EEG SIGNAL IDENTIFICATION USING SINGLE-LAYER NEURAL NETWORK

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ABSTRACT

EEG signal analysis is applied in various fields such as medicine, communication and control. To control based on EEG signals achieved good result, the system must identify effectively EEG signals. In this paper, a novel approach proposes the EEG signal identification based on image with the EEG signal processing via Wavelet transform and the identification via single-layer neural network. The system model is designed and evaluated with the dataset of 21,000 samples. The accuracy rate can obtain 91.15%.

KEYWORDS

EEG signal, Wavelet Transform, Neural Network

1. INTRODUCTION

EEG signal analysis was applied in medicine such as early detection of Alzheimer [1], epilepsy [2], etc. and applied in telecommunication such as calling or listening music based on EEG brain signal [3]. In these recent years, EEG-based control systems are more interested by researchers. However, the result of EEG signal identification must be very good, the controlling based on EEG signal will be better. The previous studies identifying EEG signals based on blink [4] or eye movement [5].

In this paper, we propose a novel approach of EEG signal identification based on the image. When users look at two different images such as animal image and landscape image, the obtained EEG signals will different. The proposed technique uses Mexican hat *W*avelet transform to convert EEG signal, then synthesize and normalize the input values for single-layer neural network to identify.

The rest of this paper is organized as follows: Section 2 presents the theoretical basis of EEG signal. System design is shown in section 3. Section 4 is experimental procedure and experimental results. Finally, section 5 concludes the paper and figures out the future works.

2. THE THEORETICAL BASIS OF EEG SIGNAL

The characteristic of EEG signals is constantly changing with the frequency from 0 - 100Hz. Figure 1 shows recorded EEG signal. EEG signals are recorded by electrode cap or headset with different channels such as 14-channel, 16-channel, 31-channel, etc. Figure 2 and Figure 3 describe the device used for recording EEG signals such as electrode cap and headset. EEG signal

DOI: 10.5121/ijci.2016.5501

is divided into 5 types of wave as follows: delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-100 Hz) [6].

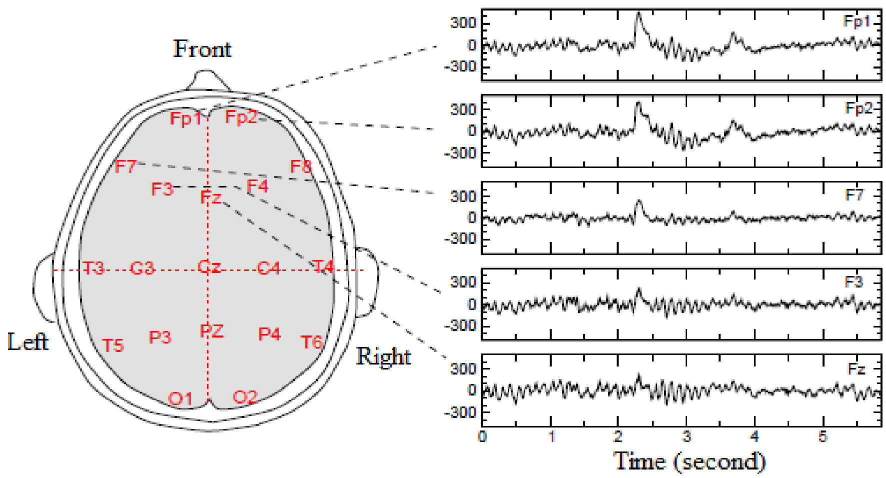

Figure 1. Description of recorded EEG signal

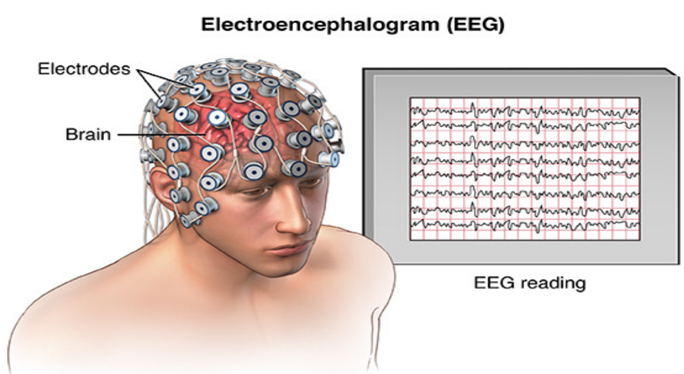

Figure 2. Electrode cap

Figure 3. Headset

3. THE SYSTEM DESIGN

3.1. System Model

The system model including 2 phases is presented in Figure 4.

