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Design and Use of Deep Confidence Network Based on Crayfish Optimization Algorithm in Automatic Assessment Method of Hearing Effectiveness

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Abstract

INTRODCTION: Listening strategy analysis and assessment not only need objective and fair sound listening strategy analysis, but also need high-precision and high real-time assessment model, and even more need in-depth analysis and feature extraction of the influencing factors of listening assessment.
OBJECTIVES: To address the problems of current automatic assessment methods, such as non-specific application, poor generalization, low assessment accuracy, and poor real-time performance.
METHODS: This paper proposes an automatic assessment method based on a deep confidence network based on crawfish optimization algorithm. First, the multi-dimensional listening strategy evaluation system is constructed by analyzing the listening improvement strategy; then, the depth confidence network is improved by the crayfish optimization algorithm to construct the automatic evaluation model; finally, through the analysis of simulation experiments.
RESLUTS: The proposed method improves the evaluation accuracy, robustness, and real-time performance. The absolute value of the relative error of the automatic evaluation value of the proposed method is controlled in the range of 0.011, and the evaluation time is less than 0.005 s. The method is based on a deep confidence network based on the crayfish optimization algorithm.
CONCLUSION: The problems of non-specific application of automated assessment methods, poor generalization, low assessment accuracy, and poor real-time performance are addressed.

Keywords: automatic assessment of listening effectiveness, listening strategy assessment system, crayfish optimization algorithm, deep learning network

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1. Introduction

Listening as an important embodiment of language communication ability, English listening has become an increasingly important part of English listening teaching, recognized and accepted by the majority of scholars [1], how to improve students' listening comprehension ability has become a common concern of experts and scholars in the field of education [2]. With the deepening of reform in the field of education, the use of diverse listening strategies to improve students' physical comprehension ability, the traditional listening assessment methods can no longer meet the use of listening strategies and effect analysis, can not meet the systematic regional analysis of strategies affecting students' English listening performance, can not meet the teachers to better guide students to use listening strategies, so as to improve the listening performance [3]. Listening strategy analysis and assessment not only need objective and fair sound listening strategy analysis, but also need high-precision, high real-time assessment model, and more need to listen to the in-depth analysis of the factors affecting the assessment and feature extraction [4].

Therefore, the study of listening strategy analysis and assessment methods is an extremely urgent task [5].

Listening strategy is the mental activity or mental process when learners consciously choose to complete the learning program [6]. The application of listening strategies to classroom teaching, the construction of a multi-strategy effect analysis system for listening, and the development of an intelligent automatic listening assessment method [7] have received more and more attention and research from experts in the field [8]. The research of listening multi-strategy effect analysis system mainly refers to the construction of the effect analysis and assessment system from an objective, complete and scientific perspective by analyzing the influencing factors of listening multi-strategy automatic assessment according to the principles of effect analysis and selection of automatic assessment elements [9]. Listening classroom effect analysis methods mainly include random forest, neural network, fuzzy theory, deep learning, intelligent optimization algorithm and other methods [10]. Literature [11] focuses on the total strategy guidance of listening pedagogy, analyzes the development trend of listening teaching, and puts forward the concept of multi-strategy listening teaching; Literature [12] takes the data of non-English majors' graduate students as the research samples to test and evaluate the effect and feasibility of the integration of listening strategies into the teaching classroom; Literature [13] constructs the model of the process of listening comprehension and the model of the training of learning strategies through methodological surveys and other methods. Random Forest method is used to construct an automatic listening evaluation method, which confirms the feasibility of listening strategies in the Chinese foreign language classroom environment; Literature [14] analyzes the automatic scoring process of listening, combines machine learning algorithms, and proposes a scoring method based on multivariate current regression and Random Forest; Literature [15] analyzes the characteristics of the scoring of the effect of English listening from the English listening strategies, and proposes a multi-intelligence method fusion of the automatic scoring method of the listening system; Literature [16] proposed the whole process of the English listening classroom in three aspects, such as teaching preparation, teaching application and teaching evaluation, and at the same time, constructed an automatic evaluation system of English listening and proposed an automatic evaluation method based on deep learning algorithms; Literature [17], on the basis of reflecting on the traditional English listening strategies, discussed language proficiency, critical thinking ability and intercultural competence as the listening learning strategy goals, and proposed a neural network-based English listening assessment method; Literature [18] analyzed different listening strategies in multimedia environments. According to the analysis of the above literature, the existing listening assessment methods have the following defects [19]: 1) the selection of influencing factors of the listening assessment system is not standard enough and cannot reflect the characteristics of the whole process; 2) the listening assessment methods lack generalization.

Deep Belief Networks (DBN) algorithm is a type of neural network for machine learning, by training the weights between its neurons, it allows the entire neural network to generate training data with maximum probability [20]. Swarm Intelligence Optimization Algorithm [21] is an algorithm or distributed strategy for explaining a problem designed by simulating the behavior of groups of insects, flocks of animals, flocks of birds and schools of fish. With the increase of course volume and the development of sensors, the accumulation of listening analysis data increases rapidly, and the construction of listening assessment models in the context of big data requires diverse intelligent optimization algorithms combined with machine learning algorithms. Deep confidence network methods based on swarm intelligent optimization algorithms have increased the assessment accuracy, and their application to the problem of automatic assessment of listening strategies has become a hot research topic for experts and scholars in the field.

Aiming at the problems existing in the current automatic evaluation method of listening strategy, this paper proposes an automatic evaluation method of listening based on the group intelligence optimization algorithm to improve the deep learning neural network. The main contributions of this paper are: (1) analyzing the problem of automatic listening assessment, selecting the characteristics of listening strategy effect analysis and assessment, and constructing the assessment system; (2) using questionnaires and tests to obtain the effect assessment data, and carrying out the correlation data analysis; (3) optimizing the parameters of the deep confidence network by using the swarm intelligent optimization algorithm, and proposing a method of automatic listening assessment based on the intelligent optimization algorithm for the optimization of the deep confidence network under the condition of big data; (4) validating the method of automatic listening assessment by simulation. (4) The validity of the proposed method is verified through simulation, and the accuracy and real-time performance of the evaluation are improved at the same time.

