

Point Spread Function Modelling with Neural Fields and a Differentiable Optical Model

M2 Internship project (*Stage de fin d'études*), 2026

Keywords: *Machine learning, Inverse problems, Point spread function modelling*

Internship synopsis

Context. Weak gravitational lensing [1] is a powerful probe of the Large Scale Structure of our Universe. Cosmologists use weak lensing to study the nature of dark matter and its spatial distribution. Weak lensing missions require highly accurate shape measurements of galaxy images. The instrumental response of the telescope, called the point spread function (PSF), produces a deformation of the observed images. This deformation can be mistaken for the effects of weak lensing in the galaxy images, thus being one of the primary sources of systematic error when doing weak lensing science. Therefore, estimating a reliable and accurate PSF model is crucial for the success of any weak lensing mission [2]. The PSF field can be interpreted as a convolutional kernel that affects each of our observations of interest, which varies spatially, spectrally, and temporally. The PSF model needs to be able to cope with each of these variations. We use specific stars considered point sources in the field of view to constrain our PSF model. These stars, which are unresolved objects, provide us with degraded samples of the PSF field. The observations go through different degradations depending on the properties of the telescope. These degradations include undersampling, integration over the instrument passband, and additive noise. We finally build the PSF model using these degraded observations and then use the model to infer the PSF at the position of galaxies. This procedure constitutes the ill-posed inverse problem of PSF modelling. See [3] for a recent review on PSF modelling.

The recently launched *Euclid* survey represents one of the most complex challenges for PSF modelling. Because of the very broad passband of *Euclid*'s visible imager (VIS) ranging from 550nm to 900nm, PSF models need to capture not only the PSF field spatial variations but also its chromatic variations. Each star observation is integrated with the object's spectral energy distribution (SED) over the whole VIS passband. As the observations are undersampled, a super-resolution step is also required. A recent model coined WaveDiff [4] was proposed to tackle the PSF modelling problem for *Euclid* and is based on a differentiable optical model. WaveDiff achieved state-of-the-art performance and is currently being tested with recent observations from the *Euclid* survey.

Goals. The recently introduced neural fields [5] have shown impressive performance in computer vision tasks. Neural fields are coordinate-based neural networks that parametrise physical properties of scenes or objects across space (and time). These networks gained particular visibility by tackling the problem of 3D scene reconstruction [6] from several 2D images of the scene.

If we consider the (x, y) focal plane coordinates as viewing directions, the PSF modelling problem can be considered as a scene reconstruction from a fixed set of 2D images (the observed stars). One goal of the internship is to adapt these ideas in recent neural fields works and combine them with the WaveDiff model. The next goal is to build a new PSF model that would allow us to better capture the spatial variations of the PSF field. One last goal is to include spurious spectral variations in the neural field and condition it on existing simulations.

The applicant profile

The successful candidate should be following an M2 master or an engineering diploma degree, with a specialisation on signal processing/statistics/machine learning or astrophysics. Basic knowledge of statistical inference, signal processing, and machine learning is expected. The candidate should be comfortable with software development (at least in Python) and, ideally, be familiar with a deep learning framework (e.g. TensorFlow, PyTorch, JAX). Experience with open-source and collaborative development tools (e.g. GitHub) is desirable. The research team is international, so speaking French is not a requirement.

The candidate will acquire expertise in astronomical image processing, Fourier optics, machine learning and deep learning. In addition, the intern will learn to work in a collaborative development environment and contribute to existing software packages. The knowledge acquired during the internship applies to a wide range of applications in various fields, e.g., biomedical imaging, and astrophysics.

Scientific environment

The successful candidate will be based in the [ALEPH group](#) from the DEDIP department of the IRFU institute from the CEA Paris-Saclay research centre which is located 20km south of central Paris in the Paris-Saclay cluster. The PhD supervision will be assured by [Dr. Tobías I. Liaudat](#). The ALPEH group focuses on signal (and image) processing and machine learning applied to astrophysics applications including gravitational wave data analysis and radio interferometric imaging. The candidate will be able to benefit from the expertise of the growing machine learning and artificial intelligence community on the Saclay plateau. We expect strong interactions with the PSF team at the [CosmoStat](#) laboratory, which has a long tradition of developing cutting-edge statistical tools for the analysis of astronomical and cosmological data and is heavily involved in several projects including the ESA *Euclid* space telescope.

Computational resources The successful candidate will have access to the [Jean Zay](#) supercomputer, largest GPU cluster for research in France, as well as the IRFU's CPU cluster. Most of the development will rely on GPUs.

Contact

- Contact: Dr. Tobías I. Liaudat, tobias.liaudat@cea.fr, <https://tobias-liaudat.github.io>
- Lab: IRFU institute at the CEA Saclay centre,
- Application deadline: 15th February 2026.

Note: This internship has the possibility to be extended into a PhD thesis.

Application Please send an application by email with a subject starting with [Internship-PSF] to tobias.liaudat@cea.fr, including a CV and a transcript of grades.

References

- [1] R. Mandelbaum. “Weak Lensing for Precision Cosmology”. In: *Annual Review of Astronomy and Astrophysics* 56 (2018), pp. 393–433. DOI: [10.1146/annurev-astro-081817-051928](https://doi.org/10.1146/annurev-astro-081817-051928). arXiv: [1710.03235](https://arxiv.org/abs/1710.03235).
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- [5] Y. Xie, T. Takikawa, S. Saito, O. Litany, S. Yan, N. Khan, F. Tombari, J. Tompkin, V. Sitzmann, and S. Sridhar. “Neural Fields in Visual Computing and Beyond”. In: *arXiv e-prints*, arXiv:2111.11426 (Nov. 2021), arXiv:2111.11426. DOI: [10.48550/arXiv.2111.11426](https://doi.org/10.48550/arXiv.2111.11426). arXiv: [2111.11426 \[cs.CV\]](https://arxiv.org/abs/2111.11426).
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