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One Class SVM and Canonical Correlation Analysis increase performance in a c-VEP based Brain-Computer Interface (BCI)

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Abstract. The goal of a Brain-Computer Interface (BCI) is to enable communication by pure brain activity without the need for muscle control. Recently BCIs based on code-modulated visual evoked potentials (c-VEPs) have shown great potential to establish high-performance communication. In this paper we present two new methods to improve classification in a c-VEP BCI. Canonical correlation analysis can be used to build an optimal spatial filter for detection of c-VEPs, while the use of a one class support vector machine (OCSVM) makes the BCI more robust in terms of artefacts and thus increases performance. We show both methods to increase performance in an offline analysis on data from 8 subjects. As a proof of concept both methods are tested online with one subject, who achieved an average performance of 133 bit/min, which is higher than any other bitrate reported so far for a non-invasive BCI.

1 Introduction

A Brain-Computer Interface (BCI) enables a user to control a computer by pure brain activity without the need for muscle control. Its main purpose is to restore communication in severely disabled persons, who are not able to communicate by muscle control due to neurodegenerative diseases or traumatic brain injuries. While there are different kinds of BCIs, this paper focuses on a BCI based on code-modulated visual evoked potentials (c-VEPs).

In a c-VEP BCI a pseudorandom code is used to modulate different visual stimuli. If a person attends one of those stimuli a c-VEP is evoked and thus can be used for controlling the BCI. This idea has been proposed by Sutter in 1984[1] and has been tested 8 years later when an ALS patient was reported to write 10 to 12 words/minute with a c-VEP BCI system using intracranial electrodes[2]. Until recently there has been no proper evaluation of a c-VEP BCI with EEG, when it was shown that a BCI based on c-VEPs outperforms BCIs based on other kinds of visual stimuli[3]. In [4] it was shown, that the use of canonical correlation analysis (CCA) increases performance and that an average online accuracy of 85 % can be reached with 32 classes.

In this paper we propose a one class support vector machine (OCSVM) as a new method to improve classification accuracy in a c-VEP BCI. Also a different

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method of using CCA to construct a better spatial filter is proposed and evaluated. Both methods are shown to increase performance on offline data and their feasibility is demonstrated in an online test with one subject.

2 Method

2.1 Configuration of the c-VEP BCI system

The system is similar to the one described in [4], consisting of an EEG amplifier, a personal computer (PC) and a CRT Monitor. Stimulus presentation and online classification are operated from the PC. The presentation of the stimuli is synchronized with the EEG amplifier by using the parallel port. The visual stimuli are presented on an 17 inch CRT Monitor with a 60 Hz refresh rate and a resolution of 640 x 480 pixel. DirectX (Microsoft Inc.) is used to ensure synchronisation of the presented stimuli with the refresh rate of the CRT monitor. A stimulus can either be black or white, which can be represented by 0 or 1 in a binary sequence. A 30 Hz flickering can therefore be represented by the following sequence: '01010101...' when using a 60 Hz refresh rate.

The c-VEP BCI consists of 32 targets with the arrangement of the targets shown in figure 1. The 32 targets are arranged as a 4x8 matrix and 28 complementary non-target stimuli are surrounding the targets. For modulation of the target stimuli a 63-bit binary m-sequence is used, because of the low autocorrelation property of m-sequences. For each target the same sequence is used for modulation, but the sequence is circular-shifted for each target by a different number of bits. An example for the circular shift of the modulation sequence can be seen in figure 1, with target T0 having no shift, T1 being shifted by 2 bit, T2 being shifted by 4 bit and so on, resulting in a time lag $\tau_s = 2/60\ s = 0.033\ s$ between two consecutive targets. In total the length of one stimulation sequence is $T_s = 63/60\ s = 1.05\ s$. Between two stimulation sequences there is a break of about 0.85 s which is sufficient enough for the user to switch to a different target.

