Hindawi
Wireless Communications and Mobile Computing
Volume 2020, Article ID 8827657, 7 pages
https://doi.org/10.1155/2020/8827657

*Research Article*

# Study on the Intelligent Selection Model of Fuzzy Semantic Optimal Solution in the Process of Translation Using English Corpus

**Li Bei**

*Foreign Language Department, Hubei Polytechnic University, Huangshi 435000, China*

Correspondence should be addressed to Li Bei; libei@hbpu.edu.cn

Received 1 July 2020; Revised 31 July 2020; Accepted 1 September 2020; Published 8 September 2020

Academic Editor: Hongju Cheng



In order to improve the accuracy and reasonableness of using English corpus for translation, a method of using English corpus to perform translation tasks based on fuzzy semantic optimal solution intelligent selection and inspired computing for wireless networks is proposed. The information extraction model using English corpus for translation is constructed, and the fuzzy semantic keyword feature directivity model of English corpus translation is established. Fuzzy semantic ontology feature registration method is used to calculate the fuzzy semantic intelligence optimal solution vector in English translation. The semantic fuzzy feature matching and adaptive subject word registration are realized in English translation. The fuzzy link relation of semantic ontology is established, and the fuzzy semantic optimal solution is obtained. The accuracy of machine translation in English corpus is improved. The experimental results show that the fuzzy semantic optimal solution has better registration performance and the feature matching degree of the subject words is higher, which improves the reasonableness and accuracy of translation in English corpus. At the same time, it provides a new idea for intelligent computation and recognition of wireless network.

## 1. Introduction

With the development of intelligent translation technology, machine translation is used to translate English, gradually replacing manual translation, and the accuracy of translation is improved. In the process of English translation with machine software, semantic recognition and feature analysis are needed, and the semantic information of English context and text is extracted by machine intelligent recognition method, and English information model is constructed. Combining fuzzy semantic recognition technology improves the intelligent level of English translation [1]. When using English corpus to do translation work, the causes of English translation usability problems are usually attributed to technical and content aspects, and the fuzzy semantic optimal solution method is adopted. The rational organization and content creation of English translation from the semantic point of view reflects the subjectivity of the originator and improves the level of intelligence and automation of English translation [2]. The use of algorithms can increase the overall analysis of the data; it has great significance to study the intelligent selection model of fuzzy semantic optimal solution in English corpus translation.

The accuracy and adaptability of machine translation have become an important subject in the future translation software research. The optimization problem of machine translation is based on semantic selection and feature extraction. By extracting the semantic information features of the English context, we combine intelligent analysis and semantic information retrieval technology, realizing ontology mapping and adaptive concomitant tracking of semantic information, combining pattern recognition method to realize English intelligent translation, studying fuzzy semantic selection technology in English semantic machine translation, and optimizing the design of machine translation software [3]. It is important to improve translation accuracy and artificial intelligence. The traditional methods include theme tree feature matching method, support vector machine algorithm, and particle swarm optimization method.

Independent extraction of emotional words and evaluation objects ignores the relationship between emotional words and evaluation objects. Therefore, many researchers conduct joint recognition of emotional words and evaluation objects in emotional analysis. Inspired computing for wireless networks is the new emerging algorithm that can deal with the above problem.

In order to improve the accuracy of translation, the linguistic evaluation set model and feature combination matching for semantic features in English translation are constructed. Some research results have been obtained, but the traditional methods have some problems, such as the poor ability of context interference suppression and coupling interference. To solve this problem, this paper proposes an information extraction model based on fuzzy semantic optimal solution, which uses English corpora to perform translation operations, and constructs an information extraction model based on fuzzy semantic optimal solution [4]. A fuzzy semantic keyword directivity model of English corpus translation is established, and the fuzzy semantic ontology feature registration method is used to calculate the fuzzy semantic intelligence optimal solution vector in English translation. In English translation, semantic fuzzy feature matching and adaptive subject word registration are realized. The fuzzy link relation of semantic ontology is established, the fuzzy semantic optimal solution is calculated, and the accuracy of machine translation in English corpus is improved. The performance of this method in improving the accuracy of English machine translation is demonstrated [5].

