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# Adaptive canonical correlation analysis for harmonic stimulation frequencies recognition in SSVEP-based BCIs

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**Abstract:** Steady-state visual evoked potential (SSVEP) is the brain's response to quickly repetitive visual stimulus with a certain frequency. To increase the information transfer rate (ITR) in SSVEP-based systems, due to the frequency resolution restriction, we are forced to broaden the frequency range, which causes harmonic frequencies to come into the stimulation frequency range. Conventional canonical correlation analysis (CCA) may be associated with error for SSVEP frequency recognition at stimulation frequencies with harmonic relations. The number of harmonics considered to construct reference signals are determined adaptively; for frequencies whose second harmonic exists in the frequency range, two harmonics are used, and for other frequencies, just one harmonic is used. After constructing reference signals and recognizing the frequency corresponding to the maximum value of correlation by CCA, the target frequency is determined after a postprocessing step. Results show that for the 8-s time window length, the average classification accuracy for the adaptive CCA was 84%, while the corresponding values for the CCA with one harmonic ($N = 1$) and two harmonics ($N = 2$) were 78% and 74%, respectively. For 4-s length, this accuracy for the adaptive CCA was 86%, while it was 78% for both harmonic selection modes of the standard CCA, $N = 1$ and $N = 2$. In SSVEP applications with harmonic stimulation frequencies, the adaptive CCA has significantly improved the frequency recognition accuracy in comparison with the popularly standard CCA method. The proposed method can be useful for SSVEP-based BCI systems that use broad ranges of stimulation frequencies with harmonic relation.

**Key words:** Brain–computer interface, steady-state visual evoked potential, harmonic frequency recognition error, adaptive canonical correlation analysis

## 1. Introduction

Steady-state visual evoked potential (SSVEP) is one of the most common brain responses in brain–computer interface (BCI) systems. Since SSVEP can be easily recorded from the scalp over the occipital area and it has high signal-to-noise ratio, many SSVEP-based BCI systems have been implemented and achieved satisfactory performances [1, 2]. SSVEP is periodic evoked potential induced by a quickly repetitive visual stimulus. The dominant frequency of SSVEP depends on the frequency of the flickering source. SSVEP signals are divided into three categories according to the visual stimulation frequency: low frequency (less than 12 Hz), middle frequency (12 to 25 Hz), and high frequency (greater than 25 Hz) [3–6]. The SSVEP has the same fundamental frequency as the visual stimulus as well as its harmonics. The traditional SSVEP detection methods cannot identify targets flickering at harmonic frequencies. Thus, stimuli with harmonic frequencies cannot be used and

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this limits the number of targets [7, 8]. One of the significant topics in BCI systems is information transfer rate (ITR). One way to increase ITR is shortening the length of the signal recording. However, to have good frequency resolution, the recording length could not be very short. Another way to improve ITR is increasing the number of frequency options that is achieved by reducing the frequency step or broadening the frequency range. If stimulation frequencies are selected very close to each other, once again we will face frequency resolution restriction, and the broader frequency range will cause harmonics to come into the stimulation frequency range. SSVEP amplitude is very unstable and varies across subjects [7–9], so occasionally the harmonic frequency component may have the most prominent amplitude [10, 11]. Therefore, entering harmonics in the frequency range may lead to harmonic recognition error [12]. As an example of solving this problem, Wong et al. proposed a modified visual stimulus generation method and a feature detection algorithm based on frequency and phase information [13, 14]. So far, various approaches have been proposed to recognize SSVEP frequency for BCI applications. Among them, canonical correlation analysis (CCA) has aroused more interest of researchers. Good performance of the CCA-based frequency recognition has been confirmed by many studies [15, 16]. However, this method may be accompanied with error in recognition of the SSVEP evoked by stimulation frequencies with harmonic relations. How to construct reference signals of sine-cosine waves is a critical issue in CCA. Some previous studies evaluated the optimization of reference signals in CCA for various purposes. Zhang et al. proposed a generalization of CCA based on multiset canonical correlation analysis (MsetCCA) to extract common features for reference signal optimization as a sophisticated calibration procedure followed by CCA, and hence improved the recognition accuracy [17]. They also proposed the multiway CCA method to find optimal reference signals rather than sine-cosine waves in order to consider the intersubject variability and trial-to-trial variability [18]. Another approach called phase-constrained canonical correlation analysis (p-CCA) [19] has improved reference signals of the standard CCA by considering the SSVEP phase. The spectrum and phase adaptive CCA approach (SPACCA) has also been proposed to improve SSVEP detection accuracy [20]. Kumar et al. presented periodic component analysis, which outperforms traditional CCA by providing discrimination between control and idle states [21]. Our goal is to find more efficient reference signals to solve the harmonic recognition error. Therefore, this paper focuses on the number of harmonics considered to construct reference signals. Due to the fact that brain dynamics perform as a low-pass filter [22, 23], high harmonic components in a square wave may be filtered. Some existing SSVEP-based BCIs [16, 24, 25] considered more than one harmonic for SSVEP frequency recognition while some others used only the fundamental frequency [26–28]. Generally, the dominance of harmonic frequency components varies across subjects. For example, for some subjects, the highest amplitude is associated with the fundamental frequency, but for others, the second harmonic has the highest amplitude. Therefore, the number of harmonics considered in reference signals is important. This issue will be more evident when stimulation frequencies have a harmonic relation. On the other hand, independent of a subject's specification, for stimulation frequencies with harmonic relations, choosing one harmonic will cause errors in low frequencies while choosing two harmonics will cause errors in high frequencies [12]. Therefore, independent of the number of harmonics that are chosen in reference signals, CCA cannot give optimal responses for the entire frequency range. A technique that can recognize the target frequency in the stimulation frequency range with harmonic relations can greatly improve the performance of CCA. In this paper, we consider that the commonly used reference signals of sine-cosine with fixed number of harmonics may not be optimal for SSVEP recognition due to subjects' variability of harmonic components and effects of harmonic relations between stimulation frequencies. Therefore, we investigate the idea of adaptive selection of the number of harmonics.

