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Prediction of AO corrected PSF for AOF NFM/SPHERE

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ABSTRACT

For Adaptive Optics (AO) assisted systems, a point spread function (PSF) may have a very complex structure and therefore be difficult to predict. An accurate and independent PSF prediction would be beneficial for the scientific analysis of the data and for quality evaluation of potential observations or even exposure time estimation before the actual observations. Ideally, one would like to have a tool able to predict the PSF morphology only based on a few external parameters, including instrument characteristics, given weather conditions, and properties of a selected target. It can be achieved with analytical PSF prediction tools (e.g., TIPTOP,¹ PSFAO²). However, in real-life scenarios, PSF can still be influenced by multiple effects which are not adequately described by such analytical models and which can still significantly affect the quality of a predicted PSF. The topic of this work is to investigate the possible application of machine learning (ML) for PSF prediction. The main idea is not to use ML blindly but rather to investigate the idea of combining existing analytical approaches with machine learning. While the analytical model retains physics, the ML part can complement it and learn from data the effects that the analytical model fails to account for, resulting in higher prediction accuracy. This paper demonstrates the accuracy of the method when applied to an extensive data set of 700+ PSF from SPHERE and 200+ PSFs from MUSE-NFM.

Keywords: Adaptive optics, Atmospheric turbulence, Point spread functions, PSF prediction, Machine learning, Image quality, Telescopes

1. INTRODUCTION

Some major fields of astronomy (exoplanetology, study of bodies in the solar system, study of galaxies/galactic centers, study of compact objects) heavily rely on observations performed using AO facilities since they require high angular resolution, precise astrometry, and photometry. In many cases, accurate knowledge of PSF is desirable. It is helpful for scientific data analysis and applicable for exposure time estimation and observation quality evaluation. Ideally, it would be beneficial to have a tool able to accurately predict the PSF morphology only based on a few external parameters, including instrument characteristics, given weather conditions, properties of a selected target, and possibly relying on external data collected from supplementary sensors (e.g., wavefront sensor (WFS) images). Additionally, since scientific PSF is affected by all possible contributors along the optical path, it provides valuable information about optical system design, calibrations, and diagnostic. Therefore, it may even assist the existing control strategies to address the effects unseen by the WFSs. However, the complex design of AO facilities, complicated control strategies, and unseen effects³ lead to the sophisticated morphology of AO-corrected PSF. This complexity requires intricate models to be precisely described. The incomplete representation of PSFs, in turn, leads to the reduced quality of the scientific analysis. One way to address this problem is to provide an extensive analytical description of each known physical contributor to the structure of PSF.

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In this work, we investigate the physically accurate Fourier-based PSF modeling tool called TIPTOP,¹ which is suited for generating realistic AO-corrected PSFs. The final goal of this work is to provide an accurate PSF prediction tool for exposure time estimation, scientific analysis, and possibly AO-system control. We validate the model on real data and introduce future prospective for improving this approach. The current baseline is to make it work with actual on-sky data provided by GALACSI NFM and SPHERE. But proposed solutions and methods can be later successfully adopted by ELT instruments (e.g., the LTAO system of HARMONI).

2. METHODS

TIPTOP is a Fourier-based model⁴ that generates AO-corrected PSFs based on power spectral density (PSD) of the pupil plane wavefront spatial frequencies.⁵ The resulting PSD is summed up from multiple contributors, each representing a distinct AO-related physical effect (Fig. 1). This approach provides high flexibility since each component can be easily added or removed from the model. It allows using TIPTOP with various AO systems (SCAO, LTAO, MCAO). Since it is physics-based, it can represent the PSF morphology with a high degree of realism once properly calibrated. It also allows using real telescope telemetry as inputs. Being a Fourier-based model, TIPTOP relies on simple FFTs and matrix multiplication. It allows executing it on modern hardware with a high level of parallelism.

