ARTICLE TEMPLATE

Alpha-band lateralization during auditory selective attention for brain-computer interface (BCI) control

Martin Spüler a and Simone Kurek a

aDepartment of Computer Engineering, Eberhard-Karls University Tübingen, Tübingen, Germany

ARTICLE HISTORY
Compiled November 7, 2017

ABSTRACT
In this paper, we investigated selective attention to auditory stimuli as control mechanism for a Brain-Computer Interface (BCI). For BCIs using visual stimuli, the use of steady state or code modulated visual evoked potentials yields a high performance. In this work, those approaches are transferred and tested in the auditory domain. The attentional modulation of code-modulated auditory evoked potentials (c-AEPs) and steady state auditory evoked potentials (SSAEPs) showed only a small effect, which is not sufficient for BCI control. However, for both kinds of stimuli, we found a spatial attention-related alpha-band lateralization which allows classification accuracies above 70% and thereby can be used for controlling a BCI.

KEYWORDS
electroencephalography (EEG), auditory steady state response (ASSR), spatial attention, covert attention, frequency tagging, noise tagging

1. Introduction

A Brain-Computer Interface (BCI) is a device that enables a user to control a computer or a computer-connected device by brain activity only [1]. While applications range from emulating mouse- and keyboard-control of a computer [2] over the control of robotic arms or wheelchairs to BCI-supported rehabilitation of stroke patients [3], restoring communication in completely paralyzed patients is one of the major goals of BCI research. There are a variety of different BCI systems available for communication, with the fastest systems relying on visual evoked potentials (VEPs). Steady state visual evoked potentials (SSVEP) [4] can be used, for which the visual stimuli are modulated with a different frequency and/or phase. The properties of the attended stimulus can be found in the electroencephalography (EEG) signal over the visual cortex and thereby it can be detected which stimulus the user is attending. By coupling a stimulus with a specific action or selection of a letter, it can be used for BCI communication. A different approach uses code-modulated visual evoked potentials (c-VEP) [5], in which the stimuli are modulated with the same pseudo-random code, but with a different time-shift of the code for each stimulus. As attention to a code-modulated stimulus results in a characteristic response in the EEG, the time-lag of the c-VEP can be used to detect which stimulus the user is attending.

CONTACT M. Spüler. Email: spueler@informatik.uni-tuebingen.de
However, BCI systems using visual stimuli cannot be used by patients with a more severe disease progression, who also suffer from paralyzed eye muscles. To enable BCI usage for those patients, different approaches were used to implement auditory BCIs. The most popular approach is to transfer the P300 speller paradigm to the auditory domain, which can provide the ability for binary decisions [6] or enable the user to select letters [7, 8].

In the visual domain, VEP-based BCIs clearly outperform P300-based BCIs in terms of communication speed, which is a strong argument to also investigate if the idea of VEP-based BCIs can be transferred to the auditory domain. When a person listens to a sound, which is modulated with a specific frequency, a steady state auditory evoked potential (SSAEP) can be measured in the EEG. This SSAEP, also called auditory steady state response (ASSR), is phase-locked to the stimulus and strongest at around 40 Hz [9]. Regarding the effect of attention on the SSAEP, literature is ambiguous with some studies finding an effect of attention-related modulation of the SSAEP, while no effect was found in other studies. A good overview over multiple studies providing different outcomes can be found in [10]. Mahajan et al. [10] also suggest that it might depend on the modulation frequency as they found an attentional modulation of the SSAEP for 16 Hz and 23.5 Hz, but not for higher frequencies (32.5 Hz and 47 Hz). However, this is also contrasted by other studies which found an attentional modulation of the SSAEP for stimuli at 37 Hz and 43 Hz [11]. So far, the reasons are unclear, why in some cases the SSAEP is modulated by attention, while attention doesn’t seem to have an effect in other cases.

Despite this unclarity, there were some approaches to utilize auditory evoked potentials for BCI communication. Kim et al. [11] and Farquhar et al. [12] used SSAEPs for an auditory version of an SSVEP BCI. While both works have shown that selective attention to auditory stimuli can be used for BCI control, Hill et al. [13] showed that using the P300 for auditory BCIs works better than using SSAEPs, as they found no attentional modulation of the SSAEP. Farquhar et al. [12] additionally used noise-modulated auditory stimuli, which are similar to the idea of using code-modulated auditory evoked potentials, providing evidence that the approach of the c-VEP BCI can be transferred to the auditory domain.

