# An Unsupervised Channel-Selection Method for SSVEP-based BCI Systems

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***Abstract*—Brain-computer interface (BCI)-based systems have been successfully implemented as a communication tool for people with motor deficits that obstruct normal communication. The accuracy of the algorithms used for determining user-selected commands directly impact their practicality to the user. These algorithms are divided into two prinicipal categories, supervised and unsupervised. While the former achieves higher accuracy, the latter is useful when training is not practical for the user.**

**In this paper, we introduce an unsupervised algorithm for steady-state visual evoked potential (SSVEP)-based BCIs, which works in three steps: (i) it selects multiple sets of EEG (electroencephalogram) channels, followed by (ii) existing feature extraction methods applied to each one of these channel sets. As its final step, (iii) it combines the extracted features from these channel sets by performing a majority vote, yielding a classification. We evaluate the information transfer rate (ITR) attained using our proposed method on a database of 35 subjects using three different (CCA, FBCCA, MSI) feature extraction methods in step (ii). We compare these results to existing methods in the literature that use a single channel set without a majority vote. The proposed method indicates an improvement in at least 7 subjects using any of the three feature extraction methods.**

***Index Terms*—Brain-computer interface (BCI); canonical correlation analysis (CCA); electroencephalography (EEG); filter bank canonical correlation analysis (FBCCA); minimum energy combination (MEC); multivariate synchronization index (MSI); steady-state visual evoked potential (SSVEP).**

## I. Introduction

Brain-computer interface (BCI) systems provide a direct link between a person and a computer. This creates an alternative communication channel for people with severe motor deficits such as *locked-in syndrome* [1] and may also have applications for people without disabilities [2]–[4]. The underlying premise of a BCI is that electroencephalography (EEG)—or some other neuroimaging technology—is used to measure the user's brain activity in (near) real-time. This brain activity is analyzed to determine the user's intended actions and a computer or robotic system is used to replace voluntary muscle activity as a means of communication and/or control.

Repetitive visual stimulation is one well-established method for eliciting brain signals for use in a BCI [5]–[7]. For example, when a user attends a light source flashing at 12 Hz (a *stimulus*), a strong EEG signal can be observed at that same frequency (as well as at harmonic frequencies [i.e., 24Hz, 36Hz, etc.]) as the stimulus. This frequency-specific response in the EEG activity is called the steady-state visual evoked potential (SSVEP). Critically, when multiple stimuli are present, the stimulus the user attends to elicits the strongest SSVEP [8]. This can be recognized using signal processing methods, which allows the user to make a selection; for example, in a *BCI speller* [9] application, different *stimuli* can be associated with different *letters*, which forms the basis of a communication device that allows a person spell words through SSVEP.

When developing an SSVEP-based BCI, one challenge is to decide how many electrodes to record EEG from and where to place these electrodes on the scalp. SSVEPs, for example, are predominantly observed over the occipital region of the scalp [10]. The performance of the signal processing system and subsequently the BCI will be lower if one attempts to measure SSVEPs using electrodes over other regions. Thus, this decision—known as *channel selection*—can have a significant impact on the overall performance of the BCI. The two general strategies for channel selection are supervised and unsupervised channel selection. While the former results in higher performance (e.g., accuracy or ITR) [11], it requires the collection of data from the user to determine the best set of channels before they can use the BCI, which may render the BCI system less practical.

In unsupervised channel selection, the set of electrodes used are chosen without collecting any additional data. These channels are often chosen based on *a priori* knowledge, such as previous research on the scalp distribution of the SSVEP. While unsupervised channel selection often results in lower performance, it doesn't require the collection of data from each user to determine the best set of EEG channels. This means that the BCI can be set up faster, which is particularly advantageous in clinical settings, where time with a participant may be limited.

One limitation of both strategies is that they assume that the best set of electrodes is time invariant (i.e., stays the same). It is possible, however, that due to factors such as participant movements or transient artifacts in specific electrodes that the best set of electrodes changes with time.

Here, we present an unsupervised channel selection method that relaxes the assumption that the best set of electrodes is time invariant. Our method achieves this by simultaneously considering multiple different sets of electrodes at each time interval. Data from each of these sets are independently processed and a final selection is made using a majority vote.

