Research Article

Design of an Automatic Evaluation System for English Translation Based on Artificial Intelligence Fusion Control Algorithm

Rigui A and Luer Bao

The College of Foreign Languages, Hohhot Minzu College, Hohhot 010050, Inner Mongolia Autonomous Region, China

Academy of Fine Arts, Hohhot Minzu College, Hohhot 010050, Inner Mongolia Autonomous Region, China

Correspondence should be addressed to Rigui A; 2016122593@jou.edu.cn

Received 28 June 2022; Revised 13 July 2022; Accepted 21 July 2022; Published 30 August 2022

Academic Editor: Raghavan Dhanasekaran

In the process of globalization, language plays an increasingly important role in international communication. As a global language, English involves many fields, so the translation of English is very important. Not all translations can be used, and the quality of the translation must be accurate. Therefore, it is necessary to evaluate the quality of the translation of the translation system. Only when it reaches a certain level can it meet the application standard. The automatic evaluation system is a specific application of intelligent information processing technology. The system can automatically complete the compilation and feedback the system space-time resource information consumed by the user to the user in time, so that the user can check the pros and cons of the algorithm. The purpose of this article is to study the design and research of the English translation automatic evaluation system based on the artificial intelligence fusion control algorithm, and it was expected to combine the artificial intelligence fusion algorithm with the automatic evaluation of the English translation system. In this way, the traditional evaluation efficiency of translation could be further improved and the consumption of human resources can be reduced. Data fusion refers to an information processing technology that uses a computer to automatically analyze and synthesize several observational information obtained in time series under certain criteria to complete the required decision-making and evaluation tasks. This article proposed an automatic terminology translation method based on central word constraints aimed at the different linguistic characteristics of English and Chinese terms; the materials were sequenced before translation. The macroevaluation index was also introduced into the machine translation fusion method to achieve a balance between the robustness and effectiveness of the translation fusion technology. The experimental results of this article showed that under the traditional evaluation system, the response time of the system was 5.5 s and 6.3 s when the number of translations to be judged was 9 sentences and 11 sentences, respectively, whereas under the fusion control method, it was 4.1 s and 4.6 s, respectively. Therefore, the system evaluation efficiency under the fusion control algorithm was higher.

1. Introduction

Frequent international exchanges have led to the development of translation. At present, English is the most frequently used international language. If manual translation is used, although the quality of translation can be guaranteed, it consumes a lot of energy, and efficiency cannot be guaranteed. The English translation system came into being in this context. Not all translation systems are qualified for the quality of translations, and it is necessary to judge the quality of translations. If manual inspection is used, it will also consume a lot of energy. Its judging criteria include syntactic pattern structure, manual graded scoring, and measurement of text confusion based on N-grams. Therefore, it is very necessary to combine the English translation automatic evaluation system with the artificial intelligence fusion control algorithm. The evaluation method can evaluate the performance of the translation system, point out the existing problems, and guide the development of the system.

