Boosting the Evoked Response of Brain to Enhance the Reference Signals of CCA Method

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***Abstract*— Brain-computer interface (BCI) systems can be used to communicate and express desires from people with severe nervous system damage. Among BCI systems based on evoked responses, steady state visual evoked potential (SSVEP) responses are the most widely used. Canonical correlation analysis (CCA)-based methods have been widely used in SSVEP-based online BCIs due to their low computation and high speed, and many methods have been introduced to improve the results. In this research, a method for constructing reference signals used in CCA based on the amplified evoked response of brain is introduced. In the proposed method, after removing the latency in the training signals, to construct reference signals, multilayer perceptron neural networks of the fitting type are used instead of the usual sine/cosine signals. The results show the success of this method in boosting the evoked responses of brain. The detection accuracy in 100-second time windows was 100%, and the information transfer rate in the same period was 240 bits per minute. Making reference signals similar to the recorded electroencephalogram allowed us to make more similarities in the CCA between the signals under consideration, and the reference signals, and to dramatically improve the results.**

***Index Terms*— Brain-computer interface, SSVEP, evoked response booster CCA (ERBCCA), CCA reference signals, MLP neural network.**

I. Introduction

BRAIN-COMPUTER interfaces (BCIs) are a direct link between the computer and the human brain and are the most recently developed type of human-computer interface (HCI) [1], [2]. Unlike traditional input devices (keyboards, mice, pens, etc.), BCIs transmit waves generated by the brain to different parts of the human head, translate these signals into actions, and issue commands that can be used to control computer(s). The original idea of designing these types of interfaces was to help patients suffering from severe nervous system damage [3]. In these types of patients, the brain sends motor commands to the muscles and organs, but due to nervous system damage, the commands sent to the organs are not transmitted. Using systems such as the brain-computer interface can facilitate communication and expression of desires for these people. Therefore, the brain-computer interface system uses commands received directly from the brain to move prostheses and wheelchairs.

BCI systems based on evoked responses are widely considered, and among the types of these responses, steady-state evoked visual potential (SSVEP) signals are common. The basis of SSVEP-based brain-computer interfaces is the fluctuations in brain activity in the visual cortex that occur after receiving a visual stimulus. For example, if a user stares at a light or image that is flashing at a certain frequency, the flashing frequency of that image affects the signals in the visual cortex of the brain, so that the change can be detected. The advantages of SSVEP-based systems include high information transfer rate, short training time, high average correct detection, and safety for the user, which makes the SSVEP signal a reliable signal for use in BCI systems [4].

Canonical correlation analysis (CCA)-based methods have been proposed to determine the frequency of SSVEP stimulation. Due to their efficiency, ease of implementation, and no need for calibration, they have been widely used in online BCIs in recent years [5]–[8]. The CCA method was first introduced by Lin *et al.* To detect the frequency of SSVEP stimulation using multi-channel signals and to detect the canonical correlation between them and sine/cosine signals with frequencies corresponding to visual stimulation [9]. In this method, when two data sets have a basic correlation, the target frequency can be determined by calculating the level of correlation and selecting the set with the highest correlation [10]. Two linear transformations are used, to achieve the maximum correlation between two data sets in this method, one on the SSVEP data and the other on the sine/cosine reference signals, and the correlation between these signals is calculated after the transformations are applied, [9], [11], [12]. Since the standard CCA has a weakness that assumes two data sets of SSVEP signals and sine/cosine reference signals are linearly related, the Kernel-CCA (KCCA) method is proposed to use a nonlinear mapping between them [11]. This method predicts data in a high-dimensional space, but the internal multiplication of new data can still be calculated using the original low-dimensional data. To achieve an asynchronous BCI system, Poryzala *et al.* proposed a method called (CACC) cluster analysis of CCA coefficient [13]. Although the standard CCA method is powerful in detecting SSVEP, its performance is often affected by the interference of spontaneous EEG activities [14]. To reduce the amount of misclassification due

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to spontaneous EEG signals, SSVEP individual calibration data, which can better describe SSVEP time characteristics (e.g., phase and latency), are included in the CCA-based visual evoked potential (VEP) detection. Pan *et al.* [15] improved the CCA method and named it the phase-limited CCA (PCCA), considering the fixed-phase sinusoidal reference signals, which were obtained based on the latency in the amplitude of the training signals. Bin *et al.* [7] also developed the individual template-based CCA (IT-CCA) method by averaging a set of training data for each subject in the EEG recording with VEP stimulation based on the standard CCA method. Researchers in [16] have proposed the multi-way CCA (MCCA) method for generating better reference signals for use in CCA, and to optimize the reference signals in this method, the L1 multi-way CCA method (L1-MCCA) is further developed [17]. Recently, the multi-set CCA (MsetCCA) method has been used to generate reference signals using common features in SSVEP training data [18]. decision-making methods that use calibration data provide better results in SSVEP stimulation frequency detection. Authors in [19] proposed a method for synchronizing SSVEP signals with sine-cosine reference signals, which, by examining the correlation coefficients, obtains the related stimulation frequency. However, Wang *et al.* [20] improved the Multivariate Synchronization Index (MSI) method and introduced it as Inter and Intra-subject Template-Based Multivariate Synchronization Index (IIST-MSI), considering interpersonal and subject-specific templates.

