EEG FEATURE EXTRACTION AND RECOGNITION WITH DIFFERENT MENTAL STATES BASED ON WAVELET TRANSFORM AND ACCLN NETWORK

Xuebin Qin*  Jun Deng  Mei Wang  Pai Wang  Liang Wang  Yizhe Zhang

College of Electrical and Control Engineering
Xi’an University of Science and Technology
Xi’an, China 710054, P.R.C.

Key Words:  BCI, recognition, feature extraction, ACCLN network.

ABSTRACT

The electroencephalogram (EEG) is a record of brain activity. Brain Computer Interface (BCI) technology has become one of the hotspots, especially for the identification of EEG characteristic signals. We here describe a novel method which involves the combination of discrete wavelet transformation and neural network to recognize different states of the human brain, including fatigue, consciousness and concentration from EEG signal. To eliminate the high frequency noise, raw signal was preprocessed by the wavelet denoising method and was then decomposed into multi-layer high frequency signal and low frequency signal. Thus, δ wave, θ wave, α wave, β wave were obtained by wavelet transformation. In this experiment, the frequency band energy of the different waves was regarded as the feature signal of EEG for further signal processing. The feature signal was then classified by both radial basis function (RBF) and annealed chaotic competitive learning network (ACCLN). The experimental results showed that the average accuracy of ACCLN network is 98.4%, which is much higher than the traditional method. The results together showed the effectiveness and feasibility of the proposed method. The proposed algorithm has a good practical value in the analysis of the mental states of a driver or high risk operation personnel.

I. INTRODUCTION

For driving or other high risk operations, fatigue may lead to serious consequences and even life safety. According to the U.S. National Highway Traffic Administration, fatigue contributes to about 100,000 traffic accidents each year. The electroencephalogram (EEG) measures brain neuronal activities, and EEG signals directly reflect the degree of fatigue. Monitoring EEG can provide early warning of fatigue quickly and accurately. EEG signal frequency is mainly concentrated in the low frequency range of 0.5 Hz to 50 Hz, with the potential difference in the range of 0 to 200 mV [1-2]. For analytical purpose, the EEG signal is usually divided into multiple frequency bands including δ, θ, α, and β. In recent years, brain computer interface (BCI) technology has become one of the hot research topics in computer field. Human-machine interface technology has become more sophisticated, and EEG acquisition technology has also been rapidly developing. Using BCI technology, brainwaves can be used to control the external objects [3-5]. Therefore, studies on EEG signal recognition and feature extraction are of vitally importance to BCI technology. The EEG signal is a non-stationary weak signal, which is easy to be drowned out in strong background noise. Therefore
the noise needs to be removed before feature extraction. Previous research proposed a method that extracted EEG signals by independent component analysis [6]. P300 BCIs was used to obtain an embedded channel selection approach based on grouped automatic relevance determination [7]. A robotic upper limb was controlled by human intracranial EEG and eye tracking [8]. Design of Finite Impulse Response (FIR) filters and the associated spatial weights by optimizing an objective function has been shown to effectively extract discriminative features for motor imagery-based brain-computer interface [9]. The δ wave, θ wave, α wave, β wave of EEG signal has been used to identify fatigue state [10]. Recently, a new scheme for driver fatigue detection based on the nonlinear unscented Kalman filter and eye tracking has been described [11]. Facial expression and eyes detection were also used in a driver fatigue monitoring system [12].

In a different study, a total of 19 features were computed from only one EEG channel to differentiate alertness and drowsiness stages [13]. These studies demonstrate the feasibility of an online closed-loop EEG-based fatigue detection and mitigation system that is able to detect physiological changes and can thereby prevent fatigue-related cognitive lapses [14]. In order to obtain the effective data identification, in this paper, a fatigue function is defined to deal with the EEG signal.

