



Blind deconvolution algorithm for image deblurring

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Problem statement: Motion Blur



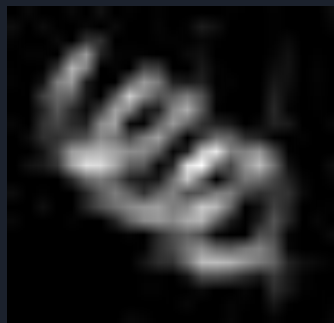
This kind of image corruption arise every time a photographer tries to make a picture in low light conditions with long exposure and without tripod.

Example of blurred image from cambridge-colour.com

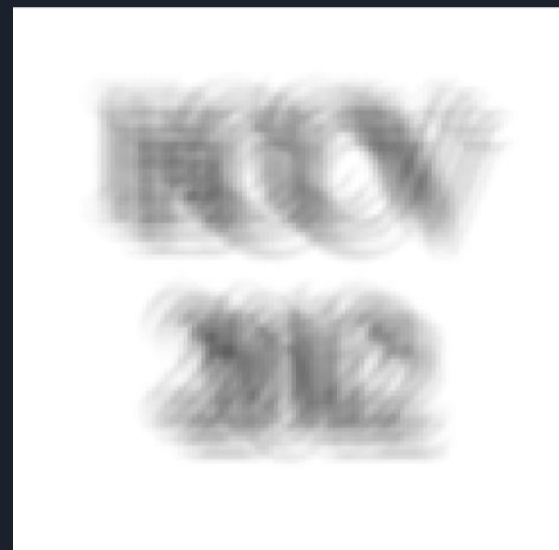
Blur as a Convolution



Initial image



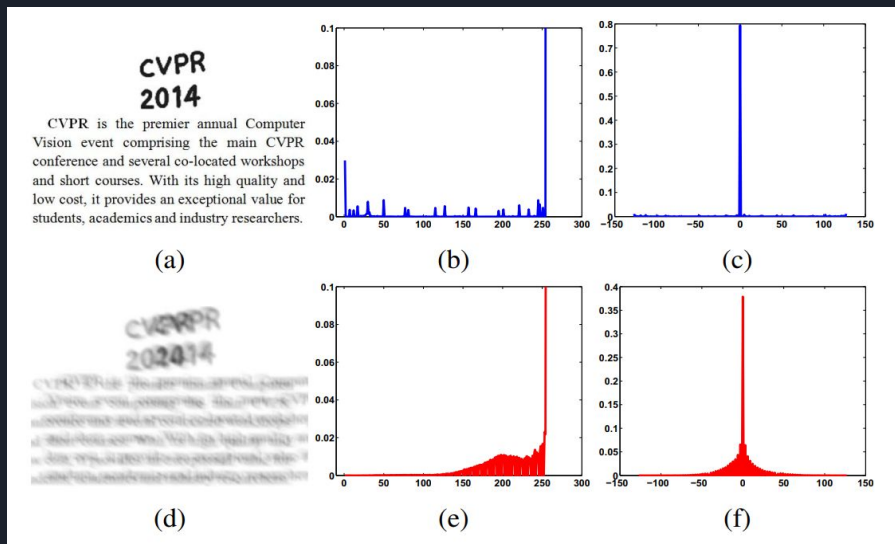
Blur kernel
(motion trajectory)



Corrupted image

Methodology

Pixel intensities and pixel gradients for clean and blurred images:



Statistics of text images. (a) clean text image. (b) histogram of pixel intensities from (a). (c) histogram of horizontal gradients from (a). (d) blurred image. (e) histogram of pixel intensities from (d). (f) histogram of horizontal gradients from (d). [1]

- Pixel values of a sharp text image are very sparse and the distribution of pixel intensities has two peaks (near 0 and 255).
- Pixel values of a blurred text image are more dense and pixel intensity distribution does not contain the zero peak.
- The same situation holds for values of image gradients.
- With these criteria we can differentiate clean and blurred images.



