Title: Recent advances in hybrid brain-computer interface systems: a technological and quantitative review

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Runnig Titel: Recent advances in HBCI systems

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the number of text pages :18 pages
the number of figures and tables: 5 figures and 2 tables

To appear in: Basic and Clinical Neuroscience

Received date: 2017/06/6
Revised date: 2018/05/29
Accepted date: 2018/05/29

Please cite this article as:
Sadeghi, S. Maleki, A. (In Press). Recent advances in hybridbrain-computer interface systems: a technological and quantitative review. *Basic and Clinical Neuroscience*. Just Accepted publication May. 29, 2017

Abstract

Brain-computer interface (BCI) is a system that enables users to transmit commands to the computer using only brain activity measured by electroencephalography. In a hybrid brain computer interface (HBCI), to increase classification accuracy, increase system speed and improve user satisfaction, a BCI control signal combines with one or more BCI control signals or with human machine interface (HMI) biosignals. HBCI systems are categorized according to the type of combined signals and the combination technique (simultaneous / sequential). They have been used in several applications such as cursor control, target selection and spellers. Increasing the number of articles published in this field indicates the importance of these systems. In this paper, different HBCI combinations and their important features in potential applications have been discussed. In most cases, the combination of a BCI control signal with a HMI biosignal yields higher information transfer rate than two BCI control signals.

Keywords:
Brain computer interfaces, BCI control signal, human machine interface biosignal, simultaneous and sequential HBCI.

1. INTRODUCTION

A brain-computer interface (BCI) system provides a non-muscular communication channel by creating a direct path between brain and computer with the aim of communicating with environment for people who suffer from severe paralysis, muscular atrophy, amyotrophic lateral sclerosis or brainstem stroke. BCI consists of sensors and signal processing tools that directly converts brain activity into commands or messages (Müller-Putz et al., 2012; Guger, Allison & Müller-Putz ,2015). The block diagram of the BCI system has been illustrated in Fig. 1. Brain activity will be measurable using several approaches such as electroencephalography, Magnetoencephalography, functional magnetic resonance imaging, Electrocorticography and near-infrared spectroscopy (Amiri et al., 2013).

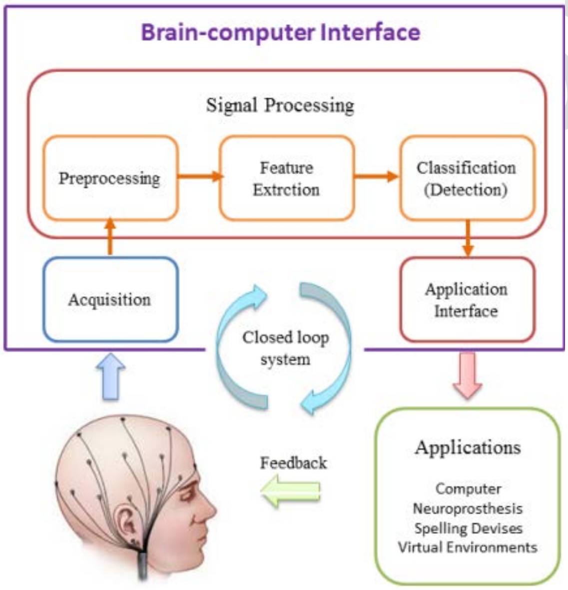

Figure 1. Block diagram of a BCI system (Graimann, Allison et al. 2010).

Often, electroencephalogram (EEG) signal is considered as the input in most BCI systems. EEG electrodes are placed on the scalp and special devices record the electric field of neural activity. Six brain rhythms can be distinguished in EEG signal based on the differences in frequency ranges: delta (1- 4 Hz), theta (4-7 Hz), alpha (8-12 Hz), mu (8-13 Hz), beta (12-30 Hz) and gamma (25-100 Hz). Delta rhythm includes all rhythms below 3.5 Hz and it happens during deep sleep, in children and the brain signals of peoples with brain disorders. Theta rhythm is further acquired from temporal and parietal areas and it is visible in children and some adults at the time of stress, disappointment and heartbreak. Alpha rhythm occurs in awake and eyes closed relax condition. It is significantly recorded from the occipital lobes but it can also be acquired from parietal and frontal regions. This rhythm completely disappears during sleep and when the subject been attracted to a particular mental activity in the waking state, it is replaced with asynchronous waves with higher frequency and lower amplitude. Beta rhythm is more acquired from parietal and frontal areas. It takes place at frequencies as high as 50 Hz in severe brain activity. It is divided into Beta I and Beta II. Beta I with the frequency of about twice as alpha rhythm, is influenced by similar mental activities affecting the alpha rhythm. Beta II appears in the central nervous system during intense activity and in times of stress. The alpha activity recorded from sensory-motor areas is called mu activity. Gamma rhythm acquired from somatosensory cortex is involved in high-level tasks such as cognitive functions and it is important for learning, memory and data processing (Amiri et al., 2013; Bharne et al., 2015).

In general, BCI systems are categorized based on the brain activity patterns into four different types: P300 component of event related potential, steady-state visual evoked potential, slow cortical potential and event related synchronization/ desynchronization.