The rest of this paper is organized as follows. Section II

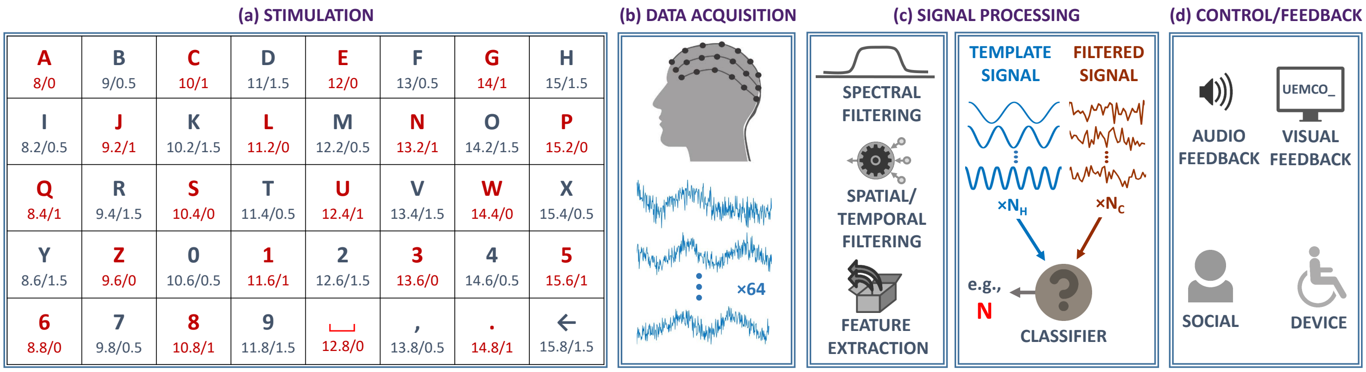


Fig. 1. A review of the BCI speller architecture. The *stimulation* component is a $5 \times 8$ matrix that is displayed on a conventional monitor. This figure shows the frequency ($f$, in Hertz) and phase ($\phi$, in $\pi$ radians) assigned to each letter (using an "$f/\phi$" format). For example, the letter "N" is presented on a tile flickering at 13.2 Hz with the delay of $\pi$ radians. In the actual implementation, tiles assigned to each letter are uniformly separated by a blank space. The *data acquisition* component collects EEG data using 64 electrodes, although we only use a subset of them in our analysis. *Signal processing* methods are used to filter and extract features from raw EEG signals that can be used for classification. In our case, this process consists of finding an amount of correlation between filtered signals and a template signal to assign a class to the signal. The classification result is then fed back to the user and their environment.

provides background information on SSVEP-based BCIs with emphasis on the signal processing system that maps EEG activity to computer commands. Section III provides a review of the BCI speller system used to generate the SSVEP dataset used in our analysis. Section IV details the signal processing methods used for our channel selection method. Section V presents experimental results that evaluate the performance of our proposed work. Finally, Section VI concludes our paper and includes additional remarks.

## II. Background and Related Work

The performance of any SSVEP-based BCI—represented graphically in Figure 1—is based on the design of multiple systems that work together to elicit brain activity (*stimulation* system), measure that brain activity (*data acquisition* system), process the acquired data (*signal processing* system), and then provide feedback to the user (*control/feedback* system). These systems are connected to together in a closed-loop and each system is itself comprised of multiple components. Here, we briefly introduce each of the systems and provide a more in-depth review of ongoing research on feature extraction (a critical part of the signal processing system).

*(a) Stimulation:* SSVEPs are elicited by an external stimulus and manifest themselves as voltages (more specifically voltage differences) between electrodes. Thus, a stimulation system is a necessary part of any SSSVEP-based BCI. Stimulation systems may be developed using different types of light sources including computer screens or light emitting diodes. In order to elicit an SSVEP, however, this lighting system must flash at a constant rate (between 1–100Hz). Factors such as the number of stimuli, the frequency of the flashes in each of these stimuli, and even the color of the stimuli can all have an affect on the overall performance of the BCI.

*(b) Data Acquisition:* In SSVEP-based BCIs, the signal acquisition system is comprised of a set of electrodes (i.e., sensors, usually small metal discs), analog filters, an amplifier, and an analog-to-digital converter. Electrodes measure weak (in the µV range) neural signals from the surface of the scalp. Multiple electrodes (1 to 512 electrode channels [not including ground and reference electrodes]) are often used to measure neural signals from multiple locations. These small signals from the scalp are then filtered (to remove nuisance signals) and amplified (to prepare them for digitization). Finally, the signals are digitized so that they can be further processed using a computer.

