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Article

Research on the Optimization Strategy of English Translation System Based on Fuzzy Control Algorithm and Its Effectiveness in Teaching Application

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Abstract: Addressing the current shortcomings of English machine translation, such as poor accuracy and ambiguity, this paper proposes a research approach based on constructing semantic mapping relationships, determining semantic order, and achieving accurate machine translation. After processing and analyzing the context of natural language using generalized relationships between concepts, fuzzy evaluations are conducted on the objectives between different ontology concepts to obtain the set of symbols with the highest semantic relevance within the domain knowledge, thereby establishing the semantic model for machine English translation. The maximum entropy training algorithm is used to classify the semantics of English machine translation, and the weighted hierarchical analysis method is employed to calculate English semantic similarity based on fuzzy selection rules, thereby achieving semantic reordering in English machine translation. Combining the fuzzy decision tree method, a hierarchical English machine translation model is constructed, and optimization strategies for the English translation system are proposed. The designed translation model demonstrates reliable application performance in assisting college English teaching, with course effectiveness achieving a positive satisfaction rate of 70.00% or higher among students.

Keywords: fuzzy decision tree; hierarchical English machine translation; translation semantics; semantic similarity

1. Introduction

The rapid development of economic globalization has led to increasingly complex trends in cultural exchange in China. In the process of exchanging talent, materials, and technology, higher demands have been placed on college students' English translation skills [1-2]. To adapt to a social environment where English is the common language and to cultivate college students' English translation abilities, high-quality translation instruction must be implemented [3]. With the widespread application of modern science and technology, information technology tools such as the internet and computers have enabled machine translation, which has to some extent reduced the difficulty of university English translation teaching and effectively improved teaching standards [4-5].

Machine translation is a new intelligent language conversion technology formed by integrating modern advanced information technology. By applying computer and AI technologies and utilizing intelligent reading programs, it converts text from one language to another, making it a product of modern high technology [6-8]. The purpose of applying machine translation is to create a more seamless and convenient communication bridge across different language environments [9]. In university English translation education, the application of English translation systems offers two advantages. On one hand, it reduces teaching difficulty, enabling students to better absorb translation instruction [10]. On the other hand, it reduces the workload of repetitive translation, thereby improving students' learning efficiency [11].

Therefore, many researchers have followed the trend of the times and applied English translation systems to English classrooms to address the translation challenges students encounter during English learning. For example, Reference [12] applied the Google Translate system to university English foundation courses as an instant translation tool to assist English translation instruction, providing students with more accurate translations at an extremely fast pace. This helps students build a certain level of learning confidence and enhances their interest in English translation learning. Literature [13] proposes a construction scheme for a flipped classroom translation assistance system (TFCAS), which utilizes cloud computing and machine translation technology to reduce teachers' workloads and help students effectively use machine translation systems, thereby supporting the sustainable development of translation instruction. Literature [14] explores the challenges faced by students and teachers when using computer-assisted translation tools (CAT) to learn English, as the complexity of language and context means that these tools cannot completely replace teachers.

Due to the professionalism and complexity of university English, the translation quality of English translation systems has become the greatest limitation constraining their application in higher education English classroom instruction [15]. To address this issue, Literature [16] employs spectral clustering to remove outliers, uses deep learning methods to enhance the classification performance of English translation models, and applies adaptive weighting to eliminate invalid hypotheses, thereby comprehensively optimizing English translation systems. Literature [17] proposes an interactive English translation system based on feature extraction algorithms, aiming to improve system translation accuracy by addressing the limitations of traditional systems. Literature [18] proposes a novel MA-Transformer framework that combines multi-level semantic feature extraction to improve text matching effectiveness in English translation systems, achieving high-precision English translation. Literature [19] introduces image segmentation algorithms to develop and optimize online English translation systems, enhancing the system's ability to process noisy images and constructing a stable and efficient English teaching network. Under the influence of fuzzy algorithms, English translation systems have been further improved and enhanced [20]. Literature [21] proposes a method using the generalized maximum likelihood ratio algorithm to identify and process fuzzy information in English translation systems, aiming to enhance quality and efficiency by reducing ambiguity and improving fluency. Literature [22] integrates the Dependency-Based Precise Translation Approach (FPTA) with deep learning and fuzzy logic to address precision verification issues, reducing errors by 12.49% while improving the understandability of translations. All these studies have improved the performance of translation models, enabling English translation systems to meet the high accuracy requirements of university English teaching.

