Cross-Cultural Fuzzy Information Recognition and Translation Processing in English Interpretation: A Perspective on Artificial Intelligence Recognition Technology

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Abstract. Aiming at the problems of traditional translation methods, such as improper recognition of spoken content and context, translation errors or serious incongruity of context, and lack of conformity of translation context, and based on the research of English interpretation under AI recognition technology environment, this paper constructs an English interpretation fuzzy information recognition translation system. The system connects the machine English translation of natural language and the semantic ontology after the model maps and analyzes the connection. The process of translation selection involves utilizing semantic similarity calculation for English translation to enhance semantic coherence. This helps ensure that the selected translations align well regarding their meaning. Additionally, a significant amount of information entropy data related to English semantics is projected. This data projection plays a crucial role in maintaining the accuracy of the translation algorithm proposed in the paper. A simulation experiment was conducted on the Windows platform to evaluate the performance of the AI-based fuzzy information recognition and translation processing system for English interpretation. The details and specifics of the simulation experiment, such as the methodology, setup, and evaluation criteria, need to be referred to in the paper for a deeper understanding of the experiment's design and outcomes. Experimental results show that the recognition accuracy of this method can reach 95.36%, which is 9.33% higher than traditional methods. This method is accurate and reliable for identifying and translating vague information into English interpretation.

Keywords: AI identification technology; English interpretation; fuzzy information identification; translation; cross-cultural.
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1 INTRODUCTION

AI (Artificial Intelligence) is a comprehensive field that has emerged from the convergence of computer science, cybernetics, information theory, linguistics, neurophysiology, mathematics, and other disciplines [4]. It represents a branch of computer science that has achieved remarkable advancements and is recognized as one of the world's top three technologies. The primary focus of AI is to explore, advance, and expand the theoretical foundations of human intelligence, aiming to comprehend the fundamental nature of intelligence and create innovative, intelligent systems capable of exhibiting human-like responses. These systems encompass various domains, such as language and image recognition, robotics, and natural language processing. Intelligence, at its essence, involves the capacity to make accurate decisions and achieve objectives within different environmental and objective contexts [8]. From an information processing perspective, intelligence encompasses acquiring, transmitting, regenerating, and utilizing information. The progress of AI products is closely intertwined with the advancement of AI technology [8]. AI technology's rapid and consistent development has facilitated constant updates, improvements, and revisions of AI products [6]. Since its inception, the technology has experienced significant enhancements, and the scope of AI research has expanded continuously. The study of AI is primarily divided into the theoretical basis, principles, and applications of AI [13]. The development of AI technology relies on the progress of computer technology, as it is the foundation on which AI is built. Looking ahead, computer AI technology will continue to evolve to serve humanity better. In this paper, AI recognition technology is applied explicitly to the recognition and translation processing of fuzzy information in English interpretation. This study explores the technical aspects of AI recognition and emphasizes the broader implications for cross-cultural communication, intercultural relations, and the fostering of mutual understanding. As we embark on this exploration, we envision a future where AI serves as a bridge between cultures, fostering communication that is not only linguistically accurate but culturally resonant.

Machine Translation (MT) has emerged as a new field with the advent of computer technology, aiming to translate natural languages using computer platforms. MT and human translation are complementary and interactive processes [12]. MT relies on human translation to provide bilingual corpora, translation strategies, methods, and the editing and refinement of human-translated texts. Simultaneously, MT can assist in addressing the challenges faced by human translators, particularly in translating technical terms. Fuzzy information is shared in natural language, encompassing lexical and semantic fuzziness. Lexical fuzziness pertains to words such as time words, age words, color words, temperature words, and taste words, where the boundaries of their meaning are difficult to define precisely, resulting in vague information. Semantic ambiguity can manifest in certain words used within sentences [15]. While most scholars agree that "fuzziness" is an inherent characteristic of natural language, some argue that high precision and accuracy in language can eliminate fuzziness in specific contexts [22]. Currently, most of the language processing mechanisms employed in MT for various natural languages are coarse and heavily rely on manual summarization by language experts. This approach could be more conducive to capturing intricate language details and can lead to significant translation errors.

