Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 3987970, 12 pages
https://doi.org/10.1155/2022/3987970

Research Article

Design and Implementation of Interactive English Translation System in Internet of Things Auxiliary Information Processing

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Received 9 June 2022; Revised 20 July 2022; Accepted 28 July 2022; Published 22 August 2022

Academic Editor: Chia-Huei Wu

Information technology has penetrated into all aspects of human life. Nowadays, with the rapid development of science and technology, information technology has gradually become the cornerstone of the development of other technologies. The Internet of Things is an important part of the new generation of information technology. Language is the medium of communication between people. Driven by economic globalization and the development of the Internet, information is growing rapidly, and there are more and more exchanges and exchanges between countries. The emergence of high-efficiency and high-economic machine translation solves these difficulties, and the interactive English translation system is the current research hotspot, which is intended to improve the output translation quality of the English translation system. The main work of this paper is to analyze the existing interactive machine translation technology, especially the interactive machine translation based on a phrase model, using the Internet of Things as a knowledge source. According to the characteristics of segment analysis and human-computer interaction mechanism, from the network, a wealth of information are available from open sources. In this paper, on the basis of the segment analysis, the human-machine cooperation translation strategy of human-machine cooperation with complementary human-machine advantages was discussed, and the system designed was verified. It is proved that the system has high performance in improving the accuracy and recall rate of machine English translation. Compared with the existing English translation system, the accuracy has improved by more than 20% in the case of fewer iterations, and in the case of 90 iterations, the accuracy can improve by 100%.

1. Introduction

A new generation of information technology is booming, and the Internet of Things technology is one of the emerging information technologies in recent years. Its technical characteristics are based on information perception technologies such as radio frequency identification and sensors and are based on Internet technology. Through information perception, the interaction and fusion of the physical world and the information world are realized, and intelligent computing technology is used to process and analyze the perceived information, thereby realizing intelligent control and decision support. In today's increasingly frequent global communication, communication between people inevitably requires mutual translation of various languages. Manual translation is costly and inefficient, making it difficult to meet large-scale translation needs. Therefore, people's demand for automatic translation technology is increasing day by day, and the development of machine translation technology is the general trend [1]. Interactive machine translation (IMT) is an important research topic in the field of computer-aided translation. In the process of translation, the system and users learn from each other to instruct the computer to decode, so as to improve the quality of the output translation of the machine translation system. Compared with fully automatic machine translation, interactive machine translation makes full use of human linguistic knowledge to guide decoding, which can improve the quality of translation and enhance the practicability of translation. Compared with human translation methods, the addition of machine translation systems can provide translators with initial translations, reduce the workload and cognitive burden of users, and improve translation efficiency. The interactive machine translation method provides an interface for mutual learning and communication between the translator and the machine translation system and combines the high efficiency of the machine translation system with the high accuracy of the translator's translation, which not only reduces the translator's workload but also improves the translation quality. With the continuous deepening and development of technology, how to effectively use existing technologies such as machine translation technology and cloud computing technology to improve the overall level and production efficiency of China's translation industry has become a focus of attention of enterprises, society, and the country [2].

In this paper, the interactive machine translation technology based on segment analysis, which takes the Internet as the knowledge source, has improved the quality and efficiency of machine translation from the perspective of expanding the scope of knowledge acquisition and adopting interactive strategies. When selecting the corpus in the test set as the analysis object of this paper, the translation platform performs poorly under certain error types, with 120 discourse errors. When analyzing the ontology errors in English translation errors, the frequency of ontology errors accounted for a low proportion of the total error frequency, but the original text recognition and sentence segmentation errors were very concentrated, much higher than other error types, with a frequency of 20 and 23. The analysis of semantic errors in segfaults shows that except for the frequent occurrence of terminology errors, other error types are basically stable below 4 times. The accuracy and recall rate of machine English translation using the system in this paper is high, and it can reach 100% in 90 iterations with good performance.

Today is a new time of digitalization and information technology. As a result, the new informatics featuring the Internet and computers have penetrated into all areas of our lives and influenced our consumption views and lifestyles. As far as translation teaching is concerned, the traditional translation teaching mode cannot satisfy the demands of contemporary education. Qiao and Wang analyzed the characteristics of m-teaching and constructed a new paradigm of interactive mobile translating instruction from the viewpoint of structuralism. The new model is initially demonstrated by using three kinds of the popular social interactive tools in China, WeChat, QQ, and Weibo, as examples. The results show that this Internet+-based approach can enhance language translation instruction [3]. To enhance the precision of English interpretation, decrease the rate of error in interpretation outcome, and improve the accuracy of interpretation, Leida Wu and Lianguan Wu proposed a design of architectures for business English interpreting based on speech detection and radio transmission. According to the functional division of the overall system design, the speech collection block, speech treatment block, and external electric module are devised on the basis of functionality request. Simultaneously, a business English interpretation database was built to meet the individual demands of customers by making use of radio transmission technique. An optimized translation model is also applied for translation error correction and intelligent checking to increase the accuracy and accuracy of translations. The results of the trial show that the system has a high correction rate and error rate, and the translating results have certain level of stability, which fully validates the system's validity and application value but has no wide application [4]. With the advancement of information technology and quality training, to enhance the comprehensive quality and subjective motivation of students, Wu has explored some new teaching methods and teaching methods. The interactive mode of English translation based on data mining is analyzed. The implementation of interactive teaching mode in English translation teaching activities has not only met the individual needs of students but also improved the effectiveness of teaching and accelerated the construction of knowledge and skills in the process of English translation [5]. Machine translation (MT) by itself is often not sufficient to generate good quality results, so humans often intervene in the translating procedure to enhance the machine translation output. One type of interference is typically postediting (PE), in which manual translators correct mistakes in the machine translation outputs. Another is interactive translation prediction (ITP), which deals with the machine translation process that suggests interpreter translations that can be acceptable or rejectable. Later, the machine translation-oriented system uses these movements to suggest new, correct ones to them. Rebecca presented the results of an empirical study of the latent neural machine translation system in ITP (NITP) on translation related to translation related creativity. The results showed that more than half of the professional translators in this study used NITP to translate faster than PE and the most favored NITP over PE [6]. The translation system design of English has been a hot research topic, but not many studies have been conducted on the interaction direction of English translation system design.

