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Design of Intelligent English Translation Algorithms Based on a Fuzzy Semantic Network

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ABSTRACT
In order to improve the quality of intelligent English translation, an intelligent English translation algorithm based on the fuzzy semantic network is designed. By calculating the distance of fuzzy semantic network, classifying and ordering the English semantics to determine the optimal similarity and outputting the optimal translation results, the experiments show the average BLEU and NIST of the three test sets are 25.85 and 5.8925 respectively. The translation accuracy is higher than 95%. The algorithm can translate 246 Chinese sentences per second. This shows it is a high-performance intelligent translation algorithm and can be applied to practical intelligent translation software.

KEYWORDS: Fuzzy semantic network; English; intelligent translation; maximum entropy; weighted hierarchy; similarity.

1 INTRODUCTION

SEMANTICS are further interpretations of data symbols. In the field of information integration, semantics can be defined as schema elements (such as classes, attributes, AND constraints) by means of schemas (for which there is no implicit unstructured or semi-structured data, their schemas are often defined for data organization before integration, and data access is also obtained by means of action patterns) which proposed by Li and Liu (2017). Accurate ordering of semantics can help English intelligent translation to better translate complex concepts. Meanwhile, correct semantics can guarantee the quality of translation information. Therefore, efficient ordering of correct, implicit and useful English semantic information has become an urgent problem in the field of English intelligent translation, which has attracted the attention of many scholars which proposed by Han and He (2017).

With the enhancement of China's comprehensive national strength and international competitiveness, trade and cultural exchanges with other countries in the world are deepening. As the most widely used language, English has become a bridge between China and other countries. As a result, the demand for English translation into other languages is increasing, and various English translation software has emerged, which proposed by Liu et al. (2016). It improves the intelligence of English translation, reduces the labor of manual translation, and improves the efficiency and accuracy of English translation which proposed by Sun et al. (2018). The history of intelligent English translation can be traced back to the 1980s. In the past ten years, the technology of intelligent English translation has undergone tremendous changes which proposed by Lei et al. (2018). There are numerous intelligent English translation algorithms designed to meet the needs of users to some extent but there are also problems. Most of them are based on word sense disambiguation, semantic role tagging and other intelligent English translation algorithms which proposed by Jing et al. (2016). This paper designs an intelligent English translation algorithm based on fuzzy semantic network, which not only has the ability of independently expressing semantics but also has the ability of describing the relationship between words. It provides a precise intelligent English translation service for users in various fields which proposed by Azali and Sheikhan (2016).

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2 MATERIALS AND METHODS

2.1 Fuzzy Semantic Network

A semantic network is a kind of annotated directed network graph which proposed by Zinszer et al. (2016), which represents knowledge through concepts and semantic relations. The nodes of a digraph are used to represent various concepts, things, attributes, situations, actions, states, etc. The arc represents some connection between the nodes it connects which proposed by Su and Li. (2016). Nodes and arcs are marked to distinguish certain attributes of different objects and different semantic relationships between objects, which proposed by Pedrycz and Wang (2016).

A basic semantic network is shown in Figure 1. Node1 and Node2 are attributes of objects, concepts, events and states in the field of knowledge, while Relation is the semantic relationship between two nodes which proposed by Chang (2017).

A semantic connection is usually expressed by an English word or its abbreviation, which is equivalent to a predicate. Because of the complexity of semantic relations in practical applications, there are many kinds of semantic relations which proposed by Vychodil (2016). There are seven common semantic relationships:

(1) Generic relation, which reflects the hierarchical relationship between things, is expressed by a-kind-of, a-member-of or is-a.

(2) Aggregation relationship, which reflects the relationship between part and whole of things, is expressed by part-of.

(3) Attribute relationship, which represents the relationship between things and their attributes, commonly used attribute relations are have and can.

(4) Time relationship refers to the sequence of different events in terms of their occurrence time. The commonly used time relations are before and after.

(5) Location relation refers to the relationship of different things in position, such as location-on, location-inside, etc.

(6) Close relationship refers to the similar or close relationship between different things in shape and content, such as near-to, similar-to, etc.

(7) Inference relation refers to the semantic relation from one concept to another, such as if-then.

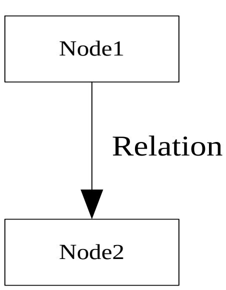

Figure 1. Basic Unit of a Semantic Network

When using semantic networks to represent complex knowledge, variables must be quantified. The basic idea is to divide a proposition expressing complex knowledge into several sub-propositions. Each proposition is represented by a relatively simple semantic network and becomes a subspace. Multiple subspaces form a large space. Spaces can be nested layer by layer, and the subspaces are connected by arcs, which proposed by Fu and Ma (2016).