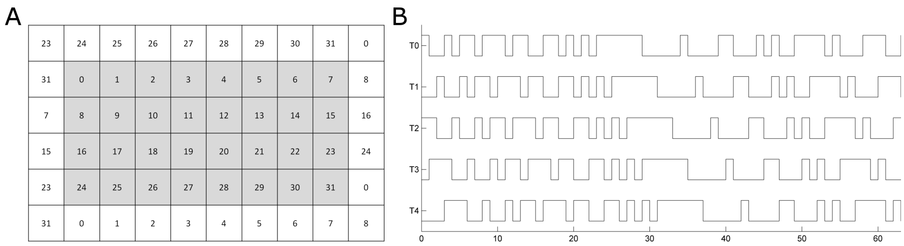

Fig. 1: A) Arrangement of the stimuli for the c-VEP BCI. The gray area shows the 32 target stimuli with the number referring to the number of the target. The stimuli in the white area are the complementary flickers, which are synchronized to the target with the same number. B) Modulation sequence for the first 5 targets.

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2.2 Classification

For identifying the attended target, a template needs to be generated first. During the calibration stage the user has to attend to a specified target T_r k times. When the user is attending to the target T_r, a c-VEP is elicited by modulation of the target stimulus. By averaging the EEG data from the k stimulation sequences an average c-VEP can be used as a template M_r for the attended target. By using the circular-shift property of the c-VEP BCI, a template for all other targets can be generated by shifting the template M_r:

$$M_x(t) = M_r(t - \tau_s \cdot (x - r)) \qquad x = 0, 1, 2 \ldots, 31 \tag{1}$$

After templates for each target are generated, the system can identify which target the user is attending to, by calculating the correlation of the recorded EEG signal with the templates of each target. The target with the highest correlation is selected and thus the system can be used to select letters.

2.2.1 *Classification by one class SVM*

Instead of using correlation for identification of the attended target, we propose the use of a OCSVM[5]. Rather than averaging the EEG data from multiple stimulation sequences, a OCSVM can be used to estimate the probability distribution of the data. The OCSVM results in a hyper-sphere with minimal radius, that encloses a given percentage of the data. The center of the hyper-sphere can be used as a template, which can be shifted to obtain templates for all targets as described in section 2.2. By calculating the euclidean distance between a new data point and all templates, the template with the smallest distance to the new data point is obtained and the corresponding target is selected.

2.2.2 *Canonical correlation analysis to design optimal spatial filters*

The goal of CCA is to find linear transformations W_x and W_s which maximize the correlation between X and S[6]:

$$\max_{W_x, W_s} \frac{W_x^T X S^T W_s}{\sqrt{W_x^T X X^T W_x \cdot W_s^T S S^T W_s}} \tag{2}$$

To obtain an optimal spatial filter W_x for classification of the c-VEPs, X is the raw EEG-data and S is the desired waveform of the average c-VEP.

To construct the spatial filter one must obtain k trials with EEG data, each consisting of a $n \times m$ matrix with n being the number of channels and m being the number of samples. All trials are concatenated to a new matrix X with new dimensions $n \times (k \cdot m)$. To obtain S, first the average c-VEP waveform R is generated by averaging over all k trials, then R is replicated k times, to obtain a $n \times (k \cdot m)$ matrix $S = [RR \ldots R]$.

These X and S can then be used for calculating the spatial filter W_x by CCA. While the matrices X and S need the same number of $k \cdot m$ columns, they are allowed to have different number of rows.

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Therefore different methods for applying CCA were tested, in which different channels for X and S were used:

best channel overall: Classification accuracy is estimated by a leave-one-out estimation for all channels and all subjects. As a result channel PO3 (referenced to Oz) was the channel that gave the best overall results. The data from PO3 is then used for S and all channels are used for X.

Bin et al. : The method as proposed in [4], where the same pre-defined channel subset is used in X and in S.

best channel individual : A leave-one-out estimation is performed for each channel and each subject individually to select the individual best channel. The channel, for which the highest accuracy is estimated, is then used for S and all channels are used in X.

best multichannels individual: A leave-one-out estimation is performed for each channel and each subject individually. If p_b is the estimated accuracy for the best channel b all channels x with $p_x \geq 0.9 \cdot p_b$ are used for S and all channels are used in X.

When doing a leave-one-out estimation, the Pearson correlation was used for target identification, because of its efficiency. For implementation of the OCSVM we used LibSVM with a linear kernel and $\nu = 0.5$.

2.3 Offline analysis

Data from 8 subjects was used in the offline analysis to compare the methods described in section 2.2. EEG data was recorded with a g.Tec amplifier at 600 Hz from 30 electrodes referenced to Oz. Each subject attended each of the 32 targets 20 times, resulting in a total of 640 trials. To estimate accuracy a 10-fold cross-validation was performed. When comparing the different approaches for constructing the spatial filter, OCSVM was used for target identification.

