# Neurofeedback of Fronto-Parietal Gamma-Oscillations

M. Grosse-Wentrup

Max Planck Institute for Intelligent Systems, Spemannstr. 38, 72076 Tübingen, Germany

moritzgw@ieee.org

#### Abstract

In recent work, we have provided evidence that fronto-parietal  $\gamma$ -range oscillations are a cause of within-subject performance variations in brain-computer interfaces (BCIs) based on motor-imagery. Here, we explore the feasibility of using neurofeedback of fronto-parietal  $\gamma$ power to induce a mental state that is beneficial for BCI-performance. We provide empirical evidence based on two healthy subjects that intentional attenuation of fronto-parietal  $\gamma$ power results in an enhanced resting-state sensorimotor-rhythm (SMR). As a large restingstate amplitude of the SMR has been shown to correlate with good BCI-performance, our approach may provide a means to reduce performance variations in BCIs.

## 1 Introduction

Although research on brain-computer interfaces (BCIs) has seen remarkable progress in recent years, a substantial percentage of subjects remains incapable of utilizing a BCI [1]. Furthermore, subjects often display a large variation in performance over the course of an experimental session [2]. These factors limit the utility of BCI systems, and hinder a successful commercialization of this technology. Understanding and eliminating across- as well as within-subject performance variations arguably constitutes one of the most relevant problems in research on BCIs.

Recent studies have provided first important insights into the neuro-physiological causes of performance variations in motor-imagery BCIs. In particular, empirical evidence has been presented that the amplitude of the sensorimotor-rhythm (SMR) at rest is a good predictor of subsequent BCI-performance [3]. This suggests that in order to perform well, subjects first need to generate a strong SMR, i.e., a high amplitude of electromagnetic oscillations over sensorimotor-areas in the  $\mu$ -(8–14 Hz) and  $\beta$ -range (20–30 Hz). Localized attenuation of the SMR by means of motor-imagery may then be used to convey a certain intention. Concurrently, our group has provided evidence that suggests a role of  $\gamma$ -range oscillations ( $\geq 40$  Hz) in determining subject-specific levels of BCI-control. In particular, we have presented empirical evidence for an inhibitory modulation of the SMR by  $\gamma$ -range oscillations originating in frontal- and parietal areas [4, 5]. This effect may have a large impact on the design of future BCI-systems, as we found group-average classification accuracies in a two-class BCI to vary by up to 22.2% depending on the state of fronto-parietal  $\gamma$ -power [2].

In this work, the hypothesis is tested that teaching subjects to attenuate fronto-parietal  $\gamma$ -power results in an enhanced SMR - a mental state that is likely to result in good BCI-performance. Online beamforming was employed to train three healthy subjects in intentional modulation of fronto-parietal  $\gamma$ -power. Two subjects acquired significant control. The third subject had to be discarded due to muscular artifacts. In agreement with the initial hypothesis, intentional attenuation of fronto-parietal  $\gamma$ -power resulted in a significant enhancement of the SMR. None of the subjects reported the use of motor-imagery for modulating fronto-parietal  $\gamma$ -power. These results establish that it is possible to learn how to intentionally control fronto-parietal  $\gamma$ -power, and that this new skill may be used to induce a state of mind that is beneficial for BCI-performance.

### 2 Methods

### 2.1 Neurofeedback paradigm & experimental data

Each session of the feedback paradigm consisted of one resting-state baseline- and three training blocks. In the baseline block, the subject was instructed to relax for five minutes with eyes open while watching a grey fixation cross on a screen at a distance of approximately 1.5 m. This resting-state data was then used to learn a beamformer for estimating fronto-parietal  $\gamma$ -power and to compute the baseline mean and standard deviation of fronto-parietal  $\gamma$ -power (as described below in the section on data processing). In each of the subsequent training blocks, the subject received real-time feedback on the state of fronto-parietal  $\gamma$ -oscillations by means of a white ball displayed on the screen. Specifically, log-bandpower of fronto-parietal  $\gamma$ -oscillations was mapped to the vertical position of the ball on the screen. Here, the center of the screen corresponded to the screen corresponded to  $\pm 2$  standard deviations. The vertical position of the ball was updated every 40 ms, while its horizontal position was fixed to the center of the screen.

