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Artificial Intelligence Method for Accurate Translation of Fuzzy Semantics in English Language and Literature

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ABSTRACT

In order to address the drawbacks of semantic ambiguity, inaccurate quantifiers, and low translation accuracy in traditional grammar-based translation methods, this paper proposes an artificial intelligence translation method based on semantic analysis for English fuzzy semantics. Firstly, a comprehensive analysis of English language semantics was carried out from different semantic levels such as language, knowledge, and pragmatics, and the key points of fuzzy semantics were identified. Then, key feature quantities for accurate translation of fuzzy semantics in English vocabulary and literature were constructed, and artificial intelligence methods were used to optimize fuzzy semantics. The experimental results show that the proposed method can avoid semantic understanding ambiguity and improve the accuracy of English language translation.

KEYWORDS

Artificial Intelligence, English Words, Fuzzy Semantics

INTRODUCTION

Fuzziness is one of the essential characteristics of natural language. Fuzzy language is a language that expresses a fuzzy meaning; that is, a language with indefinite connotation and indefinite extension (Guo, 2021). Whether in literary and artistic works or people's daily communication, the vagueness of words occupies an indispensable position, especially in the translation process of English literary and artistic works. There is a lot of ambiguity and polysemy in natural language, which makes it difficult for machine translation systems to accurately understand and translate texts. For example, the word *bank* can represent either an organization that provides various financial services (for example, keeping or lending money) or the side of a river. The specific meaning needs to be judged according to the context, which requires that the machine translation system can understand and deal with this ambiguity. The accuracy of translation affects the level of communication. High-quality translation originates from the analysis and understanding of semantics, and shaping high-precision translation methods has high application value (BENBADA & BENAOUDA, 2023). Traditional translation

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methods with grammatical type variables have drawbacks such as semantic ambiguity, inaccurate quantifiers, and low translation accuracy (Yin, 2023). In response to this drawback, this article proposes an accurate English language translation method based on semantic analysis to improve the accuracy of English language translation.

Ambiguity is one of the main characteristics of English words and literature. It is precisely because of this that English literature gives readers a wider imagination and reading space, which is also its charm (Garcés-Báez & López-López, 2017). However, when translating English words and literature, this linguistic ambiguity cannot be ignored. How to truly understand the ambiguity of English words and literature semantics to make accurate translations is an issue that needs serious consideration. If the vague semantics of English words and literature are ignored in the process of translation, it will inevitably hurt the artistic conception of literary works. However, meaning is highly dependent on the translation situation and requires an effective grasp of actual translation. This is an critical problem in the current English translation process. It is essential to deeply analyze the basic characteristics of English words and literature and propose effective translation strategies for fuzzy semantic translation. The traditional translation methods with grammatical type variables have the disadvantages of semantic ambiguity, inaccurate quantifiers, and low translation accuracy (Lin et al., 2017). Given these drawbacks, this paper proposes an artificial intelligence method based on semantic analysis for the accurate translation of vague meanings in English words and literature to improve the accuracy of English word translation.

The ultimate understanding of the English language is the understanding of semantics (Zhao, 2022). Although different languages have different characteristics and fuzziness, this greatly increases the translation practice. The fuzziness and accuracy of languages are mutually transformed to some extent, which makes translation possible. The fuzziness of language is not only the patent of literary works but is also reflected in various styles. Language fuzziness is mainly manifested in phonetics, grammar, semantics, and pragmatics.

The result of artificial intelligence applied to the information translation system—the intelligent information translation system—has brought revolutionary changes to the field of information translation. The application of artificial intelligence technology in computer-aided translation software has improved the efficiency and quality of translation, standardized some professional terms, and ensured the logicality of computer-aided translation software. Computer-aided translation is no longer limited to single grammar and sentence translation, but more focused on contextual information within language groups, paragraphs, chapters, and genres. From a semantic perspective, word semantic computation can be defined within the entire text or between individual word meanings, thus word semantics have relevance and similarity, reflecting the commonalities of two words in the same context and the aggregation characteristics between two words. At present, word semantic computing is more based on natural language processing to explore the degree of correlation between words (Grossi & Modgil, 2019). It combines Markov models to compare similar words between the input translation and the reference translation and matches them, calculating the similarity between the two (Yu & Peng, 2021). Some scholars calculate the correlation between words and concepts from the perspective of the word document case attribute degree and use statistical algorithms to determine the collinearity and correlation of the words in the document (Andrecut, 2020).

Traditional rule-based translation methods require a large amount of manual writing and integration of language rules, which cannot adapt to the complexity and variability of language. In addition, there are huge cultural and customary differences between different languages, which further increase the difficulty and challenges of machine translation. This article aims to study the issue of artificial intelligence methods for accurately translating fuzzy meanings in English words and literature. The architecture is as follows:

The first chapter is the introduction, which expounds the research background and significance of fuzzy meaning in English words and puts forth the research purpose, method, and innovation of this paper. The second chapter summarizes the relevant literature, and puts forward the research ideas of this paper. The third chapter is the method, which focuses on the precise optimization effect of fuzzy meaning combined with artificial intelligence methods. The fourth chapter is the experimental analysis, which is experimentally verified on the dataset to analyze the performance of the model. The fifth chapter reviews the main content and results of this research, summarizes the research conclusions, and points out the direction of further research.

