Airborne multi-sensor target recognition method based on weighted fuzzy reasoning network and improved DS evidence theory

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Abstract. Difficult obtainment of basic probability assignment (BPA) and inaccurate recognition due to conflicting data are the problems in applying Dempster-Shafer (DS) evidence theory to airborne multi-sensor target recognition. In order to effectively deal with them, an airborne multi-sensor target recognition method based on weighted fuzzy reasoning network (WFRN) and improved Dempster-Shafer (IDS) evidence theory is proposed in this paper. First, the feature vector consisting of 5 feature components is constructed. And then a 4-layer WFRN consisting of 3 kinds of basic units is established to obtain BPA of the feature vector. Finally, conflict data is processed through IDS evidence theory to obtain the final fusion recognition result. The simulation results indicate that the proposed airborne multi-sensor target recognition method is able to obtain BPA reasonably and deal with conflict information.

1. Introduction
In modern warfare, efficient and accurate target recognition is important for combat situation assessment and tactical decision-making[1,2]. And multi-sensor target fusion recognition can improve the accuracy and reliability of target recognition through comprehensive utilization of sensor resources, which is an important research direction of target recognition[3]. The Dempster-Shafer (DS) evidence theory is an uncertain information fusion method, which is widely used in multi-sensor target recognition[4-6]. DS evidence theory can deal with the uncertainty caused by randomness and fuzziness, and distinguish between the unknown and uncertainty. But there are two problems in applying DS evidence theory to airborne multi-sensor target recognition: difficult obtainment of basic probability assignment (BPA) and inaccurate recognition due to conflicting data.

There are mainly two ways to obtain BPA. One way is determination based on opinions of experts, and the other is mathematical modeling based on the characteristics of the data[7,8]. The first way is severely affected by human factors, which leads to conflict of BPA generally. Compared with the first way, the second way is more objective. The method in this paper adopts the second way, in which a WFRN is established to mathematically process the target feature vectors to obtain BPA by fuzzy reasoning and mathematical calculations.

To deal with conflicting data, DS evidence theory has developed many improvements, which can be divided into these ways: improvement of the Dempster combination rule[9,10], modification of the evidence source[11,12], or both[13,14]. Improving the Dempster combination rule often results in the failure of the commutative law and associative law of the Dempster combination rule which facilitate fast data
processing. In this paper, the improved Dempster-Shafer (IDS) evidence theory in reference [15] is used to modify the evidence source to process conflict data quickly and efficiently.

The rest of this paper is organized as follows. In Section 2, an airborne multi-sensor target recognition method is proposed. In Section 3, simulation results and discussions are presented. Finally, Section 4 concludes the paper.

2. Airborne multi-sensor target recognition method

2.1. Feature vector construction

The feature vector is composed of features required for target recognition, which is extracted from target information in order to express the information necessary for target recognition. The feature vector consists of \( n \) feature components \( F_i (i = 1, 2, \cdots, n) \), which is indicated by

\[
F = [F_1, F_2, \cdots, F_i, \cdots, F_n]
\]

In this paper, the velocity \( v \), acceleration \( a \), distance \( r \), height \( h \) and carrier frequency \( f \) of the radiation emitter on target platform are extracted from the target information for target recognition. So the feature vector consisting of 5 feature components is constructed in this paper, which is indicated by

\[
F = [v, a, r, h, f]
\]

2.2. Obtainment of BPA based on WFRN

In order to obtain BPA of the feature vector, a 4-layer WFRN consisting of 3 kinds of basic units is established in this paper.

WFRN is the network form of weighted fuzzy logic, whose node is weighted fuzzy reasoning units[16]. The advantage of WFRN is that it can realize the nonlinear relationship between inputs and outputs of complex problems like neural network with looser requirement of input data than neural[17], which is suitable for processing heterogeneous data.

The WFRN in this paper contains 3 kinds of basic units: basic category reasoning unit, target type computing unit and BPA computing unit. The three units are shown in Figure 1, Figure 2 and Figure 3 respectively.

(1) The basic category reasoning unit outputs the basic category membership degree \( \mu_{c_i} \) of the feature component \( F_i \) belonging to the basic category \( c_i^F \), by fuzzy reasoning method with the input feature component \( F_i \). The basic category means a set of targets with the same characteristic, such as high-speed targets, high-altitude targets, etc.

(2) The target type computing unit outputs the type membership degree \( \mu_{c_i} \) of the feature \( F_i \) belonging to the target type \( s_k \), which is calculated by weighted summation of input basic category membership degree \( \mu_{c_i} \) of the feature component \( F_i \) by weight \( \omega_{c_i} \).

\[
\mu_{s_k} = \sum_{i=1}^{n} \omega_{c_i} \cdot \mu_{c_i}
\]
(3) The BPA computing unit outputs \( m_{F}(T_k) \), the BPA of \( F \) belonging to target type \( T_k \), is calculated by weighted summation of input type membership degree \( \mu_{T_F} \) of the feature component \( F_i \) by weight \( \omega_{F_i,T_k} \).

\[
m_{F}(T_k) = \sum_{m=1}^{n} \omega_{F_i,T_k} \cdot \mu_{T_F} \tag{4}
\]

The topology of WFRN in this paper is shown in Figure 4. There are four layers in our WFRN: feature input layer, basic category layer, target membership layer and BPA output layer. The layers in the WFRN are composed of several feature components, such as basic category reasoning units, target type computing units and BPA computing units.