## 2. Materials and methods

### 2.1. Experimental paradigm

Ten healthy volunteers (aged from 22 to 33 years, two males and eight females) without any known history of BCI experience participated in the experiment. Subjects were informed about all aspects of the experiment and all signed an informed consent form. The experimental protocol was approved by the local ethical committee for research on human subjects. The SSVEP stimulation frequency is induced typically at frequencies greater than 6 Hz [7] and the best responses are obtained for frequencies between 5 and 20 Hz [29]. To achieve stimulation frequencies with harmonic relations in this study, frequencies were generated between 6 and 16 Hz with an interval of 0.5 Hz. Each subject participated in 10 sessions and all sessions were done in one day. There was one trial per frequency in each session. Therefore, each session contained 21 trials corresponding to 21 stimulation frequencies. The visual stimulus was a white flashing circle with a diameter of 10 cm rendered at the center of the black background screen as shown in Figure 1. All stimuli were presented on a 15.6" display with refresh rate of 50 Hz using the psychophysics toolbox extensions of Matlab. Subjects were seated in a comfortable chair, 40 cm away from the monitor. They were asked to gaze at the flickering stimulus for 8 s and then take a 5-s rest after each trial to avoid visual fatigue caused by flickering. There were also 5-min breaks between two consecutive sessions. EEG signals were recorded using the Bayamed system (EEG V.16.24) at a sampling rate of 1000 Hz. Signals were acquired from the surface of the scalp via one electrode placed at Oz, referenced to AFz, and grounded to the right ear lobe. The impedance was kept below 5 K$\Omega$. The signal was preprocessed to improve its quality. First, a 50-Hz notch filter was applied to reduce the noise of line frequency interference. Then, to prevent frequency aliasing during sampling and restrict bandwidth of the signal (attenuate the frequencies greater than the Nyquist frequency), an antialiasing low-pass filter at 125 Hz was applied. In the following step, the signal was downsampled to 250 Hz. Finally, the signal was band-pass filtered between 1 and 40 Hz.

**Figure 1**. The view of visual stimulation on the screen.

### 2.2. The standard CCA

Canonical correlation analysis is a statistical technique for measuring the linear relationship between two sets of multivariate data, which obtains the maximum similarity between them. For two multidimensional variables

