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Harmonic analysis of steady-state visual evoked potentials in brain computer interfaces

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ABSTRACT

The signals generated in the occipital lobe of the brain, as a result of visual stimuli flickering at a certain frequency, are called steady-state visual evoked potentials (SSVEPs). Spectral properties of the SSVEPs are extracted to use in classification stage in SSVEP based brain-computer interfaces. However, there has been no previous study examining the effects of SSVEP harmonics on classification performance. The frequency spectrum of an SSVEP consists of harmonics at frequencies that are integer multiples of the stimulus signal frequency. In this study, the effects of the first four harmonics of SSVEPs in classification performance were investigated. Total and relative band power values, extracted from various combinations of the first four harmonics of SSVEPs, are used as features. Due to the quasi-sinusoidal nature of SSVEPs, it has been observed that the classification made by the features extracted from the second harmonic gives better results than the classification made by the features extracted from the first harmonic. In addition, if more than one harmonic is used in feature extraction, it was observed that the best classification performance was obtained with the properties extracted from the set of 1st, 2nd and 4th harmonics, in almost all cases. Furthermore a statistical study was performed by applying variance analysis to the obtained data to verify the significance of the results.

1. Introduction

Brain-Computer Interface (BCI) is defined as the interface that uses brain signals to control a device, or to provide communication between the device and the user [1]. A more comprehensive definition for BCI is that the medium in which the electrical activity generated by the brain is transmitted to the nerves and muscles around it independently of normal exit pathways [2]. BCI design can benefit from one or more electrophysiological sources recorded from various regions of the brain. As a result of a visual stimulus, the electrical signals seen in the occipital and parietal lobes of the brain are called visual evoked potentials. The VEP obtained from visual cortex in consequence of stimuli at frequencies below 3.5 Hz is called transient VEP [3,4], because the stimulus cannot trigger to generate a continuous sinusoidal-like response in the visual cortex. At stimulus frequencies between 3.5 Hz and 75 Hz, a quasi-sinusoidal waveform is formed due to superimposition of the action potentials generated in the visual cortex [5]. During the presence of the stimulus, the visual cortex generates a quasi-sinusoidal signal. Therefore, the VEP obtained in consequence of stimuli at frequency of 3.5 Hz and above is defined as the steady-state VEP (SSVEP) [4]. In a SSVEP-based BCI design, stimuli must be between 3.5 Hz and 75 Hz so that a classification can be possible using the spectral properties of the signals.

Lalor et al. showed that control of computer games can be accomplished by binary classification of EEG received from O1 and O2 electrodes in a SSVEP-based BCI system [6]. They used two stimuli at frequencies 6 Hz and 25 Hz, and extracted features from the power spectral density (PSD) of SSVEP for classification. Kelly et al. made a binary classification of SSVEPs by using two stimuli at frequencies 10 Hz and 12 Hz [7]. They recorded EEG from O1 and O2 electrodes, and made a classification based on PSD of SSVEPs. Muller-Putz and Pfurtscheller showed that a four-task classification by a SSVEP-based BCI is possible to control a biaxial hand prosthesis [8]. Prueckl and Guger performed a four-task classification of SSVEPs using four stimuli at frequencies 10 Hz, 11 Hz, 12 Hz and 13 Hz [3]. They used first and second harmonics of PSD of SSVEPs recorded from O1, O2, Oz, PO3, PO4, PO7, PO8 and POz electrodes. Bin et al. made a canonical correlation analysis (CCA) based classifi-

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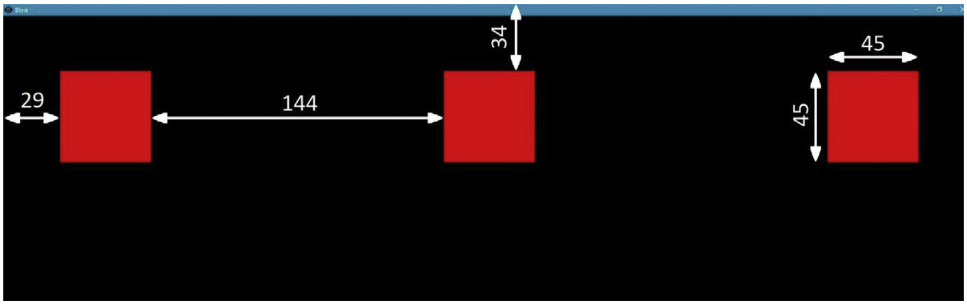