Because of the complexity and variability of the objective world and the limitation and subjectivity of a human's own knowledge, the information knowledge acquired by people often contains uncertain, inaccurate, incomplete and even inconsistent knowledge components. Therefore, the conclusions of the system will be more realistic only if the knowledge representation and processing mode can reflect this uncertainty which proposed by Rui and Mao (2016).

In order to make the semantic network describe the objective world more truthfully, the uncertain knowledge in the semantic network should be dealt with in advance as follows:

(1) Uncertainty of semantic nodes. That is to define a membership degree for a fuzzy node, which is used to express the ambiguity and importance of the node.

(2) Uncertainty of semantic relations. That is to say, we define a connection strength for the fuzzy semantic relationship, which is used to express the tightness of the relationship between nodes.

(3) Uncertainty of a semantic structure. The semantic network is described by a fuzzified and marked digraph. A standard fuzzy semantic network can be described as: A Basic_Fuzzy_Semantic_Network_Unit: (Node1, Relation, Node2, Nm1, Rm, Nm2), (Nm1, Rm, Nm2 < [0, 1]). Among them, Node1 and Node2 are the nodes representing the attributes of objects, concepts and events in the field of knowledge. Relation represents the semantic relationship between the two nodes; (Nm1 and Nm2 represent the membership degree of the nodes); and Rm represents the strength of the semantic relationship between the two nodes. A complete fuzzy semantic network can be obtained by associating several fuzzy semantic network elements with corresponding semantic rules.

For example, describe the fact in a Semantic Web Language; “it may be cold in the north”? The semantic network is used to describe the fact, the "north" and "very cold" are used to represent the nodes. The "possibility" is used to represent the semantic relationship between the two nodes. Since "North", "Possibility" and "Very Cold" are all vague concepts, it is assumed that "North" represented by "North of Huaihe River" has a membership degree of 0.5, and that "Temperature below -10℃" means "Very Cold" has a membership degree of 0.9, and the probability of "Possibility" is 0.6. The semantic representation language is as follows:

Main: (L1, possibly, L2, 0.5, 0.6, 0.9);
L1: (x: L3, is, North, 1, 1, 1);
L2: (y: L3, is, very cold, 1, 1, 1);
L3: (location (x), north-of, Huaihe River, 1, 1, 1);
L4: (Temperature (y), low-then, -10℃, 1, 1, 1).

Among them, main determines the principal relationship and L determines the subordinate relationship. In semantics, there is and can only be one principal relation but there can be more than one slave relation; slave relation can be embedded in a principal relation or nested in other slave relations. In this example, the membership degree of each node and relation is 1, because the exact knowledge is represented by the relation. This knowledge is represented by a semantic network as shown in Figure 2.

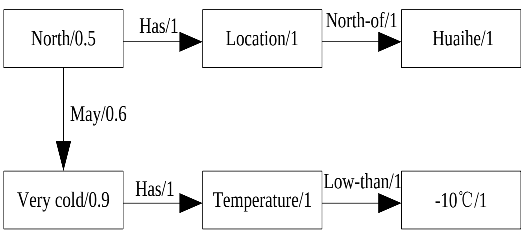

Figure 2. Examples of Semantic Networks.

In this semantic network, "very cold" is a node ("very cold", "north", "possible", "0.9, 0.5, 0.6); "north" is a root node ("arc only emitted, arc not entered"); it is a node ("north", "0", "0","0", "0", "0", 0.5, 0, 0); "Huaihe" is a leaf node ("arc only entered, arc not emitted"). It is denoted as node ("Huaihe River", "location", "north-of", 1, 1, 1).

2.2 Calculation of Distance in a Fuzzy Semantic Network

After corresponding processing of the input words to be translated, the useful information needed to be distinguished is obtained and the relevant features of the information are excavated. Through the information expression ability of the fuzzy semantic network technology introduced above, the word information can be distinguished. The operation process is as follows: Let the word features be represented by W (x, y), where w (x, y) includes the clustered word information. Then we can use the word eigenvalues w (x, y) to get the feature values and mining paths of the word information.

