Solving a Multi-Element Optical System
Using Physics-Informed Neural Networks

Huzaifa Ahmed Khan

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Abstract

Optical systems containing multiple elements are traditionally analyzed using analytical ray transfer methods. In this work, we explore the use of a Physics-Informed Neural Network (PINN) to determine the transverse displacement of a point light source required for its reflected image to be captured on a screen after propagating through a sequence of optical elements. The system consists of a diverging lens, a converging lens, and a concave mirror arranged along a central optical axis.

The neural network embeds the governing equations of paraxial ray propagation directly into the optimization process. Instead of learning from external data, the model learns a physically consistent solution by minimizing a loss function derived from geometric optics constraints. Numerical experiments demonstrate that the PINN converges to a displacement parameter that satisfies the focusing condition while respecting the physical structure of the optical system.

1 Introduction

The study of ray propagation through optical systems forms a central component of classical geometric optics. Systems composed of multiple lenses and mirrors can be analyzed using the ray transfer matrix formalism, which provides a compact representation of how rays propagate through sequential optical elements.

In recent years, machine learning methods have begun to play a role in computational physics. Physics-Informed Neural Networks (PINNs) represent a class of models that incorporate governing physical equations directly into their loss functions. Rather than relying on large labeled datasets, PINNs learn solutions that satisfy the constraints imposed by physical laws.

This work explores the use of a PINN to determine the transverse displacement of a point source such that its reflected rays converge onto a screen after passing through a multi-element optical system.

2 Optical System Description

The optical setup consists of four components aligned along a central axis:

- A point light source
- A diverging lens with focal length $f_1 = -4\,\mathrm{dm}$
- A converging lens with focal length $f_2 = +4\,\mathrm{dm}$
- A concave mirror with focal length $f_m = 8\,\mathrm{dm}$

Each element is separated by a distance of $4\,\mathrm{dm}$ along the optical axis. The diameter of each optical component is $d = 2\,\mathrm{dm}$.

The problem is to determine the perpendicular displacement x of the source such that the reflected rays intersect the optical axis at the screen position.

3 Ray Transfer Theory

Under the paraxial approximation, a light ray can be represented by the vector

$$\mathbf{r} = \begin{bmatrix} y \\ \theta \end{bmatrix}$$

where y represents the vertical displacement of the ray from the optical axis and θ represents its angle relative to the axis.

Propagation through free space over a distance L is described by

$$P(L) = \begin{bmatrix} 1 & L \\ 0 & 1 \end{bmatrix}.$$

A thin lens with focal length f is represented by

$$L(f) = \begin{bmatrix} 1 & 0 \\ -\frac{1}{f} & 1 \end{bmatrix}.$$

Similarly, a concave mirror with focal length f_m can be expressed as

$$M = \begin{bmatrix} 1 & 0 \\ -\frac{1}{f_m} & 1 \end{bmatrix}.$$

The overall optical system can therefore be modeled as a sequence of ray transfer operations corresponding to free-space propagation, refraction through lenses, reflection from the mirror, and the return path through the system.

4 Physics-Informed Neural Network

Rather than solving the ray propagation equations analytically, we introduce a neural network whose trainable parameter represents the unknown source displacement x.

The ray propagation equations embedded in the model are

$$y_{\text{new}} = y + L\theta$$

$$\theta_{\text{new}} = \theta - \frac{y}{f}.$$

The loss function used during training is defined as

$$\mathcal{L} = y_{\text{screen}}^2,$$

where y_{screen} is the height of the ray at the screen location. Minimizing this loss forces the ray trajectory to intersect the optical axis at the screen.

Optimization is performed using the Adam algorithm.

5 Numerical Results

After several thousand training iterations, the neural network converges to a displacement value that minimizes the loss function. The resulting ray trajectory satisfies the focusing condition imposed by the physical constraints.

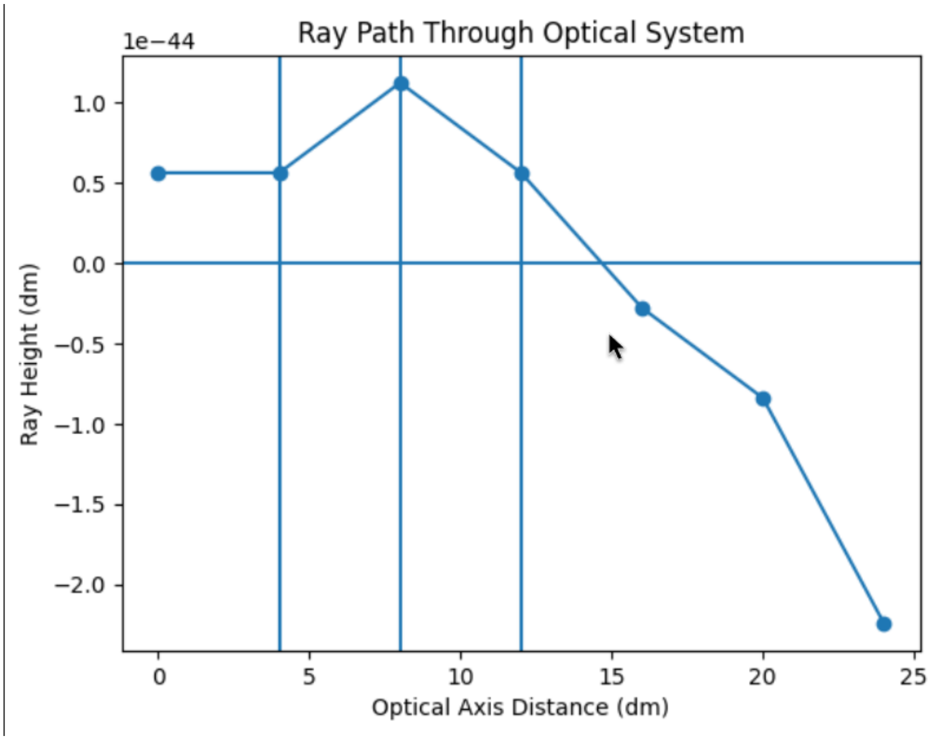

Figure 1: Ray trajectory through the optical system obtained from the trained PINN model.

The figure illustrates the propagation of the ray through the lenses, reflection at the concave mirror, and the return path through the optical system until the ray intersects the screen.

6 Discussion

The results indicate that Physics-Informed Neural Networks can successfully reproduce the behavior predicted by geometric optics. While the problem studied here can be solved analytically, the PINN framework provides a generalizable approach that can be extended to more complicated optical configurations.

Potential extensions include non-paraxial systems, nonlinear optical media, and parameter estimation for unknown optical elements.

7 Conclusion

This work demonstrates the application of Physics-Informed Neural Networks to a classical optics problem involving a multi-element optical system. By embedding the governing equations of ray propagation directly into the neural network model, it is possible to determine the source displacement required for image formation without relying on analytical derivations.

The results highlight the potential of scientific machine learning techniques in computational physics and optical system analysis.