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Comparison & Overview of Different Brain-Computer Interface Systems

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Abstract: Brain-Computer Interface is used to communicate based on human brains neural activity and its very much independent of output generated by peripheral nerves and muscles. It is avoids the use of normal muscular (hand or eye) body parts to make contact and operate the devices. The system is useful for the handicapped people which are unable to move physically. In this paper we compare different brain-computer interface systems and its classification. Also we make the overview of the BCI systems.
Keywords: BCI, HCI, exogenous, endogenous, ECoG, VEP.

I. INTRODUCTION

Human-Computer Interaction (HCI) and its advance application are very much useful in society. Another growing development in HCI is the concept of a direct Brain Computer Interface (BCI). [1] The aim of BCI is to improve the quality of one's life, and its full potential has been improved definitely. The BCI system have many other utilities in different areas like video gaming, robotics, communication etc. unlike the other researches which are mainly focus on only disabled people. Also, many challenges arise in the development of such systems[2]. The type of brain signals used as data, data acquisition methods, the algorithms which are used to translate the collected data, the hardware which facilitates user control, the type of feedback the user receives when executing commands, and the characteristics of the users themselves these are very much important factors which affects the BCI system.[3],[4]. Hence, future improvements in BCI systems require structured, well-controlled studies which give us the comparative signals combined signals and different methods of signal acquisition, for various kinds of users.

II. OVERVIEW & COMPARISON OF DIFFERENT BCI SYSTEMS

BCI divided into several categories: independent or dependent, invasive or noninvasive, and exogenous or endogenous. Figure 1 shows suggested classification on BCI development, presenting the various types of current BCI that fit into their respective categories.

A. Independent vs. Dependent

Independent and dependent BCI systems are distinguished by how reliant the system is on additional types of activity while in working state. This type BCI systems are not dependent on any physical body parts; its does not required any other signals to get EEG signals from brain to run certain commands[18]. The example is, the word or letter from the text have to choose by user and thinking deeply.

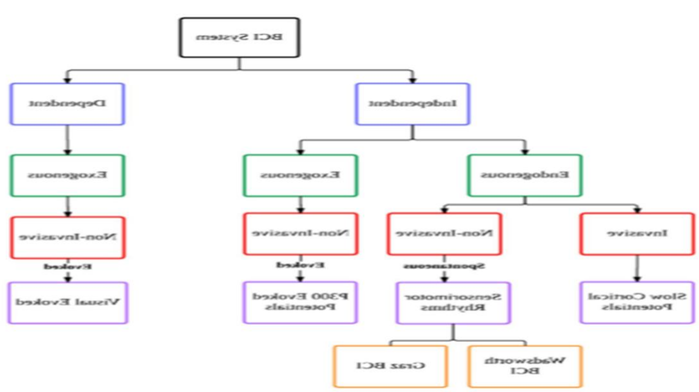

Figure 1: Classification of BCI systems [33]

When the letters flash, the user produces a P300 potential, allowing for the user to select the currently lit letter. Because of the system, the user was able to select a specific letter by looking at it. Furthermore, the users selected letter is determined by the highest recorded potential which is hi/her VEP and its recorded by visual cortex of each flashing letter. The signals are generated by users thinking but for doing the task the EEG signals are used.

B. Invasive vs. Noninvasive

The two systems, Invasive and noninvasive BCI systems are differs from each other's by the method of extraction. The first Invasive BCI requires implanting foreign materials into the subject's body. This type of things may include large electrode setups or chemical molecules. The BCI systems are improvised by different types of freedoms and used different signals to control the system, for large time of recording the BCI system faces difficulties in sustaining because of they use the electrodes in cortex. The signals are degraded in the process because of the electrodes used in cortex of the system [23]. Also, the small changes in the locations of the electrodes can move the recording sites away from the areas which are recorded very easily. Because of the low signal-to-noise ratio of EEG signals. Also, ECoG is expected to be safer and have a greater stability in the long-term, compared to the mentioned approach above.

Furthermore the BCI systems Classify, non-invasive BCIs can be classified as "evoked" or "spontaneous". This BCI depends heavily on evoked potentials, which reflects the immediate automatic responses of the brain to some external stimuli. Using the scalp electrodes it is easy to detect the evoked potentials. Also, Slow Cortical Potentials (SCP) are also sometimes used in evoked BCI systems. The need of external stimulation does, not allowed the evoked potentials are applied for some tasks.

