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Hybrid Brain-Computer Interface System : A Review

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ABSTRACT

Bio signals based control system has been employed in to the biomedical devices and prosthetic limbs for improving the life of severely disabled and elderly people. Many Research papers and study of Brain computer interface (BCI) shows a huge potential of this field for future research. Conventional BCIs are not fully advance to operate in real-time applications due to high false positive rate, low information rate, lack of high accuracy, adaptability and reliability. To overcome these difficulties, researchers have found solutions by utilizing the individual advantages of different BCI network and combined them to make a new system. These systems are known as hybrid BCI system and enhances the performance, reliability, accuracy of the system. In this paper we analyze and review different combinations of BCIs and explains their merits and demerits.

Keywords : Brain Computer Interface (BCI), Electroencephalography (EEG), Steady State Visually Evoked Potential (SSVEP), Electromyography (EMG), Event related potential (ERP)

I. INTRODUCTION

Robots are widely used in industries but now a day they have also entered into the human life. Robots provide assistance to the disabled persons in their daily and professional life, consequently creating a huge market and call for them. Normally, robots are operated by healthy users with ordinary input devices such as a mouse, a keyboard, or a joystick. However, such devices are not easily handled or controlled by the elderly or disabled people. This will culminate to isolation of these people from the mainstream and feel deprived. People who lost most of their voluntary muscle control want to be in charge of their motion as much as possible. Hence, researchers invented some interfaces like single switches, sip-and-puff system and eye tracking system [1]. Sometimes, due to severe disability and illness, these special interfaces also do not work properly due to the lack of proper communication between user and robots. Although, many autonomous systems are present yet there are lots of research required in this field.

Brain computer interface (BCI) have been developed to solve this difficulty and provided the direct link between the brain and physical devices such as robots, wheelchair etc. in real time system [2]. Signal acquisition from brain through BCI can be done in two ways 1) invasive BCI technique 2) non-invasive BCI technique. In invasive BCI techniques, special devices are directly inserted into human brain by surgery to extract the brain signals. The devices which are inserted in brain are of two types: 1) single unit device: which captures only single area of brain cells 2) multiunit devices: detects and captures multiple areas of the brain cells [3]. This type of technique provides highest quality of signal but have negative impact on the brain cells such as formation of scar tissues in the brain. While, Non-invasive is the most secured and cost effective technique where the acquisition of the signals is done by placing the electrodes on the top of the scalp. Non-invasive techniques are constructed by recording the signals from Electroencephalographs (EEG), magneto encephalogram (MEG), functional magnetic resonance imaging (fMRI), electrocardiogram (ECoG) and near infrared spectroscopy (NIRS). Initially, the temporal resolution was not so much high due to less number of electrodes used in signal acquisition but, currently, it has been improved and using up to 256 electrodes and in most of the BCI systems the EEG signals are considered as the input signals. Based on the brain activity pattern, the BCI system can be categorized as event-related desynchronization/ synchronization (ERD/ERS), steady- state visual evoked potentials (SSVEPs), P300 component of event related potentials (ERPs) and slow cortical potentials (SCPs) [4, 5]. Until few years ago, the most BCI systems used only single signal and allowed simple command and instructions.

In those systems the error rate was high and feedback system was also not advance. Hence, these systems were not used in the real time applications. Recently, many researches have been done which have made the BCI system more intelligent and efficient. The BCI system can be combined with other devices and software for better communication and execution of desired goals in the real time system.

1.HYBRID BCIs

1.1 Introduction to hybrid BCI

Recently, many articles and researches have corroborated a novel approach towards the hybrid brain computer interface [6]. After reviewing and analyzing many research papers, we have perceived the following definition of hybrid BCI network. When one BCI system is combined with at least one other system for the better communication of commands then this network is called as Hybrid BCI network. The other system or devices can be following:

- Another BCI system
- The devices which work on another physiological signals such as EMG, EOG, EEG etc. or other conventional devices such as mouse or keyboard

The hybrid system work on two modes one is the simultaneous mode and other is sequential mode. The selection of mode depends upon the requirement and necessity of work. The user can opt any of the mode for the work. Each mode has its own advantages and disadvantages.