Recent technological developments and innovations have improved the way people live with intelligent app, sensors, and mobile telecommunication nets. With respect to all of them, the Internet is the main backbone, allowing the access and delivery of essential pieces of info handling through the Internet of Things (IoT). IoT holds support for multidisciplinary applications and is an energetic physical entity in fields of engineering, surgery, and business. Raj developed a novel type of message handling system on an IoT platform through a robust medical surveillance system. With the proposed architecture, the efficient utilization of big data in IoT context is analyzed to achieve minimum delay in a real-time environment. The performance of the proposed design is compared using conventional models, and experiments are carried out to verify the excellent capabilities of the suggested approach in terms of the transfer and storage cost functions, f-measure, flexibility, and idiosyncrasies [7]. The development of the Information of Things (IoT) has enabled technology to share physical education by connecting cost-effective disparate devices and of digital-based programs into an effortlessly accessible and uncontrolled setting. Li et al. proposed IoT-assisted physical activity monitor devices to track students' physical activity and enhance outcomes. Management skills enable students to structure and accelerate physical activity in a healthy way. In a further step, the link of monitoring ability, which is an essential element of bodily activity, to physical activity was investigated. The system collects baseline information from IoT-based wearing items that interact with the data in real time through virtual devices. The IoT network includes activity from multiple units and detects a person's heartbeat and body weight. Experimental results show that the approach enables very good physical activity monitoring results compared to a conventional system [8]. In recent years, the highly prolific Industrial Internet of Things (IIoT), consisting of nodes of heterogeneous resource-constrained IoT, has received significant interest from both academic and industrial communities. Based on the emerging edge computing paradigm and the novel reliable ionic overlay (CIC) model, Wang et al. investigated how to relocate redundant IoT edge nodes to provide timely and reliable information overlay services to mitigate the auxiliary energy balance while extending the network lifetime, which is the CIC-based IoT edge node relocation (CICENR) problem. To effectively solve the CICENR problem, a load-assisted energy-balanced IoT edge node relocation method (CIC-OAEBA) and another CIC-based direct replacement method (CIC-DRA) are proposed. Experimental results show that this method significantly outperforms other peer-to-peer approach in terms of response time, energy efficiency, and especially in terms of network lifetime and coverage performance [9]. For the related work section, these studies provide a detailed analysis of English translation and IoT information processing techniques. It is undeniable that these studies have greatly promoted the development of the corresponding fields. We can learn a lot from methodology and data analysis. However, the research on the design of interactive English translation system using information technology is relatively few and not thorough enough, and it is necessary to fully apply these technologies to the research in this field.

2. Method of Interactive English Translation System in Internet of Things Auxiliary Information Processing

In recent years, the concept of Internet of Things (Internet of Things) has become very popular. Its core concept is based on radio frequency identification (RFID), Electronic Product Code (EPC), and the Internet. A tangible Internet capable of sharing global project information in real time was established. It is an extension and expansion network based on the Internet. It is a huge network formed by combining various information sensing devices with the network to realize the interconnection of people, machines, and things at any time and place [10]. The Internet of Things is actually a combination of information and industry, which connects real matter and virtual matter and connects objects and the Internet through different information perception devices to exchange, communicate, and process information to intelligently identify, locate, track, monitor, and manage [11, 12]. The basic characteristics of IoTs can be summarized as overall perception, reliable transmission, and intelligent processing. Information processing mainly includes signal preprocessing, processing, postprocessing, feature selection, and extraction. Information identification is to identify, compare, classify, and judge the information [13]. On this basis, an association model based on one-to-one correspondence is introduced to optimize the input feature information, thereby realizing the next level of communication [14].

To make things intelligent, interact with people, and interact with things, there must be strong technical support, including intelligent control, human-computer interaction, intelligent information processing, high-performance cloud computing platforms, data storage management systems, databases, enterprise resource planning, and decision support [15].

Interactive machine translation (IMT) is a technology that improves the conversion efficiency between natural languages through machine translation and human-computer interaction [16]. The basic idea of interactive machine translation is to allow users to perform manual intervention and guidance in the process of translation, so as to obtain higher-quality translations. Interactive translation systems are characterized by interactivity. Every time the user interacts with the system, i.e., after each word (or letter) is introduced, the system generates new translation hypotheses. In interactive machine translation (IMT), in each interaction, a machine translation engine is first used to predict a particular source sentence, which is then accepted, modified, or ignored by the translator (continue input) [17]. This cycle repeats until the final translation. Although the existing computer interaction translation has achieved certain achievements, it also has its shortcomings.

2.1. Instance-Based Machine Translation. For example-based machine translation, the main source of knowledge is the example translation library of the parallel corpus, which consists of mainly two fields of interest. One is the sentence in the source language, and the other is the counterpart sentence in the destination language. When a source language-based sentence is input, the translation system finds the most similar source-language sentence in the library, mimics the respective target-language sentence, and produces the respective translations [3].

The whole translating process is for finding and copying results. It only makes a comparison of the source language sentences and does not carry out analysis.

2.2. Statistics-Based Machine Translation. Statistical machine translation is to perform mathematical statistics and analysis on a large number of translation bilingual materials through machine learning for translation. That is, from the source language to the translation into the target language, the whole process is a problem of mathematical probability and statistics. Each sentence in the target language may be the translation of any sentence in the source language, but the probability is different. Therefore, machine translation is to find the target language sentence with the highest probability [18].

The current multilingual machine translation system is mainly divided into three parts, among which the data preprocessing module and the model building module are the focus of the research. Model evaluation and microservice modules are used to evaluate the overall model performance and translation generation fluency. It is finally displayed with the front-end interface. Figure 1 shows the overall architecture of the English-to-English machine translation system.

