Target intention discrimination method of event evolutionary knowledge enhancement

Ruijuan Hu, *Haiyan* Liu*, and *Lei* Ge

PLA Strategic Support Force Information Engineering University, Zhengzhou, China

Abstract. With the multi-source intelligence data grow exponentially, traditional methods can barely satisfy the requirement, which means to organize and understand the tremendous military knowledge. So, this research project aims to develop unified, highly connected military knowledge graph to integrate information. Using front-end interaction technology, supporting learning function based on inference, error-correcting and marking, this graph can continuously modify the logic model and improve the intelligence of itself, so the knowledge will be solid in our department. It can reduce dependence on the experience of special experts, and moreover, provide platform for developing data-driven general battle system.

Keywords: Event representation, Event extraction, Event evolutionary graph (EEG), Intention discrimination.

1 Introduction

With the continuous development of modern aircraft technology, the types of aircraft carrying out various combat missions are increasing. In modern warfare, the timely and accurate determination of high-value air targets on the battlefield can ensure the comprehensive control of the battlefield situation, and is conducive to the real-time analysis and judgment of the battlefield situation to make a timely response. For combat units, the combat intention determination of air targets is complex and requires a lot of time and effort. In the face of redundant flight activity text data of air targets, there is an obvious error rate in manual identification of combat intention, so it is urgent to study a method that can assist combat personnel and have good effect.

The research on the determination of air target combat intention mainly adopts two methods: one is multi-attribute decision, and the other is based on knowledge reasoning. Multi-attribute decision-making can comprehensively deal with a large amount of information but lack the reasoning ability. Air target combat intention recognition based on deep neural networks which improves the accuracy of identifying combat intention, proposed by the Air Force Engineering University. An air target intention determination model based on intuitive fuzzy generative rule reasoning (IPR) and multi-attribute decision

* Corresponding author: huruijuan01@126.com

making proposed by Dalian Naval Academy. Combining the advantages of multi-attribute decision making and knowledge reasoning, the accuracy of the results is improved, but the specific feasibility remains to be explored.

Event evolutionary graph (EEG) is a knowledge of logical logic commonly used to reveal the evolution laws and patterns between events. The rationality of the event graph to determine the operational intention of the air target is: first, the flight activity of the air target describes the flight activity of the event graph represents the relationship between the events of the flight target as a series of events with conformity relationship can be abstracted as a cause event, taking the operational intention as the outcome event, and the causal relationship between the two as the causal relationship between the events in the event graph. Application, mining the causality of the air target flight events and air target flight activities and combat intention, using the way of the graph intuitive display, can be applied to the air target flight activities and combat intention causal analysis, provides new analysis tools and ways, to provide support for predicting operational intention, and even can assist in predicting the change of air target flight activities.

This paper makes the following two key contributions: Constructing semantic representation models of flight activity events for aerial targets, defining domain typical and atypical events. We are among the first to propose constructing EEG for the task of air target combat intent determination.

2 The target intent determination framework of event evolutionary knowledge enhancement

A framework to determines the goal of achieving event evolutionary knowledge enhancement is proposed. It includes four modules: event type detection, event extraction, EEG construction, and operational intention discrimination (see Figure 1).

