



International Journal of Control Theory and Applications

ISSN : 0974-5572

© International Science Press

Volume 9 • Number 43 • 2016

Recent Trends in the Field of Brain Computer Interface Systems in Enhancing their Benefits

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Abstract: A Brain-computer Interface (BCI) system receives the brain signals and provides a communication without using muscular activity to its users to operate the external devices such as wheel chair, computer cursor, prosthetic limb etc. Research and development on both invasive and non-invasive BCI system has grown extensively over the past few decades. Though the performance of non-invasive Electroencephalogram (EEG)-based BCI system has improved over these years, they do not yet support wide usage in real world environment. Broadly these BCI systems suffer with a high degree of uncertainty. Recent research reveals that the deployment of Hybrid BCI systems in place of simple BCI systems are gaining popularity as they effectively address some of these drawbacks. This paper reviews some of the research papers on BCI system, which have appeared recently in prominent journals to gauge the new trends in enhancing the benefits of the BCI system applications in communication and operation of external devices with the users' intent.

Keyword: Non-invasive, Electroencephalogram, Hybrid Brain-computer Interface System, brain signals, muscular activity, High degree of uncertainty.

1. INTRODUCTION

A brain computer interface system is a device which connects the brain of the user with external devices such as cursor of a computer, a wheel chair or a prosthetic limb, without depending on the normal neuromuscular channels. BCI system aids and strengthens the sensory - motor functions of the users including severely disabled people, who cannot communicate via normal pathways [1]-[3]. There are two groups of BCI systems namely, (a) Non-Invasive types: Electroencephalography (EEG), Magneto encephalography (MEG), functional magnetic resonance imaging (fMRI), Near-infrared spectroscopy (NIRS) and (b) Invasive type: Electrocorticography (ECoG) or Intracortical Neuron recording [1],[3]. A simplified model of the BCI system is shown in Figure 1.

A BCI system consists of following steps: (i) Signal acquisition, (ii) Signal pre-processing, (iii) Feature extraction, (iv) Classification, (v) Translation into a command and (vi) Feedback [4], [5]. In majority of the Non-invasive BCI systems, EEG signal is used as the input signal. The EEG based BCI systems are further

classified depending on the control signals like event-related de-synchronization/synchronization (ERD/ERS), steady-state visual evoked potentials (SSVEPs), P300 component of event related potentials (ERPs), and slow cortical potentials (SCPs) [1], [3] & [6]. A user controls an output device with the help of a BCI system by producing the required brain signal patterns which will be detected and converted into device commands using suitable algorithms. Thus, the main purpose of any BCI system is to transform the intent of user into a command for operating a computer or an output device [7]. In SSVEP, repetitive visual stimulations are used to get evoked response in EEG signal. For this purpose, discrete frequencies are allotted to the repetitive stimuli of SSVEP paradigm. Later, they are detected by computing the frequency spectrum of the output EEG signal. Depending on the focus of the subject on the stimulus, a peak appears in the frequency spectrum coinciding with that of the stimulus frequency. The intent of the user can be known by finding this frequency which is then translated into a command signal for a BCI system. But the inherent issues with SSVEP BCIs are: (1) it is gaze dependent and (2) focusing on the flickering stimulus is annoying and tiresome for some users.

