Project description

Compressed sensing (CS) introduces a signal acquisition framework that goes beyond the traditional Nyquist sampling paradigm. Under strict conditions on the measurement process and structural assumptions, such as sparsity in a specific basis, on signals under scrutiny, CS demonstrates that signals can be acquired using a small number of linear measurements and then recovered by solving a non-linear optimization problem. Many algorithms have been developed to solve such problems: ISTA, AMP, ADMM, LASSO, primal-dual, etc.. All these algorithms are iterative and involve non-linear thresholding operations which depend on one or several hyperparameters that should be optimized, by cross-validation techniques or even manually, to lead to the best reconstruction.

The optimization of the non-linearities involved in the convex optimization algorithms has been widely studied in the literature. Very recently, novel methods have been proposed in which the optimal non-linear functions and/or thresholding parameters are learned from a training set through a deep neural network (DNN). Those methods usually construct the neural network architecture by "unfolding" the iterative algorithm, where each layer represents an iteration of the latter. This procedure has been successfully applied to ISTA [1], [2], AMP [3] and ADMM [4].

The idea of this project is to apply such learning procedure to the compressed sensing of images problem,

$$\boldsymbol{y} = \boldsymbol{M}\boldsymbol{\Psi}\boldsymbol{x} + \boldsymbol{n},$$

where $\boldsymbol{x} \in \mathbb{R}^N$ is the vectorized (*i.e.* column-stacked) image of $N = L \times L$ pixels to be recovered from the measurement $\boldsymbol{y} \in \mathbb{R}^M$ (such that $M \ll N$), with $\boldsymbol{M} \in \mathbb{R}^{M \times N}$ is the linear measurement matrix, $\boldsymbol{\Psi} \in \mathbb{R}^{N \times N}$ is an orthonormal basis and $\boldsymbol{n} \in \mathbb{R}^N$ is a noise vector. In order to relax the memory requirements to store the measurement matrix, a block-based approach [5] will be followed. The goal is not (at least initially) to learn the measurement matrix since it is usually known a priori, but to learn the optimal non-linearities of an iterative thresholding algorithm.

Many image datasets are available such as Standard, Berkley or LabelMe. They should not need a lot of "cleaning" (probably not at all) but a suitable pre-processing to extract patches of a relevant size in order to construct the training and testing sets.

The resulting reconstructions will be compared to state-of-the-art methods firstly in terms of accuracy with classical image distance metrics such as PSNR or SSIM, and secondly in terms of memory and computational requirements.

References

[1] K. Gregor and Y. LeCun, "Learning Fast Approximations of Sparse Coding", in *27th Int. Conf. Mach. Learn. ICML 2010*, 2010, p. 399.

[2] U. S. Kamilov and H. Mansour, "Learning Optimal Nonlinearities for Iterative Thresholding Algorithms", *IEEE Signal Process. Lett.*, vol. 23, p. 747, 2016.

[3] M. Borgerding and P. Schniter, "Onsager-corrected deep learning for sparse linear inverse problems", p. 1, 2016. arXiv: `1607.05966`.

[4] Y. Yang, J. Sun, H. Li, *et al.*, "Deep ADMM-Net for Compressive Sensing MRI", in *30th Conf. Neural Inf. Process. Syst. (NIPS 2016)*, 2016, p. 1.

[5] A. Adler, D. Boublil, M. Elad, *et al.*, "A Deep Learning Approach to Block-based Compressed Sensing of Images", p. 1, 2016. arXiv: `1606.01519`.