Furthermore, traditional methods for selecting the optimal solution for fuzzy semantics have limited scope. The choice of the optimal solution is not solely based on semantics or characterized by keywords, which can result in deviations in unclear semantics and a lack of coherence in the translated context. Therefore, based on the research of English interpretation in the modern network technology environment, this paper constructs a translation system of fuzzy information recognition in English interpretation. Its innovations are as follows:

1. The focus of this paper is to address the limitations of traditional translation methods in accurately recognizing spoken content and context, which often result in word translation errors and disruptions in the overall context. To overcome these challenges, the paper explores the

application of AI recognition technology. It proposes designing and constructing a fuzzy information recognition translation system for English interpretation. By leveraging AI technology, this system aims to enhance the accuracy and fluency of translations by properly recognizing and interpreting fuzzy information in spoken English.

2. This paper introduces the establishment of a semantic model for machine English translation, which aims to connect natural language with machine-based English translation. The model is designed to map and analyze connected semantic ontologies and incorporates semantic similarity calculations in the translation selection process to improve semantic coherence. Additionally, the paper emphasizes the importance of incorporating fuzzy semantics, where each semantic tag is carefully selected based on the characteristics of spoken English. The corresponding connections are established through contextual analysis to address the challenge of poor context translation. The research findings validate the effectiveness of this approach, highlighting it as a viable means to achieve the desired translation outcomes.

2 RELATED WORK

AI recognition technology's continuous updating and refinement have enabled machine translation systems to handle complex linguistic structures, idiomatic expressions, and contextual nuances more effectively. As a result, the accuracy and fluency of machine-translated spoken English have significantly improved over time.

Pathak et al. reviewed rule-based MT technology, delving into various aspects such as source language text processing, MT dictionary construction, MT dictionary query, semantic disambiguation, and target language text generation [10]. Mucha proposed an enhanced English MT method based on semantic features [9]. This approach defines semantic features in English, extracts essential features, categorizes them into four groups, and implements specific improvements for each category. While this method exhibits robust scalability, it heavily relies on manual summarization by language experts, resulting in potential errors in semantic feature extraction. Srivastava et al. summarized the operational principle of statistical-based MT, highlighting its treatment of the MT problem as a noisy channel problem [17]. Gu emphasized the importance of selecting appropriate language and translation probability models while estimating probability parameters for statistical-based MT [2].

Consequently, the challenges lie in constructing large-scale aligned bilingual corpora, developing accurate parameter estimation smoothing algorithms, and implementing practical search algorithms. Tanaka adopted an enhanced method for English MT based on semantics and statistics [18]. This method utilizes English and semantic analysis models to derive constraint rule semantics, which are employed to enhance English MT.

While this approach maintains low time complexity, it faces challenges in building a more accurate grammar rule base, resulting in suboptimal translation effects. Khan et al. pointed out that statistical-based MT offers the advantage of bypassing the need for extensive knowledge and instead relies on statistical results for disambiguation and translation selection, thus mitigating challenges in language understanding [3]. The disadvantage is that the statistical model only considers the linear relationship between words and does not consider the sentence structure. Bailey A L et al. proposed that the language knowledge currently used in MT is relatively limited, and more complex language knowledge needs to be introduced to solve the text problem [1]. In Lv M's study, an improved method for English machine translation (MT) is proposed, which is based on the TF-IDF (Term Frequency-Inverse Document Frequency) approach [7]. The method begins by calculating the language's information entropy and information gain. It then incorporates semantic correlation factors of words to enhance the English MT process while relaxing the strict adherence to grammar rules. This method is straightforward in its approach. However, one drawback is its limited scalability, meaning it may need help applying to larger and more complex translation tasks or datasets. Zinszer B D et al. proposed a solution to the existing shortcomings of artificial NN (Neural network) MT [23]. Its plans include introducing AI technologies from other fields, mobilizing users to correct sample errors to form machine learning interactions with users, exploring weakly supervised learning and automatic optimization of translation systems, and establishing vertical domain corpora and data extraction models. Wu X et al. compared the advantages of MT and human translation [20]. It believes that the benefits of MT lie in cost, efficiency, consistency, and accuracy. In contrast, the advantages of human translation lie in the judgment of rich language forms, the determination of ambiguity, and the control of translation style.