Fig. 1. User interface of the program used to trigger the SSVEP Response.

cation in a SSVEP-based BCI [9]. They used EEG, recorded from nine electrodes in the occipital and temporal regions. Luo and Sullivan made a four-task classification by a SSVEP-based BCI using only the PO2 electrode [5]. They used four stimuli at frequencies 9 Hz, 10 Hz, 11 Hz and 12 Hz, and made a classification based on PSD of SSVEPs. Volosyak I. developed an SSVEP-based BCI, using five stimuli at frequencies of 6.67 Hz, 7.5 Hz, 8.57 Hz, 10 Hz and 12 Hz, and made a classification based on PSD of SSVEPs [10]. Long et al. controlled a battery-powered chair using a hybrid BCI approach. While using sensorimotor EEG for direction and deceleration of the chair, they used SSVEPs obtained from O1, O2 and Oz electrodes for acceleration [11]. Lee et al. controlled a mobile robot using stimuli at frequencies 13 Hz, 14 Hz and 15 Hz that are corresponding to three different tasks [12]. Zhang et al. designed an SSVEP-based BCI with a CCA-based classification. They used stimuli at frequencies 6 Hz, 7 Hz, 8 Hz and 9 Hz [13]. They designed their BCI using the signals recorded from the O1, O2, Oz, P7, P8, P3, P4 and Pz electrodes. Chen et al. controlled a robotic arm by SSVEPs, using the signals recorded from Pz, PO5, PO3, POS, PO4, PO6, O1, Oz, O2 electrodes [14]. Park et al. used the extension of multivariate synchronization index (EMSI) algorithm over three harmonics of the frequency spectrum of SSVEPs in their study where they used stimuli at frequencies 7.5 Hz, 8.57 Hz, 10 Hz and 12 Hz [15]. Choi et al. investigated the classification performance and ease of use of BCI systems in a virtual reality environment [16]. They recorded EEG from Cz, PO3, POz, PO4, O1, Oz, and O2 electrodes, and used EMSI algorithm for feature extraction. There are many SSVEP-based BCI designs and studies in the literature. In these studies, PSD, CCA or EMSI based methods were applied to the frequency spetrum of SSVEPs. However, there is no study in literature, investigating how the harmonics of SSVEPs affect the classification performance. In this study, the classification performed with the features extracted from the harmonics obtained from the frequency spectrum of SSVEPs were compared. The feature vectors consist of the total and relative band power values of the various combinations of the first four harmonics obtained from the PSD of the SSVEPs. It is observed that the amplitude of the second harmonic is higher than the first harmonic in almost all cases. The amplitudes of the third and fourth harmonics were observed to be low as expected, and does not have an effect that can improve the classification performance at an acceptable rate.

2. Materials and methods

Emotiv Epoc was used to record the EEG in this study. There are 16 electrodes on the head-set, two of which are reference electrodes. The active electrodes in the neuro-headset are in fixed positions as AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. P3 and P4 are used as reference electrodes. SSVEPs that are recorded from the occipital region of the brain were used as the electroneurophysiological source of the BCI. The headset has only O1 and O2 channels on the occipital lobes. Therefore, only data recorded from these channels could be used. Prueckl and Guger have tried 30 different channel combinations on five different subjects in order to determine the channels from which the best SSVEP response is obtained. They applied surface Laplacian transformations as a measurement strategy. Their results show that O1, O2 and Oz are the best possible channel combination from which the SSVEP response is obtained [3]. This suggests that the O1 and O2 channels located on Epoc are sufficient for a SSVEP-based BCI application.

Table 1
Frequency set of stimuli used to trigger SSVEPs in Hertz.

