



# Design of an English Semantic Translation Accuracy Evaluation System Based on Computer Technology

Huaxin Chen<sup>(✉)</sup> and Yibo Zhang

Science and Technology College of Nanchang, Hangkong University, Gongqingcheng 332020,  
Jiangxi, China

chenhuaxin2021@126.com

**Abstract.** In order to improve the accuracy of English translation and evaluate the results of English translation, this paper proposes an accuracy evaluation system for English semantic translation based on computer technology. In this study, a constraint object selection model for English semantic translation assessment is constructed, which can constrain the inaccurate parts of translation. In this study, the context-related mapping semantic retrieval method is used to analyze the structural features of English translation, and the accuracy of English translation results is calculated. In order to achieve the accuracy assessment of English translation, weighted learning and adaptive weight analysis are used. Finally, the system is tested and run in this paper, and the final result is relatively good and has strong practicability.

**Keywords:** English Translation · Semantic Analysis · Model · System · Computer Technology

## 1 Introduction

Nowadays, machine translation is becoming more and more popular in people's lives, but there are always various problems in the results of machine translation [1]. Although machine translation can accurately translate basic words and sentences, when encountering rare words, slang words, complex long sentences, and implicit logic, machine translation results cannot accurately express the meaning of sentences. How to use computer technology to improve the quality of English translation has become a very hot topic in recent years. There are mainly two ways to improve the quality of English translation in the current research community. The first is to use neural networks to evaluate machine translation results [2]. This method can improve the quality of machine translation, but there are still some shortcomings in culture, context, and communication. The second is to use the semantic network to improve the quality of machine translation. The English machine translation method of phrase synthesis and semantic statistics based on vector mixture can effectively obtain accurate English translation results. In this study, a constraint object model is constructed and an unsupervised learning algorithm is used to obtain a system that can produce high-quality English translation results [3].

© The Author(s) 2023

K. Subramanian et al. (Eds.): CTMCD 2022, ACSR 99, pp. 689–695, 2023.

[https://doi.org/10.2991/978-94-6463-046-6\\_80](https://doi.org/10.2991/978-94-6463-046-6_80)

## 2 Constrained Object Selection Model for English Translation Assessment

The constraint object model in this system starts from the perspective of semantic translation, and uses the method of context-related mapping to realize the fuzzy fusion processing of the accuracy evaluation of English semantic translation [4]. Based on the mapping distribution association rule constraints of the English semantic context association mapping ontology, the similarity feature distribution coefficient of the English semantic context association mapping can be obtained as  $\omega = (\omega_1, \omega_2, \dots, \omega_i)$ ,  $\omega_i \in [0, 1]$ . Using natural language mapping and semantic ontology module design, the formula can be obtained as follows:

$$A = \frac{a \sum_{i=1} \omega_i}{S}$$

In the formula,  $a$  is the English semantic context related word fragment, and  $s$  is the English semantic context related map.

After decomposing the English concept features, the English semantic context association model can be obtained as follows:

$$B = \frac{A}{a + b} - \sqrt{b \sum_{i=1} \omega_i}$$

In the formula,  $b$  represents the proportion of the keyword in the full text [5].

Extract the features of the English semantic analysis process, and use the similarity transitivity principle to construct a semantic mapping relationship set, the specific relationship is shown in Fig. 1.

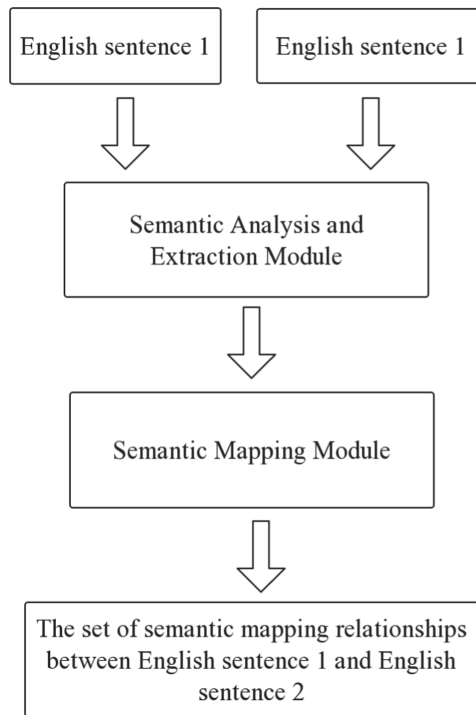
According to the distribution of the semantic mapping relationship set, the semantics of English context association mapping can be retrieved, and the semantic similarity value of each short sentence can be calculated. After that, the structural characteristics of English ontology can be analyzed [6]. To analyze the English structural features, we must first set the English semantic correlation feature quantity, that is,  $\alpha \in [0,1]$ . Next, the semantic correlation feature quantity formula is obtained as follows:

$$C = \frac{A(a + b)^\alpha}{n} + b^\alpha$$

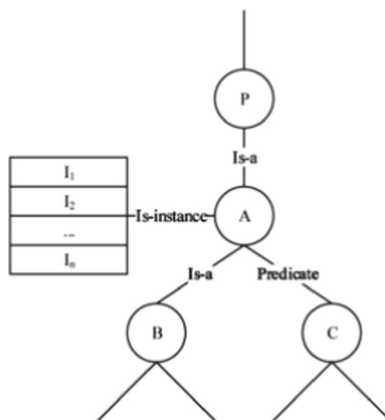
Using the Super-Concept and Sub-Concept analysis methods, the accuracy of English semantic translation can be evaluated. The formula is as follows:

$$D = a_k C - s_k \alpha - k$$

According to the above formula, it is possible to analyze the semantic structure characteristics of English, select the constraint object, and then evaluate the accuracy of English translation [7]. The English semantic structure feature model is shown in Fig. 2.



**Fig. 1.** Set of semantic mapping relationships for English semantic translation.



**Fig. 2.** Semantic Structural Features.

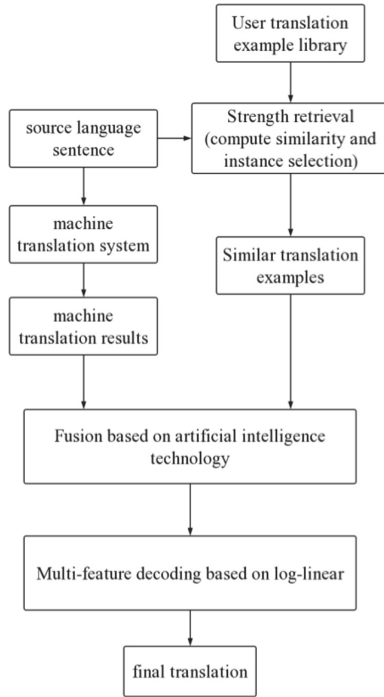


Fig. 3. English Translation Optimization Framework.

### 3 Improve the Accuracy of English Semantic Translation Algorithm

The accuracy of the results of machine English translation is not high because the translation results are vague due to factors such as language habits and contextual influences in English translation [8]. In order to improve the quality of English translation, it is necessary to optimize the English translation. To improve English semantic translation, we first need to build a translation instance library. Examples of English translations can be found in the database. In the process of machine translation, the translation results are compared, and the translation results that best fit the context are finally obtained [9]. The English translation framework of this method is shown in Fig. 3.

The translation obtained by the machine translation system is input into the system, and the bilingual translation database is retrieved according to the English phrases. Get the top n most similar translation examples in the database. Finally, the translation and the example are fused, and finally a translation result with improved accuracy can be obtained [10].

### 4 Test Analysis

This study finally uses this method to test to analyze whether this method is effective. The experiment uses the English news corpus for training. The subjects of the experiment

**Table 1.** Experimental Results.

Example	Expert rating	Semantically accurate model scores
machine translation(1)	0.67	0.7
Optimized translation(1)	0.95	0.9
machine translation(2)	0.47	0.5
Optimized translation(2)	0.92	0.9

are two English news materials [11]. This experiment mainly studies the accuracy of the experimental English-Chinese translation results. The experiment also looked for five English teachers to rate the machine translation results, and the scores were averaged. The full score is 1. The experimental results are as follows (Table 1).

As can be seen from the experimental result scores, the English translation optimization model proposed in this paper has achieved good results. This optimization model can effectively improve the accuracy of English translation, and is very practical for English machine translation [12].

