Average Power Based EEG Channel Selection Method for Emotion Recognition

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Abstract. Emotion can be defined as the neurophysiological changes people experience due to significant internal or external occasions. This work applies a channel selection algorithm based on average band power on the preprocessed EEG data frequency bands from the DEAP dataset to select the top 10 EEG channels. DWT is performed to get detail coefficients as features, and a statistical parameter RSS is used to reduce the dimension of the features for both selected and all 32 EEG channels. Finally, valence and arousal are classified using different classification algorithms (like Random Forest, Extra Trees, Naive Bayes, and MLP) to make a performance comparison between selected EEG channels and all EEG channels. The highest test accuracy, 66.8%, was retrieved from the Random Forest(RF) classifier for valence classification. Likewise, Random Forest(RF) and Extra Trees(ET) both achieved the highest test accuracy of 64.84% for arousal classification, which validates the efficiency of the proposed channel reduction technique.

Keywords: Emotion recognition, DEAP, EEG, Channel Selection, DWT, RSS.

1 Introduction

Emotion is a complex state of human beings. It consists of behavior, feelings, reactions to internal or external stimuli, etc. There is a vital relation between emotion recognition and affective computing. For the identification of human emotion many ways such as speech, facial expressions, behavior or psychological signals, fusion of information using multimodal technique are noteworthy [1–4, 14]. Researchers delineated the reliability of psychological signals as it is a subject independent approach [5]. Moreover, along with the change of emotion, EEG signals quickly capture or respond to the changes and it is better in terms of reliable feature extraction for emotion recognition tasks [6, 7]. Electroencephalogram (EEG) signals are also more insightful especially when any subject can not express his/her desired emotion [13]. Due to the high speed factor, low cost and interaction capability with our central nervous system, most of the HCI/BCI system uses EEG signals along with this many research uses physiological signals to detect human emotions appropriately [8, 12].

A few databases have been constructed with a view to help the study of emotions in recent years. One of the most remarkable datasets here is DEAP dataset that contains physiological signals and electroencephalograms and many research on this database used valence and arousal to measure emotional state [9, 11]. Therefore, it can be claimed that EEG channel selection techniques and feature extraction methods are important factors in increasing the accuracy rate of emotion recognition as well as reducing space and time complexity. A study focusing on only one specific EEG channel F4 showed significant improvement on the accuracy level [21]. On the other hand, another study that uses all 32 channels of EEG signals mainly focuses on feature extraction and performed different experiments to measure the accuracy [20]. Therefore, more focus needs to be put on feature extraction and channel selection in order to predict some good results on different emotional states of human.

In our work, we have proposed a channel selection technique based on average power to select top 10 EEG channels with highest average power values. Furthermore, for the classification task, we have used DWT detail coefficients as feature vector and a statistical parameter Root Sum Square (RSS) to reduce the feature vector dimension.

2 Background of the Study

Emotion plays a very significant role for communicating among humans. In recent years, there has been extensive work on emotion recognition. In the research of Qing et al. [10], they suggested a renewal system, the demonstration curve for the proposed method for emotion prediction using ML and only EEG signal experimenting on the DEAP and SEED data. They extracted features from the EEG signals to construct two coefficients which are entropy and correction. In another study, Wioleta et al. [15] mainly reviewed corporal stimulus, feelings as well as briefly described some of the related research works of the corporal and electrical fields in feelings identification. With the aim of bringing more accuracy in emotion classification, the authors would like to work on gaming and e-related divisions.

In their work, Chen et al. [17] proposed an EEG emotion wave based feature learning and classification technique using deep CNN based on some specific features and fusions of EEG signals in DEAP dataset in order to increase the accuracy. Their experimental outcome indicates that deep CNN's performance was better than any other identifiers. Torres et al. [18] stated that user's emotions can be recognised through EEG based Brain Computer Interfaces (BCI) devices. They also proved that positive emotional states are more easy to detect compared to negative emotional states.