$X = (X_1, ..., X_n)$ and $Y = (Y_1, ..., Y_n)$, CCA attempts to find a pair of vectors, $W_x$ and $W_y$, to maximize the correlation between $x = X^T W_x$ and $y = Y^T W_y$ (x and y are called canonical variants). Lin et al. [23] first proposed the use of CCA for SSVEP recognition. They extracted CCA coefficients for all stimulation frequencies, assuming the frequency with the largest coefficient as the SSVEP frequency. The variable X is a multichannel EEG signal and Y consists of a Fourier series of simulated stimulation signals, given that there are K targets with stimulation frequencies $f_1, f_2, ..., f_k$, respectively. The reference signal Y at the certain frequency f can be decomposed into a Fourier series of its harmonics:

$$Y = \begin{bmatrix} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ . \\ . \\ \sin(2\pi N f_k t) \\ \cos(2\pi N f_k t) \end{bmatrix} \qquad ,t = 1/F_s, 2/F_s, ..., T/F_s. \tag{1}$$

Here, $f_k$ is the stimulation frequency, N is the number of harmonics, T is the number of sampling points, and $F_s$ is the sampling rate. CCA needs to find the weight vectors, $W_x$ and $W_y$, that maximize the correlation between x and y and define the constraints expressed in (2) and (3). The total correlation is calculated as the ratio between the autocorrelation and cross-correlation of the input and output vectors, so the optimization of (4) is applied to solve the canonical correlations $r_1, r_2, ..., r_k$ corresponding to the K targets, respectively. The maximum of correlation coefficient $r$ with respect to $W_x$ and $W_y$ is the maximum canonical correlation and the frequency corresponding to the largest coefficient $r$ is the SSVEP frequency [27, 28]:

$$E[xx^T] = E[x^T x] = E[W_x^T XXW_x] = 1. \tag{2}$$

$$E[yy^T] = E[y^T y] = E[W_y^T YYW_y] = 1. \tag{3}$$

$$r = \max_{W_x, W_y} r_{x,y} = \frac{x^T y}{E[x^T x]E[y^T y]} = \frac{E[W_x^T XY^T W_y]}{\sqrt{E[W_x^T XXW_x]E[W_y^T YYW_y]}} \qquad ,O = \max_k r_k \quad , \quad k = 1, 2, ..., K. \tag{4}$$

### 2.3. The proposed method: adaptive CCA

Adaptive CCA is a modified version of CCA for SSVEP-based BCI systems, which reduces harmonic recognition errors through adaptive selection of the number of harmonics in constructing reference signals. This method consists of two parts, offline and online processing. In offline processing, a defined threshold is determined for each subject based on the training data, and in online processing, by using the determined threshold, adaptive CCA is applied to the recorded signal and the SSVEP frequency is recognized. For this purpose, 25% of the data was used for training in the offline mode and 75% was used for testing in online mode.

#### 2.3.1. Recognition strategy

Figure 2 shows the block diagram of the adaptive CCA, which is composed of two steps. In the first step, the main stimulation frequency range is divided into two groups. The first group just includes frequencies whose second harmonic also exists in the frequency range, and the second group contains other stimulation frequencies.

This division is valid for any given stimulation frequency range. In this level, unlike standard CCA, in which the number of harmonics for constructing reference signals is fixed, the proposed method uses adaptive harmonic selection corresponding to stimulation frequencies. In [7], the authors discussed the relationship between the recognition accuracy and the number of harmonics included in reference signals. They found that two harmonics are adequate to achieve a reliable result. Based on this, we used a maximum of two harmonics to construct reference signals in our analysis. Therefore, to construct reference signals, two harmonics ($N = 2$) are considered for frequencies of the first group while only the first harmonic ($N = 1$) is used for frequencies of the second group. In the following, the reference signal corresponding to each frequency is constructed according to the considered N. Then CCA is applied and the frequency that corresponds to the maximum value of correlation is recognized according to (4). In other words, the difference between the proposed method and classical CCA in the first step is the number of harmonics in constructing the reference signal corresponding to each frequency. The second (postprocessing) step is applied for further investigation of the recognized frequency using correlation values $(r_1, r_2, ..., r_p)$ obtained from CCA. For this purpose, if the recognized frequency does not belong to the first frequency group, it is accepted as the target SSVEP frequency. Similar to classical CCA, the process of determining the target frequency has been finished in this case. However, if it belongs to the first frequency group, the difference between the correlation values corresponding to the recognized frequency $(r_f)$ and its second harmonic $(r_{fh})$ should be calculated according to (5):

$$\Delta r = r_f - r_{fh}, \tag{5}$$

where f is the recognized frequency of the first step, $(r_f)$ is the correlation value corresponding to the recognized frequency, and $(r_{fh})$ is the correlation value obtained by the second harmonic of the recognized frequency. Then the difference value is compared with the predetermined threshold such that if it is higher than the threshold, the recognized frequency will be accepted. Otherwise, twice the amount of this frequency (its second harmonic) is determined as the target SSVEP frequency. The threshold value is determined based on the offline data of each subject prior to the online test.

