Fast Two-step Blind Optical Aberration Correction

Thomas Eboli, Jean-Michel Morel and Gabriele Facciolo

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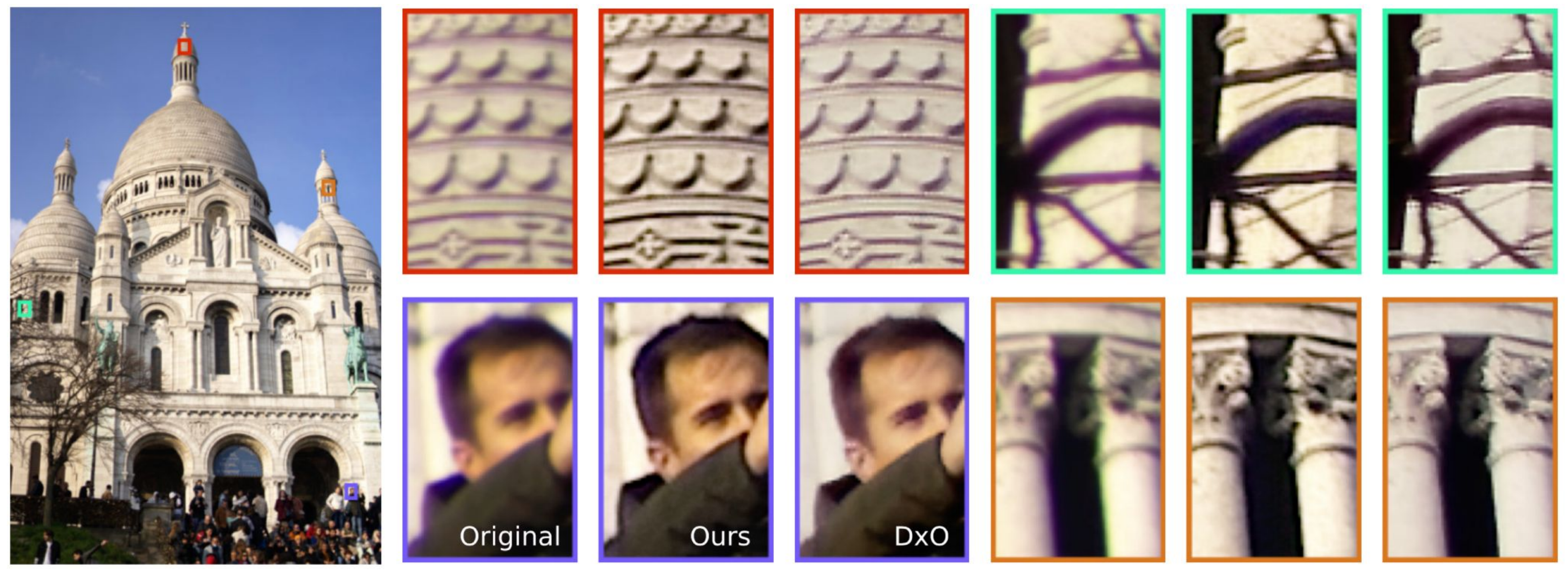
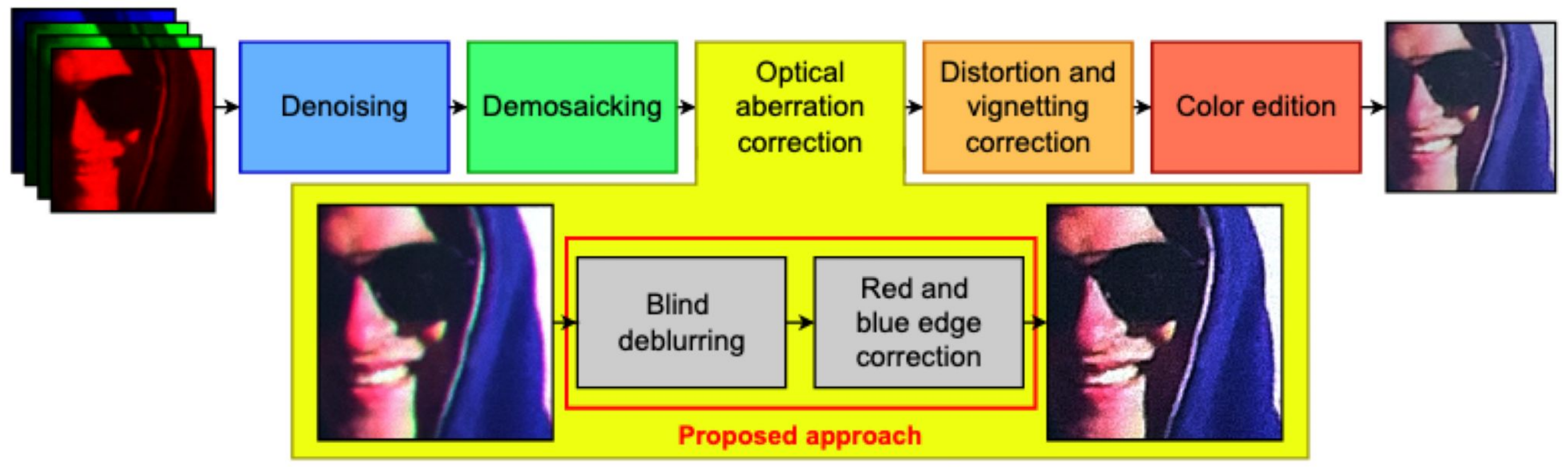
Centre Borelli
école normale supérieure paris–saclay
université PARIS-SACLAY

