

Performance Evaluation and Improvement of Deep Echo State Network Models in English Writing Assistance and Grammar Error Correction

Dongyun Chen^{1,*}

¹School of International Education and Exchange Tangshan Vocational and Technical College, Tangshan 063000, Heibei, China

Abstract

INTRODUCTION: The research on the performance evaluation model of English writing tutoring and grammar error correction is very necessary, which is not only conducive to the rational allocation of teachers' writing tutoring resources, but also more conducive to the timely and effective correction of students' grammatical errors.

OBJECTIVES: Aiming at the problems of non-specific quantification, low precision, and low real-time performance evaluation methods for English writing grammar error correction in current methods.

METHODS: This paper proposes a grammar error correction performance evaluation method based on deep echo state network with gold rush optimisation algorithm. Firstly, by analysing the process of English writing assistance and grammatical error correction, we extract the evaluation features of grammatical error correction type and construct the performance evaluation system; then, we improve the deep confidence network through the gold rush optimization algorithm and construct the grammatical error correction performance evaluation model; finally, we analyse it through simulation experiments.

RESULTS: The results show that the proposed method improves the evaluation accuracy, robustness. The absolute value of the relative error of the evaluation value of the syntactic error correction performance of the method is controlled within the range of 0.02.

CONCLUSION: The problems of non-specific quantification, low precision and low real-time performance of the application of English writing grammar error correction performance assessment methods are solved.

Keywords: English writing assistance, grammar error correction performance evaluation, gold rush optimisation algorithm, deep echo state network

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*Corresponding author. Email: chendongyun@tsvtc.edu.cn

1. Introduction

With the comprehensive informatisation of social life, English, as a world language, occupies a very important position in the language of communication [1]. English

writing, as an inaccessible part of English learning, is related to the mastery of English grammar learning effect, and the effect of the display of English learning results [2]. In the current Chinese English education, due to the irrational structure of the teacher-student ratio and the students' social competitiveness needs, it is difficult for

teachers to do meticulous corrections and guidance for the problems of writing counselling and language error correction, while the students do not have a good understanding of the English grammatical semantics and sentence structure, and they use the Chinese semantic structure and so on to fill them in, which makes the English expression wrong [3]. Therefore, the research and development of an English writing tutoring and grammar error correction performance evaluation model for Chinese students is of great necessity, which is not only conducive to the rational allocation of teachers' writing tutoring resources, but also more conducive to the timely and effective correction of students' grammatical errors [4].

Language writing tutoring and text grammar error correction can help English teachers to correct compositions and reduce their workload, and it helps learners to get timely and effective feedback so as to improve their learning efficiency and independent learning ability [5]. In order to assess whether the performance of English writing tutoring and grammar error correction models improves teachers' teaching quality and students' learning efficiency, combining artificial intelligence methods to carry out model performance evaluation methods is increasingly being paid attention to and researched by experts in the field [6]. Throughout the development of grammatical error correction, grammatical error correction can be divided into three categories, namely, rule-based grammatical error correction, classifier-based error correction, and machine translation-based error correction [7]. Literature [8] uses rule-based error correction, but the cost is very high and complex uncertainty; literature [9] through a large amount of text data, the use of recurrent neural networks from which to learn deep features such as grammar and context; literature [10] uses a bidirectional recurrent neural network to represent the context of the target word, based on the features to predict the target this from the candidate sequences, and at the same time use the attention algorithm to capture the words in the sentence between the dependencies, which improves the accuracy of error correction; literature [11] carries out training and word selection for different grammatical error types using a bidirectional long and short time domain memory network, and the learning results are significantly due to other models; literature [12] proposes an error correction method by extracting task-specific sentence features, and assembling machine translation algorithms based on large-scale networked corpus language models; and literature [13] proposes a discriminative reordering model that using sentence phrase syntactic features to deal with local contextual error effects; Literature [14] applies neural machine translation methods to the task of grammatical error correction, and for the occurrence of unregistered words in the sentence, through unsupervised alignment and word-level translation models. There are many current grammar error correction design methods, but there are fewer such studies on how to go about judging the effectiveness of error correction methods in English writing tutoring, and the performance evaluation methods are all

qualitative and lack quantitative analysis methods. Literature [15] extracts the types of grammar error correction and assessment features by analysing the English writing assistance and grammar error correction process; literature [16] focuses on the English writing grammar error correction strategy guidance, analyses the development trend of grammar error correction, and proposes the concept of multi-strategy grammar error correction assessment; literature [17] starts from the English writing tutoring and grammar error correction strategy, analyses the features of the assessment of the effect of English grammar error correction, and proposes a grammar error correction assessment method with the fusion of multiple machine learning algorithms. According to the analysis of the above literature, the existing grammar error correction performance assessment models are only analysed from a qualitative perspective, lacking quantitative methods and models, and the existing performance assessment methods are relatively simple, with low precision and lack of precision improvement strategies [18].

Echo state network, as a new type of recurrent neural network, consists of input layer, hidden layer (i.e., reserve pool), and output layer. It designs the hidden layer as a sparse network with many neurons, which achieves the function of remembering data by adjusting the characteristics of the internal weights of the network, and its internal dynamic reserve pool contains a large number of sparsely-connected neurons, which implies the operating state of the system and has a short-term memory function [19]. Due to the large number of parameters of the echo state network, it affects its prediction function. In order to improve the accuracy of the echo state network, this paper adopts the swarm intelligence optimisation algorithm to optimise the parameters of the optimiser, and applies it to the problem of evaluating the effect of English grammatical error correction [20].

Aiming at the problems existing in the current English grammar error correction performance evaluation methods, this paper proposes a grammar error correction performance evaluation method based on the swarm intelligence optimisation algorithm to improve the deep echo state network. The main contributions of this paper are: (1) selecting the features of grammatical error correction performance evaluation and constructing the performance evaluation system by analyzing the grammatical error correction problem; (2) obtaining data by using the corpus research method, questionnaire survey method, and writing test method to carry out the correlation data analysis; (3) optimizing the parameters of the deep echo state network by using the Amoy gold heuristic optimization algorithm, and proposing a method of grammar error correction performance evaluation based on the depth of Echo State Network, and proposed a grammar error correction performance evaluation method based on the optimisation of the depth of the Echo State Network by the Gold Rush Heuristic Optimisation Algorithm; (4) verified the effectiveness of the proposed method through simulation, and improved the evaluation accuracy and robustness.

