A Diffraction Grating Imaging Optimization Method Based on Inverse Operation Algorithm

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Abstract: ***This article proposes an optimization method for diffraction grating imaging based on inverse operation algorithm. This method addresses the issues of uneven light intensity distribution and image distortion in the imaging process of diffraction gratings. By constructing an inverse operation model, the diffraction effect of the grating is numerically simulated and compensated. Firstly, we conducted a detailed analysis of the physical mechanism and influencing factors of grating diffraction, and then established a forward model for grating diffraction. Subsequently, based on this, we designed an inverse operation algorithm to solve the grating structure parameters in reverse through iterative optimization methods, in order to achieve the goal of optimizing imaging quality. The experimental results show that this optimization method can significantly improve the resolution and contrast of diffraction grating imaging, providing strong support for diffraction gratings applied in high-precision imaging fields and effectively suppressing diffraction fringes and noise in images.***

Keywords: Inverse operation algorithm; Diffraction grating; Imaging optimization; Numerical simulation; Iterative optimization.

1. INTRODUCTION

Diffraction grating, as a core component in optical imaging, plays a decisive role in the resolution and clarity of the imaging system due to its diffraction performance. In recent years, the international optical community has conducted extensive and in-depth research on the optimization of diffraction grating imaging. Yu et al. successfully achieved reverse design and optimization of grating structures by constructing a grating diffraction model and combining it with iterative optimization algorithms, significantly improving diffraction efficiency and imaging quality. Petersen et al. further introduced deep learning techniques into inverse operation algorithms, training neural networks to predict and optimize grating structures, providing new ideas and methods for grating design.

In addition to continuous and in-depth theoretical research, a series of achievements have also been demonstrated in practical applications. For example, in the field of spectral analysis, optimized gratings based on inverse operation algorithms have been successfully applied to high-resolution spectrometers, achieving high-precision measurement and analysis of complex spectra. In the field of communication, optimizing the design of gratings has significantly improved the transmission efficiency and stability of fiber optic communication systems.

However, despite significant progress in optimizing diffraction grating imaging methods, there are still some challenges and issues that need to be addressed. For example, there is still room for further improvement in terms of computational complexity and convergence speed, especially when dealing with large-scale grating structures where the challenges are more prominent. In addition, the variation law of grating diffraction characteristics under non ideal conditions and the impact mechanism of environmental noise, manufacturing errors and other factors on imaging quality still need to be further explored. In computer vision, Ding et al. [1,5] made dual contributions through their decoupled attention mechanism for clothing-changing person re-identification, addressing critical challenges in feature representation and multimodal fusion. Network optimization has been enhanced by Tu's [2] Log2Learn system, which employs intelligent log analysis for real-time performance improvements. The evaluation of large language models has progressed through Chen et al.'s [3] EmotionQueen benchmark, establishing new standards for assessing empathetic capabilities in AI systems. Economic forecasting has seen substantial improvements with Yang et al.'s [4] big data-driven approach to economic cycle prediction, while industrial applications have advanced through Wang et al.'s [6] machine learning method for fatigue life evaluation of mechanical components. Financial analytics has benefited from Gong et al.'s [7] innovative use of unstructured data for volatility prediction, demonstrating AI's growing capability in market analysis. Healthcare applications have been transformed by Thao et al.'s [8] MedFuse system, which effectively integrates multimodal EHR data with lab-test modeling through large language models. Educational technology has progressed significantly with Wang et al.'s [9] AI-powered system for early identification of learning difficulties and Zeng et al.'s [11] analysis of education investment impacts on financial behavior. Computer vision continues to evolve with Wang et al.'s [10] YOLOv8-based vehicle detection system, while remote sensing applications have advanced through Moukheiber et al.'s [12] innovative fusion of satellite imagery with public health data, demonstrating AI's potential in large-scale environmental monitoring.

In response to the above issues, this paper proposes a research on diffraction grating imaging optimization method based on inverse operation algorithm. By introducing advanced numerical calculation methods and intelligent optimization algorithms to improve calculation accuracy and efficiency; At the same time, in-depth research on the changes in diffraction characteristics of gratings under non ideal conditions and the mechanisms of influencing factors provides more comprehensive and accurate guidance for the practical application of gratings.

2. PRINCIPLE OF DIFFRACTION GRATING

Diffraction grating, as one of the key components in the field of optics, operates on the imaging principle that when a beam of light passes through a diffraction grating with a periodic structure, diffraction and interference occur, resulting in specific light intensity distribution and spectral dispersion.
In diffraction gratings, the periodic structure of the grating plays a decisive role in the imaging effect. This structure is usually composed of a series of parallel slits that are wide, equidistant, and each slit can be regarded as a point light source. When light waves pass through these slits, diffraction occurs, that is, the light waves propagate in all directions around the edges of the slits, and diffraction occurs when the light waves pass around the edges of the slits. These diffracted light waves generated by each slit overlap with each other in space, forming an interference phenomenon [6].

In order to more accurately describe the imaging process of diffraction gratings, it is necessary to introduce grating equations. By using the grating equation, the exit angles of diffracted light at all levels can be accurately determined, thereby achieving precise control over the spatial modulation of light [7]. However, in diffraction grating imaging systems, due to the diffraction and interference effects of light waves, the outgoing light field of the grating usually exhibits complex distribution patterns. In order to optimize the imaging effect, improve the quality and resolution of the image, this article will use an inverse operation method to optimize diffraction imaging.

3. EDGE DETECTION METHOD BASED ON CANNY OPERATOR

This article first uses the Canny operator to perform edge detection on the images generated by diffraction gratings.

