Lifting Scheme for Human Emotion Recognition using EEG

M.Murugappan, M.Rizon, R.Nagarajan, S.Yaacob, I.Zunaidi, and D.Hazry
School of Mechatronics Engineering, Universiti Malaysia Perlis (UniMAP), 02600, Jejawi, Arau, Perlis, Malaysia
m.murugappan@gmail.com

Abstract

In recent years, the need and importance of automatically recognizing emotions from EEG signals has grown with increasing role of brain computer interface applications. *The detection of fine grained changes in functional state of human brain can be detected using EEG signals when compared to other physiological signals. This paper proposes an emotion recognition system from EEG (Electroencephalogram) signals. The audio-visual induction based acquisition protocol has been designed for acquiring the EEG signals under four emotions (disgust, happy, surprise and fear) for participants. Totally, 6 healthy subjects with an age group of 21-27 using 63 biosensors are used for registering the EEG signal for various emotions. After preprocessing the signals, two different lifting based wavelet transforms (LBWT) are employed to extract the three statistical features for classifying human emotions. In this work, we used Fuzzy C-Means (FCM) clustering for classifying the emotions. Results confirm the possibility of using two different lifting scheme based wavelet transform for assessing the human emotions from EEG signals.*

1. Introduction

Brain activity can be inferred from electroencephalograms (EEG) by placing electrodes on the surface of the scalp. The electrical potentials measured by the electrodes on the scalps are rich in information on the brain activity, and a proper signal processing would allow us to collect global information about mental activities and emotional states. In neuropsychological works [1, 2, 3] the signals measured from the central nervous system will give a relationship between psychological changes and emotions. Emotion recognition is one of the key steps towards emotional intelligence in advanced human-computer interactions (HCI). There are numerous areas in HCI that could effectively use the capability to understand emotion [4]. The next generation robot such as Sony AIBO uses the emotional ability of the human being as key factor for making an intelligent home for physically disabled peoples [5]. Brain activity of EEG signals is divided into five main frequency rhythms: theta, delta, alpha, beta and gama. For this emotion recognition experiment, the alpha frequency rhythm is having higher energy over other frequency bands. Some of the important issues to be carefully discussed in the aspect of increasing classification accuracy of human emotions are: (a) selection of an emotion elicitation method (b) proper positioning of electrodes and depth of placement of electrodes on the scalp (c) time duration of video clips and (e) proper design of acquisition protocol. Individual emotional state may be influenced by different kind of situations, and different people have different subjective emotional experiences even responses to the same stimulus. One of the hallmarks in that emotion theory is whether distinct physiological patterns accompany each emotion [6].

The objective of this study is to recognize the emotions from the alpha band frequency rhythm of EEG signals using lifting scheme and FCM. Lifting scheme based feature extraction is well established in image processing and limited work has been done in bio medical signal processing areas. It creates a possibility of achieving higher speed of computation with lesser memory requirement than compared to conventional wavelet transforms.

This paper is organized as: Section 2 describes the methodology of emotion recognition system. In Section 3, fuzzy c-means clustering is portrayed. The results are presented in Section 4. The conclusions are given in Section 5.

978-1-4244-2328-6/08/$25.00 © 2008 IEEE

2. Methodology

2.1 Subjects

Three females and three males in the age group of 21-27 years old were employed as subjects in our experiment. Once the consent forms were filled-up, the subjects were given a simple introduction about the research work and stages of experiment.

2.2 Selection of Emotional Clips

We used two commercial movie clips out of 10 for each emotion to elicit the target emotion in our experiment. A pilot panel study has been conducted over ten subjects, who are not taking part in the experiment, to select any 2 movie clip (2 trails) from the entire video clips set. The selection criteria followed for video clips are as follows: (i) the length of the scene should be relatively short. (ii) the scene is to be understood without explanation and (iii) the scene should elicit single target emotion in subjects and not multiple emotions [7].

