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Retraction

Retracted: English Language Intelligent Translation System Based on 3D Visualization Technology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] B. Song, "English Language Intelligent Translation System Based on 3D Visualization Technology," *Mobile Information Systems*, vol. 2022, Article ID 1608840, 11 pages, 2022.

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Research Article

English Language Intelligent Translation System Based on 3D Visualization Technology

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In the process of imparting knowledge, faculty should give more emphasis to the acquisition of students' direct experience. Vivid three-dimensional visualization resources should be used for classroom teaching to help students better understand and grasp the visualization of knowledge. Based on this, this paper aims to study the English language intelligent translation system based on 3D visualization technology. In recent years, 3D application technology is transforming into multiuser applications supporting network environments. This transformation also promotes the application and development of 3D GIS technology. Transformer is a universal and efficient feature extractor. This paper proposes a design scheme for constructing 3D interactive visualization resources in teaching scenes. It is designed for specific disciplines and produces visual resources. Then, it analyzes and evaluates the actual effect of the application in teaching, to provide ideas for English translation education experts and teaching staff. It also builds a translation system based on B/S architecture, connects the server model and the client, and realizes the visualization and interaction of translation functions. In the experiments, 5% and 20% of the parallel corpus with a total of 12 M sentence pairs were used for pretraining of the translation model. Then, the number of monolingual corpus is gradually increased to train the model. Experiments show that when using the same amount of monolingual corpus, the translation model can achieve a more obvious effect on the pretrained model.

1. Introduction

At present, 3D visualization resource design has made great progress in hardware. This needs to give full play to the advantages of 3D visualization resources for auxiliary teaching.

In the English translation education concept advocated by the new curriculum reform, both teaching resources and students' learning methods are changing. Students' learning style gradually develops into an independent, inquiring, and cooperative learning style, prompting the transition of teaching resources from static to dynamic. The concept of "Internet +" further promotes the in-depth integration of information technology and teaching resources. This brings a new change to the reform of teaching resources—a new form of interactive digital resources. The English language intelligent translation system can reduce language barriers between people in different countries and different ethnic groups through machine translation.

The innovations of this paper are as follows: (1) Based on the back-translation strategy in data augmentation, this paper uses the iterative back-translation method to expand the parallel corpus on a large scale. Judging from the performance improvement of the back-translation system generated in the iterative process, the quality of the pseudo corpus generated in the iterative process is constantly improving. (2) A translation system based on B/S architecture is built, which connects the multilingual translation model on the server side and the client side, and realizes the interaction and visualization of machine translation. (3) Data-dependent regularization terms are introduced through the probabilistic nature of neural machine translation models and applied to monolingual corpora to aid the training of neural machine translation models.

2. Related Work

Determining the impact of translation strategies on the quality of translation of research data is becoming increasingly important. In this case, Najjar et al. adopted a series of translation strategies such as literal translation, paraphrase, transposition, and morphology [1]. However, the translation quality is sometimes poor. The cultural translation view regards translation as a cross-cultural communicative activity. Zhang started with the influence of cultural context on Chinese-English translation, as well as the understanding and practice of translation activities from the perspective of cultural translation [2]. Fitriani aimed to describe and classify grammatical errors found in English-translated sentences, both syntactically and lexically. It has been found that temporal errors are the highest frequency errors and derivative morpheme errors are the lowest [3]. Implicit meaning is one of the linguistic phenomena that need to be overcome in translation. The Susini study aimed to investigate in what structure the implicit meaning is realized in Indonesian and how the implicit meaning is handled when it is translated into English [4]. Although the structures of the source and target languages differed in the translations studied, the meaning of the source language was successfully conveyed in English. Muravev aimed to find similarities between legal translation practice and training by analyzing the capabilities and limitations of case study methods in academic institutions [5]. Methods for statistical machine translation significantly improve the translation performance. However, it relies heavily on hidden structure and feature involvement, and local features are difficult to extract.

Therefore far, 3D visualization technology can not only be used in geological description, military, etc., but has also begun to develop in the field of English translation education. 3D visualization is the process of creating 3D objects using special computer programs. Today, computer graphics techniques such as 3D visualization techniques are in increasing demand. Sadiku et al. research findings allow the creation of 3D objects of any shape. It is widely used worldwide to create interiors of houses, offices, hotels, etc., [6]. Modeling with 3D visualization becomes essential. Zeng et al. proposed a global thresholding method based on local outlier factor (LOF) to solve the noise sensitivity problem in global thresholding. Both simulation and experimental results show that his scheme produces better results compared to the state-of-the-art [7]. Namiot and Romanov outlined a 3D visualization approach to the software architecture and metrics. Visualization facilitates and accelerates the process of understanding the structure of software components [8]. Inoue et al. automated the inspection of the infrastructure using point cloud analysis of the features of 3D structural information obtained through 3D structural visualization. The results show that it is feasible to model overhead cables with cable lengths of 10–70 m regardless of the area type [9]. Yoo et al. research proposed a deep learning-based CAD/CAE framework in the conceptual design stage to automatically generate 3D CAD designs and evaluate their engineering performance [10]. However, it cannot be shown that AI can actually be incorporated into end-use product design projects.

3. English Language Intelligent Translation Method Based on 3D Visualization Technology

3.1. Fusion of 3D Visualization Technology and English Translation Education. The proposal of "Internet + English translation education" further promotes the profound combination of informative tech and instructional materials. It also brings new changes to the reform of teaching resources. New forms of digital teaching resources are beginning to emerge. The design of visual resources in teaching resources is increasingly rich. 3D visualization resources are increasingly favored by teachers because of their vivid characteristics. Increasingly, teaching workers and developers are turning to 3D teaching resources [11]. In specific practice teaching, three-dimensional resources are often designed by design, which cannot truly reflect the teaching nature of resources. Therefore, it is necessary to design and apply research on teaching scenarios. The application field of 3D Visioning tech is shown in Figure 1.