P300 is an event-related potential (ERP) that appears approximately 300 milliseconds after a visual, auditory or tactile stimulation. Since P300-based BCI systems are vulnerable against noise, they require averaging of ERP responses from several stimuli. This will reduce speed and information transfer rate (ITR). These systems also need less training and they have high validity among users and patients (Fazel-Rezai & Ahmad, 2011; Fazel-Rezai et al., 2012; Wolpaw & Wolpaw 2012).

Visual evoked potentials (VEP) are brain oscillations that occur after receiving a visual stimulation. Steady-state visual evoked potential (SSVEP) is a kind of VEP that occurs in response to stimulus with frequency higher than 6 Hz. Although higher stimulation frequencies reduce fatigue and discomfort, the recognition of the signal will be challenging. In general, SSVEP-based BCI systems have many advantages such as better classification accuracy, higher ITR and fewer numbers of required electrodes, compared to other methods such as P300. These systems do not also need training and if necessary, the required time for training will be very little. Although SSVEP-based systems are faster than systems based on P300, but they have shortcomings such as inappropriate for patients with epilepsy, requirement of precise control of eye muscles and the need for high-speed hardware (Guger et al., 2012; Guger, Allison & Müller-Putz, 2015).

Slow cortical potentials (SCP) are negative slow potential changes in EEG signals acquired in an imagined or actual movement from sensory-motor cortex of the brain (Allison, Faller & Neuper, 2012). These potentials belong to the part of EEG signals with frequencies less than 1 Hz and they are reflection of cortical polarization. The use of these potentials is limited because of reasons such as long duration training time, high error risk and poor dimensional control.

Mu and beta rhythms both recorded from the sensory-motor cortex are caused by sensory stimulation or motor behavior. These rhythms include two types of amplitude fluctuations named event-related desynchronization (ERD) and event-related synchronization (ERS). A voluntary movement causes a limited asynchronicity in the lower bands of mu and beta that is named ERD and it takes place about 2 seconds before starting movement. In fact, the decrease in neuronal synchronization will reduce power in specific frequency bands and eventually reduction in signal amplitude. After a voluntary movement, with an increase in synchronization of neurons, the power will be increased in brain rhythms and it reaches to its maximum level, 600 milliseconds after the movement that is called ERS. The motor imagery (MI) is also a way to change in ERD/ERS and it is desired in BCI applications. This method requires more training and may not work on some subjects (Pfurtscheller & Da Silva 1999).

From another perspective, BCI systems are categorized into synchronous and asynchronous. In a synchronous system, the extraction and processing of signal features are prescheduled. It is based on the protocol that defines the `starting and ending of each operation with specified duration. In an asynchronous system that is also named automated system, feature extraction and processing are not necessarily follow a fixed schedule.

2. HYBRID BRAIN COMPUTER INTERFACE SYSTEMS

Since a BCI system based on one method may not work on all subjects, the hybrid brain-computer interface (HBCI) system has been introduced and this area has been of interest to many researchers over time.

In this paper, we reviewed and analyzed the current state-of-the-art HBCI studies. In this review, articles were sought out from the Google scholar database. Inclusion criteria were journal articles written in English from 2010 to December 2016. Other publication forms (e.g., books, proceeding papers, master's and doctoral dissertations, unpublished working papers, newspapers, etc.) were not included. Keywords used in search engines were, "Hybrid" and "Brain computer interface", "Hybrid" and "Brain machine interface", "Brain computer interface" and "Electroencephalography", "Brain computer interface" and "Electrooculography", "Brain computer interface" and "Electromyography", "Brain computer interface" and "Near-Infrared Spectroscopy", "Brain computer interface" and "evoked potential" or "Brain computer interface" and "Steady-state somatosensory evoked potential". After conducting the keyword search, some papers were found more than one time with different keywords. So duplicates were removed. Fig. 2 shows the total number of articles published in different years based on Google Scholar database. It was about 13 articles in 2010 and this number significantly rose in the following years. The total number of 60 articles and 61 articles were published in this context in 2015 and 2016, respectively. Increasing the number of articles published in the area of HBCI, indicates the high efficiency of these systems.

In a hybrid brain-computer interface, a BCI control signal combines with one or more BCI control signals or with human machine interface (HMI) biosignals. HBCI systems are categorized according to the type of signals that are combined and the combination technique (simultaneous / sequential). In simultaneous combination, the systems work concurrently with each other, while in sequential combination, they act as time-sharing. In a sequential combination, the target is selected among several options by the first system and the second system does the process on the choice. A comprehensive block diagram different modes of system operation is presented in Fig. 3. This figure completely describes the concept of system operation in both modes, simultaneous and sequential. The timing of stimulation in operation modes is depicted in this figure.

In general, the most important goals of combining signals in HBCI systems are increasing classification accuracy, enhancing system speed, improving user satisfaction and overcoming the disadvantages of BCI systems. In contrast, most of these hybrid systems are associated with greater complexity.

3. TYPES OF HBCI SYSTEMS

Until now, different combinations have been employed in HBCI systems. Fig. 4 shows the number of articles published in different years based on type of combination, derived from Google Scholar database. This figure indicates that in the early years of the use of HBCI systems, the combination of BCI control signals has been used in various studies. Over time, the combination of BCI control signals with HMI biosignals has also been taken into consideration. This figure shows the gradual increase in the use of electromyogram (EMG), electrooculogram (EOG) and steady-state somatosensory evoked potentials (SSSEP) in HBCI systems over time. However, the use of near-infrared spectroscopy (NIRS) and eye tracker has increased dramatically, especially in recent years. A summary of researches in the field of HBCI systems with an emphasis on the specific characteristics of each study has been noted in Table 1. In the following, with the introduction of a variety of signal combinations in HBCI systems, methods and results of different studies have been investigated.