Separate from an attentional modulation of the SSAEP, there is another attention-related effect described in literature: an alpha-band lateralization depending on spatial attention. This effect was shown for visual spatial attention [14] and was also used for BCIs based on visual spatial attention [15–17]. Banerjee et al. [18] compared visual and auditory spatial attention and found similar alpha-band lateralization for both modalities, but also topographic differences suggesting sensor-specific mechanisms of attention control. Thorpe et al. [19] also investigated lateralization effects to auditory speech stimuli and found lateralization effects not only in the alpha, but also in the theta and beta-band. Strauß et al. [20] also investigated cortical alpha oscillations and proposed that alpha plays a role in inhibiting noise to improve the selective attention to task-relevant sounds. To the best of our knowledge, alpha-band lateralization due to auditory spatial attention has not been investigated for BCI control, yet.

In this work, we investigated the use of different auditory stimuli to elicit SSAEPs and c-AEPs with the aim to test how well a direct transfer of the methods used in SSVEP and c-VEP BCIs works in the auditory domain. Further, we investigated if an alpha-band lateralization can be used as control mechanism for auditory BCIs.
2. Methods

2.1. Stimuli design

The subjects were presented with two different sounds simultaneously from two speakers located to the left and to the right of the subject. Stimuli were presented monophonically, so that the left stimulus was played on the left speaker, and the right stimulus on the right speaker. But as sounds from both speakers are perceived by both ears, the stimuli were perceived binaurally. The speakers were placed approximately 80 cm distance to the subject with an angle of ±45°. The sounds consisted of a carrier frequency (500 Hz for left, 700 Hz for right) which were modulated with different methods. As the aim of this study was to investigate if the approach of SSVEP and c-VEP can be transferred to the auditory domain, the following methods were used to elicit SSAEPs:

- Sine amplitude modulated (SAM): The amplitude of each carrier sound was modulated by a sine wave. For the left sound the modulation frequency was 38 Hz and for the right sound 42 Hz.
- Tone bursts (TB): Short (10 ms) tone bursts consisting of the respective carrier frequency with a 5 ms ramp up and an 5 ms ramp down were played with a frequency of 38 Hz for the left and 42 Hz for the right side.

To elicit c-AEPs, the following two methods were used:
- Code-modulated with two different codes (CMD): The amplitude of the carrier sounds was modulated with a 127 bit Gold sequence [21]. For the left and right

---

**Figure 1.** Auditory stimuli used in this experiment, with the sound of the left speaker shown on the left and the sound of the right speaker shown on the right. A: Sine amplitude modulated (SAM) B: Tone bursts (TB) C: Code-modulated with two different codes (CMD) D: Code-modulated with shifted codes (CMS)
sound, different sequences were used.

- Code-modulated with shifted codes (CMS): The amplitude of the carrier sounds was also modulated with a 127 bit Gold sequence [21], but the same sequence was used for both sides, shifted by 64 bit for the right side.

The different stimulus types are also visualized in figure 1. Due to the different carrier frequencies of the two sounds (coming from left and right), the sound volume might be perceived differently. To ensure that both sides are perceived equally loud, the subjects were asked to adjust the perceived volume of the left side to the perceived volume of the right side. Afterwards, subjects were asked to adjust the overall volume to a comfortable level.

2.2. Experimental design

Ten subjects participated in the experiment. The study was approved by the local ethics committee of the Medical Faculty at the University of Tübingen. To measure EEG, a set of 29 active electrodes (actiCap, BrainProducts GmbH) was used. They were attached to the scalp, placed according to the extended international electrode 10–20 placement system (see figure 2B for details). Three additional electrodes were used to record an electrooculogram (EOG); two of them were placed horizontally at the outer canthus of the left and right eye to measure horizontal eye movements and one was placed in the middle of the forehead between the eyes to measure vertical eye movements. Ground and reference electrodes were placed on the left and right mastoids, respectively. After recording the data, the signals were re-referenced to FCz. EOG and EEG signals were amplified by two 16-channel biosignal amplifier systems (g.USBamp, g.tec) and sampled at a rate of 512 Hz. EEG data were high-pass filtered at 0.5 Hz and low-pass filtered at 100 Hz, both by an 8th order Butterworth filter, during the recording. Furthermore, a notch-filter (4th order Chebyshev filter) was applied between 48 Hz and 52 Hz to filter out power line noise.