Methodology

One of the subproblems for (3) with auxiliary variables u and g to x and ∇x respectively:

$$\min_{x,u,g} \|x * k - y\|_2^2 + \beta \|x - u\|_2^2 + \mu \|\nabla x - g\|_2^2 + \lambda (\sigma \|u\|_0 + \|g\|_0) \quad (6)$$

Solution:
$$x = \mathcal{F}^{-1} \left(\frac{\overline{\mathcal{F}(k)}\mathcal{F}(y) + \beta\mathcal{F}(u) + \mu\mathcal{F}_G}{\overline{\mathcal{F}(k)}\mathcal{F}(k) + \beta + \mu\overline{\mathcal{F}(\nabla)}\mathcal{F}(\nabla)} \right) \quad (7)$$



Methodology

$$P_t(x) = \|x\|_0 \quad (1)$$

L0-regularized prior for text image deblurring:

$$P(x) = \sigma P_t(x) + P_t(\nabla x) \quad (2)$$



Methodology

Optimization problem for text deblurring via L0-regularized prior:

$$\min_{x,k} \|x * k - y\|_2^2 + \gamma \|k\|_2^2 + \lambda P(x) \quad (3)$$

where x and y denote the latent and blurred images, respectively; k is a blur kernel with the convolution operator $*$ and L_2 regularized term $\|k\|_2^2$; and γ and λ are the weights.



Methodology

We obtain the solution for (3) by alternatively solving following subproblems:

$$\min_x \|x * k - y\|_2^2 + \lambda P(x) \quad (4)$$

$$\min_k \|x * k - y\|_2^2 + \gamma \|k\|_2^2 \quad (5)$$

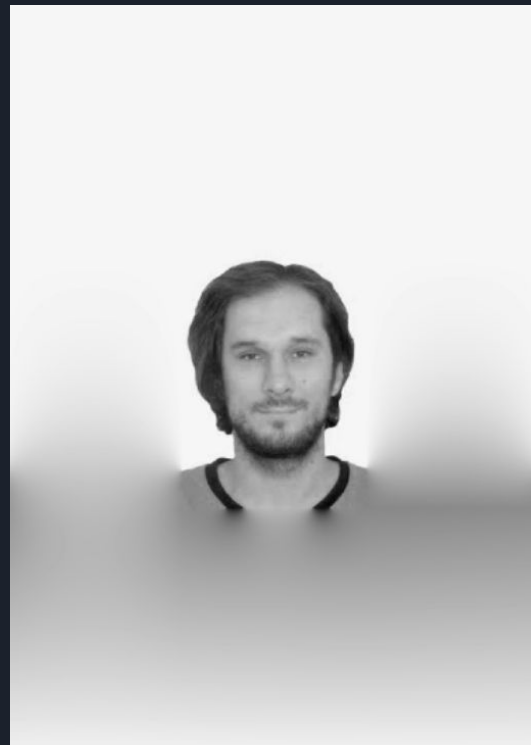
Padding for reducing boundary artifacts:



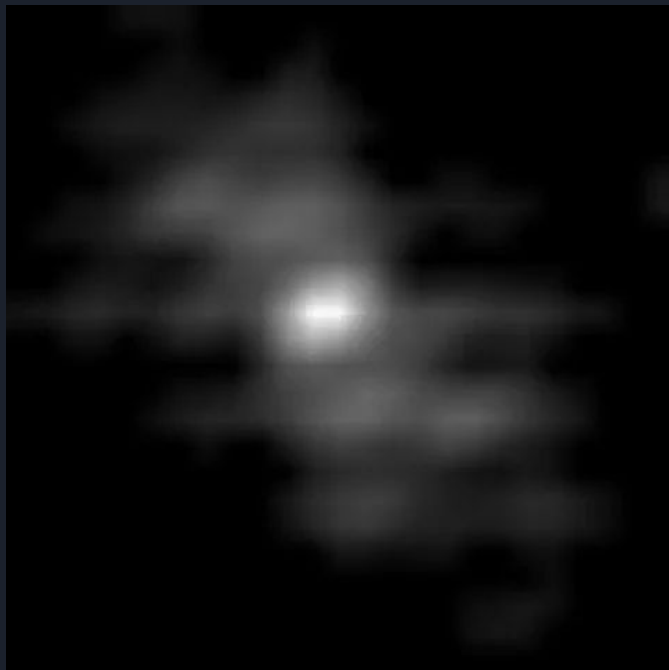
Block padding

1. Continuity
2. Continuity of gradient
3. Reflectivity

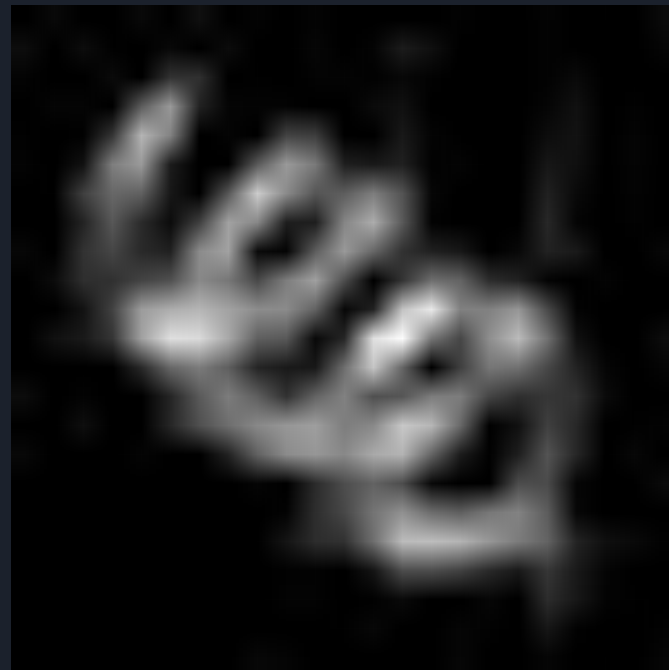
$$\min (\|\Delta A\|^2 + \lambda \|A - A'\|_{\partial A}^2)$$