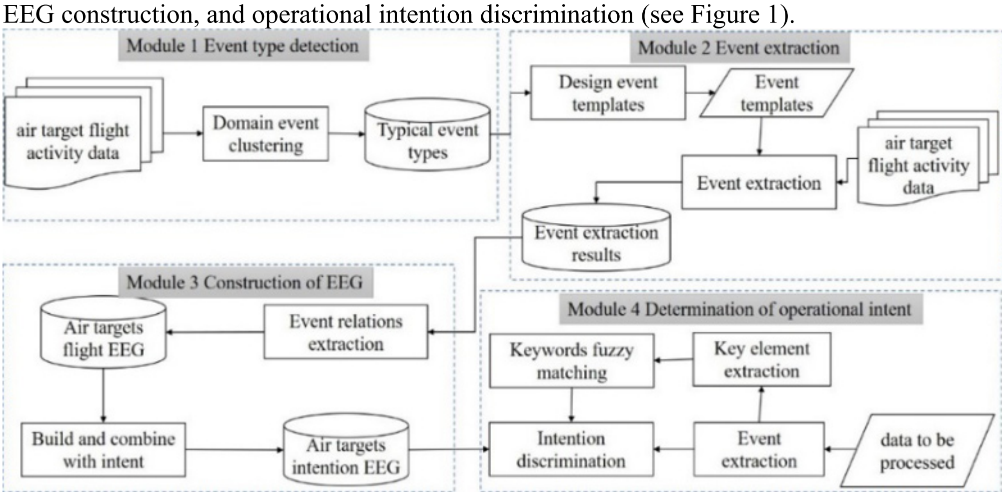

Fig. 1. Target intent determination of event evolutionary knowledge enhancement.

2.1 Formatting the title Event type detection

Event trigger words are the most important features that determine the event type, so discovery of the event type can be equivalent to discovery of the event trigger words type. The types of events in the field of air target flight activity are found by extracting trigger words and clustering them, and the types of events found are the typical event types in the field of air target flight activity, while the other event types are classified as the atypical event types in the field of air target flight activity.

The trigger words discovery process for typical events consists of three steps: trigger words extraction, trigger words filtering and trigger words clustering.

2.1.1 Trigger words extraction

The core of the trigger words extraction algorithm is to classify the text, word annotation and dependency parsing, and extract the verbs that act as important components in the sentence. The algorithm of trigger words extraction is shown followed.

Algorithm Trigger words extraction

Input: air target flight activity *text*; segment function *Segment ()*; semantic parsing function *Semantic();* extract doubles of SBV,VOB,COO function *Extract ()*

Output: candidate trigger words

Sentences <- Segment(*text*)
Words <- wordpos(*sentences*)
Trigger words <- [] // candidate trigger words set
For each *word* in *words* **do**
if *word* is verb
Trigger words. Add(*word*)
End for
Semresults<- Semantic (*sentences*)
Doubles [s1, s2]<- Extract(*semresults*) //extract SBV,VOB,COO doubles
If *doubles* in [SBV, VOB, COO] **then**
if *doubles*.s1 is verb **then**
Trigger words. Add *(doubles*.s1)
Else
Trigger words. Add *(doubles*.s2)
End if
End if
Return *Trigger Words*

2.1.2 Trigger words filtering

A large number of candidate trigger words can be obtained according to the trigger word extraction algorithm, but some noise data can filter the noise data in the set of candidate trigger words.

Filter rule 1: The verbs are divided into eight categories, namely, the system verb VX, the auxiliary verb VZ, the formal verb VF, the trend verb VQ, the supplementary verb VB, the general verb VG, the nominal verb VN, and the adverbial VD. Studies have found that, in the ACE 2005 corpus about 94% of the medium event-trigger words are general verbs or pronouns. Therefore, the general verbs and pronouns in the selected candidate triggers can be retained, and other types of verbs can be discarded.

Filter rule 2: The text data in the field of air target flight activity belongs to the field corpus, among which some words appear more frequently in this kind of text, and, to some extent, can represent the characteristics of the corpus in this field. When the extracted candidate trigger words are highly correlated with the field corpus, the events triggered by the trigger words are more likely to be typical events in the field.

This section uses domain correlation to reflect the correlation of the candidate trigger words to the field of aerial target flight activity, with the calculation formula shown in formula(1).

$$DR(V) = \frac{Freq_p(V)}{Freq_G(V)} \tag{1}$$

$DR(V)$ is the value of the domain correlation of the candidate trigger word V, $Freq_p(V)$ is the frequency that the candidate trigger word appears in the domain corpus, and $Freq_G(V)$ is the frequency that the candidate trigger word appears in the general domain corpus.

2.1.3 Trigger words clustering

The result of trigger word clustering is ultimately to get a typical event type, requiring classifying triggering words with the same meaning and usage. For the degree of similarity between the meaning and usage of the trigger word, the semantic similarity is described. This paper uses three methods to calculate the semantic similarity, namely: the word semantic similarity calculation based on the Synonymous Word Forest (extended version); Word semantic similarity calculation based on the semantic primitive concept of HowNet words and word semantic similarity calculation based on Word2Vec.