In recent years, many studies have been proposed on the combination of stimulation frequency detection methods to create a final method. These methods are usually more accurate than the primary classifiers and are called group learning. These classifiers each build their model on the data and store it. For the final classification, a weighting is done between these classifiers. Among the group learning methods, we can mention the method proposed by Oikonomou *et al.*, which uses boosting and bagging methods to combine support vector machine (SVM) and decision tree classifiers, and for SSVEP signal on EEG recording with 256 channels, better results than each classifier [21]. In studies [14], [22], [23], the authors have ensembled the standard CCA method and the IT-CCA method for detecting SSVEPs [14]. Sadeghi and Maleki Combined EMD and CCA methods to improve SSVEP frequency detection using neural network classification and reported results with higher accuracy than each method [24]. In the study [25], the authors combined the experimental mode analysis method and the decision tree classifier and were able to improve the accuracy of the detection over a wide frequency range. Ziafati and Maleki ensembled MLR and MsetCCA methods using their fuzzy ensemble system and achieved excellent results [26].

Among the improved CCA methods, such as MsetCCA and MwayCCA, which generate new reference signals using similarities in training signals, provide better results than others. However, these methods do not consider the fact that only the evoked part of SSVEP signals contains visual stimulation signal information. In addition, since in the method presented in this study, the evoked part of SSVEP is estimated, it is important to determine the latency of this signal to achieve more accurate reference signals and better frequency recognition. This issue is not considered in these methods. Methods based on sine/cosine signals also do not consider the properties of real EEG signals in generating reference signals, although they use the corresponding latencies in the recognition by training signals. Subject-dependent methods that use the properties of the signals recorded from the subjects to detect stimulation frequency from their new signals have always led to better results. The proposed method benefits from using subjects' real SSVEP signals and their latencies to generate reference signals for the CCA method. Therefore, it can be used as a subject-dependent method.

In the proposed method, a fitting type multilayer perceptron neural network is used after removing the latency in training signals, to construct reference signals instead of using the usual sine/cosine signals. Making reference signals similar to the recorded EEG allows us to find more similarities in the CCA between the signals under consideration and the reference signals.

In Section II, we will introduce the dataset used, examine the construction of reference signals corresponding to the evoked response signal of the SSVEP, and finally, construct a new reference signal-set for use in the CCA method. Then, in section III, the results related to the implementations will be reviewed. In section IV, the obtained results will be discussed and compared with other methods, and in section V, we will have conclusions.

II. Materials and Methods

A. Database

The database used in this study is taken from the dataset presented in [27], which includes EEGs taken from 10 male subjects, all between the ages of 21 and 27 (all of whom are visually normal or have been corrected). These recordings were made in an isolated room, and each subject was placed on a comfortable chair at a 60 cm distance from a standard 17-inch CRT monitor (85Hz refresh rate, 1024×768 screen resolution). Four red squares are displayed on the screen as actuators that flash at four frequencies of 6, 8, 9, and 10 Hz, respectively. Twenty recordings were completed by the subjects for each target frequency. During each recording, the subject was asked to pay attention to each of the stimuli for 4 seconds, and 2 seconds were given to shift attention to the next target. It should be noted that after recording the first 10 experiments, the subjects rested for 5 to 10 minutes, then another 10 experiments were done. A total of 80 recordings have been performed by subjects. The sampling rate of 250 Hz was recorded as 30 channels according to the international standard system 10-20. In this study, 8 channels (Pz, P3, P4, P7, P8, Oz, O1, O2) that have been introduced as selected channels in recent comparisons, including [18], [28] have been used.

B. The Structure of the Proposed Method

In this study, a method for recognizing SSVEP stimulation frequency is presented, which is based on the CCA method. For constructing reference signals in the proposed method,

