MIND CONTROLLED ROBOT USING LDA CLASSIFICATION TECHNIQUE

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Abstract: An ordinary robot those can be seen in market are helpful but still there is a great space available for further research. This paper is proposing a new type of robot which would be controlled by human. The robot being proposed would be completely controlled by human mind. Paper mainly proposes a methodology of controlling of robot's motion by the interface of brain and computer system that would be embedded in robot. Intel Computer stick is proposed to be used to achieve the embedded system. Signal classification scheme is recommended, and those signals are captured using EPOC nerve gear. The classifier being used for the purpose is Linear Discriminate Analysis (LDA). The results being achieved by the methodology proved to be efficient enough to be deployed in daily lives of human.

Keywords: *Mind-Controlled; EPOC; Brain Computer Interface (BCI), Filters, Linear Discriminate Analysis (LDA); Mean; Co-Variance.*

1. Introduction

A nterface between brain and computer is a system where electrodes are attached to the scalp of user and that is how a direct way is created between brain and computer. A human brain creates different type of signals while thinking process. So these signals represent the set of instructions a person wants system to implement. Those signals or set of instructions are noted from the scalp through Electroencephalography (EEG).

A well-defined induction is proposed by many researchers. And state of the art induction technique of electrodes over the scalp is presented in figure 1 [3]. Electrodes being recommended by researchers are of Silver Chloride [4].

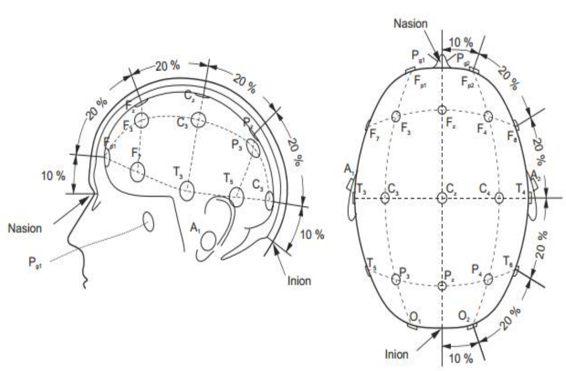

Figure 1 Induction of Electrodes over Scalp

For recording some accurate signal researchers have proposed an impedance of 1 to 10 [5], for which we can also be needed to use some type of gel so that we can keep impedance under our range.

Signals being acquired from the scalp are of different ranges. So, in order to classify the signal frequency should must be in users control. Five different frequency ranges are observed which are Gamma, Beta, Alpha, Theta and Gamma.

Table 1 discusses about different frequency bands those are acquired by the scalp for signals of instruction to the robot. These different bands hold different information regarding the motion being conveyed by the user.

Table 1 Different frequency Bands

Frequency Band	Band Range	Information	Reference
Delta	Below 4Hz	Very low frequency therefore confusion occurs as muscles also produce low frequency in normal.	[6]
Theta	Between 4Hz to 7Hz	Are being observed in meditative concentration.	[7-9]
Alpha	Between 8Hz to 12Hz	Band is more related to the visual information or instruction.	[10-13]
Beta	Between 12Hz to 30Hz	Only produced while muscles produce greater motion.	[14]
Gamma	Between 30to 100Hz	Strongest among all, there for very less chance of confusion.	[15]

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Emotiv EPOC is utilized for acquiring signals. Figure2 illustrates the model of EPOC and shows its positions of the EEG wet electrodes. The specifications include wireless transmission of signals via Bluetooth 2.0. The device is used as a head set and electrodes can easily be located on the scalp.

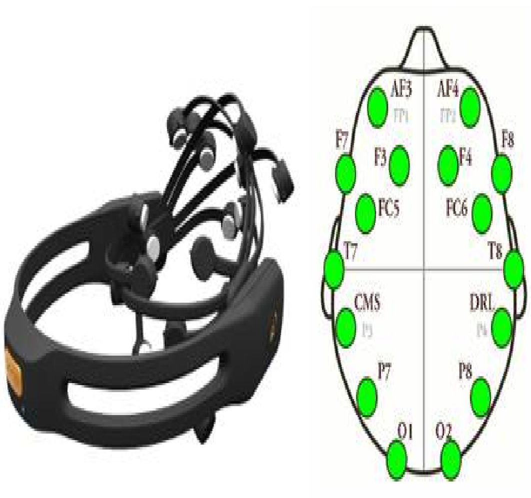

Figure 2 Headset as Hard (Left), Placement of wet electrodes (Right)

2. Methodology

The proposed methodology includes three steps which are as follows,

- Signal Acquisition
- Feature Extraction
- Classification

Further Figure 3 summarizes the overall methodology steps.

