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Combination of Wavelet and MLP Neural Network for Emotion Recognition System

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***Abstract*—**Emotional recognition from the EEG signal is one of the areas in which many scientists around the world have concerned. Two important issues are EEG feature extraction and EEG classification. The wavelet transform method allows the extraction of nonlinear characteristics of the data from which it is possible to derive smaller feature vector than other methods. The MLP neural network has proven to be a very effective classification method. Thus, in this paper, the authors present one method to construct a highly accurate emotional recognition system by combining the two above methods. The results based on Matlab simulations with the standard data from the international scientific community.

Keywords- *Emotional recognition; EEG signal; Wavelet transform; MLP neural network;*

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I. INTRODUCTION

In recent years, there has been a lot of research in the world about decoding the Electroencephalogram (EEG) and building the EEG signal recognition system that supports human communication.

In an EEG Signal Identification System (Fig 1), we can see that the three most important components are Signal Acquisition, Feature Extraction, and Classification.

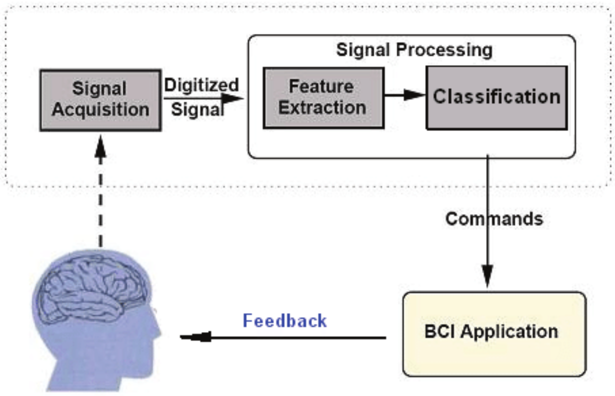

Figure 1. Basic block diagram of BCI system [1]

The EEG Signal Acquisition is a complex process that requires huge investment in hardware and high accuracy requirements. However, several large research centers as well as several scientific forums have produced large enough EEG templates for the development of EEG signal recognition algorithms [8].

In the Feature Extraction process, there are some typical methods such as Principal Component Analysis, Independent Component Analysis, and Autoregressive Modeling. These methods mainly based on linear space signal analysis, so they did not fully exploit the nonlinear nature of the EEG signal. Recently, based on the advantages of nonlinear signal representation on both frequency and time domain of the wavelet transform, there have been several published studies in the world that focus on the application of wavelet transform to extract the characteristics of EEG signals in order to obtain much higher efficiency than traditional methods [5], [7].

For the emotional recognition system operate efficiently, In addition to identifying appropriate methods to extract selected characteristics of EEG signals we need to choose a suitable classification techniques. In fact, some basic classification methods are commonly used. For example, Euclidean Distance, Support Vector Machine, Artificial Neural Networks. Currently, due to the great support of some advanced technologies such as GPU, Deep Learning, the neural network methodology has shown superiority [2].

In fact, there are some commonly used methods: Euclidean distance classifications, Support Vecto Machine (SVM) classifiers, artificial reproduction. Currently, due to the great support of advanced technologies such as GPU, Deep Learning, the neural network methodology has shown superiority [2].

Therefore, the main content of this paper is to describe the steps to build an efficient EEG signal identification system. In particular, we use wavelet transform for selective extraction and MPL for the classification. The results were evaluated by Matlab simulation with inputs as standardized signal samples.

II. FEATURE EXTRACTION OF EEG SIGNAL USING WAVELET TRANSFORM

EEG signals include some spectrum components. The amplitude of an EEG signal is between 10 and 100 µV. The frequency band of an EEG signal is limited and the most important frequencies from the physiological perspective are in

ISSN: 2454-4248
105 – 109

the range of 0.1 to 30 Hz. The clinical ranges of the standard EEG signal are delta (0.1 to 3.5 Hz), theta (4 to 7.5 Hz), alpha (8 to 13 Hz) and beta bands (14 to 30 Hz). An EEG signal with a frequency greater than 30 Hz is called a gamma wave [3].

