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Feature Extraction from GAMEEMO data sets for Emotion Recognition

[1] Tarun Kumar, [2] Rajendra Kumar, [3] Ram Chandra Singh,
[1] Research Scholar, SBSR, Sharda University, Greater Noida, UP, INDIA
[2] SET, Sharda University, Greater Noida, UP, INDIA
[3] SBSR, Sharda University Greater, Noida, UP, INDIA
[1]tarunkumar124@gmail.com

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Abstract— Feature extraction from the GAMEEMO dataset for emotion detection aims to identify boring, calm, frightening, and amusing emotional states. It is based on the isolation of significant patterns from raw EEG signals. The dataset consists of recordings of twenty-eight participants who engaged in four distinct computer games for five minutes each. Using a 14-channel Emotiv Epoc+ EEG instrument is crucial to extracting relevant information from the recorded brain signals. Time-domain and frequency-domain analysis are common methods for feature extraction in emotion identification. The dynamics of brain activity may be represented from a time-domain perspective by computing the Hjorth parameters (activity, mobility, complexity), statistical measures (mean, variance, skewness, kurtosis), and signal differences (first and second difference). Band power ratios such as those for the Alpha, Beta, Delta, Gamma, and Theta bands are examples of frequency-domain characteristics that reveal information on power distribution across various frequency bands in the brainwaves. Furthermore, non-linear properties like fractal dimension and Lyapunov exponents, as well as entropy measurements like Tsallis, Renyi, and Shannon Entropy, may be used to describe complicated brain activity patterns. The characteristics that were retrieved are being used as crucial inputs by machine learning classifiers to distinguish emotional states with extremely high accuracy from EEG data included in the GAMEEMO dataset. MATLAB was used to generate the results that were reported in the study. All analyses and calculations were completed via MATLAB platform.

Index Terms— *EEG, BCI, Emotion, Datasets, Bio-Medical Signals etc.*

INTRODUCTION

Eye-tracking systems, voice-controlled interfaces, and brain-computer interfaces are part of the human-computer interface (HCI). We can quickly identify some brain anomalies, and the workload of mental states, make predictions, and identify person models with the use of EEG. Happiness, fear, stress, surprise, sadness, calm, and disgust have been identified with the study or analysis of brain activity signals or EEG [1-2]. Emotions can be recognized with the help of facial expressions, ways of talking or feeling. EEG classification can be more accurate than other approaches, and it can also be useful for classifying emotions in people with disabilities. EEG signal classification allows for real-time emotion classification; however, facial expressions and speech patterns can be somewhat altered [3]. Signal processing, pre-processing feature extraction, classification, device command, and BCI application are crucial parts of BCI technology [4].

Brain activity is based on two diverse signals i.e. electrical and magneto. In this paper, the electrical brain signal has been discussed. In medical science, the EEG is a widely used electrical signal that indicates brain activity. Brain-computer interface Com-IV with class-4 is used for these experiments [5]. The Author's [9] contributions to the field of emotion detection on the basics of EEG signal (Physiological data sets). The authors presented two types of feature extraction. First manual feature extraction method, second, the method of automated feature extraction, and gave the results that the automatic feature extraction technique is better than the manual technique. The authors present the new technology for emotion Recognition using EEG signal classification. Classification of the EEG signal can be done using different neural networks [12]. Before this type of research, Emotions were classified with the help of facial expressions, way of speaking, and gestures. But now day Emotions can be easily detected using EEG signals also. Three different classifiers namely [13] LDA, SVM, and K-near neighbor are used for emotion identification with temporal & spectral features. Both the time-evolving and static method is used for classifier performance. Tunable Q wavelets [14] decompose the signal into the Sub-band and analysis of the oscillating signal. The concept of tuning of Q factor is not available for traditional wavelet wavelets. TQWT is introduced when the concept of tuning of the Q-factor comes into consideration.

SIGNALS ACQUISITION DEVICE

To record brain electrical activity and support research on brain-computer interfaces (BCI), neurofeedback, and cognitive studies, EEG signal capture equipment is necessary. Electrodes applied to the scalp are used by these devices to identify voltage variations brought on by brain activity. Contemporary EEG systems come in several forms and sizes, with options for channel count, signal resolution, and mobility spanning from wearable, portable devices to high-density hospital installations. With features like wireless data transfer, comfort during lengthy recordings, and convenience of use, wearable EEG devices—like the Unicorn EEG—are especially helpful for real-time applications. These include tasks like emotion identification and cognitive status monitoring in dynamic contexts. In this study 14-channel Emotiv Epoc+ EEG instrument used to extract relevant information from the recorded brain signals.

