Brain wave sensor controller based on neural network

Shiqing Zheng, Dan Meng, Zhicheng Mao, Bo Mu, Chang Liu

Liaoning University of Science and Technology, China.

gykwcs@163.com

Abstract

The brainwave wave emotion cognition method based on quantum wavelet neural network model disclosed in the present invention includes steps: regularization and regularization of brain wave data set After the data is preprocessed, the preprocessed data is extracted, and the data is classified by a three-layer forward-type quantum wavelet neural network. The hidden layer adaptive basis function of the quantum wavelet neural network uses the Mexican-hat wavelet function. The evaluation value wake-up degree analysis is performed.The invention achieves faster convergence speed and higher cognitive accuracy.

Keywords

Quantum wavelet, neural network, brain wave, emotion.

1. Introduction

In recent years, some new forms of digital media and human body interaction have great potential and market in the fields of entertainment and learning.However, emotion plays an important role in human life, so in the application of computer interface, the demand based on emotional cognition is increasing day by day.Humans have six basic emotions, namely happiness, sadness, fear, surprise, anger, and jealousy.These six emotions can be combined with each other and derived from a variety of other complex emotions such as depression, nervousness, anxiety and so on.Emotional cognition is a key technology in the fields of artificial intelligence and human-computer interaction.The advent of the information age requires machines to understand and express human emotions more friendly. In real life, emotional cognition has been applied to medical, education, business, etc., but because emotion is a very complex cognitive process, emotions If you want to achieve better results, you need to rely on in-depth research.EEG signals are electrophysiological signals that are objective and accurate and can directly reflect brain activity and are therefore widely used in emotional cognition.

Brain waves are closely related to emotions. Brain waves are formed by the sum of post-synaptic potentials that occur simultaneously when a large number of neurons are active.It records the changes in the electrical activity of the brain. It is the overall reflection of the electrophysiological activity of the brain cells on the surface of the cerebral cortex or scalp. The frequency varies from 1 to 30 times per second and can be divided into four bands, namely δ. (1-3 Hz), θ (4-7 Hz), α (8-13 Hz), and β (14-30 Hz).Among them, the α index (that is, the alpha wave accounts for the percentage of total brain waves, and the alpha index is 75% when the eyes are closed and closed) can be used as an indicator of emotional performance. People with stable mood and broad thinking have higher α index and unstable mood. The extreme human alpha index is very low.The alpha wave is susceptible to external stimuli. When blinking, the alpha wave will weaken or disappear, even in a dark environment.The beta wave is not affected by sputum or closed eyes.In the blink of an eye, emotional stress, anxiety, fear of fear or taking drugs such as diazepam, beta wave activity increased dramatically.Beta activity is also related to certain psychological qualities of people.People with β-ratio advantage often show: mental stress, emotional instability, strong emotions, easy impulsiveness, and stubbornness.In addition, when awakening and focusing on a certain thing, a gamma wave with a higher frequency than the beta wave is often seen, the frequency is 30~80 Hz, and the amplitude range is indefinite; while other waveforms may appear during sleep. Special normal brain waves, such as hump wave, σ wave, λ wave, κ-complex wave, μ wave, etc.

At present, the collection of brain waves mainly adopts the brain-computer interface mode, which is sometimes called "brain port" direct neural interface or "brain machine fusion perception" brain-machine interface, which is in the human or animal brain (or brain). A direct connection between the culture of the cell and the external device.In the case of a one-way brain-computer interface, the computer either accepts commands from the brain or sends signals to the brain (eg, video reconstruction), but cannot simultaneously transmit and receive signals.The two-way brain-computer interface allows two-way information exchange between the brain and external devices.

Quantum Neural Network (QNN) is a new computational model generated by the combination of quantum computing and neural network theory. It is one of the emerging frontier interdisciplinary subjects.The quantum neural network introduces the basic concepts and principles of quantum computing into the neural network model, and transforms the traditional neural network model to enhance the performance and speed of the neural network, and proposes new ideas for the further development of the neural network.In the emotional cognition of EEG signals, quantum neural networks make up for the lack of traditional neural networks to express EEG signals, and have the characteristics of high stability, high precision and fast convergence.

