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Operational requirements analysis method based on question answering of WEKG

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Abstract: The weapon and equipment operational requirement analysis (WEORA) is a necessary condition to win a future war, among which the acquisition of knowledge about weapons and equipment is a great challenge. The main challenge is that the existing weapons and equipment data fails to carry out structured knowledge representation, and knowledge navigation based on natural language cannot efficiently support the WEORA. To solve above problem, this research proposes a method based on question answering (QA) of weapons and equipment knowledge graph (WEKG) to construct and navigate the knowledge related to weapons and equipment in the WEORA. This method firstly constructs the WEKG, and builds a neutral network-based QA system over the WEKG by means of semantic parsing for knowledge navigation. Finally, the method is evaluated and a chatbot on the QA system is developed for the WEORA. Our proposed method has good performance in the accuracy and efficiency of searching target knowledge, and can well assist the WEORA.

Keywords: operational requirement analysis, weapons and equipment knowledge graph (WEKG), question answering (QA), neutral network.

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1. Introduction

As the current combat scenario gradually develops from “platform confrontation” to “system confrontation”, integrated joint operations (IJO) have gradually become an urgent request, and IJO require weapons and equipment to flexibly complete tasks at different strategic and tactical levels, thus the scientificity and completeness of the analysis of the weapons and equipment operational requirements is particularly important [1]. The weapon and equipment operational requirement analysis (WEORA) aims to guide the construction of the weapon and equipment system through the traction of the operational requirement, to support future operations. The WEORA starts from the source of winning future wars and can be subdivided into the following processes according to the hierarchical decomposition method of the strategic layer, the campaign layer, the tactical layer, and the equipment layer [2].

Among them, after the specific operation objectives, operation targets, and operation environment are determined at the tactical layer, the weapons and equipment need to be selected, designed and deployed at the equipment layer. The selection and design of weapons and equipment, including the operation performance analysis of weapons and equipment, the acquisition of operation parameters, and the design of operation compilation, is not only the basis of the subsequent deployment and application of weapons and equipment but also the premise of the implementation of upper-level tactics. The above process relies heavily on the knowledge of existing weapons and equipment. However, the efficient utilization of knowledge is a challenging task, among which the main two challenges are as follows: (i) Most of the existing information sources about weapons and equipment knowledge are unstructured, informal, and textual data, which make it difficult to carry out structured representation of knowledge. (ii) As most of the analysts involved in the WEORA use natural language to search the knowledge of weapons and equipment, the keyword-based retrieval method usually leads to excessive or irrelevant results requested, which makes it difficult to carry out the WEORA efficiently. Therefore, it is necessary to integrate the knowledge related to weapons and equipment from the existing information sources and express it in a structured manner. On this basis, a knowledge navigation system should be established to assist the WEORA.

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Knowledge graph (KG), as a means of structuring knowledge representation, have garnered considerable attention and research due to their robust expressive capabilities and the associated proficiency in storing and retrieving nuanced information. Introduced by Google in 2012, the KG excels in storing and retrieving structured information. It supports the use of formal query languages with well-defined syntax, such as Cypher, enabling efficient access to the knowledge encapsu lated within it [3]. However, for most users except professionals, due to the difficulty in mastering formal query language and the lack of knowledge of KG underlying structure, they still use natural language questions (NLQs) to ask questions for knowledge retrieval, which cannot be recognized by the machine. Therefore, how to accurately analyze users' NLQs, to transform them into formal query language, and use them to obtain knowledge in KG has become the top priority of knowledge navigation, and the accuracy of semantic parsing of NLQs directly affects the performance of knowledge navigation system [4]. The knowledge navigation system based on KG is called the KG question answering (KGQA) system, which has been gradually applied in many fields, such as tourism, finance, medicine, policy, and so on. However, due to the scarce and difficult nature of data in the military field, KGQA is seldom applied in the military field.

Based on the above two challenges and existing research, this paper uses a weapons and equipment KG (WEKG) to structurally represent weapons and equipment knowledge related to WEORA, making it a medium to transfer knowledge to analysts. In addition, the question answering (QA) system of WEKG is built, so that analysts can quickly acquire knowledge, to support the efficient analysis of weapons and equipment operational requirements. The rest of the paper is structured as follows. Section 2 introduces the related research work and points out the shortcomings of the existing research. Section 3 describes the details and theoretical basis of the proposed method. Section 4 conducts experimental validation and case studies of the proposed method to evaluate its performance. Section 5 analyzes and discusses the results, summarizes the work of this paper, and proposes possible future work.

