Maximizing Information Transfer Rates in an SSVEP-based BCI using Individualized Bayesian Probability Measures

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***Abstract*—Successful brain-computer interfaces (BCIs) swiftly and accurately communicate the user's intention to a computer. Typically, information transfer rate (ITR) is used to measure the performance of a BCI. We propose a multi-step process to speed up detection and classification of the user's intent and maximize ITR. Users randomly looked at 4 frequency options on the interface in two sessions, one without and one with performance feedback. Analysis was performed off-line. A ratio of the canonical correlation analysis (CCA) coefficients was used to construct a Bayesian probability model and a thresholding method for the ratio of the posterior probability of the target frequency over maximal posterior probability of non-target frequencies was used as classification criteria. Moreover, the probability thresholds were optimized for each frequency, subject to maximizing the ITR. We achieved a maximum ITR of 39.82 bit/min. Although the performance feedback did not improve the overall ITR, it did improve the accuracy measure. Possible applications in the medical industry are discussed.**

I. Introduction

A brain-computer interface (BCI) enables a user to communicate their intention to a computer without physical interaction. An ideal BCI should detect an action faster than the person's ability to act. Thus, one aim in designing a good BCI is maximizing the speed of detection. Speed, accuracy and the number of choices on the interface determine the average rate at which the BCI can transmit the user's intent to the computer – or information transfer rate (ITR).

Steady state visually evoked potentials (SSVEPs) [1] are commonly used in BCI devices because of their excellent signal-to-noise ratio. These robust brain signals are the brain's response to visual stimulation from a light source. Typically, the light source will flicker at a given frequency (or set of frequencies). When the retina is excited by a flickering visual stimulus in the range from 3.5Hz to 75Hz and above [2, 3], the neurons generate electrical responses at the same frequency, or harmonics of that frequency.

Academic and commercial interest in BCI for various applications is visible by the number of papers available. However, their use in everyday applications is narrow. Current systems lack the speed and accuracy required for consistent use. Performance enhancements for the prevailing SSVEP BCI paradigms improve either the speed or accuracy of the system, and are compared using the ITR [4]. Performance could be improved by optimizing the interface for each user independently. Studies have tested various stimulus sizes, colors, and frequency rates to determine the optimal signal-to-noise ratio for each user [5, 6]. Others increased the number of possible targets available within a small range of frequencies that have a good signal to noise ratio [7], effectively increasing the number of possible frequency targets, and increasing the ITR.

Signal filtering and processing is also important in achieving good signal-to-noise ratios and ITR. Typically, detection of the SSVEP signal is done with either minimum energy combination (MEC) or canonical correlation analysis (CCA). However, others have investigated complex signal detection [8] or classification [9] techniques to improve the performance of the BCI. We chose the CCA method, since a recent investigation into the detection accuracy of both MEC and CCA found that CCA has better accuracy as well as SNR as compared to MEC [10].

These are two approaches to improve the performance of an SSVEP based BCI system for an individual user: (1) customize the front-end stimuli in the interface, (2) optimize the back-end signal processing and classification parameters based on that user's unique data. We propose creating an SSVEP based BCI system using the second approach and present an option for the first approach. We will maximize the ITR by optimizing the classification parameters, depending on how well the user responds to each given frequency. Additionally, by customizing the window size and decision rate, we increase the overall speed of detection.

Attention has been shown to modulate the amplitude of the SSVEP response [11, 12], therefore a BCI interface that includes feedback about the user's performance might improve their attention and therefore performance. Previous studies have demonstrated that providing feedback to the user improves overall performance as well as satisfaction with the system [13, 14]. Adding feedback to our interface should improve detection speeds, especially for users who have difficulty with certain frequencies, or become fatigued. To test this, we included a calibration session where the user is allowed to see how well they are dynamically controlling their attention (and other factors that change the response amplitude of the SSVEP), via a feedback bar.

The first section of this paper provides the experimental setup, the paradigm design and detailed algorithm description, the second section contains the experimental

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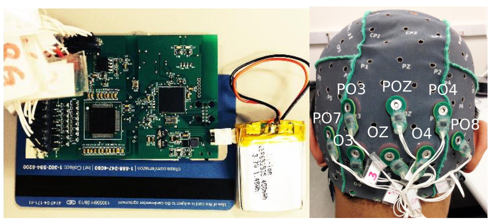
results, and the final section concludes the paper.

II. Method

A. Hardware

Continuous EEG data was recorded using dry electrodes and a custom system developed in our lab. The EEG board shown in Figure 1(a) incorporates two daisy-chained TI ADS1299 analog front ends for 16-channel EEG, and a TI MSP430 microcontroller. Data is sent wirelessly to the PC via a BlueRadios dual mode Bluetooth module. The board incorporates an active driven right leg (DRL) circuit for better common mode rejection.

