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A method for optimizing EEG electrode number and configuration for signal acquisition in P300 speller systems

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H I G H L I G H T S

- A Gibbs sampling method can identify minimal electrode sets that are important for BCI communication across a subject population without compromising information transfer.
- In healthy subjects, a reduced set of four electrodes (PO_8, PO_7, PO_Z, CP_Z) was found that performed statistically identically to a full montage in an online study.
- Reducing and optimizing the number of EEG channels may reduce cost, set-up time, signal bandwidth and computation requirements and improve clinical practicality of P300 speller systems.

A B S T R A C T

Objective: The P300 speller is intended to restore communication to patients with advanced neuromuscular disorders, but clinical implementation may be hindered by several factors, including system setup, burden, and cost. Our goal was to develop a method that can overcome these barriers by optimizing EEG electrode number and placement for P300 studies within a population of subjects.
Methods: A Gibbs sampling method was developed to find the optimal electrode configuration given a set of P300 speller data. The method was tested on a set of data from 15 healthy subjects using an established 32-electrode pattern. Resulting electrode configurations were then validated using online prospective testing with a naïve Bayes classifier in 15 additional healthy subjects.
Results: The method yielded a set of four posterior electrodes (PO_8, PO_7, PO_Z, CP_Z), which produced results that are likely sufficient to be clinically effective. In online prospective validation testing, no significant difference was found between subjects' performances using the reduced and the full electrode configurations.
Conclusions: The proposed method can find reduced sets of electrodes within a subject population without reducing performance.
Significance: Reducing the number of channels may reduce costs, set-up time, signal bandwidth, and computation requirements for practical online P300 speller implementation.

1. Introduction

The P300 speller is an example of a Brain Computer Interfaces (BCI) system designed to restore communication by translating cortical signals into simulated keyboard input (Farwell and Donchin, 1988). The system contains a graphical interface consisting of a grid of alphanumeric characters that are periodically illuminated in a pseudo random manner. While a promising technology, clinical adoption is limited by issues of practicality, speed, and accuracy (Huggins et al., 2011; Baxter et al., 2012). Several studies have focused on improving speed and accuracy, including approaches that vary flashing patterns (Townsend et al., 2010;

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Jin et al., 2010), optimize system parameters (McFarland et al., 2011; Lu et al., 2012), and adopt different signal classification algorithms (Serby et al., 2005; Krusienski et al., 2006). Recently, performance has been improved through the integration of natural language processing method such as naïve Bayes (Speier et al., 2012), partially observable Markov decision process (Park and Kim, 2012), and expectation maximization (Kindermans et al., 2012).

While system performance is an active area of research, there is comparatively little focus and investigation with respect to "ease of use." Choosing the optimal placement and number of electrodes is essential in any EEG system as it balances the amount of available data against the set-up time, cost, and system complexity. There is minimal objective and quantitative analyses of the minimal EEG electrode set that can be used to achieve optimal system performance. Several studies have found similar offline performance in the P300 speller between using a 32 channel EEG and empirically chosen sets of six (Krusienski et al., 2008), eight (Hoffmann et al., 2008), and ten (Kaper et al., 2004) electrodes. These studies did not quantitatively deduce the described electrode sets nor consider other reduced configurations, so they present potential configurations, but do not show that they are minimal or optimal. They are also restricted to P300 experiments using healthy subjects and have been shown not to translate well to situations where user gaze is limited, which is often the case in the target population (Brunner et al., 2010).

Several recent studies have developed methods to rank electrodes based on their contribution to offline classification accuracy on an individual subject basis in P300 systems using EEG (Cecotti et al., 2011; Xu et al., 2013; Colwell et al., 2014) and electrocorticography (ECoG) (Speier et al., 2013a). These studies employed methods in which an initial testing phase included data from a complete electrode set to later determine a subject's optimal configuration, only after which the number of channels could be reduced on a subject-specific basis. The configurations described in these studies varied in channel number and location between subjects, leading to the conclusion that subject-dependent configurations are necessary for optimal P300 performance. None of these studies attempt to optimize across subjects to provide a general configuration for comparison. Moreover, none of these studies validated their results with prospective trials using the reduced number of electrodes to demonstrate that they were robust across sessions. Finally, the methods employed in these studies do not improve "ease of use" for end users because the described approaches require a full set of recording electrodes and amplifiers for each subject before identifying an optimized reduced set.

