www.onera.fr

PROPOSITION DE POST-DOCTORAT

Intitulé : Estimating Sea-ice drift using deep-learning optical flow algorithm

Référence : **PDOC-DTIS-2024-02**
(à rappeler dans toute correspondance)

Début du contrat :	**Date limite de candidature :**

Durée : 12 mois, éventuellement renouvelable une fois - Salaire net : environ 25 k€ annuel

Mots clés

Sea-ice drift, optical flow estimation, SAR images, optical images, multi-modality

Profil et compétences recherchées

- A master degree in physics, in image processing or in remote sensing for the environment
- A PhD degree in image processing, with a previous experience either processing SAR images or working on deep-learning method.
- Demonstrated experience in python programming
- Demonstrated experience in working on supercomputers or computer clusters
- Fluency in English

Présentation du projet post-doctoral, contexte et objectif

The sea ice extent in the Arctic has been decreasing dramatically in recent years. This decrease of the sea ice extent comes with a diminution of the sea ice thickness (SIT) [Lindsay2015], with the disappearance of the multi-year ice. New-year ice being mechanically weaker, it increases the variability of the sea ice conditions throughout the years, with more observations of SIT anomalies, early break up or acceleration of the sea ice drift (SID) [Landy2022]. This increase in sea ice variability creates the need for frequent fine scale observations of the SID and local movement. SAR images are a good candidate to measure local SID since its acquisitions are frequent and not impacted by clouds or the absence or light. Multiple products of SID measurement using Sentinel-1 or RADARSAT-2 SAR images exist such as [DTU-SID] for the Arctic with a 10 km resolution, or [UTAS-SID] for the Antarctic with a kilometric resolution, computed using cross-correlation methods. Scatterometer-measured SID are also available [IFREMER-SID]. Moreover, a small number of SAR images and optical images are acquired by Sentinel-1 and Sentinel-2 on the same day, increasing the possible sources for short term SID measurement.

In this postdoc, we propose to work on a deep-learning method to measure SID at the pixel level and its associated uncertainty. Optical flow algorithms have already been used successfully to co-registered SAR images [Plyer2015], and to measure SID after a deep-learning super resolution step [Zisis2018]. Deep-learning optical flow estimation method have improved the estimation results in natural image processing [Dosovitskiy2015, Sun2018]. However, these methods require a large database that is not available at the desired resolution. It can be compensated using a simulated image database containing unrealistic images [Dosovitskiy2015]. A simulated image database has also been used successfully in the context of phase estimation from InSAR data [Sica2020] where the use of unrealistic images to increase the diversity of learning scenarios has been shown to improve the results.

In order to provide deep-learning optical flow method to estimation SID, we address the following research questions:

Q1. What is the level of complexity and realism of the imaged scene, the simulation of SAR images and the SID pattern to create a simulated database to train a DL model to measure SID on real SAR images?

Q2. How to design a DL model that handles multi-modal images?

Q3. What is the best way to evaluate SID uncertainty with these models?

Complex sea-ice models [Rampal2015, Nemo2019, Madec2022] have been developed and high accuracy SAR image simulator as EMPRISE [Everaere2022] are developed at ONERA, leading to the possibility to create highly representative SAR pairs. However, these models may require a high level of description of the input and a high degree of parametrization to be relevant, leading to a long data-preparation time. Creating a larger database by reducing the constraint on the levels of description of the imaged scene, the considered SID patterns and the SAR simulator, resulting in unrealistic images may be more relevant to train for the deep-learning model to learn to extract significant features. Since the level of realism of the image depends on the level of description of the imaged scene, the considered SID pattern and the SAR simulator, their impact compared to the number of data produced will have to be evaluated together in the deep-learning model training.

Multiple deep-learning strategies have been developed to co-registered SAR and optical images such as to translate optical to SAR images [Hughes2019, Maggiolo2022] or SAR to optical images [Bralet2022] before coregistration, or to specialize an encoder for optical data and another encoder for SAR data such [Hughes2019, Letornier2019, Charrier2020]. These methods will be evaluated in the case of SID measurement and compared with domain adaptation technics [Motiian2017, Yang2020].

All the SID measurements have to be associated with a measure of uncertainty, in order to detect meaningful trends. To measure the uncertainty, multiple methods have been proposed using during randomness induces during training and inference [Gal2016, Lakshminarayanan2017] or randomness induces on the input [Mi2022]. These uncertainty measurements will be evaluated in the light of incorporating SID measurement into a sea-ice model.

The measured SID as well as their uncertainty will be evaluated by comparison with other available measurements such as [DTU-SID, UTAS-SID, IFREMER-SID]

The pipeline containing a SAR image pair simulation and a deep-learning framework to measure SID and the associated uncertainty, it could be used for co-design studies. Co-design methodology proposes to optimize the acquisition instrument together with the processing with the idea that the best instrument for a human operator may not be the best instrument for automatic processing. In this subject, the satellite design has already been proposed, together with an acquisition plan. Thanks to the full simulation to training pipeline, we could evaluate what are the acquisition parameters that influence the most the results and if another acquisition plan, combined with the right processing, would enable more reliable SID measurements.

References

[Bralet2022] A. Bralet, A. M. Atto, J. Chanussot and E. Trouvé, "Deep Learning of Radiometrical and Geometrical Sar Distorsions for Image Modality translations," 2022 IEEE International Conference on Image Processing (ICIP), Bordeaux, France, 2022, pp. 1766-1770, doi: 10.1109/ICIP46576.2022.9897713.

[Charrier2020] L. Charrier, P. Godet, C. Rambour, F. Weissgerber, S. Erdmann and E. C. Koeniguer, "Analysis of dense coregistration methods applied to optical and SAR time-series for ice flow estimations," 2020 IEEE Radar Conference (RadarConf20), Florence, Italy, 2020, pp. 1-6, doi: 10.1109/RadarConf2043947.2020.9266643.