Distance in the fuzzy semantic network can represent the distinguishing features of word information more effectively. The expression of complex information of words can be realized through the distance of the fuzzy semantic network. In u (x, y), assume that the meanings of x and y are similar, and that the variables in U (x, y) change with the change of characteristics. If x and y cannot be variables at the same time, then u (x, y) will produce corresponding fuzzified expressions. In summary, the best distance expression of words can be obtained as follows:

$$u(x,y)=\left[\sum_{i=1}^{n}\left|x_i-y_i\right|^r\right]^{1/r} \tag{1}$$

Once the scalable linguistic network distance is in a similar ambiguous area, the distance difference will form the opposite linguistic network value. In this case, we need to use the method of absolute value of technology to get the corresponding distance.

$$u(x,y)=\sum_{i=1}^{n}\left|x_i-y_i\right| \tag{2}$$

The above expression can also be expressed by a standard Euclidean geometric distance:

$$u(x,y)=\left[\sum_{i=1}^{n}\left|x_i-y_i\right|^2\right]^{1/2} \tag{3}$$

By using the fuzzy definition distance, we can get the feature values of those words with high similarity. The corresponding expression formulas can be obtained by constructing a certain constraint function and scaling criteria for the corresponding feature changes.

$$u(x,y)=\left(\left(x-y\right)^{TS}\left(x-y\right)\right)^{1/2} \tag{4}$$

Among them, S is positive correlation matrix. If the dimension of word information increases, then the distance of the fuzzy semantic network is described by formula (5).

$$u(x,y)=\left[\sum_{i=1}^{n}s_{ii}\left|x_i-y_i\right|^2\right] \tag{5}$$

By increasing the distance calculation method of the fuzzy semantic network, we can accurately describe the features of the word information, thus laying the foundation for the next level of mining.

2.3 Intelligent English Translation Algorithms based on a Fuzzy Semantic Network

The focus of the intelligent English translation algorithm based on a fuzzy semantic network is to classify the English semantics. The maximum entropy training algorithm is used to classify the English semantics, which are processed by calculating the distance of the fuzzy semantic network. The maximum entropy training algorithm is essentially similar to being a word interpretation process. The algorithm can accurately divide the semantics into hierarchical semantics and staggered semantics according to its performance. Interlacing semantics is ordered according to the maximum similarity.

Hierarchical semantics includes three kinds; homogeneous semantics, interval semantics and progressive semantics. Suppose that the current ordered English semantics in the ordered semantics 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 orientation as B_i are represented by A_i, then the classified semantics are as follows:

$$f\left(A_i, B_i\right) = \begin{cases} A_{i-1}, i = 1,2,3,\cdots \\ B_{i-1}, i = 1,2,3,\cdots \end{cases} \tag{6}$$

When $B_{i-1} = 1 + A_i$, the English semantics to be ordered are the same kind of semantics, replacing the front-end data of A_i with the symbol A_{i-1}; when $A_{i-1} = 1 + B_i$, the semantics to be ordered are progressive semantics. When the semantics to be ordered are neither the same kind of semantics nor progressive semantics, they are regarded as interval semantics.

Based on the classification of the English semantics, the weighted hierarchical structure analysis method is used to calculate the similarity of the English semantics for example:

To construct an English semantic model and determine the hierarchical English semantics and the interleaved English semantics ordering process. Based on two typical semantic categories, an optional data is selected to construct an English semantic model, as shown in Figure 3.

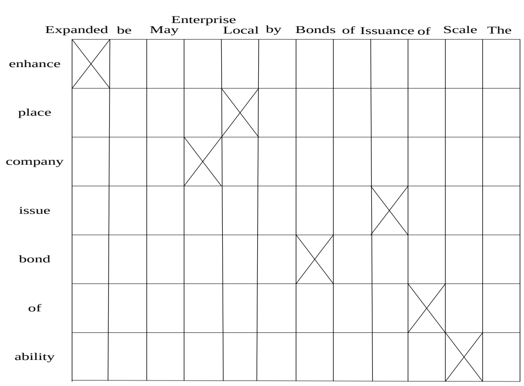

Figure 3. An English Semantic Model.

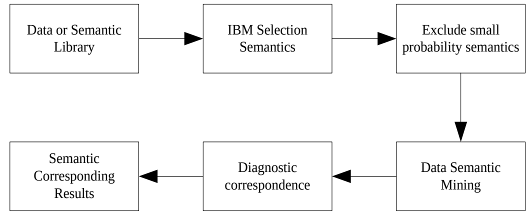

Figure 4. Layering English Semantic Order Implementation Process.

From Figure 3, we can see that the difference of two directions should be considered when ordering English semantics. Hierarchical English semantics makes use of the difference of two different directions to order English semantics. The flow chart of ordering is shown in Figure 4.

