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A study on performance increasing in SSVEP based BCI application

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ABSTRACT

People which are afflicted with neurological conditions or neurodegenerative diseases can't control own muscles by neural pathways. Brain computer interface (BCI) systems offer these people another alternative path from their own neural pathways. This alternative pathway is the direct use of brain signals by a computer without using any vocal muscle. The steady state visual evoked potential (SSVEP) approach currently provides the high performance and reliable communication for the implementation of a non-invasive BCI. In SSVEP based BCI systems, Electroencephalography (EEG) signal detection time (signal window length) and accuracy are the most important performance parameters. Performance is usually measured by Information Transfer Rate (ITR).

In the presented paper a SSVEP based BCI robot control application is introduced and system performance is analyzed for different signal window lengths. At first, the number of eye blinks of the subjects is determined by fast eye artifact detection method (FEAD) which based on visual eye blink detection. These eye blink counts are used for system activation. System usability is improved by this control. Two consecutive eye blinks which detecting by FEAD method are used for system activation. System deactivation is also provided by the same command. Synchronous and asynchronous experiments are performed on four healthy subjects for performance analyses. EEG data is analyzed in details by asynchronous experiments. During the synchronous experiments, subjects are tried to complete a predefined route which has twelve steps by navigating the robot (Lego Mindstorms EV3). The minimum energy combination (MEC) and canonical correlation analysis (CCA) methods are applied to EEG segments that are different in length in order to detect SSVEPs in both type experiments. ITR values are calculated for different signal window lengths. The results show that the detection accuracy of the MEC method is similar to that of the CCA method, although it is higher than that of the CCA method in situations where the SSVEP has low strength. In synchronous experiments, using MEC method a system peak ITR of 133.33 bit/min is reached for one subject with a 0.9 s signal window length. This ITR value is higher than previously published studies in the literature for SSVEP based BCI systems.

1. Introduction

People which are afflicted with neurological conditions or neurodegenerative diseases can't control own muscles by neural pathways. Amyotrophic lateral sclerosis (ALS), LIS (Lock in Syndrome), spinal cord injury, stroke, and many other conditions impair the neural pathways controlling muscles. Brain computer interface systems offer these people another alternative path from their own neural pathways. This alternative pathway is the direct use of brain signals by a computer without using any vocal muscle. EEG is the most common signal type used in BCI systems. These signal is generated by the firing of many neurons in the brain [1–3]. SSVEP based BCI system must reflect flickering lights stimulus at different frequencies to the user. The best response for these stimulus are obtained for stimulation frequencies between 5 and 20 Hz [4,5]. The response signals of these stimuli can be detected from the scalp. SSVEP based BCI systems analyze this signals. The success of the system is measured by ITR. ITR depends on three factors; speed, accuracy and the number of targets [6–8]. Reported average accuracy and ITR for SSVEP based BCI systems which has six target are 95.3% and 58 ± 9.6 bit/min respectively [9]. Another study is reported that average accuracy and ITR are 96.79 ± 7.881% and 61.70 ± 32.676 bit/min [8]. Another study is reported that ITR is 16.10 bit/min for elderly people, 27.36 bit/min for young group [10]. In another study [11] ITR is reported between 25.69 ± 21.37 bit/min and 39.87 ± 8.37 bit/min for SSVEP based BCI systems by multivariate synchronization index method (MSI).

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SSVEP based BCI system which can control a humanoid robot is reported an accuracy of 95% in 5 s [12]. Another SSVEP based robot control BCI system, which using Fast Fourier Transform and a Gaussian model to detect the dominant frequency component is reported an accuracy of 75% [13]. Error rate of 29% is reported in another study for SSVEP based robot control [14].

In this study a non-invasive SSVEP based BCI system is designed, which has four targets. User can control the robot (Lego Mindstorms EV3) by using this system. Eye blinks of subjects are used for system activation. Subjects eye blinks are detected by fast eye artifact detection (FEAD) method. Total of four subjects participated in the study. Synchronous and asynchronous performance of the system are analyzed with different signal window lengths by using CCA and MEC methods. Optimum signal window length is obtained which has maximum ITR value for the system. The general structure of the system is given in Fig. 1.

