Fuzzy Information Recognition and Translation Processing in English Interpretation based on Artificial Intelligence Recognition Technology

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Research Article

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Fuzzy Information Recognition and Translation Processing in English Interpretation based on Artificial Intelligence Recognition Technology

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Abstract

Interpretation is an oral expression that converts the information heard and understood in the source language into the target language quickly and accurately, thus completing the role of information transmission. However, language contains too much fuzzy information, so it is inevitable to have fuzzy information in interpretation. The characteristics of fuzzy information, the differences between different languages and cultural backgrounds, and the unpredictability of interpretation have brought great challenges to interpretation. This paper proposes an improved generalized maximum likelihood ratio algorithm (GLR) for fuzzy information processing in English. To improve interpretation accuracy, this study analyzes the characteristics of language databases, vocabulary, grammar, and translation. More specifically, the principle of natural language processing research via intelligent recognition technology is introduced in this study. Secondly, the author introduces the role of vague language in oral communication. Then, this paper introduces the fuzzy language processing method via the improved GLR method in detail. Finally, the experimental results are given to verify the effectiveness of the method.

Keyword: Fuzzy language; Intelligent identification; oral interpretation; generalized maximum likelihood ratio

1 Introduction

Language is an indispensable part of human daily communication and is one of the main
means of information exchange and communication. With the increasing degree of globalization, the mutual conversion of various languages becomes particularly important. In some formal occasions, language conversion is accomplished through interpretation, which challenges the accuracy, standardization, and rapidity of interpretation (Crowston et al. 2012; Gupta et al. 2018; Carvalho et al. 2012). But, with the emergence and use of language, vagueness is everywhere.

Ambiguity is one of the objectivity of human language, which refers to the uncertainty of the scope of words. Because people have arbitrariness and subjectivity for all transitional languages in the process of cognition, fuzzy language inevitably appears, and fuzziness is one of the essential characteristics of human thinking (Gupta et al. 2014; Wang et al. 2023). One of the important characteristics of the human brain is that it can fuzzily recognize and process external information. Some scholars once believed that the fuzziness of semantics is, in the final analysis, a reflection of the uncertainty about the category and nature of things in people's understanding, and it is the product of language as the material shell of thinking (Fang et al. 2018). The concept is the basis of the meaning elements of language, while semantics and concepts are not in the same categories. The concept belongs to the scope of thinking, while semantics belongs to the scope of language. People's thinking ability is very developed, while the language expressing concepts is relatively limited (Bobillo et al. 2009; Yu et al. 2023). Language must use the least language units to express the maximum amount of information, and the same word is often used to express different concepts. Therefore, the semantics expressed by some words and grammatical elements of a language are inevitably ambiguous (Gao et al. 2020).

In the study of interpretation, computer technology has great potential. Intelligent information technology has brought great changes to people's lives (Wan et al. 2023). Especially with the intensification of globalization, communication between different languages has become particularly important. In addition, instant messaging is also an inevitable trend in the development of modern society. The study of English interpretation is highly technical and requires the interaction of multiple disciplines. With the support of computer technology, it can provide more accurate and timely interpretation results (Ren et al. 2023; Tomsovic et al. 1987).

In order to achieve high precision English interpretation, generalized maximum likelihood
ratio (GLR) algorithm is used to recognize speech data information (Wang. 2021; Lin et al. 2021; Duan. 2021). A syntactic function based on analytic linear table is obtained by correcting the structural ambiguity in Chinese and English. The main contribution of this paper is

1. The method designed in this paper can automatically search for phrases.
2. The method proposed in this paper can accurately identify various fuzzy information.
3. The method proposed in this paper improves the accuracy of machine interpretation.

The main content of this article is arranged as follows. Section 2 shows the related work. Section 3 introduces the research principle of intelligent recognition language technology. The information fusion between different interpretation languages is introduced in Section 4. The research on fuzzy information processing in English interpretation based on improved GLR algorithm is shown in Section 5. Section 6 shows the experimental results and the conclusions is described in Section 7.

2 Related work

Machine interpretation is one of the research contents in the field of NLP. There are several methods as follows.