LITERATURE REVIEW

The fuzziness of language exists in various linguistic phenomena, such as the fuzziness of semantics, the fuzziness of grammatical structure, and the fuzziness of phonetics. The fuzziness of language mainly refers to the phenomenon that the semantic connotation or extension is difficult to determine accurately, and the semantic scope is unclear. Like other scientific research, the study of vague meaning in translation has experienced a difficult and tortuous course from generation to development, continuous improvement, revision, in-depth discussion, and finally to maturity. As Schlagel(Söderquist)put it: “All experience and knowledge are relative to various fuzzy semantics, whether physical, historical, translating cultural and linguistic, changes with fuzzy semantics.” It is said that vague meaning makes words meaningful and word translation an indispensable tool for human survival. Cognitive vague meaning critically inherits traditional fuzzy semantics and is a translation product that further cognizes linguistic fuzzy semantics, situational vague meaning, and cultural vague meaning through the communicative subject (Wei et al., 2016). Zhao clarified how people transmit the information of words (A) to the recipients of words (B) and explained and analyzed the causal chain of people’s translation thinking in this program so that people who use different words may communicate with each other (2022). Franco et al. proposed the concept of fuzzy semantic parameters that parameterized each fuzzy semantic element, thereby making vague meaning more descriptive, objectively operational, and translatable (2017). At the same time, Lu also discussed how fuzzy semantic parameters can be translated into words and sentence comprehension to function as fuzzy semantics (Lu, 2023). Yuan et al. discussed how the schema-based translation theory of knowledge can help people decode the connotation of speech information and reconstruct the vague meaning of translation in the process of speech comprehension. The schema-based theory of knowledge plays the role of cognitively vague meaning in the process of speech comprehension and the decoding function of macroscopic fuzzy semantic parameter translation numbers for cognitive fuzzy semantic parameters (2021). Borgwardt & Penaloza believed that both relevance theory and discourse understanding are always embedded in cognitive fuzzy semantics. Discourse comprehension in translation is a process of reasoning for scientifically processing discourse and finding the best relevant explanation on the premise of relying on fuzzy semantics, while relevance theory is a feasible attempt to understand discourse from the perspective of cognitive science (2017). Xie & Wu believed that the process of word communication is a step in which both parties participate in cognitive fuzzy semantic assumptions. The translation adjusts the cognitive fuzzy semantic assumptions of the listener, to achieve the assimilation of the message transmission and the listener’s understanding as much as possible (2019). Soto-Hidalgo et al. discussed the efficacy of cognitively ambiguous semantics in word communication. They emphasized that both parties in the communication should choose the appropriate word description form according to the corresponding cognitive fuzzy semantic factors of the translation to achieve the purpose of communication (2016). Mo et al. took pragmatics as the theoretical basis and analyzed the vague meaning of modern Chinese from different levels, such as the nature and composition of vague meaning in translation, vague meaning and words use, vague meaning and word teaching (2022).

Liu and Tsai also revealed the three intervening effects of cognitive vague meaning in the conversion process from source word information to translated target word information and expounded the three translation functions of cognitive vague meaning in translation activities: mining cultural connotation, reasoning of an accurate logical relationship, derivation of implied content (2021). Jabeen et al. made great contributions to the theory of fuzzy semantic parameters. They discussed the functions and characteristics of fuzzy semantic parameters and translated vague meaning as the cognitive mechanism of conceptual meaning evolution based on fuzzy semantic parameters in his research. A set of parameters composed of multiple translation parameters forms a functional relationship and is divided into two categories: conventional and unconventional. The former includes translation parameters such as theme, time, space, culture, character relationship, and context relationship. The latter is to associate parameters with cognitive translation. By judging the cognitive relevance, the parameter relationship is placed in the corresponding cognitive fuzzy semantics, to temporarily construct the cognitive fuzzy semantic parameters. Unconventional parameters are random (Wu et al., 2019).

MATERIALS AND METHOD

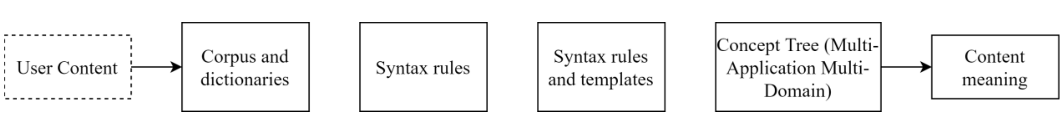
Find the Key Points of Vague Meaning by Analyzing Semantics in English Words

There are three characteristics of semantics: relativity, uncertainty, and imprecision. Uncertainty refers to Vague pronoun in English semantics because English fuzzy words and English fuzzy adjuncts have very rich semantic connotations and in the process of practical application, different meanings will have rich connotations. Therefore, to achieve different goals of semantic communication, it is necessary to deeply study the specific functions of fuzzy semantics. It helps us to re-judge and analyze the fuzzy semantics. Translation of any scientific research is not something that emerges out of nothing. The transformation of vague meaning to cognitive research, like translation, conforms to this objective law and has gone through the following three main stages of word theory evolution (Miao, 2021). In the first stage, the structuralist translation theory mainly focuses on "studying words for words' sake," focusing on word form, paying attention to the relational translation of symbols between word systems, and ignoring the cognitive subject status, but there is the shadow of vague semantics in it (Liu et al., 2021). In the structuralist view of words, vague meaning is the vague meaning within the words; in the second stage, the functional vague meaning theory analyses the vague meaning from the perspective of social translation and cultural dimensions, which breaks the limitations of the inherent fuzzy semantics; in the third stage, with the development of cognitive linguistics, scholars began to re-examine and study vague meaning from the perspective of cognitive translation, taking into account the cognitive psychology of both parties, trying to explain the cognitive process of dynamic translation in verbal communication. The problem of vague meaning turns to cognitive research and goes deeper (An, 2021).

