IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 24, 2020, accepted October 27, 2020, date of publication October 30, 2020,
date of current version November 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3034894

Application of Entity Relation Extraction Method Under CRF and Syntax Analysis Tree in the Construction of Military Equipment Knowledge Graph

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ABSTRACT In the field of military research, manufacturing and management of weapons and equipment are very important. Due to the continuous advancement of science and technology, many military equipment databases have a loose structure, which makes them difficult to be utilized efficiently, resulting in low efficiency, chaotic management, and other issues. In order to solve these problems, an entity-relation extraction method based on CRF and syntactic analysis tree is proposed according to the latest text extraction algorithm. Finally, a military knowledge graph construction method is optimized via massive data training, model comparison and improvement. The ternary data extraction method is significantly better than the single algorithm extraction method, and the accuracy of the extracted training model can reach 72%. Compared with the traditional entity-relation extraction method, the accuracy of the entity-relation extraction method based on the fusion of CRF and syntax analysis tree is improved by 12.6% when the confidence model is added, and the comprehensive evaluation accuracy can reach 78.11%. This result has significant practical value for the construction of knowledge graphs in the field of military equipment.

INDEX TERMS CRF, military equipment, knowledge graph, entity relation extraction, confidence model.

I. INTRODUCTION

With the continuous development of informatization, the data generated in various industries has also increased dramatically. However, the development of data is shallow. Data can often bring substantial economic benefits and play an essential role in social life [1]. At the same time, in the field of military equipment, many data, such as equipment types, models, and parameters, are crucial for the development and use of military equipment [2]. Huang (2018) proposed an algorithm to build an efficient distributed multicast tree construction algorithm for mobile networks, which could monitor the tank movement in real-time through multiple data methods [3]. Gui (2018) proposed a method to calculate tracking quality based on armament data [4]. However, while obtaining armament data, critical points cannot be obtained efficiently. Therefore, it is impossible to command armament work [5]. Some investigations have shown that due to the lack of adequate data display methods, there is no perfect military equipment knowledge system. Therefore, it is impossible to deeply mine and apply the data [6]. Most of these massive data on the Internet are high-quality and semi-structured knowledge. Many entries are edited manually and contain much-standardized knowledge, such as article titles, classification labels, and information frames. They have high credibility. The feasibility of using these data to construct a knowledge graph is high.

There are many Internet data, but these data are often scattered. Therefore, how to use specific rules to obtain the desired data quickly is a problem. The knowledge graph is a way of extracting information from the massive knowledge system on the Internet according to specific rules with the help of computer information technology to rapidly display information and clearly grasp the information structure [7]. This method first emerged in Western countries. Pujara *et al.* (2013) proposed the concept of knowledge graph and applied it to Google's search function to improve the quality of retrieval [8]. Wikipedia also uses this technique to construct a multilingual knowledge graph [9]. Microsoft has also constructed a large-scale, high-quality Chinese concept graph to

The associate editor coordinating the review of this manuscript and approving it for publication was Shunfeng Cheng.

improve data usage [10]. Shanghai Jiaotong University has also constructed the first Chinese general domain knowledge graph [11]. Nevertheless, most of the data of the constructed knowledge graph come from the existing data sources of Wikipedia and Baidu Encyclopedia. There is no way to obtain industry data in a field, and the scope of coverage is narrow somehow [12]–[14]. However, when facing the field of military equipment, because this field is confidential, it is difficult to obtain essential equipment data. Moreover, due to subtle differences between military equipment, different types of weapons are produced. Thus, the data requirements are high. Consequently, investigations on knowledge graphs in the field of military equipment are few.

Researching knowledge graph plays a vital role in specialized tasks, such as military intelligence analysis, combat command, intelligence research and judgment, and target analysis. The correlations between intelligence are the bridge and means for comprehensive analysis between various types of intelligence, which are useful tools for intelligence correlation analysis. The entity-relation extraction will be the focus, and the core task is knowledge graph construction. According to different types of extraction tasks, two methods, limited entity relation extraction and unrestricted entity relation extraction will be proposed, and the storage technologies of knowledge graph will be explored. As for specific applications, a military equipment knowledge graph system and its application system are built and developed at the system application layer. The results can provide a comprehensive and accurate knowledge system for military equipment workers and assist those workers to quickly and accurately acquire the knowledge they need.

