Unsupervised Online Calibration of a c-VEP Brain-Computer Interface (BCI)

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Abstract. Brain-Computer Interfaces (BCIs) can be used to give paralyzed patients a means for communication. But so far, only supervised methods have been used for calibration of an online BCI. In this paper we present a method that allows to calibrate a BCI online and unsupervised. Based on offline data we show that the unsupervised calibration method works and validate the results in an online experiment with 8 subjects, who were able to control the BCI with an average accuracy of 85 %. We thereby have shown for the first time that an online unsupervised calibration of a BCI is possible and allows for successful BCI control.

Keywords: Brain-Computer interface (BCI), unsupervised learning.

1 Introduction

A Brain-Computer Interface (BCI) is a device that enables a user to control a computer by pure brain activity, which is usually recorded by electroencephalography (EEG). The main application for BCIs is to give paralyzed people a means to communicate, but so far, there are no reports for successful BCI control in complete locked-in patients [1].

Recently, we could show a BCI based on code-modulated visual evoked potentials (c-VEPs) to achieve very high communication speeds that made it possible for subjects to spell an average of 21.3 error-free letters per minute [2]. While this BCI used an unsupervised online adaptation, it still depended on a supervised calibration, for which labeled data is needed to calibrate the BCI on the users brain activity. When looking at BCIs that use other paradigms like motor imagery or P300, there are also different unsupervised adaptation methods [3], but they all depend on a supervised calibration, which needs labeled data.

So far, Eren et al. [4] are the only ones, who have shown that a BCI can be calibrated completely unsupervised without the need for labeled training data. Using Gaussian Mixture Models, they have shown in an offline analysis of motor imagery BCI data that their method works for 3 out of 6 subjects.

In this paper, we present a method for completely unsupervised calibration of a c-VEP BCI and show it to work for all our subjects in an online study. We further discuss how unsupervised calibration might be useful for complete locked-in patients, for whom supervised calibration does not work [1].

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2 Methods

The c-VEP BCI that we used is based on the system we described in previous publications [2,5]. It consists of 32 visual stimuli (called targets), which are modulated by a pseudo-random code with a length of 63 bit. Each target is modulated with the same code, but the code is circular-shifted by a different number of bits for each target. When the subject is looking at one of the stimuli, a c-VEP can be found in the EEG signals. Based on multiple trials, the average c-VEP waveform can be extracted. By circular-shifting the average c-VEP waveform, a template for each target can be obtained, which represents the average c-VEP waveform that is expected when the subject looks at the corresponding target. To identify which of the targets the user wants to select, the EEG-signal is compared to all templates and the template which is closest to the measured EEG signal is chosen.

While the previous system with supervised calibration used 32 targets, we only used two targets (J and W) for the unsupervised calibration. Regardless of the number of targets used for calibration, the system can be tested and used with 32 targets after calibration is finished.

To achieve an unsupervised calibration of the c-VEP BCI, the first step is to perform an unsupervised channel selection to find the EEG channel on which the c-VEP is strongest. If that channel is found, the templates can be generated in an unsupervised manner, as described below.

2.1 Unsupervised Channel Selection

The goal of the unsupervised channel selection is to find the channel for which the c-VEP is strongest, which means finding the channel for which the c-VEP has the lowest variance.

Since only two shifts are possible (20 bit and 46 bit, representing targets J and W), a new dataset is created that contains each trial of the calibration dataset twice, one shifted by -20 bit and the other by -46 bit. By doing this, the data should contain 3 clusters: one cluster containing the data that is shifted with the correct shift, one cluster for data with a true shift of 20 bit that was shifted by -46 bit, and one cluster with a true shift of 46 bit that was shifted by -20 bit. Since the cluster with the data shifted by the correct number of bits should contain twice the number of trials than each of the other 2 clusters, a one-class Support Vector Machine (OCSVM) [6] can be trained to reject the smaller clusters as outliers.

Therefore, the data for each channel is normalized to have a mean of zero and a variance of 1. The normalized data is used to train a OCSVM with a linear kernel and $\nu = 0.4$ to find a hyperplane which separates the one large cluster from the two small ones. The size of the margin can then be used as an approximation of the variance. A larger margin means a smaller variance of the c-VEP data and thereby a stronger c-VEP response. The channel for which the margin is largest is then chosen for the unsupervised template generation.

2.2 Unsupervised Template Generation

When the channel with the strongest c-VEP is found, the k-means algorithm [7] is applied on the calibration dataset using the respective channel to find two clusters that represent the data for the two targets. Since the k-means algorithm is only used to find clusters, it is unknown, which cluster represents which class. To assign classes to both clusters, two leave-one-out estimations are performed, in which both of the two possible assignments are tested (Cluster A -> Class A or Cluster A -> Class B). For each of the n folds of the leave-one-out estimation, templates are generated using the calibration data of n-1 trials (with the labels associated with one of the possible assignments), and the remaining trial is classified by choosing the template which has the highest correlation. Due to the circular-shift property of the c-VEP BCI, templates were generated for 32 classes with each class having an additional 2 bit shift (total length of modulating code was 63 bit). For the classification of the remaining trial, also 32 possible classes were used.

Since templates for all 32 classes are generated, but only data containing 2 classes is used for the calibration, and the difference in the shift of both classes is uneven depending on the direction of the shift (46-20 = 26 bit or 20-46 = (-26 mod 63) = 37 bit), the assignment with the highest estimated accuracy is the one that assigns the correct class to each cluster.

Thereby class labels are available for each target. Although the unsupervised channel selection is an important step for the unsupervised template generation to work, we empirically found a subsequent channel selection based on the estimated labels to further improve the results. Therefore, leave-one-out estimations are performed for all channels to find the channel that yields optimal results.

After class labels and the best channel for classification are known, templates and spatial filter can be generated as explained in our previous publication [5].

2.3 Offline Analysis

To evaluate the unsupervised calibration method, data recorded from a previous c-VEP study [2] was used for an offline analysis, in which an online experiment was simulated. The first 64 trials (used for supervised calibration in the previous online study) were used for unsupervised calibration. Since the data was recorded with the subjects attending each of the 32 targets 2 times, the trials were shifted in a way that half of the trials had a shift corresponding to target letter J with a shift of 20 bit and the other half corresponding to target letter W with a shift of 46 bit.

The remaining 576 trials of the session were used to estimate the accuracy. Two different approaches were tested: One approach, in which the shift of the trials did not change and thereby all 32 classes were present in the data. For the other approach, the trials were shifted similar to the calibration data to simulate the use of a 2-class c-VEP BCI system.

In addition, the benefit of the unsupervised channel selection was evaluated by replacing the unsupervised channel selection with a fixed selection of either electrode P4 or PO3, which are the electrodes where the c-VEP is strongest on average.

Since the signal-to-noise ratio of the signal may be too low to allow for unsupervised calibration, tests were run in which multiple trials were averaged, similar to the method using multiple sequences in the popular P300 BCI speller. x subsequent trials were averaged to generate one new trial, thereby decimating the total number of trials by a factor of x. While still the first 64 trials of the new dataset were used for calibration, the number of test trials varied depending on x.

2.4 Online Experiment

To validate the results from the offline analysis, another online experiment was conducted, in which a c-VEP BCI with 2 targets was calibrated unsupervised and tested afterwards. Eight subjects (mean age 25, 2 female) participated in this experiment, with none of them having previous BCI experience.

Calibration was done in a co-adaptive manner, in which the first 64 trials were used for unsupervised calibration and the classifier was updated after every trial, so that feedback could be given also during the unsupervised calibration. The subjects were instructed to decide freely, which of the two targets to attend, but not to switch the target consistently every time and not to attend one target for more than 5 consecutive trials.

After calibration was finished, the accuracy of the calibrated c-VEP BCI was tested in another 128 trials. For testing the BCI with 2 targets, the subjects were instructed to alternate between both targets.

Calibration and testing were done two times. One time without averaging over trials and one time with averaging 2 trials.

Since the subjects could freely decide what targets to attend during the calibration, the data could not be used to simulate a supervised adaptation. Instead, another experiment was run with the same subjects, in which a supervised calibration [5] was used with 2 targets and 64 trials. To test the accuracy, the BCI was run with 2 targets for another 128 trials. This experiment was only done once without averaging for each subject.

3 Results

3.1 Offline Analysis

The accuracies obtained during a simulated online session with 2 targets after an unsupervised calibration are displayed in table 1 for a different number of trials averaged. Table 2 shows the obtained results for a simulated online session with 32 targets.

