Research on Sea Battlefield Data Fusion Method based on D-S Evidential Theory and Event Net

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ABSTRACT

The battlefield data accumulated during the naval formation mission, which shape and content are various for the different detection body, needed to be fused before application to the decision-making support. Aiming at the data fusion problem in sparse information environment, the semantic structure of battlefield situation events for situation assessment was analyzed, and the research framework was designed, and the framework for judging the reliability of battlefield events was set up. Based on this, the model of event reliability was established, the algorithms of single event reliability calculation and multi event fusion analysis were proposed, the effectiveness of the method was proved by the empirical analysis.

INTRODUCTION

Situation assessment derives from a comprehensive analysis on the situation of the enemy, the situation of our party, geography situation, and weather etc. [1]. Battlefield data mainly comes from active or passive reconnaissance [2], as the subjective mapping of an objective phenomenon, its form and content are subject to detection body, process and means. The studies have shown that, data collection and compilation take up 40-80% of the time of planners [3]. Therefore, the reorganization of sea battlefield data is very important to improve the benefit of situation assessment.

In terms of the study, Cheng Libin et al. [4] considers that effective judgment should be targeted, comprehensive, dynamic and applicable etc. Li Guangjian et al. [5] points out that the judgment should avoid oversight or misjudgment, which means that the reorganization of judging data shall deal with the data reliability recognition and fusion. According to the grading standard of Joint Directors Laboratories [6], it belongs to the level of “objective assessment”, which is a process of multi-source information fusion. In this process, multi-source information is equal to the observation of same object from different perspectives.

The theory of evidence was first proposed by Dempster in 1967 and developed by his student Shafer in 1976. It is also called the Dempster/Shafer evidence theory (D-S theory). Zhang Hongbing et al. [7] proposes an information fusion method combining with D-S theory and phase transformation theory Potts2 model in the statistical physics. Chen Peibin et al. [8] presents a hierarchical fusion method based on fuzzy aggregation and genetic algorithm, these studies have focused on the fusion method, and are lack of the method, theoretical research and technical practice on how to serve the situation assessment for objective assessment. The situation is expressed by the global behavior.
of specific time and space area, naval battlefield data often can only reflect some local fragments of the global behavior, so the information itself is sparse and non-redundant, which even cannot realize the coverage requirements, this puts forward new challenges for fusion method. According to information fusion problem under sparse information environment, this article studies on how to realize the naval battlefield data fusion based on D-S theory by taking occurrence net as fusion carrier.

ANALYSIS ON THE FUSION OF BATTLEFIELD INFORMATION

The emphasis of situational assessment is to analyze the correlation between information events in various situations, so we should reorganize relevant patterns in the battlefield at first. To be specific, it usually takes three stages to form a situation data: first, an entity observes the particular environment at a certain time; then, obtains some kind of information from the observation; finally, induct and interpret this information to obtain information that is more meaningful.

In fact, each piece of information from the foregoing situation data meets the definition of “event”, thus the foregoing situation data can be expressed with the combination of three events, and we respectively define them as “observation event (OE)”, “sensing event (SE)” and “explaining event (XE)”. Of course, there are many situations where the composition structure of situation data can exist:

1) Regular type.
2) Non-explanatory type.
3) Nested observation type.
4) Multi-sensing type.
5) Multi-explanatory type.
6) Comprehensive explaining type.

Based on the above analysis, a piece of situation data contains more than one event that constitutes the network structure, we call it “event diagram”, after the continuous collection of a batch of situation data, it can form an event diagram containing multiple subgraphs, and need to carry out effective systematic integration based on lateral connection of information.

SITUATION EVENT FUSION BASED ON D-S THEORY

Reliability Judgment and Identification Framework for Situation Event

In the situation analysis, the reliability judgment of the information is critical, the reliability of single situation data can be judged by observing the event state, its reliance, observation ontology, observation device or space-time state at the time of observation, in such cases, the reliability of explaining event relies on the state of sensing event. When a batch of situation data gathers, the information from different observation processes may be confirmed or conflicted, and these transverse correlation may provide more comprehensive support for the reliability judgment of the event.

According to the evidence theory, we must construct an authentication framework for the discriminant information, which is the power set of all possible situations. Here we need to judge the reliability of the (sensed or explained) event, but it is often difficult to obtain all the other situations associated with the event attribute. As a result, for a
specific event e, its domain of discourse is defined as Θ (e) = {e, ^e}, where ^e indicates that event e has not occurred, that is, we only judge whether the event has occurred or not, but do not judge the reliability of event attribute. The reason is that the attribute judgment requires a lot of background knowledge instead of situation data only. Then in this setting, the corresponding authentication framework is:

$$2^{\Theta (e)} = \{\emptyset, \{e\}, \{^e\}, \{e, ^e\}\}$$ (1)

