Multi-Level Curriculum for Training A Distortion-Aware Barrel Distortion Rectification Model

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1. Supplemental Material

1.1. Overview

In this document, we provide the following supplementary contents:

- Details of the comparison experiment (Section 1.2).
- More qualitative results of the comparison methods and our approach (Section 1.3).

1.2. Details of the Comparison Experiment

In the experiment, we compare our approach with the barrel distortion rectification methods including the traditional methods: Alemán-Flores [1], Santana-Cedrés [7] and learning methods: Rong [6], DR-GAN [4], DeepCalib [2], Li [3], and Liao [5]. For Rong [6], due to its simple network architecture (AlexNet) and common loss function, we reproduce this work following the relevant settings and details described in the paper. The reproduced rectification performance is consistent with the previous reports. For Li [3], we first used their pre-trained model to correct the barrel distorted images. In this work, the authors aim to correct different types of distortions, and the training dataset contains the barrel, pincushion, rotation, shear, wave, and perspective distortions. As a consequence, when only conducting on the barrel distortion, this method can introduce other correction structures. To show a fair comparison, we retrain Li [3] using the barrel distorted images alone and retest its rectification performance. For other methods [1][7][5][4] that are proposed to rectify the barrel distortion specifically, we directly implement the available codes or pre-trained model to test the rectification performance.

We found that some methods achieve poor quantitative evaluations while the visual results show plausible rectification appearances, such as DeepCalib [2] and Li [3]. The main reason is that these methods crop and resize the rectification results, leading to a mismatched global distribution with the ground truth. Thus, it is unfair for DeepCalib [2] and Li [3] to compute the quantitative metrics such as the PSNR and SSIM directly. Having observed this fact, we design a fairer evaluation method as shown in Fig. 1. To match the global distribution between the rectification results and the ground truth, we crop an inscribed rectangle sub-image from the ground truth and resize it with the original resolution. Then, we compare the local matched regions and compute the PSNR and SSIM. As listed in Table 1, the traditional evaluation method limits the quantitative performance of DeepCalib [2] and Li [3]. In contrast, our evaluation enables a consistent quantitative metric with the visual rectification results.

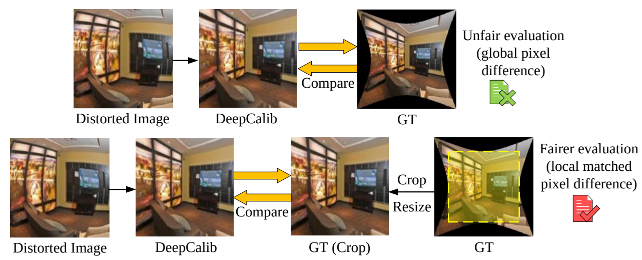

Figure 1. Evaluation comparison of the traditional method (top) and the proposed method (bottom). Due to the mismatched global distribution between the rectified image the ground truth, the traditional method limits the quantitative performance of some distortion rectification methods.

Table 1. Quantitative evaluation results of Li [3] and DeepCalib [2], in which we dub the traditional evaluation results as Li* and DeepCalib*, respectively.

Metrics	Li* [4]	Li [4]	DeepCalib* [2]	DeepCalib [2]
PSNR ↑	14.02	**17.19**	16.10	**18.43**
SSIM ↑	0.49	**0.63**	0.54	**0.67**

