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Emotion Recognition using Smart Devices

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Abstract: *The progress of communication systems has allowed us to think beyond traditional communication systems, and the scene has been set for thought-oriented communication systems. Thousands of thoughts are formed and then evaporate in a short period of time, yet certain notable concepts remain and we carry on with our daily routines. EEG has advanced to the point that it is now possible to see the activity in the human brain in a non-invasive manner. The approach for emotion identification utilizing EEG data recorded and processed on smart devices is presented in this study. The results demonstrate the use of a computational neural network to recognize emotions from EEG data. It was discovered that the correct categorization rate was 90.17 percent.*

Keywords: *Emotions, EEG, FAST Independent Component Analysis, Computational Neural Network*

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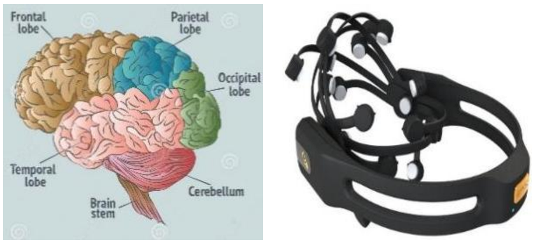
I. Introduction

We are approaching the next communication assessment, which will see a significant change in communication channels and mechanisms. When it comes to human-machine communication, we've come a long way from punch cards to keyboards and mice to touch screens and gesture recognition to BCI devices. We can now analyze enormous real-time data in various complicated algorithms to derive essential information thanks to developments in computer and network capability. A brain-computer interface (BCI) is a type of neuro-technology that decodes a user's central nervous system signals [1]. The BCI enables direct thought–based communication with other users or operation of different appliances (e.g., a direct brain–robot interface) without efferent peripheral nervous system fibers or muscles being involved [2]. In the case of locked-in-syndrome (LIS) users who cannot focus or regulate their eye movements, BCIs offer feasible alternatives, and in certain circumstances they are the more appropriate communication augmentation solutions [3]. EEG has a lot of untapped potential since it has a lot of untapped information that is directly related to real-time brain activity. This data is being processed using advanced approaches, resulting in novel applications for EEG interpreted data. Controlling smart devices with brain signals, performance assessment of persons using EEG analysis on generated cognitive work load, control of prostate organs using EEG, and so on are only a few instances [4, 5]. BCIs (Brain Computer Interfaces) are an emerging prospective study field. Researchers in this field are attempting to make the system more resilient and scalable. The researchers encounter considerable hurdles such as computational errors, delays, false positive detections, inter-person variations, high prices, and restrictions on intrusive technologies, all of which necessitate more study in this field. The fundamental study that makes use of EEG technology is based on the concept that this rhythmic activity is impacted by mental state and can be altered by alertness or other mental illnesses. Eye movement and blinking are one of the most prominent sources of artefacts, but additional causes include the usage of scalp, neck, or other muscles, or even insufficient contact between the scalp and the electrodes [6]. In a Human-in-the-Loop Cyber-Real-Systems scenario, users' intentions are inferred from brain and body sensor networks linked to them and sent directly into sensors and actuators in the physical environment, allowing for autonomous system adaption to their demands. Humans must be instrumented and integrated into the system in this scenario. This is a future that is still a long way off and far from ideal, because the desire of people and the general public to engage is still a huge issue, and it is not addressed by [7]. Similarly, several automated EEG signal categorization and seizure detection systems existed and were built using various methods. Gotman et al. [8] presented a computerized system for detecting a variety of seizures, while Qu and Gotman [9] proposed using the nearest-neighbor classifier on EEG features extracted in both the time and frequency domains to detect the onset of epileptic seizures, which is in line with previous research. While Adeli et al. [11], Guler et al. [12], and Ubeyli et al. [13] discussed the potential of nonlinear time series analysis in seizure detection, Gigola et al. [10] used a method based on the evolution of accumulated energy using wavelet analysis for the prediction of epileptic seizure onset from intracranial epileptic EEG recordings. Several studies have suggested artificial neural network-based detection methods for epilepsy diagnosis [14-15]. Weng and Khorasani [16] present an adaptable structured neural network that incorporates the characteristics suggested by Gotman and Wang [17], namely average EEG amplitude, average EEG length, variation coefficient, dominant frequency, and average power spectrum, as inputs. Pradhan et al. [18] offer a technique that uses raw EEG data input to a learning vector quantization network. Nigam and Graupe [19] introduced a novel neural network model called LAMSTAR (Large Memory Storage and Retrieval), which uses two time-domain EEG properties, namely relative spike amplitude and spike rhythmicity, as inputs to identify seizures. In line with the methodologies described in the literature, the study of EEG Signals in the framework of cognitive science. Based on data extraction, preprocessing, feature extraction algorithms, and classifiers, this literature proposes a completely new approach of processing EEG signals utilizing Smart Computing/Communication Devices such as smart phones, tablets, and notebooks. Using the aforementioned approaches, the team conducted research to recognize emotions from real-time EEG data, which may then be utilized to operate smart devices or to offer as input to external systems, which can then use it to carry out user activities in the context of the apps. The following sections organize the material of this work. The backdrop is presented in Section I, followed by database specifications in Section II, the methodology employed and performance analysis of the technique in Section III, and the work's conclusion in Section IV, which is followed by acknowledgements and references.

