MacSeNet
Machine Sensing Training Network

BLIND IMAGE DEBLURRING USING CLASS-ADAPTED IMAGE PRIORS

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Introduction - Blind Image Deblurring

- Observation model: $\mathbf{y} = \mathbf{H}\,\mathbf{x} + \mathbf{n}$

  $\mathbf{y} \in \mathbb{R}^n$ - observed image; $\mathbf{x} \in \mathbb{R}^n$ - (underlying) sharp image;
  $\mathbf{H} \in \mathbb{R}^{n \times n}$ - observation matrix; $\mathbf{n}$ - Gaussian noise (zero mean and known variance σ^2).

- Different images have different structure[1].

- Different causes of blur.

[1] *Images*. URL: https://www.dreamstime.com/.

- Severely ill-posed problem!
- Prior information on both the sharp image and the blur.
- **Problem:** Image priors are usually tailored for natural images.
- In many applications, the image being recovered is known to belong to some specific class: text, face, fingerprints.

- **The challenge:** Class-adapted image priors.

Proposed method

Objective function

$$O_\lambda(\mathbf{x},\mathbf{h}) = \frac{1}{2}||\mathbf{y} - \mathbf{H}\,\mathbf{x}||_2^2 + \lambda\phi(\mathbf{x}) + \Psi_S(\mathbf{h})$$

- $\phi(\mathbf{x})$ - prior on the image: **Gaussian mixture model (GMM).**
- $\lambda \geq 0$ - regularization parameter.
- $\Psi_S(\mathbf{h})$ - weak prior on the blurring filter: set of filters with positive entries on a given support.

$$\Psi_S(\mathbf{u}) = \begin{cases} 0 & \text{if } \mathbf{u} \in S \\ \infty & \text{if } \mathbf{u} \notin S \end{cases}$$

Proposed method - BID Algorithm

- **Alternating estimation** of the image and the blurring filter.

Algorithm 1 BID Algorithm

Input: Blurred image $\mathbf{y}$

Output: Estimated sharp image $\hat{\mathbf{x}}$ and the blur kernel $\hat{\mathbf{h}}$

1: **Initialization**: $\hat{\mathbf{x}} = \mathbf{y}$, $\hat{\mathbf{h}}$ set to the identity filter, $\lambda > 0$
2: **repeat**
3: $\quad \hat{\mathbf{x}} \leftarrow \underset{\mathbf{x}}{\operatorname{argmin}} \; O_\lambda(\mathbf{x}, \hat{\mathbf{h}})$ {estimating $\mathbf{x}$ with $\mathbf{h}$ fixed}
4: $\quad \hat{\mathbf{h}} \leftarrow \underset{\mathbf{h}}{\operatorname{argmin}} \; O_\lambda(\hat{\mathbf{x}}, \mathbf{h})$ {estimating $\mathbf{h}$ with $\mathbf{x}$ fixed}
5: **until** stopping criterion is satisfied

- Solver for each minimization: alternating direction method of multipliers (**ADMM**).

ADMM: a quick review

- **Variable splitting**

Unconstrained problem:

$$\min_{\mathbf{z}} \; f_1(\mathbf{z}) + f_2(\mathbf{z})$$

Constrained problem:

$$\min_{\mathbf{z},\mathbf{v}} \; f_1(\mathbf{z}) + f_2(\mathbf{v}) \quad \text{subject to} \quad \mathbf{z} = \mathbf{v}$$

The so-called augmented Lagrangian function:

$$\hat{\mathbf{z}}, \hat{\mathbf{v}} \leftarrow \min_{\mathbf{z},\mathbf{v}} \; f_1(\mathbf{z}) + f_2(\mathbf{v}) + \mathbf{d}^T(\mathbf{z} - \mathbf{v}) + \frac{\mu}{2}||\mathbf{z} - \mathbf{v}||_2^2$$

ADMM: a quick review

Minimize alternatingly the augmented Lagrangian function (over $\mathbf{z}$ and $\mathbf{v}$).

Update the vector of Lagrange multipliers $\mathbf{d}$.