Results obtained: Kernel estimation



Iterations



Real kernel

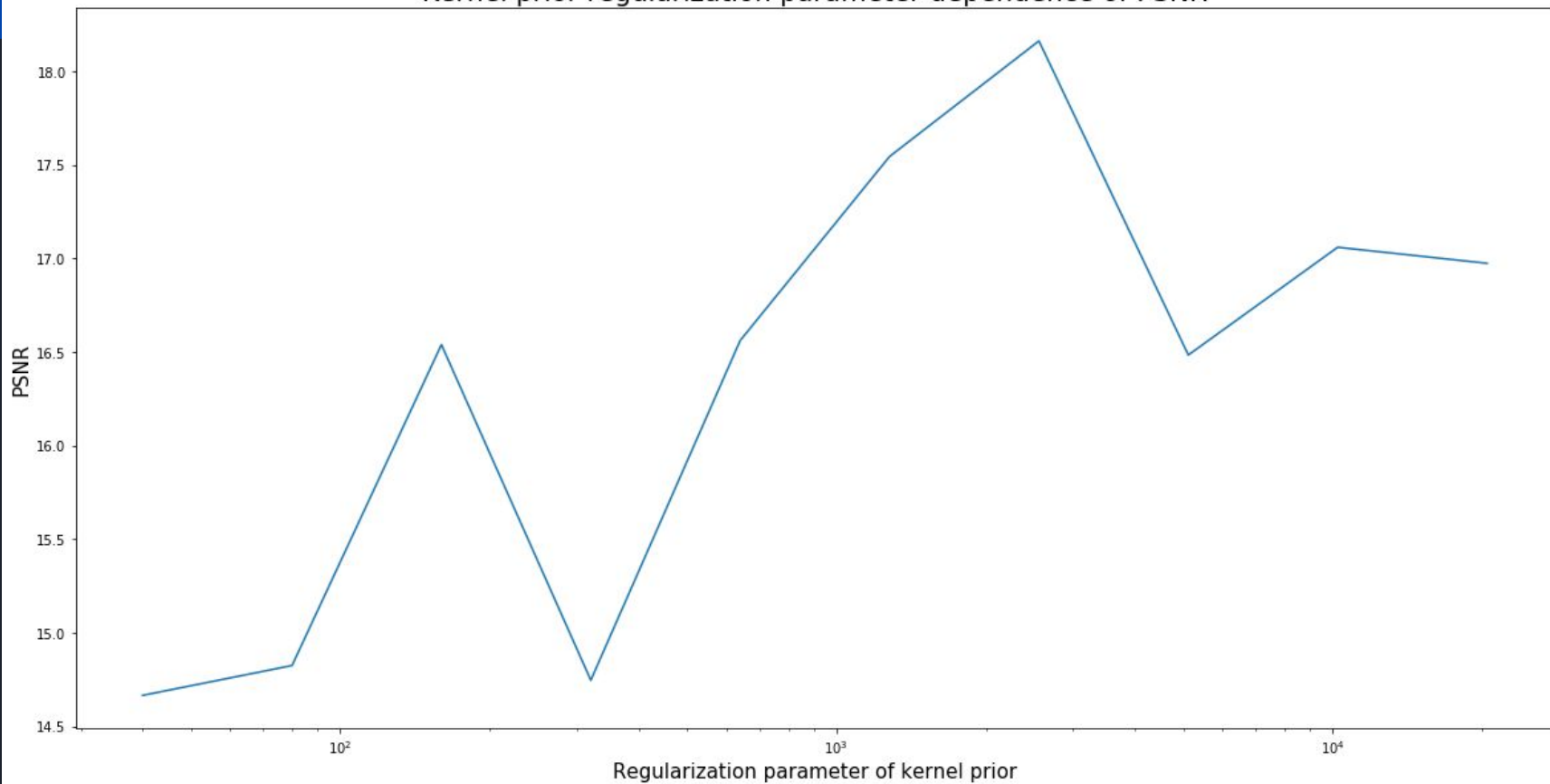


Results obtained



