Deep Image Reconstruction for Hyperspectral Imaging

Master Project (Lyon, France)

The Camille Jordan Institute and the **CREATIS laboratory** announce the opening of a six-month internship position, starting in March 2021. This project is a collaboration between a laboratory in mathematics and a laboratory in biomedical imaging.

Keywords Inverse Problem, Image Reconstruction, Deep Learning, Numerical Optimization, Computational Optics, Single-Pixel Imaging.

Background Image reconstruction from noisy measurements where the number of unknowns is larger than the number of measurements is a generic problem that has several applications in computational imaging. While such inverse problems have long benefited from the compressed sensing theory, which exploits sparsity priors, recent advances in deep learning have been revolutionizing the field [1, 2, 3]. In particular, convolutional neural networks have shown great success at solving computed tomography problems, either by learning a direct inverse mapping [4], or through the use of adversarial neural networks [5]. Much effort is currently devoted to bridging the gap between more traditional approaches for image reconstruction and the deep-learning-based approach to solving inverse problems.

In a series of works, we have proposed new deep network architectures that can be interpreted in a Bayesian framework [6, 7, 8]. Such networks have been successfully applied to the experimental data acquired by a single-pixel camera. Single-pixel imaging is an extreme configuration of computational optics, where a single point detector is used to recover an image [9]. It has has been successfully applied to fluorescence microscopy, hyperspectral imaging, diffuse optical tomography [10], image-guided surgery, short-wave infrared imaging [11], and imaging through scattering media [12].

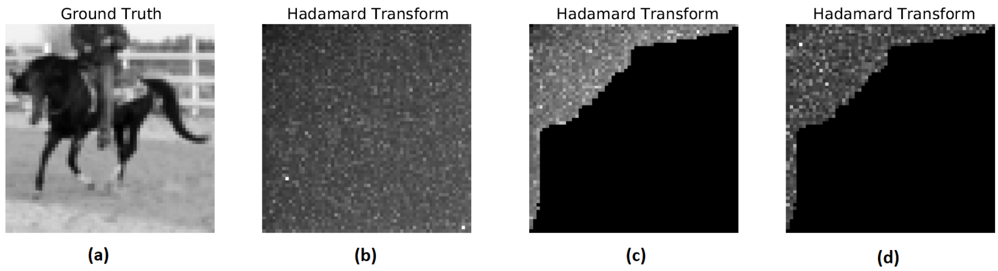

Figure 1: An image from the stl-10 dataset, alongside its Hadamard transform, the Hadamard transform with missing coefficients (down-sampled Hadamard transform), and the Hadamard transform with missing coefficients (noisy down-sampled Hadamard transform). The noisy coefficients are subject to Poison noise, and we chose $\alpha = 10$ ph. Our problem consists in reconstructing the image (a) from the measurements (d).

Project Capitalizing on our previous results, this project will propose and examine new network architectures, aiming to establish new bridges between deep learning and traditional image reconstruction methods. For instance, we would like to introduce additional regularization strategies in the data (measurement) domain and image (reconstruction) domain. Our idea is then to help the network data denoising step proposed in [7, 8] by incorporating in the network architecture classical smooth or non-smooth variational regularization techniques. An other idea is to build a reconstruction network based on the idea of momentum acceleration (e.g., Nesterov's accelerated gradient descent).

The successful candidate will implement and compare the different reconstruction methods considering data simulated from an image database (e.g., STL-10) and from experimental data. Therefore, he is expected to contribute to the in-house Python toolbox for image reconstruction, which is expected to be publicly released by the start of the Project.

The successful candidate will work in close collaboration with a researcher in biomedical imaging and a mathematician, and will have access to an experimental acquisition device.

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. Strong programming skills in Python are required.

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

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

References

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