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EEG DATA PROCESSING FOR BRAIN COMPUTER INTERFACE

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BCI - Brain-computer interfaces make it possible to communicate between a computer and the brain using neural activities. Generally, electroencephalogram(EEG) signals are used for this communication.

In this work, we worked in two ways. In the first way, we used Riemannian geometry and in the second we used Neural Networks - as baseline architecture we used EEGNet, a compact convolutional neural network for EEG-based BCIs. Riemannian geometry is the branch of differential geometry that studies Riemannian manifolds. We used it for feature extraction. Because we are converting the EEG signals to covariance matrices, during these estimations, we used several covariance estimations like ERPCovariances and XdawnCovariances. So, by using Riemannian geometry, we are writing these matrices in the vector. At last, we can use any classification to classify these vectors. In the deep learning part, We use EEGNet which is used depthwise and separable convolutions to construct the model which encapsulates well-known EEG feature extraction concepts for BCI.

We make several tests for parameters of EEGNet (table 1), PyRimannian library (table 2), and parameters during the pre-processing of datasets like decimation, filtering and scaling. Brain-computer interfaces (BCI) make it possible to communicate between a computer and the brain using neural activities [1]. Traditionally, BCIs are used for medical applications. The studies have opened the chance for brand-spanking new BCIs targeting enhancing the performance of the users, with noninvasive approaches grounded on EEG. Generally, a BCI consists of five main processing stages [2] the information collection, sign processing stage, feature extraction stage, and feedback step. While these stages are largely identical across BCI paradigms, each paradigm relies on nonautomatic specification of signal processing, feature extraction, and classification methods [3, 4].

The filtering algorithm is often seen as a data-driven dimension reduction method that aims at promoting variance differences between two conditions. during this fashion, covariance matrices are handled within the metric space inconsiderately of the curvature of the space of Symmetric Positive Definite (SPD) matrices to which they belong. This paper provides a straightforward thanks to take under consideration the non-Euclidean geometry for EEG signal classification. Furthermore, a replacement kernel springs by establishing a reference to the elliptic geometry of SPD matrices. Similar approaches are applied, resulting in the definition of various kernels looking at the Riemannian metric considered. [5, 6].

Neural networks have largely soothed the necessity for feature extraction, achieving state-of-the-art performance in fields just like computer vision. Specifically, the utilization of CNNs has grown due partly to their success in numerous image classification problems [7], surpassing styles relying on hand-crafted features. During this work, we used EEGNet, a compact CNN for the classification and interpretation of EEG- grounded BCIs. during this EEGNet structure, it's used Depthwise and Separable convolutions, preliminarily utilized in computer vision [8], to construct an EEG-specific network that encapsulates several well-known EEG feature extraction conceptions, like optimal spatial filtering and filter-bank construction, while contemporaneously reducing the number of trainable parameters to suit in comparison to being approaches [9].

Table 1. Results from EEGNet

Classifier	accuracy	f1	precision	recall	roc-auc
EEGNet	0.864653	0.506274	0.764358	0.377845	0.661713

Table 2. Results from PyRiemann libraries

Classifier	accuracy	f1	precision	recall	roc-auc
ERPCov TS LR	0.953653	0.856285	0.885698	0.829846	0.981511
Xdawn LDA	0.950128	0.848273	0.884239	0.819141	0.977125
SVM	0.947137	0.829210	0.893059	0.775881	0.974534
LDA	0.944750	0.828423	0.868455	0.799009	0.967462
LR	0.941905	0.815382	0.868115	0.775330	0.970644

Riemannian approaches are successfully applied to EEG signals for brain-computer interfaces. Acting on covariance matrices in Riemannian spaces offers a good choice of distances, embedding desirable invariances: it’s thus possible to avoid the computation of user-specific spatial filters which are sensitive to artifacts and outliers. Nonetheless, the estimation of the Riemannian mean incorporates a strong impact on the classifier accuracy. This study investigates the performance of several distances and divergences on a true EEG dataset within the context of the BCI-supported paradigm. That’s if you are working with not only EEG signals, for all time series - Riemannian geometry is one of the first choices. On the other hand, by using neural networks, like EEGNet you can create a strong model with big datasets.

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