BLIND IMAGE DEBLURRING USING CLASS-ADAPTED IMAGE PRIORS

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Introduction - Blind Image Deblurring

- Observation model: $y = Hx + n$
  
  $y \in \mathbb{R}^n$ - observed image;  
  $x \in \mathbb{R}^n$ - (underlying) sharp image;  
  $H \in \mathbb{R}^{n \times n}$ - observation matrix;  
  $n$ - Gaussian noise (zero mean and known variance $\sigma^2$).

- Different images have different structure$^1$.

- Different causes of blur.

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$^1$Images. URL: https://www.dreamstime.com/.
Introduction

- 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

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

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

\[
\Psi_S(u) = \begin{cases} 
0 & \text{if } u \in S \\
\infty & \text{if } u \notin S
\end{cases}
\]
Proposed method - BID Algorithm

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

**Algorithm 1 BID Algorithm**

**Input:** Blurred image $y$

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

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

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

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ADMM: a quick review

- **Variable splitting**

  Unconstrained problem:

  \[
  \min_z f_1(z) + f_2(z)
  \]

  Constrained problem:

  \[
  \min_{z,v} f_1(z) + f_2(v) \quad \text{subject to} \quad z = v
  \]

  The so-called augmented Lagrangian function:

  \[
  \hat{z}, \hat{v} \leftarrow \min_{z,v} f_1(z) + f_2(v) + d^T(z - v) + \frac{\mu}{2}||z - v||^2_2
  \]
Minimize alternatingly the augmented Lagrangian function (over $z$ and $v$).

Update the vector of Lagrange multipliers $d$.

**Algorithm 2 ADMM**

1: **Initialization**: Set $k = 0$, $\mu > 0$, initialize $v_0$ and $d_0$
2: repeat
3: $z^{k+1} \leftarrow \min_z f_1(z) + \frac{\mu}{2} ||z - v^k - d^k||^2_2$
4: $v^{k+1} \leftarrow \min_v f_2(v) + \frac{\mu}{2} ||z^{k+1} - v - d^k||^2_2$
5: $d^{k+1} \leftarrow d^k - (z^{k+1} - v^{k+1})$
6: $k \leftarrow k + 1$
7: until stopping criterion is satisfied
Plug-and-play approach

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

$$\text{prox}_g(u) = \arg\min_x \frac{1}{2} \|x - u\|^2 + g(x)$$

- 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.

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Image estimation problem

\[ \hat{x} = \arg \min_x \frac{1}{2} \| y - H x \|^2_2 + \lambda \phi(x) \]

- 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):

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

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

Blur estimation problem

\[ \hat{h} = \arg\min_h \frac{1}{2} \| y - X h \|^2_2 + \psi_S(h) \]

- Line 4 of Algorithm 2 becomes

\[ \text{prox}_{\psi_S}(u) = P_S(u), \]

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).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<tbody>
<tr>
<td>Almeida et al.⁴</td>
<td>0.78</td>
<td>0.86</td>
<td>0.46</td>
<td>0.79</td>
<td>0.59</td>
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<tr>
<td>Krishnan et al.⁵</td>
<td>1.62</td>
<td>0.12</td>
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<td>0.94</td>
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<td>PlugBM3D</td>
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<td>8.19</td>
<td>8.94</td>
<td>13.08</td>
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<td>PlugGMM</td>
<td>8.88</td>
<td>8.99</td>
<td>9.40</td>
<td>11.48</td>
<td>16.44</td>
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</tbody>
</table>

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).

<table>
<thead>
<tr>
<th>Experiment</th>
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</thead>
<tbody>
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<td>Almeida et al.</td>
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<td>5.30</td>
<td>8.95</td>
<td>7.07</td>
<td>7.33</td>
</tr>
</tbody>
</table>

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Results: strong noise

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

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: \textit{CVPR}. 2009.

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.\textsuperscript{10}, ISNR = 0.36; (d) Krishnan et al.\textsuperscript{11}, ISNR = -0.64; (e) PlugBM3D, ISNR = 0.56; (f) PlugGMM, ISNR = 1.19.


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


*Images*. URL: https://www.dreamstime.com/


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