Adaptive acquisitions for fast computational optics

PhD/Postdoc proposal, CREATIS, Lyon, France

The CREATIS laboratory announce the opening of a 36-month, fully funded PhD, or a 2-year Postdoc position starting in September 2025.

Keywords Image Reconstruction, Deep Learning, Optimization, Computational Optics.

General context Hyperspectral imaging is crucial in medical imaging because it allows for the precise identification and analysis of different biomolecules and tissues. This non-invasive technique enables early disease detection, accurate diagnosis, and effective treatment planning.

However, the acquisition of hyperspectral (x, y, λ)-images, with both high spatial and spectral resolutions in real time, is excessively challenging. Indeed, hyperspectral imaging implies an acquisition in 3D using only 2D arrays of sensors, which requires the acquisition to be multiplexed, typically across time, which imposes a trade-off between the total acquisition time and the spatial or spectral resolution. The shorter the acquisition time, the lower the spatial or spectral resolution. Moreover, light throughput is intrinsically reduced in spectral imaging, compared grayscale or few-colour imaging, as light across a large number of spectral channels. This imposes a trade-off between the total acquisition time and the noise level. To leverage this compromise and pave the way to real-time high-resolution hyperspectral imaging, we consider complementary acquisitions.

Complementary acquisitions We have developed a hyperspectral computational imager that measures linear transformation $Y = AX \in \mathbb{R}^{m\times\ell}$, where $A \in \mathbb{R}^{m\times n}$ represents the spatial multiplexing matrix, and $X \in \mathbb{R}^{n\times\ell}$ is the hyperspectral image. In practice, such measurements can be taken with a system based on a digital micromirror device (DMD) and a compact spectrometer. Recently, we complemented our system with a traditional camera that measures $Z = XB \in \mathbb{R}^{n\times c}$, where $B \in \mathbb{R}^{\ell\times c}$ represents a spectral degradation. While the number of spectral channels of the hyperspectral arm is large (e.g., $\ell = 2,048$), the number of spectral channels of the traditional camera is small, e.g., $c = 1$ (grayscale image) or 3 (RGB image). In our system, the different rows of A are uploaded sequentially onto the DMD. Therefore, we must choose $M \leq N$ to limit the acquisition time, which in turn degrades the spatial resolution.

Objective After the complementary acquisition of a pair (Y, Z), one needs to reconstruct the hypercube X given the pair of direct models (A, B), which is an ill-conditioned inverse problem. Inverse problems have been extensively studied in the past decades. First based on the optimization of hand-crafted functionals, their resolution now benefits from the advances of the 'artificial intelligence' framework [1, 2]. A simple yet powerful strategies consists in the supervised training of neural network (e.g., UNet or CNN) that post-process the reconstruction obtained using a 'standard' (e.g., pseudo inverse) solution.

In this thesis, we will rather focus on i) the design on the direct model A and ii) reconstruction methods where A is not known in advance. This problem is related to the choice of projection matrix design in compressed sensing, where sparsity is used as a signal prior. While compressed sensing is non adaptive, the adaptive design of A has remained largely unexplored. Here, we intend adaptive designs as the design of A adapted to the complementary image Z. E.g.,

$$A \in \operatorname*{argmin}_{A} f(A; Z), \tag{1}$$

where the function f is a quality criterion to be defined. To simplify the analysis, the quality criterion can rely on a predetermined reconstruction operator $\mathcal{R}$ that estimates X from (Y, Z) or even from Y only (e.g., $\mathcal{R} = (A^\top A)^{-1} A^\top$). However, our ultimate goal will be to design both A and a reconstruction operator $\mathcal{R}_A$ associated to it.

Existing work on the topic includes [3, 4] where the authors consider jointly signal priors (e.g., sparsity) and noise levels to design the sensing matrix. More recently, [5, 6] proposed techniques where the matrix A is designed in an adaptive manner during the acquisition process. Deep learning based-approaches have been proposed for reconstruction (e.g., see [7] in hyperspectral imaging or [8] in magnetic resonance imaging).

General framework The reconstruction problem can be set in the more general framework of multi-modality imaging [9]

$$\mathsf{y} \sim \mathcal{N}_\mathsf{y}(Ax_1) \tag{2a}$$
$$\mathsf{z} \sim \mathcal{N}_\mathsf{z}(Bx_2) \tag{2b}$$

where $\mathcal{N}$ represents the stochastic errors of the acquisition process. Traditional reconstruction techniques (a.k.a. pansharpening in remote sensing [10]) solve

$$\operatorname*{argmin}_{x_1, x_2} \alpha\, \mathcal{D}(y - Ax_1) + \beta \mathcal{D}(z - Bx_2) + \gamma \mathcal{S}(x_1, x_2), \tag{3}$$

where $\mathcal{D}$ is a similarity measure, $\mathcal{S}$ is a regularization term that favors certain signals and α, β, γ balance the contribution of the different terms. This general framework includes hyperspectral single-pixel imaging, SPECT/CT, cryo-ET/X-ray tomography, correlative light-electron microscopy, etc.

Preliminary results In a series of works, we have proposed various reconstruction methods under the hypothesis that the acquisition matrix A is a Hadamard matrix [11, 12, 13]. Given homoscedastic noise, Hadamard matrices minimize the trace of the covariance matrix of the residual error, a property known as Fellgett's advantage [14]. In general, obtaining higher resolution reconstruction of the unknown signal/image can be done by i) using super-resolution techniques (e.g. structured illumination), or ii) leveraging redundancy across frequency thanks to deep learning. We have shown that the later can be done in an efficient and robust manner [15, 16]. When no training dataset is available, we can estimate the optimal sampling scheme while reconstructing the unknown signal(s). NeRF-like parametrization appear as a promising choice for regularizing the associated ill-posed inverse problem [17].

Skills We are looking for an enthusiastic and autonomous candidate with a strong background in applied mathematics (statistics, optimization), signal/image processing and machine learning. The applicant can be enrolled in either a Master or Engineering degree program.

How to apply? Please send a curriculum, a motivation letter, and your academic records before **May 19th** to nicolas.ducros@creatis.insa-lyon.fr and valentin.debarnot@creatis.insa-lyon.fr

Expected beginning date September 2025. The precise starting date can be adjusted according to the availability of the selected candidate.

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