In terms of architecture, it consists of three parts: user interface, multilingual neural translation model, and data processing module. The human-computer interface usually refers to the part that is visible to the user, where the user communicates with the system through the human-computer interface and performs operations. Only by integrating the concept of human-computer interaction and the concept of people as the main body into the design can it be favored by consumers. Human-computer interaction design can directly affect the user experience. The overall design structure of the interactive English-Chinese machine translation system based on segment analysis with the Internet as the knowledge source is shown in Figure 2 [19].

Given a source language sentence l, the purpose of statistical machine translation methods is to find a target language m such that the conditional probability $p(m \mid l)$ reaches the maximum value [20]. The modeling of phrase machine translation mainly adopts the logarithmic line model. In the logarithmic line model, the conditional probability $p(m \mid l)$ can be expressed by

$$p(m \mid l) = \frac{\exp\left[\sum_{t=1}^{T} \gamma_t h_t(l, m)\right]}{\sum_{m'} \exp\left[\sum_{t=1}^{T} \gamma_t h_t\left(l, m'\right)\right]}. \quad (1)$$

Among them, T is the feature dimension, and γ and h are the feature value (model score) and its corresponding weight, respectively. In the phrase-based statistical machine translation system, translation model features, language model features, lexical ordering model features, counting features, and translation distortion features are mainly used [21].

The goal of machine translation is to learn translation knowledge from large-scale bilingual parallel corpora for automated translation. On this basis, the goal of machine translation to solve the optimal translation can be written as formula (2), which is the optimal translation to be solved.

$$t' = \arg\ \max_{m} p(m \mid l) = \arg\ \max_{t}\ \exp\left[\sum_{t=1}^{T} \gamma_t h_t(l, m)\right]. \quad (2)$$

In practical applications, a machine translation model is composed of multiple models (features). Using a log-linear model to model the above formula can combine all the models. The formula is as follows:

$$\widehat{r} = \arg\ \max_{t}\left\{\sum_{i=1}^{N} \gamma_i \bullet \log f_i(m, l)\right\}. \quad (3)$$

Among them, $f_i(m, l)$ is represented as a model, N is the number of all models, and γ_i is the weight of the model. Using the log-linear model can adjust the contribution of different models by assigning different weights to the submodels to improve the translation quality of the translation. At the same time, the structure of the log-linear model does not limit the number of submodels, and submodels can be added, deleted, or modified at any time according to needs. [22].

Interactive machine translation is that on the basis of machine translation, the translation system searches for qualified translation suffixes according to the source language and the prefix constraints specified by the translator and makes appropriate changes to the machine translation framework to obtain the framework of interactive machine translation. Its formula is shown in (4) [23].

Meanwhile, Formula (4) can be written as

$$\widehat{t_l} = \arg\ \max_{m_l} \Pr\left(m_l, m_p l\right). \quad (4)$$

Via Bayes' rule, it can be converted to

$$\widehat{t_l} = \arg\ \max_{m_l} \Pr\left(l \middle| m_p, m_l\right) \bullet \Pr\left(m_l \mid m_p\right). \quad (5)$$

$\Pr(m_p)$ in Formula (6) is input by the translator, not related, so it is omitted. Compared with statistical machine translation, the prefix-based human-computer interaction mechanism enables translators to participate in machine translation and decoding, so that translators can fully utilize the advantages of language knowledge, and the accuracy of translators and the efficiency of machine translation can be combined well.

SWECCL is a typical learner corpus. The full name of SWECCL is China English Corpus, which contains a large number of learning tools and research materials and is of great help to English two-way translation. The translation function of this system is centered on the main function of the system. It uses the artificially input vocabulary and the vocabulary in the SWECCL corpus to perform the correlation operation and uses the weight function method to calculate the similarity between the translated words and the SWECCL corpus. And on this basis, the information required by the user is given.

Assuming that the user manually enters the vocabulary n and the vocabulary in the SWECCL corpus is m, the basic form of calculating the similarity between two words is as follows:

$$r(n, m) \approx \sum_{c \in m} \varepsilon(c, m) \varepsilon(c, n). \quad (6)$$

Since the term n has been defined, the weight of c can be ignored in the calculation. In the formula, c represents the term, $\varepsilon(c, m)$ represents the weight of c in m, and $\varepsilon(c, n)$ represents the weight of c in n. c's power is given as

$$\varepsilon_c = \log \frac{N}{N_c}. \quad (7)$$

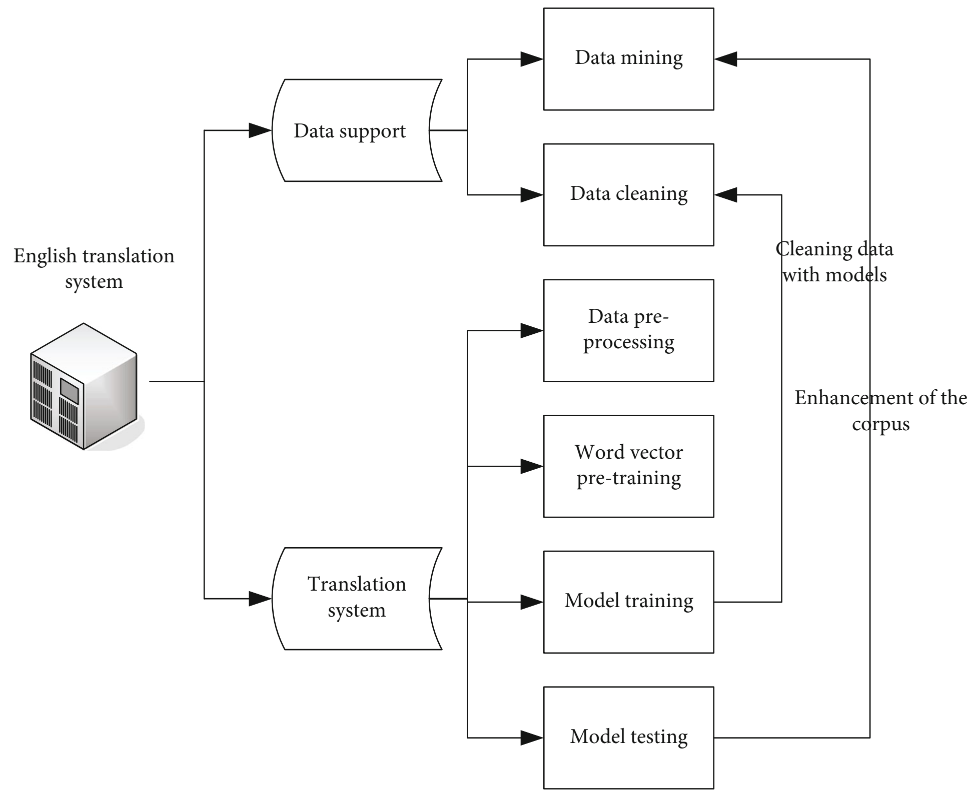

FIGURE 1: Frame diagram of machine translation-to-English system.