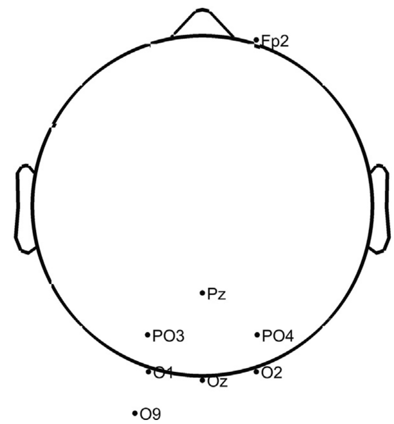

Fig. 2. Electrodes placement.

2. Materials and methods

2.1. Data acquisition

The data are collected from four healty subjects at multiple sessions including several trials each. The subjects mean age is 35.75 years, ranged between 30 and 41 years. During the asynchronous experiment, a subject had to perform look four different square (100 x 100 pixel) which are stimulate by 6.66 Hz 'up', 7.50 Hz 'right', 8.57 Hz'down' and 10 Hz'left' on the LCD screen(1366 x 768 resolution, 60 Hz refresh rate). Subject is informed by voice command about target which has to look (left, right, up, down). In the experiments two different computers which has i7 2.8 GHz and i3 2.27 GHz processors are used for Graphical User Interface (GUI) and signal processing. Both computers are run with Windows 10 operating system and 4 GB of RAM. Subjects are seated in front of the GUI screen at a distance of about 50 cm. The time series of the electrical brain activity is picked up during these trials using 8 gold EEG electrodes which is placed on scalp. Electrodes are placed at predefined locations $P_Z, PO_3, PO_4, O_1, O_2, O_Z, O_9$ and FP_2. EEG conductive paste is applied between the electrodes and the scalp. Electrodes are placed near the occipital region in accordance to international 10–20 system. In addition, generalization error estimation approach is used for choosing of electrodes, by testing classification success of channels. Every trial is recorded for 5 s duration. Asynchronous experiment dataset, consists 56 labelled data for each class, per subject. Electrodes placement are shown in Fig. 2. EEG signals are acquired using a biosignal amplifier (Bioradio, Great Lakes NeuroTechnologies, USA). The sampling frequency is set to 500 Hz. During the synchronous experiments, subjects are tried to complete a predefined route by navigating a robot that is able to move forward, backward, to the left and to the right. Subjects can complete the route by twelve correct commands. The subjects are so placed that they could easily watch both the robot and the computer screen. In addition, users are received instant voice feedback about their commands. The graphical user interfaces (GUI) are designed in the MATLAB 2105a by using Psychtoolbox and Lego Mindstorms EV3 Support libraries. Synchronous GUI screenshot is given in Fig. 3.

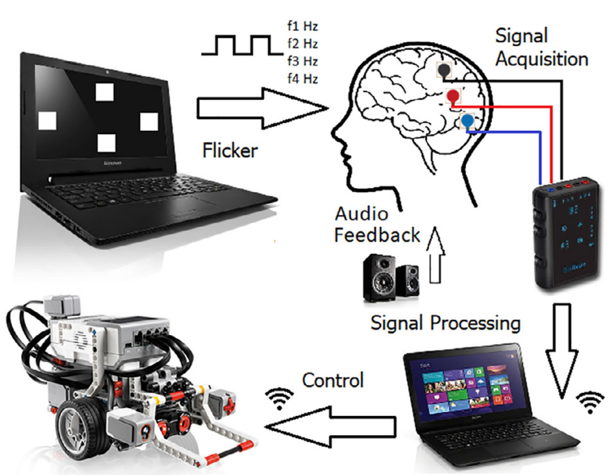

Fig. 1. The general structure of the system.

2.2. Signal processing and classification

Classification process is applied to raw EEG signals. Signal processing steps are given in Fig. 4.

2.2.1. Standardization

EEG data are obtained at different session. This makes a significant difference in voltage amplitude. Amplitude difference may arise from the result of physiological changes of subject and environmental changes. This difference negatively affects the classification. Therefore, EEG signals are scaled by z-score method, train by train for every channel and voltage value measured at the same time from all channels. This method aims to improve the signal to noise ratio of the EEG signals. Z-score generally represents the distance from the average data. Z-score is described in Eq. (1) where $\bar{x}$ represents the signal mean and σ standard deviation value [15].

$$Z = \frac{x - \bar{x}}{\sigma} \tag{1}$$

Fig. 3. Experiment sample by GUI.