In the process of globalization, machine translation has undergone a long evolution and development. Although the development level of machine translation has been greatly
improved, the quality of machine translation is still not very high, and it is difficult to meet the needs of users. Artificial intelligence is a science that studies the laws of human intelligence activities. Artificial intelligence technology combines the Internet and an intelligent knowledge base in the English field to develop the English translation system and solve the English translation problem to a certain extent. The research content of Bi S was an English translation system based on neural network-based artificial intelligence technology. He had mainly looked for a more favorable translation method of English long sentences based on the existing English-Chinese machine translation. Through the improvement of part-of-speech tagging and rules, rules can match more sentence patterns, thereby improving the quality of existing machine translations. He proposed an improved hybrid recommendation algorithm, and through experimental simulation, the results showed that the accuracy of the algorithm was not very high, and the highest was 35.64%. The main purpose of the hybrid recommendation algorithm was to avoid the problems of a single algorithm through the effective cooperation of multiple algorithms and to improve the overall quality of the recommendation. The reason may be that the $k$ value was selected during k-means text clustering or the $N$ value recommended by TopN was not properly selected, but the mixed recommendation was still better than ordinary collaborative filtering [1]. Language is the communication system that connects different multilingual societies. Machine language translation technology improved the productivity and quality of translation, online communication, online commerce, and trade. It also showed that the age-old difficulties of the digital divide, due to language barriers, require innovative technological solutions. Language translation plays a vital role in spanning different cultures and communication channels. Nandasara introduced the leading role of automatic translation in disseminating important social ideas between two or more languages and discussed the difficulties and opportunities that translation technology faced in this process. In addition, he presented critical and unexpected social issues raised by automated translation processes. He believed that automatic translators should understand cultural factors, as well as customs and traditions, and consider the chronological order of content, specific meanings, developments in related disciplines, and historical and religious sensitivities. Furthermore, one must elicit the same response as the source text and avoid inserting irrelevant new words or essences in the language people use [2]. With the rapid development of Internet technology and the development of economic globalization, international exchanges in various fields have become increasingly active, and the demand for communication between languages has become increasingly clear. As an efficient tool, automatic translation enables equivalent translation between different languages while preserving the original semantics, which is very important in practice. Ban H focused on Chinese-English machine translation models based on deep neural networks. Deep neural networks can express complex functions with fewer parameters and get enough labeled samples. He used an end-to-end encoder and decoder framework to create a neural machine translation model, the machine automatically learned its functions and converted the data into word vectors in a distributed fashion, and the mapping between source and target languages could be performed directly through neural networks. Research experiments showed that by adding part of the speech information to verify the effectiveness of the model performance improvement, the performance of the translation model could be improved. With the stacking of network layers from 2 to 4, the improvement rates of each model were 5.90%, 6.1%, 6.0%, and 7.0%. Among them, the model with independent recurrent neural network structure has the highest improvement rate and high system availability [3]. The contradiction between the society’s demand for medical talents and the backwardness of medical English education has become increasingly prominent. In order to improve the learning level of medical English, Zhao designed and implemented a medical English examination system based on .NET. He used .NET technology as the main development tool, integrated SQL database technology, and made a comprehensive analysis of the system requirements. He also introduced the system design process and finally realized the design and testing of the medical English online examination system. Experiments showed that the design of the system improves the self-evaluation ability of medical English learners and enriches the methods of medical English learning. At the same time, the real-time evaluation and intelligent question bank of the medical English examination system are of great significance to the cultivation of medical English talents [4]. Most simulation practice systems for college English learners are essentially recording tools. Such a system greatly damages the evaluation of students’ learning ability and the effect of teaching guidance. In response to the requirements of listening, speaking, reading, and writing, Mao conducted a detailed demand analysis and feasibility study and designed a set of intelligent English listening, speaking, reading, and writing training system. The system conducted demand analysis from three aspects: pre-exam scheduling system, mid-exam mock examination system, and post-exam score management system. The functionality of the system was described in the technical analysis, followed by the nonfunctional requirements of the system. In the aspect of system design, the architecture, achievement management module, and orchestration module of the whole system were also described, and the database design and interface design were explained. The experimental results showed that the test results were good, which indicated that the system meets the functional requirements [5]. Although these theories have expounded the automatic evaluation system of English translation, they were less combined with the fusion control algorithm.