As shown in Figure 1, users use computers to simulate the real environment and observe complex things. And the use of computers and other devices for interactive operations has attracted increasing attention [12, 13]. 3D visualization resources have an important impact on the teaching and learning of teachers and students.

3.2. Status Quo of English Language Intelligent Translation System. Nowadays, the globalization of economic exchange continues to deepen. The advent of the sharing economy era has brought closer exchanges and connections between different countries and regions. The exchanges between peoples of various countries and nationalities are also becoming increasingly frequent [14, 15]. Language is the most important tool in human activities, and the importance of translation between different languages is becoming increasingly prominent. In today's society, the effect of human translation can be more fluent and natural, and the text conforms to human writing habits. However, because of its short supply and high price, machine translation came into being to meet people's growing demand for translation [16]. Machine translation has the advantages of high efficiency and low cost. However, because its development has just started, it is still in its infancy. There are often various difficulties in related research and experiments. Therefore, how to achieve more efficient and high-quality machine translation has become a hot research topic in academia and industry.

3.3. Transformer Model Based on Attention Mechanism. The biggest feature of Transformers is the introduction of a self-attention mechanism. It refines the model of classical neural machine translation. The role of the attention mechanism is to calculate the degree of association between the words in the current source language sentence and it when predicting the vocabulary of the target language during training [17]. When searching the dictionary, the corresponding words in the dictionary can be directly generated.

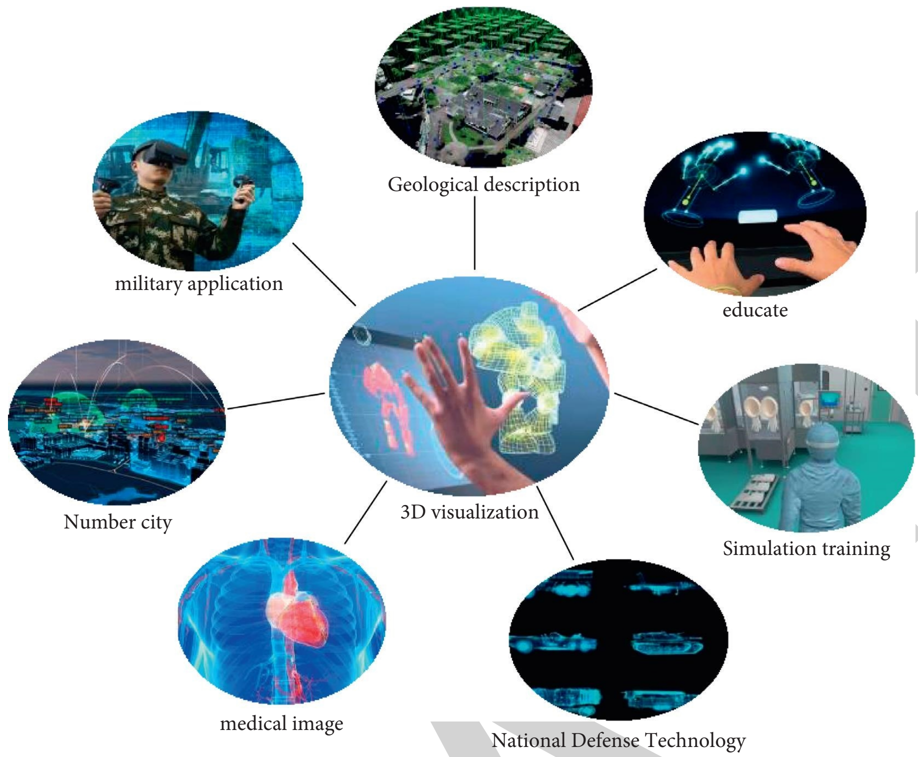


Figure 1: 3D visualization technology application field.

The encoder in Transformer consists of N identical layers. Each layer consists of two sublayers, a multihead attention mechanism, and a fully connected feed-forward neural network. Each of these sublayers contains residual connections and normalized outputs [18]. Therefore, the output of the sublayer can be expressed as

$$\text{output} = \text{LayerNorm}(x + \text{BotLayer}(x)). \tag{1}$$

The self-attention mechanism calculates three new vectors called query, key, and value. In the formula, they are abbreviated as A, B, and C, respectively. These three vectors are the result of multiplying the word embedding vector by a matrix as

$$\begin{aligned} \text{output} &= A(A, B, C), \\ MH(A, B, C) &= \text{Con}\left(h^1, \ldots, h^h\right)W^0, \\ H^1 &= A\left(AW_i^Q, BW_i^K, CW_i^V\right). \end{aligned} \tag{2}$$

The self-attention mechanism takes A, B, and C the same. In addition, the calculation of attention parameters adopts a scaled dot product, namely,

$$A(A, B, C) = \max\left(\frac{AB^C}{\sqrt{d_k}} V\right). \tag{3}$$

The Transformer model has three attention mechanisms, including the encoder multihead attention mechanism, the decoder mask multihead attention mechanism, and the encoder-decoder multihead attention mechanism [19]. The neural machine translation system based on the Transformer's structure not only improves the training speed but also achieves excellent results in translation tasks. It has become one of the most mainstream methods in the current machine translation field [20].

3.4. Design of Word Vector Algorithm for Location Information. To simplify the complexity of the word vector model, both the bag-of-words CBOW model and the skip-gram model remove the word order information. However, according to the characteristics of sequence-to-sequence machine translation tasks, it believes that the context closer to the target word can carry more word meaning information.

