Underwater Target Multi-feature Fusion Recognition Technology Based on D-S Evidence Reasoning

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Abstract. Underwater target recognition is a key technique in military command system. Decision recognition is the last key step. It fully makes several sensor 、several kinds of feature and classifier to be combined to form the uniform description to the target according to the optimizing criterion. The paper mainly studies Dempster-Shafer decision theory and its application. Based on the theory, the target feature and Fuzzy Adaptive Resonance Theory(FART) network is combined to form the decision fusion domination. The results show that the decision recognition ratio improves percent two than the single classifier and single feature. It shows that the application of the method is well in target recognition fields.

Introduction

Underwater target recognition is important in the military. Its three main important aspects are Feature extraction, feature optimization, decision recognition. Feature extraction is mainly obtained through mathematical and statistical transformation. Transformation can characterize the signal and compress the interference component (background noise, reverberation, etc.) and improve the SNR or distributing it in different regions of space, in order to facilitate the decision analysis at the same time. Moreover, the different features highlights the different signal attributes. This suggests that the decision by multi-feature fusion recognition can improve the accuracy of the system discrimination.

Data fusion in target recognition is the utilization of multiple sources of information to obtain a combined discrimination conclusions. It takes full advantage of multiple sensors, features, classifiers and other resources to combine all kinds of information by a certain optimization criterion. It produces a consistent interpretation or description of the observed target through a variety of sensors, features, classifiers and other classified information reasonable controlling and using. So it forms a more accurate and complete estimate and judgment than a single source information. It makes the system's performance better than its every subsystems.

Data fusion can be spread out three levels according to the abstraction degree of target information: the data-level, feature-level and decision-level fusion. Decision-level fusion simulates human thinking based on completing the target classification of the acquired data preliminary and gives a combination or judgment of the every result with a certain rule or algorithm of features. At present, the method of decision fusion is mainly included Bayesian inference, Dempster-Shafer (D-S) evidence theory, voting, etc.

The paper has explored multi-feature fusion recognition based on DS evidence reasoning theory according to the actual characteristics of underwater acoustic signals. Based on above knowledge, it has combined the decision fusion strategy, The Fuzzy Adaptive Resonance Theory (FART) neural network and the characteristics of three kinds of underwater targets to achieve target recognition. The method makes up recognition rate uneven and low reliability in a single feature recognition problem.

Target Recognition Fusion Simplified Model

Target Fusion Recognition model is shown in Figure 1. It is not only an important model for target fusion recognition in the actual work, but also the basic block diagram of the present systems.

The local decision-maker in the figure employs fuzzy adaptive resonance neural networks. Decision-level fusion has focused on D-S reasoning, and discussed its applicability.

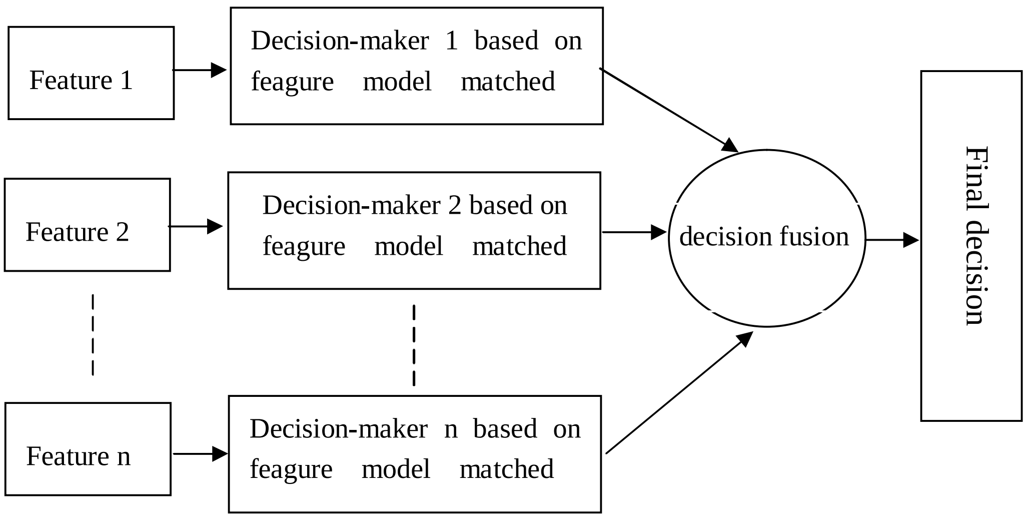

Figure 1 Target Recognition Fusion simplified model

D-S evidence theory

A basic strategy in D-S evidence theory is to divide evidence collection into two or more unrelated parts, and use them to judge every frame independently, and then use Dempster combination rule to combine them.

