Image denoising using diffractive optical processors

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Abstract: We report an image denoising analog processor composed of passive diffractive layers engineered through deep learning to filter out various types of noise from input images, instantly projecting denoised images at the output field-of-view.

1. Introduction

Image denoising algorithms have been extensively explored in the past decades [1]. Conventional digital denoising methods generally involve many iterations, limiting their practical use in applications that demand real-time operation. Recently, deep neural networks (DNNs) have been employed to develop non-iterative, feed-forward digital methods with outstanding efficacy in image denoising, even at interactive speeds essential for applications such as real-time Monte-Carlo renderings. However, the advantages of these quicker and superior digital image denoisers come at the cost of using graphics processing units (GPUs) with a higher cost and resource demand.

Here, we present an all-optical analog image denoiser comprising spatially engineered diffractive layers to process noisy input images at the speed of light and synthesize denoised images at the output field-of-view (FoV), as illustrated in Fig. 1 [2]. After its one-time training on a computer [3-5], this coherent image processor, equipped with its fabricated passive layers, scatters out the optical modes related to undesired noise/artifacts on the input images while preserving the optical modes representing the desired spatial features of the object with minimal distortions. Consequently, it instantly synthesizes denoised images at its output FoV without digital computation. We validated the all-optical denoising performance of this diffractive visual processor by eliminating salt and pepper noise from intensity input images. Additionally, the all-optical denoising framework was experimentally confirmed at the terahertz spectrum by removing salt-only noise from intensity input images using a 3D-fabricated diffractive denoiser that axially spans <250×λ, where λ is the illumination wavelength [2].

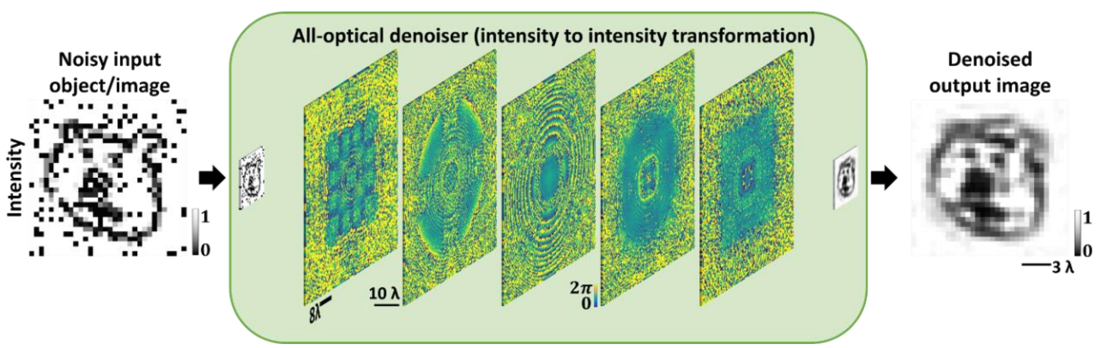

Fig. 1. Overview of a 5-layer all-optical diffractive image denoiser network trained to filter noisy intensity images [2].

2. Results

The denoising performance of 5-layer diffractive denoiser networks in handling different levels of salt and pepper noise is visualized in Figs. 2a. These coherent visual processors are illuminated by a uniform monochromatic plane wave. Phase profiles of the diffractive layers within these processors were obtained through supervised learning using the *tiny quickdraw* dataset [2]. During the training phase, noisy input images were randomly generated by introducing salt and pepper noise at different rates onto ground truth images from the dataset. The noise probability (P_{tr}), defined as the ratio of noise-affected pixels to the overall number of pixels, was uniformly sampled from $U(0, \rho)$ where $\rho \in \{0.1, 0.2, 0.4\}$. $P_{tr} = 0$ refers to the baseline diffractive imager model that was trained using noise-free input images. These trained models were blindly evaluated using test images from the *tiny quickdraw* test dataset, with different test noise probabilities (P_{te}). Figure 2a illustrates sample output images alongside the corresponding Peak-Signal-to-Noise Ratio (PSNR) values for the trained diffractive denoisers across different sampling ranges of P_{tr}. This comparison highlights the superior performance of the image denoising diffractive processors; for example, the diffractive processor trained using $P_{tr} \sim U(0, 0.2)$ achieves average PSNR improvements of 0.65, 1.47, and 1.90 dB for $P_{te} = 0.1$, 0.2, and 0.4, respectively, when compared to the baseline diffractive imager trained without any image noise ($P_{tr} = 0$).

