Implementation of Tactical Decision Aids Based on Event Knowledge Graph

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Abstract. This paper proposes a new tactical decision aids method based on event knowledge graph (EventKG). In the warfare domain, EventKG can be constructed through event types design, event network construction and transition probability computation between events. Initially, four event classes are introduced in accordance with the OODA loop, and eighteen subclasses are further decomposed. With the aids of a common event template, all the events taking place in the battlefield can be described. Event networks are built by adopting the hierarchical task network (HTN) and described through Bayesian network, to exhibit various relations between battle events. Transition probability, namely the occurrence probability of next possible event, is computed by using the prior probability and conditional probability of event occurring. On the basis of structured EventKG, entity knowledge graph (EKG) and entity relation knowledge graph (ERKG), tactical decision aid instructions can be generated by combining with the battlefield situation information.

1. Introduction
As one branch of artificial intelligence, knowledge graph (KG) has been widely applied in a variety of scenarios, such as information retrieval, question-answering system, electronic commerce and financial risk management [1, 2]. However, traditional KGs are insufficient to predict next occurring battle event under the rapidly changing battlefield situation. EventKG is an emerging KG, made up of different events [3], of which historical battle events are just taken advantage. Tactical decision aids provided for the combat commander can therefore be achieved by constituting and exploring EventKG.

Instead of event prediction, certain KGs have been leveraged to make decision and predict change trend. Chen et al. proposed a method of constructing dispatching operation knowledge based on knowledge graph technology to assist the dispatcher in making decisions when encountering the risk of power failure [4]. Long et al. utilized the knowledge graph and graph embeddings techniques to select the relevant stocks of the target for constructing the market and trading information, integrated with a deep neural network model to predict stock price trend [5]. Celebi et al. aimed to present realistic evaluation settings to predict DDIs using knowledge graph embeddings, and proposed a simple disjoint cross-validation scheme to evaluate drug-drug interaction predictions for the scenarios where the drugs have no known DDIs [6].

EventKG is attracting the attention of researchers from a variety of countries. In the fields of Semantic Web, NLP and Digital Humanities, Gottschalk et al. presented a multilingual event-centric temporal knowledge graph (EventKG), incorporating over 690 thousand contemporary and historical events and over 2.3 million temporal relations, and made them available through a canonical representation [3]. Then they developed a novel system (EventKG+TL) that generated cross-lingual event timelines using EventKG, and facilitated an overview of the language-specific event relevance
and popularity along with the cross-lingual differences [7]. In the field of news articles searching, Rudnik et al. presented a general method that leveraged the Wiki data knowledge base to produce semantic annotations of news articles, and could search articles by using an event knowledge graph leveraged by Wiki data [8]. And a few researchers employed EventKG to infer and predict new events. In the field of multi-event forecasting, Deng et al. studied a temporal graph learning method with heterogeneous data fusion for predicting concurrent events of multiple types, and proposed a graph learning framework based on event knowledge graphs to incorporate both relational and word contexts [9]. In the field of risk warning, Wang et al. constructed an event knowledge graph about permit to work, and used data mining to analyze unreasonable work objects and work methods, succeeding in risk warning for special work for petrochemical enterprises [10]. However, none of them were devoted to constructing combat EventKGs, much less making use of it to support decision aids.

In order to predict battle events and generate decision instructions, a novel tactical decision aids method based on EventKG is proposed in this paper. A combat EventKG is built by devising event types, building event networks and calculating transition probability in sequence. The newly designed decision aids process mainly include four steps, i.e. information analysis, submap matching, constraint filtering and similarity computation. The generated instructions are able to guide combat units to perform different operational tasks.

2. Construction of Event Knowledge Graph

EventKG is a directed cyclic graph, of which nodes represent different types of events, and directed edges a variety of logic relations. In order to construct a complete EventKG, events and their types need to be defined, and then event network can be formed by combing the relations between various events, with the computed transition probability marked on each edge.