Unlike the other types, the cognitive process is used by spontaneous BCI systems freely because it eliminates the need for external stimulation. This type of a method is especially beneficial when controlling robotic devices. From all signals some are spontaneous BCI may depend on are event related de/synchronization (ERD/ERS) and Steady State Evoked Potentials (SSEP).

C. Exogenous vs. Endogenous

The exogenous or endogenous are types of BCI systems, depending on the nature of the recorded signal. In this type of systems the neuron activity evoked is done by external stimuli. VEPs or auditory evoked potentials BCI systems are used in this systems i.e. . Exogenous do not require intensive training since it is easy to setup their control signals (SSVEPs and P300). It's shown with a single EEG channel, capable of an information rate of up to 60 bits/min .

At the other side, endogenous systems do not rely on an external stimulus; it is based mainly on brain rhythms and other potentials. Training the users using neuron feedback usually does this. A period of the training varies by subject as well as the experimental strategy and training environment. Technique chosen for the experiment determines how the user learns and what they must do to produce the required brain activity patterns. Grumman et al describes two approaches for endogenous systems: Operant conditioning and performance of specific mental tasks.

The strategy used in calibration- free robotics, the same strategy used in this type of system [22]. IN different, motor imagery is the most common mental work used to produce brain patterns that can be trustily generated and distinguished. The image of motor is activated through the imagination of changes of limbs. The users have to perform such mental tasks without physically executing the corresponding movement. Doing so produces de-synchronization (ERD) and event-related synchronization (ERS) [24].

III. LITERATURE REVIEW

For controlling Home Appliances varies techniques were used. In A Brain Computer Interface for Smart Home Control paper they used Emotive EPOCH headset to capture EEG signal and virtual environment had created. If user wants to select any device from that home then user had to raise an eyebrow [2].

In another paper they displayed varies devices on computer screen in matrix form and each device flashes for particular period of time. If user wants that flashed device to operate then user had to create p300 signal in the brain [3]

Christian I. Penaloza, applied the technique that perform Brain Machine Interface using the sensor and the other body part for capture waves from the brain for further processing and then Automation Considering User Preferences and Error Perception Feedback is done[4].

Kenji Nakayama introduced efficient pre-processing techniques in order to attain high probability of exact mental task classification. The preprocessing technique includes segmentation along time axis, amplitude of FFT of brain waves, reduction of samples by averaging and nonlinear normalization.[12]

Charles W. Anderson applied PCA (principal component analysis) independently to little segments of data and for classification vectors are used as features. Also, the EEG added every sample using time embedding and represented as PCA results which give time and space factor using EEG signals. The BCI paradigm is performed by mental task as u a subject and using these results the features are classified in all the categories .[13].

Jinyi Long introduced a hybrid BCI that uses the motor imagery-based mu rhythm and the P300 potential to control a brain-actuated simulated or real wheelchair. The user performs left- or right-hand motor imagery to direct a left or right movement and performs foot imagery or focuses on a flashing button to adjust the speed of the simulated or real wheelchair. [1].

In this paper the author investigate the use of a temporal extension of Independent Component Analysis (ICA) for the discrimination of three mental tasks for asynchronous EEG-based Brain Computer Interface systems.[25].

In another paper, the identification of features and its explanation is given. There are three features explained. Here the classification is given and the small mean square difference is explained, because of this the all points are coverd26].

The author Rizwan Bashirullah presents a brief overview of the hardware challenges and considerations in BCI systems.[27].

The Sebastian Bosse makes an overview over the shortcomings of conventional approaches, present the state-of-the art of BCI-based methods and discuss open questions and challenges relevant to the BCI community [28].

The Dan M. Dobrea, Monica C. Dobrea ,presents a new concept for a BCI bioinstrumental complex, namely the iBiAoRS - inspired from the HMS hierarchical organization and able to deal with the compromise between the online processing and the classification accuracy.[29].

In this paper Siamac Fazli, Sven D¨ahne, Wojciech Samek studies various types of data fusion techniques which are developed in now a days for BCI systems. They have focused on sensorimotor rhythm-based type of BCI systems [30].

Rajesh G N, Pavan Kumar E are aiming for VLSI design and testing of EEG acquisition system to acquire brain signals. Initially the low power and high gain generalized operational amplifier is designed.[31].

Lin Yao, Natalie Mrachacz-Kersting, Xinjun Sheng, investigated the performance of a multi-class brain-computer interface (BCI). The BCI system is based on the concept of somatosensory attention orientation (SAO), in which the user shifts and maintains somatosensory attention by imagining the sensation of tactile stimulation of a body part.[32].