II. METHODS

A. THEORETICAL FRAMEWORK

Usually, methods for knowledge graph construction can be divided into three types: expert construction, crowdsourcing construction, and automatic construction. Expert construction methods are standard in the early research stage of the knowledge graph. Due to the constraints of hardware and technology, most of the Resource Description Framework (RDF) triples are constructed by experts and scholars via manual compilation, among which the representative knowledge bases include WordNet and synonyms Cilin [15]. The advantage of the expert construction method is that the knowledge is highly accurate. However, the disadvantage is also very apparent. The knowledge obtained by manual compilation of experts is minimal, and both the scale and the construction speed are greatly restricted. Crowdsourcing construction relies on the cooperation of volunteers from all over to express the relevant knowledge in a structured form, thereby organizing a large-scale general knowledge graph [16]. The advantage of the crowdsourcing construction method is that it can construct a large-scale knowledge graph at a low cost, but the quality of the knowledge edited through crowdsourcing is difficult to guarantee. Automatic construction methods mostly use rule-based methods to obtain RDF triples. Representative scholars extract attributes by defining corresponding rules and using heuristic methods. According to the automatic construction method, Wikipedia and WordNet web pages are extracted to obtain the ontology knowledge bases. Based on the scope of the covered knowledge, some currently released knowledge graph projects can be divided into general knowledge graphs and domain knowledge graphs. The general knowledge graph is oriented to all things in the natural world. It constructs a knowledge graph by acquiring entities and their relations, focusing on the breadth of knowledge [17]. The domain knowledge map is oriented to specific domains and is constructed to portray specific domain knowledge. It focuses on the depth of knowledge and is highly specialized.

Entity-relation extraction is the core of knowledge graph construction. Its task is to parse the rich semantic relations between the entities contained in the text, and extract the corresponding entity relations and express them in the form of triples [18]. Entity-relation extraction includes classification relation extraction and non-classification relation extraction. The relation extraction of the current classification system does not have too many technical obstacles; the difficulty is the extraction of non-classification relations. Non-classification relation extraction can be divided into two different problems: (1) discovering the relation between a pair of concepts, and (2) marking this relation, according to semantics [19]. For the entity-relation extraction algorithms, Xu *et al.* (2016) investigated the feature-based kernel method, the extended path graph kernel method, and the multi-core learning method in the five most authoritative evaluation corpora; the results showed that the performance of the fusion core method in five corpora was better than two separate single-core methods [20]. Shi *et al.* (2019) employed Deep Neural Networks (DNNs) in entity relation extraction tasks, which were better than traditional relation extraction methods; the method of adding active learning is more effective by comparing the performance of the Attention Long Short Term Memory (ALSTM) model and the two-way LSTM model under the entity-relation extraction task [21]. The above results reveal that the research on entity-relation extraction is mostly concentrated on the deep learning-associated algorithms.

Deep learning algorithms often require many data for training. However, the current construction of knowledge graphs is less concerned. Hence, data for research are less, especially in the field of military equipment. Due to its confidentiality, military data are challenging to obtain, the relation between entities is complicated, and the accuracy of extracting knowledge from unstructured data is limited; consequently, constructing military equipment knowledge graph faces a series of difficulties. Therefore, the research methods of natural machine learning are utilized, including the latest CRF-based and syntactic analysis algorithms, which are analyzed and compared with the maximum entropy algorithm. The parameters are reasonably adjusted to ensure the optimal performance of the model by introducing a confidence model.

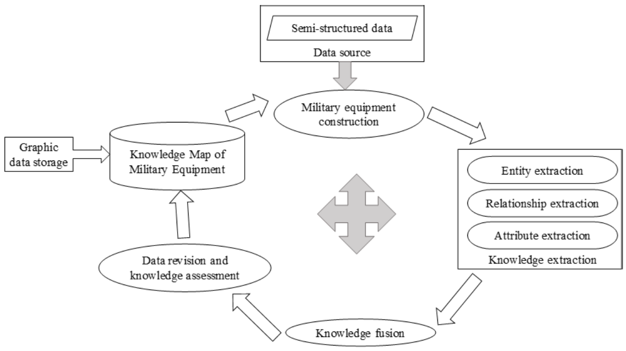

FIGURE 1. The construction process of knowledge map.