2. Related work

2.1 WEORA

WEORA is an inevitable requirement of weapons and equipment development, and also the key to carrying out integrated joint operations. Aiming at the inaccurate requirements in the process of WEORA, Yu et al. [5] used the GM (1,1) model to predict the possible performance parameters of future weapons and equipment. It is often difficult to quantify the important relationship between indicators in WEORA, which leads to the lack of convincing analysis results. For the above problems, Zhang et al. [6] proposed the WEORA method based on quality function depolyment (QFD) and set pair analysis (SPA) methods, which combined the calculation framework of House of Quality and multiple connection numbers to establish the relationship between equipment operational requirements and performance indicators. To establish the mapping relationship between military requirements and operational performance, Xu et al. [7] proposed a method of WEORA based on QFD and analytic network process (ANP). Taking the evaluation of system contribution as a major issue in WEORA, Chen et al. [8] used system of systems engineering (SoSE) theory to construct a contribution evaluation model for the equipment system. It can be seen that the above studies are all based on a certain problem of WEORA, and the model construction or method exploration is carried out to meet a certain task or process, instead of studying the integration and acquisition of weapon equipment knowledge, an important link in WEORA, which is also an urgent problem to be solved in WEORA at present. Therefore, a method needs to be designed to satisfy the structured representation and navigation of equipment knowledge in WEORA.

2.2 KGQA

KG is defined as a network of entities and their semantic relations, which is widely used in knowledge representation in different fields [9]. Compared with traditional relational databases, KG can represent more complex relationships and knowledge, and realize knowledge navigation faster [10]. Based on these advantages, KG is widely used in recommendation [11], QA [12], data integration [13] and other fields, and has achieved good results. Based on the above research, this paper proposes to apply the KGQA method to knowledge integration and knowledge navigation to assist the WEORA.

KGQA mostly uses a semantic parsing-based approach [14]. With the rapid development of neural networks, recent KGQA methods based on semantic parsing have adopted a large number of models based on deep learning [4]. For example, Maheshwari et al. [15] proposed an attention-based method to calculate the different representations of NLQs of each relation in formal query statements and evaluated their methods on large-scale complex question answering dataset (LC-QUAD) and question answering over linked data challenge 7 (QALD 7) datasets, respectively. To compare the performance of the neural network-based and non-neural network-based methods at each stage of semantic parsing KGQA, Mohammed et al. [16] evaluated the advantages and disadvantages of each method in the Simple-Questions dataset, and finally adopted bidirectional long short-term memory (Bi-LSTM) and bidirectional gated recurrent unit (Bi-GRU) models to complete tasks in each stage of semantic parsing. Yavuz et al. [17] improved the traditional semantic parsing system agenda-based parser (AGENDAIL), and used the Bi-LSTM model to represent the content before and after the entity and used it to predict the correct type of the entity. The above methods have verified the effectiveness of neural network-based KGQA for KGQA tasks. Based on the above research, the practical application of KGQA in various fields is also becoming the focus of research. For example, to improve the service quality of Vietnam tourism, Do et al. [18] used a deep learning algorithm to build the Vietnamese tourism QA system. Huang et al. [19] constructed a QA system based on the medical domain KG through a reasoning method based on the weighted path ranking of KG. To improve the efficiency of intelligent manufacturing, Wen et al. [20] proposed a method using domain ontology, a pattern-based extraction framework, and a meta path-based QA over knowledge graphs. In summary, the construction and research of KGQA systems are currently being carried out in many fields, but there are few research and application examples in the military field. Although Gao et al. [21] built a QA system of WEKG, the QA system based on rules and templates is not intelligent, and it is difficult to meet the personalized and diverse requirements. Therefore, it is of great practical significance to build a KGQA system in the field of weapons and equipment based on the neural network method to improve the efficiency of the integration and acquisition of weapons and equipment knowledge.

Based on the above-mentioned gaps in existing research, (i) we firstly study the construction of WEKG, including the crawling and integration of semi-structured data such as website data, and the processing of some unstructured data; (ii) the construction of the KGQA system of weapon and equipment is studied through semantic parsing, and finally the auxiliary support for WEORA is realized.

3. Method

In this section, we propose a method for KGQA in the field of weapons and equipment, which consists of two main modules, namely, the construction of WEKG and the construction of a QA system based on WEKG. The construction of WEKG is the basis of the proposed method, which is used to integrate the knowledge of weapons and equipment and make a structured representation, and the KGQA method is the core step of the proposed method, which are introduced in Subsection 3.1 and Subsection 3.2, respectively.