Problem statement



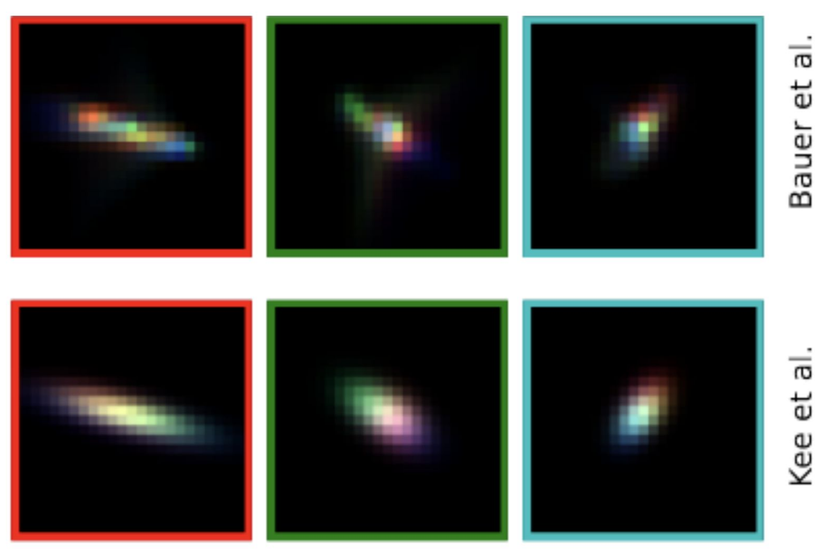
- The photographs are naturally degraded by optical aberration artifacts.
- Existing solutions (e.g., DxO PhotoLab) are **non-blind:** based on tedious calibration.
- We propose a fast **blind** method: give the image and press the button!