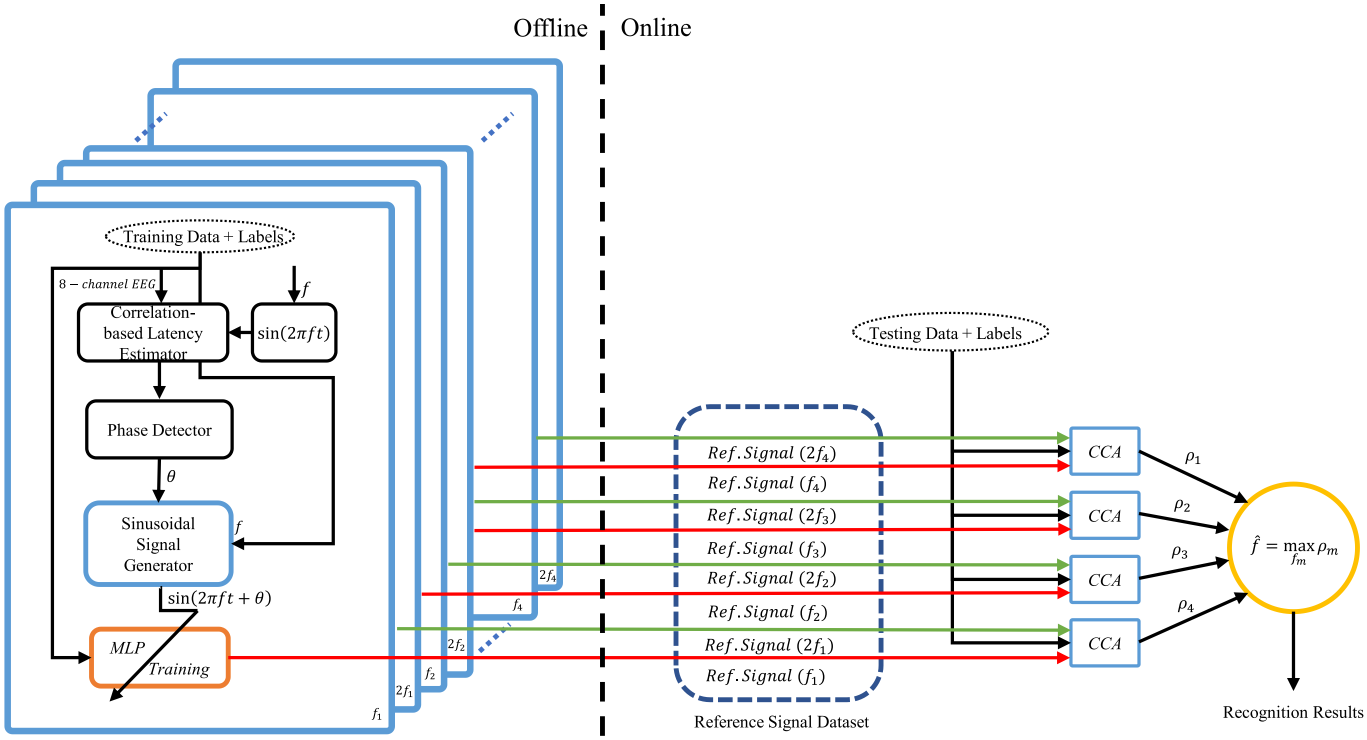

Fig. 1. The general structure of the proposed method, including offline and online.

a fitting multilayer perceptron neural network is used to boost evoked response of brain and generate new evoked-boosted SSVEP signals instead of the usual sine/cosine signals. Making reference signals similar to the recorded EEG allow us to find more similarities in the CCA between the signals under consideration and the reference signals. In addition, phase mismatch in the reference signals with the SSVEP signal reduces system performance. Therefore, we obtained an estimate of their phase and generated sine/cosine signals appropriate to the extracted phase before making new reference signals using training signals by the cross-correlation method, to use in the training stage of the neural network.

In the method introduced in this research, such as MsetCCA and MwayCCA methods, we used some of the labeled signals in the training section and used them to produce suitable reference signals for CCA. Then, in the evaluation section, we used the generated signals to detect the stimulation frequency of unknown signals. The general structure of the proposed method is shown in Figure 1.

The proposed method consists of several main parts, which we will introduce in the following.

C. Offline Section

The offline part of the method includes the subsections of latency detection, sine/cosine signal construction with obtaining latency, MLP neural network training, and the use of a trained neural network to generate new reference signals by boosting the evoked responses of brain.

D. Signal Preprocessing

The obtained data were filtered with a low-pass filter with a cut-off frequency of 70 Hz and a high-pass filter with a cut-off frequency of 0.1 Hz; then a sixth-order Butterworth filter was applied to the entire data in the range of 4 to 45 Hz. In addition, after estimating the signal latency using the proposed cross-correlation method, several initial samples of each signal were removed to synchronize the signal phases with the sine/cosine base signals generated with stimulation frequencies for use in the CCA method.

E. Latency Calculation by Cross-Correlation Method

The phase delay will always cause two sinusoidal signals to be dissimilar. Since in the EEG signals recorded with SSVEP stimulation, the sine signal corresponding to the stimulation frequency is implicit, it is necessary to estimate the phase of the recorded signals before producing the appropriate reference signals.

In this study, we used the cross-correlation method to extract the location of the most similarity between sine/cosine and training signals. In this method, we used two input signals, one of which is a zero-phase sinusoidal signal and the other an EEG signal from our training dataset, to generate a new signal with a maximum that occurs in a place where the two signals are more similar. The cross-correlation signal length is obtained from Equation (1).

$$Length_{Cross-Correlation}\,(x, y) = Length\,(x) + Length\,(y) - 1 \tag{1}$$

If the two signals x, and y, are co-phased and with equal length, the location of the maximum will be exactly in the middle of the cross-correlation signal. Now, if the two signals x and y are non-phase, the difference between the maximum location of this signal and its center can determine a suitable approximation of the delay rate in the phase for us.

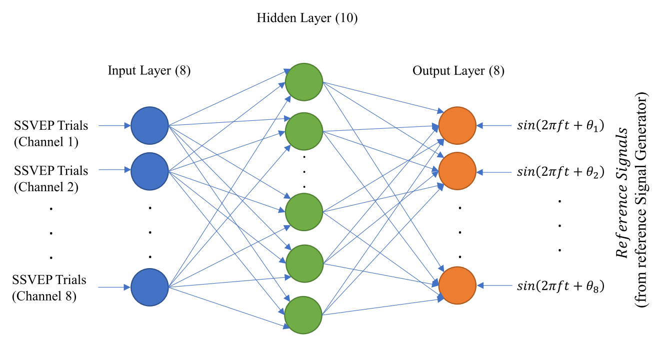

Fig. 2. Schematic of the proposed neural network for generating reference signals, which include 8 neurons equivalent to 8 SSVEP channels in the input layer, 10 neurons in the hidden layer, and 8 neurons equivalent to 8 channels of SSVEP signals in the output layer.