STANDARD INPUT DATA SETS

Standard EEG datasets are crucial for brain-computer interface (BCI) and neuroscience study validation, as well as for benchmarking algorithms. A few popular datasets include DREAMER, SEED, and DEAP data sets. These datasets are made up of EEG recordings made by several participants in controlled settings, frequently during the performance of various emotional, cognitive, or motor activities. Usually, the data is pre-processed and tagged for several categories, such as mental workload, emotions, or distinct brain states. Researchers can create more precise emotion identification algorithms and enhance human-computer interaction by comprehending and reacting to users' emotional states thanks to SEED's extensive, well-structured data [18-20]. These datasets support breakthroughs in fields like emotion identification, neurofeedback, and mental health monitoring by allowing researchers to compare results and enhance model accuracy. Data Sets are DEAP, MAHNOB-HCI, DREAMER. GAMEEMO, SEED, and AMIGOS.

The dataset contains video recordings of facial expressions in addition to EEG, ECG, GSR, and other signal data. In addition, the participants self-reported their personality characteristics and emotional states [1]. To support research in stress and emotion identification, the SAFE (Stress and Affect identification using Physiological and Environmental Sensor Data) dataset was created. It contains multimodal data from wearable sensors that record environmental factors like humidity and ambient temperature in addition to physiological signals like skin temperature, electrodermal activity (EDA), and ECG. SAFE data, gathered from individuals in real-world contexts, offers insightful information on how different circumstances impact stress and affect. In This study, GAMEEMO data sets are used for feature extractions [15].

literature survey

Emotion classification using psychological signals or brain activity for higher accuracy. There are different types of emotions like Happiness, fear, stress, surprise, sadness, calm, and disgust [2]. Recognition with the help of facial expressions, way of talking, or feeling [3]. In [1] authors find out the authentic data set for testing purposes. We explained a comparison between the external and internal observations of arousal & valence. The authors carry out correlation analysis for the long and short videos. And will discuss the baseline methods and outcomes for valence and arousal prediction by using EEG, GSR, and ECG [1]. In [2] the authors categorize calm, anger, and happiness emotions based on EEG. There are four steps for classification, the first acquisition of the EEG signal during the video watching with a different emotion, the second recording of the EEG signal, the third extraction of the EEG signal's feature extraction process, and the fourth classification of the emotion categories. Happiness, anger, and calm are the categories of emotion in this problem. The different categories of emotion namely frustration, fear, pleasant, sadness, happiness, and satisfaction are commonly used. Several feature extraction techniques and classifiers are available to classify emotions. so, our objective is to select the appropriate combination of feature extraction methods with good classifiers for better accuracy [3]. Explained the comparative study with Decision Trees, K-nearest neighbor, Support Vector Machine, Linear Discriminates Analysis, and L.R. We employed PCA to test dimensional reduction [7].

Through the use of questionnaires, participants' self-reported emotional states are recorded, offering subjective insights into their experiences. Using valence, arousal, and dominance measures, participants also self-assessed their emotional states. The recognition model is a useful tool for the development and validation of algorithms targeted at identifying and interpreting human emotions because it combines physiological signals with subjective evaluations.

Feature Extraction

In feature extraction, there are three categories for feature extraction namely time domain, time-frequency domain, and frequency domain. The characteristics that were retrieved offer a thorough depiction of EEG signals, including metrics based on entropy, frequency, and time domains. These characteristics are essential for differentiating between the emotional states (boring, calm, scary, hilarious) evoked by various game genres. For example, during frightening and hilarious games, we found different patterns in frequency-domain properties such as enhanced beta and gamma power, indicating more arousal and cognitive involvement. On the other hand, quieter and more monotonous games were associated with increased alpha band power, which is suggestive of neutral or relaxed moods. Tsallis and Renyi entropy, two entropy-based properties, varied significantly between games, especially in horror game-playing participants, where higher entropy values indicated emotional instability. These characteristics highlight how non-linear dynamics may be used to effectively describe complicated emotional responses. We will provide a thorough tabular comparison of the retrieved attributes for each player and each game in the next section. This will demonstrate the feature set's ability to differentiate between various emotional states even further. For the participant S01, the band power for each EEG signal concerning each emotion is shown below. All results are calculated through MATLAB.