Stimuli	1st Harmonic	2nd Harmonic	3rd Harmonic	4th Harmonic
1 st	4	8	12	16
2nd	4.6	9.2	13.8	18.4
3rd	5.3	10.6	15.9	21.2

EEG recordings were obtained from seven different subjects. Six of them were completely inexperienced with BCI while one subject has a history of BCI experience. A total of 12 min of EEG were recorded for each subject. An interface with three buttons flickering at different frequencies was designed, and the subjects were asked to look at each of the three buttons for four minutes. This means 840 data samples per class for 2-s time windows, and 420 data samples per class for 4-s time windows. The stimulus frequencies, each corresponding to a separate pseudo-task, are given in Table 1. A four-minute EEG was recorded for each stimulus, and subjects were rested for three minutes between recordings.

2.1. Stimuli type and frequency

A computer program was developed to trigger a SSVEP in the visual cortex. There are three buttons flickering at the specified frequencies to trigger a SSVEP as shown in Fig. 1. The distances of the buttons to each other and to the edges of the monitor are also given in Fig. 1. These distances are measured on a 21.5″ monitor with a resolution of 1920 × 1080 pixels, when the program is in full screen. The monitor's distance to the subjects is set to be approximately 60 cm during the recordings.

There is an asymmetry in SSVEPs as shown in Fig. 2. A significant difference is observed between the amplitude of the response obtained at the time of switching from the off position to the on position and the amplitude of the response obtained at the time of switching from the on position to the off position. Asymmetry in the luminance of on and off positions of the stimulus also creates an asymmetry in the response. Therefore, the response includes not only the fundamental frequency of the stimulus, but also higher harmonics [4]. Even and odd harmonics of fundamental frequency are observed in the asymmetric SSVEP response. On the other hand, symmetric SSVEPs only contain even harmonics of fundamental frequency [4]. A symmetric SSVEP response can be obtained by using opposite checkerboard patterns as stimuli. However, a uniform surface was used as a stimulus, taking into account that a more

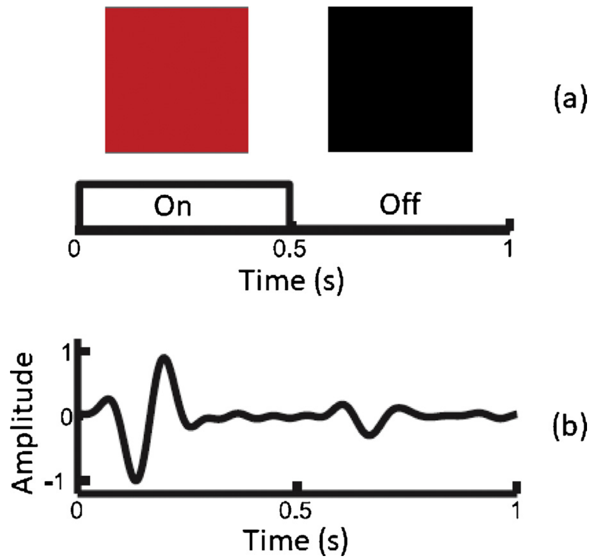

Fig. 2. (a) Stimulus signal as a square wave, and (b) asymmetric response in the visual cortex.

provocative stimulus such as a pattern would cause more fatigue because of long-standing SSVEP recordings [5].

The three stimuli shown in Fig. 1 are applied with button controls changing background color at specific frequencies. The adjustment of the frequencies of the buttons is one of the difficulties encountered in the use of a computer program with a SSVEP-based BCI. When determining the frequency of a stimulus, the time resolution of the operating system, the programming language and the monitor must be considered.

Monitor-based time resolution constraints cause major problems in design of stimulus programs in BCI applications. Only the part of the SSVEP response between 3.5 Hz and 30 Hz is measurable by a monitor with a 60 Hz refresh rate. When assessed in terms of bandwidth, it can be concluded that the monitor is not a significant restriction of adjusting the frequency of a stimuli. However, due to the time resolution of the monitor, only stimuli at certain frequencies can be obtained in a smooth square waveform. For example, frequency of a stimulus cannot be exactly 9 Hz on a monitor with a refresh rate of 60 Hz. In order for a frequency of a stimulus to be seen at a precisely set value, the frequency must be divisible by 60. In other words, the stimulus frequencies that can be seen in a regular square wave form on a monitor with a refresh frequency of 60 Hz are 1 Hz, 2 Hz, 3 Hz, 4 Hz, 5 Hz, 6 Hz, 6.67 Hz, 7.5 Hz, 8.57 Hz, 15 Hz, 20 Hz, and 30 Hz [17]. On the other hand, as a result of the spectral analyzes carried out, it is observed that stimuli that are not in perfect square wave form, such as 9 Hz and 11 Hz, trigger SSVEPs whose frequencies are approximately 9 Hz and 11 Hz. For instance, the first and second harmonics of a 20-s long SSVEP record, triggered by a stimulus with a frequency of 4.6 Hz, are observed at 4.56 Hz and 9.16 Hz, respectively, as seen in the frequency spectrum shown in Fig. 3.

