A REVIEW ON BIO-SIGNAL PROCESSING TO IDENTIFY COGNITIVE STATES FROM EEG SIGNAL

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Abstract — A Brain-based skill that is essential to carry out every task varies from the modest to the extreme complex is cognitive ability. In cognitive abilities emphasizes is not on actual knowledge, it is concern with the how to learn, recall, pay attention and solve the problem. Cognitive science learns about the environment, the chores, and the roles of cognition. The purpose of the cognitive science is to study the mind and behavior. Cognitive neuroscience is all about in what way the brain assists the mind. It is the field which deals in systematic learning of the biological developments and traits that motivate cognition, with a precise emphasis on association of neural in the brain which is involved in conceptual processes. Electro encephalography is a reliable biomedical signal that gives approximate estimation of an individual cognitive ability. Many researches are working in the domain of the development algorithm aimed at feature extraction of EEG. In this study, several effective feature extraction algorithms are studied to identify cognitive state.

Keywords—Image Acquisition, Image Processing, MATLAB, Real time, Video input

I. INTRODUCTION

Electroencephalography is a technique to record electrical movement of the brain. The voltage variations are measured from EEG. In brain neurons there is ionic current which results in voltage variations.

Figure 1: A nerve system

In health library of Johns Hopkins medicine figure describes that in a brain there are abnormal electrical impulses during a seizure [Siuly Siuly et. Al.2017]. For various brain disorders, EEG is used. Whenever epilepsy is there seizure action will seems as fast growing spiking waves in the EEG [Yvonne Holler et al.2015].

People with wounds in their brain, which may be the result of tumors or stroke, may have abnormally slow EEG waves, subject to size and the location of the wound. The EEG is used to define
the complete electrical movements of the brain like to assess trauma etc. In surgical procedures, EEG is helpful to observe the flow of blood in the brain.

In EEG, there are manifold electrodes which are situated on the scalp. From these electrodes, brain's spontaneous electrical activities are recorded.

**Figure 2: Electrodes placed on the scalp & EEG reading**

In above figure Olav Krigolson, who is neuroscientist in University of Victoria, discusses what is EEG or brain waves and how it looks when recorded.

This is a test which is used to detect deviations correlated to electrical movement of the brain. In this test wave shapes of brain are recorded. For this test, electrodes are positioned on the scalp. Electrodes are the small metallic discs with tinny wires. For results, signals are taken from electrodes which are then sending to a PC.

From the ordinary electrical activities of the brain, a recognizable pattern is made [Fabrizio Beverina et al. in 2003]. This test gives abnormal patterns which show monitor seizure and other disorders. From EEGs, one can identify causes of several problems like disorders of sleep, coma, brain death, encephalopathies and variations in behavior. This test is also helpful to assess brain activity in case of head injury or it’s a first step in any liver transplantation or heart.

Cognitive involves the capability to obtain actual information, generally the kind of knowledge which can easily be tested. The cognition is different from emotional, social, creative development and ability. Cognitive science is an emergent field which deals with thinking, human perception, and learning. The learning of the brain through neuroscience, computer science, psychology, anthropology, dialectology, and philosophy is the cognitive science. Basically, Cognitive science is thinking of how we think. To comprehend the mind it’s important to know about how the brain mechanism works and to comprehend the mind psychology generally uses behavioral experiments. The neuroscience offers numerous ways to look at the brain in many methods that limits our theories.

N.Srinivasan et al.(2007) describes that cognitive neuroscience of creativeness is widely studied with the use of non-invasive electrical recordings taken from scalp known as electroencephalograms and event related potentials.

**II. LITERATURE SURVEY**

Bradley J. Edelman et al. (2016) applied a novel technique to extend preceding EEG source imaging work which interpret natural hand or wrist operations to categorize four complex motor imaginations of the right hand: flexion, supination, extension and pronation. They conclude that ESI can enhance BCI (Brain Computer Interface) performance of interpreting difficult right hand motor imagery jobs. Nima Akhlaghi et al. (2015) used a computationally effective technique and show the practicability of real-time graded control. They differentiate various complex hand gestures depends on ultrasound
imaging of forearm physiques and validate the viability of a robust muscle–computer interface using ultrasound imaging and the average classification precision is 92%.