As shown in Figure 4, the Hierarchical English semantic ordering Model uses IBM software (a business software that provides a resource integration function) to order semantics, and then excludes English semantics with a probability of less than 0.18 in the model. The remaining words will be sequenced successfully, and then whether they correspond to the original data will be diagnosed. The sequencing result after diagnosing becomes the final result.

Interleaved English semantics is different from hierarchical English semantics. A simple ordering model cannot accurately correspond to the correct target semantics. Therefore, it is necessary to calculate the maximum similarity between English semantics to order semantics. The workflow of the interleaving semantic ordering model is shown in Figure 5.

The Interleaved English semantic ordering model parses the original data of the English semantic dependency to be ordered in the English semantic database, generates the semantic dependency tree to be ordered, and calculates the maximum similarity according to the rules of the fuzzy selection, so as to avoid the disorder of the semantic ordering structure and prevent a similar semantic disorder in the process of ordering. After that, the sequencing is implemented, and the results of the sequencing are diagnosed twice, and then the results are output.

To determine the similarity between the English semantics, and to use the weighted hierarchical analysis is to obtain the optimal similarity assuming that I_1 is any semantics in the semantics to be ordered, I_2 is the result of I_1's fuzzy correspondence, d is the distance between I_1 and I_2, and the sign η is used to represent the parameters of the dependency tree's fuzzy adjustment.

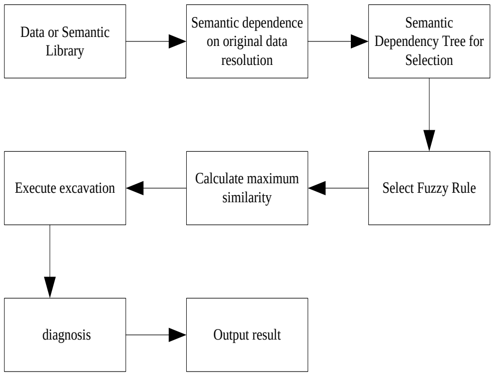

Figure 5. **Interlocking English Semantic Ordering.**

Thus, the similarity between I_1 and I_2 can be obtained as follows:

$$sim(I_1, I_2) = \frac{\eta}{\eta + d} \tag{7}$$

Obtaining the optimal similarity is the process of changing the weight η of the fuzzy adjusting parameter continuously and that is to say, formula (7) is described by using the weighted hierarchical structure analysis method. The expression is as follows:

$$sim(s_1, s_2) = \sum_{i=1}^{4} \delta sim(I_1, I_2) \tag{8}$$

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

The Weighted Hierarchical Structure Analysis (WHIA) has been described four times, namely, the independent relationship description of I_1 and I_2, the same structure description, the same semantic function description and the same data center description. After the weighted hierarchical structure analysis, the optimal similarity expression is determined as follows:

$$S_{\max} = \frac{\sum_{i=1}^{n}\left[\varphi_1 \operatorname{sim}(s_1, s_2) + \varphi_2 \operatorname{sim}(I_1, I_2)\right]}{n} \tag{9}$$

In the formula; n is the number of sub-nodes; φ_1 and φ_2 are the proportion of ordering and weighted hierarchical analysis in sub-nodes, $\varphi_2 = 1 - \varphi_1$.

After the above analysis, two kinds of fuzzy parameters of English semantics are given, which are the fuzzy influence parameters of the current semantics and front-end semantics on the ordering probability. They are expressed by $P(o|A_i)$ and $P(o|A_{i-1})$, respectively, and their expressions are as follows:

$$P(o|A_i) = \frac{\xi P(o) + \omega(o|A_i)}{\xi + \omega(A_i)} \tag{10}$$

$$P(o|A_{i-1}) = \frac{\sum_{A_i} \omega(o|A_i)}{\sum_o \sum_{A_i} \omega(o|A_i)} \tag{11}$$

In the formula; o is the order of the two adjacent data; $p(o)$ is the probability of the two adjacent data being ordered at the same time; ξ is the data optimization factor; $\omega(A_i)$ and $\omega(o|A_i)$ represents the target semantic decoded data before and after the ordering respectively.

Based on the semantic ordering method of the fuzzy theory, fuzzy data block A is selected, and then given the same class structure and intermodulation class structure in turn. Fuzzy data A_1 and A_2 are selected to merge A. In the fuzzy theory, the maximum entropy training algorithm requires that combined A should have the largest area, and the structure of A is the same as that of A_1. Contrary to the structure of A_2, a constraint structure N is needed to define the fuzzy data block aa. The definition of NN is as follows:

$$N = P_\theta(o|A_1, A_2) \tag{12}$$

In the formula; P is a classified combination function; θ is a weight.

