

Retraction

Retracted: Research on Machine Learning-Based Error Correction Algorithm for Spoken French

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] J. Gao, "Research on Machine Learning-Based Error Correction Algorithm for Spoken French," *Security and Communication Networks*, vol. 2021, Article ID 6259995, 10 pages, 2021.

Research Article

Research on Machine Learning-Based Error Correction Algorithm for Spoken French

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In order to overcome the problems of low error capture accuracy and long response time of traditional spoken French error correction algorithms, this study designed a French spoken error correction algorithm based on machine learning. Based on the construction of the French spoken pronunciation signal model, the algorithm analyzes the spectral features of French spoken pronunciation and then selects and classifies the features and captures the abnormal pronunciation signals. Based on this, the machine learning network architecture and the training process of the machine learning network are designed, and the operation structure of the algorithm, the algorithm program, the algorithm development environment, and the identification of oral errors are designed to complete the correction of oral French errors. Experimental results show that the proposed algorithm has high error capture accuracy and short response time, which prove its high efficiency and timeliness.

1. Introduction

French is an independent language belonging to the Romance language family of Indo-European family in Europe, and it is one of the independent Romance languages with the largest number of speakers after Spanish. It is now spoken as a mother tongue by 87 million people worldwide and as a second language by 285 million others [1]. French is also the official language of regional and international organizations such as the United Nations and the European Union.

French characters belong to phonetic characters, which are composed of phonetic letters. The composition of the letters is related to pronunciation. According to different letter combinations, the pronunciation of the words can be read directly. This is clearly different from the Chinese character system. Because of its strict usage, important documents such as strict laws are written in French internationally. The United Nations has designated French as the first speech language and the first written language [2].

As one of the six working languages of the United Nations, French is widely used in international social and diplomatic activities. It is not only the official language of France but also the official or common language of more

than 40 countries and regions across five continents, with an estimated 120 million French speakers [3]. Although the number of French speakers in the world is small, the number of French-speaking countries is very big. If English is the largest language in terms of the global distribution of languages, then French is the second largest language.

At present, more and more universities and even middle schools are offering French as a subject, and more and more Chinese students are learning French. With the continuous improvement of the level of computer information technology, in the background of the computer era, computer systems have not only been applied to professional academic occasions but also gradually infiltrated into various fields of social work and life. However, in the process of popularizing the application of computers, how to better master computer language is of great importance to people's language learning [4].

Despite the large number of people learning French, the level of spoken French is poor, with only about 15% of the population meeting the standard. Speaking has become the most difficult part of learning French. The reasons for this phenomenon are as follows: there are few similarities between French and Chinese oral pronunciation. There is a

serious shortage of qualified oral French teachers in domestic schools, and teachers only pay attention to students' writing, reading comprehension, and grammar but ignore oral French. Learners lack the environment and time to practice spoken French.

Therefore, an automatic pronunciation calibration algorithm based on single target tracking is designed in [5]. The algorithm first uses UNIX-style subroutines to construct the framework results of the automatic calibration algorithm and analyzes the data resource extraction module flow according to the inner high aggregation principle. Analog-to-digital signal conversion is used to improve the efficiency of data sampling, and the A/D circuit of the pronunciation calibration engine is designed. Then, a single target tracking algorithm is used to extract relevant features and form a logical layer. Finally, the embedded kernel structure is developed and the speech recognition code is studied. However, it is found in practical application that the algorithm has a low accuracy in capturing spoken French errors. An intelligent detection and correction algorithm for spoken pronunciation errors is designed in [6]. Firstly, the algorithm collects the speech signal of the spoken language test system and performs matching filtering on the speech signal to remove the interference noise. Then the purified speech signal is processed with adaptive beam focusing to enhance the strength of useful speech signal. Finally, a correlation spectrum detection method is used to extract the spectrum of the spoken speech signal of the spoken speech test system, and then the pronunciation error detection is realized according to the spectrum difference. However, it is found in practical application that the algorithm has the problem of long response time.

According to the existing methods, there are many problems, such as low error capture accuracy and long response time of traditional spoken French error correction algorithms. The motivation of this paper is to design a new method which can deal with the shortcomings of traditional algorithms. This paper designs a French oral error correction algorithm based on machine learning.

The contribution of this paper is to design an error correction algorithm for spoken French. The proposed method in this paper is based on machine learning. The rest of this paper is structured as follows: Section 2 discusses the method to catch French spoken errors. Section 3 introduces how to design an oral French error correction algorithm based on machine learning. Experimental results and analysis are given in Section 4. Then, the last section is the conclusion.

