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EEG INTERFACE MODULE FOR COGNITIVE ASSESSMENT THROUGH NEUROPHYSIOLOGIC TESTS

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Abstract. The cognitive signal processing is one of the important interdisciplinary field came from areas of life sciences, psychology, psychiatry, engi-neering, mathematics, physics, statistics and many other fields of research. Neurophysiologic tests are utilized to assess and treat brain injury, dementia, neurological conditions, and useful to investigate psychological and psychiatric disorders. This paper presents an ongoing research work on development of EEG interface device based on the principles of cognitive assessments and instrumentation. The method proposed engineering and science of cogni-tive signal processing in case of brain computer in-terface based neurophysiologic tests. The future scope of this study is to build a low cost EEG device for various clinical and pre-clinical applications with specific emphasis to measure the effect of cognitive action on human brain.

Keywords: *Cognitive Assessment, EEG, Brain, Neurophysiologic Tests, EEG Device, Brain Computer Interface.*

1. INTRODUCTION

In different cognitive studies, brain waves have their own importance and use-fulness for the estimation of variations in cognitive states parameters in study of stress, work-load, emotion, neural activities, neuro-logical disorders etc (Hamid at all, 2010; Lisetti and Nasoz, 2004; Lisetti and Nasoz, 2004; Knoll at all, 2011). In view of psychophysiology, the most suggested way of experimentation is based on cognitive test batteries (Gualtieri and Johnson, 2006; Ladner, 2008)which bias subjects towards the aim of experimental protocol in order to get the accurate and good results, however the tests must be distinct for different cases and properly investigated by psychologists for best suitability.

Neurophysiologic tests (Schuhfried at all, 1985) are designed to investigate a variety of cognitive functioning, including attention, memory, language, speed of information processing and executive functions, which are important for aimed behavior. Through neurophysiologic testing, a neurophysiologist can make conclusions about underlying brain function. As Neurophysiologic testing play a less essential role in localization of brain abnormalities, clinical neurophysiologist found new uses for their knowledge and skills. By identifying which cognitive abilities are preserved or impaired in subjects with brain illness or in-jury, neurophysiologists can declare how well subjects will respond to various forms of treatment or rehabilitation. Although patterns of test scores serve as example profiles of cognitive weakness and strength, neuro-physiologists can also learn an excellent deal about subjects by observing how they come near to a particular test.

While neurological examination CT, MRI, EEG and PET (Dietrich and Kanso, 2010) scans look at the structural, physical, and metabolic condition of the brain, the neuropsychological examination is the only way to formally assess brain function. Neu-ropsychological tests extend over the range of cognitive processes from simple motor performance to problem solving and complex reasoning.

Among all these techniques, EEG is the best neuroimaging technique taking all of reliability, cost effectiveness, temporal resolution,

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data portability and system mobility perspectives in consideration so it is majorly being used for BCI applications.

2. GENERAL STRUCTURE

The general structure of a BCI (Brain Computer Interface) is following:

A. Signal Acquisition

The EEG signals are obtained from different regions of scalp through non-invasive EEG channels. After that, the signal is amplified and sampled for further analysis procedures. Some of the famous EEG acquisition systems are Neuroscan, EGI geodesic, BrainVision, RMS maximus, Biopac, Emotiv etc.

B. Pre-Processing

It is necessary to recover original EEG signal for analysis from acquired signal (amplified/modulated) via various methods such as normalization, filtration and transfor-mation.

The power of the scalp EEG can vary between different subjects due to several factors, including also anatomical characteristics. For this reason, it is necessary to have a way to account for differences in broad-band power across subjects. This can be achieved with different normalization approaches.

To remove linear trends, it is often desirable to high-pass filter the data. For power line noise removal we use notch filter. for different noise frequency bands we can use appropriate band stop filters. Some of the main pre-processing methods/tools are normalization, filtering, wavelet, ICA, PCA, etc (Lakshmi, 2014).

C. Feature Extraction

We can't consider the huge time domain data points of EEG to operate a microcontroller/processor to perform the desired action so we select few appropriate features of the data like power, energy, entropy, fractal dimension etc. This feature is calculated for a fixed time segment and fed to processor for classification. For example, suppose we use 32 channel EEG system with 1000 Hz sampling rate for BCI operation and power as feature. If we fix one second data segment, it will select blocks of 1000 data points during data acquisition and will operate queuing for processing. The Fourier transform is also widely used in the applications of spectrum analysis because it takes a time domain discrete signal and transforms into frequency domain discrete signal. Hilbert transform is also a very useful transform in EEG feature extraction. Some of the most common features are power, energy, nor-malized power, entropy, amplitude, latency, fractal dimension, sample entropy, Largest Lyapunov exponent etc (Yin and Cao, 2011; Napoli and Barbe, 2012; Tonga and Bezerianos; 2002).