Rule-based approach. At first, the linguistic school used this method to analyze the source language text by context-sensitive grammar, then translate it, and finally output the voice by computer. In theory, this method has the highest accuracy. However, the formal grammar of the natural language is extremely complex, difficult to summarize, and large in number. The rule-based method is extremely complex, and it has high requirements for the correctness of rules, and the accuracy is easy to degrade (Anandika et al. 2023; Andrade et al. 2023).

Statistical-based approach. After research, the complexity of translation methods based on statistical methods is relatively low. Compared with the rule-based method, the translation based on statistics is smoother. For a long time, the statistics-based method is the traditional method of machine interpretation (Magalhães et al. 2023).

Recurrent neural networks (RNNs)-based approach. With the development of deep learning technology, the method based on the neural networks has become one of the hot fields.
RNNs has been used for machine translation, and long-short term memory (LSTM), gate recurrent unit (GRU) and other structures have emerged. With the emergence and development of multi-core processors, the shortcomings of RNNs that cannot be parallelized are exposed. To overcome this problem, relevant scholars have proposed a coder-decoder model, which can be combined with an attention mechanism, residual connection, and other technologies. In 2017, Google proposed to use the self-attention transformer model to deal with machine translation problems, abandoning the practice of using RNN/convolutional neural networks (CNN), and only using the attention mechanism (Jantscher et al. 2023; Czmil. 2023; Herrera et al. 1995).

3 Research principle of intelligent recognition language technology

In terms of research principles, it should include the following aspects: First, when language signals are sent out, they will be arranged according to the time sequence, and then the language information will be encoded and converted into a coding form that can be recognized by the computer. Secondly, after the language information is correctly encoded according to the time sequence, this encoding can transmit the content with acoustic signals, and express different coding languages with different discrete symbols. Finally, through the intelligent perception of the computer, the specific semantics and voice of the language can be distinguished. The scene structure, grammar and semantics of the language are expressed in a form similar to human voice by using computer intelligence recognition technology (Mortezaee et al. 2020; Al-Absi et al. 2011).

At present, the language model is mainly constructed in the way of the statistical model. This is because the semantic and voice of language have similar frequencies to a certain extent. Modeling in statistical mode will improve the accuracy of interpretation. The structure block diagram of language recognition based on statistical mode is shown in Figure 1.
The identification method consists of the following parts.

3.1 Feature extraction

The feature extraction of speech signal processing needs to analyze the speech signal. First, it needs to analyze and extract the feature parameters that can represent the essence of the speech. Only with feature parameters can these feature parameters be used for effective processing. Different from the way of parameter extraction, speech signal analysis can be divided into time domain, frequency domain and other domain analysis methods. The speech signal analysis method can be divided into model analysis method and non-model analysis method. The template is mainly used to extract relevant features from the acquired language information for acoustic model processing. At the same time, in the whole feature extraction, we should also pay attention to the influence of external interference and noise.

3.2 Statistical acoustic module

In the process of voice transmission, there will be many obstacles with different sizes, shapes, and properties in the sound field, resulting in an extremely complex sound field. To ensure that the language is not distorted in the process of transmission, the first-order hidden
Markov model is generally used in the statistical acoustic module to build, to maintain the consistency between the sound emitted by the acoustic module and the received signal. At this stage, language research in intelligent recognition is based on N-ary grammar in statistics.

3.3 Decoder module

Decoder module is one of the core parts of intelligent NLP. Its main task is to output the correctly recognized signal string with the maximum probability through statistical acoustics, linguistics, and other disciplines.

The working principle of the decoder is as follows:

First, the language signal or feature extraction of the input language is obtained according to intelligent recognition technology. Now, \( m_i \) is used to represent the voice vector sequence under the condition of time, which can be specifically expressed as:

\[
M = \{m_1, m_2, \ldots, m_L\}
\]  

(1)

Then, intelligent language recognition technology can be expressed as:

\[
W^* = \arg \max_w \left\{ P(W|M) \right\}
\]  

(2)

where \( W = \{w_1, w_2, \ldots, w_L\} \) is a sequence of words, which is a continuous language.

Through Bayesian rule, Eq. (2) can be written as

\[
W^* = \arg \max_w \left\{ P(W, M) \right\} = \arg \max_w \left\{ \frac{P(W|M)}{P(M)} \right\}
\]  

(3)

\[
= \arg \max_w \left\{ \frac{P(M|W)P(W)}{P(M)} \right\} = \arg \max_w (P(M|W)P(W))
\]

Since the input language string is a specific \( m \), its \( P(M) \) is also determined. Therefore, omitting it will not affect the final result.

