Automatic quantitative assessment of English writing proficiency based on multi-feature fusion

Fengtian Xu

Department of Foreign Language and International Education,
Henan Polytechnic Institute,
Nanyang 473000, China
Email: ftxu@36haojie.com

Abstract: In the existing quantitative evaluation methods of English writing level, the accuracy of feature extraction is low and the error is high. An automatic quantitative evaluation method of English writing level based on multi-feature fusion is put forward. By using vector space model and Jekard similarity coefficient to determine the cosine similarity of English text, the features of English text are extracted by Manhattan distance. Through kernel function, the multi-feature fusion of English writing text is realised. The multivariate linear regression model is used to determine the feature weight of English text and to quantitatively process the feature data. The automatic quantitative evaluation model of English writing level is constructed to complete the automatic quantitative evaluation of English writing level. The experimental results show that the accuracy of the proposed automatic quantitative evaluation method is always higher than 90 and the minimum error of text feature extraction is about 2%.

Keywords: multi-feature fusion; English writing; automatic assessment; corpus.

Reference to this paper should be made as follows: Xu, F. (2023) 'Automatic quantitative assessment of English writing proficiency based on multi-feature fusion', *Int. J. Continuing Engineering Education and Life-Long Learning*, Vol. 33, No. 1, pp.114–127.

Biographical notes: Fengtian Xu received his BA in English from the Xinyang Normal University in 2007. He is a Lecturer in the Department of Foreign Language and International Education of Henan Polytechnic Institute. His research interests include vocational English education and linguistics.

1 Introduction

With the growing global demand for learning English as a second language, students' English writing has become an important part of English education curriculum in China. In the process of English learning, students' writing level has become an important factor affecting their English learning ability (Wang et al., 2018). Objective assessment of English writing is of great significance to improve students' English learning ability. The automatic quantitative evaluation of English writing level can analyse the composition structure, words, etc. reasonably, and finally judge the quality of the article and point out the problems in English writing (Jiang et al., 2020). English writing plays an important role in English education in China, which affects the improvement of English teaching quality. Therefore, how to improve the assessment ability of English writing level has become a key research issue in this field.

Oh et al. (2020) proposes to design an auxiliary assessment system for English writing proficiency. Through this system, students' English writing level is evaluated. Second language automatic evaluation method is analysed, and the disadvantages that exist in the analysis of the existing evaluation methods, aiming at the insufficiency, the introduction of Gaussian mixture model to analyse the key points in English writing, existing in the application of writing structure and syntax errors, according to the potential of this process is not smooth, not grammar text, and different classification error, and realised the English writing level of assessment. However, due to the small number of key points to be considered and analysed in the process of evaluation, this method still needs to be further improved. Tai and Liu (2017) proposed to construct formative assessment criteria for English writing ability to evaluate English writing level. The method for English writing level by means of questionnaire survey in microscopic indexes of evaluation, will evaluate level summary to a discourse, discourse generated and individual mechanism, and has carried on the division with different levels of ability, determine the key factors influencing the level of writing and the secondary privacy, and then to evaluate English writing level according to this standard. This method can effectively obtain the key influencing factors in the assessment of English writing proficiency, which can improve the accuracy of the assessment of English writing proficiency. However, there is some one-sidedness in the assessment of the key factors of articles, which still needs to be further improved. Zhao (2018) proposed and designed a writing proficiency assessment method based on multiple regression analysis model. This method first analyses the meta linear regression model and the differences between the multivariate nonlinear regression model, and determine the problems existing in writing assessment method, with the aid of multivariate linear regression method for English writing level evaluation, the method is more comprehensive evaluation of the English writing level, but this method is based on the analysis of linear regression takes longer, there are some limitations.

Although all of the above methods are helpful to the improvement of English writing level, and can help students reflect the shortcomings of English writing level, they all have certain defects. Therefore, in view of the shortcomings of the above methods, this paper proposes to design an automatic quantitative evaluation method of English writing level based on multi-feature fusion.

2 Multi-feature extraction from English written text

The multi-characteristics of English writing mainly refer to the characteristics of the main components of the article. By analysing these characteristics, the quality of English writing can be determined. Therefore, in view of the current composition of English writing, this paper first determines the multi-features in English writing, which lays the foundation for the subsequent research.

