INTERNSHIP: DEEP LEARNING 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, it is not yet clear how they compete with sparsity-based approaches in astronomical applications. For galaxy shape measurement in particular, 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.

The objective of this internship is therefore to compare several of these machine learning approaches to the sparse approaches that were developed in the laboratory, and improve them in an Euclid scenario. For that purpose, the intern would be in charge of 1) implementing and improving several deconvolution approaches based on machine learning in the context of Euclid, 2) applying these techniques on simulated Euclid-like galaxies, 3) comparing such approaches with what was proposed in [Farrens2017]. New deep learning architectures better suited to galaxy representation could also be investigated.

Any candidate should have a background in image/signal processing, ideally with knowledge in machine learning techniques, sparse signal processing and convex optimization.

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