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EEG Based Emotion Monitoring Using Wavelet and Learning Vector Quantization

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***Abstract*— Emotional identification is necessary for example in Brain Computer Interface (BCI) application and when emotional therapy and medical rehabilitation take place. Some emotional states can be characterized in the frequency of EEG signal, such excited, relax and sad. The signal extracted in certain frequency useful to distinguish the three emotional state. The classification of the EEG signal in real time depends on extraction methods to increase class distinction, and identification methods with fast computing. This paper proposed human emotion monitoring in real time using Wavelet and Learning Vector Quantization (LVQ). The process was done before the machine learning using training data from the 10 subjects, 10 trial, 3 classes and 16 segments (equal to 480 sets of data). Each data set processed in 10 seconds and extracted into Alpha, Beta, and Theta waves using Wavelet. Then they become input for the identification system using LVQ three emotional state that is excited, relax, and sad. The results showed that by using wavelet we can improve the accuracy of 72% to 87% and number of training data variation increased the accuracy. The system was integrated with wireless EEG to monitor emotion state in real time with change each 10 seconds. It takes 0.44 second, was not significant toward 10 seconds.**

Keywords—emotion monitoring; EEG signal; Wavelet; LVQ; Brain Computer Interface

I. INTRODUCTION

Emotion is a physiological process triggered by conscious and/or unconscious perception of an object or situation and is often associated with mood, temperament, personality, disposition, and motivation [1]. Emotion plays an important role in human communication that can be expressed through gesture, facial expression, text or speech. Emotion is a feeling and a particular thought in human, such as pleasure, anger, sadness, passion, and disappointment. Emotion can be divided into positive and negative emotion. Emotional control is very important, but some people have problems for it so that therapy is needed. When emotional therapy is performed, it is necessary to identify and monitor the impact of therapy on emotional change to be positive. One instrument that can identify the emotion state in real time is the Electroencephalogram (EEG).

EEG signals involve a great deal of information about the function of the brain, which may reflect a state of mind, such as level of attention [2], relax condition [3], mental activity [4], human grasping [5] [6], human attention [7], alertness level [8], or emotional conditions [9], [1], [10], and [11], [12]–[18]. Several studies on identification of emotional states through EEG signals are the response of sound stimulation [19], after watching movies [20], watching ads [21], listening to music [11], playing video game [12] , and watching videos [22], [23]. Moreover, wireless EEG provide comfort so emotional identification of brain signals can be an intermediate device in the development of Brain Computer Interface (BCI) [24] [25].

EEG signal transform becomes a model and by analyzing it provides an effective way to classify the EEG signal. In general, EEG signal consists of wave components, differentiated by their frequency regions. They are alpha waves (8-13 Hz), very often appears when people are in conscious and relaxed conditions; beta wave (14-30 Hz), often occurs when people are in thinking; theta wave (4-7 Hz), usually happens when people take a nap, feel sleepy, or suffer emotional stress; and delta wave (0.5-3 Hz), very often appears when people are in deep sleep. As a consequence, a lot of researches concerning EEG signal analysis represent the signal into frequency domain. It can be used like Power Spectral Density [26] [27] [24], Wavelet [18], [28]–[31] [2], [8], [32] [33]. Besides, EEG model used Autoregressive [5], [34]–[36], and Fractal Dimension [37] [10].

This research focuses on identifying emotion state. Prior research on EEG based emotion identification using statistical [38], Support Vector Machine (SVM) [39], Multilayer Perceptron [40] and Learning Vector Quantization (LVQ) [23]. Although there are varieties of emotional states to describe the human's feelings, until now only limited types of emotions can be recognized using EEG. They are time constrains, accuracy, number of electrodes, number of the recognized emotions, and benchmark EEG affective databases [37].

This research developed emotional response identification system in real time every 10 seconds. It used Wavelet transformation and LVQ. One of the emotional identification information based on the emotional identification can be informed the presence of Alpha, Beta, Theta, and Delta waves. Some research introduced Gamma wave can be represented Beta wave. Therefore using Wavelet for the signal extraction in the frequency area is very useful to improve the accuracy [9], [19], [29]. While the ability LVQ in machine learning to identify signals having fast computation [2], and quite accurately, so it is suitable for use as an identification system in real time.