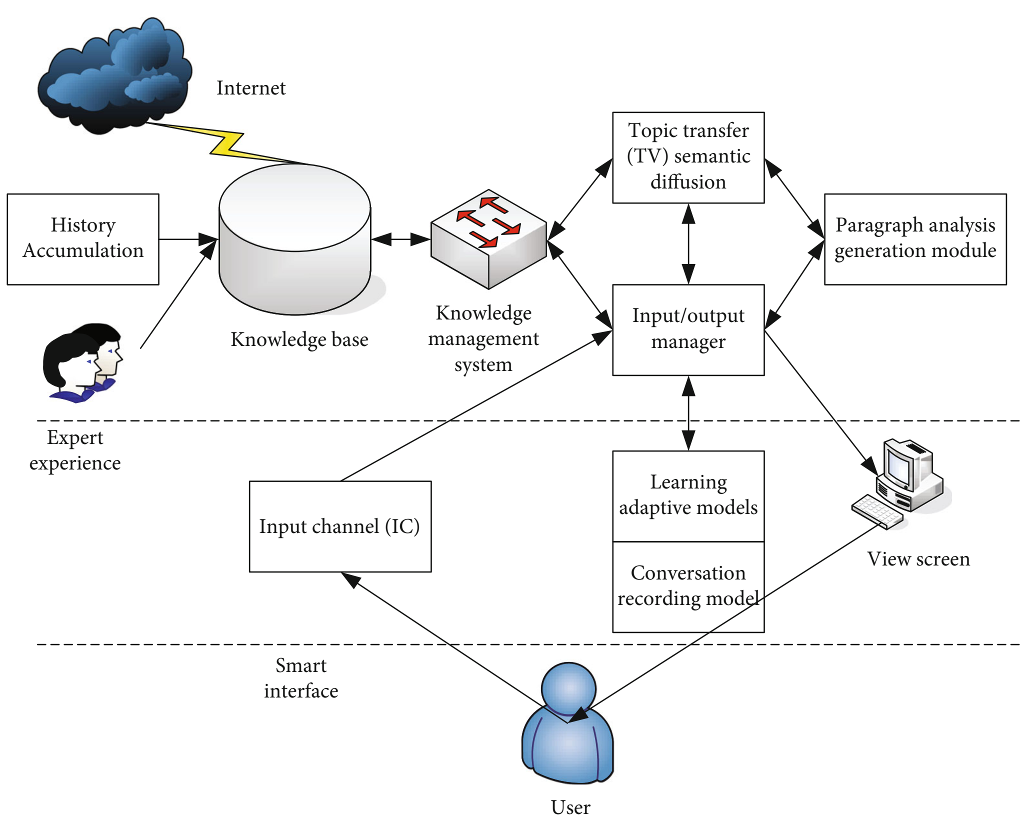

FIGURE 2: Design diagram of English translation system.

The weighted function that combines the terms is carried into Equation (8) to obtain Equation (9).

$$r(n,m)=\sum_{c\in m}\varepsilon(si)c\log\frac{N}{N_c}. \tag{8}$$

In this equation, $\varepsilon(si)c$ denotes the value of si weight of the knot opposite to entry c, which denotes the importance of this entry. In order to prevent the entry importance from influencing the likeness computing, log is used to process si, and the basic equation for the likeness computing of the weighted network-based message translation module is obtained.

$$r(n,m)=\sum_{c\in m}\log(\varepsilon(si)c)\,\log\frac{N}{N_c}. \tag{9}$$

According to the above formula, the vocabulary size manually entered by the user in the SWECCL corpus can be obtained and compared with the similarity in the SWECCL corpus. The SWECCL corpus is used as the research object, and the SWECCL corpus is applied to the system data.

On this basis, a new feature extraction method is proposed to apply the optimal context mapping to translations to achieve the standard extracting of characteristic situations, and the optimal context is depicted by the Semantic Ontology Mapping Model. Assume that there are N different translating contexts in the translation process, consisting of G -level semantic conversions. The number of translation contexts is $N_i(i=1,2,\cdots,G)$, the probability of G-level semantic transitions is $X_i=\{X_{i1},X_{i2},\cdots,X_{\mathrm{iN}}\}$, and $X_{ij}=\{i=1,2,\cdots,K\,;j=1,2,\cdots,N_i\}$ is the result of an n-dimensional vector in one direction. In the course of definition, the fundamental standard context of translation can be implemented.

$$\vartheta_i=\frac{1}{N_i}\sum_{j=1}^{N_i}x_{ij}. \tag{10}$$

In the formula, ϑ_i is the context of translation-ready terminology translation, and the best context ϑ is chosen by the procedure.

$$\vartheta=\frac{1}{K}\sum_{i=1}^{K_i}\vartheta_{ij}. \tag{11}$$

The matrix A_w of the context of nonsemantic interpretation and the context matrix A_B of the proper translation of context of meaning are separately calculated as shown below.

$$A_w=\sum_{i=1}^{K}\sum_{j=1}^{K_i}\left(\vartheta_{ij}-\vartheta\right)\left(\vartheta_{ij}-\vartheta\right)^K, \tag{12}$$

$$A_B=\sum_{i=1}^{K}\left(\vartheta-\vartheta_{ij}\right)\left(\vartheta-\vartheta_{ij}\right)^K. \tag{13}$$

