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EEG based emotion recognition using entropy features and Bayesian optimized random forest

Abstract: Electroencephalography (EEG) based emotion recognition is a widely preferred technique due to its non-invasiveness. Also, frontal region-specific EEG signals have been associated with emotional processing. Feature reduction-based optimized machine learning methods can improve the automated analysis of frontal EEG signals. In this work, an attempt is made to classify emotional states using entropy-based features and Bayesian optimized random forest. For this, the EEG signals of prefrontal and frontal regions (Fp1, Fp2, Fz, F3, and F4) are obtained from an online public database. The signals are decomposed into five frequency bands, namely delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (30-45 Hz). Three entropy features, namely Dispersion Entropy (DE), Sample Entropy (SE), and Permutation Entropy (PE), are extracted and are dimensionally reduced using Principal Component Analysis (PCA). Further, the reduced features are applied to the Bayesian optimized random forest for the classification. The results show that the DE in the gamma band and SE in the alpha band exhibit a statistically significant ($p < 0.05$) difference for classifying arousal and valence emotional states. The selected features from PCA yield an F-measure of 73.24% for arousal and 46.98% for valence emotional states. Further, the combination of all features yields a higher F-measure of 48.13% for valence emotional states. The proposed method is capable of handling multicomponent variations of frontal region-specific EEG signals. Particularly the combination of selected features could be useful to characterize arousal and valence emotional states.

Keywords: EEG, emotions, audio-visual stimuli, entropy, classification, random forest

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1 Introduction

In advanced human-machine interaction, emotion detection is a crucial step toward emotional intelligence. Emotional abnormalities are linked with mental health disorders [1]. The total number of people with anxiety disorders in the world is estimated to be 264 million, which is equivalent to 3.6% of the world's population [2]. Emotional state analysis can provide relevant information to identify these disorders earlier and improve diagnosis.

Emotions have been described using a variety of models like the Positive Activation – Negative Activation (PANA) model, the Circumplex Model of Affect (CMA), and the PAD (Pleasure, Arousal and Dominance) model [3]. CMA is a frequently used dimensional model to describe emotions. It describes all emotional states in two fundamental, independent, and orthogonal dimensions: arousal and valence. Arousal dimension is a measure of the strength of the reaction to a stimulus: neutral or dominating. Valence is a measure of positive or negative affect towards the stimulus.[4]

Emotions can be studied in two traits: non-physiological and physiological [5]. Non-physiological trait refers to recognizable emotional cues such as facial expression, body gesture, and voice that express emotion. In contrast, the physiological trait refers to information provided by physiological signals such as Electrocardiogram, Electrodermal Activity, Electroencephalogram (EEG), and facial Electromyography [6]. EEG is a widely preferred emotion classification technique because of its high adaptability, high temporal resolution, non-invasiveness, ease of use, portability, and safety [7].

Region-specific EEG analysis is not only faster but provides a spatial information about the underlying cognitive processes. The frontal lobe has previously been linked to emotion identification in studies using neurophysiological and functional neuroimaging techniques [8]. The prefrontal cortex has also been studied for emotion regulation [9].

Characterizing EEG signals has traditionally been examined from a linear perspective [10]. Many metrics for describing EEG signals have been proposed, with the EEG signals considered to represent the output of a linear system.

Nonlinear analysis measures have recently been shown to perform better than conventional metrics [11].

Entropy is a popular nonlinear metric for EEG signals, and it has been utilized in emotion classification [12]. An entropy-based analysis is used to access the irregularity, randomness, and complexity of the EEG signals [13]. Many studies have explored various entropy metrics with machine learning to predict emotional states from EEG [14,15]. Due to multiple electrodes and bands, the number of relevant features needs to be reduced. Feature reduction approaches such as Principal Component Analysis (PCA), singular value decomposition have been employed to reduce the extracted features from EEG [16,17]. PCA is an efficient statistical approach for feature reduction in data with many dimensions [18].

As per literature, several classification algorithms such as support vector machines, random forest (RF), and k-nearest neighborhood has been employed to classify emotional states [19,20]. Random forest (RF) combines the benefits of tree and integration models, making it ideal for processing high-dimensional data [19]. The RF parameters can have an impact on the classification model's performance. Bayesian optimization can utilize the least cost to discover optimal parameters with fewer iterations and quicker optimization, avoiding parameter explosion [21].

In this work, an attempt is made to classify arousal and valence emotional states using existing entropy features such as permutation entropy (PE), sample entropy (SE), and dispersion entropy (DE) [11,18], and then PCA for dimension reduction and finally Bayesian optimized RF for classification.

2 Methodology

Figure 1 shows the framework of the proposed emotion recognition system using EEG. The channels, namely Fp1, Fp2, Fz, F3, and F4, are selected based on the literature. The signals from the selected channels are filtered using the 4th-order Chebyshev bandpass filter into delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (30-45 Hz). Features, namely SE, PE, and DE, are extracted from selected electrodes and frequency bands. PCA is then employed for the reduction of features. The reduced features are then put to Bayesian optimized RF for classification. MATLAB® 2020b software was used for the analysis of the signals.

2.1 Database Description

The DEAP has been used by many of the authors of previous papers, and hence the EEG signals are obtained for this study [22]. While watching 40 distinct one-minute video clips, the EEG signals are recorded. The database contains 32 participants' pre-processed physiological signals sampled at 128 Hz. Each recording is self-annotated using a self-assessment mannequin (SAM). The annotation is done by individual subjects based on the emotions they are experiencing on arousal and valence dimension ranging from 1 to 9. If a dimension's score is greater than 4.5, it is considered high, and if the score is less than 4.5, it is considered low.