2.3 Acquisition protocol

The protocol design for our experiment is shown in Figure 1. The maximum length of the video clip is 24 sec and the minimum length is 5 sec. The x1* and x2* denote the time periods of video clips. The recording of EEG signal has been done through Nervus EEG, USA with 63 channel electrodes at a sampling frequency of 256 Hz. AFz electrode (an electrode placed between AF1 and AF2) and ear lobe electrodes are considered as reference and ground electrode for our experiment respectively. The subjects were informed that between each movie clips they would be prompted to answer questions about the emotions they experienced under self-assessment section. In this section we posted four questions to subjects: (a) What emotion did you experience from this video clip? (b) Rate the intensity of emotion in 6 point scale (c) Did you experience any other emotions at the same intensity or higher than the stated emotion, and if so, specify (d) Have you seen these movie clips in an earlier period?

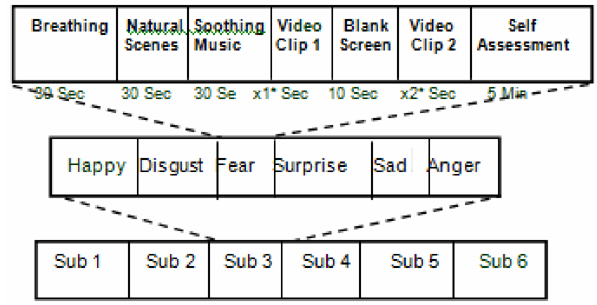

Figure 1: Acquisition protocol for EEG recording

From the above protocol, we found that, four emotions say happy, disgust and fear have been realized strongly by the subjects among the six emotions. Hence, we consider these four emotions in all our future analysis of this work.

2.4 Preprocessing and Normalization

The noises due to the electronic amplifier, power line interference and external interference have been reduced by using Average Mean Reference (AMR) method. The value of mean is calculated for each channel and it is subtracted from the original raw signal value. Normalization is also carried out to reduce the effects of individual differences due to their fundamental frequency rhythms and to reduce the computational complexity. All values of the attributes are normalized to lie in some common range of zero to one.

2.5 Feature Extraction

2.5.1 Wavelet Transform.

Various temporal and spatial approaches have been applied to extract features from the physiological signal. However, they are lacking in simultaneous time-frequency measurement with multi-resolution analysis (MRA) [8]. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter-regions where we want high frequency information. Discrete Wavelet Transform (DWT) has emerged as a powerful technique in diverse areas such as Multi-Resolution Analysis (MRA), peak detection and feature extraction of physiological signals and biomedical images.

Normally, the EEG signals are non linear and complex in nature. The non linearity and complexity of EEG signals can signify the different emotions of the human [9]. Different types of emotions have different waveform characteristics. Hence it is not always the optimal wavelet function which is suitable for detecting all the emotions. Moreover, the classical wavelet basis method does not improve the further properties of the wavelet basis. The conventional convolution based implementation of the DWT has high computational complexity and memory requirements. These are the key problem when using the wavelet functions for emotion detection [10].

2.5.2 Lifting Scheme.

The lifting scheme is a new method of constructing a wavelet with some desired properties. This method of wavelets to design orthogonal and biorthogonal wavelets has been developed by Sweldons and Daubechies [11-12]. The basic concept behind the wavelet is any wavelet with FIR filters can be Table 1) from the EEG signal. The preprocessed EEG signal is decomposed into sequence of wavelet coefficients using Daubechies wavelet functions.