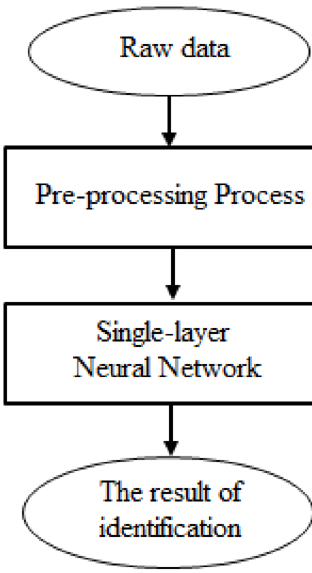

Figure 4. System model

The first phase: The pre-processing process converts raw EEG signals into delta, theta, alpha, beta and gamma waves. Then, synthesize to 5 delta, theta, alpha, beta and gamma waves.

The second phase: The single-layer neural network including 5 input nodes (delta, theta, alpha, beta and gamma) and one output node used for determining the result of identification.

3.2. Pre-Processing Process

Pre-processing process including two phases is presented in Figure 5.

The first phase: Convert EEG signal into delta, theta, alpha, beta and gamma waves using Mexican hat Wavelet transform by (1) and (2) [7].

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \quad (1)$$

$$\psi(t) = \frac{2}{\pi^{1/4}\sqrt{3}}(1-t^2)e^{-t^2/2} \quad (2)$$

where, $x(t)$ is the signal at interval a and time b. Mexican hat Wavelet is illustrated in Figure 6.

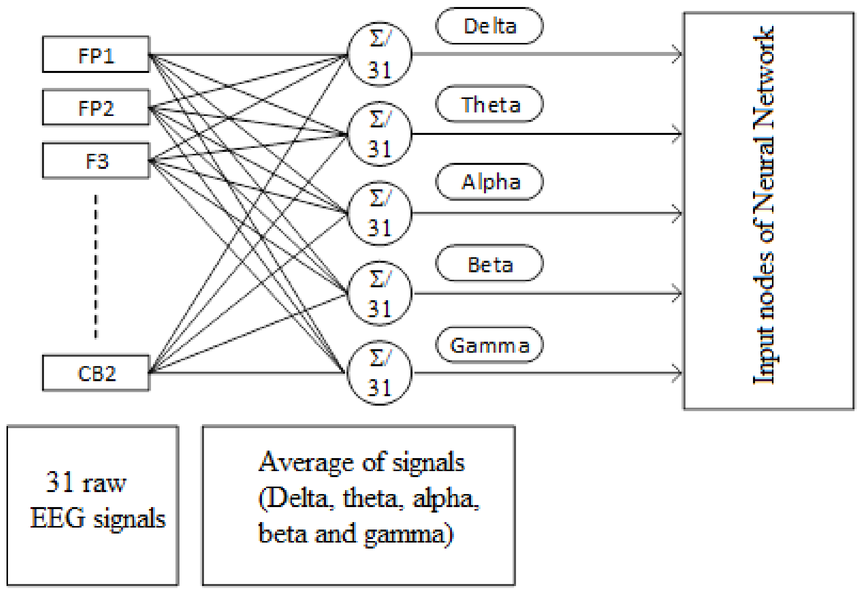

Figure 5. Pre-processing process

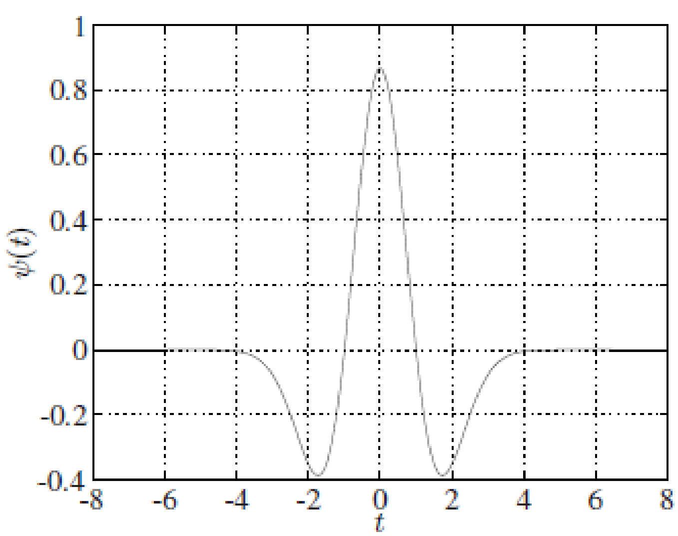

Figure 6. Mexican hat Wavelet

The second phase: Synthesize 5 delta, theta, alpha, beta and gamma waves by (3).