The goal of this project was to provide a method for optimizing EEG electrode placement for P300 studies across a subject population, which we demonstrate by providing a minimal set of electrodes for studies conducted on healthy subjects. In this study, we initially use a retrospective offline analysis approach using a previously published data set of 15 healthy subjects with 32 electrodes (Speier et al., 2014). Gibbs sampling was used to find sets of electrodes based on the joint distribution of the subjects' EEG signals and the known labels. Offline testing with a naïve Bayes classifier (Speier et al., 2012) was performed using data from each of these electrode sets to show the relationship between the number of electrodes and system performance. The optimal four electrode set was then evaluated prospectively online against the full 32 electrode set as well as the six electrode set presented by Krusienski et al. (2008) to validate its viability in a real time BCI system.

Ultimately, these studies demonstrate an important method to generate a clinically and practically non-inferior reduced electrode set for a P300 speller that can and should be applied to target populations to determine if an optimal reduced electrode set can be identified in affected patient populations.

2. Methods

2.1. Data collection

The previously published dataset used in the sample implementation of our method consisted of 15 healthy graduate students and faculty with normal or corrected to normal vision between the ages of 20 and 35 (Speier et al., 2014). Only one subject (subject F) had previous experience using a BCI for typing. Data was acquired using g.tec amplifiers, active EEG electrodes, and electrode cap (Guger Technologies, Graz, Austria) with 32 channels in an established configuration (Lu et al., 2012; Sharbrough et al., 1991). The signals were sampled at 256 Hz, referenced to the left ear, grounded to AF_Z, and filtered using a band-pass filter of .1–60 Hz. The system used a 6×6 character grid, row and column flashes, and an interstimulus interval (ISI) of 125 ms. Subjects underwent between 8 and 10 trials, each consisting of spelling a five letter word with 15 sets of 12 flashes (six rows and six columns) for each letter. The choice of target words for this experiment was independent of the trigram language model used. Gaze was not fixed or tracked.

The subjects for the online study consisted of 15 healthy volunteers with normal or corrected to normal vision between the ages of 20 and 30. The training sessions for these subjects consisted of three sessions of copy spelling 10 character phrases. Each subject then chose a target phrase to spell in online sessions. Subjects then had either one 5-min (subjects P–U) or two 2-min (subjects V–AD) online sessions for each of three electrode configurations: the full 32 electrode configuration, the six electrode subset proposed by Krusienski et al., and the optimal four electrode set found during offline analysis. Subjects were instructed not to correct errors and to repeat the phrase if they completed it in under 5 min. The order of the three online sessions was chosen for each subject using a random number generator. One volunteer could not participate in the study because connection in the occipital electrodes could not be obtained due to hair thickness.

BCI2000 was used for data acquisition and online analysis (Schalk et al., 2004). Offline analysis was performed using MATLAB (version 7.10.0, MathWorks, Inc., Natick, MA).

2.2. Feature selection

For each stimulus, the 32 channel EEG data for the next 600 ms was decimated by a factor of 12 and concatenated into a feature vector, z_t^i, for use in classifying that stimulus. Stepwise linear discriminant analysis (SWLDA) used a stepwise method to separate the available features into two groups based on whether the feature was significant in classification. The probabilities of adding and removing features were 0.1 and 0.15, respectively. These steps were repeated until the number of significant features reached a threshold of 60 features or until the feature groups reached equilibrium. These significant features were then stored in a weight vector, w (Krusienski et al., 2006).