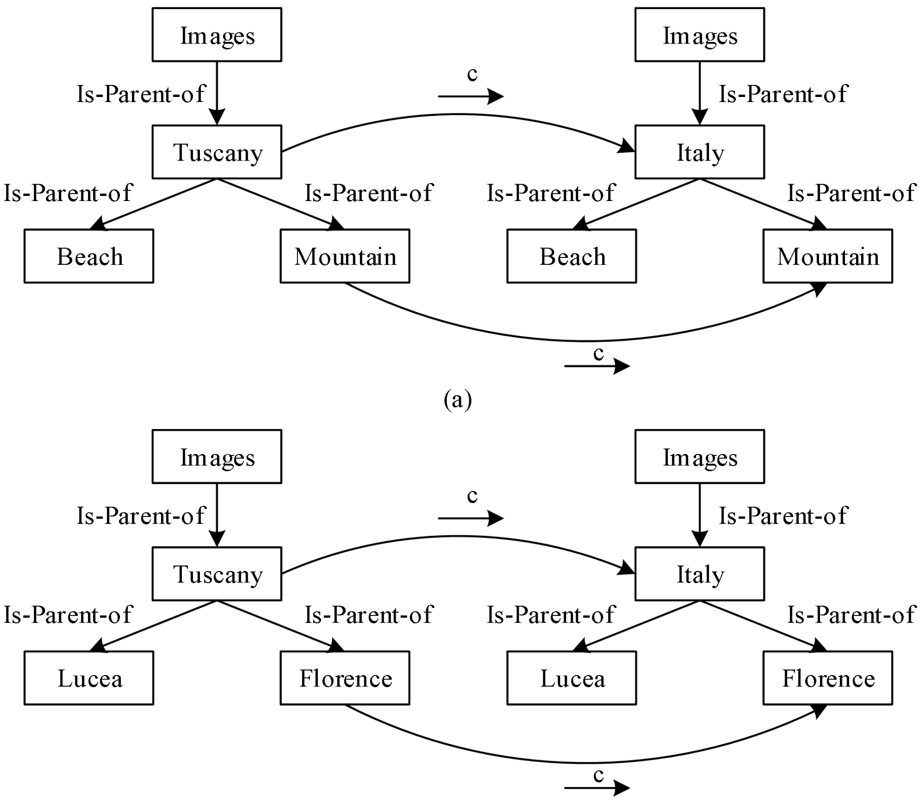
This paper first describes the natural language processing workflow and semantic ontology mapping methods in machine English translation, establishing a semantic model for machine English translation. It briefly outlines the English semantic classification workflow, and based on this, further designs methods for calculating English similarity and obtaining optimal similarity, proposing a semantic reordering method for English machine translation. It then details the concepts and entropy definitions of the fuzzy decision tree method, constructs a hierarchical English machine translation model, and integrates these to form an optimization strategy for the English translation system. Next, the performance of the proposed model is compared with traditional models from two aspects: semantic mapping feature matching rate and recall rate. The training performance of the model is analyzed to determine the pre-training method. Finally, the designed model is applied to university English teaching, with an experimental group and a control group established while controlling variables (learning level, learning style), and a comparative experiment on student course satisfaction is conducted to validate the practical feasibility of the designed model.

2. Optimization Strategies for English Translation Systems

2.1. Semantic Model of Machine English Translation

2.1.1. Natural Language Processing in Machine English Translation

The ontology fragments of the two sets of English translation examples are shown in Figure 1. Before constructing the semantic model for machine English translation, we first consider the ontology fragments of the two sets of English translation examples shown in Figure 1.



(b)

Figure 1. The ontology fragments of two sets of sets of English translation examples.

Take Figure 1 as an example. In natural language processing for machine English translation, the English word "image" can refer to a picture. The synonyms 'image' and "picture" have a fuzzy mapping relationship. The possible semantic mapping relationship between synonyms and semantic information in English translation is described by Equation (1):

$$\theta : S \to S \times [-0.5, 0.5] \tag{1}$$

Establish semantic mapping relationships in the ontology model to solve the problem of fuzzy mapping between similar words in natural language.

Definition 1 Let two concepts labeled as Mountain nodes have a semantic constraint coefficient $\beta \in [0, T]$, representing the set of real words after the machine English translation evaluation set S is matched with concept-related domains. Where T is the semantic information analysis evaluation set, then the structural knowledge point β in the ontology fragment can be expressed by the function Δ in equation (2):

$$\Delta : [0, T] \to S \times [-0.5, 0.5) \tag{2}$$

The binary semantic information of natural language in machine English translation is expressed by equation (3):

$$\Delta(\beta) = \begin{cases} s_k, & K = round(\beta) \\ a_k = \beta - k, & a_k \in [-0.5, 0.5) \end{cases} \tag{3}$$

In the formula, $round$ is an automatic semantic information rounding operator.

Combining the two labels of the "Mountain" node on the left side of the natural language processing in the machine English translation in Figure 1(a), the generalization relationship (Is-less_than) between concepts is used to process and analyze the natural language context, thereby improving the intelligence level of machine language translation.

2.1.2. Analysis of the Establishment of a Semantic Text Mapping Model

Based on the natural language processing performed by machine English translation as described above, fuzzy evaluation is conducted on the targets (or objects, criteria) between concepts in different ontologies. The set of symbols representing the maximum semantic relevance values in domain knowledge is analyzed, and the confidence level of machine English translation between any two words W_i and W_j is represented by the tuple (s_k, a_k).