*(c) Signal Processing:* The signal processing system then takes these digital signals and processes them in multiple steps. First, the signals are preprocessed to reduce noise or eliminate transient artifacts. Then features—numerical representations of the data—are extracted. Finally, a classifier uses these features to create a mapping from the EEG data to class labels (e.g., recognized letters in the case of a BCI speller).

Two major *spatial* characteristics of EEG can be utilized to depress these fluctuations (the term "spatial" refers to electrodes' distribution over the surface of the scalp). First, the spatial distribution of SSVEP differs from subject to subject. Second, both the background activities of the brain (e.g., blinking, breathing, etc.) and the noise induced by external sources are known to have a non-uniform impression on the electrodes. Therefore, *spatial filtering* techniques are typically employed to compute a linear combination of individual electrodes (termed *channels*) that amplifies SSVEP and suppresses none-SSVEP components.

Minimum energy combination (MEC) is a notable example of spatial filtering [12]. In this method, the SSVEP elicited by a target is modeled as a linear combination of a sinusoid's harmonics with the fundamental frequency of that target, which is modeled as in (1). MEC computes the weights of the spatial filter such that the energy of none-SSVEP components is minimized in each channel (hence the name, minimum energy combination). Since the attended target is unknown during the classification, the process must be repeated for every target. The one with the highest average SNR is then selected as the output of the classifier. In their work, Friman et al. show that MEC can achieve higher accuracy (84%) and lower standard deviation than PSDA-based classification [12].

Lin et al. propose canonical correlation analysis (CCA) as another alternative for spatial filtering and feature extraction [5]. In CCA, a linear combination of the captured signals is estimated to maximize the correlation coefficient with a template signal. The template is defined similarly to the method used in MEC. The correlation coefficients are extracted as the features and the classification is carried out based on the maximum coefficient. The authors report a classification accuracy of $\approx 70\%$ for nine targets and a signal length of 1.5 seconds. Since its introduction, multiple variants of CCA have been proposed in the literature, including CCA-RV developed in [13] that simultaneously considers the correlation coefficient of both target and non-target signals to improve the classification accuracy as well as the Deep CCA (DCCA), which combines deep learning with CCA to better capture non-linear characteristics of EEG signals [14]. Another notable example is the work of Chen et al. with Filter Bank CCA (FBCCA). The proposed system yields an average ITR of 267 bits/min [9].

Both MEC and CCA are linear filters, which may fail to capture the non-linear quality of the EEG signals. To remedy this drawback, Zhang et al. proposed the multivariate synchronization index (MSI) [7]. This spatial filter employs non-linear time series analysis techniques (the S-estimator [15]) to measure the synchronization between a template signal and the captured EEG, where the former is constructed similarly to CCA and MEC methods. When extended to include time delay embedding, MSI can outperform traditional CCA algorithms [16].

The aforementioned spatial filters can dynamically select a suitable linear combination of a given group of electrodes for every trial. This implies that the efficacy of these algorithms hinges on the size and formation of the initial pre-selection of electrodes. For example, increasing the number of electrodes improves the chances of detecting oddly distributed SSVEP (which is common among users with disabilities). However, our analysis shows that extending the coverage over the occipital and parietal regions of the scalp from ten electrodes to twenty decreases FBCCA's classification performance by $\approx 4$ percent. Similar patterns can be observed for CCA, MSI, and MEC as well. In many existing works, training and careful observation of data determine the initial selection of electrodes. However, there is still a need for an unsupervised dynamic electrode selection for large feature spaces.

Randomizing electrode selection can be an effective candidate for feature reduction. For example, Sun et al. [17] propose the random electrode selection ensemble (RESE) classifier, where multiple random electrode combinations are fed to Fisher discriminants (FD) to create an ensemble classifier. This reduces the dimensionality of features and thus mitigates the instability of FD against large features spaces. Additionally, randomizing electrode selection increases the immunity of the system against electrodes defects.

The last system involved in SSVEP-based BCIs is the feedback system. The purpose of the feedback system is to update the user on how the BCI is interpreting their brain activity. This may include auditory sounds, changes to the a visual user interface, or even the movements of a unmanned aerial vehicle. This information then allows the user to change their behavior (attend to a new stimulus) and start the process of using the BCI over again.

## III. BCI Speller and Benchmark Dataset

Here we provide an overview of the cue-guided, SSVEP-based BCI speller system used by Wang et al. [18] to generate the benchmark dataset—that we use in our study—as well as the format of the dataset itself.