The contributions of the paper can be summarized as follows:

(1) The semantic fuzzy feature matching and adaptive subject word registration are realized in English translation. The semantic fuzzy feature can improve the accuracy of translation effectively

(2) Inspired computing for wireless networks is used to deal with the problem that emotional words and evaluation objects ignores the relationship between emotional words and evaluation objects

(3) The fuzzy link relation of semantic ontology is established to provide the more flexibility of translation

The rest of this paper is organized as follows. Section 2 discusses semantic feature selection and information extraction in translation, followed by the intelligent selection and implementation of fuzzy semantic optimal solution designed in Section 3. Section 4 shows the simulation experimental results, and Section 5 concludes the paper with summary and future research directions.

## 2. Semantic Feature Selection and Information Extraction in Translation

*2.1. Information Extraction of English Corpus for Translation Assignments.* In order to realize fuzzy semantic selection and translation adaptive following optimization in English semantic machine translation, a fuzzy semantic ontology mapping model is constructed. The fuzzy semantic ontology mapping method is used to filter semantic features of English machine translation, semantic analysis and module extraction of machine English translation are carried out, and semantic mapping relationship structure is set up. In the semantic mapping module, binary semantic judgment and grammar analysis and correction of English translation are carried out, and the process of fuzzy semantic ontology mapping in English machine translation is obtained. The semantic ontology model of English translation is constructed by using NLP technology [6], and a shared conceptual model for translation operations using English corpus is obtained. First, consider the ontology fragments of two sets of English translation instance set shown in Figure 1.

Taking Figure 1 as an example, using English corpus for natural language processing, the English word “image” can represent a picture, the synonyms “image” and “picture” have fuzzy feature matching and adaptive subject word registration. The possible semantic ontology fuzzy link relation between synonyms and semantic information in English translation is described as

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

$$\theta(s_i) = (s_i, 0), s_i \in S. \tag{2}$$

If $s_k \in S$ is a phrase using English corpus for translation, the semantic compatibility mapping is expressed in the form of $M : C * C' \rightarrow (\rightarrow^{\subseteq})C_s$ binary semantic mapping, and the semantic ontology fuzzy link relation is established in the ontology model, to solve the problem of fuzzy feature matching and adaptive subject word registration for natural language of similar words between concepts [7].

Two conceptual semantic constraint coefficients $\beta \in [0, T]$, $S$ is Mountain nodes, $T$ is the set of semantic information analysis and evaluation. Then, the structural knowledge point $\beta$ in the ontology fragment can be represented by the following function $\Delta$:

$$\Delta : [0, T] \rightarrow S \times [-0.5, 0.5). \tag{3}$$

The binary semantic information of natural languages using English corpus for translation is

$$\Delta(\beta) = \begin{cases} s_k, K = \text{round}(\beta), \\ a_k = \beta - k, a_k \in [-0.5, 0.5). \end{cases} \tag{4}$$

In Figure 1, the two labels of “"Mountain” node on the left side of the natural language processing of English corpus are used to process and analyze the context of natural language using the generalized relation between concepts (is-less-than). The level of intelligence in machine language translation is improved.

*2.2. Analysis of Semantic Ontology Mapping Model for Translation with English Corpus.* On the basis of the natural

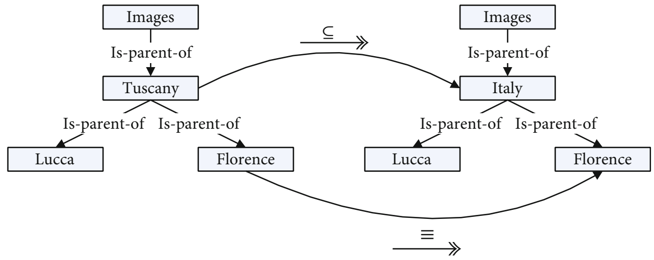


Figure 1: Ontology fragment of two sets of English translation instances.

