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A review: development of named entity recognition (NER) technology for aeronautical information intelligence

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Abstract
The rapid development of data and artificial intelligence technology has introduced new opportunities and challenges to aeronautical information intelligence. However, there are many obstacles in the sharing, reasoning and reusing aeronautical data due to the disunity of norms, the opacity of sharing and semantic ambiguity. To a large extent, as a basic method for processing, storing and deducing aeronautical data in the future, NER provides a new idea for the natural language processing of aeronautical information intelligence. In this paper, the problem with NER for aeronautical information is deeply analyzed, the relationship among the data model, the knowledge system and the named entity (NE) is combed, and the main characteristics of NE are summarized. At the same time, the resources that are useful to NER involving thematic databases, aviation domain ontology and evaluation indicators are described. Finally, two main directions of NER are suggested for further research, which is helpful in aviation development. This paper first provides a comprehensive survey of the approaches and directions of NER in a specific domain: aeronautical intelligence information.

Keywords Named entity recognition (NER) · Aeronautical information intelligence · Deep learning · Transfer learning

1 Introduction

With the advent of the big data era, the explosion of information has introduced severe data overload problems to aviation. The main reason for this is that modern aeronautical information intelligence not only involves massive amounts of land, sea, sky, and space data but also contains multidimensional information and media, including data for early warning, investigation, intelligence, etc. Big data raises unprecedented challenges in the processing of aeronautical information intelligence and higher requirements during information

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processing. Accurately and quickly picking up information, associating and integrating information from massive scattered and one-sided data, transforming information superiority into knowledge superiority, and proposing decision-making superiority are key steps in the future development of aeronautical information intelligence technology. To extract knowledge from aeronautical data and reduce information overload, an effective entity recognition technology has been developed and applied to understand, associate and manage the aeronautical data.

The concept of the NE was first proposed at the Sixth Conference on Message Understanding (MUC-6) (Grishman and Sundheim 1996). Its tasks are mainly used to recognize the names of people, locations and organizations in text, as well as currencies, times and percentages. For instance, we select this sentence of aeronautical intelligence information, "On October 10, the Australian Transportation Safety Authority issued a report confirming that flight MH370 may have eventually crashed into the Indian Ocean as fuel ran out after spinning at a low speed over the sea." In this example (Zhao et al. 2021), "October 10", "MH370", "Indian Ocean" and "Fuel Run Out" are entities of the accident time, the flight number, the accident site and the reason, respectively. Since MUC6, entity recognition has experienced explosive growth, which could be seen at the Conference on Natural Language Learning (CONLL) (Sang and Meulder 2003) and International Workshop of the Initiative of the Evaluation of XML Retrieval (IREX) (Demartini et al. 2009). NER is the recognition of entity boundaries from the text of predefined semantic types (person, location, organization, etc.) and classifies them into semantic types. Formally, given a sequence of tokens $< w_1, w_2, \dots w_n >$, NER outputs a tuple $< i_s, i_e, t >$. Here, i_s and i_e are the start and end indices of an NE, and t is the entity type. Figure 1 shows an example where an NER system recognizes two NEs from the given sentence. NER is not only an important tool for information extraction (IE) but it also plays a pivotal role in natural language processing (NLP), such as for understanding text (Tian et al. 2020; Cheng and Erk 2020), information retrieval (Mahalakshmi 2015; Brandsen et al. 2021), intelligent question answering (Cowan et al. 2015; Li et al. 2019), machine translation (Li et al. 2018; Jain et al. 2019), and the construction of a knowledge base and a knowledge graph (Sakor et al. 2019; Nguyen et al. 2021).

NER in aeronautical information intelligence is a comprehensive combination of aeronautical knowledge. Based on a recognized knowledge system in aviation, the standardized coding of aeronautical information (including the basic concept, object, phenomenon,

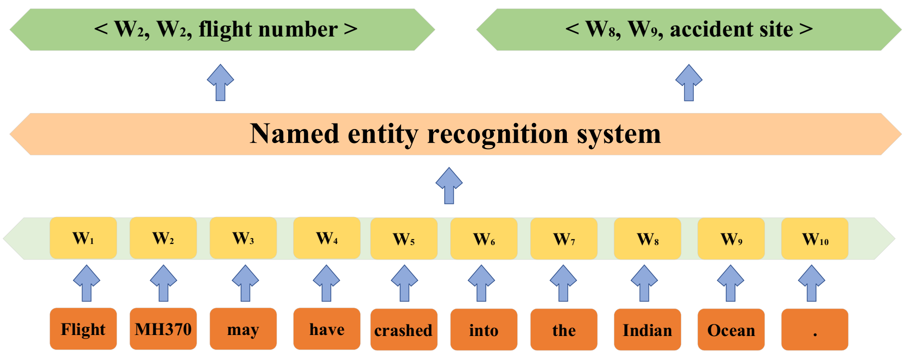

Fig. 1 An example of the named entity recognition task

process, criteria, methods, etc.), as well as the knowledge relationships serve to provide a clear and definite explanation and distinguish the connections between the various types of objects. NER provides standards, forming aeronautical knowledge understood by machines with a flexible visualization method (Qi et al. 2020).

In this survey, we provide an inclusive analysis of the dilemma within the aeronautical intelligence information NER task. Furthermore, we discuss various notable NER approaches in the general, specific and military domains. The approaches are reviewed, and three summaries are provided for the aeronautical intelligence information. Then, the resources referring to the dataset, ontology and evaluation are shown to promote NER development in aeronautical intelligence information. Finally, several improvements, recommendations, and opportunities are suggested to address these limitations, which point to directions for future research. The contributions of this paper are as follows:

- To the best of our knowledge, this is the first paper to provide a comprehensive review of NER in aeronautical intelligence information.
- Through the analysis of approximately 100 papers, the review reveals the problems in NER and proposes solutions.
- The research highlights that the approaches and resources are both substantial in NER and suggests avenues for future research.

The rest of this paper is organized as follows: Sect. 2 discusses the problems that the research faces in this study. Section 3 analyzes the NER approaches in three directions. Section 4 presents an in-depth discussion of the current resources in the research analyses of the KG construction approaches in seven domains. Section 5 proposes two future possibilities for developing NER in aeronautical intelligence information. Section 6 concludes the paper. Additionally, the basic architecture of the paper is shown in Fig. 2.

2 The problems with aeronautical information intelligence NER

At present, NER achieves high accuracy on many common datasets, such as NCBI (Doğan et al. 2014), N^3 (Röder et al. 2014) and NNE (Ringland et al. 2019). However, in specific domains also including aeronautical information intelligence, it is far from meeting the requirements of the NER tasks. After conducting a comprehensive investigation, there are two main problems that urgently need to be solved in NER for aeronautical information intelligence.

