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Brain-Computer Interfacing and Classification of Cognitive Activities

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***Abstract*— Human intellect can be straightforwardly associated with the computers through a modern innovation known as Brain Computer Interface (BCI). Electroencephalography (EEG) and functional Near Infrared Spectroscopy (fNIRS) based BCI empowers to associate the individuals with the encompassing world through brain signals noninvasively. This strategy of perusing the intellect through physiological signals by EEG and fNIRS sensors has made critical advance in neurological science and engine control inquire about. The BCI framework can record, analyze and decipher the framework input, procured from the brain in terms of commands. These commands can assist be utilized to activate outside gadgets of choice concurring to the user's intellect. The BCI is rising as one of the capable instruments in reasonable biomedical applications such as recovery, cognitive forms, prosthetics and numerous neuro-feedback utilitarian exercises. Be that as it may, the usefulness of BCI depends upon the acknowledgment and classification of brain signals for segregating errand and resting exercises of the brain. We have developed two algorithms for assessment and classification of EEG and fNIRS alone and combined as hybrid (EEG+fNIRS) signals recognizing brain activities under the given tasks. We have tested our classifiers from open source EEG-fNIRS dataset. The dataset is consisting of EEG and fNIRS simultaneously recordings acquired from twenty-six healthy participants during word generation (WG) tasks. In this work, we have achieved an average classification accuracy peak of 85 %, 84 % and 78 % Hybrid, EEG and fNIRS respectively for SVM with the dataset.**

Keywords*— EEG, fNIRS, Brain Computer Interface, SVM and Classification

I. Introduction

Mind based intellectual exercises are human's capacity to perform different mental undertakings related with learning and critical thinking aptitudes. The assignment could be from the easiest to the most mind boggling. The cognizance depends upon internal discourse and visual symbolism. Evaluation of these two segments shows the psychological degree of the individual which is a proportion of neuronal action of the mind. Essentially, a wide range of employments expect laborers to practice their psychological aptitudes productively. Especially in understudies, it is imperative to realize their cognizance level that assists with adjusting successful technique for instructing. As per education insights of US, about 14% of young people stay secondary school dropouts because of the troubles in understanding fundamental subjects including text perusing and numerical issue arrangements [1]. Aptitude for mathematics among youngsters is normally tested by their skill at solving arithmetic, algebra and fractions which are domains of mathematics. Most of the students struggle in solving numerical problems in their classes [2]. Commonly, the skills of individuals are evaluated by questionnaire which is not much accurate because the cognitive skills are driven by neural mechanism of the brain in individuals. Despite of considerable advances in understanding cognitive and behavioral mechanisms through various models, little is known about the brain dynamics by experimental techniques. Therefore, it is important to understand and monitor the brain dynamics while performing simple assigned tasks.

Brain Computer Interfacing (BCI) is a strategy that gives correspondence between human mind and machine or a gadget that can be enacted without inclusion of solid action. A few utilizations of BCI have been investigated including rehabilitation [3], cognition, diagnosing neurological issues and activation of gadgets. Scientists have likewise evolved business and non-clinical BCI frameworks with novel investigation calculations and sign handling strategies. Among the numerous potential modalities for estimating mind action in BCI frameworks, EEG and fNIRS have been well known; since they are noninvasive, basic and relatively easy to use. EEG has been famous as a methodology for applications, for example, BCI and estimating cognitive levels [4;5]. Normally, BCI framework involves estimation of cerebrum action, preparing of the mind waves, extraction of unmistakable highlights from the signs and order of the signs to change as orders required in working the ideal gadget through interfacing convention. Procurement and estimation of signs are conceivable by reasonable sensors and related hardware which decides the affectability and SNR (sign to clamor proportion) while the handling, include extraction and grouping of the signs extraordinarily impacts the presentation exactness of the BCI.

fNIRS is another method in the field of neuroscience contemplates. There is developing enthusiasm for this instrument in neuroimaging, cerebrum enactment, mental examinations and conduct science. fNIRS measures hemodynamic reaction instigated from an undertaking. Cerebrum based psychological exercises are human's capacity to perform different intellectual and mental undertakings related with learning and critical thinking abilities. The undertaking could be from the least difficult to the most intricate. The perception depends upon internal discourse and visual symbolism. Evaluation of these two parts demonstrates the intellectual degree of the individual which is a proportion of neuronal action of the mind.

