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Brain-Heart Connection for Psychological Health

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Abstract

With growing stress in our lives, there has been a major impact on our hearts and brain, leading to several mental and heart-related problems that sometimes are fatal and so severe that they leave a spot on us for the rest of our lives. To see the effect of the stress level on our brain and heart, we have designed a model to analyze the EEG (Electroencephalography) and the ECG (Electrocardiography) signals. Our study aimed to correlate two biosignals, EEG and ECG. We have focused on two important emotions, namely valence and arousal. We used the DREAMER dataset, which consists of both ECG and EEG signals. We evaluated nine different classifiers, including nearest neighbors, linear SVM, RBF SVM, Gaussian process, Decision tree, Random-forest, Neural net, AdaBoost, and Naive Bayes. We found AdaBoost had the best mean accuracy (97%) but with the longest processing time of around 5-10 milliseconds, whereas other classifiers had a mean runtime of around 1 millisecond. We discuss three things: preprocessing and feature extraction of the dataset, evaluation of classifiers for arousal and valence, and data visualization for correlation of arousal and valence values for all the extracted features.

Keyword: Electroencephalography (EEG); Electrocardiography (ECG); DREAMER dataset; Classifiers

Introduction

A natural human response to stress which can be defined as being a state of worry caused by a variety of circumstances. Everyone has a different reaction to stress, it can be divided into three components: behavioral, physiological, and psychological stress. In behavioral stress, features such as facial expressions and body gestures can be used to determine the stress level, in physiological stress, changes in body chemistry can indicate stress, and in psychological stress, changes in biosignals can be detected by changes in EEG (Electroencephalography) and ECG (Electrocardiography). The stress of an individual can be predicted using these three components. Still, behavioral and physiological stress does not give the exact emotional state of an individual, since they can either fake their facial expression or behavior and even their physiological condition. Still, psychological stress is an efficient method to predict an individual's emotional state [1]. Based on the language of humans, emotions can mainly be classified into six types: happiness, sadness, anger, fear, surprise, and disgust.

Stress levels can be predicted using these emotions. Wiem et al. [2] states that the brain controls the heart, so ECG and EEG signals are related to each other and can be correlated to predict an individual's emotion. The features extracted from these signals can be used in predicting the emotional state by using an individual's target emotion of stimuli.

Electrocardiograms and electroencephalograms are commonly used techniques to study the correlation of signal complexity in the brain and heart activity. Jianga et al. [3] reported that a degree of correlation between the two parameters should be determined by recording EEG and ECG simultaneously. These two interact with each other in neurocardiology, where there is an interaction between the nervous and cardiovascular systems. Throughout the body, neurons control various motor, sensing, and regulating signals. The neurons give measurable electrical signals due to the dynamics of inion transport. Then, to evaluate the brain, these are taken into account by EEG. In contrast, Billones et al. [4] says ECG displays a graphic representation of the heart function by analyzing the electrical activity of the body's surface due to heart activation and repolarisation, this study has shown that a universal pattern of brain rhythms and interactions with the heart can be observed during sleep. Laufs et al. [5] investigated the effect of meditation and found that cardiac rate and EEG alpha activations are directly correlated. Borghini et al. [6] simultaneously observed and analyzed both EEG and ECG in subjects participating in drivers' simulations. They have been able to identify neuropsychiatric features that separate drivers with a higher or lower risk of fatigue. Asadpour et al. [7] used a mathematical techniques-based architecture to analyze HRV (Heart Rate Variability) measured by ECG about EEG on patinets during cardiac catheterization and coronary artery interventions. Billones et al. [4], reported a trial that involved 87 patients who volunteered for being under experimentation. A multiscale entropy analysis of the correlation between the complexity of cerebral and cardiac electrical activity was carried out on them by being monitored for 19 hours of ECG and eye-closed routine EEG measurements. When the subjects engage in different activities of stimulation, ECG and EEG recordings become more valuable. It seems to suggest that there's a strong correlation between heart rate and brain activity. There seems to be a fairly obvious correlation between heart rate and brain activity. According to Kong et al. [8], coherence analysis is a fundamental signal-processing technique to synchronize ECG and EEG signals. Vaseghi et al. [9] evaluated a very complex and dynamic reflex in the autonomic nervous system, consisting of metasyntactic channels, which control the heart directly through sympathetic and parasympathetic branches.