Band Power for Boring

Delta Band: 26.827807
Theta Band: 13.473073
Alpha Band: 10.891055
Beta Band: 68.997469
Gamma Band: 8.591164

Band Power for Calm

Delta Band: 20.485551
Theta Band: 8.943606
Alpha Band: 4.790339
Beta Band: 56.402239
Gamma Band: 10.579749

Band Power for Horror

Delta Band: 19.438695
Theta Band: 7.572727
Alpha Band: 6.716644

Beta Band: 47.346595
Gamma Band: 9.299463
Band Power for Funny:
Delta Band: 12.395684
Theta Band: 9.260340
Alpha Band: 6.916176
Beta Band: 51.202854
Gamma Band: 14.930255

EEG Signal Classification

The next step is to use the classifier to group the feelings into four categories: high arousal low valence, low arousal low valence, high arousal high valence, and low arousal high valence. Major classifiers identified for emotion recognition (namely positive and negative emotion) are GNB, LDA, QDA, I-SVM, NI-SVM, GB, KNN, and RF. For EEG-based emotion identification, several classifiers are used, each with advantages and disadvantages. Conventional techniques like as Decision Trees, k-nearest Neighbors (k-NN), and Support Vector Machines (SVM) are effective for small datasets with manually crafted features. By merging many decision trees, more sophisticated Gradient Boosting and Random Forests are two techniques that improve classification accuracy. The capacity of deep learning models to automatically extract characteristics from unprocessed EEG data has made them popular in recent years. Convolutional neural networks and Fig long short-term memory (LSTM) networks are two examples of these models. Hybrid models are also being used more often to improve performance and resilience in emotion identification tasks. These models combine deep learning with conventional classifiers.

Result and discussion

Four emotionally different computer games were played by the 28 volunteers whose EEG signals were collected using the 14-channel Emotiv Epoc+ device: boring (G1), calm (G2), frightening (G3), and hilarious (G4). A subject's EEG data was collected for 20 minutes during each of the five-minute gaming sessions. The Self-Assessment Manikin (SAM) scale was used by the individuals to appraise the games, yielding ratings for both arousal and valence, to assess the emotional states. 28 unique characteristics were extracted from the EEG data for each channel, game, and person through analysis [15].

For every gaming session, a total of 28 characteristics were retrieved from the 14 EEG channels, giving a thorough picture of the brain's activity throughout various emotional states. Typical EEG measurements, such as band power ratios (theta/beta, alpha/beta), which show emotional and mental effort, are among these characteristics. The attributes that were collected offer insightful information about the various emotional reactions that each game evokes. Figure 1-4 are shown the classification of EEG signals for different emotions.

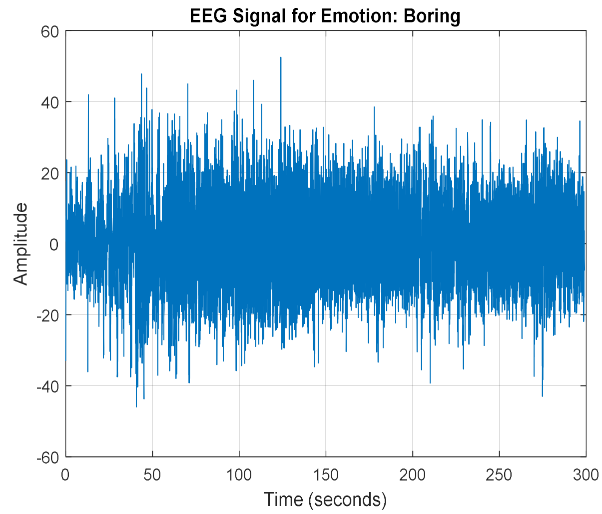

Fig.1. Wave Signal for Boring Emotion (S01)

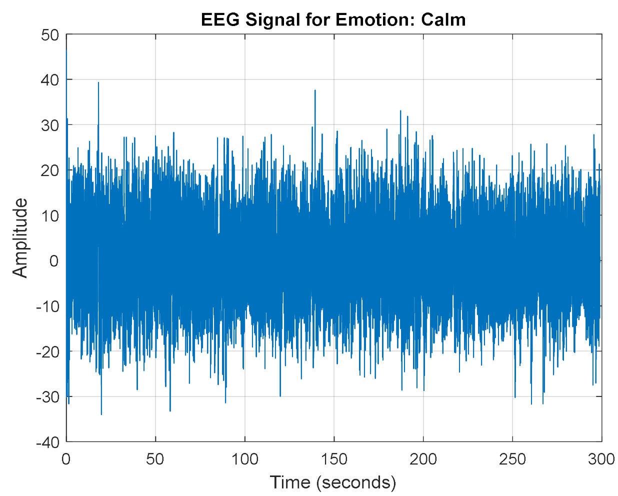

Fig.2. Wave Signal for calm Emotion (S01)