3.1 Construction of WEKG

In this paper, a bottom-up method is used to construct the WEKG, which generally includes three steps: information extraction, knowledge fusion, and knowledge processing [22]. According to the characteristics of weapons and equipment knowledge and related data sources, the construction process of WEKG is divided into the following steps.

3.1.1 Data acquisition and processing

The data used to construct WEKG in this paper is mainly obtained from the crawlers of related websites such as the global military network, and the structured or semi-structured data obtained by crawlers are partially processed manually to obtain triplet data. For unstructured data, entity recognition and attribute extraction are firstly carried out, and then through entity disambiguation and co-reference resolution, the structured knowledge representation in the form of triples is obtained.

3.1.2 Ontology construction

Ontology is defined as an explicit specification of conceptualization [23], which is the framework of the whole KG and provides an upper-level data model to describe the concepts, object attributes and data attributes of entities in the KG [24]. As we construct the KG in a bottom-up manner, the ontology is constructed according to the data and attributes related to weapons and equipment by analyzing the relevant triplet knowledge obtained above, as shown in Fig. 1.

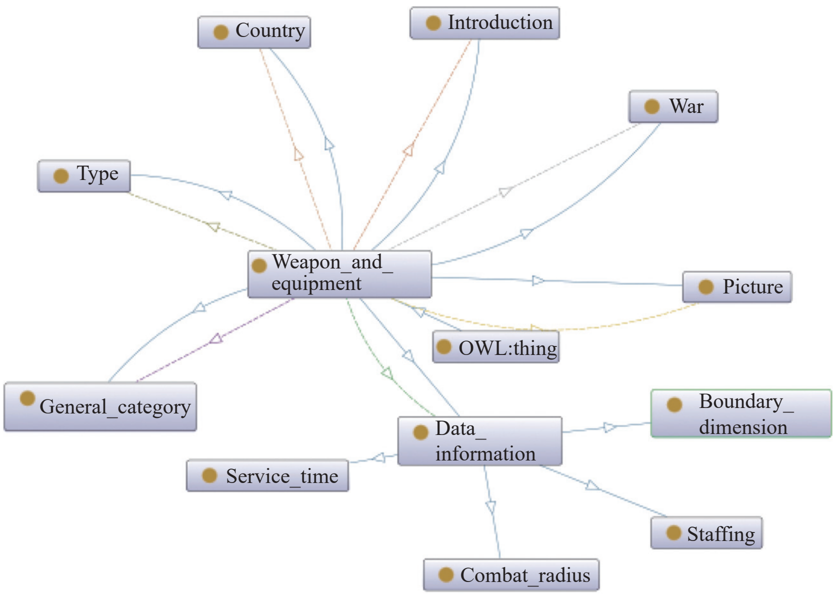

Fig. 1 Ontology construction of WEKG

3.1.3 Knowledge storage

Based on the concept level of the ontology constructed above, knowledge inference is carried out to discover new knowledge, and after quality assessment, the acquired knowledge is stored in the neo4j database. The Cypher formal query language embedded in the neo4j database can efficiently query the knowledge in the neo4j database, thus supporting the operation of the QA system well.

3.2 Construction of QA system based on WEKG

The process of constructing KGQA based on the semantic parsing method can be summarized as follows: firstly, users input a NLQ, then the question is semantically parsed by the QA system, which transforms it into a formal query language, and then acts on the KG to obtain the final answer. According to [16], this process can be divided into four parts: (i) entity recognition; (ii) entity link; (iii) relation recognition; (iv) cypher query generation and answer acquisition. Corresponding model flow chart is as shown in Fig. 2.