The work of converting the input vector to the neural network is done through a weight matrix. When outputting, a matrix is also needed to restore it to a vector form similar to the input, which is convenient for the computer to output the words in the corresponding vocabulary. The calculation process and steps are as follows:

(1) First, the weighted average operation of the input vector is converted through the matrix operation, and the hidden layer output h is obtained. The formula is as follows:

$$h = \frac{1}{c} W\left(\sum_{i=1}^{c} \lambda_i e(w_i)\right). \tag{4}$$

(2) The output of the hidden layer needs to be obtained by the same matrix operation formula is as follows:

$$u_j = v_j^{\prime T} h. \tag{5}$$

Among them, $v_j^{'T}$ is the jth column of the output matrix $w\prime$, and u_j is the value of the jth column of the output layer, which is a scalar.

(3) The output word (probability) of the output layer is calculated, the jth node outputs y_j, formula is as follows:

$$y_j = p(w_j|w_1, \ldots, w_{2c}) = \frac{\exp(u_j)}{\sum_j^V \exp(u_j)}. \tag{6}$$

Weight matrix W'_{N*V} and W_{V*N} update method: the first step is to define the loss function formula is as follows:

$$\begin{aligned} L &= -\log\ p(w_o|w_I) \\ &= -\log\ u_j + \log \sum_{j=1}^{V} \exp(u_j) \\ &= -v_j^{'T} h + \prod_{j'=1}^{V} v_{j'}^{'T} h. \end{aligned} \tag{7}$$

The second step is to derive the abovementioned probability to obtain the update rule formula (8) of the output weight matrix $w\prime$:

$$w_{ij}^{'(\text{new})} = w_{ij}^{'(\text{old})} - \mu(y_j - t_j) \cdot h_j. \tag{8}$$

In the same way, the update rule of the weight matrix W is

$$w_{ij}^{(\text{new})} = w_{ij}^{(\text{old})} - \mu \cdot \frac{1}{c}(y_j - t_j) \cdot x_j. \tag{9}$$

PW-CBOW uses the context x_{t-2}, x_{t-1}, x_{t+1}, x_{t+2} with position weights to train the target word w_t.

3.5. LSTM Model. LSTM can capture the information of words with long distances before and after. It is difficult for RNN to integrate messages with present messages. When dealing with long sequences of messages. It is far superior to RNN to LSTM. The LSTM pattern is shown in Figure 2.

As shown in Figure 2, each LSTM layer contains a forget gate, an input gate, and an output gate. The goal of LSTM is to control the transmission of information through these three control gates to solve the gradient vanishing phenomenon that may occur in the neural network. The working status of the three doors is as follows:

(1) The forget gate is used to control how much information from the previous layer can be transmitted to the next step and selectively send the information of the previous layer to the next layer.

$$f_t = \text{sigmoid}(w_f \cdot [h_{t-1}, x_t] + b_f). \tag{10}$$

(2) It is implemented by two neural network layers. These include the sigmoid layer and the tanh layer. The first one decides which information is updated, calculated as formula (11). The second is used to create new candidate data. The two values are combined to update.

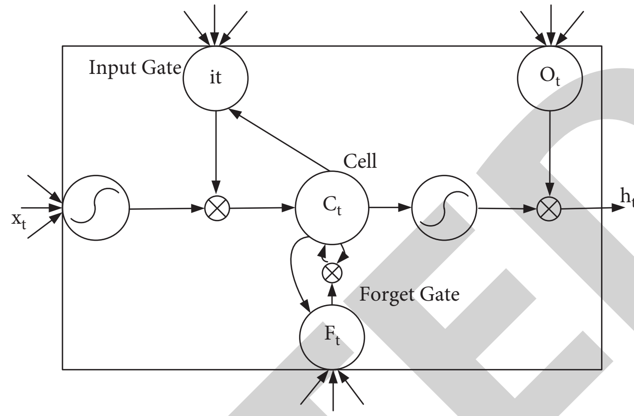


Figure 2: LSTM model.

$$i_t = \text{sigmoid}(w_i x_t + u_i h_t + b_i), \tag{11}$$

$$c_t = f_t * c_{t-1} + i_t * \tanh(w_c x_i + u_c h_{t-1} + b_c). \tag{12}$$

(3) The information to be output is determined by the sigmoid layer. The updated information is converted to a value between -1 and 1 by tanh, and the output threshold value O_t and output value h_t are calculated.

$$\begin{aligned} O_t &= \text{sigmoid}(w_o x_t + u_o h_{t-1} + b_o), \\ h_t &= o_t *\ \tanh(c_t). \end{aligned} \tag{13}$$

This subject intends to use the most commonly used BLEU value as the evaluation index of the quality of machine translation. BLEU uses the accuracy rate of the candidate translation n-grams to calculate the geometric mean to obtain the similarity of sentences. The calculation method is as follows:

$$\begin{aligned} \text{BLEU} &= BP \cdot\ \exp\left(\sum_{n=1}^{N} \frac{\log\ P_n}{N}\right), \\ \text{BP} &= e \min\left(\frac{1-r}{c, 0}\right). \end{aligned} \tag{14}$$

Among them, P_n represents the N-gram confirmation rate, and BP represents the sentence length penalty factor. c is the number of words in the candidate translation, and r is the length of the reference translation closest to the length of c. It does some research and adjustment on the evaluation of the BLEU test method.