The fuzzy theory uses a likelihood function to predict the maximum occupied area of the fuzzy English semantic block A.

$$P(o|A_1, A_2) = \frac{P(o|A_i)}{P(o|A_{i-1})} \tag{13}$$

By substituting Form (13) into Form (12), the results of the English semantic ordering based on the theory of fuzziness are obtained. The expressions are as follows:

$$N = \frac{\exp\left[\sum_i \theta_i P(o|A_i)\right]}{\exp\left[\sum_i \theta_i P(o|A_{i-1})\right]} \tag{14}$$

To sum up, based of determining the optimal similarity of the English semantics, the fuzzy theory is used to adjust the English semantics, and then the logarithmic linear method is used to output the optimal translation.

The logarithmic linear method is a judgment method based on multi-feature thinking. For a given sentence $f_I^J = f_I \cdots, f_j \cdots, f_J$, the translation $e_I^J = e_I \cdots, e_j \cdots, e_J$ is formed, and its maximum entropy translation is as follows:

$$e_I^J = \sum_{m=1}^{M} \lambda_m h_m \left(e_I^J, f_I^J\right) \tag{15}$$

The logarithmic linear method is extensible and can set corresponding features according to the different target requirements. It can apply various linguistic methods to machine translation. Based on the actual requirements of the translation algorithm, the feature functions and corresponding privilege weights are automatically set, and the optimal translation with the highest score is obtained and output according to formula (15).

3 RESULTS

3.1 Experimental Data

IN order to verify whether the intelligent translation algorithm based on the fuzzy semantic network designed in this paper can obtain accurate translation results, the following experiments are carried out. The experimental data consisted of a subset of the LDC corpus containing 4 million parallel sentence pairs, including 98.9 million Chinese words and 112.6 million English words. The development set of the experiment is TEST05, which includes 1082 Chinese sentences, and each Chinese sentence has four translation results, namely a total of 4328 English sentences. TEST06, TEST07 and TEST08 are the test sets. TEST06 contains 1664 sentences and 4 subordinate English sentences, namely 6656 English sentences; TEST07 contains 1452 sentences and 4 subordinate English sentences, namely 5808 English sentences; TEST08 contains 1357 Chinese sentences and 4 subordinate English translated sentences, namely 5428 English sentences.

3.2 Experiment setup

The C++ version of the Hierarchical Phrase Decoder is used as the decoder in the experiment. Detailed steps are as follows: The alignment of the word information in English Chinese and Chinese-English directions is realized by the GIZA++ tools, and the heuristic function of the growth-diag-fina-and is used to achieve a multi-to-many word alignment. The more cross-links of the word alignment in the translation results, the better translation performance of the illumination system. The translation results of the proposed algorithm are compared with those of the neural network algorithm and machine learning algorithm.

3.3 Experiment results

In order to verify the accuracy of the proposed algorithm in English translation, the translation results of the proposed algorithm, neural network algorithm and machine learning algorithm for different data sets are shown in Table 1.

Table 1. Comparative Results of Different Translation Algorithms.

Translation algorithm	TEST06		TEST07		TEST08	
	BLEU value	NIST value	BLEU value	NIST value	BLEU value	NIST value
This paper's algorithm	25.84	5.8942	25.87	5.8917	25.84	5.8917
Neural network algorithm	25.42	5.7452	25.43	5.7465	25.46	5.7426
Machine learning algorithm	25.13	5.7157	25.16	5.7163	25.18	5.7148

The evaluation index of this experiment is the BLEU value and the NIST value. The BLEU value is a comparative analysis of the n_unit fragments of the evaluated translation and the reference translation. The higher the number of matched fragments, the better the quality of the translated text to be evaluated. The NIST value is the measurement standard of the translation quality evaluation. It is used to evaluate the quality of translation per unit quantity. The higher the NIST value, the better the quality of translation. The analysis of Table 1 shows that based on the test sets; TEST 06, TEST 07 and TEST08, the BLEU value of the translation results obtained by the algorithm in this paper increases by 0.42 and 0.71 compared with that of the neural network algorithm and machine learning algorithm respectively and the average growth is 0.41 and 0.69 respectively based on test sets TEST06, TEST07 and TEST08. The NIST value ratio of the translation results obtained by the algorithm in this paper is 0.44, 0.71 and 0.38, 0.66 respectively. The NIST values of neural network algorithm and machine learning algorithm increased by 0.1490, 0.1798, 0.1452, 0.1754, 0.1491 and 0.1769, respectively, with an average increase of 0.148 and 0.177, respectively. It shows that the English translation results obtained by this algorithm are more accurate and scientific, and the translation performance of this algorithm is better. It is an effective intelligent English translation algorithm.

