Using deep learning to improve stray light optical simulations in space telescopes

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ABSTRACT

Stray light (SL) control is an important aspect in the development of optical instruments. Iterations are necessary between design and analysis phases, where ray tracing simulations are performed for performance prediction. This process involves trial and error, requiring to be able to perform rapid evaluation of SL properties. The limitation is that accurate SL simulations require sending many rays, which can be time consuming. In this paper, we use deep learning to improve the accuracy of SL maps even when obtained with very few rays. Two different deep learning methods are used. The training process is performed by generating a large database of artificial SL maps, with different noise levels reproduced with a Poisson distribution. Once the training completed, we show that the autoencoder performs the best and improves significantly the accuracy of SL maps. Even with extremely small number of rays, it recovers complex SL patterns which are not visible on raw ray traced maps. This method thus enables more efficient iterations between design and analysis. It is also useful for developing SL correction algorithms, as it requires tracing SL maps under large number of illumination conditions in a reasonable amount of time.

Keywords: Stray light, ghost, scattering, ray tracing, deep learning, Harvey-Shack, AI

1. INTRODUCTION

Stray light (SL) is a critical concern for space optical instruments as it degrades image quality and consequently limits the data's utility for end users [1]. For this reason, controlling stray light through design is essential [2][3][4][5], and when this is insufficient, additional post-processing correction may be necessary [6][7][8][9][10]. Ray tracing is a fundamental step in stray light analysis. It involves building an optical model of the system where rays are bent by lenses or mirrors [1][2]. The optical properties of various elements are defined, including reflectivity and transmission for specular interactions, or the bidirectional scattering distribution function (BSDF) for scattering interactions. These interactions might occur due to surface roughness, contamination, or the application of black treatments on non-optical surfaces.

Ray tracing serves multiple purposes. Primarily, it predicts the performance of an optical system. In addition of quantitative information about the amount of stray light, it also offers qualitative insights and helps identify design flaws. This process often requires multiple iterations between design and analysis to achieve a satisfactory outcome. Furthermore, in scenarios where stray light algorithms are employed, ray tracing is used to derive stray light kernels. This can be part of a simulation of future algorithms, where the kernels will eventually be replaced by actual measurements, or, if the kernel closely approximates actual measurements, it can be directly used to derive these kernels.

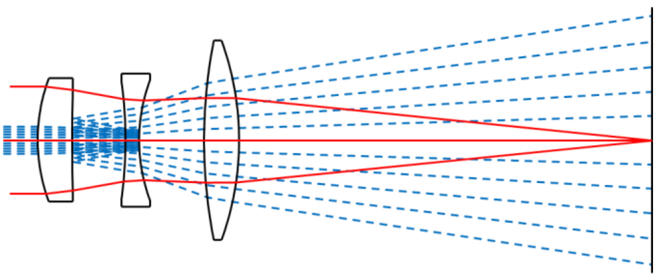

Figure 1. Stray light in an optical instrument

Ray tracing operates by projecting rays through an optical system. The accuracy of this method improves with the number of rays used; however, using only a few rays can introduce a large noise in the image (Fig. 2). Various techniques can optimize ray tracing to enhance accuracy while reducing computational time[11]. For instance, the tracing of ghost reflections is generally limited to two specular reflections since higher orders are typically negligible. For scattering effects, ray aiming is employed to direct rays only towards useful directions, thus avoiding unnecessary calculations. Recently, software like FRED has significantly advanced its computational capabilities through the utilization of GPUs.

Despite these optimization techniques, ray tracing an optical system across a large number of configurations can lead to prohibitively long computation times. In this paper, we describe an approach that employs deep learning to enhance the accuracy of ray tracing. Prior to this, we introduce a concept known as the stray light entrance pupil, or SLEP, which can also be used to improve ray tracing accuracy while minimizing computation time.