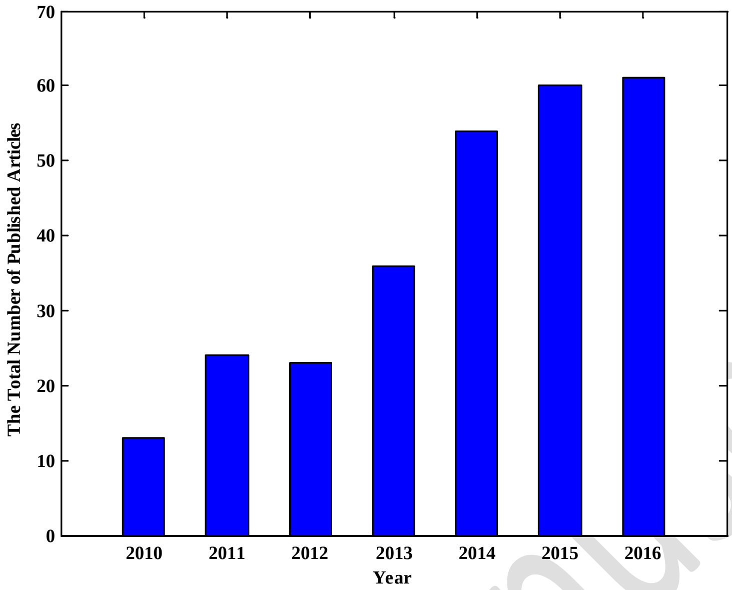

Figure 2. The annual publication of articles based on Google Scholar database in the area of HBCI systems.

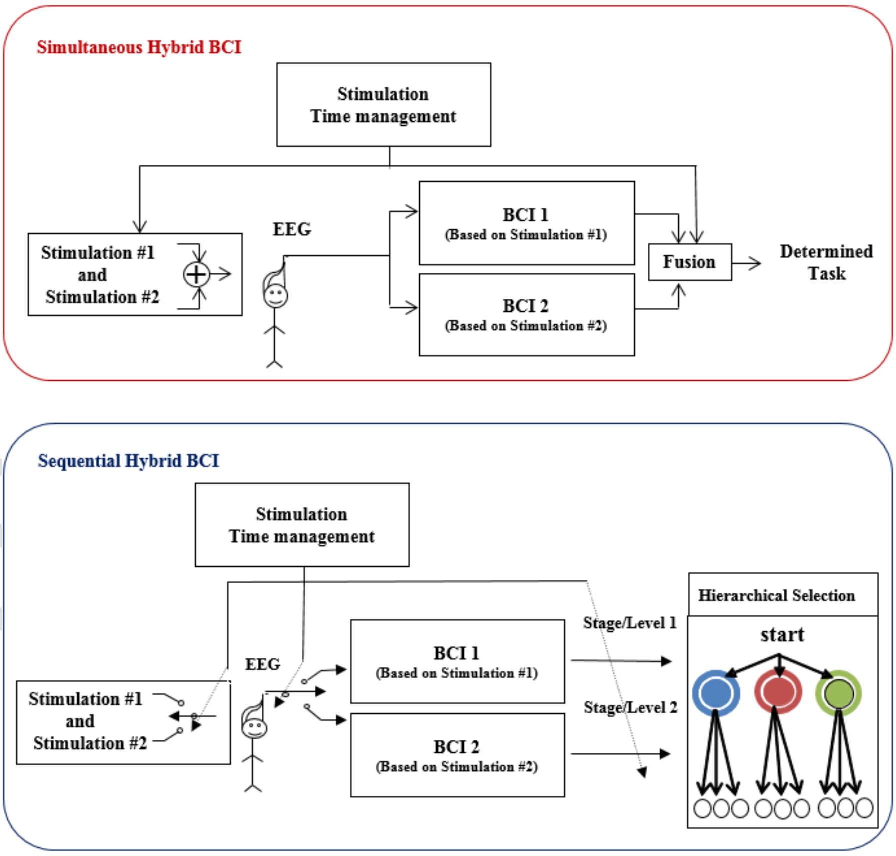

Figure 3. The types of combinations in HBCI systems. Upper figure: simultaneous Combination, lower figure: sequential combination.