In which, ∅ indicates that there is no information, \{e, ^e\} indicates the occurrence or non-occurrence information of e. Corresponding to the unknown state of the environment, for each sensed event or explained event in the event network, we need to specify the evidence quality m(∗)(i.e., information reliability) respectively corresponding to four information states; the evidence theory usually provides m(∅) = 0. The information correlation between two events is a conditional probability relationship from a data perspective. If an event e1 affects another event e2, it means that when e1 occurs, the reliability of the e2 information states in $$2^{\Theta (e2)}$$ will be affected:

Each arrow line in the Figure 1 represents the degree of support for the reliability of the corresponding information state of the subsequent event e2 when the event e1 occurs, equivalent to the conditional probability P (∗ | {e1}). Accordingly, we take P (∗ | {e1}) as the weight of the directed edge pointing to the information state ∗; P (∅ | {e1}) does not exist because the event correlation always provides some information. This conditional probability is usually not included in the situation data, which can be assigned a value according to a priori knowledge of the military personnel in the actual analysis and should conform to:

$$P (\{e2\} | \{e1\}) + P (\{^e2\} | \{e1\}) + P (\{e2, ^e2\} | \{e1\}) = 1$$ (2)

**Reliability Calculation of Single-situation Event**

Based on the above analysis, we can always construct the corresponding event network for each situation data. For the observed event, we can think that it has occurred; otherwise, we will not get the report. As a result, for any observed event oe, we can set m({oe})=1, while m(∅)=m({^oe})=m({oe, ^oe})=0. In this case, the reliability of any sensed event se can be set directly as the corresponding conditional probability, that is, if se is obtained from the observed event oe, then 

$$m(se)=m({oe})P(se | {oe})=P(se | {oe})$$. The specific value of the conditional probability needs to be determined according to the specific priori knowledge, but we can analyze the distribution of the reliability in a variety of information states in a more general case. Such reliability actually expresses the degree of trust in the observation and the significance of the observation error. It is clear that the significance of the observed event is correlated to the observer and the specific form of the observation behavior. On the whole, there are two forms of observation:
(1) Monitoring observation. It refers to a continuous, specialized observation of a particular type of goal or region, in which case it is highly reliable if a situation is sensed, and the reliability of non-occurrence is also high if a situation is not sensed. Therefore, in this case, \( m(\sim se) \approx 1 - m(\{se\}) \), while \( m(\{se, \sim se\}) = 1 - m(\{se\}) - m(\sim se) \) will be a very small number.

(2) Occasional observation. Some situation data are derived from occasional observations, for example, fishermen occasionally see a particular maritime situation, in which case the reliability of the corresponding sensed event is much lower than that of the monitoring observation. More importantly, the opposite of the observation is not non-occurrence of event, but rather an unknown to the occurrence state of the event, corresponding to the \( \{se, \sim se\} \) state. Therefore, in this case, \( m(\{se, \sim se\}) \approx 1 - m(\{se\}) \), while \( m(\sim se) = 1 - m(\{se\}) - m(\{se, \sim se\}) \) will be a very small number.

Based on the setting of sensed event reliability, we can further determine the reliability of the correlated explained event. If an explained event \( xe \) depends only on a single sensed event \( se \), then \( m(*) = m(\{se\}) \cdot P(*)/\{se\} \), where \( P(*)/\{se\} \) represents a priori situation explanation rule. If \( xe \) depends on multiple sensed events \( se_1 \ldots se_n \), let \( X \) represents all the set of interpreted events deduced from the perception event \( se_1 \), and \( Y \) represents all the set of interpreted events deduced from the perception event \( se_2 \), then the reliability of \( xe \) needs iterative calculation by use of Dempster’s evidence combination rules, as shown in Formula (3):

\[
m_1 \oplus m_2(xe) = \frac{\sum_{X \cap Y = xe} m(\{se\}) \cdot P(xe|\{se\}) \cdot m(\{se_2\}) \cdot P(xe|\{se_2\})}{1 - K(xe)}
\]

\( K(xe) = \sum_{X \cap Y = \emptyset} m(\{se\}) \cdot P(xe|\{se\}) \cdot m(\{se_2\}) \cdot P(xe|\{se_2\}) \).

Correlation and Fusion of Multiple-situation Event

In the case of the batch situation data, the reliability of the situation event can be further corrected according to the horizontal correlation between the situations so as to realize systematic discrimination of the situation data. The quality of the situation data essentially depends on the quality of the sensed event, the explained event results only from the re-processing of the situation analysis, so this paper only analyzes the horizontal correlation correction method of the sensed event reliability. When multiple situation data relate to the same or similar sensed events, there may be verifying or conflicting relationships between them, which can have an impact on the initial reliability assessment. Of course, this also involves the similarity judgment problem of sensed events. Since the event element contains both the concept information and space-time information, it is necessary to judge from the perspectives of concept similarity and space-time similarity. This paper does not conduct an in-depth discussion about it, but assumes that there has been similarity judgment rule to meet military specifications. For the given two events \( e, se \notin OE \), and \( se \in SE \), if \( e \) is similar to \( se \), then information relevance of \( e \) to \( se \) can be used to correct the reliability of \( se \) items in the authentication framework. Such information relevance actually indicates the probability adjustment of \( se \) items in the case of \( \{e\} \) established, its expression form is similar to Figure 1, but the impact form is simpler, as shown in Figure 2.