Let σ be the best semantic background of the contextual association matrix $A_w^T A_B$ and f be the measure of semantic contextual association; then the numerical value of ϑ can directly reflect the mapping of the association process. The optimal situation of the extracted context is $A_w^T A_B$; then the semantics of the characteristics in the optimized situation can be denoted by β. The maximum number of optimal translation contexts in the semantic context association matrix $R(R\le K-1)$ is $K-1$.

$$\beta=[\vartheta_1,\vartheta_2,\cdots,\vartheta_R]. \tag{14}$$

Intuitively, the higher the quantity of words cooccurring in both words, the larger the similarity, and the similarity calculation on the basis of cooccurring words is based on this. The resemblance here is not only influenced by the number of cooccurring words but can also be measured by the total number of words contained in the sentence, i.e., the sentence length, which can be more intuitively expressed by the following equation:

$$\mathrm{SimScore}(I,O)=\frac{\mathrm{Inter}(I,O)}{\mathrm{Union}(I,O)}. \tag{15}$$

Among them, $\mathrm{Inter}(I,O)$ is the number of cooccurrence words between the input sentence I and the retrieved sentence R, and $\mathrm{Union}(I,O)$ is the number of words in the set composed of the words of the two sentences.

Computer-aided translation has become a hot research topic in the current machine translation field because it cleverly avoids the bottleneck problem in linguistics. It uses database and other methods to store pairs or more source language sentences and translations that have been translated into translation memory. When the user is translating, the auxiliary translation system automatically analyzes and searches the content according to the current input sentence in the source language and provides the translation that is closest to the input sentence in the memory to the user for reference. In special cases, when the input sentence can be completely matched with the sentence stored in the memory, the translation in the memory is directly used for translation. Under normal circumstances, it is difficult for the translated input sentence to have a completely matching translation. At this time, the system will calculate the similarity and return the Top N translations in the translation memory that are closest to the input sentence to the user for reference. At the same time, according to the similarity, it is sorted for easy selection by the user. Another special case is that the sentence in the translation memory does not match the sentence to be translated at all; that is, the sentence entered by the user is a completely new sentence (this happens frequently for translation memory with a small corpus). At this time, the user needs to perform manual translation, and the system automatically recovers and stores the translation results as translated sentence pairs. The technical composition involved in the computer-aided translation system is shown in Figure 3.

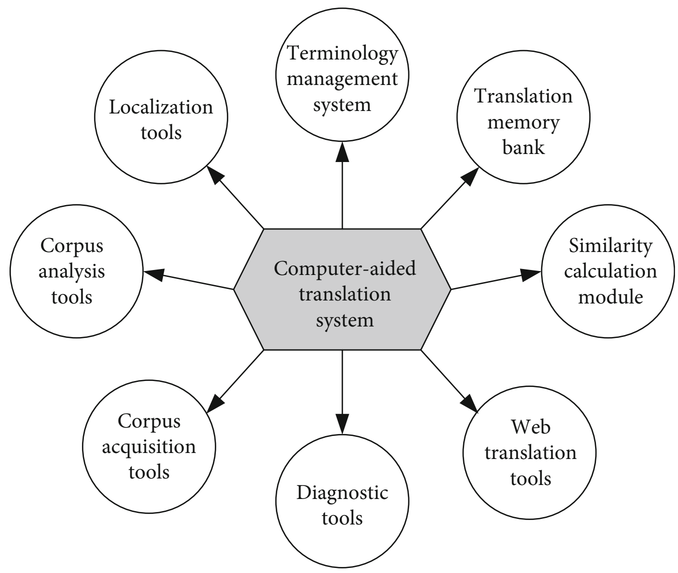

Figure 3: Technical composition of computer-aided translation system.

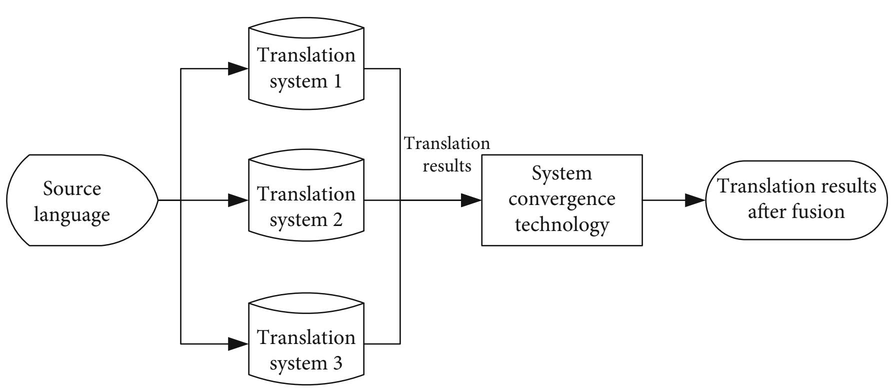

Figure 4: English translation system fusion technology.

Through the above process, the process of extracting the optimal context in the translation process is completed. System fusion technology has been successfully applied in many fields and has brought considerable performance improvement on the basis of the fused system. In a certain task, when multiple system output results are obtained, the system uses the information in the process of the task or only uses the output results to process the multiple system outputs to obtain a final fusion result to optimize the task output quality. In machine translation, the significance of system integration is that different methods are used to build models and different translation techniques will be used to produce different translation results. Different models and translation techniques have different implementations, with their own strengths and weaknesses. System fusion technology is aimed at multiple systems and integrates the translations of these systems, in line with the purpose of promoting strengths and avoiding weaknesses, to achieve the effect of producing better translations. System fusion technology has been successfully applied to many fields of natural language processing, and more and more people now apply system fusion technology to statistical English translation technology and have achieved good results. The principle of the English translation system fusion is shown in Figure 4.

In the interactive case, the input of the system is not only the source language sentence but also the translation prefix confirmed by the user. Search decoding in an interactive environment becomes a restricted decoding process; that is, paths that do not satisfy the restriction are not considered. Figure 5 shows a framework diagram of a phrase-based interactive machine translation system.