Definition 2: Let (s_k, a_k) be a binary feature combination that semantically modifies a target, where s_k is the kth element in the set S, and $a_k \in [-0.5, 0.5)$. Then, in a simple semantic unit, the English translation's attributive modification function is given by Equation (4):

$$\Delta^{-1} : S \times [-0.5, 0.5) \to [0, T] \tag{4}$$

Assume that (s_k, a_k) and (s_l, a_l) are two binary semantics. In machine English translation, when attributive clauses are incorporated into the main clause, the selection of the clause scope is described by a grammatical ontology mapping model for binary semantics as follows:

(1) During semantic analysis, if $k < l$, then $(s_k, a_k) < (s_l, a_l)$.

(2) If $k = l$, then: $a_k = a_l$, so $(s_k, a_k) = (s_l, a_l)$, $a_k < a_l$, then $(s_k, a_k) < (s_l, a_l)$, $a_k > a_l$, then $(s_k, a_k) > (s_l, a_l)$.

2.2. Semantic Reordering in English Machine Translation Based on Fuzzy Theory

2.2.1. English Semantic Classification

The focus of the English semantic reordering model based on fuzzy theory is the classification of English semantics. The maximum entropy training algorithm is selected to classify English semantics. The maximum entropy training algorithm is essentially similar to a word explanation process. This model can accurately classify semantics into hierarchical and interleaved semantics based on their performance. Interleaved semantics are reordered based on maximum similarity, while hierarchical semantics include three types: same category, interval, progressive categories. Assuming that the current ordered English semantics in the semantics to be ordered are represented by the symbol B_i, the extended English semantics of B_i are B_{i-1}, and the target semantics in the same arrangement position as B_i are represented by A_i, then the classification semantic expression is given by Equation (5):

$$f(A_i, B_i) = \begin{cases} A_{i-1}, & i = 1, 2, 3, \cdots \\ B_{i-1}, & i = 1, 2, 3, \cdots \end{cases} \tag{5}$$

When $B_{i-1} = 1A_i$, the semantics of the English to be ordered are homogeneous, and the symbol A_{i-1} is used instead of the front-end data of A_i. When $A_{i-1} = 1B_i$, the semantics of the order to be modulated are progressive. When the semantics to be ordered are neither homogeneous nor progressive, they are regarded as interval semantics.

2.2.2. Calculation of Optimal Semantic Similarity in English

Based on the classification of English semantics, the weighted hierarchical analysis method is used to calculate the similarity of English semantics.

(1) Construct an English semantic model and determine the hierarchical English semantics and interleaved English semantics sorting process. Based on two typical semantic categories, select any data to construct an English semantic model, as shown in Figure 2.

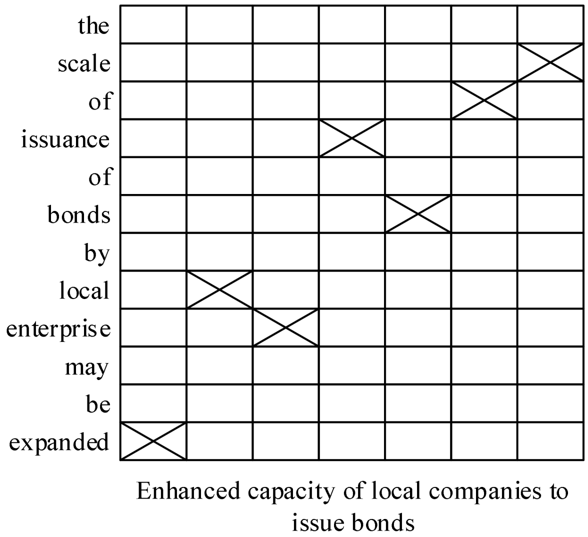


Figure 2. English Semantic Model.

As shown in Figure 2, when performing English semantic reordering, it is necessary to consider the issue of reordering structures that differ in two directions. Hierarchical English semantics utilizes the differences between two different directions to perform semantic reordering, with the reordering process flow shown in Figure 3.

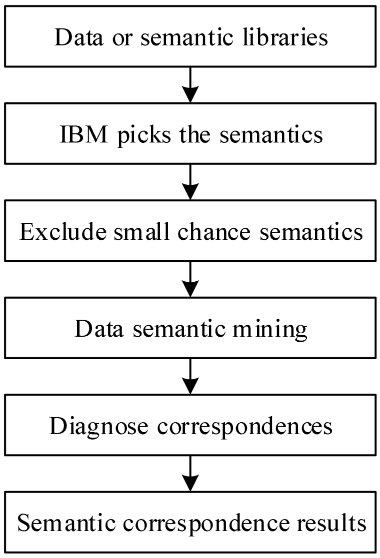


Figure 3. The implementation process of hierarchical English semantic reordering.

As shown in Figure 3, the hierarchical English semantic reordering model uses IBM software (a business software that provides resource integration functions) to reorder semantics, thereby excluding English semantics with a probability of less than 0.18 from the model. The remaining words will be successfully reordered, and then diagnosed to see if they correspond to the original data. The reordered results after diagnosis are used as the final results.