Another research showed the statistical analysis of an EEG-based emotion recognition system using a self-organizing map for boundary detection. The proposed method improved the accuracy to 84.5% and it proved that the class difference helps rising the emotion identification accuracy using EEG signals [19]. Ozerdem et al. [22] proposed a positive and negative emotion classification method using five selected EEG channels using the DEAP dataset. The average overall accuracies were 77.14% for MLPNN and 72.92% for KNN. In near future, they plan on using all of the secondary bands individually on their proposed model.

Unlike these studies, we have applied a channel selection technique to select top 10 effective channels on the basis of average power to make any system efficient enough in terms of computational complexity, memory usage and training time. Finally, in the classification task of valence and arousal, a statistical parameter RSS is introduced for the dimension reduction of DWT detail coefficient feature vector.

Table 1: Performance comparison with related works.

Article	Database	Classifiers	No. of EEG channels	Highest test accuracy (%)
Pandey et al. [28]	DEAP	DNN SVM	4	valence: DNN - 62.50 arousal: DNN - 61.25
Jirayucharoensak et al. [20]	DEAP	DLN SVM NB	32	valence: DLN - 53.42 arousal: DLN - 52.03
Pandey et al. [21]	DEAP	MLP	1	valence and arousal average accuracy: 58.5
Zhang et al. [23]	DEAP	SVM	8, 19, 29	average accuracy of 4 emotional states: 8 channels: 58.51 19 channels: 59.13 29 channels: 59.98
Yan et al. [29]	DEAP	LSTM RNN	32	valence and arousal average accuracy: 59.03
Kumar et al. [30]	DEAP	SVM	2	arousal: 64.84 valence: 61.17
Proposed	DEAP	MLP ET NB RF	10	valence: RF- 66.8 arousal: RF and ET - 64.84

3 Materials and Methodology

3.1 Database Description

This study is mainly focused on the electroencephalogram (EEG) signals that is used for identifying emotion. Hence, we have used the dataset collected from the DEAP database [16] for extracting the EEG features and perform experiments. It is a multimodal dataset which contains the EEG and circumferential physiologic signals from 32 participants [16]. Data down-sampling rate for all 40 channels are 128Hz and they are segmented into a 60 second trial where the 3 second pre-trial baseline is removed. Each participant file contains two arrays: data and labels. Data array contains video/trial x channel x data with the shape 40x40x8064 and the label array contains video/trial x label (valence, arousal, dominance, liking) with the shape 40x4 [16]. On this note, we have taken only first 32 EEG channels in consideration for this experiement.

3.2 Methodologies

Our proposed methodology mainly divided into four major steps- dataset preprocessing, EEG channel selection, feature extraction and classification of valence and arousal using all 32 EEG chanels and selected 10 EEG channels. The overall methodological illustration of this study is given in Figure 1.

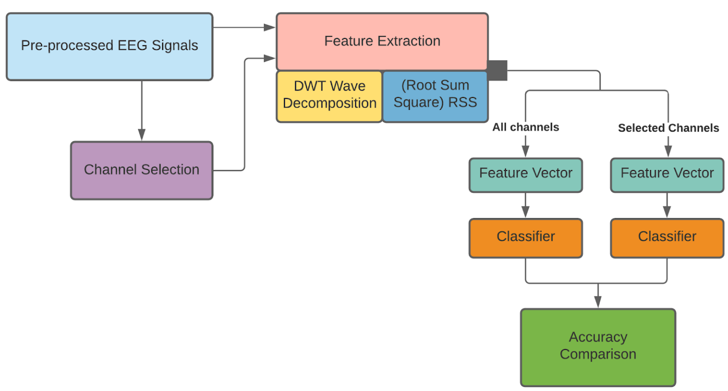

Fig. 1: Proposed methodology.

