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Recognition Of Digits From EEG Signals: An Innovative Approach

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Abstract
Communicating with computers through thought has been a remarkable achievement in recent years. This was made possible by the use of Electroencephalography (EEG). Brain-computer interface (BCI) relies heavily on Electroencephalography (EEG) signals for communication between humans and computers. With the advent of deep learning, many studies recently applied these techniques to EEG data to perform various tasks like emotion recognition, motor imagery classification, sleep analysis, and many more. This study proposes a methodological combination of EEG signal processing techniques and SVM models for the classification of digit. Also, it explores DCT and LDA techniques for feature extraction and selection. As a result, the proposed classification pipeline achieves comparable performance with the existing methods.
Keywords: *Electroencephalography, Antarang, EmoEngine*

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I. Introduction

Communication with computers through thought/brain signals has been a remarkable achievement in recent years. A brain-computer interface (BCI) is an interface where we do not need peripheral devices to communicate with computers. Recently, many studies have been conducted to classify EEG signals using Convolutional Neural Networks, Gated Recurrent Units, and many other deep learning architectures. However, very few studies try to solve the specific problem of classifying given EEG signals into respective digits that the user was thinking about.

Given a multichannel EEG signal recording from a person thinking/seeing a digit from 0 to 9, can we recognize if the user was thinking about a particular number? This is the fundamental question that this study tries to address. However, the problem is non-trivial and is expected to be much more challenging as very little work has been done on such datasets. This problem can be formulated as a classification problem (Binary and Multiclass) from the machine learning point of view. Also, EEG signals can be considered multivariate time series data where different channels are equivalent to various timeseries variables. So the problem boils down to multivariate time-series classification. According to [1] and [2], the number of publications has increased drastically from 2015 to 2020 with the introduction of deep learning in BCI. This implies that the application of deep learning to EEG-based BCI is a topic of growing interest among the community.

II. Literature Review

Many studies have reported that human emotional states can be traced in EEG [3-5]. In [3], Sammler et al. have studied the correlation between EEG theta power at frontal midline and emotions induced by pleasant and unpleasant music. They reported that emotions induced by pleasant music were accompanied by an increase of theta activity at frontal midline. The investigation by Kroupi et al. [4] has revealed that arousal was positively correlated with logarithmic mean theta power on the right hemisphere. In [5], Aftanas et al. reported that valence was associated with theta ERS (Eventrelated Synchronization) in anterior temporal regions. Negative valence provoked greater right hemisphere ERS activities while positive valence triggered prominent left hemisphere ERS activities. In order to ensure the standardized placement of EEG electrodes on the scalp, systems that regulate the positions as well as the names of EEG electrodes have been devised and widely adopted in EEG research. This section introduces the two well-recognized nomenclature systems, namely the international 10 – 20 system [6] and its extended version guided by American Electroencephalographic Society [7].

EEG recorded at the surface of the scalp comprises the summated postsynaptic potentials created by numerous nerve cells underlying the scalp in the cerebral cortex [8]. A resting membrane potential is maintained by the efflux of positive ions (e.g. potassium) from intracellular to extracellular, establishing an electrochemical equilibrium of around - 70 microvolts [9]. As a common practice, EEG can be divided into several frequency bands, such as alpha band, beta band, delta band, gamma band, theta band etc. The correlates between EEG rhythms and brain states have been studied [10-12]. However, it must be pointed out that there is no absolute consensus on the band range definition of these frequency bands—different studies could respect different band range definition. In our work, unless otherwise stated, we refer to the definition listed in Table 2-1. The same definition is also respected in [13-15].

III. Methodology

To implement the above digit recognition system on smart devices, the critical aspect of consideration is the accuracy of the EEG based thought recognition algorithm. This paper presents a method of acquiring, pre-processing, feature extraction, normalization and classification model from raw EEG signal. In this section, we provide an overview of proposed approach and ANTARANG framework for interpretation of EEG data.

