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# A user-friendly SSVEP-based brain–computer interface using a time-domain classifier

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**Abstract**

We introduce a user-friendly steady-state visual evoked potential (SSVEP)-based brain–computer interface (BCI) system. Single-channel EEG is recorded using a low-noise dry electrode. Compared to traditional gel-based multi-sensor EEG systems, a dry sensor proves to be more convenient, comfortable and cost effective. A hardware system was built that displays four LED light panels flashing at different frequencies and synchronizes with EEG acquisition. The visual stimuli have been carefully designed such that potential risk to photosensitive people is minimized. We describe a novel stimulus-locked inter-trace correlation (SLIC) method for SSVEP classification using EEG time-locked to stimulus onsets. We studied how the performance of the algorithm is affected by different selection of parameters. Using the SLIC method, the average light detection rate is 75.8% with very low error rates (an 8.4% false positive rate and a 1.3% misclassification rate). Compared to a traditional frequency-domain-based method, the SLIC method is more robust (resulting in less annoyance to the users) and is also suitable for irregular stimulus patterns.

## 1. Introduction

Steady-state visual evoked potential (SSVEP) is the electroencephalograph (EEG) response to visual stimulus flashing at some predefined patterns. For example, when the retina is excited by a visual stimulus at presentation rates ranging from 3.5 Hz to 75 Hz [1], the brain generates an electrical activity at the same (or multiples of the) frequency of the visual stimulus. SSVEP is strongest in the visual cortex, when the stimulus is flashing at around 15 Hz [15]. A typical SSVEP-based BCI system uses lights that flash at various frequencies. This system can be useful to control a variety of peripheral devices solely with the EEG, which not only may improve the quality of life of those who suffer from severe motor disabilities but can also be employed as a means for entertainment, such as in video games [10].

Compared to other modalities for brain computer interface (BCI) applications, such as the P300-based and the slow cortical response-based BCIs, an SSVEP-based BCI system has the advantage of better accuracy, higher information transfer rate (ITR) and short/no training time [10]. However, similar to other BCI modalities, most current SSVEP-based BCI techniques also face some challenges that prevent them from being accepted by the majority of the population. In this paper we introduce an applicable user-friendly SSVEP-based BCI system which addresses those drawbacks and has several advantages, described below.

(1) *Ease of use*. Traditionally EEG has been recorded with Ag/AgCl electrodes, which required the use of a conductive gel; this thus needed long preparation time and caused discomfort to the user. For better performance, multi-channel EEG is often used which takes longer to prepare and adds more discomfort.
For ease of use, an EEG device with a single dry sensor has been developed. This device does not require any conductive gel and can be easily put on or taken off from the subject. To record EEG from a subject, the experimenter simply puts the EEG cap on the subject and slightly adjusts the sensor such that it is on the right scalp location, and then a recording can begin.

(2) *Robustness*. It will be annoying to the user when a device controlled by BCI often receives wrong commands and

 

changes its function accordingly. Thus, an ideal BCI system should have high accuracy with low error rates, including misclassification and false positive rates.

To better evaluate the performance of our BCI system, we investigate three rates that evaluate different aspects of an SSVEP-based BCI system: correct light classification rate (accuracy), misclassification rate and false positive rate. The latter two rates are measures of error and our objective is to achieve a high classification rate while keeping the error rates low.

(3) *Safety*. Depending on the stimulus' flashing rate/pattern, size and color, it is possible that an SSVEP-based BCI will trigger adverse effects, including seizure, in photosensitive people. Photosensitivity, an abnormal EEG response to light or pattern stimulation, occurs in 0.3–3% of the population [5].

When designing our stimulus, the frequency, size, color and pattern of the flashing lights were carefully chosen such that the features more provocative to a photosensitive user are avoided. We will discuss the influence of these features in more detail in the next section.

When an SSVEP-based BCI system is designed in consideration of the ease of use, robustness and safety to the users, its accuracy and information transfer rate may be diminished. But we deem these features essential for it to be accepted by the majority of the population and we show satisfying performance using a novel SLIC method that is based on stimulus-locked inter-trace correlation in EEG.

(4) *System flexibility*. So far most SSVEP classification algorithms have been developed in the frequency domain. For example, many researchers have used discrete Fourier transform (DFT) to extract features for classification, such as [3, 11]. The frequency-domain-based SSVEP detection algorithms usually made use of the first [9, 12], or the first and the second [3, 6], or even the first three harmonics of the frequency at which the stimulus is presented [13].

However, all frequency-domain-based SSVEP classification methods have limitations. Oftentimes the flashing frequency of the visual stimuli cannot be well controlled due to hardware limitations. For example, when the visual stimuli are shown on a computer screen, the refresh rate of the screen and the interference from the operating system have to be considered. Or when the visual stimuli are controlled by a microcontroller whose CPU frequency varies slightly across devices, the flashing rate of the visual stimuli will inevitably vary as well. In both of these cases, a more flexible classification method which does not require prior knowledge of the flashing frequency of the visual stimulus is desired. It is also worth noting that some researchers study SSVEP elicited by visual stimulus with irregular patterns, such as [4, 18]. A frequency-domain-based method is likely to fail when this type of stimulus is used.

Müller-Putz *et al* have adopted a lock-in amplifier in the time-domain and have shown improved accuracy over the frequency method [13, 14]. This result suggested that EEG signal may contain important information about the flashing stimulus on the time-domain as well, which makes sense as SSVEP is essentially evoked by a series of visual stimuli; thus it is strongly locked to the light events. In [18] the author analyzed EEG in the time domain by computing the correlation between event-related potentials time-locked to the stimulus onset and a known response waveform (template) of the subject. This time-domain method is able to classify SSVEP elicited by both regular and irregular patterns of flashes, but prior knowledge still needs to be used to construct a response waveform for each subject.

