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Neural Network Based Analysis of Polychromatic PSFs for Wavelength-Specific Extraction

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Abstract

The initiation of CMOS simulations involves input scene data composed of wavelength-specific radiance, for which the application of lens PSF effects necessitates monochromatic PSFs corresponding to each wavelength. However, most lens manufacturers supply clients with lens files that contain polychromatic PSFs. Typically, upon opening these lens design files, only the weights for each wavelength can be discerned. Therefore, the ability to decompose these polychromatic PSFs into their monochromatic constituents is essential to accurately apply lens effects in CMOS simulations and to facilitate the intricate analysis of light interactions within optical systems.

To address this need, our study utilizes deep learning techniques to decompose polychromatic PSFs into their constituent monochromatic elements. Leveraging lens data obtained from LensNet, we construct a polychromatic PSF which serves as the input for our deep neural network model. This model is specially trained to predict the monochromatic PSFs, revealing the distinct characteristics of each wavelength involved.

The effectiveness of our approach is validated through extensive testing and detailed visualization methods. These include both 2D contour plots and 3D surface plots, which confirm the model's capability to accurately extract the monochromatic PSFs. This process is not only vital for current optical analysis but also paves the way for future advancements in neural network architectures and machine learning methodologies to refine the extraction process.

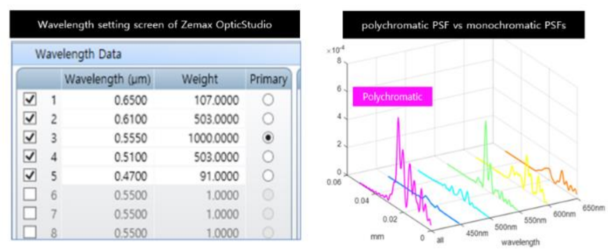
Keywords: Point Spread Functions (PSFs), Deep Learning, Optical Systems, Monochromatic Decomposition.

Introduction

Point Spread Functions (PSFs) are crucial in optical system analysis, capturing the system's response to a point source or object. An in-depth understanding of PSFs facilitates detailed insights into optical system performance, enabling the development of more precise and sophisticated designs. However, typical input scenes for CMOS simulations [1] start with radiance data across various wavelengths, requiring the application of wavelength-specific monochromatic PSFs. While most optical systems encounter light of multiple wavelengths, forming a polychromatic PSF[2], lens manufacturers commonly provide files with polychromatic PSF applied, offering only wavelength weighting information. This necessitates a method to extract the underlying monochromatic PSFs to accurately simulate lens effects on the scene data.

Decomposing these polychromatic PSFs into monochromatic components provides an opportunity to explore the details embedded within each wavelength [3]. This decomposition is challenging due to the complex interplay of wavelengths in the formation of the polychromatic PSF. Therefore, conventional analytical methods have been found to be insufficient, demanding the need for more sophisticated techniques.

With the recent advancements in machine learning and artificial intelligence, we propose a novel method leveraging deep learning to decompose polychromatic PSFs into their monochromatic counterparts. Deep learning provides a promising avenue to handle the high-dimensional, non-linear nature of this decomposition problem. The primary objective of this study is to train individual deep neural networks for each wavelength that can effectively estimate the corresponding monochromatic PSFs from a given polychromatic PSF.



(a) (b)

***Figure 1.** Wavelength Setting Screen in OpticStudio and Cross-Sectional Contours of Polychromatic PSFs.*

***(a)** Wavelength Setting interface of Ansys OpticStudio, where lens manufacturers provide lens design files with weighted wavelengths to deliver polychromatic Point Spread Functions (PSFs) to their clients.*

***(b)** Cross-sectional contours of monochromatic PSFs at different wavelengths, with the weighted monochromatic PSFs combined to form the three-dimensional cross-sectional contour of the Polychromatic PSF.*

In the domain of optical design, the standard practice for lens manufacturers is to supply polychromatic Point Spread Functions (PSFs) with lens files, represented in Figure 1(b), which aggregate light interactions across various wavelengths. Nonetheless, clients frequently require access to the individual monochromatic PSFs within these composite files for precision-focused applications. Recognizing this industry gap, our research presents a methodical approach that employs deep learning to deconstruct polychromatic PSFs into their monochromatic components. This paper outlines the process of generating these PSFs, the intricacies of neural network design and training, and the techniques for visualizing the detailed monochromatic PSFs. This innovative strategy is poised to revolutionize optical system analysis and significantly advance lens design capabilities, catering to the specialized needs of clients and setting a new standard in optical system optimization.