If in the intelligent recognition system, the words \( w_i \) and \( w_j \) are independent of each other, then their input values \( m_i \) and \( m_j \) are also independent of each other, and \( m_i \) is highly sensitive to \( w_i \), then the other form of formula (3) is
where \( P(m_i|w_i) \) is the number of occurrences of \( w_i \) in the text data. Use the text data corresponding to the voice database to directly calculate \( P(w_i) \), namely

\[
P(w_i) = \frac{P(m_i|w_i)}{H}
\]

where \( H \) represents the total number of occurrences of all words in the text data.

### 3.4 Principles of Computer Translation

Semantic analysis of the original words is necessary for machine translation. A connection between the original statement and the matching English phrase can be made using the guidelines for converting Chinese to English grammar. It simultaneously creates the translation's output phrase, concluding the machine translation. (Cordón et al. 2008; El Hossainy et al. 2023).

Computer translation can be expressed by the following formula

\[
NE_x = \frac{\omega \times S \times H_{en}}{k^*G_{en}} \eta
\]

where \( \omega \) is the extracted source statement characteristics; \( S \) is any entry in the dictionary; \( k^* \) is the value of entries in different grammatical formats; \( \eta \) is the knowledge redundancy.

### 4 Information fusion between different interpretation languages

#### 4.1 Fusion function

Assuming that there are \( N \) kinds of interpretation language information, \( m \) features can
be extracted from each language information, and there are $K$ words of the same type in each feature, then the membership function can be expressed as

$$
\mu = \begin{bmatrix}
\mu_{11}(x_1) & \cdots & \mu_{1K}(x_1) \\
\vdots & \ddots & \vdots \\
\mu_{N1}(x_N) & \cdots & \mu_{NK}(x_N)
\end{bmatrix}
$$

(7)

where $u_{NK}(x_N)$ is the membership function of the $N$-th words under a certain feature of the $K$-th interpretation language.

It can be seen that if the two interpretation languages are mutually supportive, the difference between their membership functions is relatively small. Therefore, the degree of mutual support between different interpretation languages can be expressed by the difference between membership functions. In this article, European distance is introduced to express this difference

$$
d_{ij} = \sqrt{(\mu_i - \mu_j)(\mu_i - \mu_j)^T}
$$

(8)

where $\mu_i$ and $\mu_j$ are line vectors. Its physical meaning is that a certain feature of the $i$-th interpretation language and the $j$-th interpretation language belongs to the membership vector of all words. One result can be obtained:

$$
d_{ij} = \sqrt{\frac{\sum_{k=1}^{K} (u_{ik}(x_i) - u_{jk}(x_j))^2}{K}}
$$

(9)

where $0 \leq d_{ij} \leq 1$ is the confidence distance, the greater the $d_{ij}$, the lower the level of support between the two interpretation languages, and the higher the contrary. Then, the fusion function of the two interpretation languages is defined as

$$
h_{ij} = 1 - d_{ij}
$$

(10)

Therefore, if the $i$ and $j$ interpretation languages can be expressed as fusion functions, then the fusion matrix can be expressed as

$$
h = \begin{bmatrix}
h_{11} & \cdots & h_{1N} \\
\vdots & \ddots & \vdots \\
h_{N1} & \cdots & h_{NN}
\end{bmatrix}
$$

(11)
Now, given a fusion vector \( g = [g_1, g_2, \cdots, g_N]^T \) to represent the interpretation language that can be recognized by all other interpretation languages, in order to ensure the maximum reliability, it is necessary to determine the minimum amount of fusion between other interpretation languages and the \( i \)-th interpretation language, i.e.

\[
g_i = \min(h_{i1}, h_{i2}, \cdots, h_{iN})
\]

where \( g_i \) indicates the degree of integration between the \( i \)-th interpretation language and other interpretation languages, and bringing (10) into (11) will get the following results

\[
g_i = \min \left(1 - \sqrt{\sum_{k=1}^{K} \left(\mu_{ik}(x_i) - \mu_{jk}(x_j)\right)^2}\right), j = 1, 2, \cdots, N
\]

4.2 Information fusion between different interpretation languages

In this paper, it is necessary to describe the same features between different interpretation languages. The proportion of different interpretation languages in the integration can be expressed by weight coefficient

\[
l = [l_1, l_2, \cdots, l_N]^T
\]

As mentioned earlier, the larger the \( g_i \), the higher the degree of recognition of the \( i \)-th interpretation language by other interpretation languages, and the greater the fusion weight. Therefore, a hypothesis is given as follows

\[
l_i = \frac{g_i}{\sum_{i=1}^{N} g_i}
\]

where \( \sum_{i=1}^{N} l_i = 1 \).