Each training block consisted of twenty trials in pseudo-randomized order, in which the subject was instructed to try moving the ball to either the upper or lower border of the screen (subsequently termed conditions "Up" and "Down"). For this purpose, two grey rectangles were placed centrally on the upper and lower border of the screen, which changed their color to yellow in order to indicate the current target. The current target turned green whenever the subject managed to position the ball over it. The end of a trial was indicated by changing the color of both rectangles back to grey and hiding the ball. Each trial lasted for 60 s and was preceded by a baseline, randomly varying in length between 3.5 and 4.5 s.

During each session, a 121-channel EEG was recorded at 500 Hz using a QuickAmp amplifier with built-in common average reference (BrainProducts GmbH, Germany). Electrodes were placed according to the extended 10-20 system. Three healthy subjects participated in this study (S1, S2, and S3). The first subject performed three training sessions on different days, corresponding to a total training time of three hours. This subject was a member of the BCI-lab with experience in motor-imagery. For this subject, only the results of the last training session are reported. The remaining two subjects performed one training session on a single day, with the third subject only completing two of the three training blocks. The second and third subject were naive to BCIs.

#### 2.2 Data processing

To learn a beamformer for estimating fronto-parietal  $\gamma$ -power, the resting-state baseline data was first temporally filtered between 55 and 85 Hz using a third order Butterworth filter. The spatial covariance matrix of this data was then used in conjunction with the topography shown in Figure 1.a to compute a linearly constrained minimum variance (LCMV) beamformer [6]. The topography and frequency band chosen here correspond to the fronto-parietal  $\gamma$ -oscillations that were found to negatively correlate with motor-imagery performance in [2,5]. This beamformer was then used to spatially filter the resting-state baseline data. Subsequently, log-bandpower in the 55–85 Hz range was computed by a FFT in conjunction with a Hanning window, using a sliding window of 5 s length in steps of 40 ms. The resulting mean and standard deviation were used to calibrate the feedback procedure. During the actual training sessions, the same beamformer and slidingwindow procedure were employed for estimating log-bandpower of fronto-parietal  $\gamma$ -oscillations and providing feedback in real-time. Stimulus-presentation and real-time data-processing was performed with the BCI2000-framework [7] and its extension BCPy2000 (http://bci2000.org/ downloads/BCPy2000/).

### 3 Results

To assess the capability of each of the three subjects to intentionally control fronto-parietal  $\gamma$ -power, we divided the difference of mean ball position across conditions "Up" and "Down" by the



Figure 1: a) Topography used for beamforming. b) Estimated probability densities [8] of ball position (in standard deviations relative to resting-state baseline) for conditions "Up" and "Down" (group average). c) Topography of effect size  $d_{\rm SMR}$  between 8–14 Hz (group average). d) Effect size  $d_{\rm SMR}$  across spectral bands, averaged across electrodes over sensorimotor areas (dashed lines in c) (group average).

mean of the standard deviation of each condition. This resulted in effect strengths  $d_{\gamma}^{S1} = 0.7273$ ,  $d_{\gamma}^{S2} = 0.3419$ , and  $d_{\gamma}^{S3} = 0.3723$ . Based on random permutation tests with 10.000 iterations, these effect strengths were found to be sufficient for rejecting the null-hypothesis of zero effect strength with  $p_{\gamma}^{S1} < 1e^{-4}$  (N = 60),  $p_{\gamma}^{S2} = 0.0005$  (N = 60), and  $p_{\gamma}^{S3} = 0.0078$  (N = 40). As  $\gamma$ -range oscillations may be caused by muscular artifacts, it is crucial to investigate whether

As  $\gamma$ -range oscillations may be caused by muscular artifacts, it is crucial to investigate whether observed changes in  $\gamma$ -power may have been confounded by systematic changes in muscle tone. While non-cortical components of the EEG can not be completely eliminated, their influence may be attenuated by artifact correction procedures, e.g., based on Independent Component Analysis (ICA). Here, the SOBI algorithm was employed to decompose the recorded EEG of the training blocks of each subject into independent components (ICs) [9, 10]. IC topographies and spectra were then manually inspected, and questionable ICs were discarded. The remaining ICs were reprojected to the scalp electrodes. To determine whether an observed modulation of fronto-parietal  $\gamma$ -power may have been caused by artifactual components, effect sizes before and after artifact correction were compared. Recomputation of effect sizes after artifact correction resulted in  $d_{\gamma}^{S1} = 0.7578$ ,  $d_{\gamma}^{S2} = 0.0249$ , and  $d_{\gamma}^{S3} = 0.3051$ , i.e., a slight increase for the first subject, a strong decrease for the second subject, and a mild decrease for the third subject. Effect sizes S1 and S3 remained large enough to reject the null-hypothesis of zero effect strength with  $p_{\gamma}^{S1} < 1e^{-4}$  (N = 60) and  $p_{\gamma}^{S3} = 0.0241$  (N = 40). Subject S2 did not show a significant effect anymore ( $p_{\gamma}^{S2} = 0.4351$ , N = 60). This indicates that S2 employed muscle activity for cursor control. The data of subject S2 was hence discarded.