Proposed Methodology

In optical systems, understanding the propagation and diffusion of light is paramount. One key tool for interpreting this behavior is the Point Spread Function (PSF), which typically encapsulates polychromatic information due to the multi-wavelength nature of the incident light. Separating this polychromatic PSF into its constituent wavelength-specific, monochromatic PSFs is a challenging yet crucial problem in optical science. This difficulty arises from the complex interactions of different light wavelengths within the optical system, and the inability of traditional methods to effectively extract wavelength-specific information from the mixed data[2].

This paper proposes a methodology for decomposing polychromatic PSFs into their monochromatic counterparts using deep learning techniques. Deep learning, with its powerful ability to model intricate patterns and structures, provides an ideal framework for tackling this complex problem. The objective of this research is, therefore, to leverage these techniques to model and predict monochromatic PSFs from a given polychromatic PSF, effectively separating the inherent wavelength-specific information.

The methodology commences with the creation of polychromatic PSFs from individual monochromatic PSFs, each corresponding to a selected wavelength. These wavelengths, carefully chosen as 400, 475, 550, 625, and 700 nm, represent a broad spectrum of light. Each monochromatic PSF is weighted according to its contribution to the polychromatic PSF, with the weights summing up to one, thereby ensuring the preservation of the intensity information of the overall polychromatic PSF.

The constructed polychromatic PSFs, as depicted in Figure 2, are utilized as input data, while the corresponding monochromatic PSFs serve as output targets, thus forming a robust dataset for the training and testing of deep learning models. As shown in Figure 2, a Fully Connected Neural Network (FNN) is employed to learn the relationship between these monochromatic PSFs and the polychromatic PSF. These models, which are comprised of fully connected deep neural networks with multiple layers, undergo a meticulous training and optimization process through iterative learning. Upon completion of training, these models are adept at predicting the monochromatic PSFs from the given polychromatic PSFs, and their performance is assessed based on the accuracy of these predictions. Consequently, this methodology unveils a promising path for the effective decomposition of PSFs in optical science.

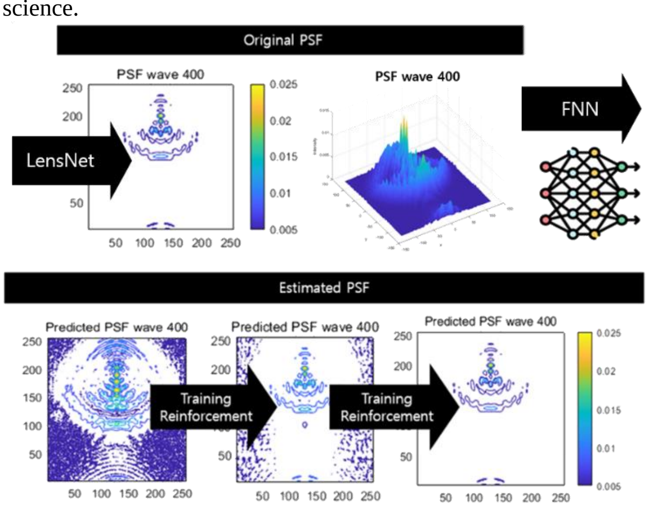


Figure 2. *Multistep Process for Deriving Monochromatic PSFs from Polychromatic PSF Using LensNet and FNN.*

Data Preparation

In the proposed methodology, the preparation of data is a vital initial step, as it forms the basis for all subsequent analysis and model training. The generation of polychromatic Point Spread Functions (PSFs) is a critical aspect of this stage. With the help of LensNet[4], a deep learning-based system for optimizing lens designs, an infinite quantity of lens training data can be obtained. LensNet's capability to generate lens designs based on specific user-input parameters allows the creation of a comprehensive dataset, providing a robust foundation for the deep learning models we intend to develop.