By having the sampling rate and the phase of delay of the sinusoidal signal compared to the training EEG signal, it is possible to determine the phase difference between these two signals. The phase corresponding to the sine signal is obtained from Equation (2) for each training signal.

$$z_{Lag} = z_{maximum\ correlation} - \frac{Length_{Cross-Correlation}(x, y)}{2}$$
$$\theta = lag \times \frac{f}{f_s} \times 2\pi \quad (2)$$

F. Construction of Sinusoidal Signals in Phase With Training Signals

It is sufficient to generate signals using the phases from the previous step, to obtain synchronous sinusoidal signals with training EEG signals. Equation (3) shows how to generate sinusoidal signals with training data.

$$Sine/Cosine_{new} = Sin(2\pi ft + \theta) \quad (3)$$

The resulting sinusoidal signals can be used to train the MLP neural network, which is used to generate new reference signals.

G. Generation of Reference Signals Using a Neural Network for Use in CCA

In the proposed method, eight channels of EEG training signals were applied to the input layer of a network consisting of three layers (input-hidden-output) with 8-10-8 neurons, and in the output layer, the phased sinusoidal signals were placed in proportion to the input signal. Then, network training was performed using the gradient descent method with momentum as 90 percent of training data and the remaining 10 percent of data to validate network performance. Figure 2 shows a schematic of the proposed neural network.

As shown in Figure 2, the neural network used in this research was a fitting multilayer perceptron with eight neurons in the input layer, 8 neurons in the output layer, and 10 neurons for the hidden layer. The number of hidden layer neurons was estimated to be equal to 2/3 of total neurons in the input and output layers, based on the method presented in [29]. In figure 2, f is the stimulation frequency, and $\theta_1, \theta_2, \ldots, \theta_8$ are corresponding phases with the latency of 8 SSVEP input channels. The transfer function of the hidden layer and the output layer were hyperbolic tangent sigmoid and linear, respectively. The training method was gradient descent with momentum. The network used mean squared normalized error performance function, and it was trained with 1000 epochs. The data was supplied to the network in two modes, subject-dependent, and subject-independent, which have dimensions of 19×1000 and 18×1000, respectively. 90% of this data was used for network training and the rest for network validation.

According to research conducted in [30], the velocity and distance of the brain wave propagation in the axons, by distancing from the main propagation site, which in the case of SSVEP signals is the primary visual cortex in the occipital region, will delay the signal. In the neural network used to generate SSVEP signals with the boosted evoked part, for each input SSVEP channel, an output channel is used considering the latency of the same channel obtained from the proposed method using correlation. Since the main harmonic of the visual stimulation signal is sinusoidal, it is expected to be seen in the evoked part of the SSVEP signal. as a result, the synchronized sinusoidal signals corresponding to the SSVEP channels were used as the desired output. Therefore, the output generated by the trained network will be a signal similar to SSVEP with the boosted evoked part. In order to generate new reference signals, the signals used in the training section are reentered into the trained neural network and the signals obtained from the output layer of the neural network are used as new references in the classical CCA method. Considering that in the dataset used, there are two signal recordings from each subject; we examined the problem in two ways, subject-dependent or subject-independent. To check the subject-independent mode, after removing the test data from the data used in the reference construction, we deleted another recording from the same subject, and for the subject-dependent mode, we used the second signal of the subject to construct the reference signal.

H. Online Section

The evaluation part of the method includes entering new reference signals to the CCA method, detecting the stimulation frequency using CCA, and calculating the accuracy and information transfer rate (ITR) of the proposed method, which are calculated in the form of Equations (4) and (5).

$$P = \frac{correctly\ recognized\ frequencies}{total\ testing\ signals} \times 100\% \quad (4)$$
$$ITR = \frac{60}{T}(log_2 N + Plog_2 P + (1-P)log\left[\frac{1-P}{N-1}\right]) \quad (5)$$

Equation (5) describes the information transfer rate in which the ITR is in bits per minute, N is the number of classes, T is the length of the signal time windows, and P is the classification accuracy [31].

In addition, we used the signal-to-noise ratio (SNR) to evaluate the improvement of the reference signals. Signal to Noise ratio (SNR) is a measure of the amount of useful signal versus disturbing signal (or noise) in electrical signals.

This number is the ratio of signal power to noise power. In the case of SSVEP signals, the ratio of the signal amplitude in the frequency domain for the desired frequency band to the amplitude of its neighboring frequencies can be considered. In the paper [36], formula (6) was used to calculate the signal-to-noise ratio in the SSVEP signal for each optimal frequency in the range of 8 to 15 Hz.

$$SNR = \frac{28 \times y(f)}{\sum_{k=8}^{k=15} y(k) - y(f)} \tag{6}$$

Due to the presence of 28 samples in the range specified in this signal, its numerator is multiplied by 28 to obtain a reasonable ratio.