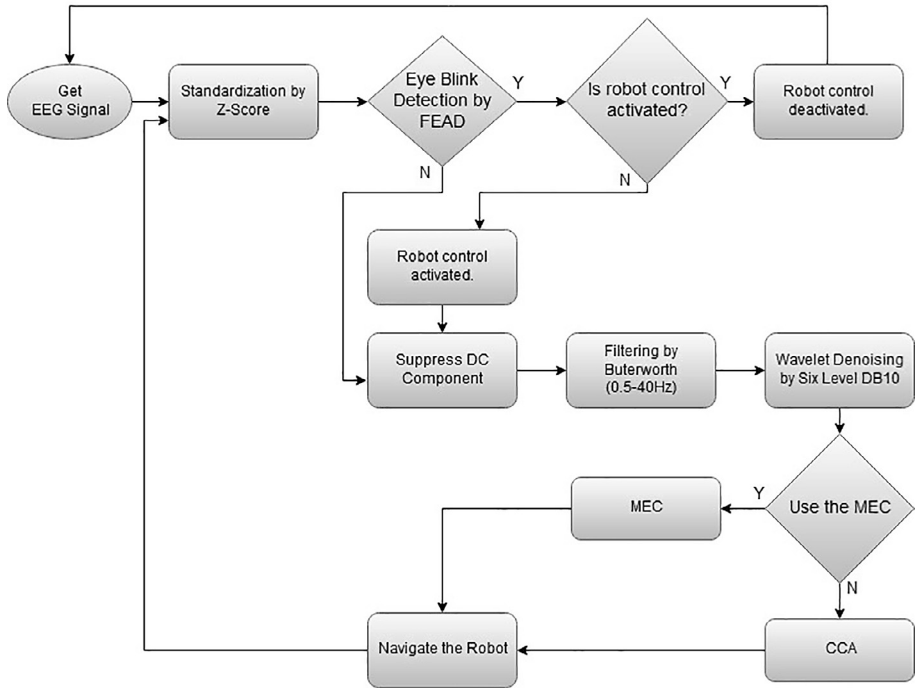

Fig. 4. Signal processing steps.

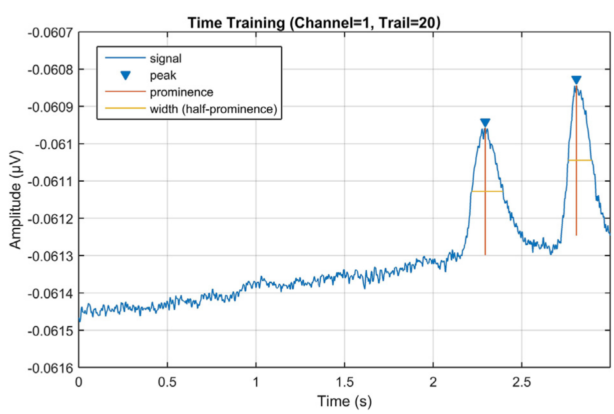

Fig. 5. Samples trial by eye vertical blink artifact and FEAD properties

Standardization of data is obtained by calculating the z-scores of each signals with the help of Eq. (1).

2.2.2. Eye blink detection by FEAD

Number of eye blinks of the subjects are determined by FEAD method. These counts are used to make the system active or deactive. The system is started to control the robot by two consecutive eye blinks which are obtained from a subject, that is like double clicking of a mouse, and the control process is terminated by the second command which has same features. Vertical eye blinks sample and FEAD algorithm flow diagram are given in Figs. 5 and 6 respectly. Trials with vertical eye blink artifacts are detected by using some pick properties such as minimum peak prominence value (MPPV) and minimum peak distance value (MPDV) by FEAD. MPPV and MPDV values are taken as 0.3 ms and 2e-04. Vertical eye blinks are detected from channel FP_2.

2.2.3. Filtering

Each trial of EEG data extracted from 8 channels for asynchronous and synchronous experiments, sampled at 500 Hz.