The methods for EEG signal processing include single category information [15], traditional time-frequency feature combination [16], neural network analysis and wavelet transform [17-18]. A multiple kernel Support Vector Machine (SVM) algorithm is used for the identification of EEG signals including mental and cognitive tasks [19]. The detected EEG signals of epileptic seizures is classified by BP network [20]. The classification algorithm has been used by multiple neural network such as neural fuzzy networks, feed forward networks, radial basis function network and also has been widely applied to medical as well as drowsy driving detection fields [21-25].

In this paper, the Mindwave Mobile, launched by United States Neurosky Co. Ltd., was used to collect and monitor the brainwaves from the frontal lobe. The characteristic features of the EEG signal, including δ wave, θ wave, α wave, β wave, were obtained by using wavelet transformation for raw EEG data. Furthermore, the energies of these characteristic components were used as the feature and classified by annealed chaotic competitive learning network (ACCLN) method to recognize the three brain states: fatigue, conscious, concentrated. This method has high recognition accuracy and a good practical value.

The traditional Fast Fourier Transformation (FFT) method has a wide frequency range and a large classification error. Our proposed method regards the sub-band energies of wavelet transformations as features. Furthermore, a simulated annealing mechanism embedded in competitive neural networks called ACCLN network was utilized in downstream data processing. This fusion algorithm has a higher recognition accuracy.

The rest of this paper is organized as follows: The related research is introduced in the next section. A new EEG signal recognition method is described in detail in section 3. The experiment results are given in section 4. Finally, we conclude in section 5.

II. RELATED RESEARCH

Annealed chaotic mechanism is described in this section.

The traditional neural network is easily trapped into local-minima instead of finding the global-minima during the training process. So the utilization of chaotic simulated annealing is necessary to escape from local-minima and get global-optimal solution. The energy function of the neural network demonstrates the convergence process (formula 20). The related research approached has been demonstrated [26-27]. A single chaotic dynamics neuron-annealing model is shown in Eqs. (1) and (2):

$$P(t) = \frac{1}{1 + e^{-t^3/4}}$$  \hspace{1cm} (1)

$$q(t + 1) = \mu q(t) - E + T(t)(p(t) - I_0)$$  \hspace{1cm} (2)

where:

- $p(t) =$ transient state of the interconnection strength between input neurons and output neurons
- $q(t) =$ internal state of the interconnection strength between input neurons and output neurons
- $I_0 =$ input bias for each neuron
- $\mu =$ damping factor of nerve membrane ($0 \leq \mu \leq 1$)
- $E =$ energy function of the neural network
- $\lambda =$ steepness factor of the output function ($\lambda > 0$)
- $T(t) =$ Self-feedback connection weight for input neurons and output neurons.

$p(t)$ is expressed by a value of the self-feedback connection weight $T(t)$ in Eqs. (1) and (2). The various bifurcation states are demonstrated for the weight $T(t)$ during 4000 iteration in Fig. 1. The initial value of weight $T$ is 0.0677. While $T < 0.0677$, the transient state $p(t)$ shows a process from chaotic state though periodic bifurcation to a steady
Qin, X. et al.: Eeg Feature Extraction and Recognition with Different Mental States

\( T(t) = 0.0677 \)

\( p(k) \)

\( p(k) \)

\( T(t) = 0.0611 \)

\( T(t) = 0.0533 \)

\( T(t) = 0.0328 \)

Number of iteration \( k \)

Number of iteration \( k \)

Number of iteration \( k \)

Number of iteration \( k \)

\( \lambda = 0.004, \mu = 0.899, E = 0, I_0 = 0.649 \) (Fig. 1(d)). The chaotic behavior is used in a neural network. An annealed function is used to converge to a stable equilibrium point for a dynamic weight \( T(t) \).

