Necmettin Erbakan Üniversitesi
Fen ve Mühendislik Bilimleri Dergisi
Journal of Science and Engineering (NEJSE)
DOI: https://doi.org/10.47112/neufmbd.2021.5

Cilt: 3 Sayı:1 Yıl: 2021 | Araştırma Makelesi / Research Article | E-ISSN: 2667- 7989

Tek Kanallı Durağan Hal Görsel Uyandırılmış Potansiyel Temelli Beyin-Bilgisayar Arayüzü İçin Deneğe Özgü Sinüzoit Yaklaşımı

Abdullah Talha SÖZER [1]

[1] Karabuk University, Faculty of Engineering, Department of Electrical and Electronics Engineering, Karabuk, Turkey, talhasozer@karabuk.edu.tr *(Sorumlu Yazar/ Corresponding Author)*

Makale Bilgileri

Makale Geçmişi
Geliş: 17.12.2020
Kabul: 24.06.2021
Yayın: 30.06.2021

Anahtar Kelimeler:
Beyin Bilgisayar Arayüzü
Durağan Hal Görsel Uyarılmış Potansiyel
Tek Kanal Tespit
Deneğe Özgü Sinüzoit

ÖZ

Beyin-bilgisayar arayüzünün (BBA) amacı, ciddi engelli bireylerin günlük yaşamlarını desteklemektir. Pratik BBA için en önemli faktörlerden biri olan kullanım kolaylığı, az sayıda elektrot kullanıldığında artmaktadır. Ancak az sayıda elektrot kullanılması BBA performansını olumsuz yönde etkiler. Bu çalışmada, tek kanallı durağan hal görsel uyarılmış potansiyel (DHGUP) temelli BBA'nın performansını artırmak ve böylece kullanım kolaylığını desteklemek için, deneğe özgü sinüzoit yaklaşımı (DÖSY) ile yeni bir tek kanallı DHGUP algılama yöntemi geliştirilmiştir. DÖSY'de deneğe özgü sinüzoitler, eğitim aşamasında DHGUP'nin frekans ve faz özelliklerinden faydalanılarak tanımlanmıştır. Tanımlanan bu sinüzoitler, test aşamasında, DHGUP yanıtının tespitinde referans olarak kullanılmıştır. Geliştirilen yöntemin tespit performansı, bir kıyaslama veri setinde, iyi bilinen güç spektral yoğunluk analizi (GSYA), minimum mutlak büzülme ve seçim operatörü (MMBSO) ve gelişmiş kanonik korelasyon analizi (KKA) yöntemleri ile karşılaştırılarak test edilmiştir. Deneysel sonuçlar, DÖSY yöntemiyle, GSYA, MMBSO ve gelişmiş KKA yöntemlerine kıyasla önemli ölçüde daha yüksek tespit doğruluğu ve bilgi aktarım hızı (BAH) göstermiştir. Ve deneğe özgü sinüzoitlerin gelişmiş KKA'da kullanılan şablon sinyallerden daha iyi DHGUP yanıtını temsil ettiği gösterilmiştir. Ek olarak önerilen yöntem, tek kanallı DHGUP tabanlı BBA için maksimum 125 ve ortalama 81 bit / dak BAH ile, bildirilen en yüksek BAH değerlerinden birine ulaşmıştır.

Subject-Specific Sinusoid Approach for A Brain–Computer Interface Based on Single-Channel Steady-State Visual Evoked Potential

Article Info

Article History
Received: 17.12.2020
Accepted: 24.06.2021
Published: 30.06.2021

Keywords:
Brain Computer Interface
Steady-State Visual Evoked Potential
Single Channel Detection
Subject-Specific Sinusoid

ABSTRACT

The aim of brain–computer interface (BCI) is to support the daily life of individuals with severe disabilities. For practical BCI, ease of use is one of the most important factors, which is enhanced when fewer electrodes are used. However, using fewer electrode affect the performance of BCI negatively. In this study, a novel single-channel steady-state visual evoked potential (SSVEP) detection method with subject-specific sinusoids approach (SSSA) was developed to enhance the performance of single channel SSVEP based BCI, therefore, to assist the ease of use. For the SSSA, subject-specific sinusoids were defined from training data based on SSVEP frequency and phase features. To detect the SSVEP response, defined sinusoids were used as reference. To evaluate the detection performance of the developed method, it was compared with the well-known power spectral density analysis (PSDA), least absolute shrinkage and selection operator (LASSO) and advanced canonical correlation analysis (CCA) methods on a benchmark dataset. The experimental results showed significantly greater detection accuracy and information transfer rate (ITR) with the SSSA method compared to the PSDA, LASSO and advanced CCA methods. And it is worth to noting that subject-specific sinusoids better represent SSVEP response than template signals that used in advanced CCA. Also proposed method reached one of the highest ITRs reported with max 125 and average 81 bits/min ITRs for single-channel SSVEP based BCI.

Atıf/Citation: Sözer, AT. (2021). Subject-specific sinusoid approach for a brain–computer interface based on single-channel steady-state visual evoked potential *(Necmettin Erbakan Üniversitesi Fen ve Mühendislik Bilimleri Dergisi*, *3*(1), 1-12.

INTRODUCTION

The brain–computer interface (BCI) is an alternative communication channel which interprets the user's intention and produces an output command, independent of nerves and muscles, to control external devices such as a speller [1] or wheelchair [2]. The main goal of BCI is to support the daily life of individuals with severe disabilities. There are already numerous BCI studies reported in the literature focusing on patients with locked-in syndrome (LIS) [3]. Lately, BCI studies focusing on patients with completely locked-in syndrome (CLIS) have started to appear in the literature as well [4,5].

