PHD POSITION IN ARTIFICIAL INTELLIGENCE FOR OCEAN OBSERVATION Learning Optimal Measurement and Sampling Strategies for Multi-platform Ocean Monitoring Surveillance

Context

The design of observing systems for ocean monitoring and surveillance is a key issue for a wide range of applications and scientific challenges. Multi-platform observing systems naturally arise as appealing solution to best exploit different observation modalities (e.g., satellite vs. in situ observation, surface vs. interior observation, passive vs. active sensors,....). In this context, the ability to design optimal monitoring and sampling strategies is a key challenge. The emergence of deep learning [1], especially end-to-end learning and deep generative models, provides new means to investigate this challenge jointly to the design of the inverse model, that is to say the design of optimal monitoring and sampling strategies so that one can retrieve the best reconstruction of some processes of interest and/or reduce the associated uncertainty.

Subject

In the framework of AI Chair OceaniX (https://cia-oceanix.github.io/about/), this PhD will investigate this generic issue and its application to ocean monitoring and surveillance through relevant case-studies (i.e., design of future earth observation missions, optimal synergy control between satellite platforms and in situ sensor networks, data-driven adaptive sampling strategies for in situ networks). From a methodological point of view, the proposed framework will explore synergies between Deep learning planning schemes [4], Bayesian variational setting [3], learning-based data assimilation models [2] and solvers and deep generative models, especially GANs [5]. The expected outcome is the ability to jointly learn observation operators, priors and solvers w.r.t. performance measure for hidden dynamics. Through relevant constraints (e.g., sparsity priors) on the observation operators, we expect to derive the targeted optimal measurement and sampling strategies.

Numerical experiments will be carried out initially on toy examples (e.g., low-dimensional chaotic systems). OSSEs (Observing System Simulation Experiments) generated from realistic numerical simulations will also be considered. Applications to real datasets might also be of interest in the last stage of the PhD.

Qualifications

Applicants must hold a M.Sc degree in signal processing, mathematics or physics and have some knowledge in the field of Bayesian modeling and inference. Applicants must be fluent in Python.

Practical information

Funding: AI Chair OceaniX (https://cia-oceanix.github.io/about/) Localization: Lab-STICC (UMR CNRS 6285), IMT Atlantique & ENSTA Bretagne, Brest, France Supervision: Ronan Fablet, Florian Sevellec and Angélique Drémeau (see contact below) Starting date: from september 2021

Application procedure

All applicants must submit a cover letter, a CV and contact details of previous internship supervisors or teachers. Any other material (*e.g.*, recommendation letter, distinction...) that might strengthen the application is welcome. All materials must be sent by e-mail to Ronan Fablet, Florian Sevellec and Angélique Drémeau (see contact below). Applications should be examined **from May**, **15**th **2021**.

Contact

Ronan Fablet (HDR, IMT Atlantique, Lab-STICC) Phone : +33 2 29 00 12 87 E-mail : <u>ronan.fablet@imt-atlantique.fr</u> Webpage : <u>https://rfablet.github.io/</u>

Florian Sevellec (HDR, CNRS, LOPS/IUEM) E-mail : florian.sevellec@univ-brest.fr

Angélique Drémeau (PhD, ENSTA Bretagne, Lab-STICC) Phone : +33 2 98 34 89 71 E-mail : <u>angelique.dremeau@ensta-bretagne.fr</u> Webpage : <u>http://angelique.dremeau.free.fr</u>

Short bibliography

[1] LeCun et al. Deep learning, Nature, 2015.

[2] Fablet et al. Learning Variational Data Assimilation Models and Solvers, arXiv 2020.

- [3] Okada et al. Adaptive Sensor Placement for Continuous Spaces, arXiv 2020.
- [4] Hafner et al. Learning Latent Dynamics for Planning from Pixels, ICML 2019.

[5] Nowozin et al. F-GAN: Training generative neural samplers using variational divergence minimization. Neurips, 271-279, 2016.