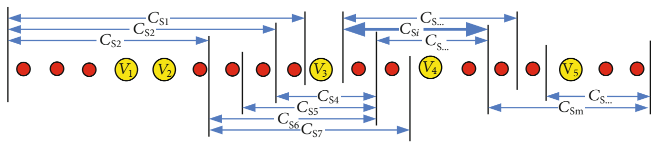


Figure 2: Fuzzy semantic keyword feature directivity model.

language processing of English corpus, the semantic ontology model of English corpus translation is constructed, and the binary semantic information analysis method is adopted. It is obtained that the fuzzy link relation of semantic ontology translated by machine English is an "is-less than" relationship [8]. The fuzzy evaluation of the object (or object, criterion) between concepts of different ontology is carried out, and the symbol set of maximum semantic relevance value in domain knowledge is analyzed, $a_k \in [-0.5, 0.5)$. In the simple semantic unit, there are attributive modifiers in English translation:

$$\Delta^{-1} : S \times [-0.5, 0.5) \to [0, T]. \tag{5}$$

The approximate words are identified under the simple semantic unit, assuming that $(s_k, a_k)$ and $(s_l, a_l)$ are two binary semantics. In the translation of English corpus, the attributive clauses are assigned to the main sentence. When selecting the scope of clauses, a syntactic ontology mapping model for binary semantics is described as

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

(2) if $k = l$, ① $a_k = a_l$, then $(s_k, a_k) = (s_l, a_l)$; ② $a_k < a_l$, then $(s_k, a_k) < (s_l, a_l)$; and ③ $a_k > a_l$, then $(s_k, a_k) < (s_l, a_l)$

## 3. Intelligent Selection and Implementation of Fuzzy Semantic Optimal Solution

*3.1. Fuzzy Semantic Intelligence Optimal Solution Vector Computation in English Translation.* On the basis of constructing the semantic model of English corpus for translation and processing of natural language information extraction, this paper improves the design of intelligent selection method of fuzzy semantic optimal solution and improves the use of English corpus. At the level of intelligence in translation [9], a fuzzy semantic keyword directivity model using English corpus is established, which is shown in Figure 2.

In Figure 2, a fuzzy semantic keyword directivity model using English corpus for translation is established. The fuzzy semantic ontology feature registration method is used to calculate the fuzzy semantic intelligence optimal solution vector of English translation [10]. If the semantic binary groups $(s_k, a_k)$ and $(s_l, a_l)$ of each subject list are English translation information of any directly superior word, the Euclidean distance for each subvector is as follows:

$$d((s_k, a_k), (s_l, a_l)) = \Delta\left(\left|\Delta^{-1}(s_k, a_k) - \Delta^{-1}(s_l, a_l)\right|\right). \tag{6}$$

The binary semantic information in the English corpus translation software is defined as the average reliability factor of English adverb translation based on the ontology fragment search engine in the English translation software:

$$(\bar{s}, \bar{a}) = \varphi_1((s_1, a_1), (s_2, a_2), \cdots, (s_n, a_n)) = \Delta\left(\sum_{j=1}^{n} \frac{1}{n} \Delta^{-1}(s_j, a_j)\right). \tag{7}$$

By searching the vector space, the fuzzy semantic intelligence optimal solution vector of each word segment vector is defined as

$$\min\left(w, \xi, \xi^*\right) = \dot{X}\frac{1}{2}\|w\|^2 + \dot{Y}C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right),$$
$$s.t. H_i(z)\begin{cases} y_i - w^T\Phi(x) - b \le \varepsilon + \xi_i^*, \\ -y_i + w^T\Phi(x) + b \le \varepsilon + \xi_i, \\ \xi_i^*, \xi_i \ge 0, \end{cases} \tag{8}$$

According to the result of fuzzy semantic intelligent optimal solution vector [11], the semantic fuzzy feature matching and adaptive subject word registration are realized in English translation, and the fuzzy link relation of semantic ontology is established [12].

