Position-aware and Symmetry Enhanced GAN for Radial Distortion Correction

Yongjie Shi, Xin Tong, Jingsi Wen, He Zhao, Xianghua Ying and Hongbin Zha
Peking University

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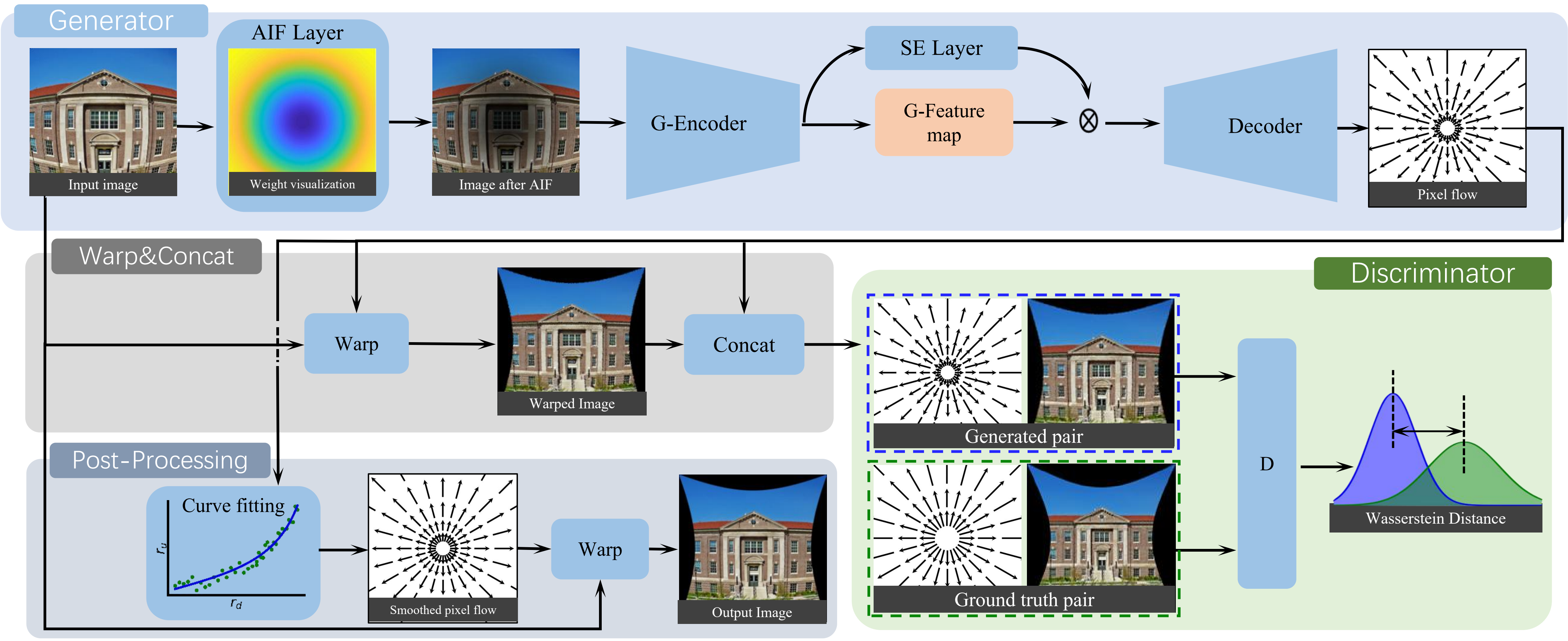
Introduction

- Traditional computer vision algorithms, such as pose estimation and 3D reconstruction, usually depend critically on the assumption of the ideal pinhole camera model.

- However, most lenses in commonly used cameras suffer from lens distortion.

- Eliminating the radial lens distortion of an image is a crucial step for many computer vision applications.

Method overview



Adaptive Inverted Foveal (AIF) Layer

- AIF can be described as

$$I' = W \odot I$$

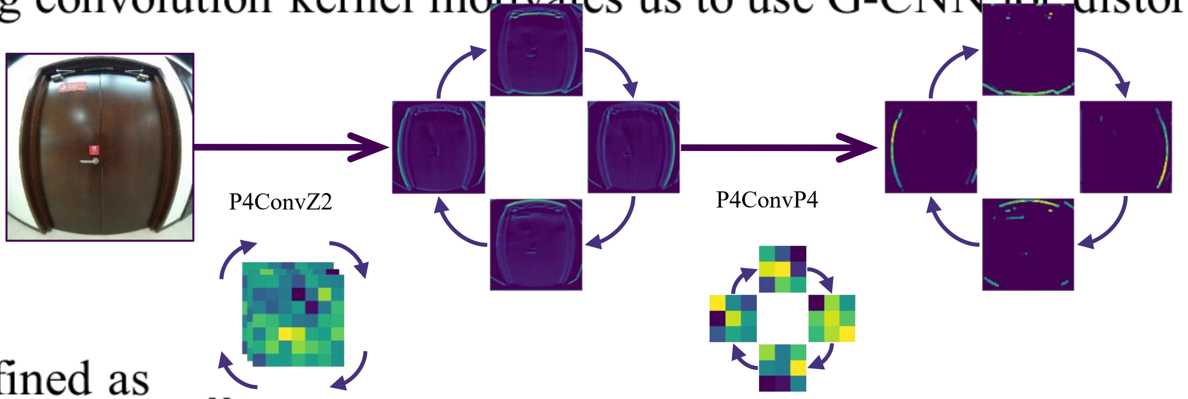
Where I is the input image. I' denotes image after intensity adjustment. W is the weight of AIF layer:

$$W(x,y) = \alpha \times \left(1 - e^{-\frac{\left(x-\frac{w}{2}\right)^2 + \left(y-\frac{h}{2}\right)^2}{2\sigma^2}}\right) + \beta$$

- AIF is significant since AIF layer is able to transform the deformation to the intensity of the image.

