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3D Super-resolution Optical Imaging Using Deep Image Prior

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Abstract— **Deep learning based super-resolution methods have received much attention, especially unsupervised super-resolution due to the difficulty of collecting images pairs (low-resolution and high-resolution images from the same scenario) in many fields, such as optics. Optical imaging is typical technique in advance optical measurement equipment and optical super-resolution imaging has received much attention. In this paper, a novel model, deep image prior with design surface model (DIP-DSM), based on deep image prior to improve the resolution of optical imaging is presented. It makes use of single image instead of using random input in which the design surface model is regarded as prior information. To validate the model, a series of experiments are conducted, and the results show the superiority of the proposed model as compared with deep image prior. Furthermore, the performance of different neural networks are explored and it is find that the U-Net achieve best reconstruction quality and reach to PSNR, 32.937.**

Keywords: Super-resolutuon; optical imaging; deep learning; measurement; Deep image prior; precision surface measurement; precision metrology

I. INTRODUCTION

Deep learning has experienced rapid development in recent years and has many successful applications in imaging tasks, including classification [1], segmentation [2], detection [3], dehazing [4], deblurring [5], super-resolution [6]. Super-resolution (SR) imaging has received many researchers' attention since the increasing demand of high-resolution images or videos in many industrials, such as medical [7], entertainment [8], surveillance [9], optics [10], etc. It is an approach which recover high-resolution (HR) images based on low-resolution (LR) images. There are many methods and deep neural networks proposed to deal with this problem. These methods could be divided into two categories, namely supervised SR and unsupervised SR. Deep learning based supervised image super-resolution methods normally are trained with pairs of HR and LR images to learn the mapping between them.

Various SR neural network models were proposed in recent years. Dong et al. [11] adopted an end-to-end trainable deep convolutional neural network to learn a mapping between HR and LR. A generative adversarial network for SR model (SRGAN) [12] was developed to firstly achieve 4×upscaling factors for natural images. Haris et al. [13] exploited iterative up- and down-sampling layers to capture the mutual dependency information of LR and HR images, thereby further improving image resolution. For adapting arbitrary scale factor, Meta-SR model [14] was proposed a meta-upscale module to achieve various scale SR images in one model. Dai et al. [15] improved the visual quality through enhancing the convolutional neural network (CNN) representation based on a second-order channel attention module.

Although many powerful networks are proposed, it depends on considerable dataset. Since collecting images in many fields is difficult or time-consuming, unsupervised SR methods become more popular. Shocher et al. [16] proposed a "Zero-Shot" SR model, which extracted features from a single image trough a small CNN. Bulat et al. [17] used generative adversarial network (GAN) to obtain super-resolution face images. Yuan et al. [18] further proposed an improved GAN network through cycle-in-cycle structure. Different from most other methods, Ulyanov et al. [19] adopted random variables as an input of CNN to generate a super-resolution image. Although the performance of this method, deep image prior (DIP), is not competing with the state-of-the-art supervised methods, it performs better than traditional bicubic up-sampling with high time-efficiency.

SR imaging has widely used in optical imaging, in order to improve the performance of image quality of measured surface, a novel method is proposed based on DIP, named as DIP-DSM (deep image prior with design surface model). Instead of using random input, we use designed surface model as prior to improve image resolution. The model yields better result compared with original model.

II. METHODOLOGY

In the proposed method, DIP-DSM, the super-resolution image x which needs to be recovered defined by (1) as DIP [19].

$$x = f(\theta|z_p) \tag{1}$$

where f denotes the neural network; θ are the parameter of neural network; z_p is the input of the neural network and image prior. In this model, it is the depth map of designed surface model. The objective of model minimizes the different of recovered SR image (x) and LR image (x_0). It becomes a minimization optimization problem, as represented in (2). Plugging (1) in (2) becomes (3). Adam optimization method [20] is used to solve this problem.

$$\min_{\theta} \|x - x_0\| \tag{2}$$

$$\min_{\theta} \|f_{\theta}(z_p) - x_0\| \tag{3}$$

Peak signal-to-noise ratio (PSNR) is the most general metric to evaluate the performance of reconstruction quality. It is defined by (4)

$$PSNR = 10 * \log_{10}\left(\frac{L^2}{\frac{1}{N}\sum_{i=1}^{N}\left(I(i) - \hat{I}(i)\right)^2}\right) \tag{4}$$

where L is the maximum pixel value; N is the number of pixels; I and $\hat{I}$denote ground truth image and reconstruction image.

III. Experiments

In order to validate the proposed model, a simulation experiment is performed. As shown in Fig. 1, the design surface model is the desired freeform surface aims to be manufactured.