While for 2 classes, without averaging multiple trials, a mean accuracy of 90.85 % could be reached, averaging of 2 trials reached a mean accuracy of 97.4 % which is significantly better than without averaging trials ($p = 0.0051$, paired t-test). Looking at the results with a higher number of averages, the use of 3 or more averages is not significantly better than its preceding number of averages ($p > 0.1$).

For 32 classes, a mean accuracy of 76.43 % could be reached, while averaging over 2 trials yields a mean accuracy of 92.61 %, which is significantly higher ($p < 0.001$). Again the use of more than 2 averages does not yield a significant improvement ($p > 0.1$) compared to its preceding number of trials averaged.

Table 1. Offline results for unsupervised calibration with 2 targets and different number of trials used for averaging

	Number of trials averaged				
	1	2	3	4	5
AA	87.81 %	100.00 %	100.00 %	100.00 %	100.00 %
AB	65.94 %	81.25 %	69.81 %	85.00 %	85.94 %
AC	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
AD	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
AE	65.94 %	82.50 %	95.28 %	98.75 %	100.00 %
AF	96.56 %	100.00 %	100.00 %	100.00 %	100.00 %
AG	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
AH	78.75 %	90.62 %	80.19 %	77.50 %	85.94 %
AI	70.31 %	99.38 %	99.06 %	100.00 %	100.00 %
BA	97.50 %	99.38 %	100.00 %	100.00 %	100.00 %
BB	98.44 %	100.00 %	100.00 %	100.00 %	100.00 %
BC	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
BD	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
BE	95.00 %	100.00 %	100.00 %	100.00 %	100.00 %
BF	99.06 %	100.00 %	100.00 %	100.00 %	100.00 %
BG	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
BH	81.25 %	100.00 %	100.00 %	100.00 %	100.00 %
BI	98.75 %	100.00 %	100.00 %	100.00 %	100.00 %
mean	**90.85 %**	**97.40 %**	**96.91 %**	**97.85 %**	**98.44 %**

To estimate the benefit of the unsupervised channel selection, the results for the comparison of the unsupervised channel selection with channels PO3 and P4 is shown in table 3 and table 4. When pooling the results for all tested number of averages, the unsupervised channel selection in the simulated c-VEP BCI with 2 targets performs significantly better than a fixed selection of channel PO3 ($p < 0.0005$, paired t-test) and significantly better than a selection of P4 ($p < 0.05$). When simulating the use of a c-VEP BCI with 32 targets, the unsupervised channel selection still performs significantly better than PO3 ($p < 0.005$) and P4 ($p = 0.01$).

3.2 Online Experiment with 2 Targets

The results from the online experiment are shown in table 5. The results show that the BCI worked well for all subjects after unsupervised calibration with an

Table 2. Offline results for unsupervised calibration with different number of trials used for averaging. While calibration was done on data from 2 targets, data with 32 targets was used for performance evaluation.

	Number of trials averaged					supervised
	1	2	3	4	5	1
AA	75.94 %	99.38 %	100.00 %	100.00 %	100.00 %	96.88 %
AB	21.56 %	46.88 %	53.77 %	70.00 %	85.94 %	80.03 %
AC	98.44 %	99.38 %	100.00 %	100.00 %	100.00 %	98.61 %
AD	99.69 %	100.00 %	100.00 %	100.00 %	100.00 %	98.96 %
AE	18.75 %	58.13 %	87.74 %	97.50 %	100.00 %	60.24 %
AF	86.88 %	98.75 %	100.00 %	100.00 %	98.44 %	97.74 %
AG	99.69 %	100.00 %	100.00 %	100.00 %	100.00 %	99.83 %
AH	41.88 %	73.75 %	69.81 %	68.75 %	76.56 %	72.72 %
AI	43.75 %	99.38 %	99.06 %	98.75 %	100.00 %	96.18 %
BA	88.12 %	98.75 %	100.00 %	100.00 %	100.00 %	94.44 %
BB	87.19 %	96.25 %	92.45 %	100.00 %	96.88 %	97.48 %
BC	96.88 %	99.38 %	100.00 %	100.00 %	100.00 %	98.09
BD	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
BE	86.88 %	100.00 %	100.00 %	100.00 %	100.00 %	99.31 %
BF	92.81 %	98.12 %	99.06 %	100.00 %	100.00 %	94.97 %
BG	98.75 %	100.00 %	100.00 %	100.00 %	100.00 %	98.96 %
BH	55.00 %	98.75 %	100.00 %	100.00 %	100.00 %	86.98 %
BI	83.44 %	100.00 %	100.00 %	100.00 %	100.00 %	94.79 %
mean	**76.43 %**	**92.61 %**	**94.55 %**	**96.39 %**	**97.66 %**	**92.57 %**