In order to verify that the translation performance of this algorithm is better than other algorithms, the sentence "Lanzhou Price Bureau Limits Beef Noodle Price" in the TEST08 test set is translated, and the sentence "only because the increase is too large" is translated into English by using this algorithm, the neural network algorithm and the machine learning algorithm, respectively, to obtain the performance of the three algorithms in the English translation. The experimental results are shown in Table 2. The reference translations are given for comparison.

Analysis Table 2 shows that in the specific translation process, the three algorithms have not translated the word "price bureau", then the word "explain" is analyzed. The translation results given by the neural network algorithm and machine learning algorithm are explained. The translation result given by the algorithm in this paper is a given explanation of, which is consistent with the reference translation.

Table 2. Comparison of Translation Example 1.

Source language sentences	Lanzhou Price Bureau translated the beef noodle price limit, "just because the increase is too large."
Translation	Lanzhou price bureau gives explanation of price control on beef noodles: it is only because the raises have been too large
This paper's algorithm	Lanzhou gives explanation of beef noodles reduced only because of the excessive price raises
Neural network algorithm	Lanzhou explained beef noodles reduced only because of the excessive price
Machine learning algorithm	Lanzhou explained that beef noodles reduced only because of the excessive price increase

It shows that the English translation result of the algorithm in this paper is more accurate.

Table 3 is the translation of the sentence "the information industry is developing rapidly" in TEST06, which is a test set of three algorithms.

The differences in the translation of the three algorithms in Table 3 lie in the word "rapid development". The translation of the neural network algorithm is "fast change". The translation of the machine learning algorithm is "keeping the momentum going," which has a high deviation from the original word and does not conform to the grammar and semantics of English. Although the translation result of this algorithm is inconsistent with the word order of the reference translation, its semantics meets the requirements and has high accuracy.

Table 3. Comparison of Translation Example 2.

Source language sentences	The information industry is developing rapidly
Translation	The information industry is developing rapidly
This paper's algorithm	The information industry is high speed development situation
Neural network algorithm	The information industry is keeping the momentum going
Machine learning algorithm	The information industry is fast change developing rapidly

Table 4 is the translation of the sentence "Although it is raining heavily, the opening ceremony is still going on" in TEST07 using three algorithms.

Table 4. Comparison of Translation Example 3.

Source language sentences	Despite the heavy rain, the opening ceremony continued.
Translation	Though it was raining hard, the opening ceremony still went on
This paper's algorithm	It was raining hard, but the opening ceremony still went on
Neural network algorithm	Though it was raining hard, but the opening ceremony still went on
Machine learning algorithm	The opening ceremony continued despite the heavy rain

Analysis of the translation results of the three translation algorithms in Table 4 shows that "though" appears in the concessional adverbial clause, and "but" can no longer be used after it. Therefore, although the translation results of the algorithm in this paper are not the same as those of the reference translation, they are of high accuracy.

Through the translation of the above three examples, we can see that the algorithm in this paper has the most accurate translation results, no grammatical errors and a better translation performance.

The experimental settings mentioned that the more the number of cross-links in word alignment in the translation results, the better the translation performance of the system. Three algorithms are used to analyze the number of the cross-links in the English translation results. The results are shown in Table 5.

Table 5. Cross Connection Comparison of the Translation Results.

Translation algorithm	TEST06	TEST07	TEST08	average value
This paper's algorithm	16.2	15.8	16.1	16
Neural network algorithm	29.2	31.5	30.5	30.4
Machine learning algorithm	24.8	23.5	24.3	24.2

From Table 5, we can see that the average number of cross-links in the translation results of the neural network algorithm is 30.4; the average number of cross-links in the machine learning algorithm is 24.2, which is 6.4 less than that of the neural network algorithm; and the average number of cross-links in the translation results of the algorithm in this paper is 16, which is significantly reduced compared with the previous two, which shows that the algorithm in this paper has a higher translation performance.

The accurate semantics ordering of sentences to be translated helps to better translate complex concepts in the intelligent English translation. The temporal state of the English semantic ordering refers to the overall response time that can be ordered at the same time. However, it is difficult to obtain the state of the sequence directly, so the experiment verifies the state of the time sequence by increasing the total amount of English semantics, observing the number of the sequence of the algorithm, machine learning algorithm and neural network algorithm in unit time. The larger the number of temporal ordering per unit, the better the temporal state of semantic ordering. With the ordination unit time as the ordinate coordinate and the total amount of English semantics as the abscissa coordinate, the time-consuming result of the ordination is shown in Figure 6.