B. CONSTRUCTION PROCESS OF MILITARY EQUIPMENT KNOWLEDGE GRAPH

Many documents and materials reveal an absolute hindrance to the establishment of the knowledge graph due to the confidentiality of military data and the particularity of military equipment, resulting in little structured data and challenging data collection. The reliability of unstructured data is not high, and the accuracy of extraction is also low, which is difficult to meet the standards of military use. Therefore, a top-down, cyclical approach is used to build a military equipment knowledge graph. This approach can ensure the accuracy of the knowledge graph and the correctness of the structure level. Its construction process is shown in Figure 1. First, specific rules are defined to ensure the correctness of the data structure hierarchy. Then, different knowledge extraction methods are adopted for different data. After the fusion of knowledge and the evaluation of system rules, the triples with higher accuracy are finally obtained to visualize the data. The entire process is cyclical, and the knowledge graph needs to be continuously updated according to the new data.

C. TRAINING CORPUS PREPROCESSING OF MILITARY EQUIPMENT KNOWLEDGE GRAPH

When extracting knowledge, it is necessary to classify the data according to the language recognized by the computer. The Chinese classification system HanLP of the open-source JAVA toolkit can separate different texts according to specific rules (part of speech, functions, entities). This method is composed of a series of models and algorithms that can support functions such as part-of-speech tagging, named entity recognition, dependency syntax analysis, and keyword extraction. It has the characteristics of high performance and clear structure. The method uses data display methods such as double array Ttie tree and DAWG, which is more efficient and can implement custom functions through its tools. The HanLP word segmentation system used is partially displayed, as shown in Table 1. The custom module method is mainly used, which can mark the type of information of entity words; for example, the government displays as nto, the human displays as nr, and the title displays as nnt.

TABLE 1. HanLP partial annotation results.

HanLP partial annotation results				
Adjective	c	Conjunctions	d	Adverb
Verb	p	Prepositions	q	Quantifier
Particle	s	Place Words	r	Pronoun
Time Word	ns	Place Names	nt	Institution Name
Work Word	nr	Human Lives	nnd	Occupation
Position /	nto	Government	nth	Hospital

D. ENTITY RELATION EXTRACTION METHOD BASED ON THE MAXIMUM ENTROPY MODEL

Entity relation extraction method based on maximum entropy model: this is a relation tree-based relation structure that relies on the maximum entropy model to predict the relationship between the original data or text, identify the keywords in the sentence, and complete the extraction task. The most prominent feature of this method is that it can be classified according to sentence features. This feature can fully mine the relationship between sentences and phrases, thereby producing a better classification relation. Therefore, the result of extraction is ideal. In this method, a special algorithm is used to extract features from the sentence after preprocessing the training corpus and comprehensively analyzing parts of speech, grammatical features, and n-gram features. Then, the relation is classified based on the maximum entropy model.

The principle of maximum entropy is that based on a certain number of data structures, a typical model can be obtained through the combination of data. Then, based on the latest data, subsequent events are predicted and distributed as uniformly as possible. Military equipment needs to be classified. Because there are many parameters involved, it is appropriate to use the maximum entropy method as the classification model. First, the conditional probability is estimated without the need for independence. According to the principle, for the sentence text x and the corresponding label y, the conditional probability obtained by giving x can be defined as in (1).

$$P\left({}^{y}/_{x}\right) = \frac{1}{Z\left(X\right)} exp\left[\sum_{i=1}^{k} \lambda_i f_i\left(x, y\right)\right] \tag{1}$$

In (1), $f_i\left(x, y\right)$ represents the feature model corresponding to the f feature, λ_i represents the weight calculated by the feature model $f_i\left(x, y\right)$, k represents the total number of features, and $Z\left(X\right)$ represents the normalization factor. It is necessary to ensure that the sum of the probabilities is 1.

The feature model $f_i\left(x, y\right)$ is defined by the sentence text x and the corresponding label y. When x and y meet a particular condition, their value is 1. Otherwise, their value is 0. After classifying the relationship between sentence texts, the following equation can be used to define the characteristic equation.

$$f_i\left(x, y\right) = \begin{cases} 1, & (y = relation) \wedge (x = feature) \\ 0, & otherwise \end{cases} \tag{2}$$

In (2), $x = feature$ is the feature corresponding to the relation that has a specific relationship with the sentence text x. The model of maximum entropy generally uses the maximum likelihood method to estimate the parameters of the data. Two algorithms commonly used are GIS and IIS. The GIS algorithm is used to calculate the parameters.