In this work, we have selected three statistical features for emotions classification using FCM.

i) *Energy:* The energy feature can be calculated by squaring the wavelet coefficients on each frequency sub-bands.

ii) *Recoursing Energy Efficiency (REE):* In order to measure the recoursing energy efficiency of the approximation and detail coefficients, REE is calculated using the equation (1).

$$\text{REE} = \frac{\text{Energy of the sub-band}}{\text{Total Energy of the DEV}} \times 100 \qquad (1)$$

where DEV is the decomposition coefficient vector composed of energy at all frequency bands [16].

iii) *Root Mean Square (RMS):* The root mean square value of the wavelet coefficients on alpha frequency band has been calculated using the equation (2).

$$RMS\ (j) = \sqrt{\frac{\sum_{i=1}^{j} \sum_{n_i} D_i[n]^2}{\sum_{i=1}^{j} n_i}} \qquad (2)$$

where D_i and n_i are the detail coefficients and the number of detail coefficients at ith level. The feature vector is obtained by $rms(j)$ $(j = 1,2,3...N)$ was the deepest level of decomposition.

factorized into a finite number of alternating primal and dual lifting. The main difference with such conventional wavelet is that entirely relies on spatial domain. Therefore, it is ideally suited for constructing wavelets that lack translation and dilation, and thus the Fourier transform is no longer available. This scheme is called second-generation wavelets. Obviously, it can be used to construct first-generation wavelets and leads to a faster, fully in-place implementation of the wavelet transform. This method of lifting based implementation is not only reducing the number of computations but also achieves lossy to lossless performance with finite precision [13]. The mathematical implementation of lifting scheme can be viewed in [11-13]. In this study, we used Daubechies wavelet function with different order (“db4”and “db8”) for extracting the statistical features (

Table 1. Statistical features for emotions detection

FEATURE NO	FEATURE NAME
1	Energy
2	Recursive Energy Efficiency (REE)
3	Root Mean Square (RMS)

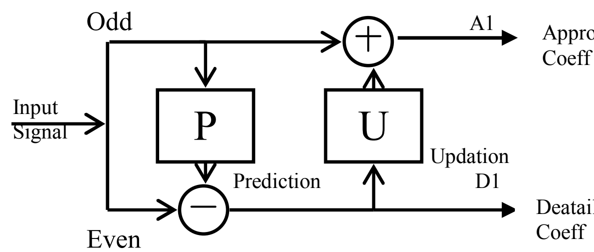

Figure 2. The block diagram for basic lifting scheme

The Figure 2 shows the basic block diagram of lifting scheme implementation. In the simplest form, the lifting scheme consists of three steps: i) splitting the signal into even and odd sub-arrays ii) prediction (P) of the odd array through linear combinations if even samples and extraction of predicted values from the existing one (D1) iii) lifting (updating- U) the even arrays using an already updated odd array which smooths this array (A1). The lifting scheme is subsequently applied on the approximation coefficients (A1) to derive new approximation and detailed coefficients.

This process is carried out iteratively producing a set of approximation signals at different detail levels (lifting stages). The extracted lifting wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Table 2 presents frequencies corresponding to different lifting levels with a sampling frequency (fs) of 256 Hz [14]. The frequency bandwidth of above frequency bands are lies within the range of standard frequency [15].

The feature extraction algorithm based on lifting scheme based Daubechies wavelet functions ("db") consists of 4 steps as

a) Perform 5 level lifting decomposition on all 63 channels of EEG signal for four emotions.
b) Calculate the values of statistical features for each channel on alpha frequency band.
c) Repeat the above steps (i) and (ii) for all six subjects.
d) Form the feature vector matrix for emotions classification.

Table 2. Frequencies corresponding to different levels of decomposition for "db4" wavelet with a sampling frequency of 256 Hz

Lifting levels	Sub-Bands Decomposition	Frequency Bands	Frequency Bandwidth (Hz)
1	CD1	Noises	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

3. Fuzzy C-Means (FCM) Clustering

From the paradigm presented in section II, feature extraction is performed on different data set of classes aiming at distinguishing emotions. Clustering is the task of categorizing objects having several attributes into different classes such that the objects belonging to the same class are similar, and those that are broken sown into different classes are not. Clustering is mostly unsupervised process that helps to find the inherent structure in the data. The Fuzzy C-Means technique is proved to be more general and useful in case of overlapping clusters. The FCM is based on minimization of an objective function. One of the issues in using fuzzy clustering based classification is setting the number of clusters to use in each class. The generalization is acceptable only when large sets of samples are available for classification [17]. In our work, the features derived for four emotions from the six subjects on 63 channels have been used as input for distinguishing emotions. In this paper, we have presented the results for Fuzzy C-Means [18] for 63 electrodes for discrete emotions clustering. This algorithm is implemented and stimulated in MATLAB 6.