The analysis of an English word's content semantics can be completed in four steps: (1) determine the standards to be met by content semantics and collect and arrange data; (2) determine the factors for content semantic analysis and create analysis categories for each factor; (3) select a part, and (4) overall management of the parsed data, verifying whether the coders are consistent, and completing the interpretation of the data expression. In the field of information technology, the semantics are also analyzed in four steps. As can be seen from Figure 1, the user content is analyzed and processed layer by layer to clarify the final content meaning.

The semantic web is an intelligent network that can judge according to the semantics and realize barrier-free communication between people and computers. It is like a giant brain, with a high degree of intelligence and strong coordination ability. Each computer connected to the semantic network

Figure 1. Content analysis process based on the semantic web



can not only understand words and concepts, but also understand the logical relationship between them, and can do what people do.

(1) Corpus and dictionary: User content comes from all the information resources of "corpus and dictionary," covering word form, part of speech, and word analysis.
(2) Grammar analysis: The "grammatical rules" stage deeply analyses the structure of sentences and interprets and analyses the subject, predicate, attribute, and direct and indirect objects of the English words.
(3) Semantic analysis: High-level semantic analysis is covered in "Semantic Rules and Templates" and patterns are set. According to grammatical rules, semantics, and semantic relevance, the system first clarifies the content and then expresses it through appropriate semantic templates.
(4) Visual representation: In the process of developing the 'concept class tree,' taking 'ontology' as an example, the authors define abstract, concrete, and class definitions related to various fields based on the hierarchical and structured extended tree words definition.

The translation is the conversion between English and Chinese through various translation templates. A translation template with syntactic type variables is a common translation template, where each variable corresponds to a syntactic category. The following is its expression:

$$T_a \longleftrightarrow T_b if X_1^{T_{a1}} \longleftrightarrow Y_1^{T_{b1}} and...and X_n^{T_{an}} \longleftrightarrow Y_n^{T_{bn}} \tag{1}$$

In the Formula (1): when $n = 1$, use $T_{a1} - T_{an}$ and $T_{b1} - T_{bn}$ to describe the variables. Each variable representation is a non-empty string. Example 1) is a translation template with variables of syntactic type:

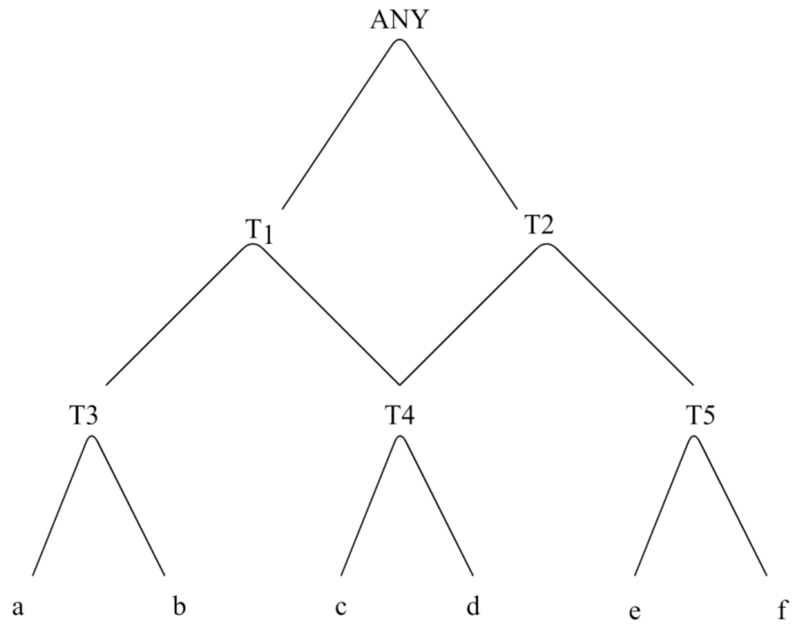
$$IX^{verb} + Past \longleftrightarrow (I)Y^{verb} + Adverb\left(Past\right)$$
$$ifX^{verb} \longleftrightarrow Y^{verb}$$

It can be seen from the formula 1) that on the basis of the correspondence between "X^{verb}" and "Y^{verb}," the English sentence "$IX^{verb} + Past$" and the Chinese sentence "Wo $(I)Y^{verb} + Adverb\left(Past\right)$" are also corresponding. In Example 1), "$+Past$" represents the past tense of English verbs, and "+ *Adverb* (*Past*)" represents the word describing the past in Chinese. The Chinese sentences in Example 2) can be translated using the translation template in Example 1), as long as "Lai « Come" correspond.

Chinese: Wo lai guo Þ I came
Wo lai+ *Adverb* (*Past*) I come +Past

The syntactic variable type of network shown in Figure 2 describes different types of syntactic variables and their grammatical roles in sentences. Through this syntactic variable type of network, we can distinguish the grammatical types of variables and better understand the role of grammatical roles in sentences. In Figure 2, naming the vertex 'Any' indicates that the node can accept any type of syntactic variable. Except for vertices, all nodes in the variable type of network have one or more parents, indicating that the node can act as the syntactic role represented by its parents. In addition, the type names on various variable types are mostly grammatical types, such as nouns, verbs, adjectives, etc. These types penetrate the entire syntactic variable type of network and guide us on how to judge

Figure 2. Structure diagram of syntactic variable type network



and use different types of syntactic variables in language analysis. T2 T3 represents different syntactic structures, which are subdivided in terms of lexicality and tense.

