Institut des Géosciences de l'Environnement

PhD thesis - Université de Bordeaux

Learning for satellite Imaging: SWOT Mission

Abstract This PhD project aims at developing learning methods for the automatic processing (denoising, inpainting) and physical analysis of image data provided by the future satellite SWOT (CNES/NASA) from 2021.

When:	3 years starting between September and December 2020
Where:	Institut de Mathématiques de Bordeaux, Talence, France
Salary:	≈1500 €/month
Expected skills:	Master degree in computer science or applied mathematics Image processing and analysis, machine learning, Matlab, python.
Application:	**before June 11th**, on the CNRS platform link. Reference UMR5251-AGNCHE-002 Job type: PhD student contract; Region: Aquitaine and Limousin; Keyword: SWOT

Context and challenges The future altimetric observations provided by SWOT (Surface Water and Ocean Topography, NASA/CNES, see Figure 1) from 2021 should transform our understanding of oceanographic turbulent processes. The measurement system is designed to resolve ocean circulation patterns at scales down to the order of 2 km, whereas the present-day constellation of conventional altimeters only resolves scales of 30 km and above. In addition to potentially unexpected discoveries, this order-of-magnitude gain in resolution will help quantifying several oceanic processes much more accurately than today. Among those processes are vertical motions, which are key to the vertical exchanges between the ocean surface and the atmosphere, and between the ocean surface and the deep ocean.

Considering the geostrophic approximation, the ocean surface velocity fields can be computed from spatial gradients of Sea Surface Height (SSH) maps provided by SWOT. With the accurate knowledge of the ocean surface velocity fields, it will be possible to estimate the mixing that controls the energy cascade between different scales. This will provide, for the first time, observations for the small scales of numerical schemes modelling ocean dynamic.

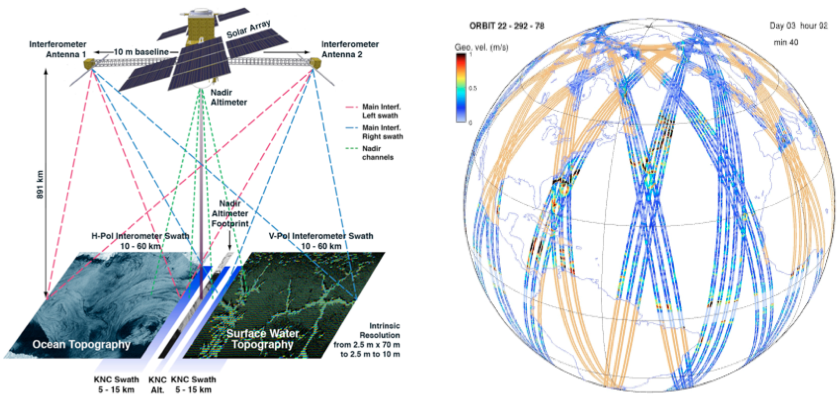

Figure 1: SWOT is a joint spatial mission by NASA/CNES that will be launched in 2021. The satellite will provide an unprecedented two-dimensional view of ocean surface topography at a pixel resolution of 2 km. SWOT's wide-swath altimeter, based upon SAR interferometry technology, will measure Sea Surface Height (SSH) over a 120-km wide swath with 20-km gaps. Left: global conception of the satellite. Right: illustration of 3 days of measurements. Website of SWOT mission: https://swot.jpl.nasa.gov/

Unfortunately, SWOT data will very likely be contaminated by small-scale noise that prevents the direct computation of SSH derivatives. The expected measurement noise gathers several components with different spatial coherences and different amplitudes. Errors due to the satellite roll, the baseline dilation, and the path delay induced by atmospheric humidity, exhibit significant spatial correlations with different characteristic patterns.

To be prepared to exploit the future SWOT data, a simulator [2] has been developed to generate plausible realizations of SWOT uncertainties. Classical image processing tools such as variational methods [3] and patch-based methods [4] give promising denoising results on synthetic data provided by the simulator (see Figure 2). It is nevertheless necessary to develop automatic and faster algorithms to deal with the huge amount of data that will be brought by SWOT.