In this experiment, the test data come from 500 sentence texts selected from texts on the Internet search engine to express the relationship between military equipment names, equipment classifications, and equipment attributes. Two different 2-pattern and 3-pattern features are designed in the experiment. The extracted value F of the n-pattern mode is defined as 3. The features of 2-gram and 3-gram are defined for comparison. The features of the text are collected in different ways.

E. ENTITY RELATION EXTRACTION METHOD COMBINING CRF AND SYNTACTIC ANALYSIS TREE

Entity relation extraction method combining CRF and syntax analysis tree: it is a method to classify the original data based on different annotations and syntax analysis rules. The specific steps can be divided into the following. (1) All the feature data words are shuffled and annotated according to the four different levels (characteristic features, part-of-speech features, entity categories, and word boundary features) and the order of the CRF sequence model. (2) The specific manual annotating methods are combined to form a particular training set. (3) These sets are put into the CRF sequence model for multi-level verification, and a large number of subsets with relation features are obtained. (4) The role of each vocabulary in the sentence is analyzed in a structured form of syntactic analysis tree, to identify the most likely combination of ternary entities with relation feature words. Furthermore, the task of extracting entity relation is completed. Among them, the modified algorithm is to put all the datasets into the confidence model to evaluate the quality of the result of its ternary combination. Finally, the ternary relation combination with a lower quality coefficient is removed by setting an appropriate threshold to ensure the quality of entity relation extraction in the vocabulary.

Based on the fundamental training corpus preprocessing data, a relation vocabulary that can automatically extract the entities and features in the sentence is used to form the entity-relation-entity ternary structure combination further. The purpose is to solve the problem of annotating the sequence. The specific steps are as follows. (1) The extraction task is decomposed into corresponding relation feature words for annotation. Relation feature word annotation can be regarded as an annotating model that is modeled as a sequence. Through continuous training of the data, the sequence labeling model based on CRF is generated. (2) The combination of data ternary extraction is mainly to use the syntax analysis tree to distinguish the entity pairs in the data that are most likely to form the ternary with the relation feature words in the ternary extraction stage, thereby completing the entity relation extraction task further.

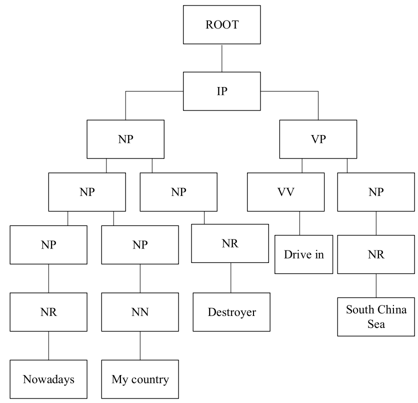

FIGURE 2. Ternary extraction algorithm combined with syntax analysis tree.

The test data for this experiment come from 500 unrestricted relation type sentence texts manually selected from military equipment documents. The extraction method is used to extract the entity relation of the test data and manually determine the extraction result.

F. TERNARY EXTRACTION ALGORITHM COMBINED WITH SYNTAX ANALYSIS TREE

The idea of syntactic analysis in the process of extracting relation ternary is different from the traditional method, and it usually depends on the relative position relation between the entity pairs and the relation feature words in the sentence. It can effectively improve the extraction quality of relation ternary. The steps are as follows. First, the structure of the sentence is analyzed, and the analysis results are displayed in the structure of the syntax analysis tree to clarify further the role of each vocabulary and phrase in the sentence structure. Second, the entity pairs that are most likely to form a ternary relation with the relation feature words are determined. StanfordParser is used to complete the dependency structure analysis task of the sentence and generate the analysis tree. The sentence structure of ‘‘Nowadays, my country destroyer drive in the South China Sea’’ is shown. The result of the analysis tree is shown in Figure 2.