The quality of translation using translation templates with syntactic variables is higher than using translation templates with no type-restricted variables. However, in specific locales, translation templates with grammatical variables also have translation errors. Therefore, this paper proposes a translation template with syntactic type variables based on fuzzy semantic analysis. The fuzzy meaning is analyzed first, and then combined with the grammatical type constraints of variables, the substitution of variables is constrained to reduce the probability of errors in translation results. Each variable in the translation template of the syntactic fuzzy semantic variable has a corresponding syntactic semantic type. The following is the translation template formula with the syntactic fuzzy semantic variable:

$$ST_a \longleftrightarrow ST_b if X_1^{ST_{b1}} and ... and X_n^{ST_{an}} \longleftrightarrow Y_n^{ST_{bn}} \tag{2}$$

In the Formula (2): when $n = 1$, the syntactic fuzzy semantic categories are "$ST_{a1} - ST_{an}$" and "$ST_{b1} - ST_{bn}$." The number of variables on both sides of the common translation formula" $\longleftrightarrow$" is the same, and the variables on both sides correspond to each other. Use "$\longleftrightarrow$" to describe this template as a bidirectional template. There are two malformed translation templates:

$$abX_1c \longleftrightarrow uY_{1v}Y_2 if X_1 \longleftrightarrow Y_1$$
$$aX_1bX_2c \longleftrightarrow uY_{1v}Y_2 if X_1 \longleftrightarrow Y_1 and X_1 \longleftrightarrow Y_2$$

The reason for the error is that the two templates do not conform to the principle that the number of variables on both sides of the template is the same.

During actual English words translation, such malformed translation templates are deprecated. However, during the formation of the translation template technology with syntactic and semantic variables proposed in this paper, translation templates in the form of " $abX_1c \longleftrightarrow uY_{1v}Y_2ifX_1 \longleftrightarrow Y_1$ " will continue to be used. The template runs in the following two scenarios, where the Chinese syntactic semantic type tree used is described in Figure 3.

The tree is first divided into two parts according to the word nature and tense. The word nature is divided into verbs and adjectives and nouns, and verbs are divided into verbs of action and verbs of thought, and adjectives are divided into those that describe the body and the mind. Nouns are divided into personal pronouns and place names, and tenses are divided into progressive and past tenses.

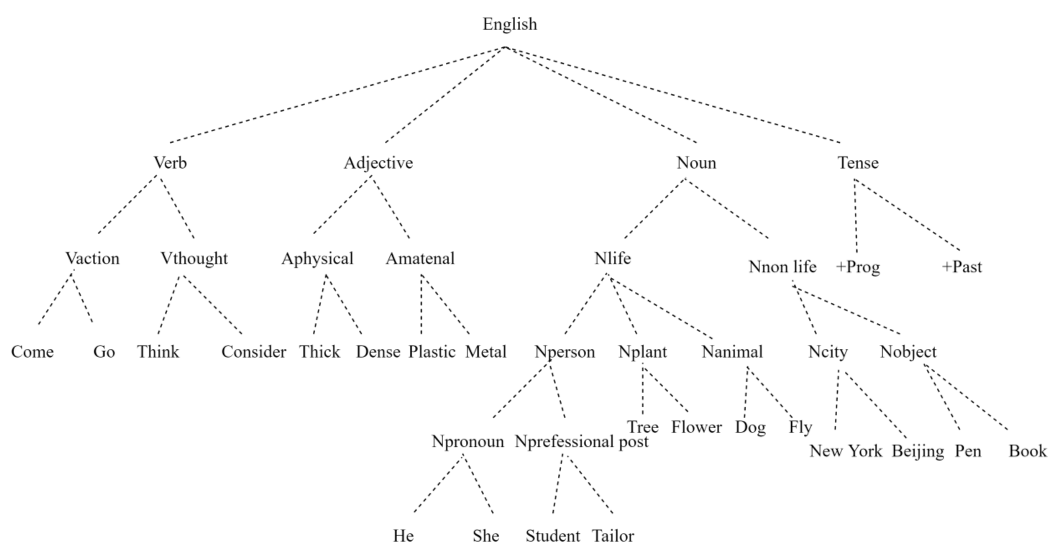
The first scenario: when the length of variable Y_1 is equal to the length of variable Y_2, and Y_2 is the subject noun of Y_1, the template $abX_1c \longleftrightarrow uY_{1v}Y_2ifX_1 \longleftrightarrow Y_1$ for translation.

The second scenario: when Y_1 is a quantifier in Chinese and is adjacent to Y_2, the translation template $abX_1c \longleftrightarrow uY_{1v}Y_2ifX_1 \longleftrightarrow Y_1$ can continue to be used.

Artificial Intelligence-Based Methods for Accurate Translation

In past decades, statistical machine translation has been the dominant machine translation model until the birth of neural machine translation (NMT). NMT is a new machine translation model that attempts to construct and train a single large-scale neural network that can read input text and output translation results. The operation principle of the artificial intelligence translation system is divided into two steps: the first step is the operation of the encoder; that is, the neural network encodes the Chinese words of the input sentence into a column of vectors, each vector representing the meaning of all the words read so far. After the entire sentence has been read, the first step is completed. The second step is the operation of the decoder, which generates the English sentence corresponding to the input sentence word by word. In this process, the decoder adopts an attention mechanism to form a weight distribution according to the close relationship between the encoded vector and the English word to be generated.

