Tutoring Analysis of Foreign Language Learning Anxiety Psychology Based on Intelligent CAD

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Abstract: To improve the analysis effect of foreign language learning anxiety, this paper combines big data technology and intelligent psychological and emotional ECG signal recognition technology and analyzes the anxiety and mental health of foreign language learners through Intelligent CAD technology. Moreover, this paper analyzes the principle of the wavelet threshold denoising algorithm, determines the wavelet function suitable for ECG signal analysis, and combines morphology and wavelet algorithm. In addition, this paper conducts experimental teaching of foreign language learning volunteers through practical experiments and analyzes the actual situation of foreign language teaching. Finally, the experimenter's foreign language learning data is collected through the simulation platform, and the experimental research shows that the method proposed in this paper has a certain effect.

Keywords: Intelligent CAD; Foreign Language Learning; Anxiety Psychology; Tutoring Analysis
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1 INTRODUCTION

Many of the existing studies on foreign language learning anxiety are conducted by teachers or other personnel in foreign language colleges. Many of their studies focus on the discussion of classroom teaching, mainly trying to alleviate students' classroom anxiety levels by changing teachers' teaching response methods and classroom organization forms and improving teaching content [1]. It can be said that the time and space of these studies are largely in the classroom and classroom. In fact, in college, students' autonomous learning is very important. College students have a lot of time at their disposal, and foreign language learning is largely done outside the classroom [2]. Literature [3] mainly studies students' foreign language anxiety from the aspects of effort and learning motivation. In terms of effort, it is mainly considered according to students' usual study time, study frequency, and learning situation before and after class; the classification of motivation is mainly from achievement motivation theory, including the onedimensional classification method of motivation of achievement motivation theory and self-worth A two-dimensional taxonomy of theoretical motivations [4].

Generally speaking, motivation can be divided into two types: extrinsic motivation and intrinsic motivation. Extrinsic motivation mainly includes need motivation, expectation motivation, etc. [5]. On the one hand, extrinsic motivation can play a certain role in promoting learning, but on the other hand, it often makes the learning effect short-term, which is not conducive to enthusiasm for learning and lasting intrinsic motivation [6]. Intrinsic motivation mainly comes from basic interests and self-expectations. In English learning activities, students with intrinsic motivation can often get a sense of achievement and pleasure. For them, learning itself is a kind of interest and happiness [7]. Intrinsic motivation can effectively enhance students' endogenous motivation to learn English and greatly reduce their anxiety in English learning. It is a more positive and fundamental benign learning motivation [8].

Practice has proved that learners' difficulties, confusion, and learning anxiety in English learning can be effectively reduced through good methods. For example, in English listening teaching, there are several effective cognitive methods: one is the imaginative method, that is, combined with the daily life learning experience, the imagination is fully utilized according to the listening target materials; the other is the prediction method, that is, the effective vocabulary and information captured Quickly predict and grasp the following [9]; the third is the inference method, that is, the accumulation of extension and judgment results based on relevant information; the fourth is the association idea, that is, the full splicing of listening information and existing knowledge can be used quickly. These methods are all powerful weapons to effectively reduce psychological pressure, strengthen psychological counseling and regulation, relieve learning anxiety, and improve the effect of English learning [10].

Its development tends to be a spiral upward trend, or a vicious circle, or a virtuous circle. Negative self-focus naturally has a negative impact on learning. Quite a lot of students in higher vocational colleges do not trust their English ability, which is a reflection of their low self-evaluation. It is a combination of communicative fear and negative evaluation fear [11].

2 OBJECTIVES

These activities related to speaking or communication are the manifestations of foreign language learning anxiety affecting students' communication ability. Moreover, learners' anxiety, learning motivation, self-confidence, and other non-intellectual factors play a great role in learners' foreign language learning. Therefore, teachers should actively explore and flexibly use various teaching methods to change the education mode of compulsory indoctrination and restraint. This paper combines big data technology and intelligent psychological and emotional ECG signal recognition technology to analyze the anxiety psychology of foreign language learners so as to improve the psychological improvement effect of foreign language learners and improve the efficiency of foreign language learning.