2.3. Target fusion recognition based on IDS evidence theory

2.3.1. DS evidence theory

The frame of discernment is indicated by \( \Theta = \{ A_1, A_2, \ldots, A_m \} \), which is the set of mutually incompatible basic proposition indicated by \( A_i \) \( (i = 1, \ldots, m) \). The power set of \( \Theta \) is \( 2^{\Theta} \).

There is a function \( m: 2^{\Theta} \rightarrow [0,1] \) called basic probability assignment of \( \Theta \), which satisfies \( m(\emptyset) = 0 \) and \( \sum_{A \in \Theta} m(A) = 1 \).

The fusion result can be obtained by calculation according to the Dempster combination rule:

\[
m(A) = \begin{cases} 
\frac{1}{1 - K} \sum_{B \subseteq \Theta \setminus A} m_1(A)m_2(B), & A \neq \Phi \\
0, & A = \Phi
\end{cases}
\]

\[
K = \sum_{B \subseteq \Theta \setminus \Phi} m_1(A)m_2(B) 
\]

The large value of \( K \), the severe conflict between evidence \( A \) and \( B \).
2.3.2. IDS evidence theory
In this paper, the IDS evidence theory in reference [15] is used to modify the evidence source to process conflict data quickly and efficiently.

Step 1: The trust degree of each evidence is obtained by the evidence distance.

The average BPA $\bar{m}(A_k)$ of $n$ groups of evidence for each proposition $A_k$ is obtained:

$$\bar{m}(A_k) = \frac{1}{n} \sum_{i=1}^{m} m_i(A_k) \quad k = 1, 2, \ldots, m$$

(7)

The evidence distance between BPA of evidence $m_i(A_k)$ and average BPA $\bar{m}(A_k)$ is calculated:

$$d_i = \sum_{i=1}^{m} |m_i(A_k) - \bar{m}(A_k)| \quad k = 1, 2, \ldots, m$$

(8)

The weight $\omega_i$ is obtained according to evidence distance:

$$\omega_i = \frac{d_i^{-1}}{\text{sum}(d_i^{-1})}$$

(9)

The large value of weight $\omega_i$, the severe conflict between evidence $m_i(A_k)$ and most evidence.

Step 2: With the average weight as the threshold, only the evidence whose weight is less than the average weight is selected as the conflict evidence to modify by discount degree.

$$\text{discount} = \frac{\omega_i}{\max(\omega_i)}$$

(10)

$$m_i'(A) = \text{discount} \cdot m_i(A), A \subset \Theta$$

(11)

$$m_i'(\Theta) = \text{discount} \cdot m_i(\Theta) + 1 - \text{discount}$$

(12)

Step 3: The processed evidences are combined by the standard Dempster combination rules.

2.3.3. fusion decision
In order to make a decision, suppose $\forall A_1, A_2 \subset \Theta$ satisfy:

$$\begin{cases} m(A_1) = \max \{m(A_k), A_k \subset \Theta\} \\ m(A_2) = \max \{m(A_k), A_k \subset \Theta, A_k \neq A_1\} \end{cases}$$

(13)

Set thresholds $\varepsilon_1$ and $\varepsilon_2$, and decide $A_1$ as the fusion result when it satisfies:

$$\begin{cases} m(A_1) - m(A_2) > \varepsilon_1 \\ m(\Theta) < \varepsilon_2 \\ m(A_1) > m(\Theta) \end{cases}$$

(14)

3. Simulation and results
3.1. Setting of simulation
There are three types of targets in simulation: fighter, bomber and early warning aircraft, represented by letters F, B and E in this paper. The target types and their characteristics are introduced.

(1) Fighter(F): high speed, strong maneuverability, fighting in air combat area, extensive flight altitude and carrying airborne fire control radar (support for air combat mainly).

(2) Bomber(B): medium speed, general maneuverability, fighting in air combat area, high flight altitude and carrying airborne fire control radar (support for bombing mainly); low speed and low flight altitude when penetrating.
(3) Early warning aircraft (E): low speed, weak maneuverability, flying outside the air combat area, medium flight altitude and carrying airborne early warning radar.

The targets are divided into these basic categories in Table 1 based on the characteristic and extracted features of target.

### Table 1. The basic category definitions based on characteristics and features

| Characteristic | Feature | The basic categories                  |
|----------------|---------|---------------------------------------|
| Speed          | $v$     | high-speed, medium-speed, low-speed    |
| Maneuverability| $a$     | high-acceleration, medium-acceleration, low-acceleration |
| Active airspace| $r$     | long range, medium range, close range |
| Altitude       | $h$     | high altitude, medium altitude, low altitude |
| Radar emitter  | $f$     | radar of F, radar of B, radar of E    |

There are 5 feature components, 5 basic category reasoning units, 15 target type computing units and 3 BPA computing units in WFRN. And the fuzzy reasoning of the basic category reasoning unit is based on triangle fuzzy numbers, whose calculation amount is small and modelling effect is good with saved calculation time and cost [11].