Regarding the SSVEP signals in the dataset we used in this study, we calculated the signal-to-noise ratio as Equation (7).

$$SNR = \frac{4 \times y(f)}{\sum_{k=f-2}^{k=f+2} y(k) - y(f)} \tag{7}$$

In other words, for each target frequency, we considered two samples before and two samples after it as noise and calculated the SNR accordingly. Finally, due to the small amount of data in the database, the proposed method was validated in two ways. The leave-one-recording-out cross-validation method was used for subject-dependent mode, and the leave-one-subject-out cross-validation method was used for subject-independent mode. In the first method, one of the recordings was used for the test section and the rest for the training section, and in the second method, all recordings of a subject were used for testing, and the remaining data were used for training. This process was repeated for each recording in the first method and each subject in the second method. The accuracy and ITR were used to compare the proposed method with other methods.

III. Results

SSVEP data recorded with a length of 4 seconds were entered to generate reference signals in the proposed method, which is shown in Figure 3 as an example of these signals for the frequency of 6 Hz.

In order to investigate the similarity of the reference signals made with the proposed method and the raw SSVEP signals and also the sine/cosine signals used in the standard CCA method, first, the amplitude of all the mentioned signals is normalized, and then the level of cross-correlation of these signals with the entire dataset is calculated. The results are shown in Figure 4.

As can be seen, the correlation of the reference signals obtained from the proposed method in terms of correlation to the stimulation signals and the raw SSVEP signals, showed a higher numerical value, which indicates the proximity of these signals to the evoked response signal of the brain.

In addition, we used the signal-to-noise ratio (SNR) to evaluate the improvement of the reference signals. Signal to Noise ratio (SNR) is a measure of the amount of useful signal versus disturbing signal (or noise) in electrical signals. This number is the ratio of signal power to noise power. In the case of SSVEP signals, the ratio of the signal amplitude in

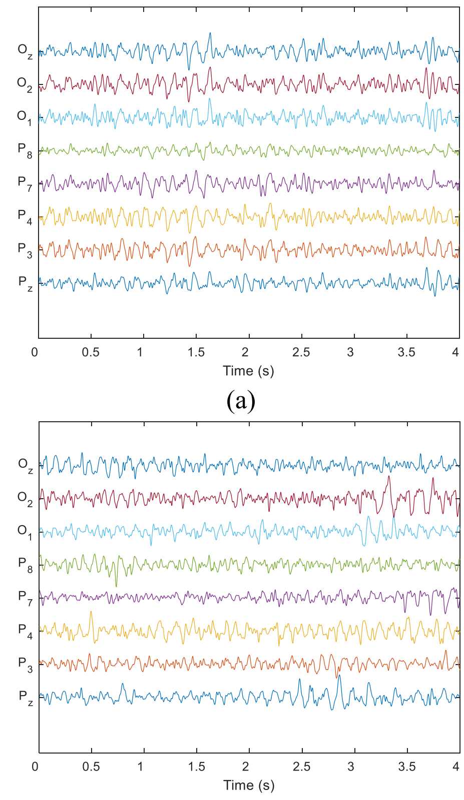

Fig. 3. (a) Sample of 8 channels of SSVEP raw signals at 6 Hz frequency, (b) Sample of 8 channels of reference signal made by the proposed method at 6 Hz frequency.

the frequency domain for the desired frequency band to the amplitude of its neighboring frequencies can be considered. In the paper [32], the formula (6) has been used to calculate the signal-to-noise ratio in the SSVEP signal for each optimal frequency in the range of 8 to 15 Hz.

$$SNR = \frac{28 \times y(f)}{\sum_{k=8}^{k=15} y(k) - y(f)} \tag{8}$$

Due to the presence of 28 samples in the range specified in this signal, its numerator is multiplied by 28 to obtain a reasonable ratio.

Regarding the SSVEP signals in the dataset we used in this study, we calculated the signal-to-noise ratio as Equation (7).

$$SNR = \frac{4 \times y(f)}{\sum_{k=f-2}^{k=f+2} y(k) - y(f)} \tag{9}$$

In other words, for each target frequency, we considered two samples before and two samples after it as noise and calculated the SNR accordingly.

The results of the signal-to-noise ratio for the proposed reference signals to the signal-to-noise ratio of the raw SSVEP signals with frequencies of 6, 8, 9, and 10 Hz in the dataset are shown in Table I.

Figure 5 shows the average value of the signal-to-noise ratio of the signals of different subjects from the Oz channel with the stimulation of 10 Hz in the dataset using Formula (7).