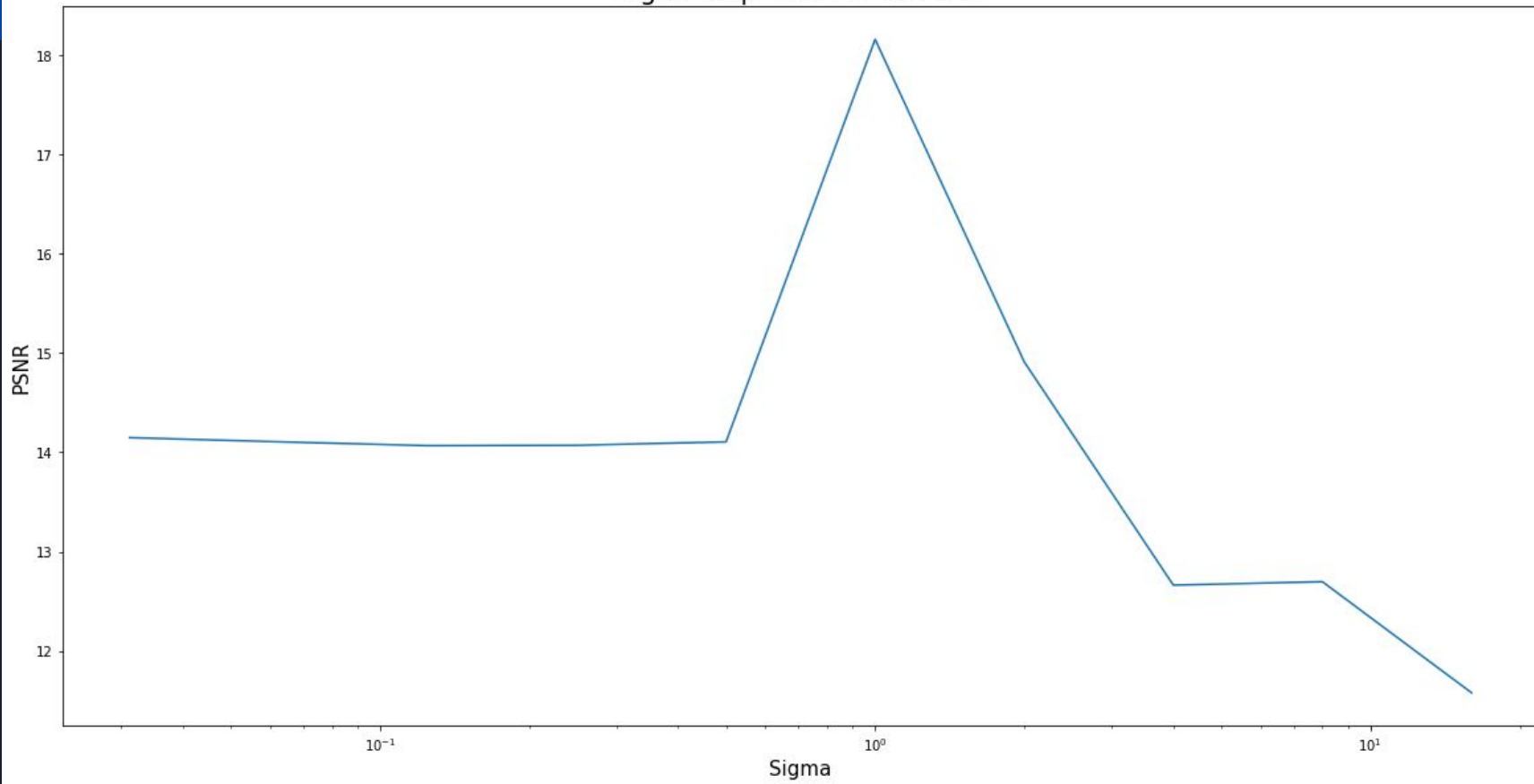
$$\min_{x,k} \|x * k - y\|_2^2 + \gamma \|k\|_2^2 + \lambda(\sigma P_t(x) + P_t(\nabla x))$$

