fully based on known evidence, but increase the original assignment proportion, weights are the ratio of known reliability function. Then consider the advantage of reliability with experience knowledge, to make the evidence of higher reliability value obtain the greater proportion, the more conducive to the combination result decision. The PCR5 rule is the most effective one in the PCR series, so the new method is improved by following the example of the PCR5 rule, the improved rule denoted as PCR5f rule. Combination equation is $\forall(X \neq \phi) \in G^{\Theta}$.

When the information source number $s = 2$,

$$m_{\mathrm{PCR5f}}(X) = m_{\cap}(X) + \sum_{\substack{Y \in G^{\Theta} \setminus \{X\} \\ Y \cap X = \phi}} \left[\frac{f\{m_1(X)\}}{f\{m_1(X)\} + f\{m_2(Y)\}} \cdot m_1(X) m_2(Y) + \frac{f\{m_2(X)\}}{f\{m_2(X)\} + f\{m_1(Y)\}} \cdot m_2(X) m_1(Y) \right] \quad (1)$$

When the information source number $s \geq 2$,

$$m_{\mathrm{PCR5f}}(X) = m_{12\ldots s}(X)$$

$$+ \sum_{\substack{2 \leq t \leq s \\ 1 \leq r_1, \ldots, r_t \leq s \\ 1 \leq r_1 < r_2 < \ldots < r_{t-1} < (r_t = s)}} \sum_{\substack{X_{j_2}, \ldots, X_{j_t} \in G^{\Theta} \setminus \{X\} \\ \{j_2, \ldots, j_t\} \in P^{t-1}(\{1,2,\ldots,n\}) \\ X \cap X_{j_2} \cap \ldots \cap X_{j_s} = \phi \\ \{i_1, \ldots, i_s\} \in P^s(\{1,2,\ldots,s\})}} \frac{f\left\{\prod_{k_1=1}^{r_1} m_{i_{k_1}}(X)\right\} \cdot \left(\prod_{k_1=1}^{r_1} m_{i_{k_1}}(X)\right) \cdot \left[\prod_{l=2}^{t} \left(\prod_{k_l = r_{l-1}+1}^{r_l} m_{i_{k_l}}(X_{j_l})\right)\right]}{f\left\{\prod_{k_1=1}^{r_1} m_{i_{k_1}}(X)\right\} + f\left\{\prod_{l=2}^{t} \left(\prod_{k_l = r_{l-1}+1}^{r_l} m_{i_{k_l}}(X_{j_l})\right)\right\}} \quad (2)$$

where $m_{\cap}(X)$ represents combination rule for the combination belief of X; G^{Θ} represents that different models could be chosen; $Y_j \in G^{\Theta}$ is the corresponding information source j; $f(m_i(Y_j))$ is the belief function. $m_{12\ldots s}(X)$ represents information source for the support reliability sum of the proposition X; In $P^k(\{1, 2, \ldots, n\})$ set $\{1, 2, \ldots, n\}$, the subset constitute of the all k elements (regardless of the order of the elements).

According to the improved rule, as long as the belief function is an increasing function, to make the increase rate of the big belief more than the small one can meet the requirements. According to the function monotonicity theorem, if the derived function of belief function is an increasing function of its own, it will be an increasing function. Based on this, reliability function should be constructed by following the example of the simplest linear function.

Definition Assume that the derived function of belief function is $f'(x) = ax + b$, the belief function is the following one

$$f(x) = \frac{a}{2}x^2 + bx + c \quad (3)$$

$f(x)$ requires the derivative to be an increase function in the interval $[0, 1]$, the standard form of $f(x)$ is showed as,

$$f(x) = \frac{k_n}{n!}x^n + \frac{k_{n-1}}{(n-1)!}x^{n-1} + \cdots + \frac{k_3}{3!}x^3 + \frac{k_2}{2!}x^2 + k_1 x + k_0 \quad (4)$$

The Eq.(3) shows: bx is a linear function, c is a constant, $a/2$ is the coefficient, those do not affect the results. Therefore, considering the convenient calculation, the Eq.(5) can be simplified as,

$$f(x) = x^2 \quad (5)$$

Similarly Eq.(4) can be simplified as,

$$f(x)=\sum_{n=0}^{\infty}\frac{k_n}{n!}x^n \quad (n=0,1,2,3,\cdots) \tag{6}$$

Need to point out that, when the times of $f(x)$ increase, the amount of calculation increase.

