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Brain Computer Interfaces Using SSVEP: An Overview

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Abstract

Brain Computer Interface (BCI) can be defined as a co-system for communication between brain and computer. In BCI, for sending or receiving messages or commands to the computer person need not to do any muscular activities. Electroencephalography (EEG) along the scalp is the recording of electrical activity. The system is using EEG signals for the interface with brain to the computer. The extraction of information from brain is a very challenging task. Brain signals are mixed with other signals coming from a finite set of brain activities that overlap in both time and space. Steady-state visually evoked potentials (SSVEPs) are visually evoked potentials by external stimulus flickering at fixed frequency. The user visually fixes attention on a target and the BCI identifies the target through SSVEP features analysis. The increased SSVEP amplitudes reflect an enhancement of neural responses to a stimulus that falls within the spatial attention. This method is used for taking input as stimulus frequencies via SSVEP signals. SSVEP BCI gives a simple system configuration for users which need no training for use of the systems with higher information transfer rate. There is need of very little training for use of higher ITR and high accuracy for living environment.

Keywords: *Brain Computer Interface (BCI), Steady State Visual Evoked Potential (SSVEP), Information Transfer Rate (ITR).*

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1. Introduction

Brain Computer Interface (BCI) uses very uncommon way of communication with the system and brain. Though it is uncommon it is the most direct way as the intentions are directly sent to the computer. With a BCI person such as subjects ideally do not need to use common output pathways of peripheral nerves or muscles, which is the main function of a BCI system. Cerebro-electrical brainwaves are measured with the electroencephalography (EEG), which is used to have primarily used for clinical purposes in the past, with amplification and fed into a system under certain circumstances and with proper algorithms able to process them satisfy application needs [21]. BCI can be classified in two categories by input system; those two categories are synchronous and asynchronous BCI. In synchronous BCI, there is a predefined window is given in the system for a time variant. If there is any signal is generated outside that time window it is ignored by the system. This means that the user must use application in a specific time window which is specified by the BCI system. There are lots of advantages for the synchronous BCI, as

only predefined signals are allowed in the system no other artifacts can be generated because of the user's fault. This makes the system more reliable and simple. On the other hand, asynchronous BCI is more complex and demanding. Asynchronous BCI needs continuous processing of the data even though the action of user is not a proper command system will continue the process [4]. This is the reason that asynchronous mode is a more natural way of interaction to the human with computers.

There are two types of headsets can be used for the collection of the data. They are 10-10 and 10-20. The difference between two headsets is according to their separation of the electrodes. Electrodes in 10-10 system are having distance among them as that of 10% of the total headset while 10-20 system is having distance between electrodes as 10% for boundary electrodes and 20% for other electrodes of the headset. There are total 18-21 electrodes in 10-20 system while 31-38 electrodes in 10-10 system. In 10-20 system, we use less power than that of 10-10 system because of numbers of electrodes. Complexity in 10-10 system is more compared to 10-20 system and most of the electrodes in 10-10 systems are covered by electrodes of 10-20 system, because of these attributes generally most of the experiments are done with 10-20 system [2, 29].

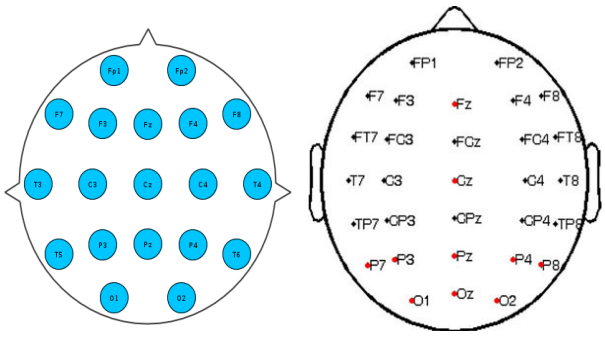

Fig. 1: 10-20 and 10-10 EEG headset

SSVEP-BCI offers the classification of a large number of symbols simultaneously and hence we can say that SSVEP-BCI is multiclass in nature and provides high performance. Visual evoked potentials (VEPs) are electrical potential differences; those can be derived from the scalps after a visual stimulus, for example a flash-light [28]. There are three types of VEP's in BCI time modulated VEP (t-VEP) BCIs, frequency modulated VEP (f-VEP) BCIs, and pseudorandom code modulated VEP (c-VEP) BCIs [14]. BCI t-VEP's having relatively very low information transfer rates i.e. less than 30 bits/min. There is high necessity of synchronous signals in t-VEP BCI. Frequency modulated BCIs having high information transfer rates i.e. 30-60 bits/min. They need simple system for configuration and it is more suitable for the applications which need few options. Pseudorandom code modulated VEP (c-VEP) BCIs are having very high information transfer rates i.e. greater than 100 bits/min. There is need of synchronous signals in c-VEP. It is suitable for applications which need many options. The drawback of c-VEP is that it needs user training for the use of applications while in other two BCIs user do not need or very low training required to use the applications [8].