### A. Stimulation

As shown in Figure 1a, the target stimuli (flashing lights) are presented on a computer monitor (23.6-inch LCD display). There were 40 stimuli in total, each flashing at a unique frequency ($f_i \in \{8.0, 8.2, 8.4, ..., 15.6, 15.8\}$) with neighboring stimuli having different phases (using phases $\phi \in \{0, 0.5\pi, \pi, 1.5\pi\}$). These differences in both frequency and phase are termed joint frequency and phase modulation (JFPM) by Wang et al. in [18].

### B. Data Acquisition

The data acquisition system (see Figure 1b) includes 64 electrodes positioned over the scalp according to an extended 10/20 system [19]. The Synamps2 EEG system (Neuroscan®, Inc.) was used to record EEG data, which was digitally sampled at 1 kHz. A notch filter was applied at 50 Hz to remove power-line interference.

### C. Signal Processing

The data was first preprocessed by downsampling the data from 1 kHz to 250 Hz. The CCA and FBCCA methods were used to extract features (see Section IV-B1 and IV-B2). Signal classification was done with the maximum feature classifier, which selects the target index corresponding to the maximum correlation between a template signal and an EEG signal. Refer to Figure 1c for a depiction of the signal processing stage.

### D. Control and Feedback

The control and feedback stage (Figure 1d) of the BCI speller consists of a cue (i.e., alphanumeric character) being displayed on the monitor first, then the estimated target is displayed after the classifier makes a decision. The estimated target is recorded for analysis.

### E. Benchmark Dataset

The benchmark dataset is comprised of experimental data collected from 35 participants. Each of the participants was asked to complete a cue guided target selection task. A cue was first displayed on the screen and then the user was asked to gaze at that character (i.e., the target). This data was recorded in 6 s epochs (i.e., trials). The cue was displayed for 0.5 s, the participant was given 5 s to gaze at the target, and then the subject was given 0.5 s to rest their eyes. Six blocks of data were collected, each including data obtained from 40 trials, where each of the trials involved the cue of one of the 40 stimuli.

## IV. Methods

Here we detail the signal processing techniques we used to evaluate our majority vote channel selection method.

### A. Preprocessing

We applied a zero-phase 7-90 Hz Butterworth infinite impulse response (IIR) filter of order 20 to EEG signals. The first cut-off frequency is set to 7 Hz, which is the lowest target frequency. The second cut-off frequency is set to 80 Hz to include the fifth harmonic of the maximum stimulation frequency ($f_{max} \times 5 < 80$).

### B. Feature Extraction

We chose three well-known multichannel feature extraction methods to evaluate our majority voting scheme; namely, CCA [5], FBCCA [6], and MSI [7].

All three of these feature extraction methods involve finding a measure of correlation between template signals and EEG signals. These template signals are defined as:

$$Y_i = \begin{bmatrix} \sin(2\pi \cdot f_i \cdot t) \\ \cos(2\pi \cdot f_i \cdot t) \\ \vdots \\ \sin(2\pi \cdot N_h \cdot f_i \cdot t) \\ \cos(2\pi \cdot N_h \cdot f_i \cdot t) \end{bmatrix}, \; t = \frac{1}{F_s}, \frac{2}{F_s}, \ldots, \frac{N_t}{F_s}, \quad (1)$$

where $f_i$ is the SSVEP stimulation frequency to model, $F_s$ is the sampling frequency of the SSVEP data, $N_h$ is the number of harmonics to consider ($N_h$ = 5 in this study), $N_t$ is the number of signal samples, and $t$ is the vector of time points. A reference signal is found for $N$ stimulation frequencies as $Y \in Y_1, Y_2, \ldots, Y_{N_f}$.

*1) CCA:* For SSVEP detection, CCA [5] is a statistical method that finds an optimal linear combination to maximize the correlation between a set of template signals ($Y$) and multichannel EEG signals.

