Visual Spatial Attention Tracking Using High-Density SSVEP Data for Independent Brain–Computer Communication

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***Abstract*—The steady-state visual evoked potential (SSVEP) has been employed successfully in brain–computer interface (BCI) research, but its use in a design entirely independent of eye movement has until recently not been reported. This paper presents strong evidence suggesting that the SSVEP can be used as an electrophysiological correlate of visual spatial attention that may be harnessed on its own or in conjunction with other correlates to achieve control in an independent BCI. In this study, 64-channel electroencephalography data were recorded from subjects who covertly attended to one of two bilateral flicker stimuli with superimposed letter sequences. Offline classification of left/right spatial attention was attempted by extracting SSVEPs at optimal channels selected for each subject on the basis of the scalp distribution of SSVEP magnitudes. This yielded an average accuracy of approximately 71% across ten subjects (highest 86%) comparable across two separate cases in which flicker frequencies were set within and outside the alpha range respectively. Further, combining SSVEP features with attention-dependent parieto-occipital alpha band modulations resulted in an average accuracy of 79% (highest 87%).**

***Index Terms*—Alpha, brain–computer interface (BCI), electroencephalography (EEG), gating, spatial selective attention, steady-state visual evoked potential (SSVEP).**

I. Introduction

FOR SOME people with very severe disabilities (e.g., amyotrophic lateral sclerosis or brainstem stroke), a brain–computer interface (BCI) may be the only feasible channel for communicating with others and for environment control [1]. The most favorable brain imaging method employed in BCI's is electroencephalography (EEG), in which electrical signals of high temporal resolution are recorded noninvasively from the scalp. The existing EEG-based BCI designs rely on a variety of EEG signal features, e.g., slow cortical potentials [2], oscillatory activity [3], [4], P300 potentials [5], motor-related potentials [6] and visual evoked potentials (VEPs) [7]–[9].

One BCI solution, which has had success in optimizing performance in terms of both speed and accuracy, relies on an involuntary response known as the steady-state visual evoked potential (SSVEP). This is a periodic response elicited by the repetitive presentation of a visual stimulus, at a rate of 6–8 Hz or more [10]. While the existing SSVEP-based BCIs are exceptionally robust and convenient to implement [8], [9], most designs require reliable control of eye movement—the subject makes selections by shifting gaze direction. This unfortunately rules out applicability to those whose severe disabilities extend to impaired ocular motor control.

Though the specific underlying mechanisms of the SSVEP are as yet not well understood, there have been several accounts of its reactivity to cognitive variables such as attention, stimulus classification and memory search [11], [12]. Of particular interest are reports of the SSVEP behaving as an index of *visual-spatial selective attention* [13], which is the mechanism by which the brain identifies and focuses on discrete locations in visual space for preferential processing. This attentional selection can be performed independent of gaze direction, i.e., components in peripheral vision (covert attention) may be selected for processing just as those in foveal vision (overt attention) [14]. In [13], it was found that when subjects covertly attended to a flicker stimulus in one visual field the amplitude of the SSVEP resulting from that stimulus was enhanced by about a factor of two, compared to when the subject attended to the opposite visual field.

Prompted by the aforementioned results [11], [13], a pilot version of the visual-spatial attention control (V-SAC) BCI was developed [15]. In this study, the feasibility of making selections in real time by deploying visual spatial attention on cue was demonstrated using a basic paradigm with bilateral stimuli, and with the aid of feedback. Of 11 subjects, six succeeded in producing the required SSVEP modulations to achieve reasonable accuracy [15].

Operation of the real-time implementation of [15] was based on measurements from only two bilateral occipital electrodes. However, due to anatomical differences in the visual cortex, the spatial distribution and amplitude of electrophysiological responses to covertly attended visual stimuli differ across individuals. Also, the scalp distribution of the SSVEP is influenced by

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other factors such as frequency of stimulation and location in space [10].

Thus, the aim of this study was to use high-density (64-channel) EEG data to characterize the topography of SSVEP modulations, so that separability of features during covert attention to the left and right visual field could be optimized.

Further, in [15], flicker frequencies were set within the alpha band (8–14 Hz) due to the resulting high signal to noise ratio, but it is not clear whether this is advantageous over nonalpha band frequencies. Accordingly, a second aim of this study was to compare frequencies within and outside the alpha band. We address these critical issues by performing offline left/right classification of SSVEP data. In addition, effects of behavioral performance on BCI accuracy are assessed.