Here only select $f(x)=x^2$ as an example to illustrate. Respectively put $f(x)=x^2$ into Eqs.(1) and (2) to obtain, when the information source number $s=2$,

$$m_{\mathrm{PCR5x^2}}(X)=m_{\cap}(X)+\sum_{\substack{Y\in G^{\Theta}\setminus\{X\}\\ Y\cap X=\phi}}\left[\frac{m_1^2(X)}{m_1^2(X)+m_2^2(Y)}\cdot m_1(X)m_2(Y)+\frac{m_2^2(X)}{m_2^2(X)+m_1^2(Y)}\cdot m_2(X)m_1(Y)\right] \tag{7}$$

when the information source number $s\geq 2$,

$$m_{\mathrm{PCR5x^2}}(X)=m_{12\dots s}(X)$$
$$+\sum_{\substack{2\leq t\leq s\\ 1\leq r_1,\dots,r_t\leq s\\ 1\leq r_1<r_2<\dots<r_{t-1}<(r_t=s)}}\ \sum_{\substack{X_{j_2},\dots,X_{j_t}\in G^{\Theta}\setminus\{X\}\\ \{j_2,\dots,j_t\}\in P^{t-1}(\{1,2,\dots,n\})\\ X\cap X_{j_2}\cap\dots\cap X_{j_s}=\phi\\ \{i_1,\dots,i_s\}\in P^s(\{1,2,\dots,s\})}}\frac{\prod_{k_1=1}^{r_1}m_{i_{k_1}}^2(X)\cdot\left(\prod_{k_1=1}^{r_1}m_{i_{k_1}}(X)\right)\cdot\left[\prod_{l=2}^{t}\left(\prod_{k_l=r_{l-1}+1}^{r_l}m_{i_{k_l}}(X_{j_l})\right)\right]}{\prod_{k_1=1}^{r_1}m_{i_{k_1}}^2(X)+\prod_{l=2}^{t}\left(\prod_{k_l=r_{l-1}+1}^{r_l}m_{i_{k_l}}^2(X_{j_l})\right)} \tag{8}$$

In the rule of PCR5x^2, the derivative for $f(x)=x^2$ is $f'(x)=2x$, both of them are increasing function, which ensure the improved rules meet the demands of the $f(x)$. But the derivative growth rate is higher than the PCR5x^2 rule, so as for the results, combination reliability obtained by the PCR5x^2 rule is higher than the PCR5 rule. However, the amount of calculation of the PCR5x^2 rule is higher than the PCR5x rule. In the area of engineering, PCR5x^2 rule, the PCR5 rule, $f(x)$ or other increasing function should be selected according to the characteristics of the actual system and satisfy the practical requirements.

IV. Simulation and Analysis

In order to improve the effectiveness of the improved DSm rules, four examples of target recognition are given combined with the specific application of emitter recognition. The examples consider the high conflict evidence and low conflict evidence comprehensively with the Shafer model and the hybrid DSm model. The comparison combination rules are as follows: Dempster combination rule, Smets combination rule, PCR5 rule and improved PCR rule.

Background: There are N sensors to detect some radiation source. The radiation source signal is one from 8 classes. The 8 types of signals are as Refs.[12,13]. The membership degree of signal is obtained by the preceding methods, and it was taken as the BBA. The result is gotten by using combination rules to fuse BBA.

1) The low conflict under Shafer model

Suppose that there are 5 sensors to obtain information, respectively correspond to m_1-m_5, model is Shafer model which has 8 kinds of features. Therefore, identification framework is $\Theta=\{\theta_1,\theta_2,\cdots,\theta_8\}$. What can be concluded is that data from the 5 sensors show that there is a strong possibility that feature 1 is most effective.

2) The low conflict under Shafer model

Suppose that information can be gained from 5 sensors, respectively correspond to m_1, m_2, m_3', m_4, m_5, the same model with Section IV.1). A conclusion can be drawn that sensor 3 show that the possibility of selection signal 1 might be 0, while the other four sensors tend to select signal 1.