During testing, the dot product between the feature vector for each stimulus and the feature weight vector was taken to determine a score for that stimulus, y_t^i. The means and standard deviations were then found for the scores for target and non-target stimuli. Assuming a normal distribution, the probability density function (PDF) for the likelihood probability were computed,

$$f(y_t^i|x_t) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma_a^2}} e^{-\frac{1}{2\sigma_a^2}\left(y_t^i-\mu_a\right)^2} & \text{if } x_t \in A_t^i \\ \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\frac{1}{2\sigma_n^2}\left(y_t^i-\mu_n\right)^2} & \text{if } x_t \notin A_t^i \end{cases}$$

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where μ_a, σ_a^2, μ_n, and σ_n^2 are the means and variances of the distributions for the attended and non-attended scores, respectively, and A_t^i is the set of characters included in stimulus i for letter t.

2.3. Generating channel sets

Channel sets were found using Gibbs sampling to optimize the joint probability of the EEG data and the known labels of the offline data set. Gibbs sampling is a Markov chain Monte Carlo (MCMC) method for estimating high dimensional distributions by generating a "random walk" through the state space (Liu, 2001). An initial configuration of the variables is set randomly along with a set of transition probabilities to new configurations based on their relative likelihood. The system then moves randomly through the state space and the frequency of a given state is proportional to its probability.

Here, the state of the system is the set of channels included in analysis. Channel inclusion was represented by a vector of binary variables, c, where $c_j = 1$ if channel j was used in classification. The feature weight vector when trained using the data in the channels indicated by c is represented by w_c. Scores are obtained as before by taking the dot product with the feature vector:

$$y_t^i(c) = w_c \cdot z_t^i$$

In Gibbs sampling, one variable is chosen, c_j, and the remaining, c_{-j}, are held constant. The chosen variable is then assigned a new value according to its probability distribution conditioned on the other variables, c_{-j}, and the known values for the signal, $z^{(s)}$, and the targets, $x^{(s)}$, for all subjects s:

$$p(c_j|c_{-j}, x, z) \propto p(x|y(c))p(c_j|c_{-j}) = p(c_j|c_{-j})\prod_s p\left(x^{(s)}|y(c)^{(s)}\right)$$

When each stimulus response is treated as independent, the posterior probability of the known targets can be computed from the likelihood PDFs:

$$p(x|y(c)) = \prod_t\prod_i \frac{f(y_t^i(c)|x_t)p\left(x_t \in A_t^i\right)}{\sum_{x_t'} f(y_t^i(c)|x_t')p\left(x_t' \in A_t^i\right)}$$

Once c_j is assigned, another variable is chosen and the process is repeated. The prior probability $p(c_j|c_{-j})$ defines a spatial bias based on expected features of an optimal configuration. Here, it is determined by an Ising model which gives reduced weight to configurations containing adjacent channels, which are likely to contain redundant information:

$$p(c_j|c_{-j}) \propto e^{-\beta\sum_{k\in n(j)} c_j c_k}$$

where $n(j)$ represents the indices of electrodes that are adjacent to electrode c_j in the initial 32 channel configuration.

For each electrode set size, the channel set that occurred most often in the Gibbs sampling was chosen as optimal. The offline data set was censored based on each of these configurations and then evaluated using a naïve Bayes classifier.

2.4. Classification

Classification was performed using a naïve Bayes classifier which has been described in detail in a prior publication (Speier et al., 2012). Briefly, we determined the conditional probability of a target character, x_t, given a set of flash scores and the history of previous decisions (Speier et al., 2012).

$$p(x_t|y_t, x_{t-1}, \ldots, x_0) \propto p(x_t|x_{t-1}, \ldots, x_0)\prod_i f\left(y_t^i|x_t\right)$$

where $p(x_t|x_{t-1}, \ldots, x_0)$ is the prior probability of a character given the previous selections and $f(y_t^i|x_t)$ are the PDFs for the likelihood probabilities. A trigram model was used, where the target character only depends on the previous two selections (Manning and Schütze, 1999). In this study, prior probabilities for characters were obtained from frequency statistics in an English language corpus (Francis and Kucera, 1979). After each stimulus, if the probability for any character exceeds a set threshold value, that character is chosen and the system moves on to the next character in the sequence. Although the number of flashes was fixed for all trials in the offline study, different selection rates were simulated by limiting the amount of data available for the classification algorithm. In online trials, the threshold was set to 0.95 for all subjects based on previous experiments (Speier et al., 2014).