Symmetry Enhanced Generator

- Symmetry enhanced CNN is proposed to solve the equivariance in CNN under a certain transformation
- The operation of rotating convolution kernel motivates us to use G-CNN for distortion correction



- The total loss can be defined as

$$L_G = \frac{1}{N}\sum_{i=1}^{N}\left(-D\left(\widehat{F}_i, \widehat{I}_i\right) + \lambda_G\left|\widehat{F}_i - F_i\right|\right)$$

Where $\widehat{F}_i$ and F_i are the output pixel flow map ground truth, respectively. $\widehat{I}_i$ are warped image. D is discriminator.
The first term and the second term indicate adversarial loss and content loss, respectively.

Discriminator

- For discriminator, the loss function can be defined as

$$L_D = \frac{1}{N}\sum_{i=1}^{N}\left(D(\widehat{F}_i, \widehat{I}_i) - D(F_i, I_i)\right) + \lambda_D \frac{1}{N}\sum_{i=1}^{N}(|| \nabla_{\widehat{F}} D(\widehat{F}_i)|| - 1)^2$$

The first term and the second term denote adversarial loss gradient penalty, respectively.

Experiment

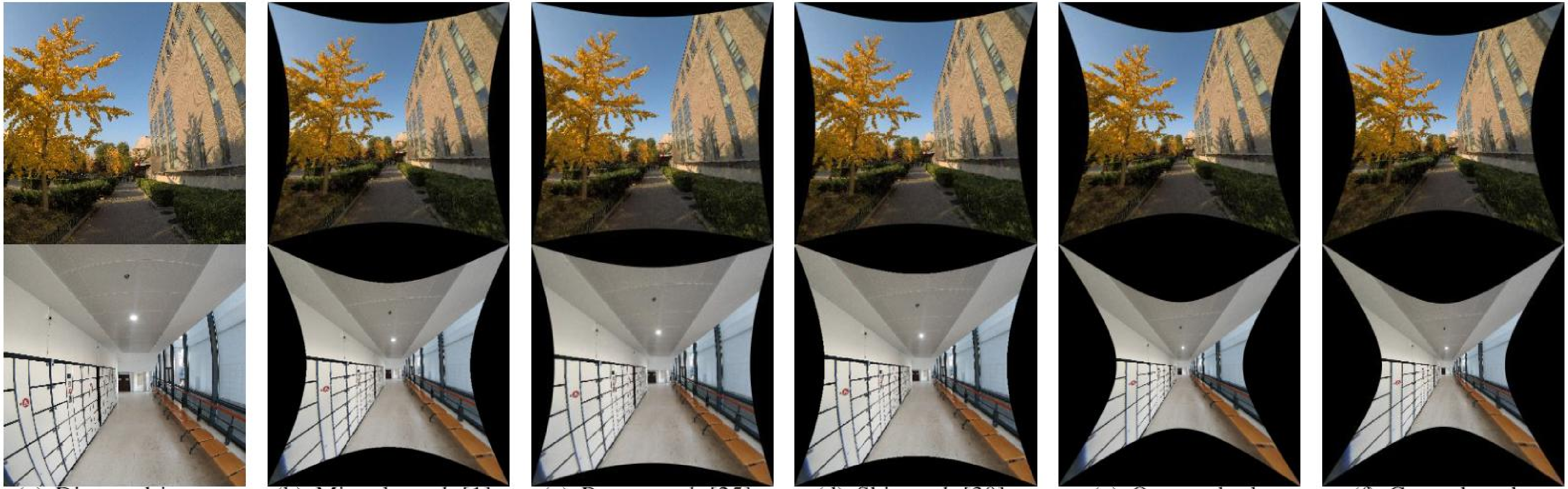
We first compare our method with previous method in synthetic dataset.

Method	#Params (M)	Dataset [25]
Rong *et al.* [25]	70.66	6.71
Shi *et al.* [30]	11.21	4.98
Miguel *et al.* [1]	–	5.46
Pixel2pixel [20]	54.41	6.22
Unet [26]	54.41	6.27
Ours	**2.90**	**3.54**

(a) Distortion image (b) Miguel *et al.* [1] (c) Rong *et al.* [25] (d) Shi *et al.* [30] (e) Our method (f) Ground truth

Experiment

Then we compare our method with previous method in real image taken by ourself.



(a) Distorted image (b) Miguel *et al.* [1] (c) Rong *et al.* [25] (d) Shi *et al.* [30] (e) Our method (f) Ground truth

Conclusion

- In this paper, we present a novel method based on GAN for radial distortion correction.
- We develop a position-aware AIF layer to transform the deformation to the intensity of the image.
- Rotation symmetry enhanced convolution kernels are applied to learn geometric features from structured scenes explicitly.
- Further experiments show our method outperforms previous methods in both synthetic and real images.