average accuracy of 85.06 % and that averaging over 2 trials improves classification accuracy for all subjects. During the supervised calibration the subjects achieved an average accuracy of 94.43 %.

4 Discussion

In this paper, we have shown that an unsupervised calibration of a c-VEP BCI is possible and that all subjects were able to control the BCI online with an average accuracy of 85 %. Thereby it was shown for the first time that an online BCI can be calibrated in an unsupervised manner.

While the online study used a BCI with only 2 targets, we have shown in the offline analysis that a BCI with 32 targets can successfully be used after an unsupervised calibration on 2 targets. By averaging over multiple trials the accuracy can further be increased.

Although it was shown that an unsupervised calibration works well and can be used to calibrate a BCI, it does not perform better than a supervised calibration. Therefore the use of an unsupervised calibration method needs to be discussed.

So far, there are no reports of BCI working online in complete locked-in (CLIS) patients, who do not have any residual muscle control. With the transition into CLIS, the last possibility to move any muscle is lost. Thereby the patient loses

Table 3. Offline results with 2 targets and different methods for channel selection. Different number of trials were used for averaging. Unsupervised channel selection was compared to a fixed selection of channel PO3 or P4, respectively.

	Number of trials averaged				
	1	2	3	4	5
PO3	86.58 %	89.41 %	91.88 %	90.69 %	92.62 %
P4	87.81 %	92.78 %	94.24 %	94.79 %	94.53 %
unsupervised	90.85 %	97.40 %	96.91 %	97.85 %	98.44 %

Table 4. Offline results for different methods for channel selection using data with 32 targets. Different number of trials were used for averaging. Unsupervised channel selection was compared to a fixed selection of channel PO3 or P4, respectively.

	Number of trials averaged				
	1	2	3	4	5
PO3	72.87 %	81.95 %	85.43 %	85.83 %	87.24 %
P4	70.21 %	86.70 %	89.94 %	90.63 %	90.89 %
unsupervised	76.43 %	92.61 %	94.55 %	96.39 %	97.66 %

Table 5. Accuracies during the online experiment for different calibration methods: unsupervised calibration without averaging, unsupervised calibration with averaging over 2 trials, supervised calibration without averaging

	unsupervised		supervised
Subject	no averaging	average over 2 trials	
CL	64.06 %	78.13 %	95.31 %
CM	85.94 %	99.22 %	100 %
CN	78.13 %	87.50 %	92.19 %
CO	85.16 %	92.19 %	89.06 %
CP	89.84 %	95.31 %	82.81 %
CQ	93.75 %	80.47 %	100 %
CR	89.84 %	83.59 %	96.09 %
CS	93.75 %	85.94 %	100 %
mean	**85.06 %**	**87.79 %**	**94.43 %**

the last possibility to interact with the environment and he has no longer any means to follow his plans or goals. Since there is no possibility to achieve any goals, the goal-directed thinking is assumed to be extinct [1] and thereby the patient would not be able to follow any instructions that are necessary when calibrating a BCI in a supervised manner.

Unsupervised calibration might solve this problem, since it allows to calibrate a BCI and give the user feedback without the need for any goal-directed action [8]. Although it is still speculation if patients without eye-movement control can use a c-VEP BCI, it might be possible with a modified stimulus presentation (as it was already done for SSVEP BCIs [9,10]). Thereby the patient could influence his environment again and may regain the ability for goal-directed thinking, since he has now a means to communicate and achieve potential goals.

5 Conclusion

In this paper we have presented a method that allows for an unsupervised calibration of a c-VEP BCI. In an online study we have shown that all subjects were able to control the BCI with an average accuracy of 85 % after an unsupervised calibration. Although the accuracy is lower than for a supervised calibration, unsupervised methods could be used to establish communication in complete locked-in patients, for whom supervised methods does not work.

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