3.2.1 Entity recognition

To efficiently obtain the entities contained in NLQs, the BiLSTM-conditional random field (CRF) entity recognition model based on bidirectional encoder representations from transformers (BERT) pre-trained word vector is adopted in this paper [25]. The advantages of the BERT-BiLSTM-CRF model are as follows: (i) the BiLSTM model[26] can obtain bidirectional semantic information of text from both ends of input on the basis of long distance information obtained by the LSTM model; (ii) the CRF model[27] can learn some global constraint information through corpus training, so as to reasonably consider the dependency between labels. Therefore, the BiLSTM-CRF model can combine the advantages of BiLSTM and CRF models. It can not only use the BiLSTM layer to extract text context information to predict tags but also add some constraint rules through the CRF layer to ensure that the final recognition result is reasonable. In addition, the BERT model [28] at the bottom of BERT-BiLSTM-CRF can better obtain the context information, and the next sentence prediction training goal can obtain the semantic information between sentences, to solve the polysemy of a word in the text. Based on the above advantages, this model has a good effect on named entity recognition and has become the mainstream model for this task at present. The model uses the Bert word vector to obtain the basic semantic information contained in NLQs, uses two bi-directional LSTM layers to encode questions to obtain the semantic relations between questions, and uses the CRF layer to limit the results of entity recognition to improve the accuracy of entity recognition. The structure of the model is shown in Fig. 3.

The functions of each layer in the model are as follows:

(i) BERT layer: embed the segmented question sentence into a word vector, output the question vector containing semantic information, and add [CLS] and [SEP] to the beginning and end of the sentence respectively, where [CLS] contains the information of the whole question, [SEP] represents the separator of the question, and complement the insufficient part with [pad] according to the maximum sentence length.

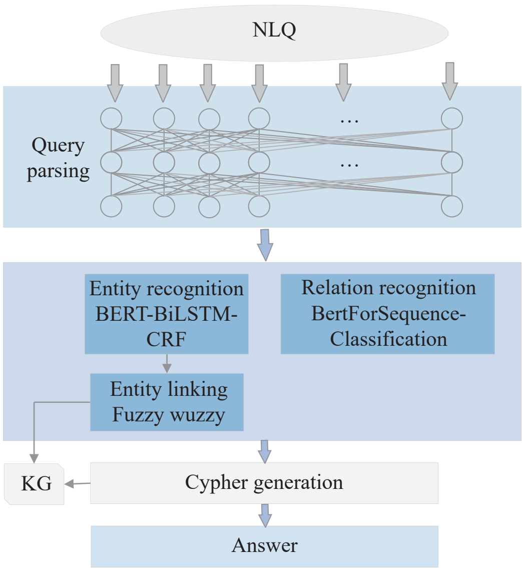

Fig. 2 Flow chart of QA system based on WEKG

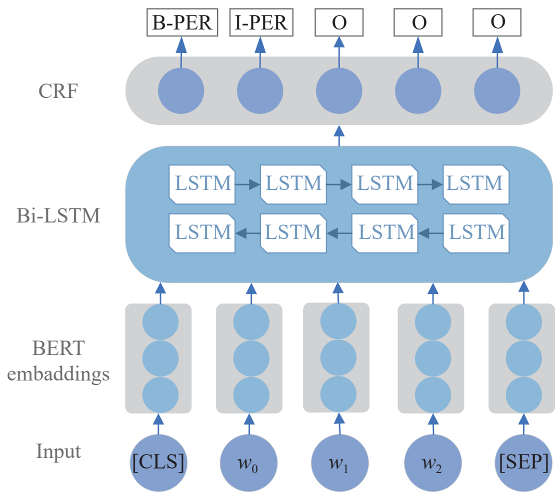

Fig. 3 Entity recognition model

(ii) Bi-LSTM layer: L word vectors $\boldsymbol{x}_t (t = 1,2,\cdots,L)$ obtained by the BERT layer are taken as input, and Bi-LSTM layer is used to encode these word vectors to obtain a two-layer hidden state sequence of forward and backward. The hidden state sequence of forward is $(\boldsymbol{h}_1,\boldsymbol{h}_2,\cdots,\boldsymbol{h}_L)$, and the hidden state sequence of backward is $(\boldsymbol{h}'_1,\boldsymbol{h}'_2,\cdots,\boldsymbol{h}'_L)$. Taking $(\boldsymbol{h}_1,\boldsymbol{h}_2,\cdots,\boldsymbol{h}_L)$ as an example, the specific calculation process is shown as follows:

$$f_t = \sigma(W_f \boldsymbol{x}_t + W_f \boldsymbol{h}_{t-1} + b_f), \tag{1}$$

$$i_t = \sigma(W_i \boldsymbol{x}_t + W_i \boldsymbol{h}_{t-1} + b_i), \tag{2}$$

$$o_t = \sigma(W_o \boldsymbol{x}_t + W_o \boldsymbol{h}_{t-1} + b_o), \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c \boldsymbol{x}_t + W_c \boldsymbol{h}_{t-1} + b_c), \tag{4}$$

$$\boldsymbol{h}_t = o_t \cdot \tanh(c_t), \tag{5}$$

$$f_t = \sigma(W_f \boldsymbol{x}_t + W_f \boldsymbol{h}_{t-1} + b_f), \tag{6}$$

where f_t represents the forgetting gate, i_t represents the input gate, and o_t represents the output gate. c_t stands for the unit state. σ stands for sigmoid activation function. tanh represents the hyperbolic tangent activation function. $\odot$ represents matrix element multiplication. W and b represents the parameters of the model. The model joins forward and backward hidden vectors to get $\boldsymbol{h}_t = [\boldsymbol{h}_t, \boldsymbol{h}'_t]$.