2.2. Signal pre-processing and digital filtering

The only signal pre-processing in this study is to clear the direct-current (DC) offset values that vary between 4–5 mV. At first glance it can be considered that the DC offset value can be cleared with a high-pass filter (HPF). It is necessary to attenuate by 100 dB or higher to clean the high amplitude-low frequency noises [18]. However, DC offset cannot be removed by applying a HPF with a stopband attenuation of 100 dB due to certain limitations encountered in the digital filter design. A very strong attenuation, such as

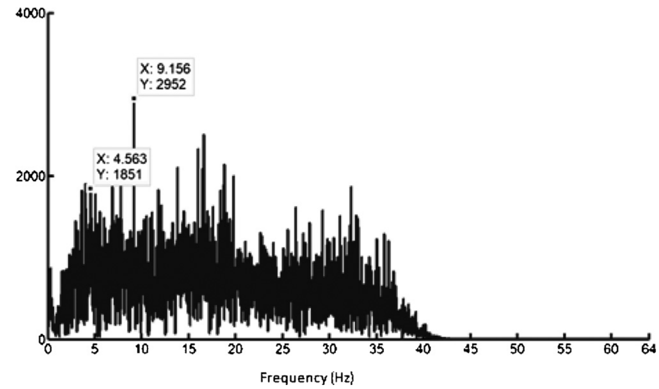

Fig. 3. Frequency spectrum of SSVEP that contains first and second harmonics at the frequencies of 4.56 Hz and 9.16 Hz.

Table 2
Characteristics of HPF and LPF applied in filtering EEG signals.

Filter characteristic	HPF	LPF
Attenuation	37 dB	60.5 dB
Passband Ripple	0.33 dB	0.1 dB
Transition Width	4.6 Hz	12 Hz
6 dB Point	2.48 Hz	38 Hz
3 dB Point	3.22 Hz	36.7 Hz
Filter Length	45	42

100 dB, will cause a time delay well above the acceptable values. For this reason, the DC offset is removed by taking the difference between the signal and its arithmetic mean. In electrophysiology Butterworth IIR filters or FIR filters are usually applied [18]. In this study, FIR filter design was applied in order to avoid signal distortions especially due to nonlinear phase. Table 2 shows the characteristics of the HPF and low-pass (LPF) filters.

2.3. Feature extraction and classification

The features used in classification of EEG are generally classified into time domain and frequency domain. Time domain features used in BCI studies can be waveform-based, such as peak value of the signal or block-based such as average over a specified time window [19]. There are also BCI studies involving template matching as feature extraction. In these studies, the similarity of the EEG with a predefined template was used as a feature [19]. BCI users are best at modulating the spectral characteristics of the stimuli. Hence, the spectral features of EEG signals are mostly used in SSVEP-based BCI applications [3,6,10,12,19–21]. In this study the feature vectors consist of the total and relative band power values of the various combinations of harmonics obtained from the frequency spectra of the SSVEPs.

It is observed that the most widely used classification methods in BCI design are artificial neural networks (ANN), support vector machines (SVM) and Naive Bayes (NB) [2,22]. In this study, binary and ternary classifications were performed. Three-layered perceptron network, trained by back-propagation algorithm, was used in the classification of EEG signals. The input and the output layers contain neurons as many as the number of features and number of classes, respectively. Number of neurons in hidden layer is set to be the mean of the number of neurons in the input and the output layers. The learning rate of the network is 0.3 and the number of training iterations is 40. Grid search and cross validation were used for hyper-parameter optimization of ANN and DVM algorithms. A 10-fold cross-validation model was used to evaluate the classification results. Each fold is composed of random samples with equal class distribution.

