Context Aware Combat COA Recommendation using Preference Learning

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Abstract. In the daily combat readiness duty, faced with emergencies, time window left for decision-making is limited, far from enough to research and design a totally new COA (Course of Actions). However, using the state-of-the-art AI technologies, it is yet unable to autonomously generate COAs of trust. From the perspective of practicality, it is effective to improve emergency response efficiency, by making use of historically accumulated COAs. Similar problems have similar solutions, which is especially suitable for fields with incomplete knowledge systems and limited data accumulation. An intelligent method of COA recommendation is proposed, which can accurately recommend appropriate COAs based on current mission requirements, battlefield situation, and preferences. Based on the recommended COAs, user can form a new COA more efficiently, faced with emergencies. As a solution for AI technology supported combat decision making closer to practical, the method has certain reference value.

1. Introduction
With the wide application of AI (artificial intelligence) technologies in the fields of Intelligence processing, unmanned systems, etc. In the domain of combat decision making, as the core step of C2 (Command and Control), there is also a general trend of development towards intelligence. However, it is extremely difficult to realize, as combat decision-making is rich of human experience and art. It is not an exaggeration to compare intelligent combat decision making as the jewel in the crown of intelligent C2.
On the other hand, users put forward an urgent demand for intelligent combat decision making. With complexity of the international situation increasing, the pressure of daily combat readiness duty is constantly increases. Limited by the sensing range, unexpected situation comes very sudden, and the staffs need to make a combat COA within a few minutes and report it to the commander. Therefore, it is hoped that AI technology will provide support for combat decision-making.

2. Related researches
In the field of intelligent combat decision making, some explorations have carried out [1-6], which mainly focus on using current mainstream AI technologies to solve the problem of automatic generation of combat COAs.
Nowadays mainstream AI technology can be roughly divided into 2 categories. One category is represented by deep learning technology, which needs large-scale and high-quality annotation data as the foundation. However, combat decision making is a typical small sample problem domain, where large amount of sample data does not exist. The other category is represented by reinforcement learning technology, widely used in chess, real-time strategy games, air combat and other game domains, and has made outstanding achievements. However, application of this method in the military field still faces problems such as interpretability and high reliability.

In addition to the mainstream AI technologies, some other technologies have gradually matured, such as recommendation system technology. Its core theory behind lies that "in the problem domain without complete knowledge system, the successful solution of similar problems is often effective to current problems". And this theory is suitable for the daily combat readiness scene. In peacetime, commanders design COAs for hypothetical situations, which get accumulation over time. Use this technology and make good use of accumulated COAs, can also relieve the pressure of commanders to some extent. Recommendation system technology has been widely used in domains such as transportation, power system, fire protection and so on [7-16]. However, there is little research on applying it to the generation of combat plans.

### 3. Method

A method is proposed to quickly find out a COA from the historical COAs, which is most similar to the current situation and has fine performance in all aspects, as a reference case when an emergency occurs, and then make local modification according to the current situation. This paper aims to study a case recommendation system, which can accurately recommend similar cases according to the current situation. The more accurate the case recommendation is, the smaller the revision workload will be.

Traditional case recommendation generally adopts keyword retrieval method. However, the accuracy is low, and users still need to spend a lot of time on result browsing and filtering. The method proposed in this paper is based on context awareness and preference learning, including three steps, as shown in Figure 1: First, perceive the current mission requirements and battlefield situation; Then, according to the performance of situation similarity, force availability and effectiveness, the COA database is filtered to generate a case recommendation list; Finally, collect the user's case selection operation, so as to learn the preference, and improve the accuracy of recommendation system.

![Figure 1: General principle](image)

3.1. **Context awareness**

"Context awareness" refers to the perception of who the user is, and what he is currently doing. For the commander on duty, it means mission requirements and battlefield situation (usually includes enemy situation, our situation and battlefield environment). However, cognition of mission requirements and battlefield situation is still unsolved by AI technologies. An alternative method is to manually extract features of mission requirements and battlefield situation.
Which features are extracted is closely related to the combat style. Taking the joint fire strike of sea targets as an example, features are extracted in Table 1.