Let $X \in \mathbb{R}^{N_c \times N_t}$ be a multichannel EEG signal and $Y \in \mathbb{R}^{N_m \times N_t}$ be a corresponding reference signal, where $N_c$ is the number of electrode channels used for analysis and $N_m = 2N_h$. The weights $W_x$ and $W_y$ are found in order to achieve the maximum correlation between $x = X^T W_x$ and $y = Y^T W_y$. These weights are found by solving the following problem:

$$\max_{W_x, W_y} \rho(x, y) = \frac{W_x^T \cdot XY^T \cdot W_y}{\sqrt{W_x^T \cdot XX^T \cdot W_x \cdot W_y^T \cdot YY^T \cdot W_y}}. \quad (2)$$

A solution to (2) is found using the singular value decomposition (SVD) of

$$\Omega = C_{XX}^{-1/2} \cdot C_{XY} \cdot C_{YY}^{-1/2}, \quad (3)$$

where $C$ is the correlation matrix of $X$ and $Y$, detailed in (6). The singular values $\rho_1, \rho_2, \ldots, \rho_M$ of matrix $\Omega$ are the canonical coefficients ($M$ is the smaller of $N_c$ and $N_m$). The maximum canonical coefficients correspond to the maximum correlation between $X$ and $Y$, thus $\kappa_i = \hat{\rho}_i = \rho_{max}$ are used as features for $N$ stimulus frequencies.

*2) FBCCA:* FBCCA [6] extends CCA [5] by combining the maximum CCA coefficients from multiple frequency sub-bands of EEG. These sub-bands of EEG are extracted using a filter bank. The maximum coefficients $\hat{\rho}_i^1, \hat{\rho}_i^2, \ldots, \hat{\rho}_i^{N_s}$ are combined according to [6]:

$$\bar{\rho}_i = \sum_{n=1}^{N_s} w(n) \cdot (\hat{\rho}_i^n)^2, \quad (4)$$

where $n$ is the index of $N_s$ sub-bands and

$$w(n) = n^{-a} + b, \; n \in [1, 2, \ldots, N_s]. \quad (5)$$

The parameters $a$ and $b$ can be determined using a grid search, and were set to 1.25 and 0.25, respectively (according to previous research [6]). The weighted coefficients $\kappa_i = \bar{\rho}_i$ are used as features for $N$ stimulus frequencies.

*3) MSI:* MSI is a measure of synchronization between two signals [7]. In this method, the correlation matrix between $X$ and $Y$ is found as:

$$C = \begin{bmatrix} C_{XX} & C_{XY} \\ C_{YX} & C_{YY} \end{bmatrix}. \quad (6)$$

To reduce autocorrelation within $X$ and $Y$ (which can cause false detections of SSVEP), the correlation matrix is whitened using the following linear transformation (zero-phase component or ZCA whitening [20]):

$$U = \begin{bmatrix} C_{XX}^{-1/2} & 0 \\ 0 & C_{YY}^{-1/2} \end{bmatrix}. \quad (7)$$

The whitened correlation matrix is calculated as

$$C' = UCU^T. \quad (8)$$

The eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_G$ (where $G = N_c + N_m$) of $C'$ are then normalized according to

$$\lambda'_k = \frac{\lambda_k}{\mathrm{tr}(C')}. \quad (9)$$

Finally, the synchronization index is:

$$\beta = 1 + \frac{\sum_{k=1}^{P} \lambda'_k \log(\lambda'_k)}{\log(G)}. \quad (10)$$

The synchronization indexes calculated for $N$ stimulus frequencies $\kappa_i = \beta_i$ are used as features.

### C. Classification

The third and final signal processing step is classification. The features are used by the classifier to assign a class label (a number) between 1 and $N$ to the filtered signals. Here, we review the maximum feature classification method used by [5]–[7] and describe our majority voting classification method to combine the classification results obtained using the signals from multiple sets of EEG electrode channels.

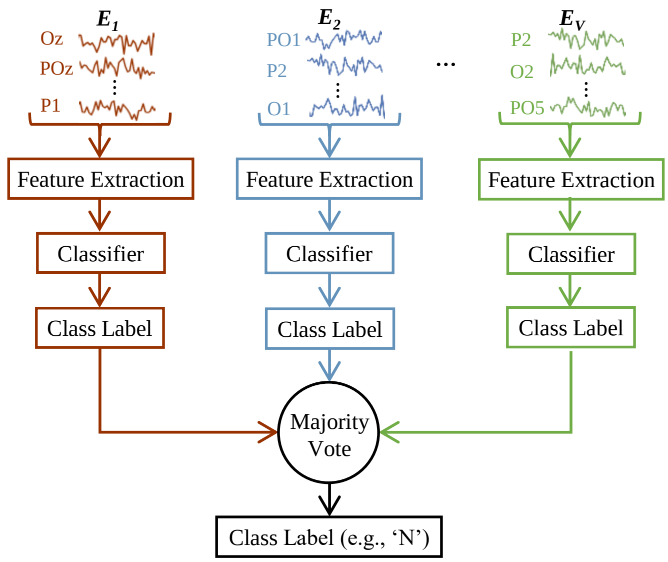


Fig. 2. Majority vote classification process for our channel selection method. Each of the electrode channel combinations $\{E_1, E_2, \ldots E_V\}$ is fed into a classifier, and the majority vote of the class labels output by these classifiers is the final classification result. For example, one combination includes the signals from channels {Oz, POz,. . ., P1}, and the classifier uses these signals to estimate a class label $L_n, n \in [1, 2, \ldots, V]$. This class label is added to a pool of $V$ votes, and the majority is chosen as the estimated target.

