Ecole Doctorale STIC

Sciences & Technologies de l'Information et de la Communication

MINES ParisTech — Université Nice Sophia Antipolis

ED STIC - Proposition de Sujets de Thèse

pour la campagne d'Allocation de thèses 2017

Axe Sophi@Stic : BioSanté|

Titre du sujet : Dimension Reduction in Manifolds using Barycentric Subspaces - Applications to Computational Anatomy and Brain Computer Interfaces

Mention de thèse : ATSI

HDR Directeur de thèse inscrit à l'ED STIC : Xavier Pennec

Co-encadrant de thèse éventuel :

Nom : Clerc

Prénom : Maureen

Email : maureen.clerc@inria.fr

Téléphone :

Email de contact pour ce sujet : xavier.pennec@inria.fr

Laboratoire d'accueil : INRIA

Description du sujet :

In many applications, data belong to non-linear manifolds. Taking into account the underlying geometric structure often allows improving the results. This is the case in Computational Anatomy (CA) and Brain Computer Interfaces (BCI) where data naturally belong to shape spaces, Lie groups and symmetric positive definite matrices. An important effort has been made so far around the computation of the mean in these types of manifolds (Battacharya & Patrangenaru 2003, Pennec 2006, Pennec & Arsigny 2012). The goal of this PhD is investigate higher dimensional approximations of geometric data living in manifolds, either globally (extension of PCA or PLS) or locally (extension of statistical manifold learning). The difficulty is to reduce the dimensionality of the data manifold without losing the original structure, in order to end-up with a consistent hierarchical subspace decomposition. This is a significantly harder problem than classical manifold learning in Euclidean or Hilbert spaces.

An interesting research avenue is the extension of Principal Component Analysis to manifolds based on barycentric subspaces proposed by (Pennec 2015, Pennec 2016). This theory is still in its early development. The objective of this PhD is to study a number of conjectures and to design algorithms for an efficient implementation in general and particular case. Applications of this framework will be investigated in two domains. First, in computational anatomy, the goal will be to improve the statistical modelling of the variability of the anatomical shape of different organs (brains and hearts), in collaboration with the other members of the Asclepios lab. An example application of Barycentric Subspace Analysis to 3D cardiac image sequences through non-linear image registration 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]. We would like to extend this framework to multi-atlases medical image segmentation, in order to define a globally consistent graph of transformations between these templates ensuring the transitivity of registrations. One expect in particular improvements in large inter-subject groupwise image registration.

The second main application will be in brain-computer interfaces (BCI), in collaboration with Maureen Clerc from the Athena project-team. 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. 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, a signal is thus represented by a covariance matrix belonging to a high dimensional Riemannian manifold of Symmetric Positive Definite matrices endowed with an affine-invariant metric. Dimensionality reduction in this space is expected to significantly improve the results [Gayraud et al., 2016].

Bibliography:
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• [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. Barycentric subspace analysis on manifolds. arXiv preprint. arXiv:1607.02833.
• Pennec, 2015. Barycentric Subspaces and Affine Spans in Manifolds. In Geometric Science of Information GSI'2015, Second International Conference, volume 9389 of Lecture Notes in Compuer Science, Palaiseau, France, pages 12-21, October 2015.

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• Pennec 2006. Intrinsic Statistics on Riemannian Manifolds: Basic Tools for Geometric Measurements. Journal of mathematical imaging and vision 25(1):127-154.
• [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 Proc of MICCAI 2016, pages 300-307. Springer.

Candidate profile:
- Second year of Master’s degree or equivalent diploma.
- Strong background in applied mathematics, in particular differential geometry signal processing, statistics.
- Solid programming and IT skills are necessary (Python, bash scripting, version control systems), along with strong communication abilities.

website: https://team.inria.fr/asclepios

Keywords: submanifold learning, computational anatomy, brain-computer interface, geometry, statistics.

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English version: