Asymmetric Ratio and FCM based Salient Channel Selection for Human Emotion Detection Using EEG

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Abstract: - Electroencephalogram (EEG) is one of the most reliable physiological signals used for detecting the emotional states of human brain. We propose Asymmetric Ratio (AR) based channel selection for human emotion recognition using EEG. Selection of channels reduces the feature size, computational load requirements and robustness of emotions classification. We address this crisis using Asymmetric Variance Ratio (AVR) and Amplitude Asymmetric Ratio (AAR) as new channel selection methods. Using these methods the 28 homogeneous pairs of EEG channels is reduced to 4 and 2 channel pairs respectively. These methods significantly reduce the number of homogeneous pair of channels to be used for emotion detection. This approach is illustrated with 5 distinct emotions (disgust, happy, surprise, sad, and fear) on 63 channels EEG data recorded from 5 healthy subjects. In this study, we used Multi-Resolution Analysis (MRA) based feature extraction the original and reduced set of channels for emotion classification. These approaches were empirically evaluated by using a simple unsupervised classifier, Fuzzy C-Means clustering with variable clusters. The paper concludes by discussing the impact of reduced channels on emotion recognition with larger number of channels and outlining the potential of the new channel selection method.

Key-Words: - EEG, Human Emotions, Asymmetric Ratios, Channel selection, Wavelet Transform, Fuzzy C-Means (FCM) clustering.

1 Introduction

The electric potential measured at the scalp through a set of electrodes (channels) are rich in information about the brain activity. Researchers believe that the state of the brain changes as emotions change, therefore the EEG is suitable for the task of recording the changes in brainwaves which vary in accordance with emotions [1]. Most of the useful information about the functional state of human brain lies in the frequency range of DC-30 Hz. EEG signals are discern as: delta band (0 to 4 Hz), theta band (4 to 8 Hz), alpha band (8-12 Hz), beta band (12-16 Hz), and gamma band (16- 30 Hz). The primary research on emotion recognition depends on alpha band [2]. In this work, alpha band of EEG frequency rhythm is considered for both channel selection and feature extraction.

In recent days, many emotion detection schemes focus only on external activities such as speech, face and gestures. Though these methods have many advantages, still it is a challenging issue of assessing the emotions with high precision. In addition, these methods are not applicable in the case of physically disabled, introverted and impassive learners. Today, the researchers are focusing on multi-modal system that can detect the non-verbal behavior and physiological changes for assessing the emotions. Many works discuss the correlation of physiological signals such as EMG, Blood Volume Pressure (BVP) and Skin Conductance Resistance (SCR) with human emotion detection [3, 4, 5]. However, very little research has been performed on EEG for human emotion recognition. The main inadequacy lies in the fact that, it is very hard to uniquely map physiological patterns onto specific emotion types. Since the physiological data are sensitive to artifacts and noises.

A considerable amount of research efforts have been channeled towards the identification and utilization of information about the electrical activity of human brain for Human Computer Interaction (HCI) applications.

In this paper, we discuss two methods: (a) Asymmetric Amplitude Ratio (AAR) and (b) Asymmetric Variance Ratio (AVR), for deducing the channels from original set of channels. The Multi-Resolution Analysis (MRA) of wavelet function is used for extracting the statistical features from original and reduced set of channels for emotions classification. The method of channel selection can also be treated as feature selection problem. The basic system on emotion classification is shown in Fig 1.

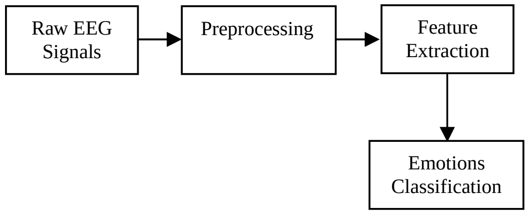

Fig 1 Basic diagram of emotion recognition system

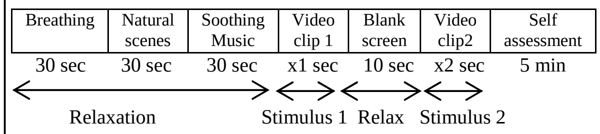

Fig 2 Data acquisition protocol for EEG recording

2 Experimental Setup

2.1 Data Acquisition Protocol

In our work, we have used an audio-visual induction based protocol for eliciting the primary emotions. To elicit the target emotions in our study, we used two commercial video clips out of 10 for each emotion. A pilot panel study has been conducted on 10 subjects, those who are not taking part in the experiment to select any 2 video clips from the entire video clips sets. The audio-visual stimulus protocol for two trials EEG recording for our experiments is shown in Fig 2. In the same way the other emotions over 5 subjects are considered for acquiring the EEG signals. The x1 and x2 denote the time periods of selected video clips. Three females and two males in the age group of 21-27 years 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. The recording of EEG signal has been done through Nervus EEG, USA with 64 channel electrodes at a sampling frequency of 256 Hz and band-pass filtered between 0.05 Hz and 70 Hz. The reference electrode is placed between AF1 and AF2. Two ground electrodes are placed on right and left ear lobes. The impedance of the electrodes are kept below 5 KΩ.

