Progressively Complementary Network for Fisheye Image Rectification Using Appearance Flow

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1. Supplemental Material

1.1. Overview

For a better view of results, in this file, we provide our supplementary material as following:

- More instances for the progressively complementary mechanism (Section 1.2);
- More visualization examples of multi-scale corrected results (Section 1.3);
- More subjective results of our method and state-of-the-art methods (Section 1.4).

1.2. Progressively complementary mechanism

For a more intuitive understanding, we provide more instances of progressively complementary mechanism in Fig.1. The first row of each instance is the distorted features on the encoder layer, whose distortion degree is gradually decreased. The second row of each instance is the predicted flows on each decoder layer, whose displacement is progressively reduced. The third row of each instance is the corrected features on each encoder layer. For images with complex structures, their feature maps are complicated and hard to understand. Therefore, we only visualize the instances with simple structures here.

As shown in Fig.1, from low-level to high-level, the encoder features on the distortion correction module show a gradual slight reduction in distortion. In the meantime, the decoder outputs at the flow estimation module also decrease progressively on displacement. We leverage the progressive changing flows to correct the progressive changing distortion features. As a result, the distorted feature map of each layer has been well corrected.

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1.3. Multi-scale output

To verify the effectiveness of our method in multi-scale correction, we demonstrate more multi-scale outputs. The concatenated features on the distortion correction module are sent to the convolutional layer with 3×3 kernels to obtain 3-channels multi-scale corrected images. As shown in Fig.2, from left to right are the input images, the output of the each decoder layer and the final results. As can be seen, the texture of the image becomes increasingly abundant, but the structure of the image has not changed much, because the structure of each layer has been well corrected. It proves the effectiveness of our multi-scale correction.

1.4. Subjective comparison results

In this Section, we present more subjective comparison results of our method and state-of-the-art methods in Fig.3. Specially, we compare images with different number of harris points ($N \leq 200$, $200 \leq N \leq 400$, and $N \geq 400$) separately. The resolution of results is 256×256, zooming in for better comparison.