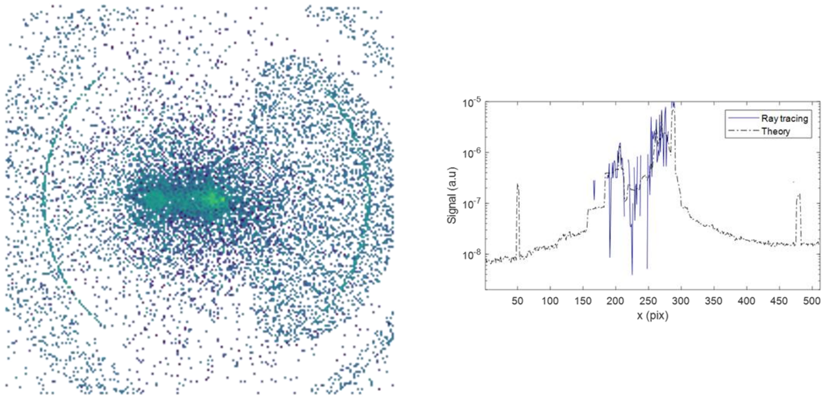

Figure 2. Noise due to ray tracing on the simulation of the stray light pattern in an optical system

2. THE STRAY LIGHT ENTRANCE PUPIL (SLEP) TECHNIQUE

When ray tracing is used to simulate ghost images in an optical system, not all projected rays result in a ghost ray reaching the detector. We introduce the concept of the stray light entrance pupil, or SLEP, defined as the pupil whose illumination results in stray light reaching the detector (see Fig. 3) [12][13]. Rays that strike the system outside this pupil may generate ghost images, but these are typically blocked before reaching the detector.

The SLEP depends on the optical system and its properties and varies with the field of view, as illustrated in Fig. 4, and to a lesser extent, with the wavelength. It can be determined through ray tracing, requiring only a limited number of rays to define its footprint. Once the SLEP is identified, ray tracing of stray light at the detector can be performed with greater accuracy by sending rays only through the SLEP. Moreover, as demonstrated in Fig. 4, different areas of the SLEP contribute varying amounts of stray light. By capitalizing on this characteristic, we can further enhance the accuracy of ray tracing. This is achieved by increasing the ray density in areas that contribute more stray light, while maintaining a uniform irradiance profile. Consequently, each ray in denser areas carries less energy. Employing this technique, the accuracy of ray tracing improves significantly, as shown in Fig. 5. Typically, this approach reduces computation time by a factor of 20 for reaching the same desired accuracy.

Additionally, the SLEP is an especially useful tool for experimental characterization, particularly when calibrating stray light in instruments with large input apertures that can only be illuminated through a pupil scan. The SLEP reduces the duration of measurements by focusing the scan on useful areas, specifically those that overlap with the SLEP.

The full SLEP principle and application is described in details in the paper [12][13] *Clermont, L.; Michel, C.; Blain, P.; Loicq, J.; Stockman, Y. Stray light entrance pupil: An efficient tool for stray light characterization. Opt. Eng. 2020, 59, 025102*.

