IMPROVING SPEED AND ACCURACY OF BRAIN-COMPUTER INTERFACES USING READINESS POTENTIAL FEATURES

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ABSTRACT

To enhance human interaction with machines, research interest is growing to develop a 'Brain-Computer Interface', which allows communication of a human with a machine only by use of brain signals. So far, the applicability of such an interface is strongly limited by low bit-transfer rates, slow response times and long training sessions for the subject. The Berlin Brain-Computer Interface (BBCI) project is guided by the idea to train a computer by advanced machine learning techniques both to improve classification performance and to reduce the need of subject training. In this paper we present two directions in which Brain-Computer Interfacing can be enhanced by exploiting the lateralized readiness potential: (1) for establishing a rapid response BCI system that can predict the laterality of upcoming finger movements before EMG onset even in time critical contexts, and (2) to improve information transfer rates in the common BCI approach relying on imagined limb movements.

1. INTRODUCTION

A brain-computer interface (BCI) is a communication channel from a human's brain to a computer which does not resort to the usual human output pathways such as muscles [1]. A BCI could, e.g., allow a paralyzed patient to convey her/his intentions to a computer application. But also applications in which healthy users can benefit from the direct brain-computer communication are conceivable, e.g., to speed up reaction times. Different approaches to transform brain signals into control signals are possible. For instance, invasive BCI systems make use of implanted electrode arrays which measure local field potentials, cf. [2, 3, 4]). The non-invasive approach typically uses surface EEG electrodes. This has the appeal of an easy applicability and a low procedural risk. However, the precision of measurement is impeded by the low skull conductivity resulting in signal attenuation and spatial smearing.

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In the setting of man-machine interfaces, there are two different adapting systems involved: the operator and the computer. One approach to BCI technology is therefore to rely on the ability of the human brain to adapt quickly to new tasks. The strategy confronting the user with a biofeedback can take months until it works reliably [5, 6].

The BBCI pursues another objective in this respect, i.e., to impose the major part of the learning task on the machine, which also holds the potential of adapting to specific tasks and changing environments given suitable algorithms are used. By the use of state-of-the-art machine learning techniques [7] computers get the ability of learning and distinguishing patterns in complex data. However, when dealing with few samples of data (trials of the training session) from a high-dimensional feature space (multi-channel EEG), overfitting is a major concern. On one hand, the complexity of the data should be reduced by suitable feature extraction methods, e.g., by taking into account the neurophysiological characteristics of the data. On the other hand, classification methods should include careful regularization techniques.

In this paper, we will focus on the non-invasive EEG-approach and will show that the use of the lateralized readiness potential (LRP) enhances BCI performance in two directions by applying machine learning techniques appropriately: in the first section, we will point out that the readiness potential can be used to classify a motor task before the actual movement even in time critical situations. In the second part we will illustrate that the readiness potential can be used as an add-on to a common ERD approach by feature combination techniques that substantiate neurophysiological a-priori knowledge. The hypothesis that essential improvements in classification accuracy can be reached in this manner, will be fortified by new data.

2. RAPID RESPONSE BCI

We investigated the LRP [8, 9] in two different experimental settings. In an earlier study we recorded spontaneous motor activity during self-paced typing on a computer keyboard and were able to classify the pre-movement potentials of left vs. right hand finger movements before EMG onset, cf. [10]. These findings suggested that it might be possible to use a BCI system to enhance reaction times in time critical applications. To pursue this idea further we made an experiment where subjects had to react with finger movements in a two-alternative forced choice task under time pressure. Here we will show how these conditions affect the movement-related potentials, and that it is possible to distinguish the pre-movement potentials before EMG onset even in the reaction time task.

2.1. Neurophysiological Background

In preparation of motor tasks, a negative readiness potential precedes the actual execution. Using multi-channel EEG recordings it has been demonstrated that several brain areas contribute to this negative shift (cf. [8, 9]). In unilateral finger or hand movements the negative shift is mainly focussed on the frontal lobe in the area of the corresponding motor cortex, i.e., contralateral to the performing hand. Based on the laterality of the pre-movement potentials it is possible to discriminate multi-channel EEG recordings of upcoming left from right hand movements.

