Multimodal Unsupervised Spatio-Temporal Interpolation of satellite ocean altimetry maps

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Motivations

- Ocean observation by satellites leads to various image inverse problems.
- Some data are easier to measure through remote sensing, and we are interested in combining them to enhance Ocean's state reconstruction.
- Deep Neural Networks provide a flexible reconstruction method, able to fuse physically linked heterogeneous observations.
- Using the inductive bias of their architectures, we aim to train an interpolation method on real-world observations directly.

Case study

Interpolation of Sea Surface Height

Two variables of importance:

- The Sea Surface Height (SSH) is very useful in oceanography applications as it is used to derive Ocean currents. Currently, it is measured by nadir-pointing altimeters only able to take vertical measures. A new altimetry technology (SWOT) will soon be able to provide wider measures.
- The Sea Surface Temperature (SST) is linked to ocean circulation as well (as heat is advected by currents) and is measured through direct infrared imaging.

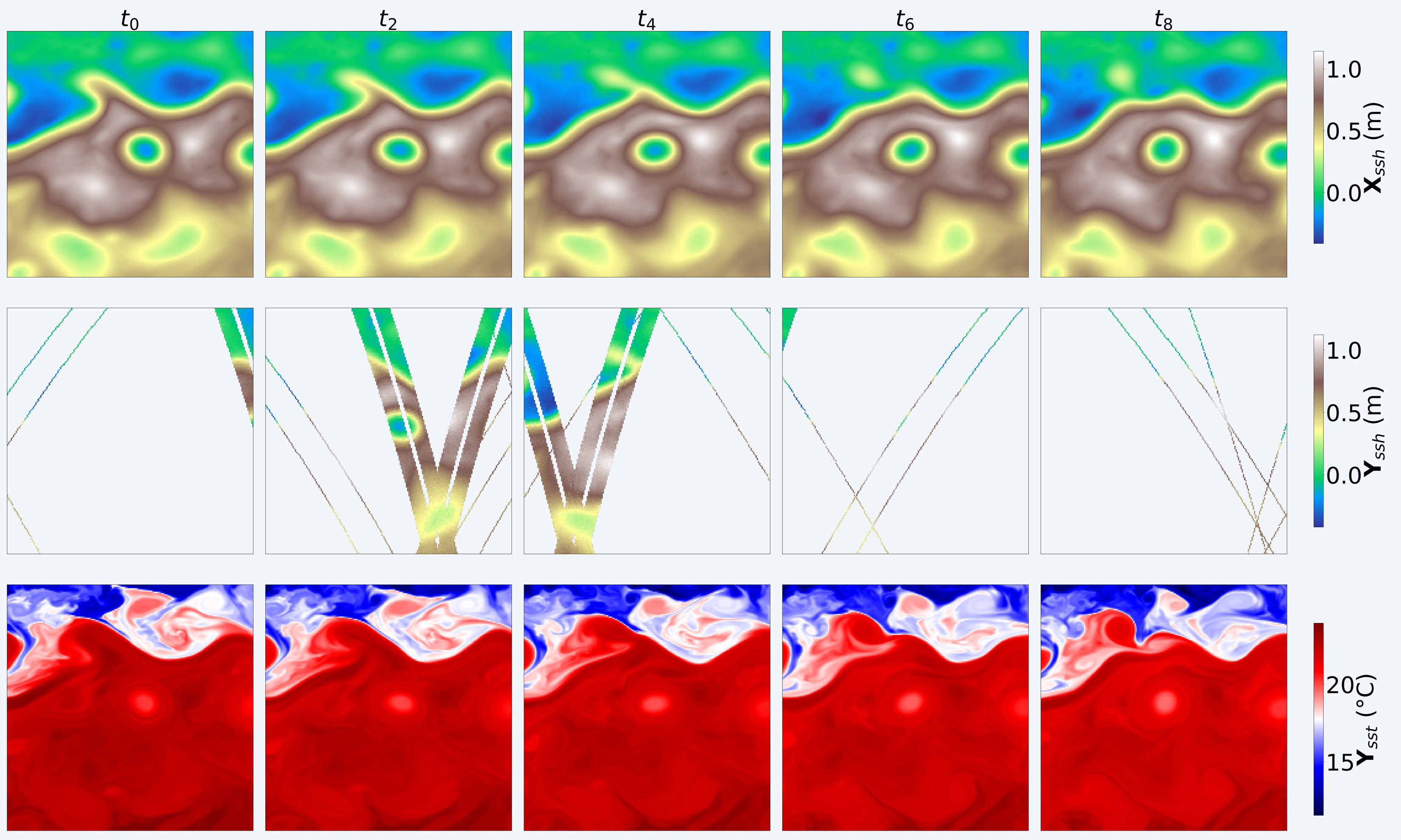

Figure 1. Observing System Simulation Experiment of the satellite observations. The first row is the ground truth SSH, and the second is the twin experiment on SSH along tracks. The wide satellite tracks simulate SWOT satellites whereas the fine tracks simulate nadir observations. The last row is the modeled SST.

Problem statement

We denote hereafter:

- Y^t_{sst} and Y^t_{ssh} the SST and SSH observations at time t, X^t_{ssh} the true SSH state (gridded image).
- Y^t_{ssh} are obtained from X^t_{ssh} through a masking operator $\mathcal{H}_{\Omega_t}$ such as in Eq. (1):

$$Y^t_{ssh} = \mathcal{H}_{\Omega_t}\left(X^t_{ssh}\right) + \varepsilon_t \tag{1}$$

- Ω_t is the support of the SSH observations at time t and ε_t is the observation noise.

Multimodal Unsupervised Spatio-Temporal Interpolation

In the past, several methods have been developed to perform the inversion:

- The operational product: DUACS is a linear optimal interpolation leveraging covariances matrices tuned on 25 years of observations.
- Data assimilation methods: combining physical models with observations.
- Supervised deep learning: trained on simulations and applied to the real world. If this method is promising, transferring the multi-physical link from simulations to real data is still a challenge.

- Training a deep learning network **directly from observations.**
- Encoding the SST observations as in Eq. (2) as a latent vector $\tilde{\mathbf{Z}}$
- Decode $\tilde{\mathbf{Z}}$ as $\tilde{\mathbf{X}}_{ssh}$ following Eq. (3).
- Apply $\mathcal{H}_\Omega$ to $\tilde{\mathbf{X}}_{ssh}$ as in Eq. (4)

Encoding: $$\tilde{\mathbf{Z}} = f_{\theta_1}\left(\mathbf{Y}_{sst}\right) \tag{2}$$

Decoding: $$\tilde{\mathbf{X}}_{ssh} = g_{\theta_2}\left(\tilde{\mathbf{Z}}\right) \tag{3}$$

Masking: $$\tilde{\mathbf{Y}}_{ssh} = \mathcal{H}_\Omega\left(\tilde{\mathbf{X}}_{ssh}\right) \tag{4}$$