3 METHODOLOGY

This paper analyzes the psychological state of anxiety of foreign language learners by measuring the ECG signal of foreign language learners, and firstly studies the measurement algorithm and signal processing of anxiety psychological state.

4 RESEARCH ON PREPROCESSING TECHNOLOGY OF ECG SIGNAL

Due to the influence of factors such as instruments and the surrounding environment, the following three main interferences often exist in the collected ECG signals. They will be introduced separately below:

(1) Power frequency interference

Figure 1: ECG waveform with power frequency interference signal.

Power frequency interference mainly includes 50Hz power line interference and high-order harmonic interference, as shown in Figure 1. Due to the existence of the distributed capacitance of the human body, the human body has an antenna effect, and in general, there are always long lead wires exposed and common in the ECG signal. Depending on the situation. Due to the change in the grid load, the center frequency of the power frequency interference is not exactly 50Hz, but there are random fluctuations in a certain range, and the amplitude of the interference is also changing. This fluctuation is essentially a random process, and it is difficult to eliminate the disturbance completely. In addition, the electromagnetic interference of the surrounding environment is also an aspect of noise in ECG measurement. Although it is filtered by a notch circuit in hardware, due to the existence of line asymmetry, there is still 50Hz power frequency interference mixed into the ECG signal, which needs to be processed by software.

(2) EMG interference

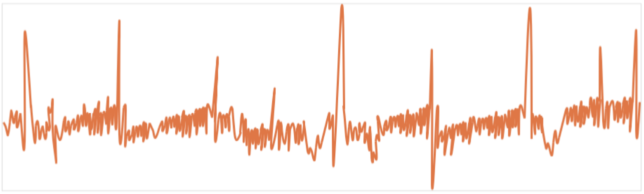


Figure 2: ECG waveform containing EMG interference signal.

ECG waveform containing EMG interference signal is shown in Figure 2.

(3) Baseline drift

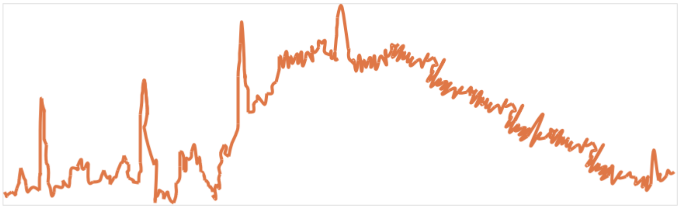


Figure 3: ECG waveform with baseline drift signal.

Among the various noises of the ECG signal, it has the greatest impact on the signal, as shown in Figure 3.

Wavelet threshold denoising algorithm

Set the observed signal to be:

$$y(n) = f(n) + z(n), n = 1, 2, \dots N \tag{1}$$

In the formula, f(n) is the useful signal, y(n) is the noisy signal, and z(n) is the Gaussian white sound that obeys the $0, \sigma^2$ distribution.

In practical applications, the size of the threshold should be determined first. There are four commonly used threshold forms at present. In the following introduction, it is assumed that the signal model is as shown in the formula, and the signal length is N.

(1) Fixed threshold

A threshold is proposed to fix the situation:

$$\lambda = \sigma\sqrt{2\ln N} \tag{2}$$

(2) Stein unbiased likelihood estimation threshold

The threshold can be expressed as:

$$\lambda_k = \sqrt{z(k)}, k = 0,1,\ldots,N-1 \tag{3}$$

$$\mathrm{Risk}(k) = \frac{1}{N}\left[N - 2k + (N-k)z(N-k) + \sum_{i=0}^{k} z(i)\right] \tag{4}$$