In EEG-based BCIs, steady-state visual evoked potential (SSVEP) response is often preferred to determine the user's intent. Because it provides a high information transfer rate (ITR) and requires short/no training time. Current SSVEP-based BCI studies are most often executed under laboratory conditions with healthy individuals [6]. Furthermore, the experiments are led by experts with high-level measurement devices. However, as real-life conditions differ from those of a laboratory, some important factors summarised below must be considered when developing a SSVEP-based BCI which is suitable for real life.

SSVEP-based BCIs have been investigated for about two decades, however, disabled patients have rarely been included in studies [6,7]. Clinical SSVEP studies should be extended to real-life SSVEP-based BCI, and the long-term feasibility of the SSVEP paradigm must be investigated. In real life, BCI must meet the needs of its users. It must interpret the user's intention quickly and reliably, and it must be robust. In this way, the user can partially regain their lost functions. A very robust SSVEP detection method was recently developed [8]; however, it must be tested in disabled people under real-life conditions. Ease of use is another important factor for patients and caregivers. Most SSVEP detection methods use multiple EEG electrodes, which negatively affect ease of use. Furthermore, the difficult and time-consuming set-up procedure can be overcome by using a small number of dry electrodes. Finally, the system should be affordable.

This work is focused on single-channel SSVEP detection method to assist the ease of use and cost. Single-channel SSVEP detection was realized largely by PSDA methods [9–13]. As the frequency of the SSVEP response is the same as the flickering frequency and harmonics of a focused stimulus, the simplest solution for detecting a target stimulus in single-channel SSVEP detection is frequency domain analysis. But it has a drawback. The number of possible selections is an important parameter for BCI. With a greater number, more useful BCIs can be designed. The use of stimuli with different frequencies increases the number of possible selections in SSVEP-based BCI. But the use of more stimuli leads to a smaller frequency step, and the frequencies used at these stimuli become closer together. As the EEG epochs shorten, the resolution of the frequency decreases. Furthermore, when more stimuli are used, target stimulus detection becomes more difficult. In this case, PSDA method were deemed not suitable for SSVEP detection of short EEG signals [14]. Another method to access frequency feature of SSVEP response is canonical correlation analysis (CCA) [13,15,16]. Besides system that exploits time-domain based method was also reported [17]. Also, the combination of standard CCA and individual template based CCA (IT-CCA), which gave the highest ITR for multichannel SSVEP based BCI [18,19], was used for single-channel SSVEP detection. Thanks to this combinatorial method, the frequency and time features of SSVEP could be exploited [20]. However, detection accuracy of SSVEP based BCI systems that use single channel is lower than those that use multiple channels. To achieve robust SSVEP based BCI systems single-channel SSVEP detection methods that provide higher ITR must be developed.

In this study, we developed a novel single-channel SSVEP detection method, named the subject-specific sinusoid approach (SSSA), to increase the ITR of single channel SSVEP based BCI, therefore, to help the ease of use of it. With this method, subject-specific reference sinusoids are defined, taking advantage of the frequency and time-locked features of SSVEP. As a result, the references reflect an individual's SSVEP response. Target stimulus detection was performed using these references. Using subject-specific sinusoids instead of sinusoids at zero phase allowed us to apply the frequency and phase feature of the stimulus. In addition, we compared the SSSA method with traditional power spectral density analysis (PSDA), least absolute shrinkage and selection operator (LASSO) and CCA & IT-CCA methods, which were preferred to single-channel SSVEP detection [9–12,20,21], using a benchmark dataset. Very high detection accuracy and ITR were provided by the proposed method when compared with the other methods for all time windows. And obtained coefficients of variation showed that it also provided more consistent detection accuracy with regard to inter-subject differences. Thus, the proposed method can contribute the ease of use of BCI.

The rest of the paper is organised as follows: section 2 explains the proposed method, the dataset and data analysis; section 3 presents the experimental results; section 4 discusses the findings, and section 5 concludes the study.

MATERIAL AND METHODS

Subject-Specific Sinusoid Approach

In addition to its frequency characteristics, the SSVEP response is time-locked to the onset of the stimulus. About 80–160 milliseconds after stimulus onset, the SSVEP response arises [22]. This delay varies with age, stimulus frequency and number of harmonics [23]. The time difference between the stimulus onset and the response signal is called the SSVEP phase (Figure 1). The SSVEP phases of an individual at different stimulus frequencies can be determined, from which sinusoids that represent the individual's SSVEP response can be defined. These subject-specific sinusoids can be used as reference for target detection [24].

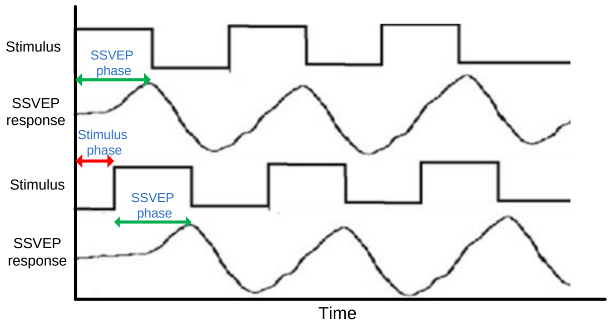

Figure 1. *Visual stimulus onset and steady-state visual evoked potential (SSVEP) response*

As mentioned below steps and shown in the flow diagram of the SSSA method, illustrated in Figure 2, subject-specific reference sinusoids were defined during the training stage.

Step 1 (Filtering): EEG signals were filtered by band-pass filters. To calculate SSVEP phases belong to each harmonic, cut-off frequencies of FIR band-pass filters are selected as 8-16 Hz, 16-32 Hz and 24-48 Hz.

Step 2 (Averaging): The filtered signal is averaged.