2.5. Evaluation

Evaluation of a BCI system must take into account two factors: the ability of the system to achieve the desired result and the amount of time required to reach that result. The efficacy of the system can be measured as the selection accuracy, which was defined as the proportion of correct characters in the final output string. The speed of the system was measured using selection rate (SR), the average number of selections per minute. In offline analysis, SR was found by taking the inverse of that average time required to make a selection. In online trials, the selection rate was computed by dividing the number of selections by the time required for those selections. For this analysis, the time was defined as the period between the start of the trail and the timestamp of the final character selected.

As there is a tradeoff between speed and accuracy, we also use information transfer rate (ITR) (in bits per minute) for evaluation, which takes both into account. The bits per symbol, B, is a measure of how much information is transmitted per selection on average (Pierce, 1980):

$$B = \log_2 N + P\log_2 P + (1-P)\log_2\frac{1-P}{N-1}$$

where N is the number of possible characters (36) and P is the selection accuracy. ITR can then be found by multiplying the selection rate by the bits per symbol. Friedman tests were used to evaluate significant differences between different electrode configurations and Wilcoxon signed-rank tests were used for pairwise comparisons and post hoc analysis.

3. Results

3.1. Channel sets

In general, the average bit rate increased with the number of channels used for classification. Sets of one, two, or three electrodes produced average offline ITR values of 12.1, 20.1, and 26.4 bits/min respectively (Table 1). These values were all signifi-

Table 1
Channels and average bit rates for the first six electrode sets, the Krusienski set, and the full 32 electrode configuration.

Channel set	Included channels	Average bit rate	Incremental p value
1	PO_8	12.10	<0.001
2	PO_8, PO_Z	20.13	<0.001
3	PO_8, PO_Z, PO_7	26.42	<0.001
4	PO_8, PO_Z, PO_7, CP_Z	28.93	0.003
5	PO_8, PO_Z, PO_7, CP_1, CP_2	29.34	0.079
6	PO_8, PO_Z, PO_7, CP_1, CP_2, FC_Z	29.83	0.56
Krusienski	PO_8, PO_7, O_Z, P_Z, C_Z, F_Z	29.46	N/A
32	All	31.80	N/A

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cantly lower than the average performance using a set of four electrodes (PO_8, PO_Z, PO_7, CP_Z; Table 1). The average bit rate plateaued with incremental increases after four channels (Fig. 1). Because increasing the number of electrodes did not provide a significant improvement in bit rate ($p = 0.072$) beyond four electrodes, the optimal four electrode set was selected for comparison against the six electrode set proposed by Krusienski et al. (2008) and the full 32 electrode configuration.

The four electrodes in the reduced set all showed strong excitatory response potentials (ERP) in response to target stimuli (Fig. 2). The PO_8 and PO_7 channels showed a pronounced negative inflection after a delay of about 200 ms and a smaller positive inflection after 300 ms. The PO_Z and CP_Z waveforms did not include the first negative inflection, but showed a higher positive response after the 300 ms delay. All of the channels showed an oscillatory component at the stimulus frequency (8 Hz), but it was generally larger for the occipital electrodes.