The second step in data preparation is the selection and weighting of wavelengths. Light, being polychromatic, consists of various wavelengths, each of which contributes differently to the overall PSF. For the purpose of this study, five specific wavelengths (400, 475, 550, 625, and 700 nm) were chosen to represent a broad spectrum of light. These wavelengths were weighted based on their contribution to the polychromatic PSF, ensuring the preservation of intensity information.

Next, the process involved the construction of training and test datasets. The synthesized polychromatic PSFs served as input data for the models, while the corresponding monochromatic PSFs acted as output targets. This configuration offered an intricate dataset, wherein the models could learn the complex relationships between the polychromatic and monochromatic PSFs, laying the groundwork for reliable and accurate predictions.

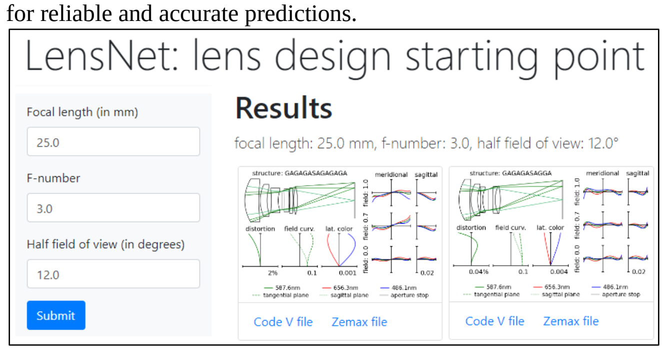


Figure 3. *LensNet Interface for Initial Lens Design Parameters and Results.*

In summary, the preparation of data involved generating an expansive set of polychromatic PSFs, strategically selecting and weighting wavelengths, and constructing comprehensive training and testing datasets. These preparatory steps were critical in the successful development of deep learning models that could predict monochromatic PSFs from polychromatic ones effectively. The extensive and varied dataset, prepared with the aid of LensNet, served as a robust platform for training the deep learning models, ultimately enabling the separation of PSFs into their wavelength-specific counterparts.

Deep Learning Model Architecture

The process of training the model to learn the relationship between polychromatic and monochromatic PSFs is a two-step procedure. Initially, the polychromatic PSF is created by accumulating the weighted monochromatic PSFs. Then, using this information, the deep learning model is trained to predict the monochromatic PSFs.

Creation of Polychromatic PSF

The first step in our procedure involves the aggregation of various monochromatic Point Spread Functions (PSFs) into a singular polychromatic PSF. This is performed by assigning appropriate weights to each of these monochromatic PSFs, reflecting their corresponding contributions to the final polychromatic PSF. This contribution is determined by the wavelength of the monochromatic PSF and is captured in the following mathematical formulation:

Let's denote:

At any given location (x, y) within the optical system, the monochromatic Point Spread Function (PSF) for a specific wavelength λ can be denoted by $P(x, y, \lambda)$, with $w(\lambda)$ representing the weight assigned to each wavelength, indicating its contribution to the overall PSF. As Figure 4 illustrates, the resultant polychromatic PSF, $P(x, y)$ is obtained by summing these weighted monochromatic PSFs according to the formula:

$$P(x, y) = \sum_{i=1}^{N} w(\lambda_i) P(x, y, \lambda_i) \tag{1}$$

Here, N stands for the total number of wavelengths considered, and the summation iterates over all wavelengths from 1 to N, creating a comprehensive mapping of how various wavelengths contribute to the final polychromatic PSF within the optical system.

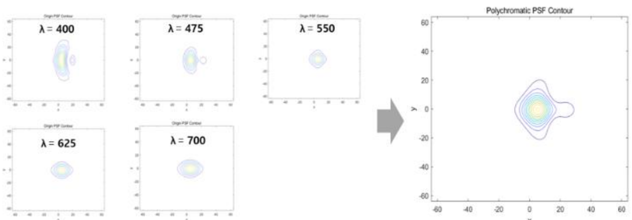


Figure 4. *Contour Representation of Monochromatic to Polychromatic PSF Transformation.*

Model Architecture

The model we employ to tackle our problem is a fully connected neural network, also known as a multi-layer perceptron (MLP)[5], as illustrated in Figure 5. In this architecture, the input x is transformed through a series of computations in multiple layers to produce an output.