$$W_k = \frac{\sum_{i=1}^{31} x_{ik}}{31}, k = 1..5 \tag{3}$$

Where, k ranges from 1 to 5 corresponding to 5 signal such as delta (k=1), theta (k=2), alpha (k=3), beta (k=4), gamma (k=5) and x_{ik} is the value of the kth signal and the ith raw signal.

Figure 7 shows EEG signal received from the 31-channel device, Figure 8 shows a signal channel converted by the Wavelet transform via Matlab.

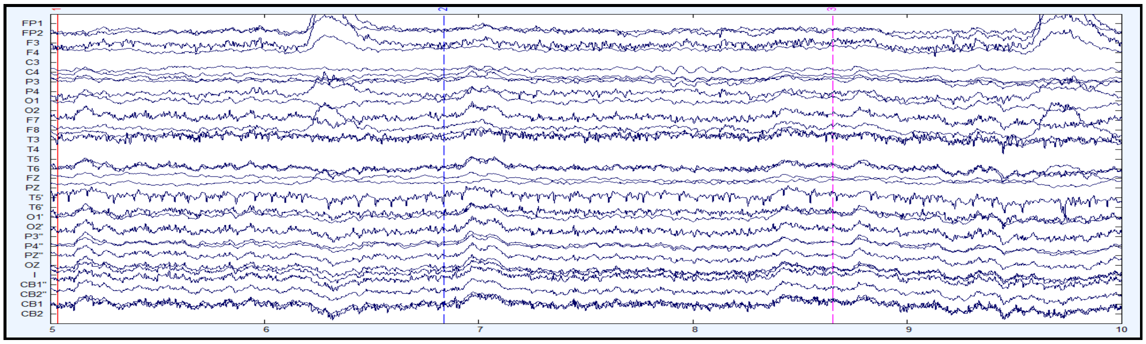

Figure 7. 31 recorded EEG signal

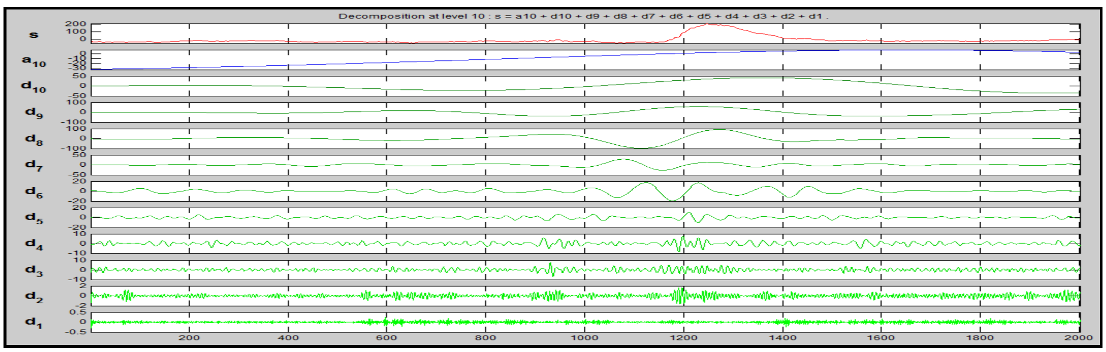

Figure 8. A signal channel is processed by Wavelet transform

3.2. Single-Layer Neural Network

The model including 2 layers is presented in figure 9.