Nowadays various digital signal-processing tools such as Fourier Transform (FT), Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT) and Wavelet Transform (WT) have been introduced for EEG signal feature extraction. Wavelet Transform has been more efficient for signal analysis in comparison to other transform methods such as Fourier transform, Short Time Fourier Transform. The process of extracting EEG signal characteristics using wavelet transform includes four steps: Raw signal acquisition, followed by pre-processing of signals, separation of raw signals into basic waveforms (delta, beta, theta, alpha, gramma), calculating the characteristic parameters for emotional identification (Fig 2).

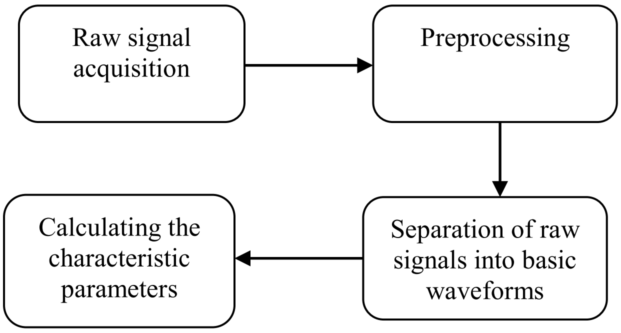

Figure 2. Four Steps to extract EEG signal feature using Wavelet transform

A. *Raw signal acquisition and Preprocessing*

In this article, the author uses a standard database of three emotional states: neutral, happy, and sad [1], [9], [10]. Data were collected by using an Emotiv Epoc headset of 14 electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) and 2 reference electrodes (Fig.3). EEG data used here was recorded according to the international 10-20 system. Each emotional state was sampled 500 times and stored in file *.mat.*

Figure 3. Emotive Epoc Headset

B. *Separation of raw signals into basic waveforms*

Because EEG is a non-stationary signal, so it is more suitable to use time-frequency based method such as discrete wavelet transforms (DWT). DWT analysis is important to address the different behavior of EEG signal on both time and frequency domain [4].

Thus, in order to perform Feature Extraction process in the emotional recognition system, the authors used the discrete wavelet transform method. Each EEG signal in the database was separated into five basic wave components: Delta, Theta, Alpha, Beta and Gamma. As for the company's datasheet, the Epoc headset collects data at the frequency of 128Hz (sample frequency). We therefore choose the level of DWT analysis of five to obtain the basic waveform. In fact, there are many different wavelet selection options, but in this paper, we select the Debugies4 wavelet for EEG signal processing (Table.1).

TABLE I. WAVELET DECOMPOSITION OF EEG SIGNAL

Decomposition levels	***Sub-band Decomposition***	***Frequency bands***	***Frequency bandwidth***
1	CD1	Noise	64-128
2	CD2	Gama	32-64
3	CD3	Beta	16-32
4	CD4	Alpha	8-16
5	CD5	Delta	4-8
	CA5	Theta	0-4

C. *Calculating the characteristic parameters*

From the basic wavelet components (Table.1), we can calculate the characteristic parameters for the emotional classification system such as mean, power, standard deviation…However, the three most important are Arousal, Valance and Dominance [8].

Mean: The mean value is the median value of the data set. Assume that X is a random variable, the mean value of X is calculated by the following formula:

$$\mu_X = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

Power: Power is the measurement of the amplitude of the EEG signal and is calculated by the formula:

$$Power = \sum \frac{X^2}{L(X)} \tag{2}$$

Standard deviation: The standard deviation of X is calculated by the following formula:

$$\sigma_x = \left(\frac{1}{N-1}\right)\sum_{n-1}^{N}(X_n - \mu_x) \tag{3}$$

Arousal: characterized by the power of beta waves and the attachment of the temporal lobes as well as the weakening of the alpha wave. Beta waves are related to the state of an alert or excited mind. Meanwhile, alpha waves are more dominant in the relaxed state. Thus, the ratio of beta/alpha factor is reasonable to point out an excited state of a person.

$$Arousal = \frac{\alpha AF3 + \alpha AF4 + \alpha F3 + \alpha F4}{\beta AF3 + \beta AF4 + \beta F3 + \beta F4} \tag{4}$$