4. Design and Implementation of the English Machine Translation System

To make better use of the research results of English language neural machine translation model, this chapter will build an online English language translation system on this basis. This makes it easier and more immediate to handle translation tasks for users. The system is based on B/S (browser/server) architecture, in which the core translation

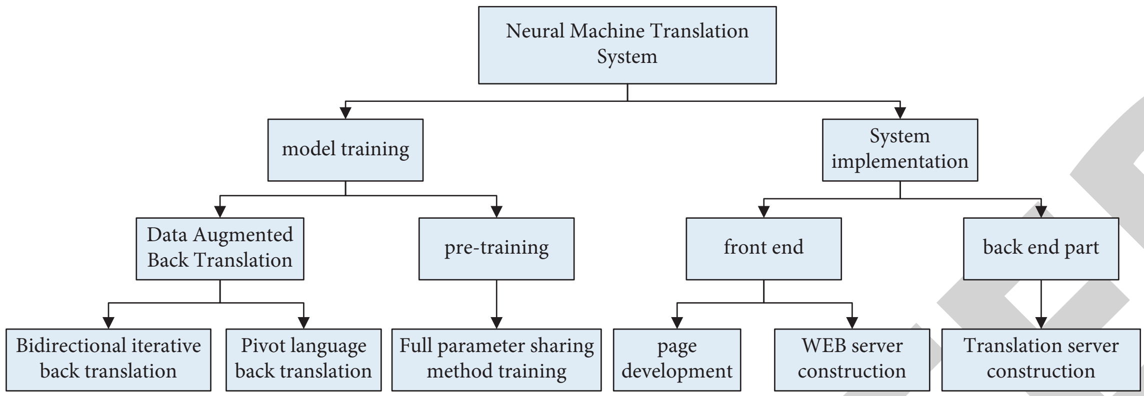


Figure 3: The structure of the English language translation system.

function is deployed on the server side. Users can access the page through a web browser and send translation requests. The server-side translation model can feed back the translated text to the WEB page after completing the translation task. This chapter describes the English language translation system in detail from the aspects of overall system design, system deployment, and system interface display, and shows some translation examples under different input situations. The structure of the English language translation system is shown in Figure 3.

As shown in Figure 3, this section describes all aspects of the system implementation in detail. First, the logical hierarchy of the translation system and the main functions of each level are introduced on the overall level. Then, each part of the whole role becomes reasonable module, and the functions of each module and the logical relationship between the modules are introduced in detail.

4.1. System Architecture. The design of this English language translation system follows a hierarchical structure. It also modularizes the specific functions of each part of the system. This design facilitates the maintenance, update, and upgrade of the system in the future and greatly simplifies the development and use of the system.

The translation system is divided into two logical layers from top to bottom, namely, the WEB layer and the translation service layer. The English language translation roll is shown in Figure 4.

The structure of the roll adopts the B/S (browser/server) mode. The client provides a visual translation interface and human-computer interaction functions through a WEB browser. The server side is responsible for processing the user request from the client side and judging whether the request and the input content meet the system requirements. If it matches, the translation function will be executed normally, and the translation result of the specified language will be returned to the client browser interface.

4.1.1. WEB Layer. The WEB layer provides users with a visual interactive interface. Users can access WEB pages through a browser as a WEB client. Thus, the task request and translation content are submitted to the server side. The main functions of the WEB layer are: to submit the translation information input by the user and display the translation results returned by the server.

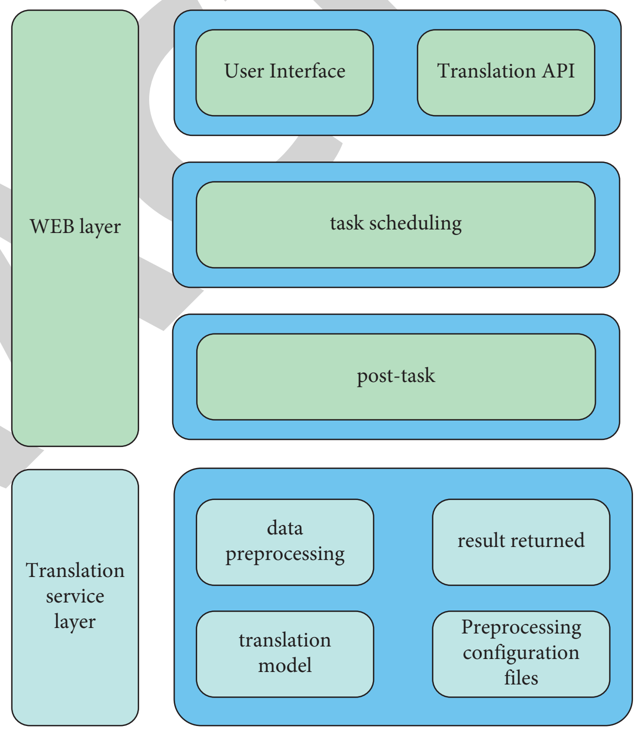


Figure 4: the structure of the English language translation roll.

4.1.2. Translation Service Layer. The major functions of the translation service layer are task scheduling and text translation. Among them, task scheduling mainly judges translation requests and tasks to be translated, and performs task scheduling for requests sent from the WEB layer. In this way, the reasonable allocation of server resources is ensured, the response speed of the system is improved, and system crashes are avoided. The text translation task includes three parts: data preprocessing, text translation, and result feedback. Preprocessing is to convert the input content for translation into a data format that meets the requirements of the model. The translation service layer processes the input text data through a set of preprocessing tools. The translation model then digitizes and translates the preprocessed sentences. Finally, the translation result is returned to the WEB layer for display.

The system is constructed following the hierarchical design principle. According to the two-layer structure of the system, the specific functions of each layer are allocated in detail. And the corresponding modular design is carried out for different types of tasks at different levels. This provides great convenience for future maintenance and updates. All functional modules of this system can be divided into five parts according to the system level, including WEB part, task scheduling part, and translation part. The internal logic illustration of the device function module is shown in Figure 5.