Proposed approach

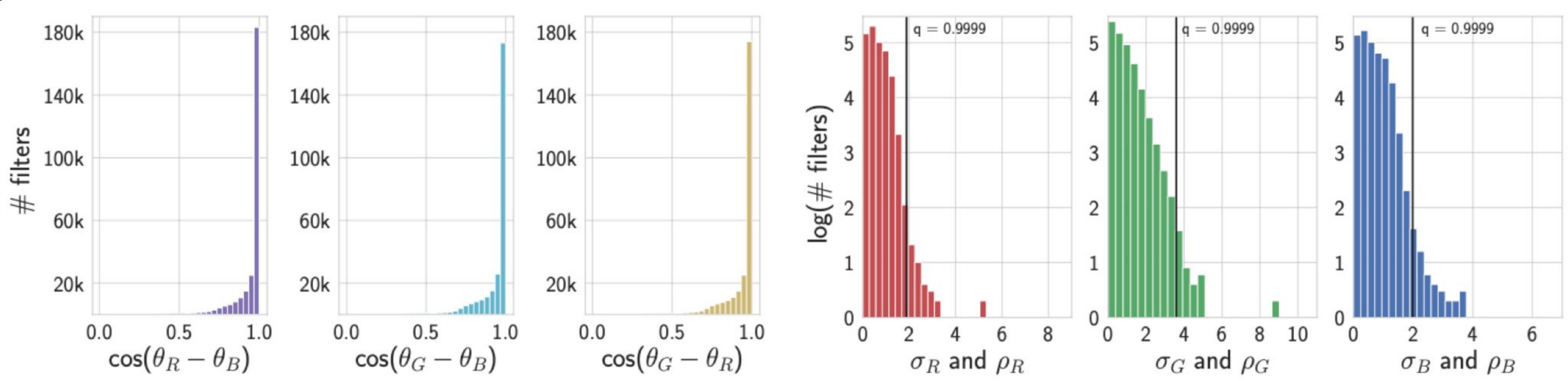


- Optical aberration correction usually happens in the ISP pipeline, after denoising and demosaicking.
- After analysis of the aberration, we decompose them into blur and warp.
- We address these two issues in two separate steps:
  - **Blind Gaussian deblurring:** we remove simple small parametric blurs.
  - **Edge correction:** we correct the remaining red and blue shifted edges.

Gaussian blind deblurring

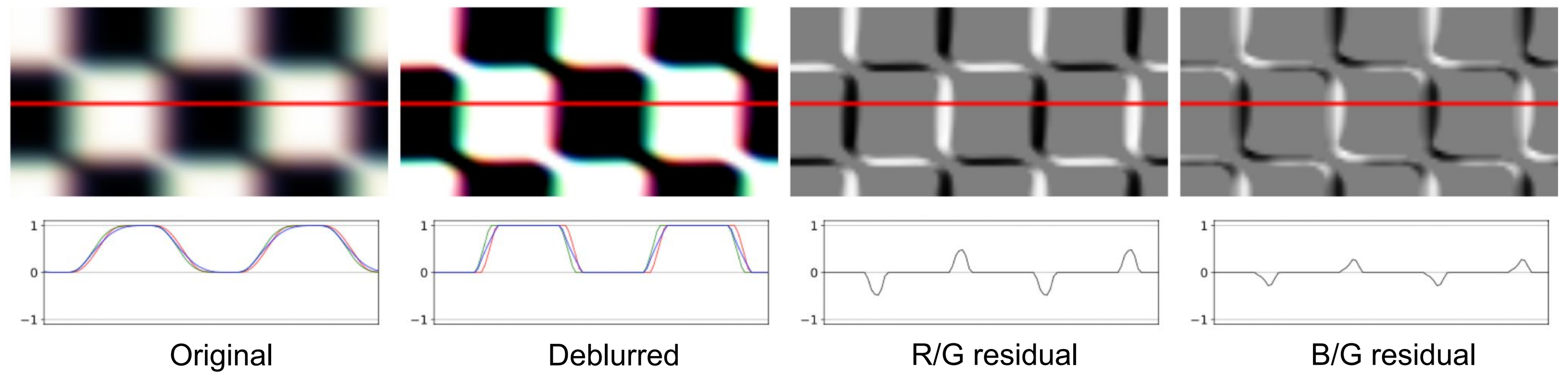


- We show from 273K calibrated local PSFs [Bauer et al., ICCP'18] the blurs may be approximated with Gaussian blurs [Kee et al., ICCP'11].
- The standard deviation is mainly smaller than 4 and the orientations are the same across the colors.
- The monochromatic blurs may be removed by a blind Gaussian deblurrer.
- We use Polyblur [Delbracio et al. TCI'21].



(a) Assumption on θ_c. (b) Assumption on σ_c and ρ_c.

Red and blue edge correction

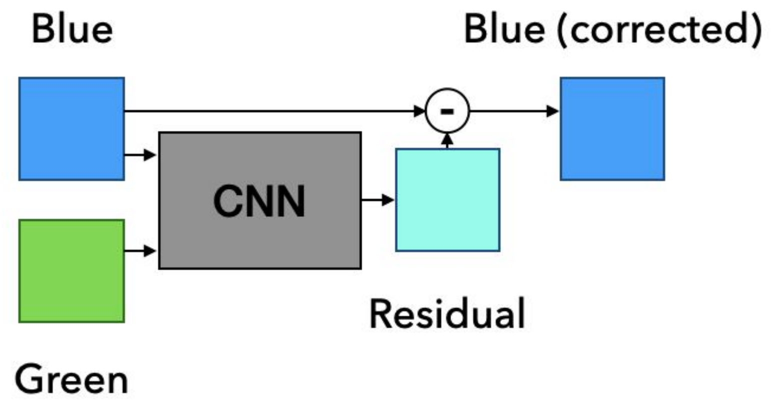


- The chromatic aberrations result in color fringes next to the salient edges.
- According to [Cheng et al., TIP'13] the red-green and blue-green color residuals are good detectors of the chromatic aberrations.
- Therefore, after deblurring, we correct the chromatic aberrations.
- We propose a CNN and a training loss tailored to correct color fringes.