#### 2.3.2. Threshold determination

Figure 3 illustrates the process of determining the threshold for each subject. Assume that $X_{1,m}, X_{2,m}, ..., X_{T,m}$ denotes the whole training dataset recorded from T experimental trials at the $m$th stimulus frequency $f_m$. This training dataset is divided into two categories of trials based on stimulation frequencies. The first category includes trials with stimulation frequencies belonging to the first frequency group ($f_m \in [f_1, f_2, ..., f_l]$) and the second category contains trials with stimulation frequencies equal to the second harmonic of the first frequency group ($f_m \in [2 \times f_1, 2 \times f_2, ..., 2 \times f_l]$). Other frequencies that do not have harmonic relations are not included in these categories. In the following, first CCA is applied in trials of each category and the frequencies corresponding to the maximum values of correlation are recognized. Then, if the recognized frequencies belong to the first frequency group, the difference between the correlation values corresponding to these frequencies and their second harmonics ($\Delta r$) are calculated according to (5). This process is repeated until the number of trials in which the condition if $f \in F_1$ is true reaches a sufficient number. To achieve a favorable response, we consider that the number of these trials ($T_1$ in the first category and $T_2$ in the second category) should reach at least 10 trials. In the following, by averaging the ($\Delta r$) values of each category across all its trials, mean and standard deviation values are determined for that category. Finally, the threshold value is obtained