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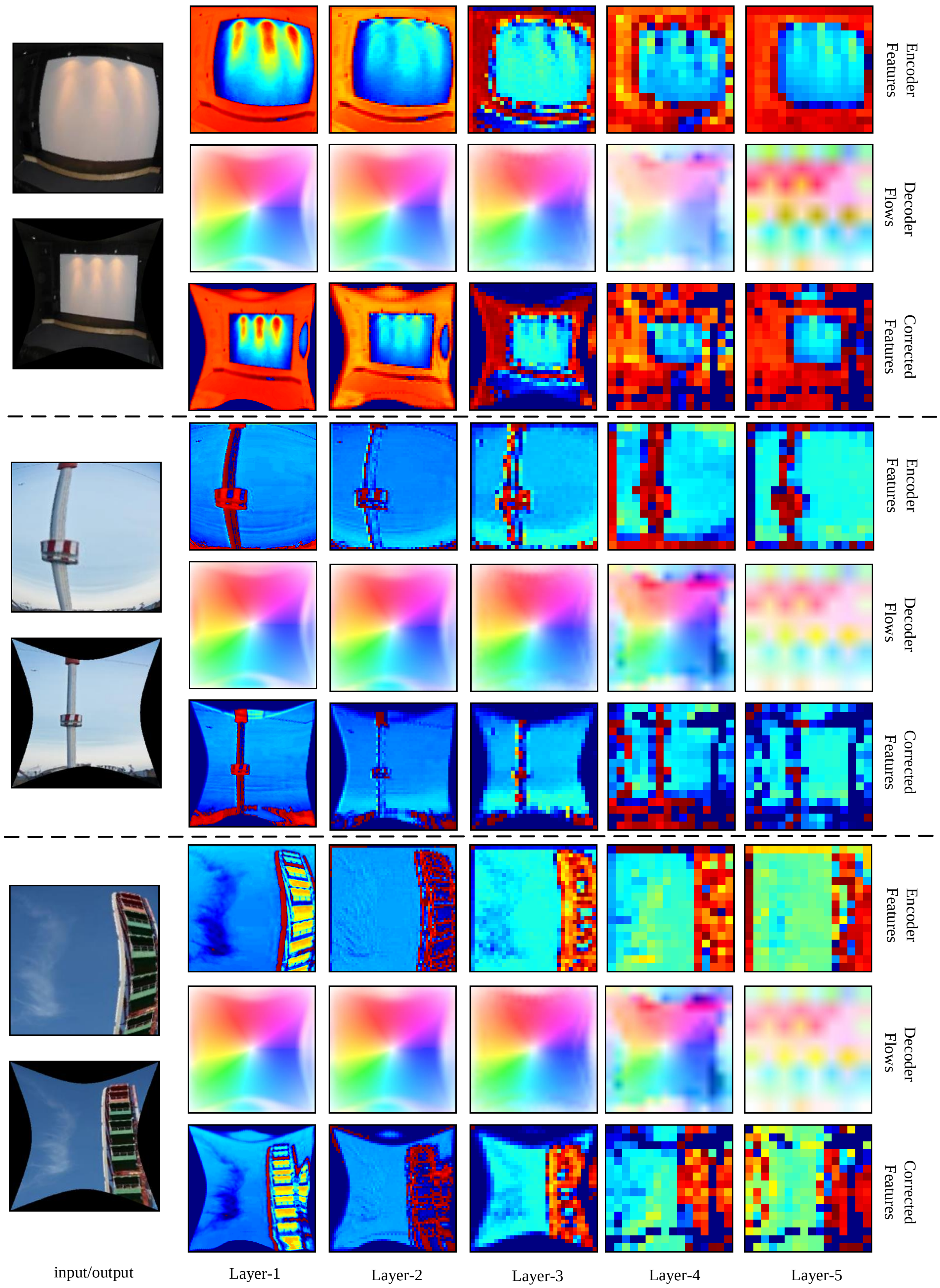
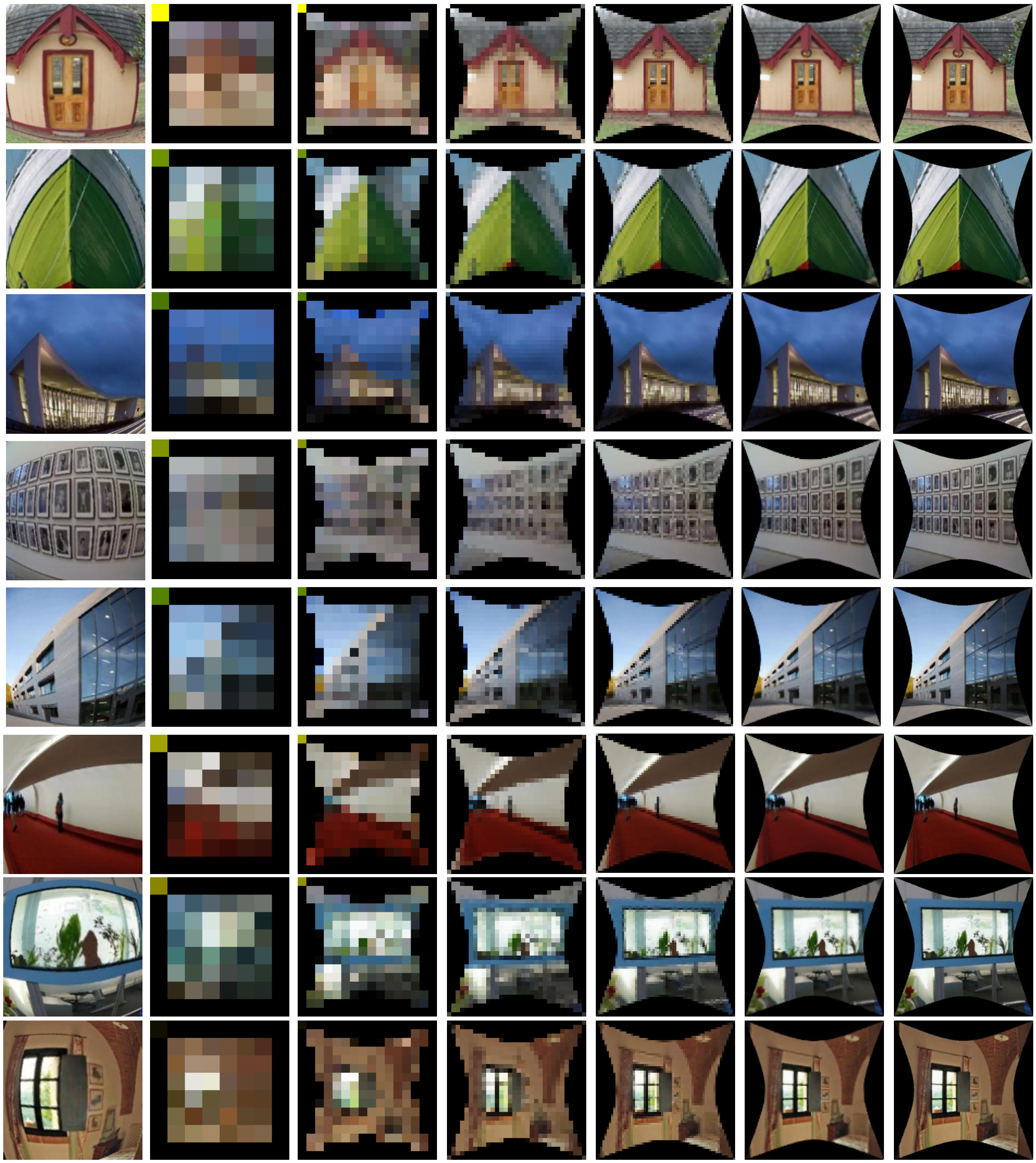


Figure 1. **Progressive complementary samples.** The progressive changing flows are leveraged to correct the progressive changing distortion features.