The closed value of Stein's unbiased likelihood estimation is defined as:

$$\lambda = \sigma\sqrt{z\ \ k_{\min}} \tag{5}$$

(3) Heuristic threshold

The heuristic threshold is a combination of the first two thresholds and is the optimal predictor threshold selection, namely:

$$\lambda = \begin{cases} \sigma\sqrt{2\ln N},\ \mathrm{eta}\ <\ \mathrm{crit} \\ \min\ \sigma\sqrt{2\ln N}, \sigma\sqrt{z\ \ k_{\min}}\ ,\ \mathrm{eta}\ \geq \mathrm{crit} \end{cases} \tag{6}$$

Among them,

$$\mathrm{eta}\ = \frac{1}{N}\left[\sum_{i=0}^{N-1} (y(i))^2\right],\ \mathrm{crit}\ = \sqrt{\frac{1}{N}\left(\frac{\ln N}{\ln 2}\right)^3} \tag{7}$$

(4) Maximum and minimum criterion threshold

This is the threshold selected to minimize the estimated maximum risk using the minimax principle. The threshold selection algorithm is:

$$\lambda = \begin{cases} \sigma\left[0.3936 + 0.1829\left(\frac{\ln N}{\ln 2}\right)\right], N > 32 \\ 0, N \leq 32 \end{cases} \tag{8}$$

It should be noted that the standard deviation σ of the noise is used in the calculation of the above four thresholds. In practical applications, σ is often unknown and is usually estimated by the first layer of wavelet coefficients, namely:

$$\hat{\sigma} = \frac{\mathrm{median}\ \left|d_{1,k}\right|}{0.6745} \tag{9}$$

However, the wavelet coefficients between different scales have a "persistent" characteristic. Then, it is unreasonable to use a threshold to process the wavelet coefficients at all scales, and good results are often not obtained. Therefore, in practical applications,

$$\hat{\sigma} = \frac{\text{median } \left|d_{j,k}\right|}{0.6745} \tag{10}$$

In this way, corresponding to different scales j, the corresponding threshold λ_j is used to process the wavelet coefficients.

In this paper, a thresholding method for estimating the wavelet coefficients of a signal is proposed. The basic idea is to combine the wavelet components generated by the noise on each scale according to the characteristics of different spatial distributions of the wavelet coefficients of the noise and the signal on each scale. In particular, it removes or greatly attenuates the noise wavelet components on the scales where the noise components are dominant and then reconstructs the original signal using wavelet transform. Threshold-based wavelet coefficient estimation methods are often divided into two forms: hard thresholding and soft thresholding:

(1) Hard threshold function

The estimated wavelet coefficient $\hat{d}_{j,k}$ after the threshold is applied is:

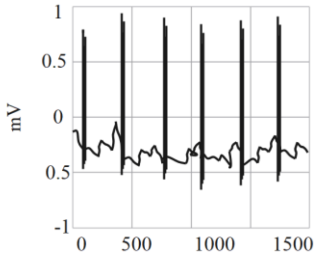
$$\hat{d}_{j,k} = \begin{cases} d_{j,k}, \left|d_{j,k}\right| \geq \lambda_j \\ 0, \left|d_{j,k}\right| < \lambda_j \end{cases} \tag{11}$$

(2) Soft threshold function

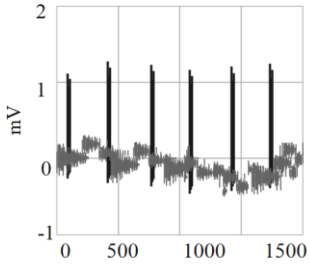
$$\hat{d}_{j,k} = \begin{cases} \operatorname{sgn}\ d_{j,k}\ \ \left|d_{j,k}\right| - \lambda_j\ \ , \left|d_{j,k}\right| \geq \lambda_j \\ 0, \left|d_{j,k}\right| < \lambda_j \end{cases} \tag{12}$$

5 SIMULATE SIGNAL PROCESSING

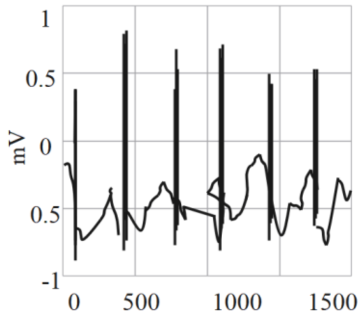
The simulation results of wavelet filter filtering out three kinds of interference signals are shown in Figure 4.