2. Problem analysis of automated listening assessment

2.1. Analysis of Listening Strategies

According to the framework of categorization of such frontal categories of language learning, learning to measure listening learning strategies were classified into metacognitive, cognitive and social/emotional strategies [22].

Listening metacognitive strategies

Listening metacognitive strategies mainly include self-management strategy X1, self-evaluation strategy X2, self-monitoring strategy X3, advance preparation strategy X4 and focused attention strategy X5. self-management strategy refers to the learners to make a listening learning plan, rationalize the time to carry out the listening learning, select appropriate listening materials, determine the listening training methods to improve the listening learning effect; self-evaluation strategy refers to the learners to Self-assessment strategy means that learners test their listening comprehension and listening strategies at the end of a certain stage of listening learning, in order to understand the deficiencies, adjust the learning plan, and improve listening comprehension; Self-monitoring strategy means that learners infer the content of the text during the listening process, and monitor whether the strategy is appropriate; Pre-preparation strategy refers to the background of the listening material before learning, which helps to understand the content of the listening; Concentration strategy means that before starting listening, learners focus their attention on the learning task; Concentration strategy means that they focus their attention on the learning task before starting it. focusing attention to the learning task before starting, and at the same time focusing attention to the listening task during the listening process.

Cognitive strategies

Cognitive strategies mainly include using target language resources strategy Y1, speculation strategy Y2, association strategy Y3, shorthand strategy Y4, and summarization and categorization strategy Y5 [22]. The strategy of utilizing target language resources refers to increasing target language input by using target language reference materials during the learning process; the strategy of speculation refers to predicting the main topics appearing in the listening materials based on the questions, graphs, and options of the listening materials; the strategy of association refers to the process of establishing the relationship between the new information and the previous experience and knowledge during the process of listening learning; the strategy of shorthand refers to the methods of symbols, abbreviations, numbers, key words, and so on, to Record the key information of the listening learning material; Summarize and categorize strategy refers to classify the key words and phrases in the language material at the beginning of the end of listening, which makes the knowledge more systematic.

Social/emotional strategies

Social/emotional strategies include self-talk strategy Z1, cooperative learning strategy Z2, and problem-solving strategy Z3 [23]. The self-talk strategy refers to reducing anxiety and successfully completing the task through self-regulation before listening; the cooperative learning strategy refers to achieving mutual promotion and progress by exchanging learning experiences and experiences with each other; and the problem solving strategy refers to seeking reexplanations, confirmations, and repetitions from the teacher or classmates in response to a certain linguistic problem so as to get out of the learning dilemma.

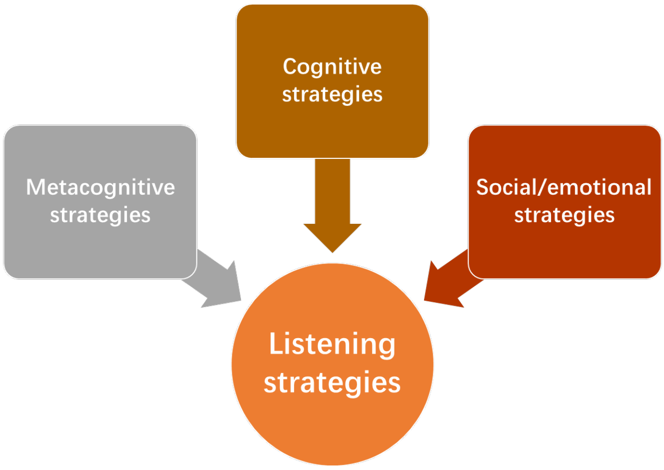


Figure 1. Diagram of listening strategy analysis

2.2. Automated Hearing Assessment System

The automatic assessment system based on multidimensional listening strategies takes the aspects of metacognitive strategies, cognitive strategies and social/emotional strategies [24] as the first-level elements, and takes the self-management strategies X1, self-evaluation strategies X2, self-monitoring strategies X3, pre-preparation strategies X4, focusing attention strategies X5, utilizing resources of the target language strategies Y1, inferring strategies Y2, associating strategies Y3, shorthand remembering strategies Y4, summarization categorization strategy Y5, self-talk strategy Z1, cooperative learning strategy Z2, problem solving strategy Z3 and other 13 influencing factors as secondary indicators, constructed a multidimensional listening strategy automatic assessment system, the specific schematic diagram is shown in Figure 2.

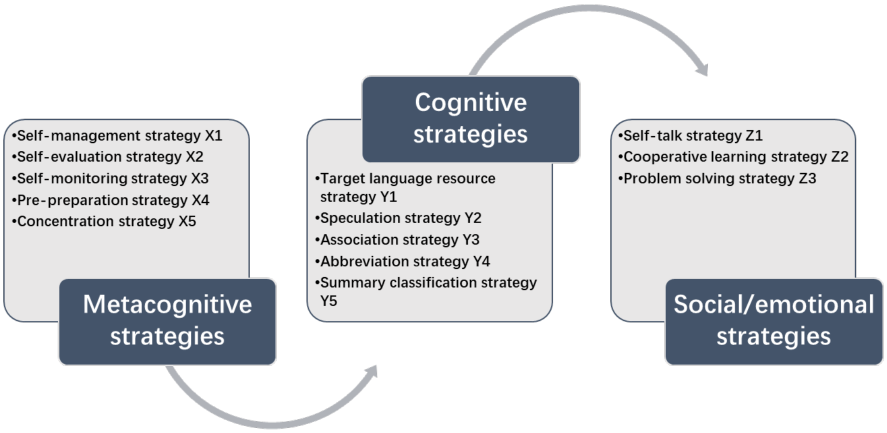


Figure 2. Multi-dimensional listening strategy automatic evaluation system

3. Data acquisition and analysis

3.1. Data acquisition

In order to obtain reliable statistics about hearing, this paper uses hearing questionnaires and hearing tests to obtain data [25], and the schematic diagram of the data acquisition method is shown in Figure 3.

