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Digit Recognition from EEG Signals on Smart Devices a Novel Approach

Subodh Kumar Jha[1], Chandrakant Patil[2], Sushil Pandharinath Bedre[3], Pratik Jaiswal[4], Pravin Yannawar[5], Mukta Dhopeshwarkar[6]
[1, 3, 5]*Vision and Intelligent system laboratory, Dr. Babasaheb Ambedkar Univarsity, Aurangabad, Maharashtra - 431004 India.*
[2, 4, 6]*Department of Computer Science & I.T, Dr. Babasaheb Ambedkar Univarsity, Aurangabad, Maharashtra - 431004 India.*

Abstract: The Advancement of communication system has given us the freedom to think beyond traditional communication system and stage is set for thought oriented communication system. There are thousands of thoughts generated and vanished in a timeframe but out of these some prominent thoughts persist and we proceed with the same in our day to day activities. The advancement in Electroencephalogram has provided a chance to see the activity in the human brain in non-invasive manner. The proposed research work presents the method for Digit recognition using the EEG signals acquired and processed on smart devices. The results show the implementation of Computation neural network for the recognition of digits from EEG signals. It was seen that, the 90.64% correct classification was achieved.
Keywords: EEG, FAST Independent Component Analysis, Computational Neural Network

I. INTRODUCTION

An electroencephalography (EEG) based Brain Computer Interface (BCI) enables people to communicate with the outside world by interpreting the EEG signals of their brains to interact with devices such as wheelchairs and intelligent robots described by Zhang et.al. 2018[1]. Recent advancement in Electroencephalography (EEG) allows user to measure recording of the electrical signals (*voltage potential developed across the human scalp due to iconic transfer between the neurons of brain cells during its activity*) by using arrays of sensor placed across the across the scalp of subject. These potentials are recorded from different regions of the scalp for which each region of scalp has got its own importance and it depicts the neuron activity activated on different locations of the brain. Although there is plentiful research have been made in past several years and dedicated towards exploiting EEG technology in the fields of neuro and cognitive science. The researchers have explored the possibility of controlling electronic devices based on thought signals based on EEG measurements and gives rise to the potential area of Brain Computer Interface.

The Brain Computer Interface is upcoming potential area of research. The researchers working in this domain are trying to make system more robust and scalable. The major challenges faced by the researchers are like *computational inaccuracies*, *delays*, *false positive detections*, *inter people variances*, *high costs*, and *constraints on invasive technologies* that needs further research in this area. The primary research that utilizes EEG technology is based on the fact that this rhythmic activity is dependent upon mental state and can be influenced by level of alertness or various mental diseases. One of the most common cause of *artifacts* is *eye movement and blinking*, however other causes can include the use of *scalp*, *neck*, or other muscles or even poor contact between the scalp and the electrodes by Millett, D. 2001[2], Rampil, I. J.,1998[3] and Fetz, E. E, 1969[4]. Kennedy, P et.al 1997[5] has describe in his work in Electroencephalography (EEG) is the process of picking up the electrical activity from the cortex. Hans Berger et.al, suggested that periodic fluctuations of the EEG might be related in humans to cognitive processes. Carey, B. 2008 used the electrical activity recorded of the scalp with surface electrodes constitute a non-invasive approach to gathering EEG data, while semi-invasive or invasive approaches implant electrodes under the skull or on the brain, respectively [6].

Hochberg, L. R et.al., 2006 worked on the recent technological advances were helpful for the researchers to design of some of the state of art prototype system based on thoughts [7]. The group at Carnegie Mellon University and the University of Pittsburgh allowed a monkey to feed itself via a prosthetic arm using only its thoughts. The work described by Gotman, J. 1982 was extremely promising for the disabled, and indeed by 2006 a system was developed for a *tetraplegia* that enabled subject to use prosthetic devices such as a mouse cursor, and a television via a 96-micro-electrode array implanted into primary motor cortex of subject [8].

Similarly, many automated EEG signal classification and seizure detection systems were also in-place and designed by using different approaches.