From Figure 6, we can see that the curve with the highest ordering performance is the algorithm in this paper, followed by the neural network algorithm. With the passage of time, the number of scheduling per unit time of each algorithm decreases to some extent, which is related to the resource regulation ability of the semantic scheduling and can be optimized by means of the software control. The experimental results show that the proposed algorithm has the smallest time-consuming for the semantic ordering and is obviously superior to other algorithms.

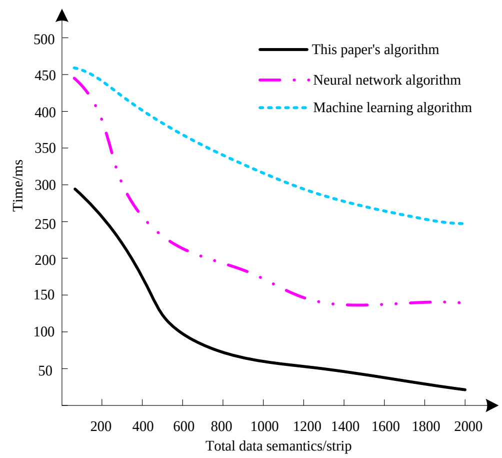

Figure 6. **The Semantic Ordering Time Comparison.**

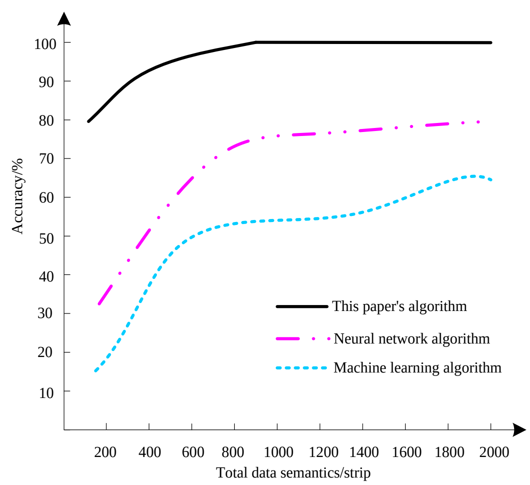

Figure 7. **Comparison of the Semantic Sequence Accuracy.**

The accuracy of the English semantic ordering indicates the higher the accuracy, the better the English translation performance. When ordering the English semantics, the number of English semantics is taken as abscissa, and the accuracy of ordering is taken as ordinate. The experimental results are shown in Figure 7.

As seen from Figure 7, the order accuracy of the proposed algorithm is higher. When the number of English semantics is 800, the accuracy is as high as 100%, while the order accuracy of the neural network algorithm and machine learning algorithm is lower than 80%.

The statistical analysis shows that the smaller the average number of sentences translated by the three algorithms, the higher the accuracy of the translation results. The average number of sentences translated by the three algorithms is shown in Table 6.

The results of Table 6 show that the average of the proposed algorithm is 1.5, while the average of the machine learning algorithm and the neural network algorithm are 4.7 and 4.9, respectively. The algorithm in this paper is significantly smaller than the other two algorithms, which shows that the inaccurate results of the proposed algorithm are less.

Table 6. **Comparison of the Average Translation Results for Each of the Three Algorithms.**

Translation algorithm	TEST06	TEST07	TEST08	average value
This paper's algorithm	1.5	1.7	1.3	1.5
Neural network algorithm	4.5	5.4	4.8	4.9
Machine learning algorithm	3.8	4.5	5.7	4.7

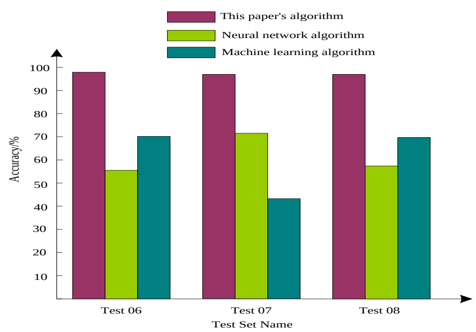

Figure 8. **Comparison of the First Precision Rate of the Translation Results.**

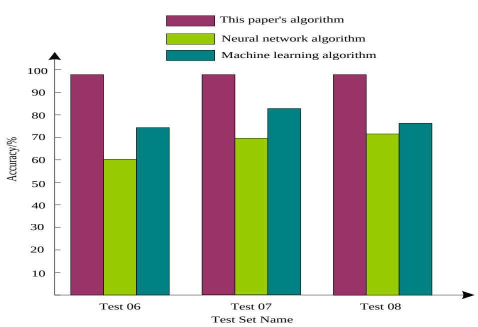

Figure 9. **Comparison of the First Two Accuracy Rates of the Translation Results.**

