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NUMBER RECOGNITION SYSTEM USING ELECTROENCEPHALOGRAM (EEG) SIGNALS

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Abstract- This paper focuses on number recognition from feature extracted using Electroencephalogram (EEG) readings. EEG signals were recorded at Department of Computer Science and IT, Dr. B. A. M. University, India, from 6 volunteer subjects. A random number generator Graphics User Interface was developed in VB7. It is used to display numbers from 0 to 9 which worked as Visually Evoked Potential (VEP) for the experiment. The database of 6 male right-handed subjects in the age group of (20-25) was created and used as training data set. By exposing the same set of subjects to the GUI again, new EEG recordings were collected. This new set of EEG readings was considered as testing data set. The testing data was searched and matched with trained data set for recognizing pattern of each number. The experiments were conducted by concentrating on Beta signal and Linear discriminate analysis (LDA) was implemented to classify the data. The recognition rate observed was different for different numbers. Overall recognition rate observed was 68.33%. It is also seen that there exist a unique pattern for each number .
Key words- Beta signals, EEG, GUI random number generator, VEP, LDA, recognition rate

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Introduction

Functional brain imaging techniques that are designed to measure an aspect of brain function can be employed to obtain tangible information related to brain activity. EEG is one such technique which measures the electric fields that are produced by the activity in the brain [1, 2]. EEG signals arise due to electrical potential produced by the brain. Mostly EEG analysis has been used clinically for pathologies and epilepsies since Hans Berger's recordings of electrical potentials from the Human scalp. More recently new interaction techniques which directly connect a human brain and a machine are in use. EEG spectrum contain characteristic waveforms which fall in 4 frequency bands viz alpha(8-13 Hz), beta(13-30 Hz), theta (4-8 Hz), delta(< than 4 Hz). Alpha waves are found in normal awake people, not engaged in intense mental activity, which disappear when a person is asleep. Beta waves with higher frequency are seen during intense mental activity and stress. Delta waves occur during deep sleep, during infancy and in serious organic brain diseases. Theta waves appear during emotional stress in adults in sleep, particularly during disappointment and frustration [3].

Literature review of similar work which focuses more on identification from EEG of healthy subjects rather than classification of pathological cases for diagnosis was made. It was found that individual-specific information from EEG signals started from 1930's, and results became available from 1960's. Different cases of research such as one based on members of same family, other case on common characteristics between twins was considered, in yet another case different EEGs of same person were compared, the objective was extraction of common features [4]. EEG is collected at the millisecond level, in contrast to the longer time intervals required for traditional measures such as mouse clicks or user responses. This permits effective monitoring of workload fluctuations in very rapid decision-making processes that are unobservable using traditional methods [5]. As security issue is always challenging to the real world applications many biometric approaches, such as fingerprint, iris and retina, have been proposed to improve recognizing accuracy or practical facility in individual identification in security. However, there is little research on

individual identification using EEG methodology mainly because of the complexity of EEG signal collection and analysis in practice [6]. In future we can work to extract individual specific information from a person's EEG and use this information to develop identification methods like EEG biometry.
The remaining sections are organized as follows. Section 2 provides experimental data acquisition setup used in this research work. Section 3 details the experimental analysis of EEG data, followed by results and conclusion in section 4.

Experimental Data Acquisition
EEG recordings of 6 male right-handed subjects in the age group of (20-25) were taken. The subjects were normal without any mental disorder. They did not have any problem in communicating and had normal vision. 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.
For the EEG data, experiments were conducted in which subjects were shown visual stimuli consisting of the Random Number Generator. Graphics User Interface was developed in VB7 .The GUI was shown for one minute and then there was a gap for certain time interval, wherein subjects were asked to take rest with eyes closed. A single experimental session typically comprised of 4 trials of complete display of GUI from 0 to 9. The record of the displayed number was maintained for reference during analysis and pattern matching. Figure 1 shows the snap shot of the GUI.

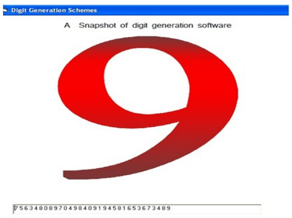

Fig. 1- Snap shot of the GUI developed in vb6. The Nineteen Electrodes

[FP1,FP2,F7,F3,Fz,F4,F8,T3,C3,Cz,C4,T4,T5,P3,Pz,P4,T6,O1,O2] were spread over the surface of the scalp and recordings taken as shown in figure 2. As the architecture of the brain varies with different locations, EEGs can vary depending on the location of recording electrodes. The 10-20 system for electrode placement was used. Electrodes consist of flat discs connected to an isolated wire. They have identifying names; those on the left side have odd numbers, while those on the right have even numbers. Those near the midline have smaller number and the more lateral ones have larger numbers. The names include the first letter of the place where the electrode is placed. A body earth and reference electrode was placed on forehead and behind the two ear lobes.

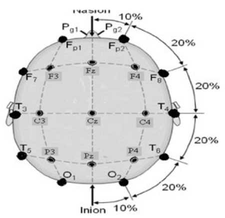

Fig. 2- The international 10-20 system

The EEG signals were captured using RMS (Recorders and Medicare systems, Chandigarh India) EEG-32 Super Spec machine for 30 minutes with sampling rate of 250 samples per second. The other parameters were set as follows
Low filter 1 Hz,
High filter 70 Hz,
Number of channels: 19,
Sweep speed 30 mm/s and
Montage: BP PARA (R).

Experimental Analysis
The EEG recordings were captured according to the time of numbers generated on the GUI. The readings were statistically analyzed. There are four frequency bands associated with the EEG signals. All fours bands with their functionalities are listed in table 1[7].