Fig. 2 shows the time evolution of output \( p(t) \) and annealing process \( T(t) \). The initial value for single neuron is as follows: \( E = 0, I_0 = 0.65, T_0 = 0.09, \lambda = 0.004, \mu = 0.899, \alpha = 0.9998, \beta = 450 \) [28]. \( p(t) \) converges to a steady-state.
value. Our result in Fig. 2 demonstrates the process of a number of iterations and bifurcation of chaotic dynamics. Exponential damping of $T(t)$ is a process of simulated annealing [26]. The dynamic structure embeds into the competitive learning network in the experiment. Furthermore, the initial value of the parameters influences the dynamics process in training network. The selected parameters are therefore valid for all the bifurcation processes. These experiment results show the annealed chaotic mechanism converges rapidly in the competitive network. Fig. 2(a) demonstrates the output of a single neuron $p(t)$. Fig. 2(b) demonstrates annealing process of a damping variable.

$$T(t + 1) = \frac{1}{\beta + 1} [\beta + (\tanh(\alpha))^T] T(t)$$

$$t = 0, 1, 2, 3...$$

$$T = \text{self-feedback connection weight or refractory strength (} T > 0).$$

III. PROPOSED METHOD

The process of EEG signal recognition based on the Discrete Wavelet Transform (DWT) and neural network (Fig. 3). Signal processing was the first step of the EEG signal recognition process. During the process of signal transmission and collection, the EEG signal was polluted regularly by noise. Denoising was achieved using the thresholding of the wavelet method to obtain a clean EEG signal. Then, feature extraction was performed. In this step, DWT was carried out on the pre-cleaned EEG to obtain six layers of low frequency signals. The high frequency signals of the second to the sixth layer, the $\delta$ wave, the $\theta$ wave, the $\alpha$ wave, and the $\beta$ wave were selected by FFT. The subband energy was then calculated. Lastly, during the signal recognition, the ACCLN network was used to recognize the EEG signal generated from a different brain state.

1. Signal Processing

Raw EEG signals collected by a sensor contain a large amount of noise (Fig. 4(a)). This has an enormous impact on the subsequent feature extraction and recognition if left unprocessed. As shown in Fig. 4(b), for wavelet denois-
Table 1  Relationship between EEG frequency and brain states

<table>
<thead>
<tr>
<th>wave</th>
<th>frequency (Hz)</th>
<th>Activity description</th>
</tr>
</thead>
<tbody>
<tr>
<td>δ</td>
<td>0.5-3</td>
<td>Extreme fatigue and deep sleep</td>
</tr>
<tr>
<td>θ</td>
<td>4-7</td>
<td>Suffer a setback or a mental depression</td>
</tr>
<tr>
<td>α</td>
<td>8-12</td>
<td>Quiet state and state of concentration</td>
</tr>
<tr>
<td>β</td>
<td>13–40</td>
<td>Nervous, emotional or excited state</td>
</tr>
</tbody>
</table>

![Wavelet decomposition and reconstruction diagram](image)

Fig. 6  The wavelet decomposition and reconstruction

The wavelet function was used to carry out the 5 layer decomposition of the raw EEG signal, the new decomposition of the raw EEG signal, the new wavelet coefficients \( \hat{W}_{j,k} \) was obtained by thresholding based on Eqs. (4) and (7). The denoised EEG signal was shown in Fig. 5 and the wavelet were restructured by using \( \hat{W}_{j,k} \).

The threshold selection is to identify and eliminate noise and other high frequency signals. In this paper, the threshold \( T \) is determined by Bayes Shrink threshold estimation as shown in Eq. (4):

\[
T = \begin{cases} 
\delta^2 / \text{max}(\delta^2 - \delta^2, 0) & \delta^2 < \delta^2 \\
\text{max}(w_n) & \delta^2 \geq \delta^2 
\end{cases} \tag{4}
\]

where \( w_n \) is the wavelet coefficients and \( \delta^2 \) is the noise variance. The median estimate was performed with the first layer of high frequency coefficient \( w_{HH} \):

\[
\delta^2 = \left( \text{Med} \left( |w_{HH}(m,n)| \right) / 0.6745 \right)^2 \tag{5}
\]