(iii) CRF layer: taking the output sequence $\boldsymbol{h} = (\boldsymbol{h}_1,\boldsymbol{h}_2,\cdots,\boldsymbol{h}_L)$ of the Bi-LSTM layer as input, the entity recognition sequence $y = (y_1,y_2,\cdots,y_L)$ of the question is finally obtained. First of all, the score $s(\boldsymbol{X},y)$ is used to represent the score of sequence $\boldsymbol{X}$ output after the input question y. Details of the calculation are expressed as follows:

$$s(\boldsymbol{X},y) = \sum_{t=0}^{L} \boldsymbol{A}_{y_t,y_{t+1}} + \sum_{t=1}^{L} \boldsymbol{H}_{t,y_t} \tag{7}$$

where $\boldsymbol{A}$ is the transition matrix, representing the probability of all states transferring to the next state. $\boldsymbol{H}$ is the output matrix of the Bi-LSTM layer. $\boldsymbol{H}_{m,n}$ takes the number from the mth word to the nth word as a specific entity probability, and takes the output sequence with the highest s score as the result of entity recognition. The specific formula details are as follows:

$$L(\theta) = \arg\max_{\tilde{y}\in Y_X} s(\boldsymbol{X},\tilde{y};\theta). \tag{8}$$

(iv) The “B-ENT”, “I-ENT”, and “O” annotations correspond to the beginning of an entity, the continuation of an entity, and non-entity tokens respectively, within the context of a generalized entity recognition framework.

3.2.2 Entity linking

It is necessary to link the entity obtained after entity recognition to the KG to find the entity closest to it. In this paper, Levenstein distance is used to measure the relationship between the identified entity and the entity in the KG. Levenstein distance represents the minimum number of editing operations required to change a word into another word between two strings. Here, the entity with the lowest Levenstein distance is taken as the corresponding entity in NLQs. In addition, a threshold value is set for this distance. If it is lower than this threshold, it is considered that the identified entity is not in the KG, that is, knowledge navigation cannot be realized.

3.2.3 Relation recognition

After finding the entity, it is necessary to determine the relational properties involved in the question. Here, the Bert-sequence Pair Classification model [28] is adopted to calculate the similarity between NLQs and the corresponding triple relation attributes, and the model structure used is shown in Fig. 4. The model will judge whether the input Sentence 1 and Sentence 2 are similar, give the similarity, and use the relationship attribute with the highest similarity as the final relationship attribute.

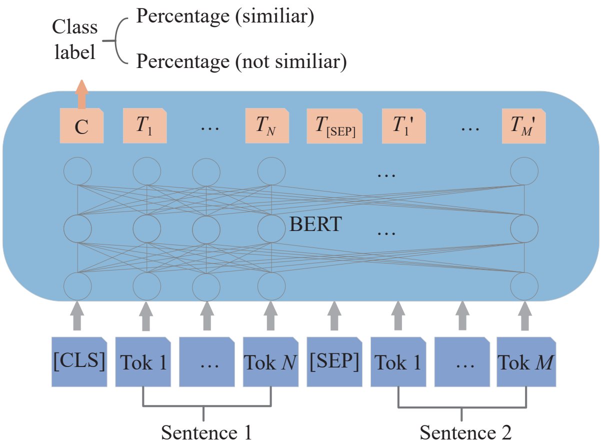

Fig. 4 Relationship recognition model

3.2.4 Cypher query generation and answer acquisition

The formal query language of the neo4j graph database is Cypher language, so finally, it is necessary to map the entity and relationship or attributes obtained by NLQs through the above model into Cypher query statements, and apply it to the KG to obtain answers. First, the predefined Cypher query template is as follows: MATCH (e1)-[r: relation name]->(e2) WHERE e1.name = "entity name" return e2.name, replace the corresponding position of the above template with the entity and relationship attributes in NLQs, and then get the cypher query statement.

