Multi-source Information Data Fusion Method under Complex Battlefield Situation

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Abstract. Under complex battlefield situation, the situation information is instantaneous and changeable. The uncertain information always causes difficulty in acquisition information and miscalculation, and lead to low efficiency and poor accuracy for aircraft situation awareness. In order to solve the problem, in this paper it proposes a deep-learning based multi-sensor situation awareness data fusion method. With data acquitted from multiple sensors in multi-band and multi-angle, it realizes multi-sensor information data fusion by comparing and analysing of two AI data fusion methods that one is based on classical evidence theory and the other is based on deep learning. The simulation results indicate that the deep-learning based data fusion method presents higher efficiency in dealing with the environment information fusion with large evidence conflict.

1. Introduction
Since the 1990s, especially the 21st century, information technology has been spread to all areas [1-2]. The concept of informatization has been penetrated into all aspects of various sophisticated weapons and new concept weapons. In the future informatization battlefield, situation awareness and recognition are very important prerequisites for mastering the battlefield situation, accurately attacking and winning the war, and have important military value as well [3-4]. How to accurately identify the battlefield unit in the complex instantaneous and changeable battlefield environment has become a hot topic in recent years.

If using a single sensor to obtain the environmental target features for recognition, it is easy to be affected by the external environment, and this results in a fuzzy and uncertain perception. However, Profit from Multi-sensor data fusion technology, information fuzziness can be reduced, system survivability can be increased, time and space coverage can be expanded, system reliability can be improved, and Spatial resolution ability can be enhanced [5-6].

Multi-sensor data fusion technology, also known as multi-source information fusion technology, is mainly for the study in the overall performance of complex sensor information system. It is a further interpretation of information fusion technology. Since it was proposed, it has been widely used in automatic target recognition, automatic aircraft navigation, robot and other fields. It is of great significance to make a profound study of Multi-sensor data fusion technology, not only because of it has become an important technology for accurate target recognition in complex battlefield...
environment, but also it lays a solid foundation for future battlefield situation assessment research [7-9].

The classical evidence theory is a method to realize multi-source information fusion. It can combine the evidence of multiple uncertain information, eliminate and integrate contradictory information, and finally outputs the determination of the nature of the observed object. At the same time, evidence theory can enhance the system credibility by fusing multiple evidences [10-12]. Based on deep mathematics roots, by reinterpretation of probability, definition of trust function and likelihood function, etc., evidence theory can avoid outputting indeterminate probability. Therefore evidence theory is commonly used to solve the reasoning problems of uncertain knowledge and widely used in multi-source information data fusion [13]. The development of evidence theory is hindered by the existence of conflict evidence, that directly leads to the invalidation of Dempster combination rules or deviation from the real recognition results. However, there are two main problems in the evidence of battlefield target recognition. One is that each evidence does not in accordance with the nature of sum is 1, and the other is in some situations the evidences are contradictory [14-15].

Deep learning is a new machine learning theory, which can find out the non-linear association characteristics between different data, and predict the unknown data according to the deep characteristics between data [16-17]. Therefore, data-level location enhancement based on deep learning has attracted more and more attention of domestic and foreign research institutions and scholars. However, at present no public information presents any in-depth study on the perception of multi-sensor fusion system in the case of changeable target background and moving target occlusion.

Based on the existing knowledge, this paper proposes an aircraft situation awareness background and scheme, and makes a comparison of the classical evidence theory and deep learning data fusion method

2. Aircraft Intelligent Perception System Scheme

2.1. Application Scenarios
In the future, even though under complex battlefield environment, aircraft will be able to implement and complete the measurement of battlefield environment information for subgrade radar, air based radar, space-based radar, collaboration radar, and Interceptor, etc. by adopting timing multi-source sensor satellite receiver, active-passive composite radar, penetration jamming device, burst datalink, additionally fuses the multi-source information and perceive the battlefield situation environment outside the aircraft. Figure 1 is a schematic diagram of multi-source information perception under high-precision timing conditions.

![Figure 1. Multi-source perception schematic diagram.](image-url)
2.2. Aircraft Intelligent Perception System
The aircraft intelligent perception system classifies and stores data from each data acquisition sensor into the database, recognizes and fuses the measurement data according to the information fusion theory and method, and finally gets recognition results. The overall system structure is shown in figure 2.