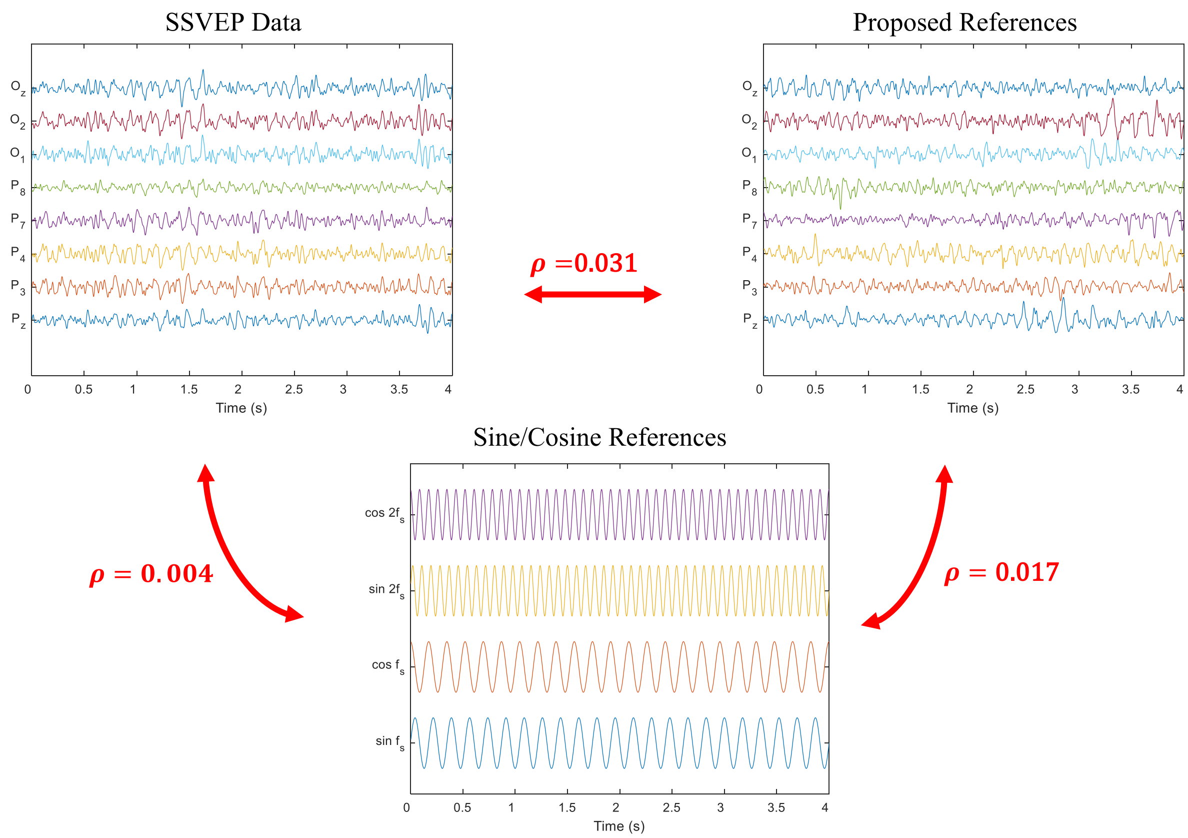

Fig. 4. The average correlation between sine/cosine reference signals, SSVEP raw data, and proposed reference signals.

TABLE I
THE AVERAGE RATIO OF SNR OF GENERATED DATA TO SNR OF RAW DATA IN DIFFERENT TIME WINDOWS

Target Signal	The average SNR ratio of the generated data to the SNR of the raw data in different time windows				
	4s	3s	2s	1s	0.5s
SSVEP with 6, 8, 9, and 10 Hz stimulus	1.8102	1.7397	1.4520	1.8745	1.4328

TABLE II
AVERAGE ACCURACY OF STIMULATION FREQUENCY RECOGNITION FOR DIFFERENT FREQUENCIES OF DATA SET BASED ON TIME WINDOW LENGTH WITH STEP 0.1 SECONDS TO THE 1-SECOND LENGTH

Frequency / Time-Window	Subject-dependent				Subject-independent			
	10	9	8	6	10	9	8	6
0.1	10	40	30	10	5	70	25	10
0.2	30	50	35	15	20	45	40	10
0.3	60	60	80	40	45	65	80	50
0.4	90	85	100	90	90	85	95	85
0.5	100	100	100	100	95	100	100	95
0.6	100	100	100	100	100	100	100	100
0.7	100	100	100	100	100	100	100	100
0.8	100	100	100	100	100	100	100	100
0.9	100	100	100	100	100	100	100	100
1.0	100	100	100	100	100	100	100	100

The blue lines correspond to the SNR of the raw SSVEP data and the red color indicates the corresponding SNR of the generated reference signals. As it shows, the SNR for the generated signal has the main peak at 10 Hz, and the second harmonic (20 Hz) also has the second peak. However, in the SNR of the raw SSVEP signal, these peaks are weak or unobserved, which will cause an error in the stimulation frequency detection. This indicates the amplification of the evoked response signal of the brain, which is done with the proposed method. Figure 6 and Table II show the average accuracy obtained in detecting the stimulation frequency for different frequencies of the dataset based on the length of the time window and the different subjects of the dataset in subject-dependent and subject-independent modes using the proposed method.

In the next step, the reference signals obtained from the proposed method were used using the CCA method to recognize the stimulation frequency of SSVEP signals, the accuracy of which was checked with time intervals of 0.1 second.

By examining the accuracy of recognition as subject-dependent and subject-independent, it is found that subject-dependent recognition is associated with higher accuracy and has a 100% accurate recognition in 500 milliseconds, which is the case for subject-independent for 500 milliseconds the proposed method obtained 97.5 percent and 100 percent of accuracy for 600 milliseconds.

In the case of ITR, both the subject-dependent and subject-independent forms of the results are shown in Figure 7.