There are many technical terms and complex concepts in aeronautical information intelligence. Some examples are as follows:

2.1 Diversity and ambiguity of NE

The diversity and ambiguity of NE in aeronautical information intelligence texts bring great challenges to natural language processing. In different contexts or languages, the denotation of NE is different, which is the fundamental NER problem to be solved. After obtaining a large amount of text data, due to the different granularities of knowledge representation, different confidence levels, lack of normative constraints and other problems, the phenomena of ambiguous designations and diverse representations of NE appear. Because the same entity can be located at different positions in the text, a recognition method based

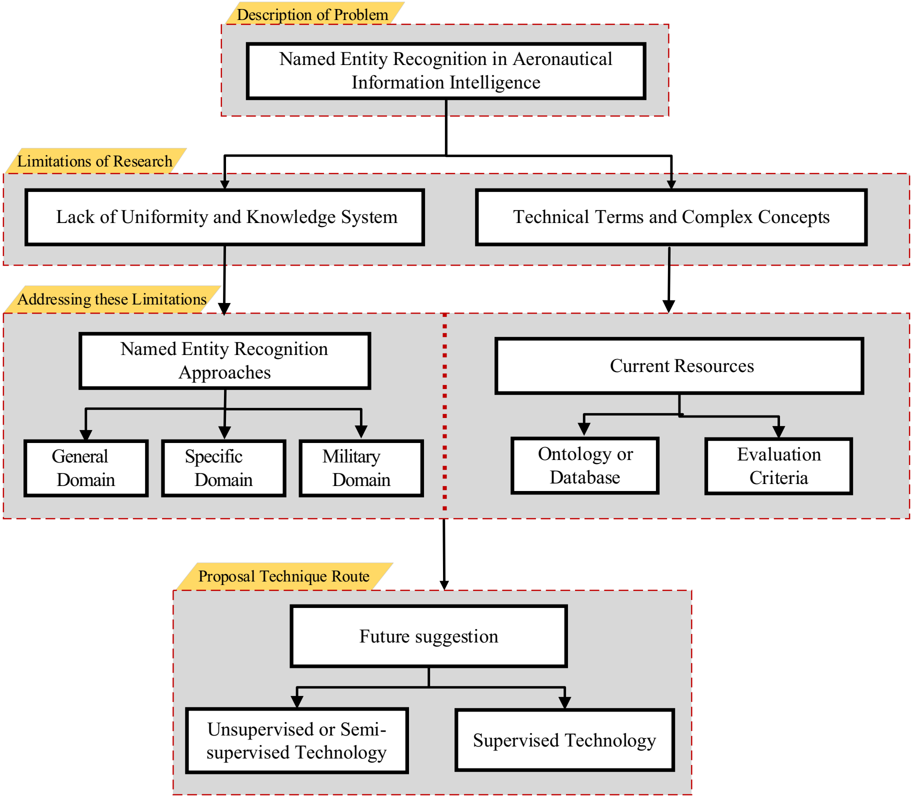

Fig. 2 The basic architecture of the paper

on a single sentence cannot focus on the context of the full text, which leads to inconsistencies in entity labeling. Although the phenomenon is common in most domains, the single alphabet abbreviation is specific in aeronautical information intelligence, which leads to much ambiguity. As shown in Fig. 3, the abbreviation "M" corresponds to two completely

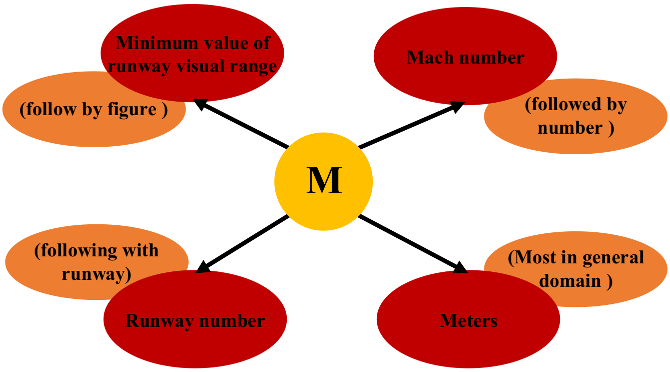

Fig. 3 Example of NE ambiguity

different entities: "Meters", "Mach number", "Runway number" and "Minimum value of runway visual range." This requires that the four entities be represented in different vector dimensions in the recognition process with the corresponding context.

2.2 Complexity and openness of NE

Traditional entity types focus only on a small number of types, such as the name of the person, location or organization. The complexity of an NE in aeronautical information and intelligence is reflected in the complexity of entity types in real data. It is necessary to identify fine-grained entity types and assign NE to more specific entity types. For example, as shown in Fig. 4, due to the complexity of NE types a, "friction coefficient tester" can be used as an instrument, while a "friction coefficient" can be used as a key parameter to recognize the aircraft category, and a nested NE such as this is common in aeronautical information and intelligence, which is mainly due to the lack of strict naming rules in aviation. The openness of an NE means that the content and type of an NE are not permanent and change with time, eventually becoming invalid. Compared with other fields, aeronautical information intelligence knowledge is updated. Thus, acquiring and integrating this knowledge quickly and accurately will be essential. The openness and complexity of an aeronautical NE bring great challenges to entity analysis, which is also an important problem to be solved.

However, due to the constant data updates, technology and methods, as well as aeronautical knowledge enriched by experts, there may be disputes on the classification, definition and method of knowledge, which makes it difficult to complete these tasks. As a result, the lack of aeronautical information resources causes the absence of labeled datasets, making it difficult to directly carry out model training. Because of the lack of a standard aeronautical dictionary, there are some errors in the segmentation of the aeronautical information corpus, which affect the model's performance.

The original knowledge system is described in natural language, which is systematic, scientific and rigorous. It is a common language for practitioners in the field to communicate in. However, its greatest limitation is that it cannot be understood and recognized by the machine. Therefore, we must refer to the domain database or ontology model to generate the knowledge system that can be understood by the machine. An ontology or database model can clearly express the basic concept of NER. As shown in Fig. 5, the relationship between the database model or the ontology, the knowledge system and NER are described. Database models or ontologies include professional vocabulary and basic knowledge points in the field. A knowledge system is a scientific, complete and systematic description of knowledge points and related relationships. NE normalizes the knowledge system to form a language that can be understood by machines.

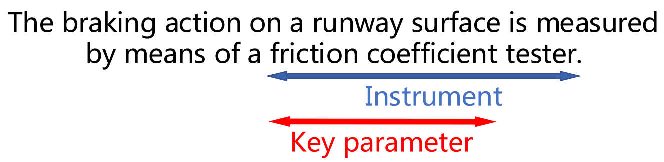

Fig. 4 Example of NE complexity

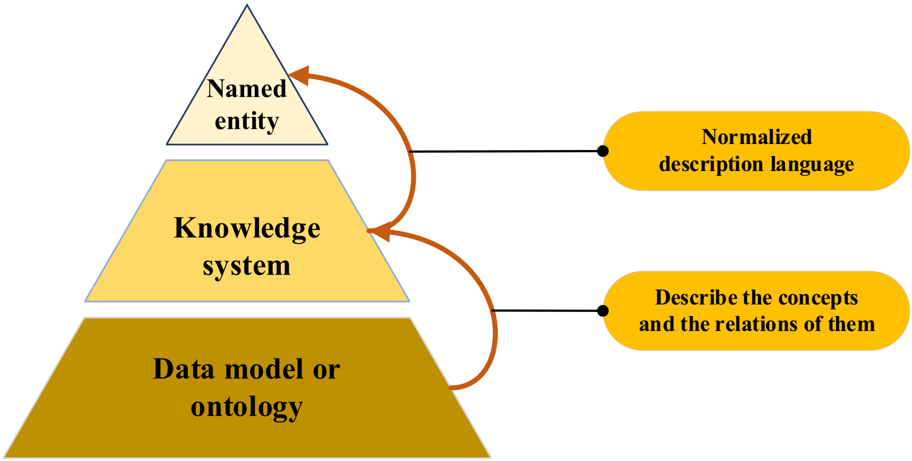

Fig. 5 The relationship among the ontology, the knowledge system and the NE

3 NER approaches

After years of development, NER in the general domain has formed a relatively mature system, but in specific domains of NER, the task is restricted to NE characteristics, such as complexity and diversity, and there is a scarcity of nested and corpus resources. The results of the direct transplantation of methods in the general domain to a specific domain are not desirable, especially for this paper. Reviewing the previous paper reveals that there are almost no relevant methods of research in aeronautical information intelligence. For specific domains, as shown in Fig. 6, research on NER methods has begun to take shape in the biomedical domain, but this domain is larger than aeronautical information intelligence. In addition, NER in the military domain has developed, and there are some familiarities