At present, MT has made some progress. However, it still needs to be explored in designing models with more expressive power, improving linguistic interpretability, reducing training complexity, combining prior knowledge, and improving low-resource language translation. Based on the in-depth study of relevant literature, this paper puts forward a series of solutions to the problems of improper recognition of spoken content and context by traditional translation methods, which leads to translation errors of a word or serious inconveniences in context. Moreover, the semantic model of machine English translation is established, and the natural language of machine English translation is connected. The model is used to map and analyze the connected semantic ontology, and the semantic similarity calculation of English translation is used in the process of translation selection to improve semantic coherence. The research shows that this method can achieve the expected effect. It is an effective means to identify and translate vague information into English interpretation.

3 METHODOLOGY

3.1 AI Identification Technology and MT

AI transcends the boundaries of computer science and encompasses a wide range of disciplines, including cybernetics, information theory, linguistics, neurophysiology, and mathematics. It is widely recognized as one of the most significant branches of computer science and is ranked among the top three technologies worldwide [19]. The fundamental goal of AI is to explore and expand the theoretical foundations of human intelligence. In this context, intelligence refers to making accurate decisions and achieving goals in diverse contexts and environments. It involves acquiring, transmitting, regenerating, and utilizing information. AI is an interdisciplinary field investigating human intelligence and aims to construct artificial systems capable of exhibiting intelligent behaviors and capabilities. The paper categorizes AI systems into analytical AI, human-inspired AI, and humanized AI. Analytical AI primarily focuses on cognitive intelligence. It aims to generate mental representations of the world and utilizes past experiences to make informed decisions for the future. This type of AI system emphasizes cognitive factors in its decision-making process. AI incorporates elements of both cognition and emotional intelligence. It considers human emotions when making decisions, in addition to mental factors. This AI system aims to mimic certain aspects of human decision-making and behavior. Humanized AI represents the most comprehensive type of AI system. It possesses advanced abilities, including self-awareness and the capability to interact with others. Using computer systems, humanized AI systems simulate human cognitive processes, such as perception, thinking, and reasoning. These systems aim to replicate human-like intelligence and behavior as closely as possible. AI research and applications span various domains, including pattern recognition, natural language understanding and generation, expert systems, automatic programming, theorem proving, association and thinking mechanisms, intelligent data retrieval, robotics, intelligent speech, natural language processing, and more. AI has made significant advancements in these areas and continues to drive innovation and development in the technology landscape. AI has witnessed essential technological advances and the expansion of its research domains. The study of AI can be categorized into three levels: the theoretical basis of AI, which involves mathematical theory, cognitive science theory, and computer science theory; the principles of AI, covering knowledge representation, processing, acquisition, learning, and problem-solving; and the application of AI, including expert systems, natural language understanding, and more. In the context of this paper, AI recognition technology is applied to the recognition and translation processing of fuzzy information in English interpretation.

Translation involves reordering or rearranging a sequence of data or records based on a specific keyword [16]. Machine Translation (MT) is a relatively new field that emerged alongside the development of computer technology. Its objective is to translate natural languages from one to another using computer platforms. The research in MT has evolved with advancements in computer technology, linguistics, and other relevant disciplines. It has progressed from early dictionary matching and rule-based MT to statistical MT and currently employs Deep Learning (DL) techniques based on artificial neural networks (NN) [5]. DL, a branch of machine learning, aims to simulate the human brain's mechanisms for analysis, education, and research and development. It leverages neural networks to imitate the transmission and processing of information between neurons in the brain. The fundamental characteristic of DL is to replicate the brain's information processing and transmission modes.