Real time monitoring system was developed with 10 subject each 15 trials. Then it was segmented each 10 seconds and extracted into Alpha, Beta, and Theta waves using Wavelet. The

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three waves of four channels was identified using LVQ into three emotion i.e. excited, relax, and sad.

The system's ability to identify emotions is highly dependent on training data that precisely identify emotional state before. One way to obtain certain emotion state was by stimulation with music that can generate waves related to the emotional state [19]. Some music evoke Beta waves related to excited emotional state, slow music generate theta wave representing sad emotion, and some music evokes alpha waves for a relaxed emotional class. The system implemented in software to identify three emotional states in real time that can be used for monitoring emotional therapy.

II. Material and Methods

Monitoring system of emotion state as illustrated by Fig. 1.

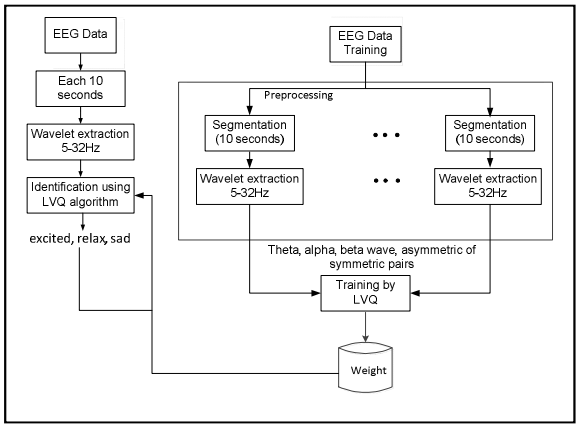

Fig. 1. Emotion state monitoring using Wavelet and LVQ

The system first learns by using the training data so that it can be obtained generalization in the form of weights which stored in the database. To improve recognition accuracy then the EEG signal is first extracted in the frequency range 5-32 Hz using Wavelet as Fig. 1

A. EEG Data Acquisition

EEG data is recorded with Emotiv Insight wireless EEG from 10 subjects for machine learning. In order to minimize other variables electrical activity in the brain, we selected the subject from a 20-25 years old, healthy and declared willingness as subject in this research. We used wireless EEG recording by placing electrodes on the four channels, namely AF3, T7, T8 and AF4 and with 128 Hz sampling frequency. It was recorded three sessions: in the morning, noon, and night. Before recording, the subject was asked to get enough sleep between 7-9 hours, then starting light sport and not hungry. The recording took place in a dim lighting level and not noisy. Each subject was recorded sit and open eyes. Everything were set to minimize the influence of other variables than emotional. The recording is performed for three minutes which were segmented every 10 seconds per channel, thus resulting in a set of 128 x 10 = 1280 points in a data set. EEG signal recording was used by 10 people for training data and 10 people tested offline test data before the system was used.

The face video was recorded to compare the result. Subjects performed three emotion state, excited, relax, and sad. System identification of the condition of emotion EEG signals constructed based on wavelet extraction as the input of LVQ. Experiments performed as illustrated by Fig. 2.

Fig. 2. EEG recording

Each subject is recorded with three different emotional states, namely excited, relax and sad. Recording begins with a stimulus of instrumental songs that can evoke beta waves or excited state. After that subject given about 30 minutes to rest and then proceed to record with sound stimulation that generate alpha waves or relaxed emotional state. Finally subjects given a sound stimulation that can generate Theta waves to evoke sad emotions.

B. Wavelet Extraction

EEG signals contain 0-128 Hz frequencies. Using Wavelet transform, EEG signal was extracted into needed frequencies (5-32 Hz) which contained Alpha, Beta, and Theta waves. Discrete wavelet transforms against x(n) signal is described as (1):

$$C(j,k) = \frac{1}{\sqrt{\left|2^{j}\right|}} \sum_{n} x(n)\psi^{*}\left(2^{-j}n - k\right) \quad (1)$$

is a wavelet base function, with and is a scale factor and shift.

Some of the wavelet functions are convolutions as well as down sampling which filtered the resulting signal value from each wave. Using wavelet transform, signal may be composed of signal approximation and detail. For example signal with 128 Hz sampling rate contains 0-64 Hz frequency band. It can be extracted into 5-32 Hz frequency band after five steps decomposition as Fig.3.