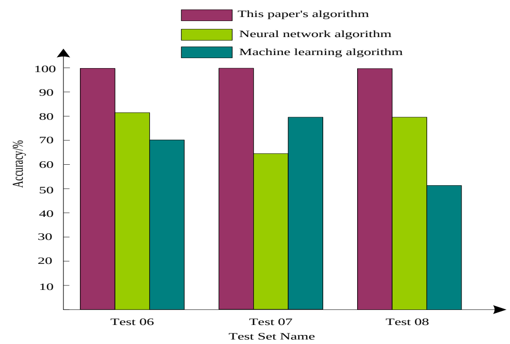

Figure 10. **Comparison of the Translation Results.**

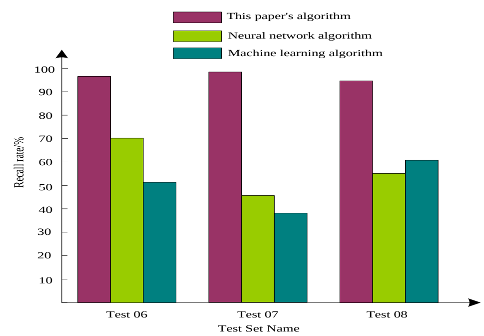

Figure 11. **The Comparison of Recall Rates between the Three Algorithms.**

According to the above simulation environment and parameter setting, the three algorithms are used to simulate the intelligent English automatic translation of the phrase translation combinations in the test sets TEST06, TEST07 and TEST08, respectively. The results are shown in Figure 8 to 11 by taking the first two parts of the translation output as well as the total accuracy and recall rate of the English semantic information as the test indicators.

From the analysis of Figures 8 to 10, the translation accuracy of the first two and all sentences in the English translation results of the proposed algorithm is above 95%. The translation accuracy of the first two and all sentences in the English translation results of the machine learning algorithm is only 82% and the translation accuracy of the first two and all sentences in the English translation results of the neural network algorithm is only 84%. The analysis of Figure 11 shows that the recall rate of the proposed algorithm is above 95%, while the recall rate of machine learning algorithm and neural network algorithm is only 70% and 63%. The accuracy and recall rate of the proposed algorithm are higher, which improves the intelligence level of English translation. By analyzing these results comprehensively, the proposed algorithm improves the accuracy of the translation results and has a high translation performance and stability of the English language and literature.

To verify the translation speed of the algorithm, the number of sentences translated in one second by the three algorithms is counted. The results are shown in Table 7.

From Table 7, we can see that the algorithm can translate 246 Chinese sentences into English on average per second, while the machine learning algorithm and the neural network algorithm can translate only 3.4 and 2.7 Chinese sentences per second. Therefore, the translation speed of this algorithm is obviously better than the other two algorithms.

Table 7. Comparison of the Translation Speed of the Three Algorithms.

Translation algorithm	Translation speed (sentence / s)
This paper's algorithm	246
Neural network algorithm	3.4
Machine learning algorithm	2.7

4 DISCUSSION

THE intelligent English translation algorithm based on the fuzzy semantic network designed in this paper has the advantage of a fast translation speed and high accuracy. The following discussion is made on the algorithm in this paper.

(1) The distance in the fuzzy semantic network represents the distinguishing features of word information more effectively. The expression of the complex information of words can be realized through the distance of the fuzzy semantic network. This algorithm can accurately describe the features of words and improve the accuracy of the translation by increasing the distance calculation method of the fuzzy semantic network.

(2) The maximum entropy training algorithm is used to classify the English semantics after computing the distance of the fuzzy semantic network. The maximum entropy training algorithm is essentially like a word interpretation process. The algorithm can accurately divide the semantics into hierarchical semantics and staggered semantics according to its performance. The staggered semantics are ordered according to the maximum similarity, and the hierarchical semantics include the same kind and staggered semantics. There are two types; interval and progressive. Therefore, the translation speed of the algorithm is faster, and the accuracy is higher.

5 CONCLUSION

THE intelligent English translation algorithm based on the fuzzy semantic network designed in this paper has a high translation performance. It cannot only independently express semantics but also describes the relationship between words based on eliminating ambiguity, and finally gives accurate English translation results. In a narrow sense, this algorithm provides users with a reference medium for English translation. In a broad sense, this algorithm is conducive to promoting cultural exchanges and trade exchanges between countries. In the future, the Intelligent English Translation will develop in the direction of big data and multi-information.

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7 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

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9 NOTES ON CONTRIBUTORS

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