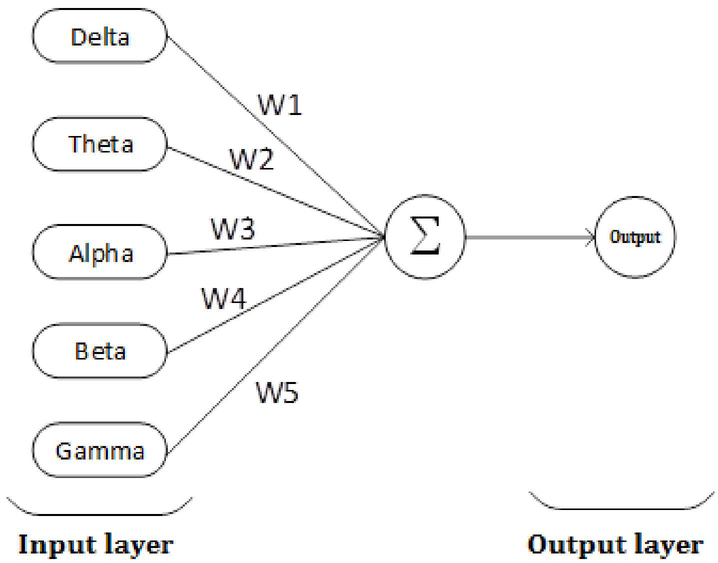

Figure 9. Single-layer Neural Network

The first layer contains 5 nodes such as delta, theta, alpha, beta and gamma waves. This layer is called the input layer.

The second layer contains one node, the result of this node is used to identify EEG signal. Due to the action function used in this model is hyperbolic tangent function, the value of the output node ranges in the interval [-1, 1]. If the output value ranges in the interval [0, 1], the identification result is a landscape image. If the output value ranges in the interval [-1, 0), the identification result is a animal image. Figure 10 shows the output result.

The network training algorithm for this model is the back-propagation algorithm [8]. After the training, the optimal weights will be used for the identification process.

The identification process is performed in 2 phases as follows:

The first phase: synthesize input nodes by (4).

$$O = \sum_{i=1}^{5} x_i . w_i \tag{4}$$

Where, x_i, w_i are the value and the weights of Alpha, Beta, Delta, Gamma, Theta node.

The second phase: The value of output node is calculated by (5).

$$f = \frac{e^{O} - e^{-O}}{e^{O} + e^{-O}} \tag{5}$$

Where, O is the output value is calculated from (4).

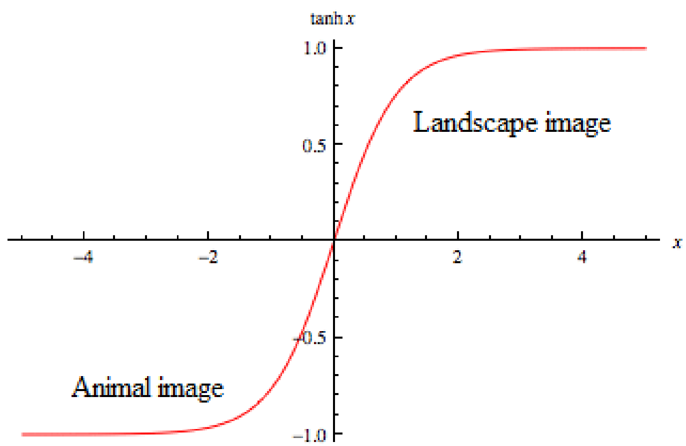

Figure 10. Classification of identification results

4. EXPERIMENTAL RESULTS AND DISCUSSION

We have selected 21,000 samples including 10,000 animal image samples and 11,000 landscape image samples from [9]. We create the training dataset that contains 7,000 animal image samples and 8,000 landscape image samples and the testing dataset that contains 3,000 animal image samples and 3,000 landscape image samples.

The data collected on the experimental process of some volunteer participants are as follows: The participants wear hat with recording 31-channels EEG signals and sit in front of a computer screen about 110cm, they perform two tasks alternately: classification and identification. The participants will perform in two days: the first day including 11 persons perform and the second day including 10 persons perform. Each person performs 1,000 pictures for one task.

To start work, the participant will press and hold the touch button. An 8-bit color image (256 pixels of width and 256 pixels of height) appears in about 200ms, the participant will release the button if the image is the animal picture. The first period of 1000ms is considered the reaction time of the participant, the total time for an experimental image is 2000 ± 200ms described in Figure 11

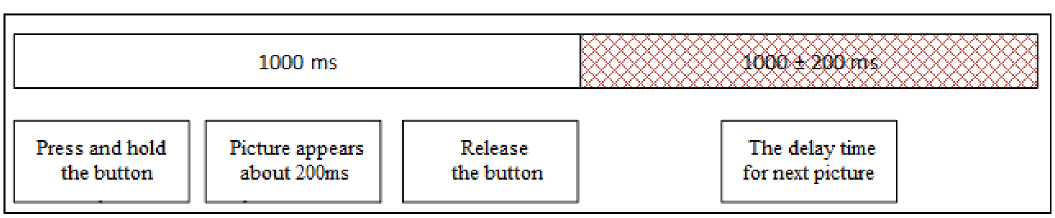

Figure 11. The schema for an image

In the classification, the participants will react whenever there was animal or landscape in image, then signal will be recorded.