In the first mode, BCI and other device are operated concurrently and operations and commands are executed simultaneously by the user. While in sequential mode, the user chooses one system as a primary system for execution of tasks and the supplementary system helps the primary system in many ways such as in minimization of the errors, improvement in the training time, providing better assistance and feedback.

1.2 Key challenges and parameters in designing of Hybrid BCI

Major challenge with the hybrid BCI system is the integration of the signals from devices and mental tasks. Imagined movements are always hard to combine with other tasks which requires visual or motor imaginary movement. The major issue is to ensure that two devices support and communicate each other very well. The main motive behind hybrid BCI is to increase the efficiency and reducing the false positive rate. It is necessary to improve the weakness of the primary device with the help of secondary devices.

Other challenge is the feedback system. In the real time application, feedback plays important role in the execution of task and shows the ability of the input methods to the user. For example, if user wishes to move cursor right by imagining right hand movement and also by focusing on the right LED. Then it is difficult to tell which movement plays major role in movement of cursor [7]. So, there should be different feedback bars to show the strength of various signal. Hence, the BCI network should be designed in such way that feedback is more intuitive.

Error potential(ErrP) is another parameter while designing the system. It is a feedback provided by the user to the BCI system and occurs instantly when user feels he or she made a mistake [8]. The role of ErrP is limited in BCI systems but can be used to prevent the BCI to implement the task and modify the previous command.

II. REVIEW OF DIFFERENT HYBRID BCI

Many combinations of hybrid system can be formed by using various BCI systems. The various combinations of EEG, EMG and EOG have been discussed in this section. The comparison of all combinations has also been discussed in Table 1.

2.1 EEG-EMG hybrid BCI

Leeb et al. [9] fused EEG and EMG to obtain the Hybrid BCI system. EEG signals were acquired through 16 channels and the placement of four EMG channels was at flexor and extensor of the left and right forearm. They monitored both the signals i.e. EEG and electromyography (EMG) concurrently. 12 healthy subjects were participated in experimentation. Two classifier were used for calculations and the results obtained from these classifiers were used to control the feedback of BCI network. In the first approach, for the fusion equally balanced weights were used between the two classifier of the two inputs signals and in the second approach, the Bayesian fusion method was utilized in which two conditions were considered for EEG and EMG separately and four conditions for the fusion of EEG and EMG depending on the increase of muscular fatigue. The accuracy of all subjects for EEG and EMG alone was 73%, 87% respectively. The accuracy was increased for Hybrid BCI network and for first approach i.e. equally weighted sources it achieved 91% accuracy. With the increase of muscular fatigue, from 10% to 50%

and to 91%, the performance was also degraded to 90%, 85%, 73% respectively. the same trend was followed in second approach with smaller standard deviation. For 50% fatigue the accuracy was 92% and for 90% it was 60.4%. multimodal fusion approach of muscular and EEG activities produced better results than the single computation of signals.

Rocon et al. [10] combined EEG, EMG and inertial sensors (IMUs) for evaluation of generation, transmission and execution of volitional and tremors movements. 128 channels EMG amplifier and EEG amplifier manufactured by g.Tech, and IMU sensors were used for the experimentation. The experimentation was performed on 12 patients. Tremors generally happens in the range of 3-12 Hz band whereas activities of daily living (ADL) are performed below 2 Hz. Hence, Algorithms were developed to identify intention to move, tremor onset, tracking and extraction of tremor characteristics. From the experimentation, an average tremor amplitude estimation error was 0.001± 0.002 rad/sec.

Kiguchi and Hayashi [11] proposed power-assist robots with perception-assist using EEG and EMG signal to monitor the interaction of user and environment with the help of some sensors. When power assist robot performed perception-assist test then, meanwhile, EEG and EMG signals were also measured to improve the rate of the proper learning of the robot. 16 channel EMG and 256 channel EEG amplifiers were used for acquisition of signals. EEG signals were used for the judgment of the effectiveness of the performed perception-assist in addition to the EMG signals. A seven Degree of Freedom (DOF) power-assist exoskeleton robot was used in this work. Two experiments were performed with EMG and EEG alone as well as with combination of both. For both experiments, accuracy was 75% and 90% for EMG alone while for hybrid system it was 85% and 95%. Hence, the recognition-rate of the perception-assist of Hybrid BCI is higher than that of either EEG signals or EMG signals.

