INTERNSHIP: DEEP LEARNING WITH SHAPE CONSTRAINTS FOR GALAXY IMAGE DECONVOLUTION

In the context of the Euclid space mission (https://www.euclid-ec.org), the shape of about a billion of galaxies over a large fraction of the sky needs be estimated with a very high accuracy to derive cosmological information. One of the main challenge associated with this task is to correct the galaxy images for the effect of the spatially varying point spread function (PSF) of the instrument, modeled and/or estimated from the images of stars in the field. This critical step to recover as accurately as possible the shape of the galaxies requires advanced deconvolution methods.

Sparsity and sparse representations are at the heart of many state-of-the-art signal processing methods to solve inverse problems such as deconvolution. These techniques typically consists in modeling the sought after signals in either fixed representations (e.g. wavelets, curvelets, shearlets...) or learned representations adapted to their geometrical content so that information is compressed in a few elementary atoms. This property allows to regularize ill-posed inverse problems then solved by convex optimization algorithms [Starck2015]. In this framework, sparsity in a wavelet domain and low-rankness constraints have been recently employed for the deconvolution of galaxy images, in the context of galaxy shape measurement [Farrens2017].

In the quest for the best adapted representation for given signals and tasks, deep learning techniques have proved to be very competitive for image classification (e.g. [Krizhevsky2012]), segmentation (e.g. [Yu16]) or denoising [Burger12]. Recently, several machine learning approaches have also been proposed for deconvolution:

- brute force deconvolution followed by artifact removal and denoising using deep learning [Schuler2013, Jin2017]
- deconvolution by integrating the approximation or estimation of the inverse filter in a deep neural network [Xu2014, Schuler2016]
- iterative deconvolution where deep neural networks are used as "denoisers" or regularizers [Zhang2017, Bigdeli2017, Meinhardt 2017]

Although these deconvolution techniques using machine learning have shown promising results on several benchmark data sets, they are not adapted to the problem we consider: for galaxy shape measurement, each galaxy is experimenting a different PSF and the quality of deconvolution is best assessed on the recovered galaxy shape (by measuring ellipticity errors) rather than standard image quality errors such as PSNR. We have recently investigated two new approaches were we couple regularized deconvolution and deep learning, either as post-processing or integrated as a denoiser in a plug-and-play ADMM. We showed improvements in a Euclid-like scenario in both pixel and ellipticity errors compared to sparsity or low-rank deconvolution methods [Farrens2017].

In parallel, we have shown in the laboratory that constraints on the shape (via the moments) reduce ellipticity errors when used in particular in denoising problems. The next step is therefore to integrate such constraints in the learning step of our deep networks by adapting the cost function, so as to investigate if we can improve further on shape measurement. For that purpose, the intern will :

- 1. Implement and investigate deep neural networks with shape constraints to remove noise and deconvolution artefacts without degrading the shape measurement, after a simple non-iterative deconvolution technique (Tikhonov deconvolution). The intern will start from a previously developed architecture, based on the multiscale U-net approach as in [Jin2017] with several improvements added (dense blocks [Huang2016] of separable convolutions [Chollet2016]).

- 2. Develop new deep representations for galaxy images with shape constraints, and use them as regularizers in iterative deconvolution approaches. In this case, the shape constraints can be used in both deconvolution and regularization to ensure consistency along iterations.

- 3. Investigate if time allows the impact on shear measurement, based on processing several million of galaxies.

All these approaches will be validated in GalSim simulations with realistic galaxy morphology and realistic Euclid-PSFs (space-variant). They will also be compared to the sparsity/low-rank approach of [Farrens2017] and our previous deep learning approaches in the context of shape measurement.

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