However, at present, the eeg emotional cognition calculated by quantum neural network is not only inefficient, but also not accurate.

In response to the appeal problem, the designer designed a faster and more accurate brainwave emotional cognition method based on quantum wavelet neural network model.

2. Design content

The purpose of this design is to provide a brainwave emotional cognition method based on quantum wavelet neural network model, which achieves faster convergence speed and higher cognitive accuracy.

In order to achieve the above objectives, the design adopts the following technical solutions:

The brainwave emotional cognition method based on the quantum wavelet neural network model includes the following steps:

Step 1: Regularize the collected brain wave data set, and the regularized value is between 0 and 1.

Step 2: pre-processing the regularized data, specifically using independent principal component analysis (ICA) to remove the interference data from the brain wave data;

Step 3: performing feature extraction on the preprocessed data, and specifically using a clustering technique (ct) to reduce the size of the data set by selecting a specific feature;

In step 4, the data is classified by a three-layer forward quantum wavelet neural network (QWNN). The hidden layer adaptive basis function of the quantum wavelet neural network uses the Mexican-hat wavelet function. The specific expression of the function is:

Where t is a time variable;

In step 5, the evaluation value wake-up degree analysis is performed.

Removing the interference data by using the independent principal component analysis specifically includes the following steps:

(1) The data normalized in step 1 is denoted as $K_2(t)$, $K_3(t)$...$K_n(t)$ and is used together with the desired signal $K_1(t)$ as the input signal $K(t)=[K_1(t) \ K_2(t); \ K_3(t);...K_n(t)]$ performs independent principal component analysis to obtain the separated signal $S(t)=[S_1(t); \ S_2(t); \ S_3(t); \ ...S_n(t)]$;

(2) separately performing the spectrum analysis on the separated signals, and determining the target signal $S_1(t)$ according to the characteristics of the ideal signal $S'(t)$;

(3) Spectrum recovery method is used to recover the spectrum of the separated signal $S_1(t)$ after independent principal component analysis, and finally the $Y(t)$ signal for removing the interference signal is obtained.

The steps of performing feature extraction using the clustering technique (ct) include:

1) Dividing each brainwave data into n groups, each group being called a special time interval cluster;

2) Divide each cluster into sub-clusters of m special periods;

3) Extract eight statistical features from the data points of each sub-cluster. The statistical characteristics of these brainwave data are: minimum, maximum, mean, median, first quartile range, third quartile range , quartile full range and standard deviation.

The training of the three-layer forward-type quantum wavelet neural network includes the following steps:

1) All training input vectors are input to the quantum wavelet neural network. The quantum wavelet neural network uses a three-layer forward neural network. The input layer contains ni nodes, the hidden layer contains nh multi-layer nodes, and the output layer contains no nodes. .Wjl represents the weight of the lth input node to the jth hidden layer node, and vij represents the weight of the jth hidden layer node to the i-th output layer node.Let m denote the number of expected vectors of data set X; suppose a multi-layer hidden layer node has ns discrete quantum layers, then the excitation function can be written as a superposition of ns sub-excitation functions and converted by θs, the hypothesis model The specific expression is as follows:

Wherein, the excitation function representing the hidden layer node, β represents the slope parameter, θs represents the quantum interval, λj represents the expansion factor, and τj represents the transfer factor;

The output vector of the output layer is:

The general expression of the qwnn model is:

Where k represents the number of samples;

2)Update of qwnn weight:

The cost function is where k = 1, 2, ..., m, m is the total number of training samples, and the parameters wjl, vij, λj, τj are updated by minimizing the cost function:

Where α is the learning rate, 0 < α < 1.

3)Update of quantum spacing:

The output variance of the ci class is:

Wherein, the output sum of the hidden layer nodes belonging to the class ci is represented.

Quantum spacing is adjusted by minimizing the cost function g:

Finally calculate its update equation:

Update according to the following formula:

The step 5 performs an analysis of the degree of awakening of the evaluation value, specifically:

By changing the control parameters of the facial muscles, six Haptek mood factors are defined, which are: happiness, sadness, fear, surprise, anger, ambiguity, which have been classified by the algorithm described in step four;

A mapping of the evaluation value and the degree of awakening, wherein the degree of awakening can only be selected from the markers 0, 1, and 2, and the evaluation value can only be selected from the 0 and 1 of the marker.