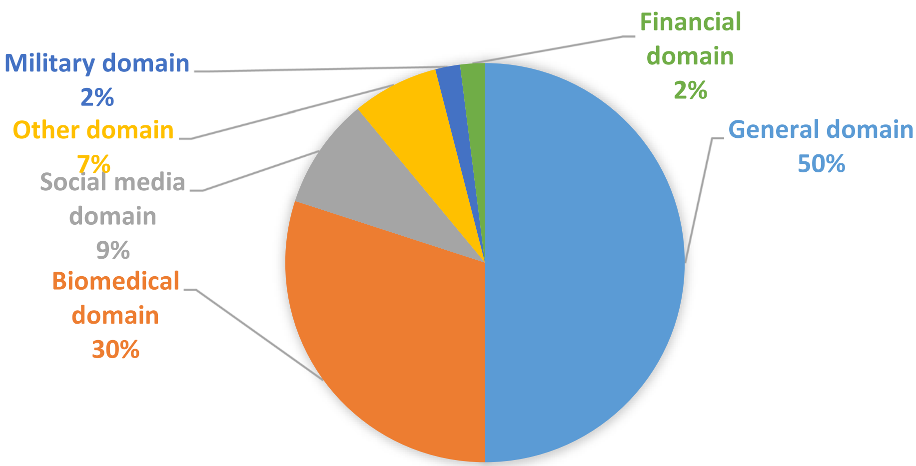

Fig. 6 NER task domain proportions

between military and aviation. Even the NE in the military domain can be directly applied to aeronautical information intelligence for the following reason. The knowledge system and the ontology between the two domains are extremely similar. Aeronautical information intelligence can usually be classified as civil aviation and military aviation. Thus, military information about aircrafts accounts for a large part of aeronautical information intelligence. Therefore, this section analyzes the issue from three perspectives.

3.1 The NER system in the general domain

As shown in Fig. 7, NER methods in the general domain have evolved from early methods based on dictionaries and rules to methods based on statistical models to current methods based on deep learning.

3.1.1 The rules and dictionaries approach

The rules approached by experts involving the linguistic structure rule template and the prescribed rules can be based on the domain expert and combined with a dictionary for NER to improve the accuracy of the entity recognition (Sakor et al. 2019). Often, these dictionaries can be realized through Python crawler technology to utilize the internet, such as for obtaining name dictionaries, gazetteers, institution dictionaries and other dictionaries. Famous rule-based NER systems include Lasie-II (Ringland et al. 2019), NetOWL (Krupka and IsoQuest 2005) and Facile (Black et al. 1998). In general, the rule-based and dictionary-based approach relies too much on text and semantic style. At the same time, the portability of NER systems based on rules and dictionaries is poor, and they often need to reformulate rules or construct domain dictionaries when facing different domains each time. A high accuracy and recall rate can be obtained on small datasets, but with an increasing data volume, the periodicity of system construction becomes longer.

3.1.2 The statistical model approach

In the statistical model approach, NER could be seen as more than a classification and sequence annotation problem. Additionally, the classification of the general difference of sequence annotation in the current label also needs to consider the current input features and those previously predicted. For a given annotation dataset, feature definition can be used to represent each training sample, and then by using the model of a machine learning algorithm, similar features can be used to recognize the unknown dataset.

Bikel et al. (1999) proposed an NER system based on hidden Markov models (HMMs) for the first time, which was used to recognize and classify names, dates, times, etc. The HMM directly modeled the transition probability and expression probability, and then calculated the co-occurrence probability. Borthwick et al. (1998) proposed the maximum

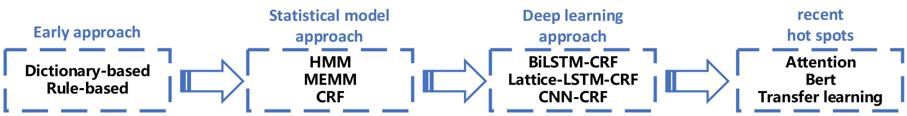

Fig. 7 The NER technology research development trend in the general domain

entropy named entity (MENE) using the maximum entropy theory, and the MENE was able to utilize diverse knowledge sources when making labeling decisions. McNamee and Mayfield (2002) used 1000 language-related features to train a support vector machine (SVM) classification model; the SVM did not consider "proximity" words when predicting entity tags. McCallum and Li (2003) proposed an NER method based on the feature induction of conditional random fields (CRFs). In traditional machine learning, CRF is regarded as the mainstream model of NER. The advantage is that CRF can make use of internal and contextual feature information in the process of labeling a location.

3.1.3 Deep learning approach

In the last few years, deep learning-based models have become the mainstream of natural language processing and have achieved good results. Compared with feature-based statistical model approaches, deep learning-based approaches more easily discover hidden features. The NER methods based on deep learning are generally divided into three stages (Li et al. 2020), as shown in Fig. 8 below.

First, distributed representations map words or characters into low-dimensional real-valued dense vectors, where each dimension represents a potential feature. There are three types of distributed representations: word embedding, character embedding, and