Then, the membership vector for different interpretation languages is

\[
\alpha = \eta^T \times l = [\alpha_1, \alpha_2, \cdots, \alpha_K]
\]

where \( \alpha_K \) represents the membership of the fused \( k \)-type words, and
The method described above can complete the integration of different interpretation languages. For different features, the same method can also be used for feature fusion.

5 Research on fuzzy information processing in English interpretation based on improved GLR algorithm

5.1 Constructing phrase corpus

In English interpretation, the establishment of corpus is very important. In the process of interpretation, it can accurately match the parts of speech of English and Chinese phrases and effectively improve the accuracy of machine interpretation. The information flow of phrase library is shown in Figure 2. This paper marks the English-Chinese phrase corpus and distinguishes the tenses of different phrase corpora.

![Figure 2. Structure block diagram of language recognition based on statistical pattern.](image)

Phrase speech recognition is the core part of intelligent interpretation, which is capable of handling many words and unclear sentence components. Secondly, in English sentences, because each word exists independently, it can be divided between words and sentences. Finally,
this paper uses syntax analysis to create a syntax tree. The methods proposed in this study can improve the interpretation accuracy.

Table 1 The classification of hedges in vague English.

<table>
<thead>
<tr>
<th>Category</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modal auxiliary</td>
<td>can, may,</td>
</tr>
<tr>
<td>Modal verbs</td>
<td>seem, guess</td>
</tr>
<tr>
<td>Modal adjective</td>
<td>possible, likely</td>
</tr>
<tr>
<td>Adverbial of manner</td>
<td>almost, perhaps</td>
</tr>
<tr>
<td>Modal noun</td>
<td>possibility, probability</td>
</tr>
</tbody>
</table>

5.2 Improved GLR method

In the field of spoken English, structural ambiguity is one of the difficult problems. This study introduces an intelligent English interpretation model via improved GLR method.

GLR method can interpret the relationship between sentences and translate them. If the semantic ambiguity is not detected during the translation process, the GLR algorithm will need to be calibrated again. If ambiguity is detected in the statement, the principle of local optimization is used to improve the content quality. Different identification channels are used to identify symbols and improve the accuracy of identification results.

In general, the traditional GLR algorithm is quite accidental, and has a large coincidence probability in the process of identifying data, which cannot meet the current accuracy. The accuracy of machine interpretation can be enhanced by the improved GLR method is shown in the Formula (7)

\[ G_E = (V_N, V_T, S, \alpha) \]  

where \( S \) is the start symbol cluster; \( V_N \) is the circular symbol cluster; \( V_T \) is the termination symbol cluster; \( \alpha \) is phrase action cluster.

5.3 Correction methods of English interpretation
In the traditional English interpretation problem, its final result can be obtained by speech recognition. However, part of speech recognition does not change the ambiguity between structures. Therefore, it is necessary to correct structural ambiguity in English interpretation. The analytic linear table is used for phrase recognition, which examines the areas of error in the findings of part-of-speech detection. With the pointers of advance, reduction, acceptance, termination and error, and corrects the error points by searching the phrase marker content in the phrase corpus. Figure 3 shows the algorithm correction flow chart.

Multiple recognition results can be written into the same node of the phrase structure tree when multiple recognition results need to be output simultaneously (for instance, when two phrases are adjacent in the sentence). The receiver pointer will then consider it automatically as one recognition result.

6 Experimental results

6.1 Experimental scheme

The impact of the proposed method was tested on the processing of fuzzy information in interpretation. The evaluation of interpretation mainly consists of the following aspects: interpretation accuracy, interpretation speed and updating ability. The experimental group was
completed by professional interpreters and computers.