In this study, we propose a novel SLIC method which analyzes EEG in the time domain by computing the correlation between single-trial event-related potentials time-locked to a visual stimulus. This method is able to correctly classify SSVEP elicited by any type of flash patterns and it does not require prior knowledge about the frequency of the flashing stimulus or the response waveform of a subject. The only information it requires about the stimulus is the relative timing of EEG and the stimulus onsets. We will describe in detail in section 2 how we generate this information in our hardware system.

Besides SLIC, in this paper we also implement a frequency-domain-based method that makes use of the first and the second harmonics of the stimulus-flashing frequency in EEG. We show that our SLIC method performs better than the frequency-domain method.

The rest of the paper is organized as follows: section 2 describes the hardware system, online classification platform, experimental paradigm, and our SLIC method and another frequency-domain-based method; section 3 presents classification performance using different strategies and parameters; and section 4 summarizes the paper.

## 2. Methods

### 2.1. *Design of SSVEP-based BCI system*

The hardware system consists of an EEG data acquisition device, a light display box and a computer that analyzes EEG and lighting information and makes a decision in real time. A picture of the system together with one user testing the system is shown in figure 1.

*2.1.1. EEG device.* The EEG system front end consists of a dry, active EEG sensor, a dry reference sensor, an ear clip (ground) and a support board. The size of both sensors is 3 cm in diameter. Previous versions of the sensor have been described and evaluated in detail in [16, 17]. Metallic spring-loaded fingers are used on the surface of the active sensor to penetrate the hair and make an ohmic connection between the scalp and the sensor. When there is no hair between the sensor surface and the scalp, the PCB board itself is used as the sensor surface, such as in the reference sensor. Unlike typical EEG sensors, our sensors does not require conductive gel. This makes the experimental setup much easier while creating a more pleasant user experience.

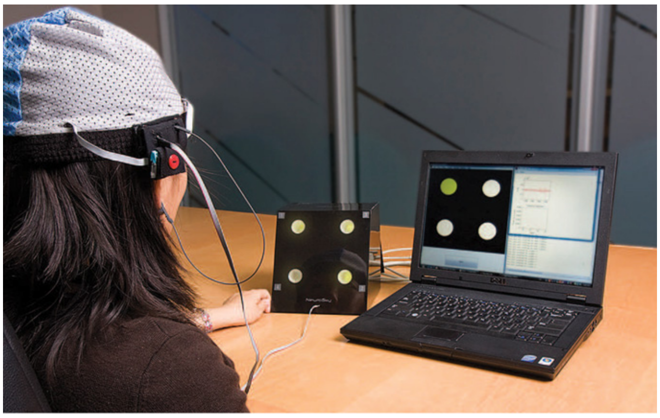

**Figure 1.** A picture of the system being used by a user. The EEG device is mounted on the right side of the cap. Two sensors (one active and one reference) are placed on the user's head inside the EEG cap and are connected to the EEG support board. An ear clip that clips on to the right ear provides the ground to the support board. A serial wire sends EEG data to a controller circuit board inside the light box. The controller circuit board controls the four lights on the facade of the light box to flash at different frequencies, combines the EEG and light control signals while preserving the relative timing between the two, and sends them to the laptop computer through a serial port. The laptop computer implements the online classification and displays the visual feedback. On the computer screen a black square with four circles is shown which resembles the actual light box. If a circle turns green from white, that means the computer has decided that the corresponding light array on the light box is being attended by the user. The raw EEG data are shown on the top right side of the screen, and text information of the classification result is shown on the bottom right side.

(This figure is in colour only in the electronic version)

The EEG sensor was placed over PO2 which is close to the visual cortex and the SSVEP signal is strong [20], and the reference sensor was placed on the right side of the forehead. Both of these sensors were mounted on the inside of a skull cap with the subject grounded to the EEG system through an ear clip. These sensors and ground clip are connected to a support circuit board that processes the EEG data and is attached to the outside of the same cap. The support board communicates the processed data to a light controller circuit board through a serial wire.

*2.1.2. Light display.* Inside the light display box there is a controller circuit board which is responsible for driving four flashing LED lights mounted on the facade of the light display box. The frequency of the flashing is set by the controller circuit board. We chose to implement just four lights as a proof-of-concept. The EEG data and light control signals are combined while preserving the timing information between the two and sent to a laptop computer through a serial port.

When designing our light stimulus, special care was taken to minimize the potential risk to the photosensitive population. They include the following.

(1) The size of each light array is small (2.5 cm in diameter) such that it only occupies a very small portion of the visual field so is less provocative [5].
(2) The color of the lights is green, as studies show red, especially saturated red at wavelengths of 660–720 nm, is more provocative [5, 19].
(3) The pattern of our lights are dots, which are less provocative than stripes or gratings [5].
(4) It has been shown that when presented with flashing lights at 15–25 Hz, photosensitive subjects showed increased rate of EEG photosensitive responses [5, 7]. In our system we selected the frequencies of the four lights to be 9 Hz, 10 Hz, 11 Hz and 12 Hz to produce a strong SSVEP signal [15] and reduce the risk to the subjects.