2. Catch French Spoken Errors

2.1. Model and Feature Analysis of Spoken French Pronunciation Signal

2.1.1. Construction of French Spoken Pronunciation Signal Model. In order to correct the errors of spoken French, a detection model of spoken French pronunciation signal is designed firstly, and the original data of spoken French pronunciation signal is collected by multisensor detection

method. Scale decomposition and feature extraction are carried out on the collected signals, and the errors of spoken French pronunciation and feature detection are carried out in the delay direction graph grating. The mathematical model expression of spoken French pronunciation signals is as follows:

$$z(t) = H \times a(t) \times \phi(t), \quad (1)$$

where $a(t)$ represents the signal amplitude received by the spoken French pronunciation signal in the n -th array, $\phi(t)$ represents the phase of the multiuniform linear broadband array, and H represents the step transmission function of the spoken French pronunciation signal.

Then, the modeling of spoken French speech signal is completed based on particle swarm optimization algorithm, and the matrix distribution of speech information sampling is $v_m, m \in [1, n]$, so the echo pulse of spoken French speech signal can be written as

$$\tilde{y}(t) = b(\tau, \varphi) \exp[j2\pi\varphi t] \tilde{f}(t - \tau) dt, \quad (2)$$

where $b(\tau, \varphi)$ represents the output expansion function of the spoken French pronunciation signal, $\tilde{f}(t)$ represents the complex envelope of each frequency component of the spoken French pronunciation signal, τ represents the signal acquisition characteristic expansion bandwidth, and φ represents the frequency shift characteristic quantity of the pronunciation signal [7]. When receiving linear frequency modulation signals, the separation results of spoken French pronunciation features are as follows:

$$y(t) = \iint_{a,b} \rho(a, b) \frac{1}{\sqrt{|\partial|}} f\left(\frac{t-b}{\partial}\right), \quad (3)$$

where $f(t)$ represents the instantaneous frequency estimation of the received spoken French pronunciation signal, $\rho(a, b)$ represents the delay component of the broadband signal incident to the array element, ∂ represents the higher-order statistical characteristic information of the signal, and b represents the frequency shift distribution. At the new cluster head node, the characteristic components of the spoken French pronunciation information obtained are

$$\begin{aligned} X_p(u) &= F^p x(t) \\ &= F^\alpha [x(t)] \\ &= \int_{-\infty}^{+\infty} K_p(t, u) x(t) dt, \end{aligned} \quad (4)$$

where p represents the order of the optimal receiving polarization vector, which can be any real number, and the phase of speech detection is $\alpha = (p\pi/2)$. When $\alpha = (\pi/2)$ meets the requirements, it rotates to the frequency axis, so as to realize the statistical information modeling of the French-spoken pronunciation signal.

2.1.2. Analyze the Spectral Features of Spoken French Pronunciation. After the multisensor fusion tracking and recognition method is used to collect the spoken French signals, the features of the signals are extracted with the

time-frequency feature decomposition method. Assuming that the length of spoken French pronunciation signal is l , the spectral characteristic quantity of spoken French pronunciation signal is

$$f = \frac{X_p(u) \times \beta}{l}, \quad (5)$$

where β represents the block sparse feature parameter of spoken French speech signal [8]. For the given broadband high-resolution signal $x(n)$ and scale d , the method of expectation and variance joint estimation is adopted to dynamically detect the spoken French pronunciation signal. The variance of signal $x(n)$ at scale d is denoted by $\bar{E}(n_i, d)$, and its maximum power spectrum characteristic quantity is denoted by $\max\{E(n_i, d)\}$. Then the ambiguity identification parameters of spoken French pronunciation signal are as follows:

$$z_{\max} = \max\{\max_{x=m_1}^{m_2}\{z_{xy}\} - \min_{x=m_1}^{m_2}\{z_{xy}\}\}. \quad (6)$$

After sampling and filtering $x(t)$, the discrete characteristic component $x(n)$ of the signal is obtained. Then, the width of the integration window function $h(t)$ of the French spoken pronunciation signal is set as $T = (2d + 1)T_s$, and the signal is windowed to make the French spoken pronunciation signal uniformly distributed on the spectrum distribution interval $[m_0 - (\Delta m/2), m_0 + (\Delta m/2)]$. Thus, the spectral characteristic quantity of the French spoken pronunciation signal can be extracted as follows:

$$r(t) = \frac{h(t)(g(t) + x(n))}{T}, \quad (7)$$

where $g(t)$ represents the probability density function. On this basis, multistage filtering is used to detect sparsity of spoken French pronunciation signals [9]. The structure of the detection model is shown in Figure 1. In this model, the spectral features of spoken French signals can be analyzed according to the results of spectral feature separation.

