Classification of Mental Workload Spatial Effects using Riemannian Manifold

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Abstract

This study investigates the use of Riemannian geometry to classify mental workload from an EEG dataset collected in an aeronautical context. The analysis, based on EEG data recorded from 16 participants performing a Simon task, aimed to differentiate low and high workload conditions. Using covariance matrices and a Minimum Distance to Mean (MDM) classifier, the results demonstrate spatial effects of mental workload irrespective of the investigated spectral domain. This demonstrates that spatial information is distributed evenly across all explored frequency bands.

Keywords: Mental workload; Riemannian geometry; Classification; Electroencephalogram; Covariance Matrices

Context—Framework

The increasing role of Artificial Intelligence (AI) within society is notably transforming various sectors, including aeronautics, where the integration of automation and embedded AI into technical-industrial systems is shifting the role of human operator from agent to controller of systems. In this context, optimizing the design of future systems to better align with operators' needs and capabilities requires a deep understanding and characterization of the operator's cognitive states. Electroencephalography (EEG)—a widely used technique for measuring brain electrical activity —provides valuable insights into an individual's cognitive state.

Covariance Matrices (CMs), computed on the EEG signals, contain discriminative spatial information, such as variance of recorded signals and coherence between pairs of channels. As Symmetric Definite Positive (SPD) matrices, CMs can be exploited in the more relevant context of Riemannian geometry to provide a robust state-of-the-art machine learning approach for classification (Barachant et al., 2011).

This perspective enhances signal processing by improving robustness, accuracy, and classification performance, thus offering advantages over traditional Euclidean geometry-based methods (Congedo, Barachant et Bhatia, 2017).

Material

The study reported here was conducted using an existing dataset focused on mental workload within an aeronautical context, previously conducted at ONERA (the French Aerospace Lab) (Deshayes et al., in preparation). EEG data were obtained from 21 volunteers who participated in different manipulated workload conditions. EEG signals were recorded using 64 active electrodes (international system positioning 10/20) with a sampling rate of 500 Hz.

To assess mental workload, the Multi-Attribute Task Battery II (MATB-II) was employed (Santiago-Espada et al., 2011). This task battery was configured with two difficulty levels (low and high) performed during separate sessions. Following the MATB-II tasks, participants engaged in the Simon task (Craft & Simon, 1970). The task was administered immediately after the MATB-II sessions to capture the cognitive effects of the varying workload levels.

Analysis—Algorithm

The analysis was conducted on data from 16 participants: 5 of the 21 subjects were excluded due to artifact rejection during the preprocessing phase. For each subject, EEG data were firstly pre-processed as follows: interpolation of bad channels, application of a notch filter to clean the 50 Hz band (and its harmonics), a high-pass filter (cut-off at 0.1 Hz), and common average re-referencing. Artifact correction was then conducted using Signal-Space Projection (SSP). Ocular artifacts were identified using EOG electrodes for blinks and AF7/AF8 EEG electrodes for saccades.

The primary objective of the study was to classify mental states from EEG data between low and high workload over frequency sub-bands. The following sections will describe the proposed methodology. The algorithm was implemented using Python and libraries such as *MNE* (v.1.8.0) for EEG data processing, *pyRiemann* (v.0.7) for Riemannian geometry computations, and *scikit-learn* (v.1.5.1) for machine learning.

Algorithm.

Firstly, the Power Spectral Density (PSD) was computed on the raw data segmented into overlapping windows (duration = 4s, overlap = 25%) using Welch's method. The spectral domain was restricted to the range [0.1-50] Hz. For each of these windows, CMs were estimated using the Oracle Approximated Shrinkage (OAS) method (Chen et al., 2010). Finally, classification was performed using the Minimum Distance to Mean (MDM) classifier (Barachant et al., 2011) based on Riemannian's metrics, and performance was assessed through a shuffle-split cross-validation scheme consisting of 20 splits with 80% of the data used for training.