2.1 Preprocessing

The noises due to the electronic amplifier, power line interferences and other external interference have been reduced by using Average Reference Mean (AVR) 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 by using Zero Mean Unit Variance (ZMUV) method to reduce the effects of individual differences due to their fundamental frequency rhythms and computational complexity. All values of the attributes are normalized to lie in the common range of 0 to 1.

3 Channel Selection Methods

There are several studies proposed for channel selection on EEG signals for feature reduction. The conventional feature selection methods are based on Principal Component Analysis (PCA), Independent Component Analysis (ICA), Fast Independent Component Analysis (FICA), and Moments Based Feature Reduction (MBFR) [6]. To the authors' knowledge, there is no work on channel selection for primary emotion recognition using EEG. In this work, we use the Asymmetric Variance Ratio (AVR) and Amplitude Asymmetric Ratio (AAR) for selecting salient EEG channels. The basic diagram for channel selection is shown in Fig 3. Asymmetric Ratios are used for determining the alpha band asymmetry in brain hemisphere studies on human cognition [7]. In our work, the ratio of variances between hemisphere channels is considered as a physiological indicator for assessing the region of brain and the channels which are responsible for detecting the emotions [8]. In addition, ratios of spectral power between two hemispheres are used to accurately estimate the changes of electrical activity [9, 10]. The method to calculate asymmetric ratios for channel selection is given in Table 1.

3.1 Channel Selection Algorithm

In this work, we propose Asymmetric Ratios (AR) based selection of salient homogeneous pair of electrodes for emotion detection. The steps in channel selection algorithm for the proposed method are given below:

1. The raw EEG signals from five subjects over five discrete emotions are collected using 63 electrodes which are placed through standard International 10/20 system on the scalp.
2. In the preprocessing level, these raw signals are filtered by using 5th order band-pass filter at a cut of frequency of 0.05 Hz – 45 Hz for removing the noises and artifacts. These filtered EEG signals are normalized using zero mean unit variance and converted to the attribute values into a common range of zero to one.
3. This preprocessed signal is divided into five different EEG frequency bands such as delta, theta, alpha, beta, and gamma using 5th order Butterworth filter.

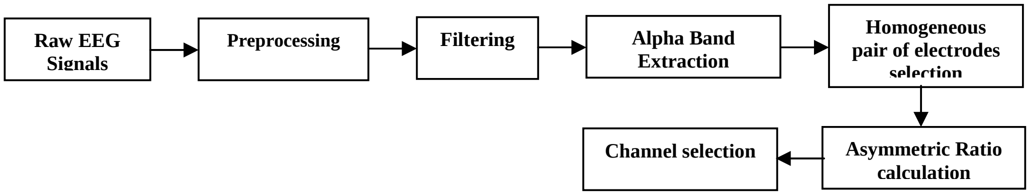

Fig 3 Process of channel selection using asymmetric ratio calculation

Fig 4 The methodology for feature extraction using wavelet transform

Table 1 Method to calculate Asymmetric ratios from the EEG channels

Parameter 1	Parameter 2
Asymmetric Variance Ratio (AVR): $$AVR = \frac{V(i) - V(j)}{V(i) + V(j)} \quad (1)$$ where $V(i)$ – Variance of left hemisphere channel; $V(j)$ – Variance of right hemisphere channel	Amplitude Asymmetry Ratio (AAR): $$AAR = \frac{P(i) - P(j)}{P(i) + P(j)} \quad (2)$$ where $P(i)$ - Spectral power of left hemisphere channel; $P(j)$ - Spectral power of right hemisphere channel
where i =0,1,2…….N , j=0,1,2…..N and N is the number of homogeneous electrodes on left and right hemisphere	