2. English Writing Assistance and Grammar Correction Problem Description

2.1. English Writing Assistance and Grammar Correction Process

When using machine learning models for English writing assistance and grammar error correction, assessment feature extraction is performed on the corresponding writing question type writing assistance and grammar error correction dataset, and the obtained scoring feature data are used to train the original model to obtain the assistance and grammar error correction model for the writing question type [21]. When writing assistance and grammar error correction are assessed, the same scoring feature extraction is carried out on the text to be assessed, and the obtained feature data are input to the corresponding writing assistance and grammar error correction assessment model to obtain the analysis and assessment results, the specific process is shown in Figure 1.

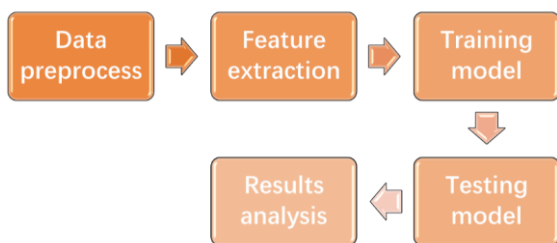


Figure 1. Automated scoring process

2.2. Description of English Writing Assistance and Grammar Error Correction Performance Evaluation

In order to assess the performance of English writing assistance and grammar error correction more systematically, objectively and meticulously, according to the types of writing errors, this paper selects different types of errors as the evaluation features, including word form errors, lexical errors, grammatical errors, and discourse errors [22].

1) Word Formation Errors

Lexical errors E1 are mainly English words that are misspelled, incorrectly capitalised and, in a few cases, incorrectly punctuated.

2) Vocabulary errors

Vocabulary errors E2 mainly refer to incorrect word collocations, poor word choice and narrow vocabulary. Vocabulary collocations are fixed-ground phrases or word groups in English, including collocations of prepositional phrases, collocations of nouns and verbs, and so on.

3) Grammatical errors

Grammatical errors E3, as the most important aspect of teaching English, mainly includes lexis and syntax.

4) Discourse errors

Discourse errors E4 are mainly unclear and coarse examination of the topic, essay running on the topic, opening up that introduction is too long, improper use of logical connectives between paragraphs and sentences, etc.

The English writing assistance and grammar error correction performance evaluation system takes word form error E1, lexical error E2, grammatical error E3, and discourse error E4 as the influencing features, and constructs the language writing assistance and grammar error correction performance evaluation system based on the error type statistics, which is shown schematically in Figure 2.

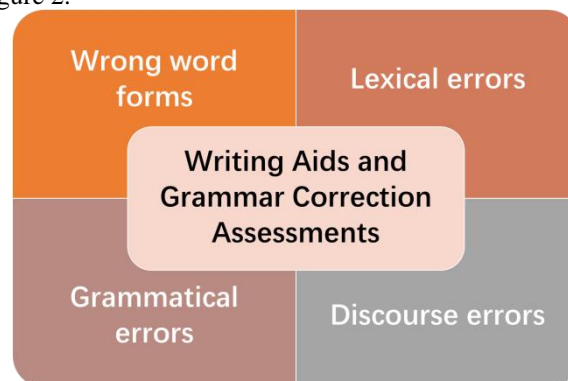


Figure 2. Performance evaluation system for English writing assistance and grammar correction

3. Data acquisition and analysis

3.1. Data acquisition

In order to obtain objective and effective statistics on error correction in English writing, this paper adopts corpus research method, questionnaire survey method and writing test method to obtain data [23], and the schematic diagram of the data acquisition method is shown in Figure 3.

Corpus research methodology

In this paper, we refer to the method of "Chinese Learner Corpus" to create a small corpus to find, mark, classify and count the errors in the real corpus of English compositions, and use a combination of qualitative and quantitative methods to study and analyse them [24].

Questionnaire method

In this paper, two questionnaires were given to the experimental students before and after the experiment, which were used to provide comparative data. Before the experiment, the questionnaire "Students' Basic English Writing Questionnaire" was used to find out the status of English writing, the degree of understanding of their own writing and their attitudes, consisting of 21 questions. Post-experiment questionnaire "Students' English Writing Grammar Error Correction Questionnaire" was used to explore the status and attitude of students' writing after the experiment, consisting of 14 questions.

Writing Test

This paper carries out a reading followed by writing test on an essay of the same topic before and after the

experiment, with a prescribed time limit of 30 minutes. The essay test chosen before the experiment is from the 2021 National College Entrance Examination Paper 1, with the subject of people and society; the essay test chosen after the experiment is the October Monthly Examination Reading Follow-up Writing, with the subject of people and society. In order to ensure fair marking, reference was made to the GCE model of "two assessments, three assessments and four arbitrations", and the teachers responsible for the assessment had experience in marking GCE papers.

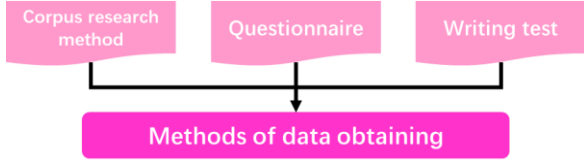


Figure 3. Schematic diagram of data acquisition method

3.2. Data analysis

In order to analyse the redundancy of the input indicators, this paper investigates the correlation analysis of the factors affecting English writing assistance and grammar correction. The indicator parameter variables are all normal continuous variables, and the correlation coefficients can be calculated by Pearson with the range of $[-1, 1]$. The calculation formula is as follows:

$$\rho(x, y) = \frac{\text{cov}(x, y)}{\sigma(x) \cdot \sigma(y)} = \frac{E[(x - \mu_x)(y - \mu_y)]}{\sigma(x) \cdot \sigma(y)} \quad (1)$$

Where $\text{cov}(x, y)$ is the covariance coefficient and $\sigma(x)$ and $\sigma(y)$ are the standard deviations.

In order to analyse the redundancy of English writing assistance and grammar error correction influencing factors, this paper analyses the influencing characteristics, and the specific analysis statistics are shown in Figure 4. In Figure 4, E1-E4 represent word form errors, lexical errors, grammatical errors, and discourse errors, respectively, and there is no redundancy between E1 and E4 two by two, which can be used as the indicator features for the evaluation of the performance of English writing assistance and grammatical error correction.