*2.1.3. Real-time computation.* A real-time classification algorithm was developed on a modular Matlab-based platform, called NeuroSkyLab, which was created for online EEG acquisition, analysis and presentation. NeuroSkyLab decodes the EEG and lighting information received from the computer serial port, performs data analysis (including filtering and classification) and outputs classification result onto the computer screen in real time. On the computer screen, the raw EEG data and the classification result are shown. The classification result can be one of the three conditions: (1) a movement is detected, (2) the subject is not looking at any lights and (3) the subject is looking at a specific light. A graphical output which mimics the light display box is also shown on the screen, and when it is determined that a light is being attended, the corresponding circle in the graphical output turns from white to green (please refer to figure 1).

### *2.2. Experiment paradigm*

Fourteen subjects (12 male, 2 female, aged 23–55) volunteered for the experiment. All subjects had normal or corrected-to-normal vision. They were seated in an armchair in front of the light display box. Before recording they adjusted their distance to the light display box such that the lights were most comfortable to their eyes. The minimal distance from their eyes to the light display was 25 cm. Their brain response was recorded with our single dry-sensor EEG device with a 256 Hz sampling frequency in an office setting with regular fluorescent lightings. The active sensor was placed on the scalp location PO2 according to the international 10–20 system. The reference sensor was placed on the right temple and the right ear lobe served as the ground via an ear clip. No conductive gel or water was used. For each subject the experimental paradigm consisted of two steps: a real-time SSVEP classification followed by an offline data acquisition process. During the real-time detection, the frequency-domain-based method was briefly tested to verify that our BCI system is able to correctly classify their SSVEP and the corresponding circle on the computer screen turns green. Out of the 14 subjects, 12 of them could control the output on the computer screen to some degree. These 12 were 'good subjects' and the performance of our algorithm, including accuracy and error rates, was measured based on their data.

During data acquisition for offline analysis, 30 sessions of EEG were recorded per subject, with each session lasting 10 s. Among these 30 sessions, 20 sessions were recorded

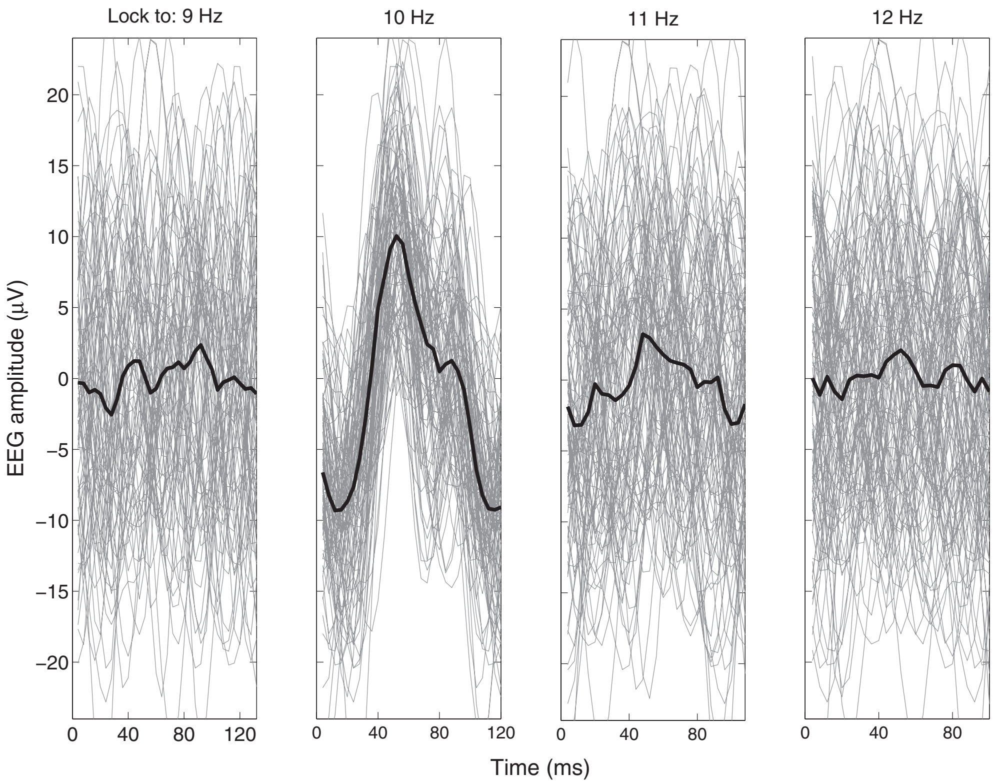


**Figure 2.** Example EEG traces (shown in gray curves) time-locked to the onsets of four different lights, flashing at 9, 10, 11 and 12 Hz, respectively. The EEG was recorded when the subject was attending to the 10 Hz light for 20 s. The black curves show the mean of the EEG traces.

when the subject was instructed to attend to one of the four lights, with each light being attended for five sessions, and 10 sessions were recorded when the subject was instructed to fixate at the center of the light display box so the four lights all appeared in their peripheral vision (baseline condition). Sessions were recorded in random order from each subject.

### 2.3. Data analysis

*2.3.1. Stimulus-locked inter-trace correlation (SLIC).* As stated before the SLIC method was developed to classify SSVEP signals. One advantage of SLIC is that it is suitable for analyzing EEG evoked by both regular (such as fixed frequency) and irregular/random visual stimuli. It requires neither prior knowledge about the visual stimulus nor a response template for the subject. It is also suitable for conditions in which the timing of the lights cannot be well controlled. The requirement for this method is the relative timing between the EEG signal and the repeated light onsets, along with the EEG signal itself.