2.2. Experimental Design

In the 'self-paced' experiments, subjects were sitting in a normal chair with fingers resting in the typing position at the computer keyboard. In a deliberate order and on their own time (but instructed to keep a pace of approximately 2 seconds), they were pressing keys with their index and little fingers.

In the second experimental setting, each subject was confronted with a variant of the "d2"-test, [11]. Sitting on a normal chair, facing a monitor, the subjects had to respond as quickly as possible to different stimuli provided by the computer. On encountering a "target" (a visual stimulus consisting of the letter "d" with exactly two horizontal bars that may occur in four possible positions) they should respond by a keypress with the right index finger and on a "non-target" with a keypress with the left index finger. Non-targets either show the letter "b" and an arbitrary number of bars surrounding it, or the letter "d" with a wrong number of bars. After the subject's keystroke the reaction time was displayed on the screen, either in green if the response was correct, or in red if it was erroneous. Both classes, targets and non-targets, appeared in the same quantity. The next trial began 1.5 ± 0.25 s later.

EEG data was recorded with 27 up to 120 electrodes, arranged in the positions of the extended 10-20 system, referenced to nasion and sampled at 1000 Hz. The data were downsampled to 100 Hz for further offline analyses.

Surface EMG at both forearms was recorded to determine EMG onset. In addition, horizontal and vertical electrooculograms (EOG) were recorded to check for correlated eye movements.

2.3. Feature Extraction

For both experiment types, the LRP served as the key to distinguish between the classes "left" and "right". We use a band-pass filter which relies on the fast Fourier transform (FFT): A section of 128 samples (i.e. 1280 ms) is convoluted with a window ($w(n) := 1 - \cos(n\pi/128)$). Then, all bins not belonging to the frequency 0.4–3.5 Hz are discarded. The inverse Fourier transform gives a filtered signal, the last 150 ms of which are downsampled to 50 Hz, such that 3 samples per window remain. Concatenating these values over all selected channels results in the (LRP-) feature vectors for the given time window. For more details refer to [12, 10].

2.4. Classification

Due to our observation that LRP-data under particular movement conditions are normally distributed with equal covariance matrices ([10]), the classification problem meets the assumption of the popular Fisher discriminant method. The data processing described above preserves gaussianity, hence we classify with linear discriminant analysis ([13],[14]). Since we are dealing with a high-dimensional dataset with only few samples available, we also apply regularization ([13]) to avoid overfitting; details can be found in [10].

The evaluation of the classification results is performed by cross-validation. For a 10×10-fold cross-validation the data is divided into 10 parts by random. 9 parts are assigned to be the training set for the classifier, and the test is then performed on the 10th part (i.e., on 10% of the data). Assigning every partition of the data to be the test set once and iterating the whole process 10 times with different division, yields a set of 100 test error values. The mean is referred to as the cross validation error and serves as a estimator of the generalization error.

2.5. Results

On the left side of Fig. 1, the EEG signals at channel C3, averaged over all "right hand" trials of subject *ac*, reveal the LRP for both the d2 (light curve) and self-paced experiment (dark). As its negative shift starts already at 600 ms before the keypress, the LRP of the spontaneous movement from the self-paced experiment develops a very regular potential descent. However, the reactive potential, produced in reaction to the stimuli of the d2 experiment, starts 250 ms before the keypress. Then it decreases steeply, and reaches a slightly higher negativity than in the spontaneous movement.

The right side of Fig. 1, shows the relation between classification on EEG and on EMG data for the "d2" experiment

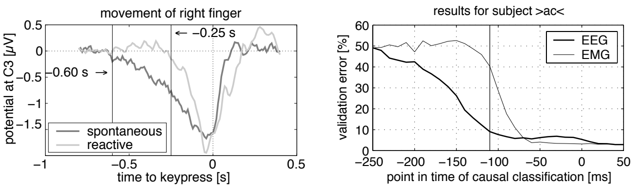

Fig. 1: The figure on the left shows the averaged readiness potential of subject *ac* in the case of spontaneous (dark) and reactive finger movement. The figure on the right shows the classification error with RLDA in relation to the time point of classification; the light-colored line indicates classification on EEG channels only, the dark line classification on EMG.

for subject *ac*. Classification was performed in sliding windows for "left" vs. "right" hand trials and the value on the horizontal axis specifies the endpoint of the window. We notice that the classification precision on EMG is in the range of 50%, as long as the causal window lies at least 110 ms before keypress, whereas the decrease in the classification error curve for EEG is almost monotone, starting already at 200 ms before the movement. It grows even steeper until it reaches 12% at $t = -110$ ms, a point where classification on EMG is still almost at chance level.