3.2. Validation

In offline analysis, the average bit rates for the four channel, six channel (Krusienski et al., 2008), and 32 channel electrode configurations were 28.93, 29.46, and 31.80 bits/min respectively (Table 2). Both the four and six electrode configurations' bit rates were statistically significantly lower than the full 32 electrode configuration ($p = 0.004$ and $p = 0.021$ respectively), but the differences were relatively small (9.0% and 7.4%, respectively). In online testing, subjects achieved average bit rates of 20.83, 20.91, and 21.67 using the four, six, and 32 electrode configurations respectively (Table 3). No significant difference was found between subjects' results when using the three electrode configurations ($p = 0.92$).

4. Discussion

Using Gibbs sampling, the number of electrodes required for an EEG-based BCI system can be reduced without significantly compromising information transfer. The application of this novel methodology to identify and validate a reduced electrode set within a subject population provides a potentially important resource for optimizing system design and performance in target populations. While the methodology is evaluated using a specific application (P300 speller) in a specific population (able-bodied subjects), the current methodology is agnostic to application or population.

4.1. Methodological validation in sample population

In the population studied, users achieved comparable bit rates using the four electrode configuration as with the six electrode Krusienski set as well as the full set of 32 electrodes in both on and offline analysis. In the retrospective offline exploratory study, the difference between the four electrode set and the full set was statistically significant, but the results using the four electrode set were sufficient to make the system clinically viable. In prospective online validation analyses, no significant difference was found between the results using these configurations, further indicating the potential power of this new methodology to identify a reduced electrode set without loss of information.

The optimal four electrode configuration found in our test population was consistent with previously published channel sets for healthy subjects. Methods that chose subject-specific sets of electrodes showed a high variability, but generally favored occipital and parietal electrodes, which was consistent with the coverage of our reduced set. The three most common electrodes chosen by Colwell et al. (2014), PO_8, PO_Z, and PO_8, completely overlapped with our four electrode set. Cecotti et al. (2011) and Xu et al. (2013) commonly included P_8, P_Z, and P_7, which were the closest available locations to those that we found most effective. The empirically derived configurations proposed by Kaper et al. (2004), Krusienski et al. (2008), and Hoffmann et al. (2008) all included either PO_7 and PO_8 or P_7 and P_8. All three empirical sets also included four midline electrodes: F_Z, C_Z, P_Z, and O_Z which, while disjoint from the reduced set proposed here, are in close proximity to two of the electrodes (PO_Z and CP_Z) and are likely to capture similar information.

In general, the true optimal electrode configuration may vary between subjects. However, it is also likely that it varies between sessions based on the state of the user and his or her environment. Variability can also arise from the setup as electrodes need to be reconnected for each use and the exact location and strength of the connection will not be completely constant. As a result, any study that attempts to find a subject-specific configuration must use multiple sessions in order to verify that they are truly finding variation between subject rather than session. Also, prospective tests using a fixed configuration are necessary to show that results using the configuration are reproducible.

In general, subjects realized a decrease in accuracy when using the system in online trials using each montage, resulting in average accuracies (73.21%, 69.28%, and 67.57%) that were lower than those published by several previous studies. The low accuracy in this study is largely a result of the speed/accuracy tradeoff inherent

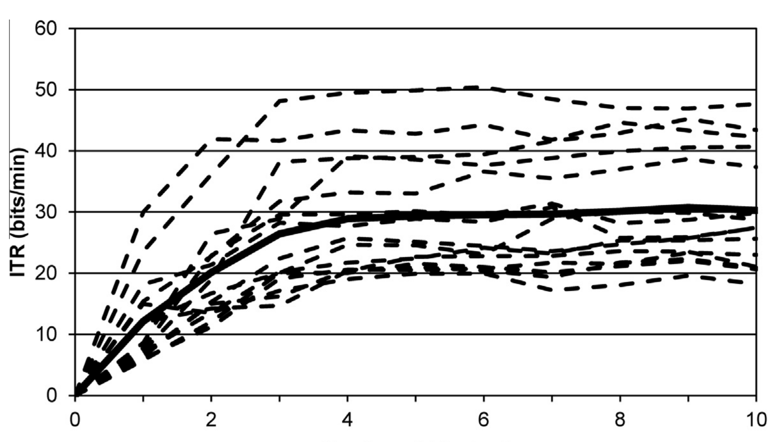

Fig. 1. Individual (dashed) and overall average (solid) bit rates for the 15 subjects in offline analysis versus the size of the electrode set used.