This method takes advantage of the fact that when one focuses on a flashing light, there is an event-related brain potential time-locked to the stimulus presentation. Thus EEG can be segmented into multiple traces, with each trace being the EEG activity recorded between two adjacent stimulus onsets. Figure 2 shows one subject's EEG traces while attending to the 10 Hz light, and each of the four panels shows the traces as they are locked to onsets of one of the four lights (lashing at 9, 10, 11 and 12 Hz, respectively). The black curves show the mean of the EEG traces. Note here that each trace is longer than what should be used for calculation, so the reader can see that the ending part of each averaged waveform (almost) repeats its beginning part. When the traces were used in the SLIC method, the correct time length was used (for example, 100 ms for 10 Hz light). From this figure we can see that when EEG is segmented into traces locked to the repeated onsets of the stimulus being attended, there exists significantly higher inter-trace correlation. In this paper, we used the median value of the correlation coefficients between all pairs of EEG traces to measure this correlated activity.

*2.3.2. Data analysis process.* A flowchart illustrating the process of our data analysis is shown in figure 3. The overall process can be broken down into several steps.

- *Preprocessing*. Upon data acquisition, raw data without detected movement were filtered by a low-pass FIR filter with a cut-off frequency at 40 Hz to remove the high frequency noise. When EEG changed beyond a predefined threshold, it was assumed that movement noise contaminated the EEG, so the data were not processed.
- *Feature extraction*. Features were extracted based on the most recent $M$ seconds of filtered data (for example, $M$ may range from 2 to 6 s). In this step, SLIC was used for extracting features. We extracted the EEG traces time-locked to light onsets for each light. For example,

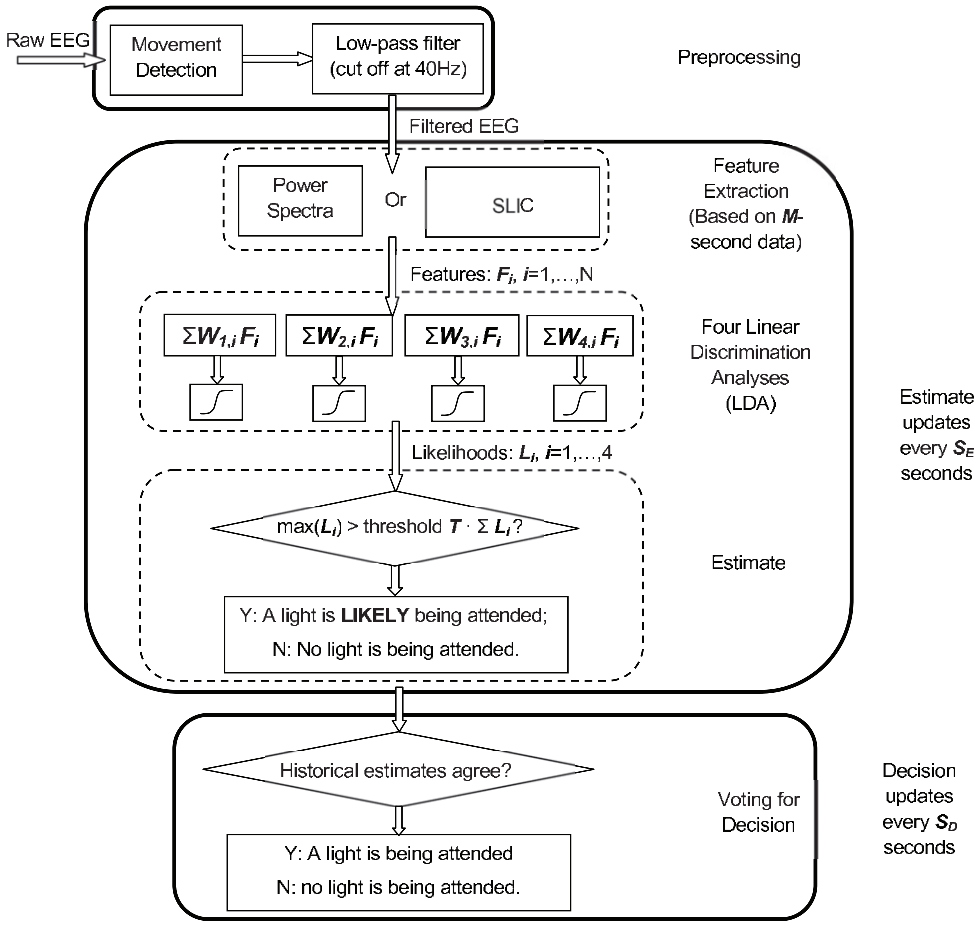


**Figure 3.** Flowchart of the data analysis process. It consists of preprocessing, feature extraction, LDA, estimation and decision stages. More details are discussed in the text.

when we locked the EEG to the 9 Hz light, using a 4 s time window, $9 \times 4 = 36$ traces were extracted from EEG with each trace $1000\,\text{ms} \div 9\,\text{Hz} = 111\,\text{ms}$ long. The correlation coefficient between every possible pair of these 36 traces was then computed and the median value of the correlation coefficients was calculated.

Alternatively, a frequency-domain-based method was implemented. We did this via Welch's power spectral density estimate method [21]. Namely we estimated the power spectra of $M$ seconds of data, and the power values at the four base frequencies (9, 10, 11 and 12 Hz in our case) and second-order harmonics (18, 20, 22, 24 Hz, respectively) were extracted.

- *Linear discrimination analysis (LDA)*. After features were extracted using the SLIC method or the frequency-domain method, they were fed to four LDAs. Each LDA was a one-versus-the-rest discriminator; the output of each LDA, $L_i, i = 1, \ldots, 4$, was the logistic function of a weighted sum of all the inputs and ranged between 0 and 1, indicating the likelihood that the corresponding light was being attended.