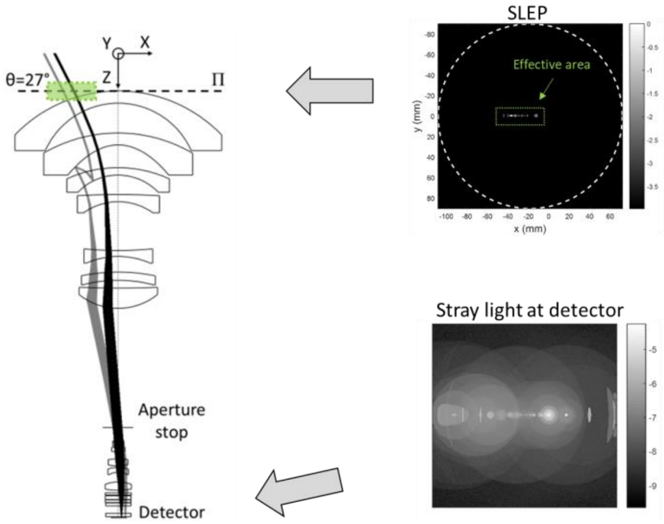

Figure 3. Concept of the SLEP

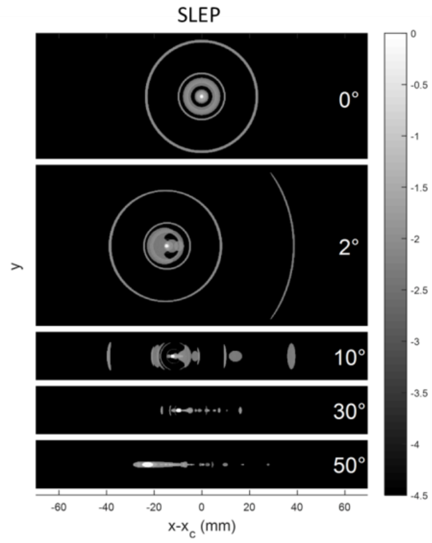

Figure 4. SLEP for various angles

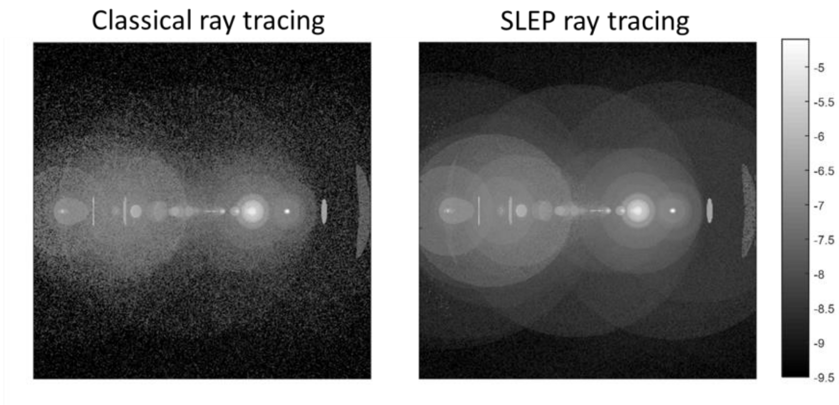

Figure 5. Comparison of the stray light map computed with classical ray tracing or using the SLEP

3. DEEP LEARNING

In this section, we describe a method that uses deep learning to improve the accuracy of ray tracing. This approach provides a tool that takes a noisy stray light map, produced with a limited number of rays, and recovers the map with high accuracy, similar to what would be achieved with a larger number of rays[14][15][16]. Implementing this method involves initially training a neural network, which can be very time-consuming. However, once trained, applying the neural network to a trial map is nearly instantaneous.

The principle of training the neural network is illustrated in Fig. 6. The training process involves presenting the network with a large set of maps: one group consists of noisy maps generated through ray tracing with a few rays, and the other group consists of corresponding maps obtained using a large number of rays. The first group is referred to as 'noisy maps,' and the second group as 'perfect maps.' By exposing the neural network to many such pairs, the training process optimizes the network's weights, enabling it to learn how to transform noisy maps into perfect maps.

A challenge in the training process is the need for a large number of noisy and perfect stray light maps. One straightforward but inefficient approach to obtaining these maps would be to simulate stray light in thousands of different optical instruments under various illumination conditions and using varying numbers of rays, including simulations with nearly infinite rays. Although this method would generate a valid database for training, it is highly inefficient, even if used solely for this purpose.

The alternative approach used here involves ray tracing individual ghosts in a large telescope under various illumination angles. A large number of rays is considered to minimize ray tracing noise. This process generates a database of ghosts varying in size, profile, and shape. A total of 1,500 individual ghosts are obtained, some of which are shown in Fig. 7. By randomly recombining ghosts from this database, we can simulate typical stray light maps that would be obtained in realistic optical systems. These simulations provide the 'perfect' maps for the training database.

To generate equivalent maps with ray tracing noise, we can apply Poisson noise to the individual ghosts before combining them to create a stray light map. Ray tracing inherently follows a Poisson distribution, as illustrated in Fig. 8, where 's' represents the average number of rays sent to a single pixel. When 's' is very large, the Poisson distribution approximates a Gaussian distribution. Finally, Fig. 9 displays an example of a stray light map created by randomly combining individual ghost patterns, with and without applying Poisson noise, to produce both perfect and noisy maps. Training the neural network with thousands of these noisy and perfect maps took several days.