Eight recording electrodes, shown in Figure 1(b), were placed over the visual cortex in the occipital regions according to the international 10-20 system, and referenced to the right mastoid. Five users were recorded, 3 males, and 2 females.



(a) (b)

Figure 1. EEG board (a), and electrode configuration (b)

B. BCI Interface Design

The SSVEP paradigm interface, shown in Figure 2, consisted of 4 rounded white squares on a black background. The 4 boxes flickered at a different frequency: 6Hz, 7.5Hz, 8.5Hz, or 10Hz, which corresponded to the refresh rate of 60Hz divided by 10, 8, 7, and 6 (respectively). A Samsung Galaxy Note tablet was used to display the stimulus. The EEG data was sent via Bluetooth to a PC.

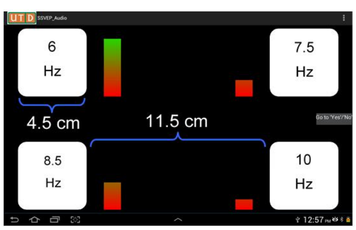


Figure 2. Tablet interface design (*with feedback bars)*

The users were prompted, via auditory instruction from the tablet interface, to focus on one of the 4 boxes for 10 seconds. Each box was viewed in random order for a total of 20 times, making the training session about 16 minutes.

After a 2 minute break, the user repeated the same procedure, but the second time they were allowed to view their performance with the help of a feedback bar.

C. Algorithm Design

The continuous EEG data from the calibration session was bandpass filtered between 0.1 and 30 Hz. Next, the data from the calibration phase was used to build a Bayesian probability model for subsequent classification.

Data segments of length 0.1 to 4 seconds were passed independently to the canonical correlation analysis (CCA) function, to determine which frequency (out of a known set) was most represented in the data [15, 16]. Assume the multi-channel EEG signal is X and the reference signal for each frequency and its harmonics is Y; the CCA looks for the linear combination for X, $x = X^T W_x$ and Y, $y = Y^T W_y$ such that the correlation between x and y is maximized as in (1). We used a CCA with 3 harmonics as suggested by [17].

$$\max_{W_x, W_y} corr(x,y) = \frac{E[W_x^T X Y^T W_y]}{\sqrt{E[W_x^T X X^T W_x] E[W_y^T Y Y^T W_y]}} \quad (1)$$

The maximum of $corr$ with respect to W_x and W_y is the canonical correlation coefficient. The CCA matrix $Coef_i(n|f = f_m)$ is obtained, where each element is the CCA coefficient of frequency f_i in trial n when target frequency is f_m. Next we calculate $R_i(n|f = f_m)$, which is the ratio of the CCA coefficient of frequency f_i over the largest CCA coefficient of others in the nth trial when the target frequency is f_m, as in (2):

$$R_i(n|f = f_m) = \frac{Coef_i(n|f = f_m)}{\max_{j \neq i}(Coef_j(n|f = f_m))} \quad i, j, m = 1, \dots M \quad (2)$$

Based on the $R_i(n|f = f_m)$ across different trials, we can approximate the likelihood $P(R_i|f = f_m)$ for all frequency indices m and ratio indices i by performing the *hist* function in MATLAB. Based on the Bayes' rule, the posterior probability of detecting the target frequency given R_i is:

$$P(f = f_m|R_i) = \frac{P(R_i|f = f_m) * P(f = f_m)}{P(R_i)} \quad (3)$$

Where the evidence $P(R_i)$ is:

$$P(R_i) = \sum_{m=1}^{M} P(R_i|f = f_m) * P(f = f_m) \quad (4)$$

Assuming the ratios of the CCA coefficients are time-series observations, denoted by R_i^t, a threshold limit on the product of the ratio of target frequency's posterior probability over the maximal posterior probability of the others is used to decide whether there is enough confidence to make a classification decision at time T, shown in (5):

$$\prod_{t=1}^{T} \frac{P(f = f_m|R_m^t)}{\max_{i \neq m} P(f = f_i|R_i^t)} > Th \quad (5)$$

Where f_m is the target frequency, R_m^t is the CCA coefficient ratio of target frequency over the maximal of others and Th is the predetermined confidence-related threshold. However, realizing that each user has different responses and therefore different performance measurements for different frequencies, a general Th for all frequencies might not be optimal for maximizing ITR. ITR is determined using recognition time T, recognition accuracy ρ, and the number of targets M as shown in Equation (6):

$$ITR = \frac{60}{T}\left(log_2 M + \rho log_2(1-\rho) + (1-\rho) log_2\left(\frac{1-\rho}{M-1}\right)\right) \quad (6)$$