3. Experiment Preparation for Interactive English Translation System

The English online-assisted translation system based on human-computer interaction has adopted the B/S three-layer structure. Through the two different processing methods of the front end and the back end, through the modular design, the functional modules of the whole system

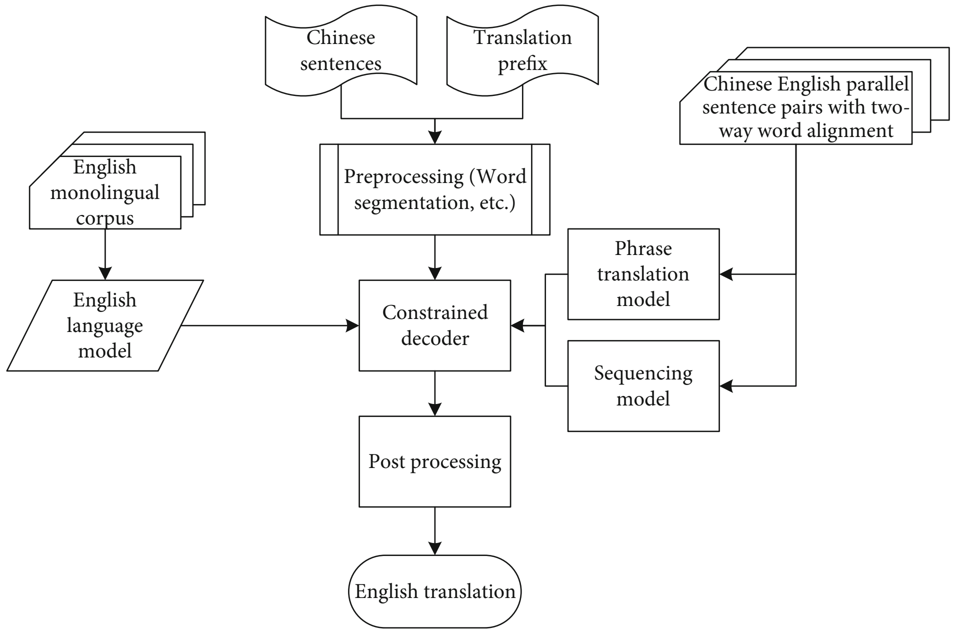

Figure 5: Framework diagram of a phrase-based interactive English translation system.

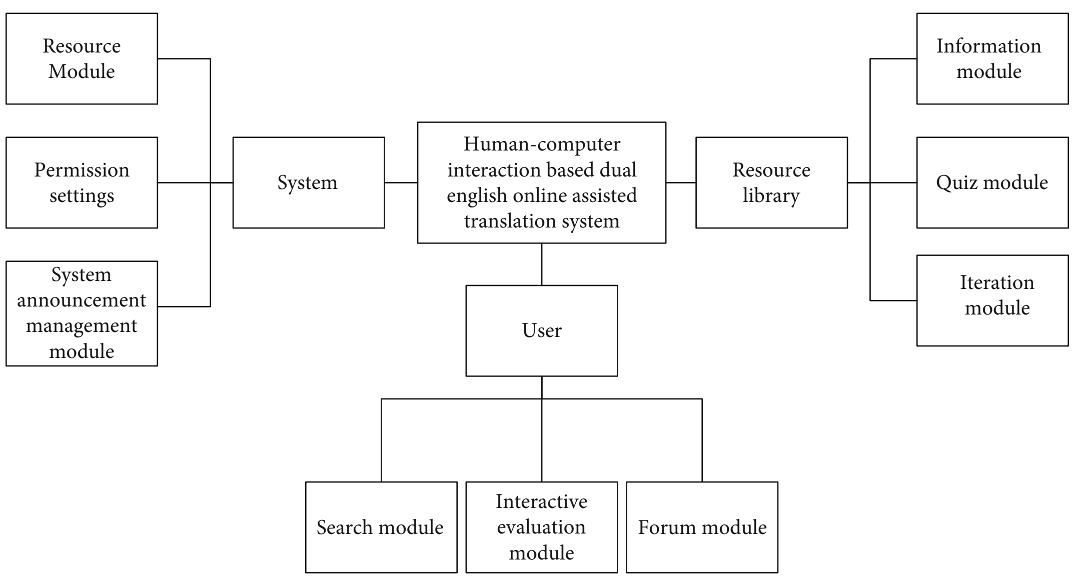

Figure 6: English online translation system module diagram.

are planned according to the user's role. Specific modules are depicted in Figure 6.

Table 1 lists the hardware configuration of the operating environment and the necessary software versions for the front and back ends.

The corpus used in the experiment is a Chinese-English parallel corpus, which contains a total of 66,530 parallel sentence pairs. 5000 sentences from the total corpus were manually extracted as the development set. In addition, 5000 sentences were randomly selected as the test set, and the rest were used as the training set. For the training, development, and test sets, some basic information statistics are made, and the statistical results are shown in Table 2.

A translation phrase pair is the basic unit of a phrase-based statistical machine translation system. An abstract representation needs to be learned for each phrase pair as the representation of the neural network leaf nodes. A simple way is to direct and supervise the learning of the representation of each phrase pair through bilingual data based on the above training process. Such learning is similar to the learning of lexical representations. However, since the amount of bilingual data is far less than the amount of

Table 1: Environment configuration.

Versions	Configuration	Versions	Configuration
Moses versions	V2.1.0	LM version	V6.13.7
Tokenize versions	V2.13.0	Fairseq version	V8.0.17
FastBPE versions	V12.6.0	CUDA versions	V11.0
Processor	Intel(R)Xeon(R)CPU E5-2620 v3@2.40GHz	Operating system	Ubuntu 14.04.5 LTS

Table 2: Experimental corpus information statistics.

Language	Training set	Development set	Test set
Number of sentence pairs	66530	5000	5000
Chinese-file size	2.80 MB	200 KB	201.5 KB
English-file size	8.01 MB	301 KB	352 KB
Chinese-number of words	60190	33912	33741
English-word count	55292	31728	30273

Table 3: Relationship between the number of training data and the number of model parameters.