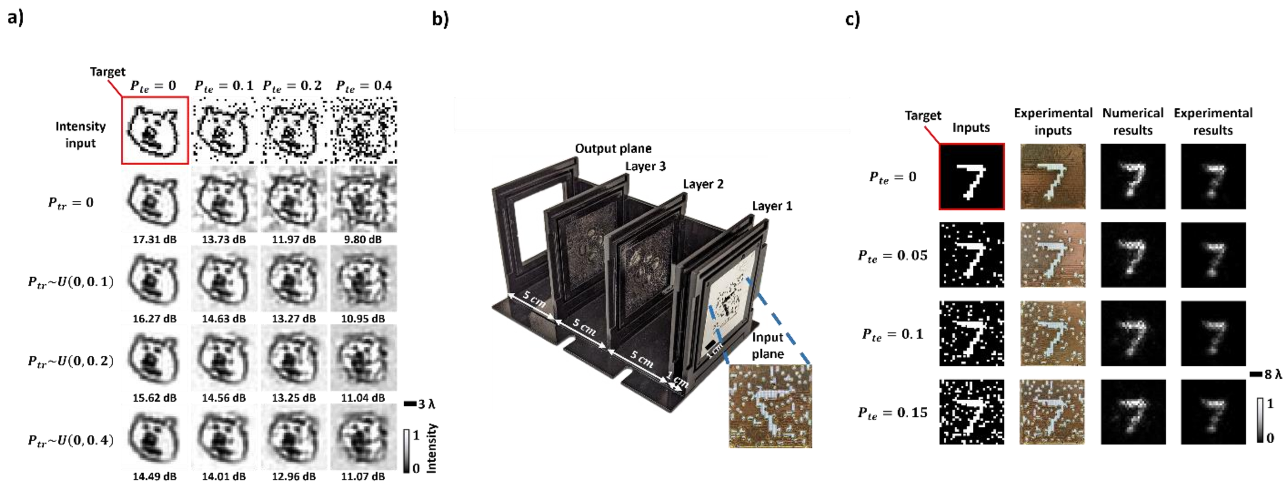

Fig. 2. Numerical and experimental demonstrations of all-optical image denoisers for removing salt and pepper noise. a) All-optical image denoising performance of different diffractive denoisers with 5 passive layers trained using different noise probabilities P_{tr}. b) 3D-printed diffractive image denoiser designed to remove salt-only noise from input intensity images under THz illumination (λ = ~0.75 mm). c) Experimental and numerical results of the designed diffractive image denoiser for noisy intensity images containing different rates of salt-only noise.[2]

We also demonstrated the functionality of the all-optical diffractive denoiser framework through a proof-of-concept experiment using a 3-layer visual processor designed for terahertz illumination (λ = ~0.75 mm), as shown in Figs. 2b-c. This 3-layer diffractive image denoiser configuration was trained to process noisy intensity images containing salt-only noise, where P_{tr} was uniformly sampled from $U(0, 0.2)$ during the training phase. Then, the design was 3D-fabricated and carefully aligned to be experimentally tested, as depicted in Fig. 2b. The numerical and corresponding experimental results are depicted in Fig. 2c for $P_{te} = 0$, 0.05, 0.1, and 0.15, demonstrating the denoising performance of the diffractive image processor, which revealed a decent match between our numerical and experimental results.

The presented diffractive image denoiser framework composed of passive modulation layers operates at the speed of light to instantly mitigate noise and spatial artifacts at the input images without consuming power (apart from the illumination light) and is able to function at any part of the electromagnetic spectrum, including the visible spectrum. These diffractive all-optical image denoisers can be extended to filter out other types of image noise, such as the low-sampling related spatial image artifacts observed in Monte Carlo renderings [2]. These designs can also achieve large output diffraction efficiencies of e.g., ~30-40%, with minimal compromise in their denoising performance, as demonstrated in [2].

3. References

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