Step 3 (Optimization): The phase is determined in order to maximise the correlation between average EEG and f_i Hz sinusoid by equation 1:

$$\theta_{ih} = argmax_{\theta}[cor(S'_{mean}, \cos(2\pi f_i n \times h + \theta))], \quad i = 1,2 \dots K \tag{1}$$

where S'_{mean} is the averaged EEG, f_i is the stimulus frequency, h is the number of harmonics, K is the stimulus number and θ_{ih} indicates the optimal phase. θ was calculated by $\tan^{-1}(-b/a)$ where

$a = (S'_{mean})^T \times \cos(2\pi f_i n \times h)$ and $b = (S'_{mean})^T \times \sin(2\pi f_i n \times h)$.

Using these phases, subject-specific reference sinusoids are defined according to equation 2:

$$\begin{aligned} r_{f_{i1}} &= cos(2\pi f_i n \times 1 + \theta_{i1}) \\ r_{f_{i2}} &= cos\ (2\pi f_i n \times 2 + \theta_{i2}) \\ &\vdots \\ r_{f_{ih}} &= cos(2\pi f_i n \times h + \theta_{ih}) \end{aligned} \tag{2}$$

At the test stage, the references were used for target stimulus detection. To detect the target, total correlation values between filtered signals and subject-specific sinusoids were compared using equation 3:

$$f_t = \max_{f_i} \rho_i, \qquad i = 1,2, \ldots, K \tag{3}$$

where ρ_i is the total correlation value at f_i frequency and K is the stimulus number.

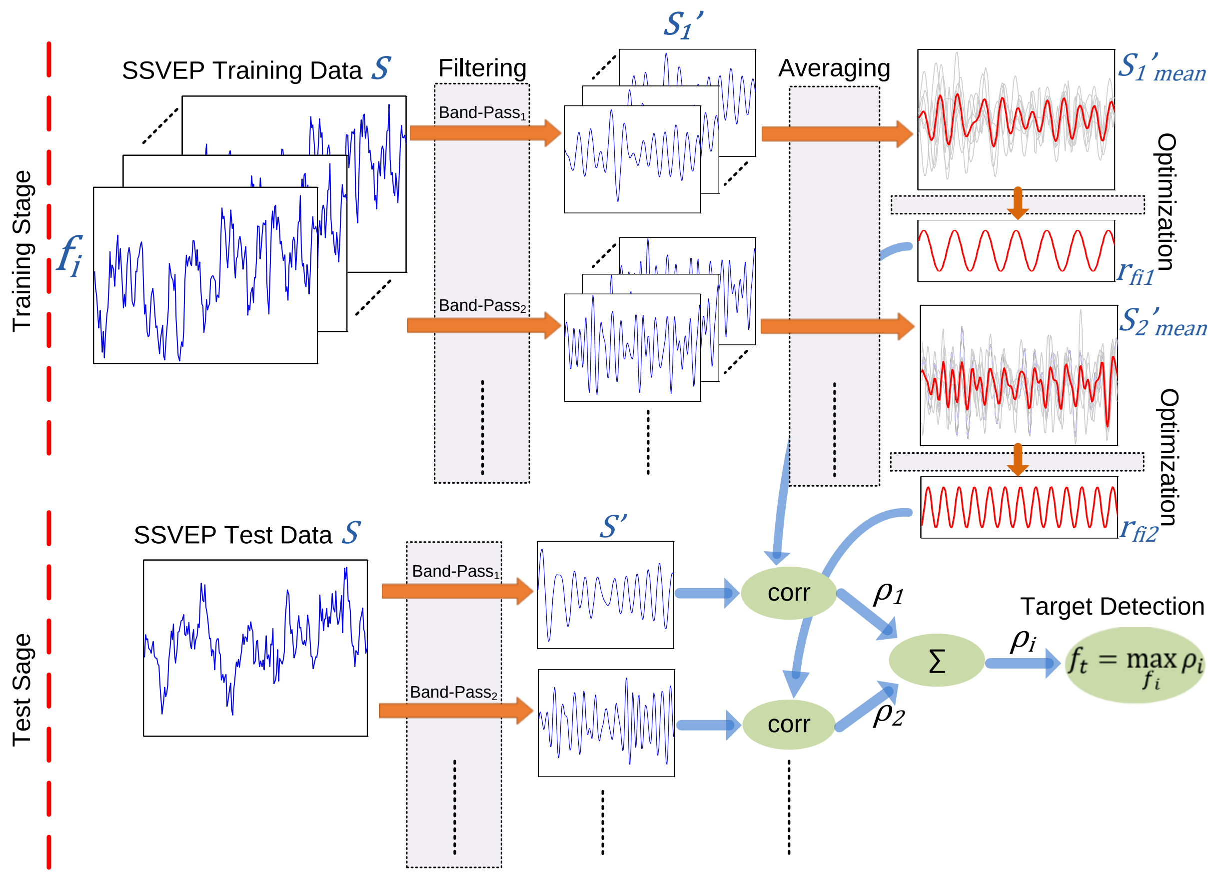

Figure 2. *Flow diagram of the proposed method*

Comparison Methods

Power spectral density analysis is a common and basic method for SSVEP detection. The SSVEP components can be detected by examining the EEG spectrum. In this method, PSD values that correspond to stimuli frequencies are found. The frequency with the maximal PSD value is accepted as the target frequency, determined by equation 4:

$$f_t = \max_{f_i} P_i\,, \qquad i = 1,2,\dots,K \tag{4}$$

where P_i is the PSD value at f_i frequency and K is stimulus number.

Although LASSO-based SSVEP detection was developed for multiple-channel systems [25], it has been used successfully in single-channel SSVEP-based BCI [21]. The EEG epoch y is defined as a linear regression model in the LASSO method, calculated by equation 5:

$$y = \boldsymbol{X}\beta + \varepsilon \tag{5}$$

where ε is the noise vector, β is the contribution coefficient vector and $\boldsymbol{X}$ is the sine and cosine functions at each stimulus frequency and harmonic. With LASSO estimation, the contribution of each of the functions to the EEG epoch can be determined. For target detection, coefficient vectors are found, and the absolute values of components of the coefficient vector are summed for each stimuli frequency. The frequency at which the highest total value is obtained is considered the target frequency. A detailed explanation of LASSO can be found elsewhere [21,25,26].

