# BLIND IMAGE DEBLURRING VIA REWEIGHTED GRAPH TOTAL VARIATION

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## BACKGROUND

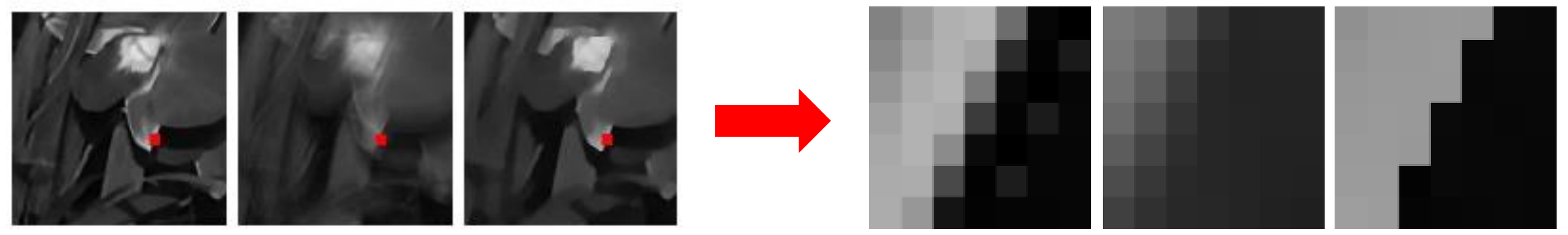
- Image blur model: $\mathbf{b} = \mathbf{k} \otimes \mathbf{x} + \mathbf{n}$, where $\otimes$ is a convolution process.
- Blind image deblurring (BID) is to recover both the latent sharp image $\mathbf{x}$ and blur kernel $\mathbf{k}$, from only blurry observation $\mathbf{b}$ with noise $\mathbf{n}$.
  - highly ill-posed problem because the feasible solution is not only **unstable to noise** but also **non-unique**.
  - Previous image priors either can't solve BID [1] or suffer from high complexity. [2]
- Previous graph Laplacian regularizer [3] in GSP has shown to promote piecewise-smooth (PWS) recovered signal behavior.
  - We explore the relationship between graph and image blur, and propose a graph-based prior for blind image deblurring.

## OBSERVATION AND MOTIVATION

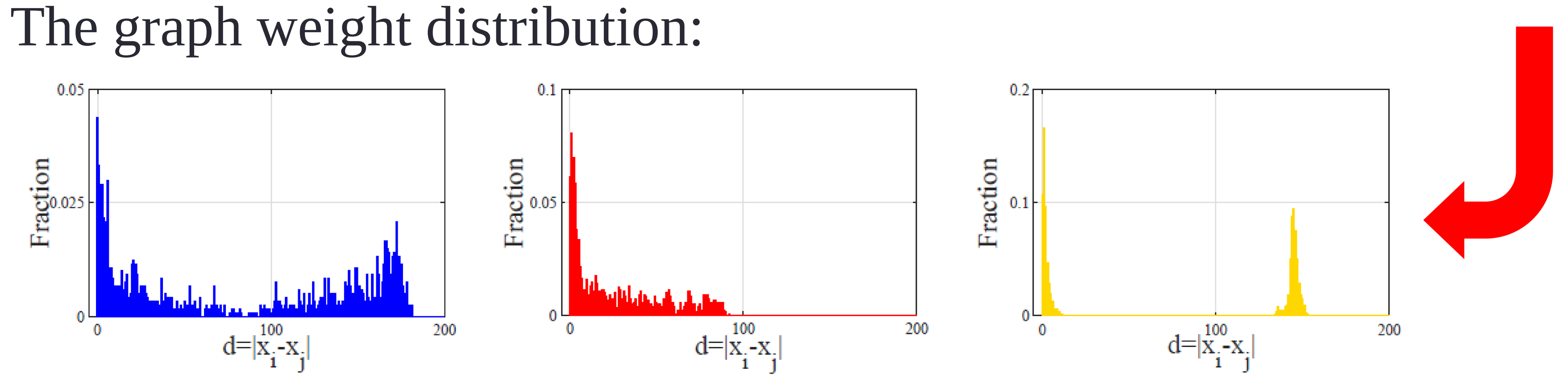
- Graph weight is defined using Gaussian kernel:

$$[\mathbf{W}]_{i,j} = w_{i,j} = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{\sigma^2}\right)$$

- A **skeleton image** is proposed as a proxy, which is a PWS version of the original image that preserves strong edges while removes textural details.



- The graph weight distribution:




- Observation:
  - Sharp patch and its skeleton version have bi-modal distribution.
  - Bi-modal distribution of skeleton image is more desirable.