The system using Matlab for experimental process, the neural network is divided into two experimental phases:

The training phase is performed on the training data set with the following parameters:

- Learning rate: 0.7
- Number of epochs: 5,000
- The weights: initialize weights random values from 0 to 1.
- Mean error threshold value: 10^{-5} and based on RMSE (Root Mean Square Error).

The identification phase based on the optimal weights received from training phase and equations (4), (5) to determine the identification results on the testing dataset.

Experimental results on the testing dataset is shown in Table 1.

Table 1. The experimental results on testing data set

Categories	**Picture**	**Accuracy rate**
France	Landscape	99,13%
Wild sheep	Animal	98,67%
Wild cats	Animal	99,28%
Bali, Indonesia	Landscape	62,44%
Wild animals	Animal	99,64%
California	Landscape	56,89%
Wolves	Animal	98,64%
Mushrooms	Landscape	95,16%
Kenya	Animal	99,76%
The big Apple	Landscape	98,79%
Snakes,	Animal	98,32%
Caves	Animal	67,18%
Polar bears	Animal	99,03%
Exotic Hong	Landscape	98,72%
Images of	Landscape	99,37%
Fabulous fruit	Landscape	98,25%
Wild animals	Animal	93,97%
Sand & solitude	Animal	98,42%
Lions	Animal	62,78%
Great Silk Road	Landscape	98,47%

From the experimental results in Table 1, we found that the average accuracy rate of 91.15%. This result is also compared to some previous studies such as the technique [4] identify EEG signals based on blink with 15,360 samples and reach 90.85%, the technique [10] based on eye movement by 2 experiments with 3,600 samples and 8,320 samples and reach 85%. We found that the proposed technique identifies better. Moreover, the proposed technique may apply for people with weak eye muscles or people with one eye. Figure 12 shows the comparison of techniques..

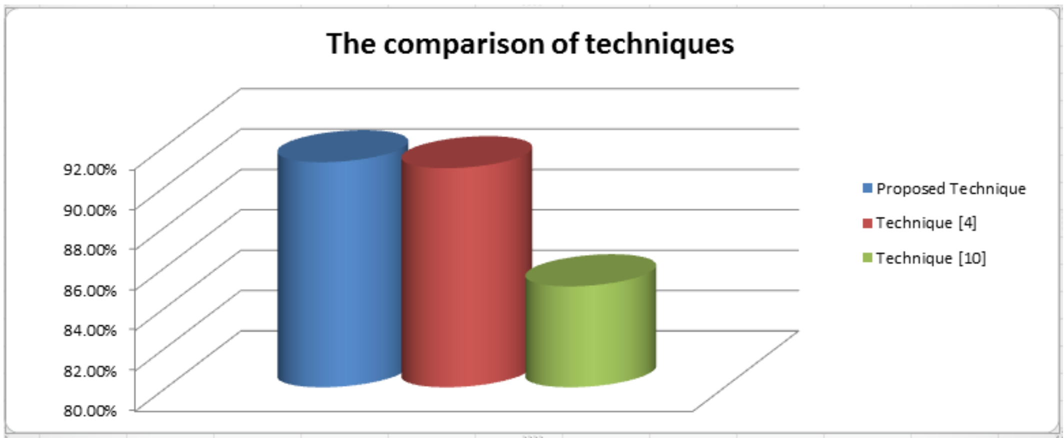

Figure 12. The comparison of techniques

5. Conclusion

In this paper, we propose a novel approach to identify EEG signals based on recorded signal when looking at the animal image or landscape image by using Mexican hat Wavelet transform and single-layer neural network. The proposed technique is experimented with 21,000 samples via Matlab and the achieved result is 91.15%.

In the future, we will develop this technique by improving pre-processing process to remove noise from original EEG signal before Wavelet transform, and improving neural network to enhance the efficiency of identification. Besides, the system will improve to identify more different types of image for EEG signal.

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