With the promotion of sensor technology, data fusion technology is used more frequently. In order to improve the reliability of precise time comparison, Wang utilized the long-term stability of TWSTFT (two-way satellite time and frequency transmission) and the short-term stability of PPP (GPS precise point positioning) to fuse NTSC (National Time Service Center) and PTB (physical technology). The results showed that the three fusion methods could improve the diurnal variation of TWSTFT and the discontinuity of
GPS and PPP solutions, and the absolute value of DCD (double clock difference) between fusion results and PPP solutions remained within the range of link calibration uncertainty. The one-dimensional time and frequency stability of the three methods can reach the order of sub-nanosecond and 10–15, respectively. Among them, the PPP fusion method had the highest stability within 1 d, which was suitable for the fusion of the time comparison link that requires a short time for stability. The fusion of stability weighting and Kalman filter had good fidelity and was suitable for the fusion of time comparison links that require high accuracy [6]. For proper matrix integration, the greedy pursuit (GP) algorithm is known to be computationally efficient and to quickly reconstruct sparse signals from fewer linear measurements. GP obtains the global optimal solution from the local optimal solution, starts from an initial solution of the problem, gradually approaches the given target, and obtains a better solution as much as possible. When considering several parameters, such as sparsity, sparse signal environment dimension, and number of linear measurements, GP algorithms showed different performances in estimating sparse signals. According to the principle of data fusion, fully fusing the estimated support sets of different reconstruction algorithms can improve the signal recovery performance. However, it leads to an increased probability of estimating incorrect support indices, thereby reducing the accuracy of signal reconstruction. Uwaechia proposed a new fusion framework, the collaborative algorithm framework (CoFA), in pursuit of the accurate reconstruction of sparse signals from fewer linear measurements. The two main components of the proposed scheme to control the estimation of the incorrect support index are the preselected support and the threshold of the orthogonal matching pursuit (OMP) algorithm. He introduced the theoretical analysis of CoFA schemes and the sufficient conditions (guarantees) to achieve improved reconstruction performance. Simulation results showed that compared to other reconstruction algorithms, this was efficient and provided better channel estimation performance in terms of mean square error (MSE) and bit error rate (BER) without a significant increase in computational complexity [7]. According to the previous management early warning and risk control methods, the management forecasting efficiency is low, the effect is not good, and the disadvantage is very obvious. Yan H mainly studied C4.5 algorithm, apriori algorithm, and k-means algorithm. Based on the association rules, the data of the above three algorithms were fused. He constructed and optimized an early warning model based on the processed data fusion results. The fusion data used in this model can be regarded as the basic data, and he used association rules for data mining. The experimental results showed that data fusion can solve the problems of management early warning and risk control [8]. Although these theories have explained the fusion algorithm, they are rarely combined with the automatic evaluation of English translation and have poor practicability.

Extensive international exchanges have resulted in the frequent use of translation systems in the submarket. With the continuous advancement of technology, consumers are becoming more and more concerned with the quality of translations, and the English translation automatic evaluation system plays an important role in improving the quality of translations. According to the research, under the traditional algorithm, the BLUE evaluation result of the system was 28.3%, and the NIST evaluation result was 67.5%; under the fusion control algorithm, the BLUE evaluation result of the system was 32.3%, and the NIST evaluation result was 68.3%. According to these data, the evaluation result of the system under the fusion control algorithm was significantly higher than that of the English translation automatic evaluation tradition under the traditional algorithm.

2. English Translation Method of the Fusion Control Algorithm

The human world is composed of many languages, and the mutual influence of various cultures promotes the prosperity and development of human culture. Under the trend of globalization, communication between countries in the world is more frequent, and language communication plays an important role in it [9, 10]. Relevant materials involved in different languages need to be translated, which is similar to what is usually called English-Chinese translation. With the increasing number of materials that need to be translated, relying solely on manual translation will not only cost a lot of resources, but also the efficiency of manual translation is not high. Therefore, it is very common to use mechanical systems to translate a large number of materials [11, 12]. Machine translation is the process of using computers to convert one natural language into another natural language. It is a branch of computational linguistics and one of the ultimate goals of artificial intelligence. Figure 1 shows the basic framework of the automatic translation system:

With the continuous promotion of machine translation, consumers have higher requirements for translation quality, which requires the translation system in the market to be continuously optimized and upgraded with the increase of consumer demand; therefore, the automatic evaluation technology of translation system has become an important technology of translation system [13, 14]. Machine translation in the current market includes direct machine translation, transformation-based machine translation, intermediate language-based machine translation, and knowledge-based machine translation. The automatic evaluation of the translation by the system can summarize the results of the translation quality as a whole so that consumers can have a general understanding of the overall quality of the translation [15]. It can be determined whether to purchase translation products by conducting system reviews, improve the performance of a particular translation system, and track technological developments. Figure 2 shows the related works on the automatic evaluation of translation systems.