3.3 Dataset Preprocessing

The valence and arousal target labels are classified as high and low class. The high class is indicated by '1' whereas the low class is indicated by '0'. For both valence and arousal data, where the ratings are in range of 1 to 9, a threshold value of '5' is considered to classify the data, where values less than 5 are classified as low class. On the other hand, values greater than or equal to 5 is

Table 2: Selected channels from different frequency bands using channel selection algorithm.

Frequency bands	Selected channels
Alpha (8-13 Hz)	Fp2, F7, T7, AF3, Fp1, F8, Cz, AF4, Oz, P7, T8, O1
Beta (13-30 Hz)	Fp2, F7, Fp1, T7, AF3, T8, F8, AF4, O1, Cz, F4, P7
Gamma (>30 Hz)	Fp2, F7, T7, T8, Fp1, AF3, F8, O1, AF4, FC6, F4, P7
10 Common Channels	Fp2, F7, T7, AF3, Fp1, F8, AF4, P7, T8, O1

classified as high class. Total number of high and low class in valence is 724 and 556, similarly, high and low class in arousal is 754 and 526 respectively. Thus it can be depicted that the dataset is balanced for any classification task.

3.4 Channel Selection

The cortical spectral power activity holds an important statistical significance in analyzing the EEG signals [25]. Different research works relied on three frequency bands- alpha (8-13 Hz), beta(13-30 Hz) and gamma(>30 Hz) for emotion classification task [26,27]. In this work, 12 most effective channels from each band are selected using the channel selection Algorithm 1 which is based on average band power and finally, top 10 common channels (Fp2, F7, T7, AF3, Fp1, F8, AF4, P7, T8, O1) from these three frequency bands are taken as shown in Table 2. The proposed algorithm results a time complexity of $O(n \times v \times c)$ where the number of participants, the number of videos, and the number of channels is denoted as ‘n’, ‘v’ and ‘c’ respectively. The average band power of a particular EEG channel data is calculated using SciPy welch method [24].

3.5 Feature Extraction

For the feature extraction process, at first we have used DWT multilevel decomposition where wavelet is db2 of Daubechies family and the level is 4. As the EEG signals are non stationary data, wavelet transformation is more suitable to extract the effective features. Hence, the proposed methodology uses the Discrete Wavelet Coefficients as it depicts the degree of reciprocity between the signal and the wavelet function at various times [21]. Therefore, four levels of detailed coefficients which are cD1, cD2, cD3 and cD4 has been generated and one approximation coefficient is found [22]. The next feature extraction tasks has been performed on these four detailed coefficients. To reduce the dimension of these detailed coefficient feature vectors and training time of the models, we have implemented a statistical method named Root Sum Square (RSS) which is shown in Equation 1. Hence, in this method four RSS features are extracted for each EEG channel data. According to our literature knowledge so far, this particular statistical method has not been used on emotion recognition feature extraction tasks using EEG signals.

For generating more information from these detailed coefficients following steps are performed to add four more features for a particular eeg channel data,