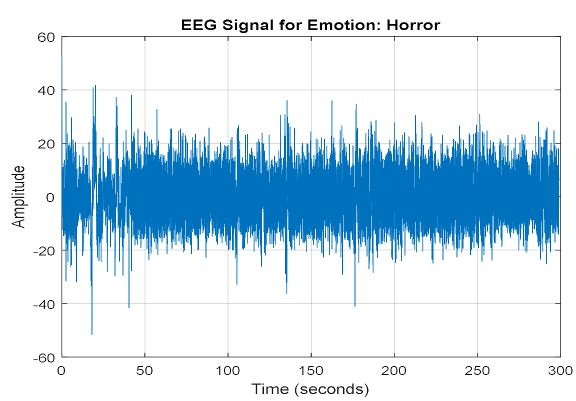

Fig.3. Wave Signal for Horror Emotion(S01)

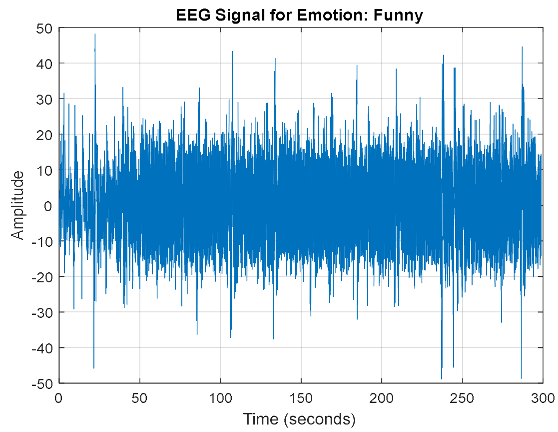

Fig.4. Wave Signal FOR funny Emotion (S01)

Time Domain Features: Insights into the brain's power and dynamic changes are provided by the Hjorth parameters (Activity, Mobility, and Complexity), which are essential for differentiating between various emotional states. Stronger EEG pattern variations, such as those associated with Hjorth Activity, may indicate elevated arousal. For example, for highly charged stimuli like scary or humorous games, skewness and kurtosis might convey emotional intensity by measuring the asymmetry and peakedness of the signal. First and Second Differences provide scale-independent examination of emotional fluctuations, while their normalized versions reflect the pace of signal change across time. Mean Energy and Mean Curve Energy, on the other hand, convey the overall power of the signal and tend to rise with increased arousal, like in horror video games. Rapid changes in brain activity are detected by the Teager Energy feature. Band Power over the five frequency bands (Alpha, Beta, Gamma, Theta, and Delta) is a crucial property for emotion identification in the frequency domain. Increased Beta activity, for example, is associated with excitement (horror games), whereas Alpha power is associated with tranquility (boring games). Entropy and Statistical Features: The unpredictability of the signal is captured by Shannon and Log Energy entropy, which helps identify nuanced emotional reactions. While statistical characteristics like mean, variance, and extremes (A_M, S_D, and Median Value) provide fundamental signal descriptions, Tsallis and Renyi entropy give deeper insights into complexity. In Table 1 shows only a few features extracted values for subject S01. MATLAB was used to create all of the results that are given in this study. Features have been extracted from subject S1 while playing games G1, G2 and G3. Similarly, Features have been extracted from subjects S2-S28 while playing games G1, G2, G3, and G4.

Table 1: Value of Extracted Features for S01

S. No	Feature Name	S1G1	S1G2	S1G3	S1G4
1	HA	15.2	8.39	10.36	11.19
2	HM	0.55	0.57	0.55	0.54
3	HC	1.16	1.15	1.15	1.16
4	SK	-0.03	-0.001	-0.002	-0.03