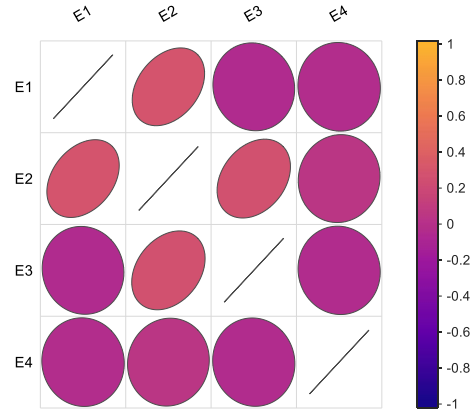


Figure 4. Correlation analysis

4. Related Technologies

4.1. Deep Echo State Networks

In order to solve the problem of tactical manoeuvre meta-prediction in the long time domain, a deep echo state network (DeepESN) based on a self-encoder is proposed in this section.

Echo state network (ESN) [25] is a kind of recursive neural network, using the "reserve pool" method to build the network hidden layer, usually used for time series prediction[19]. ESN is mainly composed of the input layer, the storage layer, the output layer, the specific structure is shown in Figure 5. The connection weights from the input layer to the storage pool $\mathbf{W}_{in}^{r \times n}$ are not trained and will not be changed after the initial randomisation. The reserve pool input comes from the output of the previous state of the input layer and the reserve pool respectively, and the state feedback weight $\mathbf{W}^{r \times r}$ is randomly initialised and does not need training. Reserve pool to the output layer weights $\mathbf{W}_{out}^{m \times r}$ need to be trained, generally using Ridge regression (Ridge regression) method for connection weights, which is expressed as follows:

$$\mathbf{W}_{out} = \mathbf{Y}_{long} \mathbf{H}^T (\mathbf{H} \mathbf{H}^T + \lambda_r \mathbf{I})^{-1} \quad (2)$$

Where \mathbf{H} is the storage pool state and λ_r is the regularisation factor. The state of the pool at \mathbf{H} is shown below:

$$\mathbf{H}(t) = \tanh(\mathbf{W}_{in} \mathbf{X}_{long}(t) + \mathbf{W} \mathbf{H}(t-1)) \quad (3)$$

where \tanh denotes the hyperbolic tangent activation function.

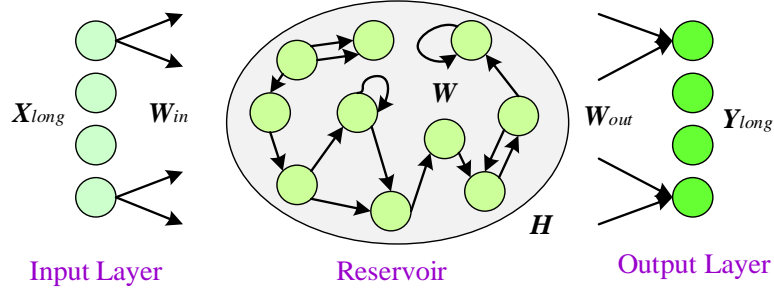


Figure. 5 Echo state neural network

The process of ESN algorithm includes two phases: initialisation of weight parameters and training. The ESN network contains a relatively large number of neurons, and the connection weights between neurons in the storage pool are randomly generated and their connections are sparse. The hyperparameters of the ESN affect the prediction effect, and the adjustment of the hyperparameters is very important, in which the ESN hyperparameters include the size of the storage pool N_r , the spectral radius SR , the input scaling factor IS , the sparsity of storage pool degree SD .

In order to capture the predicted input parameters at multiple scales, this section combines the self-encoder and ESN to propose a self-encoder based Deep Echo State Network (DeepESN). DeepESN is based on the ESN's and increases the number of layers in the reserve pools through the mapping of the self-encoder. In DeepESN network structure, the previous reserve pool echo state is reduced to low dimensions by AE, input to the next reserve pool, and so on to the last layer, collate all the echo states, and output the final result to the network through the output layer. The DeepESN network structure is shown in Figure 6. The mathematical model of DeepESN network is represented as follows:

$$\mathbf{H}_{in}^{(l)}(t) = \mathbf{W}_{in}^{(l)} \mathbf{X}_{in}^{(l)}(t) + \mathbf{W}^{(l)} \mathbf{H}^{(l)}(t-1) \quad (4)$$

$$\mathbf{X}_{in}^{(l)}(t) = \begin{cases} \mathbf{X}_{long}(t), l=1 \\ f_{enc}(\mathbf{W}_{enc}^{(l-1)} \mathbf{H}^{(l-1)}(t)), l>1 \end{cases} \quad (5)$$

$$\mathbf{H}^{(l)}(t) = (1 - SD^{(l)}) \mathbf{H}^{(l)}(t-1) + SD^{(l)} \tanh(\mathbf{H}_{in}^{(l)}(t)) \quad (6)$$

$$\mathbf{Y}_{long}(t) = g(\mathbf{W}_{out} \mathbf{H}(t)) \quad (7)$$

Where, $\mathbf{H}_{in}^{(l)}(t)$ denotes the weighted input data of storage pool in layer l at time t , $\mathbf{W}_{in}^{(l)}$ denotes the connection weight from input to storage pool in layer l , $\mathbf{X}_{in}^{(l)}(t)$ denotes the input in layer l at time t , $\mathbf{W}^{(l)}$ denotes the state feedback weight of storage pool in layer l , $\mathbf{H}^{(l)}(t-1)$ denotes the state of storage pool in layer l at time $t-1$, $\mathbf{W}_{enc}^{(l-1)}$ denotes the self-encoder projection weight in layer $l-1$ at time t , $f_{enc}(\cdot)$ denotes the activation function of the self-encoder, $\mathbf{X}_{long}(t)$ denotes the input variable in layer t , $\mathbf{H}^{(l)}(t)$ denotes the state value of storage pool in layer l at time t , and denotes the degree of sparsity of the storage pool in layer l at time t . is the state value of storage pool in layer l at time t , $SD^{(l)}$ is the sparsity degree of storage pool in layer l . The state value of storage pool in layer l at time t is the sparsity degree of storage pool in layer l . $\mathbf{H}(t)$ The vector formed by the states of all storage pools is denoted as $[\mathbf{H}^{(1)}(t), \mathbf{H}^{(2)}(t), \dots, \mathbf{H}^{(l)}(t)]$; $g(\cdot)$ denotes the activation function of the output layer.