2.1 Vocabulary density feature extraction

Word density is one of the most important features in multi-feature extraction of English writing. Therefore, it needs to be analysed effectively. Generally speaking, English words can be divided into two categories: grammatical words and lexical words (Zeng et al., 2019; Diamond et al., 2019). In a sense, grammatical words reflect the fluency, clarity, and predictability of the sentence (Abdi et al., 2020). Because words represent the amount of information contained in the English text. Therefore, the lexical density features extracted in this paper are based on the collection of vocabulary words in English texts, that is, the higher the lexical density, the more information contained in the English text and the higher the level of English writing. On the contrary, the lower the vocabulary density, the smaller the amount of information contained, and the lower the level of English writing.

First, the similarity of vocabulary features was determined by using cosine similarity. Text similarity based on word frequency is a method to calculate text feature weight by vector space model. In order to reduce the other interference factors on the text features in the vector space model, the influence of the paper when using this method to extract the lexical density, the two sentences in English text is only a word to be used in the lyrics (Sun et al., 2017; Eleftheriadis et al., 2016), the weights of elements of each word for word, to calculate the reference corpus of English text and the paper establish the corpus of the text of the cosine similarity between the English text (Pawel and Jiwu, 2018; Dimitrios Moshou et al., 2018; Ni et al., 2018), as shown in formula (1).

$$\cos\theta = \frac{A \times B}{\|A\|\|B\|} \tag{1}$$

In the formula, $\cos\theta$ represents the cosine similarity of the text, $A = (a_1, a_2, \ldots, a_n)$ and $B = (b_1, b_2, \ldots, b_n)$ represent the English text sentence vectors in the reference corpus and the corpus established in this paper, respectively.

The Jekard similarity coefficient is used to compare the similarity and difference between word collections in limited English texts. The greater the value of the Jacquard similarity coefficient, the higher the lexical similarity of English text.

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{2}$$

In the formula, J represents the Jecard similarity coefficient.

The set similarity measure function (Tao and Lu, 2019) is usually used to calculate the similarity between two English texts with a range of [0, 1].

$$Dice(A, B) = \frac{2 \times comm(A, B)}{leng(A) + leng(B)} \tag{3}$$

Among them, $comm(A, B)$ is the number of the same words in a sentence A, B, $leng(A)$, $leng(B)$ is the length of the sentence A, B.

On the basis of the above analysis, features are obtained with the help of Manhattan distance (Hu et al., 2018), namely:

$$d_{AB} = |a_1 - b_1| + |a_2 - b_2| \tag{4}$$

$$d_{AB} = \sum_{n=1}^{n} |a_n - b_n| \tag{5}$$

Among them, d_{AB} represents distance, n is the total number of sentences in English text.

On the basis of the above research, the distribution table and vocabulary density of the two corpora are obtained, as shown in Tables 1 and 2.

Table 1 Distribution of terms

	NN	*NNS*	*NND*	*NNPS*	*Total*
Reference corpus	7,896	2,639	4,852	36	165,269
Building a corpus	8,023	2,968	5,031	45	167,953

	VB	*VBD*	*VBG*	*VBN*	*VBZ*	*VBP*	*Total*
Reference corpus	453	236	1,322	593	368	120	2,964
Building a corpus	449	215	1,204	506	324	113	2,715

	JJ	*JJR*	*JJS*	*Total*
Reference corpus	3,205	35	105	3,526
Building a corpus	3,156	32	96	3,267

	RB	*RBR*	*RBS*	*Total*
Reference corpus	2,569	40	36	2,674
Building a corpus	2,488	38	34	2,495

Table 2 Glossary density table

Part of speech	*Reference corpus*		*Building a corpus*	
	Corpus quantity	*Vocabulary density/%*	*Corpus quantity*	*Vocabulary density/%*
Noun	165,269	5.63	16,7953	6.89
Verb	2,964	2.56	2,715	4.62
Adj.	3,526	2.03	3,267	3.89
Adv.	2,674	1.24	2,495	2.33
Total	174,433	11.46	176,430	17.73

According to Tables 1 and 2, the lexical density of the corpus established in this paper is higher than 17.73%, while the lexical density of the reference corpus is 11.46%, which indicates that the corpus established in this paper contains more information and the English writing level is correspondently higher. This result is in line with the normal expectation at the time of this study, that is, word density can be a quantitative assessment of English writing proficiency.