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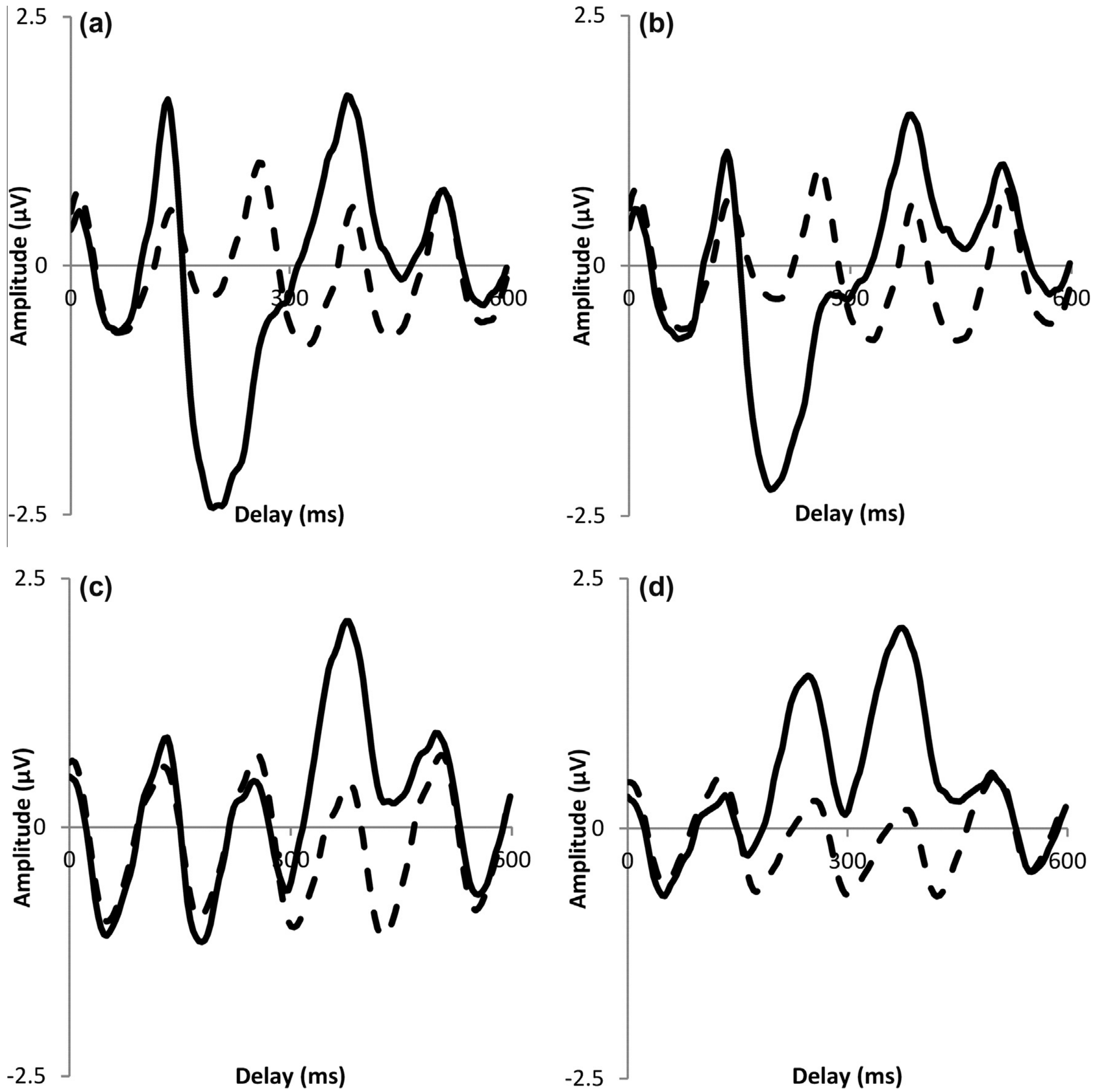

Fig. 2. Grand average EEG responses for attended (solid) and nonattended (dashed) stimuli for channels PO_8 (a), PO_7 (b), PO_Z (c), and CP_Z (d).