The validation of our approach is as follows: The different lifting based wavelet transforms (LBWT) using two different wavelet functions were employed to decompose the EEG signal into several frequency sub-bands. The statistical features on alpha band have been derived to provide information about the EEG signal, after this stage FCM was used to maximize the separability of different emotions.

4. Results and Discussion

The five level lifting stages have been used for decomposing the EEG signal and 4^{th} level detail coefficients (alpha band) are used for extracting the features. In order to evaluate the selection optimal transform for efficient feature extraction in emotion recognition, we have calculated the value of objective function of FCM for three statistical features over six subjects. The value of objective function should be minimized for finding the best location for the clusters. Figure 3 through Figure 5 shows the performance of extracting the features using two lifting based wavelet transforms (LBWT) on discrete subjects. The lifting based db4 (LDB4) wavelet function perform well on minimizing the objective function on energy and RMS features. Besides the subject 3, all remaining subjects have evoked different emotions during our experimental time. The FCM plots for three different statistical features on discretizing emotions of subject 1 have been shown in Figure 6 through Figure 8.

5. Conclusions

We briefly reported the lifting based multi-resolution analysis of two different wavelet functions based feature extraction for emotions recognition using EEG signals. An acquisition protocol for recording the EEG signal under an audio-visual induction environment is designed to acquire emotional data. The extracted features from the lifting scheme based wavelet transform have been classified using FCM. We compared the results of different statistical features of 63 channels of EEG data using different wavelet functions. FCM based clustering performs well on classifying 63 channels EEG emotional data. Hence, the wavelet based feature extraction of EEG signal in alpha band activity has proved to be successful in distinguishing emotions from the EEG signals.

978-1-4244-2328-6/08/$25.00 © 2008 IEEE

6. Acknowledgement

This work is supported by Ministry of Science and Technology Innovation (MOSTI), Malaysia. Grant code 9005-00002. The authors gratefully acknowledge G Chanel from University of Geneva and Charles L from Korea Advanced Institute of Science and Technology (KAIST), Korea for a number of helpful suggestions on EEG measurement.

7. References

[1] Egon L, Broek V D, Schutt M H, Westerink J H D M, Herk j V, and Tuinenbreijer K, "Computing Emotion Awareness Through Facial Electromyography ", *HCI/ECCV 2006*, 2006, pp, 52- 63.

[2] Ekman P, Levenson R.W, and Freison W.V, Autonomic Nervous System Activity Distinguishes Among Emotions, *Journal of Experimental Social Psychology*,1983, pp, 195-216.

[3] Winton WM, Putnam L, and Krauss R, Facial and Autonomic Manifestations of the dimensional structure of Emotion, *Journal of Experimental Social Psychology*, 1984, pp, 195-216.

[4] Kim K.H, Band S.W, and Kim S.B, "Emotion Recognition System using short-term monitoring of physiological signals", *Proceedings on Medical & Biological Engineering & Computing*, Vol 42, 2004, pp, 419-427.

[5] Arikin R.C, Fujita M, Takagi T, and Hasegawa R, "Ethological modeling and architecture for an entertainment robot", *IEEE Proceedings on Robotics and Automation*, 2001, pp, 453-458.

[6] Cacioppo C.J and Tassinary LG, "Inferring Physiological Significance from Physiological Signals", *American Psychologist*, 1990.

[7] Nasoz F, Lisetti C.L, Alvarez K, and Finkelstein N, "Emotion Recognition from Physiological Signals for User Modelling of Affect", *Proceedings on Engineering Applications on Artificial Intelligence*, Vol 20(3), 2007, pp, 337-345.