The DeepESN neural network training process generally includes initialising the network, obtaining stored state values, and training the output weights. The computation of the output weights \mathbf{W}_{out} remains a regression problem and is generally solved using regularised ridge regression.

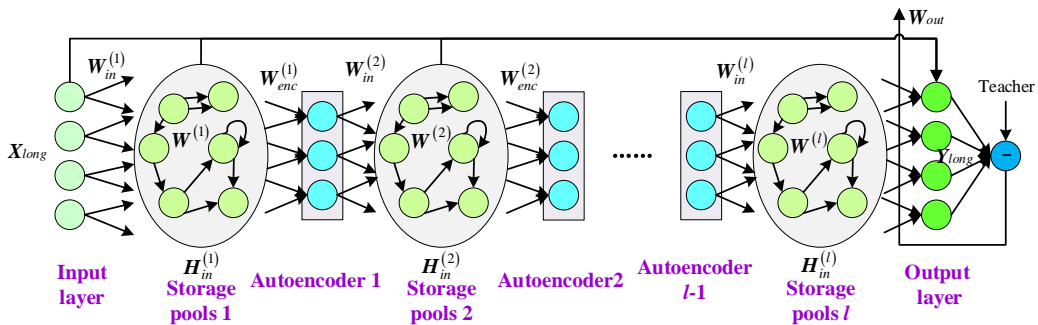


Figure 6. Self-coding based deep echo state network

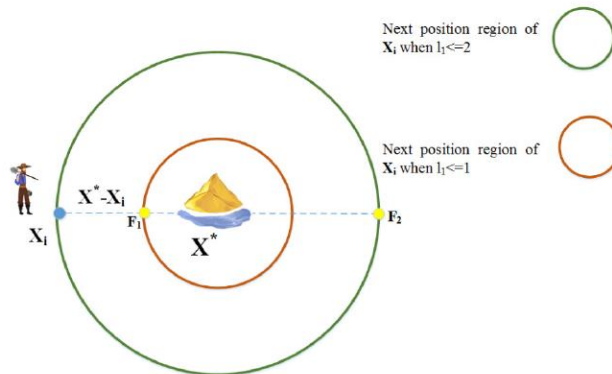
4.2. Optimisation algorithm for gold panning

Inspiration

Gold is a lustrous, yellow, precious metal. Its chemical stability and continued physical properties allow gold to be made into coins and jewellery that retain their luster and value for decades or even centuries in harsh environments. Gold can be used for minting coins, investments, jewellery, conductors, mirrors, decoration, dental restoration and more. Gold is usually found in two types of mines, including rock-textured mines and riverbed mines. The most significant historical event for gold is the gold rush. Gold panning was the thing that prehistoric civilisations of humans were most eager to do, and many of them took place in the 19th century in the United States, Australia, Canada, and South Africa. When gold was discovered, news spread quickly and thousands of people were hired to carry out gold panning and digging; in the process of gold panning, gold diggers arrived at the gold digging area, gained considerable wealth, and left the mining area; in the process of digging, people helped each other to co-operate; gold miners would gain wealth in a short period of time but at the same time, they caused damage to the environment, such as rivers. From this, it can be seen that the gold panning behaviour in the process of gold panning includes behavioural mechanisms such as migration, gold mining, cooperation, and the impact of gold panning. According to the mechanism of gold rush behaviour, Gold rush optimizer (GRO) [26] was proposed. GRO algorithm simulates the gold behaviour before going to search for the optimal solution.

In the GRO algorithm, the gold prospector plays the role of a population individual, and the gold prospector location information is defined as X_i and the gold prospector population as M_{GP} :

$$M_{GP} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} \\ x_{21} & x_{22} & \cdots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nd} \end{bmatrix} \quad (8)$$



where x_{ij} denotes the j th dimensional position of the i th prospector, d denotes the dimension size, and n denotes the number of prospectors.

In the optimisation process, the objective function is defined to evaluate the prospector according to the problem situation. The prospector evaluation matrix M_F stores the prospector evaluation values:

$$M_F = \begin{bmatrix} f(x_{11}) & x_{12} & \cdots & x_{1d} \\ f(x_{21}) & x_{22} & \cdots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ f(x_{n1}) & x_{n2} & \cdots & x_{nd} \end{bmatrix} \quad (9)$$

where f denotes the evaluation function.

Prospector migration behaviour

After the discovery of a gold mine, the prospector moves in and acquires the gold. Defining the location-dimensional optimal solution for the richest gold mine, whose location is unknown, the optimal prospector location can be used to estimate the optimal mine location information, as shown in Figures 7 and 8. The mathematical simulation of the prospector migration behaviour is as follows:

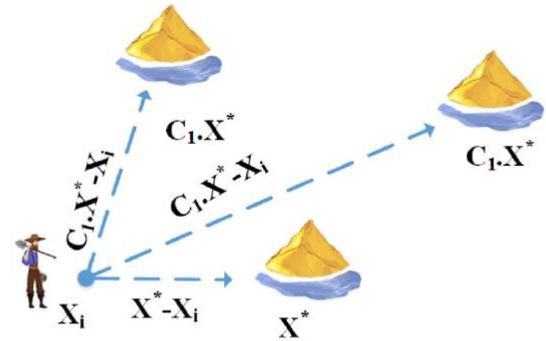


Figure 7. Schematic diagram of prospector migration

Figure 8. Simulation of prospector migration behaviour

$$D_1 = C_1 \cdot X^*(t) - X_i(t) \quad (10)$$

$$X_{new_i}(t+1) = X_i(t) + A_1 \cdot D_1 \quad (11)$$

where X^* , X_i and t denote the optimal gold mine location, prospector i 's location and the current iteration number, respectively; X_{new_i} denotes the new location of prospector i , and the vector factors A_1 and C_1 are defined, respectively:

$$A_1 = 1 + l_1(r_1 - 0.5) \quad (12)$$

$$C_1 = 2r_2 \quad (13)$$

Where r_1 and r_2 denote the random variables in the range of $[0,1]$ and l_1 denotes the convergence factor, respectively, which is calculated as follows:

$$l_1 = \left(\frac{\max_{iter} - iter}{\max_{iter} - 1} \right)^e \left(2 - \frac{1}{\max_{iter}} \right) + \frac{1}{\max_{iter}} \quad (14)$$

Gold seekers settle next to a hypothetical mining area, A_1 is mainly used to simulate migratory behaviour. When $A_1 = 1$, prospectors migrate to a set gold mining area. Seekers may consider similar areas for migratory settlement, and C_1 is primarily used to simulate this.