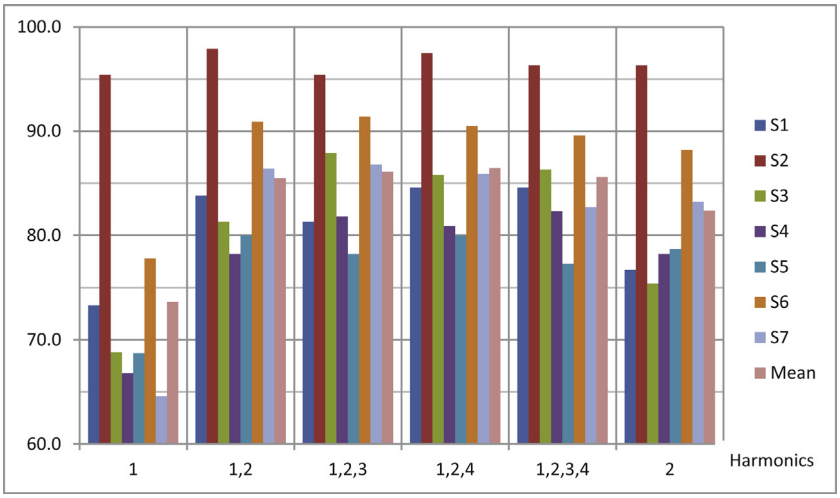

Fig. 4. Binary Classification Accuracy for several harmonic sets for 2 s Time-Windows.

3. Results and discussion

This study has shown that the most prominent features can be extracted from the second harmonic of the SSVEP response. It has also been observed that the first and second harmonics together are more prominent than any other binary set of harmonics combinations. In addition, 1 st, 2nd and 4th harmonic-based features provide better classification performance than 1 st, 2nd and 3th harmonic-based features, albeit with a slight difference. The accuracy percentages of binary and ternary classifications using 2-s window length for all subjects are given in Figs. 4 and 5, respectively. When both the binary and ternary classification results given in Figs. 5 and 6 are examined, it is observed that the effect of the first harmonic on the classification performance alone is inadequate. On the other hand, in the classifications where second, third and/or fourth harmonics are used together with the first harmonic, the accuracy rate increases drastically.

We also performed binary and ternary classifications with 4-s window length. In doing so, we wanted to see the effects of the features extracted from different harmonic sets on the classification performance more significantly by collecting properties over a longer period of time. The accuracy percentages of binary and ternary classifications using 4-s window length for all subjects are given in Figs. 6 and 7, respectively. In the classifications made with 4-s window length, parallel results were obtained with those in 2-s window length.

When examining the average performances of classifications based on only first and only second harmonics, the results show that the second harmonic-based features are more prominent than the first harmonic-based features. Therefore, the second harmonic-based features should be preferred if only single harmonic is sufficient for classification. As expected, the classifications based on the first two harmonics together is far superior to the classifications based on the first and second harmonics alone, independent of the subject, variety of tasks, and the window length. It is also understood that in all cases in which the first and second harmonics are used together, the classifications perform better than the cases in which the first two harmonics are used alone.

It is clear that in the case of using three harmonic frequencies together, the first and second harmonics are more prominent. Normally, third harmonic is considered to be more powerful than the fourth harmonic. However, as a result of the this study, it was observed that the fourth harmonic-based features are more prominent than the third harmonic-based features. This result is believed to caused because of the asymmetric response of the visual cortex to the flickering stimulus.

Table 3
Summary of the SSVEP Harmonic Analysis.

Harmonics	Mean accuracy			
	2-s		4-s	
	2-Class	3-Class	2-Class	3-Class
1	73,6	53,6	78,1	56,0
1,2	85,5	68,9	88,7	74,5
1,2,3	86,1	71,6	88,9	76,1
1,2,4	86,5	71,6	89,8	75,4
1,2,3,4	85,6	70,6	88,1	74,4
2	82,4	66,3	87,3	71,8

Table 3 shows the mean classification accuracies of all harmonic sets. In Table 3, the results obtained from harmonic sets such as 2,3,4 or 3,4 are not included. The reason for this is that the classification accuracy with the features extracted from these harmonic sets is very low. Best classification performances are highlighted as bold characters. It is seen that 1 st, 2nd and 4th harmonics-based features are the best preferences in classification of SSVEPs in terms of classification accuracy.