2.1. Event Types Design of EventKG

As for the combat unit, events are always used to describe activities of the unit entity, e.g. plane activities include taking off, flying, attacking, returning, landing, evading, etc.; cruiser activities include pierside, underway, patrolling, attacking, etc. Based on the OODA loop, the initially designed events are classified as observation, orientation, decision and action classes, which can be further divided into 18 sub-classes, as shown in Table 1. Typically, an event is made up of subject, predicate and object, and hundreds of warfare events can therefore be assembled from this sentence structure.

| No. | Event Class       | Event Subclass         | No. | Event Class       | Event Subclass         |
|-----|------------------|------------------------|-----|------------------|------------------------|
| 1   | Observation Event| Monitoring Event       | 10  | Action Event     | Air Event              |
| 2   | Environment Event | Environment Event      | 11  |                  | Damage Event           |
| 3   | Orientation Event | Communication Event    | 12  |                  | Engagement Event       |
| 4   | Detection Event  | Detection Event        | 13  |                  | Logistic Event         |
| 5   | Data Fusion Event | Data Fusion Event      | 14  |                  | Task Performing Event   |
| 6   | Decision Event   | Command & Control Event| 15  |                  | Weapon System Event    |
| 7   |                  | Task Plan Event        | 16  |                  | Asset Tactical Event   |
| 8   |                  | Report Event           | 17  |                  | Electronic Attack Event|
| 9   |                  | Evaluation Event       | 18  |                  | Mine Warfare Event     |

For instance, an air event may be “an M plane is taking off from the N air base”, “an M plane is landing at the N air base”, etc.
2.2. Event Network Construction of EventKG

Event network consists of a number of events and directed edges connecting to them. In the mission layer, mission target KG, objective KG and task KG have been constructed. With the decomposed operational tasks, HTN can be adopted to build the event network, described by Bayesian network.

HTN covers sequential and dependent relations between operational tasks, requirements of task for capability, and relations among mission targets, objectives and tasks. HTN can be formed by analyzing and integrating the mission-layer KGs and combat-layer KGs, as shown in figure 1. Here \( T \) represents a decomposed mission task, \( E \) a combat unit entity, and \( A \) a requirement of task for combat unit capability; black arrow indicates a sequential or dependent relation, and red arrow a requirement relation of task for combat unit and its capabilities.

Mission tasks in HTN can further be decomposed in accordance with tactical task lists. That is, each mission task will be decomposed into actions, which will be resolved into combat unit activities, state conditions, and plan fragments, resulting in a network structure graph based on mission tasks. For example, missile interception task can be depicted in terms of Bayesian network as shown in figure 2.

It can be seen that, Event \( A \) “A target submarine enters the search scope” is State Condition; Event \( B \) “Torpedoes strikes the target” is Plan Fragment, which has two optional combat units and tactical activities, i.e. Event \( C \) “A anti-submarine helicopter strikes the target” and Event \( D \) “A submarine strikes the target”; The former includes Event \( C 1 \) “The plane takes off”, Event \( C 2 \) “The plane locates the target” and Event \( C 3 \) “The plane fires a missile” sub-activities, and the latter includes Event \( D 1 \) “The shipboard radar locates the target” and Event \( D 2 \) “The ship fires a missile” sub-activities. By analyzing the network structure in figure 2, the nodes Event \( A \), Event \( C 1 \), Event \( C 2 \), Event \( C 3 \), Event \( D 1 \) and Event \( D 2 \) are transformed into events, while the intermediate nodes Event \( B \), Event \( C \) and Event \( D \) are removed. The generated event network structure is shown in figure 3.

2.3. Transition Probability Computation of EventKG

In the event network structure, different tasks could have the capability demand for the identical combat unit. Therefore, whether combat units and their capabilities could be employed simultaneously should be considered. This could cause a conflict when using the entity in the time or spatial domain, as shown in figure 4.

Dotted lines mean that there are requirement conflicts between tasks and combat units and their capabilities. Note that it is uncertain whether combat units could perform the corresponding tasks, and which actions they will select to complete these tasks. However, the probability of choice can be obtained by experience, i.e. the prior probability, or according to the current state, i.e. the conditional probability. Take the missile interception task for example, the initial supposed prior probability is listed in Table 2, by which the conditional probability of Event \( A \), Event \( B \), Event \( C \) and Event \( D \) can be computed respectively. Here take the conditional probability of Event \( C \) enumerated in Table 3 for example.