Listening questionnaire

The questionnaire used for this data collection was referred to Oxford's SILL (Strategy Inventory for Language Learning) [26]. The questionnaire was divided into two main parts, the first part was a background test, which mainly included basic information about the learners' age and gender, and the second part was a questionnaire on listening learning strategies, with a total of 36 questions, including cognitive strategies (1-15 questions), cognitive strategies (16-30 questions), and affective strategies (31-36 questions). The questionnaire was rated on a 5-point scale, with 1 representing not applicable, 2 representing basically unadaptable, 3 representing uncertain, 4 representing basically applicable, and 5 representing fully applicable.

Listening test

This listening test refers to the 2012 Jiangsu Provincial College Entrance Examination English Listening Test questions, full marks are 20, and the test form is conducted in full accordance with the operation of the college entrance examination listening test. The test questions include multiple-choice, judgmental, and fill-in-the-blank questions, and the corrections are made by filling in and applying the answer cards, and the machine corrections are completely reliable, true and accurate.

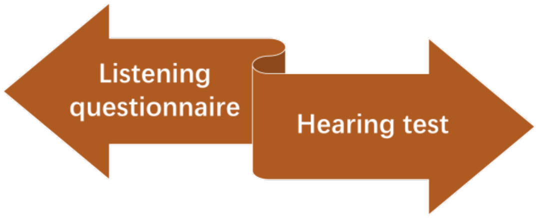


Figure 3. data acquisition method

3.2. Data analysis

In order to analyze the redundancy of the input indicators, this paper investigates the correlation analysis of the influencing factors related to teaching effectiveness in higher education. 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:

$$\rho(x,y)=\frac{\operatorname{cov}(x,y)}{\sigma(x)\sigma(y)}=\frac{E\left[(x-\mu_x)(y-\mu_y)\right]}{\sigma(x)\sigma(y)} \tag{1}$$

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

In order to reduce the redundancy of input indicators, this paper chooses the principal component analysis method for dimension reduction. In the process of dimensionality reduction feature extraction, the input indicators are usually transformed to generate comprehensive indicators, i.e., principal components, so that the principal components improve the precision of evaluation effect than the original variables. The steps for dimensionality reduction of the influencing factors of listening classroom effect analysis based on the principal component analysis method are as follows:

Step 1: Standardized processing of indicator characteristics. In order to eliminate the quantitative differences between the influencing factors of different elements, the original data matrix is standardized, and the standardized matrix Z is obtained by using the Z-Score method, where n is the number of samples, and d is the dimension of the characteristics of the sample indicators.

Step 2: Determine the matrix of correlation coefficients between indicators Σ :

$$\sigma_{ij} = \frac{\sum_{k=1}^{n}\left(z_{ki}-\bar{Z}_i\right)\left(z_{kj}-\bar{Z}_j\right)}{\sqrt{\sum_{k=1}^{n}\left(z_{ki}-\bar{Z}_i\right)^2\left(z_{kj}-\bar{Z}_j\right)^2}} \tag{2}$$

Where z_{ki} denotes the standardized value of the ith indicator for the kth sample; $\bar{Z}_i$ is the mean value of the ith indicator; σ_{ij} is the covariance of the vectors Z_i and Z_j .

Step 3: Determine the characteristic roots as well as the eigenvectors of the correlation coefficient matrix Σ . The symmetric positive definite matrix $\Sigma = \left[\sigma_{ij}\right]_{d\times d}$ is necessarily orthogonally similar to the diagonal matrix Λ , i.e:

$$U^T \Sigma U = \Lambda = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_d \end{bmatrix} \tag{3}$$

where, assuming $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d$. U is an orthogonal matrix consisting of eigenvectors corresponding to the eigenroots.

Step 4: Calculate the contribution of the ith principal component ω_i :

$$\omega_i = 1 \Big/ \sum_{j=1}^{d} \lambda_j \tag{4}$$

Step 5: Sort the components one at a time according to the magnitude of their contribution, determine the information retention threshold after decoupling α , and if the cumulative contribution of the first k components ρ is greater than α , then the number of principal components is k.

$$\rho = \sum_{i=1}^{k} \omega_i \tag{5}$$

Step 6: Output the k indicator features associated with the principal components.

4. Related Technologies

4.1. Deep Confidence Networks

Deep Belief Networks (DBN) [27] consist of multiple Restricted Boltzmann Machines (RBM) layers, a typical type of neural network is shown in Figure. These networks are restricted to a visible layer and a hidden layer with connections between the layers but not between the units within the layers. The hidden layer units are trained to capture the correlation of higher order data exhibited in the visual layer, the structure of which is shown in Figure. 4. As can be seen from Figure. 4, the input layer v and the hidden layer h^1 constitute the first layer of the RBM, and the input data is mapped through the activation function to the hidden layer h_1 , which is inputted to the second layer of the RBM (the hidden layer h_1 and the hidden layer h_2), and the data is passed through the hidden layer sequentially to reach the output layer.

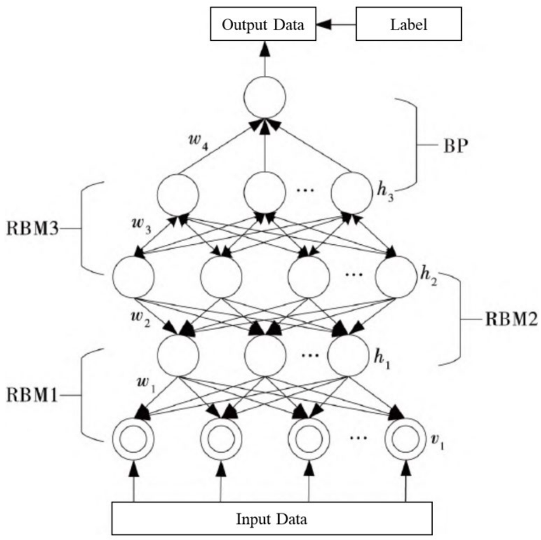


Figure 4. DBN structure diagram

(1) Calculate the RBM energy function. Assuming that $\theta = (\omega, a, b)$ is the DBN network parameter, the energy function of RBM is expressed as:

$$E(v,h|\theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i \omega_{ij} h_j \tag{8}$$

where (v,h) is the state value of DBN, ω is the connection weight of the visible and hidden layers, a and b are the bias of the visible and hidden layers, respectively, and the hidden and visible layer states are binary states, i.e., $v \in \{0,1\}$ and $h \in \{0,1\}$.