In the process of feature extraction of lexical density, cosine similarity is used to determine the similarity of lexical features, and then jacquard similarity coefficient is used to compare the similarity and difference between limited English text lexical sets to complete the feature extraction.

2.2 Feature extraction of high frequency words

On the basis of word density feature extraction, high frequency words in English writing are also very important features. Therefore, it is necessary to extract features.

High-frequency words can be used to evaluate lexical repetition rate or redundancy (Xia et al., 2017; Gong and Shu, 2020). Word frequency refers to the frequency of occurrence of the same word in the corpus. The more high-frequency words in the corpus, the higher the occurrence frequency of words. Based on this, the number of features of high-frequency words is extracted, as shown in Table 3.

Table 3 Number of high-frequency characteristics

Item	*Actual corpus*	*Reference corpus*	*Building a corpus*
Number of items	125	86	120
Cumulative proportion/%	53.64	36.96	52.98

According to the data in Table 3, the high-frequency words in the corpus established in this paper account for the largest proportion, which is 16.02% higher than the 36.96% of high-frequency words in the reference corpus, indicating that the words in the corpus established in this paper have high repeatability. Therefore, the number and proportion of high frequency words can be used as reliable parameters for quantitative evaluation.

2.3 Feature extraction of word length in English writing texts

The length of a word indicates the complexity of the word to some extent. The longer the length of a word, the more difficult and complicated it is. If there are more long words in English writing, it means they are better at using compound words, have a larger vocabulary, and have a corresponding higher level of English writing. The comparison of word lengths extracted in this study is shown in Table 4:

Table 4 Comparison of word length

Length of words	*Reference corpus*	*Building a corpus*
1	9,408	10,127
2	49,119	52,476
3	60,992	55,163
4	46,646	39,171
5	31,620	28,104
6	24,726	19,649
7	25,677	25,838
8	16,486	22,207
9	12,213	15,594
10	8,493	11,258
11	6,161	9,191
12	2,309	4,370
13	1,549	3,154
14 (14 above)	659	1,657
Average	7.49	10.24

It can be seen from Table 4 that the average word length of the reference corpus is 4.97, while that of the corpus established in this paper is 5.14, which further proves that the words in the English text of the corpus established in this paper are longer and more complex. This index is also consistent with our expectation, indicating that average word length can be used as a reliable parameter to quantitatively evaluate English writing proficiency.

2.4 Feature extraction of English writing sentence length

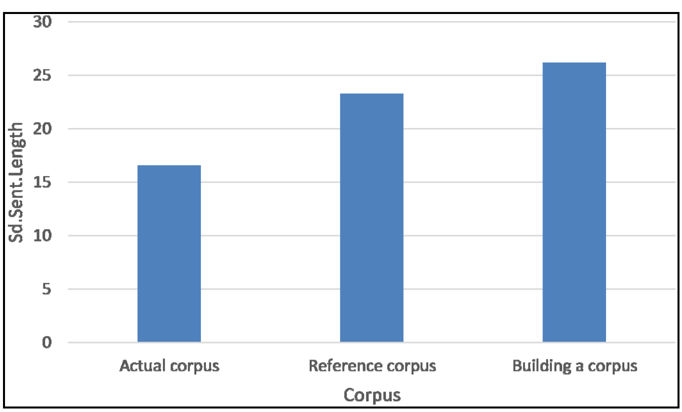
Sentence length in English writing usually indicates how many words there are in a sentence. The average length of a sentence is the average number of words in the corpus (Gong and Shu, 2020; Prince et al., 2017). Of course, the complexity of a sentence cannot be measured simply by the sentence length of an English text, but for a corpus, the average length of a sentence can reflect its complexity to some extent. Average sentence length depends on the vocabulary of corpus. In this paper, when extracting the sentence length features of English texts, the standard average sentence length is adopted to determine the complexity of sentences, so as to obtain the statistical situation of sentence length of texts, as shown in Table 5.