Analysis of variance (ANOVA) is applied to verify whether there is a statistical significance in classification accuracies of different harmonic sets. When the accuracy percentages of binary classification using 2-s window length were analyzed by one-way ANOVA, a statistical significance between harmonic groups was observed ($F(5,36) = 3.164$, $p = .018$). A statistical significance was also observed between harmonic sets of ternary classification using 2-s window length ($F(5,36) = 4.067$, $p = .005$). It is observed that a statistical significance between harmonic sets exists after analyzing the accuracy percentages of binary classification using 4-s window length, ($F(5,36) = 3.355$, $p = .014$). Finally, a significant difference was observed between harmonic sets for the accuracy percentages of ternary classification using 4-s window length ($F(5,36) = 7.117$, $p = .000$). These one-way ANOVA results show the statistically significant differences in mean classification accuracy values between different harmonic sets.

Tukey test was used for conducting post hoc tests on one-way ANOVA to determine statistically significant differences between harmonic sets. Tukey post hoc test revealed that for binary classification using 2-s window length, the accuracy of first harmonic (73.6 ± 10.5) was statistically significantly lower than first-second harmonics (85.5 ± 6.9, $p = .049$), first-second-third harmonics (86.1

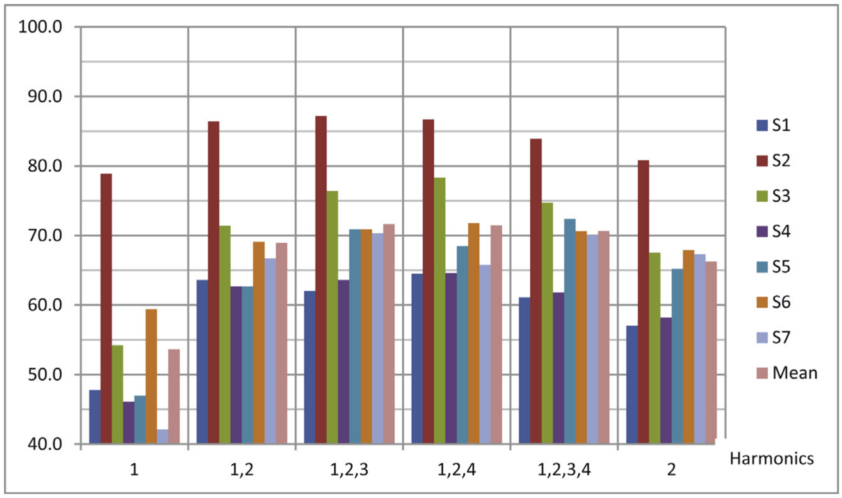

Fig. 5. Ternary Classification Accuracy for several harmonic sets for 2 s Time-Windows.

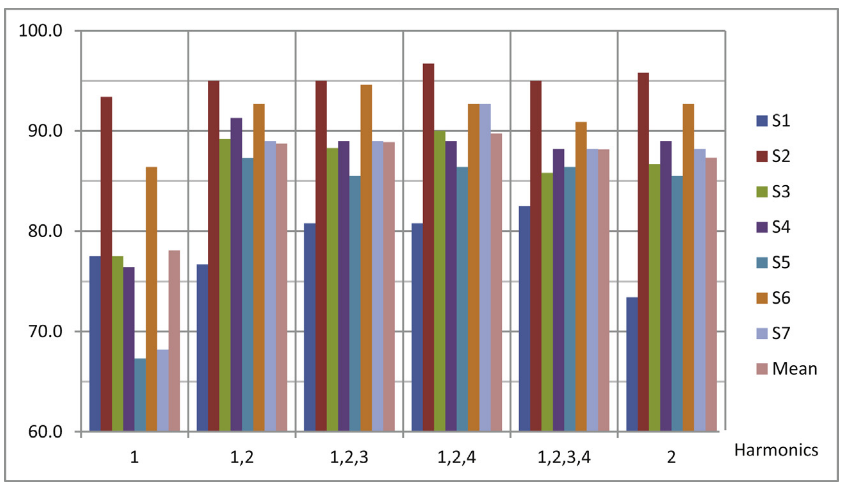

Fig. 6. Binary Classification Accuracy for several harmonic sets for 4 s Time-Windows.