2.2. Capture of Spoken French Pronunciation Errors

2.2.1. Feature Screening of Spoken French Pronunciation Signals for Classification and Recognition.

Consider the input spoken French pronunciation signal is a single frequency signal $\cos 2\pi f_0 t$, where f_0 represents the initial frequency of the signal. Set the French spoken pronunciation signal detected by the first element as the benchmark component, and, on the basis of constructing the signal feature screening model, adopt the time-frequency feature transformation method to complete the feature screening process [10]. Then the characteristic quantity of the sparse characteristic of the m -th block is

$$s_m(t) = \cos[2\pi f_0 [t + \tau_m(\theta)]]. \quad (8)$$

Then, the target source signal detection method is adopted to monitor the characteristics of spoken French speech signals, and the distribution of spoken French pronunciation errors is as follows:

$$c(t) = \left(\sum_{m=1}^M u_m \right) \cos(2\pi f_0 t) - \left(\sum_{m=1}^M v_m \right) \sin(2\pi f_0 t), \quad (9)$$

where

$$\begin{aligned} u_m &= \cos[2\pi f_0 \tau_m(\theta)], \\ v_m &= \sin[2\pi f_0 \tau_m(\theta)]. \end{aligned} \quad (10)$$

On this basis, beamforming method is adopted to process the feature focusing of spoken French pronunciation signals. The appropriate output results are as follows:

$$y(t) = \exp\{[F(t - t_a)\ln(t - t_a) + f_{e1}t - F \ln Dt + f_{e2}t]\}, \quad (11)$$

where f_{e1} represents the beam-domain cutoff frequency and f_{e2} represents the harmonic cutoff frequency. Statistical feature analysis was used to separate spoken French pronunciation features [11], and the spectrum of spoken French pronunciation signals was obtained as follows:

$$\begin{aligned} Y_p(u) &= F^a[y(t)] \\ &= F^a[s(t) + n(t)] \\ &= F^a[s(t)] + F^a[n(t)]. \end{aligned} \quad (12)$$

When the prior probability of the signal meets the convergence condition, calculate the time width of the spoken French speech signal:

$$T = \frac{4\pi}{Y_p(u)} \int_{-\infty}^{+\infty} (t - t_m)^2 |x(t)|^2 dt. \quad (13)$$

The frequency domain characteristics of spoken French speech signal are described as follows:

$$B = \frac{4\pi}{Y_p(u)} \int_{-\infty}^{+\infty} (v - v_m)^2 |X(v)|^2 dv. \quad (14)$$

On this basis, Bayesian formula is used to screen the features of spoken French pronunciation signals, and the output results of the screened feature categories are as follows:

$$s'(t) = \frac{\sqrt{B}u[s(t - \tau_0)]}{T}. \quad (15)$$

2.2.2. Catch Speech Errors in French Spoken Pronunciation.

After establishing the statistical feature analysis model of French spoken pronunciation signals, this study uses deep neural network classifier and Bayesian formula to complete the screening and classification of signal features and realizes the capture and recognition of category features according to the result of feature classification. In order to prevent overfitting from occurring in this process, fuzzy state separation method is adopted to process L block characteristic quantities [12], and the characteristic parameters obtained are determined by the following formula:

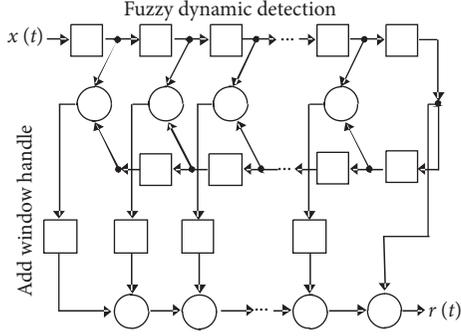


FIGURE 1: Spectral feature detection model of spoken French pronunciation signal.

$$\begin{cases} a_1(t) = -2m(t)\cos(\theta(t)), \\ a_2(t) = m^2(t). \end{cases} \quad (16)$$

Then, abnormal features of spoken French pronunciation are screened, and the output of screening results is

$$\begin{cases} \chi(t) = \sqrt{s^2(t) + x^2(t)}, \\ \phi(t) = \arctan\left\{\frac{x(t)}{s(t)}\right\}, \end{cases} \quad (17)$$

where $\chi(t)$ represents the instantaneous amplitude of the complex signal $z(t)$ of the spoken French pronunciation signal and $\phi(t)$ represents the fuzzy state component of the abnormal features of spoken French pronunciation. Then, the following detection thresholds are used to detect the features of spoken French pronunciation errors, and the upper and lower limits of the features are as follows:

$$\begin{aligned} x_{\min,j} &= \max\{x_{\min,j}\chi(t) - \phi(t)(x_{\max,j} - x_{\min,j})\}, \\ x_{\max,j} &= \min\{x_{\max,j}\chi(t) + \phi(t)(x_{\max,j} - x_{\min,j})\}. \end{aligned} \quad (18)$$

Combined with prior probability and likelihood function estimation method, the detection output of French spoken pronunciation error features is as follows:

$$E = \gamma \sum_{j=0}^{\infty} h(j)h^3(j + \tau), \quad (19)$$

where γ represents the characteristic component of French spoken pronunciation errors, which can be captured by the spectral feature detection method.

3. Design an Oral French Error Correction Algorithm Based on Machine Learning

On the basis of capturing spoken French errors, this study designs a specific algorithm to correct spoken French errors.