Finally, the utility of using the SSVEP magnitude features in conjunction with attention-dependent alpha band activity was explored. Increases in parieto-occipital alpha have been reported to mark the disengagement of processing of visual input during a biased attentional state [16], [17]. In [17], this was found in the cue-stimulus interval of a visual spatial cueing paradigm involving bilateral stimuli. Focal increases of alpha band activity were seen over occipital cortex contralateral to the direction of the to-be-ignored stimulus, reflecting anticipatory biasing of visual spatial attention. This effect was utilized in offline left/right classification for a BCI in [18], in which, alpha modulation features on their own provided an average accuracy of 73% using the data of the present study. It is predicted that combining these features with the SSVEP features will increase accuracy across a group of individuals.

II. Experimental Methods

A. Subjects

Ten subjects aged between 22 and 30 participated in the study. All had normal or corrected-to-normal vision.

B. Experimental Setup

Subjects were seated 60 cm from a CRT monitor on which was displayed two white rectangular flicker stimuli situated 2.9° bilateral to a central fixation cross (centered on the horizontal meridian) on a black background, as shown in Fig. 1. The actual refresh rate of this monitor, while on the 85-Hz setting, was measured as 85.05 Hz. Two stimulus settings were used in testing. For the first setting (ALPHA) the left rectangle was switched ON (white) for one frame and OFF (black) for eight frames giving a flicker rate of 9.45 Hz. The right rectangle was ON for one frame and OFF for seven giving a flicker rate of 10.63 Hz. For the second setting (NONALPHA), the left rectangle was flickered at 14.17 Hz and the right rectangle was flickered at 17.01 Hz.

Event-related potential (ERP) studies examining the static allocation of visual spatial attention normally involve the task of target detection. In the center of each of the white rectangles ($4.2 \times 4.2°$ of visual angle), letters from "A" through "H" ($1 \times 1°$) were presented in a random pattern, similar to the paradigm employed in [13]. Embedded in the sequence of letters was the target letter "X," occurring with equal probability (~ 0.11). Subjects were instructed to keep count of target presentations during each trial and report this number on completion of the trial. This provides a behavioral measure of spatial attention performance in terms of error rates and ensured that spatial attention mechanisms are engaged in the correct way. The letter in each rectangle was changed after three flashes of the white rectangle on which it was superimposed.

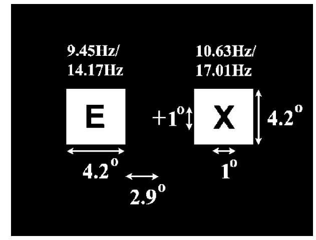

Fig. 1. Stimulus display.

Continuous EEG signals were recorded from 64 electrode positions referenced to location AFz, filtered over the range 0–134 Hz and digitized at a rate of 512 Hz using the BioSemi Active Two system. In addition, horizontal electrooculographic (EOG) data were recorded using two electrodes placed at the outer canthi of the eyes, with the left rereferenced to the right in the offline data.

C. Procedure

Each subject underwent a total of ten sessions, each lasting under 5 min. For five of the sessions the stimuli were flickered at the ALPHA setting, while the NONALPHA setting was used for the other five sessions, ordered alternately with the beginning setting counterbalanced across subjects. Each trial started with a red warning stimulus lasting 0.5 s, followed by a cue stimulus consisting of a white fixation cross of the same size with an arrow on the left or right arm, lasting 0.5 s. Depending on the direction of the arrow, the subject was instructed to covertly attend to the left or right rectangle while strictly maintaining fixation on the central fixation cross for 8 s. Following the attend period a green fixation cross was presented for 5 s, signifying a rest period. Each session consisted of 20 trials, with an equal number cued-left as cued-right, in random order.

In addition, six subjects underwent one session in which eye movement to the cued stimulus was permitted. This enabled a comparison of performance for overt versus covert attention.

III. Analysis Methods

A. Channel Selection

Scalp maps were plotted for each subject, indicating the magnitude of the EEG power at the stimulus frequencies when the subject was attending left versus attending right, averaged over all sessions and all trials. For most subjects, this yielded a very concentrated and localized region of maximum SSVEP magnitude difference between attend-left and attend-right trials. From these plots, a subset of subject-specific channels was chosen from which to extract the SSVEP features.