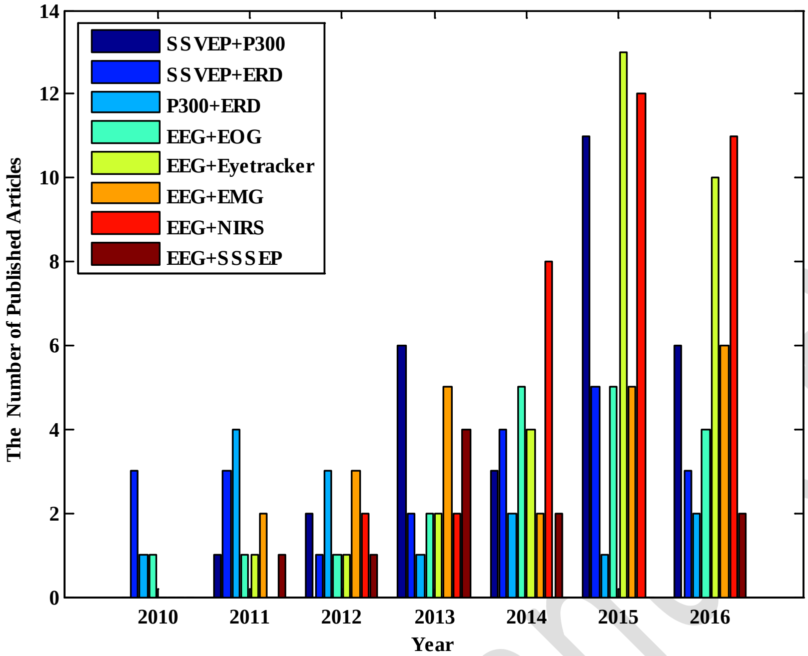

Figure 4. The annual publication of articles based on the type of HBCI combination derived from Google Scholar database.

TABLE 1. COMPARISON OF THE SPECIFIC CHARACTERISTICS OF RESEARCH IN THE FIELD OF HBCI.

Paper	Combined control signals	Combination type	Classification	Application	Results
(Yin et al., 2014)	P300 + SSVEP	Sequential	FLDA, BLDA	Object control	Fast and accurate detection of the control state of subject
(Wang et al., 2015)	P300 + SSVEP	Sequential	SWLDA	speller	Increase the classification accuracy
(Bharne et al., 2015)	P300 + SSVEP	simultaneous	SWLDA	speller	Reduce errors, increase the classification accuracy and ITR
Panicker, Puthusserypady) (& Sun, 2011	P300 + SSVEP	simultaneous	SWLDA,CCA	speller	Increase the classification speed
Edlinger, Holzner &) (Guger, 2011	P300 + SSVEP	simultaneous	BLDA,CCA	Target selection	Increase the classification speed
(Yin et al., 2013)	P300 + SSVEP	Sequential	LDA	Object control	Increase the classification speed
(Xu et al., 2013)	P300 + SSVEP	simultaneous	SVM-FLDA	Curser movement	Inappropriate speed and ignoring the control state of subject due to system synchronization
(Liu et al., 2016)	P300 + SSVEP	Sequential	Kernel FDA,SVM	Object control	Increase the classification accuracy
(Peng et al., 2016)	P300 + SSVEP	Sequential	SVM	Object control	Increase the classification accuracy
(Cheng et al., 2016)	P300 + SSVEP	simultaneous	LDA,SWLDA	speller	increase the classification accuracy and ITR
(Capati et al., 2016)	P300 + SSVEP	Sequential	SVM,LDA	speller	Increase the ITR
(Allison et al., 2010)	SSVEP+ERD	simultaneous	FLDA	Curser movement	Increase the classification accuracy
Savić, Kisić & Provic,) (2011	SSVEP+ERD	Sequential	LDA	orthotics control	Decrease the Positive error rate
(Brunne et al., 2011)	SSVEP+ERD	simultaneous	LDA	Curser movement	Increase the classification accuracy and ITR
(Pfurtscheller et al., 2010)	SSVEP+ERD	Sequential	-	Neural prosthesis control	Reduce the time spent

(Allison et al., 2012)	SSVEP+ERD	simultaneous	LDA	Curser movement	Continuous and simultaneous movement in two dimensions
(Li et al., 2013)	SSVEP+ERD	simultaneous	LDA	Wheelchair control	Simultaneous control of direction and speed
(Li et al., 2014)	SSVEP+ERD	simultaneous	SVM	Wheelchair control	Simultaneous set of direction and speed with spend the least possible time and high classification accuracy
(Cao et al., 2014)	SSVEP+ERD	simultaneous	RBF-SVM	Wheelchair control	Realization of eight control command
(Ji et al., 2016)	SSVEP+ERD	simultaneous	SVM	Object control	Achieve optimal performance
(Rebsamen et al., 2008)	P300+ERD	Sequential	-	Wheelchair control	To determine and fulfill the stop command
(Long et al., 2012)	P300+ERD	simultaneous	LDA	Wheelchair control	Direction and speed control
(Finke et al., 2011)	P300+ERD	Sequential	FDA	robot control	Providing movement in various dimensions
(Su et al., 2011)	P300+ERD	simultaneous	SVM,FLDA	Object control	realization of more complex tasks
(Riechmann et al., 2011)	P300+ERD	sequential	LDA	robot control	Robot control
(Yu et al., 2016)	P300+ERD	Sequential	LDA	speller	Increase the classification accuracy and ITR
(Yu et al., 2016)	P300+ERD	Sequential	LDA	speller	Increase the classification accuracy and ITR
(Usakli et al., 2009)	EEG+EOG	sequential	-	robot control	Affective robot control
(Yang et al., 2016)	EEG+EOG	simultaneous	SVM	Prosthesis control	Increase the the classification accuracy
(Zheng et al., 2016)	EEG+EOG	simultaneous	-	vigilance estimation	Improve the performance
(Kim, Kim & Jo, 2015)	EEG+ Eye Tracker	sequential	SVM	Curser movement	Increase the ITR
(Evain et al., 2016)	EEG+ Eye Tracker	sequential	LDA	Curser movement	Increase the ITR
(Lin et al., 2015)	EEG+EMG	simultaneous	-	speller	Increase the classification accuracy
(Leeb et al., 2011)	EEG+EMG	Sequential	-	speller	Increase the classification accuracy, ITR and the number of target items
(Riccio et al., 2015)	EEG+EMG	Sequential	-	speller	Improve the performance and ITR
(Lin et al., 2016)	EEG+EMG	simultaneous	CCA	speller	Increase the the classification accuracy ,the number of targets and ITR
(Liu et al., 2016)	EEG+EMG	simultaneous	LDA	Object control	Increase the the classification accuracy
(Mercado et al., 2016)	EEG+EMG	simultaneous	SVM	Object control	Improve the object control
(Ahn. et al., 2013)	EEG + SSSEP	Sequential/ simultaneous	-	Curser movement	Decrease the classification accuracy in simultaneous combination
(Yao et al., 2014)	EEG + SSSEP	simultaneous	-	Curser movement	Providing multi-class BCI system
(Breitwieser et al., 2016)	EEG + SSSEP	simultaneous	LDA	Object control	Increase the classification accuracy
(Pokorny et al., 2016)	EEG + SSSEP	simultaneous	LDA	Object control	Achieve optimal subjects' performance
Khan, Hong & Hong) (2014	EEG + NIRS	simultaneous	-	Wheelchair control	Realization a large number of commands
(Buccino et al., 2016)	EEG + NIRS	simultaneous	LDA	-	Increase the ITR
(Shin et al., 2016)	EEG + NIRS	simultaneous	LDA	-	Provide open access Dataset
(Al-Shargie et al., 2016)	EEG + NIRS	simultaneous	SVM	stress assessment	Increase the classification accuracy and improve sensitivity and specificity

