Fronto-Parietal Gamma-Oscillations are a Cause of Performance Variation in Brain-Computer Interfacing

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***Abstract*— In recent work, we have provided evidence that fronto-parietal γ-oscillations of the electromagnetic field of the brain modulate the sensorimotor-rhythm. It is unclear, however, what impact this effect may have on explaining and addressing within-subject performance variations of brain-computer interfaces (BCIs). In this paper, we provide evidence that on a group-average classification accuracies in a two-class motor-imagery paradigm differ by up to 22.2% depending on the state of fronto-parietal γ-power. As such, this effect may have a large impact on the design of future BCI-systems. We further investigate whether adapting classification procedures to the current state of γ-power improves classification accuracy, and discuss other approaches to exploiting this effect.**

I. INTRODUCTION

While brain-computer interfaces (BCIs) based on motor imagery can be employed by most healthy subjects with only brief calibration periods [1]–[3], there exists a large variation in performance across as well as within subjects. Consider Figure 1, showing a typical range of performance across 193 subjects in a two-class motor-imagery paradigm (adapted from [4]). As can be seen here, between five and ten percent of subjects do not perform substantially above chance level, the bulk of subjects performs moderately well, and only a few subjects achieve excellent performance. Besides this across-subject variation, there also exists a substantial within-subject performance variation. Figure 2 shows the trial-wise performance of a representative subject over the course of an experimental session in a two-class motor-imagery paradigm. Here, each cross represents one trial of motor imagery of either the left or the right hand, and the value on the y-axis represents the certainty of the employed machine-learning algorithm in classifying this trial (the derivation of this certainty measure is described in Section II). The green region denotes correct classification, while crosses in the red region represent misclassified trials. In spite of a rather good performance of on average 76.67%, this subject showed large variations in performance across time. While initially she performed almost perfectly, with hardly any trials in the red region, performance declined continuously. After approximately ten minutes into the experimental session, classification accuracy reached chance level. Towards the end of the experimental session, however, performance improved again. Such performance variations within as well as across subjects pose a substantial challenge to research on BCIs, as a successful commercialization of this technology can hardly be envisioned without robust performance across subjects

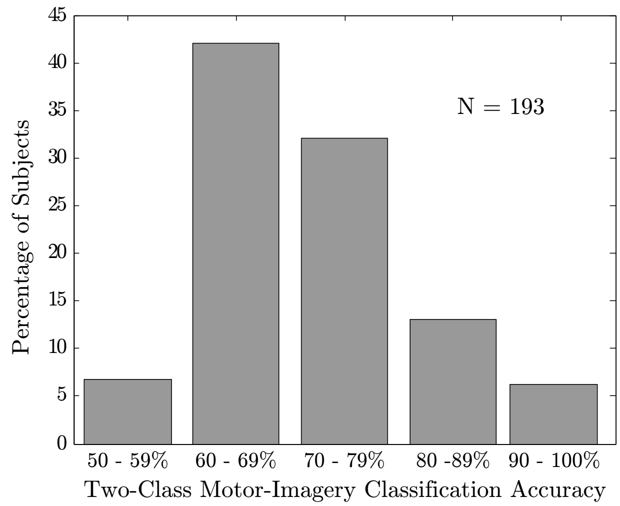

Fig. 1. Across-subject performance variation in a two-class motor-imagery paradigm (adapted from [4]).

as well as across time. It is thus of utmost importance to study and understand the neuro-physiological causes of performance variations in BCIs, and utilize these insights to develop systems that are robust to such variations.

In recent work, we have provided evidence for the significance of γ-oscillations, i.e., oscillations of the electromagnetic field roughly above 50 Hz, for explaining and understanding performance variations in motor-imagery [5], [6]. More specifically, we have argued in [6] that a fronto-parietal network of γ-oscillations exerts a modulatory influence on the sensorimotor-rhythm. Here, we re-analyze this effect with regard to its significance for research on BCIs. We provide evidence that, depending on the state of γ-power in the fronto-parietal network, classification accuracy differs by up to 22.2% on a group-average. As such, the effect described here may have a large impact on the performance and future design of BCIs based on motor imagery. Furthermore, we investigate whether training classifiers independently for different states of γ-power improves classification accuracy. We do not find any evidence in support of this hypothesis, which suggests that the influence of γ-oscillations on the sensorimotor-rhythm is not merely a covariate-shift.

The remainder of this paper is structured as follows. In Section II, we describe the experimental paradigm, recorded data, and machine-learning procedures employed in this study. We then present the experimental results in Section III. In Section IV, we discuss the relevance of the presented results for research on BCIs.