Valance: Frontal lobes (F3 and F4) play an important role in regulating emotions and conscious experiences. Stopping the activity of the left side shows a negative emotion, and not even the activity of the right front shows a positive emotion. Thus, to determine the valance value, we compared the activation levels of the two hemispheres. In addition, other studies have

 ISSN: 2454-4248
105 – 109

demonstrated that hemispheric differences tell us about the direction of motivation. The hemispheric difference gives us a state of valance.

$$Valence = \alpha F4 / \beta F4 - \alpha F3 / \beta F3 \qquad (5)$$

Dominance: characterized by increased beta-alpha activity in the frontal lobe and increased beta activity in the temporal lobe.

$$Dominance = (\beta FC6 / \alpha FC6) + (\beta F8 / \alpha F8) + (\beta P8 / \alpha P8) \qquad (6)$$

Thus, in addition to the basic parameters (mean, standard deviation, power), we can calculate three important parameters (Arousal, Valance, Dominance) to serve the distinction of emotional state. The advantage of using the three parameters Arousal, Valance, and Dominance is to reduce the input variable of the staging of the emotional states.

III. EEG SIGNAL CLASSIFICATION USING MLP NEURAL NETWORK

A. *MLP network architecture for EEG signal recognition*

In the parameters obtained after the selective extraction process, the parameters Arousal, Valance, and Dominance are used as inputs of the MPL neural network for the process of classifying the emotional states. This is shown in Fig.4.

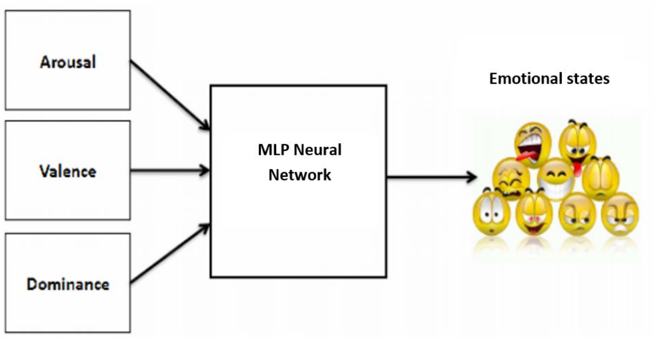

Figure 4. Identify emotions using MLP neural network

MLP is an artificial neural network that consists of a more number of processing elements called as neurons. These neurons are connected to one another and the strength of the connections is called weights. MLP consists of three layers: input layer, hidden layer and output layer. In order to increase performance multiple hidden layers are used (Fig.5)

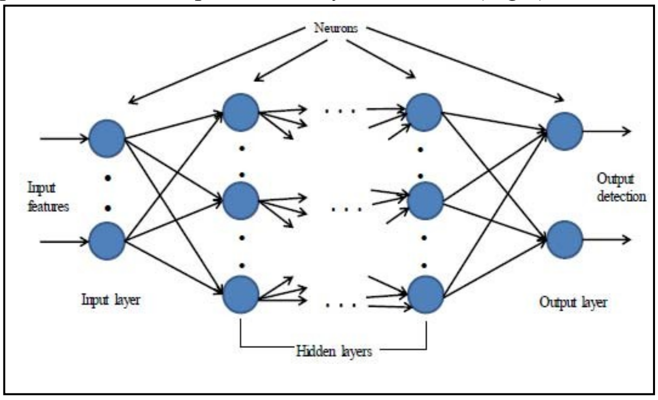

Figure 5. MPL Neural Network [4]

The neural network architecture used in this paper is described in Fig.6, which is an MPL network with two hidden layers; the neurons in each hidden layer are five and three respectively.