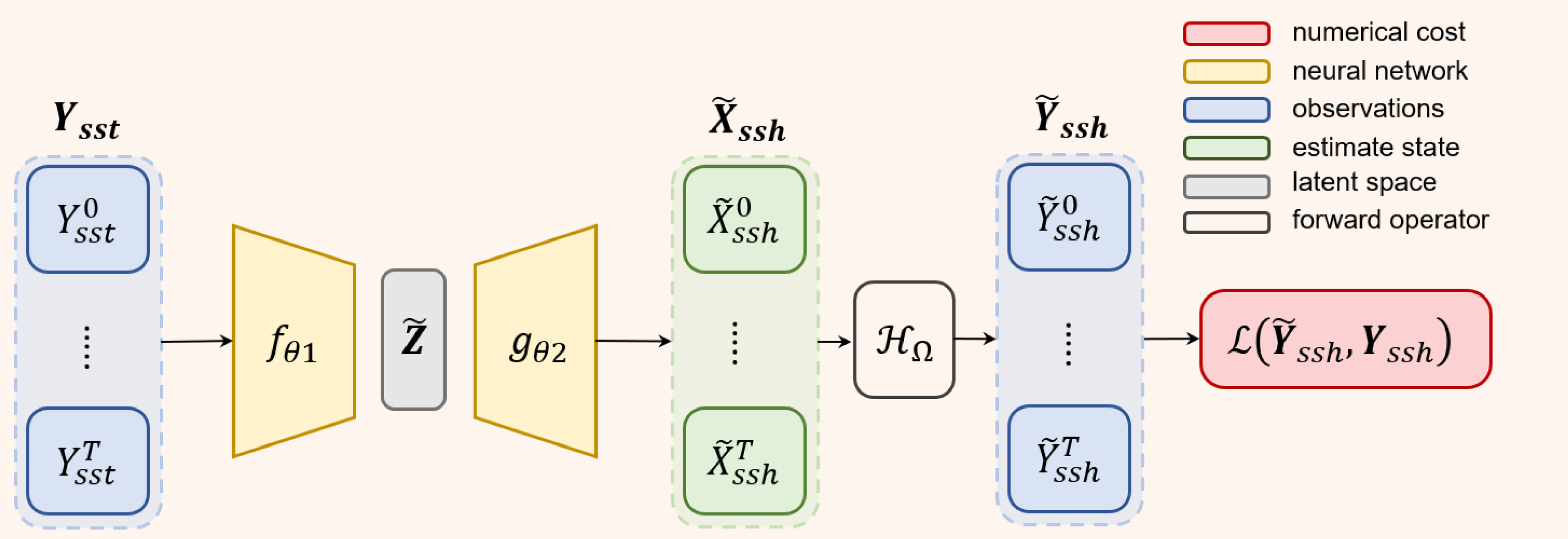

Figure 2. Computational graph of the proposed method (MUSTI)

