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Efficiency of SSVEF Recognition from the Magnetoencephalogram
A Comparison of Spectral Feature Classification and CCA-based Prediction

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Abstract: Steady-state visual evoked potentials (SSVEP) are a popular method to control brain–computer interfaces (BCI). Here, we present a BCI for selection of virtual reality (VR) objects by decoding the steady-state visual evoked fields (SSVEF), the magnetic analogue to the SSVEP in the magnetoencephalogram (MEG). In a conventional approach, we performed online prediction by Fourier transform (FT) in combination with a multivariate classifier. As a comparative study, we report our approach to increase the BCI-system performance in an offline evaluation. Therefore, we transfered the canonical correlation analysis (CCA), originally employed to recognize relatively low dimensional SSVEPs in the electroencephalogram (EEG), to SSVEF recognition in higher dimensional MEG recordings. We directly compare the performance of both approaches and conclude that CCA can greatly improve system performance in our MEG-based BCI-system. Moreover, we find that application of CCA to large multi-sensor MEG could provide an effective feature extraction method that automatically determines the sensors that are informative for the recognition of SSVEFs.

1 INTRODUCTION

Brain–computer interfaces (BCI) are intended to assist patients who suffered a severe loss of motor control. One of the most robust physiological signals used to control a BCI are the steady-state visual evoked potentials (SSVEP) (Vialatte et al., 2010). This signal is a stimulus driven neuronal oscillation that can be measured over the visual cortex and reflects the fundamental frequency of a flickering stimulus a person focuses on. In BCI-applications multiple stimuli with different frequencies are simultaneously presented and the task is to decide from the SSVEP which flicker frequency the subject is focussing.

Most studies measure SSVEPs noninvasively with the electroencephalogram (EEG) (Bin et al., 2009; Friman et al., 2007; Horki et al., 2011; Lin et al., 2007; Müller-Putz et al., 2005; Volosyak, 2011). In this study we investigate the discrimination of steady state visual evoked fields (SSVEF) from the magnetoencephalogram (MEG). Recently, it was shown that classification of event related magnetic fields can provide higher accuracies than classification of simultaneously recorded event related potentials (Quandt et al., 2012). To date only a few studies investigated SSVEFs (Müller et al., 1997; Thorpe et al., 2007) and we are not aware of any study that tested the success of SSVEFs to provide neuro-feedback in a BCI setting. In our paradigm we present virtual reality objects with relatively small stimulation surfaces. The scenario simulates a real world setting in which patients could select objects for grasping with a robotic gripper (Reichert et al., 2013).

Our aim was to compare the performance of the Fourier feature based classification approach of SSVEFs, which is standard in the EEG, to a canonical correlation based approach and to improve decoding of SSVEFs in MEG. We first performed online decoding with Fourier features without feature selection. In order to improve the decoding performance we did an additional offline analysis with canonical correlation analysis (CCA). This method was successfully applied to EEG based SSVEPs (Bin et al., 2009; Lin et al., 2007; Horki et al., 2011) and provided excellent decoding performance. The concept of CCA is to find an optimal channel weighting to detect the SSVEP. However, in the aforementioned EEG studies at most nine channels are included in the weighting. In the MEG, however, reliable weights must be found for a much higher number of channels. Thus, the relative performance of a BCI based on MEG derived Fourier features or CCA is currently unclear.

In addition, we aimed to test potential performance gains that may be obtained by inclusion of stimulation frequency harmonics (Müller-Putz et al., 2005) or variations of length of analyzed signal interval. The latter is of particular importance for high throughput BCIs and their usability.

2 METHODS

In total, 22 subjects participated in the experiment. The MEG was recorded with a BTi system, equipped with 248 magnetometers, at a sampling rate of 678.17 Hz and processed in real-time.

2.1 Stimulation and Task

A VR scenario consisting of four different objects (mobile phone, banana, pear, cup) placed in a square configuration on a table was projected on a screen 1 m in front of the subject. The edges of the square formed by the objects were 8.5° visual angle long. A circular region of the table surface under each object was used to provide flicker stimulation and feedback. On each trial, objects were placed in random order but the stimulation frequencies were held fixed for each position (upper left: 6.67 Hz, lower right: 8.57 Hz, lower left: 10.0 Hz, upper right: 15.0 Hz). The subjects were instructed to direct their gaze to a predefined target object. Flicker duration was 5 s, followed by the appearance of a green circular shape around the decoded object.

The online decoding experiment consisted of training runs and test runs, each run consisted of 32 trials. While in training runs random feedback was provided, in test runs the trained learning algorithm was used to decode the object selected by the subject. Subjects performed six to nine runs. Three subjects only completed training runs (excluded from online results); three subjects completed four, 16 subjects two training runs.