3.1. Machine Learning Network Architecture. Machine learning is an interdisciplinary subject involving probability theory, statistics, and other disciplines. This algorithm focuses on how computers simulate or realize human learning

behavior, so as to obtain new knowledge or skills, reorganize the existing knowledge structure, and continuously improve its performance. Typical machine learning algorithms include Decision Trees, Naive Bayesian classification, and Ordinary Least Squares Regression.

Based on the design of machine learning network model, this study adjusts the weight parameters of hidden layer and visible layer to generate target data of deep network. The machine learning network architecture is shown in Figure 2.

According to this figure, we can see that this network includes hidden units, hidden layer, visual layer, and output signal. In essence, this is a neural network model.

In Figure 2, multilayer Boltzmann sets form a machine learning network. Neural network divides neurons into dominant neurons and recessive neurons. There are associative memory units between upper and lower neurons. This connection has no direction and can be used to realize associative memory function.

3.2. Machine Learning Network Training. Machine learning network training mainly includes two steps: unsupervised training and tuning:

Step 1. Unsupervised training: The specific task is to train the restricted Boltzmann machine in layers, and each layer of output can be used as the upper input layer. When the upper neurons are labeled, combined labeling training is required [13].

Step 2. Tuning: Tuning takes place in two phases: the cognitive phase and the production phase. In the cognitive stage, feature information is input based on machine learning model, structure is output layer by layer, and then weight parameters are generated layer by layer based on gradient descent method. The basic state information is composed of the top label annotation and the downward weight information in the generation stage, and the upward weight information is also modified in this stage.

In the process of feature extraction of machine learning networks, input signals need vector representation and training. The highest level of associative memory unit divides tasks according to the clues provided by subordinates [7]. Through the feedforward neural network based on labeled data, the machine learning network can accurately adjust the classification performance and perform recognition in the last layer of training. Compared with using forward neural network directly, this method has higher efficiency, because machine learning network only needs to modify the weight parameters to carry out local training, so the training speed is fast and the convergence time is short.

3.3. Algorithm Running Structure. In the machine learning network architecture designed above, a specific French oral error correction algorithm is constructed.

The spoken French error correction algorithm is designed in the Android-based Linux platform, which has a wide open range and does not cost any money.

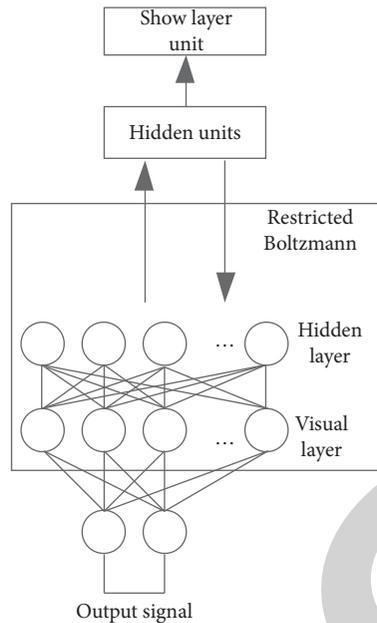


FIGURE 2: Machine learning network architecture.

The operation structure of French oral error correction algorithm is mainly divided into four parts, namely, Linux kernel, runtime, application framework, and application program. The specific structure is shown in Figure 3.

3.3.1. Part One: The Linux Kernel. The core service of the spoken French error correction algorithm is provided by the Engineering Computing GNU/Linux kernel. Kernel is located in the center of the algorithm running structure. It encapsulates the bottom layer and provides convenient interface for the upper layer software in real time. It is the core part of the algorithm running structure.

3.3.2. Part Two: Runtime. It is composed of two parts: system library and runtime library. The system library contains some C/C++ standard library files that can be used by any component of the Android platform, which provide convenience for the system platform developers. The runtime is mainly divided into two parts, namely, the core library and the Dalvik virtual organization. The core library is responsible for providing functions required by Java programming, while Dalvik VM is responsible for storing data. As a virtual device, the intermediate code it performs is completely different from the Java programming mechanism of the core library. It was assumed to run the device with the minimum storage resources and support multiple virtual machines to work at the same time when it was written and developed [14].

3.3.3. Part Three: Application Framework. The application framework is the backbone of the algorithm running structure, which shows the design concept of the algorithm running structure. The application framework layer is the theoretical basis for Android research and development, and

developers interact with the last layer of Android through the framework. Structure design simplifies program development but follows the framework development philosophy. This part consists of components, Windows, information, and communication management services. All services are stored in the core part of the algorithm running structure. In the running process, each of the services has its own thread and they can transmit data to each other.

3.3.4. Part Four: Applications. Java technology is used to write it in the virtual machine running program. The workflow is as follows: compile the Java code and related resource files, generate a .Apk package, and set the contacts, main screen, and browser programs in Android and so forth. Application developers can pass through the interface functions of the application framework layer to provide convenience for developers. Therefore, the openness of Android makes the algorithm running structure have more space to use.