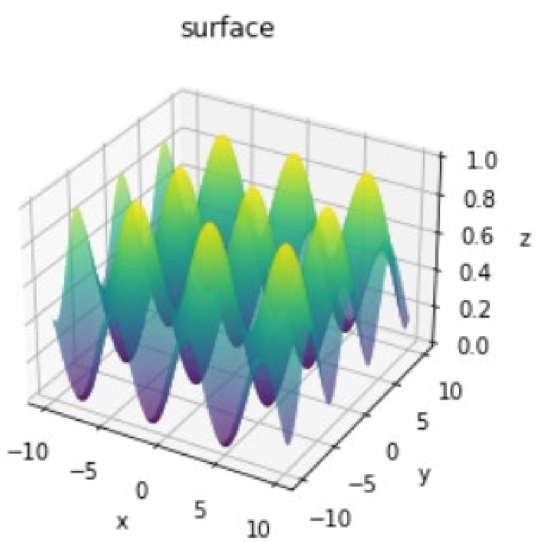

Figure 1 design surface model

The function of design surface is defined by (5). 384 x 384 points are sampled on the surface and convert it into depth map as shown in Fig. 2, which is the image prior, z. Hence, it is assumed that 96 x 96 measured points are obtained with Gaussian noise ($\mu = 0, \sigma = 0.1$), which is the LR image, x_0 (Fig. 3).

$$z = \sin(x) + \cos(y)\,, x, y \in [-10,10] \tag{5}$$

The skip-connection convolutional neural network is chosen to recover the SR image. The model was trained 400 iterations, reconstruction images was shown as shown in Fig.4(b) and the

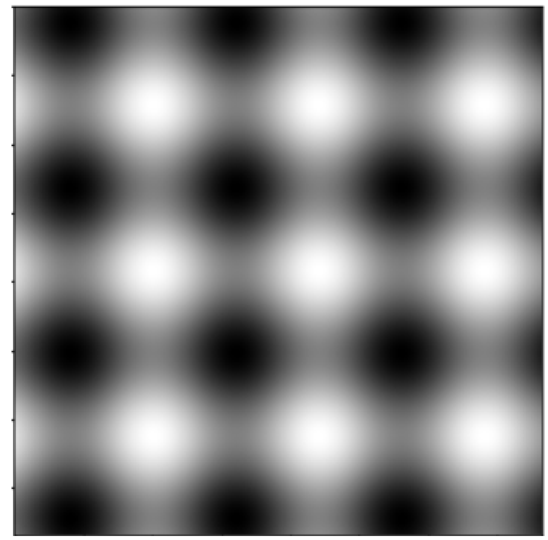

Figure 2 depth map of design surface model

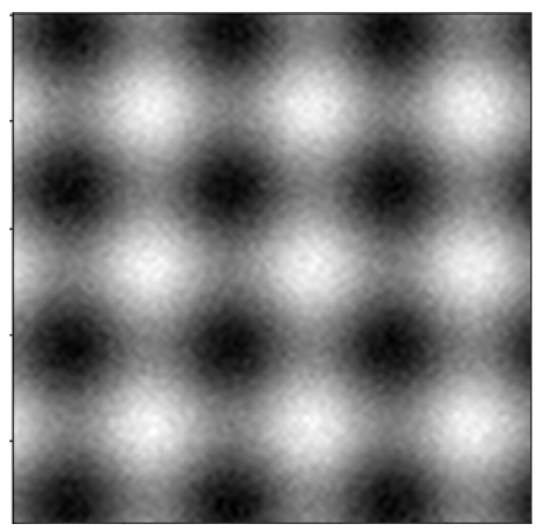

Figure 3 depth map of measured surface

model achieved PSNR 32.842 Similarly, the same procedure is conducted using DIP, the result showed in Fig.4(a). It achieved PSNR 31.854. The proposed model outperformed DIP about 1dB.

To further explore the influence of neural network, experiments were conducted using other popular neural network, such as ResNet [21], U-Net [22]. The results are shown