After adopting the above scheme, the beneficial effect of this design is that the wavelet theory is applied to the quantum neural network algorithm, and the quantum neural network algorithm is improved. The quantum wavelet neural network algorithm is obtained and applied to the emotional cognition of brain waves. In terms of dealing with eeg emotional cognition, quantum wavelet neural network algorithm has faster convergence speed and higher precision than traditional neural network and quantum neural network algorithm.

The design will be further described below in conjunction with the drawings.

3. Specific implementation

The brainwave wave emotion cognition method based on the quantum wavelet neural network model disclosed in the embodiment shown in FIG. 1 specifically includes the following steps:
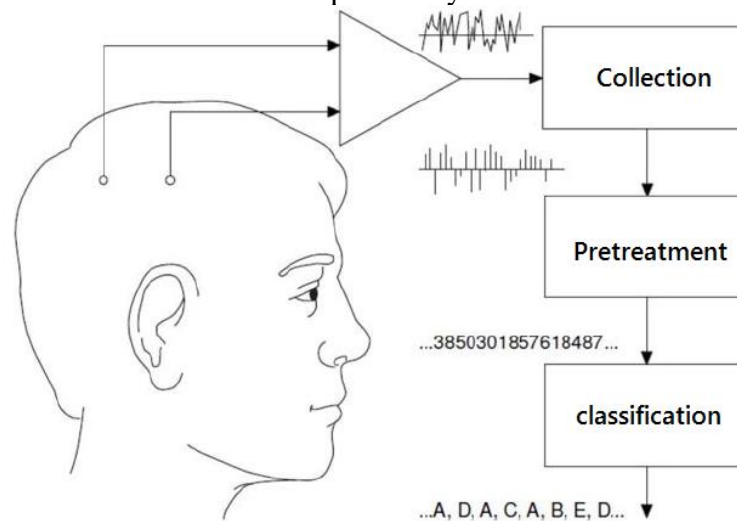

Figure 1 Flow chart of brain wave data processing.

Step 1: Regularize the collected brain wave data set, and the regularized value is between 0 and 1.

Step 2: pre-processing the regularized data, specifically using the independent principal component analysis (ICA) to remove the interference data from the brain wave data, and the interference data is mainly noise data;

Removing the interference data by using the independent principal component analysis specifically includes the following steps:

(1) The data normalized in step 1 is denoted as K2(t), K3(t)...Kn(t) and is used together with the desired signal K1(t) as the input signal K(t)=[K1(t) K2(t); K3(t);...Kn(t)] performs independent principal component analysis to obtain the separated signal S(t)=[S1(t); S2(t); S3(t); ...Sn(t)];

(2) separately performing the spectrum analysis on the separated signals, and determining the target signal S1(t) according to the characteristics of the ideal signal S'(t);

(3) Spectrum recovery method is used to recover the spectrum of the separated signal S1(t) after independent principal component analysis, and finally the Y(t) signal for removing the interference signal is obtained.

Step 3: performing feature extraction on the preprocessed data, and specifically using a clustering technique (ct) to reduce the size of the data set by selecting a specific feature;

The steps of performing feature extraction using the clustering technique include:

1) Dividing each brainwave data into n groups, each group being called a special time interval cluster;

2) Divide each cluster into sub-clusters of m special periods;

3) Extract eight statistical features from the data points of each sub-cluster. The statistical characteristics of these brainwave data are: minimum, maximum, mean, median, first quartile range, third quartile range , quartile full range and standard deviation.

In step 4, the data is classified by a three-layer forward quantum wavelet neural network (QWNN). The hidden layer adaptive basis function of the quantum wavelet neural network uses the Mexican-hat wavelet function. The specific expression of the function is:

Where t is a time variable;

In step 5, the evaluation value wake-up degree analysis is performed.