Figure 2 reflects two different forms of horizontal correlation. Figure 2(a) shows the mutual verification, that is, the occurrence of event \( e \) will support the possibility of \( se \) occurrence; Figure 2(b) indicates the mutual conflict, that is, the occurrence of event \( e \) will suppress the possibility of \( se \) occurrence. In either case, the remaining information...
of the particular correlation is unknown, which is the difference from Figure 1. The directed line in Figure 2 also corresponds to the conditional probability \( P(\hat{y}|e) \), so under the influence of the new horizontal correlation, the reliability of each information state

![Figure 2](image2.png)

Figure 2. Schematic diagram of the event correlation between situation data.

corresponding to \( se \) can also be re-corrected. Furthermore, due to the addition of horizontal correlation, the whole situation data set constitutes a large data system, and D-S evidence theory becomes the information fusion theory of this system.

**EMPIRICAL ANALYSIS**

We can use a simple example to express the role of the foresaid event network analysis method, assuming that the situation center receives the following two messages:

1. According to the report from no.xx observation and communication station, a periscope was found at xx◦direction and xx nautical miles from the station at xx o’clock on the x day of x month;
2. According to the report from Chinese fisherman, a periscope was found at xx.xx east longitude and xx.xx north latitude at xx o’clock on the x day of x month.

The initial two event networks are obtained thereby:

(1) \( oe_1 = \{ \text{no.xx observation and communication station, found, at xx o’clock on the x day of x month, at xx◦ direction and xx nautical miles from the station} \}; se_1 = \text{periscope, found, at xx o’clock on the x day of x month, at xx◦ direction and xx nautical miles from the station} \).  

(2) \( oe_2 = \{ \text{fisherman, found, at xx o’clock on the x day of x month, at xx.xx east longitude and xx.xx north latitude} \}; se_2 = \text{periscope, found, at xx o’clock on the x day of x month, at xx.xx east longitude and xx.xx north latitude} \).

Two independent event (chain) networks are established, according to a priori knowledge, the information reliability index corresponding to the event network is obtained, as shown in Figure 3:

![Figure 3](image3.png)

Figure 3. The case-based initial information reliability setting.
We assume that se1 and se2 are similar in terms of the relevant concept elements and space-time elements of the submarine, and then it can be considered that the determination of submarine driving is supported to some extent. Therefore, se1 and se2 reflects the mutually supported correlation in the horizontal direction. According to the a priori knowledge of submarine driving, in the case of an event se1, the probability of occurrence of se2 is 0.7, thus a joint event network as shown in Figure 4 will be formed.

![Figure 4. Joint event network structure of horizontal correlation.](image)

Then the correlative judgment will have an impact on the information reliability of the se2. We show the results in TABLE I:

|                | m1(|se2|) = 0.5 | m1(|~se2|) = 0.1 | m1(|se2, ~se2|) = 0.4 |
|----------------|----------------|-----------------|---------------------|
| m2(|se2|) = 0.56 |                 |                 |                     |
| m2(|se2, ~se2|) = 0.24 |               |                 |                     |

<table>
<thead>
<tr>
<th>X (\cap) Y</th>
<th>m</th>
<th>X (\cap) Y</th>
<th>m</th>
<th>X (\cap) Y</th>
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<td>{se2}</td>
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<td>(\Phi)</td>
<td>0.056</td>
<td>{se2}</td>
<td>0.224</td>
</tr>
<tr>
<td>{~se2}</td>
<td>0.12</td>
<td>{~se2}</td>
<td>0.024</td>
<td>{se2, ~se2}</td>
<td>0.096</td>
</tr>
</tbody>
</table>

Seen from TABLE I, \(K = 0.056\), so the reliability of se2 event after the correction is: \(m2(|se2|) = (0.28 + 0.12 + 0.224) / (1-0.056) = 0.661 > m1(|se2|)\). Obviously, the original reliability of the event se2 has been improved due to the presence of other data that can confirm the event se2.

**CONCLUSIONS**

This paper extracts the basic events of “observation event”, “sensing event” and “explaining event” from the sea battlefield data, which is composed of multiple time and space events, as the semantic structure of battlefield situation event oriented to situation assessment. On the basis of this, this paper proposes a data fusion solution based on DS evidence theory, include the research strategy of judging the reliability of information through event correlation, the initial value setting method of single event state and the correlation analysis method of multi-events. Example show that the sea battlefield data was incorporated into the event network based on the solution, which improves the reliability of the original event and establishes a good data foundation for the situation assessment.
ACKNOWLEDGEMENT

Supported by the National Natural Science Foundation of China under Grant No. 71701208.

REFERENCES