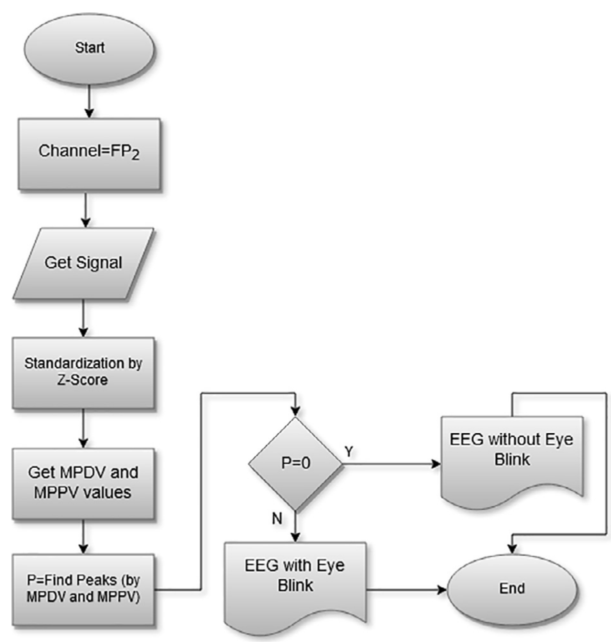

Fig. 6. FEAD flow diagram.

The signals are filtered by 0.5–40 Hz Butterworth filter. Before the filtering signal DC component is suppressed.

2.2.4. Wavelet denoising

Classical solution for noise removal from non-stationary signal is Wavelet denoising (WD) which is considered for improving the separation results.By this method decomposing the signal on a wavelet basis we obtain a representation of the signal that concentrates most of its energy distribution in few wavelet coefficients having large absolute value. W and W^{-1} respectively represent the forward and backward wavelet transform then the WD will be performed for a given signal in the following process;

$$W_i = W(x_i) \tag{2}$$

$$\widehat{W}_i = T(W_i, \lambda) \tag{3}$$

$$\widehat{C}_i = W^{-1}(\widehat{W}_i) \tag{4}$$

where, W is wavelet coefficients vector $T(\lambda)$ thresholding operator, λ threshold, $\widehat{W}$ is the wavelet coefficients after thresholding, $\widehat{C}$ is the denoised signal [16]. WD is applied on the signal to reduce the noise. Daubechies 10 (DB10) mother wavelet is used in sixth level WD. DB10 wavelet as the fundamental function to analyze the analog signal [17]. The classification success is observed to increase by about %3 by using WD.

2.2.5. Minimum energy combination method

Minimum energy combination method (MEC) [8,18] is used in signal processing. The method generally consists three steps.

Three steps as follows:

- All information about the frequencies of interest should be extracted from recorded signals. Obtained signals include only information that is uninteresting. Therefore it can be considered as noise components belonging to the original signals.
- A linear combination is achieved, suppressing the noisy signals obtained in the first stage.
- Finally, we apply this linear combination to the original signals to produce low noise signals.

The voltage $y_i(t)$ between the electrode i and a reference electrode at time t, $y_i(t)$ is described in Eq. (5) Where f represents stimulus frequency and N_h the number of considered harmonic.

$$y_i(t) = \sum_{k=1}^{N_h} (a_{i,k} sin2\pi kft + b_{i,k} cos2\pi kft) + E_{i,t} \tag{5}$$

The signal consists of two parts. The first part relevant to the SSVEP signal, which is composed of a number of sine and cosine functions with the stimulus frequency and a number of N_h harmonics. $a_{i,k}$ and $b_{i,k}$ represents sine and cosine terms amplitudes. The second part of the signal $E_{i,t}$ is the noise and all the information that are not relevant to the SSVEP signal. EEG signal for the electrode i in the time segment is given in Eqs. (6) and (12 respectively where N_t represents samples of the signal i, X represents information matrix (size: N_t X $2N_h$) which contains sine and cosine components associated with the N_h harmonics and g_i (size: $2N_h$ X 1) represents amplitudes $a_{i,k}$ and $b_{i,k}$.

$$y_i = Xg_i + E_i \tag{6}$$

$$y_i = [y_i(1), \ldots, y_i(N_t)]^T \tag{7}$$

Eq. (6) can be generalized for N_y electrodes,

$$Y = XG + E \tag{8}$$

$Y = [y_1, \ldots, y_{N_y}]$ contains the sampled EEG signals from all the channels. Channel vector s is given in Eq. (12) which is a linear combination of the electrode signals y_i where W is a vector of weights associated with the electrode signals. Eq. (12) can be generalized for N_s channels in as Eq. (12) where channel vector $S = [S_1, \ldots, S_{N_s}]$ and weight matrix $W = [W_1, \ldots, W_{N_s}]$.