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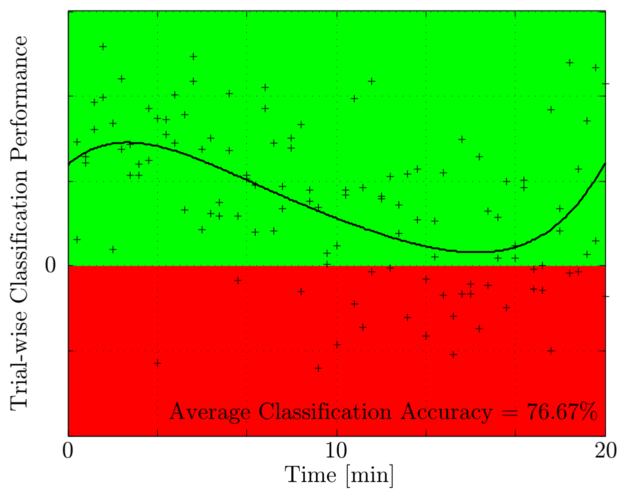

Fig. 2. Performance of a representative subject over the course of an experimental session. Crosses in the green region denote correctly classified trials and crosses in the red region classification errors. Interpolated with a fifth-order polynomial.

II. METHODS

Due to space constraints and similarity of the methods employed in this study to earlier work, we only describe the essential steps here. For a more detailed description, we refer the interested reader to [5] and [6].

A. Experimental Paradigm

Subjects participated in a classical two-class BCI-paradigm, involving motor imagery of the left and the right hand. Subjects were placed in a comfortable chair approximately 1.5 m in front of a computer screen, and were asked to alternate between kinesthetic motor imagery of either hand and relaxed wakefulness according to instructions on the screen. Each trial started with a rest period lasting between 3.5 to 4.5 s, in which a gray fixation cross was displayed centrally on the screen. Then, a gray block on either the left- or right-hand side of the screen instructed subjects to initiate motor imagery of the respective hand. After 6 s the block disappeared again, indicating the end of one trial and start of the subsequent baseline.

Each subject performed two sessions of 30 trials per condition in pseudo-randomized order with a brief intermission between sessions, resulting in a total of 120 trials per subject.

B. Experimental Data

During the experiment, EEG was recorded at 121 channels with a sampling rate of 500 Hz, using a QuickAmp amplifier with a built-in common average reference. Electrode impedances were ensured to be below 10 kΩ at the start of the first session. Channels exceeding this threshold were switched off by manually connecting them to the ground channel of the amplifier. Fourteen healthy subjects (five female, mean age of 25.1 years with a standard deviation of 3.4 years) participated in this study, four of which had previously participated in studies on motor imagery.

C. Data Analysis

To classify trials of each subject as motor imagery of either the left or the right hand, the following procedure was employed. First, the data was spatially filtered using a Laplacian setup [7]. Then, for each trial log-bandpower during the first 5.5 s of motor imagery was computed in frequency bins of 2 Hz width ranging from 7–39 Hz for 18 channels covering left and right sensorimotor areas, using a FFT in conjunction with a Hanning window. These bandpower features were then used to train a linear ν-support vector machine (SVM) [8]. To avoid overfitting, a 12-fold cross-validation procedure was employed, and parameter selection of the SVM was carried out by 10-fold cross-validation on each of the 12 outer folds. The resulting continuous-valued output of the SVM for each trial was then multiplied by -1 for each trial of left-hand motor imagery. In this way, we obtained a measure of motor-imagery performance in which large positive values reflect easy to classify trials, small values represent uncertain decisions, and negative values represent incorrectly classified trials (cf. Figure 2). In [6], we have used this metric to identify brain activity that is correlated with motor-imagery performance. Using Independent Component Analysis (ICA) in conjunction with source localization methods, we uncovered a fronto-parietal network in which γ-range oscillations (between 55–85 Hz) are significantly negatively correlated with motor-imagery performance (cf. Figure 4). Here, we investigate to which extent γ-power in this network affects single-subject classification accuracy. To do so, we computed γ-power in the fronto-parietal network on a single-subject level as done in [6]. Briefly, we first employed ICA to separate the recorded EEG of each subject into (ideally) statistically independent components, manually rejected artifactual ICs by visual inspection, and identified ICs showing a significant ($p \leq 0.05$) negative correlation of γ-power and the performance metric introduced here, only using data from the first experimental session of each subject. The cortical sources contributing to these ICs (averaged across subjects) are shown in Figure 4. The first experimental session is subsequently called the training set. Then, we computed γ-power in this fronto-parietal network for each trial of the second experimental session, subsequently called the test set, by first scaling the γ-power of each IC by its correlation with motor-imagery performance on the training set, and then taking the average across all ICs identified as potentially relevant on the training set. In this way, we computed a single scalar value of fronto-parietal γ-power for each trial in the test set. Importantly, the separation of our data into a training- and a test set ensured that any effects reported here are not due to overfitting. For a more detailed description of this procedure please refer to [6]. For each subject, we then computed classification accuracy on the test set as a function of γ-power. We employed a sliding window encompassing 10% of all trials in the test set, and investigated how classification accuracy changed when sliding this window from the 10% of trials with lowest- to the 10% trials with highest γ-power.