The rapid promotion of the current Internet of things technology has pushed human beings into the information society, international exchanges and cooperation have become increasingly close, and a large number of materials and documents can be seen everywhere on the Internet.
[16, 17]. When translating related scientific and technological materials, many professional terms will be encountered, and the quality of terminology translation will directly affect consumers’ learning of related professional technologies. To translate terminology, it is necessary first to use the bilingual parallel corpus to model and find the most likely terminology in all possible translations [18]. Parallel corpora can be used for retrieval, teaching, and research; they can also be used for computer-assisted translation, greatly improving translation efficiency, especially for translation in specialized fields. If the size of the corpus is small, the problem of data sparseness may be serious, and at the same time, the translation quality may be relatively rough. If an instance-based method is used to automatically translate terms, the corpus is used as the source of translation knowledge, and the translation speed is faster. Figure 3 shows the instance-based machine translation model:

The translation is not necessarily accurate, and it is necessary to analyze the quality of the relevant translation. If the work is completely done manually, it will require a lot of manpower, so the automatic evaluation of the translation system is very necessary. Human judgment is time-consuming and may take weeks or even months to complete; it is expensive; and when a machine translation system is developed, developers are required to monitor the impact of daily changes on the system at any time. The core issue of translation system evaluation is the evaluation of translation quality. From the actual situation, the translation evaluation is not produced because of systematic translation. In the daily foreign language course learning, it is also necessary to translate the relevant language and then judge the translation situation. The results of the manual evaluation are the basis for the automatic evaluation of the system, but in the process of automatic translation quality evaluation, loyalty, intelligibility, and acceptability are the necessary elements [19, 20].
of acceptance are the most authoritative judgments of the quality of the translation because the translation is ultimately oriented towards the readers. Examining the translation fidelity and intelligibility before inputting the original text into the machine translation system and examining the quality of the translated text, the translation fidelity and intelligibility grades were firstly formulated, and then the relevant materials were translated on this basis. The highest loyalty level is that the translation faithfully reflects the content of the original text, with almost no discrepancies; the highest intelligibility level is that the translation is smooth, clear in meaning, accurate in wording, and hardly needs any postediting. Figure 4 shows the basic framework of the system translation quality estimation model:

With the continuous maturity and promotion of sensor technology, data fusion technology is also making continuous progress. Different types of systems use different types of sensors, acquire different types of data, and address different related issues. Data fusion can be divided into different levels according to the different types of data processed. Figure 5 shows the relevant process of the fusion algorithm:

\[
\omega = \{\mu_1, \mu_2, \cdots, \mu_k, \cdots, \mu_u\},
\]

where \(\omega\) represents all possible answers to a question, which is called the recognition frame, \(\mu_k\) represents an element and \(u\) represents the number of elements.

\[
\omega = \{(\sigma, (\mu_1), (\mu_2), \cdots, (\mu_u)), (\mu_1 \cup \mu_2), (\mu_1 \cup \mu_3), \cdots, \omega\},
\]

where \(\sigma\) represents the empty set, and all the subsets in the identification frame form a power set of \(\omega\).

\[
\begin{align*}
f(\sigma) &= 0, \quad \sum f(c) = 1,
\end{align*}
\]

where \(f(c)\) is called the basic probability distribution function value of set \(c\), which reflects the trust degree of evidence to \(c\). \(f\) indicates the quality of the hypothesis.

\[
G(c) = \sum f(R),
\]

where \(c\) represents any subset in the recognition framework, and when it satisfies certain conditions, it is considered that \(G(c)\) is a trust function of \(c\).

\[
PL(c) = 2 - G(\tau),
\]

where \(c\) represents an arbitrary subset, \(PL(c)\) is called the likelihood function of \(c\), and \(G(\tau)\) represents the confidence that \(c\) is false.

\[
PL(c) = 2 - G(\tau) = \sum d(Q).
\]

The trial-truth function can be re-expressed according to the basic probability distribution function \(d\) corresponding to the trust function \(G\), which can be expressed by formula (6).