While the BCI system will use only EEG signals, we analyzed the EMG classification to determine the average point in time of EMG onset (in the case of Fig. 1, we set it to 110 ms before keypress) for every subject. For that point, we calculated the (causal window) classification results which are shown in table 1.

3. CONTINUOUS CONTROL BCI

Most BCI research for continuous control is done on the so called ERD (Event-Related Desynchronizations) effects, cf. [15]. Recent studies ([16]) offer the opportunity to reduce error rates by using LRPs additionally to the ERD features. The gain of using the combined LRP/ERD approach is demonstrated on recent BCI experiments.

	aa	*ab*	*ac*	*ad*	*ae*	*af*	*ag*	*ah*	∅
cl	12.8	16.8	9.4	14.8	25.7	26.3	12.5	27.7	18.3
rt	539	434	556	477	551	504	497	529	511
os	-80	-70	-110	-100	-100	-120	-120	-110	

Table 1: The first row shows for 8 different subjects the classification error (left vs. right hand, cl) and their mean in percent on a 10×10-fold cross validation on LRP features using linear discriminant analysis with regularization (RLDA) in the "d2"-experiments. The second row shows mean reaction times (rt) and the third row shows the point in time of EMG onset (os), which is the rightmost point for the EEG classification window of each subject.

3.1. Neurophysiological Background

During imagination or execution of a movement, a lateralized attenuation of the μ- and/or central β-rhythm can be observed localized in the corresponding motor resp. somatosensory cortex. Besides a usual spectral analysis, this effect can be visualized by plotting ERD curves [17] which show the temporal evolution of the band-power in a specified frequency band.

One of the problems when using LRP for BCI control is the disturbance of these signals by eye movements. Especially horizontal eye movements generate a lateralized DC shift in the EEG channels that is similar to LRPs. This holds the problems that the BCI classifier could be susceptible to EOG artifacts, or even could be controlled by left vs. right side eye movements. In order to antagonize such effects we used an experimental setting (see training approach (2) below) which enforces eye movements that are *un*correlated to the motor imagery condition. This leads to an LRP classifier that is invariant to eye movements. Furthermore we checked the classification results not being influenced by EOG activity.

In [18], first indications that movement-related potentials and event-related desynchronizations contain different information during brisk, self-paced finger and foot movements were presented. These studies were also supported by the finding of Babiloni et al. [19], that different spatio-temporal activation patterns across primary (sensori-)motor cortex (M-1), supplementary motor area (SMA) and the posterior parietal cortex (PP) can be observed.

3.2. Experimental Design

We present results from recent experiments with 6 healthy subjects performing motor imagery. The subjects were sitting comfortably in a chair with their arms in a relaxed position on an arm rest. Two different sessions of data collection were provided: In both a target "L", "R" and "F" (for left, right hand and foot movement) is ordered for the duration of 3.5 seconds to the subject on a computer screen. In the first session type this is done by visualizing the letter on the middle of the screen. In the second session type the left, right or lower triangle of a moving gray rhomb is colored red. For the whole length of this period, the subjects were imagining a sensorimotor sensation/movement in left hand, right hand resp. one foot. After stimulus presentation, the screen was blank for 1.5 to 2 seconds. In this manner, 35 trials per class per session were recorded. After 25 trials, there was a short break for relaxation. Four sessions (usually two of each training type, but for two subjects only one of the first and three of the latter according to their request) were performed.

EEG data was recorded with 128 electrodes together with EMG from both arms and the involved foot, and EOG as described in Section 2. No artifact rejection or correction was employed.

3.3. Feature Extraction and Classification

The CSP (Common Spatial Patterns) algorithm is especially well suited to extract ERD effects from multi-channel recordings, cf. [20]. Applying the CSP method to band-pass filtered signals (from different conditions) reveals spatial filters that optimally reflect class-differences in band-power. The algorithm is based on the idea of simultaneous diagonalization and can in this way be extended to multi-class problems, cf. [21]. After applying the spatial filter we extract the feature vectors from a given time window by calculating the logarithm of the variance of the projected channels. Since only a few CSP filters (1 to 3 per class) provide enough discriminative information, the resulting feature vectors are low-dimensional and classification can be done by simple LDA without regularization. (In evaluating the classification performance it has to be noted that the calculation of the CSP filters is class dependent and must hence be done *within* the cross-validation.) Free parameters like window length and frequency band are chosen appropriately by analyzing spectra and ERD curves.