There is a very high possibility of information transfer rate with minimal training time to the subject and very low requirements in SSVEP base BCI. Secondly if the system is carefully designed then it can be relatively robust with respect to noise and artifacts. The very important advantage is that we can easily extend the commands of the system because of the input process and short timing phase. The aim is to detect the reliably of frequency with the high accuracy. Furthermore the aim is to detect when the frequency is not present, hence when the person or subject does not look at the stimulus.

2. Methodology

A. Preprocessing

After the signal acquisition from the headset, it will be processed to identify the SSVEP response. However, before processing it, there would be several things to be done to preprocess the data to isolate the occipital channels and sanitize the signal. The SSVEP response should appear in all the channels and averaging to eliminate some of the noise and non-important differences between all the channels. This common average reference is an average number for all used electrodes of the required headset over the course of the signals for time. This helps to eliminate the unimportant signals from the needed signal by expressing lobe signal as variations from the overall EEG activity [18].

Artifacts are unwanted signals present in BCI. Artifacts have various origins, which include the utility frequency like noise, body and eye movements, or attention blinks. We can handle artifacts by three main approaches: avoidance, rejection and removal. By artifact avoidance the user should not execute any movement which may result in EEG artifacts. This can reduce artifacts, but obviously we cannot stop eye movements and blinks, so sometimes these artifacts may occur. Because of constant restraining from blinking by user can cause fatigue.

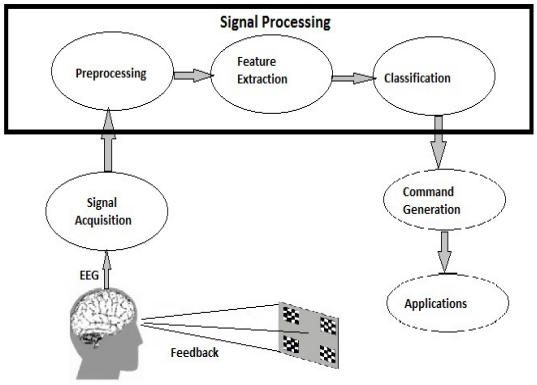

Fig. 2: Steps in generation of SSVEP signals

Another approach is the rejection of all trials which are introduced by artifacts. This can be done in any way manually or automatically. By a manual artifact rejection procedure, we determine which of the trials are introduced through visual examination and in automatic artifact rejection an algorithm may be implemented which is able to determine contamination of artifacts. Artifact rejection may reduce the size of the training set; this can lead to consequences in the classification accuracy [30]. High-pass filtering of the signal is the simplest method for artifact removal. The eye artifacts generally occur in the low frequency range of 0–4 Hz, we may reduce the EOG artifacts by filtering these components out.

There are two types of signal processing methods can be used in the SSVEP generation according to filtering types for preprocessing. Those are frequency filtering and spatial filtering. We can use any of these in our second step of preprocessing.

a. Frequency Filtering

The signals are filtered according to the characteristics of the frequencies related signals. We have two types frequency filtering, can use for the preprocessing of the SSVEP signals. They are Band pass filter and Notch filter. In Band pass filter, frequency range is designed according to the frequency harmonics or to the simulation frequencies. Band pass filter is relatively simple to implement but the drawback is that it may be very stringent for explaining the time-varying signals whereas Notch filter is used for removing the power line interferences.

b. Spatial Filtering

In spatial filtering, there is combination of signals from different channels to magnify the SSVEP responses. This can be done with the reduction of the interference of the noise. Signals from multiple channels are less affected by noise. The most affected signals are either unipolar or bipolar systems. This technique also can be used for the feature extraction techniques. Spatial filtering is classified techniques those are explained below.