The semantic similarity calculation algorithm based on the Synonymous Word Forest uses the coding and structural characteristics of the synonym word forest to obtain the semantic similarity of words starting from the similarity and correlation of words. The similarity and correlation of words can better reflect the semantic similarity of words. The word semantic similarity calculation algorithm based on the HowNet word semantic origin concept excavates the number of all the two words and the same number of semantic elements with the help of HowNet. The Word2Vec-based word semantic similarity is calculated by vectorizing the trigger words and then obtaining the similarity of the trigger words based on the distance between the vectors.

Semantic similarity between any two candidate trigger words can be obtained in the above three ways. Considering the semantic similarity calculated in three ways, the words with high semantic similarity are grouped, and finally get various typical events and their event trigger words.

2.2 Event type detection

2.2.1 Selection of typical events

Three steps are commanded for the event extraction of typical events. First of all, identify the typical event templates and the matching algorithm, as well as recognize trigger words from the text. Secondly, Determine the event type from the trigger words and then draw the event elements form the event template. Finally, complete the typical event extraction.

Event type and event element definition. According to the typical event type of the air target flight activity found, the event template of the air target flight activity was defined by discussing and manually reading the event template of the typical activity type, namely the event type and the argument. Event types include takeoff, companion, flight, stop, arrival, general flight, deployment, circling and landing. For 8 typical events of the air target flight activity, the pattern is expressed as <trigger word; event element>, classifies the fighters present in various events as one, and the final event pattern is shown in Table 1.

Table 1. Typical events templates.

Event type	Elements
takeoff	time, takeoff place, takeoff aircraft
companion	time, flight fighter, companion object, companion location
stop	time, stop aircraft, stop place
arrival	time, arrival of the aircraft, arrival place
ordinary flight	time, flight fighter, flight location, flight direction
deployment	time, deployment of the aircraft, deployment location
circling	time, circling fighter, circling place
landing	time, landing aircraft, landing place

2.2.2 Typical event extraction

The identification of time can use named entities to identify combined pattern matching methods. Accurate named entity recognition task can be time recognition, combined with common forms of time expression for pattern matching. For the identification of sites, the method of naming entity identification is combined with pattern matching, taking the entities identified as sites and organization as sites, combined with the designed mode "taking xx as the take-off and landing ground", "flying over xx", etc. For the information extraction of fighter entities, mainly the fighter model, fighter call number, fighter number, number, etc. Here, the mode matching method is mainly used, considering the characteristics of various attributes, to select qualified letters and number strings, such as: the number is generally 6 or 7 digits, the middle of the model has a horizontal bar, etc.

Selection of atypical events**.** For atypical events in the field of air target flight activities, that is, flight activities that do not belong to typical event types, two methods based on syntactic analysis and semantic dependency will be used for event extraction. Determine the method for effect comparison.

Event extraction based on parsing. For atypical events, because there is no fixed pattern for which elements of the event in the text should have, you can use based on dependent syntactic analysis to obtain the main elements describing the event in the text by analyzing the relationship between the syntactic components. Existing Chinese text dependent syntax analysis includes 15 dimensions, Subject-Predicate relation (SBV), verb-object relationship (VOB), inter-object relation (IOB), fore-object language(FOB), concurrently (DBL), definite relationship (ATT), medium structure (ADV), dynamic structure (CMP), parallel (COO), mediation (POB), left attachment (LAD), right attachment (RAD), independent structure (IS), punctuation (WP), and core relationship (HED).

Draw the trigger words and event elements of atypical events based on dependent syntactic analysis, set the core words according to the dependent syntactic analysis results, the core word is the predicate of the sentence; then draw the subject and object in the dependent syntactic analysis results, and combine the attributives of the two components as the elements of the event. Take a Chinese sentence for example, "A C-17 transport aircraft has entered Jordanian airspace". The dependent syntactic analysis structure is shown in Figure 2. The core word is "enter"; the subject is "transport aircraft"; the predicate is "airspace"; the subject and predicate combined attributive component (ATT) get the event element is " A C-17 transport aircraft ", "Jordanian airspace ". The final event drawn was {(A C-17 transport aircraft); (enter); (Jordanian airspace)}.