3.4. Algorithm Program. The flow of the spoken French error correction algorithm application is shown in Figure 4.

The spoken French error correction algorithm application uses Java software with powerful authoring language capabilities, as shown in Figure 2. As with Java SE, the spoken French error correction algorithm program needs to write the source French speech files into computer-recognized bytecode files, that is, class files, and convert the entire bytecode files into DEX files according to DX software. To speed up the generation of application packages, the algorithm comes with a package, namely, AAPT software. Through AAPT, multiple French voice resource files in the program can be packaged to form APK file, which can be called application installation package APK. This installation package can be unpacked and

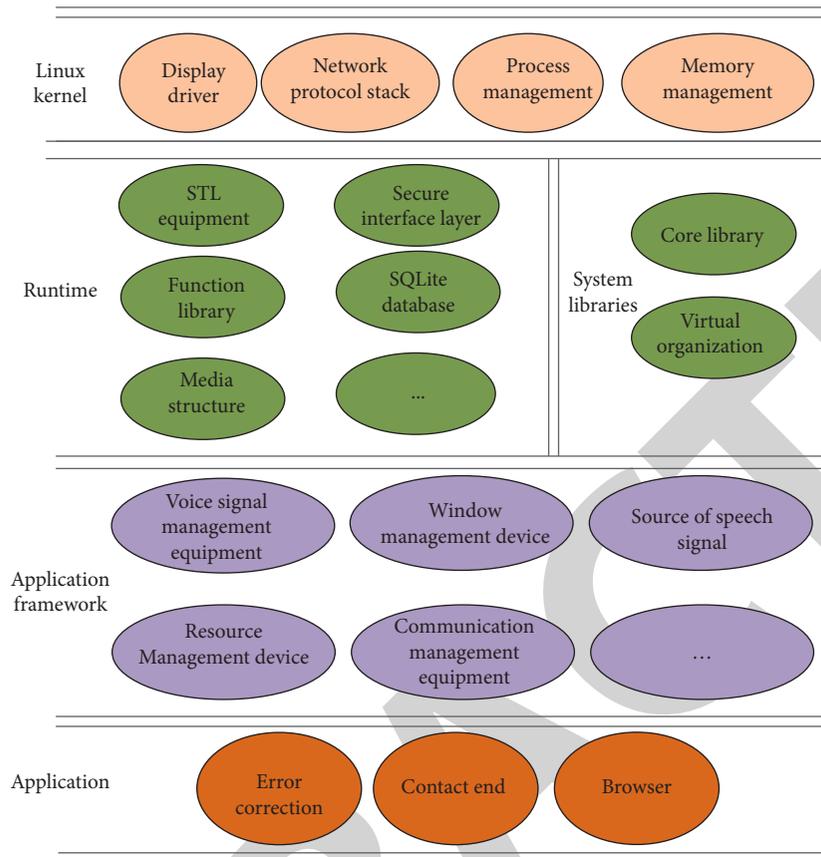


FIGURE 3: Schematic diagram of algorithm running structure.

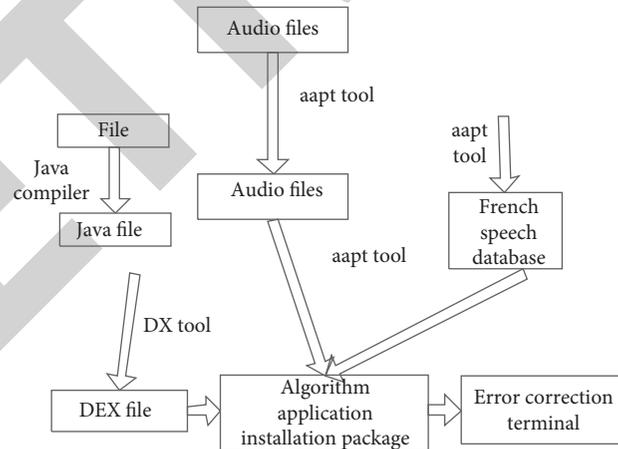


FIGURE 4: Application flow of the French spoken error correction algorithm.

installed on your phone to generate an executable program. The Dalvik virtual machine can retrieve instructions and data and make the application work.

After the APK file is installed, the algorithm before the program runs will optimize the DEX file in the program, generate the DEY file, and save it in the cache. The virtual machine can directly execute the optimized DEY file to make the program work properly. Optimized files remain in the cache until APK files are changed.

3.5. Algorithm Development Environment. The application development environment for oral French error correction algorithm is Eclipse, which can be a cross-platform collection of software. Eclipse originated from the development of Java programming language and began to support the integration of various plug-ins. Because its plug-in extension ability is good, compared with other software programs, its flexibility is extremely strong. The algorithm development environment is shown in Figure 5.