*3.2. Intelligent Selection Calculation of Fuzzy Semantic Optimal Solution.* On the basis of calculating the optimal solution vector of fuzzy semantic intelligence, the fuzzy semantic optimal solution intelligence is selected in the process of ontology mapping, and the fuzzy link relation of semantic ontology is established. The fuzzy semantic optimal solution is calculated and improved in the process of ontology mapping. The accuracy of machine translation in English corpus [13] is obtained. According to the fuzzy semantic keyword directivity model based on the English corpus, the optimal matching search of the subject word semantics in the English translation process is carried out, and the circular stack control search method is adopted. Fuzzy semantic matching control is performed. The schematic diagram of semantic registration search in English translation is shown in Figure 3.

According to the semantic search process of English machine translation given in Figure 3, this paper calculates the similarity of the comprehensive weight of document in English translation [14]. Let $\{(s_1, a_1), (s_2, a_2), \cdots, (s_n, a_n)\}$ be a set of binary semantic information, $\omega_j \in [0, 1]$, and let $\{(s_1, a_1), (s_2, a_2), \cdots, (s_n, a_n)\}$ be two words to be compared. The binary semantic weighted arithmetic average operator $\varphi_2$ is defined as

$$(\bar{s},\bar{a}) = \varphi_2\left(\left((s_1,a_1),\left(\omega_1,a_1'\right)\right),\left((s_2,a_2),\left(\omega_2,a_2'\right)\right),\cdots,\left((s_n,a_n),\left(\omega_n,a_n'\right)\right)\right) = \Delta\left(\frac{\sum_{j=1}^{n}\Delta^{-1}\left(\omega_j,a_j'\right)\Delta^{-1}\left(s_j,a_j\right)}{\sum_{j=1}^{n}\Delta^{-1}\left(\omega_j,a_j'\right)}\right) = \Delta\left(\frac{\sum_{j=1}^{n}\beta_j\beta_j'}{\sum_{j}^{n}\beta_j'}\right), \tag{9}$$

where $\sum_{j=1}^{n}\omega_j = 1, \bar{s} \in S, \bar{a} \in [-0.5, 0.5]$.

In English translation, some commonly used phrases are divided into several words. Because of the recognition of common words and the accuracy control of translation, in the course of using English corpus for translation [15], the common words are used as vague words. The semantic center vector $C(Y)$ of word $Y$ is calculated according to the position of words in the text. The similarity of $X$, $Y$ in English translation is [16]

$$\mathrm{Sim}(X, Y) = \mathrm{Cos}(X, Y) = \frac{C(X)\cdot C(Y)}{|C(X)|\cdot|C(Y)|}, \tag{10}$$

The center vector $C(X)$ of the semantic fuzzy concept set $R(X)$ before and after the translation of the English corpus is used. The probability density of the joint feature of the reliable translation of the two words is expressed as follows [17]:

$$C(X) = \frac{1}{n}\sum_{i=1}^{n}\frac{v_i}{|v_i|}. \tag{11}$$

According to the specific context of the words in the text, every vector is modified by the method of semantic mapping before and after the text, and the binary semantic correlation operators in the subject list are normalized to improve the reasonableness of English translation and to realize English translation [18]. The semantic fuzzy feature matching and

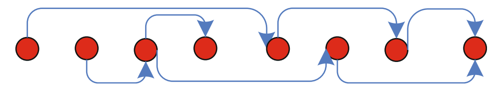

Figure 3: Schematic diagram of semantic registration search for English translation.