First, we applied the proposed methodology on the full spectral domain [0.1-50] Hz. Then, we conducted a similar analysis by classifying the mental workload using band-pass filtered data along windowed signal (size 4 Hz without overlapping). Windows were used to study the variability of mental workload's spatial signature with frequency range.

Results

Power Spectral Density (PSD).

The PSD shows strong variations between conditions, mainly in the lower frequency ranges (α-band). In the high workload condition, a tendency towards decreased spectral power was observed in the Alpha (8-12 Hz) frequency band, consistent with previous findings in the literature (Borghini et al., 2012).

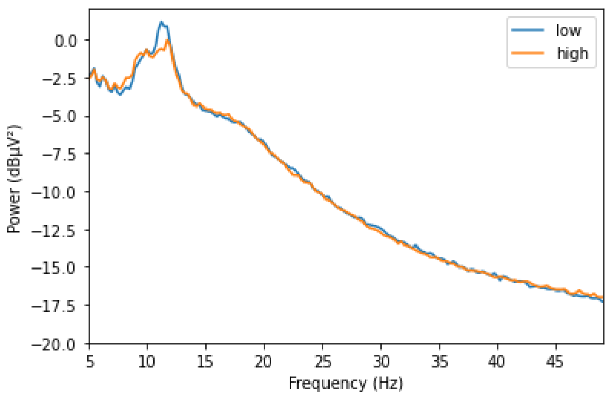

Figure 1: Average PSD distribution for the 16 subjects between conditions (low vs. high) at the P_z electrode

Classification scores.

The classification of mental workload, based on the full spectral signal [0-50] Hz, achieved a mean accuracy level of 0.69 with a standard deviation of 0.04.

Additionally, classification performance was assessed across windowed frequency sub-bands (windowed signal of 4 Hz) and cross-validation folds. We obtain a classification score identical to the one computed with the full frequency domain, whatever the sub-band used (see Figure 2 below). This demonstrates that the spatial signature of the workload effect in the brain manifests itself over the full spectrum.

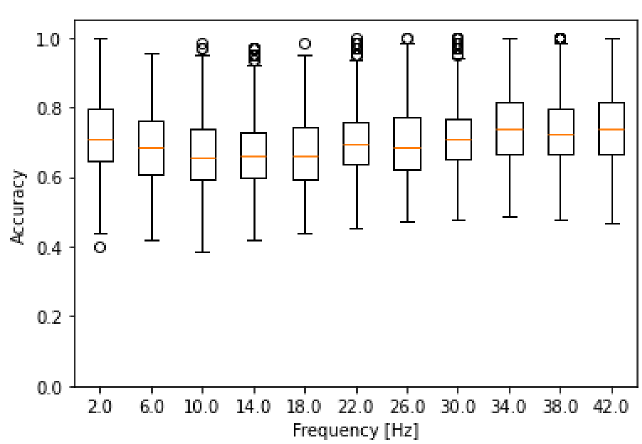

Figure 2: Distribution of classification accuracy across frequency sub-bands

Discussion

The application of Riemannian geometry to EEG covariance matrices demonstrated robust classification accuracy for mental workload, achieving an accuracy score about 70%. Which is supporting the existence of a spatial effect in the brain associated with mental workload.

Furthermore, PSD shows a mental workload effect on the alpha frequency band that had been widely reported in the literature.

Although amplitude variations in spectral power were observed, classification results did not exhibit significant improvements across individual frequency bands. This invariance in performance is attributed to the classification algorithm's input employed. Specifically, the method relies on covariance matrices in a Riemannian manifold and focuses on modeling spatial relationships between features. This aligns with the brain neural networks distribution engaged during cognitive tasks, whose spatial dynamics are captured effectively by the Riemannian framework.

Conclusion

This study applied Riemannian geometry-based machine learning to classify mental workload states from EEG signals. To do so, we used CMs capturing spatial relationships in the data. Classification results show the presence of a mental workload effect on all the frequency sub-bands. In future studies we plan to localize the spatial sources of these effects for the identification of specific locations, significantly contributing to the classification process.

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