i) Maximum Contrast Combinations (MCC): MCC is most frequently used method for spatial filtering. MCC tries to maximize ration between SSVEP and background signals. The computation for MCC is complex.
ii) Principle Component Analysis (PCA): For the decomposition of signals into components of SSVEP signals and brain activity we need to use PCA. The dimension of the original data can be reduced by the help of PCA.
iii) A Common Spatial Pattern (ACSP): ACSP method is based on the analytical representation of signals. Based on CSP method, ACSP reflects amplitude as well as phase information of SSVEPs.
iv) Component Average Filter (CAR): The average values of all the electrodes are subtracted from the channel of interest to make EEG recording nearly reference free.
v) Canonical Correlation Analysis (CCA): The relation between two multivariable data sets is computed by CCA after linear combinations of linear data. Other methods are KCCA, Multiway CCA and p-CCA. KCCA is used for the high dimension data sets. Multiway CCA uses optimal reference signals while p-CCA uses the phase information in reference signals.

B. Feature Extraction

Feature extraction is an important step in getting emotion assessment, because features with very high discriminative power are very crucial for efficient in pattern recognition. These are the most often used features which are computed from the signal's power spectrum [26]. The power of the EEG signals is used by the researchers at several frequency bands which may often range from 2 Hz to 45 Hz or a combination of the energy to different frequency bands, as it may be done by computing the ratio of energies with the help of left and right lobes to obtain indexes. ERP is only moderately using for a BCI as it is necessary to take the average of the signals over several trials of the same emotional class for obtaining reliable ERP [5, 28]. Feature extraction is key issue in the signal processing. A variety of feature extraction methods can be used for the system. Following are some typical methods used:

a. *Fourier Transform*

Fourier transform generally used for the power spectrum density analysis. Comparatively this method is simpler and can be used for the smaller computation time. We can use this method for stimulation frequency's power computation and harmonics for frequency coded SSVEP. Problem with this method is that it needs more time window for the frequency resolution.

b. *Wavelet Transform*

Wavelet transform is also based on Fourier Transform but the difference is that it can have adjustable time window. This helps to extract feature from non stationary signals like SSVEP.

c. *Value comparison*

If we are having some reference values we can set the target by comparing the values with the reference. We can use the threshold as the reference. For this we may have two situations: Maximum value and minimum value. Maximum value can be used for the power values and minimum values can be used for the phases. There are some basic steps in feature extraction:

a) Filtering of the signals using extraction filters.
b) Epoching on stimulation.
c) Epoching on time.
d) Sum calculations of the channels used in the system.
e) Computation of baseline data.
f) Classification of the data.

Some of the newer feature extractions filters other than band pass filters can be used in the designing of the framework are standard moving average filter (MA) and Savitzky-Golay filter. MA is used to analyze data points by creating calculations of a series of averages of different subsets of data sets. MA is also called a moving mean (MM). A Savitzky–Golay filter is a digital filter. This filter can be applied to a set of digital data points. This can be done for the purpose of smoothing the data by doing this, there is increase the SNR without greatly distorting the signal.

C. *Classification*

There are many classification algorithms can be used for the SSVEP generation process, but most effective are LDA, SVM and ANN. Linear Discriminant Analysis (LDA) is method used in pattern recognition and machine learning to find linear combinations of features those are characterized or separated by two or more classes of events or objects. The result may be used as a linear classifying combination or for dimensionality reduction before later classification [31]. Support Vector Machines (SVMs) supervise learning models along with associated learning algorithms in machine learning those analyze data and recognize patterns which used for classification and regression analysis. Within the given set of training examples, each marked as belongings to one of given categories [27]. SVM training algorithms build models those assign new examples into one of the category by making it as a non-probabilistic binary linear classifier [32]. In artificial neural network algorithm, with the help of Supervised Learning, the perception can be trained. It can be done by adjusting the weights of the inputs. In this learning technique, the patterns to be recognized are known in advance by subjects, and a training set of input values is already classified with the desired output [27, 33].

3. Applications

There are many real time applications based on SSVEP signals in a BCI system like gaming, neural message recovery from disabled person, moving the objects like vehicle or wheelchair etc. Some of them are discussed here:

A. Thought Translation Device

Malik et al. stated for the physically disabled person it is not possible to write or type their thoughts. This system using SSVEP subject can enter their thoughts in the system. There are total 28 buttons in the system. The buttons constituted keypad, representing the 26 alphabets, BACKSPACE, and ENTER. Users could input alphabets using their gaze on the buttons. By the

SSVEP coded frequencies the system can enter the letters thought by subject efficiently with high transfer rates [19].