Gold mining behaviour

Each prospector excavates a gold mine in search of more gold. The mathematical model for each gold prospector as an individual close to the location of the gold excavation is as follows:

$$D_2 = X_i(t) - X_r(t) \quad (15)$$

$$X_{new_i}(t+1) = X_r(t) + A_2 \cdot D_2 \quad (16)$$

wherein X_r , X_i , t and X_{new_i} denote randomly selected prospector r position, prospector i position, current iteration number, and new position of prospector i , respectively. The specific schematic diagram of the gold mining behaviour is represented in Figure 9.

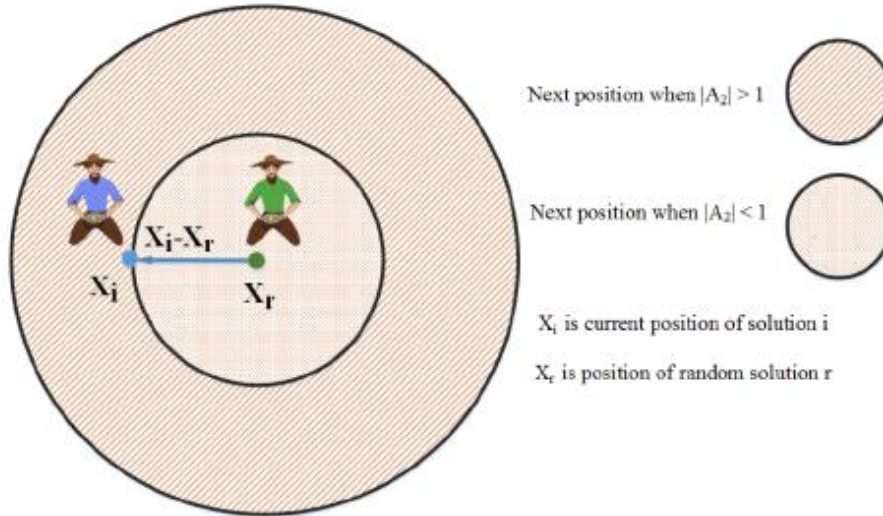


Figure 9. Simulation of gold mining behaviour

A_2 Indicates that the vector factor is calculated as follows:

$$A_2 = 2l_2r_1 - l_2 \quad (17)$$

Among them, the parameter l_2 is mainly used to increase the exploitation capacity of the mining method.

Cooperative behaviour

The gold prospector uses three-person cooperation to implement the simulated cooperative behaviour, as shown

schematically in Figure 10. The mathematical model of prospecting cooperative behaviour is as follows:

$$D_3 = X_{g2}(t) - X_{g1}(t) \quad (18)$$

$$X_{new_i}(t+1) = X_i(t) + r_1 \cdot D_3 \quad (19)$$

where $g1$ and $g2$ denote random integers.

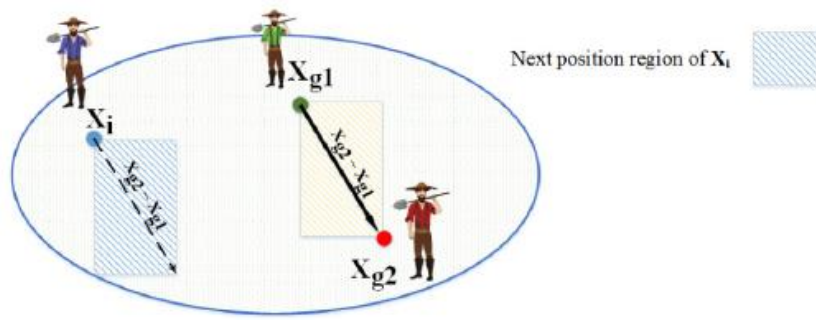


Figure 10. Simulation of co-operative behaviour

Prospector Resettlement

Gold miners go through parameters to determine their movement. In order to determine the movement of the prospector, the fitness function is utilised, which is formulated as follows:

$$X_i(t+1) = X_{new_i}(t+1) \quad (20)$$

$$\text{if } f(X_{new_i}(t+1)) < f(X_i(t+1))$$

Domain control

If the $X_{new_{ij}}$ location information in dimension d exceeds the decision variable range, the new location should be considered; otherwise the previous location information is still retained.

Process steps

According to the algorithm heuristic mechanism and optimisation strategy, as shown in Figure 11, the specific steps of the GRO algorithm are as follows:

Step 1: Initialise the population parameters as well as the population position, set the maximum number of iterations and other parameters;

Step 2: Calculate the fitness value and record the current optimal individual;

Step 3: Update population locations using the prospector relocation strategy;

Step 4: Calculate the control parameters l_1 and l_2 ;

Step 5: Update the population position using migratory behaviour, gold mining behaviour or cooperative behaviour;

Step 6: Calculate the fitness value and record the current optimal individual;

Step 7: Determine whether the number of iterations reaches the maximum number of iterations. If the maximum number of iterations is reached, carry out the output of the optimal solution and optimal value; otherwise, go to step 3.

Algorithm GRO	
1	Initialize the gold prospectors' population
2	Initialize the gold prospectors' new positions
3	Initialize t, l_1, l_2
4	Obtain best search agent
5	While $t \leq T_{max}$ do
6	for each search agent i do
7	Calculate fitness
8	Update positions
9	Update best solution
10	end
11	Update l_1, l_2
12	for each search agent i do
13	Calculate the next position with one of the migration, mining or collaboration
14	end
15	$t = t + 1$
16	end

Figure 11. GRO Pseudo-Code

5. A Methodological Process for Evaluating the Performance of English Writing Tutoring and Grammar Error Correction Based on Gold Rush Optimisation Algorithm for Improving DeepESN Networks

Combining GRO and DeepESN, this section proposes a method to evaluate the performance of English writing tutoring and grammar error correction based on GRO algorithm to improve DeepESN network.

