M2 Internship : Uncertainty quantification for image restoration. Application to Landsat-8 image recovery for analysis of river dynamics

Key-words : Model-based neural networks, image reconstruction, uncertainty quantification, Markov Chain Monte Carlo, variational Bayesian methods, proximal algorithms.

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Context: Image restoration techniques have significantly evolved over the past 10 years with the rise of neural networks. The proposed topic concerns the so-called model-based neural network approaches, which are now at the core of most current developments, as they allow for the combination of theoretical foundations from traditional variational methods with the expressivity of neural networks.

The two most studied strategies are unfolded neural networks, which aim at mimicking proximal algorithm iterations to design end-to-end task-specific neural networks, and Plug-and-Play (PnP), which exploit pretrained denoisers to tackle reconstruction tasks without the need of further training. While both approaches produce a restored image, they often overlook the quantification of uncertainties on the reconstructed image, which is an essential aspect for assessing the reliability of the reconstruction.

Quantifying uncertainty is a long-standing subject of research that has been addressed through a wide variety of methods, ranging from Metropolis Adjusted Langevin Algorithms, Hamiltonian Monte Carlo, or belief and expectation propagation, to name just a few [1]. While this problem has been extensively studied in the context of standard variational formulations, leveraging their Bayesian interpretation, it remains largely underexplored in model-based neural network approaches (see a contrario [2]).

Subject : During this internship, we aim to revisit standard uncertainty quantification procedures from the perspective of model-based neural networks. Our approach will focus on two main directions : first, addressing spatial correlations to reduce the overestimation of uncertainty regions [3], and second, exploring the potential of multiscale techniques to improve or accelerate uncertainty estimation. The objective is to investigate both the theoretical aspects and their practical implementation within the Python library DeepInverse [4].

The developed method will be applied to the spatio-temporal analysis of river dynamics, which is a key factor in studying and understanding human impacts on floodplains. More specifically, the objective will be to increase the resolution of Landsat-8/9 images (30m) to the resolution of Sentinel-2 images (10m) for a detailed analysis of the dynamics (see Figure 1), using the database and preliminary results developed in [5].

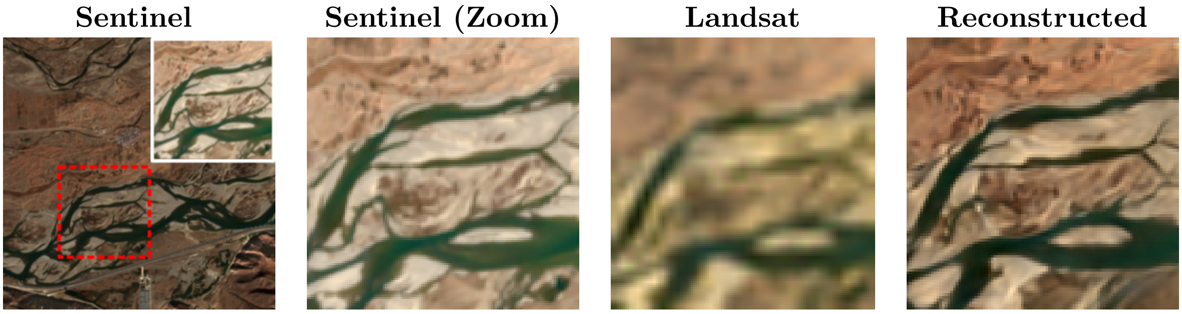

Figure 1 – Reconstruction of two sections of the Lhasa River (Tibet) using a PnP method, from synthetic Landsat images (degraded Sentinel-2).

Expected Results

- Develop and compare uncertainty quantification procedures.
- Software prototype in Pytorch.
- Demonstration on an already available satellite image dataset.

Required Skills

- Data science, optimization, image processing, signal processing, neural networks.
- Python, PyTorch, Git.

Références

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