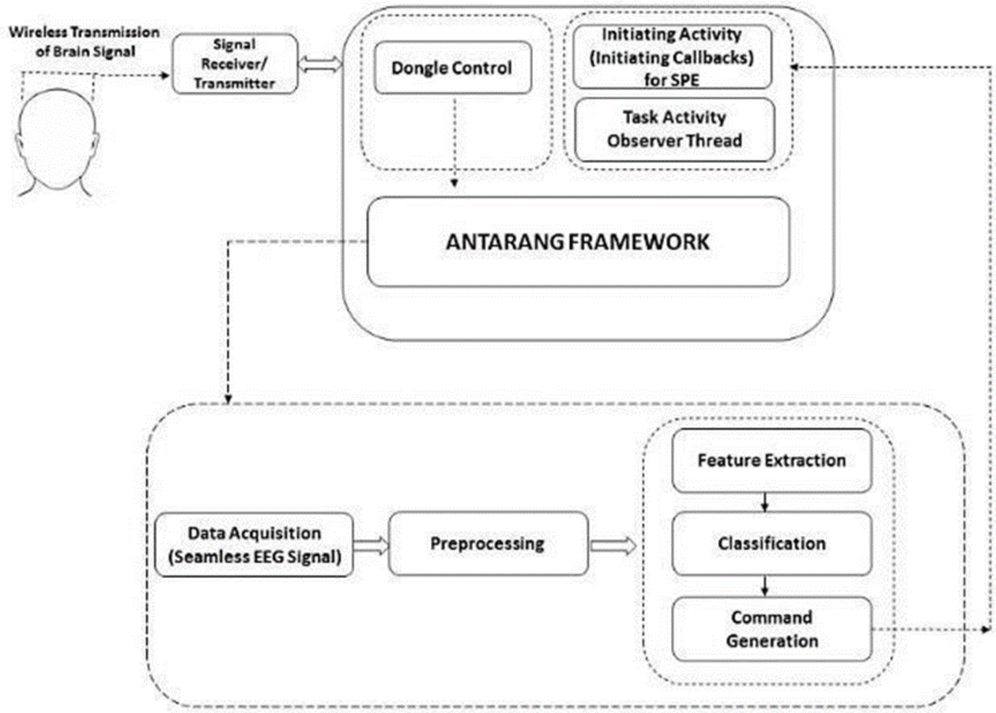


Figure 2 (a)

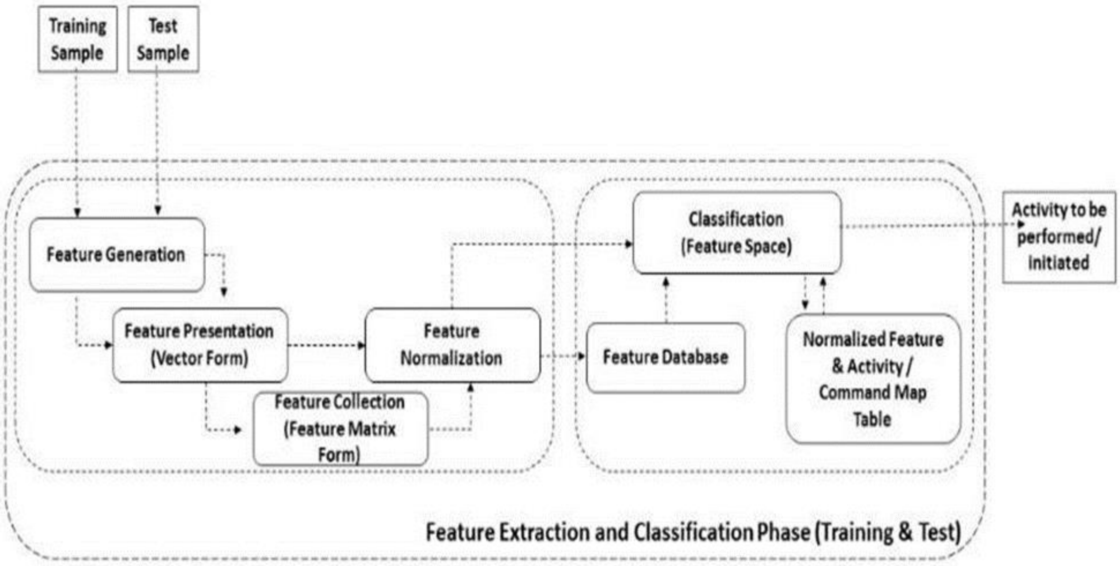
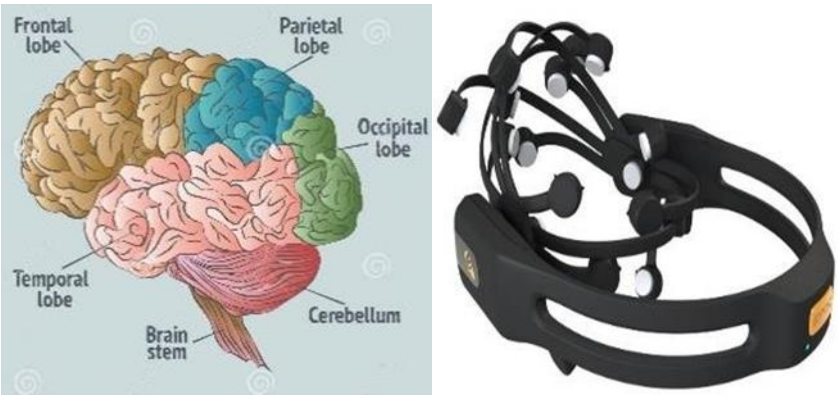