  For the frequency-domain method, the weights of the four LDAs were obtained in advance through logistic regression [8] using other data sets.

  Compared to the frequency-domain method which had eight features as LDA inputs, the SLIC method produced four features. For simplicity, the four weights for the four base frequencies in the frequency-domain method were used for the LDAs in SLIC.
- *Estimate*. Every $S_E$ seconds an estimate was formed based on the previous $M$ seconds of data. First, the outputs $L_i$ of each of the four LDAs was normalized by dividing by the sum of the LDA outputs, $\sum L_i$. If the largest of these normalized outputs exceeded a threshold $T$, then the algorithm tentatively declares that the subject was looking at the corresponding light.
- *Voting for decision*. A voting scheme was adopted, such that if the majority of several recent estimates agreed on one light, a decision was reached indicating that light was being attended. The decision was updated every $S_D$ seconds. As the exact time when the viewer starts to look at a new light is unknown, the decision should be updated in a timely manner to report the new light. On the other hand, $S_D$ should not be too low, because (1) the EEG will not change much since the last decision has been made, so most likely the new decision will remain the same and (2) the computation takes some time. Based on our experience, $S_D = 0.5$ or 1 s seems to be an appropriate selection.

### 2.4. Parameter selection

The threshold for the lights, $T$, is a critical parameter for the classification algorithm. A lower value of $T$ would make it easier to reach a non-baseline decision (one light is being attended) but increase the error rates, such as false detection and misclassification; while a higher value of $T$ would make it harder to detect a light being attended. Since the likelihoods, $L_i, i = 1, \ldots, 4$, range between 0 and 1, the range of $T$ should be between 0.25 and 1. Moreover, optimal $T$ may vary across subjects. For those subjects that have stronger SSVEP signals, their $T$ could be set higher to further reduce errors. However, in spite of the difference in $T$ across subjects, based on our observation $T$ ranged consistently between 0.28 and 0.40 for the classification algorithm to have a satisfactory performance for all subjects. During offline analysis, to test how this threshold affects the algorithm's performance, we varied the thresholds such that the same threshold was used for all subjects consistently, and this value varied between 0.25 and 0.5. Other parameters that may affect the classification algorithm's performance include $M$, $S_E$, $S_D$ and whether a voting scheme was adopted. $M$ should be longer than 1 s for the classification algorithm to have a smaller-than-1 Hz resolution. The longer it is, the more robust the algorithm will be. However, it should also be kept as short as possible for the classification algorithm to have a fast response time. The values of $S_E$ and $S_D$ together with the voting scheme also determine the robustness and response time of the algorithm. In general, the estimate should be updated frequently enough such that EEG dynamics can be captured in a timely manner. In our experiments, we found that $M = 4$s with $S_E = 0.5$ s, $S_D = 0.5$ or 1 s and a 3-out-of-4 (a positive decision is reached when three out of the four recent estimates agree on a same light) voting scheme were a good combination of parameters. In data analysis, we started from these parameters and measured the classification algorithm's performance when different $T$ values were tested; we then varied these parameters to see how their change affected the performance. The results will be discussed in section 3.

### 2.5. Evaluation of algorithm

As we have stated in the Introduction, we consider both accuracy and error rates important when evaluating the performance of a BCI system. In other words, an ideal SSVEP-based BCI system should be sensitive to real SSVEP signals as well as conservative such that no command would be sent out by mistake when the subject was not looking at any stimulus.

The performance of our classification algorithm was measured by three values, which were

- correct light detection rate $R_D$, where one of the four lights was attended by the subject and detected by the algorithm;
- misclassification rate $r_M$, where one light was being attended, but another light was detected and
- false positive rate $r_F$, where no light was being attended but one light was detected.

Other than the above three values, there are two other rates that also reflect the system performance, one is the false negative rate (one light was being attended but no light was detected, an error) which equals $1 - R_D - r_M$; the other is the true negative rate (no light was attended and detected) which equals $1 - r_f$. Because these two rates can be derived from $R_D$, $r_M$ and $r_F$, and a false negative error is not as annoying to the user as a misclassification or a false positive error, in this paper we report the classification performance of our algorithm using $R_D$, $r_M$ and $r_F$. The goal of our algorithm would be to maximize the light detection rate $R_D$ while keeping $r_M$ and $r_F$ (error rates) low.

During data acquisition for offline analysis, each session was 10 s long, where the subjects were looking at a light (or the center of the display box). The decision of our classification algorithms was made based on an $M$-second time window ($M < 10$) with an $S_D$-second update rate ($S_D$ may range between 0.5 and 1); thus we had more than one decision for each 10 s session. For an easy measure of the performance, we classified each session with a single label, which was the first non-baseline decision that the classification algorithm made about that session. If all the decisions about a session were concluded as baseline we then labeled that session as 'baseline'.

## 3. Results

### 3.1. Classification performance versus the threshold T

As stated in section 2, the threshold $T$ is critical for the algorithm's performance. Figure 4 depicts our classification algorithm's average performance, including correct light detection rate $R_D$, misclassification rate $r_M$ and false positive rate $r_F$, as a function of $T$. $T$ ranged between 0.25 and 0.5 and was the same for all subjects. Note here that we excluded results from two subjects whose SSVEP could not be detected. The light detection rate, $R_D$, for these two subjects was consistently below 20%, so were not included in the group average result. The performance of these two subjects is reported later in section 3.4.