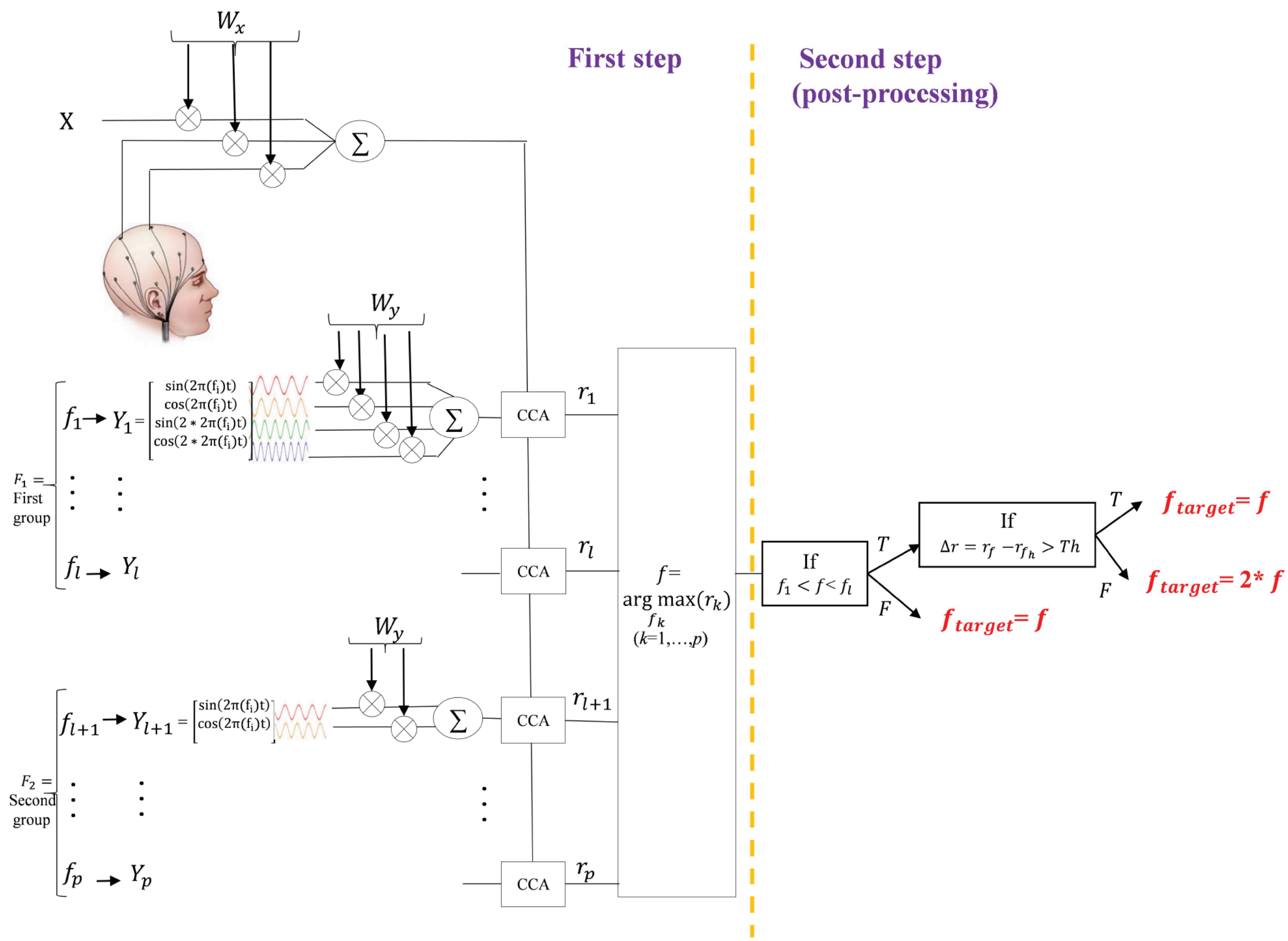



**Figure 2**. SSVEP frequency recognition model based on the proposed method. X is the recorded signal, $Y_1, \ldots, Y_p$ are reference signals, $F_1$ is the first frequency group, $F_2$ is the second frequency group, r is the correlation value obtained from CCA, $f$ is the recognized frequency calculated in the first step, $r_f$ is the correlation value corresponding to the recognized frequency, $r_{fh}$ is the correlation value corresponding to the second harmonic of the recognized frequency, $(\Delta r)$ is the correlation difference, $Th$ is the threshold, and $f_{target}$ is the target recognized frequency of the system.

by averaging two mean values, taking into account each standard deviation according to (6):

$$Th = \frac{(1/V_1) \times M_1 + (1/V_2) \times M_2}{2}, \tag{6}$$

where $M_i$ is the mean value of the $i$th category, $V_i$ is the standard deviation of the $i$th category, and $Th$ is the threshold obtained for each subject.

### 2.4. Evaluation criterion

The classification accuracy is used for quantitative evaluation of results according to (7):

$$Accuracy = N_c/N_t, \tag{7}$$

where $N_C$ is the number of trials in which the stimulation frequency is correctly recognized and $N_t$ indicates the total number of trials.

