

Medical Research on Mental Health Education of College Students Based on Artificial Intelligence

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Abstract. To promote the improvement of the effect of college students' mental health education, this paper combines the artificial intelligence measurement method to conduct real-time measurements of college student's mental health. Moreover, this paper uses the fast algorithm of Mallat orthogonal wavelet transform to decompose and filter and then uses the relationship between wavelet transform and signal singularity to optimize the problems of missed detection and false detection in ECG signal processing using wavelet transform in the past. At the same time, this paper verifies the effect of the method proposed in this paper on the mental health education of college students. Based on expert evaluation, this paper explores whether the mental health education method for college students based on artificial intelligence calculation is effective, conducts research through the teaching evaluation method, and counts the results of experimental research. Finally, the simulation test results verify that the method and system proposed in this paper are scientific.

Keywords: artificial intelligence; measurement; college students; mental health; Medical Research. **DOI:** https://doi.org/10.14733/cadaps.2024.S24.60-68

1 INTRODUCTION

The Internet shows a whole new world to college students with its vast space and rich information resources. Fully stimulate the curiosity and thirst for knowledge of college students. College students can quickly find the information resources they need on the Internet. It can also help them appreciate the knowledge content, news events, masterpieces, film, and television information not readily accessible in the natural environment [7]. These have greatly satisfied the curiosity of college students about the outside world. It stimulates their desire to learn and master network knowledge and application skills, and at the same time, it also stimulates the imagination and creativity of college students [3]. The dissemination of online literary works by college students and the self-

Computer-Aided Design & Applications, 21(S24), 2024, 60-68 © 2024 U-turn Press LLC, <u>http://www.cad-journal.net</u> employment of college students through network resources are good examples. However, the cognitive ability of college students is still in a stage of rapid development. The screening and selection process of knowledge could be better. Its moral judgment is still at an imperfect level, therefore. For college students who often contact the Internet [2]. Due to the frequent browsing of a large amount of ever-changing information. It is challenging to form proper cognition. Cognitive bias is prone to occur. For example, we often find that some students arbitrarily make evaluation judgments on some events in some forums or post bars. These judgments are usually profoundly influenced by other speeches on the Internet [2].

In the real world, college students may face various pressures from society, family, school, teachers, and classmates. This kind of pressure often cannot be released in the natural environment. Still, on the Internet, they can relax and get rid of it by chatting with people, posting on Weibo, playing online games, watching entertainment movies, and so on[9]. When many college students encounter various confusions and psychological problems, they are often reluctant to talk and vent to outsiders. More unwilling or not have the courage to seek the help of a psychiatrist. This attitude is not conducive to the individual's mental health. It is also not conducive to promptly solving individual psychological problems in the network environment.

The virtuality of the network provides a safer channel for college students to vent their destructive emotions [10]. Let them release their negative emotions in time. Obtaining the corresponding psychological support College students can talk about their troubles, confusions, and wishes in real-time by interacting with netizens, and at the same time, they can also get the maximum understanding, support, and help from others, which can relieve their tension and depression to a great extent. Psychology, so that the state of mind can be balanced [8]. Emotions are stabilized. However, the emotional development process of an individual is an essential process of individual socialization. It follows specific rules. People will follow corresponding norms for emotion recognition, expression, and control in the natural environment once the specification is not observed [4]. Will be subject to pressure from all aspects, such as college students in honest interpersonal communication can not be accessible to lose their temper.

Feel free to generate impulsive emotions. Otherwise, it may be forced to control and converge due to the vision or evaluation of the surrounding people. Still, in the network environment, the binding force of this environment will be significantly reduced. People's ability to control their emotions will also decline. It is easy to have impulsive emotions, make hasty remarks, etc. [12]. For some college students who are addicted to the Internet, It is often more dependent on interpersonal relationships on the Internet. More inclined to seek psychological comfort and emotional satisfaction in the network. They usually pin their emotional experience on interpersonal interaction and passionate and dynamic communication. Then, there are distortions of emotional development in real life, such as apathy, lack of empathy, etc. [11].

The most significant difference between mental health education courses and other essential and professional courses is that mental health education courses focus on students' experience teaching, focusing on students' practice, experience, perception, and discovery [6]. There is no fixed teaching content, and it is flexible. Class hours can be added or reduced at any time according to the situation generated in the classroom; there are no rigid regulations and restrictions so that students can internalize them.[5].