CNN architecture

$$\widehat{u}_c = z_c - \phi_\nu(z_c, z_G)$$

- We design a residual CNN.
- It takes as input two color channels.
- We take the green image as the reference and restore the red and blue channels.
- It predicts a red or blue residual to be subtracted to the red or blue input channel.



Training loss

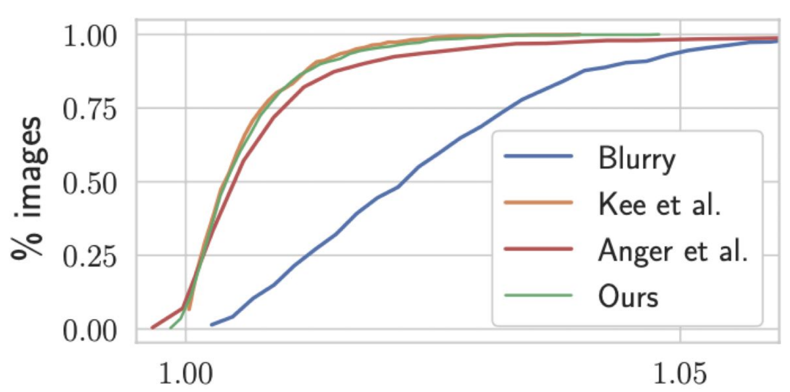
- A typical training loss compares the pixel colors of the images.
- We instead minimize the color residuals of the prediction and the target to favor **achromatic** edges.

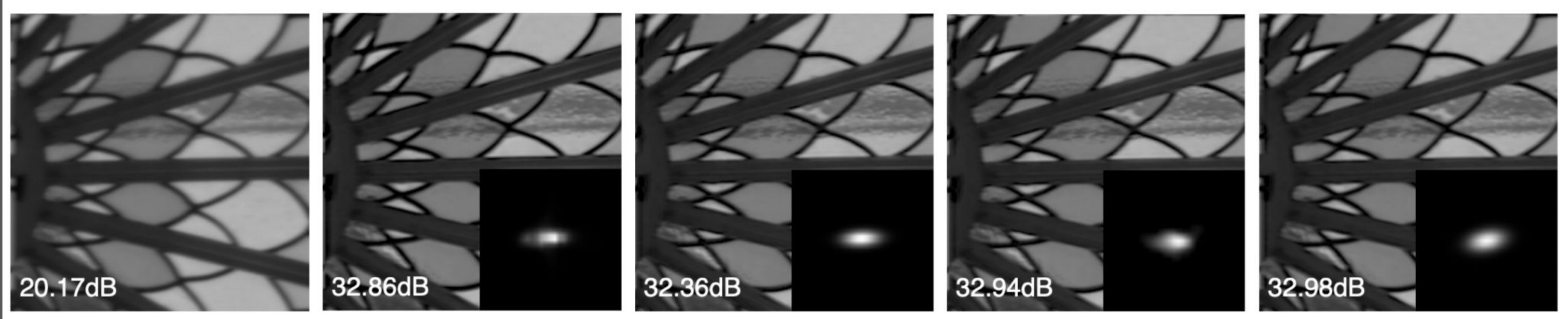
$$\sum_{i=1}^{N} \sum_{c\in\{R,B\}} \left\| \left(u_c^{(i)} - u_G^{(i)}\right) - \left(z_c^{(i)} - \phi_\nu(z_c^{(i)}, z_G^{(i)}) - z_G^{(i)}\right) \right\|_1$$