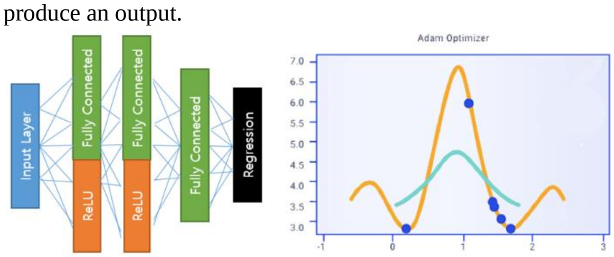


Figure 5. *Neural Network Architecture and Optimization Algorithm.*

The first hidden layer's output, h_1 is calculated by applying the Rectified Linear Unit (ReLU) activation function σ to the input's weighted sum:

$$h_1 = \sigma(W_1 \cdot x + b_1) \tag{2}$$

Subsequently, the process continues in the second hidden layer, which provides output h_2, and is defined as:

$$h_2 = \sigma(W_2 \cdot h_1 + b_2) \tag{3}$$

Finally, the output layer yields the final model output y using the formula:

$$y = W_3 \cdot h_2 + b_3 \tag{4}$$

Here, W_1, W_2, and W_3 are the weight matrices for the first, second, and output layers, respectively, while b_1, b_2, and b_3 are the corresponding bias vectors. These parameters are fine-tuned during the training phase, employing optimization techniques like the Adam Optimizer[6], to enhance the model's performance in predicting outcomes.

Loss Function

To optimize the performance of our neural network, it is essential to have a metric that reflects how well the model is predicting outcomes. For this purpose, we employ a loss function, specifically the Mean Squared Error (MSE) in the case of regression tasks[7]. The MSE offers a clear indication of the model's accuracy by comparing the network's predictions with the true output values.

The MSE is computed as the average of the squares of the differences between the predicted outputs, denoted as y_{pred} and the true outputs, denoted as y_{true}. For our particular application, this can be mathematically represented as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(y_{true_i} - y_{pred_i} \right)^2 \tag{5}$$

Here, the subscript i indexes the samples in our dataset, and n is the total number of samples.

In the context of our optical systems problem, y_{true_i} refers to the actual reshaped monochromatic PSF, while y_{pred_i} is the network's estimate for the same. The total loss, L, is calculated by summing the MSE across all individual samples, which serves as a feedback mechanism to guide the training of the network by minimizing this loss.

Optimization Problem

The parameters of the neural network are adjusted through an optimization process that seeks to minimize the loss function. The update rule for a single weight W in the network using the Adam optimizer is as follows:

In the first step, we calculate the gradients g of the loss function with respect to the weights W:

$$g = \nabla_W L \tag{6}$$

Then, we update the running averages of the gradients m and the squared gradients v:

$$m = \beta_1 m + (1 - \beta_1) g \tag{7}$$

$$v = \beta_2 v + (1 - \beta_2) g^2 \tag{8}$$

Finally, the weights are updated using the following rule:

$$W = W - \alpha \frac{m}{\sqrt{v} + \epsilon} \tag{9}$$

Here, α is the learning rate, β_1 and β_2 are exponential decay rates for the moment estimates, ε is a small constant for numerical stability, and g is the gradient of the loss function with respect to the weights.

Training Procedure

The training process is illustrated in Figure 6, which shows the training progression of neural network models for PSF decomposition over iterations. It involves iterating through the dataset multiple times. Each complete pass through the dataset is called an epoch. The number of epochs is a hyperparameter that defines the number of times that the learning algorithm will work through the entire training dataset.