Du et al. [12] fused EEG and EMG to analyze the intelligence technology of robots. An optical fiber motion capture system was present which detects the motion gesture of human. the direction and pattern of human motion was predicted by EEG and EMG measurement system respectively. This design could improve the pattern recognition rate by combining the EEG and EMG. The combination of robotic hydraulic driving device and fiber motion capture system made the close loop system and made more accurate system.

2.2 SSVEP-motor imagery hybrid BCI

Allison et al. [13] proposed a hybrid BCI system which was evaluated and compared with the other networks for different tasks. Hybrid BCI was combination of SSVEP and ERD. While performing the ERD task, two arrows appeared on the screen. Patients were instructed to open and close the left hand when left arrow appeared on the screen. Similarly, when right arrow appeared on the screen then patient imagined the closing and opening of right hand. In SSVEP task, two LEDs, left LED (8 Hz) and right LED (13 Hz), glow with some pattern and patients were instructed to stare at that glowing LED. In the hybrid task, when right arrow appeared on the screen, patients imagined the movement in the corresponding hand and meanwhile also stare continuously to Right LED also. The average accuracy of SSVEP and ERD was 76.9% and 74.8% respectively, while accuracy of hybrid network was higher than the individual network and was recorded as 81%.

Pfurtscheller et al. [5] introduced a hybrid BCI system for orthosis control applications. SSVEP and imagery based BCI worked in a sequential manner. Only two EEG channels were used for data acquisition. First at the motor cortex and second at the visual cortex. Six healthy subjects were participated in the experiment. sampling frequency was 256 Hz. Imagery based BCI was used as a switch to activate SSVEP based process when it was required and deactivate the LED when during resting period. The experiment was to control a four step electrical hand orthosis by gazing at 8 Hz LED open it, and gazing at 13 Hz LED to close it. After completion of full orthosis cycle SSVEP BCI was turned off by opening the brain switch. Brain switch was kept open for sixty seconds for the comparison of performance, the tasks were done again without using the switch. For SSVEP alone power density spectrum was used. It was calculated that false positive rate was reduced by 70% when hybrid BCI was used.

Savic et al. [14] proposed a two stage BCI system for controlling Functional Electrical Stimulation (FES) system. In the first stage, the SSVEP was used for selection of one of the three object for grasping. After identification of the object, the ERD signals were utilized to reach at the identified object for grasping. There were three subject for experimentation. Three channels O1, Oz, O2 were used for detection of SSVEP signal, and Cz and forehead were selected as reference and ground. one additional channel C3 was added for acquisition of ERD signals. Oz channel was chosen for analysis because it had more noticeable activity than other channels. Butterworth band pass filters were for classification of frequency bands and threshold for each subject was adjusted manually. After selection of object next stage was to reach at the identified object for grasping, which was done by ERD signals. Butterworth filters were used to extract the mu and beta rhythm of the signals and threshold was set manually. When the signal was below the threshold level then it was considered as the movement command. The performance of the hybrid system was based on the three parameters: a) number of true positive (TP) and true positive rate b) number of false positive rate c) time interval between cue and next detection. The accuracy of SSVEP stage was 98.1% and for next stage it was 100% and 98.1% for mu and beta band respectively.

Brunner et al. [7] proposed a hybrid BCI system for a simultaneous task. Hybrid BCI consisted of ERD and SSVEP. Bipolar channels were used to obtaining the signals from the users. For online SSVEP run task, two LED were present at top and bottom of the user interface module. Top LED was flickering with 8Hz and bottom with 13Hz. While during ERD run task, when cue pointed at top of the screen then subject were instructed to imagine the closing and opening of both the hands. When bottom LED glows subject were instructed to imagine moving both feet. LDA classifier was used for classification and decision making. The accuracy was calculated for both the sessions i.e. training as well as for online. The training accuracy of ERD, SSVEP and Hybrid system was calculated as 79.9%, 98.1%, and 96.5% respectively. While, on-line task accuracy for ERD, SSVEP, and Hybrid was 76.9%, 94%, and 95.6% respectively. At last, questionnaire was asked to the subject about performance and difficulty level of using Hybrid system. Two subjects concluded that hybrid network was difficult to operate and their performance was affected due to complexity of system. While, four subject responded with good performance of hybrid network and felt same difficulty level as that of SSVEP alone. Comprehensively from the responses of subject it was indicated that hybrid network was moderately difficult.