Validation of deblurring

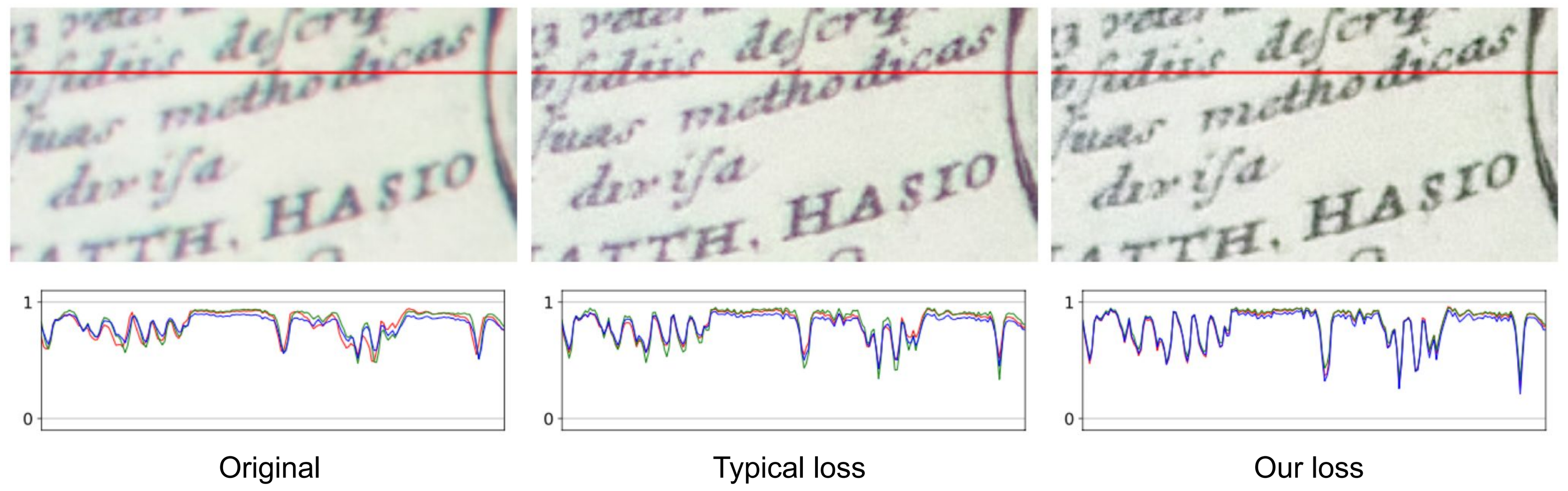
- We valide the Gaussian blur assumption for local PSF correction.
- We compare our approach to parametric [Kee et al., ICCP'11] and non-parametric [Anger et al., IPOL'19] blind deblurring.
- We achieve similar results to Anger et al.'s and GT kernel inversions.
- We are much faster than Anger et al. while being as accurate.

$$R(\widehat{g_G}, g_G) = \frac{\mathrm{SSIM}[p(g_G) * v, u] + 2}{\mathrm{SSIM}[p(\widehat{g_G}) * v, u] + 2}$$