If the detection rate were the only measure of our SSVEP system's performance, the group average performance is 87.5% for SLIC ($T = 0.26$) and 82.1% for the frequency-domain method ($T = 0.28$). However, at these low $T$ values, we also see high misclassification rates and false positive rates which can be annoying to the users. So here we emphasize again that the goal of our SSVEP classification algorithm was to maximize the light detection rate (high precision) while keeping the error rates low.

From figure 4 we see that as the threshold values increased, all three rates decreased. As $T$ increased from 0.25 to 0.35, the SLIC method had consistently lower error rates compared to the frequency-domain method while its light detection rate was very close to that of the frequency-domain method. For example, at $T = 0.31$ (marked by a black vertical line in figure 4), the SLIC misclassification rate and false positive rate were both below 10% (1.3% and 8.4%, respectively), while its average light detection rate was 75.8%; to match these error rates the frequency-domain-based method had to employ a threshold of $T = 0.34$ (marked by the gray vertical

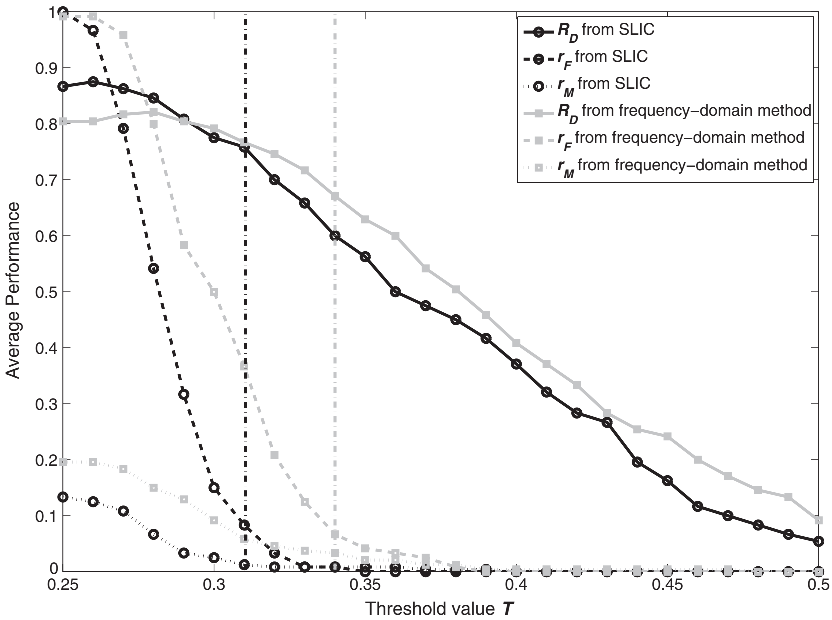


**Figure 4.** Classification algorithm's performance as a function of the threshold $T$, for SLIC and the frequency-domain-based method. Results were averaged across the 12 good subjects.

**Table 1.** Classification performance of the SLIC method and the frequency-domain method across a variety of parameters. Higher $R$ values are shown in bold comparing the SLIC and frequency-domain method with same parameters.

| Method | | Frequency-domain method | | | | | SLIC | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $M$ (s) | | 2 | 3 | 4 | 5 | 6 | 2 | 3 | 4 | 5 | 6 |
| $S_E = 0.5$ s | No voting | **0.44** | **0.47** | 0.51 | 0.52 | 0.55 | −0.29 | 0.28 | 0.51 | **0.59** | **0.60** |
| | 2/3 voting | **0.48** | **0.55** | 0.56 | 0.56 | 0.57 | 0.00 | 0.52 | **0.63** | **0.66** | **0.65** |
| | 3/4 voting | 0.38 | 0.56 | 0.57 | 0.56 | 0.57 | **0.42** | **0.62** | **0.66** | **0.68** | **0.67** |
| $S_E = 1.0$ s | No voting | **0.48** | **0.51** | 0.55 | 0.55 | 0.57 | −0.19 | 0.42 | 0.55 | **0.61** | **0.62** |
| | 2/3 voting | 0.40 | 0.54 | 0.57 | 0.56 | 0.56 | **0.41** | **0.64** | **0.68** | **0.69** | **0.68** |
| | 3/4 voting | 0.28 | 0.46 | 0.55 | 0.54 | 0.53 | **0.56** | **0.63** | **0.64** | **0.64** | **0.65** |

line in figure 4); however its detection rate was 67.1%, which was significantly lower than the SLIC result at $T = 0.31$ ($p < 0.01$ from the two-tailed Wilcoxon signed-rank test with 12 degrees of freedom). From this figure we can see that although the detection rates $R_D$ were similar, the SLIC method was significantly more robust. Thus when the error rates were the same, a higher detection rate could be achieved with SLIC.

### *3.2. Classification performance as a function of other parameters*

When we analyzed how the selection of thresholds affected the classification performance, we adopted $M = 4$ s, $S_E = 0.5$ s, $S_D = 1$ s and a 3-out-of-4 voting scheme since previous data analysis had shown a satisfying result using these parameters. We have also discussed previously that the selection of these parameters would affect the algorithm's performance, such as the robustness and system response time. In this section, we study how the change of these parameters influenced the classification performance.

The algorithm's performance was measured by a single value $R$, where

$$R = R_D - r_M - r_F. \quad (1)$$

The thresholds for LDAs were selected based on the two points in figure 4. The conditions we studied include:

- window length $M = 2, 3, 4, 5, 6$ s;
- estimate update rate $S_E = 0.5, 1$ s;
- voting scheme: no voting, 2-out-of-3, 3-out-of-4 voting;
- decision update rate $S_D = 1$ s.