To extract LRP features, we have to modify the algorithm described above. To be invariant w.r.t. artifactual DC-shifts we subtract moving averages of the last 1 s in the ongoing EEG. As window we choose 500–3500 ms after stimulus and calculate on the channels of the motor cortex five equidistant and non-overlapping means. The concatenated vector over time and channel forms the features which we are classifying by regularized LDA (see above).

In [16] different methods of combining features for the classification of EEG imagery trial were investigated. It turned out that the typical approach of concatenating features did hardly improve classification when compared to the best single feature result. The key idea was to incorporate the independence between the LRP and the ERD features into an algorithm called PROB, which minimizes the misclassification risk under the assumptions that the features for each class are gaussian distributed with equal covariances, and that the features of different type are independent. Here we used the PROB method to combine the CSP and LRP features.

3.4. Results

In our experiment two classes were chosen for each subject that gave the best binary classification results for CSP features. For the chosen class combination, table 2 shows the cross-validation error for classification on the single (CSP resp. LRP) features and for the combined classification method PROB. The last column indicates the increase (or decrease) [%] of the combination result compared to best single feature result. Since one subject did not produce any meaningful results on both features (classification is on chance level), we have omitted his results.

	classes	LRP	ERD	PROB	gain
aa	L-R	15.6 $\pm$ 0.9	21.1 $\pm$ 1.1	10.4 $\pm$ 1.0	-33 %
al	L-F	9.1 $\pm$ 1.1	2.1 $\pm$ 0.0	1.1 $\pm$ 0.0	-48 %
av	L-F	19.3 $\pm$ 1.4	22.0 $\pm$ 0.6	14.1 $\pm$ 3.9	-27 %
aw	R-F	23.1 $\pm$ 1.4	6.6 $\pm$ 0.3	5.9 $\pm$ 0.4	-11 %
ay	L-R	37.2 $\pm$ 1.5	2.0 $\pm$ 0.4	3.0 $\pm$ 1.4	+50 %

Table 2: The table shows for the 5 subjects the classification error in percent on a 10×10-fold cross validation on LRP and on ERD with CSP calculated features and the used best binary class combination for the ERD features. Furthermore the combination results and the gain to the best single feature are presented.

A significant decrease of error could be obtained by the feature combination method PROB for 3 out of 5 subjects, and a slight decrease for one further subject. In the extrem case of subject *ay* where classification for the LRP feature was at chance level feature combination could not increase the already very good CSP result.

4. DISCUSSION

In the first part of this paper, the use of readiness potentials for early classification of motor tasks (even before the actual EMG onset) was exemplified with classification on data from different experimental setups. These properties of readiness potentials establish its value for the use in time-critical BCI applications.

In the second part, we have shown that also in combination with the widely used ERD features, readiness potentials can improve the classification and result in an increased robustness. The application of the PROB algorithm, which combines LRP and ERD features based on an independence assumption, substantially enhanced the classification performance in comparison to the sole use of CSP in a motor imagery BCI data set.

5. REFERENCES

[1] Jonathan R. Wolpaw, Niels Birbaumer, Dennis J. McFarland, Gert Pfurtscheller, and Theresa M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, pp. 767–791, 2002.

[2] M. Laubach, J. Wessberg, and M.A. Nicolelis, "Cortical ensemble activity increasingly predicts behaviour outcomes during learning of a motor task," *Nature*, vol. 405, no. 6786, pp. 523–525, 2000.

[3] P.R. Kennedy, R.A.E. Bakay, M.M. Moore, K. Adams, and J. Goldwaithe, "Direct control of a computer from the human

central nervous system," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 198–202, 2000.

[4] G. Anthony Reina, Daniel W. Moran, and Andrew B. Schwartz, "On the relationship between joint angular velocity and motor discharge during reaching," *J. Neurophysiol.*, vol. 85, no. 6, pp. 2576–2589, 2001.