Basic unit	Word	Translate word pairs	Translate phrase pairs
Amount of training data	1G	7 M	7 M
Number of entities	500 K	$(500\,\mathrm{K})^2$	$(500\,\mathrm{K})^4$
Number of parameters	$2 \times 500\,\mathrm{K}$	$20 \times (500\,\mathrm{K})^2$	$20 \times (500\,\mathrm{K})^4$

monolingual data and the number of translated phrase pairs is very large, it is difficult for the above supervised training methods to learn effective representations.

Table 3 presents the relationship between training data and model parameters. On the dataset, the amount of data used to train the monolingual vocabulary representation is 1G, while the monolingual vocabulary size is only 500 K. For the word pairs composed of the source language and the target language, there are a total of $(500\,\mathrm{K})^2$, and the training data is limited to a small amount of bilingual data.

4. Data Deconstruction of the Design and Implementation of the Interactive English Translation System

This paper has selected the corpus in the test set as the analysis object of this paper and compared and described the corpus of the translation and the official reference translation word by word. Figure 7 shows the statistical results of the frequency of error types in the machine translation-to-English system.

This paper has divided many types of errors. Due to the mutual influence of certain types of errors, the problem of translation quality is caused by the synthesis of multiple errors. Therefore, it is neither realistic nor scientific to propose correction strategies for these types of errors alone. The translation platform performed poorly under certain error types, with discourse errors reaching 120 times. The types with typical significance and analytical value were selected for in-depth description and diagnosis.

Figure 8 shows the statistical results of ontology errors in English translation errors. As can be seen from Figure 8, from the frequency statistics of error types, the frequency of ontology errors accounts for a low proportion of the total error frequency, but the original text recognition and sentence segmentation errors are very concentrated, much higher than other error types, with a frequency of 20 and 23. From the performance of the machine translation platform, the English translation performance is relatively good, and the performance in the original text recognition and sentence segmentation errors is good. The problem of Chinese recognition and sentence segmentation is still the focus of machine translation researchers. In terms of recognition and sentence segmentation, the main mistakes of machine translation are as follows. (1) It is unable to correctly identify Chinese sentence structures, especially parallel structures, biased structures, and subject-predicate structures. (2) It cannot handle complex sentence structures well. Therefore, it can only be stacked literally and cannot convey any effective meaning in English. (3) Improper sentence segmentation will cause the machine translation to be too long, causing readers to have difficulty in reading.

Figure 9 is a frequency map of semantic errors in segfaults. As can be seen from Figure 9, except for the frequent

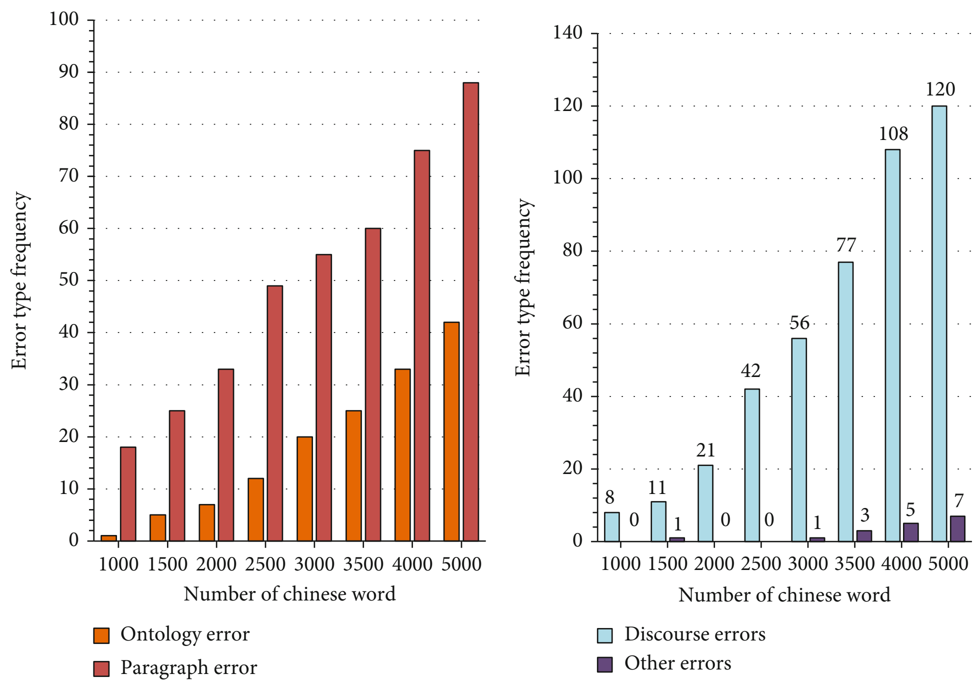

Figure 7: Statistical chart of the frequency of error types in the machine translation-to-English system.

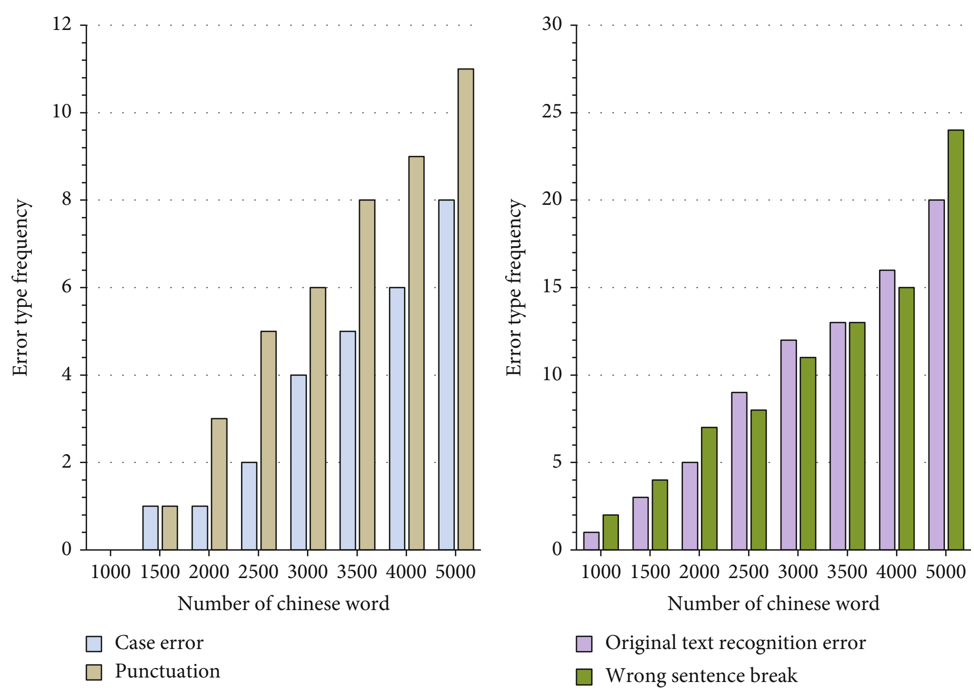

Figure 8: Statistical chart of ontology error among English translation errors.