(2) The stochastic gradient method is used to solve the DBN network parameters θ . The corresponding parameters θ^* are obtained by solving the maximum of the log-likelihood function:

$$\theta^* = \arg_\theta \max L(\theta) = \arg_\theta \max \sum_{k=1}^{K} \ln p\left(v^k \middle| \theta\right) \tag{9}$$

where K is the number of training samples.

(3) The joint probability distribution function can be determined from the energy function:

$$p(v,h|\theta) = \frac{e^{-E(v,h|\theta)}}{Z(\theta)} \tag{10}$$

$$Z(\theta) = \sum_v \sum_h e^{-E(v,h|\theta)} \tag{11}$$

(4) Determine the visual layer state. The activation probability of the jth network node of the hidden layer is

$$p(h_j = 1|v,\theta) = sigmoid\left(b_j + \sum_{i=1}^{n} v_i \omega_{ij}\right) \tag{12}$$

(5) Determine the hidden layer state. The activation probability of the ith network node of the visualization layer is

$$p(v_i = 1|h,\theta) = sigmoid\left(a_i + \sum_{i=1}^{n} h_j \omega_{ij}\right) \tag{13}$$

(6) According to Gibbs sampling theorem, the RBM parameter θ is updated with the following formula:

$$\Delta\omega_{ij} = \frac{\partial \log p(v)}{\partial \omega_{ij}} = \varepsilon\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{predict}\right) \tag{14}$$

$$\Delta a_i = \frac{\partial \log p(v)}{\partial a_i} = \varepsilon\left(\langle v_i \rangle_{data} - \langle v_i \rangle_{predict}\right) \tag{15}$$

$$\Delta b_j = \frac{\partial \log p(v)}{\partial b_j} = \varepsilon\left(\langle h_j \rangle_{data} - \langle h_j \rangle_{predict}\right) \tag{16}$$

where ε denotes the learning rate, $\langle \square \rangle_{data}$ is the expectation of training after input data, and $\langle \square \rangle_{predict}$ is the expectation of the model itself.

4.2. Crayfish optimization algorithm

Crayfish optimization algorithm (COA) [28] is inspired by crayfish foraging, heat avoidance and competition behaviors. Crayfish foraging and competitive behaviors belong to the exploitation phase of COA, and summering behavior belongs to the exploration phase of COA. Assume that the crayfish population X is defined as the initial stage of the algorithm, X_i is the position of the *ith crayfish*, representing the candidate solution $X_i = \{X_{i,1}, X_{i,2}, \cdots, X_{i,\dim}\}$, and $\dim$ is the feature quantity (decision dimension) of the optimization problem. The crayfish candidate solution obtains the fitness value through the objective function $f(\cdot)$.

According to the COA algorithm inspired mechanism, the steps of COA algorithm are as follows:

Step 1: Population initialization.The COA algorithm initialization uses a random uniform distribution strategy with the following data model:

$$X_{i,j} = lb_j + (ub_j - lb_j) \times rand \tag{17}$$

Where $X_{i,j}$ denotes the jth dimensional location information of the ith crayfish, lb_j and ub_j denote the lower and upper bounds of the jth dimension, respectively, and $rand$ denotes a random number in the range of $[0,1]$.

Step 2: Calculate temperature and crayfish intake using the temperature definition equation. When the temperature is higher than 30 °C, crayfish will choose a cool residence in the summer; in the right temperature, crayfish control to carry out foraging behavior and is affected by temperature. Crayfish intake is best at 15 °C, 30 °C, and 25 °C. The mathematical model of COA intake was constructed as follows:

$$p = C_1 \times \left(\frac{1}{\sqrt{2 \times \pi \times \sigma}} \times \exp\left(-\frac{(temp - \mu)^2}{2\sigma^2}\right)\right) \tag{18}$$

$$temp = rand \times 15 + 20 \tag{19}$$

Among them, crayfish intake is approximately normally distributed, $temp$ represents the temperature of the environment where crayfish live, μ represents the most adaptive temperature of crayfish, σ and C_1 are mainly used to control the intake of crayfish at different temperatures. The temperature influence of crayfish intake is shown in Figure 5.

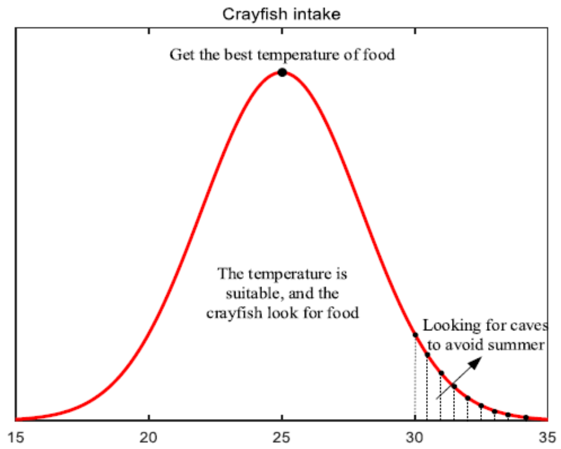


Figure 5. Temperature effect plot of crayfish intake

Step 3: Heat avoidance behavior and competitive behavior implementation. When the temperature is greater than 30°C, it causes crayfish to choose heat avoidance behavior, where the crayfish burrow location is defined as follows:

$$X_{shade} = \left(X_G + X_L\right)/2 \tag{20}$$

Where X_G denotes the optimal solution position for the current iteration number and X_L denotes the optimal position for the current population.

When $temp > 30$ and $rand < 0.5$, the COA enters the heat avoidance behavior phase:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + C_2 \times rand \times \left(X_{shade} - X_{i,j}^{t}\right) \tag{21}$$

where t denotes the current iteration number, $t+1$ denotes the next iteration number, and C_2 is a reduced parameter:

$$C_2 = 2 - t/T \tag{22}$$

where T denotes the maximum number of iterations.