2.3 P300-SSVEP hybrid BCI

Li et al. [15] proposed a hybrid BCI system to improve the performance of asynchronous control and also used as application to produce the go/stop command in real time wheelchair control. SSVEP and P300 were used to obtaining the signals from the patients. There were four group of flickering light buttons were used for user interface, and each light button group consisted one large button at the center and eight small buttons were arranged every 45◦ in a peripheral around large button. Buttons groups flickered at frequencies of 6, 6.67, 7.5, 8.57 Hz. While performing experimentation, large center buttons intensified through shapes and colors in a random order to evoke the P300 potentials. Meanwhile, small buttons also intensified at fixed frequency to generate the SSVEP potential. During control state, patients focused on the target buttons, which were flashed on the user interface, to generate the SSVEP and P300 potentials. The discrimination of go and start command was based on the detection of SSVEP and P300 signals. This method was utilized in real time application to controlling wheelchair. The experimental result showed significant improvement in the performance of Hybrid BCI system in terms of detection accuracy and response time.

Fan et al. [16] proposed driver-vehicle interface using a hybrid network of SSVEP and P300 for severely disabled people. The proposed work was composed of two steps. First step was the selection of predefined destination using P300. There was a LCD display of 3 × 3 matrix of characters, and each character signifies a predefined destination. If a person wanted to reach at particular destination, then he had to pay attention to that particular characters. After selection, next step was confirmation which was done by SSVEP module. There were two rectangular checkerboards present in the SSVEP stimuli module. The left checkerboard, which flashed 12 times per second, represented the acceptance of the command and right checkerboard, flashed 13 times per second, represented the rejection of the command. The experimentation was carried out on 16 subjects in laboratory as well as in real time conditions. The average accuracy for selection and confirmation for laboratory and real time conditions was 90.6%, 93.55% and 88.99%, 90.48% respectively. Overall accuracy of the system for laboratory and real driving conditions was 99% and 98.93% respectively. The proposed model enhances the accuracy of selection of destination compared to individual P-300 based selection system.

Yin et al. [17] fused the P300 and SSVEP brain signals for selection of 64 items. Two hybrid paradigms were created by integrating the row/column (RC) P300 and two level SSVEP. This hybrid system was termed as double RC 4-D speller. To generate the P300, the rows and columns are flashed simultaneously in pseudorandom order. Hence, two potentials were generated one for row and other for column flash. Appearance and disappearance of white rectangular, against a black background, in the matrix generated the SSVEP potential. In RC hybrid mode, the items in the same row was flickered at same frequency and subsequently items in same column was flickered. This collected the data of SSVEP signals for same axes which were used to collect stimulus for P300. In 4D hybrid BCI mode, the flickering items were oriented parallel to anti diagonal of matrix and then parallel to the diagonal matrix. These axes were differing from P300 axes. The target was simultaneously detected by both the brain signals. Maximum probability estimation (MPE) was used for fusion of the signals. The results showed that DRC hybrid technique Outclassed the 4-D hybrid technique. The accuracy of 4-D technique was 95.18%.

Hwang et al. [18] proposed a hybrid speller using combination of peripheral SSVEP and P300. The SSVEP stimuli was synchronized with P300 for identification and provided the feedback to the system for correct identification of the target character. In SSVEP, yellow color LED was present at the visual stimulus block and stimulus was to designed to flicker at the rate of 12 and 15 Hz. The experimentation was performed in two phase i.e. with P300 only and with hybrid system. The accuracy of the system was 74% for P300 alone and 83.9% for hybrid system. Results shows improvement in the accuracy and reduced the fatigue level of the patients.