CCA, that is used detection of target frequency by searching correlation between reference sinusoids and EEG signals, is a very popular statistical method. CCA-based SSVEP detection was developed for multiple-channel BCI [27] but also it was applied successfully to detect target stimulus in single-channel SSVEP-based BCI [13,15,16]. Since CCA-based SSVEP detection was a revolutionary method, some upgraded versions were developed to advance its detection performance. One of them is combination of CCA & IT-CCA method [19]. It utilizes standard CCA and templates EEG signal of subjects and it offered the highest ITR for SSVEP based BCI [18]. In this method, that also was used for single-channel SSVEP detection [20], the total correlation value between EEG signals and standard reference sinusoids and individual template signals are used to detect target stimulus. A detailed explanation of CCA & IT-CCA can be found in [19].

Dataset

The developed method was evaluated using a benchmark dataset [28]. A Synamps2 EEG system with 64 channels was used to collect EEG data from 35 healthy individuals. The EEG signals sampled at 1000 samples/s were down-sampled to 250 samples/s to reduce computation and storage costs. Only a 50-Hz notch filter was applied to raw data.

The SSVEP-based BCI experiments were executed with 40 repetitive visual stimuli. The stimuli were rendered on a 23.6-inch LCD monitor with a 60 Hz refresh rate. To obtain a unique stimulus property, different combinations of frequencies and phases were used. Forty different frequency values between 8 and 15.8 Hz in steps of 0.2 Hz were used, together with four different phase values between 0 and 1.5π with steps of 0.5π. The flicker sequence was obtained according to equation 6:

$$s(f, \emptyset, i) = \frac{1}{2}\{1 + sin[2\pi f\left(\frac{i}{refreshrate}\right) + \emptyset]\} \tag{6}$$

where f is the flicker frequency, $\emptyset$ is the flicker phase and i indicates the frame index of the sequence.

The experiments consisted of six sessions, each of which contained 40 trials that lasted for 6 s. At the onset of the trial, a cue was presented for 0.5 s to guide the subject to the target stimulus. Afterwards, all stimuli flickered for 5 s. At the end of each trial, a blank screen was displayed for 0.5 s. Subjects were allowed a few minutes to rest between sessions.

Data Analysis

Target stimulus detection by SSSA, PSDA, LASSO and CCA & IT-CCA were performed on signals collected from Oz location. Analyses were carried out at varying epoch lengths. Because of visual latency, the first 135 ms of each data epoch was extracted. First three harmonics were used to detect target stimulus. Target visual stimulus detection accuracy were calculated and compared. Leave-one-run-out cross-validation was applied to evaluate the SSSA method. Among the six sessions conducted, five were used in training to determine references and the remaining session was considered test data.

In addition to target stimulus detection accuracy, performances of the methods were also evaluated by ITR. The ITR is defined by equation 7:

$$ITR = \frac{60}{T} \times [log_2 N + Plog_2 P + (1-P)log_2 \frac{(1-P)}{(N-1)}] \tag{7}$$

where T is time window, N is the number of stimuli and P is detection accuracy between 0 and 1.

RESULTS

The SSVEP response is time-locked to the onset of the stimulus and in the proposed method it is claimed that this characteristic can be used as a distinctive feature. To prove this, a subject's SSVEP phases that corresponds to stimuli with different phase is shown in the Figure 3. In the figure, the frequencies of the stimuli are close, about 8 Hz, but there are phase differences between them. It is seen that the SSVEP phases is related to time difference between the stimulus onset, and it can be used to detect target stimulus. Also, SSVEP phases related to 8 Hz 0° stimulus for 6 session of each subject was obtained then standard deviations of each subject's phases calculated. Average of standard deviations of 35 subject's phases is 27°.

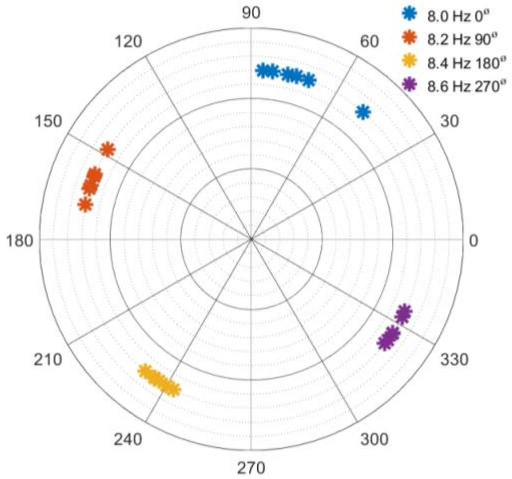

Figure 3. *SSVEP phases related to 8 Hz 0° stimulus (blue), 8.2 Hz 90° stimulus (red), 8.4 Hz 180° stimulus (yellow), 8.6 Hz 270° stimulus (purple),*

The accuracy and ITR of target stimulus detection using the SSSA, PSDA LASSO and CCA & IT-CCA methods are presented in the figures. Statistical analysis of the accuracy of each method is also reported. Figure 4 shows the average target detection accuracy at various time windows ranging from 1 to 4 s. The SSSA method provided higher detection accuracy when compared to the other methods for all time windows.