Figure 3. English syntax and semantic fuzzy type tree



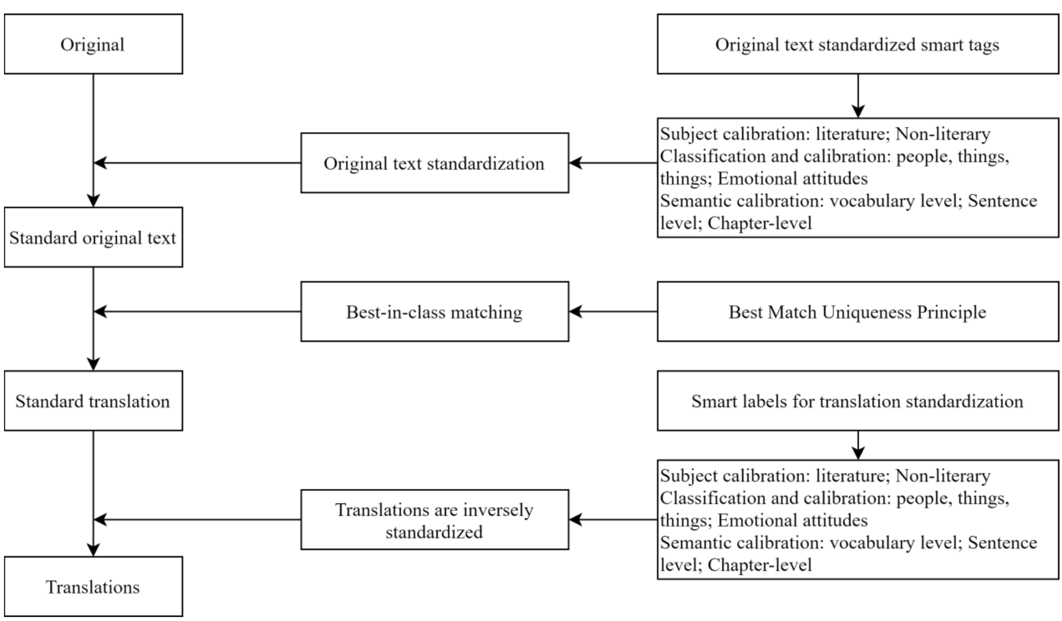
Classification according to the type of object to be analyzed in the text: people, things(static) things(dynamic). For example, the theme of the original text revolves around writing people, and the computer automatically extracts background knowledge about "people" from the corpus, including detailed information such as their biography, character characteristics, main works, main deeds, and contributions. The retrieval is beneficial to the machine's understanding of the article, to match the standard expression. Compared with " *things (static)*," " *things (static)*" belong to the category of static texts. The description of "*things (dynamic)*" belongs to the category of dynamic text. For the dynamic analysis of the text, the most important thing is the diversified description of the shape and state of the object over time.

The realization of English word standardization is mainly divided into the following steps: First, the style of the article is determined through the machine's recognition of the high-frequency words in the original text; that is, the topic calibration in the smart label. After the topic is determined, the machine classifies the text according to the text analysis object. Three categories of people, things(static), and *things (dynamic)*, and at the same time, the emotional attitude of the text content is graded. Finally, the text content is adjusted from the vocabulary level, sentence level, and text level, for example, by transforming some words, phrases, or sentence patterns in the original text. If necessary, processing methods such as provincial translation, addition translation, and subtraction translation for some content is adopted to make it the standard words of the source words. Conversely, this method is also applicable to the inverse standardization of the translation, as shown in Figure 4.

RESULT

A translation template with syntactic type variables was used to obtain test sample 1 for 6,807 English-Chinese sentences selected from "Family Album U.S.A." A traditional translation method with grammatical and semantic variables was used to translate 1,619 English-Chinese sentences related to the Olympics, and test sample 2 was obtained. The test results are described in Table 1.

Figure 4. Theoretical flow chart of the transition layer



Calculate the recall (R) and precision (P) of different translation methods. Use Table 2 to describe the frequency, recall rate, and precision of various situations. Among them, R=number of times the correct translation is output/number of preposition occurrences=$a+b/N \times 100\%$ and P=number of times the correct translation is output/number of times the translation is output=$a+b/(a+b+c) \times 100\%$.

By analyzing Tables 1 and 2, it can be seen that the recall and precision of the translation method with syntactic and semantic variables used in this article are higher than those of the traditional translation method with syntactic type variables, indicating that this method is effective in semantic disambiguation and can achieve accurate translation of English language.

DISCUSSION

Referential means "the interpretation of the elements of the sentence appearing below depends on the item that has appeared before referring to the same thing." References are divided into three categories: personal reference, indicative reference, and comparative reference. References can be subdivided into inner and outer references. If the reference point of the word's component can be found inside the text, it is the internal reference, and the internal reference is subdivided into the anaphora and the lower reference; if it is necessary to find the corresponding reference point from the outside of the text, it is the external reference.