During the pandemic, information technology has opened a window for students' psychological counseling and curriculum education. This paper combines the artificial intelligence measurement method to measure the mental health of college students in real-time to provide theoretical reference for the mental health education of college students to improve the physical and psychological health

of college students and provide a reliable foundation for the subsequent development of college students.

2 METHODOLOGY

This paper uses an artificial intelligence calculation method to measure college students' mental health data.

2.1 Waveform Detection and Feature Point Recognition of ECG Signals

A spline wavelet, which has a simple form, is obtained from the spline function. The Fourier transform of quadratic spline wavelet $\psi(t)$ is:

$$\psi(\omega) = j\omega \left(\frac{\sin(\omega/4)}{\omega/4}\right)^4 \tag{1}$$

$$H(\omega) = \left(\cos\frac{\omega}{2}\right)^3 e^{(-j\omega/2)}$$
(2)

$$G(\omega) = 4j \sin\left(\frac{\omega}{2}\right) e^{(-j\omega/2)}$$
(3)

The corresponding scale function is $\phi(x)$, and its Fourier transform is:

3.5

3 2.5

2

i=5

$$\phi(\omega) = \left(\frac{\sin(\omega/2)}{\omega/2}\right)^3 e^{(-j\omega/2)}$$
(4)

When A = 0.505 and B = 0.522, the spline wavelet satisfies the stability condition:

$$\psi(\omega) = j\omega \left(\frac{\sin(\omega/4)}{\omega/4}\right)^4 \tag{5}$$

The signal f(n) is wavelet transformed by the binary wavelet, and the Fourier transform is performed to obtain:

$$WTf(\omega) = f(\omega)\psi(2^{j}\omega)$$

$$G(\omega)f(\omega)\phi(\omega) \qquad j = 1$$

$$G(2\omega)H(\omega)f(\omega)\phi(\omega) \qquad j = 2$$

$$G(2^{j-1}\omega)H(2^{j-1}\omega)\dots H(\omega)f(\omega)\phi(\omega) \qquad j > 2$$

(6)

j=2

i=1



i=3

Figure 1: Frequency-phase curve of the equivalent filter.

Its corresponding equivalent filter is:

$$Q(\omega) = \begin{cases} G(\omega) & j = 1\\ G(2\omega)H(\omega) & j = 2\\ G(2^{j-1}\omega)H(2^{j-1}\omega)\dots H(\omega) & j > 2 \end{cases}$$
(7)

The frequency response curve of the matching filter $Q(\omega)$ is shown in Figure 1.

Based on the above analysis, the commonly used wavelet functions with better effect are quadratic B-spline wavelet and Mexican hat wavelet, which have higher detection accuracy. The frequency domain representation $\psi(\omega)$ is:

$$\hat{\psi}(\omega) = i\omega \left[\frac{\sin\left(\frac{\omega}{4}\right)}{\frac{\omega}{4}}\right]^4 \tag{8}$$

The transfer function of the filter is:

$$\begin{cases} H(\omega) = e^{\frac{i\omega}{2}} \left[\cos\left(\frac{\omega}{2}\right) \right]^3 \\ G(\omega) = 4e^{\frac{i\omega}{2}} \sin\left(\frac{\omega}{2}\right) \end{cases}$$
(9)

The corresponding filter coefficients h_k and g_k are:

$$h_{0} = 1/4, h_{1} = 3/4, h_{2} = 3/4, h_{3} = 1/4g_{0} = -1/4, g_{1} = -3/4, g_{2} = 3/4, g_{3} = \frac{1}{4}$$
(10)
$$B_{0} = 1/4, h_{1} = 3/4, h_{2} = 3/4, h_{3} = 1/4g_{0} = -1/4, g_{1} = -3/4, g_{2} = 3/4, g_{3} = \frac{1}{4}$$

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Figure 2: Wavelet transform of ECG signal at different scales.

As shown in Figure 2, using the selected quadratic spline wavelet, data in the No. 100 record of the MIT-BIH arrhythmia database is decomposed into different frequency bands through a wavelet transform.

2.2 QRS Complex Detection

After the wavelet base and characteristic scale are determined, the QRS complex is detected below. The processing steps of the algorithm are:

We set f(n), n = 1,2,3,...,N to be a time series of an ECG signal with a total of N points.

1. The algorithm selects the decomposition scale;

2. For the digital ECG signal f(n), the algorithm uses quadratic spline wavelet and Mallat algorithm to decompose into four scales to obtain the wavelet coefficient $W_{2j}f(n)$, (j = 1,2,3,4);

3. Under the 2^3 scale, the algorithm finds the positive and negative significant value points and gives the threshold r.