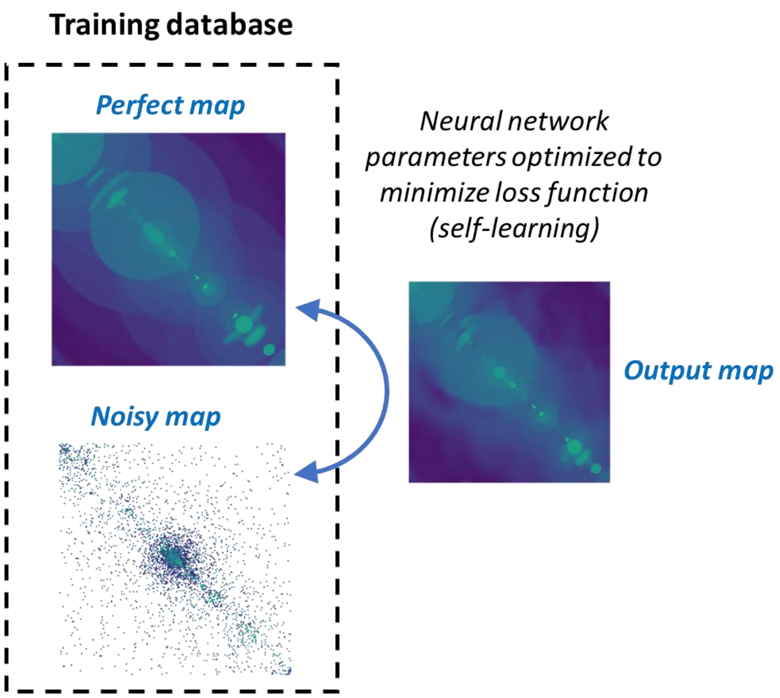

Figure 6. Deep learning training process

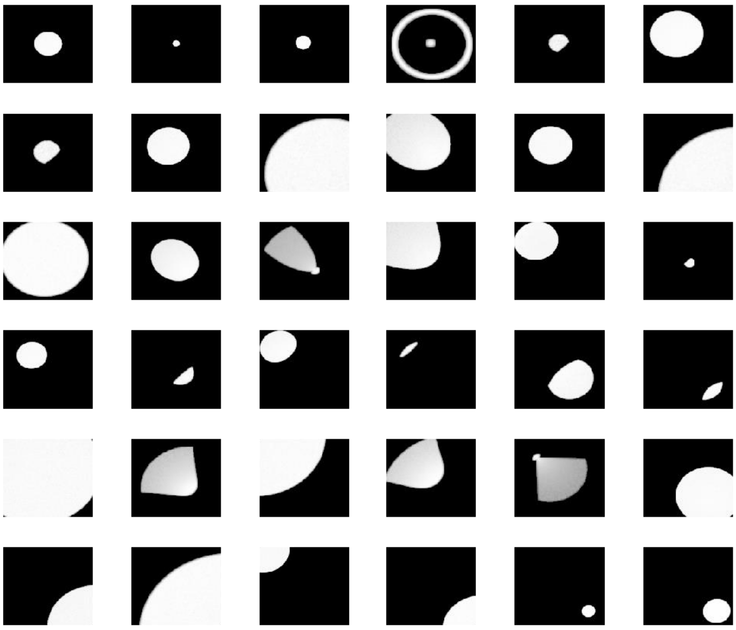

Figure 7. Database of individual ghosts

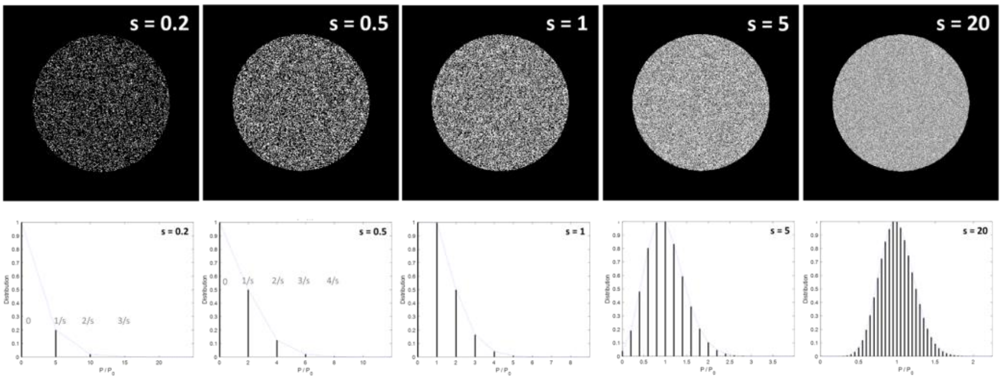

Figure 8. Evolution of the noise on a single ghost when considering different number of rays (s is the average number of rays sent per pixel)

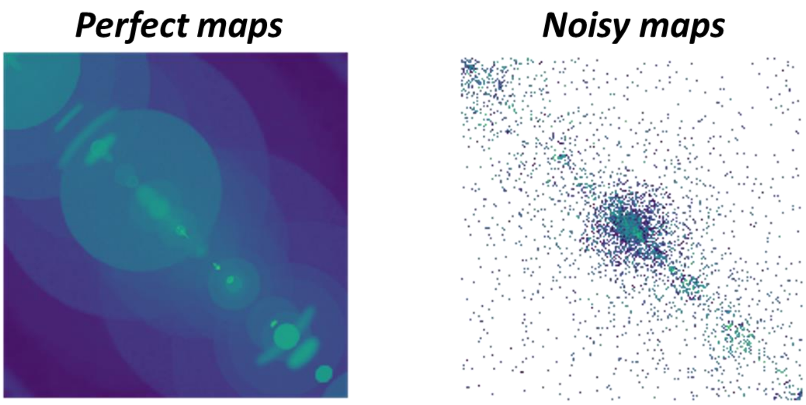

Figure 9. Perfect and noisy map, reproduced by combining randomly the maps from the database, with or without the ray tracing statistical noise

Fig. 11 presents examples of stray light maps generated by ray tracing with a limited number of rays (100), which exhibit a highly noisy pattern. This figure also displays the results after applying a deep learning algorithm, which significantly reduces the noise level. For comparison, it includes theoretical maps—those that would be obtained if a very large number of rays were used. The deep learning algorithm proves highly effective in recovering stray light patterns, even those not visibly discernible in the initially ray-traced maps, thanks to the specific distribution of rays in the initial image. Although the maps are not perfect, they closely resemble the theoretical maps, achieved with only a few rays and the nearly immediate application of the deep learning algorithm. Fig. 12 shows similar results for initial ray tracing maps obtained with 1,000 rays. While these maps are less noisy and some patterns are visually discernible, they are still too noisy for practical applications, such as use in an engineering report. However, the deep learning outcomes are remarkably close to the theoretical maps, to the extent that distinguishing between the two is nearly impossible.

The full details of this deep learning method for improving ray tracing accuracy is presented in the paper [16]: *Clermont, L., Adam, G., "Using deep learning for effective simulation of ghost reflections", Results in Optics, Vol 15, 100643 (2024). doi.org/10.1016/j.rio.2024.100643*