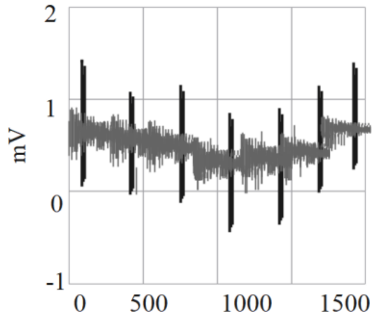
(a) The normal ECG signal of No. 100 before adding;



(b) The mixed ECG signal after adding power frequency interference



(c) The clean ECG signal after wavelet filtering



(d) The filtered interference signal

Figure 4: The filtering results of wavelet filter filtering out three kinds of interference signals.

Figure 4 is the effect diagram of wavelet filtering. Figure (a) is the normal ECG signal of No. 100 before adding; Figure (b) is the mixed ECG signal after adding power frequency interference, baseline drift, and EMG interference, and Figure (c) is the clean ECG signal after wavelet filtering; Figure (d) is the filtered interference signal. It can be seen that the wavelet filtering method can filter out several kinds of interference signals, especially for high-frequency interference signals such as EMG interference and power frequency interference, and the effect is excellent.

ECG signal denoising algorithm based on morphology and wavelet transform

When the size of the structuring element is too small, the closing operation cannot realize the connection of the fracture edges with large cracks, and the opening operation cannot realize the removal of large bulges and adhesions. When the size of the structuring element is too large, the targets will interfere with each other during the closing operation, resulting in excessive adhesion, and during the opening operation, false fractures will be caused. The calculation of the size of the structuring elements is an issue that needs to be explored.

Open operation: $A^{\circ}B=(A\Theta B)\oplus B$

Structural element B can be decomposed into the expansion of small structuring element C to small structuring element D, namely: $B=D\oplus C$.

$$\begin{aligned} A^{\circ}B &= (A\Theta(D\oplus C))\oplus(D\oplus C) \\ &= (A\Theta D\Theta C)\oplus D\oplus C \end{aligned} \tag{13}$$

At that time, it can be concluded that:

$$A^{\circ}B=(A\Theta S\Theta S)\oplus S\oplus S \tag{14}$$

If the 2-time corrosion expansion of the above formula is extended to K times, then:

$$A^{\circ}B=(A\Theta B)\oplus B=(A\Theta \underbrace{S\Theta S..S}_{k})\oplus \underbrace{S\oplus S....S}_{k} \tag{15}$$

Therefore, the opening operation is converted into continuously using the small structuring element S to corrode the original image, and then using the small structuring element S to dilate it in turn. The choice of the structuring element size is transformed into how to select the small structuring element size and the number of times of corrosion. In the same way, the choice of the size of the closed operation structuring element is transformed into how to choose the size of the small structuring element and the number of times of expansion.

There is the following calculation formula:

$$R=(r\quad-1)\times k+1 \tag{16}$$

Among them, R is the size of the structuring element, r is the size of the small structuring element, and k is the number of expansion or corrosion.

Mathematical morphology provides a very effective nonlinear signal processing method, which can be used for ECG signal filtering. It can keep the necessary ECG geometric information unchanged while filtering out noise.

The flow chart of the mathematical morphology filter algorithm is shown in Figure 5.