The classification algorithms' group average performance, measured by R, is listed in table 1.

From this table we see that when $M$ ranges from 3 to 6 s, the SLIC method has significantly higher $R$ values than the frequency-domain method for different $S_E$ and voting schemes ($p < 0.001$ from Wilcoxon signed-rank test, 24 degrees of freedom). When the window length is short ($M = 2$ s) and when there is no voting, neither method yields a satisfying performance, although the frequency-domain method performs better.

Next we see how $S_D$ affects the two algorithms' performance, measured by $R$. $S_E$ is set to be 0.5 s, and a

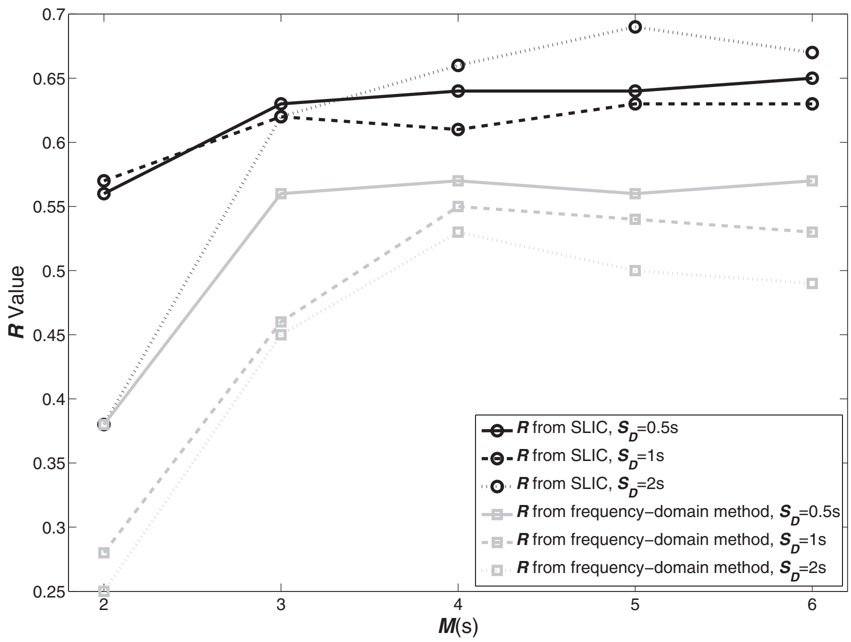


**Figure 5.** Average performance as a function of the window size $M$ for SLIC and the frequency-domain-based method with $S_D = 0.5$, 1 and 2 s, respectively.

3-out-of-4 voting scheme is employed. The result is shown in figure 5. From this result we can see that again the SLIC method outperforms the frequency-domain method. Although the $R$ values were very similar between $S_D = 0.5$, 1 and 2 s, in practice a smaller $S_D$ value is preferred as a large $S_D$ would delay the report of a newly detected light.

### 3.3. Subject variance

So far we have presented the average performance under a variety of situations for the 12 good subjects. However, there also exists significant variance across subjects for the SSVEP detection. Figure 6 presents the performance of the SLIC method for each subject. This algorithm performed very well for half of the subjects (RD > 80%, low error rates), and only two subjects' performance was below 20%. For all subjects the error rates were consistently low, especially the misclassification rate. So this system can be used by the majority of the population; even for those that could not have their SSVEP detected by this system, there were minimal false positives and misclassifications.

### 3.4. System response time

The system response time is the time delay from the subject fixating on a light until the algorithm detects the corresponding SSVEP. There are theoretical barriers that keep the SSVEP from being detected instantly, such as the time delay between eye fixating on a light and SSVEP generated in EEG (about 100 ms) and the minimal window length necessary for the detection algorithm to have enough frequency resolution (about 1 s). Increasing the response time of a classification algorithm could also reduce the robustness (higher error rates) of the system. Based on table 1, to reach a good performance $M$ should be no smaller than 3 s for both the traditional frequency-domain method and the SLIC method.

To measure the response time of our system, one of the better subjects (subject ID = 4) sat in front of the light display box and attended to the flashing stimuli consecutively. When the computer screen showed the corresponding light being selected, the subject moved to the next stimulus. In 70 s our system was able to detect the correct stimulus 20 times (5 times for each of the four stimuli), with two misclassifications. This corresponds to a 34.3 bit min$^{-1}$ information transfer rate (ITR) ( $20 \div 70 \times 60 \times \log_2 4 = 34.3$). This response time also includes the time delay between the classification result being shown on the screen and the subject-shifting gaze to the next stimulus. As an SSVEP-based BCI system is very likely to be used in a similar way, we believe this measure is very close to the real ITR when such a BCI system is in use. A higher ITR is possible when more stimuli are used.

## 4. Conclusions and discussions

In this paper we introduce a low-cost and user-friendly SSVEP-based BCI system which would be more readily accepted by consumers. It can not only be used as a way to communicate with the outside world by those severely disabled but can also be used by healthy users as a form of entertainment.

We designed an EEG device containing only one active dry sensor with no conductive gel needed, which greatly reduces the preparation time and improves the user experience. All of our experiments were recorded in a regular office setting which contained significantly more electrical noise than shielded rooms.