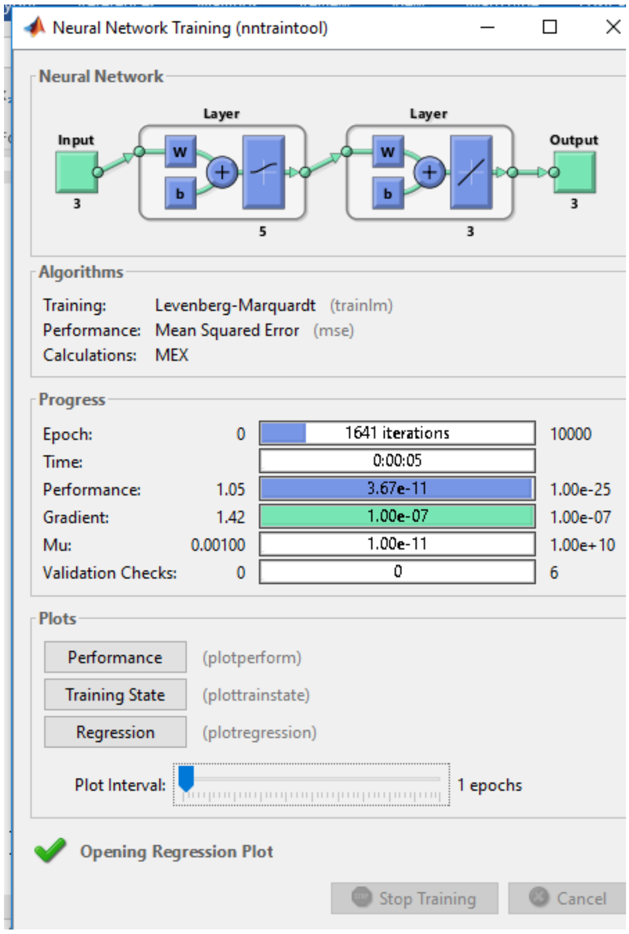

Figure 6. MPL network architecture for emotional classification

B. *Data for neural network training and testing*

Input data: Sample data for neural network training consisted of 1500 samples representing three emotional states (each emotional state was sampled 500 times), so the input matrix ($\vec{x}$) was defined as follows:

$$\vec{x} = \begin{bmatrix} \vec{a} \\ \vec{v} \\ \vec{d} \end{bmatrix} = \begin{bmatrix} a_{1,1}, a_{1,2}, ..., a_{1,500}, a_{2,1}, a_{2,2}, ..., a_{2,500}, a_{3,1}, a_{3,2}, ..., a_{3,500} \\ v_{1,1}, v_{1,2}, ..., v_{1,500}, v_{2,1}, v_{2,2}, ..., v_{2,500}, v_{3,1}, v_{3,2}, ..., v_{3,500} \\ d_{1,1}, d_{1,2}, ..., d_{1,500}, d_{2,1}, d_{2,2}, ..., d_{2,500}, d_{3,1}, d_{3,2}, ..., d_{3,500} \end{bmatrix}_{3\times1500}$$

Output data: To validate the emotional identification algorithm by combining the wavelet transform and the MLP network, the paper presents a classification of three emotional states: happy, sad, normal, so the output matrix ($\vec{y}$) is a matrix of three rows and three columns.

$$\vec{y} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}_{3\times3}$$

Test data: The test data includes 200 samples. This data is independent of the 1500 data samples that are used to train the MLP network.

IV. SIMULATION RESULTS

Based on the above analyzes, we have developed Matlab simulation software to evaluate the effect of combining discrete wavelet transform and MLP neural network for the emotional identification problem. The software consists of two modules: wavelet analysis and MLP training - testing.

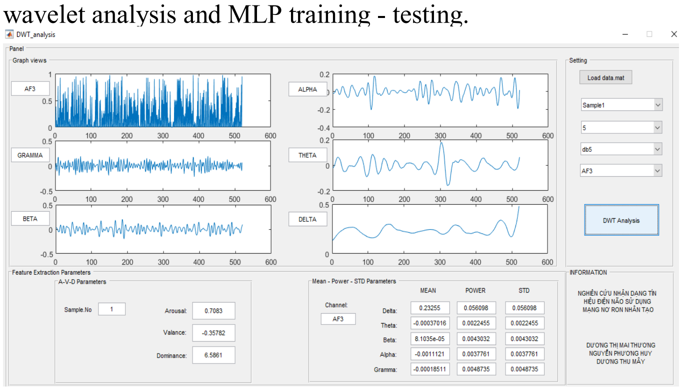

Figure 7. Result of DWT analysis

Fig.7 depicts the operation of the wavelet analysis module. It represents the EEG signal measured at the AF3 and Delta, Theta, Alpha, Beta and Gamma components obtained after the wavelet analysis. At the same time, the characteristic parameters for the EEG signal measured at AF3, including mean, standard deviation, and power, Arousal, Valance, and Dominance are calculated and expressed.