Dempster combination rule

Suppose Bel_1 , Bel_2 are two trust functions on the same discernable frame Θ, m_1, m_2 is the basic probability assignment respectively, m is the combined probability distribution function, the focus element is respectively $A_1, A_2, \mathbf{L}, A_k$ and $B_1, B_2, \mathbf{L}, B_r$. Then the D-S combination rule can be expressed as:

$$m(C) = \sum_{C=A_i \cap B_j} m_1(A_i) \cdot m_2(B_j) \tag{1}$$

This expression is generally called orthogonal addition. Easy to prove, the combined m(C) meet:

$$\sum_{C \subseteq \Theta} m(C) = 1 \tag{2}$$

If introducing the orthogonal addition operator $\oplus$, then the expression can be expressed as

$$m = m_1 \oplus m_2 \tag{3}$$

Describing above is a combination rule of two evidence. Here is a combination rule of a plurality of evidence.

Suppose Bel_1 ,Bel_2 ,Bel_3 ,…, Bel_n are the trust function on identification framework, *Bel* is the trust functions after combination. Then

$$Bel = \{[(Bel_1 \oplus Bel_2) \oplus Bel_3] \oplus \cdots\} \oplus Bel_n \tag{4}$$

The conclusive evidence, which obtained from combination of evidence has nothing to do with the order taken in the combination process. Such as m_1 , m_2 , …m_n and m represent the probability distribution function of Bel_2 , Bel_3 , …, Bel_n and Bel, Then the evidence combination rule can be expressed as:

$$m = \{[(m_1 \oplus m_2) \oplus m_3] \oplus \cdots\} \oplus m_n \tag{5}$$

Likewise, it can be obtained overall evidence for the n same evidence following way. Suppose the level of support to hypothesis A for every evidence is $m_1(A),m_2(A),\ldots,m_n(A)$, respectively and $m_1(\Theta),m_2(\Theta),\ldots, m_n(\Theta)$, and there is

$$m_1(\Theta) = 1 - m_1(A)$$
$$m_2(\Theta) = 1 - m_2(A)$$
$$\cdots$$
$$m_n(\Theta) = 1 - m_n(A)$$

The degree of combination of n sensors evidence supported to hypothesis A can be obtained.

$$m_1^{\ n}(A) = 1 - \prod_{i=1}^{n} m_i(\Theta) \tag{6}$$

The above has described the case that n evidence supporting the same one hypothesis. If the m evidence support the m different hypothesis $A_i, i = 1, 2, \cdots, m$, the corresponding support degree is $m_1(A_1),m_2(A_2),\ldots,m_m(A_m)$, Then the support degree for A_i combined m mutually exclusive evidence fusion is

$$m^m(A_i) = \frac{\dfrac{m_i(A_i)}{m_i(\Theta)}\prod_{i=1}^{m} m_i(\Theta)}{1 - \sum_{k=1}^{m-1}[\sum_{j=1}^{k}\dfrac{m_j(A_j)}{m_j(\Theta)}\prod_{i=1}^{k} m_j(\Theta)]m_{k+1}(A_{k+1})} \tag{7}$$

Combination rules containing fixed conflict

Now consider about two different basic probability assignment function m_1 and m_2. If there is a set $A, B, A \cap B = \Phi$, and $m_1(A) > 0, m_2(B) > 0$, then using Dempster combination rule will obtain:

$$m(\Phi) = \sum_{A' \cap B' = \Phi} m_1(A')m_2(B') \geq m_1(A)m_2(B) > 0 \tag{8}$$

This is conflict to the basic probability assignment function, called A, B two conflict set, for this, DS combination rule must be amended as follows:

$$m(C) = \begin{cases} \dfrac{\sum_{C = A_i \cap B_i} m_1(A_i) \cdot m_2(B_j)}{1-K} & \forall C \subset \Theta, C \neq \Phi \\ 0 & C = \Phi \end{cases} \tag{9}$$

Where,

$$K=\sum_{A_i \cap B_j=\Phi} m_1(A_i)\cdot m_2(B_j)=\sum_i\sum_j m_1(A_i)\cdot m_2(B_j)<1 \tag{10}$$

In the formula, if K≠1, then m is a determine basic probability assignment. If K = 1, then m_1, m_2 is considered contradiction, basic probability assignment can't be combined, the combination rule of evidence given by the formula is called D-S combination rules. To the combination of multi-evidence, the evidence can be pairwise combined according to D-S combination rules.