Figure 2 shows an optimal connection path between every two words. According to the rules of grammar extraction, the connection path with the shortest distance can often be obtained. The steps of determining the optimal ternary combination of data vocabulary and feature relation are as follows. (1) According to the rule, the feature relation and the entity vocabulary are calculated. The shortest connection distance sum between them is calculated. (2) According to the minimum feature distance of the entity relation, the optimal ternary relation combination is formed. The specific example shows that the shortest connection distance sum of the entity pair ‘‘Nowadays-My country’’ and the relation feature word ‘‘My country’’ is the smallest through calculation. Therefore, the relation ternary combination <Nowadays-My country-Destroyer> is extracted. By performing the above operations on all sentences labeled by the CRF, the relation ternary combination included in the sentence is extracted.

G. MODERN TRAINING AND GENERATION

In the training phase, the Java-based natural language processing toolkit Miller is used to train the CRF annotation model. The toolkit is widely used in text classification, topic modeling, information extraction, clustering, and many other fields. The bottom layer uses the L-BFGS algorithm, which can estimate the maximum likelihood of the function to be optimized by the model.

In the training phase, MALLER, a natural language processing toolkit based on JAVA, is used to train the CRF annotation model. The toolkit is widely used in many fields, such as text classification, topic modeling, information extraction, and clustering. The bottom layer adopts the L-BFGS algorithm, which can estimate the maximum likelihood of the function to be optimized by the model. The Marler toolkit can convert text into mathematical expressions, thereby more effectively realizing the machine learning capabilities of the text. It not only has a rich set of tools in text classification and topic modeling but also includes some tools in the field of sequential annotation. The Marler's CRF toolkit is called. The training corpus after feature extraction and annotation is used as input for model training. At the end of the training, the model is used to label the text of a large number of unlabeled military equipment sentences. Also, through the identification of the relation feature words of each sentence, this model is used to label the word boundary features based on the biological annotation mode for the text of the unlabeled military equipment sentences.

H. DESIGN OF EXTRACTION COMPARISON EXPERIMENT

This experiment focuses on different types of entity relation extraction tasks; that is, entity relation extraction based on the maximum entropy model and entity relation extraction combining CRF and syntax analysis tree. The entity relation based on the maximum entropy model introduces the n-pattern feature extraction method, and three comparison schemes are designed through experiments. Based on the relation extraction experiment, a certain amount of text is selected to represent the relation of the three types. Finally, the best performance extraction model of the experimental results is determined. The entity relation extraction method based on the combination of CRF and syntax analysis tree uses an experimental scheme to extract a certain number of texts with unlimited relation types from military equipment sentences. Experimental evaluation indicators determine the extraction results. On this basis, the extraction results are optimized by the proposed triple relation screening model. Also, it is further evaluated based on evaluation indicators. Besides, for the problem of the threshold r of the relation triple filtering model, the optimal value is determined through experiments. In this experiment, the corpus obtained using the remote monitoring method is used as training data. The corresponding feature extraction and annotation operations of the two entity relation extraction methods are performed on the training data. Then, the dependency model is used to train two methods. According to the different experimental schemes adopted by the two methods, different data are selected and introduced into their respective experimental links.

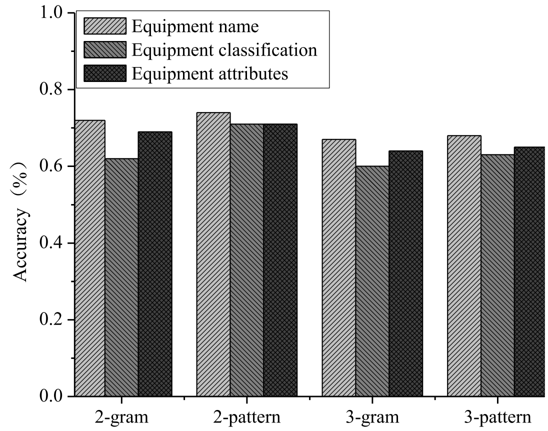

FIGURE 3. Accuracy of relation extraction results under different feature modes.