*1) Maximum Feature Classification:* The maximum feature method uses the maximum feature extracted using $N$ template signals for classification (this is referred to as the *original* classifier hereafter). The target frequency is estimated as

$$\hat{f}_{target} = \max_i \kappa_i,\ i = 1, 2, \ldots, N, \tag{11}$$

where $\kappa_i$ are the features extracted from the $N$ template signals corresponding to each of the target stimulus frequencies. The numeric index of the estimated target frequency is the class label output by the maximum feature classifier $(L_1, L_2, \ldots, L_N)$.

*2) Majority Voting Classification:* Majority voting is a method for combining the outputs of multiple classifiers [21]. For example, consider three classifiers for use in an SSVEP-based BCI: one using CCA, another using FBCCA, and a third using MSI. For a given target, each classifier outputs a class label $(L_1, L_2, L_3)$. The majority vote is the class label occurring the most frequently in that set.

We use majority voting to combine the outputs of multiple classifiers, each using a different electrode set (but the same feature extraction method). Each electrode combination set $\{E_1, E_2, \ldots, E_V\}$ was constructed by first including the three most central occipital electrode channels: Oz, O1, and O2 (previous research has confirmed that these three channels normally have the strongest SSVEP for healthy subjects [22]). The electrodes selected to complete each of the 8-electrode sets were determined by finding all unique combinations of $Q = 7$ electrodes (PO3, PO4, PO5, PO6, POz, CB1, CB2) taken $K = 5$ at a time. The number of these possible combinations is

$$V = \frac{Q!}{K!(Q-K)!} = \frac{7!}{5!(2)!} = 21. \tag{12}$$

The enumeration of these sets was found using the function *combnk* in MATLAB® [23]. For a given target, each of the classifiers corresponding to a single electrode combination outputs a class label. The final classification result is determined as the majority vote of the 21 labels (see Figure 2).

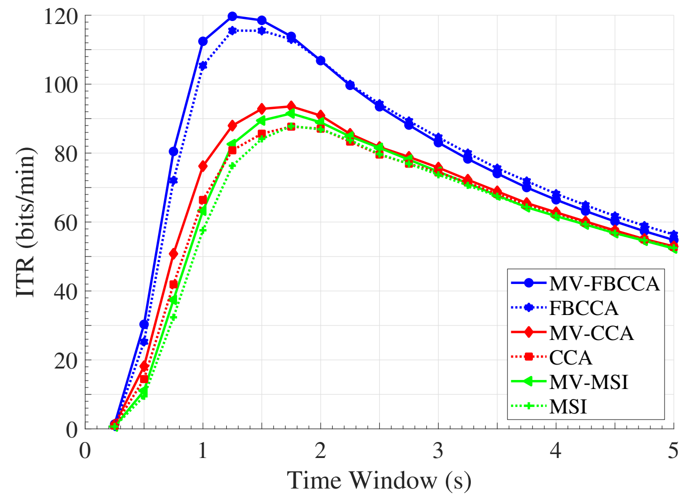


Fig. 3. Average ITR for majority vote classifiers and original classifiers, calculated for all subjects and trial blocks.

## V. Experimental Results and Insights

### A. Experimental Setup

The algorithms explained in Section IV were implemented using MATLAB® [23]. The built-in *canoncorr* and *eig* are the principal functions used for the CCA and MSI algorithms, respectively. The scripts were run remotely on an Oracle® Linux Server (Release 7.5) powered by two Intel® Zeon® E5-2680 v4 processors, 256 GB of memory, and two Nvidia® Tesla® K80 GPUs with driver version 396.26.