The logical relationship between the functional modules of the English language translation system is shown in Figure 5. The translation service layer is invisible to clients located in the WEB layer. To ensure that the training process is disturbed by data from the client, the security of the model is improved. Only the system administrator of the server has permission to operate the translation service layer.

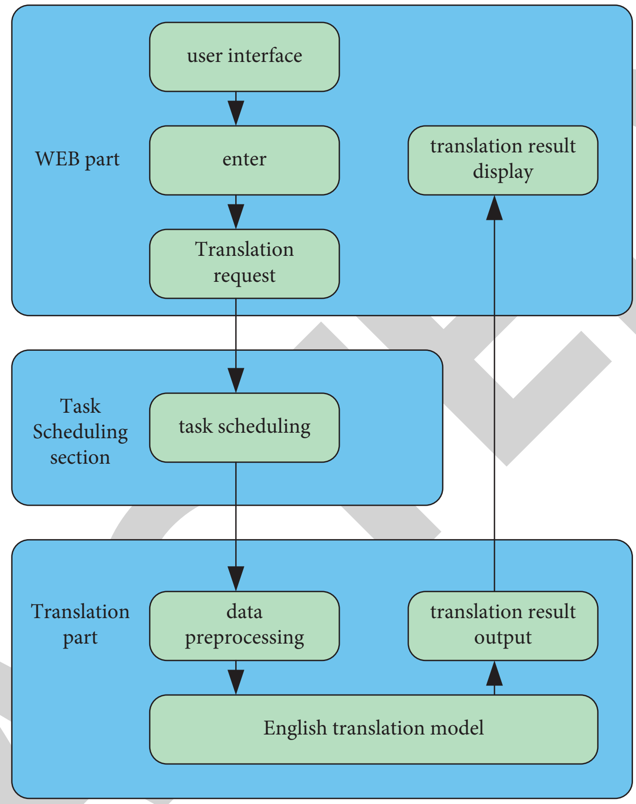


FIGURE 5: Internal logic diagram of system function module.

4.2. System Implementation

4.2.1. System Environment. The system framework is B/S mode. The client part is a WEB browser, which is a channel for users to access the client. After accepting the translation information and the translation request entered by the user, the client submits it to the server. The server judges the incoming request. If it is the input data that conforms to the format accepted by the model, the input sentence is translated into the specified language and returned to the user interface. The back end of the system is carried on the server and deployed in the local area network. The hardware information of the server operating environment is shown in Table 1:

TABLE 1: Hardware configuration table of the operating environment of the English language translation system.

Server hardware	Configure
GPU memory	16 G
Hard disk space	10 T
RAM	128 G
Network requirements	100 M bandwidth

The client is a WEB browser of any system platform. Python is a programming language for scripting and rapid application development on most platforms. The software table of English language translation system development is shown in Table 2.

TABLE 2: English language translation system development software table.

Server software	Name
System	Ubuntu
Development language	Python3.7
Server software	Apache
Front-end development	AJAX

As shown in Table 2, WEB construction can be divided into two parts, WEB server construction and WEB development based on WEB server. The WEB server is open to the network in the local area and can provide translation services for WEB browser users of most system platforms. Users can directly access the WEB server by entering the domain name plus the port number or IP address in the address bar.

4.2.2. System Deployment. This English language translation system uses the open source WEB server software Apache to build a WEB server. Its advantages are security, speed, and reliability, and can be extended to multiple platforms. WEB development uses AJAX (asynchronous JavaScript and XML) method. The deployment structure of the English translation system is shown in Figure 6.

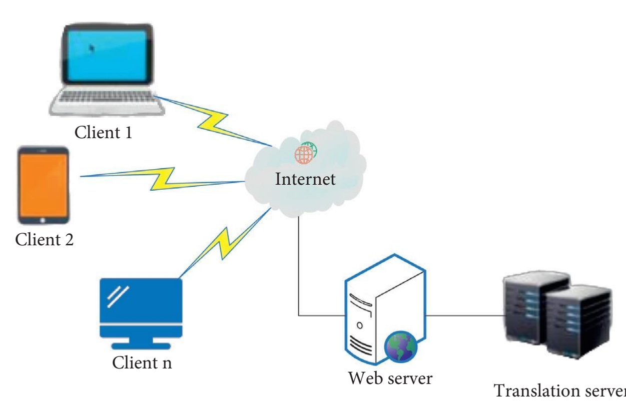


FIGURE 6: Deployment structure of the English translation system.

As shown in Figure 6, the deployment of the translation system includes two parts WEB service and translation service. The main content of WEB service deployment is WEB development, which provides users with access to IP addresses or domain names, as well as translation interfaces. The deployment of the translation service part is an important part of the WEB backend, which is used to process translation task requests and translate English language texts. To improve the response speed of the system and the ability to process tasks, this chapter adopts the design of multiple translation servers. The WEB service and the translation service are separately arranged in the WEB server and the translation server group.

5. English Language Intelligent Translation Experiment

5.1. Role of Hyperparameters. The experiments in this part analyze the influence of the parameters in the model on the experimental results. In the training objective of this chapter, there is a parameter λ used to balance the weight of parallel corpus and monolingual corpus maximum likelihood estimation training objectives. To verify the effect of λ on the translation effect of the model, experiments with different parameters λ were conducted on the German-English translation task. Figure 7 shows the English translation effects of different numbers of corpora and different balance parameters.