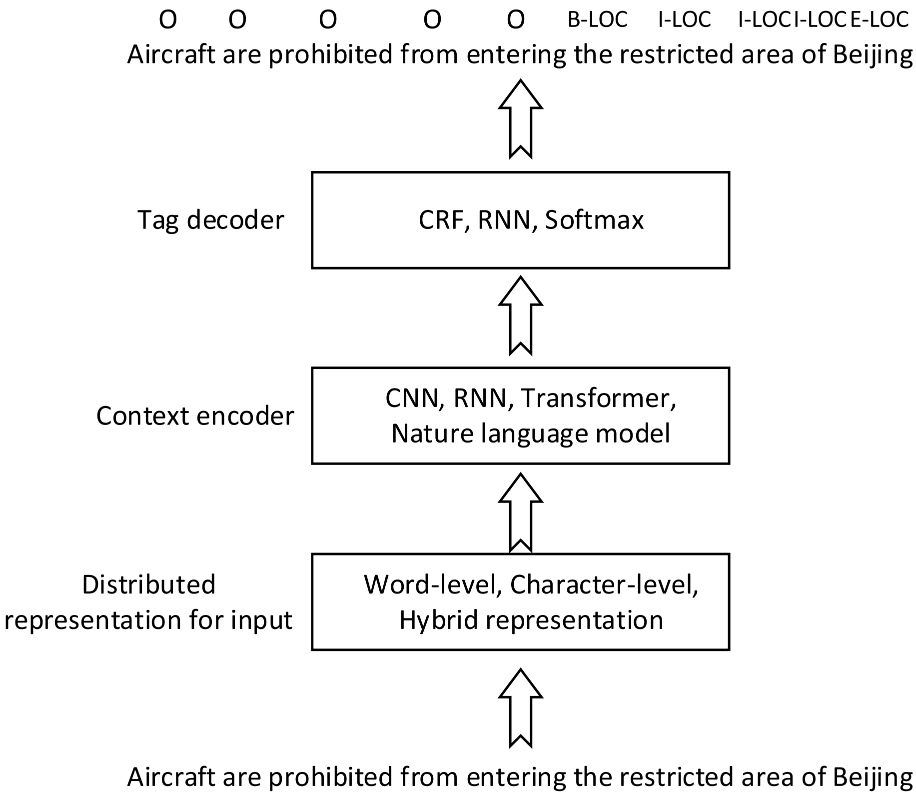

Fig. 8 Deep learning-based NER architecture

hybrid representations. Word embedding (Nguyen et al. 2016; Zheng et al. 2017) is usually pretrained by unsupervised algorithms (such as a continuous bag of words (CBoWs)) on large text sets. Commonly used word embedding methods include Google Word2Vec, Stanford GloVe, and Facebook FastText. The character embedding (Kuru et al. 2016; Tran et al. 2017) can be used to obtain information, such as prefixes and suffixes that cannot be extracted from the word vector and can deal with problems outside the dictionary. Common character embedding frameworks include convolutional neural networks (CNN) (Ma and Hovy 2016) and recurrent neural network (RNN) (Li et al. 2017) models. Bharadwaj et al. (2016) composed type-level word representations with bidirectional LSTMs to obtain token-level (cognizant of sentential context) representations. Rei et al. (2016) applied an attention mechanism to dynamically decide how much information to use from a character- or word-level component in an end-to-end NER model. Hybrid representations incorporate information, such as a gazetteer (Liu et al. 2019), a thesaurus (Ghaddar and Langlais 2018), and visual features (Lu et al. 2018) into the final representation. It is worth noting that Devlin et al. (Devlin et al. 2018) proposed a new language representation model known as bidirectional encoder representation from transformers (BERT), which could be trained in advance by jointly adjusting the context in all layers.

Second, context encoders usually adopt CNNs, RNNs and transform models to capture the context dependence of input data. CNN context encoders usually adopt a network that considers the whole sentence and can accurately extract local features in the sentence (Collobert et al. 2011). RNN contextual encoders usually consider the relationship between the characters in the sentence. Popular structures include gated recurrent units (GRUs) (Huang et al. 2015) and long short-term memory (LSTM) (Yang et al. 2016). In addition, Zukov-Gregoric et al. (2017) explored the self-attention mechanism in NER, where the weights were dependent on a single sequence. Vaswani et al. (2017) proposed that transformers could be completely separated from CNNs and RNNs.

As the final stage of NER, the tag decoder takes the context-dependent representation as input to generate the corresponding tag sequence. Common structural models of tag decoders include three types: multilayer perceptron + softmax, CRF and RNN. As an early tag decoder layer, the multilayer perceptron + softmax (Li et al. 2017; Xu et al. 2017) subtly transforms the sequential labeling problem into a multiclass classification problem, where each word is independent of its neighboring words to predict the context representation. CRF is a sequence labeling model that fully considers the relationship between tags under global conditions (Lafferty et al. 2001). At present, CRF has been widely used in context decoders. For example, in the Bi-LSTM layer (Peters et al. 2018; Lin et al. 2019) and in the CNN layer (Strubell et al. 2017; Yao et al. 2015), the constraint relationship between tags can be effectively established, and the accuracy of the model can be improved. Shen et al. (2017) proposed that the performance of a tag decoder based on an RNN was better than that of a CRF, especially when the entity type volume was large, and the training speed of the RNN tag decoder was faster.

In summary, external knowledge is usually fed into the input layer to boost the NER performance. Especially in a specific domain, prior knowledge is more important for helping the input layer capture more features. In the encoder, the deep learning Bi-LSTM model is the most popular. However, the transform is more effective than LSTM when it is pretrained on a large corpus. Nevertheless, the transformer encoder is faster than recursive layers when the length of the sequence n is small enough. CRF is the most common choice for tag decoders. CRF is powerful for capturing label transition dependencies when adopting nonlanguage-model embeddings, such as Word2vec and GloVe. For the aeronautical intelligence information domain, the model to choose is data and domain task dependent. If data is abundant, training models with RNNs from scratch and fine-tuning contextualized language models could be considered. However, data is sparse in this domain, and fine-tuning general-purpose contextualized language models with domain-specific data is often an effective method.

3.2 NER system in a specific domain

The approaches based on rules and dictionaries, statistical models and deep learning have achieved remarkable results in the general corpus. However, in specific domains, especially in the aeronautical information intelligence field studied in this paper, there are general problems due to a lack of resources and a small number of annotations, and the NER task cannot be solved well. From the perspective of transfer learning (Lee et al. 2017), corresponding solutions from the biomedicine, social media and chemistry domains are given. The similarity between the transfer learning field is cleverly applied to build up the data sharing between different domains and the shared channel model since, a specific domain can provide the theoretical basis for an NER task. From the perspective of transfer learning, NER methods for specific domains, including aeronautical information intelligence, can usually include four methods based on data enhancement, transfer models, feature transformation and knowledge links.

3.2.1 Data enhancement

The data enhancement approach (Dai et al. 2007) uses old data to build a high-quality classification model for new data when a small amount of labeled new data is obtained. Even if the new data is not sufficient to train the model alone, the data enhancement approach allows knowledge to be effectively transferred from the old data to the new data, and the iterative algorithm can converge well to an accurate model. Specifically, there are three methods. The first method is synonym substitution. Zhang et al. (2015) used synonym substitution retrieved from a thesaurus (such as WordNet). Kobayashi (2018) used linguistic models to predict other word substitutions. Wei and Zou (2019) randomly selected two words in a sentence to exchange their corresponding positions, thus achieving the purpose of expanding the training set of text classification. Second, Min et al. (2020) attempted to use syntactic conversion (e.g., subject/object inversion) to increase the training data of natural language reasoning. Sahin and Steedman (2019) synthesized new sentences around a dependency tree to expand the training dataset with low resources and few annotations. Third, a translation model is adopted to map high-resource data to low-resource data. Yu et al. (2018) trained a question–answer model by using the data generated by a neural network machine translation model in reverse translation. Xia et al. (2019) used bilingual dictionaries and unsupervised machine translation models to convert data from high-resource languages to low-resource languages, and extended the machine-translation training datasets of low-resource languages.

3.2.2 Transfer model

The transfer model approach is also known as transfer modeling based on the parameter learning method; its core idea is shown in Fig. 9. It uses the similarity between the target domain and the source domain. Their correlation, the source domain characteristic parameter, or the distributed neural network model of the transfer part to the target model