B. SSVEP Feature Extraction

From each 8-s attend period, three segments were extracted using rectangular windows starting at 0, 2, and 4 s, each of which counted as a single case for which the feature is derived. For the ALPHA sessions, these segments were 3.39 s long and for NONALPHA sessions, they were 3.52 s. These segment lengths where chosen so that they contained an integral number of cycles of the corresponding frequencies in order to minimize spectral leakage [19].

For ALPHA sessions, the power at 9.45 and 10.63 Hz was calculated for each of the preselected channels by multiplying each segment by sine and cosine functions at the corresponding frequencies and taking the root mean square of these two values. This is equivalent to performing a fast Fourier transform (FFT) at single frequencies. Similarly, the power at 14.17 and 17.01 Hz for preselected channels was calculated for NONALPHA sessions.

The following four-dimensional feature was then extracted for each case

$$F(n) = \left(X^{A}{}_{n}(f1), X^{A}{}_{n}(f2), X^{B}{}_{n}(f1), X^{B}{}_{n}(f2)\right) \quad (1)$$

where $X^{A}{}_{n}(f1)$ is the power at frequency $f1$ at electrode location *A* for case n. This feature was extracted for $\sim$ 10 pairs of electrodes *A* and *B* from the subset identified for each subject in order to identify exactly which pair would yield the best performance for each subject.

C. Alpha Band Feature Extraction

For each segment extracted as detailed in the previous section, the FFT was calculated at two pairs of electrode locations, PO7 and O1 over the left hemisphere and PO8 and O2 over the right hemisphere. The mean power over the alpha range (8–14 Hz) was then calculated at each electrode location, and consequently averaged over each electrode pair providing a measure of alpha power for each hemisphere.

D. EOG Analysis

Given the nature of the study and its intended application, it is crucial to detect, examine, and quantify horizontal eye movements as the subjects performed the task. To facilitate this, two EOG calibration sessions were carried out in order to characterize EOG patterns indicative of eye movements potentially resulting in inappropriate facilitation of SSVEP modulation. During the first EOG calibration session, subjects performed brief cued eye movements to four displacement angles between the fixation cross and the cued stimulus. This enabled a mapping from EOG amplitude (μV) to visual angle, assuming a linear relationship within the range of interest [20]. The angles used were 0.5°, 2.9°, 5°, and 7.1° corresponding to the end of the horizontal leg of the fixation cross, the inner edge, the center and the outer edge of the cued stimulus, respectively. On the basis of this mapping, prior to classification, any segments during which there was eye movement exceeding 1° visual angle were rejected. This resulted in a mean rejection rate of 5% for the ALPHA setting (range 3–53 out of 300 segments) and 7% for the NONALPHA setting (range 7–67).

The second EOG calibration session (GAZE-SHIFT) was an experimental session as described in the preceding sections but in this case the subject was instructed to shift gaze from the fixation cross to the centrally placed letters of the cued stimulus on every trial immediately following the cue, and hold for the duration of the trial. To examine the specific effect of eye movements on SSVEP modulations, EOG amplitude within each segment was correlated with a one-dimensional (1-D) feature capturing [albeit to a slightly lesser extent than (1)] the attention-dependent separability

$$F1d(n) = \log\left(\frac{X^{A}{}_{n}(f1)}{X^{B}{}_{n}(f2)}\right) \quad (2)$$

where electrode *A* is the location of maximum modulation of the SSVEP of frequency $f1$, and *B* of frequency $f2$. These correlations are calculated for all covert attention sessions and compared to those obtained from the overt sessions.

E. Classification

Linear discriminants were used as the classifier model for this study, providing a parametric approximation to Bayes' rule [21]. Optimization of the linear discriminant model is achieved through direct calculation and is very efficient thus lending itself well to real-time applications.

Performance of the LDA classifier was assessed using tenfold cross validation [21]. This scheme randomly divides the available data into ten approximately equal sized, mutually exclusive "folds." For a ten-fold cross validation run, ten classifiers are trained with a different fold used each time as the testing-set, while the other nine folds are used for the training data. Cross validation estimates are generally pessimistically biased, as training is performed using a sub-sample of the available data. For the OVERT session, due to the limited number of trials the LDA classifier performance was assessed using four-fold cross validation.

To assess performance using a combination of SSVEP and alpha band features, a six-dimensional feature vector was used, made up of the four SSVEP magnitude measures plus the alpha power for each hemisphere.