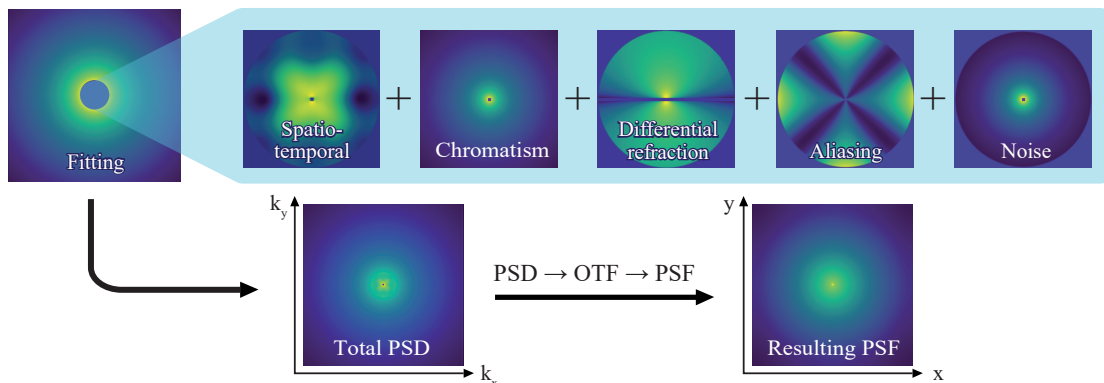


Figure 1. Being a Fourier-based model, TIPTOP relies on the analytically derived PSD contributors to simulate long-exposure AO-corrected PSFs. Each contributor describes one effect. The coupling between them is neglected.

However, flexibility and physical meaningfulness come with a cost. The resulting analytical model behind TIPTOP is defined by a large set of parameters. Meanwhile, on-sky analogs of these parameters can be measured imprecisely and be subjected to biases, meaning that the real telemetry does not one-to-one correspond to the inputs of TIPTOP. In other words, for the same telemetry, TIPTOP produces PSFs that look different from associated on-sky PSFs (Fig. 2). It is a severe obstacle to the direct prediction of the PSF. Thus, the model first must be calibrated to enable a reliable PSF prediction framework.

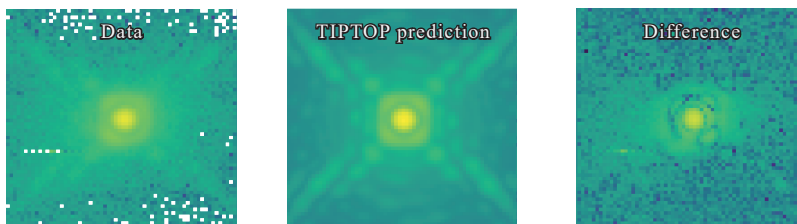


Figure 2. When existing telemetry parameters are directly passed to TIPTOP, the resulting prediction does not provide desirable accuracy, meaning that model calibration is needed.

To calibrate the model and find correlations between the telemetry and model inputs, we validate the model by fitting it to the real on-sky PSFs. However, some parameters have virtually the same effect on the morphology of

the PSF. Therefore, their structural influence may be hard to disentangle, even though very different phenomena produce them. It introduces ambiguity into the fit and prevents the determination of reliable correlations. One of the objectives of this work is to address this problem. It will be further discussed in the next section.

3. CURRENT RESULTS

The first step towards validating the model is to fit it to real data provided by SPHERE and MUSE instruments of the VLT facility (Fig. 3). The dataset contains isolated PSFs with associated telemetry data. Both datasets contain approximately 750 SPHERE PSFs and 240 MUSE NFM PSFs. The current version of TIPTOP can fit these MUSE NMF PSFs (Fig. 3a) and SPHERE (Fig. 3b) with an error of only 0.5%. This extreme level of accuracy validates TIPTOP capacities as a PSF modeling tool, showing that it can represent the shape of a PSF with great precision.