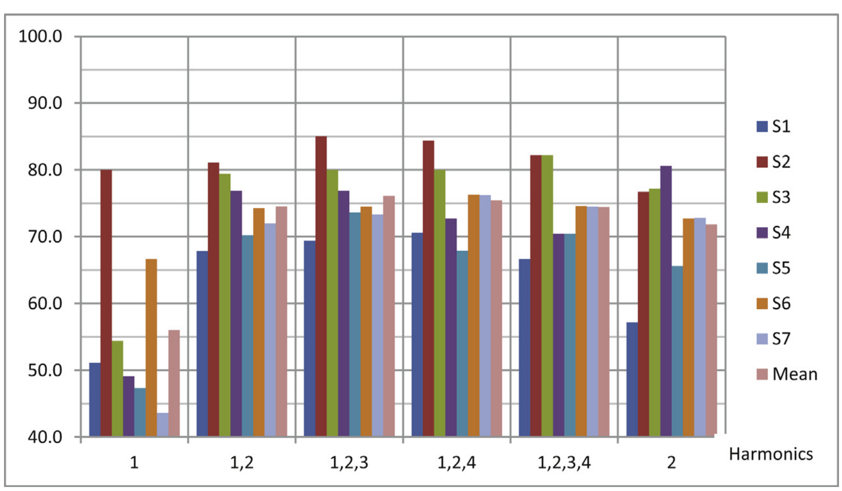

Fig. 7. Ternary Classification Accuracy of Subjects for 4 s Time-Windows.

$\pm$ 6.0, p = .033), first-second-fourth harmonics (86.5 $\pm$ 5.9, p = .027), and first-second-third-fourth harmonics (85.6 $\pm$ 6.0, p = .047). For ternary classification using 2-s window length, the accuracy of first harmonic (53.6 $\pm$ 12.5) was statistically significantly lower than first-second harmonics (68.9 $\pm$ 8.3, p = .34), first-second-third harmonics (71.6 $\pm$ 8.4, p = .008), first-second-fourth harmonics (71.6 $\pm$ 8.3, p = .009), and first-second-third-fourth harmonics (70.6 $\pm$ 7.7, p = .014). For binary classification using 4-s window length, the accuracy of first harmonic (78.1 $\pm$ 9.3) was statistically significantly lower than first-second harmonics (88.7 $\pm$ 5.9, p = .33), first-second-third harmonics (88.9 ± 4.9, p = .031), and first-second-fourth harmonics (89.8 ± 5.1, p = .016). For ternary classification using 4-s window length, the accuracy of first harmonic (56.0 ± 12.8) was statistically significantly lower than second harmonic (71.8 ± 7.9, p = .005), first-second harmonics (74.5 ± 4.8, p = .001), first-second-third harmonics (76.1 ± 5.1, p = .000), first-second-fourth harmonics (75.4 ± 5.6, p = .000), and first-second-third-fourth harmonics (74.4 ± 5.9, p = .001). Tukey post hoc test results show that accuracy percentages of first harmonic is statistically less significant than most of other harmonics in all classifications using all window lengths.

4. Conclusion

In previous years, first and second harmonics based features are used for feature extraction in SSVEP-based BCI studies. However, there has been no previous study examining the effects of SSVEP harmonics on classification performance in BCIs. To the best of our knowledge, this is the first study that investigated the effects of the frequency harmonics of SSVEPs in classification performance. In this study, the classification performed with the features extracted from the different sets of harmonics of SSVEPs were investigated. The feature vectors consist of the total and relative band power values of the harmonics. It is observed that classification performance is better with second harmonic-based features than the classification performance of the first harmonic-based features in almost all cases. The amplitudes of the third and fourth harmonics were observed to be low as expected. However, if the fourth harmonic-based features are used together with the 1 st and 2nd harmonics, it is seen that the classification performance increases slightly.

Authors' contribution

Volkan Çetin: Data curation, Formal analysis, Investigation, Software, Methodology, Writing original draft, Writing review. **Serhat Ozekes**: Conceptualization, Investigation, Validation. **Hüseyin Selçuk Varol**: Conceptualiztion, Supervision, Project administration.

Declaration of Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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