4. Under the 2^3 scale, the algorithm finds the pair of modulo maxima and its zero-crossing point. The modulo maxima pair is corrected by $\frac{2^3-1}{2} \approx 4$;

5. The algorithm detects the origin of the QRS complex at the 2¹ scale;

6. The algorithm detects the end point of the QRS complex at the 2¹ scale;

7. Optimization of the algorithm: The algorithm removes multiple inspection points and compensates for missed ones.

The flowchart of the algorithm is shown in Figure 3.



Figure 3: QRS complex detection steps based on wavelet transform.

The above technologies support the method proposed in this paper to verify the effect of mental health education on college students. This paper is systematically evaluated using the expert evaluation method, and the expert evaluation results are counted.

3 RESULTS

The pathological ECG sequences in the MIT-BIH ECG standard database (sampling frequency 360Hz) are randomly selected for analysis, and it was found that the detection accuracy is close to 100% for ECG signals with significant QRS complex features and less interference. The simulation test results are shown in Figure 4, Figure 5, Figure 6, and Figure 7.



Figure 4: ECG signal and wavelet coefficients at j=1, 2, 3, 4 Scales.



Figure 5: Modulo maxima points of wavelet coefficients of ECG signal at scale j=1, 2, 3, 4.



Figure 6: Modulo maxima points of wavelet coefficients at scale 23.



Figure 7: R wave peak and QRS wave band of ECG signal.

Table 1 shows the effect evaluation of a college student's mental health measurement method based on artificial intelligence calculations.

Number	Measuring effect	Number	Measuring effect	Number	Measuring effect
1	76.17	15	74.24	29	78.25
2	82.89	16	86.78	30	74.11
3	81.58	17	80.89	31	86.33
4	73.70	18	84.59	32	76.34
5	81.99	19	77.30	33	86.52
6	80.19	20	73.00	34	84.39
7	84.69	21	76.14	35	84.59
8	77.63	22	80.93	36	82.70
9	81.70	23	78.65	37	85.02
10	86.99	24	79.12	38	80.71
11	76.73	25	86.87	39	85.59
12	80.35	26	80.33	40	74.79
13	74.61	27	74.84	41	74.24
14	79.64	28	86.29	42	81.80

Table 1: Effect evaluation of college students' mental health measurement method based on artificial intelligence.

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Number	Educational effect	Number	Educational effect	Number	Educational effect
1	90.30	15	87.25	29	86.58
2	84.30	16	85.24	30	91.52
3	91.87	17	90.57	31	85.15
4	86.57	18	91.25	32	89.40
5	89.34	19	84.84	33	87.33
6	84.29	20	86.87	34	88.41
7	83.42	21	83.98	35	91.33
8	88.57	22	85.82	36	86.27
9	89.01	23	87.15	37	90.50
10	86.56	24	87.51	38	88.08
11	89.22	25	91.59	39	90.56
12	88.39	26	84.33	40	85.55
13	91.32	27	85.84	41	85.20
14	91.95	28	91.07	42	89.06

Table 2 shows the effect evaluation of a college student's mental health education method based on artificial intelligence calculations.

 Table 2: Effect verification of college students' mental health education method based on artificial intelligence calculation.

4 DISCUSSION

Figure 4 shows the ECG signal and wavelet coefficients at j=1, 2, 3, and 4. Figure 5 shows the modulo maxima of the wavelet coefficients of the ECG signal at the scale of j=1, 2, 3, and 4. Figure 6 shows the modulus maximum points of the wavelet coefficients at scale 2^3 . Figure 7 shows the ECG signal's R wave peak and QRS wave band.

The statistical results of Table 1 and Table 2 show that the mental health education of college students proposed in this paper has a good effect. Based on the evaluation of this paper using the expert evaluation method, the method is suitable for quantitatively measuring the mental health of college students.

The method proposed in this paper meets the needs of the research purpose of this paper.

5 CONCLUSIONS

The most significant difference between mental health education courses and other essential and professional courses is that mental health education courses focus on students' experiential teaching, focusing on students' practice, experience, perception, and discovery. Moreover, from the systematic evaluation of this article by the expert evaluation method, the process is suitable for the quantitative measurement of the mental health of college students. AI computation in mental health education research offers a promising avenue for advancing mental well-being in academic environments. Through ethical and evidence-based practices, AI has the potential to significantly enhance mental health support for college students, fostering a healthier and more supportive educational landscape.

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