Synthesis of relevant evidence

D-S theory combination rule has given a combination method of two different independent evidence, but the independent evidence is not always a reasonable assumption, therefore the synthesis issues of related evidence need to be study.

Suppose Bel1 and Bel2 are two trust functions on the same discernable frame Θ, m_1, m_2 is the basic probability assignment respectively, the focus element is respectively $A_1, A_2, \ldots, A_k$ and $B_1, B_2, \ldots, B_r$ .And suppose $\sum_{A_i \cap B_j=\Phi} m_1(A_i)m_2(B_j)<1$. Then the trust function after synthesis is given by basic probability assignment of (11), Bel is called straight addition of Bel1 and Bel2, recorded as $Bel = Bel_1 \oplus Bel_2$.

$$m(A)=\begin{cases}\dfrac{\sum_{A_i \cap B_j=A} m_1(A_i)m_2(B_j)}{1-\sum_{A_i \cap B_j=\Phi} m_1(A_i)m_2(B_j)} & A\neq\Phi \\ 0 & A=\Phi\end{cases} \tag{11}$$

The above equation shows that when $\sum_{A_i \cap B_j=\Phi} m_1(A_i)m_2(B_j)=1$, $Bel = Bel_1 \oplus Bel_2$ does not exist. That is, the two evidence can't be synthesized, then said Bel1 , Bel2 are entirely conflict.

Target recognition based on FART neural network

The four kinds of target features, like Lofar or Bispectrum, have been extracted from time domain, frequency domain and time-frequency domain based on the measured underwater target radiated noise signals. And the target is divided into three categories, which are respectively A,B and C. The Fuzzy Adaptive Resonance Theory(FART) neural network are used for local decision classification. Training and testing sample quantity ratio is 1:5, the recognition rate of training set is 100%, the recognition rate of test set as shown in the following table 1 - 4 shows.

Table 1 The First Feature Sort Result

Sort of Target	Numbers of sample	Test Set Recognition rate	Collectivity Recognition rate
B	59	91.52%	
C	320	93.44%	91.9%
E	90	86.67%	

Table 2 The Second Feature Sort Result

Sort of Target	Numbers of sample	Test Set Recognition rate	Collectivity Recognition rate
B	59	89.83%	
C	320	95.93%	92.75%
E	90	83.33%	

Table 3 The Third Feature Sort Result

Sort of Target	Numbers of sample	Test Set Recognition rate	Collectivity Recognition rate
B	59	84.74%	
C	320	94.06%	88.91%
E	90	73.33%	

Table 4 The Forth Feature Sort Result

Sort of Target	Numbers of sample	Test Set Recognition rate	Collectivity Recognition rate
B	59	74.58%	
C	320	88.13%	81.24%
E	90	61.11%	

Target recognition based on D-S evidence theory

Target D-S evidence theory fusion recognition

The feature information of each sensor as evidence, each sensor provides a set of propositions, the corresponding decision $x_1, x_2, \ldots, x_m$, and a corresponding reliability function need be established, so that the fusion of multiple sensors or feature information is essentially a process of merging different bodies of evidence into a new body of evidence in the same frame of discernment.

If the information fusion system is composed of a number of mutually incompatible goals, every sensor or parent's feature information can obtain a group reliability in the target set while discriminating targets. When the system has a N sensor or a N feature, it has n group's reliability, which are the basis of decision fusion.

The general process using the evidence theory of the fusion of multi sensors and feature information is:

(1) the basic probability, belief function and plausibility function of every sensors are calculated.

(2) All sensors or characteristics of basic probability, belief function and plausibility function are obtained under the combined action using Dempster rule of combination.

(3) The target with maximum support is chosen in a certain decision rule.