As shown in Figure 7, when using different numbers of parallel corpora, with the increase in the number of monolingual corpora, the effect of the BLEU value on the English-French test set, whether increasing or decreasing, will result in a decrease in translation quality. Similar results can be obtained on the English-French translation task. Therefore, λ is set to 2 in all experiments. The role of the back-translation model for sampling is that when the model $P/(y|x)$ is trained, the inverse model $P(x|y)$ needs to be used for sampling. To verify the influence of the quality of the reverse model used for sampling on the experimental results in the German-English translation task, reverse models of different qualities were used for sampling in the experiment, and the effect of the proposed training target in the corresponding situation was verified.

5.2. Low Resource Settings. To verify the influence of the number of parallel corpora on the translation quality, experiments under the low-parallel corpus resource setting are also carried out in this subsection. In the experiment, all 12 M parallel sentence pairs in the English-French translation task were randomly sampled and 5% and 20% of the data were taken for model pretraining. The translation quality of these low-parallel corpus resource settings is compared to the original setting with 12 M full training data. Specifically, 5% and 20% of the parallel corpus with a total of 12 M sentence pairs were used for pretraining the translation model in the experiments. Then, the number of the monolingual corpus is gradually increased to train the model, until the enhancement of model performance is no longer significant with the increase of monolingual corpus. The BLEU values on the English-French test set are shown in Figure 8.

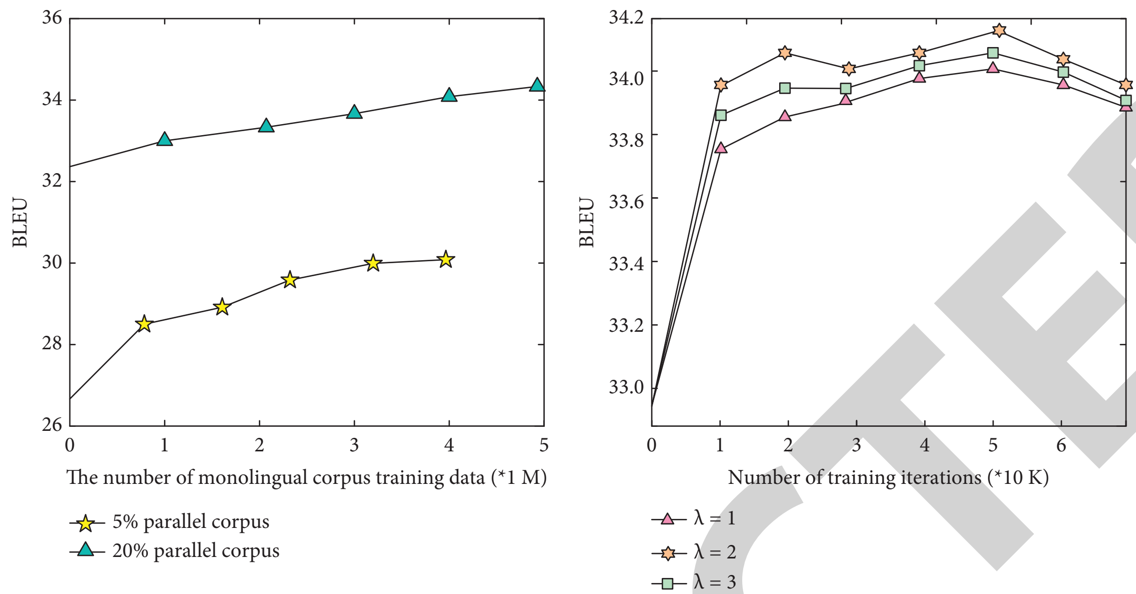
As can be seen from Figure 8, both the number of parallel corpora and monolingual corpora have an important impact on the quality of model translation. Specifically, when using fewer parallel corpora for pretraining, the translation model can obtain a more significant improvement over the pretraining model with the same number of monolingual corpora. The method proposed in this chapter can also effectively utilize the monolingual corpus. On the other hand, for each set of different numbers of parallel corpora, it can be seen from the figure that when the number of monolingual corpora gradually increases, the improvement of the translation effect of the model gradually slows down. This result is consistent with the results in the previous section on the German-English translation task.

5.3. Role of Hyperparameters. In the training objective based on probability constraints in this chapter, there is a parameter λ used to balance the weight of the training objective of the maximum likelihood estimation and the regularization term of the marginal distribution. To verify the effect of λ on the experimental results, this chapter conducts experiments with different parameters h on the German-English translation task. The translation effect on the German-English validation set under different balance parameters λ is shown in Figure 9.

Figure 9 shows the changing process of the BLEU value on the validation set when the model uses different parameters h during the training process. As can be seen from the figure, when λ is in the range of 0.005 to 0.2, the translation quality can be improved on the basis of the pretrained model. Among them, when $\lambda = 0.05$, the model can achieve the best results and increasing or decreasing h will cause a decrease in translation quality. Similar results can be obtained on the English-French translation task. Therefore, λ is set to 0.05 in all experiments in this chapter.

5.4. Influence of Sampling Size K on Experimental Results. The experiments in this part verify the effect of the sampling size K on the training target effect based on probability constraints on the German-English translation task. Intuitively, a larger sampling size will bring about an improvement in the effect, and on the other hand, it will also lead to an increase in the training time. To explore how to better balance the improvement of the translation effect and the efficiency of training, the experiment verified the difference in translation effect brought by training with different sampling sizes. The translation effect on the German-English validation set with different sampling sizes K is shown in Figure 10.

As shown in Figure 10, for the training objective based on probability constraints, it uses the BLEU values of models with different sample sizes on the validation set as the training time increases. As can be seen from the figure, when



(a) (b)

Figure 7: English translation effect of different amounts of corpus and different balance parameters: (a) BLEU values on the English-French test set; (b) BLEU values on the German-English validation set.