Algorithm 2 ADMM

1: **Initialization**: Set $k = 0$, $\mu > 0$, initialize $\mathbf{v}_0$ and $\mathbf{d}_0$
2: **repeat**
3: $\quad \mathbf{z}^{k+1} \leftarrow \min_{\mathbf{z}} \; f_1(\mathbf{z}) + \frac{\mu}{2}||\mathbf{z} - \mathbf{v}^k - \mathbf{d}^k||_2^2$
4: $\quad \mathbf{v}^{k+1} \leftarrow \min_{\mathbf{v}} \; f_2(\mathbf{v}) + \frac{\mu}{2}||\mathbf{z}^{k+1} - \mathbf{v} - \mathbf{d}^k||_2^2$
5: $\quad \mathbf{d}^{k+1} \leftarrow \mathbf{d}^k - (\mathbf{z}^{k+1} - \mathbf{v}^{k+1})$
6: $\quad k \leftarrow k + 1$
7: **until** stopping criterion is satisfied

Plug-and-play approach

- The proximity operator (PO) of some convex function g, computed at the point $\mathbf{u}$:

$$\text{prox}_g(\mathbf{u}) = \underset{\mathbf{x}}{\text{argmin}} \; \frac{1}{2}||\mathbf{x} - \mathbf{u}||_2^2 + g(\mathbf{x})$$

- This can be considered as the solution to a denoising problem.
- Plug-and-play: PO of a convex regularizer can be replaced with a state-of-the-art denoiser[2].
- **Proposal**: Class-adapted GMM-based denoiser.

[2] S. V. Venkatakrishnan, C. A. Bouman, and B. Wohlberg. "Plug-and-Play priors for model based reconstruction". In: *IEEE Global Conference on Signal and Information Processing*. 2013.

Image Estimate

Image estimation problem

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\operatorname{argmin}} \ \frac{1}{2}||\mathbf{y} - \mathbf{H}\,\mathbf{x}||_2^2 + \lambda\phi(\mathbf{x})$$

- Applying ADMM to this problem, yields to the so-called SALSA algorithm[3].
- Line 3 of Algorithm 2 becomes a quadratic optimization problem, with a closed form solution (efficiently computed via FFT):

$$\mathbf{x}^{k+1} = (\mathbf{H}^T\mathbf{H} + \mu\mathbf{I})^{-1}(\mathbf{H}^T\mathbf{y} + \mu(\mathbf{v}^k + \mathbf{d}^k))$$

- Line 4 of Algorithm 2 replaced with a state-of-the-art denoiser by following the plug-and-play approach.

[3] M. V. Afonso, J. M. Bioucas-Dias, and M. A. T. Figueiredo. "Fast Image Recovery Using Variable Splitting and Constrained Optimization". In: *IEEE Transactions on Image Processing* (2010).

Blur Estimate

Blur estimation problem

$$\hat{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{argmin}} \; \frac{1}{2}||\mathbf{y} - \mathbf{X}\,\mathbf{h}||_2^2 + \Psi_S(\mathbf{h})$$

- Line 4 of Algorithm 2 becomes

$$\text{prox}_{\Psi_S}(\mathbf{u}) = P_S(\mathbf{u}),$$

which sets to zero all negative elements and any elements outside the given support.

Results: text images

- Blurring filters: 1 - Gaussian, 2 - linear motion, 3- out-of-focus, 4- uniform, and 5- nonlinear motion blur.

Table: Results in terms of ISNR for **text** images (BSNR = 30 dB).

Experiment	1	2	3	4	5
Almeida *et al.*[4]	0.78	0.86	0.46	0.79	0.59
Krishnan *et al.*[5]	1.62	0.12	-	-	0.94
PlugBM3D	7.23	8.68	8.19	8.94	13.08
PlugGMM	**8.88**	**8.99**	**9.40**	**11.48**	**16.44**

[4] M. S. C. Almeida and M. A. T. Figueiredo. "Blind image deblurring with unknown boundaries using the alternating direction method of multipliers". In: *ICIP*. 2013.

[5] D. Krishnan, T. Tay, and R. Fergus. "Blind deconvolution using a normalized sparsity measure". In: *CVPR*. 2011.