Event extraction based on Semantic Dependency. Semantic dependency parsing (SDP) focuses on analyzing the semantic association between language units, which can directly obtain the deep semantic information of sentences without being affect-ed by syntactic structure. Take a Chinese sentence for example, " The HC-130J search and rescue aircraft ended its military actions in Iraq", Semantic dependency analysis result is shown follows(see Figure 3).

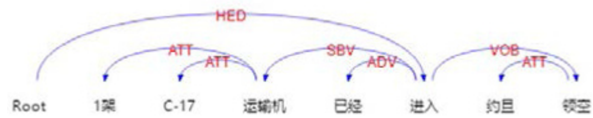

Fig. 2. A Chinese sentence example of dependency parsing.

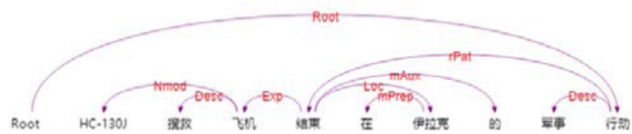

Fig. 3. A Chinese example of semantic dependency parsing.

The root node is "action". Including party relationship (EXP) and patient relationship (rPat), you can extract "aircraft" and "end". The character with name modification (Nmod) can be extracted from " HC-130J ". The final extraction result is {(HC-130 aircraft); (end); (actions)}.

2.2.3 Comparison of two algorithms

Semantic dependency performs better in analyzing the semantics of sentences. To some extent, syntactic dependency pays more attention to the role of non notional words in sentence structure analysis, while semantic dependency is derived from argument relationship, and pays more attention to notional words with direct semantic relevance. And semantic dependency analysis is related to semantic role annotation, which has a richer structural relationship.

2.3 Construction of EEG

2.3.1 Construction of air target flight activities EEG

The construction of the air target flight activities EEG is divided into three parts. The first part is to uniquely number all events so that each event can be represented by its number; the second part is to give the event relationship; the third part is the storage and visualization of the air target flight activities graph.

Step 1 Event number. Based on the results of the event extraction, on the basis of the result file, the new "id" attribute as the unique identification of the air target flight activity event, the value of the typical event "id" attribute is the serial number of each line of data in the result file, the value of the atypical event "id" is based on the last id value of the typical event, increasing in order from top to bottom.

Step 2 Event Relationship. For the extracted event results, the Tag attribute equally indicates a consistent relationship between events. Aggregating events with the same tag attribute in sequential order to get multiple (id1, id2) two-tuples.

Step 3 Contingency atlas storage and visualization. The Neo4j graph database is used to store and visualize the aerial target flight activity graph. The event atlas storage is divided into two steps: the first step is the event node storage, which divides the event results extracted in chapter 2 according to the event type. One event type is divided into a separate csv table, and then uses the Cypher statement to create the event node; the second step uses the Cypher statement to match the event relation-ship node.

2.3.2 Construction of air target combat intention EEG

According to the constructed aerial target flight activity graph, merger, operational intention association, confidence giving and other operations, so as to finally generate the aerial target operational intention graph.

Node merger. The combat intention of air targets is generally related to the model of the fighter and the location of the fighter activity, while time, call sign, number, number and other attributes play a little role. Therefore, so when the merger of event nodes is conducted, only three important attributes of event type, fighter type and activity site are retained. Association of combat intention. Create the combat intention node first, and then match the flight activity event node and the combat intention node according to the relationship data between the existing flight activity event and the combat intention. Confidence giving. The calculation of confidence includes the cis-bearing relationship confidence calculation between flight activity event nodes and the causal relationship confidence calculation between flight activity event nodes and operational intent. The calculation method of the relationship confidence is mainly to take the method of counting. According to the event id relationship tuples obtained in the previous section, the same event node points to other event nodes, and then seek the ratio to obtain weights. Cause relation confidence is similar to the things above.

2.4 Discrimination of combat intention

The combat intention discrimination method based on the air target combat intention EEG gives priority to the combat intention discrimination based on the constructed operational intention graph. If you fail to match to the battle intent node, the key-words will be vaguely matched.