5	KU	5.29	4.19	6.26	5.06
6	FD	1.59	1.23	1.30	1.34
7	NFD	0.41	0.43	0.41	0.41
8	SD	3.87	2.86	3.15	3.275
9	MCE	1.59	1.23	1.30	1.34
10	ME	15.25	8.39	10.36	11.19
11	MTE	8.12	4.76	5.64	5.81
12	LRSSV	2.61	2.49	2.52	2.531
13	SE	13.81	13.94	13.71	13.85
14	LEE	45658.91	24670.3	27915.15	33093
15	TE	0.99	0.99	0.99	1
16	RE	12.83	13.17	12.60	12.91
17	AM	8.7×10^{-5}	4×10^{-5}	-4.6×10^{-5}	7.0×10^{-5}
18	SD	3.86	2.89	3.16	3.275
19	VAR	15.25	8.39	10.36	11.19
20	MV	0.004	-0.002	0.002	0.007
21	ARM	0	0	0	0
22	MaV	28.05	18.09	25.04	23.28
23	MiV	-27.09	-18.50	-23.94	-23.0

*HA-Hjorth Activity, HM-Hjorth Mobility, HC-Hjorth Complexity, SK-Skewness, KU-Kurtosis, FD-First Difference, NFD-Normalized First Difference, SD-Second Difference MCE-Mean Curve Energy, ME-Mean Energy, MTE-Mean Teager Energy, LRSSV, SE-S Entropy, LEE-L E Entropy, TE-Tsallis Entropy, RE-Renyi Entropy, AM-arithmetic mean, SD-STANDARD MEAN, VAR-Variance, MV-Median Value, A R M, MaV-Maximum Value, MiV-Minimum Value.

EEG signals were obtained for participant S02 throughout the following games: G1 (boring), G2 (calm), G3 (horror), and G4 (funny). MATLAB programming was used to determine the characteristics shown in Table 2, such as band power ratios, entropy measurements, Hjorth parameters, and statistical features. Table 2 displays the characteristics that were retrieved for these games. Similarly, using MATLAB programming, the characteristics may be computed for the remaining individuals based on their recorded EEG signals during games G1, G2, G3, and G4. The relevant tables may then display each participant's findings in a comparable manner. Features for participants S02 shown in Table 2. In the same manner feature can be calculated for participants from S03-S30.

Table 2: Value of Extracted Features for S02

Feature Name	**S2G1**	**S2G2**	**S2G3**	**S2G4**
HA	27.33	18.67	18.21	22.43
HM	0.56	0.56	0.56	0.57
HC	1.14	1.14	1.14	1.14
SK	-0.002	-0.010	-0.009	-0.009
KU	4.58	4.74	4.72	4.03
FD	**2.17**	1.81	1.80	2.05
NFD	0.42	0.42	0.42	0.43
SD	5.21	4.29	4.23	4.71
MCE	2.17	1.81	1.80	2.05
ME	27.33	18.67	18.21	22.43
MTE	15.23	10.62	10.43	13.32
LRSSV	2.75	2.67	2.67	2.72
SE	13.86	13.89	13.89	13.93
LEE	68446.38	53983.04	53496.84	61483.49
TE	0.99	0.99	0.99	0.99
RE	13.03	13.02	12.99	13.21
AM	4.6×10^{-6}	1.2×10^{-5}	8.7×10^{-5}	0.0003
SD	5.22	4.29	4.23	4.71
VAR	27.33	18.67	18.21	22.43
MV	-0.007	10^{-5}	-0.002	0.0006
ARM	0	0	0	0
MaV	33.21	28.21	28.84	28.13
MiV	-32.61	-29.31	-30.52	-27.26

Conclusion and Future Scope

The field of emotion classification based on EEG has advanced significantly, moving from conventional signal processing methods to sophisticated deep learning and machine learning models. Notwithstanding noteworthy advancements, issues including individual variances, realtime application constraints, and EEG signal variability still exist. To create more reliable and accurate emotion identification systems, this paper emphasizes the significance of feature extraction parameter, after caculating the features other steps would be start for emotion recognitions. Future research should concentrate on boosting realtime performance, increasing user experience, and increasing classification accuracy as technology develops.

Design database with more number of participating individuals or groups with different purposes like Emotion recognition based on facial expressions. Spontaneous facial action recognition, Group happiness intensity research, Emotional recognition, and implicit tagging can be identified by EEG signals. Affect recognition, Emotional behavior research, and Personality state research can be done with the help of brain signals. it is to extend the category of emotion with a large number of participants for better accuracy. And there is a scope to explore the feature extraction method and classifier combination for better results.

The goal is to increase the accuracy of emotion identification by designing a real-time system using a huge sample set of EEG data. Different optimization parameters and the introduction of the technique for feature extraction from EEG signals will be investigated in the future to increase the popularity of BCI applications around the world. And use it in clinical applications for better results. And enhance the commercialization of the application of BCI.

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