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Poster

Shadow Removal via Cascade Large Mask Inpainting

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Abstract

We present a novel shadow removal framework based on the image inpainting approach. The proposed method consists of two cascade Large-Mask inpainting(LaMa) networks for shadow inpainting and edge inpainting. Experiments with the ISTD and adjusted ISTD dataset show that our method achieves competitive shadow removal results compared to state-of-the methods. And we also show that shadows are well removed from complex and large shadow images, such as urban aerial images.

CCS Concepts

• ***Computing methodologies*** $\rightarrow$ ***Image processing; Image representations;***

1. Introduction

Shadows are common in most natural images. Especially, many complicated and large shadows are cast from large buildings such as tall buildings and apartments in urban areas, as shown in Figure 1. In the field of computer vision and computer graphics, the presence of shadows negatively affects the processing, analyzing, and understanding of images. Therefore shadow removal is an essential task and many methods have been proposed to remove shadows from images [LS19] [IY20].

In this work, we propose a novel shadow removal framework based on image inpainting approach. Image inpainting is a task of filling missing or damaged parts (holes or gaps) in images. And there has been significant progress in image inpainting field with the development of deep learning techniques. Unlike the original image inpainting method, we apply shadow regions of the image as damaged areas to the image inpainting network for restoration of shadow regions. Our contributions are as follows: 1) Shadow inpainting network to eliminate shadows by assuming shadows as inpainting areas, 2) Edge inpainting network to reduce boundary errors generated in the inpainting process, 3) Cascade shadow removal architecture with shadow inpainting network and edge inpainting network.

Figure 1: *Aerial images with large shadows in urban areas.*

2. Proposed Shadow Removal Framework

2.1. Network Architecture

Our shadow removal framework is based on the Large-Mask Inpainting(LaMa) network model [SLM*22] using Fast Fourier Convolutions and Perceptual Loss specialized for inpainting large mask regions. The original LaMa network restores the inside of a color image masked by a binary mask of unknown pixels with contextual information outside of the mask. We modify the input, target, and mask generation of the LaMa architecture to adapt to the shadow removal process based on the LaMa network.

As shown in Figure 2, the proposed system consists of two cascade LaMa networks. First, the shadow inpainting network removes the shadows of a color image masked by binary masks. Then, the edge inpainting network restores the boundary of the shadow region smoothly. In the shadow inpainting process, we modify the LaMa network to generate a shadow removal image ***x'*** from the input image ***x*** and the shadow mask ***m***. Because the LaMa network uses the global context with an image-wide receptive field, shadow removal performance is better than before. However, there are in-

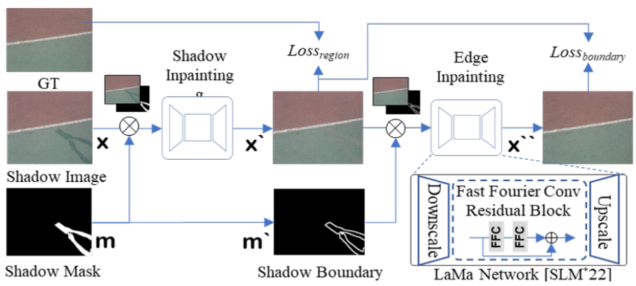

Figure 2: *The proposed shadow removal framework.*

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evitably some errors between the masked area and the real shadow area. The segmentation error of the shadow mask creates invalid thin lines at the edge of the shadow in the shadow removal image $\boldsymbol{x'}$ during the shadow inpainting process. These errors are visually easily detected. The edge inpainting model eliminates the invalid edge lines with the shadow removal image $\boldsymbol{x'}$ and the shadow boundary $\boldsymbol{m'}$. The shadow boundary $\boldsymbol{m'}$ is derived by subtracting the dilated original shadow mask from the eroded original shadow mask.

2.2. Shadow Data Augmentation

Building a large-scale, diverse dataset of shadow image/shadow-free image/shadow mask triplets is difficult. Even though there are some benchmarks for shadow removal such as the ISTD dataset, it may suffer from overfitting when there is insufficient training data. So it is essential to increase the amount of training dataset to improve performance. Since it is assumed that mask images for shadows are given in this work, we augment the ISTD dataset by focusing on diversifying shadow intensities rather than shadow shapes. Based on a physically-grounded shadow illumination model, shadow images for training are created by arbitrarily combining shadow-free images, shadow masks, and shadow attenuation parameters [IY20], as shown in Figure 3

Figure 3: *Examples of augmented shadow images with different shadow intensities.*

3. Experiments

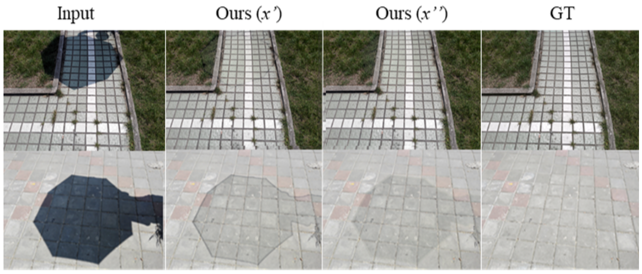
We conduct shadow removal experiments for quantitative performance evaluation on the ISTD and the adjusted ISTD [LS19]. As in the previous work, we evaluate the RMSE on the LAB color space in the shadow areas(S), non-shadow areas(NS), and all areas. Our method has improved the RMSE on the shadow area compared to the existing methods, as shown in Table 1. As shown in Figure 4 (a), edge inpainting $\boldsymbol{x''}$ following shadow inpainting $\boldsymbol{x'}$ also has the effect of reducing visual errors on shadow boundaries. Figure 4 (b) shows the results of shadow removal from the urban aerial images in Figure 1. Only the color information deformed by the shadow has been successfully restored while maintaining the object information inside the shadow area.

4. Conclusion

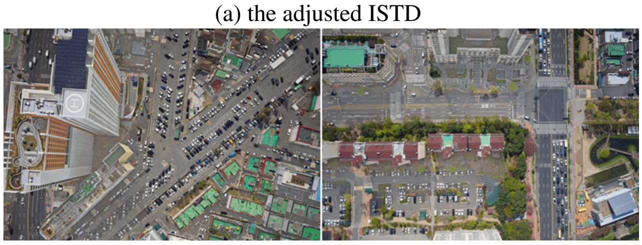
In this work, we have presented the novel shadow removal framework based on image inpainting approach. Our approach uses two cascade LaMa networks with the shadow inpainting network and the edge inpainting network. Experiments showed better RMSE performance than previous approaches. Our results showed that the proposed method can remove shadows even in complex urban aerial images with large shadows. For future work, it is necessary for shadow detection and removal based on shadow properties such as self shadows, cast shadows and so on.

Table 1: *Comparison of shadow removal methods(metric:RMSE)*

Datasets	Methods	S	NS	All
ISTD	DHAN [CPS20]	8.14	6.04	6.37
	DHAN+DA [CPS20]	7.52	5.43	5.76
	Ours ($\boldsymbol{x'}$)	4.54	3.87	3.96
	Ours ($\boldsymbol{x''}$)	**4.52**	3.88	**3.96**
Adjusted ISTD	SP-Net [LS19]	9.0	3.2	4.1
	SP+M-Net [LS19]	7.4	3.1	3.8
	Ours ($\boldsymbol{x'}$)	3.27	1.80	2.12
	Ours ($\boldsymbol{x''}$)	**3.24**	1.79	**2.10**



(a) the adjusted ISTD



(b) Urban aerial images

Figure 4: *Shadow removal results.*

5. Acknowledgements

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