4. Due to significance of alpha band of frequency rhythm on emotion studies, only this band of frequency discussed for channel selection.
5. From the 63 channel EEG signals, only 28 homogeneous channel-pairs are separated out for calculating the asymmetric ratio for channel selection. Besides the 7 center electrodes, an amount of 56 electrodes on both right and on left hemisphere forms 28 pair of homogeneous electrodes.
6. Using the equations (1) and (2) the values of AVR and AAR are calculated for all the 28 homogeneous pair of electrodes on each subject.
7. All positive or negative values of AR for five emotions on each pair of channels are ranked as 5, for four emotions as 4, for three emotions as 3 and etc. The rank value of positive AR indicates that, the left hemisphere electrodes have larger influence over the right hemisphere electrode on certain emotion and the negative rank value of AR indicates the larger influence by right hemisphere electrodes.
8. The channel pairs of higher rank value among the two methods (AAR and APR) are sorted as most significant channels for emotion recognition.

4 Feature Extraction

The multi-resolution analysis of wavelet transform is used for decomposing the EEG signals into several frequency bands. The statistical features from the EEG signals for different emotions are derived from the Alpha band. The basic methodology for feature extraction using EEG signal on emotion recognition is shown in Fig 4. In the emotion recognition research using EEG signals, the non-parametric method of feature extraction based on multi-resolution analysis of Wavelet Transform (WT) is quite new. The joint time-frequency resolution obtained by WT makes it as a good candidate for the extraction of details as well as approximations of the signal which cannot be obtained by Fast Fourier Transform (FFT) or by Short Time Fourier Transform (STFT) [11, 12].

4.1 Wavelet Transform

A wavelet is a small oscillatory wave which has its energy concentrated in time. It has an ability to allow simultaneous time and frequency analysis and it is a suitable tool to analyze transient, non-stationary or time-varying signals [13, 14]. The non-stationary nature of EEG signals is to expand them onto basis functions created by expanding, contracting and shifting a single prototype function ($\Psi_{a,b}$, the mother wavelet), specifically selected for the signal under consideration

The mother wavelet function $\Psi_{a,b}(t)$ is given as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (3)$$

where a, b $\in$ R, a>0, and R is the wavelet space. Parameter 'a' is the scaling factor and 'b' is the shifting factor. The only limitation for choosing a prototype function as mother wavelet is to satisfy the admissibility condition,

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty \qquad (4)$$

Table 2 Statistical features used for emotion recognition and their description

Features	Description
Energy & Normalized Energy	The outline of energy distribution remains the same despite variations in amplitude of EEG signal of the same emotion. It remains unaffected by the duration of emotion elicited.
Power	Measures the amplitude of EEG signal
Entropy	Measures the useful information about the EEG signal for emotion from the intrusive noise.

Table 3 Decomposition of EEG signals into different frequency bands with a sampling frequency of 256 Hz

Frequency Range (Hz)	Decomposition levels	Frequency bands	Frequency bandwidth (Hz)
0 - 4	A4	Theta	4
4 – 8	D4	Delta	4
8 – 16	D3	Alpha	8
16 – 32	D2	Beta	16
32 – 64	D1	Gama	32

where $\psi(\omega)$ is the Fourier transform of the $\psi_{a,b}(t)$. The time-frequency representation is performed by repeatedly filtering the signal with a pair of filters that cut the frequency domain in the middle. Specifically, the discrete wavelet transform decomposes the signal into an approximation coefficients (CA) and detailed coefficients (CD). The approximation coefficient is subsequently divided into new approximation and detailed coefficients. This process is carried out iteratively producing a set of approximation coefficients and detail coefficients at different levels or scales [14, 15,16].

In this work, we use “db4” wavelet function for extracting the statistical features from the EEG signals. The selected statistical features and their descriptions for our work are given in Table 2. This wavelet function “db4” has been chosen due to their near optimal time-frequency localization properties. Moreover, the waveforms of “db4” are similar to the waveforms to be detected in the EEG signal. Therefore, extraction of EEG signals features are more likely to be successful [17]. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. The EEG signal on each emotion is decomposed into 4 levels and the detailed coefficients at 3^{rd} level of decomposition are considered for deriving the statistical features (Table 3)[18].

