Internship Offer — Master's or 3rd Year Engineering School

Geodesic Flow Matching : Multi-Sensor Fusion on Manifolds for Surface Displacement Estimation

Application to Sentinel-1 and NISAR Radar Interferograms

Level	❑ Bachelor+3 ❑ Bachelor+4 ■ Bachelor+5 (Master's or 3rd Year Engineering School)
Duration	6 months, starting March 2027
City, Country	Annecy, France
Laboratory	Laboratory for Computer Science, Systems, Information Processing and Knowledge (LISTIC)
Collaborations	Planned exchanges with the CEDRIC team at CNAM Paris (A. Breloy) on Riemannian flow matching, and with MIRE sas (M. Jauvin) on operational InSAR and field validation.

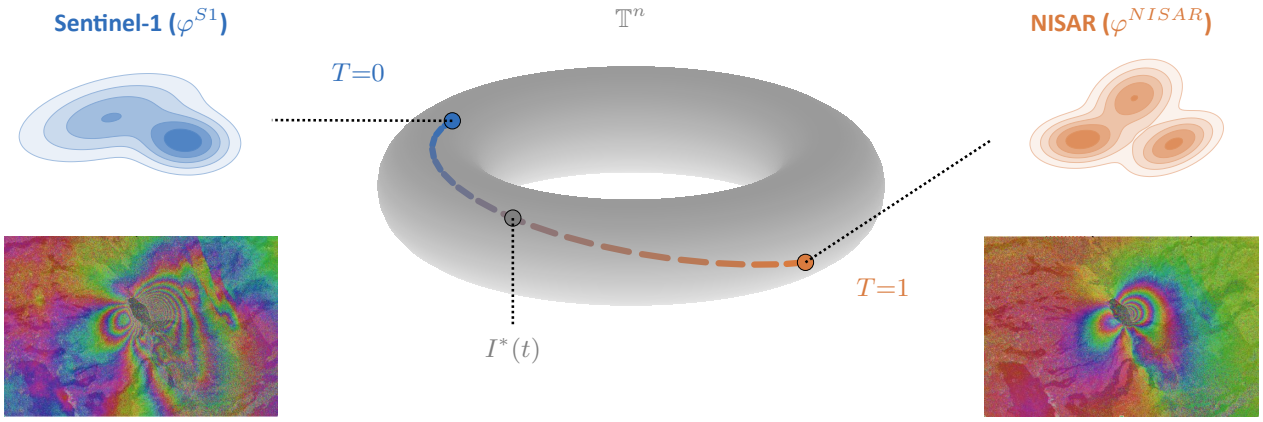


FIGURE 1 – *Internship objective : learning the path (dotted line) that continuously transports the Sentinel-1 phase distribution to the NISAR distribution on the phase torus $\mathbb{T}^n$. Density maps are schematic; the two panels show real interferograms acquired over the same area (Erta Ale volcano, November 2025).*

Context

Climate change is increasing the frequency and severity of gravitational hazards such as landslides, differential settling, and mudflows, which threaten transport and energy infrastructure, particularly in mountainous regions. Satellite-based radar interferometry (InSAR) addresses this need by measuring surface deformation with sub-centimeter precision, day or night and independently of cloud cover, by exploiting the phase difference between two radar acquisitions of the same site. Two open-data missions currently dominate this domain with complementary strengths. **Sentinel-1** (ESA, C-band, resolution ≈20 m) provides global coverage since 2014, a 6-day revisit time, and mature processing chains, but loses coherence under vegetation and cannot reliably measure displacements exceeding $\lambda/4 \approx 1.4$ cm per revisit interval due to phase aliasing [5]. **NISAR** (NASA-ISRO, L and S-band, resolution ≈10 m, launched in 2025) penetrates vegetation far more effectively and tracks larger displacement dynamics, but relies on a single satellite with a 12-day revisit and limited operational experience.

These limitations are complementary rather than cumulative : conditions unfavorable to one sensor correspond to the strengths of the other. Fusing their interferograms is therefore not redundancy but a genuine scientific bottleneck at the interface of three classical problems : reconciling different spatial resolutions, denoising non-Gaussian data, and completing images with missing or unreliable observations, known as incoherent pixels. Classical inverse-problem approaches are computationally expensive and require a detailed model of the degradation process [7], while convolutional networks, though more flexible, still lack uncertainty quantification and interpretability [6]. To overcome these shortcomings, generative AI has increasingly been applied to this type of fusion, first through generative adversarial

networks and, more recently, through flow matching techniques [1], which learn a continuous transport between two probability distributions via a vector field, making them naturally well suited to fusion tasks.