Algorithm 1 EEG channel selection algorithm based on average power

```
set band range for EEG signal
define the sampling frequency
for participants = 1 to 32 do
  for videos = 1 to 40 do
    for channels = 1 to 32 do
      calculate average band power
      save band powers along with individual channels in a form of mapping
    end for
    append the mapped data in an array or a list
  end for
end for
for each mapped data in the list do
  sort the mapped data in descending order
  select best 10 channels
  append to an array
end for
count the appearance of the channels from the array
select 10 channels with most appearance
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which are:
a) RSS ratio of cD1 and cD2 is used.
b) RSS ratio of cD3 and cD4 is used.
c) RSS absolute difference between cD1 and cD2 is used.
d) RSS absolute difference between cD3 and cD4 is used.

Finally, the extracted feature dimension for a particular participant is 8x32x40 (features x channels x videos/trials), after reshaping the dimension which is 40x256 (videos/trials x features) for all 32 EEG channels. On the other hand, the feature vector for ten selected channels after reshaping the dimension is found as 40x80 (videos/trials x features). As there are 32 participants in the experiment, hence, total rows are counted as 1280(40x32) where the features are constant for all EEG channels and selected channels.

$$X_{RSS} = \sqrt{\sum_{i=1}^{n} x_i^2} \tag{1}$$

3.6 Classification

In the classification part, we have taken four machine learning classifiers which are Random Forest(RF), Naive Bayes(NB), Multi-layer Perceptron(MLP) and Extra Trees(ET) for observing and comparing the performance of these RSS features on the selected channels. For this task, two feature datasets are shuffled randomly and splitted into training and test set where 80% of the data are taken for training and 20% of the data are utilized for testing the models. Before fitting

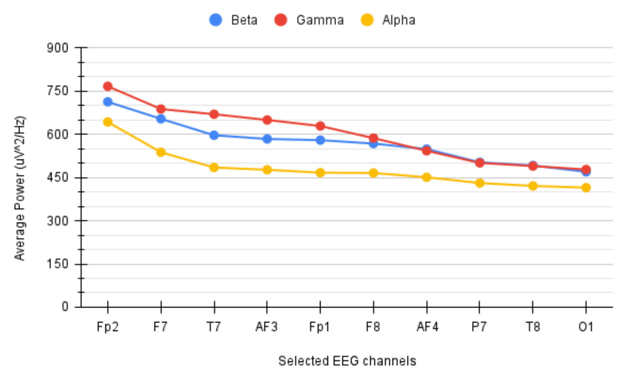


Fig. 2: Average power difference of top 10 EEG channels from alpha, beta and gamma frequency bands.

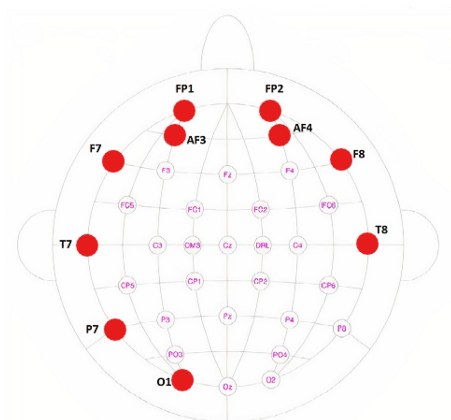


Fig. 3: Selected channel locations based 10-20 standard electrode location system [31].

the data into the models using Scikit-learn [32] package, hyperparameter tuning is done for achieving a standard non-bias accuracy. Finally, the accuracy score and different performance metrics of the classifiers like precision, recall and f1-score are taken in consideration for evaluating the effectiveness of the channel selection algorithm after classifying valence(low/high) and arousal(low/high).

4 Results Analysis

We have analyzed the performance of the selected channels using some machine learning classifiers. Our work showed a notable difference while experimenting with selected channels. For both valence and arousal classification, selected

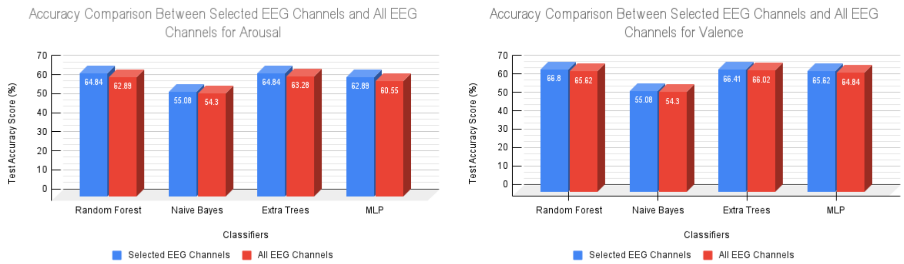
Table 3: Comparison of different performance metrics between selected EEG channels and all EEG channels.

Classifiers	Precision score				Recall score				F1-score			
	Selected channels		All channels		Selected channels		All channels		Selected channels		All channels	
	valence	arousal	valence	arousal	valence	arousal	valence	arousal	valence	arousal	valence	arousal
Random Forest	0.68	0.66	0.66	0.65	0.75	0.77	0.75	0.75	0.71	0.71	0.70	0.69
Naive Bayes	0.55	0.59	0.55	0.59	0.89	0.75	0.86	0.74	0.68	0.66	0.67	0.66
Extra Trees	0.67	0.66	0.67	0.65	0.74	0.77	0.75	0.74	0.71	0.71	0.71	0.69
MLP	0.67	0.65	0.67	0.64	0.73	0.72	0.69	0.69	0.70	0.69	0.68	0.66

