

## **2-year postdoc on Learning-Based Reconstruction of Upper Ocean Dynamics from Underwater Acoustics Data**

**Supervisors:** Xavier Carton (UBO), R. Fablet (IMT Atlantique, Lab-STICC), Yann Stephan (SHOM)

**Hosting team:** IMT Atlantique, INRIA Odyssey team, Brest

**Duration:** 2-year postdoc position, possibly extended to a three-year position

**Expected starting date:** early 2023

**Keywords:** ocean modelling and forecasting, deep learning, inverse problems, physics-aware learning, ocean eddies, underwater acoustic propagation

**Context and objectives.** This postdoc position is open in the framework of AI Chair OceaniX (<https://cia-oceanix.github.io/>) and a collaboration between OceaniX chair and SHOM (<https://www.shom.fr/>) on AI approaches for the modelling of ocean dynamics and their impact on underwater acoustic propagation. The postdoc will be hosted on IMT Atlantique campus in Brest by the newly created INRIA team Odyssey (<https://team.inria.fr/odyssey>).

Recent developments in artificial intelligence (AI) open many interesting opportunities in the context of operational oceanography and ocean forecasting systems. Current operational forecasting systems face important challenges. Ocean models and data assimilation methods, which are the scientific underpinning of these operational systems, are highly computationally-demanding when addressing large ensemble simulations with increasingly fine spatial resolution and their ability to fully exploit available data sources remains limited. Deep learning and differentiable programming are opening many opportunities in computational fluid dynamics and ocean science (Vinuesa and Brunton, 2021; Zanna and Bolton 2021) as well as to solve inverse problems (Cranmer et al. 2021; Fablet et al. 2021, Hartfield et al., 2021). Deep learning especially benefits GPU acceleration as well as from an application-centric viewpoint to better address specific application-dependent requirements.

This postdoc aims to explore and develop deep learning schemes for the reconstruction of upper ocean dynamics and associated acoustic propagation conditions from underwater acoustics observations possibly combined with other in situ data and available satellite-derived observations. From a methodological point of view, the postdoc candidate will explore new research directions to combine data assimilation formulations and deep learning paradigms (Cranmer et al. 2021; Fablet et al. 2021, Hartfield et al., 2021). He/she may benefit from the ongoing development of 4DVarNet framework which involves trainable variational data assimilation models and solvers. The versatility of this framework makes it highly flexible for the definition of underlying state-space formulation and the associated observation operators and priors. Three specific objectives are of key interest: (i) the exploration of trainable observation operators to link underwater acoustics observation and the targeted ocean variables, (ii) accounting for the reconstruction of acoustic propagation features within the set of targeted ocean variables, (iii) accounting for uncertainties in the reconstruction.

Numerical experiments will rely on Observing System Simulation Experiments (OSSE) from high-resolution numerical simulations (e.g., NEMO, CROCO, HYCOM simulation data). Different observation configurations will be considered including underwater acoustics data with different noise source types (e.g., source positions and associated spectral signature), in situ data (e.g., gliders, drones,...) and satellite-derived observations. A specific focus will be dedicated to the reconstruction of space-time eddy signatures. Specific eddy-based simulation datasets, including simulations of the

impact of eddies onto acoustic propagation, may also be explored to implement the proposed learning-based strategy.

**Skills:** Applications are encouraged from candidates with a Ph.D in applied math/machine learning/data assimilation with interest in ocean science or a Ph.D in ocean science and a strong interest in deep learning.. Candidates should have a strong interest and commitment to research. Creativity with an aim towards independent research is highly emphasized.

**Application:** Send CV, statement of research interests and the contact information of at least two references to [ronan.fablet@imt-atlantique.fr](mailto:ronan.fablet@imt-atlantique.fr). Review of applications will begin immediately and continue until the position is filled.

**Specs:** The position will initially be funded for a 2-year period and could be renewed upon scientific outcome and funding availability. The net annual salary will range from 30,000€ to 36,000€ per year depending on experience.

### References

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