II. MACHINE LEARNING

In the past, considerable progress has been made towards high performance hardware development and the researchers achieved maximum possible output from the hardware. It is now therefore, necessary to select an appropriate method for classification of the signals which can enhance the performance accuracy. Many classifiers are available in the literature to group EEG-fNIRS signals in groups and then, recognize significant differences between these groups. In recent years, Machine Learning (ML) algorithms are becoming focus of attraction among researchers to do similar tasks over the traditional classifiers. ML is a subset of artificial intelligence (AI) which makes machines to learn specific tasks through its input data, statistical parameters and trial and errors optimizing the process at faster rate. ML has capability to learn like humans and has potential to solve any complicated problem. Thus, the BCI facilitates to connect human mind with artificial intelligent devices like computers and robots through ML technology. Broadly, three types of algorithms are available in ML to make the machines to learn. They are supervised learning, un-supervised learning and reinforcement learning. In most of the practical machine learning applications, supervised learning is implemented due to its versatility, high accuracy and simple in coding. Researchers found that supervised learning algorithms are best satisfactory in the classification of EEG-fNIRS signals. Many algorithms are available in supervised learning, but SVM algorithms are very popular in the classification of signals.

BCI technology has increasingly been receiving attention as an alternative communication option for severely paralyzed patients in the last decades. Over the last years, BCIs have also been used as an augmentative tool for rehabilitation. Commercial and non-medical BCI applications were developed and novel analysis algorithms and signal processing techniques were introduced for developing practical BCIs. Among the numerous possible modalities for measuring brain activity in BCI systems, EEG and fNIRS have been popular; since they are non-invasive, simple and comparatively user friendly. The work presented in on concomitant recording of EEG-fNIRS highlight that concentration variations directly reflect the increase in blood oxygenations required to support the neural activity during a visual stimulus paradigm. Although early attempts to integrate EEG and fNIRS for monitoring brain function have been made, there is a lot of scope for research in this direction for BCI and cognitive applications.

EEG has been mainstreamed as a methodology for applications, for example, BCI and estimating intellectual levels. As of late, research bunches have begun investigating the utilization of NIRS to acquire the control orders for BCI based applications. Taking this thought forward, an endeavor to coordinate EEG-fNIRS to unravel testing issues, preparing dataset choice and member focus checking was made. Previous studies presented the recording setup using EEG electrodes and fNIRS opcodes, signal processing techniques and experiments performed. The examination including numerical errands and unwinding states gave spurring results adjusting those in the writing where oxygenation mean qualities from the ensembled preliminaries during math task were higher than the unwinding stage for all members. It was imagined that the corresponding data gave by fNIRS could be viably used to choose preparing datasets and screen member fixation utilizing EEG-fNIRS coordination. Potentially, having a synchronized framework with triggers for EEG just as fNIRS and taking a stab at a lesser relentless worldview like engine symbolism could presumably give better achievement. Despite the fact that EEG-fNIRS combination examines are still in earliest stages, ideally an inspiration for additional investigation on that front for the BCI research community and cognitive performance measures.

Mental issues become globally, 1 in 4 people in the world suffers from mental or neurological disorders at some point in their lives. According WHO 450 million people currently affected by such conditions, placing mental disorders among the leading causes of ill-health and disability worldwide [6]. About 20% of the world's children and teenagers are estimated, who have mental health troubles. Most low and middle-income countries have only one child psychiatrist for every 4 million people, leading to a large gap between supply and need for services in those areas [7].The brain image modality by fNIRS, is a new neuroimaging technique which measure the cerebral hemodynamics associated with neural activity. The NIRS technique transmits near infrared light immediately into the head. Based on the absorption, the change in concentrations of oxygenated and deoxygenated hemoglobin can be estimated using modified Beer-Lambert law. The fNIRS has found its applications in cognitive and behavioral studies. Commonly used tasks to activate the prefrontal cortex (PFC) include mental arithmetic, word generation, color word matching, Stroop task, mental rotation, working memory task and inhibition [8]. The fNIRS has several advantages over other neuro-imaging modalities, it has better spatial resolution and less affected by noise rather than EEG. Also, the fNIRS imaging modality is portable, cheaper and does not confine the subjects to lying position rather than functional magnetic resonance imaging (fMRI) and positron emission topography (PET).[9]

Figure 1. shown the historical functional Near Infrared Spectroscopy (fNIRS) developed system from single channel system to multi-channel and high density system, that can mapping the brain activities by detect the changes in brain oxygenation. [10].