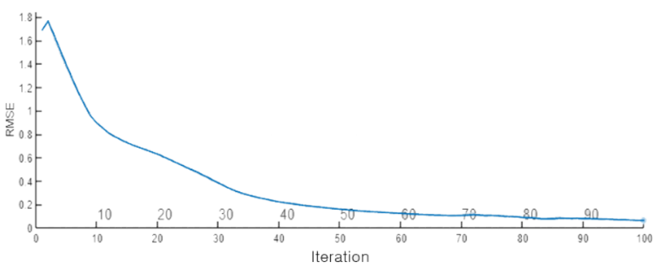


***Figure 6.** Training Progression of Neural Network Models for PSF Decomposition Over Iterations.*

The model parameters are updated for each mini-batch B of samples from the dataset. Let's denote the loss for the j^{th} sample in the i^{th} mini-batch as L_{ij}. Then, the total loss for the mini-batch is:

$$L_i = \frac{1}{|B_i|} \sum_{j \in B_i} L_{ij} \tag{10}$$

The model parameters θ are updated for each mini-batch to minimize the total loss L_i :

$$\theta = \theta - \alpha \nabla_\theta L_i \tag{11}$$

Here, α represents the learning rate, and $|B_i|$ indicates the size of the i^{th} mini-batch. In each epoch, this process is repeated for every mini-batch. The Adam optimization algorithm, known for its efficiency in handling sparse gradients and adaptive learning rate optimization, is employed. It updates model parameters using the first and second moments of the gradients, thereby enhancing the convergence speed and performance of the deep learning model, especially in complex tasks like PSF decomposition.

Multiple Models for Multiple Wavelengths

Lastly, we need to train a separate model for each wavelength[8]. Let's denote the parameters of the model for the i^{th} wavelength as θ_i and the output data (reshaped monochromatic PSFs) for the i^{th} wavelength as y_i.

The loss for the i^{th} model and j^{th} sample is L_{ij} and the total loss L_i for the i^{th} model is:

$$L_i = \frac{1}{n} \sum_{j=1}^{n} L_{ij} \tag{12}$$

The optimization problem for each model can be expressed as:

$$\theta_i^* = \arg \min_\theta L_i \tag{13}$$

$$\theta_i^* = \arg \min_\theta L_i \tag{14}$$

The model parameters θ_i are updated for each sample to minimize the total loss L_i, similar to the process described in the "Training Procedure" section:

$$\theta_i = \theta_i - \alpha \nabla_{\theta_i} L_i \tag{15}$$

Here, α is the learning rate, L_i is the total loss for the i^{th} model, and θ_i are the parameters of the i^{th} model. This update rule ensures that the model for each wavelength is tuned to minimize its specific loss, leading to a set of models that can each reconstruct a monochromatic PSF from a polychromatic PSF as defined by Eq. (1)

Each of these models is trained independently, allowing for parallelization of the training process. This can significantly speed up the training time when multiple processing units are available.

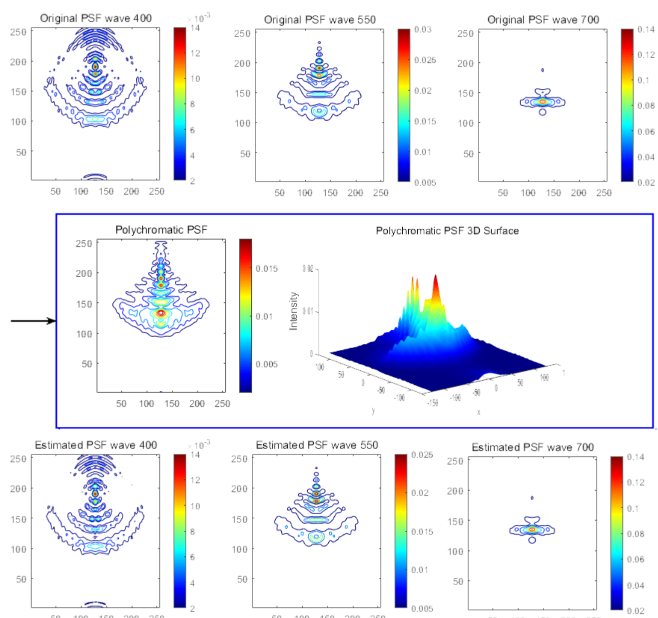


***Figure 7.** Comparison of Original and Estimated Monochromatic PSFs Across Wavelengths.*

At the end of the training process, as illustrated in Figure 7, we have N models each corresponding to a different wavelength. When a new polychromatic PSF is presented, each model applies its learned mapping to reconstruct the monochromatic PSFs. The aggregation of these reconstructions then gives a complete picture of the monochromatic PSFs that contributed to the polychromatic PSF.