A novel time-domain-based method, SLIC, has been developed which shows better classification performance than

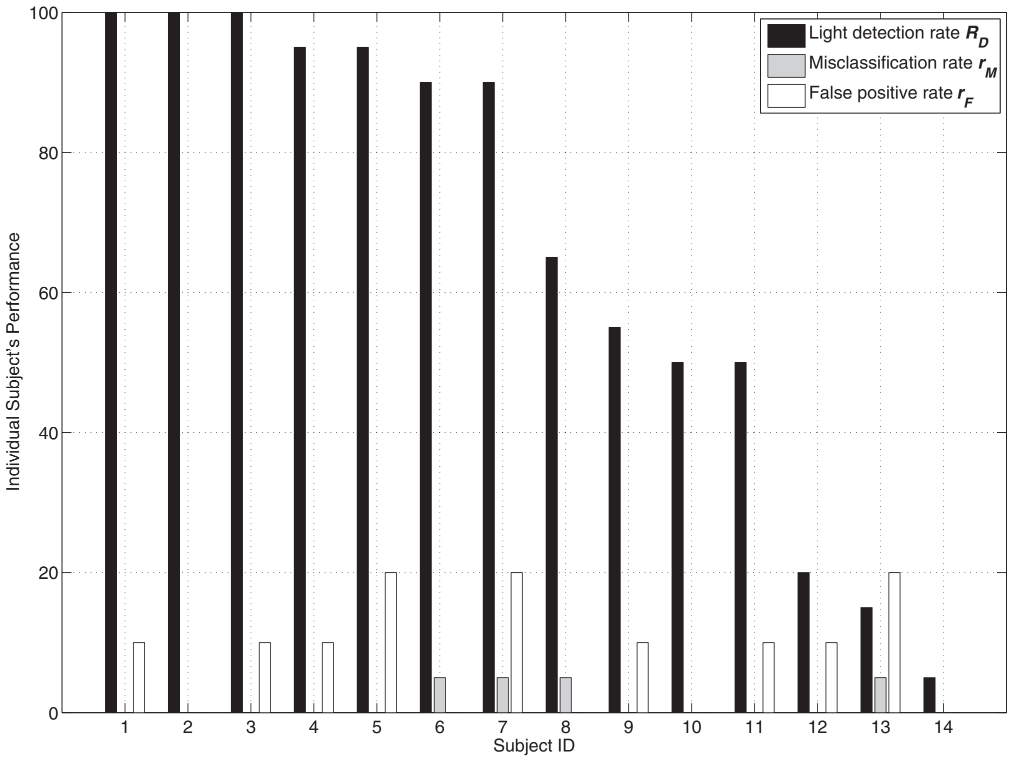


**Figure 6.** Performance of the SLIC method on each subject. Subjects were sorted by decreasing performance. In previous sections, the average performance of the first 12 subjects was presented. Thresholds were based on table 1, $S_D = 1$ s, $S_E = 0.5$ s, $M = 4$ s, 3-out-of-4 voting.

a traditional frequency-domain-based method. Moreover, it is suitable for classifying visual evoked potentials elicited by both regular and irregular flash patterns. When designing the classification method we balance the accuracy and the robustness of the algorithm such that the SSVEP can be correctly classified with low error rates in a timely manner. We showed that this system worked with high performance for 12 out of the 14 subjects over a wide range of parameter selections. Even for those subjects whose correct light detection rate was low, their error rates were also low, assuring that the possibility of triggering a device by mistake is low.

Also importantly, the characteristics of the stimuli, including their frequency, color, size and pattern, have been carefully designed such that potential risks of photic-induced clinical conditions for photosensitive patients can be significantly reduced.

However, the accuracy and ITR reported in this paper are not as high as reported by some other studies, specifically [2], where they reported a 95.5% accuracy and a 58 bit min$^{-1}$ ITR. The reason is in part due to the fact that we measured the accuracy and ITR in a different way than [2]. Also compared to their traditional gel-based multi-channel EEG system, our emphasis was on the usability of the system, so only one dry electrode was employed. We also used a small visual display and only four lights. Our detection accuracy could be close to 90% (higher ITR is also very likely) if a lower threshold value were adopted. These factors all contribute to the difference between the two systems.

To reach a satisfying light detection rate with low error rates, a window length of at least 3 s is generally required for both the frequency-domain and the SLIC methods. As the decision has an update rate of less than 1 s, when a viewer quickly switched from one stimulus to another, the EEG being analyzed by the algorithm may still be dominated by the SSVEP in response to the previous stimulus. This would in turn delay the detection of the light that is currently being attended. The current 34.3 bit min$^{-1}$ ITR would be further improved if this delay could be reduced in the future.

The detection accuracy of our system can also be further improved. For example, preliminary studies have shown that the signal-to-noise-ratio (SNR) of our EEG device can be further increased, so better performance is expected. Also in this paper we employed 9, 10, 11 and 12 Hz as the stimuli's flashing rate; however, in the SLIC method the power line noise (60 Hz in USA) can contaminate EEG modulated by the 10 and 12 Hz lights. Better detection performance is thus expected if other frequency values are used, which is easy to change within our hardware system. Moreover, adaptive methods could be used to adjust the thresholds for each individual subject to further improve the system's performance.

In this work the stimulus frequencies were between 9 and 12 Hz, which were chosen because they produce strong SSVEP [15] and are relatively safe [5]. However, these frequencies were in the Alpha range, where the closed eye EEG-signal is resident. So far we have not observed any negative effects caused by Alpha when eyes are opened, although it may be possible that an Alpha wave will be at just the right frequency to cause error when eyes are closed. This is a tradeoff between the safety/usability of the system and possible false positives with eyes closed. In this paper we focus on the former and we assume the user open their eyes most of the time while using this system. One future improvement of the system could be to add a 'do not detect' button (which may also be controlled by EEG).

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