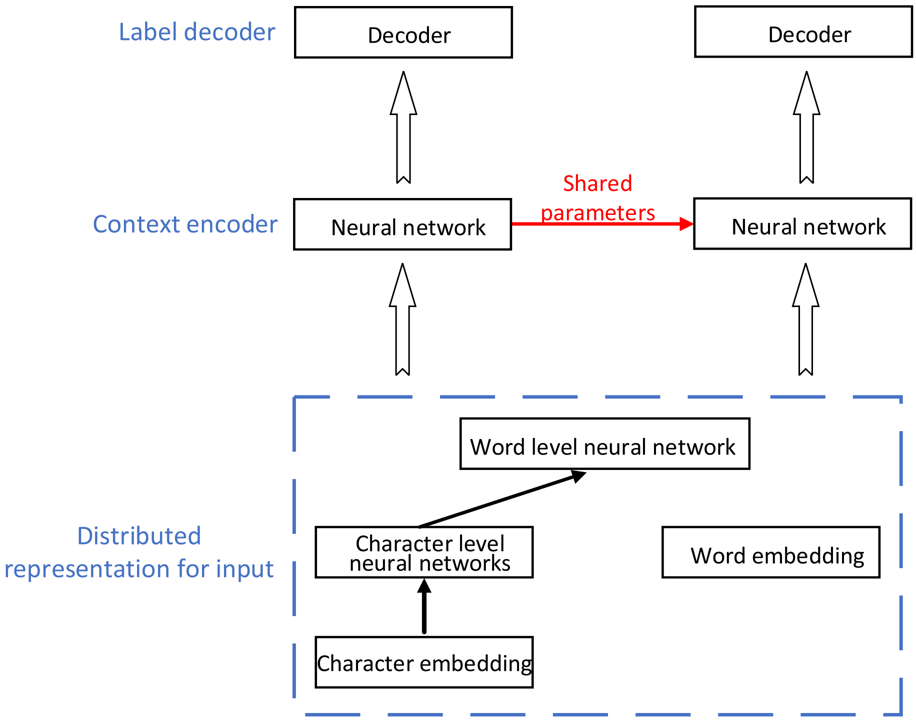

Fig. 9 NER architecture based on the transfer model

adaptively adjusts model features (Yang et al. 2017). The NER approach based on a transfer model was developed from the most classic models, such as Word2Vec and GloVe. Wang et al. (2018a) realized the NER task across medical fields by using tag perception. Lin and Liu (2018) introduced an adaptation mechanism between the context encoder layer of LSTM and the tag decoding layer of CRF to bridge the gap between the two layers. Subsequently, the embedding from language models (ELMO) model was proposed by Peters et al. (2018), which referred to the given context information to solve the polysemy problem often encountered in traditional word embedding models to a certain extent. In the last few years, the BERT model (Devlin et al. 2018) proposed by Google has more fully and effectively solved the problem of correspondence between meaning and words, and the bidirectional transformer structure (Zukov-Gregoric et al. 2017) used in this model could effectively capture semantic information.

3.2.3 Feature transformation

From the perspective of a transfer model, it is effective to solve NER tasks with low resources and few annotations. However, for a large domain span, the model's ability to grasp domain span information is not satisfactory. Therefore, the method based on feature transformation is a learning process to reduce the differences between domains by transferring features to each other or mapping data features of the source domain and the target domain to a unified feature space (Pan et al. 2010). (Evgeniou and Pontil 2007) proposed a sparse feature learning multitask learning method. First, a first-order regularized sparse representation is solved in a low-dimensional space, and then several tasks are combined to learn the sparse representation. Dai et al. (2008) proposed an unsupervised transfer learning method called STC, which minimizes information entropy as a constraint and uses iterative optimization to divide the target domain data through untagged data in the source domain. Long et al. (2014) proposed the transfer joint matching (TJM) algorithm by combining feature-based and case-based transfer learning methods to minimize the distribution distance between the source domain and the target domain.

3.2.4 Knowledge link

NER based on a knowledge link (Fries et al. 2017) assumes that there is a correlation and similarity between the data of the source domain and target domain, and knowledge transfer is realized by referring to the mapping of the relational model of the structured data model in the ontology or database and the data of the target domain (Torrey and Shavlik 2010). In essence, models supplement annotated entities with ontologies or databases. In the distant supervision sector (as shown in Fig. 10), Lee et al. (2016) completed the annotation of entities by matching and integrating text information and an entity dictionary, and then improved the annotation task of a small number of annotated datasets with active learning. The resulting model further realized the refinement of the corpus. In addition, Mihalkova et al. (2007) explored the law of the source domain structure based on the Markov logic form, and successfully realized knowledge transfer in the fields of molecular biology and social media.

In the NER task of a specific domain, the most direct and simple method is data enhancement, and its accuracy is high. However, the selection of its measurement criteria is too dependent on experience and requires a certain cost for data annotation. Due to the lack of universality between different fields or even the requirement of one method in one

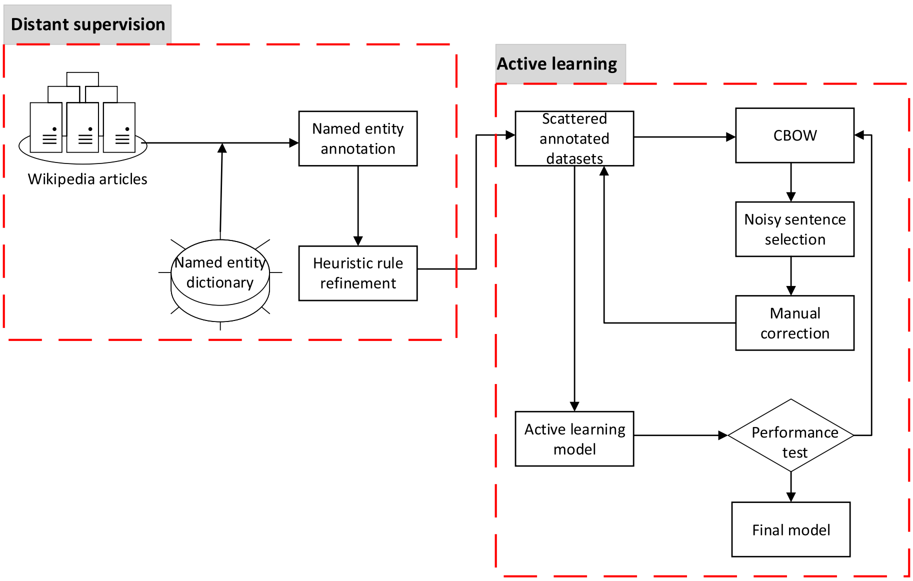

Fig. 10 NER architecture based on a knowledge link

field, the transfer model is currently the most widely used method in specific domains. The transfer model requires a small data sample size for the target domain, but the gap between the source domain and the target domain should not be too large; otherwise, divergence is likely to occur when neural network parameters are shared. The method based on feature transfer can make full use of feature information and even realize zero-shot learning, but the disadvantage is that the problem of adaptation easily occurs. A knowledge link is more effective on large-scale data because it relies too much on ontology and databases, and the construction of domain ontology and databases is not perfect; it is difficult for this method to meet the task of specific-domain NER.

In summary, the four approaches for NER in a specific domain are compared in Table 1. The most direct method is data enhancement. By preferentially selecting high-quality samples to participate in training, this method can achieve high accuracy in a specific domain. However, the strategies required for different domains are also different. Model transfer obtains knowledge from massive unstructured text. This method requires less data in the target domain. It only needs to "fine tune" the model to avoid the huge cost of retraining. However, it depends on the strong correlation of the domain. Compared with the model transfer, the feature transform pays more attention to fine-grained knowledge representation. This method uses feature reorganization and mapping to enrich feature representation, reduce the loss in knowledge transfer, and can realize "zero-shot" learning to a certain extent. However, this method often has difficulty finding the optimal solution. A knowledge link can use any structured information to extract the target entity through the semantic relationship in the knowledge base and the ontology base. However, this method is prone to noise. The mapping and matching of entities depend on strong assumptions, and the required knowledge base usually has difficulty meeting the extraction of domain entities.

3.3 NER system in the military domain

Military NER systems also face the same problem of having started late as the aeronautical information intelligence domain. At present, compared with the methods used in specific domains in Sect. 3.2, it is simpler to reuse the traditional methods in general fields in Sect. 3.1. Table 1 lists the works related to military NER systems in the last few years. As shown in Table 2, most of the literature was published in the last three years.