#### 3.2. Results

### Table 2. Target feature vectors and BPAs output by WFRN

| No. | period | $F_1 : v$ (km/h) | $F_2 : a$ (m/s²) | $F_3 : r$ (km) | $F_4 : h$ (m) | $F_5 : f$ (GHz) | m(F) | m(B) | m(E) |
|-----|--------|------------------|------------------|----------------|----------------|-----------------|------|------|------|
| 1   | $T_1$  | 801.5            | 3.262            | 71.1           | 14125          | 9.59            | 0.4529 | 0.4308 | 0.1164 |
|     | $T_2$  | 806.0            | 3.048            | 79.8           | 14015          | 9.59            | 0.4581 | 0.4301 | 0.1118 |
|     | $T_3$  | 931.0            | 3.900            | 11.5           | 14500          | 9.43            | 0.3823 | 0.4411 | 0.1766 |
| 2   | $T_1$  | 944.9            | 4.239            | 117.6          | 4828           | 9.08            | 0.4306 | 0.4340 | 0.1254 |
|     | $T_2$  | 908.7            | 2.93             | 54.99          | 7380           | 9.73            | 0.4212 | 0.3973 | 0.1815 |
|     | $T_3$  | 1013.9           | 9.72             | 29.29          | 5175           | 9.50            | 0.3564 | 0.4183 | 0.2253 |
| 3   | $T_1$  | 989.0            | 2.245            | 11.6           | 8218           | 9.48            | 0.4540 | 0.4106 | 0.1354 |
|     | $T_2$  | 870.7            | 2.528            | 78.9           | 5029           | 9.66            | 0.4323 | 0.4333 | 0.1344 |
|     | $T_3$  | 1057.3           | 4.265            | 105.9          | 5618           | 9.19            | 0.3484 | 0.4033 | 0.2483 |

The BPAs is calculated based on data from different sensors by the WFRN in this paper, which realizes the nonlinear relationship in target recognition between input target feature vectors and output BPAs of different target types. The input target feature vectors of a fighter and the BPAs output by WFRN are listed in Table2, which includes three sets.

Set $\varepsilon_1 = \varepsilon_2 = 0.1$, then the BPAs and recognition results are shown in Table3.

### Table 3. BPAs and recognition results

| No | $m_1$ | $m_2$ |
|----|-------|-------|
|    | DS evidence theory | IDS evidence theory |
|    | $m(F)$ | $m(B)$ | $m(E)$ | Result | $m'(F)$ | $m'(B)$ | $m'(E)$ | $m'(\Theta)$ | Result |
| 1  | 0.4529 | 0.4308 | 0.1164 | F      | 0.4529 | 0.4308 | 0.1164 | 0 | F      |
| 2  | 0.4581 | 0.4301 | 0.1118 | F      | 0.4581 | 0.4301 | 0.1118 | 0 | F      |
In data 1, $m_3$ is the conflict evidence, which leads to incorrect result of DS evidence theory. IDS evidence theory can identify and modify conflict evidence $m_3$. In the modified $m_3$, the $m'(\Theta)$ is the largest, which reduces the uncertainty in $m'(F)$, $m'(B)$ and $m'(E)$. Based on modified evidences, IDS evidence theory obtains the correct recognition results.

In data 2, $m_1$ and $m_3$ are the conflict evidence. IDS evidence theory can identify and modify the conflict evidences. In the modified fusion evidences, BPA of F is the largest, but does not satisfy the decision conditions. The fusion recognition result cannot be obtained, but the probability of F is the highest, which is closer to the correct recognition result than DS evidence theory.

In data 3, $m_2$ and $m_3$ are the conflict evidence, which is identified and modified by IDS evidence theory. The uncertainty of $m_2$ and $m_3$ is reduced after modification, which is beneficial for IDS evidence theory to obtain correct recognition results.

So it is obvious that IDS evidence theory can identify and process conflict data.

Based on the analysis of the result in Tables 2 and 3, we can conclude that:

1. WFRN can calculate BPAs based on data from multiple sensors, which is the basis for fusion recognition through IDS evidence theory.

2. Compared with DS evidence theory, IDS evidence theory can identify and modify the conflict data to reduce the uncertainty of target recognition, which is beneficial to obtain correct recognition results.

4. Conclusions

This paper proposes an airborne multi-sensor target recognition method based on WFRN and IDS evidence theory to obtain BPA and process conflict data. The target feature vectors are processed by WFRN for BPA obtainment, and the conflicts of BPA are processed by IDS evidence theory for target fusion recognition.

The simulation results indicate the method in this paper can obtain BPA reasonably and deal with conflict information, which can effectively realize target recognition.

The proposed method also has some limitations that is the WFRN established in this paper has fixed parameters, which leads to its limited applicability. Therefore, we plan to investigate the establishment of a highly applicable WFRN in future research.
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