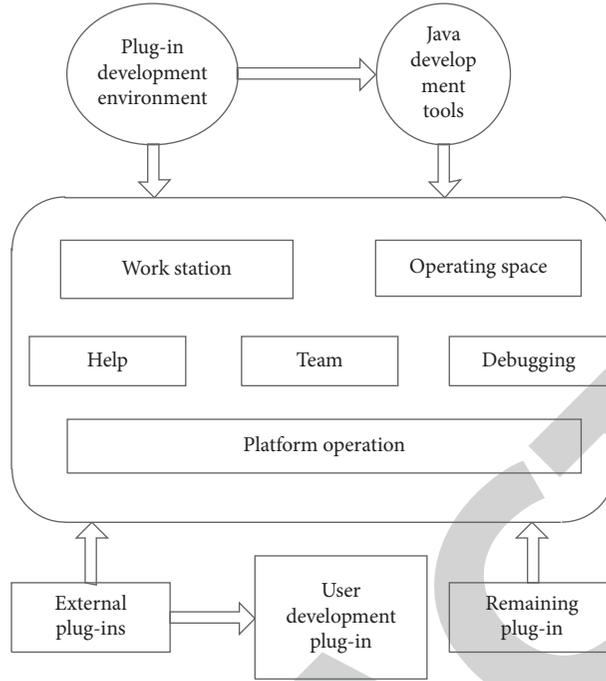


FIGURE 5: Schematic diagram of algorithm development environment.

Figure 5 shows that the algorithm development environment includes operating platform, Java development tools, and various plug-in development environments. Among them, the operating platform is the main part of the algorithm; Java development tools provide the ability to view, write, control, and run Java coded plug-ins for algorithms. Plug-in development environment provides tools for algorithm plug-in development on the basis of Eclipse platform and Java development tools.

3.6. Correct Spoken French Errors

3.6.1. Building a Corpus. From the perspective of spoken French pronunciation, corpus is the source of speech and knowledge base needed for speech recognition search. From the perspective of performance evaluation, the richness of corpus directly affects the error correction effect. Therefore, the corpus of this study was selected by Chinese with professional spoken French. Set the oral reading time for 20 minutes, read 800 sentences, the total number of people is 100, the sentences contain 1600 common French words, and staff is fixed to mark the time of each sentence recorded word level.

3.6.2. Oral Pronunciation Training Model. According to the characteristics of French pronunciation, HMM model and Baum-Welch method were used for training, and the process was as follows: initial model $\lambda = (A, B, \pi)$; by monitoring training O , a new parameter $\bar{\lambda} = (\bar{A}, \bar{B}, \bar{\pi})$ is obtained; namely, repeat the previous step and optimize the model parameters until $P(O|\bar{\lambda})$ converges, where A represents the HMM and time-independent transfer function equation, B

represents the monitoring value of a given state in HMM, and π represents the initial state space value in HMM.

3.6.3. Extract the Features of French Spoken Mispronunciation. According to the structural features of the proposed algorithm, Meier frequency cepstrum coefficient is used to extract the structural features of the user's oral French pronunciation training. Meier frequency cepstrum coefficient refers to the real cepstrum of speech signal obtained after Fourier transform. The cepstrum coefficient of Meier frequency is very different from the general cepstrum, which makes the result basically the same as that of human auditory perception system according to the nonlinear Mel frequency mode.

Before calculating the Mel frequency coefficient, it is necessary to set up multiple band-pass filter devices in the French pronunciation spectrum in advance, and the center frequency is evenly distributed in the Mel frequency. Each filter device can overlap each other, and each filter filters all devices in frequency. Perform a weighted summation on the amplitude of the generated signal. The conversion formula of frequency and Mel frequency in this process is

$$\text{Mel} = 25951g\left(1 + \frac{f}{100}\right). \quad (20)$$

3.6.4. Identify Spoken Errors. Misrecognized pronunciation feature extraction requires a process, n set indicates that the feature extraction of French oral English pronunciation frequency vibration of the extreme fluctuating P said the trough of the vibration frequency of extreme value, D said the correct audio frequency cycle, N meson transmission

frequency, amplitude of the λ said oral English pronunciation standard amplitude, ρ , said frequency parameters, Feature extraction vibration audio E of spoken pronunciation is:

$$E = \sum_{\rho=1}^n (N-1)^{-1} P(N-1) \frac{B}{\lambda(D+1)}. \quad (21)$$

The obtained audio is standardized and filled; namely,

$$\eta_E = \frac{1}{n'(n'-1)} \sum_{i=1}^1 \frac{1}{T \cdot d_{ij}}, \quad (22)$$

where η_E represents the discrete value in audio filling, n' represents the weight function difference between the maximum and minimum values of filling, T represents the hop number between two different audio nodes, and d_{ij} represents the nearest distance between node i and node j . After filling processing, the data can be made into attribute planning, and the following results can be obtained:

$$U_i = \frac{\sum_{i=j=1}^i \omega \eta_E}{i(i-1)} + \sum_{i=1}^i E, \quad (23)$$

where μ is the audio indicator and i indicates the correct audio specific period parameter. Its attributes have been labeled and error elimination identification operation has been performed, so the following formula can be obtained:

$$\vec{V} = RU_i(A^T S^{-1}) = \begin{pmatrix} M_{11} & \cdots & M_{1n} \\ \vdots & \ddots & \vdots \\ M_{n1} & \cdots & M_{nm} \end{pmatrix}, \quad n = 1, 2, \dots, N-1, \quad (24)$$

where A^T represents the jitter of audio, which is a parameter to measure spoken notes; S^{-1} represents the value of audio attribute set; M represents the corresponding audio matching factor; R represents the elevation weight contained in advanced audio; V represents the limit value identified by audio error elimination.