Figure 2 (b)

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

Dataset

In order to design robust EEG recognition system, the researchers have designed the database as per requirement that meets to their research problem in general. The EEG signals, for each mode, was captured by EmoEngine as shown in figure 1



(a) (b)

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

Data is read from the headset and sent to an output file for later analysis. The subject is asked to wear the Emotive head set which sends the data about the activity performed by the subject to the remote smart device through the available communication mechanism. The data is stored on the smart device and further be used for training and testing of the samples over Smart Devices. Traditionally, the data received from the subject is seen for five broad spectral sub-bands of the EEG signal which are generally of clinical interest they are 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 provide more accurate information about neuronal activities underlying the problem and, consequently, some changes in the EEG signal, which are not so obvious in the original full-spectrum signal, can be amplified when each sub band is considered independently. Each EEG segment was considered as a separate EEG signal resulting in a total of 125 EEG data segments.

Pre-processing

The captured test sample was pre-processed using, FAST Independent component analysis (ICA) was performed on EEG sample data to removing artifact and resulting ICs were passed for feature extraction.

Feature Extraction

The objective of this phase is to generate unique set of features such that the overall performance of classification is improved. In this research work stack of feature extraction methods were used which contains methods like Short Time Fourier Transform (STFT), Discrete Cosine Transform (DCT) and discrete wavelet transform (DWT) were utilized towards computation of features.

Feature Normalization

The computed features are normalized. This is required to reduce the size of feature space and speedup the classification of the system. The Linear Discriminant analysis were utilized towards reducing the feature space. This is feature normalization is performed with all training vectors as well the test sample is also normalized before classification.

Classification

The classification phase has immense potential in the design of any automated system. The proposed system is developed with the stack of classifiers such as Support vector machine. The result of classifier will be handed over to the native command translation mechanism which initiate the activity in the smart processing elements (Smart Devices).

IV. Experimental Results

The subject is required to gear with Emotive EEG set at the time of data acquisition as well as during testing samples. The electrode or subset of electrodes in an EEG device may move during data acquisition this may leads into bad contact with the scalp and therefore a poor-quality signal may be received. More rarely, electrodes may also have mechanical faults, for example frayed wiring, which can partially or completely degrade the signal received. Such electrodes can produce artifacts into the signals. So in a pre-processing step, FAST Independent component analysis (ICA) was performed on EEG sample data to removing artifact and resulting ICs were pass for feature extraction. Fundamentally ICA in biomedicine involves the extraction and separation of statistically independent sources underlying multiple measurements of biomedical signals.