4 Fuzzy C-Means (FCM) Clustering

In this experimental study, we used fuzzy c-means (FCM) clustering [19,20] to assess the various emotions from the overlapped electrophysiological signals. Clustering is a tool that attempts to assess the relationships among patterns of the data. The organization of patterns within a cluster is more similar to each other than patterns belonging to different clusters. The FCM seeks to group the sampled data together so as to minimize the variance (the objective function) between data in the same cluster and maximize the variance between data in different clusters. This selection method allows each cluster of data to be represented by a “cluster center”, where each center is a representation of data geometrically closest to it. All data sets can belong to all cluster centers, with a degree of membership (DOM) in each cluster in the interval [0, 1]. The DOM is directly related to the Mahalanobis distance between each data sample and the cluster center [21].

In this study, we selected the cluster centers from 2 till 5; we also selected three different performance indices to study the clustering ability of input data with different numbers of channel sets : (a) Fuzziness Performance Index (FPI) [22] (b) Modified Partition Entropy (MPE) [23] (c) Separable Distance (SD) [24]. An intimately related important issue is the “cluster validity” which deals with the significance of the structure imposed by a clustering method. Cluster validity method uses indices for a quantitative evaluation of clustering results, measuring the quality of the clustered data. The number of reduced channels has been selected on the basis of performance index values. The main objective of channel selection is based on minimizing the performances indices. In addition, the value of objective function is also considered as a measure for optimal channel selection.

5 Results and Discussions

As mentioned in Section 2, the two asymmetric ratios are calculated separately for each of 5 subjects over 28 homogeneous pair of electrodes with 5 different classes of emotions. The feature vector matrices of the channel selection algorithm have a dimension of 28 AVR values in a 25 dimensional feature space (28 electrode pairs x five emotions for five subjects). After forming the feature vector matrix, all positive or negative values over all the emotions on each subject is selected to form to new significant channel matrix. From this matrix, we selected a channel pair which is highly significant to detect all the five emotions at a time, not the single emotion. As an evaluation study to select optimal EEG channels for different emotions for different subjects, the above procedure is repeated to form another channel rank matrix using AAR values. Table 4 shows the channel selection matrix for emotion recognition with both of the asymmetric ratio rank matrixes. The channel pair which is having higher rank values on both methods of asymmetric ratio calculation are selected as most significant channels for detecting the human emotions. From Table 4, the channel pairs:(P7, P8) & (PO7, PO8) are selected as a most significant channel pair for detecting the five different emotions. The significance of emotional stimulus can influence different region of human brain.

Table 3 Ranking of channel pairs based on

Channel Pair	Electrode Pairs	S1	S2	S3	S4	S5	Rank
1	FP1,FP2	√		*		√	2/1
2	F3,F4		√	√/ *		√	3/1
3	C3,C4		√	√		√	3/0
4	P3,P4		√		√	√	3/0
5	O1,O2		√		*	√	2/1
6	F7,F8		√				1/0
7	T7,T8						0
8	**P7,P8**	**X**	√	**√/ ***	√	**√/ ***	**4/2**
9	AF7,AF8					*	0/1
10	AF1,AF2	√				√/ *	2/1
11	F1,F2	*	√				1/1
12	FC1,FC2	√		√			2/0
13	C1,C2		√				1/0
14	CP1,CP2				√/ *	√	2/1
15	P1,P2		√			√	2/0
16	PO1,PO2	√			√/ *	√	3/1
17	AF3,AF4		√			√	2/0
18	FC3,FC4		√		√		2/0
19	CP3,CP4	X	√	√/*	√	√	4/1
20	PO3,PO4		√		√/ *	√	3/1
21	F5,F6		√				1/0
22	FC5,FC6				√		1/0
23	C5,C6		√	√	√		3/0
24	CP5,CP6		√	√/ *	√		3/1
25	P5,P6	X	√	√/ *	√	√	4/1
26	FT7,FT8				√		1/0
27	TP7,TP8		√	√			2/0
28	**PO7,PO8**	**X**	√	√	**√/ ***	**√/ ***	**4/2**

asymmetric ratio

√ **:** Asymmetric Variance Ratio (AVR) method

* : Asymmetric Amplitude Ratio (AAR) method

X: No response

The regions of brain which is most active for primary emotions are parietal and occipital lobes [25]. In this work, we only consider to reduce the number of channel pairs from 28 to 2 and not a combination within channel pairs.