2.2 Online Processing

The online decoding of SSVEFs was performed conventionally by extracting amplitude information via a Fourier transform (FT) for each channel c and stimulation frequency f. In order to reduce the number of channels to process and to primarily capture visual potentials, we preselected 59 occipital sensors assumed to assess activity from visual areas. We used a 4.5 s data segment starting at stimulation onset to determine the spectral feature

$$F(f,c) = \| \frac{1}{N} \sum_{n=1}^{N} x_{n,c} \cdot \mathrm{e}^{-2\pi i f t_n} \| \tag{1}$$

where $x_{n,c}$ is the magnetic flux at sample point n in channel c and t_n denotes the time of the n^{th} sample. A regularized logistic regression (rLR) classifier was trained on the spectral brain patterns. The classifier was trained using the trials from training runs and updated after each test trial by adding the recently acquired data. This was possible because the target objects were instructed by the experimenter.

2.3 Offline Analysis

We did offline classification via rLR in a leave-one-run-out cross validation (CV) as well as in simulated online validation (SOV). While CV involves all available runs except the current test run, SOV involves only preceding trials in the classifier training. Thus, SOV mimics the process in a real BCI experiment. Classification based on CCA was carried out independent of training data. Therefore, here the determination of overall decoding accuracies is unaffected by the validation scheme.

2.3.1 Feature extraction

The decoding method described in section 2.2 (FT/rLR) was applied both online and offline. In addition, we employed the CCA which finds the weights $W_{x,f}$ and $W_{y,f}$ that maximize the correlation $\rho_{CCA}(f)$ between the optimal linear combination $x_f = X^T W_{x,f}$ of the brain signals X and the linear combination $y_f = Y_f^T W_{y,f}$ of a reference signal Y_f. For each frequency f the signal Y_f is modeled as

$$Y_f = \begin{pmatrix} \sin 2\pi f t \\ \cos 2\pi f t \end{pmatrix} \tag{2}$$

where t denotes time and Y_f can be extended by appending the sine and cosine of multiples of f to enable the involvement of harmonics.

2.3.2 Prediction of Selections

The multivariate rLR classifier was applied on FT features. In CCA, each stimulation frequency provides one reference signal and the reference signal that provide maximum canonical correlation $\rho_{CCA}(f)$ with brain activity indicates the classes. Serving as a training-independent classifier, we determined the frequency that revealed the maximum correlation (MC) between x_f and y_f:

$$f_{max} = \text{argmax}(\rho_{CCA}(f)) \quad (3)$$

for each trial separately. We compared the feature/classifier combinations FT/rLR and CCA/MC by investigating the impact of the analysis window width and the involvement of harmonics. The identical preselected sensors were used as described in section 2.2.

3 RESULTS

Subjects correctly selected the target object in 74.4 % of trials on average (25 % chance performance), when performing the experiment online.

Figure 1 shows the comparison of correct discrimination rates obtained with offline FT/rLR and CCA/MC with different window widths. Averages and standard errors were calculated over subjects. Here, FT features were derived without harmonics and CCA features were obtained involving two harmonics. Obviously, CCA/MC considerably enhances the decoding accuracies. For example, with 4.5 s window width CCA/MC achieved on average 93.8 % correct classifications compared to 77.9 % using FT features. The highest accuracies were always found at the maximum window width. However, for CCA a steeper and faster increase of correct decoding rates with increasing window width is obvious. This suggests that CCA features might provide good performance with shorter stimulation intervals than FT features. This is also indicated by the observation that the optimal information transfer rate (Wolpaw et al., 2000) is obtained with 3.0 s window widths (corresponding to 13.6 bit/min) for FT/rLR but with 1.5 s window widths (corresponding to 36.7 bit/min) for CCA/MC. When we tested the influence of harmonics with time windows 4.5 s wide, we found that accuracy obtained with FT-features considerably increased to 81.2 % (p¡0.015, paired Wilcoxon sign-rank test) when two harmonics were added. However, accuracy obtained with CCA fell only slightly (to 92.3 %) but consistently (p¡0.001, paired Wilcoxon sign-rank test) when the two harmonics were deleted and only the fundamental frequency was used. This indicates that the superiority of CCA over FT features does not depend on a higher dimensional dependent variable space spanned by the reference functions.