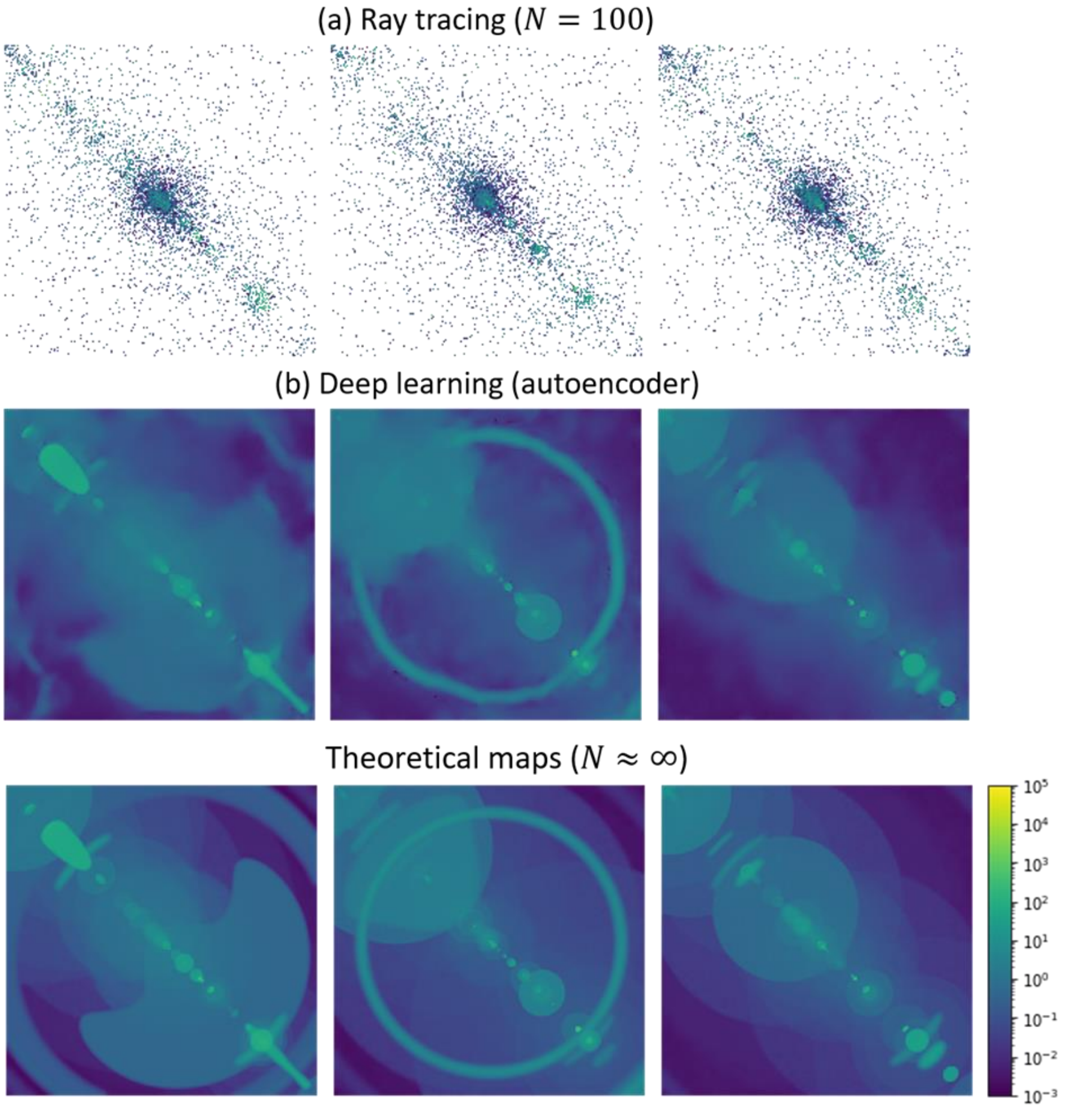

Figure 10. Ray traced maps with few number of rays (N=100), deep learning result, and comparison with the theoretical map that would have been obtained with a nearly infinite number of rays