I. EVALUATION INDICATORS OF EXTRACTION COMPARISON EXPERIMENT

In the performance evaluation indicators of the extraction relation, the accuracy, recall rate, and F value are selected. Among them, the calculation equation of the accuracy is as follows.

$$\text{Accuracy(P)} = \frac{T_1}{T_2} \times 100\% \tag{3}$$

The recall rate is calculated as follows.

$$\text{Recall rate(R)} = \frac{T_1}{T_3} \times 100\% \tag{4}$$

The F value is calculated as follows.

$$\text{F value(F)} = \frac{2 \times P \times R}{P + R} \times 100\% \tag{5}$$

In (5), T1 represents the correctly predicted relation number, T2 represents the predicted relation number, and T3 represents the total number of relations contained in the corpus.

III. RESULTS AND DISCUSSION

A. PERFORMANCE COMPARISON EXPERIMENT OF ENTITY RELATION EXTRACTION METHOD BASED ON THE MAXIMUM ENTROPY MODEL

Figure 3 shows that the accuracy of the address relation extraction results is almost the same in the n-gram and n-pattern feature selection mode. When extracting the relation between "establishment time and nature of the organization," the proposed n-pattern feature selection mode has much better extraction performance than the n-gram mode. The extraction accuracy under different n values is compared. The accuracy n of the feature selection mode with n value 3 is taken as 2-pattern features, and the accuracy of the extracted training model can reach more than 72%. Therefore, this model will have a particular optimization effect on the existing entity relation extraction algorithm.

In order to compare the recall rate of the relation extraction results under different feature modes, the corresponding data

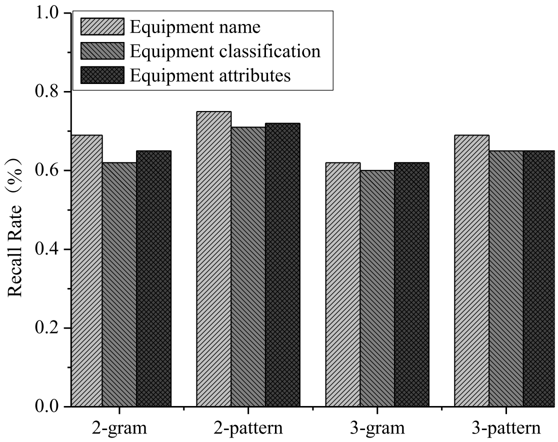

FIGURE 4. Recall rate of relation extraction results under different feature modes.

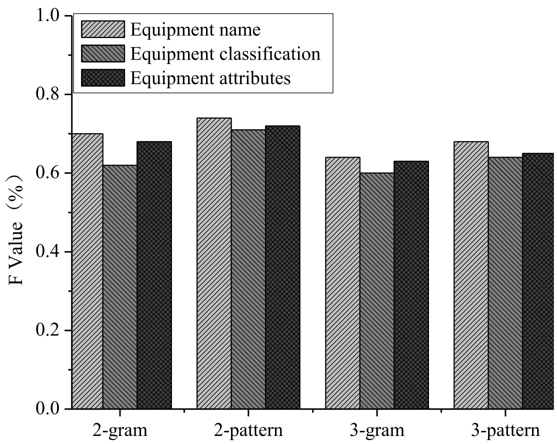

FIGURE 5. F value of relation extraction results under different feature modes.

is calculated. The result is shown in Figure 5. The n-pattern feature selection mode is superior to the n-gram mode in the three-relation extraction, indicating that the feature selection mode proposed is easier to distinguish the features of the text.

The F value is the weighted average of recall rate and accuracy. Using the F value as a metric can better reflect the performance of different feature selection modes. Figure 5 shows that the proposed n-pattern feature selection mode has significantly higher extraction performance than the n-gram mode. Given the characteristics of relation extraction in the field of military equipment, the n-pattern feature extraction mode can effectively solve the problem of sparse features compared with n-gram. Therefore, the n-pattern is used for feature extraction.

B. PERFORMANCE COMPARISON EXPERIMENT OF ENTITY RELATION EXTRACTION METHOD COMBINING CRF AND SYNTAX ANALYSIS TREE

Since this experiment aims to evaluate the extraction method of military equipment files, the performance of entity relation extraction has been improved. Therefore, in the comparison of experimental design, only the proposed ternary relation

TABLE 2. Comparative analysis of the performance of extraction methods.

Extraction method	Accuracy	Recall rate	F value
CRF combined with syntax analysis tree	65.83%	71.45%	68.52%
After the confidence model is screened	75.32%	74.60%	78.11%

TABLE 3. Comparative analysis of the performance of extraction methods.