Interleaved English semantics differ from hierarchical English semantics, and simple reordering models cannot achieve accurate correspondence between the semantics to be reordered and the correct target semantics. Therefore, the maximum similarity between English semantics must be calculated to reorder the semantics. The workflow of the interleaved semantic reordering model is shown in Figure 4.

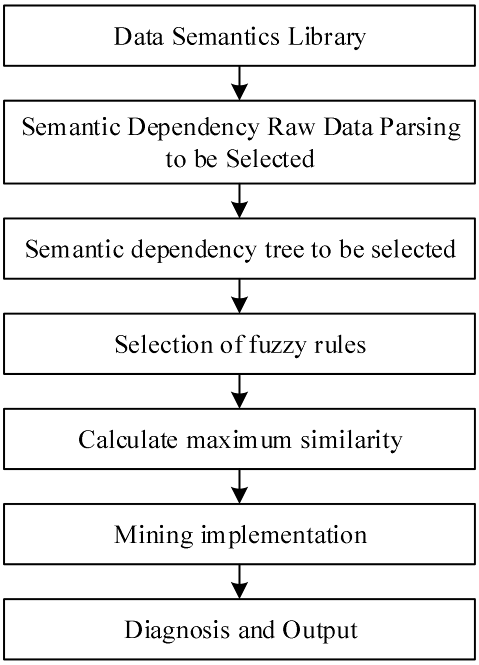


Figure 4. Interlacing English semantic reordering process.

The interleaved English semantic reordering model parses the raw data of English semantic dependencies in the English semantic database, generates a reordering semantic dependency tree, and then calculates the maximum similarity based on fuzzy selection rules to avoid disrupting the semantic reordering structure and prevent reordering errors during the reordering process. After that, reordering is implemented, and the reordering results are subjected to a secondary diagnosis before the results are output.

(2) Determine the similarity between English semantics and obtain the optimal similarity using weighted hierarchical analysis.

Let I_1 be any semantic meaning in the sequence to be adjusted, I_2 be the fuzzy corresponding result of I_1, and d be the distance between I_2 and I_1. Let η denote the fuzzy adjustment parameter of the dependency tree. The similarity between I_2 and I_1 can then be obtained using equation (6):

$$sim(I_1, I_2) = \frac{\eta}{\eta + d} \tag{6}$$

Obtaining the optimal similarity is a process of continuously changing the weight of the fuzzy adjustment parameter η, which is described by the weighted hierarchical analysis method in equation (6) and expressed as equation (7):

$$sim(s_1, s_2) = \sum_{i=1}^{4} \delta sim(I_1, I_2) \tag{7}$$

In the formula, δ represents the weight, and $\sum_{i=1}^{4} \delta = 1$.

The weighted hierarchical analysis is performed four times, describing the independent relationship between I_1 and I_2, the same structure, the same semantic function, and the same data center. After the weighted hierarchical analysis, the optimal similarity expression is determined to be formula (8):

$$S_{\max} = \frac{\sum_{i=1}^{n} \left[\varphi_1 sim(s_1, s_2) + \varphi_2 sim(I_1, I_2) \right]}{n} \tag{8}$$

In the formula: n is the number of child nodes. φ_1, φ_2 are the proportions of sorting order and weighted hierarchical analysis in the child nodes, $\varphi_2 = 1 - \varphi_1$.

2.3. Tiered English Machine Translation Model

2.3.1. Fuzzy Decision Tree

Decision trees (DT) are a widely used method for discovering new and interesting knowledge. Decision trees represent a simple yet powerful method for inductive reasoning from labeled instances. Fuzzy decision trees are an extension of decision trees in fuzzy environments. The knowledge represented by fuzzy decision trees is more natural to human thinking. Classical crisp decision trees are widely applied in pattern recognition, machine learning, and data mining. Decision trees are introduced to inductive classification models, enabling classification of samples by propagating samples along a path from the root to the leaves, which contains classification information.

Fuzzy decision trees (FDTs) are a more general method for representing knowledge. This method enables the use of numerical values and symbolic values to represent fuzzy modalities during the learning phase (tree construction) or generalization phase. Additionally, researchers believe that fuzzy decision trees are equivalent to a set of fuzzy rules and can introduce such inductive rules to optimize database query processes or infer decisions from data.

The goal of fuzzy decision trees is to achieve high interpretability, enabling fuzzy systems to exhibit progressive and elegant behavior. Therefore, fuzzy sets and approximate reasoning are used to extend symbolic decision trees for tree construction and inference processes. Simultaneously, existing decision tree methods are leveraged to handle incomplete knowledge and extended to utilize new information available in fuzzy representations.

Fuzzy entropy is a measure of uncertainty.

In particular, when ζ is a fuzzy set, take the values x_i with membership degrees, $i = 1, 2, \ldots, n$, and scholars define its entropy as shown in formula (9):

$$E[\zeta] = \sum_{i=1}^{n} s(\zeta = x_i) \tag{9}$$

When $S(t) = -1\ln t - (l - t)\ln(l - t)$ it is easy to verify that the function $S(t)$ is symmetric about $t = 0.5$, strictly increasing over the interval $[0, 0.5]$, strictly decreasing over the interval $[0.5, 1]$, and reaching its unique maximum value of $\ln 2$ at $t = 0.5$.

