BRAIN STATE DIFFERENCES BETWEEN CALIBRATION AND APPLICATION SESSION INFLUENCE BCI CLASSIFICATION ACCURACY

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ABSTRACT

The Berlin Brain-Computer Interface (BBCI) has been developed to transfer the main load of learning from the user to the machine. After a short calibration period of approx. 30 minutes, even untrained users with no previous BCI experience can achieve bit-rates of more than 35 bits/min. In some of these experiments, however, the classifier from the calibration period needs to be slightly adapted by adding a constant bias term to its output in order to maintain a stable performance throughout the feedback session. In this paper, we will provide evidence that a change in the brain states between calibration and feedback periods probably causes this need for adaptation.

1. INTRODUCTION

Operant conditioning, a classical approach to implementing BCI systems, relies on the ability of the brain to adapt to a fixed feedback application. It requires extensive training from the user to find a mental strategy which results in the desired effect in the feedback. The BBCI follows a different idea: driven by the motto "Let the machines learn", it minimizes the need for user adaptation by modifying the feedback application according to the individual brain signals, see [1]. This attempt is realized with an initial calibration ("training") period, where the users are switching between different mental states without receiving feedback from the computer. The brain signals are then used to generate a classifier which discriminates between the signals and which can then be used as the core of the feedback application.
The classification can only be successful if the brain signals produced in training and feedback session are similarly distributed, or if the change from training to feedback can be easily parameterized. It has been shown in [2] that if the distributions are sufficiently close, simple methods like adding a bias term to the classifier output can significantly increase the classification accuracy of the feedback session. In this paper, we demonstrate a change of brain states between the two sessions leading to a change in classification performance.

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2. EXPERIMENTAL PARADIGM

For an intuitive use of the interface, imagined movements of hands and feet are used as mental states. The imagination of movements is known to entail a decreasing power in the alpha and beta frequency band of the electrodes over the corresponding motor cortex. This phenomenon is termed Event-Related Desynchronization (ERD). Since the exact location of the amplitude modulation varies strongly between subjects, a spatial filter is trained individually after each training session, projecting the data on few channels that maximize the variance for one class while minimizing it for the other class. The Common Spatial Patterns (CSP, see [3]) algorithm provides an analytical solution to this problem by simultaneous diagonalization of class-wise covariance matrices.
The study presented here comprised experiments with 9 healthy subjects. While sitting in a comfortable chair in front of a computer monitor, their EEG data was recorded using 64 electrodes. In each trial of the calibration period, one of the letters 'L', 'R' and 'F' was visually presented for 3.5–4 seconds to indicate the intended type of movement (left hand, right hand or foot). 140 trials of each target class were recorded. After training a classifier for the most discriminable pair of imagined movements, feedback was presented to the subjects. It consisted of a cursor whose horizontal position was controlled by the output of the classifier. The subjects then tried to navigate the cursor into a highlighted target. The classifier was applied to a window of the preceding 1000 ms. The data was projected on the CSP vectors, then a bandpass filter was applied and the bandpower was estimated by taking the logarithm of the variance.

Subjects	*cm*	*cn*	*co*	*cp*	*cr*	*ie*	*cs*	*ct*	*cu*
TR error	16.5	25.9	43.9	21.4	29.3	18.9	13.9	14.3	32.9
FB error	19.0	46.7	33.4	28.2	35.3	24.2	34.9	25.0	23.0
Spec r^2	1.36	4.75	0.91	1.48	3.45	1.57	7.48	2.79	0.66
Alpha r	0.18	0.16	-0.08	0.11	0.04	-0.00	0.14	0.00	-0.01

Table 1. For this table, a window of 1000 ms length was extracted from each trial of calibration and feedback session. The first two rows show the classification error (in %) of the used classifier on training and feedback, respectively. The remaining rows show the neurophysiological change between these sessions. See text for details.

3. RESULTS

Table 1 summarizes some changes that occured from calibration to test period. In 7 of 9 subjects, the classification rates in the feedback session were lower than the performance on the trials from the calibration session. For the third row of table 1, we calculated the squared r-value (the bi-serial correlation coefficient between the motor imagery conditions, a formula is given in [2]) of the most discriminative spectral frequency bin from the spectrum of laplace-filtered electrodes over the motor cortex. A large r^2-value indicates a high discriminability. Then we divided the resulting maximal value of the training session by the corresponding value from the feedback session. The results are greater than 1 in the same 7 subjects as before.

For the last row, the bandpower in the alpha band (8–14 Hz) has been calculated. By subtracting the values from the feedback session from the values from the training session, we calculated the r-value for each occipital electrode and averaged over all electrodes. It turns out that for 5 of the 7 subjects the average r-value is greater than zero, which proves that the bandpower during the training session is higher.

A typical subject is shown in Fig.1. The figure reveals a strong shift of alpha bandpower over the occipital electrodes and decreasing significance levels for the class discriminability.

4. DISCUSSION

In this series of experiments, the classification performance in the feedback session was often different from the expected accuracy. Table 1 shows that in most of the subjects the performance dropped considerably. This can be accounted to the generally lower discriminability of spectral features in the feedback session, as it has been demonstrated by comparing the most informative spectral frequency bins of calibration and application session. Therefore, the performance of every other classifier relying on spectral features would have deteriorated in the feedback session.

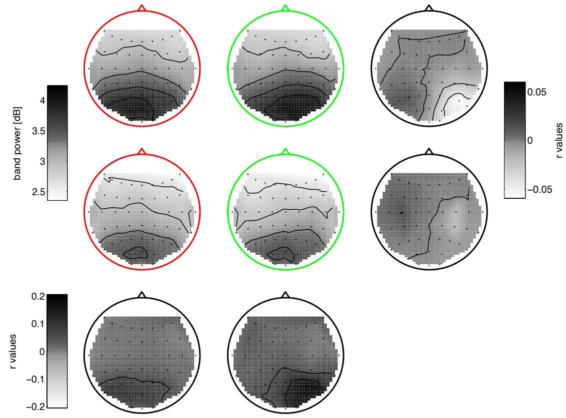

Fig. 1. The differences of brain states in training and feedback condition for subject *cm*. The first row shows the bandpower during the training session for left hand (first column) and right hand (second column) movement, and the difference between these conditions in terms of r-values. In the second row, the same evaluation is made for the feedback session. The third row shows the difference between the sessions.

In the calibration session the demand for visual processing is low as compared to the feedback session, where visual attention is high. Furthermore imagining movements in the calibration session leads to high and less distributed activity in the pericentral regions. By contrast in the feedback session subjects have to follow correct effectiveness of their imagined movements by high visual attention and more distributed cortical activity. On this account as one can see in Fig.1 pericentral activity in most of our subjects in feedback condition decreases whereas occipital visual activity increases and vice versa for the calibration session.

As the brain states between training and test apparently differ strongly, it is likely that a classifier will perform better when it is adapted to the data of the feedback session.

5. REFERENCES

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