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Enhanced Single Pixel Imaging in Atmospheric Turbulence

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Abstract: The imaging quality of single pixel imaging in atmospheric turbulence is enhanced by combining a deep learning model with classical methods. The effectiveness of this method was confirmed by optical experiments.

1. Introduction

SPI(Single-pixel imaging) is a computational imaging method that reconstructs two-dimensional (2D) images from one-dimensional (1D) barrel signals based on the principle of correlation measurement. Optical medium disturbances cause geometric distortions and blurry variations in turbulent distortion imaging. Han et al. studied the impact of atmospheric turbulence on GI(Ghost Imaging) performance, and proved that GI can reduce the impact of turbulence [1]. Integrating SPI with deep learning can significantly reduce the sampling rate required to produce high-quality images. In 2021, Zhang and Duan used multiscale generative adversarial networks to achieve GI reconstruction under turbulence [2]. In 2023, Zhang and Zhai proposed an end-to-end imaging method to suppress atmospheric turbulence [3].

This study investigates the degradation of single-pixel image quality in atmospheric turbulence. In our deturbulence approach, we enhance feature fusion within the MIMO-Unet [4] architecture by introducing a channel attention mechanism. We demonstrate the method's ability to reconstruct clear images in turbulent environments.

2. Approach and Results

Our SPI experimental system comprises a digital light projector (DLP), condenser lens, bucket detector (BD), personal computer (PC), and data acquisition system. In SPI, the measured value received by the BD typically includes the total light intensity of the reflected or transmitted light after the template is projected onto the target surface. The signal received by the BD can be described as:

$$B_i = \iint I_i(x,y) O_i(x,y) dxdy \tag{1}$$

where, $I_i(x,y)$ represents the light field intensity value of the speckle field, $O_i(x,y)$ represents the target matrix to be measured, and i represents the sampling times of the single-pixel detector. To solve the problem of target detail information loss from random grayscale templates in optical experiments, we use DLP to project Hadamard template as sampling matrix. In order to reduce the influence of optical experiment noise on imaging results, differential SPI is used to reconstruct the object. The BD difference was calculated as:

$$D_i = B_i - \frac{\langle B_i \rangle}{\langle R_i \rangle} R_i. \tag{2}$$

here, R_i denotes the sum of the speckle matrices at the i-th sampling. $\langle \cdot \rangle$ is the average operation.

During target reconstruction, the speckle obtained through the known template is correlated with the intensity received by the bucket detector to reconstruct the target management, which is described as:

$$G(x,y) = \left\langle D_i I_i'(x,y) \right\rangle - \langle D_i \rangle \left\langle I_i'(x,y) \right\rangle. \tag{3}$$

We used the reconstructed low-quality objects $G(x,y)$ as input to a trained MIMO-UNet network to enhance image quality. MIMO-UNet features a single encoder for multiscale input and a single decoder for multiscale deblurring output, thereby simplifying training. This U-shaped network structure resembles a multilevel linked U-Net. During sampling, a shallow convolution module (SCM) extracts features from subsampled images, whereas a feature attention module (FAM) adjusts image features across scales, emphasizing or suppressing features from the previous layer scale (EB output). FAM learns the spatial and channel importance, thereby facilitating attention

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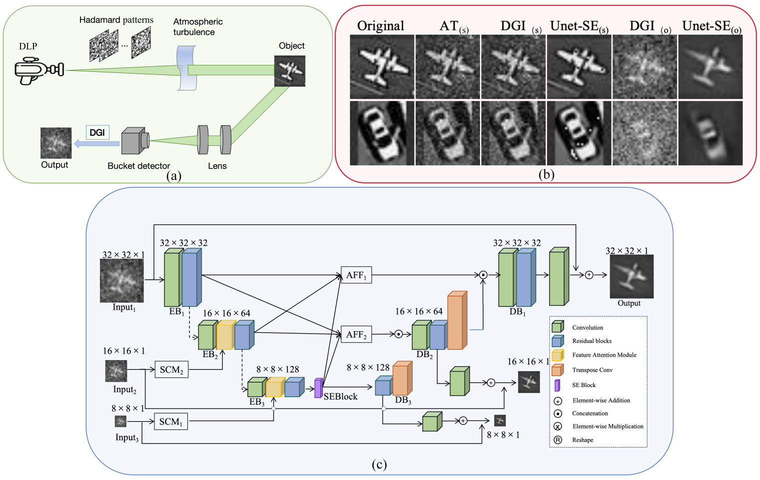

Fig. 1. (a): Optical setup of SPI experiment.(b): Results of image reconstruction.(c): Our network.

to both feature types. To enable information flow between scales, each FAM receives output from all coding blocks (EB) as input, and each decoding block (DB) utilizes multiscale features.

To improve the feature extraction from low-resolution images, we integrated a channel focus module (SEblock) into the smallest encoder. Inspired by SENet, SEblock enhances the network representation by modeling the interdependencies between feature channels. Initially, the feature map undergoes a squeeze operation to generate a channel descriptor that integrates spatial information. This descriptor encapsulates the global distribution of channel responses, aiding lower-level network layers by utilizing the information from the global receptive field. Subsequently, an excitation operation was performed, leveraging a self-gating mechanism to test the inter-channel dependencies. The resulting reweighted feature map was then passed to the subsequent layer as the output of the SE block for training.

Table 1. Results of simulation and optical experiment

	AT(s)	DGI(s)	MIMO(s)	DGI(o)	MIMO(o)
Mean Square Error (MSE)	0.0126	0.0124	0.0137	0.0568	0.0127
Correlation Coefficient (CC)	0.8689	0.8679	0.9024	0.4928	0.7116
Structural Similarity Index (SSIM)	0.9994	0.9992	0.9996	0.9876	0.9981

We added 200 layers of simulated turbulent phase screens to the dataset. Figure (b) displays the target image labeled as ‘Original’, with ‘AT(s)’ showing the simulated result after superimposing 200 layers of turbulent phase screens. ‘DGI (s)’ and ‘Unet-SE (s)’ represent simulation-generated and network deturbulence results, while ‘DGI (o)’ and ‘Unet-SE (o)’ depict results from optical experiment data using DGI and network deturbulence, respectively. In the table, the MSE, CC, and SSIM quantify the reconstruction results. Despite the inherent noise in optical experiments compared to simulated ones, our network achieved significant deturbulence results, laying a strong foundation for tasks such as target classification or identification.

3. Conclusion

In this study, we propose a deep-learning-based SPI scheme for atmospheric turbulence. Without changing the traditional SPI framework and combining it with a trained network, a satisfactory result was obtained in the optical experiment to reconstruct a small-scale gray image after turbulence degradation.

References

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