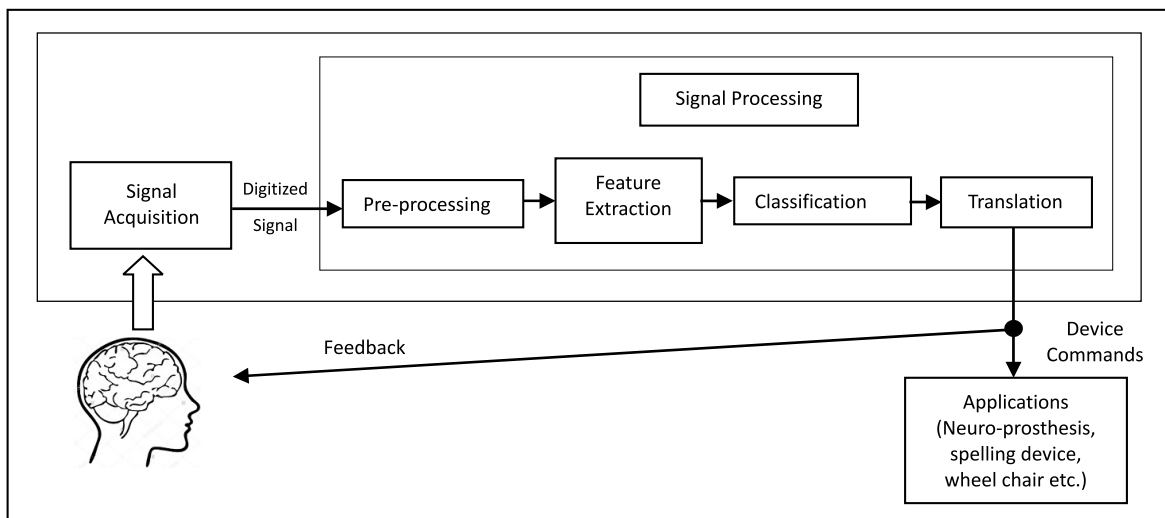


Figure 1: Simplified model of the BCI system

However the advantages with SSVEP BCIs are that they achieve higher information transfer rate and the requirement of training for the user is minimal [3], [6] & [2]. Sensorimotor rhythms are oscillations in the brain activity corresponding to the mu band (8–12 Hz), called mu rhythms, and beta band (13–24 Hz), called beta rhythms [8]. ERD occurs predominantly by motor imagery of movements over the contra lateral brain motor area, hence it is used as a signal for a BCI system [9], [10]. In BCIs based on P300, subject's intention is measured using the P300 component which is an evoked response. After the onset of stimulus, deflections that take place are referred to as event-related potential (ERP) components. The exogenous components occur until about 150ms after the eliciting stimulus. The endogenous components have longer latency. The amplitude of the P300 is depend on inter stimulus interval time and the frequency of the odd ball stimulus [3], [2] & [11].

P300 based BCI's have lower accuracy and lower information transfer rates. SCPs are slow voltage shifts in the EEG, SCPs have very low frequency below 1Hz they can occur from 300ms to over several seconds, and are related with changes in the level of cortical activity. Reduced Cortical activity is related to positive SCPs while the Negative SCPs are usually produced by movement. These brain signals can be self-regulated by users to control external devices by means of a BCI [12], [13]. SCP-based BCIs provide the rate of information relatively low with high probability of error. SCP-based BCI require longer period of training and also regular practice for several months [1], [3] & [14]. The following table lists some of the control signals used in EEG based BCIs with their main features.

Table 1
Details of Control Signals for BCI and their Main Features

Control Signals	Physiological Phenomena	User Training	Information transfer rate (bits/min.)
VEP	Signal Modulations in the region of Visual Cortex	No	60-100
SCP	Slow voltage shift in the brain signals	Yes	5-12
P300	Positive peaks due to infrequent stimulus	No	20-25
Sensorimotor rhythms	Due to motor activities	Yes	3-35

BCI systems can be classified depending on the nature of brain signal as exogenous or endogenous. Exogenous BCI is generated by an external stimulus whereas Endogenous BCI is self-regulation of brain rhythms and potential without external stimuli. Table II shows the differences between exogenous and endogenous BCIs.

Table 2
Exogenous and Endogenous BCIs and their Differences

Approach	Brain signals	Advantages	Disadvantages
Exogenous BCI	1. SSVEP 2. P300	<ul style="list-style-type: none"> • Training is minimum • Control signals can be obtained quickly and easily. • Bit rate is High • Only single channel of EEG is required. 	<ul style="list-style-type: none"> • More attention to external stimuli • It may cause tiredness to some users.
Endogenous BCI	1. SCPs 2. Sensorimotor rhythms	<ul style="list-style-type: none"> • Stimulation is not required • Operated at users free will • Sensory organs affected users are benefited. • Suitable for cursor control applications 	<ul style="list-style-type: none"> • Training might be weeks or months • All users couldn't be able to obtain control • For good performance Multichannel EEG recordings are required • Lower bit rate (20-30 bits/min)

Thus, it is seen that each BCI type has its own shortcomings and advantages. A hybrid BCI, combines either two types of BCI systems or one BCI system with another non BCI-based system, for example, EMG-based system [15], [16] & [17]. Block diagrammatic representation of the various methods used in implementing Hybrid BCI is shown in Figure 2.