\( \delta^2 \) is the energy estimation of each sub-band wavelet coefficients:

\[
\delta^2_j = \frac{1}{N} \sum_{m=1}^{N} w_n^2 \tag{6}
\]

The threshold function is a different processing strategy to process wavelet coefficients above or below threshold \( T \):

\[
\delta^2 = \frac{1}{N} \sum_{n=1}^{N} w_n^2 \quad w_{\text{new}} = \begin{cases} 
\text{sign}(w)|w-T| & w \geq T \\
0 & w < T 
\end{cases} \tag{7}
\]

High frequency coefficients of noise correlation were filtered after threshold quantization, then the denoised EEG signals were restructured based on the new coefficients \( w_{\text{new}} \).

2. Feature Extraction

The EEG signal has no obvious feature in the time domain. However, the feature became obvious and easy to obtain if the time domain signal was transformed into a frequency domain signal. The brainwave has a large range in the frequency domain. Previous research showed that the frequency of brain activity is mainly between 0.5 Hz and 40 Hz as shown in Table 1.

The EEG signal is a non-stationary signal. When the time domain signal is converted to the frequency domain by FFT, its time domain information is lost, threatening the original complexity of the extracted features. In this condition, the result of processing is not satisfactory. Here, wavelet transformation can keep the rich characteristics of the original EEG signal. The EEG signal is decomposed into different levels of reconstructed signal by using db 5 wavelet function (Fig. 6). There were 6 layers of decomposition with db5 wavelet function. High frequency signal (detail signal) was extracted from the 4th layer to the 6th layer of wavelet function and low frequency signal (approximate signal) was extracted from the 6th layer. The detail signal from the 4th, 5th, and 6th layers were used as δ, θ, α waves.
respectively. The approximate signal from the 6th layer was used as $\beta$ wave for further processing. The FFT results are similar to the original $\delta$ wave, $\theta$ wave, $\alpha$ wave, $\beta$ wave of EEG. So we can obtain these waves by using wavelet transform method in Fig. 7.

Signal decomposition expression:

\[
H_{j-1} f(x) = \sum_{k} a_{jk}^{-1} \phi(2^{-j-1} x - k)
\]

\[
D_{j-1} f(x) = \sum_{k} d_{jk}^{-1} \psi(2^{-j-1} x - k)
\]

where

Detail coefficient: $a_{jk}^{-1} = \sum_{k} h_{jk} a_{jk}^{-2}$,

Detail coefficient: $d_{jk}^{-1} = \sum_{k} (-1)^{j} h_{jk} a_{jk}^{-2}$,

Scaling function: $\phi(x) = \sqrt{2} \sum_{k} h_{jk} \phi(2x - k)$,

Wavelet function: $\psi(x) = \sqrt{2} \sum_{k} g_{jk} \phi(2x - k)$,

Signal reconstruction expression:

\[
H_{j} f(x) = \sum_{k} a_{jk} \phi_{k}(x)
\]

\[
a_{jk} = \sum_{k} h_{jk} a_{jk}^{-1} + \sum_{k} (-1)^{j} h_{jk} d_{jk}^{-1}
\]

The processed data was decomposed by wavelet transformation to obtain the $\delta(x)$ wave, $\theta(x)$ wave, $\alpha(x)$ wave, and $\beta(x)$ wave. The sub-band signal energy was calculated as follows:

\[
E(\delta) = \frac{1}{N} \sum_{n=1}^{N} (X_{\delta}(N))^2
\]

\[
E(\theta) = \frac{1}{N} \sum_{n=1}^{N} (X_{\theta}(N))^2
\]

\[
E(\alpha) = \frac{1}{N} \sum_{n=1}^{N} (X_{\alpha}(N))^2
\]

\[
E(\beta) = \frac{1}{N} \sum_{n=1}^{N} (X_{\beta}(N))^2
\]