F. Information Transfer Rate

One objective measure of BCI performance is the bit rate, as defined by Wolpaw *et al.* [22]. For a trial with N possible symbols in which each symbol is equally probable, the probability (P) that the symbol will be selected is the same for each symbol, and each error has the same probability, the bit rate can be calculated as follows:

$$\frac{\text{Bits}}{\text{symbol}} = \log_2 N + P\cdot\log_2 P + (1-P)\cdot\log_2 \frac{1-P}{N-1} \quad (3)$$

$$\text{Bit Rate} = \frac{\text{Bits}}{\text{symbol}} * \frac{\text{symbols}}{\text{minute}}. \quad (4)$$

In this offline study, we can assess the information transfer rate achievable in theory taking each $\sim$ 3.4 s segment as a separate case in determining P and symbols per minute.

TABLE I
CLASSIFICATION ACCURACIES FOR ALL SUBJECTS OVER 5 SESSIONS USING THE SSVEP FEATURE ALONE. ALSO SHOWN ARE THE OPTIMAL ELECTRODE LOCATIONS FOR EACH SUBJECT

Subject:		Accuracy	Electrodes	
1	ALPHA	68.1%	POz	PO7
	NONALPHA	68.0%	PO8	P8
2	ALPHA	64.0%	O1	Pz
	NONALPHA	62.6%	PO8	Pz
3	ALPHA	70.7%	P7	PO3
	NONALPHA	67.0%	O1	PO3
4	ALPHA	72.4%	PO8	O1
	NONALPHA	70.6%	P5	PO7
5	ALPHA	78.1%	Oz	PO4
	NONALPHA	69.4%	P8	P4
6	ALPHA	72.3%	PO4	P O3
	NONALPHA	63.0%	TP8	P9
7	ALPHA	67.4%	P4	PO4
	NONALPHA	85.1%	POz	Oz
8	ALPHA	77.7%	PO3	PO4
	NONALPHA	62.6%	CP2	PO3
9	ALPHA	81.9%	O1	P6
	NONALPHA	86.0%	PO4	P10
10	ALPHA	63.9%	O2	P8
	NONALPHA	68.8%	Oz	P7
Average	ALPHA	71.7%	-	
	NONALPHA	70.3%	-	
Overt	ALPHA	94.7%	Oz	
	NONALPHA	95.2%	only	

TABLE II
CORRELATION COEFFICIENTS CALCULATED FOR EOG AMPLITUDE AND FEATURE $F1d(n)$ INCLUDING GAZE-SHIFT CALIBRATION SESSION

Subj	1	2	3	4	5
ALPHA	-0.03	0.00	0.03	0.06	0.09
NONALPHA	-0.05	-0.04	0.06	-0.02	0.00
6	7	8	9	10	Calib.
0.17	-0.04	-0.11	-0.03	-0.07	0.43
0.08	-0.02	0.03	0.05	-0.01	0.81

