# Motion compensated reconstruction using deep learning for computational optics

Master Project (Lyon, France)

The Camille Jordan Institute and the CREATIS laboratory announce the opening of a six-month internship position, starting in March 2023. An ANR-funded PhD position will be opened in October 2023 to continue on the same topic.

**Keywords** Inverse problem, image reconstruction, deep learning, unrolled methods, plug-and-play methods, optimization.

**Medical background** Fluorescence-guided surgery (FGS) refers to surgical guidance in brain tumor resection, where fluorescence imaging has proven to be efficient for glioma resection, with improved survival rates without recurrence [1]. This technique consists of administration of 5-aminolevulinic acid to the patient, which is a molecule that is absorbed by the tumor cells and metabolized into protoporphyrin IX (PpIX). The PpIX fluorescence signal can be visualized using an intraoperative microscope equipped with a fluorescence module (excitation, 405 nm; emission, 630 nm). While initial studies have shown that only high-grade glioma resection can benefit from FGS, several recent studies have indicated that FGS is also of interest for low-grade gliomas, provided that the full-spectrum information is measured by point probes [2] or multispectral cameras [3]. While this work paves the way to a better determination of the tumor margin during surgery, the latter studies considered point measurements with an external measurement device. It will be highly desirable to perform hyperspectral measurement with the surgery microscope itself, providing the surgeon with real-time imaging rather than a few point measurements. However, a high spectral resolution is needed to distinguish the two states of PpIX.

**Preliminary results** In a previous project[1], we developed a high-spectral-resolution imager that acquires $64 \times 64 \times 2048$ hypercubes in $\sim$10 s. It has a spectral resolution of $\sim$2 nm over a range of about 230 nm, which has been optimized to detect the PpIX fluorescence emission during fluorescence-guided surgery, and a typical spatial resolution of $\sim$200 µm [4] (see Fig 1). Our acquisition device is computational, i.e., it acquires

$$y_\lambda \sim \mathcal{P}(\alpha A x_\lambda), \quad 1 \le \lambda \le 2048, \tag{1}$$

where $y_\lambda \in \mathbb{R}^M$ are the raw measurements, $\mathcal{P}$ is the Poisson distribution, $\alpha$ is the image intensity, $A \in \mathbb{R}^{M\times N}$ is a matrix containing the spatial light patterns (e.g., a subsampled Hadamard matrix) and $x_\lambda \in \mathbb{R}^N$ is a $\lambda$-slice of the hypercube of the scene. Therefore, this approach requires a reconstruction algorithm to recover the hypercube $x_\lambda$ from the raw data $y_\lambda$ given $A$. In a series of works [5, 6], we have proposed deep-learning reconstruction methods to solve this task.

**Challenge** While our reconstruction algorithms allow fast (e.g., hundreds of millisecond) reconstruction, the acquisition of a single hypercube currently takes $\sim$10 s. This may be sufficient for *ex-vivo* samples; however, *in-vivo* imaging is subject to physiological motion (e.g., heartbeat and breathing) that occurs at faster rates. Motion of the scene during acquisition creates blur artifacts in the hypercube recovered, if not taken into account. Indeed, when the scene moves rapidly compared to the acquisition time, each of the measurements (i.e., the components of $y_\lambda$) sees a different scene, while our current algorithms assume that the scene is motionless. This is an issue with our current acquisition device whose acquisition time (e.g., 10 s) typically represents ten cardiac cycles (1 cycle/s).

[1] ANR JCJC ARMONI (2018–2022)

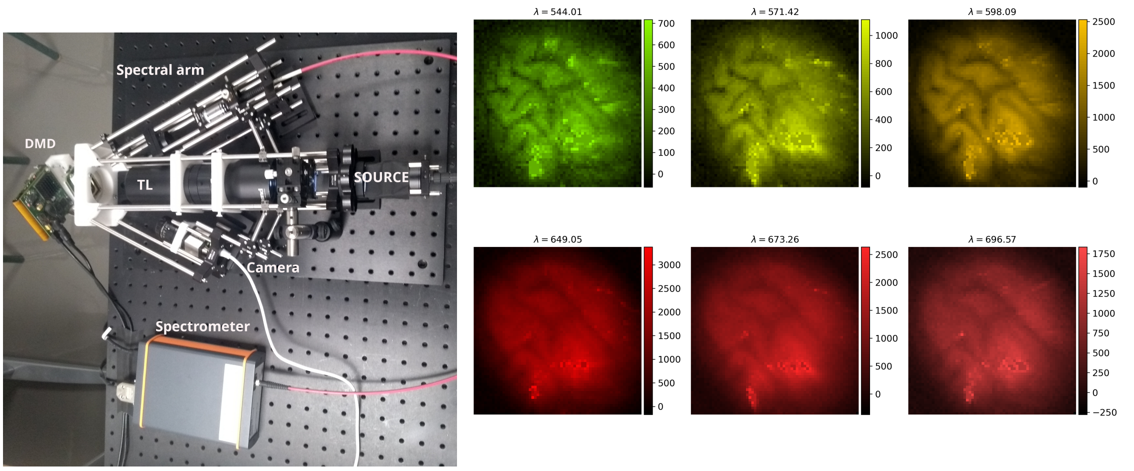


Figure 1: Left: picture of our current hyperspectral device (DMD: digital micromirror device, TL: telecentric lens). Right: Hypercube acquired and reconstructed in the range $[515 - 730]$ nm. The sample is an *ex vivo* lamb brain.