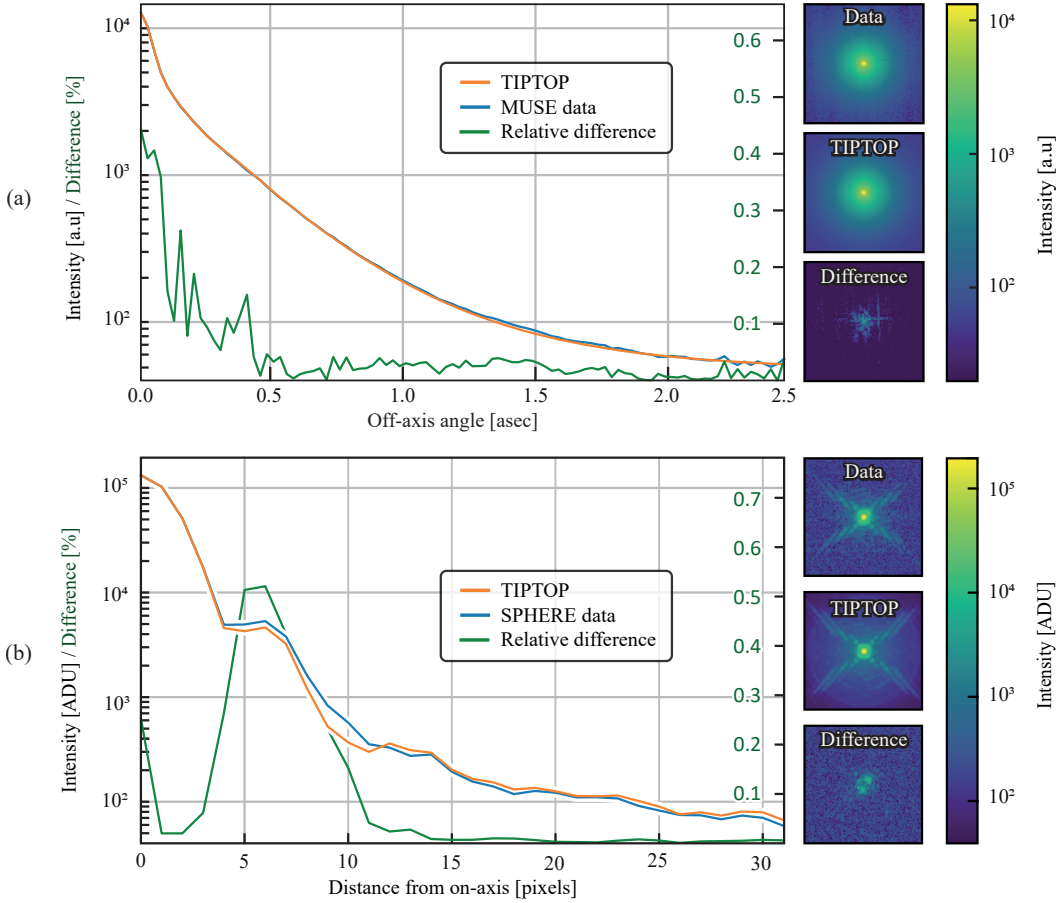


Figure 3. (a) An example of the accurately fitted on-sky MUSE NFM PSF. (b) Fitted SPHERE PSF. It demonstrates the high accuracy of the model ($< 1\%$ of error). These results clearly show the capabilities of TIPTOP.

Additional to fitting, the comparison was made between simulated data and direct predictions of TIPTOP (Fig. 4). Simulated data were obtained using PASSATA end-to-end (E2E) AO simulator⁶ with the same inputs as for TIPTOP predictions. The results showed a good correspondence meaning that the physical model behind TIPTOP is accurate and consistent with other physics-based PSF simulators.

The first attempt to calibrate TIPTOP to real telemetry was made by performing the massive fitting to the dataset of SPHERE IRDIS PSFs (Fig. 5). As mentioned in the previous section, the motivation was to reveal correlations between fitted model parameters and telemetry data. The results show that some parameters

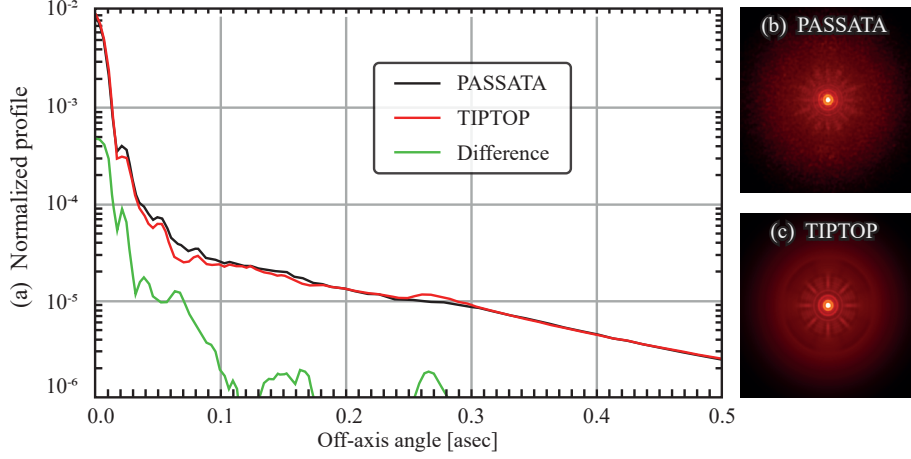


Figure 4. (b) Synthetic MAVIS-like PSF using end-to-end AO simulator. (c) Direct TIPTOP prediction of the PSF from simulated telemetry parameters. (a) Corresponding PSF profiles.