occurrence of term errors, other error types are basically stable below 4 times. When the number of Chinese words is less than 2500, there is no error of unequal semantic range.

Testing the accuracy of the system designed in this paper to implement the English translation system, the results are shown in Figure 10.

The analysis of Figure 10 shows that the precision and recall rate of machine English translation using this system are relatively high. When the number of iterations is small, the precision rate is increased by more than 20% compared with the existing English translation system. And after 90 iterations, it can reach 100% with better performance.

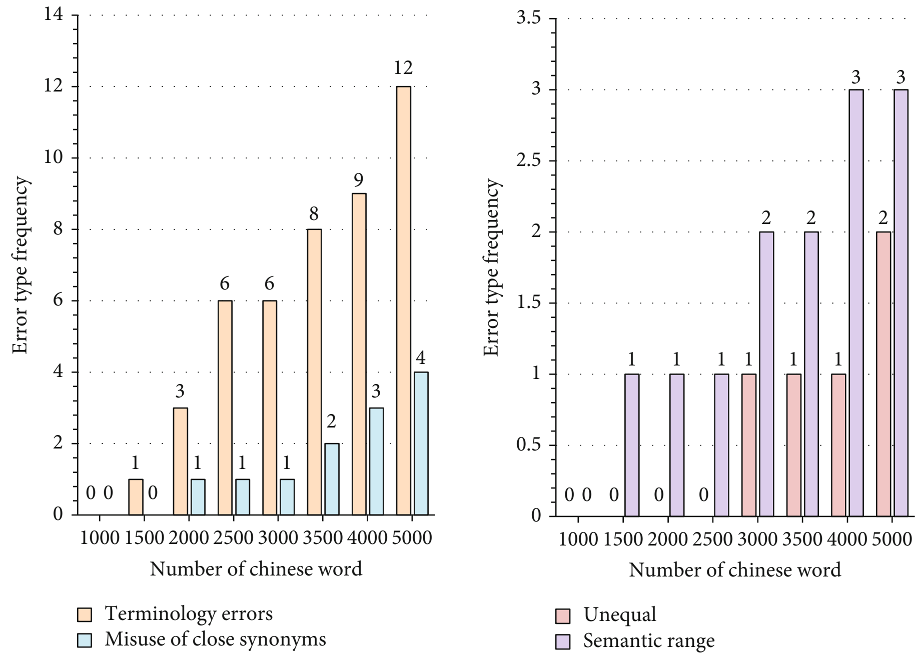

FIGURE 9: Frequency map of semantic errors in segfaults.

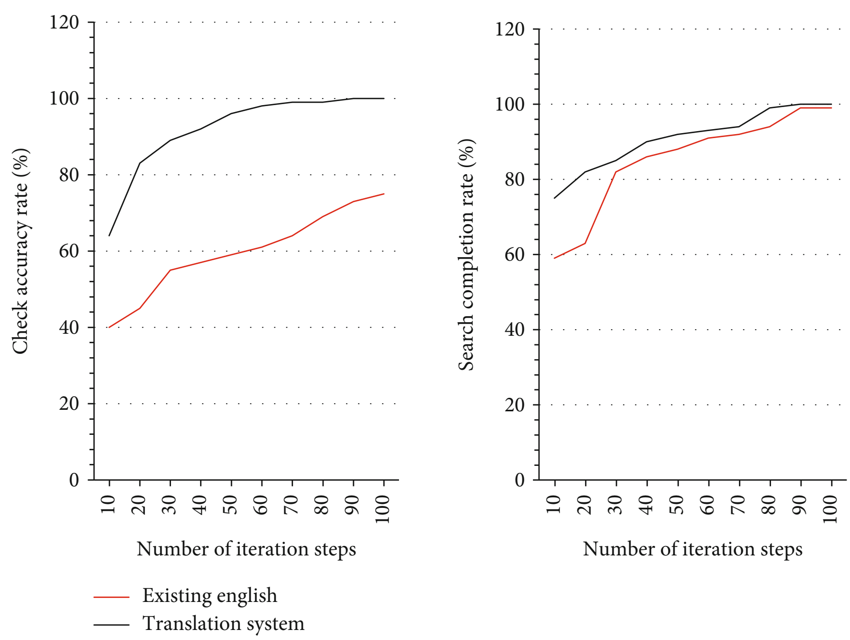

FIGURE 10: English translation precision and recall.

5. Conclusions

The IoT is a significant opportunity for the development and change of information technology. Along with the fast growth of information science and technology and the acceleration of globalization, the problem of language barriers in language communication among countries is becoming more and more prominent, and the need for effective translation methods is becoming more and more urgent. In some way, the evolution of interactive English language translating technique has combined with English translation technique. The level of machine translation technology largely determines the practicality of interactive translation technology. Through several years of progress, impressive results have been achieved in both fields. However, it should be noted that the operational use of machine translation is far from what one would expect, while interaction machine translation techniques are undergoing rapid development with the aid of interpreters. This can be said to be a transition in the recognition of the career development of translation and can also be seen as an application of the innovative results of the stage development of machine translation. In this paper, a frame for an English translation system was devised. In the interactive translator system designed in this paper, the English translation system is performing well. It is hoped that the research in this article will lead to accurate translations in the English-Chinese translation.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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