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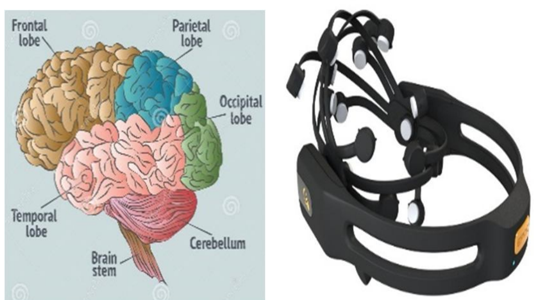
In-line with reported studies, Gotman et.al 1982 presented a computerized system for detecting a variety of seizures, while Qu and Gotman 1997[9], proposed the use of the nearest-neighbor classifier on EEG features extracted in both time and frequency domains to detect the onset of epileptic seizures. Gigola et al. 2004 applied a method based on the evolution of accumulated energy using wavelet analysis for the prediction of epileptic seizure onset from intracranial epileptic EEG recordings [10], while Adeli et al. 2007[11] and Ubeyli et al. 2006[12] & 2010 discussed the potential of nonlinear time series analysis in seizure detection[13].

Artificial neural network-based detection systems for diagnosis of epilepsy have been proposed by several researchers Tzallas, A. T., 2007[14] and Ghosh-Dastidar, S., 2008[15]. The method put forward by Weng and Khorasani 1996[16] uses the features proposed by Gotman and Wang 1991[17], namely, average EEG amplitude, average EEG duration, variation coefficient, dominant frequency and average power spectrum, as inputs to an adaptive structured neural network[18]. The method proposed by Pradhan et al. 1996 exploits raw EEG signal input to a learning vector quantization network. Nigam and Graupe 2004 proposed a new neural network model called LAMSTAR (Large Memory Storage and Retrieval) network and two time-domain attributes of EEG; namely, r*elative spike amplitude* and *spike rhythmicity* have been used as inputs for the purpose of detecting seizures [19].

In-line with the method presented by the researchers in the literature is particularly towards study of EEG Signals in the context to neuroscience and cognitive science. This paper presents an entirely new method of processing EEG signals on to the Smart Devices such as smart phones, tablets, notebook based on the preprocessing, features extraction methods and classifiers. The content of this paper is organized in following section. *Section I* has provided the background, *Section II* addresses database specification, *Section III* presents detailed methodology adopted and performance analysis of the method, *Section IV* presents conclusion of the work followed acknowledgement and references.

II. DATABASE

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.

The brain is formed using five lobes, these lobes perform all the critical neurological activities such as *frontal lobe* controls the activity of Speech, Thought, Emotions, Problem solving and skilled movements, *Parietal lobe* identifies and interprets sensations such as touch, pain etc. *Occipital lobe* collects and interprets visual images that is sight, *Temporal lobe* controls the activities related to hearing and storing memory and *Cerebellum* controls the coordinate's familiar movements. Similarly, the relationship between brain lobes that the excreted (energy) frequency of signal are as below

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

Table 1. Signal Type, Frequency and its origin

The data set designed in this research work is basically developed on two modalities that is KEYWORD and DIGITS. The dataset of DIGITS have been utilized for all experiments. This set contains digits from (0-9) and EEG Signal recordings of 10 subjects (i.e. 7 Male and 3 Female) in the age group of (20-25) were taken. The cumulative size of the database is 10x10x10 = 1000 samples. All participating subjects in the process of data collection/acquisition were normal and away from any physical and mental disorder. The data acquisition set up was developed at Vision and Intelligent System Laboratory of Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad. All subjects were made to sit comfortably on an arm chair facing the screen in electromagnetically shielded room. The subjects had given their written consent for recording EEG signals before participating. All subject has good knowledge of digits. All subjects were instructed that this experiment has been designed to be used for Brain Computer Interface applications. A simple display system in power point is prepared for the data collection under proposed research work. This system generates digit and keyword signal with interval of 2 sec. After every 2 sec a next number is displayed on the screen. Demonstration of display system was shown to each subject before experiment start so that he was more familiar to the task and we will get proper signals. This process was repeated for five times. So the total volume of digit dataset is 1000 samples and keyword is 1000 samples. After extracting the EEG Signal from all subject it will be processed as per methodology

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, preprocessing, feature extraction, normalization and classification model from raw EEG signal. In this section, we provides an overview of proposed approach and ANTARANG framework for interpretation of EEG data.