Feature Extraction using DCT

The Discrete Cosine Transform [16] is a transformation method for converting a time series signal into basic frequency components. Low frequency components are concentrated in first coefficients and high frequency in last ones. The one- dimensional DCT for a list of N real numbers is expressed by eq (1) as,

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

Where u=0, 1, 2, 3…N-1;

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

a(j) = 1, j≠0;

An acquired input EEG sample from training set is a set of 'N' data values and the output is a set of N-DCT transform coefficients Y(u). The first coefficient Y(0) is called the DC coefficient and holds average signal value. The rest coefficients are referred to as the AC coefficients [16]. DCT exhibits good energy compaction for highly correlated signals. If the input data consists of correlated quantities, then most of the N transform coefficients produced by the DCT are zeros or small numbers, and only a few are large. Compressing data with the DCT is therefore accomplished by quantizing the coefficients. The small ones are quantized coarsely and the large ones can be quantized finely to the nearest integer. Applying this feature for EEG signals allow compressing useful data to the first few coefficients. Therefore, only these coefficients can be used for classification using machine learning algorithms. This kind of data compression may dramatically reduce input vector size and decrease time required for training and classification. These features were calculated for all the samples of 'Digit set' are as shown in table 1.

Table 1 show the feature extracted using DCT

Zero (0)	One (1)	Two (2)	Three (3)	Four (4)	Five (5)	..	Nine (9)
10.62964	12.48839	10.48546	9.819233	11.02994	16.9704	..	27.57632
5.413632	7.304988	6.416848	5.132164	5.326457	8.545044	..	5.128143
1.423464	2.693033	3.74308	2.304048	0.652103	-1.00238	..	2.486984
0.543664	0.927368	3.214933	0.981311	-0.04452	-0.52716	..	-1.96868
-0.16563	-1.0361	1.963108	-0.1841	-0.70961	-0.04245	..	4.004859
-0.50003	-1.7836	1.128882	-0.54477	-1.36299	1.116709	..	-0.70907
0.288363	-1.68334	0.503528	-0.85261	-1.13287	0.399226	..	3.714574
1.684606	-0.99388	-0.03555	-0.89706	-1.03169	-0.58246	..	-8.12342
2.571268	1.571514	-0.46821	0.533503	-0.52996	1.070756	..	-2.49936
..	..	..	..	..	..	..	..
0.921427	2.309691	-0.5832	0.605643	1.048911	1.025788	..	4.177428

Feature Selection using LDA

After signal analysis as well as feature extraction using DCT, the feature vector, Y = [y1, y2, y3, ….., yn] is derived. Its dimension should be reduced since the dimension n is often too large and the design of classifiers for a large dimension suffers from various difficulties. Those are mostly numerical problems that involve operation with high-order matrices. At the same time, a classifier in n -dimensional space is very difficult to analyze and almost impossible to imagine. Thus, Linear Discernment Analysis (LDA) was applied on feature vector to deduce the feature and selecting most prominent features for classification. The aim of LDA is to use hyper planes to separate the data representing the different classes proposed by Duda, R. O.,et,at. 2012. The separating hyper plane is obtained by seeking the projection that maximize the distance between the two classes means and minimize the inter classes variance by [17-18]. To solve an N-class problem (N > 2) several hyper planes are used. This technique has a very low computational requirement which makes it suitable for BCI system. So, all the sample of 'Digit database' normalized using LDA and selected 100 features of each sample for classification.

V. Result

The recognition of EEG Signal sample was carried out by DCT and LDA. These features were calculated for all sample of training set and stored for recognition purpose. The entire pre-processed features data set of EEG Digits were divided into 70-30 ratio that is 70% (Training samples), 30% (Test samples) and evaluated using SVM [19-20] classifier. we trained the SVM classifier based on Digit database and then we tested our algorithm on digit test dataset. The training and test set accuracy was 98.05% and 97.83% respectively.

VI. Conclusion

The proposed research work presents the system for automatic classification of EEG signal of digits for smart devices. The proposed work evaluates the performance of SVM classifier evaluated over normalized features of Discrete Cosine Transform. The work also signifies method of feature minimization using linear discriminant analysis. The overall accuracy was observed to be 97.83% and the work will be also extended towards automatic classification of 'digit'. The proposed work also is extended towards design of EEG operated smart devices.

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