

Acquisition and Processing of EEG Signals for Automation

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Abstract

BCI is a system that can recognize a certain set of patterns in brain signals by following five steps: signal acquisition, preprocessing or signal enhancement, feature extraction, classification, and the control interface. The signal acquisition stage captures the brain signals. The preprocessing stage prepares the signals in a suitable form for further processing. It uses spatial filtering for noise reduction, removal of artifacts that distort our signal and amplifies it. The feature extraction stage identifies discriminative information in the brain signals that have been recorded. Signal acquired is then mapped onto a vector containing effective and discriminant features from the observed signals. The classification stage classifies the signals by taking the feature vectors into account. Hence, feature extraction is the most important step to achieve effective pattern recognition in order to identify user's intentions. Finally the control interface stage translates the classified signals into meaningful commands for any connected device, such as a wheelchair, prosthetic hand etc. BCI provides communication between human and brain signals. Hence its applications in almost every field is beyond our imaginations.

Keywords: Spatial Filtering, Neural Network, Pattern

I. INTRODUCTION

Electroencephalography (EEG) is one of the types of bio signal used to measure brain's electrical activity. It involves the placement of multiple electrodes either on the surface of the skull or underneath the skull. Our experiment is based on noninvasive method. Patient wears an electrode embedded cap (Emotiv EPOC headset) that is attached to the head by using a conductive gel to provide a smooth conductive path. Electroencephalography (EEG) is typically a noninvasive method to record electrical activity of the brain along the scalp. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. Signals acquired through this process are in few microvolts. They are amplified, filtered and fed into an onboard computer. Once features are extracted and classified, we aim to control a small car based on the observed EEG readings which are interpreted by headset worn by the user and depending on the type of brain activity detected i.e, whether to move a car forward, backward, left or right.

Objective

The main objective of the project is to design a functioning car that will respond to a user's brain activity and react accordingly. The initial purpose of this project is to practically solve a way to manipulate physical objects with your mind. The main goal will be to navigate the car using the headset.

II. BACKGROUND AND LITERATURE REVIEW

EEG generally is charted over the scalp. It ranges between 1-30 Hz and can be decomposed into five sub-bands. Delta waves are found in a frequency region of 0-4 Hz. These are the slowest recorded brain waves in human beings. They are associated with the deepest levels of relaxation and restorative, healing sleep. Theta waves are found in a frequency region of 4-8 Hz. They are involved in daydreaming and sleep. Theta waves are connected to us experiencing and feeling deep and raw emotions. Alpha waves are found in a frequency region of 8-13 Hz. Alpha wave bridges the gap between our conscious thinking and subconscious mind. It helps us calm down when necessary and promotes feelings of deep relaxation. Beta waves are found in a frequency region of 13-30 Hz. These waves are known as high frequency low amplitude brain waves that are commonly observed while we are awake. They are involved in conscious thought, logical thinking, and tend to have a stimulating affect.

Recordings of EEG are normally contaminated with artifacts. Artifacts are unwanted signals that infects brain activity. These are all physiological artifacts that are much difficult to handle than technical artifacts which includes noise created from power lines etc. Notch filter is used for removing these technical artifacts that occurs at 50-60 Hz. Electrodes should be properly grounded to avoid environmental artifacts.

Common methods for removing artifacts in EEG are linear filtering, linear combination and regression. Using the power of the human mind to control everyday objects had always been a fantasy for people. The possible applications and benefits of reading and interpreting brain-waves are endless. Examples of possible uses include medical devices for doctors and patients, new ways to control devices without a remote control, etc. Recently, however, several projects have arisen that have started to make this fictional desire into a reality. Projects such as the BrainDriver, the SWARM Extreme, RC Mind Control, and Brain-Controlled NXT Robot are beginning to use brain-waves as a means of allowing a user to control devices and applications. These projects are very similar to this project because they incorporate the use of an EEG headset and use data from it to control a device with brain waves or facial expressions.

III. Data Acquisition

Data was acquired by using EPOC Emotive headset. The Emotiv headset is the key to the entire project, being what obtains and transmits the neuro-signals. The headset comes with 14 independent sensors that consist of felt pads with gold connections to increase the sensitivity of the pickups. Its placement on the scalp is based on International 10-20 standard system. Once the headset is connected via the wireless USB receiver the headset setup panel is displayed. It has inbuilt notch filters at 50 and 60 Hz and a single ADC.

Experiment

This experiment was performed by a male of 22 years old. 3 mental imaginary tasks were performed by a single subject at the sampling rate of 256 SPS. Every task was performed 5 times and each recorded for 10 seconds. So we have a total $10\text{sec} * 256\text{Hz} = 2560$ samples. These tasks included:-

- Baseline task
- Smile task
- Blink task

Once all the data is recorded in test bench and saved in EEGLAB, it is ready for further processing.