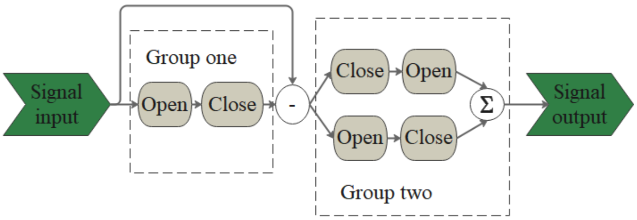
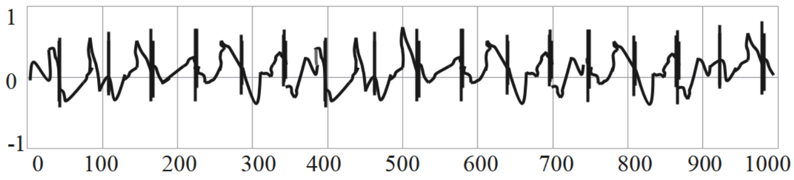
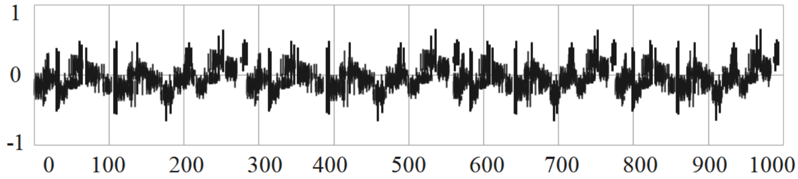


Figure 5: Flowchart of the mathematical morphology filter algorithm.

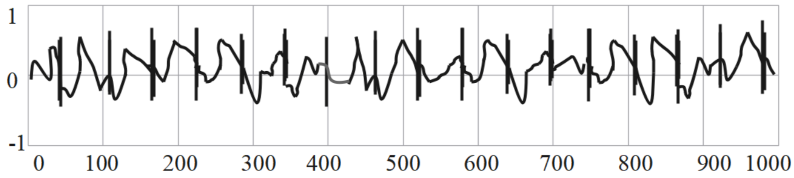
In this paper, the linear structural element is selected, and the width of the structural element is selected according to the characteristics of ECG signal waveform and clinical experience. Generally, the characteristic waveform in an ECG signal is the widest T wave sequence, and when the sampling frequency is 360 Hz (the signal sampling frequency of the MIT-BIH ECG database), its typical width is 50 to 70 sampling points. Therefore, the width of the open and closed operation structural elements when filtering out the baseline drift is 72, and the width of the structural elements for filtering out high-frequency noise is 3. The units of the above values are the number of sampling points.



(a) Clean original signal

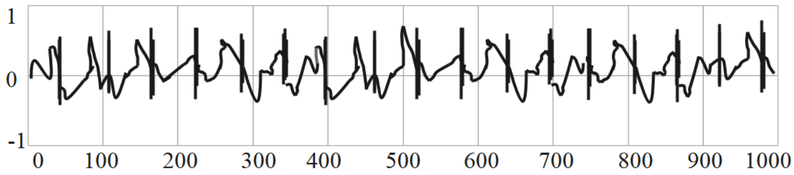


(b) Mixed signal after adding baseline drift

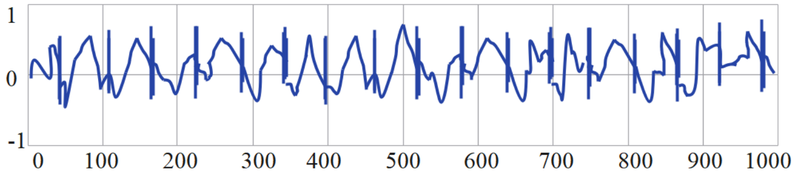


(c) Filtered clean signal

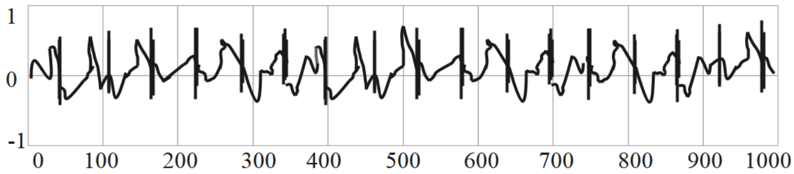
Figure 6: Processing results of morphological filter on high-frequency interference in ECG.