Kernel prior regularization parameter dependence of PSNR



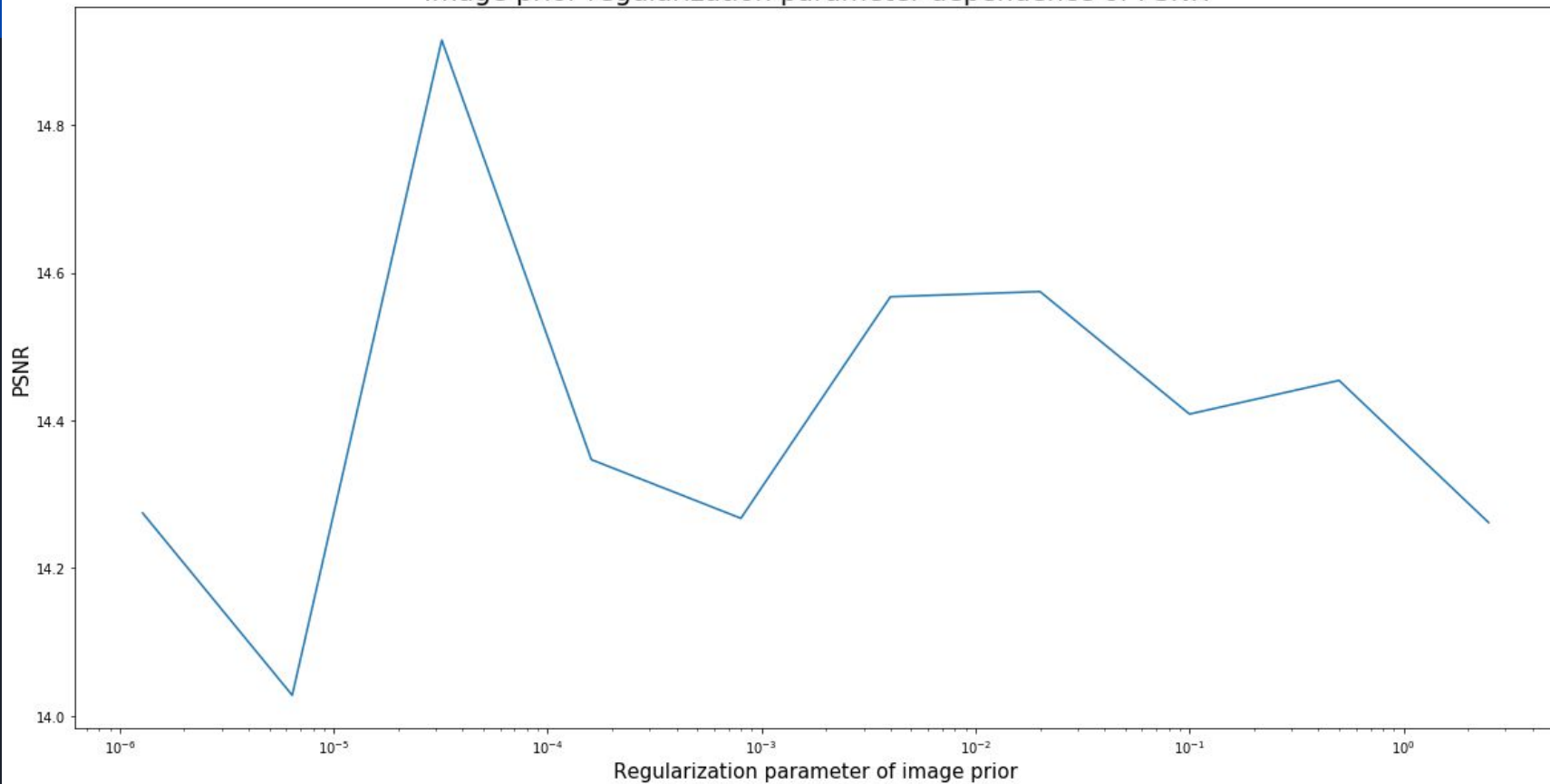
$$\min_{x,k} \|x * k - y\|_2^2 + \gamma \|k\|_2^2 + \lambda \sigma P_t(x) + P_t(\nabla x)$$

Sigma dependence of PSNR



$$\min_{x,k} \|x * k - y\|_2^2 + \gamma \|k\|_2^2 + \lambda(\sigma P_t(x) + P_t(\nabla x))$$

Image prior regularization parameter dependence of PSNR





Conclusion

- Accurate Blur kernel approximation
- Restoring blurred text image avoiding boundary artifacts
- Found appropriate parameters for algorithm



Sources

1. Jinshan Pan, Zhe Hu, Zhixun Su, Ming-Hsuan Yang. Deblurring text images via L0-regularized intensity and gradient prior. IEEE Conference on computer vision and pattern recognition. 2014
2. Renting Liu, Jiaya Jia, Reducing Boundary Artifacts in Image Deconvolution

https://docs.google.com/presentation/d/1HuNz13GFIfU6qvkzAYh3wg_yg3S7EuV44ECI-fs4SYM/edit#slide=id.p