5.1. Decision variables and objective functions

DeepESN network storage pool size N_r , spectral radius SR , input scale factor IS , and storage pool sparsity SD affect the performance evaluation accuracy. In order to improve the performance evaluation accuracy of English writing tutoring and grammar error correction, this paper adopts the GRO algorithm to optimise the DeepESN network storage pool size N_r , spectral radius SR , input scale factor IS , and storage pool sparsity SD . The optimisation decision variable of the GRO algorithm is $\theta = (N_r, SR, IS, SD)$.

To further DeepESN training accuracy, the root-mean-square error function is used as the objective function of the GRO-DeepESN algorithm and is calculated as follows:

$$\min f(N_r, SR, IS, SD) = \sqrt{\frac{1}{K} \sum_{k=1}^K (y(k) - y_{predict}(k))^2} \quad (21)$$

Where $y(k)$ is the actual value and $y_{predict}(k)$ is the predicted value.

5.2. Steps and processes

The performance assessment model of English writing tutoring and grammar error correction based on the GRO algorithm optimised DeepESN network is mainly the mapping relationship between the indicators of word form errors E1, lexical errors E2, grammatical errors E3, and discourse errors E4 as inputs, and the assessment values as outputs. The flowchart of the English writing tutoring and grammar error correction performance evaluation method based on GRO-DeepESN algorithm is shown in Figure 12. The specific steps are as follows:

Step 1: Acquire data based on corpus research method, questionnaire method and writing test method; pre-process the acquired samples with sparse smoothing data processing method; normalise the raw data with Z-Score method and divide the data into test set, validation set and training set;

Step 2: Encode the initial parameters of DeepESN using the GRO algorithm, and also initialise the algorithm parameters such as population parameters, iteration number, etc.; initialise the population and calculate the objective function value;

Step 3: Calculate vector parameters to update the population position using migratory behaviour, gold mining behaviour or cooperative behaviour;

Step 4: Calculate the fitness value and update the population position using the prospector relocation strategy;

Step 5: In each iteration, compare the objective function value of each candidate solution with the objective function value of the current global optimal solution, and update the global optimal solution;

Step 6: Judge whether the termination condition is satisfied. If it is satisfied, exit the iteration, output the

optimal DeepESN parameters, and execute step 7, otherwise continue to execute step 3;

Step 7: Decode the GRO-based optimised DeepESN parameters to obtain $\theta^* = (N_r, SR, IS, SD)$;

Step 8: Construct the GRO-DeepESN analytical model, train the analytical model using the training set, input the test set into the model, and obtain the analytical and error results.

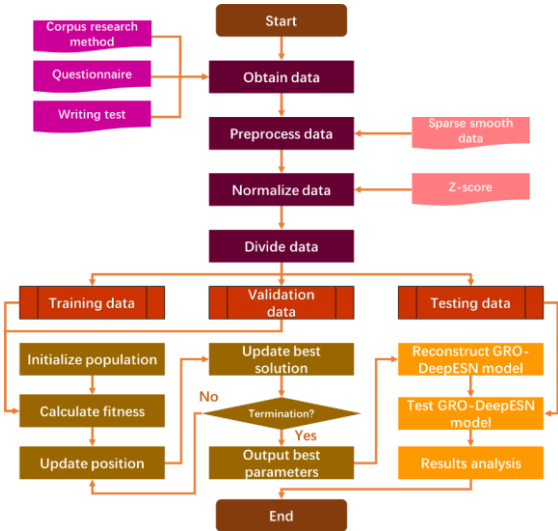


Figure 12. Flowchart for performance evaluation of DeepESN network optimised based on GRO algorithm

6. Experiments and results

6.1. Experimental set-up

In order to verify the accuracy and timeliness of the performance evaluation model of English writing tutoring and grammar error correction proposed in this paper, this paper takes the data of English writing tutoring and grammar error correction as the simulation data, and selects five analysis algorithms for comparison, and the specific parameters of each algorithm are set as in Table 1. The experimental simulation environment is Windows 10, CPU is 2.80GHz, 8GB RAM, and the programming language is Matlab2019a.

Table 1 Parameter settings for performance evaluation methods

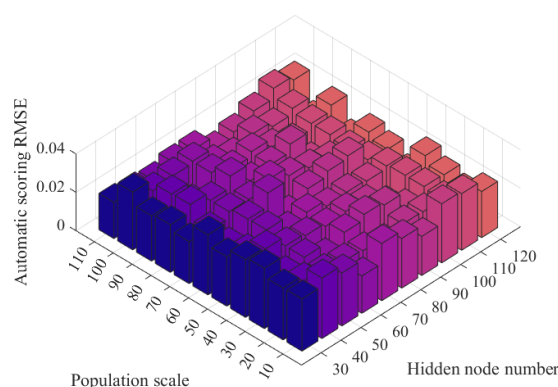
arithmetic	parameterisation
ELM	Hidden layer node is 50, activation function is radial basis function
DELM	Three hidden layers with the number of nodes in each layer 50, 50
ESN	sd=0.7, nr=100, sr=0.2, is=0.25
GRO-ESN	SD=0.7, Nr=100, SR=0.2, IS=0.25, see section 5.2 for population size
DeepESN	SD=0.7, Nr=100, SR=0.2, IS=0.25, three AE layers, see section 5.2 for reference analysis of the number of nodes in each layer
GRO-DeepESN	Three AE layers, see section 5.2 for reference analyses of the number of nodes in each layer, see section 5.2 for the number of populations

6.2. Parametric analysis

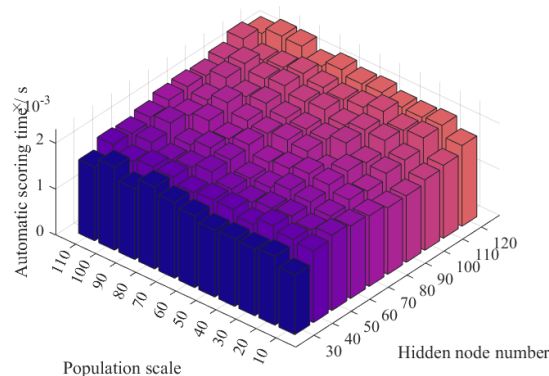
In order to obtain the appropriate number of nodes in the AE layer of the DeepESN network and the number of populations of the optimisation algorithm, this section analyses the impact of different population numbers and the number of nodes in the hidden layer on the evaluation value and evaluation time.