We focused our study on the valence arousal scale to characterize emotions. The valence dimension tells if an individual has positive or negative feelings, while the arousal dimension tells how bored or excited an individual is. Both these dimensions are plotted in a two-dimensional axis to obtain the emotional state. Another dimension called dominance can be predicted, which tells about individuals feeling with or without control. But, most dimensions are similar to valence or arousal, so the target emotion of stimuli can be obtained using the valence-arousal scale [10].

Material and Method

The proposed work is employed on the DREAMER dataset reported by Katsigiannis et al. [11]. The collected data received the authorization of the University of the West of Scotland University Ethics Committee; it contains Audio and Visual Stimuli obtained from 18 film clips. Each of these film clips was curated, and was performed on 23 volunteers whose ages ranged between 22 and 33. The recordings were captured while audio-visual stimuli were presented to all the participants to obtain the emotional state of every participant. Portable, wireless, wearable low-cost, and off-the-shelf devices were used to capture both EEG and ECG recordings. Audio-visual stimuli of every participant were taken as clips from known films to obtain their target emotion [2]. The dataset contains nine human emotions: happiness, anger, calmness, fear, sadness, surprise, excitement, disgust and amusement. Each of the clips ranged from 65s to 393s. There was an additional presence of a Neutral video. These videos had no factors of valence. This helped in obtaining baseline signals.

For EEG signals, there are different ranges of frequencies obtained, Delta waves have a frequency range from 0.5 - 3.99Hz and are caused due to hyperventilation, deep sleep, and a vague dream state, Theta waves have a frequency range from 4 - 7.99Hz cause drowsiness and normal sleep, Alpha waves have a frequency range from 8 - 13 Hz they give the dominant rhythm of fully awake state of an individual and Beta waves have a frequency above 13Hz, it is observed in children and adults transitioning from drowsiness to fully awake state. The HRV (Heart Rate Variability) is measured based on ECG signals to analyze the emotions of an individual [8]. Certain features that were required for obtaining the target emotion of stimuli from both EEG and ECG signals were extracted and based on the target emotion obtained the participant's stress levels were categorized with the help of the valence-arousal scale.

The tests were performed in a secluded room that was reasonably lit to avoid any external disturbances. The video clips were displayed on the TV with audio support. The respective ECG and EEG signals were recorded. It had a sampling rate of 256 Hz and 128 Hz respectively. The ECG signals were recorded using a Shimmer Wireless sensor. The EEG signals were recorded using the Emotiv EPOC System. It has 16 contact sensors, each of which are coated with gold. They are attached to the arms of wireless headgear. The sensor M1 acts as a mastoid and gives the ground reference point. The sensor M2 is also a mastoid sensor that gives the forward feed reference of the electrical interferences. After viewing each video, a GUI was used to record the volunteers' arousal, valence and dominance value and were marked on a 5-point scale. This was all facilitated by the usage of Self-Assessment Mankins (SAM). Each of the recorded information was stored in a database. The data was all assorted. It was implemented using MATLAB.

The signals obtained contain noise and certain unwanted features. The EEG signals show the presence of various contaminated signals like muscular movement or eye movement. ECG signals are generally less prone to interference due to their high voltage amplitudes. Hence, ECG does not require prior processing. EEG signals have a wide range of frequency divisions like – alpha, beta and theta bands. Ocular artifacts below 4Hz will include activities involving eye movements affecting the values obtained. Additionally, muscular movements will affect the values of EEG above 30Hz. The frequency divisions of the EEG also range between 4 – 30 Hz. As a result, all these unwanted signals are to be filtered out. Three different bandpass Hamming Sinc Linear Phase FIR filters are applied to extract the required frequency bands. The unwanted signals or artifacts are added as a DC offset. They pad the data by using a DC constant at the start or end of the signal. The signals are finally resampled. A built-in digital notch filter is used for interference in the 50 - 60 Hz range. The filtering cannot alone filter all the artifacts out. Therefore, the ASR (Artefact Subspace Reconstruction) method is employed. This makes use of sliding window PCA (Principal Component Analysis), which interpolates statistical techniques like introducing high variance signal components that go beyond the maximum value relative to covariance of the detected data. The final step is an application of CAR (Common Average Reference) to the mean of all the electrode values.