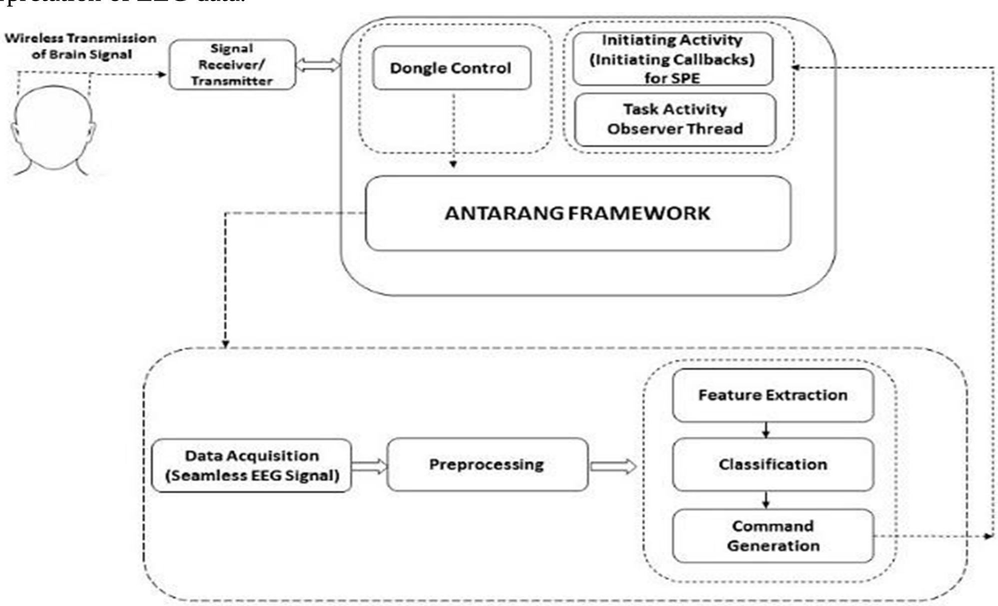


Figure 2 (a)

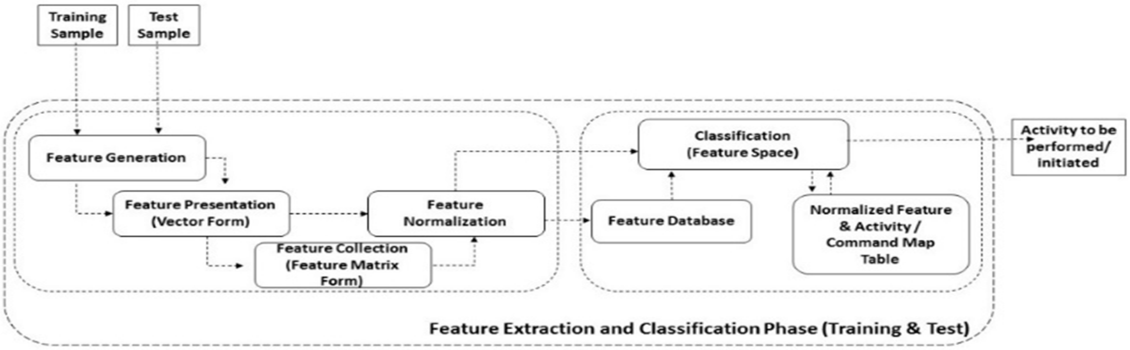


Figure 2 (b)

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

A. *Overview*

The above Figure 2 (a) and 2(b) illustrate the organization of various steps involved in the recognition of digits. The functionalities of the systems are as discussed below,

1) *Data Acquisition*: the method of data acquisition is as discussed in section II is followed. The subject is required to place EMOTIVE EPOC head gear in order to acquire EEG signals corresponding to the activity. The data is acquired by EMOTIVE head set is transferred to the wireless dongle connected to the device seamlessly via Bluetooth mechanism. The dongle control mechanism connected to the smart device acts as receiver. This will store the test sample primarily in the storage of Smart device and handed over to ANTARANG framework.
2) *Preprocessing*: the captured test sample was preprocessed using, FAST *Independent component analysis* (ICA) was performed on EEG sample data to removing artifact and resulting ICs were passed for feature extraction.
3) *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.
4) *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.
5) *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, k-Nearest Neighbor, Random forest, Naïve Bias classifier* [20], *Multi-Layer perceptron, and Convolution neural network*. 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).
6) *Command Map Table and Task observer thread:* The command map table contains information about the mapped callback corresponding the thought. The task observer thread observers the activity and invoke/dispatch the task for execution on the smart devices.
7) *Tools and Software:* As part of this work, the preprocessing and freature extraction was implemented in the SciPy and Numpy library of Python language. Convolutional neural network models were designed using the Keras library and run using Tensorflow in an attempt to classify the time-frequency representations. The matplotlib library was used to create plots the figures and data visualization.

B. *Working*

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 preprocessing 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.

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1) *Feature Extraction using DCT:* The Discrete Cosine Transform 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,

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

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. 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 feature were calculated for all the samples of 'Number set' and 'Keyword set'. The 'DCT Feature Matrix' for the samples of 'Number set', are as shown in table 2.