Numerous translation algorithms are available, but only some perform optimally in some scenarios. Therefore, it is crucial to analyze the efficiency and performance of each translation algorithm during runtime, considering their respective advantages and disadvantages in specific situations. Currently, the prevailing approach in MT is employing encoder-decoder models based on attention mechanisms. The encoder-decoder framework first generates vector representations for each Chinese word. It recursively generates the vector representation of the entire Chinese sentence from left to right using a recursive neural network (encoder). Subsequently, another recursive neural network (decoder) is employed in the target language to reverse decode the source language sentences and generate English sentences. The attention mechanism helps address the challenge of capturing long-distance dependencies in long-source sentence vectors. The DL network model is shown in Figure 1.

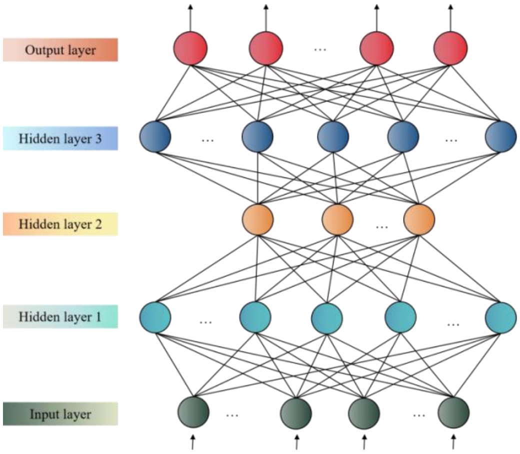

Figure 1: DL network model.

Many neurons, such as a neural network (NN), are typically utilized in a computational model. Each neuron processes and calculates the weighted input values from other neighboring neurons using a specific output function. The transmission of information between neurons is defined and analyzed through weighted values [11]. The algorithm autonomously learns and organizes significant data, continuously adjusting and changing these weighted values as needed. Training the NN algorithm relies on a substantial amount of data.

Regarding AI-based Machine Translation (AIMT), it stores the data to be translated in its memory and applies its own rules to perform the translation. This approach is suitable for handling element sequences with small data. For instance, Google's Neural Machine Translation (NNMT) model employs Long Short-Term Memory (LSTM), which consists of eight encoders and eight decoders. The operation of the Google NNMT system for translating Chinese into English can be divided into two steps. Firstly, the encoder processes the Chinese words of the input sentence, encoding them into a list of vectors where each vector represents the meaning of all words read so far. Secondly, the decoder generates English sentences corresponding to the input sentences word by word. Information fuzziness is a common phenomenon in natural language, encompassing lexical and semantic fuzziness. In various business communication scenarios, there are instances where clarity is necessary, while in others, the use of vague language is appropriate to achieve communicative goals. This paper proposes a fuzzy information recognition translation system for English interpretation based on research within the modern network technology environment.

3.2 AI-Based Fuzzy Information Recognition Translation System for English Interpretation

In AI-driven English translation, it is essential to prioritize the translation of semantic meaning. This involves leveraging intelligent recognition mechanisms to identify coherent and significant terms within the semantic structure. A language model is constructed to establish connections and contextual understanding in English to achieve this. Furthermore, fuzzy semantics play a significant role in translation, and the optimal translation solution is determined through discrimination and comparison. However, there is an ongoing need to optimize fuzzy semantic selection further and enhance translation adaptability in machine translation (MT) systems.

To enhance English MT, the initial step involves conducting a thorough semantic analysis of the source sentence. This analysis includes applying dedicated Chinese-English grammar conversion rules to establish the relevant links between phrases in the source sentence and their corresponding English counterparts. Notably, constructing a mapping model for fuzzy semantic words and contexts becomes crucial in this process. This approach enables effective selection based on the distinctive features of each semantic element and facilitates the extraction and scientific analysis of content.