2.4 EEG-EOG hybrid BCI

Yang et al. [23] proposed a hybrid system to control robotic arm using EEG and EOG signals simultaneously. Placement of the electrodes was according to international 10-20 system. The electrodes were placed at Fpz, Fp3, Fp4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6. Sampling frequency for the EEG signals was 128 Hz. Fpz channel was used to collect signals of EOG. When '+' sign appeared on the screen, which implied that imagination task was ready to perform. When red arrow appeared on the screen then subject should have to perform imagined hand movements according to instructions. Left arrow indicated imaginary left hand movement, similarly right arrow meant imaginary right hand movement. When '+' appeared again then it indicated end of experimentation. In robotic prosthesis control, there were two modes i.e. EEG mode and EOG mode. In first step, the system is powered up when triggering occurred and subjects wink considered as trigger by the system in next step, EEG signals were used to controlling movement of robotic arm according to the input signals. Gripping of glass or cup was done by winking of subject's eye twice. Common spatial pattern (CSP) and support vector machine (SVM) were used to classify the signals characteristics. 91.1% accuracy was achieved by combining EEG and EOG together.

Jiang et al. [24] designed a hybrid BCI system using EEG and EOG signals. The selection of the target was depending upon the gaze direction and motor imaginary system. When the motor imaginary activity was detected then target corresponding to gaze direction was selected. If there is no movement in the motor imaginary system, then there would not be any selection of target occur. there were three targets present on the screen i.e. on left, right and top of the screen. When desired target flashed on the screen then subjects had to imagined and gazed at the correct target. The average accuracy for motor imaginary and EOG was 90.4% and 96.9% respectively. the overall accuracy and completion time of target selection of on-line test were 89.3% and 2.4 seconds respectively. It was concluded that proposed hybrid system could be used in the rehabilitation of disabled people.

Hybrid Type	System Type	Number of Patients	Classifier	Findings	Accuracy	Reference
EEG and EMG	Simultaneous	12	Frequency analysis	Improvement in performance	91%	Leeb et al. [9]
EEG and EMG	Sequential	12	kalman filter	Improvement in the accuracy and performance	---	Rocon et al. [10]
EEG and EMG	Simultaneously	4	-	Recognition rate was improved	---	Kiguchi and Hayashi [11]
EEG and EMG	Sequential	-	Bayesian classifier and power spectrum	Improvement in performance	85% and 95%	Du et al. [12]
ERD and SSVEP	Simultaneous	14	LDA	Accuracy was improved	81%	Allison et al. [13]
ERD and SSVEP	Sequential	6	FLDA	False positive rate(FPR) was reduced	---	Pfurtscheller et al. [5]
ERD and SSVEP	Sequential	3	Filters	FES triggering was improved	98%	Savic et al. [14]

Hybrid Type	System Type	Number of Patients	Classifier	Findings	Accuracy	Reference
ERD and SSVEP	Simultaneous	12	LDA	Improvement in performance and addition of feedback	95.6%	Brunner et al. [7]
SSVEP and P300	Simultaneous	8	SVM	Performance was improved in term of response time and accuracy	---	Li et al. [7]
P300 and SSVEP	Sequential	16	LDA	Improved accuracy of destination selection	98.3%	Fan et al. [16]
P300 and SSVEP	Simultaneous	13	Bayesian and SVM	Improvement in the accuracy	95.18%	Yin et al. [17]
P300 and SSVEP	Sequential	4	Canonical correlation analysis and LDA	Make speller more time efficient	83.9%	Hwang et al. [18]
P300, SSVEP	Sequential	10	FLDA and BLDA	Improved ITR	94.44%	Panicker et al. [19]
EEG and EOG	Simultaneously	5	CSP and SVM	Improvement in the accuracy	91.1%	Yang et al. [23]
EEG and EOG	Simultaneously	4	LDA and CSP	Could be used in devices for disabled people in future	89.3%	Jiang et al. [24]
EEG and EOG	Sequential	4	CSP and SVM	High efficiency and robustness	91%	Wang et al. [25]