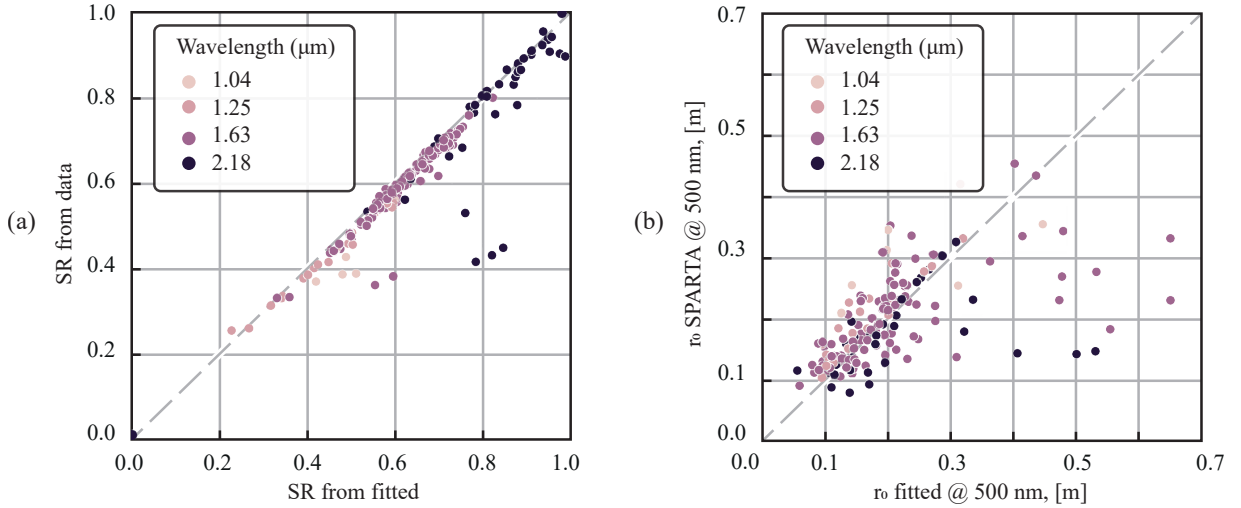


Figure 5. (a) Good correspondence of on-sky SR to the fitted SR shows that TIPTOP accurately describes the shape of the PSF. (b) Correlation between fitted r_0 and telemetry r_0 (from SPARTA⁷) is still weak. It demonstrates the fitting ambiguity due to the coupling of model parameters.

correlate almost linearly. Others, in turn, demonstrate more of a stochastic dependency. For example, good correlations are observed for characteristics that represent the general shape of PSF, like FWHM and Strehl ratio. Meanwhile, parameters responsible for specific morphological features, like r_0 , correlate weakly. The reason is that the fitting forces the model parameters to change so that the shape of the modeled PSF best matches the data. Meanwhile, the physical validity of fitted values is disregarded. Therefore, with no boundaries introduced, model parameters may converge to physically meaningless values even though the shape of a resulting PSF matches the data. Thus, introducing some regularization strategies is crucial to preserve the physical relevance and provide a basis for reliable calibration and, consequently, for PSF prediction in the future.

4. FUTURE WORK

As mentioned before, some parameters can cross-couple during fitting due to their similar effect on PSF morphology. It means that one parameter can absorb the impact of another, suppressing the latter from being fitted.

It is important to understand this degeneracy between the parameters and study its origin, which may be due to a non-atmospheric effect but phenomena not included in the current model (Fig. 6).