Additionally, in the military domain, the research methods gradually change from the dictionary and rule method to the statistical machine learning method and to the deep learning method. Early learning includes models based on statistical machine learning, mainly SVM and CRF. However, these traditional models cannot dispose of the NER task in the military domain. Therefore, military rules, grammatical features and the dictionary are combined with the statistical model to pursue better performance. With the development of NLP technology, deep learning models have achieved better performance than traditional statistical models. More importantly, a deep learning model can also be combined with a statistical model, which can not only capture the features from the statistical model but also obtain a higher result. The Bi-LSTM + CRF model, as the most classic model, has been widely applied in military NER systems and achieves excellent performance. The attention mechanism is also applied to capture features at the encoder level. Recently, with NLP technology prosperity, in the pretraining layer, an increasing number of studies have preferred to propose BERT as embedding. BERT uses a transformer as a feature extractor to fully learn contextual features and can better model polysemous words. Compared with the traditional LSTM extraction structure, the experimental results have been considerably

Table 1 Comparison of NER in specific domains

Approach	Data requirement	Advantage	Disadvantages
Data enhancement	A small amount of target annotation data and domain related annotation/no annotation data	Simple and accurate	Experience for the selection of measurement and a certain annotation cost
Transfer model	A small amount of target annotation data and domain related annotation	Training with less cost and good robustness	Difficult convergence and disposal of inconsistent data distribution
Feature transform	A small amount of target annotation data, some domain related annotation data and some raw corpora	Making full use of feature information and partially zero-shot learning	Optimization problem and over adaptation
Knowledge link	Any available structured data	Capable of handling large-scale data	Relying on strong assumptions, knowledge base noise and low accuracy

Table 2 Literature on military NER systems

No	Reference	Description	Entity Category	F1 Score (%)
1	Wen-zhi Jiang et al. (2011)	Composing the CRF model and Rule-based (with an external lexicon feature added and rules) method	person, location and organization	98.59
2	Yuntian Feng et al. (2015)	Established an efficient feature set according to the grammatical features of military text, builds the CRF model to identify the military NE and develops the method based on dictionary and method based on rules	rank, weapon, facility, organization and supply	90.90
3	Xuefeng, Wang et al. (2018b)	Using the Bi-LSTM and the CRF model to automatically extract text features based on character embedding and then identifying military NE	force, location, organization, weapon, facility, time, environment and quantity	96.00
4	Xuefeng Wang et al. (2018c)	Combining Bi-LSTM neural network's ability to remember long sentence context, the ability of character embedding to express Chinese characters and the ability of the attention mechanism to learn the correlation between input and output	affiliation, strengthen, support, deploy, route, friendly neighbor, enemy, alliance, neutral, parallel, own and target	89.00
5	Yiwei Lu et al. (2019)	Constructing an authoritative dictionary in the military field, and taking advantage of the BiLSTM neural network in dealing with the wide range of contextual information	force, organization, facilities, location, weapons, environment, services and arms, rank, position, direction, active, pre-time, outtime and number	73.90
6	Fei Liao et al. (2019)	Employing a BiLSTM neural network with a self-attention mechanism to identify the military entities automatically	weapon, location, organization and mission	89.34
7	Hao Qin et al. (2020)	Integrating with BERT-BiLSTM-CRF, to test on the People's Daily dataset and text data from military news	place, people and institution	91.73
8	Ruijuan Hu et al. (2020)	By mining Wikipedia corpus, we construct a pattern base, and iteratively find the coreference relationship in text based on the pattern, before finally using the BiLSTM + CRF model of the neural network to realize NER in military field	person, place, organization, aircraft, warship	94.30

Table 2 (continued)

No	Reference	Description	Entity Category	F1 Score (%)
9	Han Xinxin et al. (2020)	Aiming at the problem that the character and word joint entity recognition method has low recognition precision, the character level feature extraction method is improved, as well as the CWA- BiLSTM-CRF recognition framework	software level, test phase, test level, test activity, test sort, test method, test document, tester, test tool, quality characteristic	88.93
10	Xuezhen Yin et al. (2020)	Adopting an entity labeling strategy that includes the effects of fuzzy entity boundaries and a military-oriented corpus, and combing domain expert knowledge, then building a BERT Bi-LSTM CRF model	person, location, time, organization, facility, weapon, event and rank	84.07
11	Yiwei Lu et al. (2020)	Constructing the BERT Bi-LSTM CRF model to a military NER task, based on a pretraining language model, taking advantage of Bi-LSTM in dealing with the wide range of contextual information	force, organization, weapons, facilities, location, environment and services	91.70
12	Liguo Yao et al. (2020)	Attempting a novel Chinese fine-grained NER method based on symmetry lightweight deep multinetwork collaboration (ALBERT-AttBiLSTM-CRF) and model transfer considering active learning to research fine-grained NER of a few labeled Chinese textual data types	model, part, parameter, shape, function, material and structure	89.62
13	Chenguang Liu et al. (2021)	Automatically identifying weaponry equipment by a NER algorithm, Bi-LSTM CRF, thereby demonstrating the effectiveness of domain features in domain-specific entity recognition	place, time and weapons	93.88
14	Yuan Gong et al. (2021)	Proposing a method based on several basic models fine-tuned by BERT on the training data. Applying a two-level fusion strategy to the prediction results of multiple basic models to reduce the overfitting problem. The labeling errors are eliminated by postprocessing	test elements, performance indicators, system components and task scenarios	72.03

Table 2 (continued)

No	Reference	Description	Entity Category	F1 Score (%)
15	Yu and Wei (2020)	Proposing an entity recognition method based on character embedding, Iterated Dilated Convolutional Neural Networks and Conditional Random Fields	weapons and organizations	94.30

improved, but the network structure of BERT is more complicated and has more layers, and thus, the time and space cost of the model is high.

4 Resources available for aeronautical information intelligence NER

In addition to the NER approach, resources are also essential for the NER task in the aeronautical information intelligence domain. Common resources include databases or ontologies and evaluations. This section focuses on the two main resources.

4.1 The aeronautical information intelligence ontology and database

The domain database refers to the warehouse that organizes and manages data according to the specific data structure of the professional domain. It provides the connection between entities in a certain specific domain and plays a leading role in combining theories in this field. After decades of continuous construction, many data-centric aviation professional databases have been built worldwide, including comprehensive data centers and thematic databases of specific aeronautical branches. This section introduces four more specialized databases.

The NASA Air Traffic Management Data Integration System (Keller 2015, 2016; Cowell et al. 2015) is a prototype data integration system developed by the National Aeronautics and Space Administration (NASA). As shown in Fig. 11, the system can query and search various sources of heterogeneous air traffic management (ATM) data, including data from the Federal Aviation Administration (FAA), National Oceanic and

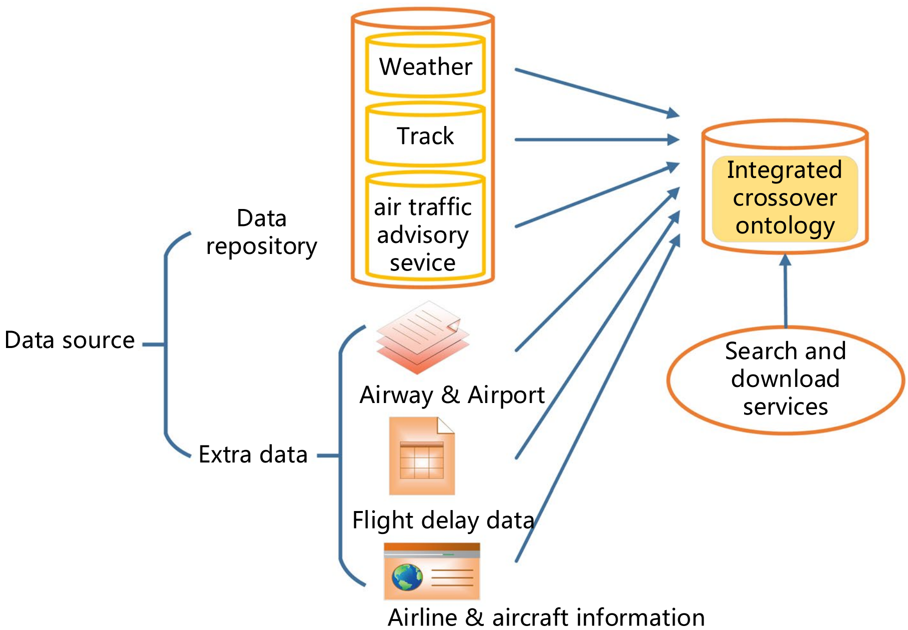

Fig. 11 NASA air traffic management data integration system architecture

Atmospheric Administration (NOAA), NASA, etc. The overall data model covers the backbone of data from multiple sources, and the coverage is wide enough to interconnect data from different branches in aviation, including flight, air traffic management, aeronautical intelligence, aeronautical meteorology and airline operations. Representative types of ontology modeling include flights (flight plans and radar flight trajectories); aircraft and manufacturers (aircraft characteristics and models); airports and infrastructure (runways, taxiways, terminals and gates); airlines; airspace system facilities (air traffic control system command center, route air traffic control center, terminal radar approach control center and tower); air traffic management plan (ground delay plan, route change); ground weather conditions and forecasts (meteorological conditions, aviation routine weather reports, terminal airport weather forecasts); airspace composition (sectors, fixed points, routes and routes); and arrival and departure routes.