To test the hypothesis that intentional control of  $\gamma$ -power modulates the SMR, the raw EEG of each training session was spatially filtered using a Laplacian setup [11]. Then, for each trial and electrode log-bandpower was computed in 2 Hz frequency bins ranging from two to 98 Hz. Group-average effect size was computed across 18 electrodes covering sensorimotor-areas in frequency bins from 8–14 Hz. These electrodes (enclosed in dashed lines in Figure 1.c) and frequencies were selected a-priori. This resulted in an effect size of  $d_{\rm SMR} = 0.2088$ , which is sufficient to reject the null-hypothesis of zero effect size with p = 0.0069 (N = 100). To illustrate the modulation of the SMR by  $\gamma$ -control, Figure 1.c displays the topography of effect size between 12–14 Hz, with positive

values corresponding to increased  $\mu$ -power due to an attenuation of fronto-parietal  $\gamma$ -power. Note that  $\mu$ -power is enhanced primarily over right sensorimotor cortex. Figure 1.d shows the effect strength averaged over sensorimotor areas across spectral bands. Only the  $\mu$ -range displays an increase in bandpower due to intentional attenuation of fronto-parietal  $\gamma$ -power.

## 4 Discussion & Conclusions

The results presented in this work demonstrate that it is possible to learn how to control the power of fronto-parietal  $\gamma$ -oscillations, and that this new skill can be used to modulate the magnitude of the SMR in a manner beneficial for BCI-performance. Importantly, none of the subjects reported the use of motor-imagery. As such, the effect reported here is likely due to a modulation of sensorimotor cortex by fronto-parietal areas independently of motor-imagery. It remains to be seen which percentage of subjects may benefit from this effect, and whether similar results as reported here can be achieved with locked-in patients.

### References

- C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller. How many people are able to operate an EEG-based brain-computer interface (BCI)? *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11(2):145–147, 2003.
- [2] M. Grosse-Wentrup. Fronto-parietal gamma-oscillations are a cause of performance variation in brain-computer interfacing. In Proceedings of the 5th International IEEE EMBS Conference on Neural Engineering (NE 2011). IEEE, 2011.
- [3] B. Blankertz, C. Sannelli, S. Halder, E.M. Hammer, A. Kübler, K.R. Müller, G. Curio, and T. Dickhaus. Neurophysiological predictor of SMR-based BCI performance. *NeuroImage*, 51(4):1303–1309, 2010.
- [4] M. Grosse-Wentrup, B. Schölkopf, and J. Hill. Causal influence of gamma rhythms on the sensorimotor rhythm. *NeuroImage*, 56(2):837–842, 2011.
- [5] M. Grosse-Wentrup and B. Schölkopf. Gamma-power in a fronto-parietal network predicts motor-imagery performance. (under review).
- [6] B.D. van Veen, W. van Drongelen, M. Yuchtman, and A. Suzuki. Localization of brain electrical activity via linearly constrained minimum variance spatial filtering. *IEEE Transactions* on Biomedical Engineering, 44:867–880, 1997.
- [7] G. Schalk, D.J. McFarland, T. Hinterberger, N. Birbaumer, and J.R. Wolpaw. BCI 2000: A general-purpose brain-computer interface (bci) system. *IEEE Transactions on Biomedical Engineering*, 51(6):1034–1043, 2004.
- [8] Z.I. Botev, J.F. Grotowski, and D.P. Kroese. Kernel density estimation via diffusion. Annals of Statistics, 38(5):2916–2957, 2010.
- [9] A. Belouchrani, K. Abed-Meraim, and J.F. Cardoso and. A blind source separation technique using second-order statistics. *IEEE Transaction on Signal Processing*, 45(2):434–444, 1997.
- [10] A. Delorme and S. Makeig. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1):9–21, 2004.
- [11] D.J. McFarland, L.M. McCane, S.V. David, and J.R. Wolpaw. Spatial filter selection for EEG-based communication. *Electroencephalography and Clinical Neurophysiology*, 103:386– 394, 1997.