(a) Clean original signal



(b) Mixed-signal after adding baseline drift



(c) Filtered clean signal

Figure 7: Processing results of morphological filter for baseline drift in ECG.

Using the above morphological filter, this paper conducts morphological filtering experiments on part of the data in the MIT-BIH standard ECG database. Figure 6 shows the processing effect of adding power frequency interference and EMG interference to the ECG signal. Figure 7 shows the processing effect after adding baseline drift to the ECG signal. As can be seen from Figure 6, the morphological filter produces a small fluctuation that is approximately rectangular or trapezoidal when dealing with high-frequency interference, which makes the ECG signal distorted in the range of high-frequency small signals. Compared with the wavelet filter in Fig. 5, the result of removing high-frequency interference of ECG signal, the morphological filter is inferior.

In view of the shortcomings and deficiencies of traditional filters in filtering ECG signals, this paper proposes a hybrid algorithm based on morphology and wavelet threshold. Morphological filtering has superior performance in filtering out baseline drift, simple calculation, and fast speed, but it will produce truncation errors when filtering out high-frequency interference. When the wavelet filter is used to filter out the baseline drift, the signal must be decomposed and reconstructed at a large scale, so the calculation amount is large. This paper uses morphological filtering, selects linear structural elements to filter out the baseline drift, and then decomposes and reconstructs the signal with a 1-4 scale wavelet. The selection of the threshold is the same as that of the wavelet filter alone, which filters out high-frequency interference, reduces the number of scale decomposition, reduces the amount of calculation, and finally obtains a clean ECG signal. The flowchart of the denoising algorithm based on morphology and wavelet thresholding is shown in Figure 8.

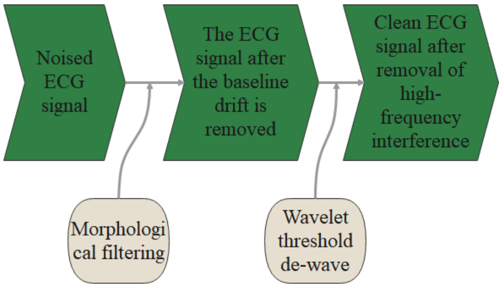


Figure 8: Flow chart of ECG signal processing.

In Figure 8, the noisy ECG signal is used as input to a morphological filter to remove baseline drift. Then, the mixed signal containing power frequency interference and EMG interference is subjected to threshold processing through a wavelet filter to filter out the high-frequency interference signal to obtain a clean ECG signal.

In order to evaluate the performance of wavelet filtering and wavelet threshold filtering based on a morphological algorithm, three indicators are used to measure the difference between the filtered signal $f''(n)$ and the noise-free signal f(n) [12]:

$$MSE = \frac{1}{N}\sum_{n=0}^{N-1} f(n) - f''(n)\;^{2} \tag{17}$$

$$SNR = 10 \times \lg\left(\frac{\theta^2}{MSE}\right) \tag{18}$$

$$\text{LocalMax} = \max_n \left| f(n) - f''(n) \right|, n = 0,1,\ldots,N-1 \tag{19}$$

In the formula, MSE is the minimum mean square error, SNR is the signal-to-noise ratio, LocalMax is the local maximum error factor, θ^2 is the noise-free signal variance, and $\theta^2 = \frac{1}{N}\sum_{n=0}^{N-1}(f(n) - \overline{f}(n))^2, \overline{f}(n)$ is the mean of the noise-free signal.

On the basis of the above system model, the psychological state of foreign language learning anxiety is analyzed through experimental research. Moreover, this paper measures the anxiety psychological data of foreign language learners through ECG signals and analyzes the anxiety psychological data of foreign language learners through big data.

In the experimental research, this paper conducts the experimental teaching by means of practical experiments, and conducts experimental teaching through foreign language learning volunteers. Moreover, this paper analyzes the actual situation of foreign language teaching and collects the psychological data of the experimenter's foreign language learning anxiety through the simulation platform. In addition, this paper counts the reliability of the psychological data collection on foreign language learning anxiety.