Figure 13 gives the effect of different population numbers and number of AE layer nodes on the assessment value and assessment time. From Fig. 13(a), it can be seen that as the number of populations increases, the assessment prediction accuracy increases; as the number of nodes in the

cryptic layer increases, the assessment prediction accuracy increases. From Fig. 13(b), it can be seen that the assessment analysis time increases as the number of populations increases; the assessment time increases as the number of nodes in the AE layer increases. In summary, the increase of population number and the number of AE layer nodes of the writing tutoring and grammar error correction performance evaluation model based on GRO-DeepESN algorithm is beneficial to the increase of evaluation accuracy, but the evaluation time increases. In order to balance the contradiction between time and accuracy, the number of population should be selected as 70 and the number of hidden layer nodes as 90.



(a) Results of impact on assessment accuracy



(b) Results of the impact on assessment time

Figure 13. Effect of different population size and number of cryptic nodes on evaluation value and evaluation time

6.3. Modelling analysis

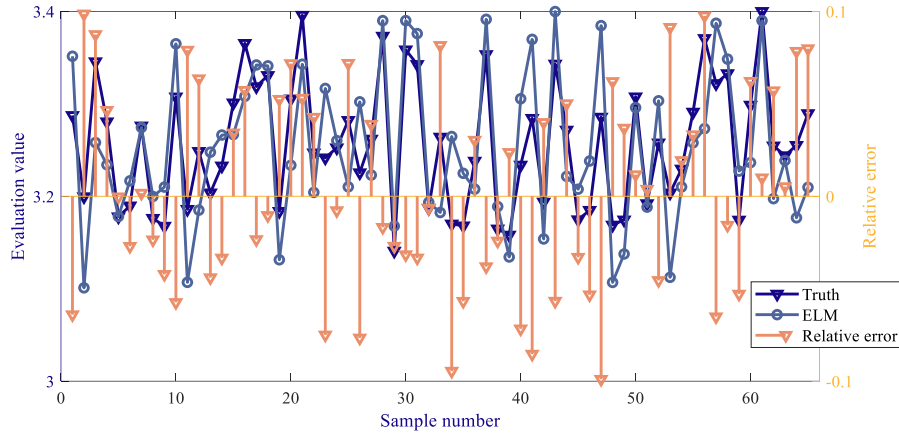
In order to verify the effectiveness and superiority of the grammar error correction performance evaluation method based on the GRO-DeepESN algorithm, GRO-DeepESN is compared with ELM, DELM, ESN, GRO-ESN, and DeepESN, and the results of the evaluation of each model are shown in Figure 14 and Figure 15.

Figure 14 gives the relative error between the assessed and true values of the grammar error correction

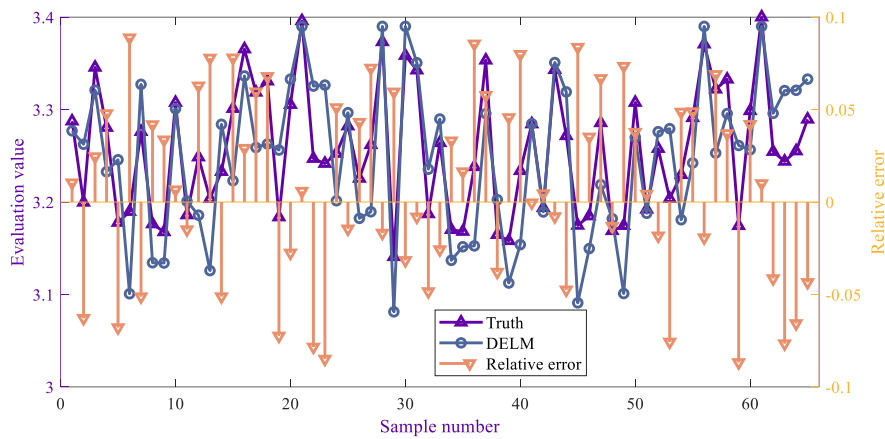
performance evaluation values based on each algorithm. From Fig. 14, it can be seen that the evaluated value of syntactic error correction performance based on GRO-DeepESN is closer to the true value, and the relative error is controlled within 0.02; the evaluated relative errors of ELM, DELM, ESN, GRO-ESN, and DeepESN algorithms are controlled within 0.1, 0.09, 0.1, 0.08, and 0.06, respectively; and comparing GRO -DeepESN with DeepESN, GRO

parameter optimisation improves the grammar error correction performance evaluation accuracy; comparing GRO-DeepESN with GRO-ESN indicates that the grammar error correction performance evaluation accuracy of

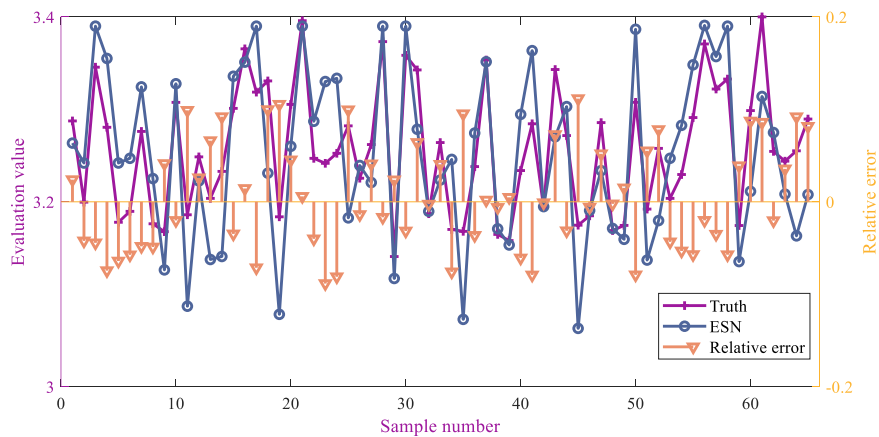
DeepESN is better than that of GRO-ESN. In summary, the error of the grammar error correction performance evaluation method based on the GRO-DeepESN algorithm is the smallest in general .