Table 1- Four bands with their functionality

Type	Frequency (Hz)	Normally
Delta	up to 4	Has been found dominant during some continuous attention tasks (Kirmizi-Alsan et al. 2006)
Theta	4 – <8	Appears in drowsiness or arousal condition in children and adults
Alpha	8 – 13	Found to be prominent in relaxed/reflecting condition.
Beta	>13 – 30	Has been found in alert/working, active, busy or anxious thinking, or active concentration.

Linear Discriminant Analysis
By observing the Table 2, we concentrated on the beta signals of all 19 electrodes for recognizing the number. The Linear discriminant analysis (LDA) is used technique for data classification and dimensionality reduction. It easily handles the case where the Within-class frequencies are unequal and their performance has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. The use of Linear Discriminant Analysis for data classification is applied for classification of all ten numbers in hopes of providing better classification. Figure 3 shows the classification between all ten numbers. The readings were statistically analyzed using mean and standard deviation. Standard deviation measures the spread of data in the given sets whereas Mean provides us centre of the distribution.

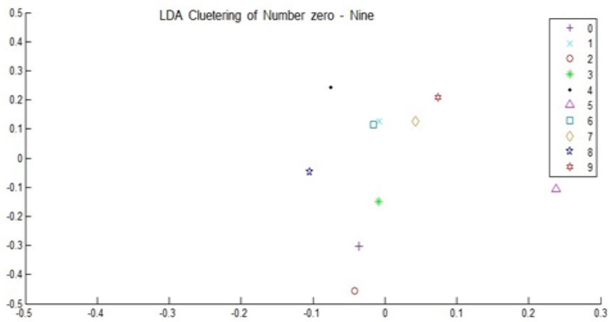

Fig. 3- Data classification of numbers from 0 to 9 using LDA

With the help of standard deviation and distance matrix, we tried to observe the distance between the values of electrodes from trained data and testing data. The result of standard deviation between the values of electrodes for different numbers from trained data and testing data is presented in table 2. The presented results are of one subject only. The average distances of all electrodes provided the difference percentage between trained and testing data set. The recognition percentage is also presented is also presented in table 2.

Results and Conclusion

While electrical brainwave activity, as recorded by EEG is not typically expected to be the same for different subjects even under the same conditions, the numbers can be recognized with EEG data with high degree of accuracy. EEG number recognition system has shown promising result, which seems to suggest that people have unique brain patterns in the way they think. The results also show a way of thinking to build a number recognition system which can further be studied from the biometric point of view. It can be an aid for paralyzed people who are suffering from severe neuromuscular disorders for whom EEG can provide a means of communication, control or rehabilitation tool to help compensate for lost abilities, for remembering their passwords consisting of numbers like codes of ATM cards etc. In this paper the activity of .In this paper the activity of number recognition system is analyzed. It is observed that there exists a special and unique pattern in each number. The recognition rates of all numbers are found to be promising and in the range of 50 to 79 except number two which is 41.6 as shown in table 2. The analysis is performed on the data of six volunteer but the result of one subject is presented in this paper. It is observed that overall recognition rate come to be 68. 33%.

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Table 2- Distance matrix For trained and tested data for 19 electrodes

Numbers/Electrode	0	1	2	3	4	5	6	7	8	9
FP1	0.45	0.34	0.22	0.17	0.15	0.19	0.2	0.06	0.34	0.6
FP2	1.02	0.1	0.07	0.13	0.04	0.18	0.15	0.24	0.28	0.1
F7	0.13	0.39	0.6	0.13	0.56	0.28	0.27	0.09	0.25	0.3
F3	0.53	0.12	0.14	0.06	0.28	0.02	0.9	0.15	0.06	0.1
FZ	0.09	0.42	0.4	0.4	0.09	0.3	0.28	0.39	0.01	0
F4	0.5	0.02	0.31	0.04	0.06	0.05	0.12	0.35	0.13	0.4
F8	0.13	0.22	0.43	0.06	0.05	0.26	0.32	0.13	0.46	0.5
T3	0.2	0.19	0.19	0.33	0.22	0.57	0.22	0.33	0.09	0
C3	0.06	0.28	0.11	0.06	0.26	0.08	0.49	0.12	0.37	0.5
CZ	0.31	0.26	2.92	0.3	0.45	0.23	0.06	0.05	0.36	0.2
C4	0.35	0.19	0.12	0.19	0.25	0.08	0.32	0.58	0.17	1.2
T4	0.53	0.32	0.04	0.04	0.13	0.26	0.06	0.23	0.38	0.1
T5	0.33	0.61	0.39	0.11	0.18	0.2	0.09	0.06	0.45	0.4
P3	0.76	0.31	0.48	0.17	0.99	0.72	0.01	0.41	0.43	0.1
PZ	0.58	0.68	1.01	0.34	0.11	0.06	0.82	0.1	0.02	0.2
P4	0.13	2.2	1.07	0.05	0.1	0.34	0.36	0.18	0.87	0.1
T6	0.42	2.7	0.29	0.3	0.22	0.12	0.08	0.16	0.39	0.1
O1	0.1	0.6	0.3	0.45	0.4	0.08	0.31	0.11	0.82	0.4
O2	0.21	1.14	0.1	0.14	0.29	0.19	0.05	0.28	0.24	0
Average	6.83	11.1	9.19	3.47	4.83	4.21	5.11	4.02	6.12	5.3
% Difference	35.9	58.4	48.36	18.3	25.4	22.2	26.9	21.2	32.2	28
% Recognized	64.1	41.6	51.64	81.7	74.6	77.9	73.1	78.9	67.8	72