### Table 1 Feature model designed for combat style of joint fire strike of sea targets

| Feature name                  | Value range                         |
|------------------------------|-------------------------------------|
| **Mission requirement features** |                                     |
| Target                       | Example: XX missile destroyer       |
| Target Num.                  | Integer                             |
| Target country               | Country code                        |
| Damage requirement           | Sink / heavy injury / minor injury   |
| Battle area                  | Area code                           |
| Time limit                   | Example: 150min                     |
| Target status                | Inact / heavy injury / minor injury  |
| Weather conditions           | Fit / unfit to fly                   |
| Sea conditions               | Example: Level 1                     |
| Day/Night                    | Day / night                          |

Mission requirement features can be extracted from the mission instructions of the superior. For example, formatted mission documents can extract key information directly. In this paper, we use natural semantic understanding technology to extract instructions from natural language orders. For example, from an order "recommended a COA of sinking XX and severely damaging XX within 150 minutes", features such as operational targets and completion time limit can be extracted. Other features can be extracted from situation data automatically.

For automatically extracted features, it is necessary to have a manual confirmation process to prevent the system from extracting errors. For some complicated missions, it may be necessary to extract features manually. For example, "whether there is possible support force around the target", this feature needs to be filled in manually, while automatic extraction is impossible to realize at present.

For each COA in the database, it is necessary to do the same extraction work, and store and manage the extracted feature data together with the COA. Because the COA is usually aimed at hypothetical situations, the features of battlefield situation need to be set manually.

### 3.2. Case filtering and ranking

Case filtering and ranking is to select the appropriate COA as recommended reference case according to the extracted situation features, and rank them according to the recommendation degree from high to low. It is proposed to comprehensively calculate the recommendation index of each case from three aspects: situation similarity, force availability, and effectiveness.

#### 3.2.1. Situational similarity.

The calculation of situation similarity can be equivalent to the calculation of feature vector similarity between current situation features and case situation features:

- For each dimension feature \( i \) in the context feature model, the corresponding context feature similarity algorithm is called to calculate the similarity \( \text{Sim}(i) \) between the current context feature value and the case context feature value;

- According to the situation feature weight system model, the similarity of all features is weighted and summed to obtain the situation similarity \( \text{Sim} \) of the case. There are many related calculation methods in this area, and they are mature, so this paper will not be expanded again.

#### 3.2.2. Force availability.

In addition to the situation similarity, it is also important to check whether the use of force in the case is available in the current situation. For each case, the force availability calculation method is as follows:
• Selecting military resources within a certain radius around the target to form a subset of peripheral military resources;
• According to each type of combat equipment i used in the case (i \in [0, n], n is the total number of equipment types used in the case), search for the same type of force resources in the force subset;
• Calculate the ratio i/n of resources with the same type of force in the case as the force Availability Ava of the case.

3.2.3. Effectiveness. Effectiveness of the cases is also an important consideration for filtering and ranking. Considering that the COAs designed according to the hypothetical situation can not get the actual implementation results, the theoretical estimation result can be used instead, e.g. attack effectiveness (damage probability), time consumption and resource consumption. Finally, according to the weighted sum, we can get the Eff of the case.

If the system can obtain the authoritative evaluation data of the designer of each plan, or the evaluation data of other users on the case, it can also be used as the evaluation basis of the effectiveness.

3.2.4. Comprehensive recommendation index. The comprehensive recommendation index is obtained by the weighted summation of three indicators: situation similarity Sim, force availability Ava and effectiveness Eff.

3.3. Preference learning

Ranking plays an important role in recommendation systems. It determines how many cases a user need to browse before finding what he wants, which directly affects the time of case filtering.

The comprehensive recommendation index on which the ranking is based is the weighted sum of the calculation results of similarity, force availability and effectiveness of multiple features. But the weights of these features are not evenly distributed. The distribution of weights represents the preference of users when selecting cases, that is, the emphasis. For example, for a fast maneuvering target, such as an airplane, relative missions are particularly sensitive to time, so when selecting a case, the time factor is more important. However, targets like destroyers move slowly, but have strong defense ability and are not easy to sink or hurt. Therefore, users often pay more attention to the striking effectiveness when selecting cases. This difference is called "preference", reflected in the distribution of weights.