4. Case study

As mentioned above, the method for QA based on the WEKG proposed in this paper mainly includes two core parts, namely the construction of the WEKG and the construction of the QA system based on this. The following is a case study on the construction of the WEKG and QA system and its application in WEORA.

4.1 Process of building WEKG

According to the construction process of the knowledge graph introduced in Subsection 3.1 above, we obtain the knowledge related to weapons and equipment from military websites and military texts, make structured knowledge representation, and store it in the neo4j database. The data in these professional websites are highly reliable, so the basic data sources are highly reliable. Then, protege is used to conducting consistency test on the constructed WEKG ontology model. The consistency test pass, indicating that the specific logical reasoning considered by the knowledge in the WEKG has no logic or formal contradiction. Finally, a WEKG is built, which contained 6576 weapons, 37341 nodes, and 80 474 triples. Some details are shown in Fig. 5.

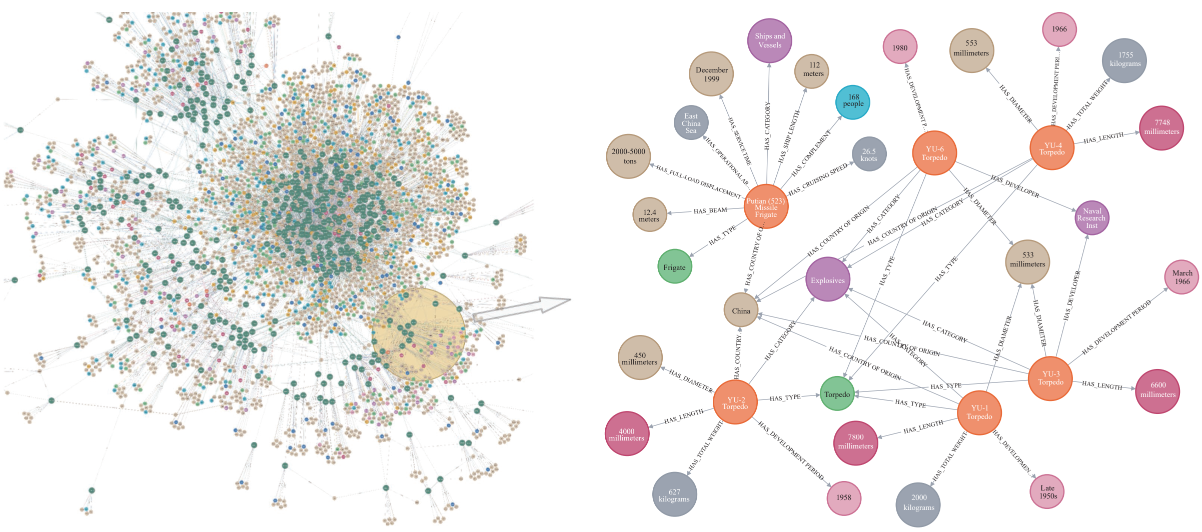

Fig. 5 Part of WEKG detail display

4.2 Construction of QAS4ORA

In this section, the WEKG-based QA model is firstly trained and tested, and then the trained model is deployed to the chat robot QAS4ORA.

4.2.1 Model training

Firstly, according to the triples in WEKG, a question-and-answer dataset is generated according to certain rules and templates, including 30 000 question-answer pairs for subsequent model training. To verify the validity of the dataset, the Knuth-Morris-Pratt (KMP) algorithm [29] is used to match tail entities and attributes and head entities in triples to check whether the tail entities are fully included in the existing triples. If no corresponding tail entity is found, the triplet is marked and rebuilt manually. In addition, KMP is used to remove duplicate triples from a dataset. Some of the question-answer pairs are shown in Fig. 6. It should be noted that the names of weapons involved in the question-answer pairs are replaced with capital letters, and the specific data of weapons and equipment are replaced with lowercase letters.

```
<question id=1389>     What is the current situation of the A?
<triple id=1389>  A|||the current situation|||in service
<answer id=1389>       in service
==================================================
<question id=415>      What is the external dimentions of the B?
<triple id=415>   B|||the external dimensions|||x long, y high, z wide
<answer id=415>  x long, y high, z wide
==================================================
<question id=483>      What range is the C effective?
<triple id=483>   C|||effective range|||n meters
<answer id=483>  n meters
```

Fig. 6 Partial display of the question-answer dataset

The question-and-answer dataset constructed above is labeled and divided according to the dataset styles of entity recognition and relationship recognition, and divided into the training set, validation set and test set according to the ratio of 5:1:1 [30]. Then the model is trained on GTX 3080 GPU, Windows 11 operating system, Python 3.8 is used for programming, and PyTorch 1.12.0 is used for the deep learning framework.