3.6.5. Error Correction. The results of formula (24) are input into the feedback control module of the algorithm for correction. The feedback control module needs to calculate the feedback path in advance; namely,

$$T(\omega_i, \omega_j) = \frac{\vec{V} \times \left(-\sum_{j=1}^i P(N-1)^{-1} \right)}{P(N-1)^{-1}}, \quad (25)$$

where ω_i represents the cohesion operator of feedback audio; ω_j represents the numerical parameter of scale communication; P indicates the encoding of audio type parameters. The feedback path and related parameters can be obtained by using this formula. If M represents the audio failure value of pronunciation, the audio failure state is expressed in the way of sequence. This method can better compare audio, and the process is as follows:

$$M = (dT - P^{-1}) \bmod 180, \quad (26)$$

where d represents the weight of the control audio path. On this basis, the comparison results are digitally arranged by sorting method to effectively improve the correction accuracy. The formula of the process comparison is

$$H_{MT} = \frac{2 \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} (\vartheta - M^{-1} T^{-1})^2}{n(n-1)}, \quad (27)$$

where ϑ represents the best parameter of audio measurement and n represents the correct rate of audio correction within a specific range. If the correct rate of pronunciation is C_i and the realistic pronunciation is C_q , the function relation can be obtained as follows:

$$C_i = \frac{1}{l} \sum_{i \in l} \frac{C_q}{\sqrt{(t_l - t_i)^2 + 1}}, \quad (28)$$

where t represents the feedback factor and l represents the extreme frequency. Then, the robust algorithm can directly show the use of the system and control the upper and lower order of audio, so that the algorithm can work normally. The calculation formula of this process is as follows:

$$\omega_{ij}(k+1) = \frac{\omega_{ij}(k) + \eta(d_j - y_j)y_j(1 - y_j)}{f(1 - f(u_{ij}))x_{ij}}, \quad (29)$$

where η represents the learning coefficient; k represents the number of iterations; ω_{ij} represents the weight of audio collection; d_j is the distance between audio nodes; y_j represents the audio output value; u_{ij} is the audio collection speed; x_{ij} represents the measured audio node. By controlling the upper and lower order, the advanced error of pronunciation correction data can be effectively reduced and the correction effect of spoken French errors can be improved.

4. Experiment and Analysis

In order to verify the practical application performance of the machine learning-based oral French error correction algorithm designed in this study, the following experimental verification process is designed.

The experiment was completed in Matlab 7 simulation platform. The number of sampling nodes for spoken French pronunciation signal is 4000, the resolution of feature extraction is 220 kHz, the length of the output spoken French pronunciation signal is 1800, the number of sources to be measured is 20, and the SNR is 15 dB–25 dB.

According to the above simulation parameter settings, the simulation analysis of capturing errors in spoken French pronunciation was carried out, and the signal model of spoken French pronunciation was obtained, as shown in Figure 6.

Taking the French spoken pronunciation signal shown in Figure 6 as the research object, the French spoken errors are captured.

In order to form an experimental comparison, the automatic pronunciation calibration algorithm based on single target tracking designed in [5] was compared with the

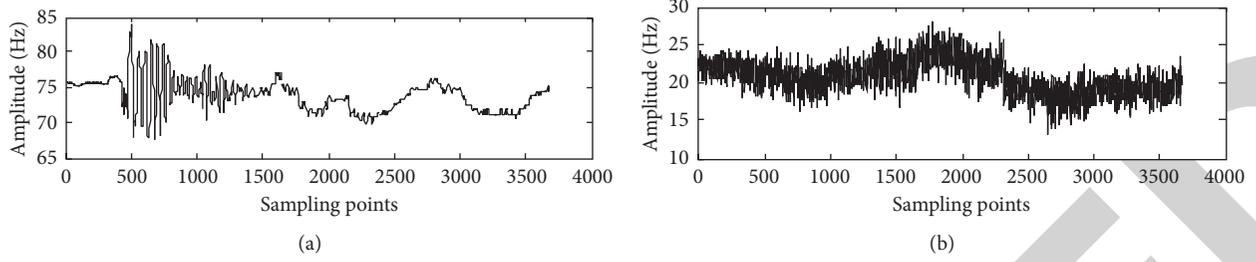


FIGURE 6: French spoken pronunciation signal collection results. (a) Pure French speech signal, (b) Noise signal.