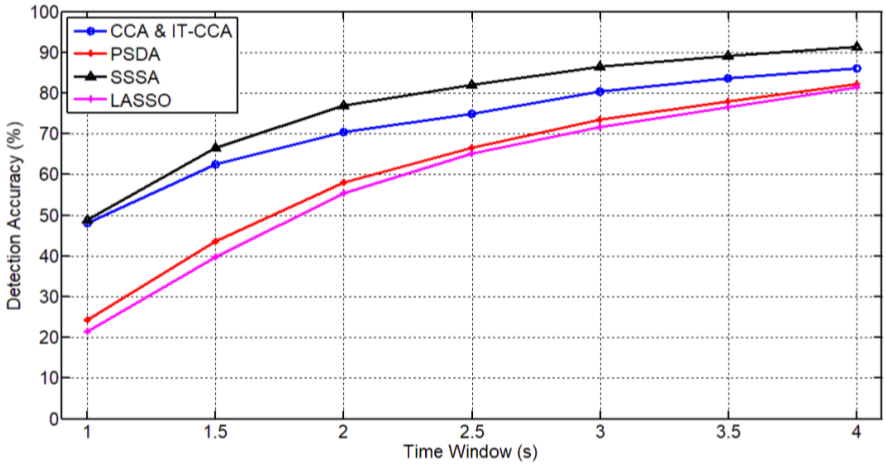

Figure 4. *Average detection accuracy at various time windows*

Figure 5 presents a comparison of target detection accuracies obtained for each subject using the four methods. The results were obtained from 2-s epochs. As seen in the figure, SSSA consistently outperformed PSDA and LASSO for each of the subjects and outperformed CCA & IT-CCA for most of the subjects. The average accuracy was 77.7%, 55.4%, 58.1% and 70.5%, for SSSA, LASSO, PSDA and CCA & IT-CCA, respectively. For each method, the standard deviations were 20.3, 22.8, 23.5 and 24 and coefficients of variation were 0.26, 0.41 0.41 and 0.34 for SSSA, LASSO, PSDA and CCA & IT-CCA, respectively.

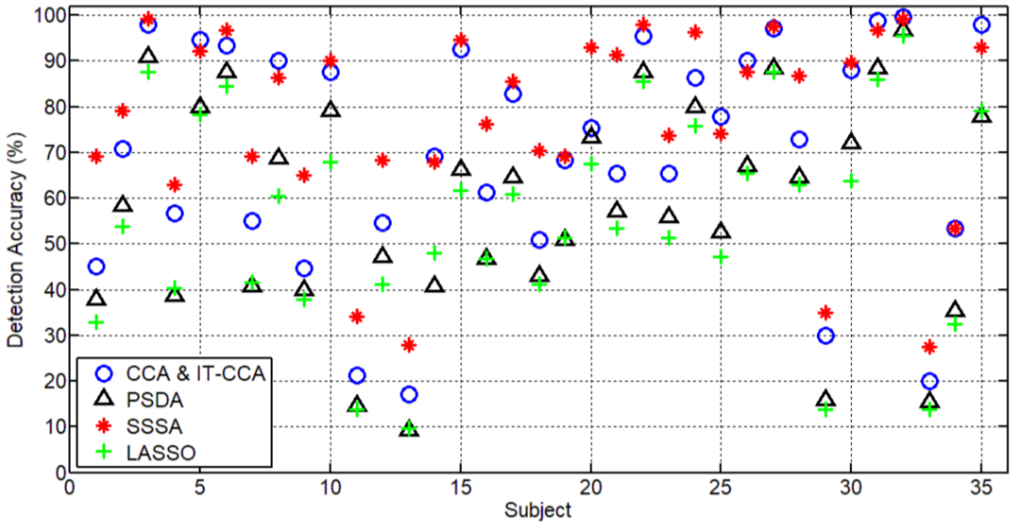

Figure 5. *Target detection accuracy for all subjects at 2-s epochs*

Statistical analysis was performed to compare the proposed method to the LASSO and PSDA methods. Paired-sample t-tests (SSSA vs. LASSO, SSSA vs. PSDA and SSSA vs. CCA & IT-CCA) were used to evaluate differences in detection accuracy. All of the results were highly significant ($p < 0.0001$), confirming that the proposed method allowed better SSVEP detection.

Figure 6 depicts the ITR obtained from the average accuracy at various time windows. As shown in the figure, the proposed method provided a much better ITR than the other methods. The highest ITR of 81 bits/min was obtained at 2-s EEG epochs. As there was a 0.5-s cue duration, the detection time used in the ITR formula for the 2-s EEG epoch was 2.5 s.

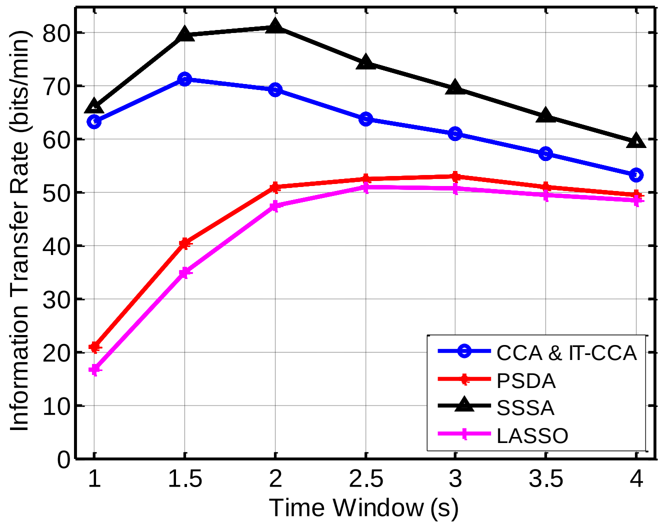

Figure 6. *Average information transfer rate (ITR) for various time windows with two harmonics*

Table 1 shows the ITR obtained by SSSA at 2-s EEG epochs for each subject. The highest ITR was 125 bits/min (subject 3), and the average ITR was 85.2 ± 31.8 bits/min.