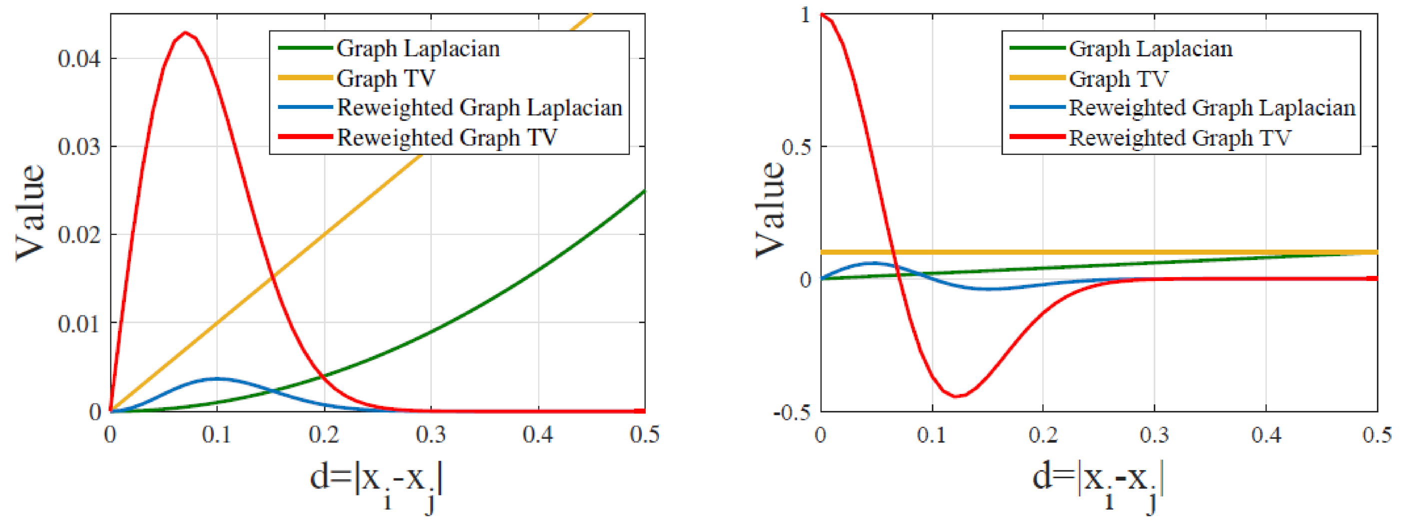
## REWEIGHTED GRAPH TOTAL VARIATION PRIOR

- We propose a novel reweighted graph total variation (RGTV) prior that can promote bi-modal distribution

$$\|\mathbf{x}\|_{RGTV} = \sum_{i \in V} \left\| \operatorname{diag}\left(\mathbf{W}_{i,\cdot}(\mathbf{x})\right) \nabla_i \mathbf{x} \right\|_1$$

$$= \sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,j}(x_i, x_j) |x_j - x_i|$$

- Different from conventional graph total variation (GTV) [4] with fixed weights, the weights of RGTV are also functions of x, which promotes bi-modal weight distribution.




## BLIND IMAGE DEBLURRING ALGORITHM

- The objective function for blind image deblurring:

$$\hat{\mathbf{x}}, \hat{\mathbf{k}} = \arg\min_{\mathbf{x},\mathbf{k}} \frac{1}{2} \|\mathbf{k} \otimes \mathbf{x} - \mathbf{b}\|_2^2 + \lambda \|\mathbf{x}\|_{RGTV} + \mu \|\mathbf{k}\|_2^2$$

- We alternatingly solve the sub-problem:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \frac{1}{2} \|\mathbf{k} \otimes \mathbf{x} - \mathbf{b}\|_2^2 + \lambda \|\mathbf{x}\|_{RGTV}$$

with a prime-dual algorithm [5] and the sub-problem

$$\hat{\mathbf{k}} = \arg\min_{\mathbf{k}} \frac{1}{2} \|\mathbf{k} \otimes \mathbf{x} - \mathbf{b}\|_2^2 + \mu \|\mathbf{k}\|_2^2$$

which has closed-form solution.

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## EXPERIMENTAL RESULTS

- **Artificial Cases**. Each sharp image convolves with a 7×7 blur kernel

  - Quantitative Comparisons (PSNR:dB):

| Methods | Butterfly | Lena | Parrot |
|---|---|---|---|
| Krishnan et al. | 29.4 | 28.9 | 29.3 |
| Levin et al. | 29.9 | 29.4 | 29.2 |
| Michaeli & Irani | 30.6 | 30.3 | 31.9 |
| Pan et al. | 30.4 | 30.8 | 32.0 |
| Ours | 30.8 | 31.0 | 32.7 |

- **Real Blurred Images.**

(a) Blurry Input. (b) Kirshnan et al. (c) Levin et al.

(d) Michaeli & Irani (e) Pan et al. (f) RGTV.

## REFERENCES

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