The EEG data was obtained by extracting the highest Power Spectrum Density (PSD) value [12]. The extracted data from EEG data has 3 major frequency bands - theta, alpha, beta. This is employed using the Welch Method [13], a commonly used technique to analyze the EEG signals. It depends on 3 factors - window length, overlap, and number of FFT points.

The preprocessing for ECG data was done using the Neurokit2 library as proposed by Makowski et al. [14]. It involves two steps. In the beginning, the data is preprocessed with the help of an available in-built method. Next, the extraction of the features was performed. Heart Rate (HR), R-R Interval (RRI), Heart Rate Variability (HRV,. Time-domain HRV features (e.g., SDNN, RMSSD, pNN50), Frequency-domain HRV features (e.g., VLF, LF, HF), QRS Complex Duration, T-Wave Amplitude, Mean Heart Rate and Heart Rate Variability (HRV) are the features that come as a byproduct of the feature extraction. However, Mean Heart Rate and HRV metrics extracted from the data help us make major analysis when EEG has to be involved. HRV can be filtered from the rest of the features by using the Pan-Tompkins method [11,15] to get the QRS detection algorithm and detect the R-peak. Next statistical features are extracted using Augsburg Biosignal [11,15] tool box. Finally the HRV can be extracted using the BioSig toolbox [11,17]. Mean heart rate is calculated by taking the average heart rate of all participants in the experimental trial. Neurokit2 [14] is a neurophysiological processing package freely available in Python. This package is made used for the processing of the ECG. A few of the most popular methods of the Neurokit2 library include: "ecg_clean(), ecg_peaks(), ecg_quality(), ecg_delineate(), and ecg_phase()". It also includes tools for extraction of rate and filtering methods. Figure 1 presents an overview of the applied methodology.