3.1. The combination of P300 and SSVEP

Since both SSVEP and P300 are evoked by visual stimulation and none of them requires training, the combination of these two signals has been used in various applications such as target selection, movement control and spellers. In order to control the direction and speed of the movement, simultaneous combination of SSVEP and P300 is associated with shortages such as low speed and ignoring the resting state in synchronous systems (Bi et al., 2014).

P300 that is associated with high ITR is considered the main mechanism of data transfer in many applications including spellers. One of the solutions to increase ITR in P300-based spellers is reducing the number of flashes. There is a compromise between ITR and classification accuracy so that by reducing one of them, the other will increase. In order to increase information transfer rate, simultaneous combination of P300 and SSVEP is used. To this end, all characters are divided into subareas by two techniques: row / column (RC) or subarea / location (SL). All of the characters in each subarea flicker at the same frequency. At the same time, cues highlight the same location in each subarea in a pseudorandom sequence. Thus, only N1 flash codes for P300 and N2 frequencies for SSVEP are required to achieve the spelling of N1 × N2 items. The RC mode is better choice compared with SL mode, due to its higher average, higher speed and lower standard deviation of ITR (Yin et al., 2014). To increase classification accuracy, simultaneous combination of SSVEP and P300 is used to reduce errors occurred in rows or columns containing target character. Coincides with P300, several SSVEP frequencies are applied so that the characters in the same row or column, may not have the same frequency (Yin, Zhou et al. 2013). To increase classification accuracy with the aim of detecting control state (period of time in which the subject is intended to convey information), the sequential combination of P300 and SSVEP is used (Edlinger, Holzner & Guger, 2011; Panicker, Puthusserypady & Sun, 2011).

In simultaneous combination of P300 and SSVEP, to avoid any disruption caused by unstable frequency of P300 on the frequency of flickering SSVEP, the P300 is used as target deformation (Wang et al., 2015). In this approach, using the stop features of SSVEP coupled with changing shape in P300, could also be affective (Xu et al., 2013).

3.2. The combination of ERD and SSVEP

SSVEP and ERD combination has been used in various applications such as control of wheelchair, orthotics and neural prosthesis. In combination of these signals, the ability to use the desired control signal at any moment, will lead to increase classification accuracy (Allison et al., 2010). This combination could also be effective to increase the number of control commands. For example, if the classification of four directions of movement is realized by using right and left wrist motor imagery and taking into account the time of imagination, it is not possible yet to control the cursor in several directions in a moment of time (Bai et al., 2010). SSVEP and ERD combination will enable continuous movement in two dimensions simultaneously (Allison et al., 2012). Moreover, the possibility of simultaneous control of direction and speed of the wheelchair is provided and the move / stop command is done by spending a short time (Li et al., 2013; Cao et al., 2014; Li et al., 2014). With the aim of increasing the ITR, the combination of these two signals is practical and better than switching from one state to another, since the fatigue resulting from this approach is not high

(Brunner et al., 2011). To increase classification accuracy, the combination of them is used to detect resting state in various applications such as opening / closing orthotics and controlling neural prosthetics during grasping. The division of task in two steps and the possibility to turn off the LED after the completion of first step, will reduce the fatigue and error rate by reduction in adverse impact of LED flashes on ERD detection (Pfurtscheller et al., 2010; Savić, Kisić & Prović, 2011).