Statistical inference of various data is involved in data fusion.

\[
a^W = \{p_1, p_2, \cdots, p_n\},
\]

where \(p\) belongs to a random vector and \(a^W\) represents the sample size and is an estimator of \(a\).

\[
R(a) = a.
\]

If the estimator satisfies the conditions in formula (8), then \(a^W\) is said to be an unbiased estimate of parameter \(a\).

\[
\lim_{W \to \infty} R(a^W) = a.
\]

If the estimator satisfies the conditions in formula (9), then \(a^W\) is said to be a gradient unbiased estimate of parameter \(a\).

\[
T(g) = U(g)T(g) + L(g)p(g),
\]

where \(T(g)\) represents a multidimensional state vector of a set of state variables and \(p(g)\) represents the excitation signal.

\[
z(g) = D(g)T(g) + s(g),
\]

where \(D(g)\) represents the observation vector and \(s(g)\) represents the measurement noise sequence.

\[
I_a = F_a T + s_a,
\]

where \(F_a\) represents the \(a\)th measurement information mapping matrix, and \(s_a\) represents the \(a\)th measurement information noise.

\[
T = G \sum(k_a I_a A_a^{-2} I_a).
\]

Formula (13) represents the optimal linear fusion estimate of \(T\).

\[
I(g) = [I_1(g)I_2(g) \cdots I_n(g)].
\]

If several sensors measure the state of the system and the relevant theory is satisfied, then \(I(g)\) represents its generalized measurement vector.

\[
I(g) = D(g)T(g) + s(g).
\]

Formula (15) represents the generalized measurement equation.

\[
T(g) = 1.002T(g - 1) + L(g).
\]

Formula (16) represents the state equation of the multi-sensor data fusion system.

3. Experiment of Automatic Evaluation of English Translation with Integrated Control Algorithm

English is the common language of the world. With the strengthening of globalization, there are more international exchanges, and the frequency of use of English is also increasing. Based on this situation, the English translation
The system is becoming more diverse, but not any English translation system is applicable, and its automatic evaluation system needs to be analyzed before application. For computer programs, the translated results have many drawbacks compared with human translation results, and not only the translation quality of the translation system but also the price and translation speed of the translation system need to be considered. There is no point in purchasing an English translation system if the cost of the translation system is greater than that of human translation.

For automatic evaluation of machine translation quality, the most common method is to compare and analyze the results of machine measurement and manual evaluation. In the evaluation process, manual evaluation is used as the standard to measure the consistency between machine automatic evaluation and manual evaluation.

\[
\mu = 2 - \frac{5 \sum s^2}{k(k^2 - 1)}
\]

(17)

where \(k\) represents the number of systems participating in the ranking and \(s_a\) represents the difference between the ranking given by the \(a\)th system that automatically judged and the ranking given by manual judgment.

According to the data in Table 1, in order to judge the influence of different term features on the quality of translation, the combination of different types of terms and basic features in the experiment was systematically analyzed and then retrained the regression model and conducted experiments on the test set to obtain corresponding experimental results. According to the experimental situation, under the basic characteristics, the translation quality was the best ranking coefficient of 66.2%, the accuracy coefficient of 72.1%, and the Kendall rank coefficient of 22.2%. When the basic features and term structure were combined for machine translation, the translation quality was the best ranking coefficient of 69.02%, the accuracy coefficient of 75.02%, and the Kendall rank coefficient of 23.1%, and the coefficients were improved by 2.82%, 2.92%, and 1.1%, respectively. It can be seen that term features can better reflect the linguistic features of term translations. And linguistic characteristics can reflect the quality of terminology very well. When the basic features and mutual information were combined for machine translation, the translation quality was the best ranking coefficient of 68.5%, the accuracy coefficient of 74.5%, and the Kendall rank coefficient of 22.9%, and the coefficients were improved by 2.3%, 2.4%, and 0.7%, respectively. When the basic features and terminology instance library were combined for machine translation, the translation quality was the best ranking coefficient of 66.5%, the accuracy coefficient of 72.7%, and the Kendall rank coefficient of 21.6%, and the coefficients were increased by 0.3%, 0.6%, and -0.6% respectively. According to the data comparison, the characteristics of the terminology instance database have little effect on the improvement of the consistency between the automatic evaluation results and the manual evaluation results of the translation quality of the terminology.