Naturally, a gap between the current data provided by the simulator and the real ones that will be available from 2021 has to be expected. As we have no control on what will be the errors in practice, it is therefore mandatory to define flexible tools able to adapt to true SWOT images.

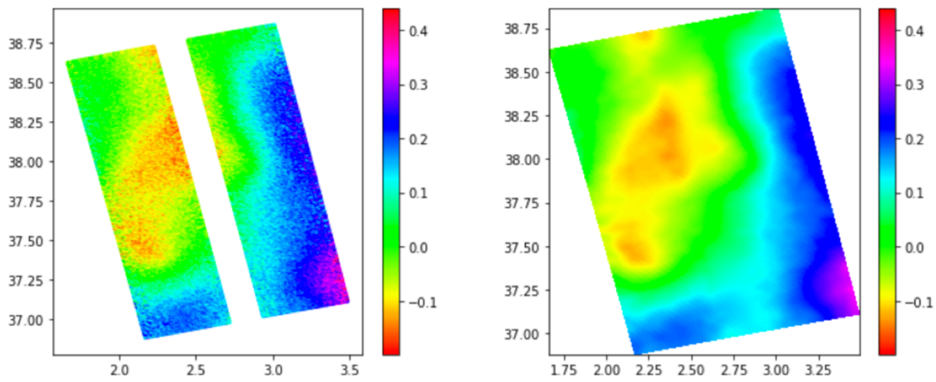

Figure 2: Processing of SWOT data. Left : simulated SSH data. Right : variational denoising and data completion (inpainting) in-between the two swaths [3].

Positionning Current approaches for processing image data in geosciences are mainly dedicated to noise that does not present spatial correlations. The limited capacity of such methods to deal with more complex noises and a huge quantity of data in reasonable computational time is a main issue in the perspective of processing the forthcoming SWOT data.

Learning approaches are extremely developed in the computer vision community, where large corpus of data are used to learn a model, being latter able to solve instantaneously inverse problems such as denoising or source separation, in a very efficient way. On the other hand, in meteorology or oceanography, a dynamical physical model is known a priori and calibrated using the data to provide accurate weather predictions. Learning methods are, up to now, less developed in geosciences and there is a real opportunity to bring new insights to oceanography issues. This is the subject of this PhD thesis, that aims at bridging the gap between scientific communities.

Objectives The main objective is to propose efficient automatic processing tools for raw SWOT data in order to deal with data noise and analyze the different scales of the underlying physical dynamic. To that end, machine learning approaches, including residual deep neural networks, will be considered as they offer an efficient methodology for tackling the denoising problem [9]. The PhD candidate will namely focus on the following points:

- Modelling: Characterization of the noise affecting SWOT data and of its spatial correlations [8, 1]; study of physical properties of SSH fields; choice of the norm/loss function for the reconstruction; integration of dimension reduction

- Proposition of network architectures for SWOT restoration: definition of well-posed network architectures [5, 7] including physical constraints on the regularity of the SSH field; extension to data completion to fill in the gap between satellite swaths (see Figure 2);
- Experimentation: Training on simulated SWOT data; adaptation of the developed methods to real data (available in 2021) through transfer learning.
- Interpretation: Analysis of estimated ocean surface velocities; identification of the different scales of the observed physics.

In order to propose flexible architecture, multi-task learning frameworks [6] will be considered. This will namely include applications such as image denoising, image inpainting or the separation of physical scales of the observed dynamic. The fallout of these work will concern different scientific aspects: (i) Better understanding of submesoscale processes in ocean dynamics; (ii) Improvement of numerical weather prediction systems; and (iii) Development of responsible numerical tools, able to compress relevant satellite information and decrease the quantity of data unnecessarily transferred and stored.

Team and supervision The PhD will be co-supervized by Nicolas Papadakis (CNRS Researcher, IMB, Université de Bordeaux) and Emmanuel Cosme (Associate professor, Univ Genoble Rhône-Alpes, IGE). The candidate will be located in Bordeaux within the Image Optimisation and Probability team of the Institut de Mathématiques de Bordeaux (IMB). Several long stay visits at the Institut des Geosciences de l'Environment (IGE) are planned all along the PhD thesis, to develop specific skills at the interface between machine learning and oceanography.

References

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