3.3. The combination of P300 and ERD

The most common practical applications of P300 and ERD combination are wheelchair and robot control. In general, control of these objects is done in two ways. In the first case, several targets are shown against the subject and the subject must select one of them. He moves towards the target through a predetermined path automatically. In this case, the individual has no control over the path. In the second case, the subject moves himself closer to the target with the voluntary movements in different directions. In order to automatic movement of the wheelchair, sequential combination of P300 and ERD is used. In the first stage, the target is selected using P300 and the subject moves himself closer to it from predetermined path. In the second stage, the ERD is used for stop command (Rebsamen et al., 2008; Rebsamen et al., 2010; Riechmann et al., 2011). On the other hand, when the voluntary control of direction and speed of movement is considered, both simultaneous and sequential combinations are used. Typically, in applications which use the simultaneous combination of these two control signals, ERD is used to move in different directions and P300 is applied to control the speed or stop command (Long et al., 2012). In sequential combination, ERD is used for routing and P300 is applied to achieve the desired object. Utilization of ERD for routing will limit the number of commands and the P300 provides the control panel for the subject that allows him the possibility of further tasks. (Finke et al., 2011; Su et al., 2011).

3.4. The combination of EEG and EOG

EEG-based systems are superior technology to increase the communication of disabled and paralyzed patients who cannot move and speak. However, if there is little ability to move eyes in patients, this ability can also be used in conjunction with EEG signals in HBCI systems. Eye movement changes the orientation of the corneal-retinal potential and the electrodes placed around the eyes can record the effects that is named Electrooculogram. The combination of EOG signal and other control signals is used in various applications such as control of virtual keyboard, wheelchairs, mobile robots, etc. The Input of eye movement does not require much training and acts very fast. The amplitude of EOG signal is about several microvolts, so it could be classified easily with high accuracy. This method is economically affordable since the number of electrodes is little. As an example of this combination in robot control, moving to the right and left direction has been obtained using only two EOG electrodes. Direct movement and complete stop has also been done by motor imagery and eye closing, respectively (Usakli et al., 2009; Punsawad, Wongsawat & Parnichkun, 2010).

3.5. The combination of EEG and Eye-tracker

Eye tracking system, is a wearable human-computer interface that provides the possibility to communicate through eye movements and blinking. The combination of this interface and EEG signals could be used in HBCI systems. The main use of this combination is curser movement on the screen. First, the subject guides the curser to the target as quickly as possible and then he selects it. Eye motion indicates the cursor movement on the screen and the target is selected by EEG signal. Although the ITR in this combination is less than using mouse, but this rate is increased compared with BCI (Kim, Kim & Jo, 2015).

3.6. The combination of EEG and EMG

Some patients may have little ability to move muscles in some organs. In many applications, this residual motion is not useful to object control because of muscle weakness, exhaustion or disruption of natural tension. However, this ability can be effectively used as a second signal in HBCI systems. For each patient, the suitable muscle is selected for electrode placement based on its ability to contract (Lalitharatne et al., 2013). The combination of EMG and motor imagery, P300 and SSVEP has been used in various applications. SSVEP-based speller despite high information transfer rate, high signal to noise ratio and no need for training, only has appropriate response in certain frequency range so that it limits the number of target items. To increase ITR and the number of characters in spellers, sequential combination of SSVEP and EMG is used, in such a way that all characters are divided into several groups and those are in the same group, flicker with different frequencies. The number of muscle activity determines the group number. So after determining the desired group, the target item is selected by SSVEP (Lin, et al., 2015). To increase classification accuracy, the simultaneous combination of motor imagery and EMG has relatively better results in comparison with BCI system (Leeb et al., 2011). In this regard, P300 and EMG combination can be used to correct the error in spellers. In other words, contrary to BCI systems which use Backspace to delete wrong letter, it is realized with the EMG in hybrid mode (Riccio et al., 2015).

3.7. The combination of EEG and SSSEP

Many people with stroke who their muscles have been damaged as well as people who have lost the ability of eye gaze, may have the ability to feel stimulation which can be used in HBCI systems. For example, a combination of steady state somatosensory evoked potential retrieved from selective sensation and motor imagery has been used in cursor control. Motor imagery is activation of efferent motor nerves and selective sensation is receiving afferent neuron inputs related to stimulation perception. ERD and SSSEP are achieved by motor imagery and tactile stimulation, respectively. In the simultaneous combination of these signals, increasing the classification accuracy could not be reached due to ERD degradation caused by tactile signals (Ahn et al., 2013). In fact, ERD reduces the SSSEP amplitude and selective sensation increases it (Yao et al., 2014).

3.8. The combination of EEG and NIRS

Non-invasive brain imaging technique that uses light with a wavelength range of 600 to 1000 nm is called near-infrared spectroscopy. It is used for measuring the hemodynamic response due to oxygenated hemoglobin, hemoglobin without oxygen, water, etc. EEG signal has good temporal resolution and poor spatial resolution, while NIRS have medium temporal and spatial resolution and it is also resistant to noise (Coyle et al., 2004; Herff et al., 2015). In HBCI systems, EEG and NIRS combination is used to increase the number of commands without reduction in classification accuracy. For example, NIRS has been used to measure brain activity caused by mental acts (mental counting or performing subtraction) and EEG signal has been applied to detect movement (Khan, Hong & Hong, 2014).