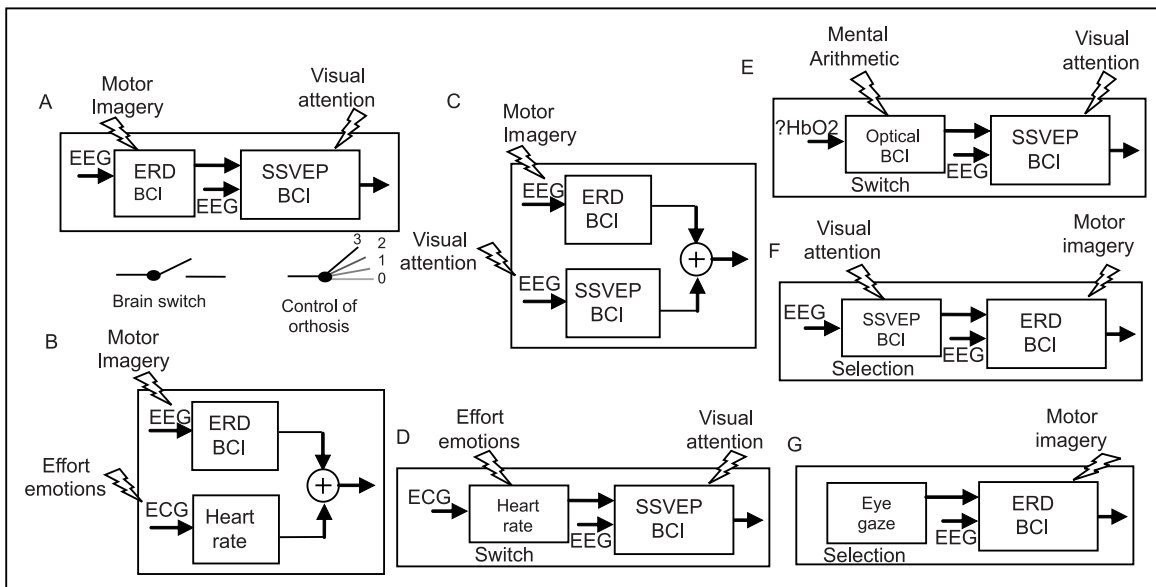


Figure 2: Methods of Hybrid BCI [19]

There are two ways of combining the systems to form a hybrid BCI system, namely sequential and simultaneous. By sequential combination many difficult tasks can be distributed in many series stages and combining different systems of BCI leads to more complication than a single BCI. Hybrid BCI, by the paradigm design plays a vital role to improve the performance of the system. Similarly, A BCI system with a non-BCI, can give better results [18], [19]. Further, some researchers have focused their research on investigating algorithms to improve the accuracy in feature extraction and classification of EEG signal [20], [21].

2. REVIEW OF RECENT PAPERS ON BCI

In this paper, various types of BCI systems including Hybrid BCIs and some innovative algorithms used in the feature selection and classification that appeared in the recent past in research journals are reviewed. **Jun Lu** et. al., [21] focused on Movement Related Potentials (MRP) feature extraction and prediction in EEG-based BCIs. MRPs of EEG are subject specific and involves huge amount of noise such as the visual α rhythm, muscle activity and eye blinks, which is a challenging problem for signal processing. The MRP is more informative about 500 ms before onset of the movement. In this paper an Adaptive Spatio-Temporal (AST) filtering algorithm has been proposed for the feature extraction and classification to adapt to variations between subjects. AST filter was compared with other algorithms such as (1) Discriminative Spatial Pattern (DSP) filter and (2) Regularized Spatio-Temporal (RST) filter. DSP filter is a spatial filter which transforms the raw EEG signal into temporal sequences such that within any particular class, the variance is minimized and between any two classes the separation is maximized. RST filter performs average of potentials of each time window to reduce the feature dimension. This is like low pass filtering and then estimates the projection of the feature vector ignoring the spatial-temporal structure. On the other hand, the proposed AST algorithm can address classification and also regression problems by building a low-pass temporal filter with Gaussian kernel and builds the spatial filter with the linear ridge regression (LRR) algorithm. It extracts meaningful information and it is tested offline without feedback. This approach directly classifies the raw EEG signal. As the intersession variability of the MRP may be large, if the interval between the sessions extends to several days or weeks, the proposed AST method cannot effectively address this problem.