When $temp > 30$ and $rand \geq 0.5$, the COA enters the competitive behavior phase:

$$X_{i,j}^{t+1} = X_{i,j}^{t} - X_{z,j}^{t} + X_{shade} \tag{23}$$

where z denotes a random individual of crayfish, calculated as follows:

$$z = round\left(rand \times \left(N-1\right)\right) + 1 \tag{24}$$

Step 4: Foraging behavior implementation. The COA algorithm enters the foraging phase when $temp \leq 30$.

In the foraging phase, after finding food, the mode of foraging behavior operation is decided by judging the food size. Food X_{food} is generally defined as the optimal solution X_G. Food size is defined as follows:

$$Q = C_3 \times rand \times \left(fitness_i / fitness_{food}\right) \tag{25}$$

Where, C_3 denotes the food factor, which represents the largest food and generally takes the value of 3; $fitness_i$ and $fitness_{food}$ denote the adaptation value of the ith crayfish and the adaptation value of the location of the food, respectively.

When $Q > \left(C_3 + 1\right)/2$, the food is too large and the crayfish needs to use its first clawed foot to tear the food, the mathematical model is as follows:

$$X_{food} = \exp\left(-\frac{1}{Q}\right) \times X_{food} \tag{26}$$

After the food is chopped and made smaller, the crayfish uses the second and third claws to pick up the food and put it into the mouth. In order to simulate the food selection process, COA uses sine function and cosine function to simulate the process, the specific foraging simulation is as follows:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + X_{food} \times p \times \left(\cos\left(2 \times \pi \times rand\right) - \sin\left(2 \times \pi \times rand\right)\right) \tag{27}$$

When $Q \leq \left(C_3 + 1\right)/2$, the crayfish needs to move to the food and eat it directly:

$$X_{i,j}^{t+1} = \left(X_{i,j}^{t} - X_{food}\right) \times p + p \times rand \times X_{i,j}^{t} \tag{28}$$

Step 5: Calculate the fitness value.

Step 6: If the maximum number of iterations is reached, stop the optimization process and output the optimal solution with the optimal value or go back to step 2.

5. Improved Deep Confidence Network Based on Crayfish Optimization Algorithm for Automatic Hearing Assessment Method Flow

Combining COA and deep confidence network, this section proposes an improved DBN network based on COA algorithm to analyze the effect of listening classroom.

5.1. Decision variables and objective functions

The traditional iterative method of DBN network optimization can easily cause the optimization of DBN network parameters to fall into local optimum. In order to overcome the above problems, this paper adopts the COA algorithm to optimize the DBN network parameters. the optimization decision variable of the COA algorithm is $\theta = (\omega, a, b)$.

To overcome the DBN training accuracy, the root-mean-square error function is used as the objective function of the COA-DBN algorithm, which is calculated as follows:

$$\min f(\omega, a, b) = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(y(k) - y_{predict}(k)\right)^2} \tag{29}$$

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

5.2. Steps and processes

The prediction model of automatic assessment based on the optimization of DBN network by COA algorithm is mainly based on the mapping relationship between indicators and assessment values with the multidimensional listening strategy automatic assessment indicators as inputs and the assessment values as outputs. The flowchart of the multidimensional listening strategy automatic assessment method based on COA-DBN algorithm is shown in Figure 6. The specific steps are as follows:

Step 1: Acquire the data according to the hearing questionnaire and the hearing test method; pre-process the acquired samples with sparse smoothing data processing method; normalize the raw data with Z-Score method and divide the data into test set, validation set and training set;

Step 2: Use COA algorithm to encode the initial parameters of DBN, and also initialize the algorithm parameters such as population parameters and iteration number; initialize the population and calculate the objective function value;

Step 3: Calculate temperature and crayfish intake;

Step 4: According to the temperature and random number size, the COA algorithm heat avoidance behavior and competitive behavior strategy is used to update the location information;

Step 5: Update the location information by calculating the food size size and using different foraging behavior strategies;

Step 6: In each iteration, it is necessary to 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 7: Judge whether the termination condition is satisfied. If it is satisfied, exit the iteration, output the optimal DBN parameters, and execute step 8, otherwise continue to execute step 3;

Step 8: Decode the COA based optimized DBN parameters to get $\theta^* = (\omega, a, b)$;

Step 7: Construct the COA-DBN analysis model, train the analysis model using the training set, input the test set into the model, and obtain the analysis results and error results.