The uncertainty in describing entropy is primarily due to the ambiguity of language rather than a lack of information, and it disappears when the fuzzy variable is a possible variable. However, it is hoped that when the fuzzy variable degenerates into a clear number, the entropy is 0, and when the fuzzy variable is equal, the entropy is maximum.

2.3.2. Model Construction

The model for hierarchical English machine translation (HEMTM) is shown in Figure 5. The input is hierarchical English machine translation, and the output is the result of constructing the hierarchical English machine translation model.

Machine translation combines relevant HEMTM with corresponding hierarchical machine translation, laying the foundation for evaluating the support relationship between relevant HEMTM and corresponding hierarchical English machine translation. In the HEMTM intelligent fuzzy decision tree algorithm, r_i and fs are machine translations of sentences, while st_i and fs are set machine translations. Machine translation between words lays the foundation for generating semantic vectors and word order vectors. The formula for machine translation between words is shown in Equation (10). Equation (10) is used to calculate the machine translation of word w_i and word w_2. l and h represent the shortest distances between w_1 and w_2 in the word network, respectively, and both w_1 and w_2 exist in that word network. Machine translation between words can be evaluated more effectively using Equation (9), where $\alpha = 0.2$ and $\beta = 0.45$.

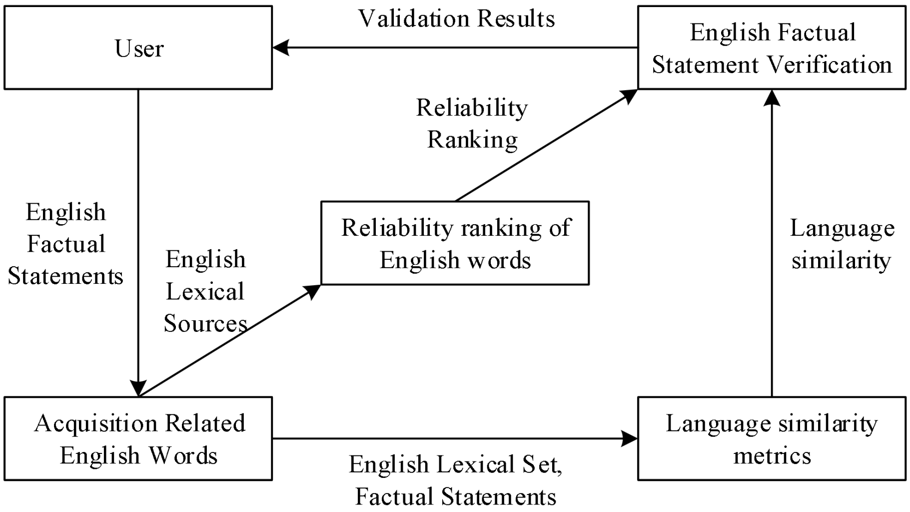


Figure 5. Graded English machine translation model.

$$S_w(w_1,w_2)=\begin{cases} e^{-\alpha l}\cdot\dfrac{e^{\beta h}-e^{-\beta h}}{e^{\beta h}+e^{-\beta h}}, & w_i\neq w_2 \\ 1, & w_1\neq w_2 \end{cases} \tag{10}$$

If $w_1 = w_2$, its relevance can be considered 1. In addition, because the information in the designed word network cannot cover all words. Therefore, if w_1 is otherwise w_2 cannot be covered by the word network, then $S_w\left(w_1,w_2\right)=0$.

Assume that s_1 is the sentence st_i selected from r_i, and s_2 is the corresponding hierarchical English machine translation of r_i and fs. Next, the machine translation process will be demonstrated by calculating the machine translation of s_1 and s_2.

3. Model Performance Evaluation and Educational Applications

3.1. Model Performance Testing

3.1.1. Feature Alignment Rate of Semantic Mapping

This section focuses on the automatic determination of multiple ambiguous semantics in machine translation, testing the feature alignment rate of semantic mapping. The model designed in this paper is compared with traditional models, and the results are shown in Figure 6. As the number of iterations increases, the feature alignment rate of semantic mapping in the model proposed in this paper gradually reaches 100.00%, with an initial feature alignment rate as high as 60.00%. In contrast, the feature alignment rate of the traditional model not only starts below 40.00% but also reaches a maximum of only 91.41%. This indicates that using the method proposed in this paper for automatic determination of multiple ambiguous semantics in machine translation can improve translation accuracy. Compared to traditional methods, the feature alignment rate of contextual semantic mapping is significantly improved, demonstrating superiority and enhancing the accuracy of machine translation.