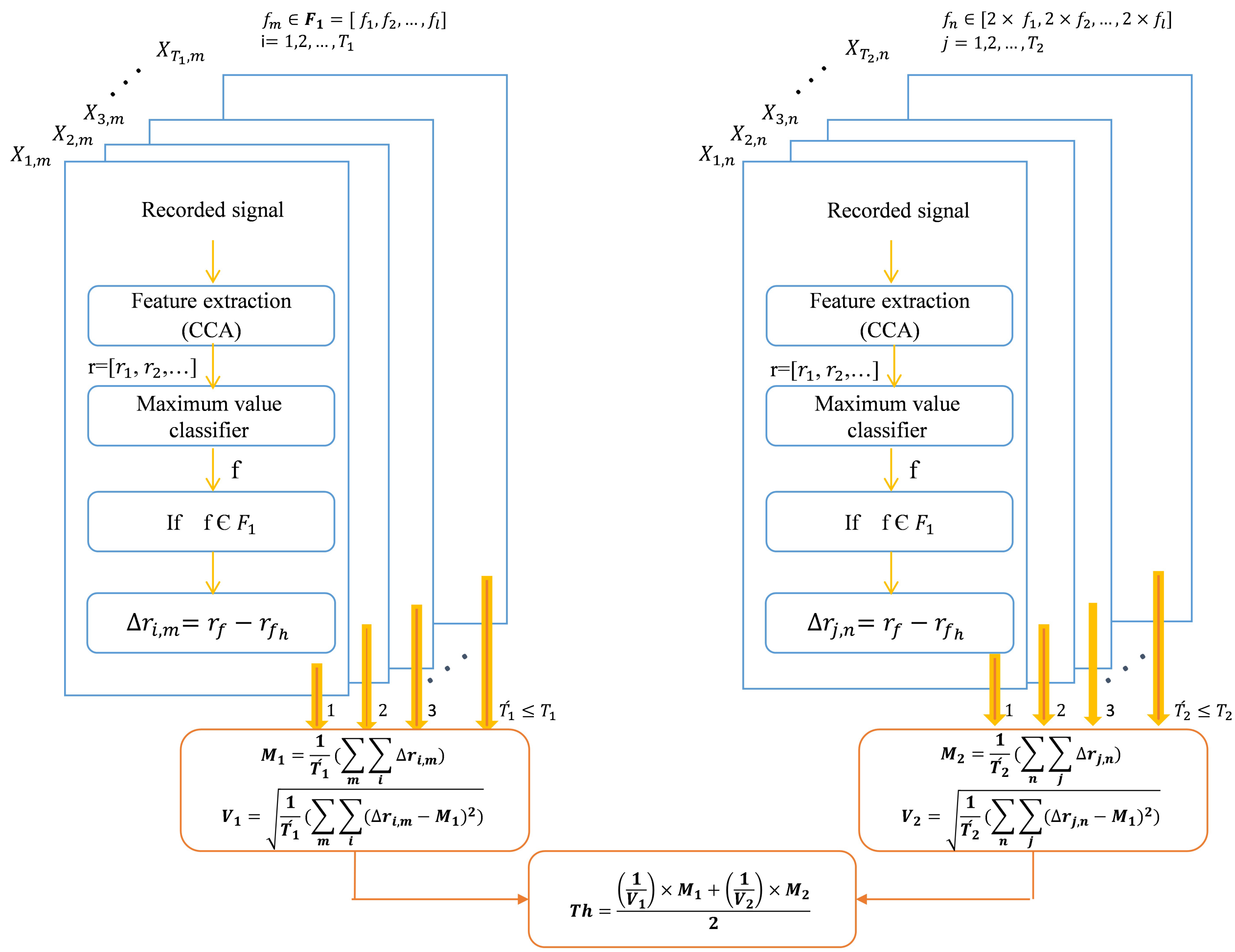



**Figure 3**. The process of determining the threshold in the proposed method. $X_(1,m), X_(2,m)$.....$X_(T_1,m)$ denote EEG training trials $(i = 1,2,...,T_1)$ at the $m$th stimulation frequency $f_m$ $(f_m = f_1, f_2, ..., f_l)$ belonging to the first frequency group, $X_(1,n), X_(2,n), ..., X_(T,n)$ denote EEG training trials $(j = 1,2,...,T_2)$ at the $n$th stimulation frequency $f_n$ $(f_n = 2 \times f_1, 2 \times f_2, ..., 2 \times f_l)$, $(T_1')$ and $(T_2')$ are parts of whole training trials $T_1$ and $T_2$ in which the condition $(if f \in F_1)$ is true, M is the mean value of $(\Delta r)$ values, and V is the standard deviation of the $(\Delta r)$ values.

## 3. Results

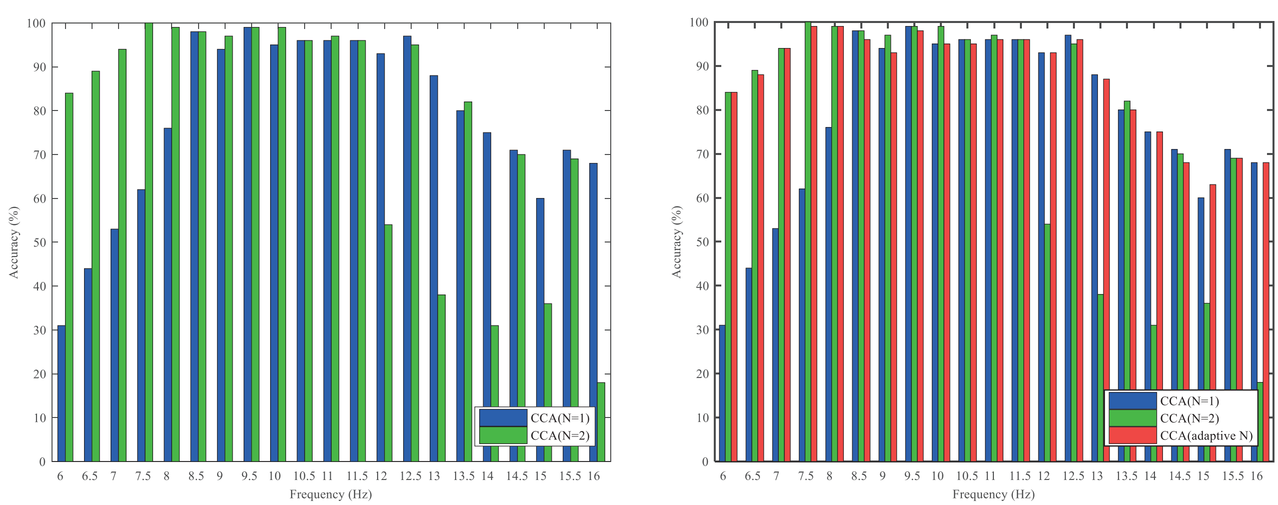
In this paper, the main stimulation frequency range (6–16 Hz) was divided into two groups: the first group (6–8 Hz) and the second group (8.5–16 Hz). Then adaptive CCA was applied to recorded signals. The Table summarizes accuracy results obtained by adaptive CCA at various time window lengths. In order to validate the effectiveness of adaptive CCA, accuracy results for standard CCA taking into account one harmonic and two harmonics in constructing reference signals are also reported. Accuracy values were obtained separately for each subject in 10 sessions and 21 trials in each session.