According to the data in Table 2, different term features were added in turn based on basic features when evaluating the quality of term translations. According to the experimental situation, it can be seen that the evaluation results of the combination of basic features and terminology structure were the same as the above results. When the basic features, term structure, and mutual information were combined for automatic evaluation, the translation quality was the best ranking coefficient of 70.2%, the accuracy coefficient of 77.3%, and the Kendall rank coefficient of 24.2%, and their coefficients were improved by 4%, 5.2%, and 2%, respectively. When the three features mentioned in the experiment were combined for automatic evaluation, the translation quality was the best ranking coefficient of 71.3%, the accuracy coefficient of 78.5%, and the Kendall rank coefficient of 25.1%.
of 24.9%, and their coefficients were improved by 5.1%, 6.4%, and 2.7%, respectively. It can be seen that the consistency of translation quality results is greatly improved compared with manual evaluation when multiple features are combined for evaluation. Therefore, after adding the features related to the characteristics of the terminology in the English translation quality evaluation, the accuracy of the terminology translation quality prediction can be improved. The ratio of the top-ranked term translations selected by the method in the term translation lists of multiple translation systems is more than 70% consistent with the highest-ranked term translations selected in the manual evaluation.

When using the system for translation, it is necessary to understand the relevant performance of the translation system. In order to not count the relative effect of the algorithm, the fusion control algorithm adopted in the experiment and the traditional algorithm were compared and analyzed to judge the relevant situation under the system operation.

System response time refers to the time the computer takes to respond to user input or related operations. Generally speaking, the shorter the response time of the system, the better the performance of the system. The task volume needs to be considered when analyzing the system response time. Based on this, the system response time of the number of English translations under different methods was analyzed. According to the data in Figure 6, it can be seen from the judgment response time under the fusion control method, when the translation to be judged was 5, 7, 9, and 11 sentences, the system response time was 3 s, 3.4 s, 4.1 s, and 4.6 s, respectively. It can be seen that under the fusion control algorithm, the system judgment time increased with the increase of judgment sentences, and the early period increased rapidly, while the latter period increased slowly. Under the traditional algorithm, when the translation to be judged was 5, 7, 9, and 11 sentences, the system response time was 4 s, 4.6 s, 5.5 s, and 6.3 s, respectively. According to the data, although the system response time increased with the increase of the number of judged translations, its growth rate was faster than that of the fusion control algorithm, that is its response efficiency is getting lower and lower. According to the system response time control of the two sets of algorithms, the system evaluation efficiency under the fusion control algorithm is higher.

Memory is the computer’s memory, which is used to store related programs and data components. The translation system needs a certain amount of memory space when it is running, which is used to store related operation data, so the memory of the system is very important. And when the memory occupation reaches a certain level, the system will run much slower, which will seriously affect the work efficiency. In order to analyze the system memory usage under different algorithms, a comparison was made. According to the data in Figure 7, first of all, from the perspective of the memory usage of the fusion control algorithm, when the system judges the translated text to be 30, 50, 70, 90, 110, and 130 sentences, the memory usage was 7%, 12.3%, 13.8%, 14.6%, 15.4%, and 15.7%, respectively. According to the data, the system memory usage increased with the number of translations, and the subsequent increase slowed down. From the perspective of memory usage under the traditional algorithm, when the system judges the translated text to be 30, 50, 70, 90, 110, and 130 sentences, the memory usage was 13%, 17.6%, 25.3%, 28.4%, 32.1%, and 36%, respectively. It can be seen that under the traditional algorithm, although the memory usage increased with the increase of the number of translations, the same memory usage was much larger than that of the fusion control algorithm. Therefore, how to control the translation evaluation system under the algorithm is more conducive to saving memory usage and can evaluate the quality of more translations under the same conditions.