Threshold R	Accuracy	Recall rate	F value
0.28	66.25%	67.38%	66.81%
0.31	69.57%	65.42%	67.43%
0.34	75.32%	74.60%	78.11%
0.37	74.17%	59.76%	66.19%
0.4	74.79%	55.31%	63.60%

screening model is used to compare the extracted results with the optimized results. The results are shown in Table 2. The analysis of the results in Table 2 reveal that after the confidence model is selected, the accuracy of the entity relation extraction method based on the fusion of CRF and syntax analysis tree will be significantly improved. The recall rate can be reduced by filtering some low-quality relation ternary. However, the F value of the comprehensive evaluation indicator remains almost unchanged. It is proved that the proposed method is useful for knowledge extraction in the field of large-scale military equipment, and more attention should be paid to the accuracy of knowledge to improve the accuracy of the extractor.

The above method is modified, and the confidence model is added. For the threshold setting of the confidence model, several sets of comparative tests are conducted. The specific performance comparison results are shown in Table 3. According to the analysis of the results in Table 3, as the threshold increases, the accuracy of the extraction results will increase, the recall rate will continue to decline, and the F value of the comprehensive evaluation indicator will rise. When the R-value is more significant than 0.34, the rate of increase in accuracy will become smaller, and the recall rate will decrease, resulting in a decrease in the F value. Hence, 0.34 is selected as the optimal value of the threshold R.

C. COMPARISON OF ENTITY RELATIONS IN DIFFERENT EXTRACTION METHODS

Figure 6 illustrates the results of the comparative investigation of the entity relation extraction method based on the maximum entropy model (using n-pattern for feature extraction experiments), original entity relation extraction method combining CRF and syntax analysis tree, and the CRF and

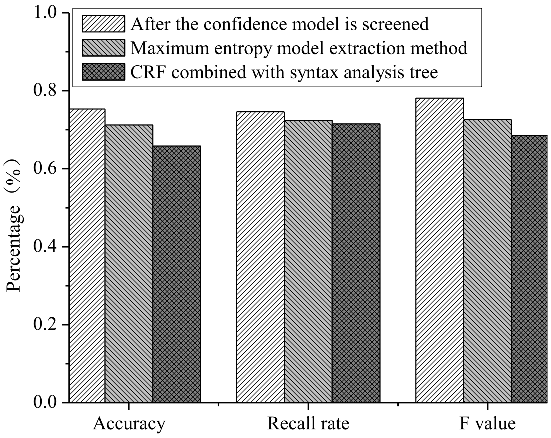

FIGURE 6. Comparison of entity relations in different extraction methods.

syntax analysis method with a confidence threshold of 0.34. The results show that the overall accuracy, recall rate, and F value of the entity relation extraction method based on the maximum entropy model are higher than the original entity relation extraction method combining CRF and syntax analysis tree. After adding the confidence threshold, the entity relation combining CRF and the syntax analysis tree is significantly higher than the entity relation extraction method based on the maximum entropy model.

IV. CONCLUSION

According to previous literature, the method based on knowledge extraction and fusion is proposed after sorting out. The simple knowledge graph of military equipment is constructed. Three methods based on the basic expected training library are clarified; that is, the entity relation extraction method based on the maximum entropy model, entity relation extraction method of CRF and syntax analysis tree, and modified the extraction method based on CRF and syntax analysis tree. They are evaluated at the level of accuracy, recall rate, and F value. A suitable knowledge graph of military equipment is eventually obtained.

The results show that: (1) In the entity relation extraction method of the maximum entropy model, the n-pattern feature selection mode has significantly higher extraction performance than the n-gram mode. (2) After selecting the confidence model, the accuracy of the entity relation extraction method based on the fusion of CRF and syntax analysis tree will be significantly improved. (3) When the threshold R is 0.34, the accuracy, recall rate, and F value of the extraction are significantly higher than the entity relation extraction method based on the maximum entropy model. The results can provide equipment workers with a comprehensive and accurate military equipment knowledge system to assist equipment workers to quickly and accurately acquire the required knowledge.

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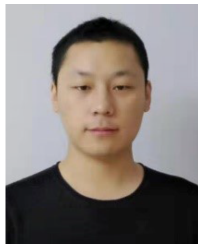

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