This methodology thus combines the strengths of deep learning with the inherent characteristics of the optical systems to efficiently and effectively solve the inverse problem of reconstructing monochromatic PSFs from a polychromatic PSF.

PSF Decomposition Analysis

In this chapter, we delve into the performance evaluation of our neural network tasked with decomposing polychromatic Point Spread Functions (PSFs) into their monochromatic counterparts. We begin our analysis by examining the Mean Squared Error (MSE) across various fields and wavelengths, a statistical metric that quantifies the accuracy of our model's PSF estimations. This approach allows us to assess the precision of the neural network in predicting PSFs at each specific field and wavelength.

Our methodical approach involved calculating the MSE for each target field, spanning wavelengths from 400nm to 700nm. For each field, the MSE was computed by comparing the predicted monochromatic PSFs to the corresponding segments of the original polychromatic PSFs. These calculations were conducted for a series of files, ensuring a robust evaluation of the neural network's performance.

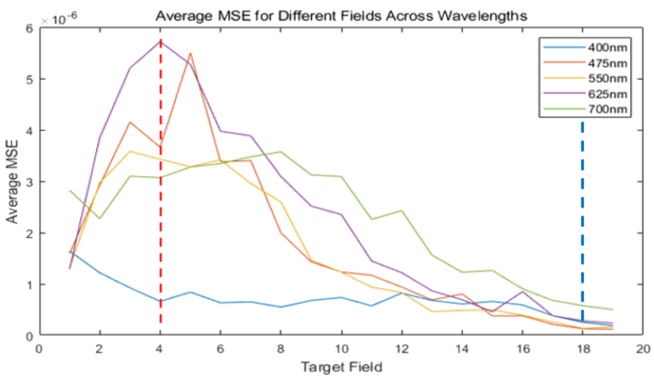


Figure 8. *Mean Squared Error (MSE) Analysis of Predicted Monochromatic PSFs Across Optical Fields and Wavelengths.*

After presenting the detailed MSE values for each field and wavelength, we proceed to visual comparisons of these results. Graphical representations are used to illustrate the neural network's effectiveness at different wavelengths, complementing our statistical analysis. These visuals aim to provide an intuitive understanding of the model's capabilities in accurately decomposing polychromatic PSFs into their monochromatic elements, offering a holistic view of its performance.

The graph presented illustrates the average Mean Squared Error (MSE) across different target fields and wavelengths, providing an insightful visualization of our neural network's PSF estimation performance. Notably, the shorter wavelengths of 400nm and 475nm demonstrate lower MSE values, suggesting that the network is more adept at learning and predicting the complex PSF shapes that occur at these frequencies. The higher spatial frequency variations inherent in shorter wavelengths could be offering more information for the neural network to learn from, leading to these lower MSE results[9].

The trend observed in the graph indicates a decrease in MSE towards the outer fields, compared to the central fields. This may be attributed to the more complex and irregular shapes of the PSF in the outer fields, providing the neural network with an abundance of features to learn. Such complexity could enhance the network's ability to differentiate and predict the characteristics of each PSF accurately, thereby reducing the MSE. This pattern persists across longer wavelengths, including 550nm, 625nm, and 700nm, showcasing the variation in the neural network's learning capability with respect to wavelength.

These results reveal a non-uniform performance of the neural network across wavelengths. While complex diffraction patterns typically arise at shorter wavelengths, our study shows that the neural network effectively handles this complexity, achieving lower MSE. This suggests that the network can accurately learn and predict more intricate PSF shapes, emphasizing the importance of considering the diverse characteristics of the optical field and wavelength when developing and training neural networks for PSF estimation. This finding is crucial for directing neural network modeling efforts to enhance the performance of optical systems.