## 5 Advantages of English Machine Translation

Although machine translation is not as lively and interesting as human translation, the efficiency of machine translation is faster and the threshold is lower, and it has strong practical value for some people with poor English ability [13]. Machine translation also has many uses in student learning. When students are reading, they can refer to the translated text of machine translation to read the article in depth, and extend it on this basis. Students who do not know how to express their ideas in English can use machine translation when they are learning to do. Machine translation results can provide students with a reference. The amount of translation data in machine translation is huge, and many rare words can be learned through machine translation. If students only use the dictionary to look up certain words, they may not be able to determine the meaning of the words or find the latest popular words. In machine translation, software provides more accurate word meanings based on context. Teaching aids with machine translation can have a positive effect on students. In the future where the accuracy of machine translation continues to improve, machine translation will gradually replace human translation and become a new way of world communication [14].

## 6 Conclusion

The English translation quality improvement system constructed in this paper mainly constrains the results of machine translation, finds inaccurate translation sentences, evaluates the accuracy of translation, and finally uses the database to improve the accuracy of English translation. Through experiments, it can be found that the English optimization method proposed in this paper has certain practicability, can effectively improve the accuracy of English translation, and can be further developed and improved.

## References

1. Brubaker Douglas K, Kumar Manu P, Chiswick Evan L, Gregg Cecil, Starchenko Alina, Vega Paige N, Southard Smith Austin N, Simmons Alan J, Scoville Elizabeth A, Coburn Lori A, Wilson Keith T, Lau Ken S, Lauffenburger Douglas A. An interspecies translation model implicates integrin signaling in infliximab-resistant inflammatory bowel disease.[J]. *Science signaling*,2020,13(643).
2. Collo Ginetta, Merlo Pich Emilio. A human translational model based on neuroplasticity for pharmacological agents potentially effective in Treatment-Resistant Depression: focus on dopaminergic system.[J]. *Neural regeneration research*,2020,15(6).
3. Guiduo Duan, Haobo Yang, Ke Qin, Tianxi Huang. Improving Neural Machine Translation Model with Deep Encoding Information[J]. *Cognitive Computation*,2021(prepublish).
4. Kazuhiro Seki. On Cross-Lingual Text Similarity Using Neural Translation Models[J]. *Journal of Information Processing*,2019,27(0).
5. Machine Translation; Recent Studies from University of Management and Technology Add New Data to Machine Translation [A Novel Natural Language Processing (Nlp)-based Machine Translation Model for English To Pakistan Sign Language Translation][J]. *Journal of Robotics & Machine Learning*,2020.
6. Machine Translation; Study Data from Konan University Update Understanding of Machine Translation (Cross-lingual Text Similarity Exploiting Neural Machine Translation Models)[J]. *Robotics & Machine Learning*,2020.
7. Mingjun Zhao, Haijiang Wu, Di Niu, Xiaoli Wang. Reinforced Curriculum Learning on Pre-Trained Neural Machine Translation Models[J]. *Proceedings of the AAAI Conference on Artificial Intelligence*,2020,34(05).
8. Nabeel Sabir Khan, Adnan Abid, Kamran Abid. A Novel Natural Language Processing (NLP)-Based Machine Translation Model for English to Pakistan Sign Language Translation[J]. *Cognitive Computation*,2020(prepublish).
9. Seki Kazuhiro. Cross-lingual text similarity exploiting neural machine translation models[J]. *Journal of Information Science*,2020,47(3).
10. Wang Lin. Urban land ecological evaluation and English translation model optimization based on machine learning[J]. *Arabian Journal of Geosciences*,2021,14(11).
11. Ying Xia. Research on statistical machine translation model based on deep neural network[J]. *Computing*,2020,102(2).
12. Zhang Yuqi, Liu Gongshen. Paragraph-Parallel based Neural Machine Translation Model with Hierarchical Attention[J]. *Journal of Physics: Conference Series*,2020,1453.
13. Zheng Hairong. Research on Computer Intelligent Proofreading System of Improved English Phrase Translation Model[J]. *Journal of Physics: Conference Series*,2021,1871(1).
14. Zheng Jiangbin, Zhao Zheng, Chen Min, Chen Jing, Wu Chong, Chen Yidong, Shi Xiaodong, Tong Yiqi. An Improved Sign Language Translation Model with Explainable Adaptations for Processing Long Sign Sentences.[J]. *Computational intelligence and neuroscience*,2020,2020.

**Open Access** This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