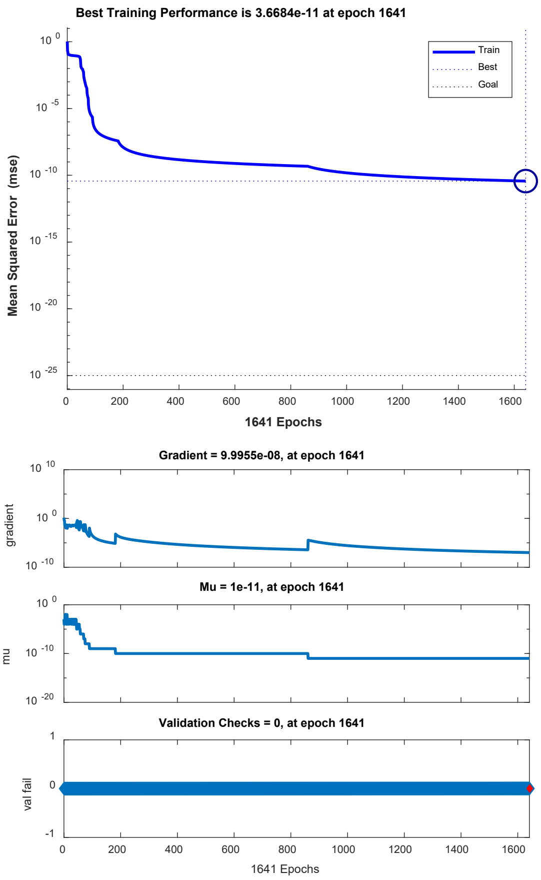

Figure 8. Quality parameters of MLP neural network training

The effect of combining Wavelet transform and MLP neural network for the emotional classification problem was tested with raw data samples obtained by Emotiv Epoc 14 channel electrodiagnostics. Samples used to verify data (happy, sad, neutral) are prescriptive. Fig. 8 shows the parameters that evaluate the quality of neural network training. Figure 9 shows the test results for the happy state.

Results showed that the algorithm yielded 93% accuracy in the identification test with 200 independent samples (different from the previous 1500 samples).

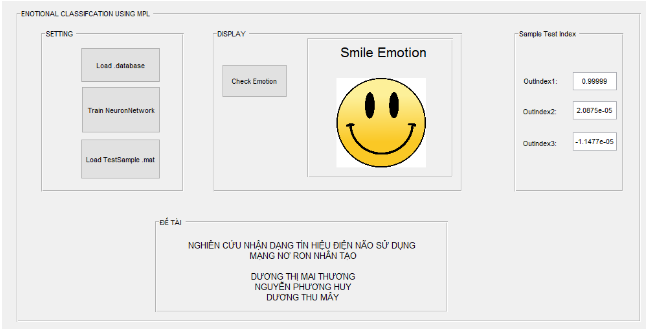

Figure 9. Recognition results of the happy emotion

V. CONCLUSION

Emotional recognition through EEG signals is a very attractive problem due to the large scope of application (from entertainment applications to medical applications such as patient support, the elderly, and children). However, in order to perform this problem, we encounter many difficulties in the processing of raw signals, the selection of characteristics and classification.

The use of basic selective extraction methods such as PCA, LDA, and AG ... will produce characteristic vectors with large dimension numbers. This will make it difficult to classify later. Therefore, using wavelet transform and calculating the three basic characteristics of Arousal, Valance, and Dominance is an important improvement. In addition, using the MLP network instead of conventional Euclid-based classification methods will allow for increased accuracy of the entire identification system.

However, the performance of MLP network completely depends on the number of hidden neurons present in the network. If hidden neurons are less the network will be incapable of differentiating between complex patterns. In contrast, if network has more number of hidden neurons it may lead to the addition of noise within the actual data because to over parameterization. Therefore, it is important to determine how many hidden layers the network is composed of, and how many neurons in each hidden layer to obtain the best possible identification. This is also the next issue that the authors wants to develop more.

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