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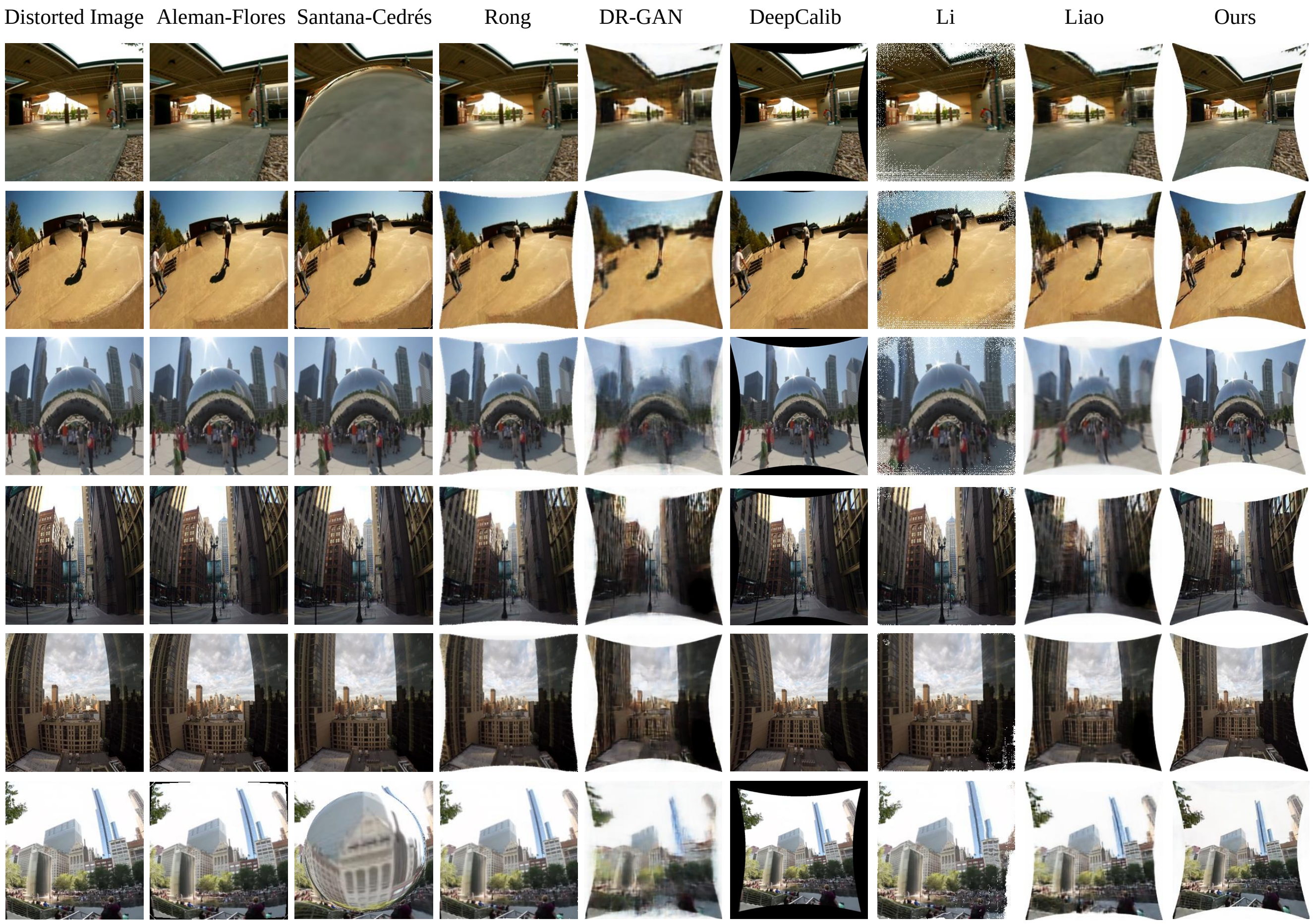

Figure 2. Qualitative results on the real-world distorted images. We show the distorted image and the rectified results from: Alemán-Flores [1], Santana-Cedrés [7], Rong [6], DR-GAN [4], DeepCalib [2], Li [3], Liao [5], and our proposed approach, from left to right.

1.3. More Qualitative Results

As illustrated in Figure 2, we compare our approach with the barrel distortion rectification methods including the traditional methods: Alemán-Flores [1], Santana-Cedrés [7] and learning methods: Rong [6], DR-GAN [4], DeepCalib [2], Li [3], and Liao [5] on the real-world images captured by various wide-angle lenses. For this evaluation, we collect the real-world barrel distorted images from the videos on YouTube, captured by widely used wide-angle lenses such as the SAMSUNG 10mm F3, Rokinon 8mm Cine Lens, Opteka 6.5mm Lens, and GoPro. From Fig. 2, we can observe that our approach well rectifies the distorted objects such as the buildings and roads, outperforming other methods in terms of global scene distribution and local visual appearance. These results demonstrate that our approach is more competent in practical barrel distortion rectification.

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