Table 2
Optimal selection rates, accuracies, and bit rates for the 15 subjects after optimizing on ITR in offline analysis.

Subject	SR (sel/min)			ACC (%)			ITR (bits/min)		
	4	6	32	4	6	32	4	6	32
A	8.44	7.74	9.26	93.33	100.00	95.56	40.29	39.99	43.33
B	5.90	6.46	7.42	91.11	80.00	82.22	26.39	22.12	26.58
C	4.15	6.43	6.09	72.50	72.50	82.50	19.43	18.70	21.96
D	8.96	10.84	10.94	100.00	95.56	93.33	49.34	50.74	48.94
E	4.56	8.73	6.22	93.33	68.89	86.67	21.55	23.41	24.38
F	7.62	8.16	9.96	91.11	95.56	88.89	34.49	38.20	40.80
G	5.52	6.12	8.19	92.00	98.00	84.00	25.98	30.14	30.42
H	8.71	9.99	10.19	96.00	90.00	92.00	42.86	41.83	44.39
I	4.93	6.17	6.72	94.00	94.00	88.00	27.77	27.97	27.06
J	4.48	6.68	5.74	86.00	82.00	96.00	19.33	23.82	27.09
K	4.78	8.07	6.50	80.00	66.00	88.00	20.77	20.19	26.16
L	6.52	7.32	8.07	90.00	88.00	84.00	29.18	29.48	29.98
M	5.10	7.54	8.59	78.00	72.00	70.00	19.18	21.71	23.63
N	7.56	8.57	9.17	98.00	94.00	90.00	37.24	38.87	38.39
O	4.21	7.30	7.12	90.00	74.00	82.00	20.08	21.96	25.38
Average	6.10	7.74	8.01	89.69	84.70	86.88	28.92	29.94	31.90

Table 3
Online selection rates, accuracies, and bit rates for the 15 subjects using the four, six, and 32 electrode configurations.

Subject	SR (sel/min)			ACC (%)			ITR (bits/min)		
	4	6	32	4	6	32	4	6	32
P	6.84	7.44	9.90	41.18	56.76	68.75	8.03	14.62	26.45
Q	8.80	8.59	8.13	87.36	82.93	75.00	34.98	31.23	25.01
R	7.32	5.08	10.33	100.00	88.00	91.11	37.82	20.44	44.23
S	6.88	8.76	8.32	70.59	62.79	43.90	19.17	20.23	10.84
T	3.35	2.66	5.95	75.00	15.38	72.41	10.31	0.56	17.30
U	3.21	4.51	6.67	62.50	68.18	18.18	7.35	11.90	1.93
V	3.46	3.52	3.87	46.15	30.77	40.00	4.88	2.56	4.35
W	4.83	5.21	6.69	41.18	57.89	68.18	5.67	10.57	17.62
X	5.49	6.76	6.04	100.00	88.00	75.00	28.40	27.19	18.59
Y	4.46	3.99	4.80	58.82	60.00	61.11	9.28	8.57	10.61
Z	5.46	8.20	6.65	80.95	87.50	64.00	19.05	32.70	15.83
AA	10.21	9.98	8.66	89.74	81.58	94.12	42.55	35.30	39.37
AB	8.98	9.94	10.26	75.00	86.96	85.42	27.64	39.19	39.21
AC	9.53	11.03	10.33	88.89	76.74	75.61	39.05	35.22	32.20
AD	5.27	4.99	6.17	80.77	95.65	80.77	18.33	23.39	21.44
Average	6.27	6.71	7.52	73.21	69.28	67.57	20.83	20.91	21.67

