Mathematics of Adaptive Acquisitions for Hyperspectral Single-pixel Imaging

Master II Project, CREATIS, Lyon, France

The CREATIS laboratory announce the opening of a six-month internship position, starting in March 2025.

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. In particular, fluorescence-guided surgery, a technique for surgical guidance based on fluorescence imaging, has proven to be efficient for glioma resection, with improved survival rates without recurrence [1]. However, the acquisition of hyperspectral images with both a high spatial and spectral resolution is very challenging.

Problem definition In a previous project[1], we developed a computational imager that can acquire a linear transformation of hypercubes $X \in \mathbb{R}^{N\times\Lambda}$ at high spectral resolution (e.g., $\Lambda = 2,048$). More precisely, our system measures sequentially a set of M spectra, each of them being the spectrum of the light selected from a portion of the pixels using a spatial light modulator. The pattern of selected pixels is a sequence of ones and zeros, stored for the ith measurement as the ith row of an acquisition matrix $A \in \mathbb{R}^{M\times N}$ designed a priori. The design of acquisition matrix A is the topic of this internship (see next section).

Repeating the experiment for M spatial light patterns yields the raw measurements that can be modeled for a given wavelength λ as

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

where $y_\lambda \in \mathbb{R}^M$ are the raw measurements, $\mathcal{P}$ is the Poisson distribution, α is the image intensity, and $x_\lambda \in \mathbb{R}^N$ is a slice of the hypercube X. Our acquisition device being computational, it requires a reconstruction algorithm to recover the hypercube X from the raw data $Y \in \mathbb{R}^{M\times\Lambda}$. This is typically performed by solving an optimization problem of the form [2]

$$\min_{X\in\mathbb{R}^{N\times\Lambda}} \mathsf{KL}(Y|\alpha AX) + g_\theta(X), \tag{1}$$

where g_θ is a regularization related to the action of a deep neural network, promoting realistic images, and KL is the Kullback-Leibler divergence.

Challenges In practice, there is a trade-off between acquisition time and quality of the reconstruction of the hypercube X. Indeed, in theory, a perfect reconstruction requires that the number of acquisitions M grows to infinity. Conversely, performing as few acquisitions as possible means that the overall procedure is shorter, making it more suitable for real-time FGS. An important factor to optimize this trade-off is to design the acquisition matrix A carefully. In a series of works, we have proposed various reconstruction methods under the hypothesis that the acquisition matrix A contains Hadamard patterns [3, 4, 5]. This choice is motivated by the so-called Fellgett advantage [6]: under Gaussian noise, Hadamard patterns minimize the trace of the covariance matrix of the residual error.

The ultimate goal of this internship is to go beyond the choice of Hadamard patterns by adapting the patterns to the scene (e.g., see [7, 8, 9]). There are a variety of possible directions:

- Considering Hadamard patterns, it is *a priori* unclear how to select a subset of these patterns to decrease M (therefore, the acquisition time). Existing theory from compressive sensing literature [10, 11], suggests sampling both low and high-frequency patterns, but this remains to be tested for single-pixel imaging.

[1] ANR JCJC ARMONI (2018–2022)

- We can design regions of interest within the image X where the acquisition patterns are sent. This allows to concentrate the acquired signal and improves the signal-to-noise ratio. However, the reconstruction procedure has to be reworked, in particular the choice of the regularizer g_θ.
- Finally, within the current setup, we are able to acquire a gray-scale projection of the hypercube X before performing the multispectral measurement, through the use of a second camera. In this scenario, it should be possible to adapt the choice of the patterns to the image X, building a data-driven acquisition matrix $A(X)$. We can also design adaptive patterns given an empirical distribution of the images X through dimensionality reduction.

Work plan This internship will include the following tasks:

- Literature review on inverse problems for image reconstruction and compressive sensing. Focus on existing literature for the design of matrix A.
- Formalize the acquisition model for the region-of-interest adaptive acquisitions, and adapt an existing reconstruction algorithm to solve (1).
- Compare existing choices of sub-sampling of Hadamard patterns with proposed stochastic approaches from compressive sensing, and combine with the region of interest approach.
- If time allows, use the grayscale image (or a collection of grayscale images from the same distribution) to define adaptive patterns $A(X)$.

Skills We are looking for an enthusiastic and autonomous candidate with a strong background in applied mathematics, inverse problems and/or image processing. 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 (numpy/pytorch in particular), collaborative development (git and github)
- Inverse problems and Compressive Sensing (ill-posed problems, regularization)
- Hyperspectral imaging
- Convex and non-convex numerical optimization

The intern will be part of a dynamic 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 `nicolas.ducros@creatis.insa-lyon.fr` and `jeremy.cohen@cnrs.fr`.

Salary The gratification of the internship corresponds to 1/3 of the hourly minimum wage (∼€550 net monthly).

References

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