Firstly, we analyze the referential situation used in accurate fuzzy semantic translation and then compare the similarities and differences between the artificial intelligence translation and the human translation processing based on fuzzy semantic precision translation. The specific situation is shown in Figure 5. "Invariant" means that the reference of the translation is consistent with the reference of the precise translation with fuzzy semantics; "adjustment" means that the translation has been adjusted based on the reference of the precise translation of fuzzy semantics, and the expression of the reference of the translation and the reference of precise translation with vague meaning is different; "deletion" means that the translation discards the referential expression of the precise translation of fuzzy semantics; "increases" means that the translation uses a reference where there is no reference to the precise translation of fuzzy semantics. A total of 290 allegations were selected from the precise translation of fuzzy semantics. Among them, the number of "unchanged" items in human translation exceeds that in artificial intelligence translation, and the other items are lower than that in artificial intelligence translation. There are 256 references in human translation for accurate translation with fuzzy semantics, which is about twice that of AI translation; there are 12 adjustments in human translation for precise translation with fuzzy semantics, which is only one-sixth of that in AI translation. And it contains 9 false allegations, with only 281 valid allegations; human traslation deleted 13 accusations of fuzzy semantic accurate translation, which is less than a quarter of the

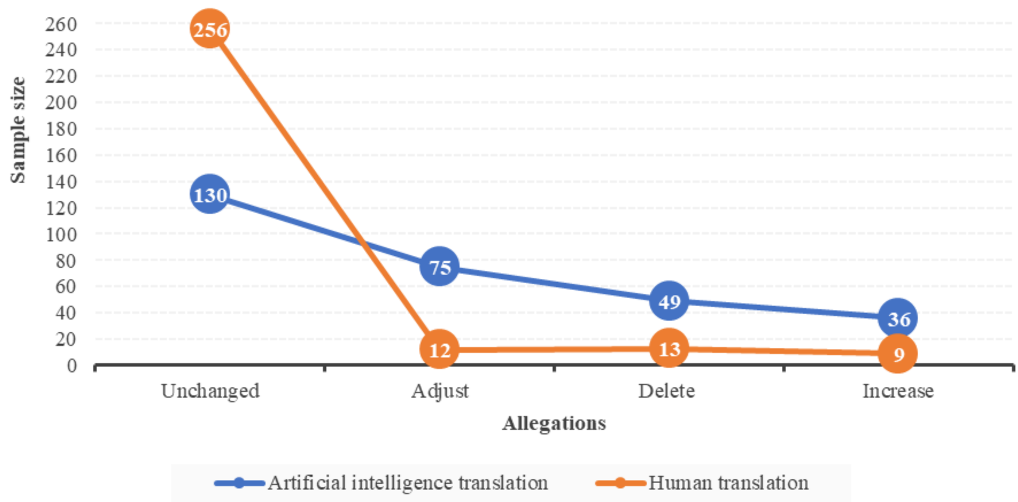
Table 1. Corpus test

Sample Type	Corpus	Total Number of Sentence Pairs	Number of Errors
Test sample 1	Family Album U.S.A.	6,792	3,416
Test sample 2	The Olympics	1,583	2,698

Table 2. Experimental results

Sample Type	Recall (R)	Precision (P)
Test sample 1	79.69	88.51
Test sample 2	65.32	83.56

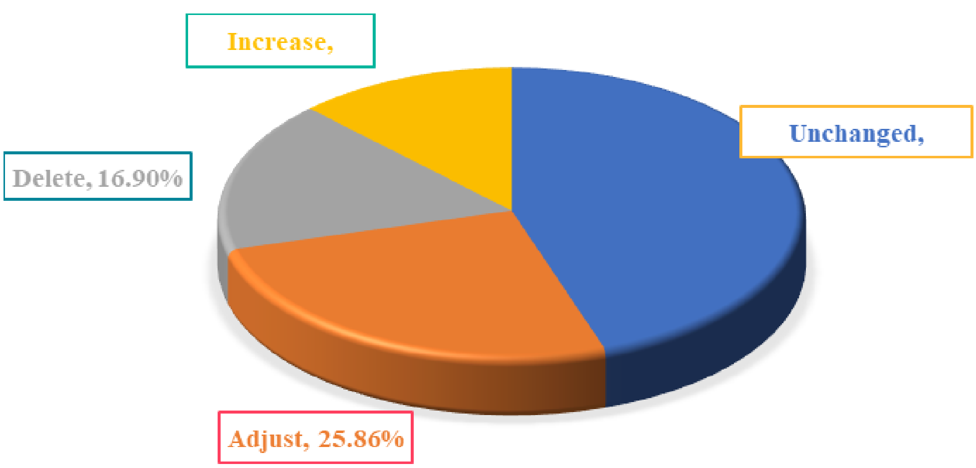
Figure 5. Comparison of the processing of fuzzy semantic references between artificial intelligence translation and human translation



artificial intelligence translation; human translation added 9 allegations, which is a quarter of the artificial intelligence translation.

In Figure 6, 44.83% of AI translation processing is consistent with fuzzy semantic precise translation, which means that these translations are very accurate and there is not much to adjust or delete. In addition, 25.86% of AI translations have been appropriately adjusted, indicating that they can identify and correct errors or inaccuracies in the translation. In addition, deletion is used in 16.90% of the places, indicating that useful information cannot be provided or cannot be correctly understood during translation. Finally, translation, which accounts for 12.41% of the total, needs further improvement. Overall, these results indicate that artificial intelligence translation has diverse processing methods and can perform appropriate processing according to different situations during