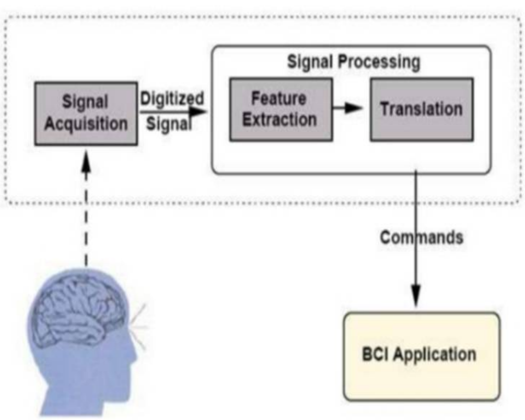

Figure 3. Overall Methodology steps

2.1 Signal Acquisition

Signals are acquired by the scalp through the help of electrodes placement over scalp. Emotive EPOC is a device that is being utilized for acquiring of signals. The placement of respective electrodes is discussed before. A timing scheme is followed for signal acquisition which is showed in figure 4.

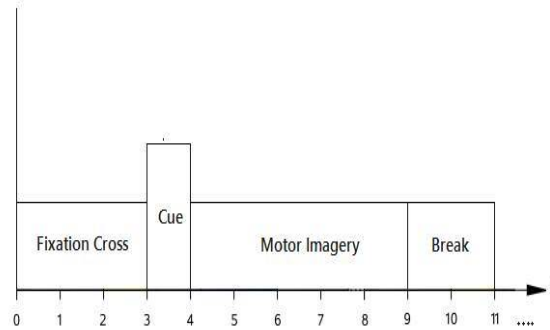

Figure 4. Timing scheme followed for acquisition of BCI data

So, the output of the first step would be signal where signal is generated using whole system.

2.2 Features Extraction

After the process of signal acquisition, the signals are recorded in the dataset. Feature Extraction is one of the most important part of the proposed methodology. As these features would be used for making feature extraction and after that those feature vectors would be used for the purpose of classification. Now the recorded dataset would be used for feature extraction. Four different filters have been utilized for this purpose. The filters proposed are Chebyshev filter, Butterworth filter, Common Spatial filter and Logarithmic Band Power. The Discrete Continuous Fourier transform of the signals in dataset is taken and the output coefficients are fed into the named filters. The coefficients of the signals would be frequency domain.

The bellow equation illustrates the formulation used for deploying Chebyshev filer. Chebyshev filter gives the features lying near its cut-off.

$$G_n(\omega) = |H_n(j\omega)| = \frac{1}{\sqrt{1+\varepsilon^2 T_n^2\left(\frac{\omega}{\omega_0}\right)}}$$

Where,

$$\varepsilon = \sqrt{10^{0.1\delta} - 1}.$$

w= The frequency being input

wo= The cut-off frequency

Below figure illustrates the recorded response of implemented Chebyshev filter for feature extraction. It depicts how different orders can be used for the extraction of features. The Chebyshev filter used in the proposed methodology is of order 2 as it holds lets lobs in comparison to others.

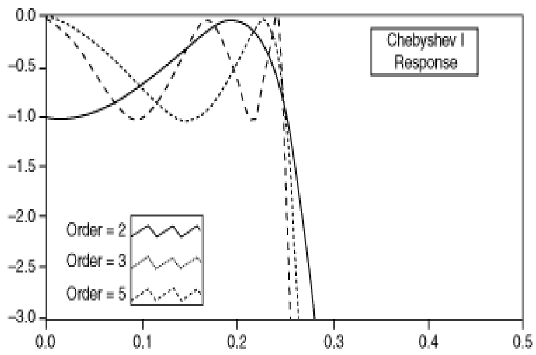

Figure 5. Chebyshev Response

Second filter been used is Butterworth filter. The equation being used for this purpose is shown below. Where w is the frequency coefficient received after discrete continuous transform.

$$G(\omega) = \sqrt{\frac{1}{1 + \omega^{2n}}}$$

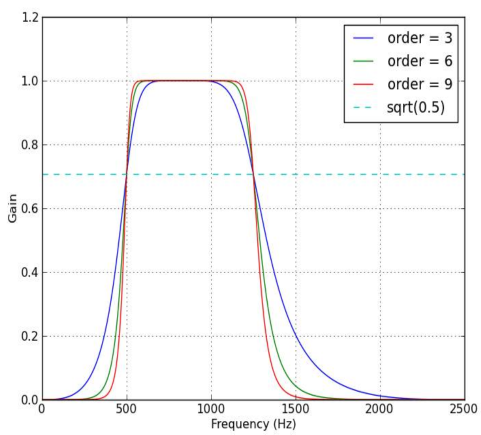

Figure 6 Butterworth Filter

Above is the response of Butterworth filter. As can be seen that Butterworth filter gives flat amplitude response. This filter can be used for comparison of amplitude of different signals. So amplitude detection can easily be done by it.