DISCUSSION

When patients and caregivers are considered, an important goal for BCI is that it is easily usable by home users, which can be achieved by successful detection through fewer measurement channels. In this regard, an advantage of the SSVEP response is that the SSVEP signal can be detected from only one channel, allowing the BCI to be designed with high ITR. Based on this, we developed a method that uses both SSVEP frequency and phase in order to increase single-channel SSVEP detection accuracy. In this method, which uses the behaviour of the SSVEP response, SSVEP phases were determined. Since several factors like individual difference, stimulus frequency [23] affect the SSVEP response delay, optimal phases of each subject were calculated for each stimulus frequency and its harmonics. Then subject-specific reference sinusoids were defined using the phases. By identifying the optimal phase, the reference sinusoids better reflect an individual's SSVEP response than the commonly used sinusoids at zero phase [19,29]. These references were able to successfully detect the target stimulus frequency.

Table 1. *Information transfer rate (ITR) for all subjects at 2-s epochs with two harmonics.*

Subject	ITR (bits/min)	Subject	ITR (bits/min)	Subject	ITR (bits/min)	Subject	ITR (bits/min)
1	69,2	10	103,8	19	69,2	28	100,5
2	85,0	11	22,0	20	112,6	29	24,6
3	125,0	12	65,9	21	107,2	30	102,9
4	60,3	13	15,8	22	122,7	31	120,5
5	108,1	14	65,3	23	75,2	32	123,8
6	119,5	15	113,6	24	118,4	33	16,6
7	67,9	16	82,1	25	78,6	34	47,4
8	96,4	17	94,8	26	100,5	35	110,8
9	61,5	18	74,5	27	120,5	Average	85.2 ± 31.8

Taking into account that high intent detection accuracy in a short time is one of the aims of BCI, importance of SSVEP detection methods cannot be ignored. The results showed that the SSSA method increased target detection accuracy, yielding even more pronounced improvement when compared to the other methods.

Besides, much better detection accuracies for each of the subjects were obtained by the proposed method. This shows that the proposed method enabled the consistent production of subject-specific sinusoids. The standard deviations obtained by the methods were close to each other; however, as the average values of groups were very different, the coefficient of variation was used instead of the standard deviation to compare results. The coefficient of variation for the proposed method was lower than the other methods. Therefore, the SSSA method appears to be more robust against inter-user differences.

Although LASSO could successfully detect the target stimulus [25], the results obtained by this method were at the same level as PSDA. In LASSO, also in standard CCA, target stimulus is detected by similarity between EEG signal and reference signals. Since sine and cosine functions with zero phase are generally used as reference, the methods don't use temporal features of SSVEPs [30]. Therefore, they are not phase-sensitive and don't use SSVEP phase feature like PSDA method. When a high noise at stimuli frequencies add to EEG, they decide this frequency as target stimulus frequency. Because they use only SSVEP frequency feature. In the proposed method, since reference sinusoids are determined taking SSVEP phase feature into account higher detection accuracy is obtained. The phase feature can be used with the FFT-based method [22], but the resolution in FFT-based methods is negatively affected by short epochs.

CCA & IT-CCA method uses both frequency and phase features of SSVEP response. Standard CCA method evaluates frequency feature of SSVEP response and IT-CCA method assess phase features of SSVEP response. Template signals (S'_{mean}, which is calculated in step 2) are obtained by averaging multiple trials in training stage. Because of time-locked property of SSVEP, this template allows using phase features. But the results showed that CCA & IT-CCA didn't give higher detection accuracy than SSSA method. Because S'_{mean} contains noise components in addition to the SSVEP signal. Since noise components are random, it causes decreases in the correlation values during the test stage. This case can be seen using S'_{mean} as reference signal for the proposed method instead of subject specific sinusoids r_{f_i}. When S'_{mean} was used as reference, the detection accuracy decreased as seen in the Figure 7. Therefore, subject specific sinusoids can better represent SSVEP response than template signals.

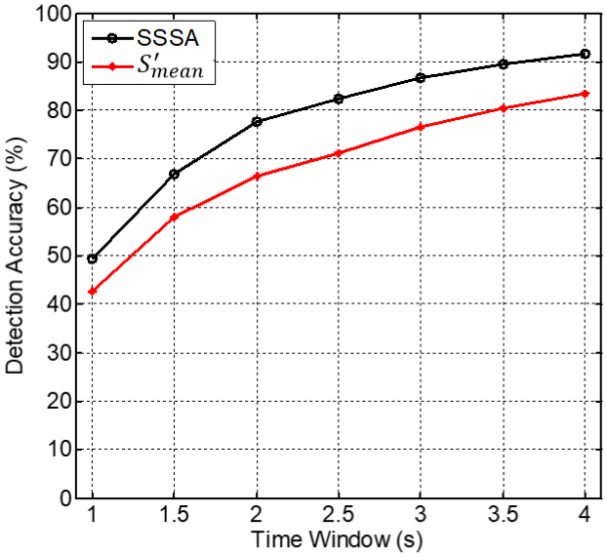

Figure 7. *Average detection accuracy using S'_{mean} as reference signal*

The performance of BCIs can be compared using the ITR. As the ITR is dependent on the intent detection time, accuracy and number of choices, it allows comparison between different systems. With the SSSA method we reached an ITR of 81 bits/min. These results are higher than those reported by other single-channel SSVEP-based BCI studies cited in Table 2.

Bipolar referencing is a simple and efficient method to eliminate noise components. To improve the method, optimal lead selection or a generated reference can be applied [33,34]. Also using different features that

Table 2. *Some other single channel SSVEP studies.*

	ITR (bits/min)	used SSVEP feature
X. Chai et al. [16]	45	Frequency feature of SSVEP by CCA
A. Bisht et al. [13]	58.3	Frequency feature of SSVEP by CCA
D. Kim et al. [20]	72	Frequency and phase features of SSVEP by CCA & IT-CCA
S. Ajami et al. [21]	67.1	Frequency feature of SSVEP by LASSO
S.-C. Chen et al. [9]	20.6	Frequency feature of SSVEP by PSDA
A. Luo et al. [17]	34.3	Time domain signal form of SSVEP
T.H. Nguyen et al. [31]	49	Frequency feature of SSVEP by PSDA
H.J. Hwang et al. [10]	40.7	Frequency feature of SSVEP by PSDA
Q. Gao et al. [32]	21	Frequency feature of SSVEP by CCA

characterize the SSVEP response may help to detect target stimulus [35]. Finally, subject-specific sinusoids can be used in multiple-channel SSVEP detection methods to facilitate the detection of a target stimulus.