Figure 6. The distribution of AI translation reference processing



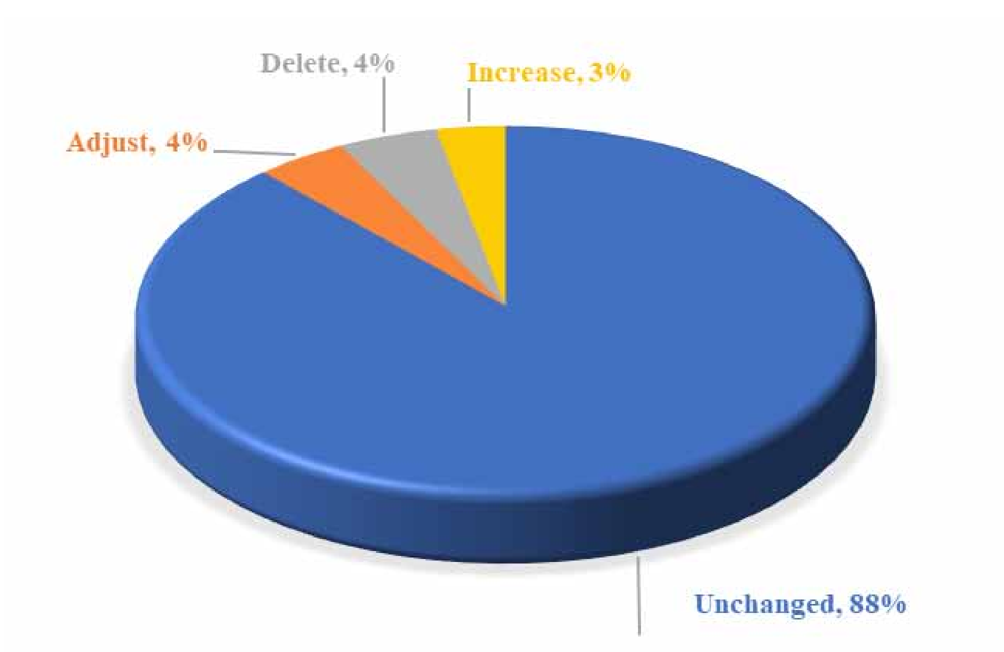
the translation process. Meanwhile, this also indicates that when using AI translation for translation, we should carefully check the translation results and make necessary modifications or adjustments based on the actual situation.

According to this data, 88.28% of translation references processed by human translators are consistent with fuzzy semantic processing, indicating that human translators can effectively understand and process fuzzy semantic references. In addition, 4.14% of translation references were adjusted, 4.48% were deleted, and 4.48% were added, indicating that human translators need to make appropriate adjustments, deletions, or additions to some vague references. In addition, the number of translated references accounts for 3.1% of the total, which also indicates that processing translated references is a very important task in human translation. Figure 7 shows that the distribution of referential processing in manual translation mainly conforms to fuzzy semantics, but it is severely differentiated. Among the four processing cases, the total proportion of the three small proportion cases is only 11.72%, indicating a lack of diversity in the processing of references by human translators. Although the way human translators handle fuzzy semantic references mainly conforms to the processing of fuzzy semantics, they may have certain limitations and singularity in reference processing, and further improvement is needed in their understanding and processing ability of fuzzy semantics.

According to the macro comparison between artificial intelligence translation and human translation on the referential processing of fuzzy semantic precise translation, the processing of artificial intelligence translation is more flexible than human translation, and human translation is more dependent on the expression of source words referents than artificial intelligence translation. Machine translation tends to form juxtapositions of clauses with logical relations defaulted and make the logical relations explicitly, adding relational conjunctions.

Linking refers to linking two sentences or larger units with logical and semantic relations, which can be realized in the form of conjunctions, linking components, or natural order. There are meaningful connections between sentences that constitute discourse, including interdependence (subdivided into juxtaposition and subordination) and logical semantic relations (subdivided into expansion and

Figure 7. The distribution of reference processing in human translation



projection). In discourse, the connection of these relations is sometimes realized by conjunctions, but sometimes there is no clear formal feature. Whether or not explicit formal features are required depends on the direction of the flow of textual information and the development and changes of things in the objective world or the sequence of readers' psychological processes. The predecessors summed up a total of nine kinds of orders and summarized five orders—chronological order, size order, general special order, causal order, and owner-by-owner order—which are collectively referred to as "natural order."

The processing of fuzzy semantic connection techniques in artificial intelligence translation and human translation is analyzed from a macro level, as shown in Figure 8. "No change" means that the translation adopts the same connection method as the source words: "adjustment" means that the translation retains the connection of the source words, but the literal expression of the source words is adjusted; "deletion" means that the translation does not retain the source words. "Increasing" means that the translation adds a conjunctive device where the source words do not use a conjunctive device. For the 95 connections used by the source words, artificial intelligence is consistent with 64 of them, and human translation is consistent with 85 of them, which is more dependent on the source words than artificial intelligence. Artificial intelligence adjusts and deletes source word connections more than twice as often as human translators (Jabeen et al., 2020). The difference in additions was the most obvious, with AI adding 53 connection forms that did not exist literally in the source words, while human translation only added 9.

For example:

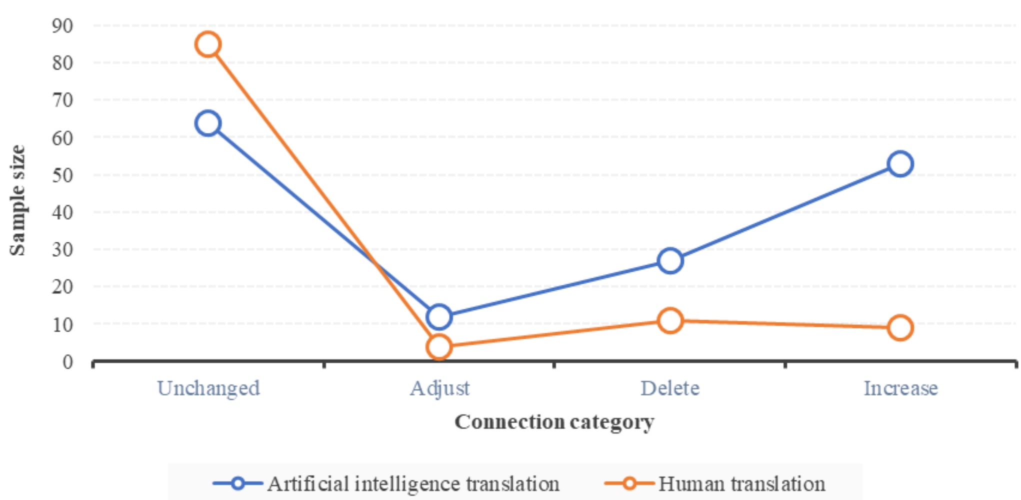
Source language: The advantages of this equipment are simple operation, and low maintenance cost, but it is poor in reliability.