4. DISCUSSION

In this paper, different HBCI systems that are resulting of the combination of a BCI control signal and other BCI control signals or HMI control biosignals, were assessed from the perspective of application, capabilities and limitations. HBCI systems have been used in many applications such as object control, movement control, spellers, etc. By using sequential combination of these systems, we can divide a complex task into several stages and only use one BCI system at each stage. This method of combination will assist in reducing errors by better distinguish the rest state from the attention state. On the other hand, the main goal of simultaneous combination of these systems is increasing the ITR. Generally, HBCI systems have higher information transfer rate and greater classification accuracy compared to conventional BCI systems but in contrast, they are usually more complex. This complexity can affect the ease of use of the system and its acceptance by the user. From this perspective, the design and implementation of these systems including the number of channels will play an important role in performance of system. Table 2 summarizes results of different studies with an emphasis on the number of channels, information transfer rate and classification accuracy. The experimental conditions and signal recording considerations are different in these studies. Accuracy and ITR measures are sensitive to the experiment protocol which makes it difficult to compare results. So, to manage this issue, we've represented these measures in the graphical form of Figure 5. In this figure, various HBCI combinations were compared with two quantitative criteria of classification accuracy and information transfer rate. In this figure, an ellipse is drawn for the ranges of ITR and classification accuracy of each method. The center of ellipse and its diameters are set based on the mean and standard deviation of average values listed in Table 2, respectively. Classification accuracy and ITR are two important parameters in evaluation of a BCI system. It is a tradeoff between these two parameters; as one increases, another decreases and vice versa. For a particular application, the increase in accuracy may be considered an advantage or an increase in ITR is desirable. Therefore, with regards to the ultimate goal and depending on the application, the appropriate combination type should be determined. By having the correct location of the accuracy and the ITR corresponding to each combination, it is easy to determine the optimal combination. Results showed that in most cases, the combination of a BCI control signal and HMI control biosignal has relatively higher ITR in comparison with the combination of two BCI control signals. According to the figure, the highest information transfer rate and the lowest rate were achieved using EEG + Eye Tracker and SSVEP + ERD, respectively. The combination of EEG signal and NIRS has also the lowest classification accuracy in comparison with others, while the accuracy values of other hybrid systems do not much different from each other and they are located within the range of 70-100 percent. Generally, in using HBCI systems, we can determine the technique of combination depending on the type of application, the main goal as well as the capabilities of patients.

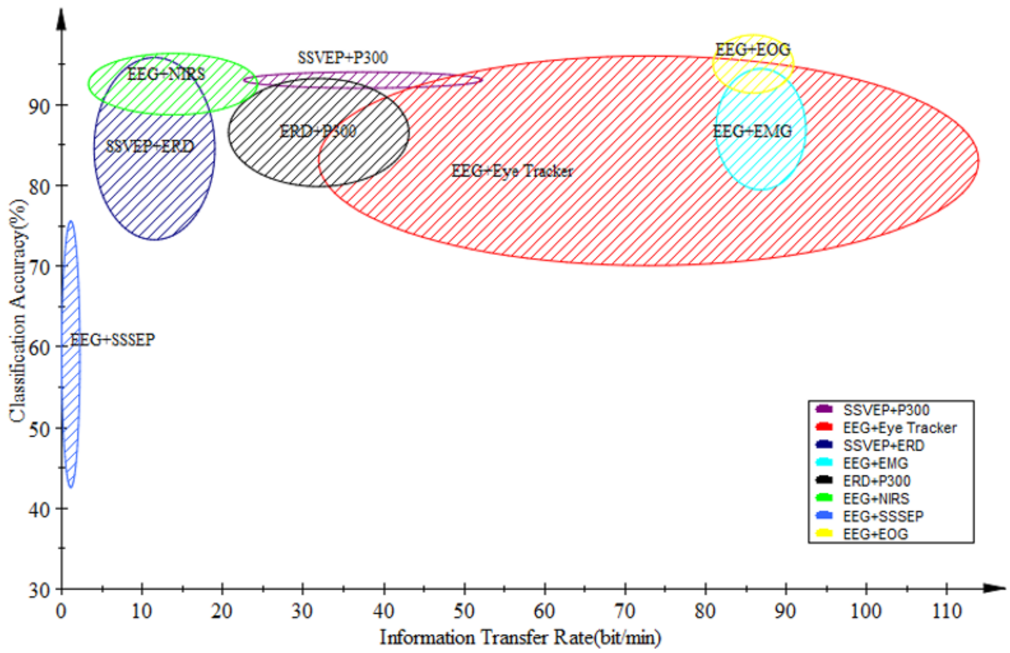

Fig 5. The comparison of different combinations of HBCI systems based on classification accuracy and information transfer rates. The range of classification accuracy and ITR have been determined based on researches that have been done.

TABLE 2. A COMPARISON OF THE RESULTS OF VARIOUS RESEARCHES IN THE FIELD OF HYBRID BCI.