CONCLUSION

In this study, a novel single-channel SSVEP detection method named SSSA was developed, which was subsequently evaluated using a benchmark dataset. Subject-specific reference sinusoids were defined in the proposed method. Due to these references, both the frequency and phase characteristics of the SSVEP response were used in target detection. The proposed method was compared with the LASSO and well-known PSDA methods, and was found to provide much better target detection accuracy and ITR. Thus, the SSSA method is suitable for single-channel SSVEP-based BCI.

ETHICAL APPROVAL

The collection of the dataset used in this study was approved by the Research Ethics Committee of Tsinghua University.

REFERENCES

[1] E. Yin, Z. Zhou, J. Jiang, F. Chen, Y. Liu, D. Hu, A speedy hybrid BCI spelling approach combining P300 and SSVEP., *IEEE transactions on bio-medical engineering*. 61 (2014) 473–83. doi:10.1109/TBME.2013.2281976.

[2] T. Sakurada, T. Kawase, K. Takano, T. Komatsu, K. Kansaku, A BMI-based occupational therapy assist suit: asynchronous control by SSVEP., *Frontiers in neuroscience*. 7 (2013) 172. doi:10.3389/fnins.2013.00172.

[3] E. Pasqualotto, S. Federici, M.O. Belardinelli, Toward functioning and usable brain–computer interfaces (BCIs): A literature review, *Disability and Rehabilitation: Assistive Technology*. 7 (2012) 89–103. doi:10.3109/17483107.2011.589486.

[4] U. Chaudhary, B. Xia, S. Silvoni, L.G. Cohen, N. Birbaumer, Brain–Computer Interface–Based Communication in the Completely Locked-In State, *PLOS Biology*. 15 (2017) e1002593. doi:10.1371/journal.pbio.1002593.

[5] C. Guger, R. Spataro, B.Z. Allison, A. Heilinger, R. Ortner, W. Cho, V. La Bella, Complete Locked-in and Locked-in Patients: Command Following Assessment and Communication with Vibro-Tactile P300 and Motor Imagery Brain-Computer Interface Tools, *Frontiers in Neuroscience*. 11 (2017). doi:10.3389/fnins.2017.00251.

[6] H.-J. Hwang, C.-H. Han, J.-H. Lim, Y.-W. Kim, S.-I. Choi, K.-O. An, J.-H. Lee, H.-S. Cha, S. Hyun Kim, C.-H. Im, Clinical feasibility of brain-computer interface based on steady-state visual evoked potential in patients with locked-in syndrome: Case studies, *Psychophysiology*. 54 (2017) 444–451. doi:10.1111/psyp.12793.

[7] D. Lesenfants, D. Habbal, Z. Lugo, M. Lebeau, P. Horki, E. Amico, C. Pokorny, F. Gómez, A. Soddu, G. Müller-Putz, S. Laureys, Q. Noirhomme, An independent SSVEP-based brain-computer interface in locked-in syndrome., *Journal of neural engineering*. 11 (2014) 035002. doi:10.1088/1741-2560/11/3/035002.

[8] N. Morikawa, T. Tanaka, M.R. Islam, Complex sparse spatial filter for decoding mixed frequency and phase coded steady-state visually evoked potentials, *Journal of Neuroscience Methods*. 304 (2018) 1–10. doi:10.1016/j.jneumeth.2018.04.001.

[9] S.-C. Chen, Y.-J. Chen, I.A.E. Zaeni, C.-M. Wu, A Single-Channel SSVEP-Based BCI with a Fuzzy Feature Threshold Algorithm in a Maze Game, *International Journal of Fuzzy Systems*. 19 (2017) 553–565. doi:10.1007/s40815-016-0289-3.

[10] H.J. Hwang, J.H. Lim, Y.J. Jung, H. Choi, S.W. Lee, C.H. Im, Development of an SSVEP-based BCI spelling system adopting a QWERTY-style LED keyboard, *Journal of Neuroscience Methods*. 208 (2012) 59–65. doi:10.1016/j.jneumeth.2012.04.011.

[11] X. Gao, D. Xu, M. Cheng, S. Gao, A BCI-based environmental controller for the motion-disabled, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 11 (2003) 137–140. doi:10.1109/TNSRE.2003.814449.

[12] L. Angrisani, P. Arpaia, D. Casinelli, N. Moccaldi, A Single-Channel SSVEP-Based Instrument with Off-The-Shelf Components for Trainingless Brain-Computer Interfaces, *IEEE Transactions on Instrumentation and Measurement*. 68 (2019) 3616–3625. doi:10.1109/TIM.2018.2882115.

[13] A. Bisht, S. Srivastava, G. Purushothaman, A new 360° rotating type stimuli for improved SSVEP based brain computer interface, *Biomedical Signal Processing and Control*. 57 (2020). doi:10.1016/j.bspc.2019.101778.

[14] Y. Zhang, G. Zhou, J. Jin, M. Wang, X. Wang, A. Cichocki, L1-regularized multiway canonical correlation analysis for SSVEP-based BCI, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 21 (2013) 887–896. doi:10.1109/TNSRE.2013.2279680.

[15] C. Farmaki, M. Krana, M. Pediaditis, E. Spanakis, V. Sakkalis, Single-channel SSVEP-Based BCI for robotic car navigation in real world conditions, içinde: *Proceedings - 2019 IEEE 19th International Conference on Bioinformatics and Bioengineering, BIBE 2019*, 2019: ss. 638–643. doi:10.1109/BIBE.2019.00120.