4.2.2 Model testing and analysis of results

Since the entity recognition model is the most important part of the question answering system constructed in this paper, we adopt three indexes to measure the performance of the BERT-BiLSTM-CRF entity recognition model: (i) P(precision); (ii) R(recall); (iii) $F1$($F1$-score). The meanings and calculation formulas of each index are as follows:

$$P = \frac{a}{b} \times 100\%, \tag{9}$$

$$R = \frac{a}{c} \times 100\%, \tag{10}$$

$$F1 = \frac{2PR}{P+R} \times 100\%, \tag{11}$$

where a represents the number of correctly identified entities, b represents the number of identified entities, and c represents the total number of entities. And $F1$-score is an evaluation index that integrates precision and recall and is used to comprehensively reflect the overall indexes.

Next, the above three indexes of the entity recognition model are tested. Meanwhile, to verify the validity of the adopted model, the model is compared and analyzed with several mainstream deep learning models for named entity recognition. The comparison model and test results are as shown in Table 1.

Table 1 Model comparison and result presentation %

Model	P	R	$F1$
BERT-BiLSTM-CRF	92.02	92.74	92.38
BERT-CRF	87.98	87.20	87.59
BiLSTM+CRF	84.98	80.42	82.65
IDCNN+ CRF	80.01	77.49	78.73
BERT+IDCNN+ CRF	88.09	89.43	88.76

It can be seen from the results that BERT-BiLSTM-CRF model is significantly superior to other models, because the combination of advantages of BERT, Bi-LSTM and CRF makes it able to obtain bidirectional semantic information of text, solve the polysemism problem, and maintain the rationality of recognition results through constraints. The reason why the effect of iterated dilated convolutional neural network (IDCNN)+CRF model is lower than other models is that IDCNN will lose local information. Although it can obtain long-distance information, such information often does not correlate [31]. Besides, the $F1$ score of the relationship recognition model is 93.69%, which shows that the model effect is ideal.

4.2.3 System implementation

The above trained question answering model is deployed into a chatbot using the Flask framework, which we call QAS4ORA. In this way, the front-end interaction of the QA system based on the WEKG is realized, so as to better serve the WEORA. The presentation effect of QAS4ORA is shown in Fig. 7. As mentioned above, the equipment its concrete data involved in the presentation effect are also replaced with code names, as is done in Subsection 4.3.

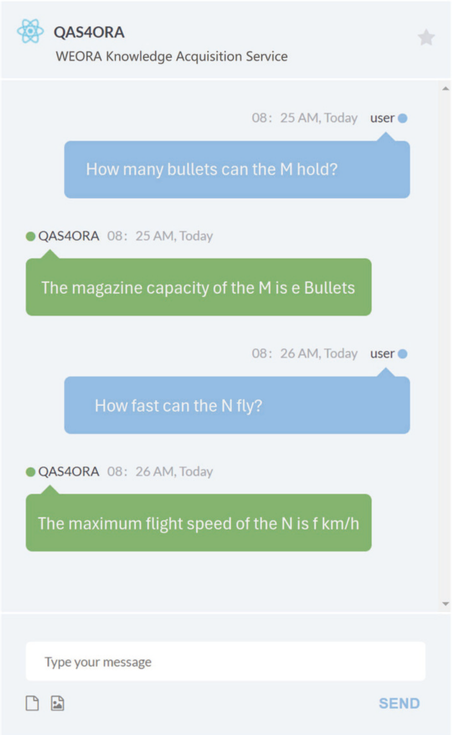

Fig. 7 Screenshot of the chatbot interface of QAS4ORA

4.3 Application case of QAS4ORA in WEORA

Assume that the sub-mission of an operation mission are as follows: carry out a ground attack mission on an enemy military facility s_1 away from our base, to complete the operation mission within t_1 and destroy ten targets in the enemy military facility. According to the WEORA for the above operation mission, it can be seen that there are certain requirements for the flight speed, maximum flight range and weapon system of the fighter participating in the combat. Set the bombing time to t_2, considering the flight distance s_2 during the bombing, the maximum flight speed of the fighter should not be less than $v = \dfrac{2s_1}{t_1 - t_2}$, and the maximum flight range should not be less than $r = 2s_1 + s_2$.