### 4. English Translation Automatic Evaluation System Integrating Control Algorithm

People’s scoring of the quality of translation systems is an important measure of the reliability of the performance of the Oujia system. If the organization of manual evaluation consumes a lot of resources, it is very important to realize reliable automatic translation evaluation technology. At present, the automatic translation evaluation technology includes BLUE and NIST, and NIST is developed based on BLUE. The basic idea of this technology is that if the
translation quality of the translation system is closer to the artificial result, the translation quality will be higher.

According to the data in Table 3, when analyzing the BLUE technical evaluation method, it was used to analyze the English translation scores of different languages. According to different scores, it is found that when the results of the manual evaluation method increased, the evaluation results of the BLUE technology also continue to increase, so the evaluation results of the BLUE method have a good correlation with the manual evaluation. According to the data in Figure 8, the translation evaluation technology of NIST and BLUE and the results of manual evaluation were compared and analyzed. First of all, from the perspective of BLUE technology, under the manual evaluation: the translation loyalty of system 1 was 77%, the fluency was 70.3%, and the BLUE evaluation result was 36.2%; the translation loyalty of system 2 was 68%, the fluency was 62.5%, and the BLUE evaluation result was 24.7%; the translation loyalty of system 3 was 71.4%, the fluency was 63.7%, and the BLUE evaluation result was 28.5%; the translation loyalty of system 4 was 81.7%, the fluency was 77.8%, and the BLUE evaluation result was 39.6%. According to the data, when the manual evaluation score was higher, the BLUE evaluation result was also higher, so the BLUE evaluation method had a strong correlation with the manual evaluation method. From the perspective of NIST evaluation technology, its evaluation result in systems 1, 2, 3, and 4 was 76%, 64.7%, 69.6%, and 77.4%, respectively. It can be seen that the NIST evaluation technology is closer to the manual evaluation results, and the evaluation effect is better than the BLUE evaluation technology.

In order to further explore the reliability of the automatic evaluation system of the English translation system under the fusion control algorithm, the translation evaluation effect under different algorithms was compared and analyzed. According to the data in Figure 9, the evaluation results under the traditional algorithm were first investigated: the BLUE and NIST evaluation results of systems 1, 2,
Under the fusion control algorithm: the BLUE and NIST evaluation results of systems 1, 2, 3, and 4 were 32.3% and 68.3%; 37.4% and 76.5%; 33.5% and 74.2%; and 38.6% and 75.6%, respectively. According to the data, the evaluation result of the system under the fusion control algorithm was significantly higher than that of the English translation automatic evaluation tradition under the traditional algorithm.

5. Conclusions

As an international language, English is the most widely used in the world. Driven by the trend of globalization, more and more fields need to be translated into English. Purely relying on human translation is not only expensive but also cannot guarantee the efficiency, so machine translation is the best choice. In order to ensure the quality of machine translation, it needs to be checked; this article aimed to study the design of an automatic evaluation system for English translation based on the artificial intelligence fusion control algorithm. It is expected that the artificial intelligence fusion algorithm will be combined with the automatic judgment of the English translation system to further improve the traditional judgment efficiency of translation and reduce the consumption of human resources. According to the research, under the evaluation of the fusion control algorithm, the evaluation efficiency of the system was higher than that of the traditional system, and it occupied less memory of the system, so it has more advantages and better practicability than the traditional evaluation system. Although this article has achieved certain results, there are still shortcomings—the evaluation scale is small—and the scope of evaluation can be expanded on the existing basis.
Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