Table 5 Statistics on length of text sentences

Item	*Actual corpus*	*Reference corpus*	*Building a corpus*
Sentences	13,965	12,698	13,856
Sent.length	20.35	37.24	38.64
Sd.Sent.Length	16.59	23.29	26.19

In order to further compare the text sentence length statistics of the corpus established in this paper, the reference corpus and the actual corpus, the standardised text sentence length statistics are quantified, and the quantified results are shown in Figure 1.

Figure 1 Quantification of length of standardised text (see online version for colours)



From Figure 1, this paper setup the corpus of the average sentence length is longer than reference corpus average sentence length, average sentence length of about six words, thus proves the sentences are relatively simple and clear reference corpus, this paper setup the corpus of the sentence is relatively complex, and further illustrates the quantitative evaluation English writing level of the average sentence length is a reliable parameter.

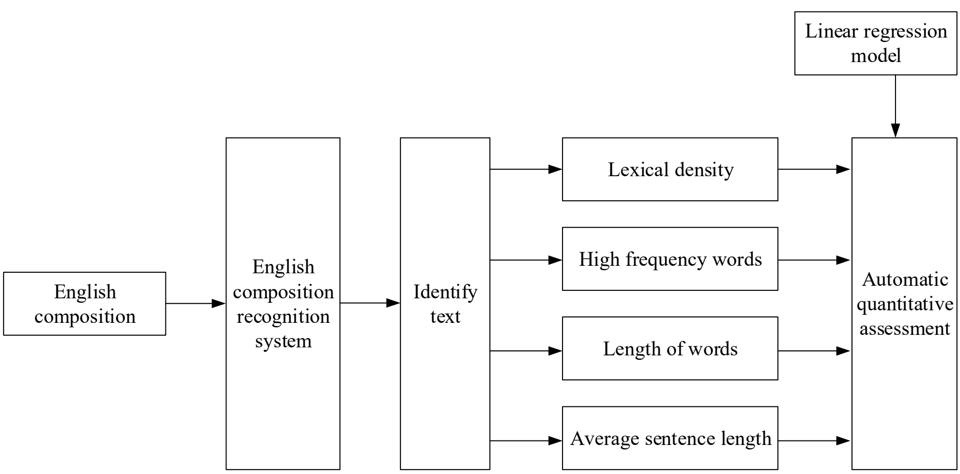
In order to realise the automatic evaluation of English writing level, this paper first determines several characteristics of English writing, including lexical density, high-frequency words, word length characteristics, sentence length characteristics. These characteristics fully reflect the basic problems encountered in English writing, and can be used as the measurement index. These characteristics are effectively determined, which lays the foundation for the next step of research.

3 Automatic quantitative evaluation of English writing level

On the basis of the above-mentioned features of English writing proficiency, these features are effectively integrated to realise the automatic quantitative evaluation of English writing proficiency.

Before the automatic quantitative assessment of English writing proficiency is realised, the English writing proficiency assessment model is first constructed, as shown in Figure 2.

Figure 2 Evaluation model of English writing level



As can be seen from Figure 2, the whole model includes three parts: writing level recognition, text feature extraction and linear regression. Among them, the lexical density, high frequency words in the text feature extraction, word length, average sentence length data feature extraction has been achieved, then the English writing text corpus data pre-processing, complete English text multiple features fusion, finally the quantised treatment to the data characteristics in the design of the linear regression model for automatic evaluation.

On the basis of the English writing level evaluation model, firstly, a corpus of English writing required by this paper is established with the classic US corpus BROWN as the reference corpus. The established corpus takes objective writing materials as the research object, and an automatic quantitative evaluation method of English writing level based on multi-feature fusion is designed.