Systematizing the structure of all fuzzy semantic mapping models makes it possible to perform timely meaning corrections throughout the translation process. This systematic approach aids in refining the accuracy and quality of translations. It also contributes to constructing a comprehensive machine English translation model that can handle fuzzy semantics with improved proficiency and precision. The possible semantic mapping relationship between synonyms and semantic information in English translation is described as follows:

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

In the formula, θ is the approximate semantics of English words; S is the language mapping corresponding to English words. This article's translation language is English, and the mapping floating range is within $[-0.5,0.5]$. The fuzzy semantic orientation is solved by establishing the mapping relationship between English semantics. The function cap delta can represent parsing knowledge point β can be represented by the function Δ:

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

The semantic secondary definition is performed using the natural language translated from English, and the formula is as follows:

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

In the formula, α_E is the conversion expression coefficient in natural language; S_E is the identification and conversion information code of English; $round$ is the English information rounding operator in the translation process.

The paper mentioned focuses on constructing a semantic model for English machine translation. It provides an example of the fuzzy mapping relationship between English words, which involves analyzing part-of-speech conversion and word deformation during translation. The optimization of English machine translation is achieved by analyzing English grammar rules and deriving the semantic Gaussian marginal rectangular window function. Additionally, a significant amount of information entropy data related to English semantics is projected. The paper's main objective is to naturalize the language of machine English translation. It conducts a fuzzy evaluation of concepts across different ontologies and analyzes the semantic population that is most relevant within a specific field. Binary coordinate groups express the credibility of approximate semantic words in the machine translation process. The text category to be translated in the paper is the information source. The relationship between word information entropy and word weight is determined by examining the information gain relationship between the category information entropy of the training dataset and the conditional entropy of words in the document category to be translated. Determining English translation similarity involves comparing various parameters, including relationship, collocation, semantics, context, and grammar. These factors are considered to assess translation similarity in the proposed approach. The translation process of this article is shown in Figure 2.

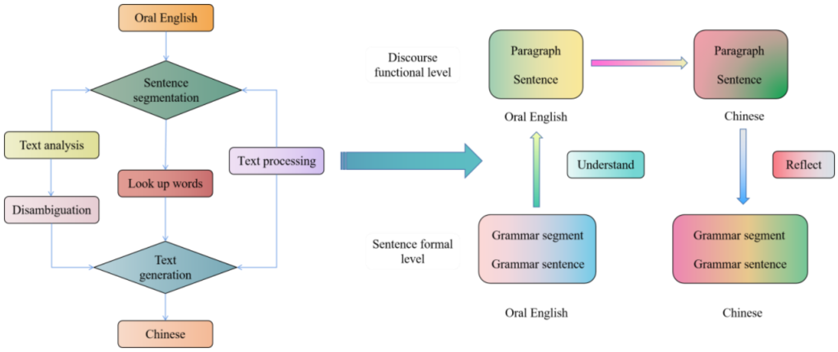

Figure 2: Translation and interpretation process.

Assuming that the word frequency is represented by tf, its function is to express the number of times the corresponding word appears in the document. idf represents the inverse document frequency, and the following formula is used to obtain the semantic feature weight function:

$$weight_{tfidf(t)} = \frac{tf(t) \times idf(t)}{d_i(n)} \tag{4}$$

Use formula (5) to calculate idf:

$$idf(t) = log\frac{N}{n}\left(weight_{tfidf(t)}\right) \tag{5}$$

In the formula, N represents the number of translated texts; n represents the number of documents in which the feature item t appears. Using the formula (6) to obtain each information gained in the sentence to be translated is the difference in information entropy:

$$G(X,y) = \frac{H(X)-H(X|y)}{idf(t)} \tag{6}$$

In the formula, $H(X)$ represents the information entropy of the text category that needs to be translated; $H(X|y)$ represents the gain relationship of the information amount between the conditional entropy of the words in the category.