Principles of combat intention discrimination. The principles of intention dis-crimination are operational intention discrimination according to the operational intention EEG and Key words fuzzy matching.

Cypher statement generation is mainly about matching event type, model, location and other elements in selected structured events according to specific regular ex-pressions, and finally spliced into Cypher statements. Node matching: Use the generated Cypher statement to match the operational intent in the operational intent atlas.

When the combat intention chart fails to match the combat intention, the combat intention matching is replaced by keyword fuzzy matching. The core of keyword fuzzy matching of combat intention is to determine the fuzzy statistics of keywords and combat intention of certain event elements based on experience and human psychological process.

3 Experiment

3.1 Style and spacing dataset description

The experiment used the Chinese text data of open-source air target flight activities obtained from the Internet. The data used in the typical event discovery and event extraction process was the US Air Force and Navy air target flight activity data in January 2020, and February US Air Force Navy air target flight activity data was used to discriminate the intent.

3.2 Results and analysis

Discovery results and analysis of typical event types. Typical event type discovery experiments were performed following four steps: trigger word extraction, filtering, clustering, and extension. The selection of activity data from US air Force and naval air targets in January yielded 64 candidates. After the first verb fine categorization rule, 23 abnormal verbs, other verbs, etc were filtered out, and 41 general verbs and verb-noun verbs were retained. The domain correlation is calculated for 41 words. When calculating the field correlation, the modern Chinese corpus of the National Language Commission is used. Some of the words not stored in the modern Chinese corpus were corrected, and the domain correlation was directly set to 1. This was then sorted, and the first 15 words were selected as the final trigger candidates. The 15 final candidate trigger words are shown in Figure 4.

The final candidate trigger word combination, and according to the three algorithms to find semantic similarity finally consider three semantic similarity and control air target flight activity data, will trigger word clustering and determine eight typical event types, in order to perfect the air target flight activity typical events trigger word set, using Synonyms project to expand the trigger words. The final extraction yielded 341 typical events and 21 atypical events, including partial abnormal events. Constructed air target combat intention EEG(see Figure 5).

Combat intention discrimination results and analysis. The combat intention is determined based on the combat intention graph, and the generated Cypher statement is: MATCH(a: takeoff{type:'KC-10A'})-[r1:sequence]->(b: normal flight{type:'KC-10A'})-[r2:cause]->(c: combat intention) WHERE (a.location CONTAINS ' U.A.E, Dahaf base ' OR ' UAE, Dahafra base ' CONTAINS a.location) AND (b.location CONTAINS ' Over Iraq ' OR ' Over Iraq ' CONTAINS b.location) RETURN (c.type).

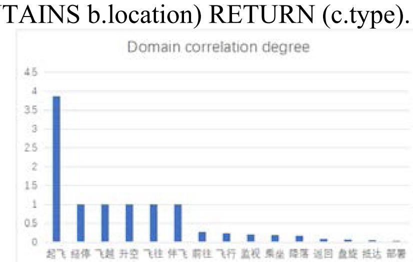

Fig. 4. Trigger words and domain correlation degree.

Fig. 5. A part of air target combat intention EEG.

Test using US Air Force Navy air target flight activity data for February. According to the results, the accuracy of combat intention discrimination based on the event logic graph is 90%. Among them, 11 data can match to the nodes in the logic graph with an accuracy of 90. 91%, and 39 data cannot match to the nodes. The combat intention is determined by fuzzy matching, and the accuracy containing correct results is 89. 7%. It is reasonable to speculate that if the event graph is larger and contains more information, the discrimination of combat intention will be more accurate. Assuming that it does not match the operational intention on the air target flight activity graph, its key elements are drawn: 'reconnaissance aircraft', ' Over Persian Gulf ', and its operational intention is ' reconnoitre Iran' according to the affiliation table. Combining the experience of relevant fighters and research on textual data yielded the affiliation of the event elements keywords and operational intent as shown in Tables 2,3and 4.

Table 2. The relationship of event type and operational intention.

Event type	Intention
deployment	military deployment, military support
circling	reconnoitre
companion	refueling pilot, refueling

Table 3. The relationship of air flight type and operational intention.