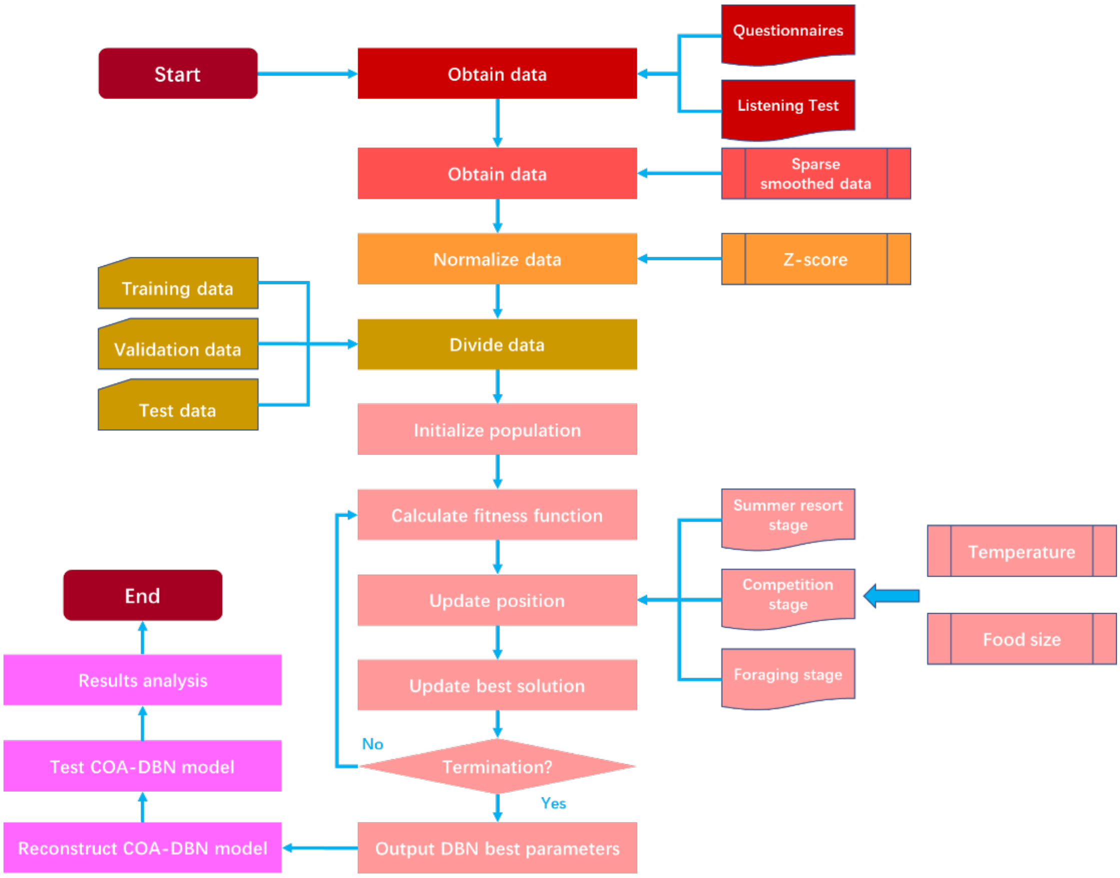


Figure 6. Flowchart of automatic evaluation for optimizing DBN network based on COA algorithm

6. Experiments and analysis of results

In order to verify the accuracy and timeliness of the listening automatic assessment model proposed in this paper, five analysis algorithms were selected for comparison with the English listening strategy assessment data as simulation data, and the specific parameter settings of each algorithm are shown in Table 1.The experimental simulation environment is Windows 10, CPU 2.80GHz, 8GB RAM, and programming language Matlab2019a.

Table 1. Parameter settings for automated assessment and analysis methods

Arithmetic	Parameterization
DBN	Three hidden layers with 100, 100, 100 nodes in each layer
GWO-DBN	Three cryptic layers, see Section 6.2 for the reference analysis of the number of nodes in each layer, GWO parameter a decreasing from 2 to 0, population size see Section 6.2
WOA-DBN	Three cryptic layers, see Section 6.2 for reference analysis of the number of nodes in each layer, WOA parameters a decreasing from 2 to 0, b = 1, and population size see Section 6.2
SSA-DBN	Three cryptic layers, see Section 6.2 for the reference analysis of the number of nodes in each layer, SSA parameter a decreasing from 2 to 0, and the number of populations in Section 6.2
HHO-DBN	Three cryptic layers, see section 6.2 for reference analysis of the number of nodes in each layer, HHO parameter $-1 < E0 < 1$, population size see section 6.2
COA-DBN	Three cryptic layers, see section 6.2 for reference analysis of the number of nodes in each layer and section 6.2 for the number of populations

6.1. Correlation analysis

In order to analyze the redundancy of the influencing factors of the automatic assessment of listening strategies, this paper analyzes the influencing indicators, and the specific analysis statistics are shown in Figure 7. In Figure 7, X1-X5 represent self-management strategy, self-evaluation strategy, self-monitoring strategy, advance preparation strategy, and focused attention strategy, respectively; Y1-Y5 represent utilization of target language resources strategy, speculation strategy, association strategy, shorthand memorization strategy, and summarization and categorization strategy, respectively; Z1-Z3 represent selftalking strategy, cooperative learning strategy, and problem solving strategy, respectively; the larger the area of the circle, the stronger the correlation. The larger the area of the circle, the stronger the correlation. As can be seen from Figure 7, X2 is strongly correlated with X3, Y5, Z1, Z2 and Z3 are strongly correlated, and X1 is strongly correlated with Y5, Z1 and Z2.

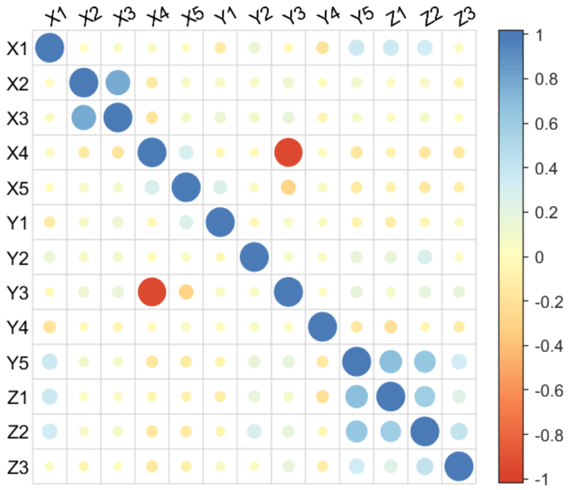


Figure 7. Correlation analysis diagram

6.2. Parametric analysis

In order to obtain the appropriate number of hidden layer nodes and optimization algorithm populations for the DBN network, this section analyzes the impact of different population numbers and hidden layer nodes on the evaluation value and evaluation time.

Figure. 8 gives the effect of different number of populations and number of hidden layer nodes on the evaluation value and evaluation time. From Figure. 8(a), it can be seen that as the number of populations increases, the evaluation prediction accuracy increases; as the number of hidden layer nodes increases, the evaluation prediction accuracy increases. From Figure. 8(b), it can be seen that as the number of populations increases, the evaluation and analysis time increases; as the number of DBN hidden layer nodes increases, the evaluation time increases. In summary, the increase in the population number and the number of hidden layer nodes of the automatic listening strategy evaluation model based on the COA-DBN algorithm are favorable to the increase in 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 50 and the number of hidden layer nodes as 60.