D. Classifier Adaptation

In the above procedure, a classifier is trained in each cross-validation fold on a subset of data chosen independently of the state of γ-power. It may be beneficial, however, to train different classifiers for subsets of trials that correspond to different states of γ-power. We explored this possibility by sorting trials of each subject into two halves of 60 trials each. The first half contained trials of lowest- and the second half contained trials of highest γ-power. Then, we retrained our classifier, again employing a 12-/10-fold cross-validation on the outer- and inner-fold, respectively, on each of these two subsets of trials independently. To ensure that a comparison of these classification accuracies with the non-adaptive classifier is not confounded by the number of trials in the training set, we repeated our initial classification procedure ten times for each subject, this time choosing 60 trials per subject randomly, i.e., independently of the current state of γ-power, and then averaged classification accuracies across the ten iterations. Subsequently, this approach is termed the baseline classification scheme. Comparing the mean classification accuracies of the adaptive- and the baseline scheme then provides information whether adapting classifiers to the current state of γ-power increases performance of the BCI.

III. RESULTS

Classification accuracies achieved by each subject when training with the initial classification scheme are shown in the first row of Table I. As typical in BCIs, accuracy varies substantially between subjects, with S5 not performing substantially above chance level and S2 performing almost perfectly. Out of these fourteen subjects, four subjects (S5, S11, S13, and S14) did not show any ICs with a significant correlation of γ-power with motor-imagery performance on the training set. These subjects thus had to be excluded from further analysis. Regarding the impact of fronto-parietal γ-power on performance, the continuous line in Figure 3 shows the group-average of classification accuracy as a function of γ-power on the test set. In agreement with [6], γ-power correlates negatively with classification accuracy. Importantly, differences in accuracy are quite substantial. While for the 10% of trials with highest γ-power average performance is on chance level (51.4%), classification accuracy improves by 11.1% to 62.5% when only considering the 10% of trials with lowest γ-power. Maximum differences even amount to 22.2%. As there is only a limited number of trials available in the test set, the dashed line in Figure 3 shows the graph obtained when considering trials from both experimental sessions. Here, a more smooth dependence of classification accuracy on γ-power can be observed, with 21.5% improvement from high to low γ-power. This second graph should be interpreted with caution though, as overfitting effects may have an impact here.

Regarding the classifier adaption, the second and third row of Table I show the classification results when training classifiers on subsets of trials sorted according to γ-power (Adapt. Acc.) and when training classifiers on subsets of trials chosen independently of γ-power (Baseline Acc.). Interestingly, on average both approaches differ by only 0.8%. The significance of this result is discussed in the next section.

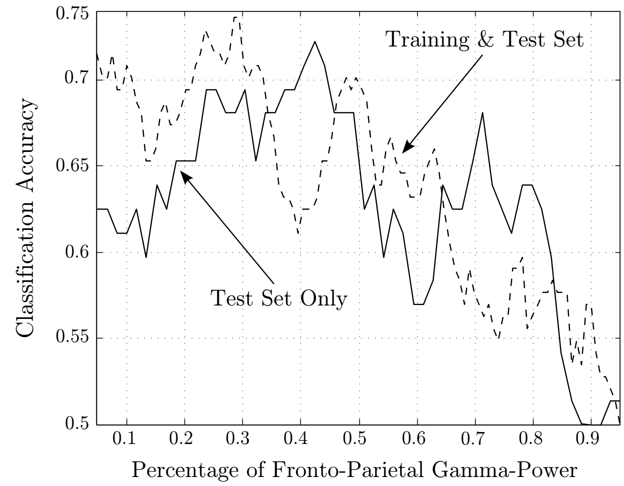

Fig. 3. Classification accuracy across subjects as a function of subject-specific fronto-parietal γ-power (normalized across all trials of each subject).

IV. DISCUSSION

In this paper, we have demonstrated that γ-oscillations in a fronto-parietal network have a large influence on performance of BCIs based on motor-imagery. As such, γ-oscillations may be considered as a cause of non-stationarity in motor-imagery paradigms. Adapting classification procedures to such non-stationarities is an active field of research in machine learning [9], and has also been addressed in the context of BCIs [10], [11]. The focus of these studies, however, is on the problem of covariate-shift adaptation. In covariate-shift adaptation, it is assumed that the distribution of features changes between training- and test sets, yet the distribution of class labels conditioned on the features remains invariant. In this case, training classifiers independently on subsets of trials belonging to different input distributions is likely to outperform classifiers trained on a mixture of input distributions [12] (assuming that the size of the training set remains constant). We have provided evidence, however, that classifiers trained on subsets of trials corresponding to different states of γ-power do not outperform classifiers trained on subsets of trials chosen independently of γ-power. While we can not rule out that more sophisticated adaptation schemes improve performance, we hypothesize that the effect of fronto-parietal γ-power on BCIs based on motor-imagery is not confined to a covariate-shift.