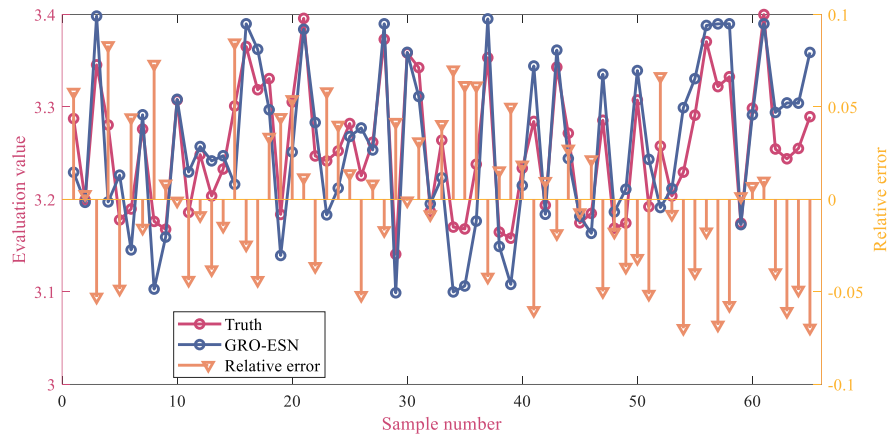
(a) ELM



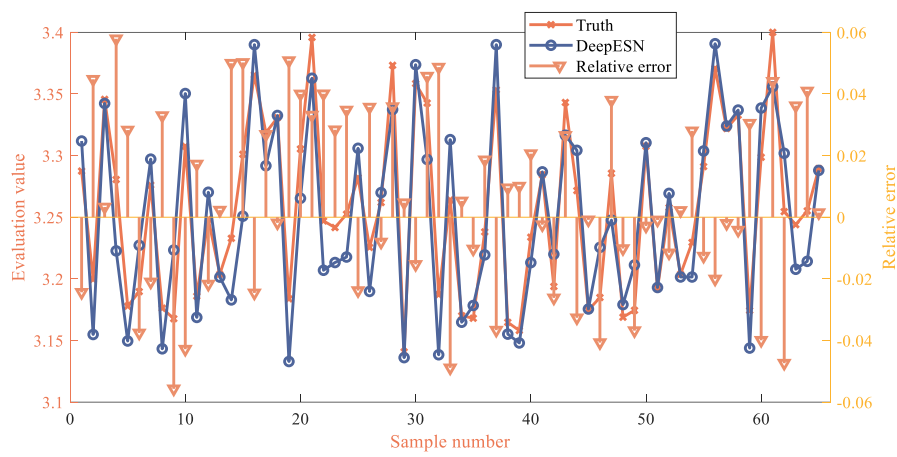
(b) DELM



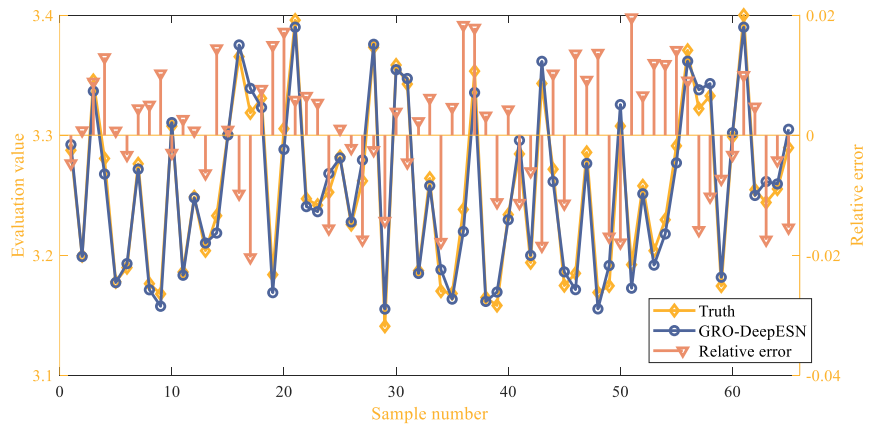
(c) ESN



(d) GRO-ESN



(f) DeepESN



(e) GRO-DeepESN

Figure 14. Evaluated values and error results of syntactic error correction performance based on each algorithm

Comparison of performance evaluation results of writing grammar error correction models based on each algorithm (Figure 15). From Figure 15, it can be seen that the writing grammar error correction method based on GRO-DeepESN algorithm RMSE, MAE, MAPE, R2 & test time is better than other algorithms. It can be seen that the

performance of the writing grammar error correction method based on GRO-DeepESN algorithm is better than other algorithms, the evaluation accuracy is better than other algorithms, and the real-time performance is also better than other algorithms.

Algorithm	RMSE	MAE	MAPE	R2	Test time / s
ELM	0.0546	0.0468	1.1706e-03	0.9573	0.0488
DELM	0.0495	0.0431	1.0765e-03	0.9648	0.0155
ESN	0.0629	0.0538	1.3442e-03	0.9431	0.0048
GRO-ESN	0.0431	0.0369	9.2354e-04	0.9734	0.0040
DeepESN	0.0285	0.0246	6.1444e-04	0.9883	0.00015
GRO-DeepESN	0.0117	0.0103	2.5636e-04	0.9980	0.00013

Figure 15. Comparison of performance evaluation results of writing grammar error correction models based on each algorithm

7. Conclusion

In order to improve the accuracy and robustness of writing grammar error correction assessment, this paper proposes an English writing tutoring and grammar error correction performance assessment method based on GRO algorithm to improve DeepESN network. The method is proposed by analysing the process of English writing assistance and grammar error correction, extracting the performance assessment features, and improving the DeepESN network assessment model by combining the GRO algorithm. The data obtained by using corpus research method, questionnaire survey method and writing test method are used to analyse the proposed method to have a comparison, and the following conclusions are obtained:

1) By comparing the analysis accuracy of the GRO-DeepESN algorithm with DeepESN, the Gold Rush optimisation algorithm improves the accuracy of DeepESN performance evaluation;

2) DeepESN algorithm evaluation time as well as robustness is better than other algorithms, evaluation real time as well as time robustness is improved.

Since the GRO algorithm can easily fall into a local optimum, it will be the next step to improve the optimisation performance of the GRO algorithm and apply it to the GRO-DeepESN model.

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