### B. Performance Evaluation

The performance metric used in this study is the information transfer rate (ITR) [24], which was calculated for each subject on a per-trial basis. The formula for ITR is

$$R = \log_2 N + P \cdot \log_2 P + (1-P)\log_2 \frac{1-P}{N-1}, \tag{13}$$

where $R$ is the ITR (bits/target) and $P$ is the target classification accuracy for a single subject. The ITR (bits/min) is calculated as $R \cdot 60/T$, where $T$ is the total classification time in seconds, and is equal to the gaze shifting time added to the stimulation time needed for a classification. In this analysis, the time required for a subject to shift their gaze to a symbol following the cue was assumed to be 0.55 s. The size of the EEG signal time interval $(\Delta t)$ used for classification was ranged from 0.25 s to 5 s in 0.25 s intervals.

TABLE I
SIGNIFICANCE OF PER-SUBJECT ITR DIFFERENCES BETWEEN MAJORITY VOTE (MV) CLASSIFIERS AND ORIGINAL CLASSIFIERS. TWO-SIDED SIGN TESTS WERE USED TO DETERMINE SIGNIFICANCE AT THE 5% LEVEL

| | FBCCA vs MV-FBCCA | CCA vs MV-CCA | MSI vs MV-MSI |
|---|---|---|---|
| Significantly Improved | 7 | 10 | 7 |
| No Significant Change | 25 | 19 | 26 |
| Significantly Reduced | 3 | 6 | 2 |

### C. Results

The classification results from the majority vote classifier and the original classifier were found for each of the three feature extraction methods under study (a total of six unique methods). The majority vote classifiers are denoted as MV-CCA, MV-FBCCA, and MV-MSI (MV for majority vote). The average ITR for all classifiers is shown in Figure 3. These results show that the average ITR of the majority vote classifiers is $\approx 4\%$ higher than that of the standard classifiers.

Figure 4 depicts individual differences in performance between the majority vote classifiers and the standard classifiers. Refer to Table I for significance test results of these differences. The statistical distribution of ITR among test subjects is shown in Figure 5. Outliers are data points that fall outside the inner fence of $1.5 \times IQR$, where the interquartile range ($IQR$) is the likely range of variation.

The Lilliefors test for normality [25] was applied to the per-trial ITR distribution for each subject, and it indicated that these distributions were not normal at the 5% significance level. Therefore, to evaluate the significance of the ITR differences between the majority vote classifiers and the original classifiers for each subject, two-sided sign tests were used to calculate the $p$-value of these difference distributions. The $p$-values of these tests were used to determine whether the majority vote channel selection method significantly improved or decreased the ITR distribution for each subject. We report this improvement or reduction as significant if $p < 0.05$. No significant change is reported if the per-subject ITR distribution was not significantly improved or reduced. The results for this individual analysis are shown in Table I.

The differences in cumulative ITR between the majority vote classifiers and original classifiers are evaluated using paired t-tests, to determine if the majority vote channel selection method significantly improves overall ITR. When all subjects are included in analysis, the only classifier showing a significant improvement is CCA, with $p < 0.01$. Because the performance for subject 18 can be considered as a significant outlier, the paired t-tests were also performed with the exclusion of that subject. This provides values of $p < 0.05$ for FBCCA and $p < 0.01$ for MSI.

## VI. DISCUSSION AND CONCLUSION

In situations when a patient needs access to a BCI system and there is not adequate time for finding optimal electrode channel selections, the proposed majority vote channel selection method can prove useful by utilizing the information from a large set of possible electrode channel combinations rather than a single combination chosen *a priori*. It could also benefit people with neurological diseases that significantly alter scalp distributions of EEG signals. One of the next steps in this research is to test our channel selection method on a dataset of EEG signals taken from people with these types of diseases.

As we observed with the performance of some test subjects, notably subject 18, the method fails in cases when maximum features extracted from the majority of electrode combinations consistently produce the same wrong result. Our hypothesis is that a soft voting process like a random forest would improve the worst cases observed for our majority vote classifier without negatively impacting the best cases. An implementation of this would involve applying weights to the maximum features extracted from the multiple electrode combinations. Another possibility to enhance the performance of our method is increasing the number of electrode channel combinations. This will be the topic of future research.

In this paper, we proposed a majority vote classifier based on a new channel selection method for SSVEP-based BCIs that does not require calibration data or optimization, and our evaluation using a benchmark dataset shows that this new method can significantly outperform the *a priori* channel selection method when using CCA for feature extraction.