Surface Laplacian is used to increase the variance between different classes of signals. The major feature by Surface Laplacian is variance which contributes towards classification.

Logarithmic Band Power is used to extract power feature from BCI signals. The power of the signals would vary as per instruction. So in proposed methodology this is the strongest feature being used for the purpose of classification. Below is the equation being used for this purpose.

$$u(x)=\log(1+x^2)$$

Further logarithmic band power is followed by feature aggregator which concatenates the features into single vector. And the Feature Vector is obtained from the described process.

2.3 Classification

After feature extraction classification between different signals needs to be performed so that different motions can be classified. In proposed methodology Linear Discriminate Analysis (LDA) is being used as a classifier.

LDA is one of the most Robust classier available, as it reduces the complexity and dimensionality. LDA is a binary classifier which is used for classification of two classes. The output of the LDA mainly classifies under mean and variance of different classes. And same stands in the proposed scheme, As variance is one of the strongest feature being extracted in our methodology. Here LDA would be classifying between right and left motion. Figure 7 discusses the flow under which mechanism LDA works, and classifies different classes.

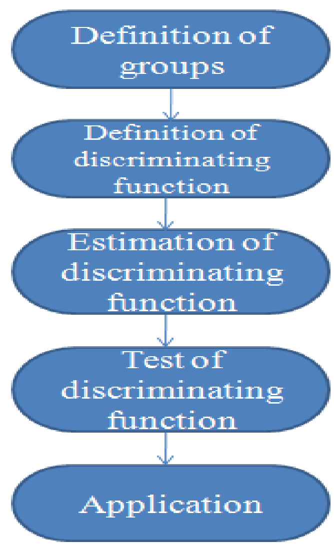

Figure 7 LDA Scheme

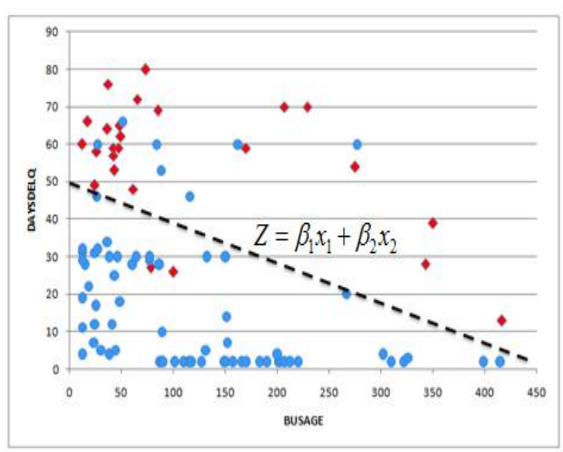

Figure 8. LDA scatter plot of Feature Separation

Further figure 8 shows how LDA classifier classifies the features. Two different type of features are plotted and how through linear regression the classifier has separated the feature clusters.

3. Result

Results are being carried out using LDA. The table 2 shows how well LDA has classified two different decisions. The main parameters used for the comparison are Mean of the feature vectors and covariance between feature vectors. Mean and variance were one of the strongest features which were extracted using different filters as discussed in the methodology. The difference between mean and covariance is high enough which clearly depicts that the classification is done well.

Table 2 Comparative results

Class (DEFAULT)	Count	Probability	Statistics	BUSAGE	DELQDAYS
N	n_1=75	$p(c_1)$=0.75	Means Vector (μ)	116.23	16.89
			Covariance Matrix (C)	$\begin{bmatrix} 9323 & -607 \\ -607 & 333 \end{bmatrix}$	
Y	n_2=25	$p(c_2)$=0.25	Means Vector (μ)	115.04	55.32
			Covariance Matrix (C)	$\begin{bmatrix} 14009 & -1053 \\ -1053 & 287 \end{bmatrix}$	

4. Conclusion

A Methodology for mind-controlled robot is being proposed in the paper. Which includes signal acquisition from scalp than feature extraction from those signals and lastly the classification part. The classification results clearly depict that the proposed methodology is highly efficient to be used for the betterment of human life. And the features those are proposed for the classification of signals for the purpose are mean and variance as proved by the results.

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