6 RESULTS

This paper uses the simulation platform to collect the psychological data of the experimenter's foreign language learning anxiety and compares the results with the actual situation. The actual situation is mainly carried out by the supervisor measurement method, and the test results obtained on this basis are shown in Figure 9.

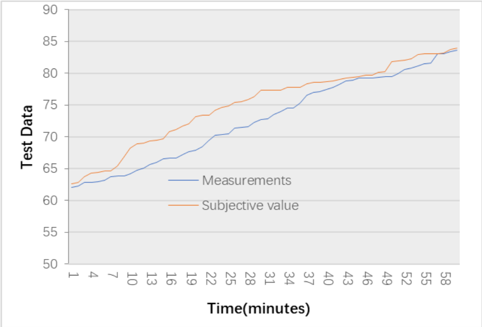


Figure 9: Data measurement effect of foreign language learning anxiety psychology.

The above analysis verifies that the data measurement method of foreign language learning anxiety psychology proposed in this paper has certain reliability. On this basis, this paper verifies the application effect of big data technology in the analysis of anxiety psychological status of foreign language learners, and the results are shown in Figure 10.

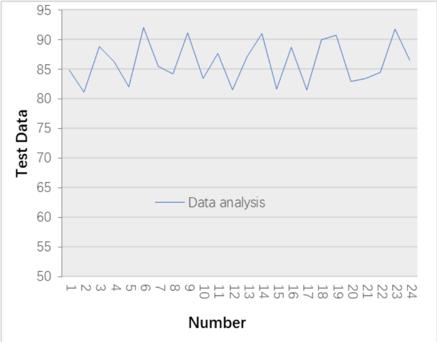


Figure 10: The application effect of big data technology in the analysis of foreign language learners' anxiety and psychological status.

7 DISCUSSION

Foreign language learning anxiety is different from other types of anxiety, and foreign language learning anxiety will have a non-negligible impact on the foreign language learning process and results. Therefore, foreign language teachers should learn to understand the theory of foreign language learning anxiety and apply the theory to foreign language teaching practice. Teachers should pay enough attention to the emotional factor of foreign language learning anxiety and pay attention to observing students' speech and behavior. At the same time, it is necessary to be good at finding those students who are anxious in foreign language classrooms and take some targeted measures to minimize their classroom anxiety so as to produce good teaching and learning effects.

This paper uses ECG signals to measure the anxiety psychology of foreign language learners and analyzes the anxiety psychology of foreign language learners through big data. As shown in Figure 9 and Figure 10, the data measurement method of foreign language learning anxiety proposed in this paper has certain reliability, and big data analysis can effectively improve the analysis effect of foreign language learners' anxiety psychological status.

8 CONCLUSIONS

Learners' anxiety, learning motivation, self-confidence, and other non-intellectual factors play a great role in learners' foreign language learning. Teachers should actively explore and flexibly use various teaching methods and change the education mode of compulsory indoctrination and restraint. This paper combines big data technology and intelligent psychological and emotional ECG signal recognition technology to analyze the anxiety psychology of foreign language learners so as to improve the psychological improvement effect of foreign language learners and improve the efficiency of foreign language learning. When conducting experimental research, this paper conducts experimental teaching with foreign language learning volunteers through practical experiments and analyzes the actual situation of foreign language teaching. Moreover, this paper collects the data of the experimenter's foreign language learning anxiety through the simulation platform. Through the experimental research, we can see that the method proposed in this paper has a certain effect.

9 RECOMMENDATIONS

These activities related to speaking or communication are the manifestations of foreign language learning anxiety affecting students' communication ability. This paper combines big data technology and intelligent psychological and emotional ECG signal recognition technology to analyze the anxiety psychology of foreign language learners and improve the effect of anxiety psychological improvement on foreign language learners. In actual teaching, teachers can combine intelligent methods and intelligent data analysis methods to monitor students' anxiety learning status in real-time and give teaching guidance in a timely manner to improve students' foreign language learning effect.

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