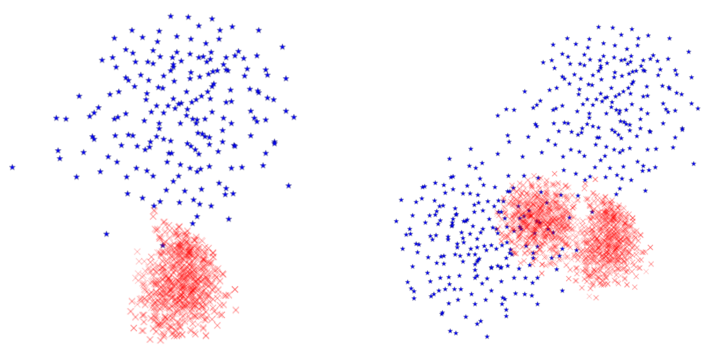
**Joint Asclepios/ Athena teams**
**Internship offer**

# Geometric Dimension Reduction Methods for Brain Computer Interface Signals

## Project Description:

### Brain Computer Interfaces (BCI)

EEG-based BCI are interfaces where the acquisition is carried out by an Electroencephalograph (EEG) and the application-specific information is extracted from the resulting signal [Clerc et al., 2016]. The goal is to classify segments of EEG signals to their corresponding mental tasks (for simplicity assume a binary classification problem with two classes). First, a classifier is trained with labeled data obtained through a tedious calibration, preceding the usage session, during which the BCI user is asked to perform the two mental tasks. EEG data have an extremely low Signal-to-Noise Ratio, while being subject to an important amount of cross-session and cross-subject variability: the reduced representation of the feature space allows to separate 2 classes (blue/red) in a single session (left figure below), but not in multiple session (right figure below).

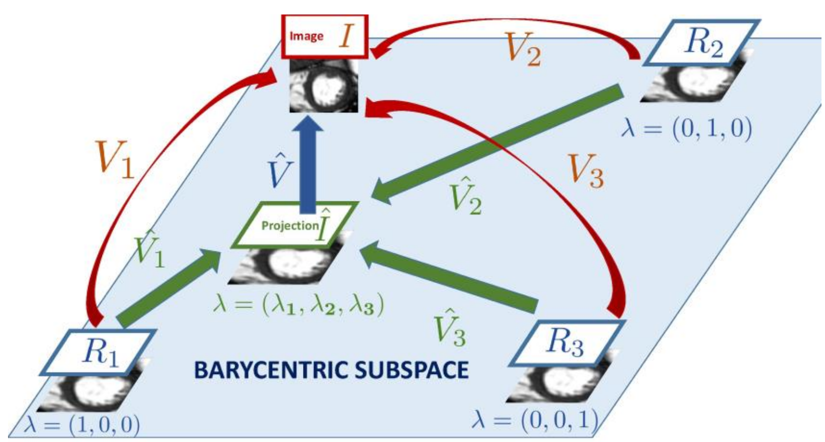


Hence, state-of-the-art classifiers generalize poorly, and calibration needs to precede each and every usage session. In the works of the Athena team, the recurring problem of pre-usage calibration is tackled by training a classifier that generalizes well. Recent researches have shown that the classification task is more robust to cross-session / cross-subject variability under the framework of Riemannian geometry [Barachant et al., 2012]. Under the assumption that each mental task follows a specific distribution, the feature vector associated to a signal segment consists of the coefficients of a large covariance matrix. The resulting feature space is the high dimensional Riemannian manifold of Symmetric Positive Definite matrices, where an affine-invariant metric is well defined. As shown in recent works by Athena, while Riemannian distance-based classifiers show promising results, the high dimensionality of the manifold is still an issue [Gayraud et al., 2016].