Input De-L5 De-L4 De-L3 De-L2 De-L1 Output

Figure 2. **Multi-scale corrected results.** Each layer output of the decoder are visualized.

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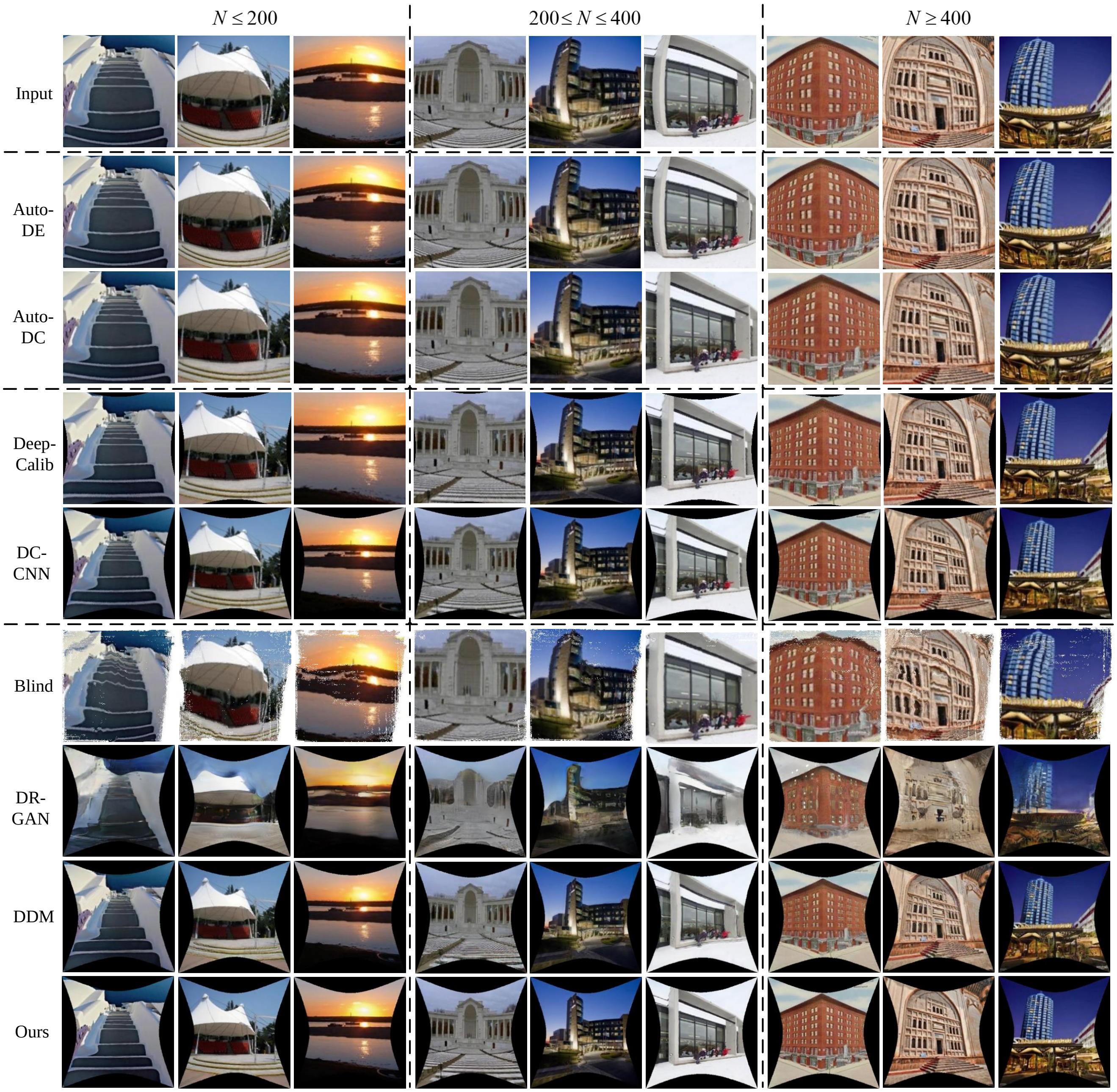

Figure 3. **Subjective comparison results.** The results of our method and state-of-the-art methods: two traditional methods(Auto-DE [3], Auto-DC [1]), two regression-based methods(DeepCalib [2], DC-CNN [7]), three generation-based methods(Blind [4], DR-GAN [5], DDM [6]).

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