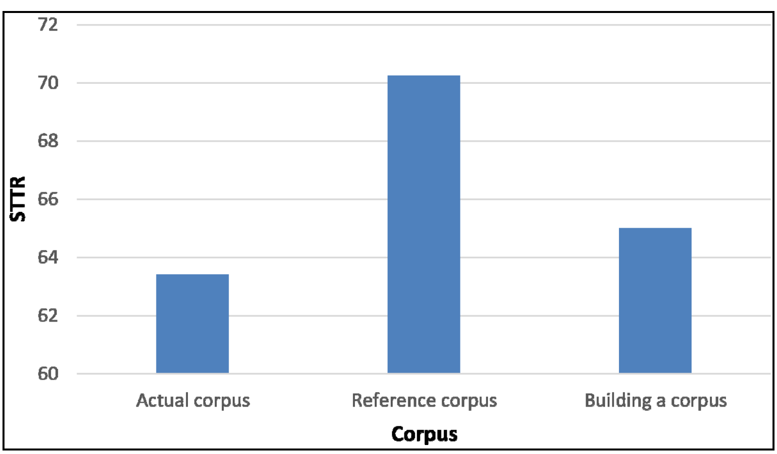
On the basis of the establishment of the predicted database, the software ANTCONC is used to extract the data from the corpus (Molkenthin et al., 2017). Data extracted in this time are mainly glyphs and class glyphs, where glyphs represent the total number of words in the corpus, and class glyphs represent that the same word in the corpus is only considered as a class (Abdi et al., 2020). The class symbol ratio represents the relationship between the class symbol and the class symbol in the corpus, which means the vocabulary of the corpus. The lower the ratio of the type symbol, the higher the repetition rate of words in the corpus, and the words in English text are basically the same, and vice versa. The corpus cover vocabulary much influence on the type of character than to a certain extent, therefore usually adopt standardised type descriptor than in order to solve this problem, that is, through the continuous an average of more than 1,000 – word corpus than the value of the type of operator, number of measure words of different reference corpus, and the paper establish the corpus of the similarities and differences, which is more reliable than type of character than parameters. Thus, corpus data were extracted, and the extraction results were shown in Table 6.

Table 6 Corpus data extraction results

Project	*Actual corpus*	*Reference corpus*	*Building a corpus*
Tokens	300,000	300,950	300,126
Types	15,927	189,823	15,863
TTR	5.86	6.59	5.23
STTR	63.42	70.26	65.02

In order to further compare the extraction results of standardised class symbol ratio between established corpus, reference corpus and actual corpus, the data in Table 1 are quantified, and the quantified results are shown in Figure 3.

Figure 3 STTR data quantification results (see online version for colours)



After the English text is quantified, the multiple features are integrated to complete the assessment of English writing level. In this paper, the extracted four features of word density, high-frequency words, word length and sentence length are used to train the weight of each feature by using multiple linear regression model (Molkenthin et al., 2017), namely:

$$X_y = \sum_{k=1}^{k} \alpha_k X \times k \tag{6}$$

In the formula, X_y represent weight, α_k represent the general characteristics of English writing, k represents multiple iterations.

After determining the feature weight of English text, the linear combination of kernel functions is carried out for English writing text, and the linear features after fusion are obtained as follows:

$$k\left(x_i, x_j\right) = \sum_{g=1}^{G} \beta_g k_g\left(x_i, x_j\right) + \sum_{f=1}^{F} \beta_f k_f\left(x_i, x_j\right) + \sum_{m=1}^{N} \beta_m k_m\left(x_i, x_j\right) \tag{7}$$

In the formula, β_g, β_f, β_m a represents the kernel function of the evaluation.

The main task in the training stage of the multi-core learning model is to determine the weight β of each SVM function in the SVM and the parameters of the SVM classifier itself α and b to determine the English writing text evaluation after multi-feature fusion, that is:

$$\min \beta_g, \beta_t, \beta_m (\alpha, b) J = \frac{1}{2}\sum_{g=1}^{G} \beta_g \alpha^T k_g \alpha + \frac{1}{2}\sum_{f=1}^{F} \beta_f \alpha^T k_f \alpha + \frac{1}{2}\sum_{m=1}^{M} \beta_m \alpha^T k_m \alpha \tag{8}$$

In the formula, α represent the characteristic factors of English writing text, b represent SVM classifier parameters, T represents transpose symbols.

The multiple linear regression model is used to determine the feature weights of English texts, and the feature data are processed quantitatively. The automatic quantitative evaluation model of English writing proficiency is constructed to complete the automatic quantitative evaluation of English writing proficiency.

4 Simulation experiment

4.1 Experimental environment

In order to verify the performance of the automatic quantitative evaluation method of English writing proficiency based on multi-feature fusion in the actual evaluation process, three methods were adopted to take 60 English essays from 30 students from Class A of A freshman foreign language department of A university as the sample data for evaluation, and processed by MATLAB software platform and Windows XP system.