## Geometric learning: Non-linear subspace approximation in non-linear manifolds

Principal Component Analysis (PCA) is the ubiquitous tool to obtain low dimensional representation of the data in linear spaces. To generalize PCA to Riemannian manifolds, one can perform the analysis of the covariance matrix of the data in the tangent space at the Fréchet mean (Tangent PCA). This is often sufficient when data which are sufficiently centered around a central value (unimodal or Gaussian-like data), but generally fails for multimodal or distributions with a large variability with respect to the curvature, which is the case for the covariance matrix of the EEG signal. Instead of maximizing the explained variance, methods minimizing the unexplained variance were proposed: Principal Geodesic Analysis (PGA) and Geodesic PCA (GPCA) minimize the distance to a Geodesic Subspaces (GS) spanned by the geodesics going through a point with tangent vector is a restricted linear subspace of the tangent space.

A new type of subspaces in manifolds was recently introduced in Pennec, 2016]: Barycentric Subspaces. These spaces are implicitly defined as the locus of weighted means of k+1 reference points. This locally define a submanifold of dimension k which generalizes previously introduced subspaces like geodesic subspaces. They can naturally be nested, which allow the construction of inductive forward or backward nested subspaces approximating data points. This results into a particularly appealing generalization of PCA on manifolds, that is called Barycentric Subspaces Analysis (BSA). In practice, a hierarchy of embedded barycentric subspaces is defined by an ordered series of points in the manifold, and data may be characterized by their barycentric coordinates inside the submanifold plus an orthogonal residual from the data points to their projection in the BS. An example application to the analysis of 3D cardiac image sequences through non-linear image registration (Figure on the right) has shown that the optima reference points were actually very meaningful transition points between the cardiac phases in the sequence. Moreover, the barycentric coordinates were powerful signatures discriminating different clinical conditions [Rohe et al., 2016].




## Program of the internship

The goal of the proposed internship will be to study and implement the barycentric subspace analysis procedure on SPD matrices endowed with the affine invariant metric and to test it with BCI datasets. In the context of BCI, the problem is not trivial. The cross-session and cross-subject variability must be taken into account during the process of selecting the optimal lower dimensional subspace. In a first step, algorithms will be developed to project points into a barycentric subspace, and then to optimize the location of the reference points themselves. In order to avoid an intensive optimization, one will usefully restrict reference points to belong to the original data points. In a second step, the barycentric coordinates will be used to describe the data in the hierarchy of embedded barycentric subspaces and one will study the power of this signature to classify / predict the correct brain state

## Hosting groups:

The Asclepios and Athena team (Inria Sophia Antipolis) are located in the tech Park of Sophia Antipolis and in Nice, in the French Riviera.

## Required competences:

Competences in signal processing and statistics are required as well as a god knowledge of mathematics and in particular differential geometry (Master 2 level). Solid programming and IT skills are necessary (Python, bash scripting, version control systems), along with strong communication abilities.

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## References:


- [Barachant et al., 2012] Barachant, A., Bonnet, S., Congedo, M., and Jutten, C. (2012). Multiclass brain computer interface classification by Riemannian geometry. IEEE Transactions on Biomedical Engineering, 59(4):920-928.
- [Clerc et al., 2016] Clerc, M., Bougrain, L., and Lotte, F. (2016). Brain-Computer Interfaces 1: Methods and Perspectives. John Wiley & Sons.
- [Gayraud et al., 2016] Gayraud, N., Foy, N., and Clerc, M. (2016). A separability marker based on high-dimensional statistics for classification confidence assessment. In IEEE International Conference on Systems, Man, and Cybernetics October 9-12.
- [Pennec, 2016] Pennec, X. (2016). Barycentric subspace analysis on manifolds. arXiv preprint. arXiv:1607.02833.
- [Rohe et al., 2016] Rohe, M.-M., Sermesant, M., and Pennec, X. (2016). Barycentric subspace analysis: a new symmetric group-wise paradigm for cardiac motion tracking. In Porc of MICCAI 2016, pages 300-307. Springer.