[Dosovitskiy2015] Alexey Dosovitskiy, Philipp Fischer, Eddy Ilg, P. Häusser, C. Hazırbaş, V. Golkov, P. Smagt, D. Cremers, Thomas Brox FlowNet: Learning Optical Flow with Convolutional Networks IEEE International Conference on Computer Vision (ICCV), 2015

[DTU-SID] https://doi.org/10.48670/moi-00135

[Everaere2022] https://sondra.fr/wp-content/uploads/2022/06/RI.P6.pdf

[Gal2016] Gal, Y., and Z. Ghahramani. 2016. "Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning." 33rd International Conference on Machine Learning (ICML 2016).

[Hughes2019] L. H. Hughes, N. Merkle, T. Bürgmann, S. Auer and M. Schmitt, "Deep Learning for SAR-Optical Image Matching," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 2019, pp. 4877-4880, doi: 10.1109/IGARSS.2019.8898635.

[IFREMER-SID] https://cersat.ifremer.fr/Data/Latest-products/Global-mapping-of-Arctic-sea-ice-drift-a-unique-database

[Lakshminarayanan2017] Lakshminarayanan, B.; Pritzel, A.; and Blundell, C. 2017. Simple and scalable predictive uncertainty estimation using deep ensembles. In NIPS, 6402–6413.

[Landy2022] Landy, J.C., Dawson, G.J., Tsamados, M. et al. A year-round satellite sea-ice thickness record from CryoSat-2. Nature 609, 517–522 (2022). https://doi.org/10.1038/s41586-022-05058-5

[LeTeurnier2019] Le Teurnier. Benjamin, A coregistration tool for optical and sar images by deep learning methods, september 2019.
https://aerospacelab.onera.fr/aerospacelab/sites/w3.onera.fr.aerospacelab/files/AL15-08_0_0.pdf

[Lindsay2015] Lindsay, R., and Schweiger, A. (2015). Arctic sea ice thickness loss determined using subsurface, aircraft, and satellite observations. Cryosphere 9, 269–283. doi:10.5194/tc-9-269-2015

[Madec2022] Gurvan Madec and NEMO System Team, "NEMO ocean engine", Scientific Notes of Climate Modelling Center (27) – ISSN 1288-1619, Institut Pierre-Simon Laplace (IPSL)

[Maggiolo2022] Maggiolo, L.; Solarna, D.; Moser, G.; Serpico, S.B. Registration of Multisensor Images through a Conditional Generative Adversarial Network and a Correlation-Type Similarity Measure. Remote Sens. 2022, 14, 2811. https://doi.org/10.3390/rs14122811

[Mi2022] Mi, L., Wang, H., Tian, Y., He, H., & Shavit, N. N. (2022). Training-Free Uncertainty Estimation for Dense Regression: Sensitivity as a Surrogate. Proceedings of the AAAI Conference on Artificial Intelligence, 36(9), 10042-10050. https://doi.org/10.1609/aaai.v36i9.21243

[Motiian2017] S. Motiian, M. Piccirilli, D. A. Adjeroh and G. Doretto, "Unified Deep Supervised Domain Adaptation and Generalization," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 2017, pp. 5716-5726, doi: 10.1109/ICCV.2017.609.

[Nemo2019] "Sea Ice modelling Integrated Initiative (SI3) — The NEMO sea ice engine", NEMO Sea Ice Working Group, Scientific Notes of Climate Modelling Center (31) – ISSN 1288-1619, Institut Pierre-Simon Laplace (IPSL)

[UTAS-SID] Heil, P. and Hyland, G. (2022) Satellite-derived high-resolution sea-ice motion in the Southern Ocean, 2015-2019 - ESA Sentinel1 Satellite Data collected under AAS project 4301, Ver. 1, Australian Antarctic Data Centre - doi:10.26179/44b1-j694, Accessed: 2023-11-16

[Plyer2015] A. Plyer, E. Colin-Koeniguer and F. Weissgerber, "A New Coregistration Algorithm for Recent Applications on Urban SAR Images," in IEEE Geoscience and Remote Sensing Letters, vol. 12, no. 11, pp. 2198-2202, Nov. 2015, doi: 10.1109/LGRS.2015.2455071.

[Rampal2015] Rampal, P., Bouillon, S., Ólason, E., and Morlighem, M.: neXtSIM: a new Lagrangian sea ice model, The Cryosphere, 10, 1055–1073, https://doi.org/10.5194/tc-10-1055-2016, 2016.

[Sica2020] F. Sica, G. Gobbi, P. Rizzoli and L. Bruzzone, "Φ-Net: Deep Residual Learning for InSAR Parameters Estimation," in IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 5, pp. 3917-3941, May 2021, doi: 10.1109/TGRS.2020.3020427.

[Sun2018] Deqing Sun, Xiaodong Yang, Ming-Yu Liu, Jan Kautz; Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 8934-8943

[Yang2020] Y Yang and S Soatto, FDA: Fourier Domain Adaptation for Semantic Segmentation, CVPR2020

[Zisis2018] Zisis I. Petrou, Yang Xian, YingLi Tian, Towards breaking the spatial resolution barriers: An optical flow and super-resolution approach for sea ice motion estimation, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 138, 2018, Pages 164-175, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2018.01.020.

Collaborations extérieures

This postdoc is part of the ANR JCJC SITEMSA, in which are participating the following epxerts:

- Frédéric Champagnat, ONERA/DTIS
- Sara Fleury, CNRS/LEGOS
- Pierre Rampal, IGE