$$S = YW \tag{9}$$

At first stage, all information about the frequencies of interest should be extracted from recorded signals. Obtained signals include only information that is uninteresting. For this an orthogonal projection is used. This calculation is given in Eq. (12).

$$\widehat{Y} = Y - X(X^TX)^{-1}X^TY \tag{10}$$

Weight vector W which minimizes the energy of the signal $\widehat{Y}$, can be calculate by the minimal eigenvalue λ_i and eigenvector υ_i of the matrix $\widehat{Y}^T\widehat{Y}$. Weight vector matrix W is given in Eq. (12) where eigenvalues in ascending order $(\lambda_1, \ldots, \lambda_{N_s})$, the corresponding eigenvectors $(\upsilon_1, \ldots, \upsilon_{N_s})$ and N_s is selected channel count which is used for classification.

$$W = \left[\frac{\upsilon_1}{\sqrt{\lambda_1}} \cdots \frac{\upsilon_{N_s}}{\sqrt{\lambda_{N_s}}}\right] \tag{11}$$

A frequency power can be calculated by Eq. (12).

$$\widehat{P} = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} ||X_k^T s_l||^2 \tag{12}$$

Normalized power value is given in Eq. (13) where $\hat{P}_i$ is the power of i th signal.

$$P_i = \frac{\hat{P}_i}{\sum_{j=1}^{N_f} \hat{P}_j} \tag{13}$$

Revised power value which is calculated with softmax function is given in Eq. (14). This revision is necessary for overcoming the problems caused by large $N_f$values.

$$\acute{P}_i = \frac{e^{P_i}}{\sum_{j=1}^{N_f} e^{P_j}} \tag{14}$$

Table 1
Asynchronous experiments results for subject one.

Signal Length (s)	CCA		MEC	
	Accuracy %	ITR $\frac{bit}{min}$	Accuracy %	ITR $\frac{bit}{min}$
2	93.30	46.18	95.98	50.80
1.5	89.29	53.56	93.30	61.57
1	85.27	69.80	91.96	88.15
0.9	80.36	64.93	91.07	94.96
0.8	78.13	67.16	89.29	100.42
0.7	75.89	70.38	87.95	109.55
0.6	74.55	77.84	84.82	114.51
0.5	65.18	61.88	82.14	124.80
0.4	63.84	72.43	72.32	106.54
0.3	51.34	45.85	63.39	94.44
0.2	36.61	14.29	49.55	60.15
0.1	25.45	0.05	27.23	1.13

Table 2
Asynchronous experiments results for subject two.

Signal Length (s)	CCA		MEC	
	Accuracy %	ITR $\frac{bit}{min}$	Accuracy %	ITR $\frac{bit}{min}$
2	94.64	48.41	95.54	49.98
1.5	83.93	44.37	91.07	56.98
1	83.48	65.50	89.73	81.59
0.9	78.13	59.69	86.16	80.04
0.8	74.55	58.38	83.93	83.19
0.7	73.66	64.35	80.36	83.48
0.6	72.32	71.03	73.66	75.07
0.5	62.50	54.14	75.89	98.53
0.4	58.48	54.42	64.73	75.69
0.3	45.09	27.33	56.70	65.33
0.2	30.36	3.17	38.39	18.83
0.1	20.54	4.80	21.43	3.05

Table 3
Asynchronous experiments results for subject three

Signal Length (s)	CCA		MEC	
	Accuracy %	ITR $\frac{bit}{min}$	Accuracy %	ITR $\frac{bit}{min}$
2	80.26	29.12	87.72	38.04
1.5	73.25	29.52	81.58	40.75
1	64.47	29.89	72.37	42.70
0.9	57.89	23.38	67.11	37.65
0.8	57.02	24.98	67.11	42.36
0.7	54.82	24.92	67.98	50.40
0.6	55.70	30.73	59.21	37.81
0.5	49.56	24.07	57.46	41.02
0.4	39.47	10.93	45.61	21.53
0.3	35.96	8.54	38.60	12.93
0.2	30.70	3.58	30.26	3.06
0.1	24.12	0.18	25.44	0.04

Table 4
Asynchronous experiments results for subject four.