Test process: first, 50 voice files with fuzzy semantics are given. Then professional interpreters and machines interpret these voice files respectively. The rater will score different algorithms through comparison. The scoring rules are as shown in Table 2.

Table 2. Scoring rule table.

<table>
<thead>
<tr>
<th>Project</th>
<th>Scoring rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification accuracy</td>
<td>Whether the evaluation content is clear and the structure is reasonable.</td>
</tr>
<tr>
<td>Identification speed</td>
<td>Total recognition time divided by the number of recognition phrases</td>
</tr>
<tr>
<td>Update capability</td>
<td>Total recognition update time divided by the number of recognition phrases</td>
</tr>
</tbody>
</table>

6.2 Comparison of scores of different methods

![Figure 4. Comparison of interpretation results of four methods.](image)

As can be seen from Figure 4, compared with the models compared, the proposed model's part-of-speech translation is the best in terms of recognition accuracy, recognition speed and
In order to comprehensively compare the performance of the proposed algorithm and other algorithms, a practical case is used for analysis. Given an actual statement, the final result is the comparison of machine interpretation results and human interpretation results based on statistical method, dynamic memory method, and GLR algorithm. The comparison experiment is depicted in Figure 5.

In this example, the vague English information that needs interpretation are “Mary has married with what’s his name—you know, the man with the curly blond hair”, “We would give you our reply as soon as possible”, and “The joint venture established by the two sides was somewhat of failure”.

From Figure 5, only the interpretation results via the proposed model are closest to the human interpretation results, and the recognition accuracy rate exceeds 96%, basically reaching the same level as professional interpreters. This also shows the superiority of the proposed algorithm.

![Figure 5. Comparison of different methods.](image)

**6.3 Identification node distribution comparison**

To fully verify the advantages of the proposed method in this study, the English interpretation proofreading test of the model in the text is realized through experiments, the
data in the process of the experiment is recorded, and the performance of the system is analyzed. In the experiment, there are 400 characters to proofread the vocabulary, 500 short articles to proofread the vocabulary, and 25kb/s word recognition speed. Compare the accuracy before and after proofreading, and the results are shown in Table 3.

<table>
<thead>
<tr>
<th>Experiment number</th>
<th>Before proofreading(%)</th>
<th>After proofreading(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>56.4</td>
<td>98.5</td>
</tr>
<tr>
<td>2</td>
<td>69.5</td>
<td>99.2</td>
</tr>
<tr>
<td>3</td>
<td>70.2</td>
<td>98.2</td>
</tr>
<tr>
<td>4</td>
<td>75.2</td>
<td>99.6</td>
</tr>
<tr>
<td>5</td>
<td>71.3</td>
<td>98.1</td>
</tr>
<tr>
<td>Average value</td>
<td>68.52</td>
<td>98.72</td>
</tr>
</tbody>
</table>

From Table 1, the highest accuracy rate before and after proofreading is 75.2% and 99.6% respectively. In addition, the average accuracy rate before and after proofreading is 68.52% and 98.72% respectively. Due to the distinct differences in accuracy between the two methods, it is demonstrated that the intelligent recognition model of systematic English interpretation is effective.

7 Conclusions

This paper presents an improved GLR method to deal with fuzzy information in computer interpretation. Compared with other traditional methods, the proposed method has higher accuracy and updating ability. Computer translation can help English learners complete basic dialogues, such as some complex lyrics and vague concepts. The use of fuzzy semantics in the process of communication and writing will not interfere with the normal expression and smoothness of sentences, but also enrich the content expressed in the same sentence and strengthen the expression effect. Only by studying and exploring these problems can the field of computer interpretation have greater development. Based on the professional fuzzy semantic theory, this study can not only improve the accuracy of translation, but also help readers grasp the emotional expression, hoping to make contributions to the translation and communication.
of literary works.

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**Data availability**

Enquiries about data availability should be directed to the authors.

**Conflict Interests**

The authors have no conflict of interest.

**Author Contributions**

Li Yin contribution lies in the design, data collection, study conception and the writing of the first draft. The author commented on previous versions of the manuscript. The author read and approved the final manuscript.

**Ethical approval**

The paper does not deal with any ethical problems.

**Informed consent**

We declare that all the authors have informed consent.

**References**