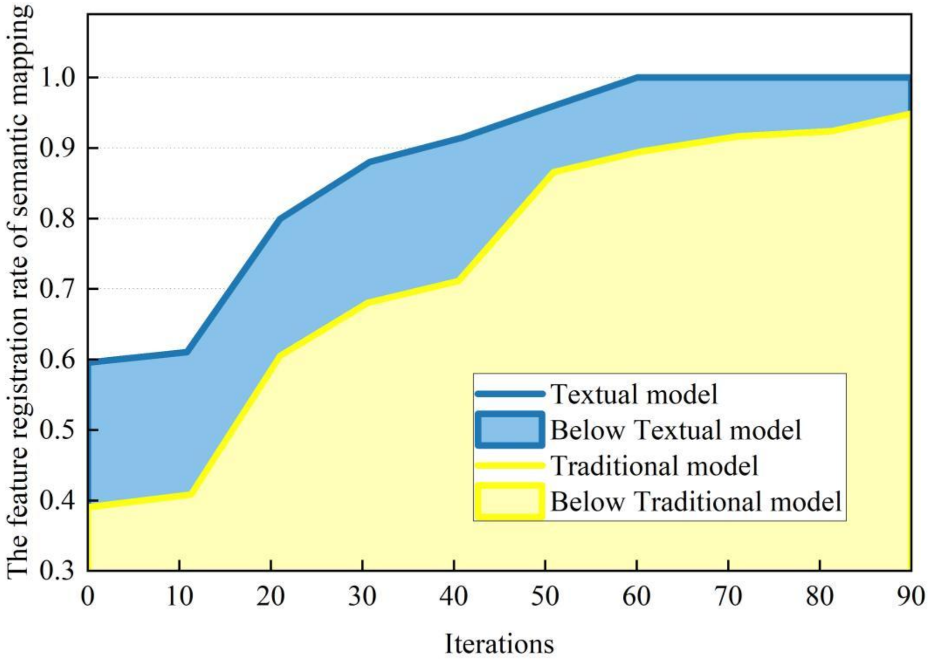


Figure 6. Comparison of feature registration rates for semantic mapping.

3.1.2. Recall rate

Four traditional machine translation models (M1-M4) were selected for comparison with the translation results of the model method proposed in this paper (M5). The recall rate results for English sentence content are shown in Figure 7. It can be clearly seen that the recall rate of the model method proposed in this paper (M5) can reach up to 95%, and the recall rate remains above 65% for sentences of various lengths. In contrast, the highest recall rate for the other four traditional machine translation models is only 80.23%, with the majority falling between 25% and 75%. This indicates that after mapping English sentence content using the model method proposed in this paper, the contextual coherence between sentences is more natural, and the semantic flow is smoother, resulting in better overall translation quality.

3.2. Model Training

3.2.1. Training Performance

The training was conducted using the open-source OpenNMT system based on the Transformer architecture, with both the encoder and decoder set to 6 layers, sharing parameters across 3 of those layers. The mixed corpus obtained by combining the real parallel corpus and the synthetic parallel corpus in each iteration is used in the next iteration, where the ratio of newly generated pseudo-parallel corpus to real corpus is set to 1:1. This means that 150,000 synthetic parallel corpus sentences are generated in each iteration. Since the process is bidirectional, a total of 300,000 synthetic parallel corpus sentences are produced in each round. A total of 3 cycles and 6 iterations are performed, with the model trained 10 times in total. The amount of data generated and model performance during the iteration back-translation process are shown in Table 1.

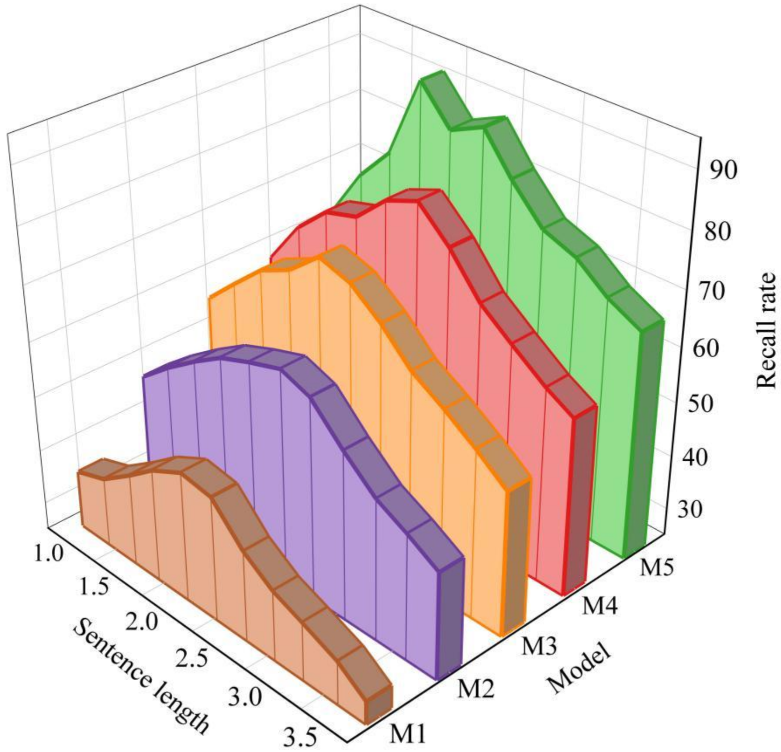


Figure 7. Comparison of recall rates among five model methods.