Assuming that there are two binary semantic units in the total evaluation set: (s_K, a_k), and (s_1, a_1), these two units can represent the translation semantic information of any direct hypernym and the Euclidean distance of each component can be expressed as:

$$d\big((s_k,a_k),(s_l,a_l)\big) = \Delta(|\Delta^{-1}(s_k,a_k) - \Delta^{-1}(s_l,a_l)|) \tag{7}$$

Through the above formula, we can calculate the search corpus fragments of English translation, and the reliability of repeated English translation can be expressed as follows:

$$\bar{s},\bar{a} = j_1\big((s_1,a_1),(s_2,a_2),\dots,(s_n,a_n)\big) = \Delta\left(\sum_{j=1}^{n}\frac{1}{n}\Delta^{-1}(s_j,a_j)\right) \tag{8}$$

Assume that a binary coordinate group, namely, can express the approximation degree of two approximate semantics:

$$v_i = \big((w_1,t_1),(w_2,t_2)\big) \tag{9}$$

By combining the difference of semantic mapping relationship in MT, the set of mapping results of word X can be obtained as $R(X)$. The weight vector corresponding to this set in the Tuscany region is:

$$\omega = (\omega_1,\omega_2,\dots,\omega_n)^T \tag{10}$$

Among them, $\omega_1 \in [0,1]$, so that the semantic similarity of each word can be expressed in the space formed by the search information; the expression is as follows:

$$\bar{s},\bar{a} = \phi_1\big((s_1,a_1),(s_2,a_2),\dots,(s_n,a_n)\big) = \Delta\big(\sum_{j=1}^{n}\omega_j\Delta^{-1}(s_j,a_j)\big) \tag{11}$$

In the formula, $\sum_{j=1}^{n}\omega_j = 1$; $\bar{s} \in S$; $\bar{a} \in [-0.5,0.5]$. Using this formula to calculate the single semantic similarity, the mapping relationship between the context and the context can be established in translating English paragraphs.

Vagueness may initially seem unclear, but it can convey nuanced information and offer a flexible and adaptable meaning. This characteristic can be harnessed to gain insights into the true intentions of others, allowing for a deeper understanding of their underlying motives. Moreover, the utilization of fuzzy information has the potential to enrich language expression, infusing it with vividness, depth, and intricacy, thus enhancing the overall impact of communication. In the present study, we aim to optimize the selection process of the best solution for fuzzy semantics by employing the grey relational matching method. By incorporating semantic features and leveraging information entropy and information gain, we introduce adaptive matching techniques that account for the nonlinear spectral features of semantics, enabling effective recognition of semantic information patterns. We employ a calculation method to determine the similarity between semantic paragraphs and further enhance the search process using the circular stack control method for spoken English word semantics. This comprehensive approach allows for the calculation of article weight similarity, enabling an accurate assessment of semantic alignment. However, it is worth noting that the translation selection operation needs to be more balanced with the drawback of excessive comparisons, resulting in slow operational efficiency due to the repeated calculation of maximum values. To address this limitation, we propose an improvement that involves extracting the two top values, leading to a significant reduction in iteration time and a substantial improvement in overall efficiency compared to conventional selective translation algorithms.

4 RESULT ANALYSIS AND DISCUSSION

Speakers deliberately use vague expressions in business translation to convey more precise and accurate information. Fuzzy language, for various pragmatic reasons, permeates all aspects of business communication. It is not a mere incidental pause or transitional element between preceding and subsequent statements but rather a deliberate choice employed in language communication, making it an integral component of effective communication. This chapter conducts simulation experiments to assess the performance of an AI-based system that recognizes and processes fuzzy information in English interpretation. The system is developed on the Windows platform and designed explicitly for faint information recognition and translation in English interpretation. For testing, 500 samples of spoken business English conversations are extracted as test data for translation. To ensure the efficacy of the proposed method for selecting the optimal solution for fuzzy semantics, initial parameters are carefully set and configured. Table 1 shows the setting of basic experimental parameters.

Serial number	*Parameter*	*Set value*
1	*Phrase translation volume*	*350 / character*
2	*Translation volume of essays*	*500 / word*
3	*Translation rate*	*14(kbit/s)*
4	*Semantic recognition rate / (kbit/s)*	*20(kbit/s)*

Table 1: Basic experimental parameters.