![Figure 2. Overall system block diagram.](image)

Data acquisition platform: Considering that the complexity of the battlefield environment and the limitations of a single sensor, according to the overall design requirements, sensors used in the data acquisition platform mainly include satellite receiver, active-passive radar, penetration jamming device, burst datalink, etc. For each sensor, it pre-processes the acquired information, and then obtains feature description, precise geographic location information, motion parameters or partial features of the environmental objectives. It applies calculation using pre-processed feature description to obtain the basic probability function assign value of each possible event in the recognition framework. Each sensor also packs all the information of the identified target in the format of message, and transmits messages to recognition fusion system platform. Every message includes the geographic location information, motion parameters, basic probability function assign value, transmission time and data source of the observation objectives.

Information classification and warehousing: The received messages are classified according to whether they belong to the same observation target or not. The evidence vectors which describing the same observation target will be stored in the same table of database. It provides convenience for the subsequent recognition and fusion operation.

Recognition fusion system platform: when messages from data acquisition platform are received, it classifies messages according to whether they belong to the same observation target or not. The evidence vectors which describing the same observation target will be stored in the same table of database. It provides convenience for the subsequent recognition and fusion operation. It can obtain the basic probability function assignment value of each observation target from the database, and applies data fusion theory Target recognition fusion processing with AI Data Fusion Theory, finally gets the recognition result. In addition, it can integrate the target type recognition results with the relevant.

3. Information Fusion Method Based on Evidence Theory

3.1. Classical D-S Evidence Theory
Evidence Theory was first put forward by Dempster, and then further developed by his student Shafer. By defining the concept of belief function and other concepts, this theory combines multiple sets of evidences in mathematical methodologies, and analyses and processes the uncertainty problem.
The evidence theory defines the entire all types of observation objects as a recognition framework \( \Psi = \{ A_1, A_2, \ldots A_n \} \), in which every two elements are mutually exclusive. The core problem of evidence theory is to determine the factor of an uncertain element belongs to a subset of the recognition framework based on the existing data. According to this purpose, the basic probability assignment function (mass function) is defined in evidence theory as follows:

1. Set \( F(H) \) as the Set which composed by all subsets \( (\Psi \text { is called Power Set}) \), mapping \( m: F(H) \rightarrow [0,1] \) is called a basic probability assignment function (mass function), when meet the following condition:

\[
m(\phi) = 0; \sum_{Q \subseteq U} m(Q) = 1
\]

2. Mapping \( Bel: F(H) \rightarrow [0,1] \) is called belief function, if:

\[
Bel : 2^U \rightarrow [0,1]. Bel(Q) = \sum_{W \subseteq U} m(W) = 1
\]

3. Mapping is called plausibility function, if:

\[
pl : 2^U \rightarrow [0,1], pl(Q) = 1 - Bel(\neg Q)
\]

Equations (1), (2) and (3) show that the belief function represents the lower estimate limit of the certainty factor of the hypothesis, is a pessimist estimate, and the plausibility function represents the upper estimate limit of the certainty factor of the hypothesis, is an optimistic estimate. These two functions obey the theorem: for any \( Q \subseteq F(H) \), there are:

\[
Bel(Q) = \sum_{E \subseteq Q} m(E); pl(Q) = \sum_{E \cap Q = \phi} m(E)
\]

Evidence theory uses belief function and plausibility function to describe the problem uncertainty. Assuming there are multiple evidences \( T_1, T_2, \ldots, T_n \) exist in the target recognition fusion system, the distribution values of the basic probability functions for each evidence corresponds to all primitives \( Q_1, Q_2, \ldots, Q_n \) are \( m_1, m_2, \ldots, m_n \), so that the rule of evidence theory synthesis is:

\[
m(\phi) = 0, m(Q) = \frac{1}{1-K} \sum_{r \cap Q = \phi} \prod_{1 \leq i \leq n} m_i(Q_i), Q \neq \phi
\]

\[
K = \sum_{r \subseteq Q = \phi} \prod_{1 \leq i \leq n} m_i(Q_i)
\]

Therein, in equation (6) \( K \) means the classical conflict coefficient. The value of \( K \) indicates the conflict factor between evidences. The larger the value of \( K \) the greater the factor of conflict between evidences. in equation (5), the normalization coefficient \( 1/(1-K) \) obtained from \( K \) value can effectively avoid assigning non-zero probability to null set in evidence synthesis process. The combinatorial rules show that the recognition result is the interaction between evidences, and the order of synthesizing evidences will not affect the result.