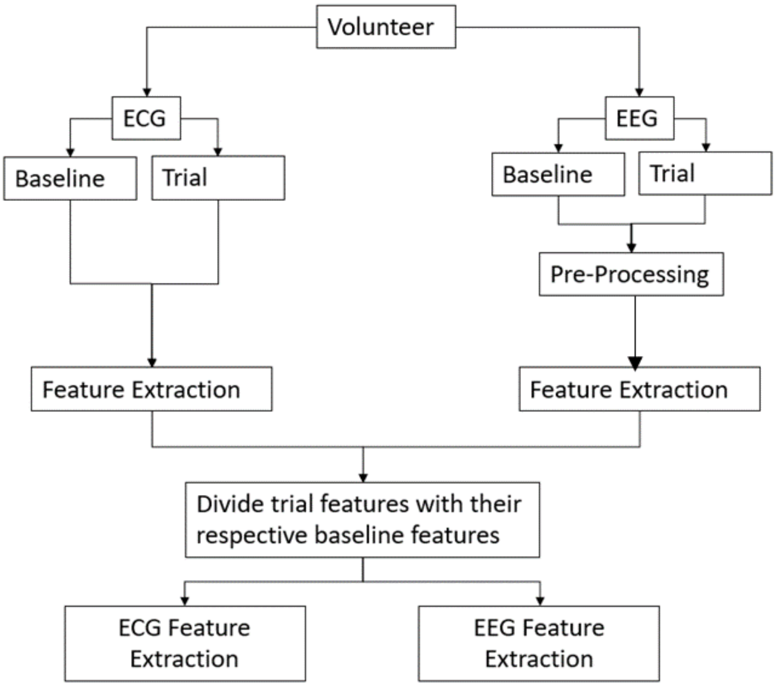

Figure 1. A generalized image of the overall processing and feature extractions

In order to assess the effectiveness of various classifiers, the biosignals were preprocessed and examined to visualize the relationship between the derived features and the emotion data. Using interactive figures, the data was visualized to understand the relationship between participants' ratings of film clips in valence-arousal space. Using group-10-fold cross-validation of the DREAMER data [11], where the training and validation sets consisted of different participants, the classifiers were evaluated to see how they would perform given biosignal data from completely new people. Mean heart rate for target emotions (calmness, anger, and fear), and a score versus prediction time for all cross-validation iterations and classifiers were visualized using matplotlib visualization tool. As a result of these visualizations, the DREAMER dataset [11] could be visualized and valence-arousal could be correlated based on the chosen target emotions (calmness, anger, and fear). It is handled all by a Python script that preprocesses data, extracts features, and evaluates classifiers.

Using binary classification, a dataset composed of the columns valence and arousal and their features were constructed. Following this, Pearson correlation was used to correlate valence with arousal. The binary classification was used to distinguish "calmness" from "anger" and "fear" on the opposite side of the spectrum, as shown in Table 1 [11, 18]. We can get a more accurate picture of their generalizability by evaluating the classifiers on emotion-correlated biosignals. A script from sci-kit learn documentation was used to select the nine classifiers.

Table 1. Binary classification of chosen target emotions

Target Emotion	Binary Score
Calmness	0
Anger	1
Fear	1

Results and Discussions

Simulation Results

Initially, the features were extracted from the ECG and EEG signals. EEG signals were sampled at a rate of 256 Hz. ECG signals were sampled at a rate of 128 Hz. A combined data frame of 413 rows of data and columns having the main headings as alpha, beta, theta and HVR and mean heart rate was formed.

A cross-validation loop where the data is split into training and testing sets for each fold. The classifier is trained on the training set, and its performance is evaluated on the testing set. The scores and runtimes are recorded for each fold.

The split data were implied in the following models - Nearest Neighbors with a k factor of 3, Linear SVM with a hyperparameter of 0.025, RBF SVM with gamma value of 2, Gaussian Process, Decision Tree with a maximum depth of 5, Random Forest with a maximum depth of 5 with 10 estimators, Neural Network with 1000 iteration, AdaBoost, Naïve Bayes. Based on these classifiers, AdaBoost was found to have the best results, with an accuracy of 97%. However, in terms of runtime, Nearest Neighbour was found to be best, with a time of 0.0022s.

Evaluation of Classifiers

Table 2 summarizes the mean scores, runtimes, and accuracy results of the nine classifiers used. From the results presented in Table 2 we can conclude that AdaBoost achieved the highest mean accuracy, but had a slower average prediction runtime than the others (around 5-10 milliseconds, while most others were around 1 millisecond).

Table 2. Mean score, mean runtime and mean accuracy for evaluation of classifiers.

Name	Mean Score	Mean Runtime	Mean Accuracy
Nearest Neighbors	0.68333	0.002238	0.86
Linear SVM	0.66667	0.002999	0.68
RBF SVM	0.741667	0.004999	0.87
Gaussian Process	0.691667	0.002999	0.71
Decision Tree	0.916667	0.003999	0.90
Random Forest	0.900000	0.009971	0.90
Neural Network	0.633333	0.003999	0.74
AdaBoost	0.975000	0.003941	0.97
Naïve Bayes	0.566667	0.005980	0.58

According to Wiem and Lachiri [2], automatic emotion recognition and stress detection, various emotion models have been used. The target emotions mentioned by Giannakakis et al. [1] of each video clip with the video ID were included with each data point. The used target emotions were: “calmness”, “amusement”, “fear”, “happiness”, “disgust”, “surprise”, “excitement”, “sadness” and “anger”. Considering this information, we could anticipate the emotions that each stimulation was meant to elicit rather than just the emotions participants reported.