channels dominates all channels with a better test accuracy. The highest test accuracy is obtained by Random Forest which is 66.8% for valence classification as shown in Figure 4b. On the other hand, both Extra Trees and Random Forest classifier has performed better than the other algorithms with the highest test accuracy 64.84% for arousal classification as shown in Figure 4a. Pandey et al. [28] used only 4 EEG channels to detect emotion; they stated that they have gained a better accuracy of machine learning classifiers using important features of the selected 4 EEG channels. In our work, we have also selected important EEG channels, hence, we have got some important features resulting better accuracy of the machine learning classifiers also. Furthermore, precision, recall and f1-score of the selected channels are also have greater values than all channels' metrics as depicted in Table 3. Therefore, this proposed channel selection technique and RSS for feature extraction make this research work efficient in terms of test accuracy and different performance metrics of the classifiers.

In the channel selection task, repeating channels are found from the three frequency bands(alpha, beta, gamma) though the ranking is different. On this note, we have observed the average power of top 10 EEG channels of alpha band is less than beta and gamma band respectively as shown in Figure 2. Furthermore, most of the selected channels are located in the prefrontal, occipital, temporal and posterior lobe as shown in Figure 3 which are important locations of the brain in terms of emotion generation [26]. Hence, this channel selection technique can locate the place of emotion generation successfully and these frequency bands are important for emotion recognition task.

While comparing with related works with the same database, our work outperformed some significant researches. Some of the previous works used less channels but they lacked accuracy. With 10 selected channels, we have improved the test accuracy for both valence and arousal binary classification as shown in Table 1. Similarly, the impact of using selective channels is promising as it saves memory space, reduce computational complexity and processing time of this huge data.



(a) (Left figure)Accuracy comparison for arousal.

(b) (Right figure)Accuracy comparison for valence.

Fig. 4: Accuracy comparison for arousal and valence.

5 Conclusion

The aim of this study is to classify valence and arousal on the basis of audiovisual stimuli with the help of EEG signals and to compare the efficiency of selected EEG channels with all 32 EEG channels. In this work, we have used DEAP database and have taken preprocessed EEG data of 32 participants to classify valence and arousal. For the feature extraction task, we have used DWT to get detail coefficient feature vectors and then, reduced the dimension of these vectors using Root Sum Square(RSS). Moreover, we have used those features on different machine learning classifiers, ensemble methods and MLP to classify valence and arousal. Top 10 EEG channels (Fp2, T7, AF4, AF3, T8, Fp1, F7, F8, P7, O1) are selected from alpha, beta and gamma frequency band using proposed channel selection algorithm which is based on highest average power. The performance of selected channels in terms of test accuracy is higher compared to all EEG channels as described in the results analysis section. Furthermore, the validation of this study is found while comparing with some recent works on this database. Hence, this proposed channel selection technique is found more efficient in terms of emotion classification on valence and arousal. Finally, it can be depicted that, with selected channels both the training time and memory space is saved as well as performance can be enhanced in this emotion recognition study. Using Root Sum Square(RSS) features from DWT vectors of different frequency bands and average power based channel selection algorithm make this research work unique.

In future studies, channel selection can be done using source localization technique of EEG signals. Blood pressure, respiratory rate, galvanic skin response, body temperature and other signals can be used to analyse their role in this emotion recognition field. Additionally, better machine learning models can be applied for achieving more accuracy in determining different emotions. Lastly, different databases containing EEG signals for emotion recognition can be analyzed with this proposed methodology to compare the performance.

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