The experiment was divided into 32 blocks. Each block consisted of 25 trials, with each trial having a length of 2 seconds. In each block, one of the stimuli was used and the subject had to attend either to the left or to the right side. The order of the blocks was randomized. In total, 200 trials for each stimulus type were recorded per subject, so that the subject attended to the left sound in 100 trials and to the right sound in 100 trials.
2.3. Classification on steady-state auditory evoked potentials (SSAEPs)

For the classification of SSVEPs, using canonical correlation analysis (CCA) for classification shows better results than classification on the power spectrum [22], which is why this method was used to classify SSAEPs in this work. As sounds were modulated with frequencies of $f_1 = 38$ Hz and $f_2 = 42$ Hz, two reference signals $Y_i$ were created consisting of the main frequency and its second harmonic.

$$Y_i = \begin{pmatrix} \sin(2\pi f_i t) \\ \cos(2\pi f_i t) \\ \sin(2\pi 2f_i t) \\ \cos(2\pi 2f_i t) \end{pmatrix}$$ (1)

The canonical correlation between the multi-channel EEG signal $X$ using all channels and both reference signals $Y_i$ is computed and the frequency with the highest canonical correlation is detected. To test if the classification accuracy is significantly above chance level, a permutation test was performed in which the labels were permuted 10,000 times.

2.4. Classification on code-modulated auditory evoked potentials (c-AEPs)

For the classification based on c-AEPs, a method based on CCA and support vector machine (SVM) was used, as this combination was successfully applied in previous works to detect code-modulated visual evoked potentials (c-VEPs) [5, 23]. First, a spatial filter is constructed using CCA [24] on all EEG channels. On the spatially filtered signal, a linear SVM is trained to classify if the left or the right stimulus was attended. For training the SVM, only the inner electrodes (F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4, O1, Oz, O2) were used.

To evaluate classification accuracy, a 10-fold cross-validation was performed with the spatial filter and the SVM being trained inside the cross-validation. To test if classification accuracy is significantly above chance level, we performed a permutation test with 10,000 iterations.

2.5. Classification on power spectral density (PSD)

For classification of the user’s intention, based on changes in the power spectral density, we first extracted the power spectrum for the signal at each electrode using Burg’s maximum entropy method [25] with a model order of 32. The power spectrum of the inner electrodes (F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, P4, O1, Oz, O2) from 8 to 30 Hz in bins of width of 1 Hz were used for classification. This frequency range was deliberately chosen to include alpha- and beta-band, but to exclude the frequencies of the SSAEP, so that only effects related to spatial attention were used for this classification. A SVM with linear kernel was trained on the data. To estimate classification accuracy, a 10-fold cross-validation was used and a permutation test with 10,000 iterations was used to test if classification accuracy is significantly above chance level.

5
3. Results

Estimating the frequency spectrum using a fast fourier transformation (FFT) revealed that a clear SSAEP was elicited at 38 Hz and 42 Hz for the two frequency-modulated stimuli (SAM, TB). However, there was no significant attention-related modulation for the SAM stimuli \( p > 0.05, \) Wilcoxon ranksum test. For the TB stimuli, we found a significant attention-related modulation \( p < 0.05, \) Wilcoxon ranksum test. The power spectrum averaged over all subjects showing the attention-related SSAEP modulation can be seen in figure 3B.

Regarding other attention-related effects in the EEG data, we found a strong attention-related lateralization of the alpha-band. Alpha-band lateralization was computed as the power difference between two corresponding electrodes over opposite hemispheres (e.g. C3 and C4). As can be seen in figure 3A, there is a shift in alpha power corresponding to an increase in alpha power ipsilateral to the attended side and a decrease in alpha power contralateral to the attended side. This effect is highly significant \( p < 0.0001, \) Wilcoxon ranksum test) for all central, parietal, and occipital electrodes.

![Figure 3](image)

**Figure 3.** A: Difference in lateralized alpha power during selective attention (attend right minus attend left) B: power spectrum during attention to tone bursts (TB) at electrode Pz averaged over all subjects. Changes in power at 38 Hz and 42 Hz due to attentional shift are significant \( p < 0.05, \) Wilcoxon ranksum test)

Regarding the classification accuracies, we found no attentional modulation of the SSAEP with SAM stimuli, as the classification accuracy was below chance level. However, with tone burst (TB) stimuli, we achieved an average accuracy of 52.9 % which is significantly above chance level \( p < 0.05, \) Wilcoxon ranksum test), but insufficient for BCI control. Detecting the c-AEP worked better with 54.3 % on average, which is significantly above chance level, but also insufficient for BCI control. In contrast, the alpha-band lateralization allowed for a much higher classification accuracy with 71.3 % on average, when the PSD was used as feature. All classification results are summarized in table 1.