2.4 Online proof of concept

To proof that the proposed system with OCSVM is viable in an online setting, it was tested with subject AB, whose data from a previous session was also used for the offline analysis. For training the OCSVM and construction of the spatial filter by CCA (based on best individual channel method) 128 trials of training data were recorded and the system was tested online with 192 trials.

3 Results

3.1 Offline analysis

Table 1 shows the results for the comparison of OCSVM with the classical correlation approach. It can be seen that the use of OCSVM gives better classification accuracies no matter if CCA is used for optimisation or not. The results also show the effect of the spatial filter generated by CCA.

The results from the comparison of different methods to construct a spatial filter are printed in table 2. It shows that constructing the spatial filter based on the best individual multichannels gives the highest accuracies with a mean accuracy of 96.29 %, while the method proposed by Bin et al. achieved an average accuracy of 92.32 %.

Table 1: Offline classification accuracies to compare OCSVM with the correlation approach with and without the use of CCA. Best values are marked bold.

	without CCA		with CCA	
	correlation	OCSVM	correlation	OCSVM
AA	84.22 %	85.47 %	**99.69 %**	99.53 %
AB	37.03 %	47.66 %	87.19 %	**87.50 %**
AC	83.13 %	87.81 %	**99.22 %**	**99.22 %**
AD	35.78 %	43.13 %	75.31 %	**83.28 %**
AE	77.03 %	83.59 %	93.59 %	**94.84 %**
AF	98.28 %	99.38 %	**100.0 %**	**100.0 %**
AG	11.41 %	15.47%	68.28 %	**76.41 %**
AH	76.72 %	85.63 %	95.94 %	**97.81 %**
mean	62.95 %	68.52 %	89.90 %	**92.32 %**

Table 2: Offline classification results, comparing different methods for constructing a spatial filter. 1: best channel overall 2: method by Bin et al. 3: best channel individual 4: best multichannels individual. Best results are marked bold.

method	1	2	3	4
AA	99.22 %	**99.53 %**	99.38 %	99.22 %
AB	70.16 %	87.50 %	87.97 %	**95.31 %**
AC	98.75 %	**99.22 %**	98.75 %	98.44 %
AD	81.25 %	83.28 %	81.56 %	**94.69 %**
AE	97.81 %	94.84 %	**97.81 %**	97.19 %
AF	99.84 %	**100.0 %**	99.84 %	99.84 %
AG	41.72 %	76.41 %	83.75 %	**86.41 %**
AH	97.66 %	97.81 %	97.50 %	**99.22 %**
mean	85.80 %	92.32 %	93.32 %	**96.29 %**

3.2 Online proof of concept

During the online test the subject achieved an average accuracy of 92.71 % in 192 trials. Considering the time of a trial with 1.05 s and the break between two trials of about 0.85 s the subject achieved an average information transfer rate[7] of 133.6 bit/min.

4 Discussion

In this paper we have proposed the use of a OCSVM as a new method for classification in a c-VEP BCI and have shown it to increase classification accuracy compared to the traditional correlation approach. Based on the work of Bin et al.[4] we also proposed a different method of constructing optimal spatial filters by the use of CCA, that selects the individual best channels to improve classification accuracy.

We have shown both methods to work and to increase classification accuracy in an offline analysis with data from 8 subjects, where we achieved an average accuracy of 96.29 % for 32 classes. As a proof of concept an online experiment was performed with one subject who achieved an average performance of 133.6 bit/min. To our knowledge this is the highest bitrate ever published for a non-invasive BCI. Due to the fact that subject AB, who participated in the online experiment, achieved below average results in the offline analysis, we think that the online experiment is representable and even higher bitrates can be (and will be) achieved with our system.

In a future study the current system will be tested online with more subjects and it will be investigated if the proposed system can be enhanced by adaptive classification, which should reduce the amount of training time needed and result in a higher and more stable performance. It also needs to be evaluated if the methods proposed in this paper can also increase performance in other BCIs, that are based on evoked or event-related potentials.

5 Conclusion

In this paper we have proposed two new methods for a c-VEP BCI and have shown them to increase performance on offline data. As a proof of concept we have also shown both methods to work in an online experiment with one subject.

With an average performance of 133.6 bit/min the subject achieved the highest bitrate reported to date for any non-invasive BCI system.

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