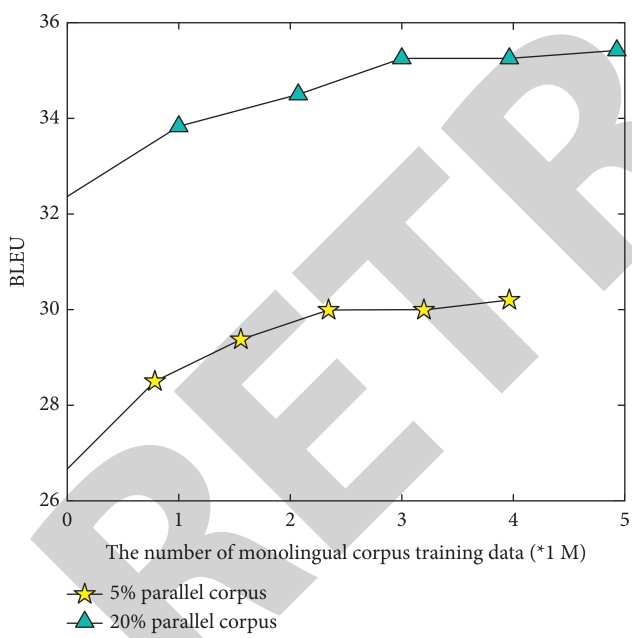


Figure 8: BLEU values on the English-French test set.

a smaller sampling size K is used, the BLEU value on the validation set rises faster, but the BLEU value at the final convergence is lower. Conversely, when a larger sampling size K is used, the model can eventually achieve higher BLEU values but requires more training time to reach the final BLEU value. Similarly, a similar phenomenon can be observed for the English-French translation task.

Considering the limited computing resources, the trade-off between translation effect and training efficiency, and a fair comparison with contrasting methods, the model effect with a maximum sampling size of 5 is verified in the experiments, and finally, the sampling size is set to 2 in all experiments. Specifically, larger sample sizes require more GPU memory and training time. And because of the limited GPU resources, too large sample size is unbearable. For every single sentence, more samples lead to a better estimation of the marginal distribution and lead to higher BLEU values. However, the improvement in BLEU value brought by more samples is not significant. which also set the sampling size to 2. Therefore, it can be considered empirically that a sufficiently good model can be obtained by setting the sample size to 2.

5.5. Regularization Term. Regularization is to express planar irreducible algebraic curves in some form of holomorphic parameters. To have a deeper understanding of the role of probability constraints in model training, this part conducts some empirical analysis on the satisfaction of the training target based on marginal distribution estimation and the constraint term derived from the full probability formula of the training target based on probability constraints on monolingual corpora on the German-English translation task. Specifically, after pretraining on the parallel corpus to obtain the German-English translation model, in the semisupervised training, the value of the regularization term of the selected single sentence during the training process is shown in Figure 11.

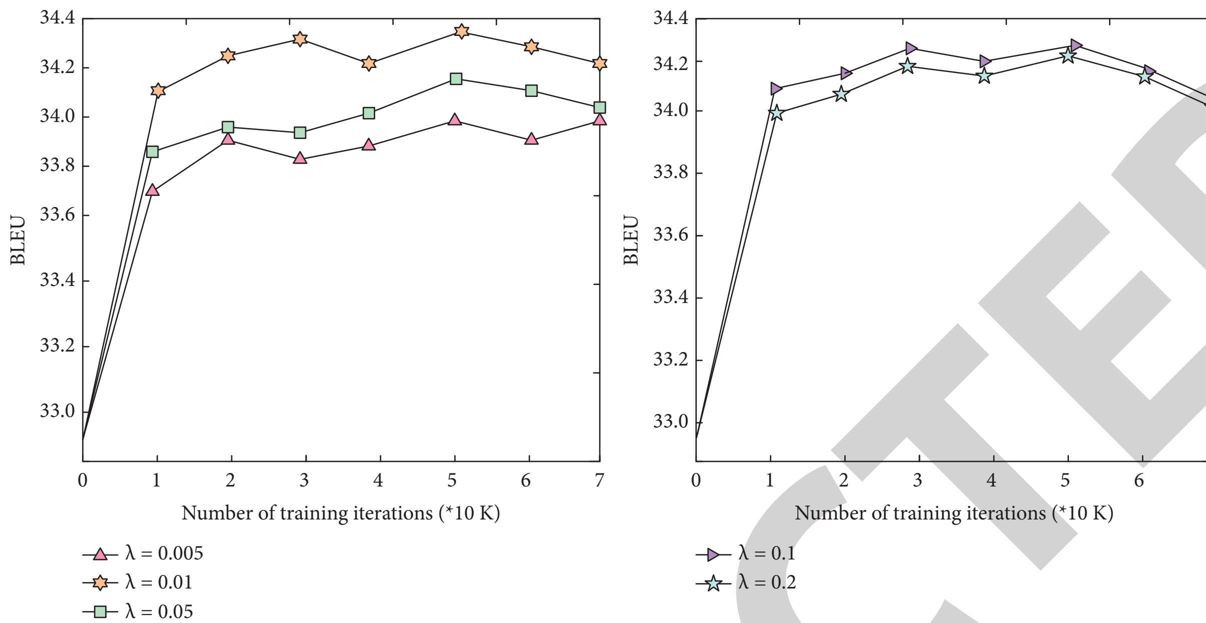


Figure 9: Translation effect on German-English validation set with different balance parameters λ.