4.2 Experimental parameters

Parameter settings in this paper are shown in Table 7.

Table 7 Experimental parameters

Parameter	*Data*
Sample number of English articles	10
Sample English articles vocabulary/vocabulary	10,000
Sample feature extraction interval/s	0.2
Data noise/dB	0~2
Number of iterations/times	100

4.3 Experimental indicators

In order to verify the effectiveness of the method in this paper, the evaluation method in this paper, the evaluation method in Oh et al. (2020) and the evaluation method in Tai and Liu (2017) were compared in the experiment, and the evaluation accuracy of English writing level, multi-feature extraction error and multi-feature fusion time were taken as experimental indexes to verify the effectiveness of the method in this paper. Among them, the evaluation accuracy of English writing proficiency is calculated by formula (9), that is:

$$Z = \frac{N - M}{ALL} \times 100\% \tag{9}$$

In the formula, N represents the number of actual assessments of English writing proficiency, M represents the number of invalid evaluations, ALL represents the total number of evaluations.

The calculation formula of multi-feature extraction error is as follows:

$$W = \frac{R_i}{T} \tag{10}$$

In the formula, R_i represents the actual amount of multi-feature extraction, T represents all features.

4.4 Experimental results

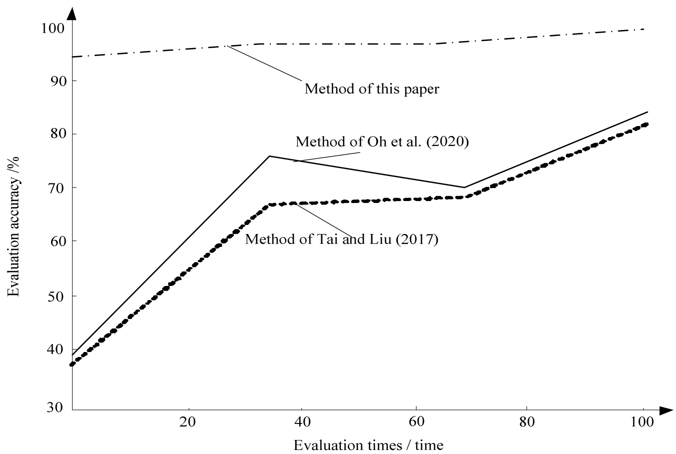
4.4.1 Accuracy analysis of English writing level assessment

In order to verify the effectiveness of the method in this paper, the evaluation accuracy of the method in Oh et al. (2020) and the method in Tai and Liu (2017) in the sample English writing data is compared in the experiment. The experimental results are shown in Figure 4.

By analysing the results in Figure 4, it can be seen that, under a certain test environment, the methods in this paper, the methods in Tai and Liu (2017) and the methods in Zhao (2018) were used to evaluate the English writing level of the samples, and the evaluation accuracy of the three methods was different to a certain extent. On the whole, the evaluation accuracy of the proposed method for sample data is always higher than 90%, while the evaluation accuracy of the method in Oh et al. (2020) first increases, then decreases and then increases again, but the evaluation accuracy is always lower than the method in this paper. The evaluation accuracy trend of the method in Tai and Liu

(2017) is similar to that in Oh et al. (2020). By comparison, it can be seen that the method used in this paper has a higher accuracy in the evaluation.

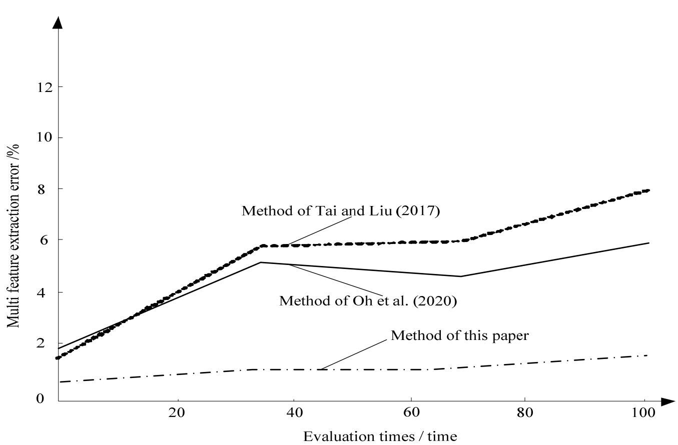
Figure 4 Comparison of accuracy of English writing level assessment by different methods



4.4.2 *Error analysis of multi-feature extraction from English text*

In the assessment of English writing proficiency, the extraction of writing features is an important way to improve the evaluation accuracy. Therefore, multi-feature extraction was carried out for English text data in the experiment, and the errors of the three methods on the set feature extraction were analysed. The experimental results are shown in Figure 5.