Paper	Combined Control Signals	Combination Type	The Number of Channels	Classification Accuracy	Information Transfer Rate (ITR)
(Panicker, Puthusserypady & Sun, 2011)	P300 + SSVEP	sequential	9	88.15	19
(Xu et al., 2013)	P300 + SSVEP	sequential	32	97.5±2.6	34
(Yin et al., 2013)	P300 + SSVEP	simultaneous	12	93.85±7.49	56.44±8.19
(Yin et al., 2014)	P300 + SSVEP	simultaneous	12	95±5	48±4
(Wang et al., 2015)	P300 + SSVEP	simultaneous	8	90.63±10.16	22±52.6
(Liu et al., 2016)	P300 + SSVEP	sequential	3	93±1	-
(Peng et al., 2016)	P300 + SSVEP	sequential	12	94±6	-
(Chang et al., 2016)	P300 + SSVEP	simultaneous	14	93±7	32±5.5
(Allison et al., 2010)	SSVEP+ERD	simultaneous	6	81±8.9	-

(Brunner et al., 2011)	SSVEP+ERD	simultaneous	8	95.6±6.7	4.7±2.4
(Pfurtscheller et al., 2010)	SSVEP+ERD	sequential	2	85±6	-
(Savić, Kisić&Provic, 2011)	SSVEP+ERD	sequential	6	98	-
(Allison et al., 2012)	SSVEP+ERD	simultaneous	35	60	-
(Cao et al., 2014)	SSVEP+ERD	simultaneous	15	90±2	-
(Choi et al., 2016)	SSVEP+ERD	sequential	13	77±11	
(Ji et al., 2016)	SSVEP+ERD	simultaneous	15	89±5.5	
(Kim et al., 2016)	SSVEP+ERD	simultaneous	14	91±1	17±1
(Bhattacharyya, Konar& Tibarewala, 2014)	P300+ERD	sequential	19	95	22.5±1
(Long et al., 2012)	P300+ERD	sequential	30	93.99	-
(Roula, Kulon & Mamatjan, 2012)	P300+ERD	sequential	14	85±12.7	-
(Riechmann et al., 2011)	P300+ERD	simultaneous	16	79.5±2.5	-
(Yu et al., 2016)	P300+ERD	Sequential	18	88±4	41±11
(Yu et al., 2016)	P300+ERD	Sequential	18	87±4	43±10
Punsawad, Wongsawat& Parnichkun,) (2010	EEG+EOG	simultaneous	5	96±2	-
(Ramli et al., 2015)	EEG+EOG	sequential	5	97.88	86±5
(Ma et al., 2015)	EEG+EOG	sequential	10	87±11.5	-
(Koo et al., 2014)	EEG+EOG	sequential	10	80	56
(Yang et al., 2016)	EEG+EOG	simultaneous	15	91±1.7	-
(Meena et al., 2015)	EEG+ Eye Tracker	simultaneous	2	60±5	-
(Huang, 2014)	EEG+ Eye Tracker	simultaneous	30	84±3.5	-
(Kim and Jo 2015)	EEG+ Eye Tracker	sequential	14	95.6±2.6	-
(Kim, Kim & Jo, 2015)	EEG+ Eye Tracker	sequential	14	84±9.5	120±7.5
(Dong et al., 2015)	EEG+ Eye Tracker	simultaneous	32	>80	-
(Evain et al., 2016)	EEG+ Eye Tracker	sequential	16	85.5±2	
(Mccullagh et al., 2016)	EEG+ Eye Tracker	sequential	-	95.3±1.5	40.5±1
(Achic et al., 2016)	EEG+ Eye Tracker	sequential	4	79	60.4
(Lin et al., 2015)	EEG+EMG	sequential	11	80.8±15.6	83.7±24
(Leeb et al., 2011)	EEG+EMG	simultaneous	20	91	-
(Riccio et al., 2015)	EEG+EMG	sequential	9	100	12
(Leeb, Sagha & Chavarriaga, 2010)	EEG+EMG	simultaneous	16	88	-
(Kiguchi & Hayashi, 2012)	EEG+EMG	simultaneous	16	84±7.7	-
(Lin et al., 2016)	EEG+EMG	simultaneous	11	86±9	91±16
(Ahn. et al., 2013)	EEG + SSSEP	Sequential/simultaneous	64	64±5.5	-
(Severens. et al., 2013)	EEG + SSSEP	simultaneous	64	77	1.2±1.14
(Yao et al., 2014)	EEG + SSSEP	simultaneous	64	83±8.5	-
(Breitwieser et al., 2016)	EEG + SSSEP	simultaneous	32	44.5±7	-
(Pokorny et al., 2016)	EEG + SSSEP	simultaneous	32	55.5±8.5	-
(Khan, Hong & Hong, 2014)	EEG + NIRS	simultaneous	20	>80	-
(Fazli et al., 2012)	EEG + NIRS	simultaneous	37	86±5	-
(Koo et al., 2015)	EEG + NIRS	simultaneous	8	88±10	-
(Khan, Hong & Hong, 2014)	EEG + NIRS	sequential	3	80	-
(Lee et al., 2014)	EEG + NIRS	simultaneous	37	59	-
(Ma et al., 2012)	EEG + NIRS	simultaneous	2	83	-
(Herff et al., 2015)	EEG + NIRS	simultaneous	3	58±14.5	-
(Tomita et al., 2014)	EEG + NIRS	simultaneous	2	-	13.9±10.5
(Bussino et al., 2016)	EEG + NIRS	simultaneous	23	94±3.5	-
(Al-Shargie et al., 2016)	EEG + NIRS	simultaneous	31	95±4	-

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