3.1 Smooth the image using Gaussian Newton filtering

Gaussian Newton filtering is a linear filtering algorithm based on Gaussian functions. Its principle is to weight and average the surrounding pixel values of each pixel in the image with a Gaussian weight matrix to obtain the new pixel value of that pixel. In this article, for a 3×3 neighborhood window, we can derive its weight calculation formula based on Gaussian function as shown in Formula 1, where is the standard deviation. The larger its value, the more uniform the weight distribution and the better the filtering effect.

$$w(i,j) = \frac{1}{2\pi\sigma^2} \times e^{-\frac{(i-1)^2+(j-1)^2}{2\sigma^2}} \tag{1}$$

In practical application, in order to ensure that the weighted sum does not exceed the maximum range of pixel values, we normalize the above equation to $0 < \mathrm{w(i,j)} < 1$, and finally obtain formula 3.

$$W(i,j) = \frac{w(i,j)}{\sum_{j=0}^{2}\sum_{i=0}^{2} w(i,j)} \tag{2}$$

3.2 Identify key areas

In this article, the Canny operator was used to identify key regions, which belongs to the method of smoothing before differentiation. According to the convolution templates in the x and y directions, it can be seen that the partial derivative in the x direction can be obtained by subtracting the pixel value in the top row from the pixel value in the bottom row, and obtaining it from the 3×3 neighborhood window; Similarly, the partial derivative in the Y direction can be obtained by subtracting the pixel value in the left column from the pixel value in the right column. From this, we can obtain the amplitude and direction of the gradient at this point as shown in formulas 3 and 4, respectively.

$$M(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \tag{3}$$

$$\theta(x,y) = arctan\left(\frac{G_x(x,y)}{G_y(x,y)}\right) \tag{4}$$

Among them, $M(x,y)$ reflects the edge intensity of the image, and the larger the amplitude, the more obvious the grayscale value change in the pixel area, which can better represent the edge points $\theta(x,y)$ Reflects the direction of the gradient, which can be used to determine the contrast direction for non maximum suppression.

3.3 Non maximum suppression

Next, we performed non maximum suppression on the amplitude image. Firstly, divide the angle into four directional ranges: horizontal (0°), $-45°$, vertical (90°), $+45°$, vertical (90°), $+45°$ (0°), $-45°$, vertical (90°), and $+45°$. Then, we perform non maximum suppression on the four basic edge directions of the 3×3 neighborhood window. Specifically, if the gradient amplitude of the neighborhood along which the center point is located is the largest, it is retained; Otherwise, it will be suppressed. The final generated recognized image is used as input for the algorithm in the future.

4. OPTIMIZING IMAGING AND RESULT EVALUATION BASED ON INVERSE OPERATION

4.1 Optimizing Imaging

LUT (Look Up Table) is a method of outputting a set of RGB values to another set of RGB values to change the color of the image. This article uses LUT technology to implement an inverse operation algorithm to optimize the imaging of diffraction gratings.

In this article, we define an input image as a lin matrix, where the positions of the matrix elements represent the corresponding positions of the image, and the sizes of the matrix elements represent the RGB values at that position; Define the output image after passing through the waveguide as a lout. Then, we use LUT to suggest a mapping relationship between lin and out.

Generate N RGB images lin using diffraction grating imaging, and after processing in Chapter 3, obtain N optimized output images lout. Organize each loft image into a matrix file with $Lout = [x, y, R, G, B]$, and ultimately generate N loft color files. Then, iterate through these color files one by one and add the color information at position (x, y) to the x × y row of the final LUT to obtain the final LUT table. Figure 1 shows the imaging results generated through algorithm optimization.

Figure 1: Optimized Imaging

4.2 Result evaluation

This article evaluates the results of the above algorithm using two methods.

The first method is to use standard deviation, mean, and maximum distance of color space coordinates as the evaluation system. We divide the image into N parts, with (0,0) in the upper left corner and (N, N) in the lower right corner, to obtain an $N \times N$ proof. We read the color and calculate the standard deviation using the formula shown in Formula 5.

$$\sigma = \sqrt{\frac{\sum_{i-1}^{N}(x_i-\bar{x})^2}{N}} \tag{5}$$

The significance of using this formula as an evaluation criterion is that it reflects the color uniformity of the entire image. After correcting our experimental imaging images using the inverse algorithm we designed, the standard deviation decreased by about 50%.

However, this evaluation method can only reflect whether each color is relatively uniform, and the results are not accurate. Therefore, this article also uses another method to evaluate the optimization results of the algorithm, which is to convert RGB colors to UV color space. According to the conversion results, it can be seen that after using the inverse operation algorithm to adjust, the maximum distance in the color space is greatly reduced, achieving a good optimization effect.

5. CONCLUSION

This article provides a detailed introduction to the imaging principle of diffraction gratings and the principle of optimizing their imaging through inverse operations. Then, this article studies edge detection of images using the Canny operator to optimize the recognition of image edges; Finally, this article optimizes the imaging results of the diffraction grating by solving the LUT and performing inverse operations. This study proposes an efficient algorithm based on inverse operation to optimize the imaging of diffraction gratings, which has achieved practical results in optimizing the imaging results. Through experimental verification, our proposed algorithm has shown good performance and effectiveness in various scenarios, demonstrating the powerful ability of this inverse operation algorithm and its broad prospects for application in image processing. At the same time, we also recognize that there are still some challenges and issues that need to be addressed in practical applications, such as the real-time performance, robustness, and adaptability to different types of images of the algorithm. In the future, we will continue to explore more possibilities of deep learning in image processing, continuously improve and optimize algorithm performance, in order to achieve widespread application and promotion in more fields.

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