The energy ratio of each signal was then calculated as follows:

\[
E_{\text{all}} = E(\delta) + E(\theta) + E(\alpha) + E(\beta)
\]

\[
E_{\delta} = E(\delta) / E_{\text{all}}
\]

\[
E_{\theta} = E(\theta) / E_{\text{all}}
\]
The energy values were normalized by the formula (15)-(19) and the results were shown in Fig. 8. In the fatigue state (Fig. 8 (a)), the sub-band energy of EEG signal was mainly focused on the $\delta$ wave; in the conscious state (Fig. 8 (b)), the energy of $\delta$ wave decreased, while the energy of other wave increased; in the concentrated state (Fig. 8 (c)), the energy of $\alpha$ wave was more prominent compared to the conscious and fatigue states. As for the frequency, with the increased concentration of the mental state, the energy of the low frequency signal was reduced, and that of the high frequency signal was increased. After wavelet decomposition, the ratio of EEG signals in different states could be quantified. The extracted features were obvious and ready to be distinguished.

3. Annealed Chaotic Competitive Learning Network

The conventional competitive learning network may be stuck with a local minimum solution in the training network. A preferable way is to embed the network with an annealed chaotic mechanism to obtain an optimal global minimum solution [29]. The sensitivity of the transient chaotic network model relies on a self-feedback connection weight. The weight is similar to a stochastic simulated annealing temperature. It changes dynamically in the process of the network. The annealed chaotic competitive network can escape the local-minima and reduce the convergence time quickly. We used a two-layer annealed chaotic competitive learning network (ACCLN) shown in Fig. 9. It is an annealed chaotic neural network topology. For the network, $n$ neurons in the input layer were divided into $c$ classes in the output layer. In another word, there were $c$ cluster-centers in the output layer. In the training process, the internal state $q_{s_j}$ and the transient state $p_{s_j}$ of the interconnection strength were tending towards achieving stability by an annealed chaotic mechanism between the input layer and the output layer of the network. The output results were updated in a gradient descending manner with a small learning-rate parameter $\eta$. This parameter was used for parallel synchronous computation in the bifurcation state.

The convergence process of the ACCLN has been shown in [30]. The neuron states were updated by the function $q_{s_j}$. A simulated annealing strategy was used as the training network by Eq. (20). The network model has $n$ neurons in the input layer, $c$ neurons in the output layer and $n \times c$ interconnection strengths. The mathematical expressions of this model are as follows:

$$E = \frac{1}{2} \sum_{s=1}^{c} \sum_{j=1}^{n} p_{s_j} |z_s - w_j|^2$$

$$p_{s_j}(t) = \frac{1}{1 + e^{-\eta s_j(t)\eta}}$$
$$q_{x_{ij}}(t+1) = \mu q_{x_{ij}}(t) + E - T(t)(p_{x_{ij}}(t) - L)$$  \hspace{1cm} (22)

$$\Delta w_j = \eta(z_j - w_j)p_{x_{ij}}$$  \hspace{1cm} (23)

$$T(t+1) = \frac{1}{\beta + 1}[\beta + (\tanh(\alpha))']T(t)$$  \hspace{1cm} (24)

$$w_j(t+1) = w_j(t) + \Delta w_j(t)$$  \hspace{1cm} (25)

where $E$ is the energy function, and $p_{x_{ij}}$ and $q_{x_{ij}}$ are the transient state and internal state of interconnection strength, respectively. $w_j$ is the weight coefficient between each input neuron node and output neuron node. $\eta$ is a small learning-rate parameter. These parameters are updated in real time in training process.

