

## M2 Internship: Multilevel plug-and-play algorithms with decreasing noise levels for large-scale image restoration

**Keywords:** Optimization, inverse problems, plug-and-play, flow matching, generative models, multilevel methods, image restoration.

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**Context:** Plug-and-play (PnP) methods solve imaging inverse problems by combining a descent step on a data-fidelity term with a pretrained denoiser acting as an implicit prior. These methods thus avoid training a network for each reconstruction task. In the classical setting, the denoiser is typically applied at a fixed noise level throughout the iterations. In practice, however, they require many iterations, hence many expensive network evaluations, and their performance is sensitive to the initialization and to the choice of hyperparameters.

To overcome these limitations, we recently proposed a multilevel PnP algorithm (ML-PnP) [1], building on multilevel methods for non-smooth optimization [2]. The inverse problem is represented at several resolutions: a coarse-to-fine initialization provides a good starting point, and cheaper iterations at coarse levels are then alternated with iterations at the fine level. A correction term enforces first-order coherence between levels, so that the algorithm converges to a fixed point of the fine problem (see Figure 1). For MMSE denoisers, this correction is expressed through Tweedie’s formula. On inpainting, demosaicing and deblurring of large-scale images, ML-PnP accelerates convergence and improves robustness to initialization.

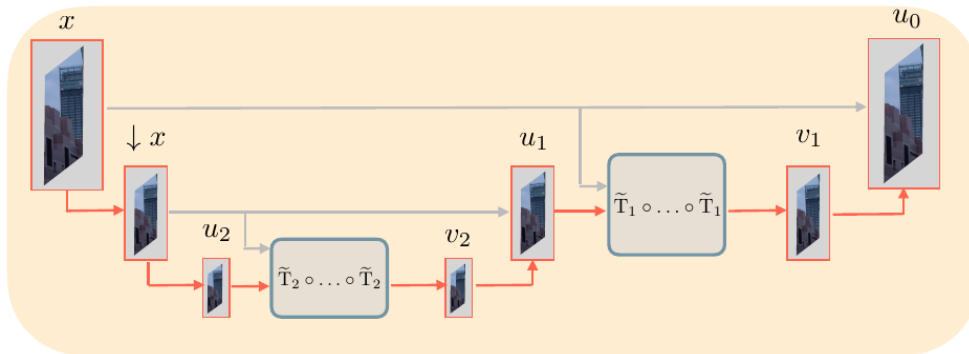


Figure 1: Multilevel step of ML-PnP [1] with  $J = 3$  levels: the iterate  $x$  is projected onto coarser levels, where cheaper corrected PnP iterations  $\tilde{T}_j$  are applied before going back to the fine resolution. The internship proposes to replace these iterations with annealed PnP iterations.

In parallel, generative models have profoundly renewed the priors used in imaging. The PnP-Flow approach [3] uses a pretrained flow-matching generative model [4] within a PnP scheme. Flow matching learns a velocity field transporting a noise distribution to the data distribution, from which denoisers at different noise levels can be derived. Each iteration combines a gradient step on the data-fidelity term, an interpolation with random noise corresponding to a decreasing noise level  $\sigma_k$ , and a denoising step. This empirical approach achieves very good reconstruction

quality, especially on highly ill-posed problems such as inpainting and super-resolution, without backpropagation through the network. However, the PnP-Flow algorithm remains heuristic, with no convergence guarantees, while its recently proposed convergent variant [7] relies on restrictive, slowly decreasing noise schedules that typically require many iterations.

In this internship, we propose to extend the multilevel framework of [1] to annealed PnP stochastic schemes, using PnP-Flow as a main example.

The developments will be carried out in the Python library DeepInverse [6], which already contains the PnP building blocks and on which the ML-PnP implementation relies.

## Expected results

- A multilevel annealed PnP algorithm with an investigation of its convergence properties.
- A software prototype in Python, integrated into DeepInverse.
- An evaluation on large-scale image restoration problems (inpainting, demosaicing, deblurring).

## Required skills

- Optimization, image processing, neural networks; an interest in generative models will be appreciated.
- Python, PyTorch, Github.

## References

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- [3] Martin, S., Gagneux, A., Hagemann, P., and Steidl, G., PnP-Flow: Plug-and-play image restoration with flow matching. *International Conference on Learning Representations (ICLR)*, 2025. (arXiv link).
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