This hypothesis implies that states of low fronto-parietal γ-power are beneficial for BCI performance independently of the marginal distribution of features derived from sensorimotor areas. As we have further provided evidence in [5] and [6] that fronto-parietal regions modulate sensorimotor areas, i.e., that the γ-oscillations described here are an actual cause of performance variations, it may be beneficial to provide subjects with feedback on their current state of fronto-parietal γ-power. This may enable subjects to train how to

Subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	Group
Accuracy [%]	76.7	96.7	86.7	76.7	55.0	75.0	87.5	68.3	65.0	60.0	57.5	65.8	70.8	61.7	71.7
Adapt. Acc. [%]	66.7	90.0	72.5	70.8	-	55.0	81.7	56.7	50.8	61.7	-	64.2	-	-	67.0
Baseline Acc. [%]	70.9	87.7	68.8	71.7	-	59.8	82.3	52.1	62.4	62.3	-	60.0	-	-	67.8

TABLE I

CLASSIFICATION RESULTS. *Accuracy* REFERS TO THE ORIGINAL CLASSIFICATION SCHEME, *Adapt. Acc.* TO THE SCHEME IN WHICH CLASSIFIERS ARE TRAINED ON SUBSETS OF TRIALS SORTED ACCORDING TO γ-POWER, AND *Baseline Acc.* TO THE BASELINE SCHEME IN WHICH CLASSIFIERS ARE TRAINED ON SUBSETS OF TRIALS CHOSEN RANDOMLY.

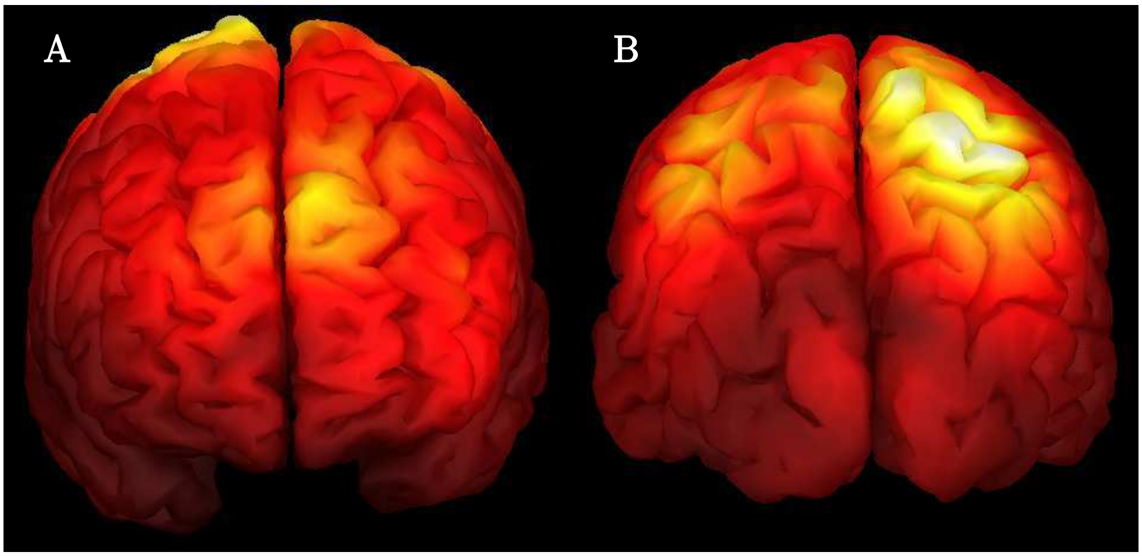

Fig. 4. Frontal (A) and parietal (B) cortical origins of γ-oscillations correlated with motor-imagery performance (adapted from [6]).

induce mental states that result in good BCI-performance. As the behavioral correlate of fronto-parietal γ-power in motor imagery is unknown at this point, it is unclear how subjects may achieve such mental states. It should be noted that interventional approaches might also be considered, e.g., stimulating fronto-parietal areas by transcranial alternating current stimulation (tACS).

Finally, it should be pointed out that even though subjects in early to middle stages of amyotrophic lateral sclerosis (ALS) are capable of operating a BCI [13], to date no communication with a completely locked-in subject has been reported. If the results reported here (and in [5] and [6]) on healthy subjects can be reproduced on patient populations with ALS, this may provide new insights into the failure to communicate with such patients and suggest potential solutions.

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