**IV. EXPERIMENT**

1. The Experimental Platform and EEG Signal Extraction

The human cerebral cortex is mainly divided into four regions; the occipital lobe, frontal lobe, parietal lobe and temporal lobe. The main processing area for the human mental state is located in the frontal lobe. In the current experiment, the EEG signal was collected by a headset manufactured by NeuroSky Inc. The acquisition electrode Fp1 of the headset was placed on the forehead (Fig. 10 (a), red circle), while the other electrode A1 clasped the ear. The EEG signal was filtered, amplified and A/D converted. The sampling frequency of the module is 512 Hz. It uses a 16 bit A/D converter. The module sends 512 packets per second.

Meditation and attention values are obtained from the same headset. Concentration and relaxation are two common states of human life. Meditation reflects the relaxation degree of the brain, with a range of amplitude being 0-100. Attention mainly reflects the concentration degree of the brain. The range of values is 0-100 [31]. Our experimental result showed that: When subjects were in a conscious state, the recorded amplitude did not differ significantly between meditation and attention (Fig. 11). However, when subjects entered the fatigue state from a conscious state, the degree of concentration significantly decreased, while the degree of relaxation increased (Fig. 12). It was found that when subjects are in a fatigue state, their meditation degree increases while the attention degree decreases. We therefore were able to determine the degree of fatigue by the
Table 2  The relationship between fatigue degree and fatigue state, conscious state, concentrated state

<table>
<thead>
<tr>
<th>Fatigue state</th>
<th>Conscious state</th>
<th>Concentrated state</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attention</td>
<td>low</td>
<td>middle</td>
</tr>
<tr>
<td>Meditation</td>
<td>high</td>
<td>middle</td>
</tr>
<tr>
<td>Fatigue Degree</td>
<td>high</td>
<td>middle</td>
</tr>
</tbody>
</table>

relative degree of attention and meditation. The following formula was defined to determine fatigue degree:

\[ F_M = \frac{Medi}{Atte + 0.1} \]  \quad (26)

where \( F_M \) is the fatigue degree, \( Medi \) is the degree of Meditation and \( Atte \) is the degree of Attention.

For the acquisition of conscious state EEG signal, all subjects were well rested (continuous sleep for 8-12 hours) before EEG recording. During the acquisition of EEG signal, all subjects were in a quiet state (reading). For the acquisition of concentrated state EEG signals, subjects were well rested (continuous sleep for 8-12 hours) before EEG recording. During the acquisition of EEG signal, subjects were playing a computer game (subjects themselves are regular game players). For the acquisition of fatigue state EEG signal, subjects were sleep deprived for more than 12 hours and were all tired or sleepy during recording. 30 subjects participated in the experiment. 10 people who slept for 12 hours were regarded as candidates of conscious subjects (reading). 10 people who had not been sleeping for 12 hours were regarded as candidates of fatigue subjects. 10 people who were playing game after sleeping for 12 hours were regarded as candidates of concentration subjects. Those conditions were the first step to obtain the signal and EEG signals were collected once per second. Sampling frequency was 512 Hz. In order to obtain the effective experimental data, we used the function of fatigue degree to identify fatigue state, conscious state, and concentrated state. The method is elaborated as followed in detail.

Because the range of meditation and attention is from 0 to 100, in order to avoid the emergence of the denominator 0, 0.1 was added for the denominator. Theoretically, this value is in the range of 0 to 1000.

In order to explain the effectiveness of the method, the tendency of meditation and attention from conscious to fatigue state is shown in Fig. 11. There was a correlation between meditation and attention, when the brain begins to enter the fatigue state, the attention value decreased significantly and the meditation increased significantly.

Table 2 shows the relationship between fatigue degree and fatigue state, conscious state, concentrated state. For example, when the fatigue degree is high and blink frequency is greater than 20 times per minute.

In the experiment, the EEG data was acquired by the TGAM NeuroSky module based on the Arduino platform. The threshold range of the parameters are shown as follows: for attention, low: 0-35, middle: 36-75, high: 76-100; for meditation, low: 0-35, middle: 36-75, high: 76-100; for meditation, low: 0-35, middle: 36-75, high: 76-100; so the fatigue degree is calculated by Eq. (28). low: [0, 0.35], middle: [0.48, 2.07], high: [2.16, 1000]; During data acquisition, the subjects wore the equipment and started to obtain data after 10 minutes. 1-second long EEG data was collected with an interval between data collection being 2 seconds.