in the P300 speller as increasing the number of stimuli presented to the user will generally increase accuracy and reduce system speed. For instance, a study by Guger et al. (2009) showed an average accuracy of 91%, but provided stimuli for a single character for 28.8 s, resulting in an average typing speed of 2.1 characters per minute and an average bit rate of 8.9 bits/min. Using the naïve Bayes algorithm, subjects in this study were typing at speeds between 6 and 7 characters per minute, resulting in an average bit rate over twice that of the Guger study. While the accuracies that subjects achieved may not be practical for patients, using a higher confidence threshold can increase the accuracy at the expense of speed. It was not practical to optimize this threshold for all subjects and all channel configurations in this study, so a constant value of 0.95 was used across all trials.

Another factor contributing to decreased performance during online trials is likely that subjects were not allowed to correct errors. When an incorrect selection is made using the naïve Bayes method, the wrong characters are used for computing the prior probability for subsequent selections, resulting in additional errors. As a result, the selection rate is relatively unaffected, but the accuracy decreases. A similar decrease in accuracy was previously shown in online implementations of the naïve Bayes algorithm without error correction, which could be addressed either by allowing the user to make corrections, or by implementing an algorithm that can automatically correct errors (Ryan et al., 2011; Speier et al., 2014).

4.2. Clinical and practical implications

While the current analysis is done in healthy subjects, the validation of this method provides an important opportunity to reduce the number of channels and therefore the usability of the system in a target patient population. Fewer electrodes translate into faster setup time, which addresses one concern expressed in a survey of locked-in patients (Huggins et al., 2011). Reducing the number of channels also makes the system more cost effective by requiring fewer amplifier channels, which provides not only hardware cost savings but also decreased configuration and maintenance demands. Because patients with fixed gaze have trouble with the traditional P300 speller system (McCane et al., 2014), reducing the number of electrodes can also improve accuracy by allowing for more complex analysis methods. Unsupervised training and adaptive classifiers, for instance, could also allow for automatic adaptation to disease progression such as the loss of eye gaze control (Kindermans et al., 2012; Speier et al., 2013b).

4.3. Limitations and future directions

While the optimization method is general, the results are dependent upon the software, equipment, classifier, and system configuration used to collect the dataset. The electrode sets found using this method are therefore not necessarily robust across sites, implementations, or populations. For example, this study has used the row–column flashing paradigm, while the checkerboard paradigm has recently become widely used (Townsend et al., 2010). While both systems rely on the same neurological paradigm, it is possible that the distribution of features is not identical and therefore would have a different optimal electrode configuration. Also, when selecting the best electrodes locations, only locations that lie within the initial configuration can be candidates. Thus, any location that was not in the initial set of 32 channels will not appear in the final set, regardless of its value in classification.

Existing electrode montages have been shown to translate poorly into situations where a user's eye gaze is limited (Brunner et al., 2010). The application presented here on a population of healthy subjects is likely to have some of the same issues, as all subjects had gaze control. The Gibbs sampling method, however, is agnostic to the patient state and could be applied to find an electrode montage that works optimally in patient populations with fixed gaze. In long term implementations, it would likely be superior to existing patient-specific optimization methods as its goal is to optimize across patient state and would therefore be more robust to disease progression such as the loss of eye gaze control. This method can also be applied to other BCI systems as well as systems using other signal acquisition paradigms such as subdural electrodes for invasive P300 systems (Speier et al., 2013a).

4.4. Conclusion

This work presented a methodology for fining optimal electrode montages across a user population. Using this method in a population of healthy subjects, a four electrode configuration (PO_8, PO_Z, PO_7, CP_Z) is proposed which is shown to produce comparable results to a traditional 32 electrode configuration in online testing. Reducing the number of channels reduces the system's set-up time, hardware requirements for end users, and computation requirements for classification. These improvements can help to make the P300 speller system a more viable solution for locked-in patients.

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