II. Database:

In order to create a reliable EEG recognition system, the researchers created a database that fits the requirements of their study topic in general. EmoEngine collected the EEG signals for each mode, as seen in figure 1.



(a) (b)

Figure 1. (a) Brain lobes and (b) Emotive EPOC device for brain wave data acquisition

The data from the headset is read and saved to an output file for further processing. The subject is required to wear an Emotive head set, which transmits data about the subject's activities to a distant smart device via the available communication method. The data is saved on mobile phones and may then be utilized for sample training and testing through mobile phones. The data acquired from the subject is traditionally analyzed for five wide spectral sub-bands of the EEG signal that are often of therapeutic interest: delta (0 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 16 Hz), beta (16 - 32 Hz), and gamma waves (32- 64 Hz). These five frequency sub-bands give more precise information about the underlying neural activity, and as a result, some changes in the EEG signal that aren't visible in the full-spectrum signal can be enhanced when each sub-band is analyzed separately. There were 125 EEG data segments since each EEG segment was treated as an unique EEG signal. The brain is divided into five lobes, each of which is responsible for a different set of neurological functions. For example, the frontal lobe is in charge of speech, thought, emotions, problem solving, and skillful movements. The parietal lobe is responsible for identifying and interpreting experiences such as touch, discomfort, and so on. The Occipital lobe receives and analyses visual images, while the Temporal lobe is in charge of hearing and memory storage, and the Cerebellum is in charge of the coordinates' familiar motions. Similarly, the association between the output (energy) frequency of signal and the brain lobes is as follows:

Table 1. Signal Type, Frequency and its origin

Type	**Frequency Range**	**Origin**
Delta	0Hz – 4Hz	Cortex
Theta	4Hz – 8Hz	Parietal and Temporal
Alpha	8Hz – 13Hz	Occipital
Beta	13Hz – 20Hz	Parietal and Frontal
Gamma	20Hz – 40Hz	Parietal and Frontal

The data set used in this study is essentially Emotions that have been analyzed. For all of the studies, the Emotions dataset was used. This collection comprises seven emotions: 'Happy', 'Excited', 'Content', 'Calm', 'Angry', 'Afraid', 'Sad' and EEG Signal recordings of ten participants (seven males and three females) in the age range of 20-25. The database has a total size of 12x10x10 = 1200 samples. All of the participants in the data collection/acquisition procedure were healthy and free of any physical or mental disorders. In an electromagnetically insulated room, all patients were told to sit comfortably in an arm chair facing the screen. Before taking part in the study, the participants had provided their written agreement to have their EEG signals recorded. Every subject has an excellent understanding of emotions. All of the participants were told that this experiment was created for use in Brain Computer Interface applications. For the data gathering under the proposed research project, a basic power point display system has been built. This device provides a 2-second interval emotion signal. A new emotion was flashed on the screen every 2 seconds. Before the experiment began, each participant was provided a demonstration of the display system so that they would be more comfortable with the job and we would receive correct signals. This procedure was carried out five times. As a result, the total number of samples in the emotion dataset is 1000. The EEG signals from all individuals will be extracted and analyzed according to the technique.