[5] J. R. Wolpaw, D. J. McFarland, and T. M. Vaughan, "Brain-computer interface research at the Wadsworth Center," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 222–226, 2000.

[6] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor, "A spelling device for the paralysed," *Nature*, vol. 398, pp. 297–298, 1999.

[7] K.-R. Müller, S. Mika, G. Rätsch, K. Tsuda, and B. Schölkopf, "An introduction to kernel-based learning algorithms," *IEEE Neural Networks*, vol. 12, no. 2, pp. 181–201, May 2001.

[8] R. Q. Cui, D. Huter, W. Lang, and L. Deecke, "Neuroimage of voluntary movement: topography of the Bereitschaftspotential, a 64-channel DC current source density study," *Neuroimage*, vol. 9, no. 1, pp. 124–134, 1999.

[9] W. Lang, O. Zilch, C. Koska, G. Lindinger, and L. Deecke, "Negative cortical DC shifts preceding and accompanying simple and complex sequential movements," *Exp. Brain Res.*, vol. 74, no. 1, pp. 99–104, 1989.

[10] Benjamin Blankertz, Guido Dornhege, Christin Schäfer, Roman Krepki, Jens Kohlmorgen, Klaus-Robert Müller, Volker Kunzmann, Florian Losch, and Gabriel Curio, "Boosting bit rates and error detection for the classification of fast-paced motor commands based on single-trial EEG analysis," *IEEE Trans. Neural Sys. Rehab. Eng.*, vol. 11, no. 2, pp. 127–131, 2003.

[11] Rolf Brickenkamp and Eric Zillmer, *D2 Test of Attention*, Hogrefe & Huber, Göttingen, Germany, 1998.

[12] Benjamin Blankertz, Gabriel Curio, and Klaus-Robert Müller, "Classifying single trial EEG: Towards brain computer interfacing," in *Advances in Neural Inf. Proc. Systems (NIPS 01)*, T. G. Diettrich, S. Becker, and Z. Ghahramani, Eds., 2002, vol. 14, pp. 157–164.

[13] J. H. Friedman, "Regularized discriminant analysis," *J. Amer. Statist. Assoc.*, vol. 84, no. 405, pp. 165–175, 1989.

[14] Klaus-Robert Müller, Charles W. Anderson, and Gary E. Birch, "Linear and non-linear methods for brain-computer interfaces," *IEEE Trans. Neural Sys. Rehab. Eng.*, vol. 11, no. 2, 2003, 165–169.

[15] G. Pfurtscheller, C. Neuper, G. Müller, B. Obermaier, G. Krausz, A. Schlögl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Woertz, G. Supp, and C. Schrank, "Graz-BCI: state of the art and clinical applications," *IEEE Trans. Neural Sys. Rehab. Eng.*, vol. 11, no. 2, pp. 177–180, 2003.

[16] Guido Dornhege, Benjamin Blankertz, Gabriel Curio, and Klaus-Robert Müller, "Boosting bit rates in non-invasive EEG single-trial classifications by feature combination and multi-class paradigms," *IEEE Trans. Biomed. Eng.*, 2004, in press.

[17] Gert Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clin. Neurophysiol.*, vol. 110, no. 11, pp. 1842–1857, Nov 1999.

[18] Camilo Toro, Günther Deuschl, Robert Thather, Susumu Sato, Conrad Kufta, and Mark Hallett, "Event-related desynchronization and movement-related cortical potentials on the ECoG and EEG," *Electroencephalogr. Clin. Neurophysiol.*, vol. 93, pp. 380–389, 1994.

[19] C. Babiloni, F. Carducci, F. Cincotti, P. M. Rossini, C. Neuper, Gert Pfurtscheller, and F. Babiloni, "Human movement-related potentials vs desynchronization of EEG alpha rhythm: A high-resolution EEG study," *NeuroImage*, vol. 10, pp. 658–665, 1999.

[20] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 4, pp. 441–446, 2000.

[21] Guido Dornhege, Benjamin Blankertz, Gabriel Curio, and Klaus-Robert Müller, "Increase information transfer rates in BCI by CSP extension to multi-class," in *Advances in Neural Inf. Proc. Systems (NIPS 03)*, 2004, vol. 16, in press.