Results for each subject show that choosing only the first harmonic provides a better response for some individuals, while selecting two harmonics leads to better results for some others. In the following, average accuracies of all subjects are also reported. For the 8-s time window length, the average accuracy is 84% for adaptive CCA, while for standard CCA it is 78% and 74% for only the first harmonic and two harmonics,

**Table**. Classification accuracy results of adaptive CCA and standard CCA with different numbers of harmonics ($N$) at various time window lengths.

| Time window | 8 seconds | | | 4 seconds | | |
|---|---|---|---|---|---|---|
| Subject | $CCA(N=1)$ | $CCA(N=2)$ | Adaptive CCA | $CCA(N=1)$ | $CCA(N=2)$ | Adaptive CCA |
| 1 | 92 | 79 | 92 | 90 | 82 | 94 |
| 2 | 86 | 74 | 86 | 83 | 76 | 84 |
| 3 | 58 | 67 | 72 | 69 | 80 | 84 |
| 4 | 71 | 65 | 71 | 75 | 72 | 75 |
| 5 | 66 | 75 | 78 | 68 | 83 | 83 |
| 6 | 74 | 73 | 84 | 69 | 75 | 82 |
| 7 | 84 | 71 | 85 | 79 | 71 | 82 |
| 8 | 65 | 69 | 77 | 70 | 73 | 83 |
| 9 | 97 | 85 | 98 | 95 | 87 | 99 |
| 10 | 85 | 82 | 92 | 83 | 81 | 92 |
| Average | 78 | 74 | 84 | 78 | 78 | 86 |

respectively. For 4-s time window length, the average accuracy of adaptive CCA is 86%, while the corresponding values of CCA for both $N = 1$ and $N = 2$ are 78%. Figure 4 shows accuracy results of these two methods in terms of stimulation frequency for a 4-s time window length, averaged across subjects. As shown in Figure 4(a), the recognition rate of standard CCA taking into account one harmonic in constructing reference signals is low for frequencies whose second harmonic also exists in the stimulation frequency range. For taking into account two harmonics, although the recognition rate is high for low frequencies, it may be accompanied with error for identifying frequencies equal to the second harmonic of them. As is clear from Figure 4(b), the proposed method is more desirable than the standard CCA for all frequencies.




(a) (b)

**Figure 4**. Classification accuracy in terms of stimulation frequency for 4-s time window length obtained by averaging across subjects: (a) comparison of choosing one harmonic ($N = 1$) with two harmonics ($N = 2$) in the standard CCA, (b) comparison of the proposed method with standard CCA.

## 4. Discussion

For wide SSVEP stimulation frequency ranges with harmonic relations, the system faces harmonic recognition error, which affects the classification accuracy. Only a few articles have addressed this problem, which is associated with limitations. The phase-tagged stimuli generation method in [13, 14] can relatively solve the harmonic frequency problem, but embedding the phase information into the visual stimulus generation requires more complex hardware and the phase of flicker is also limited by the monitor's refresh rate, which is inconvenient for practical applications. Our proposed method considers this problem from a different point of view, which does not require any complicated hardware.

We tried to modify CCA by choosing more efficient reference signals. Various studies have improved the reference signal using the information of intersubject variability. As examples, in [19, 20] the phase information of each subject was estimated based on the apparent latency. Adding the intersubject phase information into the reference signal enhanced the classification accuracy of CCA. Furthermore, in [17, 18], the reference signal was modified so that the optimized reference signal contained not only the ideal SSVEP frequency components but also the information of intersubject variability and trial-to-trial variability. We also improved the reference signal using the information of intersubject variability from the point of view of the number of harmonics.