It is observed that in the range of 0.4 to 0.5 seconds, we have the highest values of ITR with a detection accuracy of more than 90% in both subject-dependent and subject-independent implementations. This value reaches 240 bits per minute in

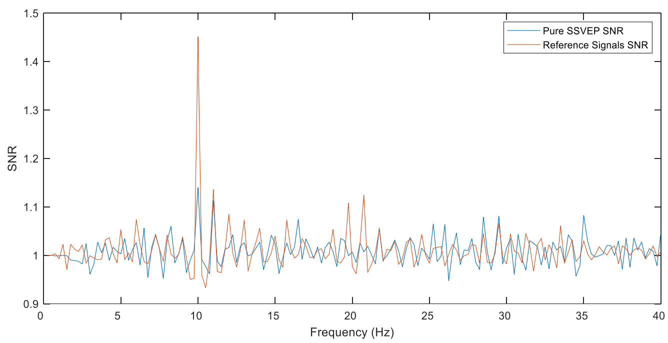

Fig. 5. The average value of the signal to noise ratio for signals of different subjects from the O_Z channel with the stimulation of 10 Hz in the dataset.

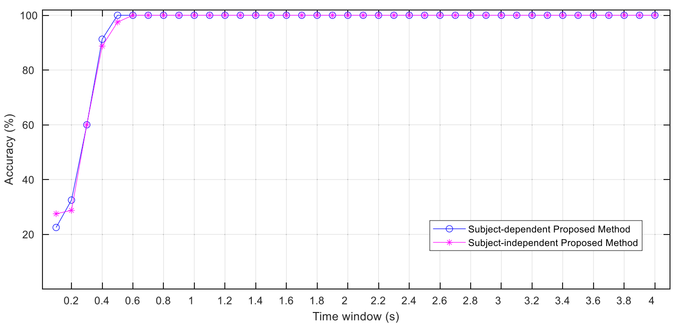

Fig. 6. Average accuracy of stimulation frequency recognition for data set based on time window length depending on the subject with a step of 0.1-second to a length of 4 seconds.

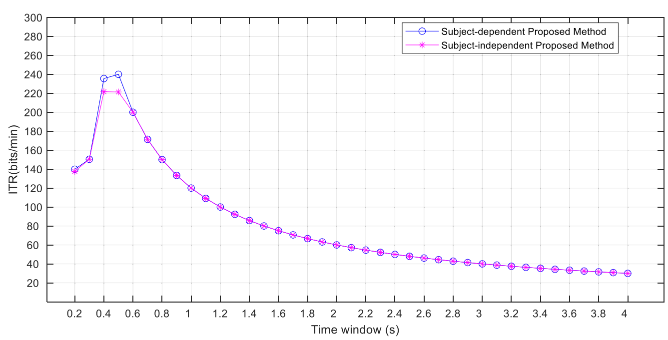

Fig. 7. Average ITR obtained for 20 subjects in different time windows subject-dependent.

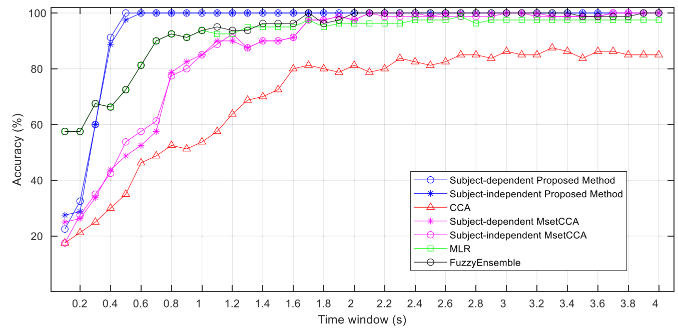

Fig. 8. Average accuracy obtained from CCA, MsetCCA, several state-of-the-art methods, and the proposed method in different time windows in subject-dependent and subject-independent modes.

the subject-dependent mode in the 0.5-second window, which is 20 bits per minute higher than in the subject-independent mode. It should be noted that the results for 0.1-second time windows are not acceptable because the accuracy of recognition in these time windows is below the minimum probability for the 4-target system.

IV. Discussion

Signals recorded by visual stimulation always have two main components; The spontaneous activity of the brain and the evoked response related to sinusoidal stimulation of the vision. If the evoked response signal brain can be extracted from the SSVEP signal, or this part is amplified in the signal, it can be expected to be detected by correlation with better results. In this study, we generated a new dataset for use in the classic CCA method by considering the SSVEP response delay and using the corresponding sine signals to train the network to make these two signals closer. In terms of correlation, (as shown in Figure 4) the signals generated by the proposed method have a higher correlation coefficient with the sinusoidal stimulation signals compared to the raw SSVEP signals, which indicates that these signals are more similar to each other. In addition, the correlation of raw SSVEP signals with the reference signals generated by the proposed method is greater than their correlation with sine signals. As a result, it would be reasonable to use the set of signals generated using the proposed method to detect the SSVEP stimulation frequency. Moreover, it has been shown in Table I, and Figure 5 that the signals generated as new references used in the CCA method have a significant improvement in terms of SNR compared to the raw SSVEP signals, which are useful for stimulation frequency detection with higher accuracy.