III. Methodology / ANTARANG framework

We created the ANTARANG framework, which is utilized to design a mobile emotion identification system. This framework or approach of obtaining, preprocessing, feature extraction, normalization, and classification model from raw EEG data is presented in this research. We give an overview of the suggested technique and the ANTARANG framework for EEG data interpretation.

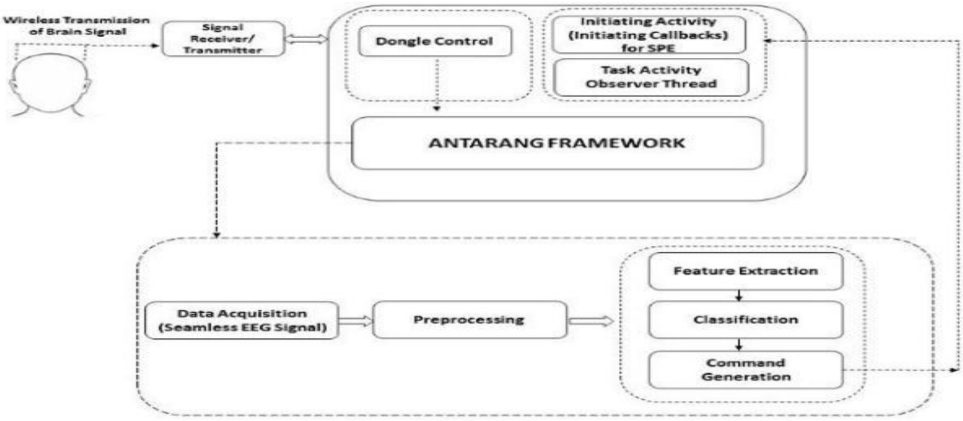


Figure 2 (a)

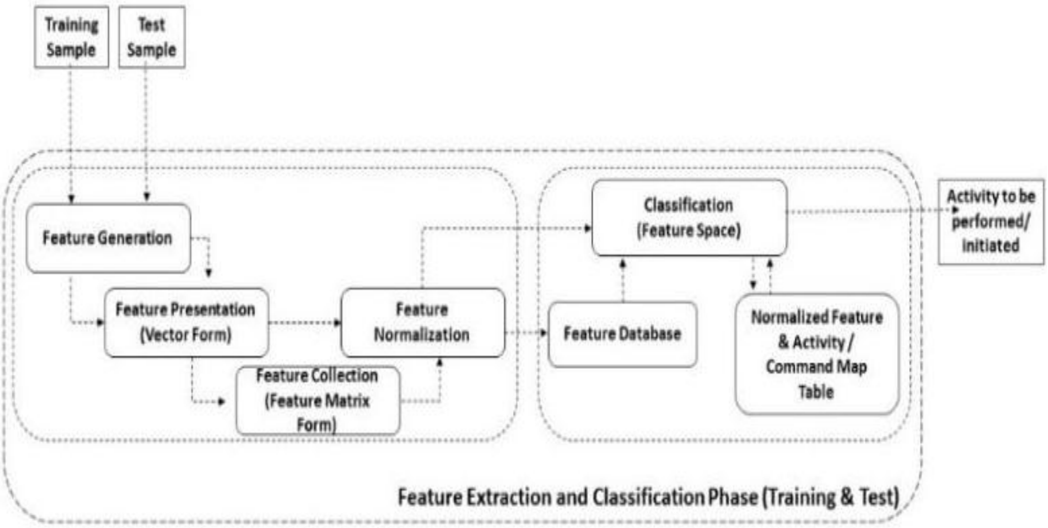


Figure 2 (b)

Figure 2: (a) and (b) Block Diagram of thought processing system 'ANTARANG'

a. Overview

Figures 2(a) and 2(b) above demonstrate how the several phases involved in emotion recognition are ordered. The systems' functions are described in the following sections,