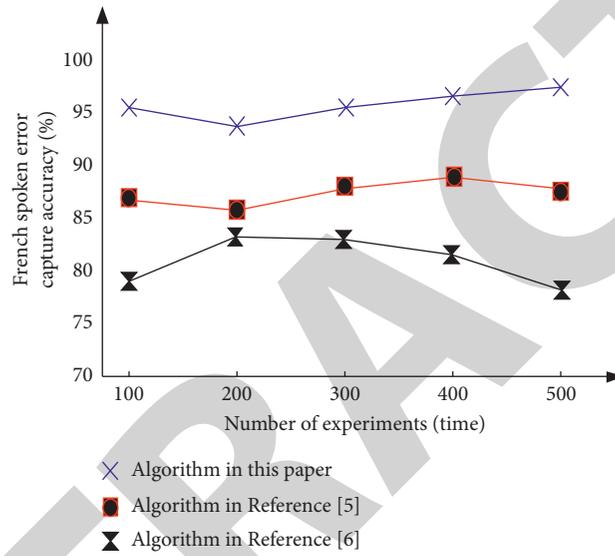


FIGURE 7: Comparison of accuracy of different algorithms for capturing spoken French errors.

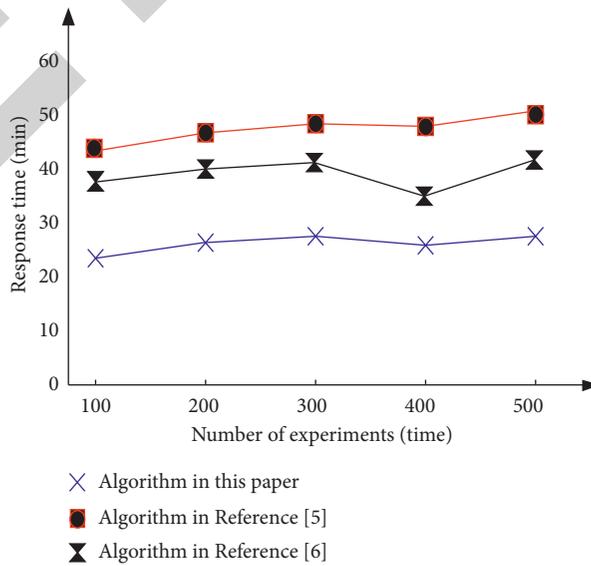


FIGURE 8: Comparison diagram of response time of different algorithms.

intelligent detection and correction algorithm for spoken pronunciation errors designed in [6]. The accuracy of capturing spoken French errors and the response time of the algorithm were used as indicators to complete performance verification together with the algorithm in this paper.

First, the accuracy of capturing spoken French errors of different algorithms is verified, and the results are shown in Figure 7.

As shown in Figure 7, when the number of experiments is 100, the accuracy of the algorithm presented in this paper is 2.8%, 6.1%, and 4.4%, respectively. When the number of experiments is 300, the accuracy of the proposed algorithm is 2.4%, 7.6%, and 4.9%, respectively, of the algorithm in [5] and that in [6]. When the number of experiments is 500, the accuracy of the algorithm in this paper is 2.7%, 7.3%, and 5.8%, respectively, of the algorithm in [5]. This shows that the accuracy of the proposed algorithm is higher and its effectiveness is stronger.

On this basis, the response time of different algorithms is verified, and the results are shown in Figure 8.

As shown in Figure 8, when the number of experiments is 100, the response time of the algorithm in this paper is 22 min, that of the algorithm in [5] is 44 min, and that of the algorithm in [6] is 39 min. When the number of experiments is 300, the response time of the algorithm in this paper is 26 min, the response time of the algorithm in [5] is 47 min, and the response time of the algorithm in [6] is 40 min. When the number of experiments is 500, the response time of the algorithm in this paper is 28 min, the response time of the algorithm in [5] is 50 min, and the response time of the algorithm in [6] is 40 min. This shows that the response time of the algorithm in this paper is shorter, which proves its timeliness is stronger.

5. Conclusion

In order to solve the problems of low error capture accuracy and long response time of traditional spoken French error correction algorithms, this paper proposed a French spoken error correction algorithm based on machine learning. Based on the construction of the French spoken pronunciation signal model, the algorithm analyzes the spectral features of French spoken pronunciation and then selects and classifies the features and captures the abnormal pronunciation signals. Based on this, the machine learning network architecture and the training process of the machine learning network are designed, and the operation structure of the algorithm, the algorithm program, the algorithm development environment, and the identification of oral errors are designed to complete the correction of oral French errors. On the basis of this, the experiment proves that the proposed algorithm has high efficiency and timeliness. Although the algorithm proposed in this paper has good performance, it needs to be further improved to adapt to different scenarios. In addition, the complexity of the algorithm needs to be further reduced.

Data Availability

The data used to support the findings of this study are available upon request to the author.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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