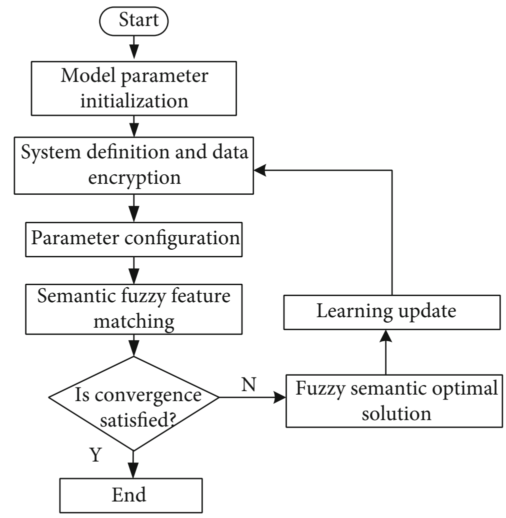


Figure 4: Semantic optimal implementation of translation using English corpus.

the adaptive subject word registration of the text before and after translation are analyzed. Then, by comparing the simple string, it is analyzed whether the selection result of the optimal solution of fuzzy semantics satisfies the optimal semantic relevance degree, and if so, the adjustment coefficient advances. The integrity and reasonableness of line translation are contrasted, the adjustment coefficient is compared and calculated, and the feature words extracted from the text are converted into the information table of the subject words recognized by the semantic text, and the machine language translation is carried out until the optimal translation is satisfied. As a result, the implementation flow of the algorithm is shown in Figure 4 [19].

## 4. Experimental Test Analysis

*4.1. Accuracy Verification of Conventional Sentence Translation.* Finally, the experiment analysis is carried out in the MATLAB simulation environment, and the performance of using the English corpus to model the veracity and rationality of translation is analyzed through the intelligent selection of fuzzy semantic optimal solution [20].

In the experiment, the standard metric index is adopted. The recall rate of semantic information and the feature matching degree of the subject words are measured. Through comprehensive decision making, ten ontological examples are used for English machine translation, and the English corpus for translation under different thresholds is obtained. The feature matching degree is shown in Figure 5. In order to compare the performance, different methods are used to obtain the information recall rate of English corpus translation. The result is shown in Figure 6.

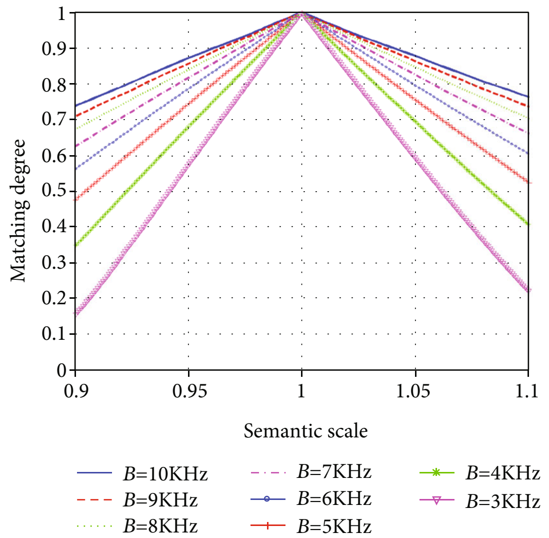


FIGURE 5: Feature matching degree under different thresholds.

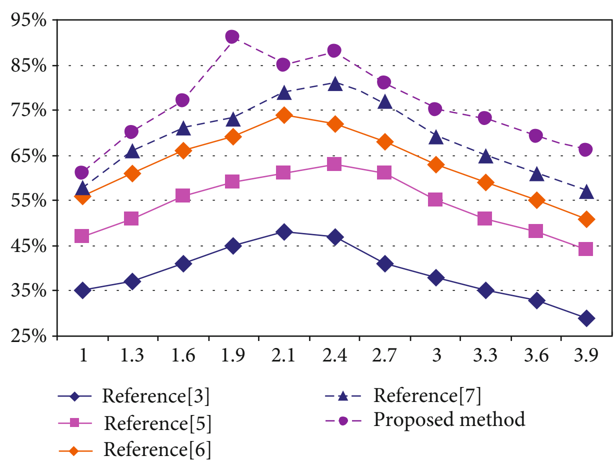


FIGURE 6: Comparison of recall performance between different methods of using English corpus for translation.