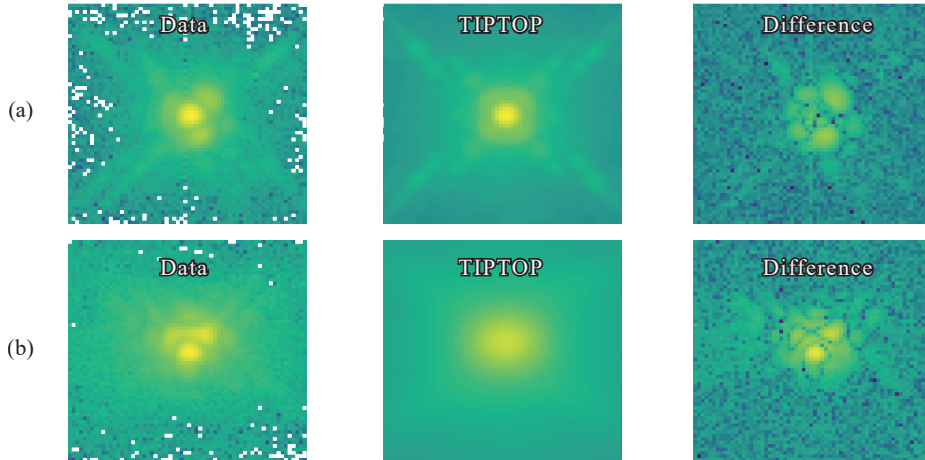


Figure 6. TIPTOP most accurately describes atmospheric-related effects. However, realistic data may be subject to effects that are not yet included in the model. During optimization, the lack of an adequate analytical description can lead to incorrect fits and parameters degeneration.

The next step is introducing approaches to resolve these degeneracies. For example, the model can also be pre-fitted to WFS PSFs (e.g., from IRLOS) to obtain initial parameter estimates, which facilitates convergence. The telemetry itself can also serve as a valuable source of information for this task. We hypothesize that correlations existing inside the telemetry data may help disentangle model inputs of TIPTOP. These correlations can be determined and exploited by applying machine learning techniques. For this sake, a simple multilayer perceptron may be used with TIPTOP attached to its outputs (Fig. 7). The perceptron preceding the TIPTOP will learn to be a universal function approximator that relates telemetry to model inputs. The TIPTOP, in turn, will serve as a regularizer in this scheme. This also might be seen as injecting the knowledge about the physics directly into the model, essentially creating a physics-informed neural network (PINN).⁸

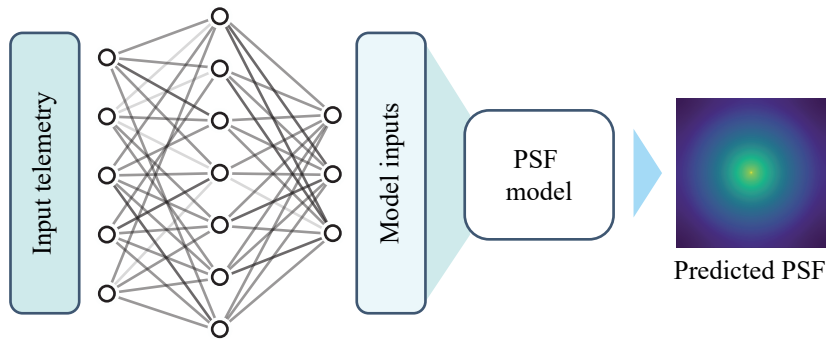


Figure 7. The proposed approach explores the ways to combine the existing analytical PSF model with a machine learning part to create a PINN. It will learn to correspond telemetry to model inputs to provide more accurate predictions directly from the telemetry. The exact choice of the telemetry set is yet to be studied and specified.

Another possible advantage of the proposed technique is that it might help to overcome the scarcity of available on-sky data. Injecting a priori physics knowledge into the model may help train it on fewer data samples and significantly reduce the number of trainable parameters. However, the proposed idea is yet to be implemented and tested. Moreover, the currently available datasets might still not be enough to learn reliable

correlations. This situation might change in the future if the technique is applied on-sky, so it will have a chance to learn online.

5. CONCLUSION

The proposed model proved its capability to describe the morphology of the AO-corrected long-exposure PSF with very high precision. We validated the model by fitting it to actual on-sky data and comparing the direct TIPTOP prediction with E2E simulation. However, the result demonstrated that real telemetry could not be straightforwardly fed to TIPTOP to provide accurate predictions. So, the model must be first calibrated with on-sky data to identify the correlations between the actual data and model inputs. For this sake, we performed the massive fitting to the large set of IRDIS PSFs and some MUSE PSF samples. Results showed that some correlations are still not determined with the desired degree of precision, so the problem must be approached differently. To address this problem, we propose to use machine learning-based techniques based on PINNs. However, a massive amount of data should be exploited in any case to provide more reliable results. So, more technical data and telemetry must be collected during future observations to make this approach efficient and accurate.

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