[16] X. Chai, Z. Zhang, K. Guan, Y. Lu, G. Liu, T. Zhang, H. Niu, A hybrid BCI-controlled smart home system combining SSVEP and EMG for individuals with paralysis, *Biomedical Signal Processing and Control*. 56 (2020). doi:10.1016/j.bspc.2019.101687.

[17] A. Luo, T.J. Sullivan, A user-friendly SSVEP-based brain-computer interface using a time-domain classifier, *Journal of neural engineering*. 7 (2010) 26010. doi:10.1088/1741-2560/7/2/026010.

[18] X. Chen, Y. Wang, M. Nakanishi, X. Gao, T.-P. Jung, S. Gao, High-speed spelling with a noninvasive brain–computer interface, *Proceedings of the National Academy of Sciences*. 112 (2015) 1–10. doi:10.1073/pnas.1508080112.

[19] M. Nakanishi, Y. Wang, Y.-T. Wang, T.-P. Jung, A Comparison Study of Canonical Correlation Analysis Based Methods for Detecting Steady-State Visual Evoked Potentials, *PloS one*. 10 (2015) e0140703. doi:10.1371/journal.pone.0140703.

[20] D. Kim, W. Byun, Y. Ku, J.H. Kim, High-speed visual target identification for low-cost wearable brain-computer interfaces, *IEEE Access*. 7 (2019) 55169–55179. doi:10.1109/ACCESS.2019.2912997.

[21] S. Ajami, A. Mahnam, V. Abootalebi, Development of a practical high frequency brain–computer interface based on steady-state visual evoked potentials using a single channel of EEG, *Biocybernetics and Biomedical Engineering*. 38 (2018) 106–114. doi:10.1016/j.bbe.2017.10.004.

[22] C. Jia, X. Gao, B. Hong, S. Gao, Frequency and phase mixed coding in SSVEP-based brain--computer interface., *IEEE transactions on bio-medical engineering*. 58 (2011) 200–206. doi:10.1109/TBME.2010.2068571.

[23] F.-B. Vialatte, M. Maurice, J. Dauwels, A. Cichocki, Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives, *Progress in Neurobiology*. 90 (2010) 418–438. doi:10.1016/j.pneurobio.2009.11.005.

[24] A.T. Sozer, Enhanced Single Channel SSVEP Detection Method on Benchmark Dataset, içinde: *2018 15th International Conference on Electrical Engineering, Computing Science and Automatic Control, CCE 2018*, *IEEE*, 2018: ss. 1–4. doi:10.1109/ICEEE.2018.8533933.

[25] Y. Zhang, J. Jin, X. Qing, B. Wang, X. Wang, LASSO based stimulus frequency recognition model for SSVEP BCIs, *Biomedical Signal Processing and Control*. 7 (2012) 104–111. doi:10.1016/j.bspc.2011.02.002.

[26] R.M.G. Tello, S.M.T. Muller, T. Bastos-Filho, A. Ferreira, A comparison of techniques and technologies for SSVEP classification, içinde: *5th ISSNIP-IEEE Biosignals and Biorobotics Conference (2014): Biosignals and Robotics for Better and Safer Living (BRC)*, *IEEE*, 2014: ss. 1–6. doi:10.1109/BRC.2014.6880956.

[27] Z. Lin, C. Zhang, W. Wu, X. Gao, Frequency recognition based on canonical correlation analysis for SSVEP-Based BCIs, *IEEE Transactions on Biomedical Engineering*. 54 (2007) 1172–1176. doi:10.1109/TBME.2006.889197.

[28] Y. Wang, X. Chen, X. Gao, S. Gao, A Benchmark Dataset for SSVEP-Based Brain–Computer Interfaces, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 25 (2017) 1746–1752. doi:10.1109/TNSRE.2016.2627556.

[29] G. Bin, X. Gao, Z. Yan, B. Hong, S. Gao, An online multi-channel SSVEP-based brain–computer interface using a canonical correlation analysis method, *Journal of Neural Engineering*. 6 (2009) 046002. doi:10.1088/1741-2560/6/4/046002.

[30] J. Pan, X. Gao, F. Duan, Z. Yan, S. Gao, Enhancing the classification accuracy of steady-state visual evoked potential-based brain-computer interfaces using phase constrained canonical correlation analysis., *Journal of neural engineering*. 8 (2011) 036027. doi:10.1088/1741-2560/8/3/036027.

[31] T.H. Nguyen, W.Y. Chung, A single-channel SSVEP-based BCI speller using deep learning, *IEEE Access*. 7 (2019) 1752–1763. doi:10.1109/ACCESS.2018.2886759.

[32] Q. Gao, Y. Zhang, Z. Wang, E. Dong, X. Song, Y. Song, Channel Projection-Based CCA Target Identification Method for an SSVEP-Based BCI System of Quadrotor Helicopter Control, *Computational Intelligence and Neuroscience*. 2019 (2019). doi:10.1155/2019/2361282.

[33] A.T. Sözer, C.B. Fidan, Novel spatial filter for SSVEP-based BCI: A generated reference filter approach, *Computers in Biology and Medicine*. 96 (2018) 98–105. doi:10.1016/j.compbiomed.2018.02.019.

[34] Y. Wang, R. Wang, X. Gao, B. Hong, S. Gao, A practical VEP-based brain-computer interface, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 14 (2006) 234–239. doi:10.1109/TNSRE.2006.875576.

[35] A.T. Sözer, C.B. Fidan, Novel Detection Features for SSVEP Based BCI: Coefficient of Variation and Variation Speed, *BRAIN: Broad Research in Artificial Intelligence and Neuroscience*. 8 (2017) 144–150. https://www.edusoft.ro/brain/index.php/brain/article/view/694/782.