Target language: 这台设备的有点是操作简便、维护成本低,但缺点是可靠性不足。

This example uses machine translation, where the transitive conjunction does not appear in the source language, but the machine translation turns up the transitive conjunction in the target language.

Linguistic context refers to the context of the chapter, while situational context refers to the surrounding situation when the chapter was produced, including time, place, and communication style, etc. Cultural context refers to the history, culture, and customs of the linguistic community in which the speaker or author lives. Machine translation is constrained by linguistic context, situational

Figure 8. Comparison of the processing of fuzzy semantic connection between artificial intelligence translation and human translation



context, and cultural context in the translation process. Among the above three contextual constraints, the cultural context has the most significant impact on the quality of machine translation.

The characteristics of mechanization and automation of machine translation led to the lack of complexity and creative thinking of machine translation, which cannot make complex reasoning and judgment on the original text, resulting in the distortion of the semantics of the translation. The following strategies can solve the shortcomings of machine translation and improve the quality of machine translation.

Firstly, human-machine interaction and collaboration are needed, and machine translation should vectorize the source language text to improve translation efficiency. Human post-translation editors edit and embellish the doubts and modify the errors of machine translation. Machine translation can handle programmed and informational texts such as scientific technical and legal texts, while for source language texts with strong literature and a high degree of emotion, machine translation needs human assistance.

With the advent of artificial intelligence and the big data era, machine translation systems are developing rapidly, mainly including rule-based machine translation systems, statistical machine translation systems, and neural network machine translation systems. Rule-based machine translation systems realize the conversion of the source language and target language through intermediate language and focus on syntax and grammar analysis. Statistical machine translation systems introduce corpus methods, multivariate statistics, and instance analysis, which enable machine translation to obtain translations relative to the source language from the corpus on a large scale. The statistical machine translation system is also the core technology of many translation companies such as Google, Baidu, and Microsoft. The neural network machine translation system has the ability of organization and self-learning, which can independently identify the language rules and characteristics of the source language from the corpus, and can perform hierarchical processing on complex source languages, transform them into forms that can be "understood" by computers, and finally form translations with high accuracy and readability. Each of the three translation technologies has its unique advantages, and if they can be combined, the quality of machine translation can be improved.

The cultural context cannot exist separately from reality and is generally generated in the environment where the event occurs, but integrating the cultural context into the corpus of the machine translation system requires the establishment of a three-dimensional or four-dimensional space, which is not possible with the current science and technology. The corpus of machine translation has the function of memory, and its corpus should be updated in real-time to adapt to the social and cultural trends and improve the contemporary characteristics of the translation.

To sum this up, artificial intelligence technology is in the process of innovation and development. Traditional computer-aided translation software can no longer meet the current practical need. The effective application of artificial intelligence technology can help relevant enterprises to complete the translation tasks of large-scale and multi languages more efficiently. The development of artificial intelligence technology based on big data is a favourable condition for enterprises, but at the same time, we should not blindly rely on artificial intelligence technology. Instead, we should see its advantages and disadvantages, use it scientifically and rationally, and ensure the quality and effect of translation work to the greatest extent through the combination of artificial intelligence and intelligence (Cao et al., 2020). This method is implemented through machine learning on a large amount of training data, so it can be applied to a wide range of texts. English literary works of different types and periods may have different linguistic features and cultural backgrounds, which may have a certain impact on the quality of translation.

CONCLUSION

This paper proposes an artificial intelligence method for the accurate translation of vague meaning in English words and literature. By analyzing the vague meaning of English words, we find the elements that affect fuzzy semantics, compare artificial intelligence translation and human translation, and finally conduct simulation test analysis. The simulation results show that the method in this paper has a certain accuracy, which is 7.65% higher than the traditional translation methods. In the text service industry, artificial intelligence translation technology is combined with the corpus accumulated by major text service providers. This new technology can provide high-quality and low-cost translation products and accelerate the delivery speed of both parties. Currently, various large text service providers are developing and using this new technology. Moreover, many popular computer-aided tools on the market integrate AI translation engines. Artificial intelligence technology has certain limitations. Based on artificial intelligence technology, manual proofreading and review are still needed to ensure translation quality. At the same time, factors such as cultural background and industry terminology may have an impact on translation, which requires necessary guidance and adjustments to artificial intelligence technology to improve translation quality. To better translate texts, we need to have a deeper understanding and understanding of the connotations of language and culture. In future research, we will continue to explore the language and cultural background of machine translation and find better ways to deal with lexical and pragmatic ambiguities.

AUTHOR NOTES

The authors of this publication declare there are no competing interests.

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The figures used to support the findings of this study are included in the article.

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