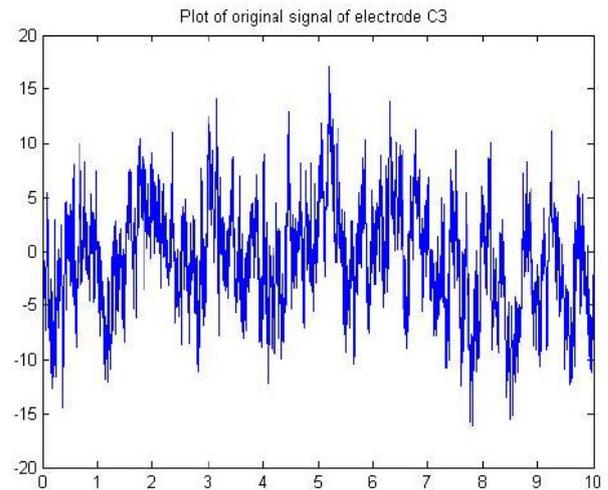


Fig. 1: Unfiltered Time Domain Signal

IV. Data Processing

a) Segmentation of signals

In order to make the response of BCI faster, brain wave measured during 10 secs is divided into 0.5 secs so we get a total of 20 segments each of 0.5 secs.

b) Fourier Transform

Brain wave is Fourier transformed in order to avoid effects of time delay. Its amplitude is used to express feature of brain wave. Segment of brain wave with 0.5 length includes 128 samples.

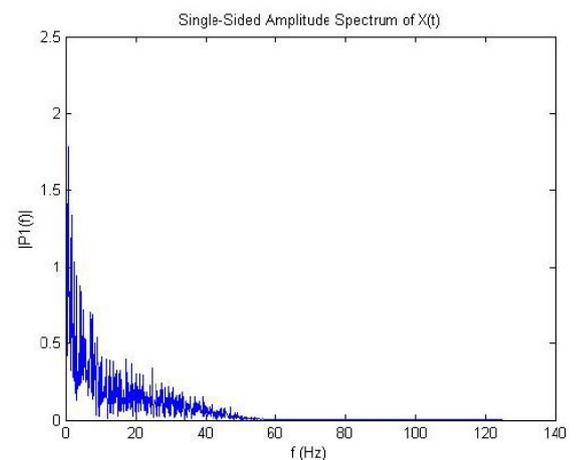


Fig. 2: Frequency Response

c) Averaging

In order to make classification compact and to remove noises, the FFT samples at every interval are averaged. Hence total number of samples are reduced to 20 for each electrode and trial. For 5 trials we get a total of 100 samples for each task and each electrode.

d) Nonlinear Normalization

Samples acquired from FFT is widely distributed. They can be large and small. However neural network treats large samples more importantly and small samples are usually neglected. Classification will not be entirely correct if large samples do not consist the desired information. It is for this reason that nonlinear normalization is employed where small samples are lengthened and large samples are compressed.

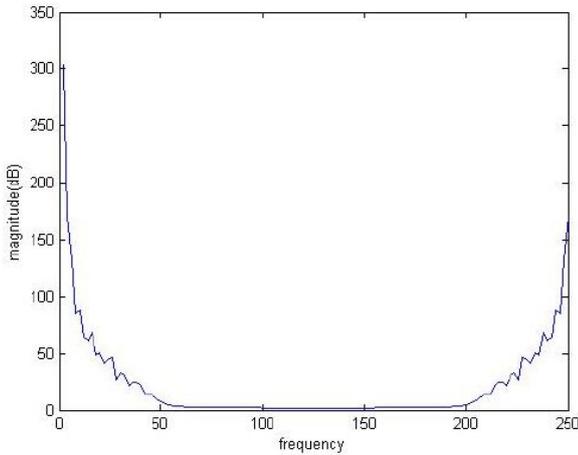


Fig. 3: Frequency Response after Averaging

$$f(x) = \frac{\log(x - \min + 1)}{\log(\max - \min + 1)} \quad (1)$$

V. CLASSIFICATION USING NEURAL NETWORK

Determination of hidden layer of Neural Network is not an easy task. After performing several trial and error methods, we came to a conclusion that a single hidden layer produces best result for our data. The number of input nodes is 20 samples * 14 channels = 280. 3 output neurons are used for 3 mental tasks. One output

neuron will respond to the applied input data. In the phase of testing, mental task corresponding to the maximum output is assigned. For example if (1, 0, 0) corresponds to (smile, baseline, blink) then clearly smile task is assigned.

VI. VALIDATION OF TEST RESULT

We performed 3 tasks with 5 trials and each for 10 secs. Out of 5 trials, 4 are used for training and 1 is used for testing. So there are 80 training samples and 20 testing samples. Task corresponding to the minimum value is considered incorrect and is ignored.

Table 1: Training of Classifier

MLPN	Training	Test
	240	60

	CORRECT	INCORECT	%
TRAINING	209	31	87.05
TEST	49	11	81.66

XI. CONCLUSION

This paper is based on offline analysis. Our aim is to perform online analysis as our next step, whose output will be used to control a small car. People worldwide are suffering from several functioning in their motor activities. This makes them dependent on others, Research groups and scientists all over the world have been working to develop electronic devices to reduce dependency and concern workload. These devices restore movement and provide communication and environment control. As mentioned earlier, BCI, so far is the most frequently used and feasible way of providing communication between brain and an external device, It detects different patterns on the persons ongoing activity as par their intentions to initiate control. Applications of BCI spread widely in the fields of military, science, medicine, gaming etc.

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