3.2. Some Problems under Classical Evidence Theory

Based on analysis of experimental data, it finds that in the case of less evidence conflict, result accuracy is higher for experiments adopting classical evidence theory; however in the case of more evidence conflict, the accuracy of the recognition results are declined, and contrary to the facts. Here are illustrate with some experimental examples.

Experiment 1, recognition framework \( \Psi = \{ \text{subgrade radar 1}, \text{air based radar}, \text{collaboration radar} \} \), for convenience we consider subgrade radar 1 as \( Q \), air based radar as \( W \), and collaboration radar as \( E \), therefore two evidences are:

- Evidence 1: \( m_1(Q)=0.969; m_1(W)=0.031; m_1(E)=0 \)
- Evidence 2: \( m_2(Q)=0; m_2(W)=0.02; m_2(E)=0.98 \)

Plainly, there is very high factor of conflict between \( m_1 \) and \( m_2 \), i.e., Evidence 1 supports subgrade radar 1 (Q) and Evidence 2 highly supports collaboration radar (E). Based on equation (6), it is easy to get the calculation result \( K \) nearly to be 1, and fusion results \( m(Q)=0, m(W)=1, \) and \( m(E)=0 \) according
to equation (5). The recognition results are contrary to the facts: certainty factor became to 0 for fusion of both subgrade radar 1 (Q) and collaboration radar (E) with better certainty factor, and certainty factor became to 1 for air base radar (W) which has lower certainty factor.

Experiment 2: recognition framework $\Psi = \{\text{subgrade radar 1, air based radar}\}$, for convenience we consider subgrade radar 1 as Q, air based radar as W, three evidences are:

- Evidence 1: $m1(Q) = 0, m1(W) = 1$
- Evidence 2: $m2(Q) = 0.9, m2(W) = 0.1$
- Evidence 3: $m2(Q) = 0.99, m2(W) = 0.01$

Based on formula (6), it is easy to get the calculation result $K = 0.997$, and fusion results $m(Q) = 0, m(W) = 1$ according to formula (5). Because of Evidence 1 can completely deny Q, the fusion result will be 0 even if the certainty factor to Q for other evidences is very high based on evidence theory combinatorial rule formula. The recognition results are contrary to the facts, also it means there is a veto over case in processing high conflict evidences with classical evidence theory.

4. Enhancement of Multi-source Data Fusion Based on Deep Learning

Combined with the characteristics of input and output data of multi-source fusion recognition enhancement problem, this paper proposes a multi-layer architecture of a deep feature fusion network, which is composed of input layer (multi-source information data), two-dimensional convolution layer, maximum pooling layer, full-connected fusion layer and output layer (data fusion result). As for the network structure, please refer to figure 3.

![Figure 3. The enhancement model structure of fusion recognition.](image)

The input layer does not simply take the multi-source data as input, but fully considers the second-order correlated characteristics of multi-source data space, constructs the data autocorrelation matrix, and standardizes the data. The specific data transformation can be expressed as follows:

$$E_k = \delta_{\text{nor}} \left( \begin{array}{c} x_1^{1,k} \\ \vdots \\ x_1^{N,k} \\ x_1^{N,k} \\ \vdots \\ x_1^{N,k} \\ x_1^{N,k} \\ \vdots \\ x_1^{N,k} \\ \end{array} \right) \in \mathbb{R}^{3M \times 3M} \quad (7)$$

Among them, $\delta_{\text{nor}}$ refers to the normalized function, just as the frequently-used normalized function of min-max and the normalized function of z-score.