III. CONCLUSION

Different BCI systems or BCI and non BCI systems can be merged together to outclass the limitation and demerits of conventional BCIs. These combinations of various BCIs is known as Hybrid BCIs. In this paper, various methods of organizing a hybrid BCI system have been discussed and compared. There are many practical applications of hybrid BCIs such as target selection, driving fatigue detection [26], ischemic stroke detection [27], automatic sleep quality assessment [28]. Sequential hybrid BCI have several advantages such as low false positive rate (FPR), reliability. Different BCI systems can be implemented based on the required type of control commands. In [5], one BCI (ERD) was used as a switch for another BCI (SSVEP) and the false positive rate was decreased for this sequential hybrid BCI system. The accuracy and high information rate of simultaneous system is more than other BCI network but the simultaneous hybrid BCI system is more complexed than single BCI and more difficult to operate by all users. Thus, in designing a hybrid system paradigm, the complexity and user acceptability are important performance parameter to be considered carefully. Another consideration for the user acceptability is the number of channels used in a hybrid BCI system. When a BCI system is combined with a non-BCI, which is not based on EEG signals, the system performance is improved. In conclusion, hybrid BCIs have shown great improvements in various performance parameters such as accuracy and information transfer rate, complexity of the system, low false positive rate. Recent study shows that it is possible to combine three BCI network sequentially or simultaneously which will improve the accuracy, and reduces the error and response time.

IV. REFERENCES

[1]. Perrin X. Semi-autonomous navigation of an assistive robot using low throughput interfaces (Doctoral dissertation, Ecole Polytechnique Fédérale de Lausanne).

[2]. Perelmouter J, Birbaumer N. A binary spelling interface with random errors. IEEE Transactions on Rehabilitation Engineering. 2000

