Generative Models for Poisson Inverse Problems: Application to Emission Imaging

Master Research Project, CREATIS, Lyon, France

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Supervision:

- Thibaut MODRZYK, PhD student, INSA Lyon, TomoRadio team, CREATIS Laboratory
- Voichita MAXIM, Full Professor, INSA Lyon, TomoRadio team, CREATIS Laboratory

Context Emission imaging relies on the detection of photons originating from radioactive decays. The two main modalities in emission imaging are positron emission tomography and single-photon emission computed tomography, referred to as *Positron Emission Tomography* (PET) and *Single Photon Emission Computed Tomography* (SPECT), respectively. Due to the acquisition process, the raw data are sinograms corrupted by Poisson noise. Reconstructing an image from these sinograms can therefore be modeled as an ill-posed linear inverse problem:

$$y \sim \mathcal{P}(Ax), \tag{1}$$

where $\mathcal{P}$ denotes a Poisson distribution. The goal is to recover the image x from the measurements y, given the reconstruction operator A.

A particularly widespread algorithm in emission imaging is the *Maximum Likelihood Expectation Maximization* (MLEM) algorithm [1], whose variants are nowadays implemented in commercial scanners. When applied to noisy data, this algorithm tends to amplify measurement noise, producing artifacts in the reconstructed images. A common strategy is therefore to regularize the algorithm by imposing *a priori* properties on the reconstructions.

Objective In recent years, neural networks have been increasingly integrated into the reconstruction process, as they allow for significantly higher-quality reconstructions compared to hand-crafted regularization techniques [2]. More recently still, generative models such as diffusion models [3] or flow matching models [4] have emerged as highly promising candidates to serve as *priors* for inverse problems [5], thanks to their ability to model complex image distributions. However, their use remains delicate: such models may generate hallucinations or structures that are not supported by the data, which is critical in medical imaging. In the specific case of Poisson inverse problems, their direct application remains largely unexplored. The main objective of this internship is therefore to integrate these generative models into the reconstruction process [6].

Work plan In order to successfully complete the internship, the student will be expected to:

- become familiar with the MLEM algorithm used for reconstruction in emission imaging;
- become familiar with generative models (diffusion, score-based methods, flow matching, etc.);
- study the mathematical *Plug-and-Play* framework for inverse problems;
- adapt a Plug-and-Play algorithm for Poisson noise [7] to diffusion models;
- perform preliminary experiments on natural images using pre-trained diffusion models;
- transfer these results to simulated emission imaging data;
- possibly extend the method to flow matching models.

Candidate profile This internship is intended for a motivated student with:

- a solid background in Python and PyTorch, and basic knowledge of deep learning;
- an interest in applied mathematics and physical modeling.

References

[1] L. A. Shepp and Y. Vardi, "Maximum likelihood reconstruction for emission tomography," *IEEE transactions on medical imaging*, vol. 1, no. 2, pp. 113–122, 1982.

[2] K. Zhang, Y. Li, W. Zuo, L. Zhang, L. Van Gool, and R. Timofte, "Plug-and-Play Image Restoration With Deep Denoiser Prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, pp. 6360–6376, Oct. 2022.

[3] Y. Song, J. Sohl-Dickstein, D. P. Kingma, A. Kumar, S. Ermon, and B. Poole, "Score-based generative modeling through stochastic differential equations," in *ICLR*, 2021.

[4] Y. Lipman, R. T. Q. Chen, H. Ben-Hamu, M. Nickel, and M. Le, "Flow Matching for Generative Modeling," Feb. 2023. arXiv:2210.02747.

[5] H. Chung, J. Kim, M. T. Mccann, M. L. Klasky, and J. C. Ye, "Diffusion posterior sampling for general noisy inverse problems," in *ICLR*, 2023.

[6] G. Webber, Y. Mizuno, O. D. Howes, A. Hammers, A. P. King, and A. J. Reader, "Likelihood-Scheduled Score-Based Generative Modeling for Fully 3D PET Image Reconstruction," *IEEE Transactions on Medical Imaging*, 2025.

[7] T. Modrzyk, A. Etxebeste, E. Bretin, and V. Maxim, "A convergent Plug-and-Play Majorization-Minimization algorithm for Poisson inverse problems," 2025.