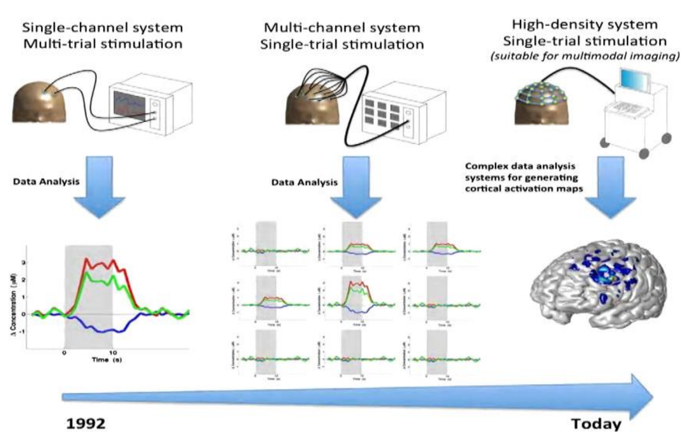

Figure 1. Development of fNIRS instrumentation [8]

A Support Vector Machine is a discriminative classifier officially characterized by an isolating hyperplane. Given named preparing information, the calculation yields an ideal hyper-plane which classifies new models. In two-dimensional space, this hyper-plane considering as line that separates a plane in two sections, wherein each class lay on either side. The SVM approach underlines boosting the edge in the preparation information. [11]

III. METHODOLOGY

The primary motivation behind our exploration is to build up a basic and precise AI calculation to help the intellectually incapacitated individuals in evaluating their discourse and psychological abilities. Further, an assistive technique can be created dependent on counterfeit insightful (AI) strategy as an instrument for them. Thus, we considered EEG-fNIRS signals procured during the discourse errands and grouped them as responsive and non-responsive classifications at higher exactness. Towards this, the initial step of our work is the structure of BCI for information securing.

An open source EEG-NIRS raw dataset [12] was used in this work. The data was collected using a multichannel BrainAmp EEG amplifier (Brain Products GmbH, Gilching, Germany) at 1 KHz sampling rate. Thirty EEG electrodes were placed on an EEG cap with 10-5 configuration system [13]. fNIRS data was acquired with a NIRScout (NIRx Medizintechnik GmbH, Berlin, Germany) at a sampling rate of 10.4 Hz. There are three sessions of dataset for each participant. Each session contains ten trials of WG and ten trials of baseline (BL), thus twenty trials in a session for each participant. For WG, a single letter was shown on the monitor for 2 s for baseline fixation and 10 s for the task. The paradigm is explained in detail by Shin J, et al. The signals acquired from the brain activities during the cognitive tasks and it was preprocessed used MATLAB R2019b (MathWorks, Natick, MA, USA) and the BBCI toolbox was used for further data processing and used some codes for features extraction and visualization [14]. EEG-fNIRS signals are classified by SVM algorithm

Figure 2 show the block diagram of each stage of operation on the EEG-fNIRS database. EEG-NIRS features were calculated using a sliding window, which was window size 5 s and step size 1 s, moved from the beginning to the end of the period (−5 to 25 s). Common spatial pattern (CSP) filtering was then applied to decompose the EEG data to decide the most discriminative CSP components. Features were finally extracted using the variance; then applied logarithm for EEG and the mean value of Oxy and Deoxy for fNIRS were estimated using the sliding window identical to the EEG analysis for the feature vectors (dimension: 36 channels × 2 chromophores). The classifier and cross-validation method were identical to the EEG classification method. All possible combinations of EEG and fNIRS chromophores (e.g., Oxy+EEG, Deoxy+EEG, and EEG+Oxy+Deoxy (Hybrid)) were considered. SVM was used as a predictive classifier. A 5 × 5-fold cross-validation was performed to evaluate the classification performance for each sliding window. At training phase, feature extraction was used to convert each train data to a feature set. These feature sets were used to classify the signals. Feature sets and labels were fed into the SVM algorithm to generate a classifier model. In second phase of the algorithm, the same feature extraction was used to convert unknown test data to feature sets. These feature sets were then fed into the classifier model, which generates predicted labels.