Take the example where there are 4 different frequencies and a user is good at responding to three of them, yet bad at the fourth frequency. If one general threshold is used for detection across all the frequencies, a 'bad' frequency may never be detected for this user since the product of the ratio of its posterior probability over the others may be lower than the preset threshold Th. Although it may be detected with a lower Th, doing this will sacrifice the false positive rate for the false negative rate by allowing more irrelevant events to be misclassified as SSVEP events. Therefore, with a general predefined threshold Th, the recognition accuracy is not optimized, and in turn lowers the ITR.

To solve this problem, we propose a search algorithm in the calibration phase to optimize the threshold Th_m for each frequency f_m that maximizes the overall ITR. The detailed procedure of the algorithm is described in Algorithm I.

Algorithm I. Threshold search for ITR optimization

Initialize the $M \times 1$ ratio threshold vector Th^j at iteration j as Th^0, and set the lower bound of Th_m^j as Th_{min}, the maximal possible recognition time as T_{max}, maximal iteration number as $Iter_{max}$ and update step size as $Step$.

1. **In the calibration iteration j, calculate the average classification accuracy acc_m^t over the recognition time $t = [0, T_{max}]$ for different target frequencies f_m $(m = 1, .., M)$ with threshold vector $Th_m{}^j$.**
2. **Calculate ITR_t^j and find the recognition time t_{max}^j that has the maximal ITR, denoted as ITR_{max}^j.**
3. **Update Th_m^{j+1}: (denote $m_{min} = arg\min_m acc_m^{t_{max}}$)**

   If $Th_{m_{min}}^j$>1

$$Th_m^{j+1} = \begin{cases} Th_m^j - Step, & m = m_{min} \\ Th_m^j, & m \neq m_{min} \end{cases}$$

   otherwise,

$$Th_m^{j+1} = \begin{cases} Th_m^j/2, & m = m_{min} \\ 1/Th_{m_{min}}^{j+1}, & m \neq m_{min} \end{cases}$$

4. **If $\min(Th^{j+1}) > Th_{min}$ and $j + 1 \leq Iter_{max}$, go back to step 1, otherwise, go to step 5.**
5. **Decide the threshold vector Th by: $Th = Th^{j_{max}}$, where $j_{max} = arg\max_j ITR^j$**

To obtain the optimal ITR in each iteration, the threshold of the frequency that has the lowest accuracy will be decreased to expect higher optimal ITR in the next iteration. Note that, in the threshold updating procedure, when $Th_{m_{min}}^j \leq 1$ the thresholds of other frequencies have to be larger or equal to $1/Th_{m_{min}}^{j+1}$ to avoid classification conflict.

III. EXPERIMENTAL RESULTS

The choice of a baseline window size and sliding window size is crucial. Since the frequencies used were 6Hz, 7.5Hz, 8.5Hz and 10Hz, the sliding window size was chosen to be 100ms, in order to add at least one period of the lowest frequency at a time. The baseline window size was decided for each user subject to maximizing ITR, such as in Figure 3:

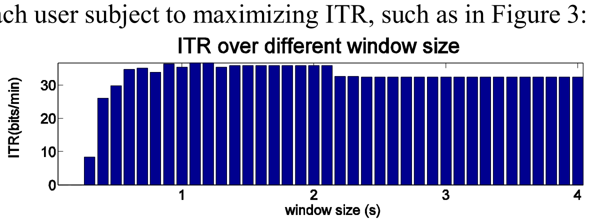


Figure 3. Information Transfer Rate over different window sizes.

While searching for the optimal window size for each user, the optimal threshold for each frequency is also determined by looking for the maximal ITR across iterations. An example of one of the ITR distributions over time, for one iteration, is illustrated in Fig. 4 and the ITR over iterations is shown in Fig. 5.

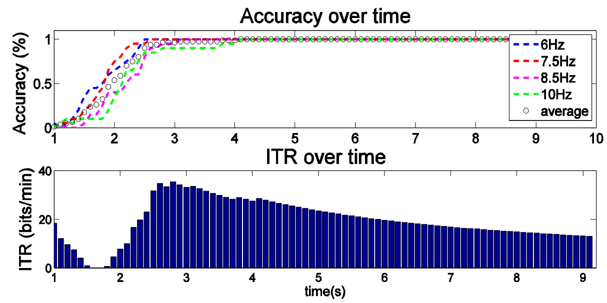


Figure 4. Information Transfer Rate (ITR) and the corresponding classification accuracy over recognition time.