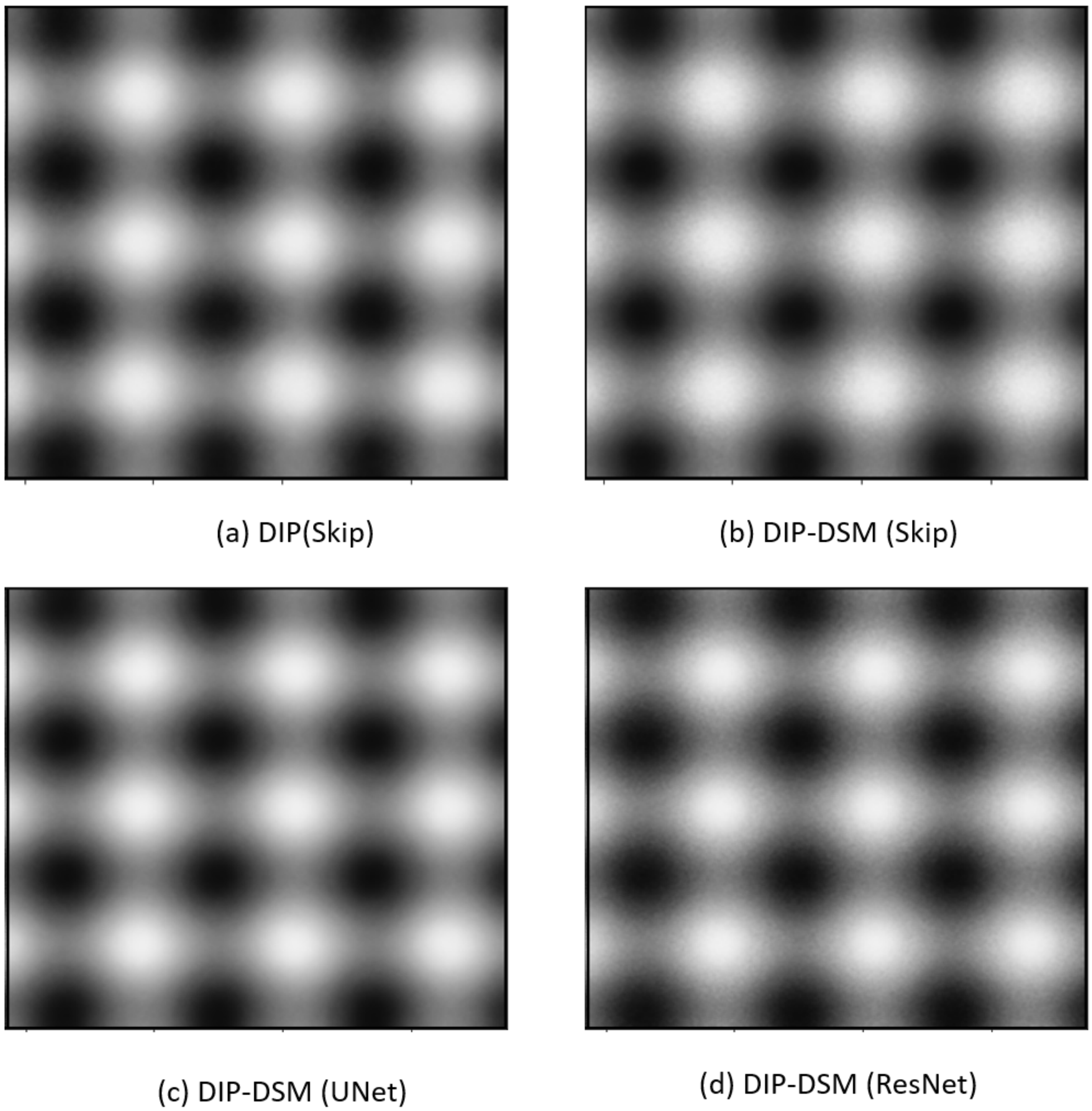

Figure 4 Reconstruction comparison of different models

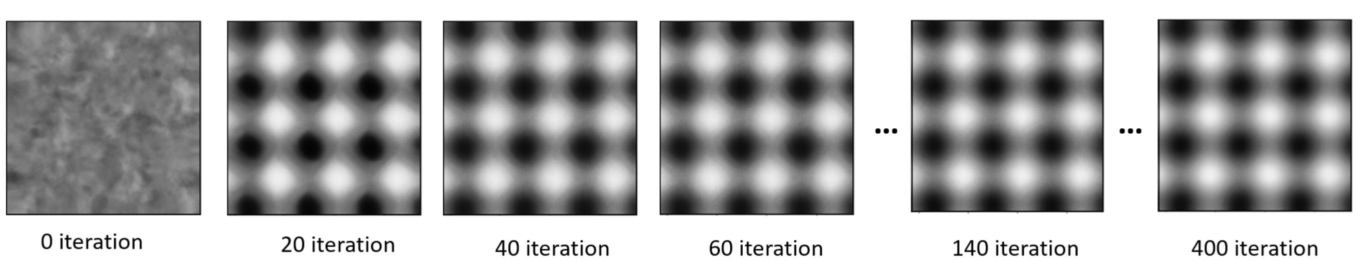

Figure 5 The reconstruction process of DIP-DSM(U-Net)

in Table 1. The reconstruction process of the proposed model are also visualized using U-Net, the reconstruction images in different iterations as shown in Fig.5.

TABLE I. PSNR COMPARISON OF DIFFERENT MODELS

Models	PSNR(dB)
DIP(Skip)	31.854
DIP-DSM(Skip)	32.842
DIP-DSM(U-Net)	32.937
DIP-DSM(ResNet)	32.336

According to the results, U-Net achieved best reconstruction performance with PSNR 32.937. In addition, ResNet has the lowest PSNR value as compared with skip-connection neural network and U-Net, which mean the fusion of low-level and high-level feature may boost the reconstruction performance.

IV. CONCLUSIONS

Optical imaging is an important process of optical measurement. Super-resolution problem is a main task during optical imaging and deep learning based super-resolution method has received much attention. However, many methods need considerable dataset. It is difficult to collect them in real-world measurement process. In this paper, a novel model, deep image prior with design surface model (DIP-DSM) is presented, which is regarded as design surface model as prior information to improve the reconstruction quality. A series of experiment were conducted and the proposed model outperformed DIP. In addition, different neural networks were used to recover the image, U-Net achieved the best reconstruction quality.

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