Step 5 analyzes the degree of wake-up of the evaluation value, specifically:

By changing the control parameters of the facial muscles, six Haptek mood factors are defined, which are: happiness, sadness, fear, surprise, anger, ambiguity, which have been classified by the algorithm described in step four;

A mapping of the evaluation value and the degree of awakening is performed, wherein the degree of awakening can only be selected from the markers 0, 1, and 2, and the evaluation value can only be selected from the markers 0 and 1, and the mapping structure is shown in FIG.

In step four, the training of the three-layer forward-type quantum wavelet neural network includes the following steps:

1) Input all training input vectors to the quantum wavelet neural network. As shown in Figure 2, the quantum wavelet neural network uses a three-layer forward neural network. The input layer contains ni nodes, and the hidden layer contains nh multi-layer nodes. The output layer contains no nodes.Wjl represents the weight of the lth input node to the jth hidden layer node, and vij represents the weight of the jth hidden layer node to the i-th output layer node.Let m denote the number of expected vectors of data set X; suppose a multi-layer hidden layer node has ns discrete quantum layers, then the excitation function can be written as a superposition of ns sub-excitation functions and converted by θs, the hypothesis model The specific expression is as follows:
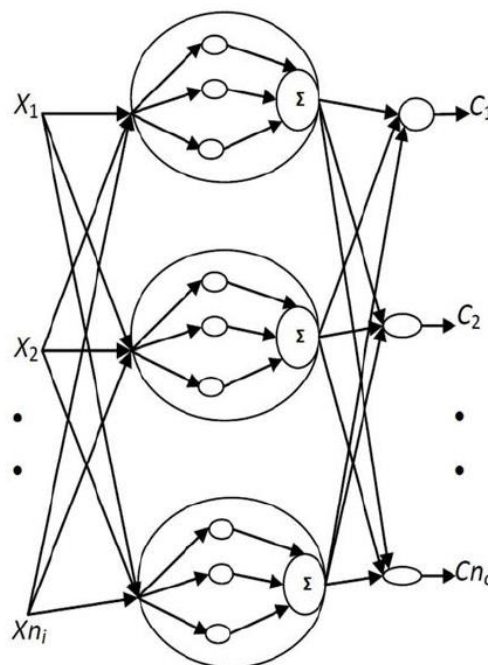

Figure 2 is a block diagram of a quantum wavelet neural network.

Wherein, the excitation function representing the hidden layer node, β represents the slope parameter, θs represents the quantum interval, λj represents the expansion factor, τj represents the transfer factor; the output vector of the output layer is: wherein the general expression of the QWNN model is: where k represents the sample quantity;

2) Update of qwnn weight:

The cost function is where $k = 1, 2, ..., m$, m is the total number of training samples, and the parameters wjl, vij, λj, τj are updated by minimizing the cost function: where for any h iterations, the parameters wjl, vij , λj, τj are all adjusted according to the following formula: where α is the learning rate, $0 < α < 1$.

3)Update of quantum spacing:

The output variance of the ci class is:

Wherein, represents the sum of the outputs of the hidden layer nodes belonging to the class ci.The quantum spacing is adjusted by minimizing the cost function G: calculating the gradient of G: where

αθ is the learning rate, $0 < \alpha\,\theta < 1$; where, let, finally calculate its update equation; update according to the following formula.

4. Conclusion

The above description shows and describes a preferred embodiment of the present design, and it should be understood that the present invention is not limited to the forms disclosed herein, and should not be construed as being excluded from other embodiments, but may be used in various other combinations, modifications, and environments. And can be modified by the above teachings or related art or knowledge within the scope of the design concept herein.All changes and modifications made by those skilled in the art are intended to be within the scope of the appended claims.

Acknowledgments

References

[1]Design of intelligent gas cooker controller [j]. Chen Susong. Journal of Shunde Vocational and Technical College. 2003(01).

[2]Electronic piano design based on 51 single chip microcomputer [j]. Xu Jiangwei, Li Fei. Electronic World. 2017 (09) .

[3] Design of controller based on single-chip microcomputer [j]. Xu Yiwu. Electronic World. 2017(11)

[4] Application and development of single-chip technology in smart furniture [j]. Li Liwen, Peng Sen. Family Life Guide. 2019 (07).