The FAA Information Management System (Cowell et al. 2015) standardizes the terminology used in FAA documents, thereby facilitating document search and document querying, and ultimately improving decision-making. As a database in aviation, the system provides a broad conceptual framework under which more specific concepts can be constructed (Gangemi et al. 2002; Mascardi et al. 2007; Gringinger 2014) and focuses on concepts related to FAA organizational functions, including the following large categories of entities: people with different identities in different organizations; air transportation activities (design, planning, supervision, evaluation and execution); resources (financial, human, information and material resources); means of transportation (aircraft, land vehicles, spacecraft and ships); aircraft systems; and rules, procedures and legislative authorization.

Notice to air man (NOTAM) is issued to pilots to establish or alter flight procedures, airport facilities, flight services or other potential operational hazards. As part of the flight plan and the preflight briefing process, pilots must review all NOTAM related to their documented flight paths. The Semantic Annotation System (SemNOTAM) is shown in Fig. 12 (Burgstaller et al. 2015; Tanguy et al. 2016) to mark the time, space, equipment and operating conditions. This system uses NOTAM annotation rules to narrow the scope of the pilot briefing package and filters out NOTAM that is irrelevant to a specific flight.

The ASRS (North American Accident Reporting Database) (Lucia 2001) and the ECCAIRS (European Coordinating Centre for Accident and Accident Reporting Systems) (Wilkinson et al. 2016) are two of the most widely used systems for managing accident reporting at different levels among airlines, government and nongovernmental organizations. The ASRS is responsible for the collection of US aviation incident reports from sources used for maintenance, policy development and training, including reports from pilots, air traffic controllers, flight crews, dispatchers, maintenance technicians, ground personnel and other personnel involved in aviation operations. Conventional ASRS reports consist of specific entities or narrative fields and sets of attributes. Each submission has multiple narrative fields corresponding to the event report, describing detailed data for a given time, wind speed, cloud cover, location and aircraft type. The entity primarily responsible for collecting aviation accident reports in Europe collects, shares and analyzes safety data and works to improve transport safety. The information is freely available to researchers and others.

The abovementioned databases greatly promote the sharing of aeronautical information intelligence worldwide, and they provide a large amount of effective information for day-to-day aeronautical activities. For aeronautical information intelligence NER, on the one hand, aviation databases provide recognition tasks with better data sources, in addition to the data in the database structure's characteristics. Additionally, it can provide references

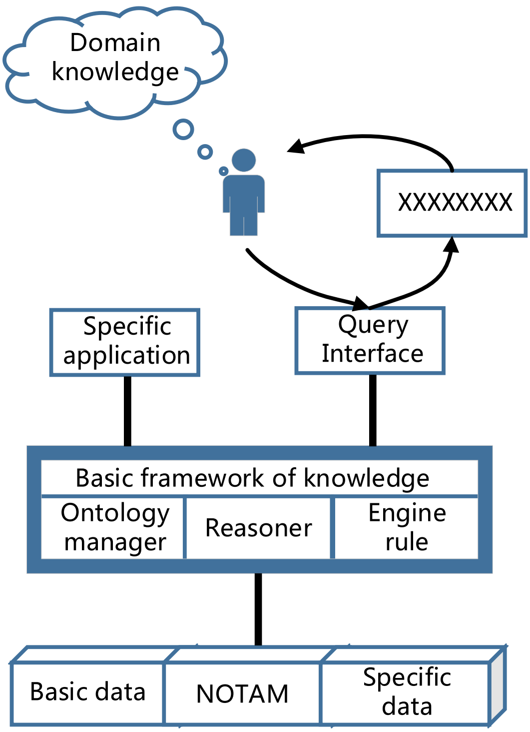

Fig. 12 Semantic NOTAM system architecture

for the classification of the entity recognition process. As shown in Table 3, the main database is summarized with a simple description and main entity.

However, the database construction standards and specifications are not uniform, their sharing mechanisms are different, and semantic heterogeneity is serious. Therefore, when large-scale data integration, sharing and fusion tasks, such as name entity recognition are completed, data in aviation databases are difficult to utilize directly. In addition, the aeronautical information intelligence includes large amounts of data in a table or in other forms that have appeared in aeronautical journal articles and also form a massive project dataset. This kind of data needs to be extracted from the text, tables and pictures of papers, to ensure the accuracy and completeness of NER tasks. This data needs to be considered by means of a web crawler for data integration work.

4.2 Evaluation criteria

The evaluation of system performance is a very essential step for the NER task. By evaluating the system, we can objectively analyze the advantages and disadvantages of the NER system, and then improve it properly. The performance of an NER system for rule, statistics and deep learning models is evaluated by comparing the output with manual annotations. Three common metrics are: Precision, Recall, and F1 score.

Precision: Precision refers to the ratio of the number of correctly classified samples to the total number of samples for a given dataset. This can be calculated as follows:

Table 3 Database for aeronautical intelligence information

Database	Simple description	Main entity
NASA Air Traffic Management Data Integration System	A prototype data integration system developed by NASA	flight, aircraft, manufacture, airport, infrastructure, airline, facility, plan, weather, airspace and route
FAA Information Management System	A terminology set used in the FAA documents	organization, air transportation activity, resource, mean, air system, rule, procedure and legislation authorization
Semantic NOTAM system	Annotation rules to narrow the scope of the pilot briefing package and filter out NOTAM irrelevant to a specific flight	flight, time, airport, accident, weather, equipment, information zone and procedure
ASRS and ECCAIRS system	Systems for managing accident reporting at different levels	accident, maintenance information, policy, time, wind speed, cloud cover, location and aircraft type

$$Precision = \frac{TP + TN}{TP + FN + FP + TN}$$

where TP refers to the entity returned by the NER task that also appears in the manual annotation.

TN refers to an entity that is not returned by the NER task, but it appears in the manual annotation.

FP refers to an entity returned by the NER task that does not appear in the manual annotation.

Recall: This is used to describe the ratio of positive cases determined to be true to the total positive cases in the classifier. The recall can be calculated as follows:

$$Recall = \frac{TP}{TP + FN}$$

F1 is the harmonic average index of the precision rate and the recall rate, and it is a comprehensive index to balance the influence of the precision rate and the recall rate. It can be calculated as follows:

$$\frac{1}{F1} = \frac{1}{Precision} + \frac{1}{Recall}$$

It is worth noting that with different purposes, there are two F1 scores, the macro average F1 and the micro average F1. The calculation of the macro average F1 score requires statistical values for each class and arithmetic mean values for all classes. However, the micro-average F1 score calculation method is designed to establish a global obfuscation matrix for every instance in the dataset, regardless of category, and then to calculate the corresponding metrics.