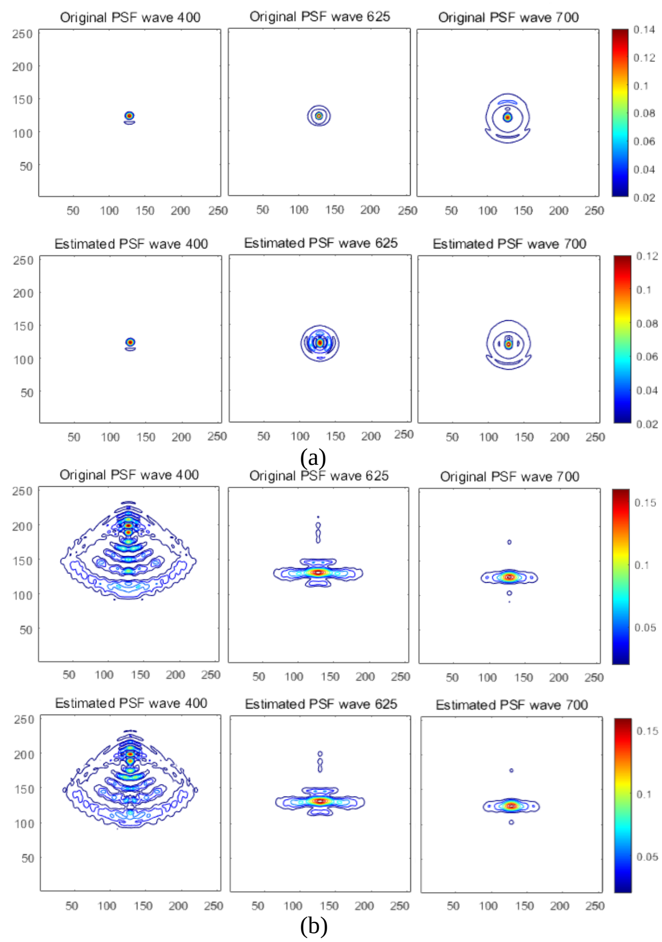


Figure 9. *Mean Squared Error Analysis of Monochromatic PSF Estimations at Central and Peripheral Optical Fields.*

(a) *This portion illustrates the estimation at a central field (field 4, Red dashed line), where the Mean Squared Error (MSE) is notably higher for shorter wavelengths, such as 400 nm. The increased MSE can be attributed to the three-dimensional shape of the PSF, which is nearly circular and symmetrical, leading to fewer distinctive features for the neural network to learn and thus a higher error rate.*

(b) *This section presents the estimation at a peripheral field (field 18, Blue dashed line), demonstrating lower MSE values across all wavelengths. The PSFs at this peripheral field exhibit complex shapes that provide more distinctive features for the network to capture, resulting in improved learning and consequently lower MSE for all measured wavelengths. The enhanced* *learning from these intricate shapes allows for more accurate estimations of the PSFs at these outer fields.*

Conclusion and Future Work

The findings of this study underscore the potential of deep learning in the domain of optical system analysis, particularly in the decomposition of polychromatic PSFs into monochromatic constituents. Our neural network models have shown a remarkable ability to discern and reconstruct the intricate patterns of PSFs across various fields and wavelengths. The successful application of these models in accurately predicting monochromatic PSFs provides a solid proof of concept for the use of deep learning in optical design and analysis. It is evident that the models are particularly adept at handling the complexity of the PSFs in the peripheral fields, as demonstrated by the lower Mean Squared Error (MSE) in these areas.

Looking ahead, we recognize the necessity of further research and development in several key areas. Firstly, expanding the dataset to encompass a wider range of wavelengths and optical system types will likely enhance the robustness and applicability of our models. Secondly, integrating advancements in neural network architecture, such as convolutional layers for spatial feature recognition[11], could significantly improve the precision of PSF estimations. Thirdly, exploring the implementation of more sophisticated optimization algorithms may yield improvements in the training efficiency and performance of the models.

In conclusion, our research aims to enhance CMOS image sensor simulations[1] by accurately analyzing lens chromatic aberration effects through wavelength-specific separation. By applying our neural network models to simulate optic effects more precisely, we intend to improve the fidelity of lens design simulations. Future efforts will involve collaborating with industry partners to apply these advancements in real-world optical systems, leveraging the synergy between machine learning and optical science to address complex challenges and advance lens technology. This endeavor is expected to lead to innovative solutions, significantly impacting the optical industry with better lens designs and more sophisticated optical systems.

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