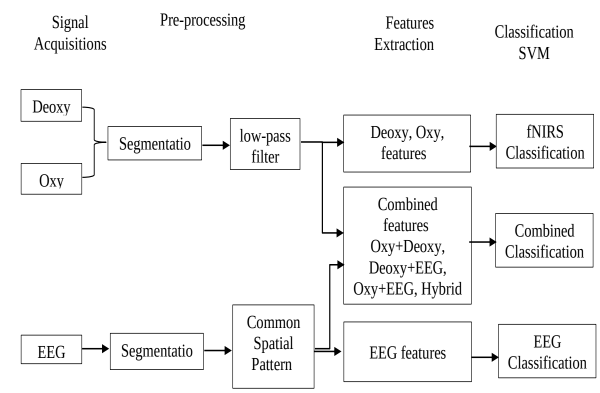

Figure 2. Block chart of the proposed SVM based classifiers for EEG-fNIRS

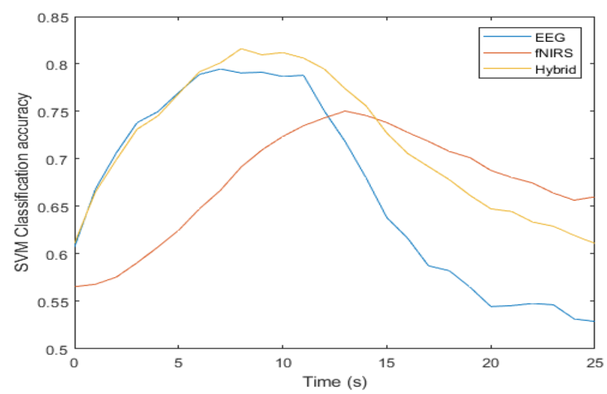

Figure 3. Hybrid, EEG and fNIRS average accuracies over time

IV. RESULTS AND DISCUSSION

SVM proposed algorithms for every single subject over the time and we investigated every participant during the performance task. Figure 3 shows SVM classifier performance accuracy with respect to time. The x-axis represents the right end of the sliding window. The y-axis indicates the classification accuracy of SVM. Overall classification's accuracy starts to increase earlier to the onset of the task period. It can be understood that the initial task condition was given at t =0 s, then the participants recognized the beginning of the task and began to think what to do in the task period. Hybrid classification accuracy peaks at t = 8 s, scoring 81.62 % accuracy. EEG classification accuracy peaks at t = 7 s, scoring 79.47 % accuracy. fNIRS classification accuracy peaks at t = 13 s, scoring 75.04 % accuracy.

Figure 4 the classification accuracy for each participant is shown. Each vertical bar in the figure represents a participant and its height represents accuracy peak. The last bar in the figure shows average value of classification accuracy which is taken over twenty-six participant. Thus, the SVM classification algorithm achieved an average accuracy of 85 %, 84 % and 78

% respectively hybrid, EEG and fNIRS. during the WG task.Simulation and Assessment of Parkinsonian Tremor.

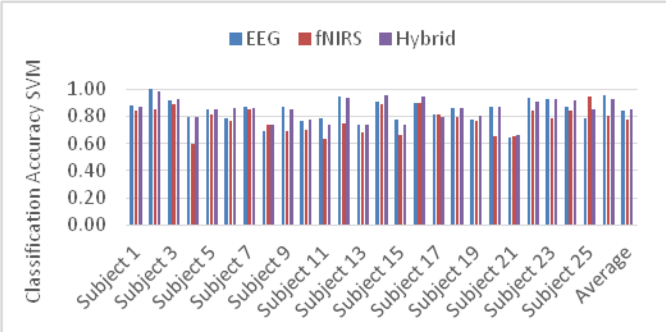

Figure 4. Hybrid, EEG and fNIRS accuracy peaks of each participant

V. CONCLUSION

In this work, we achieved the highest SVM classification accuracy with hybrid (scoring 85 %) comparing to EEG or fNIRS alone. We proposed a simple SVM algorithm forward with optimizations parameter done and getting a higher accuracy comparing to other methods used for this EEG classification without any complex.

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