Valence-Arousal Comparison

Figure 2 shows a heatmap of valence and arousal for the chosen target emotions. Both individual and fusion accuracy are shown in Table 3 for the chosen modalities. The EEG-based features have a classification accuracy of 62.48% for valence, while the combination of EEG and ECG-based features had the highest accuracy (62.31%) for arousal. The data presented in Table 3 indicates that the accuracy achieved by all modalities was comparable for all rating scales and presented well within the margin of statistical error. An analysis using the Wilcoxon signed rank test demonstrated small difference between the fusion strategy and the accuracy achieved using EEG-based and ECG-based features. This result could indicate that the EEG and ECG-based features, as a combination, are not useful for the studied impact detection problem.

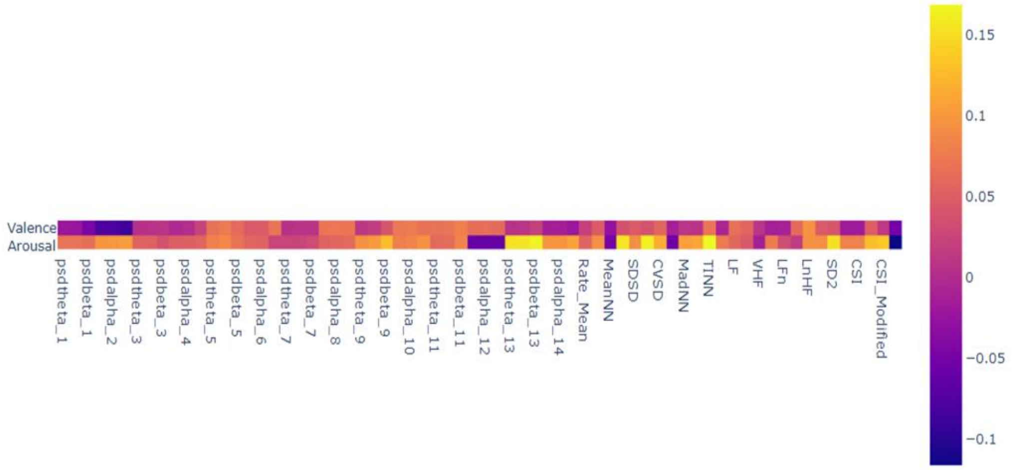

Figure 2. Accuracy for chosen modalities and baseline for the DREAMER database

In addition, analyzing the correlation of participants' EEG and ECG-based feature results using Spearman's correlation yielded a Spearman classification accuracy of $\varrho > 0.9$ for all rating scales. This indicated that the results have a strong correlation between each other. Also, the Wilcoxon signed-rank test demonstrated the difference of performance between EEG and ECG features. It was found to be not very significant.

Table 3. Accuracy for chosen modalities and baseline for the DREAMER database

Modality	**Accuracy**	
	Valence	**Arousal**
EEG	**0.6248**	0.6216
ECG	0.6238	0.6238
Fusion (EEG & ECG)	0.6183	**0.6231**

These findings give implications that features computed from the two categories provide similar descriptive power for effect. However, it is not clear whether this effect is due to disturbances of muscle and heart activity on the EEG signal, which are also recorded in the ECG signal, or to a lower descriptive power of the EEG. This is because of the lesser number of electrodes used in the Emotiv EPOC wireless device or a combination of these and other unforeseen factors.

Conclusion

The accuracy of the classification based on EEG and ECG features, and their combination, was significantly superior to the classification accuracy based on random voting or voting based on class ratio on DREAMER database.

The relationship between valence and arousal is highly correlated, which supports previous research on emotion. This could lead to a better understanding of an individual's mental state and provide new insights into the link between emotion and behavior. It could also help develop more effective interventions for mental health issues.

The AdaBoost model has a 3.9 ms runtime and 97% accuracy. To overcome this disadvantage of high runtime, the Nearest Neighbors model was selected. This model has a mean time of 2 ms despite 86% accuracy. The decision as to whether to use AdaBoost or Nearest Neighbors depends on whether accuracy or runtime is more important.

List of abbreviations

EEG = Electroencephalography
ECG = Electrocardiography
SVM = Support Vector Machine
RBF = Radial Basis Function
DC = Direct Current

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