B. Computer Gaming

It is a game in which an avatar is navigated by the player through a maze by using BCI. It analyzes the SSVEP responses recorded with EEG on the player's scalp. It is four-command control game specifically designed for an SSVEP-BCI. The game has high accuracy as that of 85% without any high level training. With accuracy there is high transfer rate as SSVEP is used [6].

C. Wheelchair Navigation

Brain-Computer Interface (BCI) based on the SSVEP can discriminate many classes once per second (Muller et al.). To extract the evoked response a statistical test is used and a decision tree is used for discriminate the stimulus frequency. Hit rates are 60-100% by the volunteers, and through an indoor environment using SSVEP, one of the volunteers can guide wheelchair. With additional feature, it incorporates a visual feedback. This is essential for improving the performance. All of these aspects allow using this BCI to command wheelchair efficiently [3, 22, 24].

4. Hybrid SSVEP based BCI

SSVEPs for brain computing require the use of different stimulus frequencies. Each of these frequencies is for different control options because of this there are increase in number of options Because of this frequencies become closer become multiples of each other, causing an increased error rate in the classification stage. By combining information we can offset the issue from more than one modality. With same frequency values we can show more options even in smaller range [9]. Methods of addressing the issue of multimodal fusion are proposed by many researchers. Rule based system for semantic fusion is very popular approach for use of multimodality. Because of the change in the performance of subjects or less in SNR classification accuracy in unimodal stimulation is low. By combining modalities these classification rates can be improved [1]. Stronger signals can be gained with the interactions between the different sensory. By cross-modal amplification multimodal stimuli provide stronger brain signals than unimodal stimuli, because of higher signal-to-noise ratio this will help for better classification [17, 20].

Multimodal Combination of BCI Paradigms with Consumer-Grade Hardware and Eye Tracking

Multimodal combinations of BCI and eye tracking in the context of a simple puzzle game involving tile selection and rotations using consumer grade EEG hardware. Eye tracking alone remains a more robust modality; the addition of BCIs with inexpensive hardware brings some interesting properties. The performance of Eye Tracking with SSVEP is quite close to that of unimodal eye tracking. Despite lower performance of Eye Tracking with Motor Imagery due to the limitations of the hardware, the interaction modality was natural [4, 13].

Multimodal interaction in the car: combining speech and gestures on the steering wheel

Implementing controls in the car becomes a major challenge. The use of simple physical buttons does not scale to the increased number of assistive, comfort, and infotainment functions. Hierarchical menus and multi-functional control devices increase complexity and visual demand. Speech control is not widely accepted, as it does not support visibility of actions, fine-grained

feedback, and easy undo of actions. By using speech for identification of functions; the visibility of objects in the car (e.g., mirror) exploits and simple access to a wide range of functions equals a very broad menu. Using gestures for manipulation (e.g., left/right), fine-grained control with immediate feedback and easy undo of actions are provided. In a user-centered process, a set of user-defined gestures as well as common voice commands are determined [10, 23].

Hybrid Type	**System organization**	**Device used to evoke visual stimuli**	**Frequency band**	**Visual Stimuli type**	**Ref.**	**Bit rate (bits/min)**	**Accuracy**
SSVEP+ Motion capture	Simultaneous	Game engine, 3D display device	-	3D graphics stimuli	[23]	-	86 %
SSVEP + Computer Vision	Simultaneous	Robot visual system, Stack of tasks controller	-	Light Stimuli, Graphics stimuli	[11]		80%
SSVEP + Gesture	Sequential	Hand recognition sensor, checker board	8-13 Hz	Light stimuli	[25]	9.54-28.34	95%
P300 + SSVEP + MIDI+ Open sound control	Sequential	Multimodal brain orchestra, checker board		Light Stimuli	[12]		72%
SSVEP+ Eye tracking	Simultaneous	Display device, LED, camera		Light stimuli	[15]	-	60-76%

5. Conclusion

In BCI, mostly there is preference to the SSVEP system. As it is Exogenous BCI and it requires very low training to use, it is possible for user to perform actions on the system by their convenience. Furthermore, SSVEP gives high information transfer rate, so, it is possible to use in real life also. Control signals can set up very easily so it is possible to use many options in one system using SSVEP. There are some disadvantages for the system; flickering visual stimuli may cause some fatigue or tiredness to the subject, if used for a long time. If the subject is having some neurological disorders like color blindness or similar disorder, it is not appropriate for a person to identify the color, frequency or pattern in the system. There is possibility of combining SSVEP signals with other Exogenous or Endogenous BCI signals. This can be done for the better performance, reliability of the system, robustness and more options to user.

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