The weights of the above features can be set manually, while difficult to quantify them accurately. To solve this problem, a preference learning method is proposed. When a user selects a case, his operation is recorded, including: for what mission and situation requirements, which cases are recommended by the system, what are the features of each case, and which one the user chooses. Then, special features with particularly high score of the selected case is analyzed, so as to adjust the corresponding weights.

Based on the above ideas, the preference learning algorithm focuses on the differences between the user-selected cases and other recommended cases in various feature scores, mainly including the following steps:

• For all cases in the case recommendation list, calculate the mean vector M and variance vector D for each case feature;
• For the reference case selected by the user, the deviation vector O from the mean value is calculated for each case feature;
• Divide the deviation vector O by the variance vector D to obtain the difference significance vector D;
• According to the difference significance value of each feature in the difference significance vector D, the weight of the corresponding feature is adjusted up or down.

4. Realization
In order to verify the effectiveness of the above method, software implementation was realized. The processing flow of the COA recommendation system is shown in Figure 2. Firstly, the current situation features are extracted from the mission order and the real-time situation data, and displayed through the interface for manual confirmation. Then, according to the current situation features, combined with the current available force data, the cases in the COA database are filtered and ranked to form a case recommendation list, which are displayed through the interface for manual selection. Finally, the case data selected by the user is submitted for preference learning.

The processing flow of the case filtering and ranking module is shown in Figure 3. First, select the cases with the same combat style from the case database. Then, the situation similarity, force availability and effectiveness evaluations are calculated in turn. Finally, the comprehensive ranking calculation is carried out to obtain the ranked set of cases.

The processing flow of the preference learning module is shown in Figure 4. Firstly, the collected sample data are ranked. Then, based on the case selected by the user, carry out weight system training. Finally, the learned preference data are summarized according to combat style, and a series of preference data models are formed.
5. Experiments
An experiment was carried out to verify the effectiveness of the method. A COA base was prepared, including more than 1,000 sets of historical joint fire strike operations COAs for ship-type targets. The software is provided for on-site use by users, with more than 5,000 case selection operations of users have been collected to construct a sample data set for decision tree learning.

The goal of the experiment is to verify the efficiency improvement brought by using this software to select reference cases compared to using traditional keyword search methods. 20 questions were prepared, each representing a combat mission context, including mission requirements and battlefield situation, formatted and stored in the system. For each question, the testers first select a case using this software, and then the traditional, and respectively calculate the time cost. 10 experienced staff members were selected as testers, and their test results were recorded respectively, as shown in Figure 5. The test result of each question is the average of the timing data of 10 testers.

![Figure 5 Experiment results](image)

It can be seen from the test results that the overall time spent using this software to select reference cases is 5.46 min on average, compared with 31.73 min of traditional, with the efficiency increased by 5.81 times. Most of the time is spent on cases browsing, about 1.45 min per case. When using this software to select cases, you need to browse 3.77 cases on average, compared with 21.88 of traditional. The use of this method can effectively improve the accuracy of case recommendation, thereby improving the efficiency of case selection.

6. Conclusions
The rapid development of AI technologies brings hope for the intelligent combat decision making. However, due to the complexity of war, high reliability and interpret-ability requirement of combat decision making, the current mainstream AI technologies are facing many difficulties in application. The short time window problem causes great pressure on users in daily combat readiness, which has created an urgent need for intelligence. However, there is still a long way to go for intelligent combat decision making.
In the domain of combat decision making with incomplete knowledge system and insufficient sample data accumulation, seeking similar historical solutions to similar problems is an effective alternative before the mainstream AI technology matures.

An intelligent recommendation method of COAs based on context awareness and preference learning is proposed. Based on the system's understanding of current mission requirements and battlefield situation features, this method can accurately recommend historical cases of similar situations according to mission preference. Considering different types of missions, staffs have different emphasis in case selection, so as to realize the learning ability of mission preference, and intelligently recommend cases that meet the user's choice of emphasis according to different missions.

7. References

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