In this paper the author M. Krauledat discusses machine learning methods and their application to Brain-Computer Interfacing. A particular focus is placed on linear classification methods which can be applied in the BCI context.[33].

IV. CONCLUSION

The paper provides the review of the various BCI systems .Different kinds of paths are developed to approach the BCI system and this paper gives the information about it and also provides the detailed information about software BCIs. There are three categories of BCIs were discussed, in addition to their relationships to modern BCI systems. Using this comparative study of BCI systems on can develop different application of human help , for research ,for entertainment etc. .

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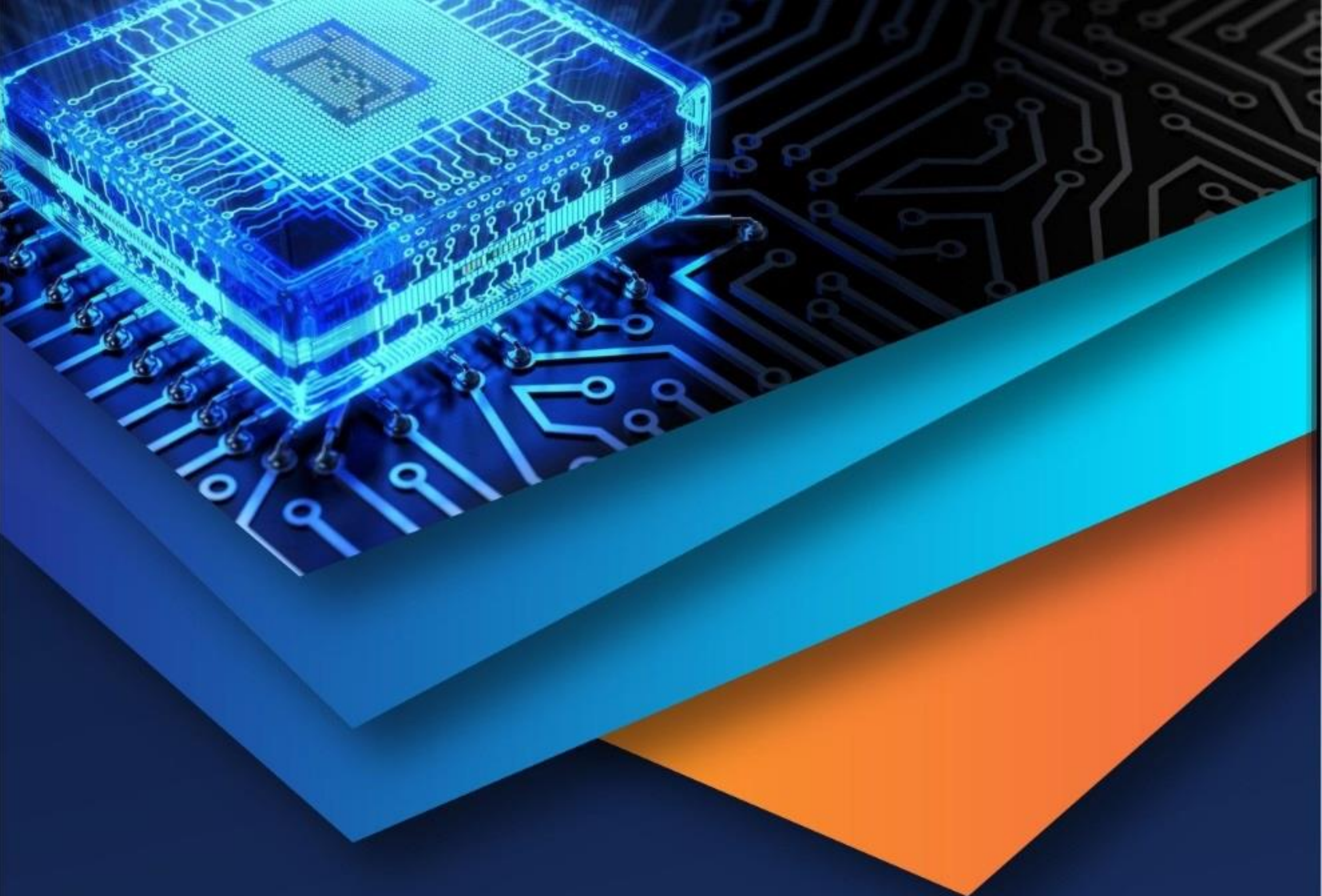

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