2.2 Feature Extraction

SE has been frequently utilized in EEG signal feature extraction [23]. SE is defined as:

$$\boldsymbol{SE(m,r,n)} = -\,\boldsymbol{ln}\left[\frac{\boldsymbol{A^m(r)}}{\boldsymbol{B^m(r)}}\right] \tag{1}$$

where m is the embedding dimension; $B^m(r)$ and $A^m(r)$ represents the probability that two sequences match for m and $m+1$ points, and r is the vector comparison threshold or similarity criterion for assessing two matches, respectively. In this work, m is considered as two and r as 0.2.

PE was initially used in [24] to calculate the complexity of signals via neighboring value comparisons. Essentially, each time series has a probability distribution p, whose elements $p(j)$ represent the frequencies associated with j possible permutation patterns, where $j = 1, \ldots, m!$. In this work, m is considered as two and r as 0.2. The PE is defined as:

$$\boldsymbol{PE(m,r)} = -\sum_{\boldsymbol{j=1}}^{\boldsymbol{m!}} \boldsymbol{p(j)\,log\,p\,(j)} \tag{2}$$

DE overcomes the shortcomings of SE and PE and is used to quantify the regularity of the time series. It is calculated

Figure 1: Proposed EEG emotion recognition framework

using the three parameters: embedding dimension (m), a class (c) – which determines the number of patterns considered for computation, and a time delay (d). The equations for estimating the DE can be referred from [18]. In this work m, a c, d is used as 2, 6, and 1, respectively. Finally, the DE can be calculated as:

$$\boldsymbol{DE}(\boldsymbol{x}, \boldsymbol{m}, \boldsymbol{c}, \boldsymbol{d}) = -\sum_{\boldsymbol{\pi}=1}^{\boldsymbol{c}^{\boldsymbol{m}}} \boldsymbol{p}(\boldsymbol{\pi}_{\boldsymbol{v}_0 \boldsymbol{v}_1 \ldots \boldsymbol{v}_{\boldsymbol{m}-1}}) . \boldsymbol{ln}(\boldsymbol{p}(\boldsymbol{\pi}_{\boldsymbol{v}_0 \boldsymbol{v}_1 \ldots \boldsymbol{v}_{\boldsymbol{m}-1}})) \tag{3}$$

where $\boldsymbol{p}(\boldsymbol{\pi}_{\boldsymbol{v}_0 \boldsymbol{v}_1 \ldots \boldsymbol{v}_{\boldsymbol{m}-1}})$ is the pattern probability.

2.3 Classification

Entropy features extracted from the respective frequency bands (3x5) are then subjected to Principal Component Analysis (PCA) for reduction of the extracted features based on principal components. The top 10 reduced features are subjected to Bayesian optimized RF with 10-fold cross-validation [25]. The classifier is evaluated using F-measure, which is defined as the harmonic mean between precision and recall. The hyper-parameter of RF was optimized using Bayesian optimization. Max-Depth, N-estimators, and Min-samples-split are essential factors that impact RF's performance. The maximum features that a unit decision tree may employ are represented by max-depth. The number of subtrees is represented by N-estimators, while the minimum number of samples required for internal node subdivision is characterized by Min-samples-split [26].

3 Results and Discussion

Table 1 shows the p-values of the features for the classification of arousal states using SE, DE, and PE. It is seen that the DE is able to differentiate the arousal states in the gamma band ($p < 0.05$). Table 2 shows the p-values of the features for the classification of valence states using SE, DE, and PE features. It is evident that the SE can differentiate the valence states in the alpha band ($p < 0.05$).

Table 1: p-values of the features for classification of arousal states

Features	Band				
	Delta	Theta	Alpha	Beta	Gamma
DE	0.8517	0.7980	0.9644	0.4807	**0.0437**
SE	0.5645	0.9485	0.7555	0.4314	0.5406
PE	0.7858	0.7710	0.7278	0.4710	0.7338

Table 2: p-values of the features for classification of valence states

Features	Band				
	Delta	Theta	Alpha	Beta	Gamma
DE	0.5754	0.5388	0.1091	0.4315	0.3388
SE	0.5088	0.4156	**0.0197**	0.4646	0.8267
PE	0.3921	0.6249	0.3694	0.9114	0.9297

Table 3: Bayesian optimized parameter for classification of arousal and valence states using RF

Dim	Feat Select	f-m [%]	Max. Depth	Min-sample-split	N-estimators
A	Yes	**73.24**	44.22	5.396	752.8
	No	71.08	118.9	2.212	489.9
V	Yes	46.98	1.333	9.643	202
	No	**48.13**	47.44	6.636	743.3

Table 3 shows the optimized parameter for classifying arousal and valence emotional states with and without the reduced PCA features using Bayesian optimization. It is seen that for classifying arousal states, the PCA yields a better f-m score (73.24%) with a max depth of 44, min-samples-split of 5, and N-estimators as 753 (considering nearest integer). On the other hand, for valence, all the features without reduction performed better with f-m of 48.13% and max depth of 47, min-samples-split of 7, and N-estimators as 743.

4 Conclusion

This paper attempts to classify arousal and valence emotional states using frontal electrodes EEG signal by employing entropy-based features and Bayesian optimized random forest. The entropy-based features, namely SE, PE, and DE, can account for the emotion-evoked EEG signal's complexity, and RF with Bayesian optimization can classify the states effectively. PCA's reduced features yield an f-m of 73.24% for arousal and 46.98% for valence emotional states. Further, the combination of all features yields a higher F-measure of 48.13% for valence emotional states. The proposed method is capable of handling multicomponent variations of frontal region-specific EEG signals. Particularly the combination of Sample and Dispersion Entropy with the Bayesian optimized random forest can classify emotions effectively.

Author Statement

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