3) The high conflict under hybrid DSm model

Suppose that information can be acquired from 5 sensors, respectively corresponding to m_1-m_5, model is the mixed DSm model which has 8 kinds of features, therefore, identification framework is $\Theta=\{\theta_1,\theta_2,\cdots,\theta_8\}$, the constraints are as follows: $\theta_1\cap\theta_2\equiv\theta_1\cap\theta_3\equiv\theta_1\cap\theta_4\equiv\theta_1\cap\theta_5\equiv\theta_1\cap\theta_6\equiv\theta_1\cap\theta_7\equiv\theta_1\cap\theta_8\equiv\theta_2\cap\theta_5\equiv\theta_2\cap\theta_6\equiv\theta_2\cap\theta_7\equiv\theta_2\cap\theta_8\equiv\theta_3\cap\theta_4\equiv\theta_3\cap\theta_5\equiv\theta_3\cap\theta_8\equiv\theta_4\cap\theta_5\equiv\theta_4\cap\theta_6\equiv\theta_4\cap\theta_7\equiv\theta_4\cap\theta_8\equiv\theta_5\cap\theta_8\equiv\theta_6\cap\theta_7\equiv\theta_6\cap\theta_8\equiv\theta_7\cap\theta_8$. As can be seen, the 5 sensors data think that feature 1 is most effective with high possibilities.

4) The high conflict under hybrid DSm model

Suppose that information can be gained from 5 sensors acquire, respectively corresponding to m_1, m_2, m_3', m_4, m_5, the same model to Section IV.3). The conclusion is that sensor 3 shows that the possibility of selecting signals 1 might be 0, while the other four sensors tend to select signal 1.

Table 1. Sensors obtain the basic belief assignment about emitter recognition characteristic

Evidence / Type	m_1	m_2	m_3	m_3'	m_4	m_5
θ_1	0.5964	0.5136	0.5771	0	0.5351	0.5330
θ_2	0.1004	0.1214	0.1054	0.5053	0.1156	0.1165
θ_3	0.0466	0.0561	0.0488	0.1488	0.0537	0.0539
θ_4	0.0503	0.0606	0.0527	0.1299	0.0580	0.0582
θ_5	0.0587	0.0707	0.0615	0.0615	0.0677	0.0679
θ_6	0.0447	0.0538	0.0468	0.0468	0.0514	0.0516
θ_7	0.0585	0.0704	0.0612	0.0612	0.0674	0.0676
θ_8	0.0444	0.0534	0.0465	0.0465	0.0511	0.0513

Valid results can be obtained by the low conflict example under Shafer model, Dempster rule, PCR rule and improved PCR rule. But the Smets rule gives the conflict empty set. It is low conflict example but most belief value is assigned to the empty set. Although the results which are not wrong, they are not helpful for making a judgment. The high conflict cases of the Shafer model, false results are gained by the Dempster rule, the Smets rule assign almost all of the belief value to the empty set, which cannot be used. Correct results can be gained by PCR rule and improved PCR rule. The example under hybrid DSm model, the targeted is stronger for the specific problems for the joined constraint conditions, the PCR rule and the improved PCR rule can better deal with the high and low conflict, and the dealing results of the improved PCR rule is better.

Through the above analysis, the Dempster and Smets combination rule can only be used in the Shafer model, while the PCR rule and the new proposed rule can be used in both Shafer model and DSm model, so the two rules has a wider range of application. PCR rule can be used in DSm theory and DS theory, and correct results can be attained. The improved PCR rule is weighted and improved in the PCR rules completely on the basis of evidence distribution ratio, so in the treatment of low and high conflict evidence, it can obtain better results. The calculation work under the improved PCR rule is relatively larger, but weight and calculate only for the distribution ratio, the number of weight calculation is determined by the part of conflicts and constraints condition. The amount of calculation work is less than that of PCR rule itself evidence combination, so the calculation of improved rule is an order of magnitude with PCR5 rule. Well controlling the increase in the amount of calculation work when improving the combination result, which makes it feasible in engineering.