Typical events	Trigger words
transport plane	Transportation personnel and materials
refueller	Refueling, refueling and pilotage
trainer	Military training and drill
fighter	Military deterrence
Special Mission Aircraft	reconnoitre

Table 4. The relationship of location and operational intention.

Location	Intention
East and South China Seas	Reconnoitre China
Over Korea	Reconnoitre Korea
Over the Persian Gulf	Reconnoitre Persian Gulf
the Baltic	Reconnoitre Russia
Cyprus	Reconnoitre Cyprus

4 Related Work

Event atlas can be used for downstream tasks, such as knowledge management, reasoning and auxiliary decision-making, recommendation system, knowledge questions and answer tasks, to help improve the effect of specific tasks. In recent years, the field event graph mainly includes the political field, the national security for situation awareness, the financial field, etc. Script event prediction requires that given the context of an event, select from the candidate list the event most likely to happen next. Typical scripting event prediction methods include event-pair-based methods and event-chain-based PairLSTM. Despite the certain success of these methods, the rich connectivity information between events is still underutilized. In order to make better use of the dense connection information between events, Zhongyang Li etc used a scalable GNN model to construct the narrative theorem graph, and then performed the network representation learning on this graph to make the event prediction more efficiently. This method is based on the Gated Graph Neural Networks (GGNN) model, which is only calculated on a small-scale correlation subgraph at a time. The model can also be applied to other network representation learning tasks. Literature modeled the sequence of events using RNN-based event encoders and neighbor aggregators that aggregate information about each moment entity connected to its neighbors through a relationship to predict the object event corresponding to the subject event at a moment. Multi-type concurrent event prediction is an important task in many areas such as health care, disaster relief, and financial analysis. Literature investigated a temporal graph learning method based on heterogeneous data fusion to predict multiple types of concurrent events and simultaneously infer multiple candidate participants.

5 Conclusion

This paper proposes the method of event knowledge enhancement, starting from the air target flight activity text data, finds the typical events in the field, represents the unstructured information in the unstructured text, and constructs the air target flight activity graph and the air target combat intention graph. It has the following advantages: determine the typical events in the field of air target flight activity, improve the storage and acquisition efficiency of text information; construct two contingency graphs to facilitate the analysis of the changes of air target flight activity and the association between air target flight activity and combat intention. The experiment shows that the target intention certification of enhanced practical knowledge can enhance the comprehensive grasp of the actual application environment situation of air targets, and is conducive to the timely control of air targets.

References

1. Wangwang, Z., Peiyang, Yao., Jie, Z. 2018 Combat intention recognition for aerial targets based on deep neural network. *Acta Areomauticaet Astronautica Sinical* vol 39 p 195-203.
2. Zhongyang, Li., Sendong, Z., Xiao, D.2017 EEG: Knowledge Base for Event Evolutionary Principles and Patterns. *Chinese National Conference on Social Media Processing* p 40-52.
3. Ting L.2017 From Knowledge graph to event evolutionary graph 2017 *China Computer Conference*. *https://blog.csdn.net/tgqdt3ggamdkhaslzv/article/details/78557548.*
4. ACE 2005 (Automatic Content Extraction) *Chinese Annotation Guidelines for Events.*
5. Gang L., Shiyun W., Jin M.2021 Research on the construction of national security event graph for situation awareness. *Journal of information* vol 11 p 1164-1175.
6. Xiao, D., Yue, Z., Ting, L. 2015 Deep learning for event-driven stock prediction. *IJCAI*, p 2327-2333
7. Pan, S., Qi, W., Huaiyu, W.2021 Script event prediction method combining event chain and event graph. *Computer engineering* vol 1 p 1-11
8. Wang, Z, Zhang, Y., Chang, Y. 2017 Integrating order information and event relation for script event prediction. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing* p 57-67
9. Li, Z., Ding, X., Liu, T.2019 Constructing narrative event evolutionary graph for script event prediction. *IJCAI'18: Proceedings of the 27th International Joint Conference on Artificial Intelligence* (AAAI Press) p 4201-4207
10. Jin, W., Zhang, C., Szekely, P. 2019 Recurrent event network for reasoning over temporal knowledge graphs. *ICLR RLGM Workshop.*