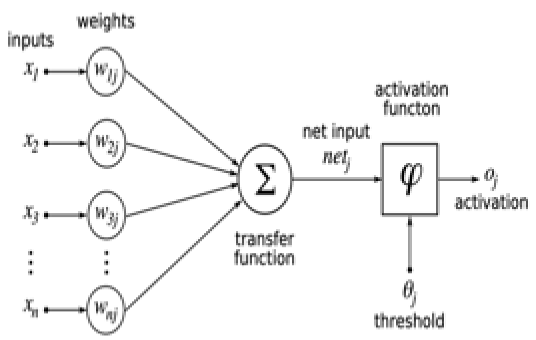
D. Classification

Classifiers are used for classifying the pattern/class of the features extracted from the segments. Classifiers may be supervised or unsupervised. Supervised means that it is designed with some defined parameters and trained with some data sets which is going to be classified while unsupervised classifiers are just like for bifurcation. The extracted features are fed through queuing to the classifier and send the class with most matching pattern then the respective task is performed. Classifiers are also considered as trained machines. The Machine learning deals with programs that learn from experience, i.e. programs that improve or adapt their performance on a certain task or group of tasks over time. Machine learning is training a machine to separate the data given for testing on basis of data given for testing based on certain features. A classifier can be considered as a class/dimension reducer. Some most common classifiers are ANN, kNN, SVM, k-means clustering, GMM, HMM etc (Mohandas and Gerropati, 2003; Lotte, 2007; Sulaiman at all, 2011; Cortes and Vapnik, 1995).

ANN (Artificial Neural Network)

Artificial neural networks are supervised classifiers which need to train before operation. They are developed on the basis of real neural networks underlying brain. Artificial neural networks are used for pattern recognition; data management and learning process similar to brain. They are made up of artificial neurons which give the concept of biological neurons and accept a number of inputs. Each input layer connected by weighted synapses. A neuron also has a specific threshold value. If the sum of the weights is greater than threshold value, the neuron stimulated. The activation function gives output of the neuron which will be the result of the problem and can be fed as input for the other neuron. A number of neurons are connected together to execute an artificial neural network which is arranged on different layers. A neural network divided in to input layer (which takes the values of in-put variables) and output layer (the predic-tions of the result) and hidden layers of neurons, which play important role in the network as hidden functioning takes place. The figure 1 gives a schematic of an artificial neural network.

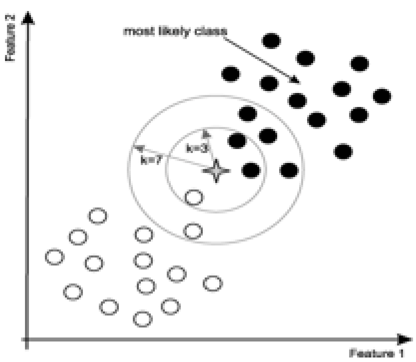
Figure 1. ANN Classifier



kNN (k-Nearest Neighborhood)

k-Nearest Neighborhood is also a type of supervised learning. kNN is moderate straight forward classifier and data are classified on the basis of class of their nearest neighbors. It is often useful to take more than one neighbor into account so the tech-nique is referred to as k-Nearest Neighbor (k-NN) classification where k nearest neighbors are utilized in determining the class. Since the training examples are needed at run time, i.e. they need to be in memory at run time; it is sometimes also called memory based classification. Because induction is delayed to run time, it is considered as lazy learning technique. Because classification is directly based on the training an example that is why also called example-based classi-fication or case-based classification. A sim-ple illustration of kNN is shown in figure 2.

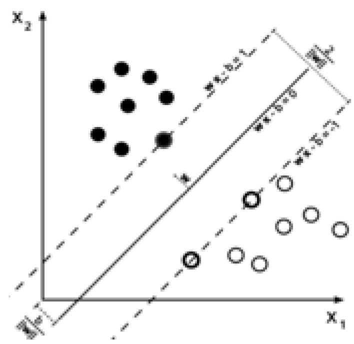
Figure 2. k-NN Classifier



SVM (Support Vector Machine)

It is an example of supervised machine learning. The support vector machine (SVM) algorithm is probably the most widely used kernel learning algorithm. It achieves relatively robust pattern recognition performance using well established concepts in optimization theory. The main plan of the trained SVM algorithm is to select new data position in a category. The svmclassify function classifies each row of data in sample using the information conveyed in the structure of support vector machine classifier svmstruct, created using function svmtrain. The figure 3 shows a simple structure of SVM.