Now the P fighter and the Q fighter are available for use, and the operation performance and parameters of the two fighters need to be evaluated to serve the design of the operation plan. Use the QAS4ORA system to conduct knowledge navigation on the operation performance and parameters of the two types of equipment mentioned above. The overall analysis process of weapon equipment selection is shown in Fig. 8.

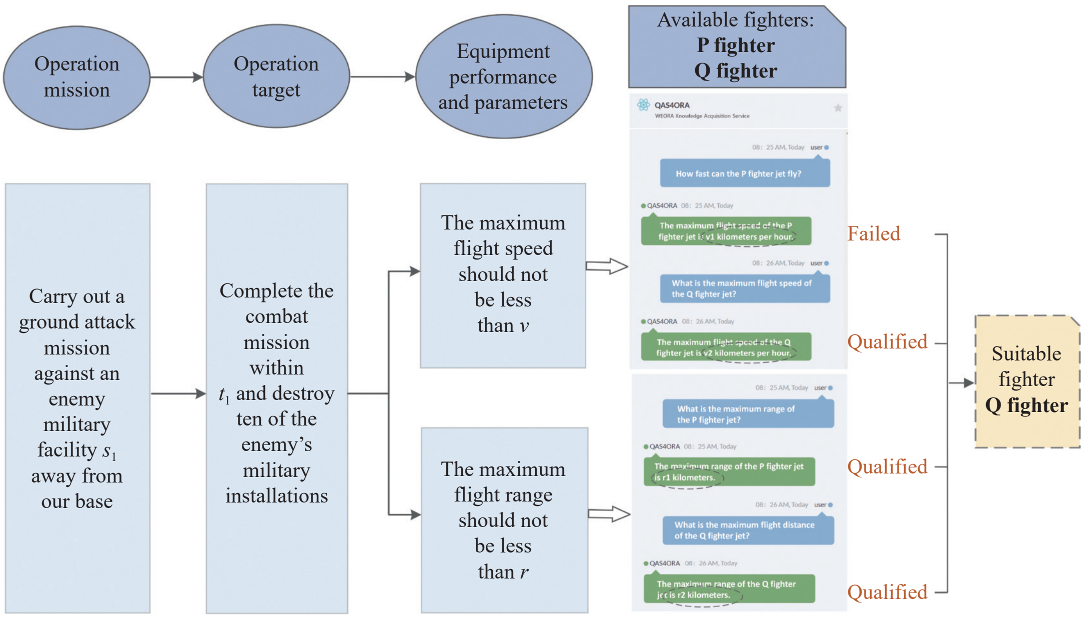

Fig. 8 Application case of QAS4ORA in WEORA

It can be seen that the P fighter cannot meet the requirements of the maximum flight speed, so this type of fighter cannot be assigned to combat missions, and the Q fighter should be selected in the end. To sum up, the system can meet the requirements of WEORA to a certain extent. In addition, compared with keyword-based web search or text search and other knowledge navigation methods, this system can greatly improve the understanding of NLQs, and accurate knowledge and answer acquisition also improve the efficiency of the whole process of WEORA.

5. Conclusions

Knowledge of weapons and equipment is the key to carrying out analysis of weapons and equipment operational requirements, and efficient and accurate acquisition of it can improve the efficiency of the WEORA process. In this paper, we propose a neural network-based QA method over the WEKG to assist WEORA, which mainly plays a role in the integration and navigation of weapons and equipment knowledge. Our main work includes the following three parts. (i) Through the processing and knowledge integration of a large number of structured and unstructured data, the WEKG is constructed for the structured representation of weapons and equipment knowledge. (ii) On the basis of the established WEKG, a neutral network-based QA system is constructed by means of semantic parsing for the navigation of weapons and equipment knowledge. (iii) The above QA system is integrated into the chatbot QAS4ORA, so that analysts participating in WEORA can use natural language to acquire relevant knowledge. Finally, the effectiveness of the method is evaluated through experimental verification and case analysis, and it is concluded that the system can greatly improve the efficiency of the whole process of WEORA.

As for possible future work, we will consider building QA systems that can answer complex questions to achieve more intelligent knowledge navigation. At the same time, more knowledge related to weapons and equipment should be integrated to expand the scale of WEKG.

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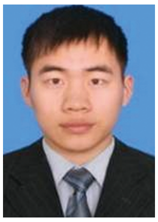

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