Figure 5 Error comparison of multi-feature extraction in English text



It can be seen from the analysis of Figure 5 that in the same experimental environment, the method in this paper, the method in Oh et al. (2020) and the method in Tai and Liu (2017) were used for multi-feature extraction of sample data, and there was a certain gap in the error. Among them, the error of feature extraction using the methods of Oh et al.

(2020) and Tai and Liu (2017) is always higher than the method in this paper. The accuracy of this method for multi-feature extraction is always less than 2%. This is because the proposed method effectively extracts the characteristics of writing proficiency assessment before the writing proficiency assessment, thus reducing the extraction error of the method in this paper.

4.4.3 Time consuming analysis of English text multi-feature fusion

On the basis of the above experiments, the time consumption of the three methods for English text multi-feature fusion was compared to highlight the scientific effectiveness of the method in this paper. The experimental results are shown in Table 8:

Table 8 Time comparison of multi-feature fusion in English text (s)

Number of fusions/times	*Methods of this paper*	*Oh et al. (2020)*	*Tai and Liu (2017)*
20	1.2	2.3	2.5
40	1.4	2.5	2.4
60	1.2	2.7	2.3
80	1.3	2.9	2.3
100	1.5	2.9	2.4

From the analysis of the data in Table 8, it can be seen that with the constant change of fusion times, the time consuming of the fusion of English text features by the three methods is different. When the number of fusion is 40, the fusion time of the method in this paper is about 1.4 s, the fusion time of the method in Oh et al. (2020) is about 2.5 s, and the fusion time of the method in Zhao (2018) is about 2.4 s. When the number of fusion is 100, the fusion time of the method in this paper is about 1.5 s, the fusion time of the method in Oh et al. (2020) is about 2.9 s, and the fusion time of the method in Zhao (2018) is about 2.4 s. In comparison, the fusion speed of the proposed method is faster and it is feasible to some extent.

5 Conclusions

This paper proposes an automatic quantitative assessment method for English writing proficiency based on multi-feature fusion. The cosine similarity of English text was determined by vector space model and Jekard similarity coefficient, and the feature of English text was extracted by using Manhattan distance. Through kernel function, multi-feature fusion of English writing text is accomplished. The multiple linear regression model is used to determine the feature weights of English texts, and the feature data are processed quantitatively. The automatic quantitative evaluation model of English writing proficiency is constructed to complete the automatic quantitative evaluation of English writing proficiency. Compared with the existing methods, it has the following advantages:

1 The evaluation accuracy of sample data using the method in this paper is always higher than 90%, with certain credibility.

2 The error of multi-feature extraction from sample data using the proposed method is always less than 2%, which verifies the feasibility of the proposed method.

3 Multi-feature fusion of sample data using the method in this paper is time-consuming and fast.

Reference

Abdi, A., Hasan, S., Shamsuddin, S.M., Idris, N. and Piran, J. (2020) 'A hybrid deep learning architecture for opinion-oriented multi-document summarization based on multi-feature fusion', *Knowledge-Based Systems*, Vol. 213, No. 1, p.106658.

Diamond, L., Bejarano, M.T., Chung, S., Ferguson, W. and Gany, F. (2019) 'Factors associated with accuracy of self-assessment compared with tested non-English language proficiency among primary care providers', *Medical Care*, Vol. 57, No. 5, pp.385–390.

Dimitrios Moshou, A., Xanthoula-Eirini Pantazi, A., Dimitrios Kateri, B. and Ioannis Gravalos, B. (2018) 'Water stress detection based on optical multisensor fusion with a least squares support vector machine classifier', *Biosystems Engineering*, Vol. 117, No. 2, pp.15–22.