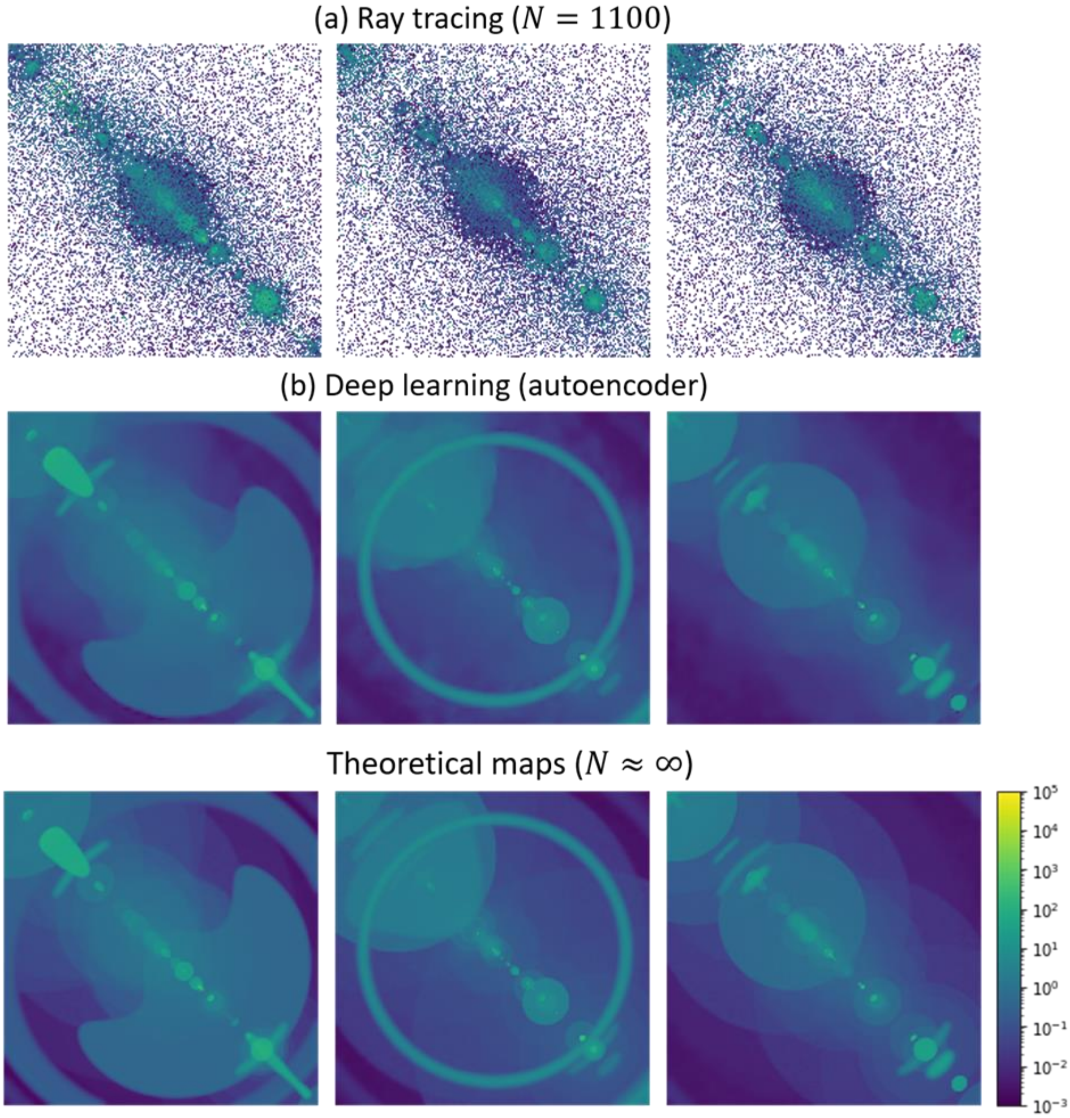

Figure 11. Ray traced maps with few number of rays (N=100), deep learning result, and comparison with the theoretical map that would have been obtained with a nearly infinite number of rays

4. CONCLUSIONS

In this paper, we discussed methods to improve the accuracy of ray tracing for stray light in optical systems. Despite existing techniques to optimize ray tracing and enhancements in computational capabilities through GPU use, there remains a need to reduce ray tracing time while enhancing accuracy. We began by describing a method using the stray light entrance pupil (SLEP), which reduces computation time by a factor of 20 and facilitates experimental stray light characterization. We then introduced a method that employs deep learning to improve ray tracing accuracy. This process starts with training the neural network, exposing it to a large quantity of stray light maps obtained with varying numbers of rays. These maps are generated by combining individual ghosts randomly and applying Poisson noise to simulate ray tracing noise. Although the training process is time-consuming, it is a one-time effort to optimize the neural network's weights. Finally, the deep learning algorithm can be applied to noisy maps to almost instantly recover the maps as if they were obtained with a very large number of rays. This tool significantly reduces ray tracing time, thereby facilitating iterative design and analysis in the development of optical instruments. Deep learning could certainly be used for other applications related to stray light, including regarding experimental characterization [17].

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