 DOI: 10.3217/978-3-99161-050-2-096

Riemannian-Based Convolutional Neural Networks for EEG Classification

Imad Eddine Tibermacine[1*], **Christian Napoli**[1,2,3]
[1]*Department of Computer, Control and Management Engineering, Sapienza University of Rome, Rome, Italy*
[2]*Institute for Systems Analysis and Computer Science, Italian National Research Council, Rome, Italy*
[3]*Department of Computational Intelligence, Czestochowa University of Technology, Czestochowa, Poland*
* E-mail: tibermacine@diag.uniroma1.it

Introduction: Electroencephalography (EEG) data are essential for BCI tasks such as motor imagery and mental state analysis. Traditional Euclidean approaches overlook the manifold structure of multi-channel covariance matrices, which reside on *Symmetric Positive Definite* (SPD) manifolds. This neglect diminishes accuracy and obscures critical inter-channel relationships[1]. Recognizing these limitations, researchers have turned to Riemannian geometry to analyze the inherent structure of SPD matrices. This paper adopts a Riemannian-based convolutional neural network (CNN) paradigm that integrates geometric insights into feature extraction and classification steps. In doing so, it maintains important spatial dependencies among EEG electrodes and takes advantage of the interpretability afforded by manifold-based representations[2].

Materials and Methods: We used the BCI Competition IV dataset 2a (BCIC-IV-2a), which provides four-class motor imagery data from nine subjects. Each session comprises 288 trials collected over 22 electrodes at a sampling rate of 250 Hz. Initial preprocessing includes noise reduction, down-sampling to 128 Hz, and extraction of 3.5-second epochs to focus on the most discriminative time window. This procedure yields 22×22 covariance matrices per trial, and these matrices are then viewed as points on the SPD manifold. In our approach, we first feed the raw EEG signals into a CNN-based feature extractor to learn preliminary spatial and temporal filters. However, instead of applying standard Euclidean operations, we compute covariance matrices from the learned features to preserve the inter-channel structure in a geometry-aware manner. A Stiefel manifold transformation reduces matrix dimensionality while maintaining orthonormal constraints, which is critical to avoid distortion of manifold geometry. We then map these lower-dimensional SPD matrices into a tangent space using the matrix logarithm, allowing subsequent linear layers to handle the features more effectively. Throughout training, orthonormal constraints on the Stiefel manifold are enforced via a custom optimizer that corrects parameters after each gradient update. This design adheres to a geometry-aware classification pipeline. Rather than flattening or ignoring inter-channel correlations, we exploit the SPD manifold structure to reflect the nuanced relationships among electrodes. By localizing covariance in a Riemannian tangent space, the model aligns with intrinsic EEG signal geometry and is better positioned to overcome the non-linearities often overlooked by purely Euclidean CNNs.

Discussion and Significance: By integrating Riemannian geometry into CNNs, we address the misalignment between Euclidean assumptions and the manifold nature of EEG covariance data. Evaluated on the BCIC-IV-2a dataset, this approach achieves a validation accuracy of approximately 80% for four-class motor imagery, representing a 10% improvement over purely Euclidean CNN approaches, credited to its faithful representation of channel dependencies and covariance-based noise robustness. Beyond boosting accuracy, this geometry-aware model improves interpretability by revealing global spatio-temporal patterns and effectively generalizing across subjects. Its promise extends to cognitive workload assessment, neurorehabilitation, and adaptive BCIs, where inter-channel dynamics are crucial. Future directions include exploring alternative Riemannian metrics and developing manifold-aware neural layers for end-to-end geometry-preserving representations, underscoring the potential for deep learning and Riemannian geometry to further advance EEG-based BCI systems.

References:

[1] Congedo, Marco, Alexandre Barachant, and Rajendra Bhatia, "Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review," *Brain-Computer Interfaces 4, no. 3 (2017): 155-174.*

[2] Yger, Florian, Maxime Berar, and Fabien Lotte, "Riemannian approaches in brain-computer interfaces: a review," *IEEE Transactions on Neural Systems and Rehabilitation Engineering 25, no. 10 (2016): 1753-1762.*

Published by Verlag der Technischen Universität Graz