Table 1. Corpus quantity and model performance.

Training times	The quantity of the corpus used	BLEU
1	150000	12.03
2	150000	4.85
3	450000	13.8
4	450000	8.13
5	750000	15.14
6	750000	9.61
7	1050000	16.4
8	1050000	10.82
9	1350000	12.03
10	1350000	4.85

3.2.2. Selection of Pre-Training Methods

This section discusses the selection of pre-training methods during the model pre-training phase. Table 2 compares the effects of the language random alignment substitution method (mRASP) and the commonly used MNMT method on language translation models across different levels of translation difficulty. Translation tasks are categorized into 10 difficulty levels based on the characteristics of Chinese-English translation, with difficulty increasing progressively as the numerical value increases. In comparison, after pre-training using the mRASP method, the translation model performed above 15 on all translation difficulty tasks, demonstrating excellent and relatively stable performance.

Table 2. The influence of pre-training methods on language translation models.

Grade of difficulty	mRASP	MNMT
1	20.16	17.55
2	16.46	13.39
3	33.9	30.96
4	32.77	30.2
5	28.01	24.77
6	25.69	22.6
7	17.79	9.4
8	19.68	4.47
9	30.82	28.17
10	25.55	22.56

3.3. Evaluation and Analysis of Teaching Application Effects

This section randomly selected two classes of second-year English majors from K University as the experimental subjects, with 25 students in each class. One class conducted teaching and learning activities under the model method designed in this paper and was designated as the experimental group (G1), while the other class continued to use the traditional teaching model and was designated as the control group (G2).

3.3.1. Learning Level

Prior to the official start of classes, to assess the initial proficiency levels of students in both classes, the instructor developed a pre-test and distributed it to students during the first class session for testing, with a duration of 45 minutes. The pre-test comprised five Chinese phrase translations (5 points), five Chinese sentence translations (15 points), one English passage translation (20 points), and one error correction question (10 points), totaling 50 points. The pre-test scores of students in the (G1) experimental group and (G2) control group were collected and imported into SPSS for data analysis. The group statistical results are shown in Table 3, and the independent samples test results are shown in Table 4.

Table 3. Group statistical results.

	G1	G2
Average	31.5226	33.7341
Standard deviation	3.9249	4.78567
Average standard error	1.76181	1.97465

Table 4. Independent sample test.

		Assume equal variance	Equal variance is not assumed
Levin variance equivalence test	F	0.853	
	Significance	0.504	
t		-1.674	-1.644
Degree of freedom		47.111	40.876
Sig. (Double Tail)		0.192	0.198
Average value equivalence t-test	Average value difference	-1.48515	-1.48515
	Standard error difference	1.00507	1.02034

	The difference is 95% confidence interval	Lower limit	-3.2838	-3.32192
		Upper limit	-0.09149	-0.12961

As shown in Tables 3 and 4, the pre-test (G1) experimental group had an average score of 31.5226 with a standard deviation of 3.9249, while the (G2) control group had an average score of 33.7341 with a standard deviation of 4.78567. The significance test P-value was 0.087, which is greater than 0.05. There was no significant difference in performance between the two classes, indicating that there is no significant difference in the academic levels of the students in the two classes. Therefore, further comparative experiments can be conducted.

3.3.2. Students' learning styles

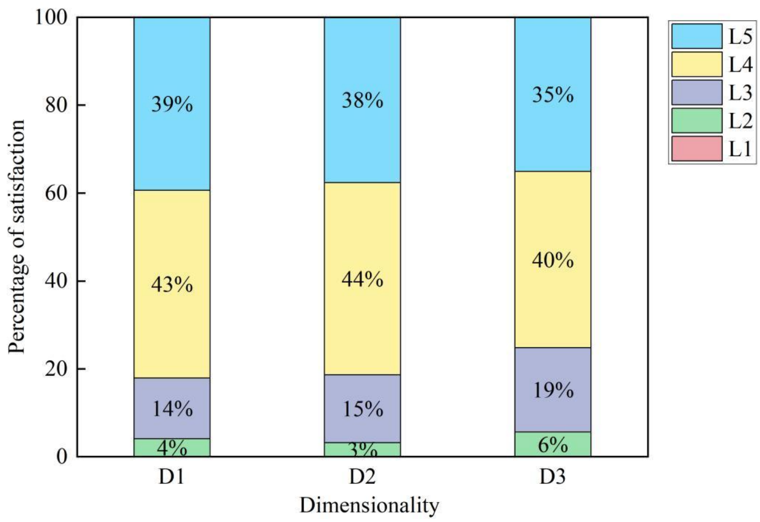
Students' learning styles are categorized into the following 15 types: (S1) Active/Perceptive/Visual/Sequential, (S2) Contemplative/Perceptive/Visual/ Sequential, (S3) Active/Intuitive/Visual/Sequential, (S4) Contemplative/Perceptive/ Visual/Sequential, (S5) Active/Perceptive/Verbal/ Sequential, (S6) Contemplative/ Perceptive/Visual/Sequential, (S7) Active/Intuitive/ Verbal/Sequential, (S8) Contemplative/Intuitive/Verbal/Sequential, (S9) Active/ Perceptive/Visual/Holistic, (S10) Contemplative/Perceptive/Visual/Holistic, (S11) Active/Intuitive/Visual/ Holistic, (S12) Contemplative/Intuitive/Visual/Holistic, (S13) Active/Perceptive/ Verbal/Holistic, (S14) Contemplative/Perceptive/Verbal/Holistic, (S15) Active/ Intuitive/Verbal/Holistic. The learning styles of students in the (G1) experimental group and (G2) control group are shown in Table 5. The data indicate that the differences in the proportions of students across different learning styles between the two groups are all within 2.00%, suggesting that there are no significant differences between the two classes in terms of learning styles such as information processing, perception, input, and understanding. Therefore, the influence of learning styles on the experimental results is excluded in this experiment.