The neural network is an adaptive pattern recognition technology; it does not need empirical knowledge and discriminant function. Instead, it can train the information from different states and obtain some kind of mapping relation. The identification process is shown in Fig. 13.

2. EEG Recognition Based on RBF Network

The overlap coefficient of RBF network was set to 0.1, 0.2, 0.3, 0.5. Feature \((E_0, E_{\theta}, E_{\alpha}, E_{\beta})\) was extracted from 500 sets of acquired data samples and was regarded as training sample. 100 sets of EEG signals were acquired in fatigue, conscious and concentration states from different subjects. The feature vector is calculated as the input to the neural network.

The expected output of the network is \((0, 1, 0)\) under the fatigue state, the conscious state is \((1, 0, 0)\), and the concentration state is \((0, 0, 1)\). The output function of the RBF net-
Table 3  The correct recognition rate of EEG signal based on RBF network

<table>
<thead>
<tr>
<th></th>
<th>Fatigue</th>
<th>Conscious</th>
<th>Concentration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>85%</td>
<td>88%</td>
<td>93%</td>
</tr>
<tr>
<td>EMSE</td>
<td>0.263</td>
<td>0.089</td>
<td>0.061</td>
</tr>
</tbody>
</table>

Table 3 shows the correct recognition rate of EEG signal based on RBF network.

The output function of the ACCLN has only two states, 0 or 1. In another word, the recognition result is true or false. Compared to the RBF network, the correct recognition rate of ACCLN network is higher. The number of the correct identification was 294 in the fatigue state, 295 in conscious state and 297 in a concentrated state. In the testing samples of the 900 groups, the recognition error was 14, and the average accuracy was 98.4%. In general, brainwave recognition rate of ACCLN network is superior to the RBF network.

Furthermore, In order to prove the validity of the pro-
Table 4  The ACCLN network output under fatigue state

<table>
<thead>
<tr>
<th>Network input</th>
<th>Network output</th>
</tr>
</thead>
<tbody>
<tr>
<td>( En(\delta) )</td>
<td>( En(\theta) )</td>
</tr>
<tr>
<td>1</td>
<td>0.854</td>
</tr>
<tr>
<td>2</td>
<td>0.818</td>
</tr>
<tr>
<td>3</td>
<td>0.715</td>
</tr>
<tr>
<td>4</td>
<td>0.756</td>
</tr>
<tr>
<td>5</td>
<td>0.781</td>
</tr>
<tr>
<td>6</td>
<td>0.817</td>
</tr>
<tr>
<td>7</td>
<td>0.808</td>
</tr>
<tr>
<td>8</td>
<td>0.738</td>
</tr>
<tr>
<td>9</td>
<td>0.826</td>
</tr>
<tr>
<td>10</td>
<td>0.795</td>
</tr>
</tbody>
</table>

Table 5  The ACCLN network output under conscious state

<table>
<thead>
<tr>
<th>Network input</th>
<th>Network output</th>
</tr>
</thead>
<tbody>
<tr>
<td>( En(\delta) )</td>
<td>( En(\theta) )</td>
</tr>
<tr>
<td>1</td>
<td>0.460</td>
</tr>
<tr>
<td>2</td>
<td>0.575</td>
</tr>
<tr>
<td>3</td>
<td>0.587</td>
</tr>
<tr>
<td>4</td>
<td>0.601</td>
</tr>
<tr>
<td>5</td>
<td>0.559</td>
</tr>
<tr>
<td>6</td>
<td>0.489</td>
</tr>
<tr>
<td>7</td>
<td>0.562</td>
</tr>
<tr>
<td>8</td>
<td>0.511</td>
</tr>
<tr>
<td>9</td>
<td>0.482</td>
</tr>
<tr>
<td>10</td>
<td>0.510</td>
</tr>
</tbody>
</table>

