STAGE
INTERNSHIP

MASTER 2

Date of offer: 07/09/2026

Deep Neuronal networks on the Riemannian Manifold of Positive-Definite Matrices;
Applications to Brain-Computer Interfaces

SUPERVISOR

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WHERE

Département Science des Données, GIPSA-lab, Saint Martin d'Hères, Grenoble Campus.

HOW LONG

During 5 months, starting on February the 1st 2027.

CONTEXT

Using a brain-computer interface (BCI) based on electroencephalography (EEG), a human being can send simple commands to a machine without relying on the motor system or the peripheral nervous system (*e.g.*, eye movements); instead, a machine learning model (MLM) interprets the intention of the user based only on the EEG signal (Fig. 1) [1]. A BCI can therefore be operated in complete stillness.

The possibilities offered by BCIs are particularly useful for patients affected by neuromuscular disorders and locked-in syndromes, for whom a BCI may represent the only hope to restore some movement and to communicate with the external world, respectively. A BCI can also be used to monitor the brain state of the user, for example to detect brain physiological parameters related to fatigue, cognitive load, attention, etc., with a large variety of applications such as devising brain-aware assistance for operating machines (e.g., driving assistance).

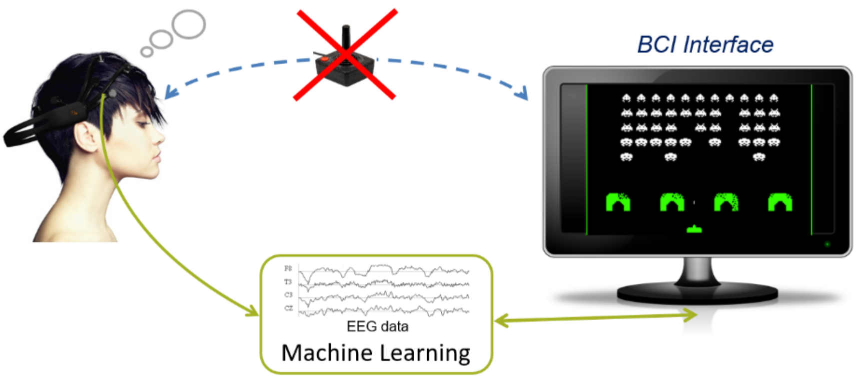

Figure 1. Schematic representation of the operation of a BCI.

MOTIVATION

Among the existing modalities for probing brain functions, EEG has unique characteristics: it is cheap, light-weight, completely safe, silent and offers excellent time resolution [2]. BCI based on EEG can be operated anywhere, from the patient's bed to the tip of a mountain and on anybody, even newborns. Although significant progress has been made by the scientific community over the last 30 years, the use of an EEG-based BCI is still cumbersome in practice because it requires a calibration of the MLM before each use. This is due to the high variability of the EEG signal between different subjects and between subsequent sessions of the same subject, which jeopardizes the generalization of MLMs [3].

On the one hand, the state-of-the-art for classifying EEG signals in the context of BCIs is the use of tools borrowed from differential geometry. EEG data segments (BCI trials during which the subject tries to send a command) are coded by means of their covariance matrices; these matrices are symmetric and positive-definite, thus are treated as points on a Riemannian manifold with a peculiar geometry [3]. On the other hand, deep neuronal networks provide powerful architectures to learn complex decision functions and are today on the forefront of the research on machine learning [9, 10].

AIM

This research aims at taking the best of both worlds: on the one hand the robustness and precision of Riemannian geometry, on the other hand the expressivity of deep neuronal networks. This is achieved by designing deep neuronal networks acting directly on the Riemannian manifold of positive-definite matrices (RDNN).

OBJECTIVES

The aim of this research is to develop and test *RDNNs* in the context of EEG-based BCIs. The construction of the models will leverage three complementary resources:

- transfer learning techniques, studied at GIPSA-lab within the framework of Riemannian geometry since 2018 [4-7], to be transposed in a deep learning framework,
- Riemannian deep learning models based on a massive and heterogeneous amount of open-access BCI databases [8],
- the intensive computing facilities available in Grenoble (GRICAD).

By applying transfer learning techniques in a neuronal learning setting, we aim at using large amounts of data to improve the accuracy of BCI decoders. Such a challenge has been shown to be feasible in a shallow learning setting [4]. The goal of the project is to explore the feasibility of transposing these finding into a deep learning setting.

DESCRIPTION OF THE WORK

The student will acquire familiarity with EEG data and, particularly, the BCI datasets used for training and testing the RDNNs. The student will study existing transfer learning methods and Riemannian deep neuronal networks to propose and test architectures that may serve the objectives of the project. Finally, the student will evaluate the performance of competing architectures, including published ones [9-11] and architectures currently under development at GIPSA-lab. The evaluations will be carried out on local PCs and/or on clusters of PCs available in Grenoble (GRICAD).

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KEY WORDS

Brain-Computer Interface, Machine Learning, Transfer Learning, Cross-Subject Generalization, Riemannian deep neural networks.

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REQUIRED SKILLS

The candidate should be proficient in computer programming with at least one of the following languages: Julia, Python, Matlab. If this internship is fruitful the candidate will be encouraged to enroll in a PhD program.

REMUNERATION

According to current legislation.

REFERENCES:

[1] Wolpaw J, Wolpaw EW. Brain-Computer Interfaces: Principles and Practice. Oxford: Oxford University Press; 2012

[2] Schomer DL, Lopes da Silva F. Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields, Sixth Edition, Philadelphia (PA): Lippincott Williams & Wilkins; 2011.

[3] Lotte F, Bougrain L, Cichocki A, Clerc M, Congedo M, Rakotomamonjy A, Yger F (2018) A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. Journal of neural engineering, 15(3), 031005.

[4] Altindis F, Banerjee A, Phlypo R, Yilmaz B, Congedo M (2023). Transfer Learning for P300 Brain-Computer Interfaces by Joint Alignment of Feature Vectors. IEEE Journal of Biomedical and Health Informatics, 2023, 27 (10), pp.4696-4706.

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[7] Zanini P, Congedo M, Jutten C, Said S, Berthoumieu Y (2018) Transfer Learning: a Riemannian geometry framework with applications to Brain-Computer Interfaces. IEEE Transactions on Biomedical Engineering, 65(5), 1107-1116.

[8] Jayaram V, Barachant A (2018). Journal of Neural Engineering, 15, 066011.

[9] Kobler RJ, Hirayama J-I, Kawanabe M (2022). Controlling The Fréchet Variance Improves Batch Normalization on the Symmetric Positive Definite Manifold", Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Singapore, pp. 3863-3867.

[10] Kobler RJ, Hirayama J-I, Zhao Q, Kawanabe M (2022) SPD domain-specific batch normalization to crack interpretable unsupervised domain adaptation in EEG. Proceedings of the 36th International Conference on Neural Information Processing Systems (NeurIPS), New Orleans, 6219 - 6235.

[11] Chevallier S, Carrara I, Aristimunha B, Guetschel P, Sedlar S, et al. (2024) The largest EEG-based BCI reproducibility study for open science: the MOABB benchmark. hal-04537061