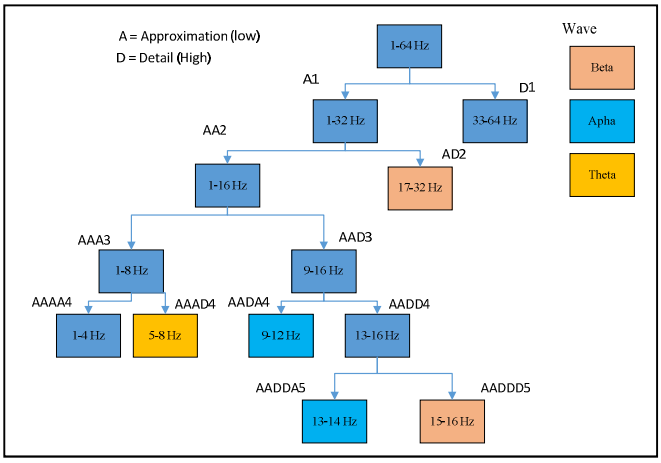

Fig. 3. Wavelet extraction into 5-32 Hz

Approximation is a resulted signal generated from convolution process of original signal with low-pass filter while detail is a signal generated from convolution process of original signal with high-pass filter. Approximation and detail described in (2) and (3):

$$\text{Approximation signal} = \text{yhigh}[k] = \sum_n x[n] * g[n-k] \quad (2)$$

$$\text{Detail signal} = \text{ylow}[k] = \sum_n x[n].h[n-k] \quad (3)$$

where

$x(n)$ = original signal
$g(n)$ = low-pass filter coefficient
$h(n)$ = high-pass filter coefficient
k, n = index 1 – till lenght of signal

Wavelet with Symlet2 function, contain four low pass filter coefficient (detoned g_n) and four high-pass filter coefficient (denoted h_n) (4) and (5).

Scale function coefficient (low-pass filter)

$$\boldsymbol{g}_0 = \frac{1-\sqrt{3}}{4\sqrt{2}},\ \boldsymbol{g}_1 = \frac{3-\sqrt{3}}{4\sqrt{2}},\ \boldsymbol{g}_2 = \frac{3+\sqrt{3}}{4\sqrt{2}},\ \boldsymbol{g}_3 = \frac{1+\sqrt{3}}{4\sqrt{2}} \quad (4)$$

Wavelet function coefficient (high-pass filter)

$$\boldsymbol{h}_0 = \frac{1-\sqrt{3}}{4\sqrt{2}},\ \boldsymbol{h}_1 = -\frac{3-\sqrt{3}}{4\sqrt{2}},\ \boldsymbol{h}_2 = \frac{3+\sqrt{3}}{4\sqrt{2}},\ \boldsymbol{h}_3 = -\frac{1+\sqrt{3}}{4\sqrt{2}} \quad (5)$$

Previous research were using Wavelet Symlet2 function in order to extract beta power [41]. Using Symlet2 in calculation actually almost the same with Daubechies4 calculation in determining values of alpha, beta, and theta waves from EEG signal. However, while the number of coefficients contained in Symlet2 and Daubechies4 are equal, their values are different. Symlet2 forms noted for asymmetric signals.

The extraction of EEG signals into theta waves was conducted in five steps by approaching the frequency range 5-8 Hz that yielding 8 points. Then, the signal was extracted in alpha waves 9-14 Hz with five steps for getting into 12 points. Beta wave extraction was after four steps (15-32), gave 36 points. After wavelet filtering, each second, using wavelet extraction we reduced 128 points into 56 points data. If the signal is 10 seconds, we got 560 points.

C. Monitoring System Using Learning Vector Quantization

Learning Vector Quantization (LVQ) is a supervised version of vector quantization that can be used when we have each input data with class label. This learning technique uses the class information to reposition the Voronoi vectors slightly as to improve the quality of the classifier decision regions, which adapted from Kohenen Map. A two stage process of LVQ shown Fig. 4.