[8] Mallat S. G, A theory for multiresolution signal decomposition: the wavelet representation, *IEEE Transactions on Pattern Anal. & Mach. Intelligence*, vol. 11, no. 7, Jul. 1989, pp, 674–693.

[9] Qin S and Ji Z, Multi-Resolution Time-Frequency Analysis for Detection of Rhythms of EEG Signals, *IEEE Proceedings on Signal Processing, 11'th International DSP Workshop*, Vol 4, 2004, pp, 338-341.

[10] Olivier Rioul and Martin Vetterli, Wavelets and Signal processing, *IEEE Signal processing Magazine*, 1991, pp, 14-38.

[11] Sweldons W, "The lifting scheme: a custom-design construction of biorthogonal wavelets", *Journal of Applied Computational Harmonic Analysis*, Vol 3(2), 1996, pp, 186-200.

[12] Daubechies I and Sweldons W, "Factoring wavelet transform into lifting steps", *Journal of Fourier Analysis Applications*, Vol 4(3), 1997, pp, 247-269.

[13] Sweldons W, "The lifting scheme: a construction of second generation wavelets", SIAM Journal of Mathematical Analysis, Vol 29 (2), 1997, pp, 511- 546.

[14] Chethan P, Cox M, Frequency Characteristics of Wavelets, *IEEE Transactions on Power Delivery*, Vol 17, No3, 2002, pp, 800-804.

[15] www.wordsworthcentre.co.uk (now available in online)

[16] Manikandan M S and Dandapat S .Wavelet threshold based ECG compression using USZZQ and Huffman coding of DSM, *Journal of Biomedical Signal Processing and control*, 2006, 261-270.

[17] Khushaba R N and Jumaily A A. Fuzzy wavelet packet based feature extraction method for multifunction myoelectric control, *IEEE Transctions on Biomedical Sciences*, Vol 2, No 3, 2007, pp, 186-194.

[18] Srinivasa K G, Venugopal K R, and Patnaik L M, Feature Extraction using Fuzzy C- Means Clustering for Data Mining Systems, *International Journal of Computer Science and Network Security*, Vol6, No 3A, 2006, pp, 230- 236.

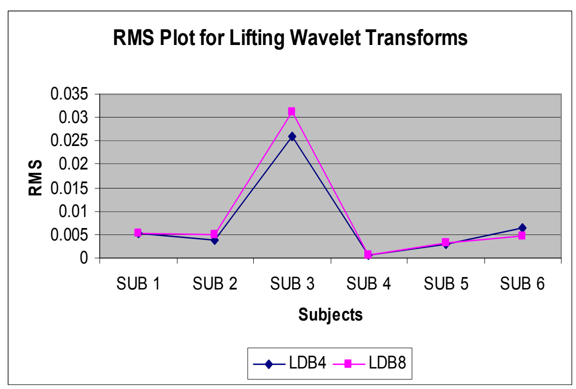

Figure 3. Objective function plot for RMS feature for two lifting based wavelet transform

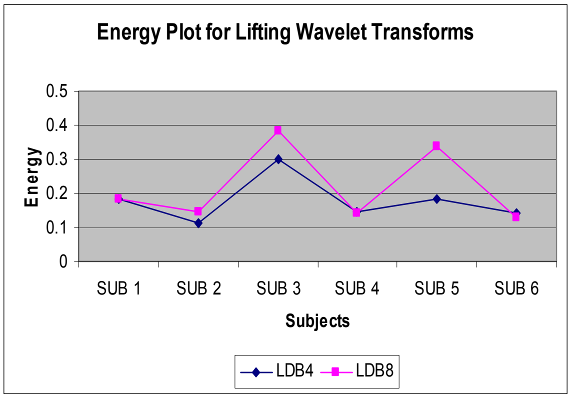

Figure 4. Objective function plot for Energy feature for two lifting based wavelet transform