1. **Data acquisition:** The data collection approach is the same as that described in section II. In order to get EEG signals relating to the activity, the individual must wear EMOTIVE EPOC head gear. The data collected by the EMOTIVE head set is easily sent to the wireless dongle attached to the smartphone via Bluetooth. The smart device's dongle control mechanism serves as a receiver. This will save the test sample primarily in the Smart device's storage and pass it on to the ANTARANG framework.
2. Preprocessing: FAST Independent component analysis (ICA) of EEG sample data was done to remove artefact, and the resultant ICs were passed for feature extraction.
3. Feature Extraction: The goal of this step is to develop a unique collection of characteristics that will increase classification performance overall. In this study, a stack of feature extraction methods was employed to compute features, including Short Time Fourier Transform (STFT), Discrete Cosine Transform (DCT), and discrete wavelet transform (DWT).
4. Feature Normalization: The characteristics that have been calculated were normalized. This is necessary to decrease the dimensionality of the feature space and speed up the system's categorization. The feature space was reduced by the use of Linear Discriminant Analysis. This feature normalization is done on all training vectors, as well as the test sample, before to classification.
5. Classification: In the design of any automated system, the categorization step has enormous potential. Support vector machine, k-Nearest Neighbor, Random forest, Nave Bias classifier, Multi-Layer perceptron, and Convolution neural network are among the classifiers used in the suggested system. The classifier's output will be sent on to the native command translation mechanism, which will start the smart processing elements working (Smart Devices).
6. Command Map Table and Task observer thread: The mapped callback corresponding to the idea is stored in the command map table. The task watcher thread watches for activity and then invokes/dispatches the task for smart device execution.
7. Tools and Software: Preprocessing and feature extraction were implemented in Python's SciPy and Numpy libraries as part of this project. In order to categories the time-frequency representations, convolutional neural network models were created with the Keras toolkit and executed with Tensorflow. To plot the figures and visualize the data, the matplotlib software was utilized.

b. Working

The participant must wear an Emotive EEG set during data collection as well as during the testing samples. During data gathering, an EEG device's electrode or subset of electrodes may shift, resulting in poor contact with the scalp and, as a result, a low-quality signal. Electrodes can also have mechanical problems, such as frayed wire, which can weaken the signal received partially or totally. Artifacts in the signals can be caused by such electrodes. FAST Independent component analysis (ICA) was conducted on EEG sample data as a preprocessing step to remove artefact, and the resultant ICs were passed for feature extraction. In biomedicine, ICA entails the extraction and separation of statistically independent sources underlying various biological signal measurements.

1. Feature Extraction using DCT

The Discrete Cosine Transform is a technique for transforming a time series signal into its fundamental frequency components. Low frequency components are concentrated in the first coefficients, whereas high frequency components are concentrated in the final. Equation (1) expresses the one-dimensional DCT for a list of N real values as,

$$Y(u) = \sqrt{\frac{2}{N}}\alpha(u)\sum_{x=0}^{N-1} f(x)cos\left(\frac{\pi(2x+1)}{2N}\right)(1)$$

Where u=0, 1, 2, 3… N-1;

$$\alpha(0) = \frac{1}{\sqrt{2}}$$

a(j) = 1, j≠0;

The output of an acquired input EEG sample from the training set is a set of N-DCT transform coefficients Y, while the input is a set of 'N' data values (u). The first coefficient, Y(0), is known as the DC coefficient and is responsible for storing the average signal value. The AC coefficients stand for the rest coefficients [20]. For strongly correlated data, DCT shows good energy compaction. If the input data is correlated, the majority of the N transform coefficients produced by the DCT are zeros or tiny values, with only a few exceptions. As a result, quantizing the coefficients is used to compress data with the DCT. The little ones are coarsely quantized, whereas the large ones can be finely quantized to the closest integer. When applied to EEG signals, this characteristic allows meaningful data to be compressed to the first few coefficients. As a result, machine learning systems can only employ these coefficients for categorization. This type of data compression can significantly reduce the size of the input vector and the amount of time required for training and classification. These characteristics were estimated for all of the 'Emotion set' samples. Table 2 shows the 'DCT Feature Matrix' for the samples from the 'Emotion set.'