Signal Length (s)	CCA		MEC	
	Accuracy %	ITR $\frac{bit}{min}$	Accuracy %	ITR $\frac{bit}{min}$
2	66.67	16.60	86.84	36.89
1.5	62.72	18.25	82.02	41.41
1	56.14	18.94	71.49	41.15
0.9	50.44	14.30	68.42	39.98
0.8	51.32	17.17	66.67	41.50
0.7	49.12	16.61	67.11	48.41
0.6	46.49	15.55	64.47	49.82
0.5	45.61	17.23	56.14	37.89
0.4	49.12	29.08	52.63	37.68
0.3	42.54	21.09	54.82	58.14
0.2	37.28	15.94	44.74	39.63
0.1	31.58	9.48	34.21	18.27

Finally, the frequency value f_{result} which has max $\acute{P_i}$ value between 1 and N_f is the actual result. This value is given by Eq. (15).

$$f_{result} = argmax(\acute{P_i}) \tag{15}$$

2.2.6. Canonical correlation analysis

CCA is a multivariable statistical method which is used to find correlation between two sets of data [19,20]. If these two sets of data $X \in R^{I_1 xJ}, Y \in R^{I_2 xJ}$ and their linear combinations are $\tilde{x} = w^T X, \tilde{y} = v^T Y$, CCA tries to find a pair of linear transform $w \in R^{I_1 xJ}$ and $v \in R^{I_2 xJ}$ to maximize the correlation between $\tilde{x}$ and $\tilde{y}$ by solving the optimization problem in Eq. (16).

$$p = max(w, v)\frac{E[\tilde{x}\tilde{y}]}{\sqrt{E[\tilde{x}^2]E[\tilde{x}^2]}} = \frac{w^T XY^T v}{\sqrt{w^T XX^T w v^T YY^T v}} \tag{16}$$

The maximum value of p corresponds to the maximum correlation between the variables $\tilde{x}$ and $\tilde{y}$. In Eq. (17), M=$(f_1, f_2, f_3, \ldots, f_m)$ represents stimulus frequencies for targets, X is the EEG signals which are obtained from I1 channels, Y_m is reference signals which are constructed by sine, cosine, m is the stimulus frequency index, H is the number of signal harmonics, f_s is the sampling rate and is the J number of sampling points.

$$Y_m = \begin{pmatrix} \sin(2\pi f_m \frac{1}{f_s}) & \ldots & \sin(2\pi f_m \frac{J}{f_s}) \\ \cos(2\pi f_m \frac{1}{f_s}) & \ldots & \cos(2\pi f_m \frac{J}{f_s}) \\ \vdots & \vdots & \vdots \\ \sin(2\pi H f_m \frac{1}{f_s}) & \ldots & \sin(2\pi H f_m \frac{J}{f_s}) \\ \cos(2\pi H f_m \frac{1}{f_s}) & \ldots & \cos(2\pi H f_m \frac{J}{f_s}) \end{pmatrix} \tag{17}$$