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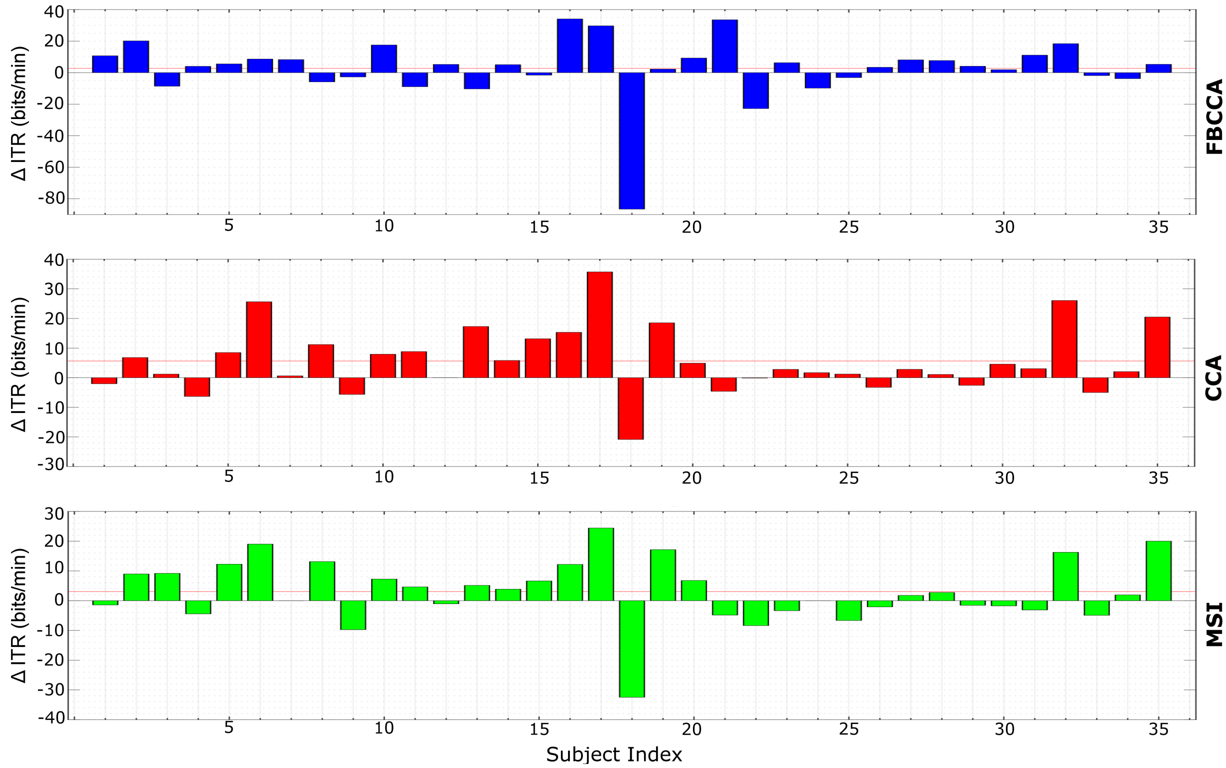


Fig. 4. Individual differences in ITR between majority vote FBCCA (MV-FBCCA) and original FBCCA methods (top), MV-CCA and original CCA methods (middle), and MV-MSI and original MSI methods (bottom). The red lines indicate the average ITR difference.

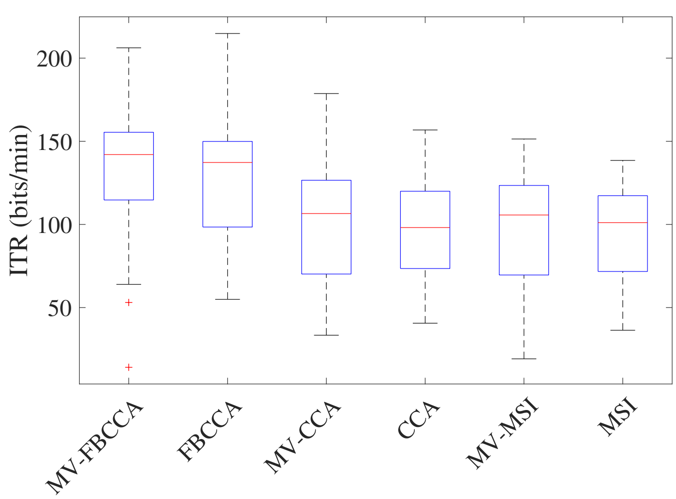


Fig. 5. Subject ITR distributions for each of the classifiers under study. The whiskers show the extreme accuracies excluding outliers. Outliers are shown as individual "+" marks. Boundaries are determined by the 25th and 75th percentiles.


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