Determining the number of harmonics in the CCA method depends on the signal condition (such as stimulation frequency range and intersubject variability). In previous studies, the number of harmonics has been determined based on the total average recognition accuracy for all frequencies and all subjects. In [18], using more harmonics had a slightly better performance than fewer harmonics, whereas the study in [15] found that only the first harmonic component makes a significant contribution to system performance. In this paper, corresponding to the stimulation frequency range and with the consideration of intersubject variability, we selected the number of harmonics adaptively, which improved the performance of the standard CCA method.

Results of this paper clearly show that choosing one harmonic reduces the classification accuracy in low frequencies, while choosing two harmonics decreases it in high frequencies. Therefore, for a wide range of stimulation frequencies with harmonic relations, choosing a fixed number of harmonics cannot achieve a proper response for the entire range. It can be seen that accuracy values of adaptive CCA were significantly higher than those of CCA (with both harmonic selection modes $N = 1$ and $N = 2$) at both 4-s and 8-s time-window lengths. Experimental results from EEG data of ten subjects show that adaptive CCA has improved the classification accuracy more than 6% compared to standard CCA. Generally, the proposed method has enhanced the frequency recognition accuracy in contrast to the traditional standard CCA.

## 5. Conclusion

To increase the information transfer rate in SSVEP-based BCI systems, we are forced to broaden the frequency range due to the frequency resolution restriction. This causes harmonic frequencies come into the stimulation frequency range. SSVEP is the oscillating component of EEG with the frequency corresponding to the visual stimulation frequency. While the peak of the power spectrum is often observed at the stimulation frequency, the power spectrum can also exhibit considerable power at harmonic frequencies of the stimulation frequency. In applications with independent stimulation frequencies, feature extraction methods can achieve good results. If stimulation frequencies have harmonic relation, this issue will cause harmonic recognition error. In the CCA method, it is possible to determine the number of harmonics. However, choosing a constant number of harmonics can be appropriate just for a limited stimulation frequency range. If the frequency range includes frequencies with harmonic relations, harmonic recognition error occurs and the classification accuracy decreases.

In this study, we proposed an adaptive CCA method in which the adaptive number of harmonics was considered to construct reference signals. Results indicate that adaptive CCA could increase the classification accuracy by reducing harmonic recognition error. Using the proposed method, the possibility of applying stimulation frequencies with harmonic relations is provided. This will increase the number of frequency options. Increasing frequency options will lead to an increase in ITR that is desirable in a BCI system. Finally, it can be concluded that the adaptive CCA could effectively enhance the performance of standard CCA at the cost of using training data. The proposed method can be useful for SSVEP-based BCI applications that use broad ranges of stimulation frequencies with harmonic relations.

Figure 5 illustrates the classification accuracy of standard CCA and adaptive CCA for 8-s time window length and each subject separately. As seen from this figure, the accuracy of CCA with one harmonic and two harmonics varies with subjects such that the case $N = 1$ has a better response for some subjects, while other subjects responded better to $N = 2$. Therefore, we cannot conclusively say which of these two harmonic selection conditions is better, while the proposed method has higher accuracies for almost all subjects. The averaged bar also shows that the classification accuracy of adaptive CCA was obviously improved in comparison with standard CCA.

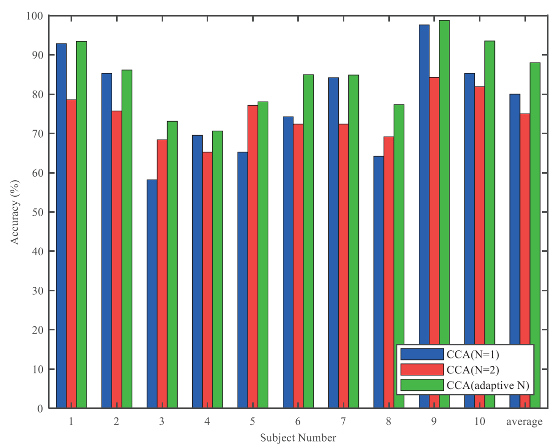



**Figure 5**. Classification accuracies for each subject separately obtained by standard CCA and adaptive CCA for 8-s time window length and the averaged accuracy across all subjects.

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