Architecture

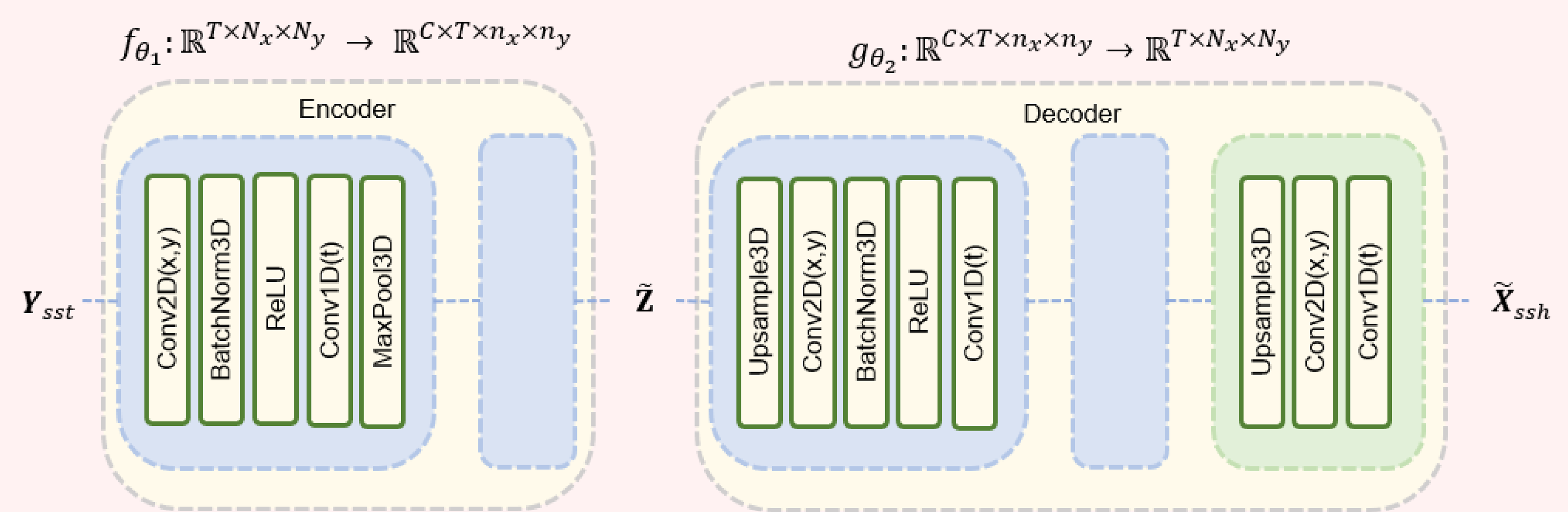

Figure 3. The network architecture: based on 2D+1 convolutions. This kind of convolution brings an inductive bias of spatiotemporal translation invariance which is well suited for outside-track generalization. The implicit hypothesis behind our method is that fitting a neural architecture to model $p\left(\mathbf{Y}_{ssh}|\mathbf{Y}_{sst}\right)$ will provide a good estimation of the true state $\mathbf{X}_{ssh}$ even on the pixels where it is not supervised to do so.

Results

Three different datasets.

- Simulation with wide swath and nadir tracks
- Simulation with only nadir tracks
- Real-world nadir tracks

Metrics: μ a RMSE-based score (1 is a perfect reconstruction), its temporal standard deviation σ_t. Two spectral metrics are used: λ_x and λ_t to measure the spatiotemporal coherence of the reconstruction.

	swot + nadir				nadir only				real-world data	
Methods	μ	σ_t	λ_x	λ_t	μ	σ_t	λ_x	λ_t	μ	σ_t
DUACS	0.922	0.017	1.22	11.29	0.916	0.008	1.42	12.08	0.877	0.065
DYMOST	0.926	0.018	1.19	10.26	0.911	0.013	1.35	11.87	0.889	**0.064**
MIOST	0.938	0.012	1.18	10.33	0.927	0.007	1.34	10.34	0.887	0.085
BFN	0.926	0.018	1.02	10.37	0.919	0.017	1.23	10.64	0.879	0.065
4DVarNet*	**0.959**	**0.009**	**0.62**	4.31	0.944	**0.006**	**0.84**	7.95	0.889	0.089
MUSTI U-net mean	0.951	0.01	1.09	6.0	0.939	0.009	1.35	5.73	0.881	0.103
MUSTI U-net ensemble	0.954	**0.009**	**0.62**	**3.44**	**0.946**	0.008	1.23	**4.14**	0.886	0.099
MUSTI STAE mean	0.945	0.011	1.02	6.32	0.931	0.012	1.13	8.78	0.885	0.086
MUSTI STAE ensemble	0.952	0.011	0.68	5.41	0.938	0.012	0.96	7.59	**0.893**	0.083