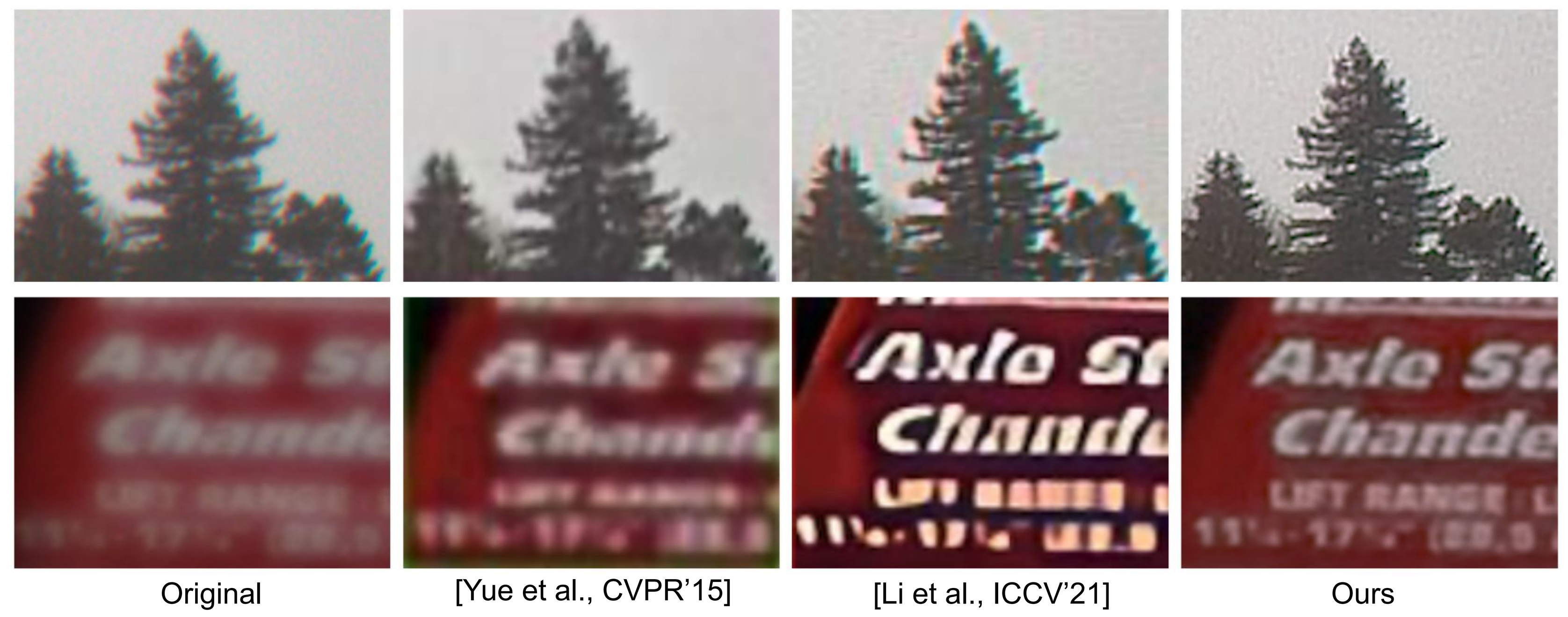


Impact of the training loss



- We trained two networks: with the typical image difference loss and our proposed residual difference loss.
- Predictions with the typical approach: the images show color tints next to the edges.
- Predictions with our approach: the images have salient edges that are much more achromatic.

Optical aberration removal results

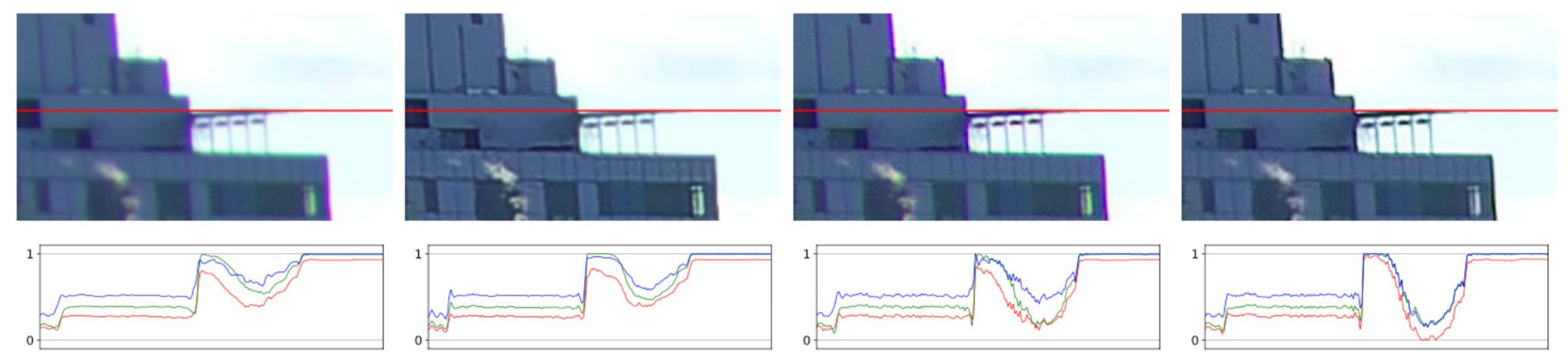


- Comparison with SOTA optimization and CNN optical aberration removal methods.
- We do much better while being faster than [Li et al., ICCV'21] by order of magnitudes.

Method	Time (s)	Flops	Params	Mem. (Gb)
[1]	29.1	27.3T	17.09M	8.9
Ours	**1.7**	**33.1G**	**0.16M**	**2.4**

Table 1. Speed and efficiency for a 6000×4000 image.

- In particular, we get rid of all the chromatic aberrations thanks to our edge filtering formulation.
- **Limitations:** we do not perfectly restore purple fringes (optical aberration + saturation) and blurs not captured by Gaussian blurs.



Conclusion

- We have presented a fast two-stage blind approach to optical aberration removal.
- We decompose the problem into blind Gaussian deblurring and defringing.
- We are much faster than the SOTA while being more accurate.
- Moving from the Gaussian blur model is left to future work.

Paper and code