Tianyou Yu et. al., [22] proposed a hybrid BCI system that provides continuous feedback based on the hybrid features of MI and SSVEP for MI training such that it reflects subject's intention more accurately. Generally, the task-specific differences of MI signals are to be enhanced suitably to provide reliable EEG control, by giving many sessions by feedback training. To evoke SSVEPs during MI tasks the subject must focus on flickering buttons during the initial training sessions. Common Spatial Pattern (CSP) is applied for MI discrimination and Canonical Correlation Analysis (CCA) is applied for SSVEP feature extraction. By the combination of SSVEP and MI features, the classifier provided feedback with better discriminative capabilities. Hence feedback is maintained accurately. Experimentally the efficacy of the proposed system was validated in the entire training period. However, other alternatives using non visual attention, like auditory attention can be explored for patients or end-users who face difficulty in focusing their eye-gaze. In spite of obtaining the results with healthy participants, studies should be conducted with patients who have impaired motor function.

Erwei Yin et. al., [23] proposed a new hybrid BCI with 64 selectable targets of 8 x 8 matrix. The hybridization of the paradigms using row/column (RC) P300 and 2-step SSVEP is done in two different ways such as (1) Double RC (DRC) and (2) 4-D modes. The P300 paradigm for Double Row Column (DRC) and 4-D hybrid BCI modes is same, but it differs in frequency arrangement for 2-step SSVEP. For P300 feature extraction,

Step-wise linear discriminant analysis (SWLDA) is used to obtain P300 classifier weights, which are then multiplied by the down-sampled epoch to get row flash and column flash P300 scores. For SSVEP feature extraction, canonical correlation analysis (CCA) approach is used. The Maximum-Probability Estimation (MPE) fusion approach shows better performance in accuracy and ITR. The 4-D paradigm has accuracy of 95.18% and the DRC paradigm has 91.33% of accuracy, hybrid approach yielded more consistent results. As admitted in this paper, the proposed Hybrid BCI needs more powerful stimulus mechanism, an adaptive calibration approach and redesign of the graphical user interface (GUI) to add real keyboard functions for use in real-time applications.

Jinyi Long et. al., [24] proposed a hybrid BCI paradigm to provide directional and speed control commands to a simulated or real wheelchair. For manoeuvring the wheelchair, the left and right hand imagery of the user are utilized for left and right direction commands respectively and to control speed a hybrid paradigm is used. To accelerate, without imagining any movement, user has to concentrate on a particular flashing button. To decelerate, the user imagines foot movement only. Linear discriminant analysis (LDA) classifiers are used for further classification. There are two feature extractions for speed detection (1) Feature extraction of motor imagery detection from EEG signal (8-32Hz) and (2) The P300 potential detection from EEG signal (0.1-8 Hz) and they can be obtained by using CSP methods. After extraction they are combined using a combination algorithm followed by LDA classifiers for necessary classification. Both the experiments have been demonstrated. The results showed that for all the five subjects, the average classification accuracy rate (ACC) is more than 71% in discrimination. However, it is very important to have an effective and fast stop command in the BCI control system of a real wheelchair which needs to be developed.

Erwei Yin et. al., [25] proposed a dynamically optimized SSVEP speller. The speller uses a Row/Column(RC) paradigm with 36 selectable items employing only 6 frequencies, between (8Hz and 14.99Hz), in the design of a periodic stimulus mechanism. A real-time biofeedback mechanism to increase attention on the visual stimuli is implemented by using Practical Information Transfer Rate (PITR). The dynamic optimization approach is implemented in this SSVEP speller design. In the SSVEP signal processing, though Canonical correlation analysis (CCA) achieves better classification performance, misspellings still occur due to the inter-frequency variation. To address this issue, CCA-RV (RV: reducing variation) method is implemented. In SSVEP spelling process to achieve better classification accuracy longer stimulus time is required which leads to lower spelling speed. If higher spelling speed is required, then stimulus time should be reduced. But then the classification accuracy is poor. The dynamic optimization approach gives the average PITR (41.08 ± 7.43 bit/min) across all subjects which is greater than the fixed optimization approach (37.71 ± 7.50 bit/min). Still there are a few shortcomings like error-related potentials, a mistake in row and column detections would lead to misspelling. For robust performance, error-related potentials (Err Ps) need to be incorporated into the proposed SSVEP speller to improve the spelling accuracy.