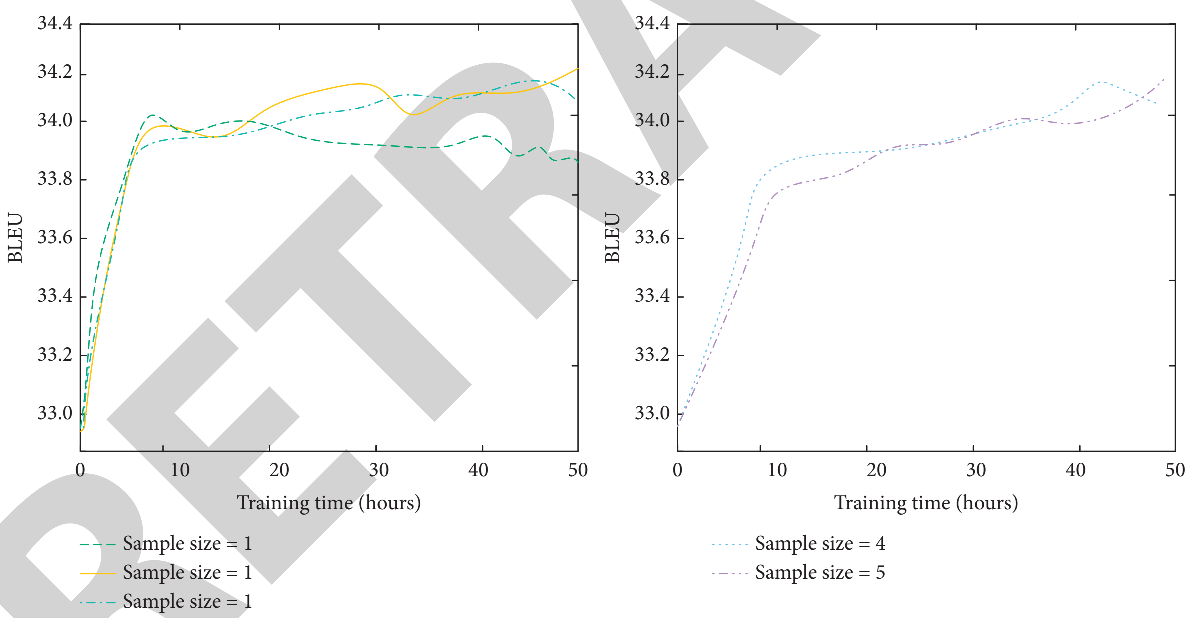


Figure 10: Translation effect on the German-English validation set with different sampling sizes K.

As shown in Figure 11, the averages calculated for the selected monolinguals and sentences for the two training targets during the training iteration are shown. As can be seen from the figure, when using either training objective, the values gradually decrease as the training process progresses. That is, the marginal distribution computed by the language model and the marginal distribution estimated by importance sampling become progressively more consistent as the model is trained. In particular, the values drop more rapidly when seen using a training objective based on probability constraints. This phenomenon is consistent with the fact that a training objective based on probability constraints will lead to better translation performance of the model when using two training objectives. On the other hand, for the training target based on marginal distribution estimation, although the full probability formula is not directly enforced in the training target, the value also gradually decreases as the model training effect becomes better. This also shows that the hypothesis that a well-trained model should satisfy the full probability formula on a monolingual corpus is valid.

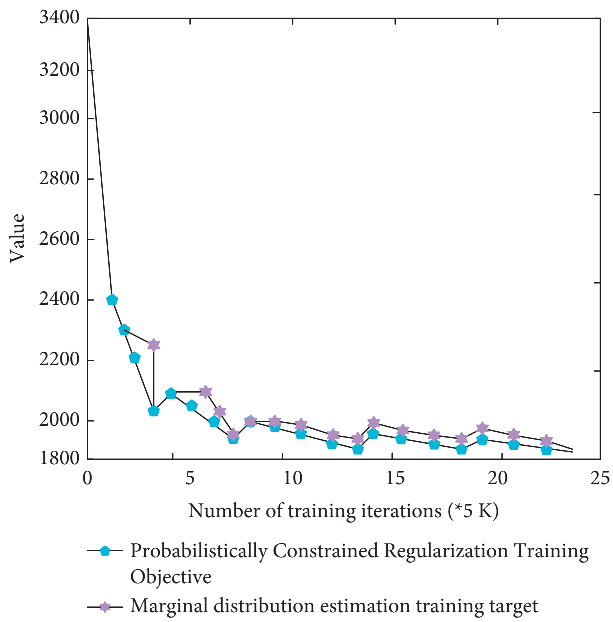


Figure 11: The value of the regularization term of the selected single sentence during the training process.

6. Conclusions

This paper mainly focuses on the research and implementation of 3D visualization technology in the English language neural machine translation system. Aiming at the scarcity of parallel corpus resources in the training corpus, the method of data augmentation is used to improve it. First, it proposes two methods centered on back-translation strategies in data augmentation to strengthen the parallel corpus involved in training. The English language random alignment alternative is then refined and streamlined to train a framework for initializing translation models. Combined with the results of the first two steps, the English language neural machine translation model is trained by the method of complete parameter sharing, the effect of the bilingual neural machine translation model is compared, and the effectiveness of the pretraining method on multilingual translation tasks is verified. Finally, a translation system based on B/S architecture is built, which connects the server model and the client, and realizes the visualization and interaction of translation functions. The system is deployed in parallel with the WEB server and the translation server group. This greatly improves the task response speed of the system and optimizes task resource scheduling. Finally, the system shows the translation results in different situations. The practice has proved that the multilingual translation system built on the basis of the translation model proposed in this paper can achieve better translation results. Data augmentation methods do not really solve the problem of corpus scarcity. To prevent its translation effect from getting worse, the effect of other language pairs can only be sacrificed.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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