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

2) *Feature Selection Using LDA:* After signal analysis as well as feature extraction using DCT, the feature vector, $Y = [y_1, y_2, y_3, \ldots, y_n]$ 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[21]. 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 Fukunaga, K. 2013[22]. 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' and 'Keyword dataset' normalized using LDA and selected 100 features of each sample for classification.

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IV. RESULTS AND DISCUSSION

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 preprocessed features data set of EEG Digits were divided into 70-30 ratio that is 70% (Training samples), 30% (Test samples) and evaluated using Convolution Neural Network (CNN). This artificial neural network is improved in both parameters that is shift and translational invariance describe in Fukushima, K. 1980[23]. CNN is a subset of deep learning which has attracted a lot of attention in recent year and used in image recognition such as analysis of x-ray medical images by Kallenberg, M et. al., 2016[24], magnetic resonance images by Pereira, S et. al. 2016[25], histopathological images by Hatipoglu, N. et. Al, 2017[26] fundus images by Tan, J. H. et. al., 2017[27], and computed tomography images describe by Setio, A. et. al., 2016[28]. But, very little research has been done on the use of CNN using physiological signals. The CNN architecture consists of three different types of layer i.e. convolutional layer, pooling layer, and a fully connected layer. CNNs are very effective models for Image classification tasks [29].

For the proposed work CNN model was designed, where EEG digit dataset data first Convolution layer takes this 1-dimensional array as input and the Convolution operation uses 10 initial convolution filters and a convolutional kernel of size 11. Where, the first convolution layer uses ‘relu’ as the Activation (‘Relu’ or Rectilinear units as Activation for Arousal model). In these proposed experiments, the choice of activation functions for this first layer are of cardinal importance, as some functions like *sigmoid or softmax* might not be able to activate neurons of later layers consistently this improper activation function contributed towards making model defective. The next layer is another Convolutional Neural Layer which again with 100 filters and 3*3 size kernel. This layer uses ‘*relu*’ as the Activation function for both Valence and Arousal classification. Thus, dropout on the outputs of *MaxPooling* layer, with a dropout probability of 0. 5, to form a flat 1 dimensional layer. The final dense layer uses ‘*softmax*’ as its activation function. The model uses the Categorical Cross Entropy as the loss function and ‘*rmsprop*’ as the optimizer used. The experiment were carried out upto 500 epochs and train the model using batches of 32 experiments each. Following is confusion matrix of CNN classification of EEG digit signal.

Digit	Total Test Sample	Training Samples										Correct Classified	Miss-classified	Accuracy
		0	1	2	3	4	5	6	7	8	9			
0	15	13	0	1	0	1	0	0	0	0	0	13	02	86.66
1	15	0	13	0	1	1	0	0	0	0	0	13	02	86.66
2	11	0	0	9	0	1	0	1	0	0	0	9	02	81.81
3	14	0	0	0	14	0	0	0	0	0	0	14	00	100.00
4	15	0	0	0	0	13	0	2	0	0	0	13	02	86.66
5	16	0	0	1	0	0	13	2	0	0	0	13	02	81.25
6	22	1	0	0	0	0	1	20	0	0	0	20	02	90.90
7	12	0	0	0	0	0	0	0	12	0	0	12	00	100.00
8	7	0	0	0	0	0	0	0	1	6	0	6	01	85.71
9	13	0	0	0	0	0	0	0	0	0	13	13	00	100.00
	139	Classification Result										126	13	90.64%

Table 3: Confusion Matrix for Digit Classification using CNN

The confusion matrix as shown in Table 3, the total 139 test samples of tested on the training data set. It was see that out of 15 samples of ‘zero’, 13 were classified correctly and 2 samples were misclassified so that the found in class of two and four. Similarly, all test samples of ‘three’, ‘seven’ and ‘nine’ were completely classified in ‘three’, ‘seven’ and ‘nine’ classes correctly, there were no misclassification seen in this.

Out of these all 139 test samples, the 16 test samples of number 'five', 13 were classified correctly and 03 were misclassified into 'two' and 'six'. The average classification resulting into 90.64% classification accuracy that is out of 139 samples, 126 samples were classified into correct classes and only 13 samples were misclassified.

V. 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 CNN 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 90.64% and the work will be also extended towards automatic classification of 'keywords'. The proposed work also is extended towards design of EEG operated smart devices.

VI. ACKNOWLEDGMENT

This piece of work is registered under Indian **Patent application number** 201621005217 **Titled** SYSTEM FOR THOUGHT BASED COMMUNICATION **Year -** 2016.

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