Feng Duan et. al., [26] proposed a hybrid BCI system, wherein, the robot movements namely, forward movement, left turn and right turn are controlled by three SSVEP signals. Three flashing squares are used as visual stimuli for SSVEP and their flickering frequencies are 8Hz, 10Hz and 12.5Hz. To generate Motor imagery signal, one has to visualize lifting up his feet. The Mu rhythms (8-12Hz) generated at the somato-sensory area increase largely whenever the user closes his eyes and this property is utilised to implement a brain switch for selecting the SSVEP signals and motor imagery signals for their respective tasks. It also discusses Canonical Correlation Analysis (CCA) Method for SSVEP classification. Further, Discrete Short-Time Fourier Transform method is used for EEG signals. The proposed system is to control a simulated wheel-typed robot and an actual humanoid robot for the execution of manipulation and mobility tasks. Simulation results show that the rate of correct recognition of the MI is 100%, while that of SSVEP and mu Rhythm are 91.8% and 86.7% respectively. In

case of actual humanoid robot, the rates are 89%, 86.7% and 93.3% for SSVEP, mu rhythm and MI respectively, which are higher compared to old methods. Similarly, with the use of this Hybrid BCI, the total number of commands has been increased to five to control the Robot to execute the basic mobility and manipulation tasks. On the contrary, there is untapped potential to increase the number of commands by incorporating the MI signals for Left and Right hand. Further, for improving the stability of the system there is a need for applying adaptive algorithms. Additionally, force feedback, obstacle avoidance and Robot navigation units would improve the performance still further.

Jinyi Long et. al., [27] proposed a Hybrid BCI based on P300 potential and Motor Imagery for target selection in 2-D cursor control. The hand motor imagery controls horizontal movements and the P300 potential controls the vertical movements of the cursor. The idle state of MI with P300 and MI with non-P300 are the two classes of Hybrid features used to select a target or to reject a target respectively. The experimental results of the classification accuracy with the proposed Hybrid features are compared with MI only and P300 only conditions and the results indicate that the average accuracy of classification of the intended commands is better (93.99%) with the Hybrid features than that obtained with either MI only or P300 only methods. Further, the online experimental results showed that using the hybrid feature, target selection or rejection process within 2s for all subjects which are not possible using only a P300. In the proposed system, 30 channels are used for signal processing, whereas the number of channels can be reduced to a large extent. Only two signals (left and right-hand) Motor Imagery are used whereas another signal relating to foot MI is not derived resulting in lesser commands available.

Erwei Yin et. al., [28] proposed a novel speedy hybrid BCI spelling approach by simultaneously utilising the P300 and SSVEP detection techniques. In this method the 2-d coordinates of the target symbol are derived by P300 and SSVEP signals. In addition to this, two types of BCI paradigms, the subarea/location (SL) and row/column (RC) modes implemented on a 6 x 6 matrix have been used. In the SL mode, the SSVEP feature is identified with the subarea in which the target item lies and the P300 feature is identified with the location of the target and in the RC mode grouping the flashing items into rows and columns. The target character is determined by row-column intersection which is detected by the SSVEP and P300 signals. The two modes are evaluated with offline and online performance by using the proposed hybrid approach and the results show that the RC mode is better than the SL mode. The simultaneous application of P300 and SSVEP signals selects the target character. Therefore, the spelling of 36 items is achieved by using six flash codes for the P300 and six frequencies for SSVEP as against 12 flashes per trial with a conventional speller using P300. In real-life environments, users should have the option for issuing the commands at their discretion. For this purpose asynchronous control is to be introduced. Since the proposed BCI is a type of gaze-dependent BCI, further investigation is required to design a gaze-independent BCI.

Xinyi Yong et. al., [29] proposed hybrid BCI system, combining an eye-tracker and a two-state self-paced system for text-entry applications for disabled people, who can still control their eye movements to some extent. For making text-entry of a word/letter, the user is required to look at the target for a specified minimum time duration which is called the dwell time and then the self-paced BCI can be activated by attempting hand extension. For typing a word/ letter, the user moves the cursor to the target with the help of his eye movements and activates the self-paced BCI by performing an attempted hand extension. Once the hand extension movement is detected by the BCI, the target gets selected. The experimental results of the proposed hybrid BCI have indicated a reduced time-normalized False Positive Rate (TNFPR) compared to a pure self-paced BCI. The proposed system uses the 'debounce block' and the dwell time. If these are not selected appropriately system speed gets reduced and further research is required to use smaller dwelling time by improving the performance. By designing improved algorithms for artefact removal and feature extraction, the performance of the system can be improved. Lastly

at the application level, the typing speed has to be determined using online trials to check whether the speed attained is satisfactory.