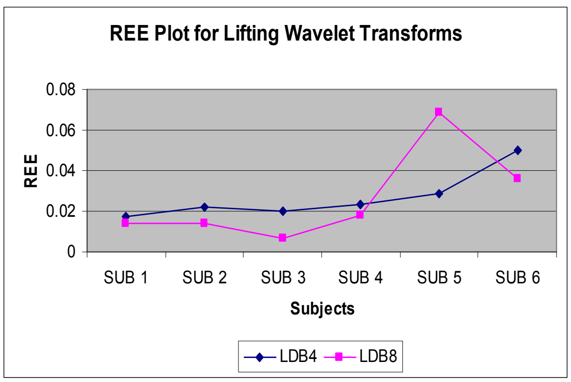

Figure 5. Objective function plot for REE feature for two lifting based wavelet transform

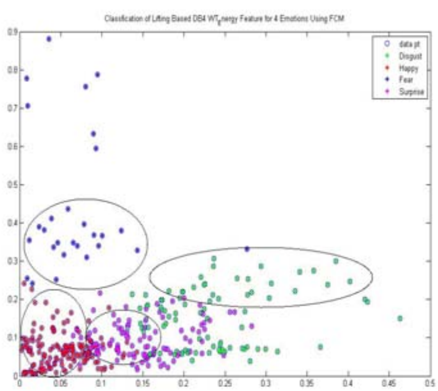

Figure 6. FCM Plot for Energy Feature for DB4 LBWT

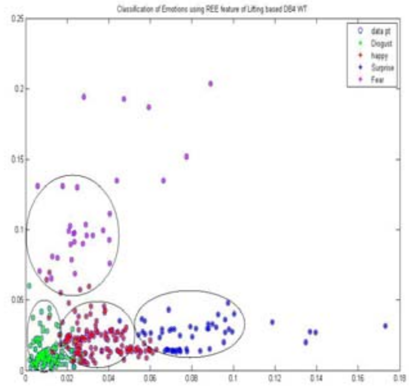

Figure 7. FCM Plot for REE Feature for DB4 LBWT

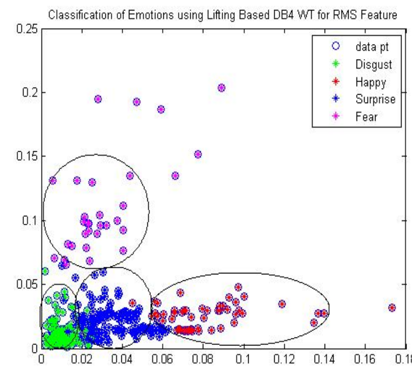

Figure 8. FCM Plot for RMS Feature for DB4 LBWT

Table 3: Objective function for different subjects for three different statistical features for two different Lifting based wavelet transform (LBWT)

Method	Objective Function Results of RMS feature for LBWT					
	SUB 1	SUB 2	SUB 3	SUB 4	SUB 5	SUB 6
LDB4	0.005114	0.003852	0.026049	0.000575	0.00305	0.00644
LDB8	0.005238	0.004882	0.031134	0.000659	0.003309	0.004663

Method	Objective Function Results of Energy feature for LBWT					
	SUB 1	SUB 2	SUB 3	SUB 4	SUB 5	SUB 6
LDB4	0.18522	0.114433	0.301577	0.146173	0.1824	0.140016
LDB8	0.183376	0.147031	0.38358	0.139754	0.338942	0.13061

Method	Objective Function Results of REE feature for LBWT					
	SUB 1	SUB 2	SUB 3	SUB 4	SUB 5	SUB 6
LDB4	0.01755	0.02184	0.01969	0.02355	0.028489	0.04984
LDB8	0.013734	0.014107	0.006808	0.01831	0.068878	0.03575

978-1-4244-2328-6/08/$25.00 © 2008 IEEE