In the simulation experiment of this chapter, the evaluation indicators used are all representative metrics in this field: semantic content recall rate, matching degree of keyword features, error, etc. Firstly, the performance of this algorithm is tested, and the test results are compared with other algorithms. The recall rate results of different algorithms are shown in Figure 3. A comparison of F1 values of different algorithms is shown in Figure 4.

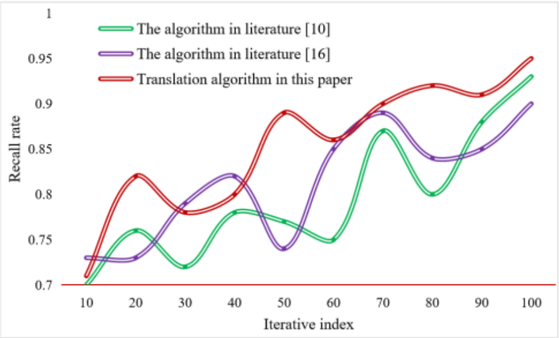

Figure 3: Recall the results of different algorithms.

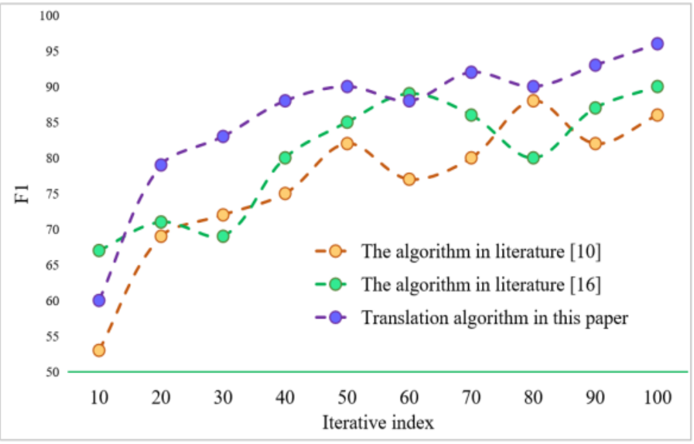

Figure 4: Comparison of F1 values of different algorithms.

Figure 3 indicates that the algorithm proposed in this paper exhibits a higher recall rate than others. Furthermore, the data analysis in Figure 4 demonstrates that the F1 value of this algorithm surpasses that of the different algorithms, further confirming its superior performance. In Table 2, Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are selected as metrics to evaluate the performance of various algorithms. The results indicate that the algorithm proposed in this paper achieves lower MSE, RMSE, and MAE values than the other algorithms, signifying its effectiveness and accuracy.

Algorithm	*MSE*	*RMSE*	*MAE*
Traditional translation algorithm	*0.237*	*0.627*	*0.803*
The algorithm in literature [10]	*0.136*	*0.298*	*0.632*
The algorithm in literature [16]	*0.092*	*0.263*	*0.537*
The translation algorithm in this paper	*0.054*	*0197*	*0.465*

Table 2: Experimental results of indicators of different algorithms.

The data in the table reveals that the errors associated with the algorithm proposed in this paper are at a low level. To optimize translation, experiments were conducted using the algorithm proposed in this paper, the algorithm mentioned in reference [10], and the algorithm mentioned in reference [16]. The word error rate and text segmentation error rate of these three algorithms were compared to assess their accuracy in translating vague information into spoken English. The comparison results for the word error rate are presented in Figure 5, while the results for the segmentation error rate are shown in Figure 6. These figures provide a visual representation of the performance of the algorithms in terms of word error rate and text segmentation error rate, allowing for a comprehensive evaluation of their effectiveness in handling vague information during translation.

From the analysis of the figure, it can be concluded that the accuracy of fuzzy information recognition and translation in English interpretation using this algorithm is higher than that of the algorithm in literature [10] and literature [16]. The experimental results show that this method is effective in most words with fuzzy semantics. Figure 7 shows the accuracy of comparing fuzzy information identification and translation in English interpretation by different methods.