Howida A. Shedeed et al. (2013) also proposed a Brain Machine Interface system which used the electroencephalography signals linked with 3 arm movements for directing a robotic arm. These three arm movements are open arm, close arm and close hand. Rashima Mahajan et al. (2014) also design a BCI which control devices that converts different states of brain into effective control signals. They also explored the capability of EEG signals to describe thoughts, unspoken words, and unspoken words.

Ruhi Mahajan et al. (2015) use a 14-channel wireless referential montage EPOC headset for constantly recording of the brain activities from the persons and at the sampling rate of 128 sps. The device bandwidth is 0.2–45Hz and digital notch filters is used to confirm the elimination of power line interventions. In (2013) her paper describes a study of activities on brain engagement in normal settings. This study is grounded on an ambulatory scalp EEG NeuroMonitor platform. In some of clinical and therapy applications like autism spectrum disorder , attention-deficit hyperactivity disorder or cerebral palsy this Engagement monitoring is very essential as it is difficult for the mentors to assess the individual responses of children who have these disorders.

Lees T et al. (2016) explore the associations among central EEG and frontal pole and cognitive recital in a mockup of female and male nurses and conclude their association’s significance. Sample size is of 57 and at positions Fp1 (frontal polar), Fp2, C3 (central) and C4 two lead bipolar EEG was recorded. To record the EEG during an active and baseline phase involves neuropsychological Stroop investigation. Cognistat screening tools and the mini-mental state exam (MMSE) was used to assess the cognitive performance of participants and important correlations between MMSE outcome, beta activity of EEG and Cognistat were exposed. Furthermore, area related cognitive recital was considerably connected to numerous EEG variables. For global and area specific cognitive performance this study acknowledged potential EEG biomarkers and to detect cognitive pathologies in expansion of upcoming biomarkers which based on EEG they provides initial groundwork. Monira Islam et al. (2014) define machine learning environment and based on it they describe a cognitive state classification system which evaluate the persons psychological states based on EEG measurements. They also concentrate on the selection of channel for the automated EEG analysis and feature extraction which is based on spectral analysis. Jingyang Chen et al. (2014) explains the necessity of cognitive science exploration and brain computer interface and designed a high accuracy EEG acquisition system grounded on the peripheral component interconnect platform.

Hao Han et al. (2016) present an original nonrigid 3-D registering technique to develop magnetic resonance (MR) cystography for the compensation of bladder wall indication and dynamic MR scans deformation for exposing and diagnosis of abnormality. This paper offered α-registration method which is applied on real patients for bladder motion compensation and its consequence on the precise and automatic division of bladder wall was evaluated. The result shows that to capture the deformation and bladder wall motion, α-information-based registering was further operational in comparison to previous approach of image registration.

K. Amarasinghe et al. (2014) describes a novel approach for identifying thought patterns which is grounded on Self Organizing Maps .They also presented method for feed-forward Artificial Neural Systems for classification and unsupervised grouping of pre-processed EEG data.

Fabio Theoto Rocha et al. (2016) give a computational framework to obtain and process EEG signals of players with distinct levels of experience. The objective is to find different patterns of cognitive brain mapping through definite familiar chess difficulties. Their results shows a neural organisation consistent by the action executed by the few groups of volunteers, emphasizing discriminant variances in cortical brain areas among beginners and experts graded by their proficiency.
levels. Naveen Kumar (2016) discuss the concept of cognitive load and used EEG power spectrum to analyze cognitive load in Human Computer interface and proposed a method which is effective for exploring cognitive load initiated because of difficult tasks in HCI systems. Advantages of this proposed method is that they are accurate, unbiased and evaluator independent but it has shortcomings that it needs costly equipment, analysis time is high and they need expertise for interpretation.

Prafulla Nath Dawadi et al. (2016) monitors the everyday activities in the home and predicts clinical scores of the citizens and perceives the unaffected benefits of smart home-based analysis and they recommend a clinical assessment using activity behavior (CAAB) method for smart home person’s daily behavior and predict their clinical scores and result shows that it is possible to predict clinical scores by the use of smart home sensor data and learning-based data analysis.