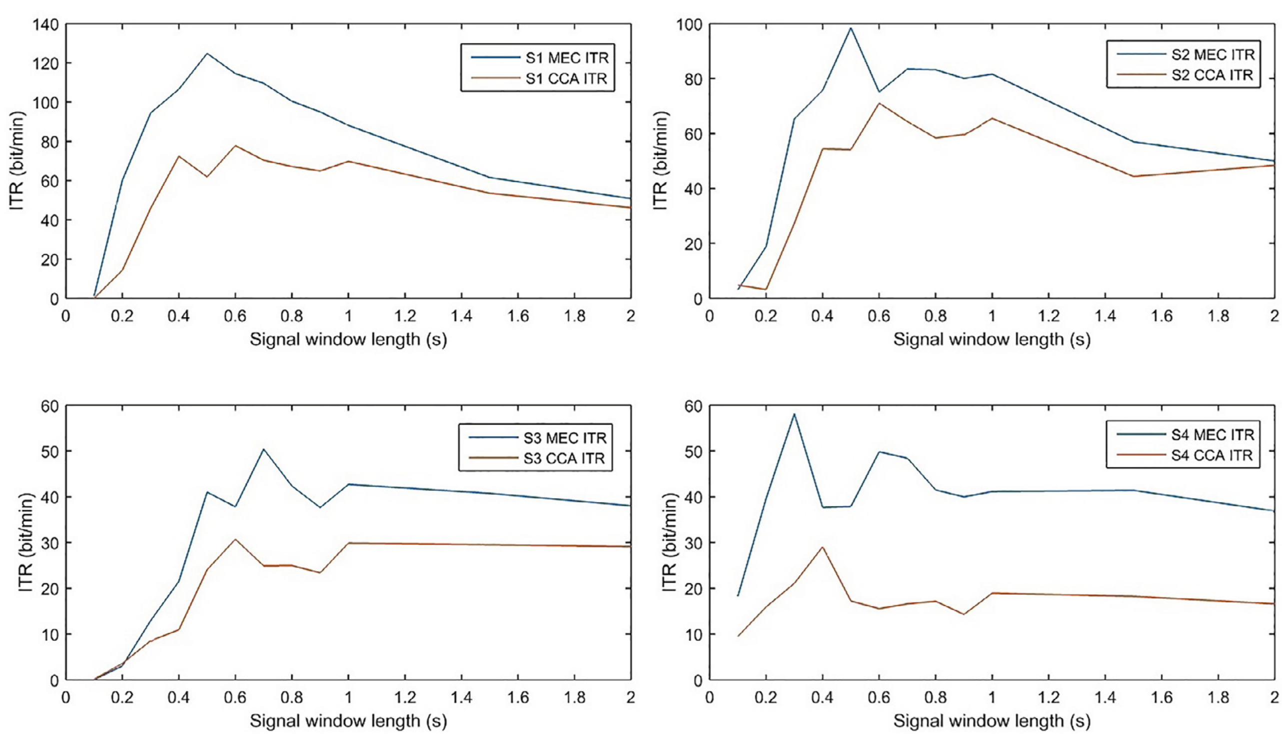

Fig. 7. Variation of system ITR values versus signal window lengths.

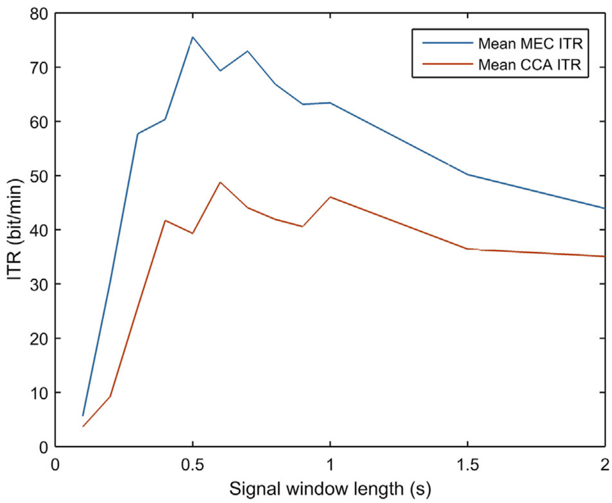

Fig. 8. System mean ITR values.

p values are calculated for every reference signals Y_m. The maximum p value represents the reference signal which has highest correlation with X signal. This reference signal with the highest correlation with X, indicates the stimulation frequency that is the subject of focus.

2.3. Calculating system information transfer rate

Bit rate or information transfer rate (ITR) is most commonly applied to assess the performance of BCI systems. B_m which is ITR and in bits per minute, can be calculate by Eq. (18) where C_N is the number of classifications and T is the process time in seconds [21,8].

$$B_m = \frac{60}{T}.C_N.B_t \tag{18}$$

B_t which is expressed in bits per trial also can be calculated from Eq. (19), where p is the classification accuracy and N is the number of targets. The number of targets mean is stimulated squares [21]. In this case N becomes 4.

$$B_t = \log_2 N + p\log_2 p + (1-p)\log_2\left[\frac{1-p}{N-1}\right] \tag{19}$$

3. Experimental results

MEC and CCA methods are applied to EEG segments which are collected by synchronous and asynchronous experiments that are different in length in order to detect SSVEPs. The number of Signal harmonics is chosen four in both methods. Accuracy and ITR values which are obtained from asynchronous experiment results are given in Table 1, Tables 2–4 for each subjects respectively.

Changes of system ITR values according to signal window lengths for each subjects are given in Fig. 7. System average ITR values also are given in Fig. 8 for both methods. High ITR values are achieved in between 0.5 and 1 s of signal window lengths for all subjects.

Synchronous experiments are repeated many times by reducing signal window length for determining optimum signal length. Synchronous experiments results by CCA and MEC methods are given in Tables 5 and 6.

Table 5
Synchronous experiments results obtained by CCA method.