The Bayesian network of mission tasks can be founded by attaching conditional probability to event network nodes. Transition probability matrices between nodes can be generated through methods of event transformation and conditional probability computation. For instance, the transition probability \( P \) between Event \( A \) and Event \( C 1 \) is

\[
P = 0.7 \times 0.9 \times 0.5 \times 0.9 = 0.2835.
\]

| Event | Event A | Event B | Event C | Event D |
|-------|---------|---------|---------|---------|
| True  | 0.7     | 0.9     | 0.5     | 0.5     |
| False | 0.3     | 0.1     | 0.5     | 0.5     |
| Event C1 | 0.9 | 0.7 | 0.6 | 0.8 | 0.9 |
| Event C2 | 0.1 | 0.3 | 0.4 | 0.2 | 0.1 |
### Table 3. Conditional probability of Event C

| Event C | Event C1 | Event C2 | Event C3 |
|---------|---------|---------|---------|
| True    | 0.45    | 0.35    | 0.30    |
| False   | 0.05    | 0.15    | 0.20    |

The rest transition probability between events can be achieved in the same manner as above mentioned, and the resulting EventKG of target missile interception is depicted in figure 5.

**Figure 1.** Hierarchical task network.

**Figure 2.** Bayesian network of target missile interception.

**Figure 3.** Event network of target missile interception.

**Figure 4.** Requirement conflict between tasks and combat unit.

### 3. Decision Aids Process Based on EventKG

In the warfare domain, the structured EventKG is actually a sequential network of combat unit actions driven by the decomposed tasks, with the purpose to achieve the mission objective. The decision aids approach can therefore be proposed in the manner of EventKG matching. The EventKG matching principle is demonstrated in figure 6. At first, receive and analyze the battlefield situation information; then, match the appropriate event in the EventKG; next, filtrate the candidate event collection by retrieving, matching and processing all kinds of knowledge graphs; finally, conclude the decision-making information under the current situation. The EventKG reasoning process can be divided into the following stages.

#### 3.1. Information Analysis

Analyzing, resolving and explaining the situation and event information. The information will be decomposed into object, property, etc., which are consistent with the built knowledge hierarchy. It can be seen from figure 7, the situation information will be classified, analyzed and described quantitatively in the light of the current situation of red and blue sides, resulting in the chain of events to be predicted.
3.2. **Submap Matching**
Matching the generated chain of events with EventKG, *i.e.* finding the nodes and their first-order neighbors in EventKG matched with the event node of the chain of events, and extracting relative background information of the chain, in order to produce a candidate event collection.

3.3. **Constraint Filtering**
Associating the chain of events with EventKG, ERKG and EKG, and filtering the candidate events with the property information of ERKG and EKG as requisite constraints, *e.g.* amount of plane fuel, number of ammunition, equipment matching, with the purpose to filter out those events partially not satisfying with the constraint conditions (see figure 8).

3.4. **Similarity Computation**
The similarity of candidate events is calculated to gain the next possible event. By combining with the EventKG transition probability, the optimal decision instruction would be generated.

![Figure 5. Event knowledge graph of target missile interception.](image)

![Figure 6. EventKG reasoning principle based on task driving.](image)

![Figure 7 Information analysis schematic diagram.](image)

![Figure 8. Three-layer knowledge graph structure.](image)

4. **Conclusions**
In this paper, we construct a combat EventKG to implement tactical decision aids. The combat EventKG construction mainly consists of event types design, event networks building and transition probability computation. And four event classes, eighteen event sub-classes are designed to cover all the battle events according to the OODA loop. Event networks revealing relations between battle events are built by HTN and described by Bayesian network. With the prior probability and
conditional probability of event occurring, transition probability between events is calculated. While
the decision aids process based on EventKG mainly includes information analysis, submap matching,
constraint filtering, and similarity computation. At first, the situation information is classified,
analyzed and described quantitatively, resulting in the chain of events to be predicted; then the
generated chain of events is matched with EventKG, to produce a candidate event collection; next,
those events partially not satisfying with the pre-set constraint conditions are filtered out; finally,
the similarity of candidate events is calculated to gain the next possible event, and generate the optimal
decision instruction.

However, the existence of a number of probabilities for battle events could be a major limitation, as
the data base may be not rich enough to construct the Bayesian network. In the future, it is expected to
convey the decision instruction generated in real time to our Marine Analysis Research System
(MARS), to drive all kinds of combat unit entities to perform different tasks.

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