To quantify the amount of information that could be transmitted using a BCI based on the alpha lateralization, we used the following equation to compute the information transfer rate (ITR) [26] for one trial:

\[
ITR(N, P) = \log_2 N + P \cdot \log_2 P + (1 - P) \cdot \log_2 [(1 - P)/(N - 1)]
\]  

(2)

With \( N=2 \) being the number of classes, \( P=71.3 \) % being the accuracy and including a 0.5 s break between two trials, this results in 3.24 bit/min.
Table 1. Classification accuracy averaged over all subjects for the different sound types using different classification methods, that either rely on classifying the steady-state auditory evoked potential (SSAEP), the code-modulated auditory evoked potential (c-AEP) or the power spectral density (PSD). Sound types are: Sine amplitude modulated (SAM), Tone bursts (TB), Code-modulated with two different codes (CMD), Code-modulated with shifted codes (CMS). If accuracy is significantly above chance level (Wilcoxon ranksum test), it is indicated by asterisks: ‘*: p < 0.01, ‘**: p < 0.001, ‘***: p < 0.0001. Values without asterisks are not significant (p > 0.05).

<table>
<thead>
<tr>
<th></th>
<th>SSAEP (%)</th>
<th>c-AEP (%)</th>
<th>PSD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAM</td>
<td>49.3</td>
<td>-</td>
<td>70.9***</td>
</tr>
<tr>
<td>TB</td>
<td>52.9*</td>
<td>-</td>
<td>70.5***</td>
</tr>
<tr>
<td>CMD</td>
<td>-</td>
<td>54.8***</td>
<td>71.3***</td>
</tr>
<tr>
<td>CMS</td>
<td>-</td>
<td>53.9**</td>
<td>72.3***</td>
</tr>
<tr>
<td>average</td>
<td>51.1</td>
<td>54.3</td>
<td>71.3</td>
</tr>
</tbody>
</table>

4. Discussion

In this paper, we tested different auditory stimuli, which should elicit SSAEPs and c-AEPs, with the aim to test if methods for detecting SSVEPs and c-VEPs can be transferred to the auditory domain. While those stimuli elicited a clear SSAEP, we found no evidence for attentional-modulation of the SSAEP for sine amplitude modulated stimuli and could not use those stimuli for BCI control. When using tone bursts, we found a significant (p < 0.05) attention-related modulation of the SSAEP and could classify the attended side with an accuracy of 52.9%. Although this is significantly above chance level accuracy, it is insufficient for BCI control. Comparing these results to the literature, this is in line with Hill et al. [13] who used sine amplitude modulated stimuli and found no attentional modulation of the SSAEP. Further, it agrees with Kim et al. [11] who found an attentional modulation of the SSAEP using burst stimuli. The fact that no attentional modulation of the SSAEP was found for sine amplitude modulated stimuli, while an effect was found for burst stimuli highlights the importance of stimulus design and that it may depend on the type of stimulus if the SSAEP is modulated by attention. As Mahajan et al. [10] speculated about the reasons why an attentional modulation of the SSAEP is found in some experiments and not in others, the influence of stimulus design needs to be added to the list of likely reasons. Bharadwaj et al. [27] go in a similar direction by suggesting that results are likely influenced by how the stimuli are presented (binaural or dichotic).

While we could show that the methods for classification of SSVEP and c-VEP can be applied to detect SSAEP and c-AEP, the classification results with accuracies below 55% are too low for sufficient BCI communication. However, we found that the selective attention to spatially located auditory stimuli causes an alpha-band lateralization, which can be used for BCI control and allow classification accuracies ≥ 70%. As vision is mostly impaired in late stage ALS patients, the use of auditory stimuli for BCI is a promising method to restore communication in those patients. While auditory P300 BCIs work well, they only offer a synchronous communication, in which a command (or letter) is selected in a predefined time interval. The use of alpha-band lateralization could be used to implement asynchronous BCI applications, which can not be properly realized by detecting an auditory evoked P300. Further, as there are also auditory P300 BCIs that rely on spatially located stimuli [28], alpha-band lateralization and P300 detection can be combined to improve the accuracy of those BCIs.
But since alpha-band lateralization to auditory spatial attention has so far been only demonstrated in healthy subjects, the effect needs to be confirmed in a patient population before it can be put to use in said patients.

Funding

This work is supported by the *Deutsche Forschungsgemeinschaft* (DFG; grant SP-1533\2-1).

References


[23] Spüler M, Rosenstiel W, Bogdan M. One class SVM and Canonical Correlation Analysis increase performance in a c-VEP based Brain-Computer Interface (BCI). In: Proceedings of 20th European Symposium on Artificial Neural Networks (ESANN 2012); 04; Bruges, Belgium; 2012. p. 103–108.