One of the methods similar to the proposed method in which new reference signals are generated for use in classic CCA is the MsetCCA method, which is suggested in [18]. In Figure 8, a comparison between the average accuracy of SSVEP stimulation frequency detection in CCA, MsetCCA, and several state-of-the-art methods, and the method proposed in this study has been made in subject-dependent and subject-independent modes using the dataset used in the proposed method.

As can be seen, the CCA method has results with an accuracy of less than 53.75% for time windows of less than one second, which has been increased to 85% using the MsetCCA method. The proposed method not only for the 1-second time window but also by using the 0.5-second time window has 100% accuracy for frequency detection, while in the 0.5-second window, the average detection accuracy in CCA and MsetCCA methods is 35% and 48.75%, respectively. The results obtained from the proposed method are also in comparison with CCA and MsetCCA methods in subject-independent mode are shown in Figure 2.

In the proposed method, the average accuracy obtained in subject-independent mode using a 0.5-seconds time window was equal to 97.5%, and using a 0.6-seconds time window was equal to 100% which is less than the subject-dependent mode but still is much higher compared to CCA and the MsetCCA methods.

TABLE III
COMPARISON OF THE ACCURACY OF STIMULATION FREQUENCY RECOGNITION AND INFORMATION TRANSFER RATE FOR DIFFERENT METHODS ON THE DATASET USED IN THE PROPOSED METHOD

Method	Accuracy @0.5s (%)	ITR@0.5s (bit/min)	Accuracy @1s (%)	ITR@1s (bit/min)	Reference
CCA	35	57.09	54	39.23	[9]
MwayCCA	-	-	62	47.24	[16]
L1-MCCA	-	-	69	55.61	[17]
MsetCCA	48.75	70.69	85	81.08	[18]
CFA	70	113.88	77	67.14	[33]
MLR	72.5	120.78	93.75	100.25	[27]
DMCCA	58	86.2	73	61.10	[34]
Fuzzy Ensemble	72.5	120.78	93.75	100.25	[26]
Proposed Method (Subject Dependent)	100	240	100	120	-
Proposed Method (Subject Independent)	97.5	221.7	100	120	-

In addition, the proposed method was compared with MLR methods and the ensemble of MLR and MsetCCA methods introduced in [26], which show a significant improvement in the accuracy of SSVEP stimulation frequency detection in the proposed method.

In the following, the results related to using the dataset obtained from the proposed method in detecting the stimulation frequency will be compared with other methods using a similar dataset in Table III. Some of these methods were also proposed to improve the classic CCA method by constructing new reference signals.

The proposed method presents much stronger results in terms of ITR and average accuracy in SSVEP stimulation frequency detection among similar and new methods implemented on a similar dataset.

One of the most important factors in using BCI systems is their ability to be used with short-length signals. Short-length data allows the system to send commands to related devices faster and makes it more suitable for practical applications. The proposed method is capable of accurate stimulation frequency recognition and achieving high ITR with short-length signals. Therefore, it is preferred to similar methods for clinical applications. In addition, the generalizability of the proposed method makes it possible to obtain acceptable detection results for new frequency options without retraining the method.

The most important factor in improving the results with the proposed method is the use of reference signals obtained using the evoked response signal of SSVEP. These signals are very efficient for use in the CCA method in two ways. First, they are more similar to sinusoidal stimulation signals because they amplify the evoked portion, and second, they are closer to the SSVEP signals understudy to maintain their spontaneous effect. As a result, the values of their correlation coefficients are higher than the use of any sine/cosine signals or methods such as MsetCCA and MwayCCA, which use only training signal subsets to generate reference signals, regardless of the evoked response signal of SSVEP stimulation frequency. In the proposed method, by increasing the number of training data, the neural networks can be trained more effectively and provide more efficient results.

V. CONCLUSION

Many methods have been proposed to detect the frequency of SSVEP stimulation, including CCA-based methods, which have been widely used in online BCIs in recent years because they are highly efficient, easy to implement, and do not require calibration. In this study, a method for recognizing SSVEP stimulation frequency is presented, which is based on the CCA method. In the proposed method, after removing the latency in the training signals, to construct reference signals, a fitting multilayer perceptron neural network was used to generate new reference signals instead of the usual sine/cosine signals. The reference signals obtained from this method have acceptable properties and similarities to the raw SSVEP signals, also have a boosted evoked response signal. Therefore, by using these signals in the standard CCA method as a reference, results with higher accuracy and higher information transfer rate were obtained using short-length signals.

The method introduced in this study significantly improved the SSVEP stimulation frequency detection results, using which we were able to achieve 100% accuracy in the subject-dependent mode in 0.5-second time windows and an ITR of 240 bits per minute. In the subject-independent mode, the proposed method achieved 97.5% accuracy in 0.5-second and 100% accuracy in a 0.6-second time window. Here, also, the maximum ITR obtained in the time window of 0.5-second, is equivalent to 221.7 bits per minute. The proposed method of this research allowed us to generate a reference signal dataset for use in the CCA method offline, and use the high-speed CCA method in online detection of stimulation frequency. Since the method presented in this paper is supervised, it has some considerations. The proposed method requires enough training data samples to train neural networks for boosting the evoked part of SSVEP signals. However, after network training, short-length signals can also be used to generate a reference signal.

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