Results: face images

- Blurring filters: 1 - Gaussian, 2 - linear motion, 3- out-of-focus, 4- uniform, and 5- nonlinear motion blur.

Table: Results in terms of ISNR for **face** images (BSNR = 40 dB).

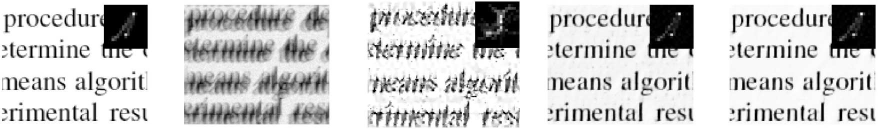
Experiment	1	2	3	4	5
Almeida *et al.*[6]	4.31	1.81	2.86	0.85	4.43
Krishnan *et al.*[7]	0.55	0.12	-	-	0.37
PlugBM3D	6.64	4.86	6.78	**8.50**	5.94
PlugGMM	**7.10**	**5.30**	**8.95**	7.07	**7.33**

[6] M. S. C. Almeida and M. A. T. Figueiredo. "Blind image deblurring with unknown boundaries using the alternating direction method of multipliers". In: *ICIP*. 2013.

[7] D. Krishnan, T. Tay, and R. Fergus. "Blind deconvolution using a normalized sparsity measure". In: *CVPR*. 2011.

Results: strong noise

- Text image corrupted with nonlinear motion blur[8] and strong noise (BSNR = 20 dB).



(a) (b) (c) (d) (e)

Figure: (a) Original image and ground truth kernel; (b) Blurred image; (c) Pan *et al.*[9], ISNR = -2.72; (d) PlugBM3D, ISNR = 9.97; (e) PlugGMM, ISNR = **11.16**.

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[8] A. Levin et al. “Understanding and evaluating blind deconvolution algorithms”. In: *CVPR*. 2009.

[9] J. Pan et al. “Deblurring text images via L0-regularized intensity and gradient prior”. In: *CVPR*. 2014.

Results: fingerprints

- Fingerprint image corrupted with linear motion blur (40 dB noise).

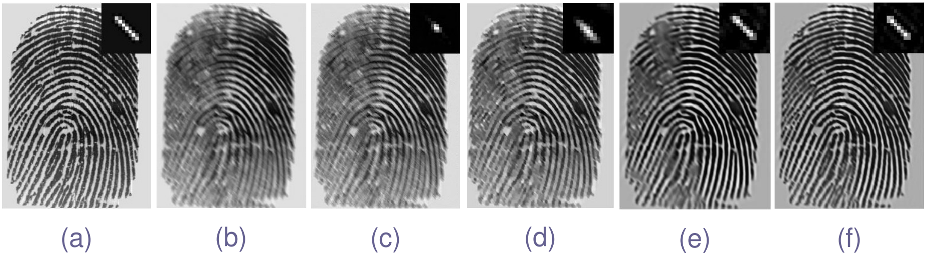

Figure: (a) Original image and ground truth kernel; (b) Blurred image; (c) Almeida *et al.*[10], ISNR = 0.36; (d) Krishnan *et al.*[11], ISNR = -0.64; (e) PlugBM3D, ISNR = 0.56; (f) PlugGMM, ISNR = **1.19**.

[10] M. S. C. Almeida and M. A. T. Figueiredo. “Blind image deblurring with unknown boundaries using the alternating direction method of multipliers”. In: *ICIP*. 2013.

[11] D. Krishnan, T. Tay, and R. Fergus. “Blind deconvolution using a normalized sparsity measure”. In: *CVPR*. 2011.

Conclusion

Summary:

- Gaussian mixture model (GMM) based denoisers, adapted to specific image classes.
- State-of-the-art results when applied to images that belong to a specific class.
- Proposed method can be used for a variety of blurring filters.
- Method is able to handle strong noise in the case of images known to contain text.

Ongoing work:

- Setting of the regularization parameter.
- Stopping criteria for the inner ADMM algorithms, as well as for the outer iterations.

References

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- Levin, A. et al. "Understanding and evaluating blind deconvolution algorithms". In: *CVPR*. 2009.
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Acknowledgements

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