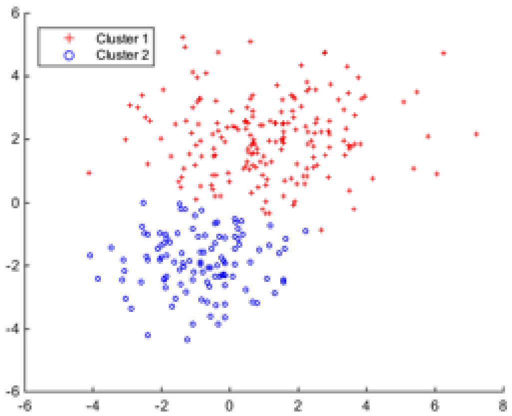
Figure 3. SVM Classifier



(GMM) Gaussian Mixture Model

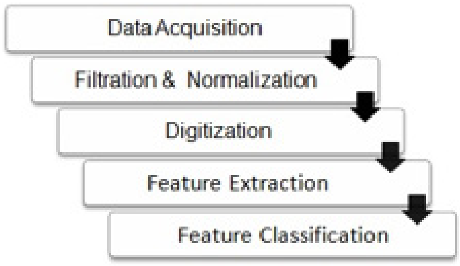
It is an example of unsupervised learning. Gaussian mixture models are the combination of multivariate normal density components. In GMM soft data clusters are assigned by choosing the component that maximizes the posterior probability. GMM may be more suitable than k-means cluster-ing when clusters of different sizes having correlation between them. Following figure shows the clustering by GMM.

Figure 4. GMM Classifier



The overall EEG signal processing steps are shown in figure 5.

Figure 5. EEG signal processing steps

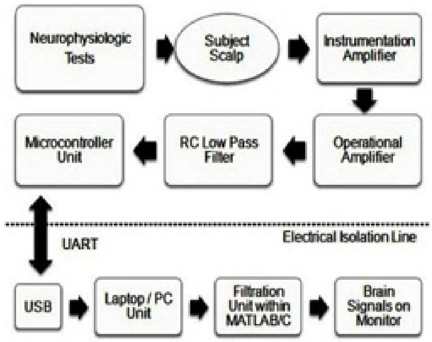


3. THE DEVICE MODULE

The main motivation is to build a brain-computer interface for neurophysiologic assessment of different parameters during various cognitive biasing tests. As per results of various studies, the most utilized and easiest way of measuring brain waves would be EEG to record potential difference across different locations on the scalp. Our attention is confined on implementation of two-stage amplification and filtering circuits. Besides, we use the builtin analog to digital conversion functionality of the microcontroller in order to give good quality digital signal as result. The optoislated universal asynchronous receiver/transmitter sends the digital values from ADC over USB/UART to a PC/Laptop unit connected to the micro-processor or microcontroller. The PC/Laptop executes all the preprocessing, trans-for-mation, feature extraction, machine learning and task performing algorithms on C/MATLAB/SciLab/Python/Simulink or other platform (Sharma and Gobbert, 2010) using few microprocessors and microcontrollers.

The structure of the device proposed consists of an amplifier circuitry consisting of an instrumentation amplifier (the common-mode noise ratio is evaluated using a right-leg driver attached to the subject's ear lobe or mastoid, along with an operational amplifier and some filters (for removal of DC offsets, 50 Hz powerline interference, and other noise artifacts). In the next step, the signal passes to the microprocessor/microcontroller unit, where it is digitized via an analog to digital converter. Now, it is send over an USB/UART connection to a PC/Laptop. The PC/Latop unit then per-forms signal processing in MATLAB/C and is proficient to output the final results (brain wave parameters energy, power spectral density, root mean square value, entropy etc. for different bands alpha, beta, gamma etc.) to the user. The other alternatives of MATLAB are GNU Octave, Sage, FreeMat, R etc. but due to some additional features such as fast prototyping, more functions, concise coding and sufficient documentation MATLAB is more preffered (Verma at all, 2012). A functional block dia-gram of the overall structure is shown in figure 6.

Figure 6. Device Module Schematic



4. CONCLUSIONS

This study concludes the requirement and present scenario of BCI development. It includes the implementation of a low cost device to access the different cognitive parameters like stress, workload, emotion, neural activities, neurological disorders etc. in various cases as per described by neurophysiologic tests. The BCIs may play very critical role in rehabilitation as well as cognitive enhancement. It also presents a general structure and module for a low cast BCI system development.

Conflict of interests
Authors declare no conflict of interest.

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