Shangkai Gao et al. (2014) describes an innovative taxonomy for telecommunication systems founded on the multiple access approaches. They describe the difficulties of transforming existing skill into real-life practices. They offer valuable strategies for exploring innovative paradigms and methodologies to expand the existing visual and auditory BCI technology.

Saleha Khatun et al. (2015) compare both stationary and discrete wavelet transforms (SWT & DWT), and shows that wavelet transform is suitable in single channel EEG for data artifact removal to implement in ambulatory real-time EEG systems.

Bin He et al. (2015) review the concepts to progress a sensorimotor rhythm EEG grounded on brain-computer interface and then describe the method which comprise of emerging BCI systems combining the control of physical devices to escalate user engagement, make better BCI systems by inversely mapping scalp recorded EEG signals to the cortical source domain, for improvement of learning method mix BCI with concept of noninvasive neuromodulation , further to improve BCI learning & results they incorporate mind-body cognizance training. The result shows that rhythm-based sensorimotor-noninvasive BCI is efficient in giving communication and control competences. BCI is continuously developed still challenges are there in SMR-based noninvasive BCIs – for proficient use of BCI a lengthy training is required.

Trevor Thompson et al. (2008) discuss the challenges to obtain EEG during movement and by giving some applied and computational methods they shows that empirical studies can handle the difficult of movement artifact. During motion EEG recording there are many problems to obtain clean cerebral data. They discuss the effective methodological tool to understand cortical processes that motivate performance in sporting and nonsporting fields. They also discuss EEG-biofeedback and shows it offers optimizing function which might have a generous application.

Martha Ann Bell et al. (2013) discuss the challenges for those who are doing advance research in EEG. He discusses EEG signal has outstanding temporal resolution, but EEG has deprived spatial resolution. The skull works as a low-pass filter which misrepresents the underlying electrical movement of the brain over a large area of the scalp. Moreover, at the scalp recorded potentials are possibly produced by numerous groupings of cortical then subcortical generators which spread across a comparatively wide area (Pizzagalli, et al. 2007). It means that a scalp electrode is possibly identifying electrical activity which generates from non-local clusters of neurons that’s why better way to discuss EEG activity is discussed it at some precise electrode location instead of from a specified area of brain. The use of compact arrays of electrode (usually taken as at least 64 electrodes) may lighten certain concerns with spatial resolution. Certainly, compact arrays permits design of the source of the electrical signal (Reynolds & Richards, et al. 2009) and the price of an EEG system is linked with the number of electrodes used.

Pega Zarjam et al. (2015) studied a cognitive task by presenting seven dissimilar intensities of workload to explore workload discrimination using EEG signals. For this study, they used two statistical approaches and presented that high task load discrimination was primarily attained in frontal lobe of the
brain. They investigate the task for 12 subjects only and under controlled measurement environment. So, there is a scope that some other features in the given task load discrimination will be explored and collection of a bigger database is taken under less controlled measurement environments.

Lees T et al. (2016) explore the associations among central EEG and frontal pole and cognitive performance in a sample of female and male nurses and conclude their association significance. Sample size is of 57 and at positions Fp1 (frontal polar), Fp2, C3 (central) and C4 two lead bipolar EEG was recorded. Cognistat screening tools and the mini-mental state exam (MMSE) was used to assess the cognitive performance of participants and important correlations between MMSE outcome, beta activity of EEG and Cognistat were exposed. Furthermore, area related cognitive recital was considerably connected to numerous EEG variables. This study acknowledged potential EEG biomarkers and offers initial foundation to detect cognitive pathologies in expansion of upcoming biomarkers.

III. CONCLUSION

Above studied concludes that Electro encephalography (EEG) is a reliable biomedical signal that gives approximate estimation of an individual cognitive abilities. Many researches are working in the domain of the development algorithm used for feature abstraction of EEG. However, less has been achieved in cataloging cognitive states using EEG in real time. Therefore, there is a requirement to construct an extensive biomedical signal database based on EEG acquisition. An efficient feature extraction algorithm shall be developed to identify cognitive state & the robustness of the algorithm developed shall be evaluated.

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