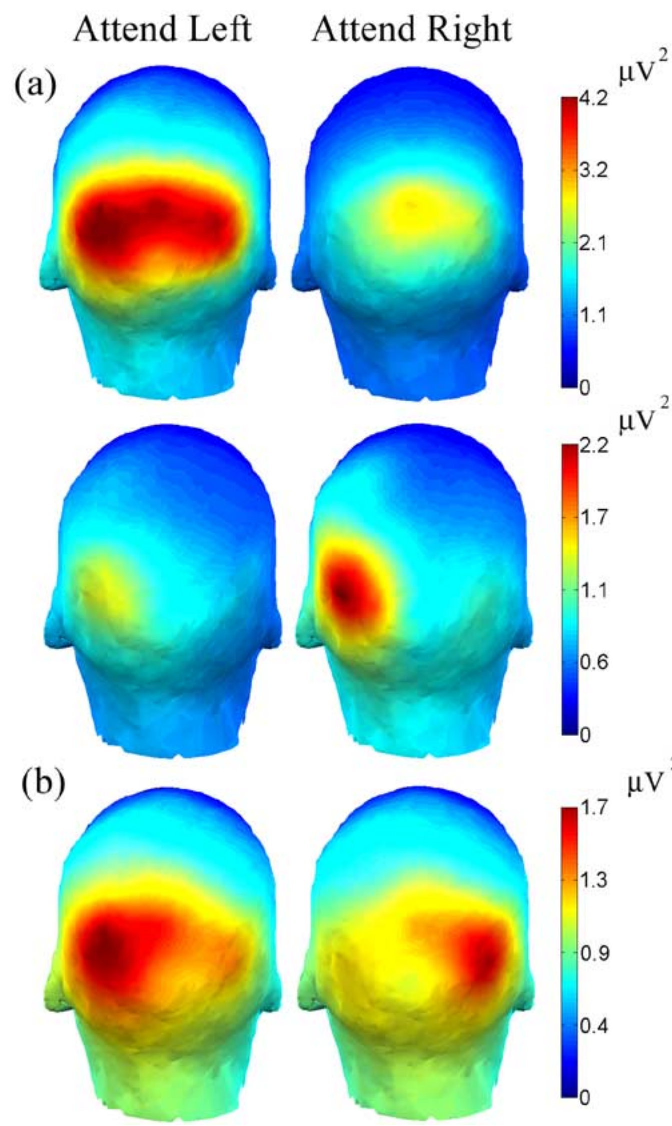

Fig. 2. Topographic maps for the NONALPHA sessions of a representative subject (4). (a) Average 14-Hz (top) and 17-Hz (bottom) SSVEP magnitude. (b) Average alpha band power for attend-left and attend-right trials.

IV. RESULTS

Table I shows the overall accuracies achieved by all ten subjects over five sessions for the SSVEP feature, as well as the optimal electrode locations for each subject. The highest accuracy was 86% achieved by subject 9. The average performance is comparable across ALPHA and NONALPHA cases and reduced considerably compared with results of overt attention sessions as expected. For further comparison, using O1 and O2 only as in [15] yields an average accuracy of 63%.

The correlation coefficients between mean EOG amplitude over each segment and the feature $F1d(n)$ were calculated for each experimental session and these were averaged for each subject (Table II). Confirming that the feature $F1d(n)$ captures SSVEP separability, the average accuracy using this feature was 67%. For comparison, the correlation coefficients for the GAZE-SHIFT EOG calibration sessions are 0.43 ($p < 0.001$, ALPHA) and 0.81 ($p < 1 \times 10^{-14}$, NONALPHA).

Example scalp maps plotting the modulations of the response to both stimulus frequencies can be seen in Fig. 2(a) for a representative subject for the NONALPHA setting. For this subject, the highest attentional modulation for the 14.17- and 17.01-Hz stimuli was seen at channels P5 and PO7.

To test the relationship between classification accuracy and behavioral performance on the task, correlations were carried out between the accuracies listed in Table I and the number of errors in counting during the experiments. Moderate negative correlations were found, approaching significance (ALPHA $r = -0.6$, $p = 0.066$; NONALPHA $r = -0.45$, $p = 0.197$). It is worth noting that a count of up to eight targets was possible in the ALPHA setting, with no repeats, and up to ten in the NONALPHA setting. In addition, targets were often presented close to the beginning or end of the attend period such that inclusion in the count for that trial was unclear. It is possible that if

TABLE III
CLASSIFICATION ACCURACIES FOR NONALPHA SESSIONS FOR ALL SUBJECTS USING THE SSVEP FEATURE, ALPHA BAND FEATURE AND COMBINATION

Subject:	SSVEP	Alpha Band	SSVEP + Alpha Band
1	68.0%	59.3%	74.5%
2	62.6%	58.5%	63.1%
3	67.0%	59.6%	70.7%
4	70.6%	85.7%	87.0%
5	69.4%	72.9%	76.1%
6	63.0%	82.7%	86.5%
7	85.1%	66.0%	85.5%
8	62.6%	83.7%	80.0%
9	86.0%	74.1%	85.7%
10	68.8%	85.5%	85.8%
Average	70.3%	72.8%	79.5%

the ambiguity was removed from the behavioral measure, and indeed with more subjects, these negative correlations would reach significance.

Table III shows the classification accuracies using the SSVEP features alone (from Table I), the alpha band features alone (reported in [18]) and all features combined. Only the NONALPHA sessions were examined, in which the lack of spectral overlap ensures independence of the SSVEP amplitudes from alpha modulations. Fig. 2(b) shows the topography of alpha band power for attend-left and attend-right trials for Subject 4. Focal increases in alpha power can be seen located contralateral to the stimulus to be ignored, similar to the findings of Worden *et al.* [17].

Average information transfer rates were calculated for all subjects across all sessions using (3) and (4). The average information transfer rate across subjects for the SSVEP features alone was 2.1 b/min, for the alpha band features it was 2.6 b/min, and for the combination it was 4.6 b/min. A peak information transfer rate of 7.5 b/min was achieved by subject 4 using the combination method.

