(PhD) Multimodal SAR-Optical Registration via Learned Covariance and Metrics

Context

Modeling and monitoring environmental phenomena such as flood, aerosol dispersion, and natural hazard analysis at a large scale require coherent virtual replica of the Earth. Space agencies, such as CNES, contribute to create such digital replica from space based measurements.

In fact, these tools require satellite images which come from multiple modalities. Synthetic Aperture Radar (SAR) images excel at detecting structural changes and monitoring natural phenomena (glaciers, volcanoes, earthquakes) with high precision while optical images (multispectral or hyperspectral) are easily interpretable for vegetation characterization. Nevertheless, the separate study of each modality provides inaccurate results and create a need for new approaches that combine these different modalities. Notably, intrinsic differences between both optical ans RADAR measurements create coherence challenges for the fusion step. In fact, RADAR data (amplitude and phase) are decorrelated from spectral reflectance and both exhibit vastly different noise statistics (SAR's multiplicative speckle versus optical noise).

This **PhD thesis** addresses geometric registration of heterogeneous satellite imagery. SAR (Sentinel-1, TerraSAR-X, ICEYE) and optical data (Sentinel-2, Pléiades Neo) provide complementary scene views but are often poorly registered. Robust multimodal registration is essential for geo-referencing and joint data exploitation, requiring displacement measurements between source and reference images. Current pipelines use statistical metrics for registration [4]. For multimodal SAR/optical images, deep neural network approaches have emerged [3] but suffer from end-to-end learning limitations: paired SAR/optical training data remain scarce despite abundant satellite data, and generalization across sensor or scene types is not guaranteed.

Objectives

In this work, we will extend statistical approaches from unimodal data [4]. They are based on two steps: covariance estimation (Sample Covariance Matrix – SCM) and comparison via Kullback-Leibler divergence or mutual information. These tools have explicit solutions only for Gaussian distributions and otherwise rely on computationally expensive estimators. Moreover, the Gaussian assumption fails for multimodal data. In this thesis, we will first replace the SCM with robust estimators [7] that disregard distribution assumptions and can incorporate structural constraints (low rank, Kronecker) into estimation algorithms [9].

Next, we will employ metrics based on covariance matrix geometry rather than statistical assumptions, such as log-Euclidean and affine-invariant distances [10]. These metrics will be more suited to multimodal data but may suffer from several drawbacks: iterative estimation algorithms are computationally expensive with sensitive hyperparameters, and strong dependence on statistical models persists even in non-Gaussian frameworks. To address this, we will leverage unrolled neural networks [6], combining learning and optimization for explainability, efficient training, model robustness, and inference speed. We propose to unroll covariance estimation algorithms [8]. Since these rely on Riemannian gradient descent [5], this represents novel work. In fact, to our knowledge, no unrolling of manifold-based algorithms exists.

A prospective direction involves a single-step approach inspired by metric learning [1], where distances and controlling matrices are learned jointly. This semi-supervised learning suits scenarios with limited annotations. Using [2] as a foundation, we will define appropriate registration criteria and unroll the geometric algorithm for enhanced robustness and speed.

We will test our approaches on SAR and optical data from current space missions (Sentinel-1/2, Pléiades Neo, TerraSAR-X, ICEYE), comparing against unimodal methods and neural network approaches [3].

Candidate profile

M2 or engineering diploma in one or more of the following fields: applied mathematics, signal and image processing, computer science, remote sensing. The candidate should have good written and oral communication skills as well as programming proficiency in Python.

Location

The PhD will take place at LISTIC, Université Savoie Mont Blanc in Annecy with possible travel to the CNES facilities in Toulouse. LISTIC is a research laboratory working on signal processing, computer science and application in remote sensing through established collaborations with CNES and other space agencies.

Application procedure

To apply to this position, please send an application including a cover letter, a CV as well as the last available academic transcripts of grades in your possession to:

- guillaume.ginolhac@univ-smb.fr
- ammar.mian@univ-smb.fr
- yassine.mhiri@univ-smb.fr
- alexandre.constantin@cnes.fr

As this PhD is part of CNES Doctoral program, all candidates will have to post their application on the CNES job platform (`https://recrutement.cnes.fr/`) **between February 2nd and March 13th, 2026**. The PhD is a 3-year contract starting **around September 2026**.

References

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[3] Lloyd H Hughes et al. "A deep learning framework for matching of SAR and optical imagery". In: *ISPRS Journal of Photogrammetry and Remote Sensing* 169 (2020), pp. 166–179.

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[6] Vishal Monga, Yuelong Li, and Yonina C. Eldar. "Algorithm Unrolling: Interpretable, Efficient Deep Learning for Signal and Image Processing". In: *IEEE Signal Processing Magazine* 38.2 (2021), pp. 18–44. DOI: `10.1109/MSP.2020.3016905`.

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[8] Can Pouliquen, Mathurin Massias, and Titouan Vayer. "Schur's Positive-Definite Network: Deep Learning in the SPD cone with structure". In: *The Thirteenth International Conference on Learning Representations*. 2025. URL: `https://openreview.net/forum?id=v1B4aet9ct`.

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[10] Yann Thanwerdas and Xavier Pennec. "O(n)-invariant Riemannian metrics on SPD matrices". In: *Linear Algebra and its Applications* 661 (2022), pp. 163–201.