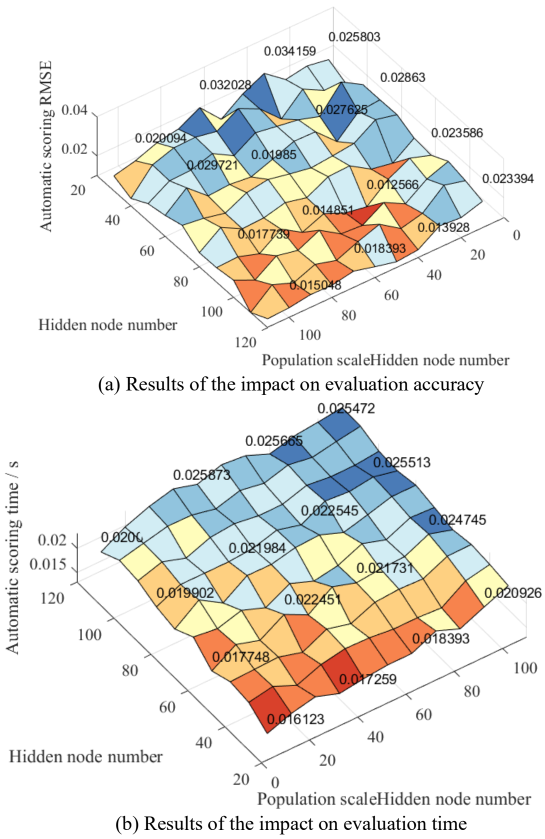
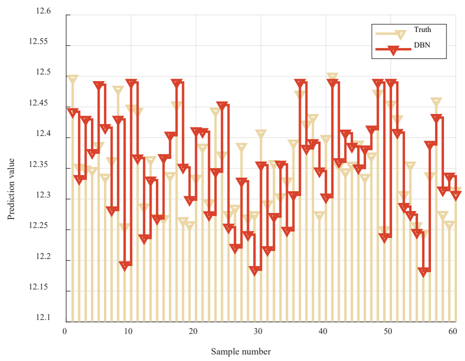


Figure 8. Effect of different population size and number of cryptic nodes on evaluation value and evaluation time

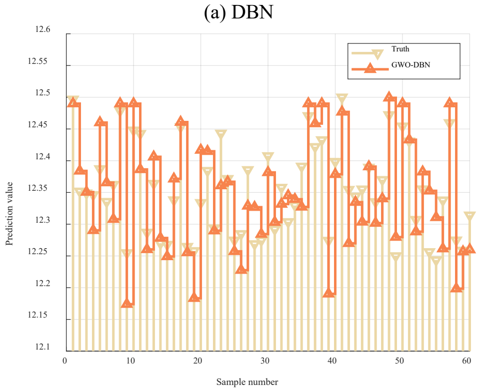
6.3. Model analysis

In order to verify the effectiveness and superiority of the automatic evaluation method of listening strategies based on the COA-DBN algorithm, COA-DBN was compared with five other models, and the evaluation results of each model are shown in Figure 9, Figure 10, Figure 11, and Figure. 12.

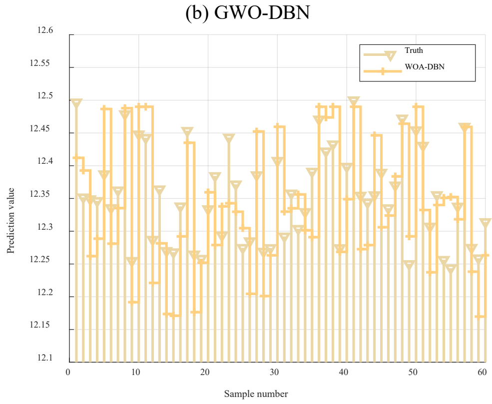
Figure 9 gives the values of the automatic evaluation of listening strategies based on each algorithm. From Figure 9, it can be seen that the results of the accuracy of the automatic evaluation of listening strategies based on COA-DBN are closer to the true values; comparing the accuracy of the GWO-DBN, WOA-DBN, SSA-DBN, HHO-DBN, and COA-DBN algorithms, the COA algorithm improves the accuracy of the automatic evaluation of listening strategies. Figure 10 gives the relative error between the listening strategy automatic assessment value and the true value based on each algorithm. As can be seen from Figure 10, the absolute value of the relative error of the hearing strategy automatic assessment values based on the COA-DBN algorithm is controlled within the range of 0.011, and the absolute value of the relative error of the hearing strategy automatic assessment values of the DBN, GWO-DBN, WOA-DBN, SSA-DBN, HHO-DBN, and COA-DBN algorithms is controlled within the ranges of 0.1, 0.08, 0.12, respectively, 0.043, and 0.049 range. In summary, the error of the automatic assessment method of listening strategies based on the COA-DBN algorithm is generally minimal.



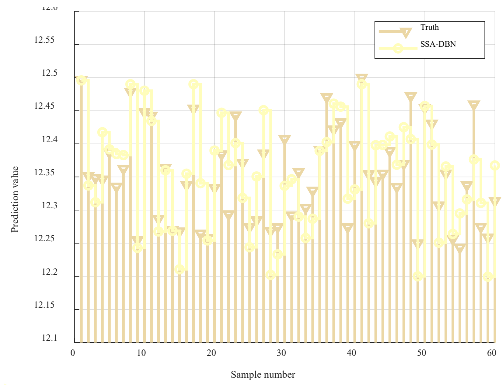
(a) DBN



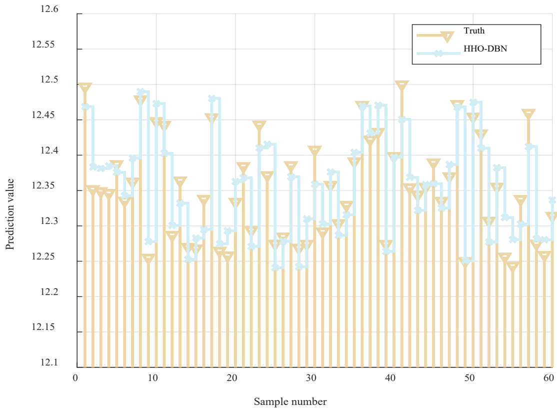
(b) GWO-DBN



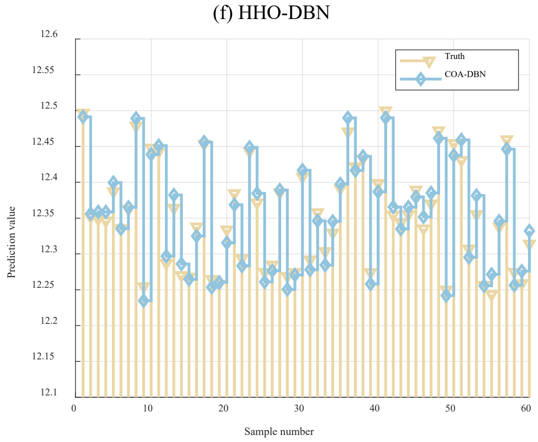
(c) WOA-DBN



(d) SSA-DBN



(f) HHO-DBN



(e) COA-DBN

Figure 9. Automated multidimensional listening strategy evaluation values based on each algorithm

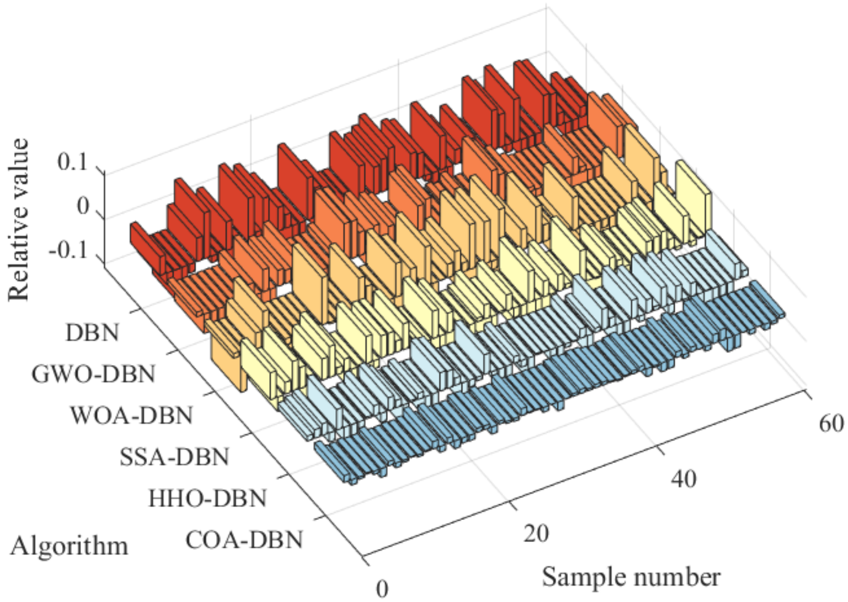


Figure 10. Relative error between the automatically evaluated and true values of multidimensional listening strategies based on each algorithm

Figure 11 gives a comparison of the time of the automatic multidimensional listening strategy assessment based on each algorithm. From Figure 11, it can be seen that the mean and standard deviation of the time of the multidimensional listening strategy automatic evaluation method based on the COA-DBN algorithm is less than that of the DBN, GWO-DBN, WOA-DBN, SSA-DBN, HHO-DBN, and COA-DBN algorithms, and the time of test and analysis is ranked first, and it satisfies real-time performance.

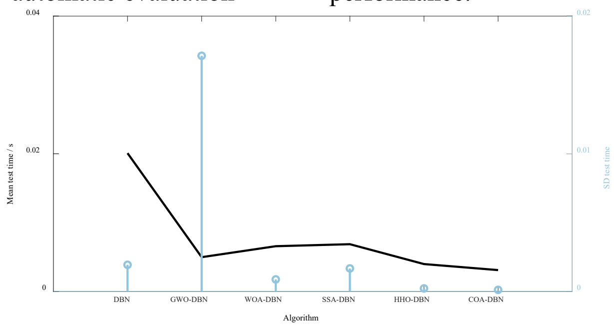


Figure 11. Comparison of time for analyzing the effect of listening classroom based on each algorithm

Figure 12 gives a comparison of the convergence curves of the optimized DBN network parameters based on each optimization algorithm. From Figure 12, it can be seen that the analytical model parameter optimization curves based on the COA-DBN algorithm converge faster than GWO-DBN, WOA-DBN, SSA-DBN, and HHO-DBN, and the GWO-DBN algorithm converges better than WOA-DBN, SSA-DBN, and HHO-DBN.

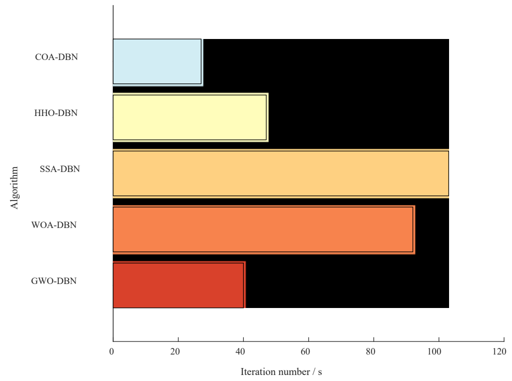


Figure 12. Results of the number of convergence iterations for each optimization algorithm to improve the DBN network

7. Conclusion

In order to improve the accuracy and robustness of automatic listening strategy evaluation, this paper proposes a multidimensional automatic listening strategy evaluation method based on the COA algorithm to improve the DBN network. The method proposes a multidimensional listening strategy automatic assessment method by analyzing the listening strategy, constructing a listening automatic assessment system, and improving the DBN network assessment model by combining the COA algorithm. The proposed method is analyzed and compared using the data obtained from the listening questionnaire and the listening test method, and the following conclusions are obtained:

1) By comparing the analysis accuracy of COA-DBN algorithm with DBN, the swarm intelligence optimization algorithm improves the accuracy of automatic DBN evaluation;

2) COA-DBN algorithm evaluation time as well as robustness is better than other algorithms, evaluation real-time as well as time robustness is improved;

3) The convergence speed and evaluation accuracy of the improved DBN parameters based on COA algorithm are better than GWO, WOA, SSA and HHO algorithms, and the optimization performance of COA is better.

Since the COA algorithm can easily fall into local optimum, how to improve the optimization performance of the COA algorithm and apply it to the COA-DBN model will be the next step.

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