**Work plan** In this internship, we will investigate strategies for the motion-compensated reconstruction of the scene. To do so, we will consider a hybrib acquisition device that also acquires monochrome/RGB images at higher frame rates (e.g., 24 fps). We will assume that the scene motion can be estimated from the monochrone/RGB video flux. In particular, we will consider the real-time motion-compensated method described in [7], which was dedicated to brain neurosurgery.

Assuming the scene motion is known at each frame, we will investigate efficient methods to reconstruct a motion-compensated hypercube. Firstly, we will solve this problem with no prior knowledge about the solution. We will also consider modern strategies that combine traditional regularization and deep learning [8]. Among them, deep unrolled methods and plug-and-play methods will be investigated. Our algorithms will be evaluated on synthetic videos with a known motion model, on video data sets with known motion models [9] , and on video data sets with no known motion models (for instance, [10]). Secondly, the monochrome/RGB acquisition arm provides complementary information compared to the spectral arm (i.e., high-spatial low-spectral resolution vs low-spatial high-spectral resolution). Therefore, we will formalize this as a reconstruction problem, where the hypercube not only satisfies the hyperspectral forward model (1), but also a monochrome/RGB forward model, up to the noise. This approach was found to be among the more memory-efficient for a similar problem known as pansharpening in the remote-sensing literature (see [11]).

The successful candidate is expected to contribute to an in-house Python package for image reconstruction. He/she will work in close collaboration with researchers in biomedical imaging, mathematics and biomedical optics, and will have access to real experimental data.

**Skills** We are looking for an enthusiastic and autonomous candidate with a strong background in applied mathematics, image processing, or deep learning. The applicant can be enrolled in either a Master or Engineering degree program. The following skills will be acquired during the internship, although prior knowledge on these topics are appreciated:

- Programming in Python, collaborative development (git and github)
- Linear algebra and inverse problems (ill-posed problems, regularization)
- Deep learning (neural network design and optimization, automatic differentiation)
- Hyperspectral imaging

The intern will be part of a team composed of several permanent researchers and engineers and other interns recruited simultaneously on related topics.

**How to apply?** Send CV, motivation letter, and academic records to `michael.sdika@creatis.insa-lyon.fr`, `nicolas.ducros@creatis.insa-lyon.fr` and `elie.bretin@insa-lyon.fr`.

**Salary** ∼€580 net monthly.

## References


[1] W. Stummer, U. Pichlmeier, T. Meinel, O. D. Wiestler, F. Zanella, H.-J. Reulen, and ALA-Glioma Study Group, "Fluorescence-guided surgery with 5-aminolevulinic acid for resection of malignant glioma: a randomised controlled multicentre phase III trial," *Lancet Oncol.*, vol. 7, pp. 392–401, May 2006.

[2] L. Alston, L. Mahieu-Williame, M. Hebert, P. Kantapareddy, D. Meyronet, D. Rousseau, J. Guyotat, and B. Montcel, "Spectral complexity of 5-ALA induced PpIX fluorescence in guided surgery: A clinical study towards the discrimination of healthy tissue and margin boundaries in high and low grade gliomas," vol. 10, no. 5, pp. 2478–2492.

[3] J. J. Bravo, J. D. Olson, S. C. Davis, D. W. Roberts, K. D. Paulsen, and S. C. Kanick, "Hyperspectral data processing improves PpIX contrast during fluorescence guided surgery of human brain tumors," *Sci. Rep.*, vol. 7, pp. 1–13, Aug 2017.

[4] A. Lorente Mur, B. Montcel, F. Peyrin, and N. Ducros, "Deep neural networks for single-pixel compressive video reconstruction," in *Unconventional Optical Imaging II* (C. Fournier, M. P. Georges, and G. Popescu, eds.), (Online Only, France), p. 27, SPIE, Apr. 2020.

[5] A. Lorente Mur, P. Leclerc, F. Peyrin, N. Ducros, and N. Ducros, "Single-pixel image reconstruction from experimental data using neural networks," *Optics Express*, vol. 29, pp. 17097–17110, May 2021.

[6] A. Lorente Mur, P. Bataille, F. Peyrin, and N. Ducros, "Deep Expectation-Maximization For Image Reconstruction From Under-Sampled Poisson Data," in *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, (Nice, France), pp. 1535–1539, IEEE, Apr. 2021.

[7] M. Sdika, L. Alston, D. Rousseau, J. Guyotat, L. Mahieu-Williame, and B. Montcel, "Repetitive Motion Compensation for Real Time Intraoperative Video Processing," *Medical Image Analysis*, vol. 53, pp. 1–10, 2019.

[8] J. Schlemper, G. Yang, P. Ferreira, A. Scott, L. McGill, Z. Khalique, M. Gorodezky, M. Roehl, J. Keegan, D. Pennell, D. N. Firmin, and D. Rueckert, "Stochastic deep compressive sensing for the reconstruction of diffusion tensor cardiac MRI," *CoRR*, vol. abs/1805.12064, 2018.

[9] S. Baker, S. Roth, D. Scharstein, M. J. Black, J. Lewis, and R. Szeliski, "A database and evaluation methodology for optical flow," in *2007 IEEE 11th International Conference on Computer Vision*, pp. 1–8, 2007.

[10] K. Soomro, A. R. Zamir, and M. Shah, "UCF101: A dataset of 101 human actions classes from videos in the wild," *CoRR*, vol. abs/1212.0402, 2012.

[11] L. Loncan, L. B. de Almeida, J. M. Bioucas-Dias, X. Briottet, J. Chanussot, N. Dobigeon, S. Fabre, W. Liao, G. A. Licciardi, M. Simões, J. Tourneret, M. A. Veganzones, G. Vivone, Q. Wei, and N. Yokoya, "Hyperspectral Pansharpening: A Review," vol. 3, no. 3, pp. 27–46.