Table 2. Fusion results of four kinds of circumstances

Method	Shafer model low conflict	Shafer model high conflict	DSm model low conflict	DSm model high conflict
Dempster rule	$m(\theta_1)$=0.9995 $m(\theta_2)$=0.0004 $m(\theta_3)=7\times10^{-6}$ $m(\theta_4)=3\times10^{-5}$ $m(\theta_5)=3\times10^{-5}$ $m(\theta_6)=5\times10^{-6}$ $m(\theta_7)=2\times10^{-5}$ $m(\theta_8)=7\times10^{-6}$	$m(\theta_1)$=0 $m(\theta_2)$=0.9392 $m(\theta_3)$=0.0127 $m(\theta_4)$=0.0151 $m(\theta_5)$=0.0133 $m(\theta_6)$=0.0033 $m(\theta_7)$=0.0131 $m(\theta_8)$=0.0033		
Smets rule	$m(\theta_1)$=0.0504 $m(\theta_2)$=0 $m(\theta_3)$=0 $m(\theta_4)$=0 $m(\theta_5)$=0 $m(\theta_6)$=0 $m(\theta_7)$=0 $m(\theta_8)$=0.9496	$m(\theta_1)$=0 $m(\theta_2)$=0.0001 $m(\theta_3)$=0 $m(\theta_4)$=0 $m(\theta_5)$=0 $m(\theta_6)$=0 $m(\theta_7)$=0 $m(\theta_8)$=0.9999		
PCR5 rule	$m(\theta_1)$=0.9192 $m(\theta_2)$=0.0300 $m(\theta_3)$=0.0073 $m(\theta_4)$=0.0083 $m(\theta_5)$=0.0109 $m(\theta_6)$=0.0068 $m(\theta_7)$=0.0108 $m(\theta_8)$=0.0067	$m(\theta_1)$=0.8614 $m(\theta_2)$=0.0780 $m(\theta_3)$=0.0089 $m(\theta_4)$=0.0101 $m(\theta_5)$=0.0129 $m(\theta_6)$=0.0080 $m(\theta_7)$=0.0128 $m(\theta_8)$=0.0079	$m(\theta_1)$=0.9213 $m(\theta_2)$=0.0232 $m(\theta_2\cap\theta_3)$=0.0031 $m(\theta_2\cap\theta_4)$=0.0038 $m(\theta_3)$=0.0050 $m(\theta_3\cap\theta_6)$=0.0008 $m(\theta_3\cap\theta_7)$=0.0012 $m(\theta_4)$=0.0069 $m(\theta_5)$=0.0092 $m(\theta_5\cap\theta_6)$=0.0013 $m(\theta_5\cap\theta_7)$=0.0019 $m(\theta_6)$=0.0060 $m(\theta_7)$=0.0092 $m(\theta_8)$=0.0071	$m(\theta_1)$=0.8177 $m(\theta_2)$=0.0736 $m(\theta_2\cap\theta_3)$=0.0159 $m(\theta_2\cap\theta_4)$=0.0181 $m(\theta_3)$=0.0069 $m(\theta_3\cap\theta_6)$=0.0015 $m(\theta_3\cap\theta_7)$=0.0022 $m(\theta_4)$=0.0101 $m(\theta_5)$=0.0149 $m(\theta_5\cap\theta_6)$=0.0018 $m(\theta_5\cap\theta_7)$=0.0026 $m(\theta_6)$=0.0093 $m(\theta_7)$=0.0143 $m(\theta_8)$=0.0111
Improved PCR rule	$m(\theta_1)$=0.9248 $m(\theta_2)$=0.0276 $m(\theta_3)$=0.0069 $m(\theta_4)$=0.0078 $m(\theta_5)$=0.0101 $m(\theta_6)$=0.0064 $m(\theta_7)$=0.0101 $m(\theta_8)$=0.0063	$m(\theta_1)$=0.9095 $m(\theta_2)$=0.0673 $m(\theta_3)$=0.0034 $m(\theta_4)$=0.0038 $m(\theta_5)$=0.0050 $m(\theta_6)$=0.0031 $m(\theta_7)$=0.0049 $m(\theta_8)$=0.0030	$m(\theta_1)$=0.9762 $m(\theta_2)$=0.0055 $m(\theta_2\cap\theta_3)$=0.0013 $m(\theta_2\cap\theta_4)$=0.0016 $m(\theta_3)$=0.0013 $m(\theta_3\cap\theta_6)$=0.0004 $m(\theta_3\cap\theta_7)$=0.0006 $m(\theta_4)$=0.0020 $m(\theta_5)$=0.0026 $m(\theta_5\cap\theta_6)$=0.0006 $m(\theta_5\cap\theta_7)$=0.0009 $m(\theta_6)$=0.0020 $m(\theta_7)$=0.0026 $m(\theta_8)$=0.0024	$m(\theta_1)$=0.9163 $m(\theta_2)$=0.0310 $m(\theta_2\cap\theta_3)$=0.0085 $m(\theta_2\cap\theta_4)$=0.0098 $m(\theta_3)$=0.0027 $m(\theta_3\cap\theta_6)$=0.0007 $m(\theta_3\cap\theta_7)$=0.0010 $m(\theta_4)$=0.0039 $m(\theta_5)$=0.0071 $m(\theta_5\cap\theta_6)$=0.0009 $m(\theta_5\cap\theta_7)$=0.0013 $m(\theta_6)$=0.0046 $m(\theta_7)$=0.0069 $m(\theta_8)$=0.0053