Happy	Excited	Content	Calm	Angry	Afraid	Sad
0.366515	1.081741	1.355358	4.177025	8.047682	1.687529	2.732452
0.639972	0.688207	1.752748	9.701809	3.125768	21.37542	31.93106
0.061715	0.542834	0.970531	2.899618	2.956171	7.894226	6.532051
0.031866	1.167931	0.613204	4.922474	6.982062	21.8817	1.435193
0.567666	0.526758	0.790951	7.802225	2.726657	22.01105	51.35523
1.073398	0.276145	0.029724	0.07606	0.027696	0.03968	0.680563
3.476802	2.356264	0.774597	0.754562	0.40443	0.505899	35.93576
0.194747	0.033649	0.033631	0.017214	0.009243	0.041233	0.107949
0.056582	0.016408	0.020714	0.024856	0.006497	0.016135	0.082541
0.402641	0.091293	0.008991	0.04552	0.04046	0.051385	13.32203

Table 2: Emotion

2. *Feature Selection using LDA*

The feature vector Y = [y1, y2, y3,....., yn] is produced after signal analysis and feature extraction using DCT. Its size should be lowered since the dimension n is frequently too huge, and designing classifiers for such a large dimension is challenging. The majority of these problems are numerical in nature and require the use of high-order matrices. At the same time, analyzing and imagining a classifier in n-dimensional space is quite challenging. As a result, Linear Discernment To determine the feature and pick the most significant characteristics for classification, LDA was used to the feature vector. The goal of LDA is to segregate data representing distinct classes using hyper planes [21]. The separation hyper plane is found by looking for a projection that maximizes the distance between the means of the two classes while minimizing the variance between them [22]. Several hyper planes are employed to solve an N-class issue (N > 2). This approach has a low processing need, making it ideal for use in a BCI system. As a result, all of the samples in the 'Emotion dataset' were normalized using LDA, and 100 features from each sample were chosen for classification.

IV. Results and Discussion

DCT and LDA were used to recognize the EEG signal samples. For the purpose of recognition, these characteristics were computed for each sample of the training set and saved. The full preprocessed features data set of EEG Emotions was split into a 70-30 ratio, with 70% (Training samples) and 30% (Test samples), then assessed using a Convolution Neural Network (CNN). The shift and translational invariance of this artificial neural network have been enhanced [23]. CNN is a subset of deep learning that has gained a lot of attention in recent years and is used in image recognition applications such as x-ray medical image analysis [24], magnetic resonance image analysis [25], histopathological image analysis, fundus image analysis, and computed tomography image analysis. However, there has been relatively little study on the application of CNN with physiological inputs. Convolutional layer, pooling layer [26], and fully connected layer are the three types of layers that make up the CNN architecture. For image classification applications, CNNs are particularly effective models.

Table 3: Confusion Matrix for emotion Classification using CNN

Emotions	Total Test Sample	Training Samples							Correct Classified	Miss-classified	Accuracy
		Happy	Excited	Content	Calm	Angry	Afraid	Sad			
Happy	**17**	15	0	0	0	0	1	0	**15**	**2**	**86.67**
Excited	**13**	0	13	0	0	0	0	0	**13**	**0**	**100.00**
Content	**13**	0	0	13	0	0	0	0	**13**	**0**	**100.00**

Calm	**10**	0	1	0	9	0	0	0	**9**	**1**	**88.89**
Angry	**12**	1	0	0	0	10	0	0	**10**	**2**	**80.00**
Afraid	**14**	0	0	0	0	0	12	0	**12**	**2**	**83.34**
Sad	**14**	0	0	1	0	0	0	13	**13**	**1**	**92.31**
	93	**Classification Result**							**85**	**8**	**90.17**

Table 3 shows the confusion matrix, with a total of 93 test samples being tested on the training data set. It was discovered that 15 of the 17 samples of the emotion 'Happy' were correctly categorized and two were incorrectly categorized, whereas 13 of the 13 test samples of the emotion 'Excited' were correctly classified and 0 were incorrectly labelled. Similarly, all 'Content', 'Calm', 'Angry', 'Afraid', and 'Sad' test samples were completely categorized. Only 8 test samples were misclassified out of a total of 93 test samples, resulting in a classification accuracy of 90.17 percent.

V. Conclusion

The method for automated categorization of EEG signal of Emotions for smart devices is presented in the suggested research effort. The proposed study assesses the effectiveness of a CNN classifier using normalized Discrete Cosine Transform information. The work also denotes a feature reduction strategy based on linear discriminant analysis. The total accuracy was found to be 90.17 percent, and the research will now be expanded to include automated categorization of 'emotions.' The suggested study is further extended to the construction of smart gadgets that are controlled by EEG.

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