There are other research works using EEG signals with arbitrarily different number of channels for detecting the primary emotions [8, 26, 27, 28]. However, no concrete reasons have been given for selecting a particular set of channels discussed in their works for classifying primary emotions. In addition there is no work found in the literature in using systematic selection of channels for detecting primary emotions. To validate the proposed method, we employed an unsupervised classification called FCM clustering to classify the primary emotions. The classification ability has been determined by minimizing the value of performance indices and objective function. A study has been made with the number of clusters varied between 2 and 5 over different set of input channel data. In addition we have compared the performance of classification by using FCM with original set of channels, reduced set of channels using AVR method and the channels used in [28] (Table 5). Finally we found that, the 4 channels derived by our approach play a significant role among other set of channels

The minimum values of FPI, MPE and SD along with minimum objective function are obtained with 5 clusters and with 4 input channels, which are based on our approach of asymmetric ratio. Table 6 shows the results of fuzzy c-means clustering on different set of input channels with 5th cluster for three performance indices on three statistical features. Since, the performance indices of 5th cluster are found to be smallest when compared to other clusters from 2 to 4. Here, we have compared the reduced set of channels derived from asymmetric ratios with original set of channels and with those from [27] for assessing the classification ability of human emotions.

5 Conclusions

Emotion occurs very differently based on the situation, age, and growth environment etc. Even for a person, it changes day in and day out. So, to get the statistical output from several numbers of subject is difficult and has no meaning [29]. In this work, we have performed the experiment with 5 young and healthy subjects for deriving salient EEG channels from the original set of EEG channels for primary emotion detection. The generalized solution for channel selection can be derived by using a larger number of data sets. This paper has proposed an approach to select subset of optimal channels for emotion recognition using EEG signals. An audio-visual induction based protocol has been used for collecting the EEG signals using 63 channels for 5 different emotions from 5 subjects. The 28 pairs of homogeneous channel pairs are reduced to 2 pairs of

Table 5 Optimal EEG channel pair illustration using different methodologies

Methods	No of Channel Pairs	Conceptual Methodology	Name of the Channels
Previous work [24]	12	Temporal and Topographic Approach	(FC3,FC4), (FC5,FC6), (C3,C4),(C5,C6), (CP3,CP4), CP5,CP6), (P5,P6), (P7,P8), (P3,P4), (O1,O2), (PO3,PO4), & (PO7,PO8)
Our Work	2	Asymmetric Variance Ratio (AVR) and Asymmetric Amplitude Ratio (AAR)	(P7,P8) & (PO7,PO8)
	4	Asymmetric Variance Ratio (AVR)	(CP3,CP4),(P5,P6),(P7,P8) & (PO7,PO8)

Table 6 Performance measures using EEG signals on classifying human emotions using fuzzy c-means clustering

Fuzziness exponent (m) = 1.300 No of Trails : 10
Max Picard iterations = 300 Stopping criteria (||u-u`||) = 0.00010
Distance Measure = Mahalanobis distance

No of channels	No of clusters	||u-u`||	OFV	FPI	MPE	SD
Energy						
4	**5**	**0.851108E-04**	**36**	**0.150051**	**0.154724**	**0.328312**
8	5	0.942585E-04	90	0.231867	0.236316	0.426569
24	5	0.936874E-04	236	0.183214	0.184551	0.482936
62	5	0.972684E-04	714	0.252708	0.246545	0.586589
Power						
4	**5**	**0.746086E-04**	**34**	**25.4449**	**0.100203**	**0.240613**
8	5	0.137279E-02	80	0.162082	0.170267	0.354066
24	5	0.982116E-04	234	0.189173	0.189334	0.461239
62	5	0.955400E-04	707	0.246573	0.240737	0.594591
Normalized Energy						
4	**5**	**0.771464E-04**	**32**	**0.982E-01**	**0.101976**	**0.304105**
8	5	0.910697E-04	68	0.120982	0.122458	0.234633
24	5	0.982116E-04	234	0.189173	0.189334	0.461239
62	5	0.862072E-04	665	0.154635	0.151209	0.346375

channels using asymmetric ratios. We have also presented an AR method of channel selection for primary emotion detection using EEG signals. By utilizing the asymmetric power and difference in variance between the EEG channels on hemispheres are considered for characterizing the channel selection. The common channel pairs between two different methods of asymmetric ratio calculation are selected on the basis of ranking the channels using the concept of exhibiting positive or negative values of AR over all the subjects for all the emotions. Since the proposed channel selection is a filter approach, it is independent of the classifiers. Using "db4" wavelet function, the EEG signals are decomposed into different frequency bands and the statistical features are derived from alpha band. In order to assess credibility of selecting the optimum channels using AR methods, we have compared our results with other different set of channels used in previous work on emotion recognition. The results confirm that the statistical features with "db4" wavelet function perform well in classifying the emotions on optimal set of channels proposed by asymmetric ratio based channel selection method.

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