V. DISCUSSION

The results of this study show that binary decision-making using covert attention to visual stimuli is indeed possible using electrophysiological correlates of spatial attention such as the steady-state visual evoked potential. With recent BCI research moving toward more invasive technologies and focusing more on signal processing, this represents a valuable new EEG-based approach that focuses on cognitive mechanisms that are developed naturally through everyday life, and that are truly independent of neuromuscular function.

Direction of spatial attention can be classified using SSVEP magnitude alone with an accuracy of approximately 71%. Importantly, correlation coefficients calculated for accuracies and error rates are negative and marginally significant, suggesting that performance in producing the appropriate SSVEP modulations on cue by effectively deploying spatial attention hinges on compliance, i.e., high motivation leads to improved performance. This is central to the success of any practical BCI systems employed by the disabled [1], [2].

The advantage in choosing subject-specific electrode locations is demonstrated by the widely varying scalp sites identified as optimal for each of the ten subjects. In [13], the authors report that, in general, attentional modulation of SSVEP's is manifest mostly over the right hemisphere. However, in [11], higher stimulation frequencies are employed, and sites of maximum modulation are identified on the hemisphere contralateral to the attended stimulus. As exemplified in Fig. 2(a), some individuals participating in this study demonstrated greater modulations over the left hemisphere. Thus, subject-by-subject identification of optimal locations appears to be needed in such a system as that proposed in this study.

The results of EOG post-processing highlight to what degree the performance in this study was indeed independent of peripheral muscles and nerves. Detection of trials containing eye movements in excess of 1° resulted in 6% cases rejected overall. Also, correlation coefficients listed in Table II quantify the effect of any eye movement measured in the EOG on the 1-D feature. Correlation values for the experimental sessions were much reduced in comparison with the correlation value for the GAZE-SHIFT EOG calibration run.

The results of using SSVEP features alone suggest that no advantage is gained by using frequencies either within the alpha band or outside. Accuracy differed by at least 15% only for subjects 7 and 8, with the advantage apparent for the NONALPHA setting for subject 7 and the opposite seen for subject 8. This may reflect a tradeoff resulting from feature properties at different frequencies. On one hand, the resonant properties of alpha [23] lead to enhanced SSVEP magnitudes on stimulation within the alpha band, and this results in clearly resolvable spectral peaks and thus a higher signal to noise ratio. This is of considerable benefit in a real-time BCI scenario where a robust baseline SSVEP level is required at all times. On the other hand, it is possible that SSVEPs generated within the alpha band are subject to the same modulations as those affecting the wider alpha band, of which there are many reports (e.g., [24]). In particular, attention-dependent increases of parieto-occipital alpha, as described in [16] and [17], may degrade performance if scalp locations for SSVEP features coincide with these alpha modulations. However this depends on the degree to which instability in the wider alpha band affects a narrow-bandwidth SSVEP signal, which is unknown. This suggests that it is not only important to select channels on a subject-by-subject basis, but that the choice of stimulus frequencies should also be specific to individual subjects.

By capitalizing on the modulations of parieto-occipital alpha [16], [17] by combining SSVEP features with bilateral alpha band features in NONALPHA sessions an improved average accuracy of 79% is achieved. As can be seen from the accuracies in Table III, the reliability of SSVEP magnitude features and of alpha band power features is somewhat independent across subjects. For example, subjects 7 and 9 performed well using SSVEP features but not so well using alpha band features. In contrast subjects 4, 6, 8, and 10 performed best using alpha band features. Combining the features however results in all six of these subjects achieving an accuracy of at least 80%. In other cases, the combination provides a significantly higher accuracy than either SSVEP or alpha band features alone.

VI. Conclusion

Utilizing a combination of electrophysiological correlates of visual spatial attention (SSVEP magnitudes and alpha band power modulations), binary selections can be made with an average accuracy of 79%. It is found in this study that careful selection of electrode locations on an individual basis leads to an advantage in optimizing separability of SSVEP magnitude features. It remains unclear as to whether an advantage can be gained in the selection of stimulation frequencies, however, stimulation outside the alpha band allows the alpha band to be used itself in improving accuracy. This provides a novel independent BCI design which relies in no way on the normal output pathways of peripheral muscles and nerves, and thus may have considerable impact on alternative communication and control technology for the disabled.

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