D-S evidence theory decision fusion recognition algorithm

Decision fusion algorithm based on multi-feature and classifier. D-S evidence theory is proposed:

(1) To the fusion problem of K (K=4) classifier, Q(Q=3) class, firstly, the reliability of the L features of the sample x, which belongs to class i is obtained by using the classifier, which are Bel_1 , Bel_2 , Bel_3 , …, Bel_L. Then the confidence level that the sample x belongs to class i is given by.

$$Bel(i) = Bel_1 \oplus Bel_2 \oplus ... \oplus Bel_L \qquad (12)$$

(2)The fusion rule is that for the sample x, if the confidence level is the largest then sample x belongs to class i:

$$x \in q \ \ ,if \ \ Bel(i) \geq Bel(j), \forall j \neq i \qquad (13)$$

Using D-S evidence theory, the four characteristics as the section 3 shown is used for decision fusion experiment at the same test conditions, the results are as follows:

Table 5 Result 1 of Decision Fusion Recognition
Based on D-S Evidence Theory

Sort of Target	Numbers of sample	Test Set Recognition rate	Collectivity Recognition rate
B	59	88.14%	
C	320	99.06%	94.24%
E	90	81.11%	

Some discussion on decision fusion

Some defects of D-S evidence theory

(1) The theory of evidence has the potential of data complexity, and it is not convenient to use the evidence theory when the chain is long.

(2) When using D-S evidence theory, the evidence theory need be independent, and the condition is sometimes limited.

(3) The D-S evidence combination rule has combination sensitivity. Sometimes, a small change of the basic probability assignment may lead to great changes in the results. In particular, the result is not ideal when the two contradictory basic probability assignment functions are integrated.

For example, Suppose $\Theta = \{A, B, C\}$, and

m1(A)=0.98 m1(B)=0.02 m1(C)=0.0

m2(A)=0.0 m2(B)=0.01 m2(C)=0.99

The synthesized basic probability assignment function m12 by applying D-S rule is:

M12(A)=0.0 m12(B)=1.0 m12(C)=0.0

The two basic probability assignment function m1(B)、m2(B) of B are very low, but it is very high after synthesized, because the D-S rule is to seek the consistency in all the evidence. Therefore, when synthesizing the two groups of data, the proposition B which appearing all is strengthened, and the proposition of A and C which appearing once are eliminated.

(4)The report of low trust level object affects highly trusted objects.

If two independent sources of evidence (sensing information sources) are assumed to be derived from the basic probability assignment function, the basic probability assignment function generated by the combination rule can be calculated under the effect of the two evidence.

Suppose the degree of a sensor supporting object A is 0.8, while another's is 0.9, which supports the object B.

$$m_1(A)=0.9 \qquad m_1(\Theta)=0.1$$
$$m_2(B)=0.8 \qquad m_2(\Theta)=0.2$$

The object A and object B are mutually exclusive, and then it is obtained by the combination rule and normalization.

$$m_1 \times m_2 = \begin{bmatrix} m(A) = 0.643 \\ m(B) = 0.286 \\ m(\Theta) = 0.071 \end{bmatrix}$$

It can be seen that the report of low trust level object affects highly trusted objects.

For this purpose, we have carried out the following experiments. The relatively poor features result of the second sections, which are based on time-domain waveform analysis, is removed. And the decision fusion with other three better recognition features based on D-S evidence theory is done. The test conditions are the same as before, and the results are as follows:

Table 6 Result 2 of Decision Fusion Recognition
Based on D-S Evidence Theory

Sort of Target	Numbers of sample	Test Set Recognition rate	Collectivity Recognition rate
B	59	91.52%	
C	320	98.75%	94.67%
E	90	82.22%	

Comparing table 5 and table 6, we can find that the recognition rate is improved uniformly after D-S evidence fusion without the relatively poor identification characteristics, the overall recognition rate is also slightly improved. Therefore, when the D-S evidence theory is applied, the characteristics which of recognition effect at the same level should be selected to do decision fusion. Otherwise, the poor performance of a class can lead to the overall recognition rate lower and uneven.

Conclusions

This paper mainly studies on the Dempster-Shafer evidence theory, and discuss its applicability. On the basis of this, the decision fusion strategy, fuzzy adaptive resonance (FART) neural network and the acquired characteristic knowledge are combined for classification and recognition of three kinds of targets. Experimental results show that the recognition rate can be improved by 2%, and the reliability of the identification can be also improved. Application of decision making method based on feature knowledge makes up the problem of the low recognition rate and low reliability of the single feature recognition. The theory can be directly applied to water target recognition.

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