Each of the classes used select one set of input vectors from the training data called weights. A competitive layer will learn to classify input vectors. The classes obtained as a result of this competitive layer depend on the Euclidean distance between reference vectors or weights compared training data each class. We are looking at based on (6).

$$D_i = \sum_{j=i}^{n} \left\| x_{ij} - w_{ij} \right\|^2 \quad (6)$$

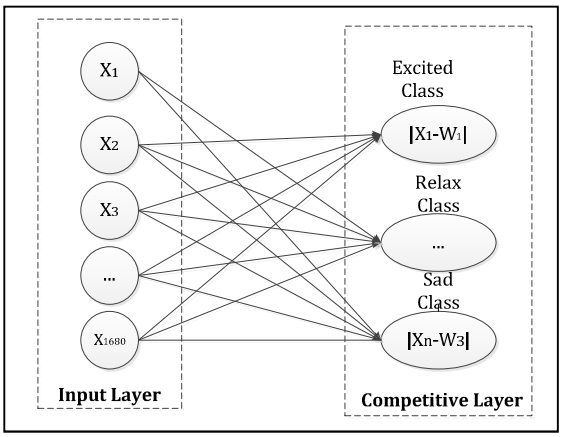

Fig. 4. LVQ Architecture

System identification was based on the results of the wavelet extraction, which is consecutive waves of theta, alpha, and beta on every 10 seconds and every channels. Considering the emotion state factor related to the asymmetric of symmetric channel, the information is also included in the identification system.

Follows is the series of input identification system:

$$x(n) = \begin{bmatrix} t_{1-8,s=1,AF3}, a_{1-12,s=1,AF3}, b_{1-36,s=1,AF3}, \cdots, \\ t_{1-8,s=10,AF3}, a_{1-12,s=10,AF3}, b_{1-36,s=10,AF3}, \\ t_{1-8,s=1,T8}, a_{1-12,s=1,T8}, b_{1-36,s=1,T8}, \cdots, \\ t_{1-8,s=10,T8}, a_{1-12,s=10,T8}, b_{1-36,s=10,T8}, \\ et_{1-8,s=1,AF3-AF4}, ea_{1-12,s=1,AF3-AF4}, eb_{1-36,s=1,AF3-AF4}, \cdots, \\ et_{1-8,s=10,AF3-AF4}, ea_{1-12,s=10,AF3-AF4}, eb_{1-36,s=10,AF3-AF4} \\ et_{1-8,s=1,T7-T8}, ea_{1-12,s=1,T7-T8}, eb_{1-36,s=1,T7-T8}, \cdots, \\ et_{1-8,s=10,T7-T8}, ea_{1-12,s=10,T7-T8}, eb_{1-36,s=10,T7-T8} \end{bmatrix}$$

Where t: theta wave, a: alpha wave, b: beta wave, et: equilibrium of theta wave, ea: equilibrium of alpha wave, eb: equilibrium of beta wave. Thus we get 560+560+560 = 1680 data input. Input of LVQ is 1680 or number of n.

The first step is feature selection – the unsupervised identification of a reasonably small set of features in which the essential information content of the input data is concentrated. The second step is the classification where the feature domains are assigned to individual classes.

The LVQ algorithm attempted to correct winning weight w_i which minimum D. The correction was by shifting:

1. If the input x_i and wining w_i have the same class label, then move them closer together by $\Delta w_i(j) = \beta(j)(x_{ij} - w_{ij})$
2. If the input x_i and wining w_i have a different class label, then move them apart together by $\Delta w_i(j) = -\beta(j)(x_{ij} - w_{ij})$

3. Voronoi vectors/weights wj corresponding to other input regions are left unchanged with $\Delta w_i(t) = 0$.

Where β(t) is a learning rate that decreases with the number of epochs of training. In this way we get better classification than by the SOM alone.

III. Result and Discussion

Wavelet extraction used Symlet2 by Wavelet extraction of 5-32 Hz reduced DC frequency and noise of signal as illustrated by Fig 5.