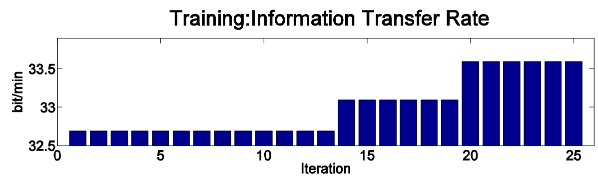


Figure 5. ITR over iterations

The average window size, detection time, accuracy, and ITR for each user are reported in Table I. The ITR ranged from 15.41 to 39.82 bit/min, with an average of 32.66 bit/min. The average detection time and accuracy were 3.48 seconds and 94.75%.

Table I. Average ITR across users (4 targets)

User	*Window (s)*	*Time (s)*	*Accuracy (%)*	*ITR (bit/min)*
U1	0.8	3.1	98.75	35.31
U2	1.7	2.6	97.50	39.82
U3	1.6	4.8	87.50	15.41
U4	1.2	3.4	92.50	25.66
U5	0.7	3.5	97.50	29.86
Average	**1.2**	**3.48**	**94.75**	**32.66**

Giving feedback to the user about their performance might help them maintain their attention. The feedback for the user was given in real time as a percent to the max target ratio (1.4, which was obtained from previous observations) where .7 gave a value of 0 and 1.4 gave a value of 1:

$$F_i(f = f_m) = \frac{\left(\frac{Coef_i(f=f_m)}{\max_{j \neq i}\left(Coef_j(f=f_m)\right)}\right)}{.7} - 1 \quad , i, j, m = 1, \dots, M \tag{7}$$

The resulting ITR values from these two sessions, with and without feedback for all 5 users are shown in Table II:

Table II. Average ITR with and without feedback

User	without feedback			with feedback		
	ITR	*time*	*Accuracy*	*ITR*	*time*	*Accuracy*
U1	35.31	3.1	98.75	29.80	2.6	96.70
U2	39.82	2.6	97.50	22.40	4.7	97.50
U3	15.41	4.8	87.50	13.14	5.9	88.75
U4	25.66	3.4	92.50	28.97	3.8	98.75
U5	29.86	3.5	97.50	33.33	3.5	100
Average	**32.66**	**3.48**	**94.75**	**27.56**	**3.8**	**96.34**

There was an improvement for most of the users in terms of accuracy when feedback is provided. However, the ITR only improved for 2 out of the 5 users, due to the increased time to detection for the other 3.

If a user does not respond well to certain frequencies, it is possible to customize their interface with a limited set of frequencies from the original set. We calculated the adjusted

ITR for user U3, who did not respond well to the 6 Hz frequency. By including only the best 3 frequencies, we achieved a higher accuracy and a better ITR:

Table III. Average ITR for U3 with 4 and 3 targets

U3	without feedback			with feedback		
	ITR	*time*	*Accuracy*	*ITR*	*time*	*Accuracy*
4 targets	15.42	4.8	87.5	13.14	5.9	88.75
3 targets	15.85	5.9	100	16.68	5.6	100

IV. CONCLUSIONS

To solve the problem of inter-user variation and inter-frequency variation in an SSVEP application, a Bayesian probability measure based on an individual user's calibration data was created for the maximization of the ITR. We also showed the advantage and feasibility of some paradigm customizations for further performance enhancement.

Our method achieved a maximum ITR of 39.82 bit/min, which is comparable to a study with 5 targets (instead of 4) that achieved an average ITR of 37.62 (best 47.18) [18] or for a 4 command interface, at 31.90 bit/min [19].

The feedback mechanism did not significantly improve the ITR for this simple paradigm, but it did help most users improve their accuracy. This finding is similar to other studies that found feedback helps the user learn to use the BCI if they are having trouble, but in general, does not improve or detract from their performance after the learning period [14, 20]. Perhaps distraction due to the feedback caused the detection time to increase, impacting the overall ITR. Although, the ITR for one user whose performance was not at ceiling was improved in the feedback condition where the number of targets in the interface was also reduced.

Even though we performed our analysis off-line, our method can be applied to a real-time system. In the real-time case, a calibration session will be performed for each user to determine the ideal probability thresholds for each frequency for that user. Customizing the interface for the user is especially important when there is a high degree of variability between users. For example, in a hospital setting where the capabilities and needs of each patient vary to a large degree, a customizable BCI will be particularly important. Here, a BCI can be invaluable in allowing communication between the patient and the care-givers where other modes of communication are not possible.

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