Jun;8(2):227-32.Wolpaw JR, Birbaumer N, McFarland DJ et al. Brain–computer interfaces for communication and control. Clinical neurophysiology 2002; 113(6): 767–791.
[3]. Birbaumer N, Ghanayim N, Hinterberger T, Iversen I, Kotchoubey B, Kübler A, Perelmouter J, Taub E, Flor H. A spelling device for the paralysed. Nature. 1999 Mar 25;398(6725):297-8.
[4]. Pfurtscheller G, Solis-Escalante T, Ortner R, Linortner P, Muller-Putz GR. Self-paced operation of an SSVEP-Based orthosis with and without an imagery-based “brain switch:” a feasibility study towards a hybrid BCI. IEEE transactions on neural systems and rehabilitation engineering. 2010 Aug;18(4):409-14.
[5]. Pfurtscheller G, Allison BZ, Bauernfeind G, Brunner C, Solis Escalante T, Scherer R, Zander TO, Mueller-Putz G, Neuper C, Birbaumer N. The hybrid BCI. Frontiers in neuroscience. 2010 Apr 21;4:3.
[6]. Brunner C, Allison BZ, Altstätter C, Neuper C. A comparison of three brain–computer interfaces based on event-related desynchronization, steady state visual evoked potentials, or a hybrid approach using both signals. Journal of neural engineering. 2011 Mar 24;8(2):025010.
[7]. Holroyd CB, Coles MG. The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. Psychological review. 2002 Oct;109(4):679.
[8]. Leeb R, Sagha H, Chavarriaga R, del R Millán J. A hybrid brain–computer interface based on the fusion of electroencephalographic and electromyographic activities. Journal of neural engineering. 2011 Mar 24;8(2):025011.
[9]. Rocon E, Gallego JA, Barrios L, Victoria AR, Ibanez J, Farina D, Negro F, Dideriksen JL, Conforto S, D'Alessio T, Severini G. Multimodal BCI-mediated FES suppression of pathological tremor. InEngineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE 2010 Aug 31 (pp. 3337-3340). IEEE.
[10]. Kiguchi K, Hayashi Y. A study of EMG and EEG during perception-assist with an upper-limb power-assist robot. InRobotics and Automation (ICRA), 2012 IEEE International Conference on 2012 May 14 (pp. 2711-2716). IEEE.
[11]. Du Y, Zhang X, Wang Y, Mu T. Design on exoskeleton robot intellisense system based on multi-dimensional information fusion. InMechatronics and Automation (ICMA), 2012 International Conference on 2012 Aug 5 (pp. 2435-2439). IEEE.
[12]. Allison BZ, Brunner C, Kaiser V, Müller-Putz GR, Neuper C, Pfurtscheller G. Toward a hybrid brain–computer interface based on imagined movement and visual attention. Journal of neural engineering. 2010 Mar 23;7(2):026007.
[13]. Savic A, Kisić U, Popović MB. Toward a hybrid BCI for grasp rehabilitation. In5th European Conference of the International Federation for Medical and Biological Engineering 2012 (pp. 806-809). Springer Berlin Heidelberg.
[14]. Li Y, Pan J, Wang F, Yu Z. A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control. IEEE Transactions on Biomedical Engineering. 2013 Nov;60(11):3156-66.
[15]. Fan XA, Bi L, Teng T, Ding H, Liu Y. A brain–computer interface-based vehicle destination selection system using P300 and SSVEP signals. IEEE Transactions on Intelligent Transportation Systems. 2015 Feb;16(1):274-83.
[16]. Yin E, Zeyl T, Saab R, Chau T, Hu D, Zhou Z. A hybrid brain–computer interface based on the fusion of P300 and SSVEP scores. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2015 Jul;23(4):693-701.
[17]. Hwang JY, Lee MH, Lee SW. A brain-computer interface speller using peripheral stimulus-based SSVEP and P300. InBrain-Computer Interface (BCI), 2017 5th International Winter Conference on 2017 Jan 9 (pp. 77-78). IEEE.
[18]. Panicker RC, Puthusserypady S, Sun Y. An asynchronous P300 BCI with SSVEP-based control state detection. IEEE Transactions on Biomedical Engineering. 2011 Jun;58(6):1781-8.
[19]. Krusienski DJ, Sellers EW, Cabestaing F, Bayoudh S, McFarland DJ, Vaughan TM, Wolpaw JR. A comparison of classification techniques for the P300 Speller. Journal of neural engineering. 2006 Oct 26;3(4):299.
[20]. Hoffmann U, Vesin JM, Ebrahimi T, Diserens K. An efficient P300-based brain–computer interface for disabled subjects. Journal of Neuroscience methods. 2008 Jan 15;167(1):115-25.
[21]. Rebsamen B, Burdet E, Zeng Q, Zhang H, Ang M, Teo CL, Guan C, Laugier C. Hybrid P300 and Mu-Beta brain computer interface to operate a brain controlled wheelchair. InProceedings of the 2nd International Convention on Rehabilitation Engineering & Assistive Technology 2008 May 13 (pp. 51-55). Singapore Therapeutic, Assistive & Rehabilitative Technologies (START) Centre.
[22]. Yang J, Su X, Bai D, Jiang Y, Yokoi H. Hybrid EEG-EOG system for intelligent prosthesis control based on common spatial pattern algorithm. InInformation and Automation (ICIA), 2016 IEEE International Conference on 2016 Aug 1 (pp. 1261-1266). IEEE.
[23]. Jiang J, Zhou Z, Yin E, Yu Y, Hu D. Hybrid Brain-Computer Interface (BCI) based on the

EEG and EOG signals. Bio-medical materials and engineering. 2014 Jan 1;24(6):2919-25.
[24]. Wang H, Li Y, Long J, Yu T, Gu Z. An asynchronous wheelchair control by hybrid EEG–EOG brain–computer interface. Cognitive neurodynamics. 2014 Oct 1;8(5):399-409.
[25]. Huo XQ, Zheng WL, Lu BL. Driving fatigue detection with fusion of EEG and forehead EOG. InNeural Networks (IJCNN), 2016 International Joint Conference on 2016 Jul 24 (pp. 897-904). IEEE.
[26]. Giri EP, Fanany MI, Arymurthy AM, Wijaya SK. Ischemic stroke identification based on EEG and EOG using ID convolutional neural network and batch normalization. InAdvanced Computer Science and Information Systems (ICACSIS), 2016 International Conference on 2016 Oct 15 (pp. 484-491). IEEE.
[27]. Velchev Y, Manolova A. Automatic sleep quality assessment based on EEG and EOG analysis and contextual classification. InIntelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), 2015 IEEE 8th International Conference on 2015 Sep 24 (Vol. 1, pp. 265-270). IEEE.