The simulation results show that this method has better semantic matching performance in the use of English corpus and adjusts the integrity and rationality of the translation by adjusting the threshold coefficient to improve the accuracy of English translation. It shows that English translation has a strong ability of context mapping and high overall quality of translation.

*4.2. Joint Recognition of Emotional Words and Evaluation Objects.* At present, the existing work is generally divided into the supervised learning method and unsupervised learning method. Most of the methods are to identify emotional words (or evaluation objects) first, and then to identify evaluation objects (or emotional words) according to emotional or semantic relations. In this paper, a fuzzy semantic machine translation model is used to identify emotional words and evaluation objects as a joint recognition task. Meanwhile, emotional words and evaluation objects are extracted and their emotional relationships are obtained. In addition to

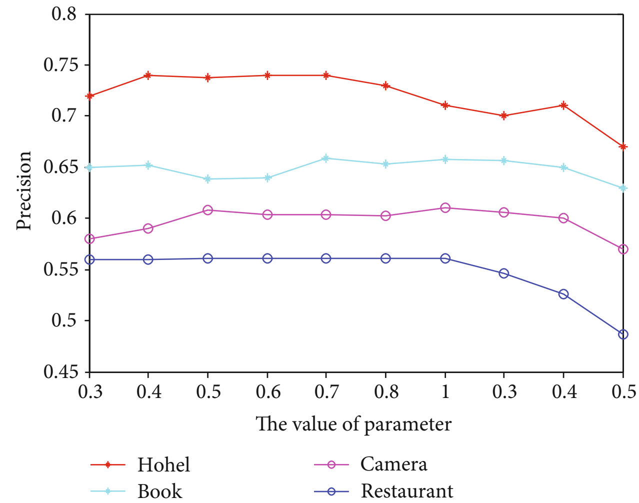


FIGURE 7: The precision validation under different dataset and different parameter value.

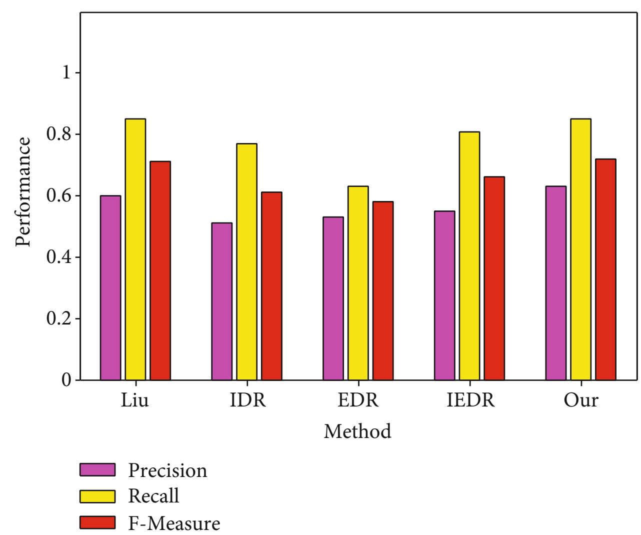


FIGURE 8: The comparisons of the results of five experiments on a restaurant.

emotional relationships, the characteristics of words themselves in text corpus, such as word frequency, word distribution ratio, and domain dependence of words, will have an important impact on identifying emotional words and evaluating objects. The simulation results are shown in Figure 7.

The method proposed in this paper has been tested on four datasets. At the same time, experiments have been carried out with Liu's method, IDR, EDR, and IEDR. Figures 8 and 9 are the results of experiments and comparison experiments in catering reviews and hotel reviews, respectively. In the table, "Our" is the experimental method; Liu is the experimental method of article; IDR, EDR, and IEDR are the three articles.

