STAGE
INTERNSHIP

MASTER 2

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Riemannian Machine Learning in the Tangent Space for Brain-Computer Interfaces

SUPERVISORS:

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PLACE OF INTERNSHIP:

Departement Images-Signal, GIPSA-lab, in the campus of Grenoble.

DURATION OF INTERNSHIP:

The internship will start on February 2020 and will end on Juin 2020 (5 months).

CONTEXT:

This project is in the context of the Brain-Computer Interface (BCI) research carried out at the GIPSA-lab since 2008. It will integrate ongoing efforts at GIPSA-lab to develop efficient data science tolls using the Julia programming language (Bezanson, 2017). It is integrated to an ongoing PhD thesis.

SUBJET:

Riemannian geometry studies smooth manifolds, multi-dimensional curved spaces with peculiar geometries endowed with non-Euclidean metrics. In these spaces Riemannian geometry allows the definition of angles, geodesics (shortest path between two points), distances between points, centers of mass of several points, etc.

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In several fields of research such as computer vision and brain-computer interface, treating data in the manifold of positive definite matrices has allowed the introduction of machine learning approaches with remarkable characteristics, such as simplicity of use, excellent classification accuracy, as demonstrated by the winning score obtained in six international data classification competitions, and the ability to operate transfer learning (Barachant et al., 2012; Congedo et al., 2017).

We are concerned with making use of Riemannian Geometry for classifying data in the form of positive definite matrices (e.g., covariance matrices, Fourier cross-spectral matrices, etc.). This can be done in two ways: either directly in the manifold of positive definite matrices using Riemannian machine learning methods or in the tangent space, where traditional (Euclidean) machine learning methods apply, e.g., linear discriminant analysis, support-vector machine, logistic regression, random forest, etc. This is illustrated in Fig. 1.

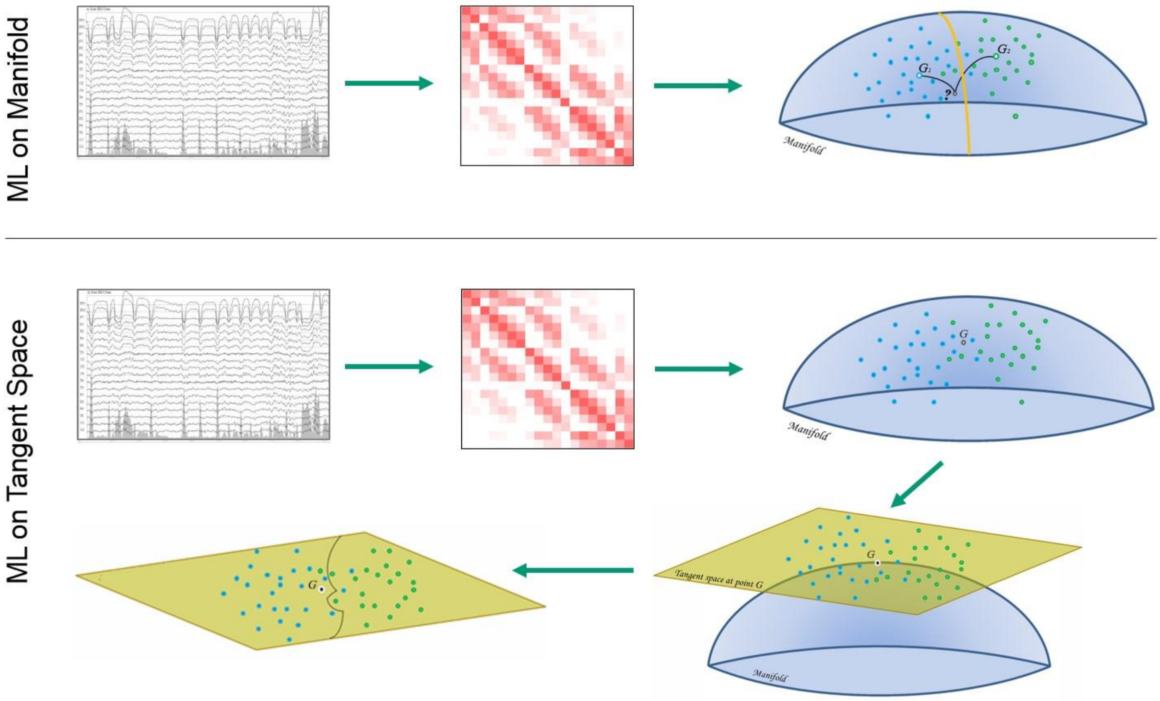

Figure 1 - *Schematic representation of Riemannian classification. Data points are either natively positive definite matrices or are converted into this form. The classification can be performed by Riemannian methods in the manifold of positive definite matrices or by Euclidean methods after projection onto the tangent space.*

RESEARCH TOPIC:

In the context of BCI research in a Riemannian framework, several studies have highlighted the accuracy of *sparse classifiers* such as the LASSO logistic regression. In fact, these classifiers allows to optimize the decision function performing a feature selection step at the same time, therefore to suppress noise. In this internship the candidate will have access to several publicly available BCI databases, including, but non limited to, those released by the GIPSA-lab. Using several databases the candidate will explore sparse machine learning strategies in order to find suitable strategies for BCI data. The goal is to recommend to the BCI community one or more suitable classifiers that display desirable characteristics in the context of BCI (accuracy, generalization, overfitting, etc.)

MOTS CLEFS:

Electroencephalography (EEG), Brain-Computer Interface, Machine Learning, Sparse classifiers.

REMUNERATION :

The internship will be remunerated at 1/3 of SMIC.

REQUISITES:

The candidate should possess good knowledge on applied mathematics, with particular emphasis on digital signal processing and machine learning. The candidate should also have experience with high-level programming language such as Julia, Python or Matlab.

PUBLICATIONS :

A. Barachant, S. Bonnet, M. Congedo, C. Jutten (2012) Multi-class Brain Computer Interface Classification by Riemannian Geometry, IEEE Transactions on Biomedical Engineering, 59(4), 920-928.

J. Bezanson, A. Edelman, S. Karpinski, V.B. Shah, (2017) A fresh approach to numerical computing, SIAM review, vol. 59, no. 1, pp. 65-98.

M. Congedo, A. Barachant, R. Bhatia R (2017) Riemannian Geometry for EEG-based Brain-Computer Interfaces; a Primer and a Review, Brain-Computer Interfaces, 4(3), 155-174.

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