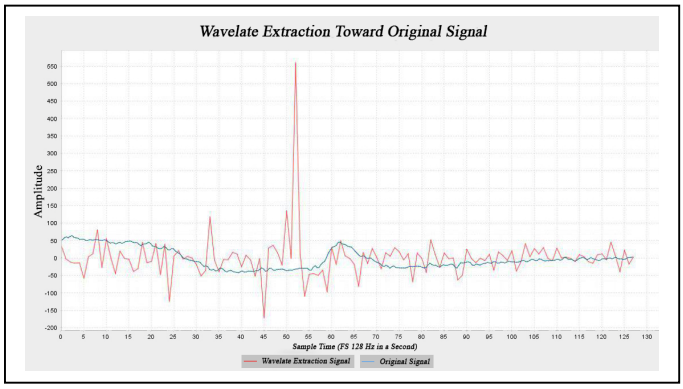

Fig. 5. EEG signal compared wavelet filtering in a second

Fig. 5 appears that the EEG signal was extracted to eliminate the signal details outside the frequency of 5-32Hz with half of data points

A. Optimizing of LVQ Parameter

Monitoring system for emotional condition needs to be tested against optimization of training parameters to find parameters that produce weight and accuracy that provide the best accuracy as shown in Table I Tests using the constant reduction of fixed learning rate, namely 0.1.

TABLE I. Optimized of Training Parameter

No	α	Epoch	Time	Accuracy (%)	
				Training Data	New Data
1	0.05	59	706	100	87
2	0.04	57	670	100	84
3	0.03	55	666	100	83
4	0.02	51	666	100	84
5	0.01	44	666	100	85

Optimized training parameters of LVQ are learning rate α 0.01 to 0.05 with 0.001 of learning rate reduction and the maximum epoch of 10000. We got that learning rate gave best accuracy 0.05. The next in the system.

B. Using Wavelet Filtering

Furthermore, the system tested the effect of using Wavelet extraction on accuracy as shown in Table II. It can be seen that 72% without extraction to 87% using extraction with asymmetric wave of pair symmetric channel and with 84% without asymmetric wave. So the identification process will be very good if it passes the stage of extraction first and using symmetric of wave.

TABLE II. Using Wavelet in Accuracy of Recognition System

State	Accuracy of (%)		
	Without Wavelet	With 3 wave of Wavelet	With 3 wave and asymmetric of Wavelet
Exited	73	84	88
Relax	74	88	90
Sad	70	79	84
Average	72	84	87

This research result that using wavelet filtering improved accuracy from 72% into 87%. While using asymmetric of pair symmetric channel improved accuracy of 84 to 87%.

C. System Monitoring of Emotion State

Recognition system tested toward training data. One of the advantages of a LVQ is revision of all weights but winner weight as the ANN method. Testing of all training data about 100% accuracy. The training processed took only under 10 minutes from all training data.

Monitoring system toward attention has implemented in integration software with wireless EEG. Each testing took 0.44 second to identify of 10 seconds. So it was not a signification lag time.

TABLE III. System Accuracy of Testing Data

Subject	Accuracy of (%)			
	Excited	Relax	Sad	Average
1	88	89	84	87
2	87	93	82	87
3	83	83	76	81
4	86	84	87	86
5	92	96	89	92
6	89	97	87	91
7	86	88	84	86
8	89	88	86	88
Average	88	90	84	87

The emotional state monitoring system that has been implemented in software is shown in Fig. 6. It can give emotional state in real time.

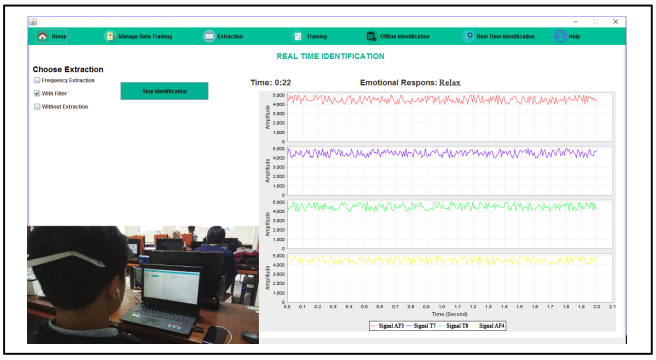

Fig. 6. Real time monitoring system of emotional state

IV. Conclusion

This research has developed an EEG signal recognition system on the attention state using wavelet extraction and LVQ. Using wavelet extraction could improve system accuracy from 72% to 87%. Using wavelet transform can also be the series

configuration theta wave, alpha and beta. Using asymmetric channel improved accuracy of 84% to 87%.

Using LVQ could reduce the computation time to be under a minute without accuracy loss. Obtaining generalization of data in LVQ training such was relatively faster and more stable than using Multilayer Perceptron. Each testing took 0.44 second to identify 10 seconds signals data. Therefore it was not a significant lag time.

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