Internship Topic

The central difficulty tackled in this internship is geometric. InSAR phase is a circular quantity, taking values on a Riemannian manifold, the torus $\mathbb{T}^n$, rather than in a standard vector space, so naively averaging or interpolating two phases in $\mathbb{R}^n$ produces physically meaningless results. Recent flow matching methods learn a vector field that continuously transports one probability distribution to another, and this formalism extends naturally to Riemannian manifolds, allowing transport paths that remain faithful to the toroidal geometry of the phase. The internship aims to exploit this framework to construct a fused representation $I^*(t)$, illustrated in figure **??**, defined as a point on the geodesic path connecting the Sentinel-1 phase distribution ($T{=}0$) to the NISAR phase distribution ($T{=}1$), then conditioned by radar coherence $|\gamma|$ so that the model draws information from whichever sensor remains coherent where the other is not. The work is therefore both methodological, combining differential geometry and generative AI, and applied, involving radar signal processing and field validation against ground-truth displacement measurements.

Internship Schedule

Coupled Sentinel-1/NISAR datasets (co-registered interferograms and associated coherence) will already be acquired and preprocessed before the internship begins.

- *Step 0 — Getting started* : familiarization with the problem and already-preprocessed data (visualization of interferograms and coherence maps), targeted bibliography on flow matching and InSAR.
- *Step 1 — ML dataset construction* : patch extraction, handling coherence masks, train/validation/test splitting *by site and date* to prevent data leakage, and definition of *circular* error metrics.
- *Step 2 — Single-sensor flow matching, Euclidean* : setting up the training pipeline on a 2D toy case (transport between two simple distributions), then on Sentinel-1 alone patches (transport between two acquisitions of the same sensor). Goal : validate implementation, metrics, and computational cost *before* introducing geometry.
- *Step 3 — Moving to the torus* : replacing Euclidean interpolation with geodesic interpolation on $\mathbb{T}^n$, and quantitative comparison of the two on fixed data. Step conducted in collaboration with **CEDRIC team at CNAM Paris (A. Breloy)**, whose Riemannian flow matching work applied to InSAR [4] provides a direct starting point.
- *Step 4 — Coherence conditioning and dual-sensor* : conditioning the vector field by coherence $|\gamma|$ (completing incoherent zones), then Sentinel-1 $\rightarrow$ NISAR transport, with the added challenge of different spatial resolutions (20 m *vs* 10 m).
- *Step 5 — Validation by displacement measurements* : (a) qualitative validation of sensor-to-sensor transfer on sites with known displacements (Mexico subsidence area), selected with support from **MIRE sas (M. Jauvin)**; (b) quantitative validation on la Valette (Barcelonnette, France) (dense vegetation, rapid motion) and Embrun landslides (monitored by 37 GNSS cubes) : conversion of fused phase to displacement and comparison against ground truth (GNSS, corner reflectors).
- *Step 6 — Final report* : thesis writing and presentation.

Depending on progress, results may be published scientifically (GRETSI, IGARSS), and the internship may be a first step toward a thesis on the topic.

Required Skills

- **Computing** : Python, PyTorch; taste for numerical experimentation and GPU computation.
- **Learning** : fundamentals of deep learning; knowledge of generative models (diffusion, flow matching) is a plus.
- **Signal & imaging** : signal and image processing, statistics.
- **Appreciated (not required)** : SAR/InSAR imaging, differential geometry or statistics on manifolds.

Stipend	According to applicable regulations
Contacts	Matthieu Gallet : matthieu.gallet@univ-smb.fr Guillaume Ginolhac : guillaume.ginolhac@univ-smb.fr

Références

1. Y. Lipman *et al.*, *Flow matching for generative modeling*, 2023. [arXiv:2210.02747]
2. R. T. Q. Chen, Y. Lipman, *Flow matching on general geometries*, ICLR 2024.
3. A. Collas *et al.*, *Riemannian flow matching for brain connectivity matrices via pullback geometry*, 2025. [arXiv:2505.18193]
4. G. Le Bellier, D. El Hajjar, A. Breloy, N. Audebert, *Modèles de flux riemanniens pour l'interférométrie SAR*, GRETSI 2025.
5. A. Manconi, *How phase aliasing limits systematic space-borne DInSAR monitoring and failure forecast of alpine landslides*, Engineering Geology, 2021. [DOI]
6. S. Vitale *et al.*, *InSAR-MoNet : Interferometric SAR phase denoising using a multiobjective neural network*, IEEE TGRS, 2022.
7. X. Luo *et al.*, *Efficient InSAR phase noise reduction via total variation regularization*, Science China Information Sciences, 2015.
8. [ESA Sentinel-1] et [NASA-ISRO NISAR] technical documentation.