Lin Yao et. al., [30] proposed a hybrid (BCI), in which left and right mental tasks are discriminated in better way by combining MI with selective sensation, e.g., the classification between left/ right stimulation sensation and MI. Vibro tactile stimulation is given to the subject's both wrists, and every subject has to perform any of the four mental tasks, i.e., right/left stimulation sensation, left/right hand MI. Selective attention modulates somatosensory oscillations in alpha, beta bands, resulting in increased beta ERD/ERS due to attention effects, motor imagery of hand movements accompanies contralateral ERD and ipsilateral ERS. In the proposed experimental setup external vibrotactile stimulation is applied to induce cortical activity through the afferent neural pathway to perceive stimulation.

In results, the proposed hybrid method gives (83.1%) ACC compared to MI (71.9%) or SS (72.6%). In the hybrid mode, the discrimination between left stimulation sensation and right MI is 4.3% higher on average than the one between right stimulation sensation and left MI. A multiclass BCI system can also be formed by the proposed hybrid modality BCI. The proposed BCI is suitable for users who lack control on their volitional gaze for using a BCI based on P300/SSVEP. In the proposed discrimination of the four-class BCI, still there is scope for improvement by better algorithms and improved experimental design. Table 3 lists some of the approaches related to application.

Different types of approaches are chosen depending upon the end-user applications. For enhancement of accuracy, Practical Information Transfer Rate (PITR) and end-user compatibility, proper choice of design-paradigms, algorithms and input signals (as those mentioned in Table 3) has to be made. The advantages and disadvantages for different approaches related to end-user application are shown in Table 4.

Table 3
Comparison of Algorithms for Different Input Signals

S. No.	Author	Year	Input Signal	Algorithm	Application
1	F. Duan [26]	2015	SSVEP, MI	CCA	Movement and Grasp task by Humanoid robot
2	T. Yu [22]	2015	SSVEP, MI	CCA, CSP	Enhancement of MI training
3	E. Yin [23]	2015	P300 & SSVEP	SWLDA, CCA	Enhancement of accuracy and ITR
4	E. Yin [25]	2015	SSVEP	CCA-RV	Improving accuracy and PITR
5	L. Yao [30]	2014	MI, SSSEP	CSP, LDA	Enhancement of classification accuracy by using MI cue paradigm and selective sensation
6	J. Lu [21]	2014	MRP	AST, LRR	Enhancement of accuracy in prediction of signal by using algorithm
7	E. Yin [28]	2014	P300 and SSVEP	SWLDA, CCA	Enhancement of Accuracy and PITR
8	J. Long [24]	2012	P300 and MI	LDA, CSP	Motion of simulated & actual Wheel chair
9	J. Long [27]	2012	P300 and MI	CAR, SVM, CSP	To control a cursor on a monitor screen
10	X.Yong [29]	2011	Eye-tracker, Self paced BCI	SWLDA, LDA	To make a Text Entry of a letter/Word by Point-and-click system

Input Signals: SSVEP-steady state visually evoked potential, MI-Motor Imagery, SSSEP-steady state somatosensory evoked potentials, MRP-movement related potential.

Algorithms: CCA- canonical correlation analysis, CSP-common spatial pattern, SWLDA-step-wise linear discriminant analysis, RV- reducing variation AST-adaptive spatial temporal, LRR-linear ridge regression, SVM-support vector machine.

Table 3
Different approaches: Advantages and Disadvantages

<i>S. No.</i>	<i>Author</i>	<i>Year</i>	<i>Input Signal</i>	<i>Advantages</i>	<i>Disadvantages</i>
1	F. Duan [26]	2015	SSVEP, MI	Rate of correct recognition of the MI is 100%	Less Stable
2	T. Yu [22]	2015	SSVEP, MI	Better Discriminative Capabilities	Not feasible for users who have difficulty in focusing their eye-gaze
3	E. Yin [23]	2015	P300, SSVEP	It yields more consistent results	Needs more powerful stimulus mechanism
4	E. Yin [25]	2015	SSVEP	It shows improved performance compared to traditional BCI approaches.	Error-related potentials need to be incorporated into the proposed SSVEP speller to improve the spelling accuracy.
5	L. Yao [30]	2014	MI, SSSEP	It is useful for users who lost volitional gaze control for setting up a P300 or SSVEP based BCI	Need improvement through advanced classification algorithms and experimental design
6	J. Lu [21]	2014	SSVEP, MI	More accurate Predictions, solves classification problems	It doesn't address the inter-session variability problem ("covariate shift").
7	E. Yin [28]	2014	P300, SSVEP.	High ITR, Spelling Error is very less.	Not suitable for patients without the eye movements.
8	J. Long [24]	2012	P300, MI	Classification accuracy is 83.1%	Effective and fast stop command is required.
9	J. Long [27]	2012	P300, MI	Classification Accuracy is of 93.99%.	Less command signals (Left & Right hand Motor Imagery) only.
10	X.Yong [29]	2011	Eye-tracker, Self paced BCI	The number of False positives per minute is reduced.	The speed of the system is slow because of Dwell time.

3. DISCUSSION

While the Non-invasive EEG based BCIs have come a long way over the last few decades in translating the desired intents of the user for communication and operating output devices/assistive devices such as wheel chairs, prosthetic limbs, 2D cursor etc., yet their use is getting restricted by the drawbacks which the present BCI systems suffer from. The P300 mechanism depends on the odd-ball paradigm, and therefore its accuracy increases if the occurrence of the odd ball is very rare which in turn leads to low information transfer rate (ITR). Whereas, an SSVEP BCI can offer higher ITR but it is gaze dependent and the flickering stimuli is not only annoying but also produces fatigue to the user. The use of other BCIs which are based on SCP, SMR and MI is also affected by low ITR, fewer numbers of commands and requirement of extensive training. Thus, these conventional BCIs do not find wide use in real-world applications.

Adaptive algorithms play very vital role in improving the accuracy of the BCI. The EEG patterns of every user are unique and can change depending on the user's mental state and the circumstances in which the user is situated. Therefore, the applications, in general, require calibration through training procedures in order to learn the EEG patterns of the users. But, at the same time, long spells of training will be tiresome and lead to deterioration in the accuracy. By adding suitable adaptive classification algorithms to BCI systems the accuracy of applications can be improved without the necessity of longer training periods.

The Hybrid BCIs, on the other hand, are offering better advantages over a conventional BCI. E. Yin [23], proposed the fusion of P300 and SSVEP scores are used and it is shown that the Maximum Probability Estimation of the Fusion method yielded better accuracies and higher ITR. But it needs more powerful stimulus and adaptive calibration approach. J. Long [24], proposed a Hybrid BCI combining ERD/ERS of the sensory motor rhythms and P300 potential to control the direction and speed of wheelchair is proposed. Though it achieved higher classification accuracies, it lacks an effective and fast stop command. Whereas X. Yong [29] proposed another

hybrid BCI, combining an eye-tracker and a two-state self-paced system for text-entry applications for disabled people suffering from high-level spinal cord injury (SCI). J. Lu [21], proposed an adaptive Spatio-temporal filtering of MRPs is proposed which outperforms DSP and RST filtering in extracting the intended commands of the user from the MRPs. Since the intersession variability of the MRPs increases with long intervals of several days, the proposed AST method has its own limitations.

4. CONCLUSION

It can be concluded from the above discussion that the conventional EEG based BCI systems which use one of the endogenous or exogenous signals as control signal have come a long way to evolve in helping the users, particularly severely disabled people, who are unable to use their normal pathways of communication in communicating and controlling their environment through their brain waves. But their use is getting restricted because of the drawbacks which are inherent to these BCI systems. Hybrid BCI systems with sequential or simultaneous combination methods, on the other hand, have proved superior performance over the conventional BCIs by improving the accuracy, information transfer rate, stability and also reducing the training periods. However, there is a constant need for further improvement through innovative methods of hardware implementation for suitable hybrid BCIs and developing intelligent adaptive algorithms for enhancing their benefits and overcoming the drawbacks. These hybrid BCIs should be more acceptable for their wide spread usage by the users including physically impaired persons in real-world environment for communication and control.

Acknowledgment

I would like to thank Mr. G. Muthukumaran, Mr. P. Vikram Kumar and Mr. P.S. Nagabhushanam for their continuous encouragement, support, inspiring thoughts and ideas for the BCI related real time application works.

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