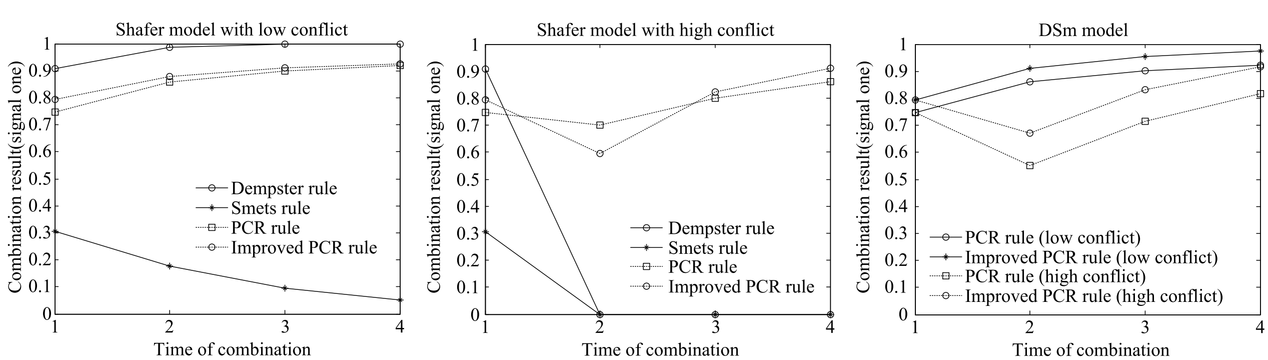

Fig. 2. Fusion recognition results comparison of four kinds of circumstances

V. Conclusions

This paper first analyzes the advantages and disadvantages of DS theory, then introduces the DSm theory by giving some examples, next analyzes the characteristics and of DSm theory systematically, after that proposes the improved rule based on PCR rule, finally, through four examples, validates the rationality of the improved method. The simulation results show that radar emitter recognition method based on DSm theory is feasible and effective.

References

[1] J. Dezert, "Foundations for a new theory of plausible and paradoxical reasoning", *Information and Security Journal*, Vol.12, No.1, pp.26–30, 2002.

[2] J. Dezert and F. Smarandache, "On the generation of hyper-power sets for the DSmT", *The 6th International Conference on Information Fusion*, Piscataway, NJ, USA, pp.1118–1125, 2003.

[3] J. Dezert, "An introduction to DSmT for information fusion", *New Mathematics and Natural Computation*, Vol.8, No.3, pp.343–359, 2012.

[4] F. Smarandache and J. Dezert, "An introduction to DSmT", *Advances and Applications of DSmT for Information Fusion*, American Research Press, Rehoboth, Vol.3, pp.3–74, 2009.

[5] Xiaoxia Wang, "Research on the combination rule of conflict evidences", *Master's Degree Thesis*, North Central University, Taiyuan, 2007. (in Chinese)

[6] F. Smarandache and J. Dezert, "Proportional conflict redistribution for information fusion", *Advances and Applications of DSmT for Information Fusion (Collected Works Vol.II)*, American Research Press, Rehoboth, pp.3–66, 2006.

[7] F. Smarandache and J. Dezert, "Information fusion based on new proportional conflict redistribution rules", *Information Fusion, 8th International Conference*, Philadelphia, PA, USA, Vol.2, pp.25–28, 2005.

[8] F. Smarandache and J. Dezert, "A simple proportional conflict redistribution rule", *International Journal of Applied Mathematics & Statistic*, Vol.3, No.105, pp.1–36, 2005.

[9] F. Smarandache and J. Dezert, "On the consistency of PCR6 with the averaging rule and its application to probability estimation", *Information Fusion, 16th International Conference on*, Istanbul, Turkey, Vol.7, pp.1119–1126, 2013.

[10] Mahdi Khodabandeh, Alireza Mohammad-Shahri, "Two generalizations of aggregated uncertainty measure for evaluation of Dezert-Smarandache theory", *International Journal of Information Technology & Decision Making*, Vol.11, No.1, pp.119–142, 2012.

[11] Hongbin Jin, "Study on evidence theory and its application to the target recognition", *Ph.D. Thesis*, Air Force Early Warning Academy, Wuhan, 2011.

[12] HAN Jun, HE Minghao, TANG Zhikai, *et al.*, "Estimating in-pulse characteristics of radar signal based on multi-index", *Chinese Journal of Electronics*, Vol.20, No.1, pp.187–191, 2011.

[13] J. Xu, M.H. He, J. Han, *et al.*, "Estimating the stability of characteristic parameters based on single-element analysis of variance", *11th International Conference on Signal Processing*, pp.1804–1807, 2012.

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