5 Future trends

Future aeronautical information intelligence NER tasks will originate from the general domain through the mature method of effective experience in combination with the current methods in the specific domains of the military. Specifically, new technical methods in the field of exploration can be derived from two ideas: labor costs for a specific entity tagging the NER task (supervised learning technology), and using the thinking of transfer learning under the condition of a small number of annotation recognition tasks (unsupervised learning or semi-supervised learning technology).

Undoubtedly, supervised learning will be the mainstream in NER for aeronautical intelligence information. However, datasets or ontology and deep learning models are also important to it. There is no unified standard for entity classification in the aeronautical intelligence information domain. Ontology can provide annotators with the criteria, which is detrimental to resources. However, a more comprehensive deep learning model is also needed. Compared with the traditional machine learning approach, the deep learning model can automatically mine the hidden features and dispose of the complex and diverse entities in the aeronautical intelligence inform domain. A supervised method architecture is shown in Fig. 13. After a comparison of the existing artificial tagging of the NE and the aeronautical dictionary by a certain proportion in the test data and in the training datasets, the process continues after the recognition of

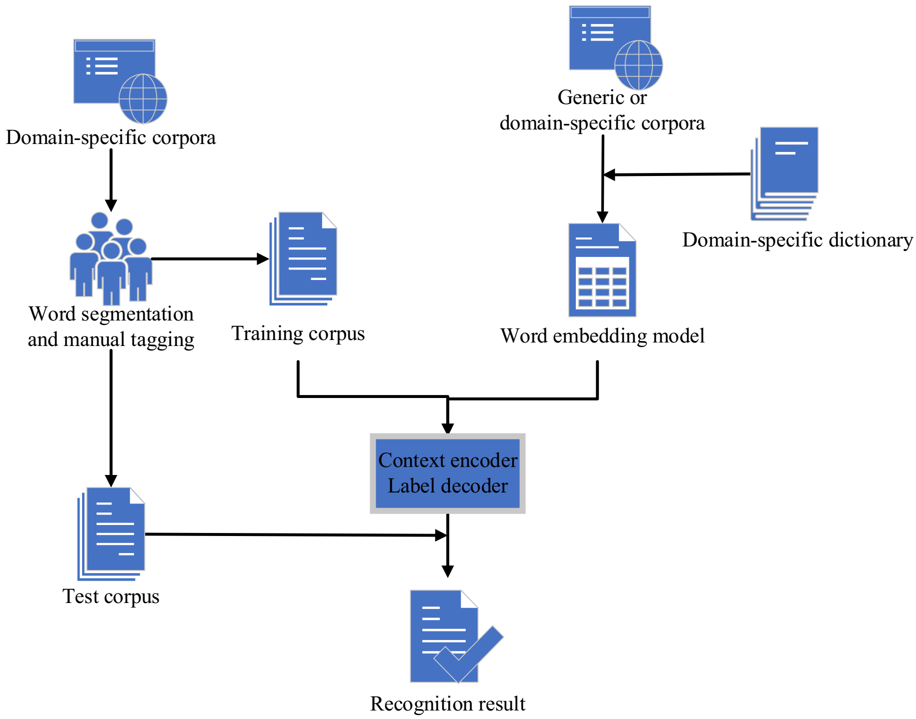

Fig. 13 NER method with manually annotated data

corpora is transformed into word embedding and is input into the neural network in the context encoder and tag decoder. After decoding, the final recognition results are obtained.

However, in the aeronautical intelligence information domain, there is a lack of datasets. Most data is from the internet, with a fast update speed and a large volume. Thus, it is difficult to obtain an accurate and practical training set, which greatly limits the performance of the supervised learning method. In the future, the application of unsupervised or semi-supervised technology should be explored. Such techniques, including data enhancement, transfer modeling, feature transformation and knowledge linking can leverage context patterns and have been quite successful in open named-entity extraction tasks. There is a semi-supervised learning technique provided in Fig. 14. In the training module, the unmarked or less marked aeronautical information intelligence corpus control dictionary is annotated manually via distant supervision, and the automatic annotated data is taken as the training dataset to obtain parameters from the training section, and are then passed into the test module. In the test section, the recognition model of the text dataset by the pretraining model will retain the strong semantic characteristics obtained from the semantic vector. After a certain amount of data and processing are introduced to the context code and the tag decoding neural network or the statistical model, the model parameters are selected, the training section is employed, and the test results are finally obtained.

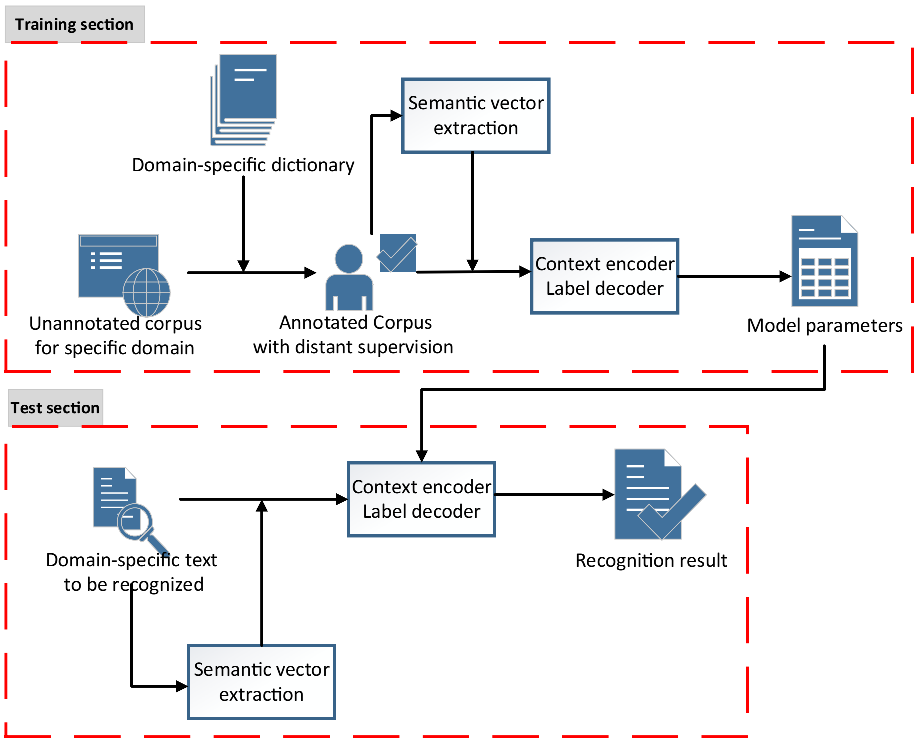

Fig. 14 NER method with annotated data scarcity

6 Conclusions

NER is an important step in the application of natural language processing. It not only detects the boundary of entities but also detects the type of an NE, which is the basis of understanding the meaning of the text. In this paper, the difficulties in the NER of aeronautical information intelligence, including the lack of unity, the lack of NE to establish a system of knowledge expression diversity and ambiguity, and the complexity and openness of NE are discussed. Then, from the aeronautical database, the problem of the data sources before NER is expounded. Finally, from the general, specific and military domain in the NER system, methods are inspired by the key technologies involved in the future development of aeronautical information intelligence and evaluation indices. With big data in the internet world, aeronautical information intelligence can implement digital and centralized data instead of isolated and scattered data to establish the concept of e-data, and thus, enables e-data to rise to the level of e-science, truly allowing data to speak for itself. This will require allowing the NE to be a link to solve the problems of airlines and to provide new ideas, new solutions and a new method of making e-data "findable, accessible, interoperable, and reusable", namely, the FAIR (Wilkinson et al. 2016) principle of data, which completes the evolution from e-data to e-science. NER provides a semantic and data basis for solving aeronautical problems driven by big data and truly opens a new paradigm of aeronautical information intelligence research.

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Declarations

Conflict of interest The authors declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any products, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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