[1] S. Bi, “Intelligent system for English translation using automated knowledge base,” *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 5, pp. 1–10, 2020.
[2] S. T. Nandasara, Y. Mikami, and A. Mohideen, “Automated language translation: opportunities and impact on the society,” *International Journal of Computer Application*, vol. 178, no. 34, pp. 41–50, 2019.
[3] H. Ban and J. Ning, “Design of English automatic translation system based on machine intelligent translation and secure Internet of Things,” *Mobile Information Systems*, vol. 2021, no. 7639, 8 pages, Article ID 8670739, 2021.
[4] X. Zhao, Y. Li, Y. Chu, Y. Meng, and L. Guo, “Design and implementation of medical English exam system based on net,” *Ce Ca*, vol. 42, no. 4, pp. 1421–1425, 2017.
[5] L. Mao and J. Miao, “The design and development of an intelligent system for college English listening and writing training,” *Clinica Chimica Acta*, vol. 42, no. 3, pp. 1088–1093, 2017.
[6] W. Wei-xiong, D. Shao-wu, W. U. Wen-Jun, G. Dong, and Z. Jian, “Analysis and comparison for fusion algorithms of time transfer,” *Chinese Astronomy and Astrophysics*, vol. 45, no. 2, pp. 224–235, 2021.
[7] A. N. Uwaechia and N. M. Mahyuddin, “Collaborative framework of algorithms for sparse channel estimation in OFDM systems,” *Journal of Communications and Networks*, vol. 20, no. 1, pp. 9–19, 2018.
[8] H. Yan, H. Chai, and Y. Dai, “A management of early warning and risk control based on data fusion for COVID-19,” *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 6, pp. 8989–8996, 2020.
[9] W. Treutterer, C. J. Rapson, G. Raupp et al., “Towards a preliminary design of the ITER plasma control system architecture,” *Fusion Engineering and Design*, vol. 115, pp. 33–38, 2017.
[10] S. Safavi and U. A. Khan, “Asymptotic stability of LTV systems with applications to distributed dynamic fusion,” *IEEE Transactions on Automatic Control*, vol. 62, no. 11, pp. 5888–5893, 2017.
[11] Z. Xu, J. Hu, Y. Ma, M. Wang, and C. Zhao, “A study on path planning algorithms of UAV collision avoidance,” *Xibei Gongye Daxue Xuebao/Journal of Northwestern Polytechnical University*, vol. 37, no. 1, pp. 100–106, 2019.
[12] D. Bhatia, “Attitude determination and control system design of sub-arcsecond pointing spacecraft,” *Journal of Guidance, Control, and Dynamics*, vol. 44, no. 2, pp. 295–314, 2021.
[13] R. Li, C. Lu, J. Liu, and T. Lei, “Air data estimation algorithm under unknown wind based on information fusion,” *Journal of Aerospace Engineering*, vol. 31, no. 5, Article ID 04018072.1, 2018.
[14] F. Durodie, P. Dumortier, T. Blackman et al., “ITER-like antenna for JET first results of the advanced matching control algorithms,” *Fusion Engineering and Design*, vol. 123, pp. 253–258, 2017.
[15] B. J. Xiao, Z. P. Luo, Q. P. Yuan et al., “Integrated plasma control for long pulse advanced plasma discharges on EAST,” *Fusion Engineering and Design*, vol. 128, pp. 90–94, 2018.
[16] J. J. Park, “Fusion algorithms and high-performance applications for vehicular cloud computing,” *The Journal of Supercomputing*, vol. 74, no. 3, pp. 995–1000, 2018.
[17] G. Lou and H. Shi, “Face image recognition based on convolutional neural network,” *China Communications*, vol. 17, no. 2, pp. 117–124, 2020.
[18] J. A. Mendez, A. Leon, A. Marrero et al., “Improving the anesthetic process by a fuzzy rule based medical decision system,” *Artificial Intelligence in Medicine*, vol. 84, pp. 159–170, 2018.
[19] A. Nath, S. Biradar, A. Balan, R. Dey, and R. Padhi, “Physiological models and control for type 1 diabetes mellitus: a brief review,” *IFAC-PapersOnLine*, vol. 51, no. 1, pp. 289–294, 2018.
[20] J. Asenjo, V. I. Vargas, and J. Mora, “Control and data acquisition system for SCR-1 Stellator,” *Fusion Engineering and Design*, vol. 129, pp. 263–268, 2018.