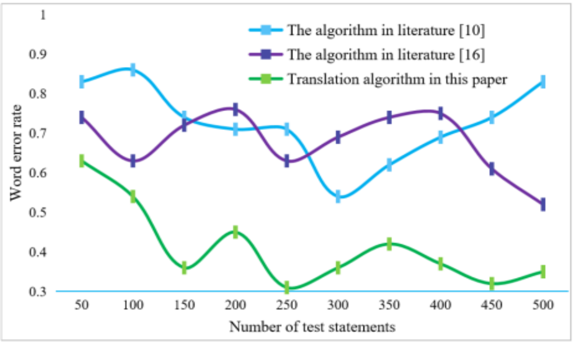

Figure 5: Word error rate comparison results.

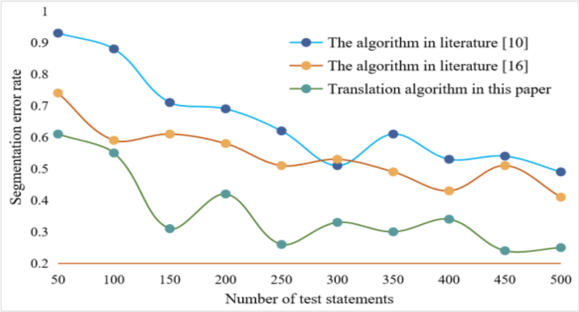

Figure 6: Comparison results of segmentation error rate.

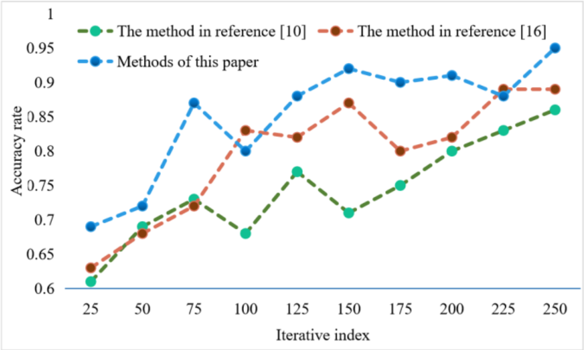

Figure 7: Accuracy comparison of different methods.

Based on the data analysis presented in the figure, it is evident that the accuracy of fuzzy information recognition and translation processing in English interpretation using this method surpasses that of the other two methods. This method exhibits superior performance in this regard. Applying the technique proposed in this paper to the recognition and translation of fuzzy information in English interpretation helps to mitigate translation errors associated with individual words and the potential disruption to the context resulting from improper recognition of word content and context. By employing this method, a more scientifically accurate and contextually appropriate translation can be achieved. Many experimental results in this chapter show that this method is feasible. The recognition accuracy of this method can reach 95.36%, which is 9.33% higher than traditional methods. The method proposed in this paper has accuracy and reliability in identifying and translating vague information in English interpretation, thus providing more decision-support information for English interpretation and improving the quality of English interpretation.

5 CONCLUSIONS

The paper emphasizes the importance of a deep language understanding in achieving accurate translation. It acknowledges that fuzzy information is frequently encountered in spoken English translation and highlights the skillful use of such information to enhance language effectiveness and conciseness while adding implicitness and politeness. It recognizes that vague language can serve strategic communicative purposes in business communication. The paper also addresses the challenges of traditional translation methods, including word translation errors and difficulties in capturing contextual nuances. To overcome these challenges, the paper proposes leveraging AI recognition technology to develop a fuzzy information recognition and translation system for English interpretation. The experimental results demonstrate that this method accurately and reliably identifies and translates unclear information, surpassing the recognition accuracy of traditional methods by 9.33%. The proposed method holds promising potential for improving the quality and efficiency of English interpretation. However, the paper acknowledges its limitations due to the constraints of the knowledge and experience level presented. The author expresses a commitment to improving the system structure and performance in future research, aiming to contribute to the field of translation.

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