Table 5. Percentage statistics of students' learning styles.

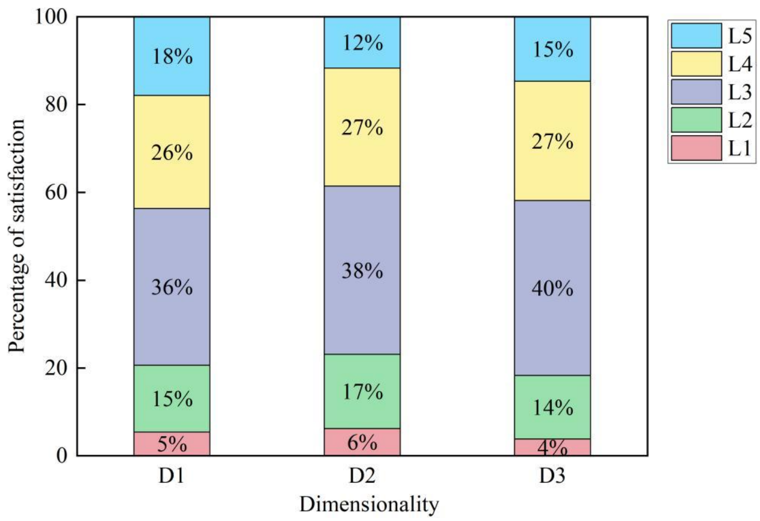
Learning style number	G1	G2
S1	9.14	9.03
S2	7.05	7.24
S3	4.79	4.59
S4	9.39	9.26
S5	5.18	6.17
S6	0.23	0
S7	8.43	8.01
S8	1.43	1.96
S9	6.99	6.54
S10	10.20	9.74
S11	4.73	5.69
S12	8.22	7.54
S13	6.71	6.31
S14	13.00	12.28
S15	4.51	5.64

3.3.3. Course Satisfaction Analysis

This paper designed a course satisfaction survey questionnaire centered on three dimensions: (D1) teaching content, (D2) classroom experience, and (D3) course outcomes. Satisfaction levels were categorized as follows: (L1) strongly disagree, (L2) disagree, (L3) neutral, (L4) agree, and (L5) strongly agree. The results of the course satisfaction survey for students in the (G1) experimental group and (G2) control group are shown in Figure 8.



(a) G1



(b) G2

Figure 8. The results of students' course satisfaction.

Overall, students in the experimental group (G1) expressed satisfaction with the teaching and learning outcomes facilitated by the model presented in this paper, with the majority of responses concentrated in the “agree” (L4) and “strongly agree” (L5) categories, both of which reached 35.00% or higher. Additionally, the “strongly disagree” (L1) category accounted for 0.00% of responses. This indicates that under the guidance of the model proposed in this paper, not only can the quality and level of teaching content be significantly improved, but the teaching model can also meet students' needs and promote the enhancement of their comprehensive language skills. In contrast, the satisfaction levels of students in the control group (G2) were primarily concentrated in the “neutral” (L3) and “agree” (L4) categories, indicating that a conventional teaching and learning model cannot effectively enhance students' enthusiasm for learning or their satisfaction with the course.

4. Conclusion

This paper establishes semantic mapping relationships for machine English translation by designing a semantic text mapping model, obtains the optimal semantic similarity of English, and performs semantic reordering for English machine translation. It combines the fuzzy decision tree method to construct a hierarchical English machine translation model and proposes an optimization strategy for the English translation system based on fuzzy control algorithms.

The designed model demonstrates outstanding performance, with an initial feature alignment rate as high as 60.00% that gradually reaches 100% with increasing iterations. The recall rate can reach up to

95%, and the recall rate remains above 65% across multiple sentence lengths. In actual educational applications, the system has achieved a satisfaction rate of 70.00% or higher among students in terms of its auxiliary teaching and learning effects. Under the optimization strategy for the English translation system based on fuzzy control algorithms, the machine English translation system not only achieves superior translation accuracy and operational performance but also effectively assists in enhancing the quality of English teaching in higher education institutions.

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