The second layer convolution contains $L=4$ pieces of two-dimensional convolution kernel $W_l \in \mathbb{R}^{2 \times 2}$. The third layer adopts single-step maximum pooling. After multi-channel convolution of the data matrix $E_k$, it is transformed by ReLU activation respectively, and the overfitting phenomenon is alleviated by dropout with a drop rate of 0.5. The multi-dimensional feature parameters of convolution output are compressed and projected in the pool layer to extract the features under variable scales. The multi-source location data fusion network mentioned in this section mainly completes the depth feature extraction of input data matrix in the two layers above, and its processing process can be expressed as follows:

$$F_i = \mu \left( \delta_{\text{drop}} (v_{\text{relu}} (E_k \ast W_l) ) \right)_{(p,q)}^{s}, l = 1, \ldots, L \quad (8)$$
$V_{\text{relu}}$ and $\delta_{\text{drop}}$ refer to the activation function and the discard function respectively. $\mu\{x\}_{(p,q)}$ refers to the pooling kernel with the dimension of $pxq(2 \times 2)$ is transformed into a pool with the step of $S(S=1)$. Relu activation function and Dropout with a drop rate of 0.25 are used for the feature fusion. The fused high-dimensional eigenvectors are sent to the all connected output layer which contains three neurons. Finally, the standardized results of fusion reasoning are transformed by unit reduction to obtain the final fusion location enhancement results.

In actuality, the data-level multi-source fusion location enhancement algorithm which is based on deep learning involves model training and real-time fusion prediction phase. In the training and learning phase, the grid simulation data should be used to train the model first, and then a small amount of high-quality measured multi-source data can be used for model optimization to further improve the fusion location accuracy.

5. Simulation and Analysis

Suppose that in the battlefield scenario shown in figure 1, the aircraft receives the radiation sources of subgrade radar 1, air based radar and collaboration radar. UPDM is adopted to simulate the battlefield environment, and generates multi-band and multi time period measurement data. The scene parameters are shown in table 1 below. MATLAB is used to generate multi-source positioning data and Origin is used to generate data graph. The classic evidence theory fusion method and deep learning fusion enhancement method are simulated and verified. Under 1000 Monte Carlo tests, the recognition probability of the classic evidence theory fusion method is 0.78, the recognition probability of the deep learning fusion enhancement method is 0.89, and the performance is improved by 11%.

In order to verify the effectiveness of evidence theory and deep learning in target recognition information fusion, the evidence theory method is compared with deep learning theory. The results of some simulation experiments are as follows.

Recognition framework = \{subgrade radar 1, air based radar, collaboration radar\}, evidence theory method receive two pieces of evidences T1, T2 from data acquisition platform, and get the recognition probability.

The fusion results are obtained by the formula and simulation, shown as follow.

Table 2 shows that both the classical evidence theory method and the deep learning enhancement method can get the correct recognition results. Compared with the classical evidence theory fusion method, the recognition result based on the deep learning method has lower ambiguity and higher definition, which indicates that the recognition accuracy is higher.

| Evidence T1 | Subgrade radar | Air based radar | Collaboration radar |
|-------------|----------------|-----------------|---------------------|
| Evidence T2 | 0.499          | 0.387           | 0.114               |

Table 2. Comparison of the results between the deep learning method and the classical evidence theory.

| Recognition framework | Subgrade radar | Air based radar | Collaboration radar |
|-----------------------|----------------|-----------------|---------------------|
| Classical Evidence Theory | 0.78           | 0.68            | 0.75                |
| Deep Learning Method | 0.84           | 0.77            | 0.85                |

6. Conclusion
In this paper, the flow of intelligent battlefield situation awareness system and multi-source information fusion system are introduced, and the information fusion algorithm based on classic D-S
criterion theory and deep learning enhancement is analysed. By introducing the intelligent algorithm, we can alleviate the negative impact of the evidence with high conflict in the classical information fusion, and improve the efficiency and accuracy of the intelligent knowledge. However, there are some problems in this method. It will take a lot of time to deal with multi-source data with great difference in positioning accuracy or situation awareness data with higher dimensions, and its adaptability is slightly insufficient. In the future, we can combine adaptive learning and fusion threshold decision technology to improve the effectiveness, rapidity and robustness of the whole command system.

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