

Effectiveness of cross-frequency phase-amplitude covariance as additional features for Riemannian BCIs

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Introduction: Riemannian geometry has been shown to significantly improve BCI classification performance [1]. However, BCIs are still not reliable enough. To further improve Riemannian BCIs, it is thus worth exploring complementary features to the conventional Riemannian feature, i.e., spatial covariance matrix. In this work, we propose to combine the phase and amplitude covariance (PAC) of cross-frequency bands (FBs) as such an additional feature, inspired by phase-amplitude coupling [2].

Material, Methods and Results: We propose a new symmetric positive definite (SPD) matrix P_{PAC+BP} , that considers multiple features based on phase, amplitude, and band power (BP) of cross-FBs in one covariance matrix (Cov). As summarized in Fig. 1, P_{PAC+BP} consists of two different block matrices P_{PAC} and P_{BP} diagonally arranged with null off-diagonal matrices. P_{PAC} quantifies the covariance between the phase of low FB (LF) and the amplitude of high FB (HF). The best FB pair LF-HF is selected among 6 pairs (δ - β , θ - β , α - β , δ - γ , θ - γ , α - γ , β - γ) using the classDis FB selection algorithm from [3]. P_{BP} arranges the conventional spatial Covs in LF and HF diagonally as block matrices. We evaluated the usefulness of P_{PAC+BP} for mental workload classification using a public passive BCI dataset from [4]. To investigate the contributions of PAC and BP features, we also compared performances of P_{PAC} and P_{BP} individually. As a baseline, we built a Cov with the same structure as P_{BP} but with θ and α bands, the two most used FBs for EEG-based mental workload classification. Artifacts from that EEG dataset were reduced using ICA.

$$\begin{array}{l}
 P_{PAC}: \text{cross-frequency phase and} \\
 \text{amplitude Cov.} \\
 X_{PAC} = \begin{pmatrix} \cos(\phi_{L_L}(t)) \\ \sin(\phi_{L_L}(t)) \\ a_{H_H}(t) \end{pmatrix} \in \mathbb{R}^{3N \times T} \\
 P_{PAC} = \frac{1}{T-1} X_{PAC} X_{PAC}^T \in \mathbb{R}^{3N \times 3N} \\
 \phi_{L_L}(t) \dots \text{phase of low frequency band} \\
 a_{H_H}(t) \dots \text{amplitude of high frequency band}
 \end{array}
 \quad
 \begin{array}{l}
 P_{BP}: \text{cross-frequency band-power} \\
 \text{Cov.} \\
 \Sigma_{X_{L_L}} = \frac{1}{T-1} X_{L_L} X_{L_L}^T \in \mathbb{R}^{N \times N} \\
 \Sigma_{X_{H_H}} = \frac{1}{T-1} X_{H_H} X_{H_H}^T \in \mathbb{R}^{N \times N} \\
 P_{BP} = \begin{pmatrix} \Sigma_{X_{L_L}} & 0 \\ 0 & \Sigma_{X_{H_H}} \end{pmatrix} \in \mathbb{R}^{2N \times 2N} \\
 X_{L_L}(t) \dots \text{filtered EEG at low frequency band} \\
 X_{H_H}(t) \dots \text{filtered EEG at high frequency band}
 \end{array}
 \quad
 \begin{array}{l}
 P_{PAC+BP}: \text{combined Cov. of } P_{PAC} \text{ and} \\
 P_{BP} \\
 P_{PAC+BP} = \begin{pmatrix} P_{PAC} & 0 \\ 0 & P_{BP} \end{pmatrix} \in \mathbb{R}^{5N \times 5N}
 \end{array}$$

Figure 1. Formulas of proposed cross-frequency SPD matrices

The dataset consisted of EEG data from 29 subjects who performed zero or two back tasks. The first two blocks were used as the training set, and the final block as the test set. Mean classification accuracies (%) using Minimum Distance to Mean classifier [1] were 74.1 ± 15.1 , 76.6 ± 20.6 , 78.5 ± 21.4 and 84.4 ± 18.4 for the baseline, P_{PAC} , P_{BP} , and P_{PAC+BP} respectively. Repeated measure ANOVA revealed significant differences between methods ($p = 0.01$). P_{PAC+BP} showed statistically significant improvement from baseline ($p=0.01$). **Discussion:** All Cov showed better mean accuracy than baseline, with P_{PAC+BP} showing the greatest improvement. This suggests the effectiveness of PAC as an additional feature to BP.

References

- [1] Congedo M, Barachant A, Bhatia R. Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review. *Brain-Computer Interfaces*, 4(3), 155-174, 2017.
- [2] Tort AB, Komorowski R, Eichenbaum H, Kopell N. Measuring phase-amplitude coupling between neuronal oscillations of different frequencies. *Journal of neurophysiology*, 104(2), 1195-1210, 2010.
- [3] Yamamoto MS, Lotte F, Yger F, Chevallier S. Class-distinctiveness-based frequency band selection on the Riemannian manifold for oscillatory activity-based BCIs: preliminary results. In *EMBC 2022*.
- [4] Hinds MF, Jahanpour ES, Somon B, Pluchon L, Dehais F, Roy RN. COG-BCI database: A multi-session and multi-task EEG cognitive dataset for passive brain-computer interfaces (Version 4) [Data set], Zenodo, 2022. <https://doi.org/10.5281/zenodo.7413650>