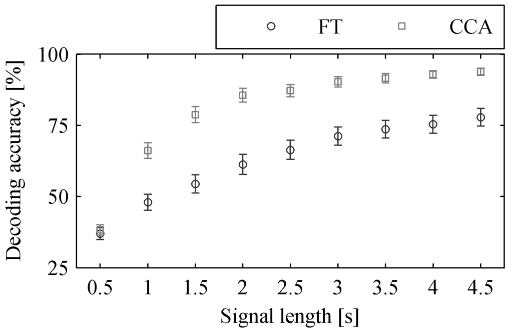

Figure 1: Dependence of decoding accuracy on signal interval length (windows of 0.5–4.5 ms width) and feature space. Average CV performance over subjects is shown. Squares represent accuracies obtained with CCA/MC classification and circles depict accuracies obtained with FT feature/rLR classification. Error bars show the standard error of the mean.

In order to verify BCI applicability, we performed an SOV. The group results of the SOV deviate slightly from the online results since here all subjects were involved in the analysis, regardless of the number of test runs they performed, and a constant number of two training runs were assumed. We depict the single subject results in Figure 2. There, subjects are sorted by performance obtained by the FT decoding method. It is important to note that the CCA/MC method involves all performed trials for validation and single trials are validated independent of others. In contrast, the rLR requires training data and was re-trained with each successive trial starting from the third run. The average decoding accuracy was 76.6 % with the FT/rLR method and much higher at 93.7 % with the CCA/MC method. Fourteen out of 22 subjects obtained accuracies above 95 % with the CCA/MC method.

Computation time for the FT algorithm using equation 1 as well as for CCA has linear complexity with regard to the signal length. A single thread on a 2.8 GHz AMD Opteron 8220 SE processor takes 1.3 ms for the FT but 19.9 ms for the CCA with a 1 s long segment, 59 channels, 678.17 Hz sampling rate and four frequencies without harmonics. Although FT provides an advantage in terms of processing time, CCA processing time is still short enough for application in real-time experiments.

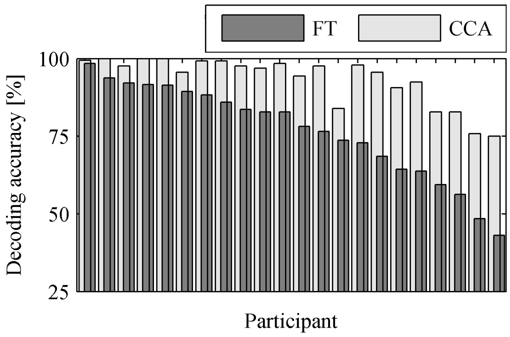

Figure 2: Single subject performance obtained in an SOV. Each of the 22 subjects shows improvement of decoding accuracy with the CCA method (light gray bars) compared to classification of FT features (dark gray bars, sorted in descending order).

4 DISCUSSION

We compared FT as a conventional spectral feature extraction method combined with multivariate classification to CCA/MC regarding their performance in MEG based BCIs. With the CCA approach, decoding accuracy was considerably improved compared to FT. This held already for at analysis windows as short as one second. The higher accuracy of CCA even with short data windows considerably increased the information transfer rates as compared to FT. This result suggests that CCA/MC is an efficient method for high throughput SSVEF-BCIs. A further advantage of CCA/MC over FT/rLR in the context of BCI is that CCA/MC, as opposed to FT/rLR does not require training blocks. Thus, lengthy initial phases for acquisition of training data can be avoided. In BCI-practice, the model estimation for each single trial in CCA can lead to improved robustness against sensor replacement, sensor malfunction and non-static brain patterns. This renders the CCA method as a flexible and reliable feature extraction method for multichannel BCIs controlled by shifting attention to oscillating visual stimuli.

We confirmed in our study the finding that inclusion of harmonics significantly increases classification accuracy in SSVEP BCIs (Müller-Putz et al., 2005). The performance increase was small for CCA but statistically significant. However, other authors did not find such a benefit (Bin et al., 2009). Importantly, the better performance of CCA/MC than FT/rLR was independent of whether harmonics were included or not.

In this study we demonstrate for the first time that magnetic SSVEFs are suitable to control a BCI. In particular, SSVEFs were decoded for selection of objects, presented in a VR scenario. Furthermore, we showed that the CCA is a powerful method to rapidly detect target frequencies in the MEG. The method introduced in this work is capable of decomposing frequency components of sources that are spatially distributed over dense sensor arrays. Importantly, the proposed algorithm can be executed in several milliseconds and, consequently, it is suited for BCI implementation and can be applied online.

Even though MEG is not suited for home use, this modality is suited for BCI development Despite reports of higher ITRs in some EEG based SSVEP studies (Bin et al., 2009) we believe that the BCI accuracy strongly depends on the visual stimulation. Therefore, comparison of bitrates should be treated with caution. Furthermore, an MEG system could serve as a training device to familiarize patients with BCI paradigms.

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