Eleftheriadis, S., Rudovic, O. and Pantic, M. (2016) 'Joint facial action unit detection and feature fusion: a multi-conditional learning approach', *IEEE Transactions on Image Processing*, Vol. 25, No. 12, pp.5727–5742.

Gong, M. and Shu, Y. (2019) 'Chinese event detection based on multi-feature fusion and BiLSTM', *IEEE Access*, Vol. 32, No. 9, p.1.

Gong, M. and Shu, Y. (2020) 'Real-time detection and motion recognition of human moving objects based on deep learning and multi-scale feature fusion in video', *IEEE Access*, Vol. 11, No. 99, p.1.

Hu, H., Zhou, L., Guan, Q., Zhou, Q. and Chen, S. (2018) 'An automatic tracking method for multiple cells based on multi-feature fusion', *IEEE Access*, Vol. 6, No. 15, pp.69782–69793.

Jiang, F., Chiba, Y., Nose, T. and Ito, A. (2020) 'Automatic assessment of English proficiency for Japanese learners without reference sentences based on deep neural network acoustic models – ScienceDirect', *Speech Communication*, Vol. 116, No. 17, pp.86–97.

Molkenthin, C., Scherbaum, F., Griewank, A., Leovey, H., Kucherenko, S. and Cotton, F. (2017) 'Derivative-based global sensitivity analysis: upper bounding of sensitivities in seismic-hazard assessment using automatic differentiation', *Bulletin of the Seismological Society of America*, Vol. 107, No. 2, pp.984–1004.

Ni, N., Chen, N., Ernst, R.E., Yang, S. and Chen, J. (2018) 'Semi-automatic extraction and mapping of dyke swarms based on multi-resolution remote sensing images: applied to the dykes in Kuluketage region in the Northeastern Tarim Block', *Precambrian Research*, Vol. 13, No. 12, pp.17–19.

Oh, Y.R., Park, K. and Jeon, H.B. (2020) 'Automatic proficiency assessment of Korean speech read aloud by non-natives using bidirectional LSTM-based speech recognition', *ETRI Journal*, Vol. 42, No. 10, pp.12–18.

Pawel, K. and Jiwu, H. (2018) 'Multi-scale fusion for improved localization of malicious tampering in digital images', *IEEE Transactions on Image Processing*, Vol. 25, No. 3, pp.1312–1326.

Prince, D., Sidike, P., Essa, A. and Asari, V. (2017) 'Multifeature fusion for automatic building change detection in wide-area imagery', *Journal of Applied Remote Sensing*, Vol. 11, No. 2, p.26040.

Sun, C., Guo, S. and Zhang, H. (2017) 'Automatic segmentation of liver tumors from multiphase contrast-enhanced CT images based on FCNs', *Artificial Intelligence in Medicine*, Vol. 83, No. 12, pp.58–66.

Tai, Z. and Liu, Q. (2017) 'A study of the construction of formative assessment criterion for English writing ability', *Journal of Sichuan International Studies University*, Vol. 33, No. 5, pp.143–149.

Tao, H. and Lu, X. (2019) 'Automatic smoky vehicle detection from traffic surveillance video based on vehicle rear detection and multi-feature fusion', *IET Intelligent Transport Systems*, Vol. 13, No. 2, pp.252–259.

Wang, Y., Gales, M.J.F., Knill, K.M., Kyriakopoulos, K., Malinin, A., van Dalen, R.C. et al. (2018) 'Towards automatic assessment of spontaneous spoken English', *Speech Communication*, Vol. 104, No. 2, pp.47–56.

Xia, S., Peng, C., Zhang, J., Li, X. and Bing, W. (2017) 'Utilization of rotation-invariant uniform LBP histogram distribution and statistics of connected regions in automatic image annotation based on multi-label learning', *Neurocomputing*, Vol. 228, No. 2, pp.11–18.

Zeng, T., Han, B., Zhai, M. and Mu, Y. (2019) 'The effect of language proficiency on L2 English learners' processing of morphologically complex words: evidence from masked transposed letter priming', *Neuroscience Letters*, Vol. 704, No. 12, pp.84–88.

Zhao, J. (2018) 'A method of writing assessment based on multiple regression analysis model', *Technology Wind*, Vol. 15, No. 33, pp.15–22.