As we can see from the Figure 8, the method proposed in this paper is applied to catering reviews. The recall rate is the same as Liu's method, and the accuracy and $F$ value are slightly higher than Liu's experimental method. The results

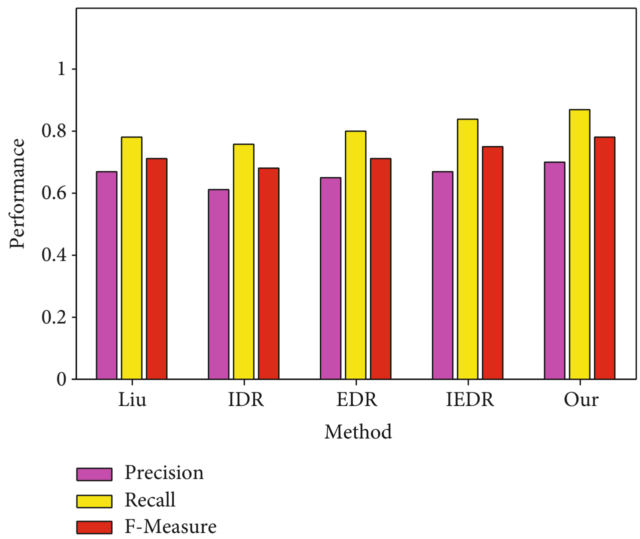


Figure 9: The comparisons of the results of five experiments on restaurant.

of the experiment using the method in this paper are far higher than those in the article.

As can be seen from Figure 9, the method of extracting evaluation objects proposed in this paper is applied to hotel reviews, and its accuracy, recall rate, and $F$ value are greater than those of the baseline experimental method.

## 5. Conclusions

In this paper, a method of using English corpus to perform translation tasks based on fuzzy semantic optimal solution intelligent selection is proposed. The information extraction model using English corpus for translation is constructed, and the fuzzy semantic keyword feature directivity model of English corpus translation is established. Fuzzy semantic ontology feature registration method is used to calculate the fuzzy semantic intelligence optimal solution vector in English translation. The semantic fuzzy feature matching and adaptive subject word registration are realized in English translation. The fuzzy link relation of semantic ontology is established and the fuzzy semantic optimal solution is obtained. The accuracy of machine translation in English corpus is improved. The experimental results show that the fuzzy semantic optimal solution has better registration performance and the feature matching degree of the subject words is higher, which improves the reasonableness and accuracy of translation in English corpus. This method has a good application value in the machine translation algorithm design.

## Data Availability

The data is available from the author.

## Conflicts of Interest

There is no conflict of interest in this paper.

## Acknowledgments

This study was supported by the Scientific Research Project of Hubei Polytechnic University, Project Name: A Study on Translation Strategies of Key Philosophy Concepts in Chinese Thought and Culture from the Perspective of Communication (Project Number: 19xjr04y); Teaching Research Project of Hubei Polytechnic University, Project Name: School-Based Research on College English Paperless Examination under the Background of Internet. (Project Number: 2019b11); and General Project of Philosophy and Social Science Research of Hubei Provincial Department of Education, Project Name: Corpus-Based Critical Discourse Analysis of American Mainstream Media on Chinese Diplomatic News (Project Number: 19y121).

## References

[1] L. Dong, Q. Guo, and W. Wu, "Speech corpora subset selection based on time-continuous utterances features," *Journal of Combinatorial Optimization*, vol. 37, no. 4, pp. 1237–1248, 2019.

[2] B. Anqi, A. Dong, and A. W. Shitong, "A dynamic data stream clustering algorithm based on probability and exemplar," *Journal of Computer Research and Development*, vol. 53, no. 5, pp. 1029–1042, 2016.

[3] H. Hongwei, G. Xiaotian, and C. Xuansong, "Density clustering method based on complex learning classification system," *Journal of Computer Applications*, vol. 37, no. 11, pp. 3207–3211, 2017.

[4] J. Yugang, L. Yitong, and S. Chuan, "Aspect rating prediction based on heterogeneous network and topic model," *Journal of Computer Applications*, vol. 37, no. 11, pp. 3201–3206, 2017.