* supervised

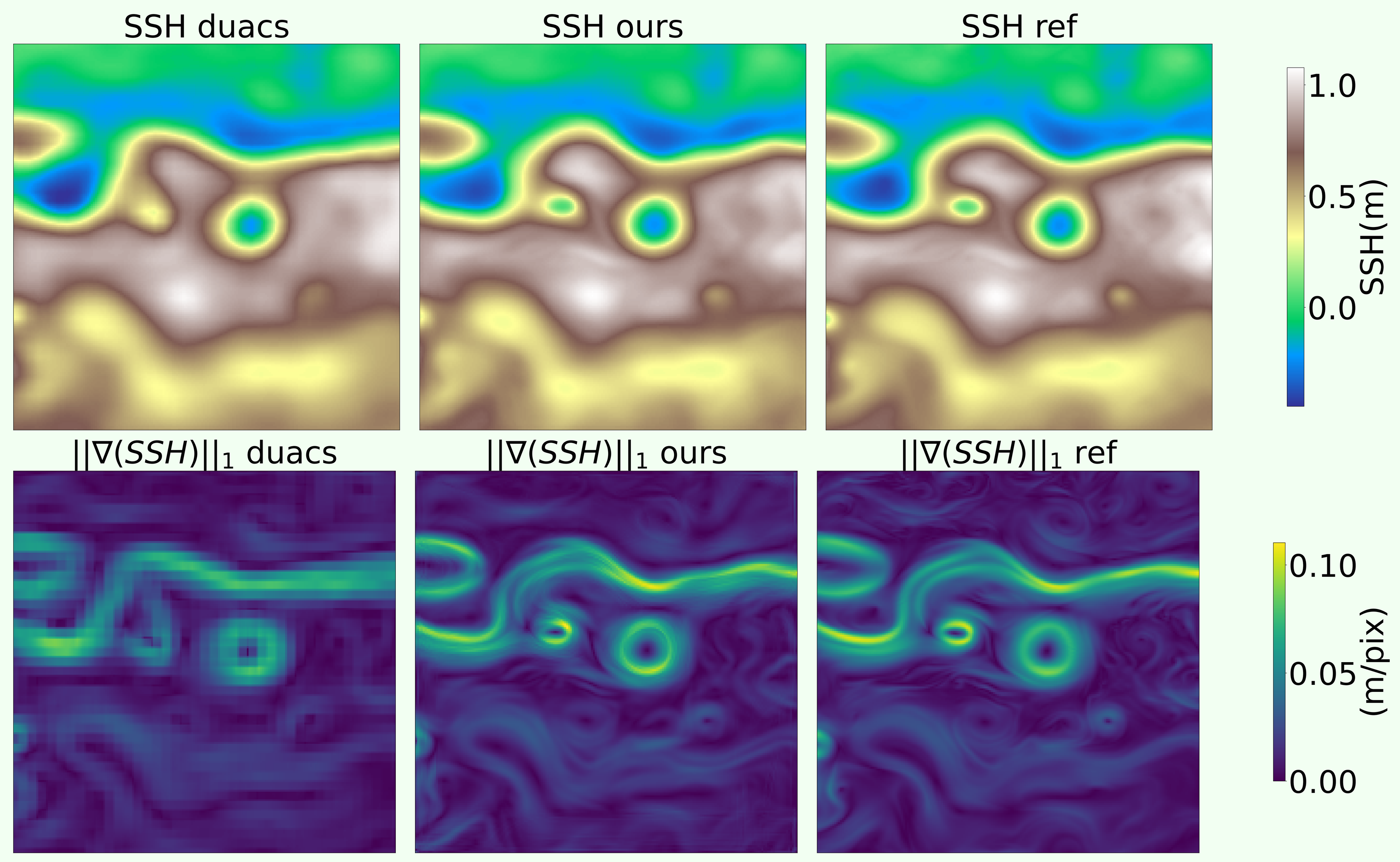

Figure 4. Overview of the results in the 3 datasets, and visual comparison with the operational product DUACS on a realist simulation.

Conclusions

- Our method includes multimodal information in Spatio-Temporal interpolation in an unsupervised way.
- We show that the multimodal transfer performed by the network on the along-tracks data generalizes well where it has not been supervised.
- On real-world data, we report a relative improvement of 13% compared to the operational product (DUACS) in terms of RMSE. We also show that our method is able to outperform supervised state-of-the-art interpolation architectures as they suffer from overfitting of the simulation upon which they are trained.

References

- DUACS: *DUACS DT2018: 25 years of reprocessed sea level altimetry products.* Taburet, G. and Sanchez-Roman, A. and Ballarotta, M. and Pujol, M.-I. and Legeais, J.-F. and Fournier, F. and Faugere, Y. and Dibarboure, G., **Ocean Science**, 2019
- 4DVARNET: *End-to-end physics-informed representation learning for satellite ocean remote sensing data: Applications to satellite altimetry and sea surface currents* Fablet, R. and Amar, M. and Febvre, Q. and Beauchamp, M. and Chapron, B., **ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences**, 2021

Code and data