Table 6  The ACCLN network output under concentrated state

<table>
<thead>
<tr>
<th>Network input</th>
<th>Network output</th>
</tr>
</thead>
<tbody>
<tr>
<td>( En(\delta) )</td>
<td>( En(\theta) )</td>
</tr>
<tr>
<td>1</td>
<td>0.232</td>
</tr>
<tr>
<td>2</td>
<td>0.327</td>
</tr>
<tr>
<td>3</td>
<td>0.459</td>
</tr>
<tr>
<td>4</td>
<td>0.428</td>
</tr>
<tr>
<td>5</td>
<td>0.451</td>
</tr>
<tr>
<td>6</td>
<td>0.506</td>
</tr>
<tr>
<td>7</td>
<td>0.410</td>
</tr>
<tr>
<td>8</td>
<td>0.285</td>
</tr>
<tr>
<td>9</td>
<td>0.318</td>
</tr>
<tr>
<td>10</td>
<td>0.353</td>
</tr>
</tbody>
</table>

posed method, Table 7 shows the comparison of classification accuracy of the present work with that obtained by other researchers. The recognition accuracy of the method proposed in the current paper is superior to the traditional method.

V. CONCLUSIONS

In this paper, a new method is proposed to recognize EEG signals using discrete wavelet transformation and neu-
Table 7  Comparison of classification accuracy of the present work with that obtained by other researchers

<table>
<thead>
<tr>
<th>Authors</th>
<th>Method</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Li et al. [19]</td>
<td>Classification of EEG Signals Using a Multiple Kernel Learning Support Vector Machine</td>
<td>82.5%</td>
</tr>
<tr>
<td>Sivasankari, et al. [20]</td>
<td>Automated Epileptic Seizure Detection in EEG Signals Using FastICA and Neural Network</td>
<td>84.7%</td>
</tr>
<tr>
<td>Güler et al. [21]</td>
<td>Lyapunov exponents-Recurrent neural network</td>
<td>94.8%</td>
</tr>
<tr>
<td>Sadati et al. [22]</td>
<td>Discrete Wavelet Transform-Adaptive neural fuzzy network</td>
<td>87.6%</td>
</tr>
<tr>
<td>Tzallas et al. [23]</td>
<td>Time Frequency analysis-Artificial neural network</td>
<td>97.8%</td>
</tr>
<tr>
<td>Sivasankari et al. [24]</td>
<td>EEG Signal Classification using ICA, STFT &amp; Feed Forward BPNN</td>
<td>97.8%</td>
</tr>
<tr>
<td>Kala et al. [25]</td>
<td>Evolutionary Radial Basis Function Network for Classificatory Problems</td>
<td>93.3% (λ = 0.5)</td>
</tr>
<tr>
<td>Our work</td>
<td>EEG Signal Recognition based on Wavelet Transform and ACCLN Network</td>
<td>98.5%</td>
</tr>
</tbody>
</table>

Our future direction includes the improvement of the real-time performance of the proposed algorithm.

ACKNOWLEDGEMENTS

The authors are grateful for the support from the Industrial Science and technology research foundation of Shaanxi province (No.: 2015GY020), the Industrial Science and technology research foundation of Shaanxi province (No.: 2016GY040), foundation of Shaanxi Educational Committee (No.: 15JK1472), and the National Natural Science Foundation of China (Grant No.: 51704229).

REFERENCES


nealing and Neural Networks for Chaotic Time Series Forecasting.” Chaotic Modeling and Simulation 1: 81-90.

Manuscript Received: Nov. 10, 2016
First Revision Received: Nov. 18, 2016
Second Revision Received: Apr. 09, 2017
and Accepted: Apr. 13, 2017