Signal Length (s)	S1 Acc. %	S1 ITR $\frac{bit}{min}$	S2 Acc. %	S2 ITR $\frac{bit}{min}$	S3 Acc. %	S3 ITR $\frac{bit}{min}$	S4 Acc. %	S4 ITR $\frac{bit}{min}$)	Mean Acc. %	Mean ITR $\frac{bit}{min}$)
2	100.00	60.00	100.00	60.00	100.00	60.00	100.00	60.00	**100.00**	**60.00**
1.5	100.00	80.00	100.00	80.00	100.00	80.00	100.00	80.00	**100.00**	**80.00**
1	100.00	120.00	100.00	120.00	91.67	87.25	91.67	87.25	**95.83**	**103.62**
0.9	91.67	96.94	83.33	72.39	83.33	72.39	83.33	72.39	**85.42**	**78.53**
0.8	91.67	109.06	91.67	109.06	75.00	59.44	83.33	81.44	**85.42**	**89.75**
0.7	83.33	93.07	83.33	93.07	66.67	47.43	75.00	67.93	**77.08**	**75.37**

Table 6
Synchronous experiments results obtained by MEC method

Signal Length (s)	S1 Acc. %	S1 ITR $\frac{bit}{min}$	S2 Acc. %	S2 ITR $\frac{bit}{min}$	S3 Acc. %	S3 ITR $\frac{bit}{min}$	S4 Acc. %	S4 ITR $\frac{bit}{min}$)	Mean Acc. %	Mean ITR $\frac{bit}{min}$)
2	100.00	60.00	100.00	60.00	100.00	60.00	100.00	60.00	**100.00**	**60.00**
1.5	100.00	80.00	100.00	80.00	100.00	80.00	100.00	80.00	**100.00**	**80.00**
1	100.00	120.00	100.00	120.00	100.00	120.00	100.00	120.00	**100.00**	**120.00**
0.9	100.00	133.33	91.67	96.94	83.33	72.39	91.67	96.94	**91.67**	**99.90**
0.8	91.67	109.06	91.67	109.06	83.33	81.44	91.67	109.06	**89.58**	**102.15**
0.7	83.33	93.07	83.33	93.07	75.00	67.93	75.00	67.93	**79.17**	**80.50**

4. Conclusion

In SSVEP based BCI systems, signal detection time and accuracy are the most important performance parameters. This paper provides a study on BCI robot control application and performance analysis of the system using CCA and MEC methods. Activation of the BCI application is provided by specific eye blinks of subjects. FEAD method is developed for fast detection of specific eye blinks. By this way, we were able to design a BBA system that execute commands when the user wishes. It is observed that the system has become more user friendly by using FEAD. Z-score method and Wavelet denoising (WD) is used for signal standardization and noise reduction in system. The classification success is increased about 3% by using WD.

Experiments are performed synchronous and asynchronous type for performance analysis. Data is collected by simulation in asynchronous experiments and BCI system is tested with a robot that is able to move forward, backward, to the left and to the right in synchronous experiments. System performance is tested with two different signal detection methods (CCA and MEC) by reducing signal window length in both types of experiments. ITR values are calculated for each subject and signal window lengths. The results of analysis show that the detection accuracy of the MEC method is similar to that of the CCA method, although it is higher than that of the CCA method in situations where the SSVEP has low strength. By the MEC method, the highest ITR value of 133.33 bit/min is obtained for one subject, by using just three occipital region channels (O_1, O_2, O_Z) in synchronous experiments. This ITR value is higher than the previously published studies in the literature for SSVEP based BCI systems [8–14]. The highest ITR values are highlighted in Tables 5 and 6. All subjects are completed predefined route in synchronous experiments without errors for signal window lengths 2, 1.5, and 1 s, achieving a mean accuracy of 100% as shown in Table 6. Over 100 bit/min ITR values are obtained in signal window lengths 1 and 0.8 s. Synchronous experiments are more successful than asynchronous experiments because of the subjects are received instant visual and voice feedback about their commands by navigating the robot. Also, synchronous experiments time is shorter than the other. Long experiment times are decreasing signal detection success by reducing focus. In synchronous experiments, successful signal detection are not achieved in signal window lengths below 0.7 s.

It is observed that the channels outside the occipital region negatively affected the signal detection. System performance is also affected negatively from stress of subjects and better signal detection is obtained by naturally calm subjects. Further research might also consider human factors that can influence performance.

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