[5] B. Z. Zhang, X. Gui, and T. He, "A novel recommender algorithm on fusion heterogeneous information network and rating matrix," *Journal of Computer Research and Development*, vol. 51, no. S2, pp. 69–75, 2014.

[6] X. Y. Lin, L. L. Dai, S. H. Shi, and F. Li, "Matrix factorization recommendation based on topic model," *Journal of Computer Applications*, vol. 35, no. S2, pp. 122–124, 2015.

[7] F. Slimeni, B. Scheers, V. L. Nir, Z. Chtourou, and R. Attia, "Learning multi-channel power allocation against smart jammer in cognitive radio networks," in *2016 International Conference on Military Communications and Information Systems (ICMCIS)*, pp. 1–7, Brussels, Belgium, May 2016.

[8] Z. Liu, L. Lei, N. Zhang, G. Kang, and S. Chatzinotas, "Joint beamforming and power optimization with iterative user clustering for MISO-NOMA systems," *IEEE Access*, vol. 5, pp. 6872–6884, 2017.

[9] M. S. Ali, H. Tabassum, and E. Hossain, "Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (NOMA) systems," *IEEE Access*, vol. 4, pp. 6325–6343, 2016.

[10] H. Xiong, X. Zhu, and R. Zhang, "Energy recovery strategy numerical simulation for dual axle drive pure electric vehicle based on motor loss model and big data calculation," *Complexity*, vol. 2018, Article ID 4071743, 14 pages, 2018.

[11] Y. Jiang, F. L. Chung, S. Wang, Z. Deng, J. Wang, and P. Qian, "Collaborative fuzzy clustering from multiple weighted views," *IEEE Transactions on Cybernetics*, vol. 45, no. 4, pp. 688–701, 2015.

[12] B. Anqi and W. Shitong, "Transfer affinity propagation clustering algorithm based on Kullback-Leiber distance," *Journal of Electronics & Information Technology*, vol. 38, no. 8, pp. 2076–2084, 2016.

[13] M. Long, J. Wang, G. Ding, S. J. Pan, and P. S. Yu, "Adaptation regularization: a general framework for transfer learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 26, no. 5, pp. 1076–1089, 2014.

[14] X. Xing, S. Ying, R. Zhao, and L. I. Zheng, "Pheromone updating strategy of ant colony algorithm for multi-objective test case prioritization," *Journal of Computer Applications*, vol. 36, no. 9, pp. 2497–2502, 2016.

[15] T. J. Hsieh, "A bacterial gene recombination algorithm for solving constrained optimization problems," *Applied Mathematics and Computation*, vol. 231, no. 15, pp. 187–204, 2014.

[16] D. Li and J. Wu, "Energy-efficient contention-aware application mapping and scheduling on NoC-based MPSoCs," *Journal of Parallel and Distributed Computing*, vol. 96, pp. 1–11, 2016.

[17] M. Abdel-Basset, G. Manogaran, D. El-Shahat, and S. Mirjalili, "A hybrid whale optimization algorithm based on local search strategy for the permutation flow shop scheduling problem," *Future Generation Computer Systems*, vol. 85, pp. 129–145, 2018.

[18] M. Abdel-Basset, G. Manogaran, H. Rashad, and A. N. H. Zaied, "A comprehensive review of quadratic assignment problem: variants, hybrids and applications," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, 2018.

[19] M. Abdel-Basset, G. Manogaran, L. Abdel-Fatah, and S. Mirjalili, "An improved nature inspired meta-heuristic algorithm for 1-D bin packing problems," *Personal and Ubiquitous Computing*, vol. 22, no. 5-6, pp. 1117–1132, 2018.

[20] M. Zhang, D. Zhang, F. Goerlandt, X. Yan, and P. Kujala, "Use of HFACS and fault tree model for collision risk factors analysis of icebreaker assistance in ice-covered waters," *Safety Science*, vol. 111, pp. 128–143, 2019.