Class-Adapted Blind Image Deblurring

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***Abstract*—Over the past few decades, significant progress has been made in solving image deblurring problems; however, most of the developed methods are focused on deblurring of natural images. Specific classes of images, like text, face, fingerprints are found in many important applications, such as document analysis or forensics. State-of-the-art blind image deblurring methods are usually based on edge extraction or on typical statistics of natural images. When there is not much texture in a blurred image (e.g., face images), performance of methods based on edge extraction is limited. On the other hand, methods tailored for natural images do not take into consideration the particular structure of images of a specific class (e.g., text or fingerprints). In this work, we proposed a method with a patch-based class-adapted image prior trained from a dataset which contains clean images of a specific class. Results obtained so far show that the method can be used for at least two specific classes of images: text and face. Additionally, the proposed method uses a week prior on the blurring filter (positivity and support) and, because of that, is able to recover a wide variety of blurring filters.**

I. Introduction

Blind image deblurring (BID) is the process of recovering an (unknown) underlying sharp image and a corresponding blur kernel from a blurred input image. The problem is usually formulated as a linear model of the form $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$, where $\mathbf{y} \in \mathbb{R}^n$ and $\mathbf{x} \in \mathbb{R}^m$ denote the vectorized observed data and the original image, respectively, $\mathbf{H} \in \mathbb{R}^{m\times m}$ is the matrix representing the convolution with the blurring filter $\mathbf{h}$, and $\mathbf{n}$ is noise (assumed to be Gaussian, with zero mean, and known variance σ^2). In recent years, researchers have investigated a variety of approaches to single-image BID with significant advances [1], [2], [3], [4], [5]. To deal with the ill-posed nature of BID, most methods use prior information on both the image and the blurring filter. Probably, the most common approach to build an image prior is to exploit the statistic of natural images [1], [6], [3]. Although this approach gives good results for generic cases, the prior itself is not designed to capture the properties of images of specific classes [7], [8]. Here, we proposed a method that uses a patch-based image prior learned from a dataset of clean images of a specific class. Our method is based on the so-called "plug-and-play" approach recently proposed in [9], where one step of the algorithm for imaging inverse problems is replaced with a state-of-the-art denoiser. In contrast with [9], we do not use fixed denoisers, we use a Gaussian mixture model (GMM) based denoiser learned from patches of clean images that belong to the specific class of interest. Although a similar idea has been recently proposed for non-blind deblurring and compressive imaging [10], here we are showing that it can be used for BID. The rationale behind this approach is that with class-adapted image priors, we may achieve better performance than with a fixed, generic denoiser, when we process images that do belong to the same specific class.

II. Proposed algorithm

The image $\mathbf{x}$ and the blurring operator $\mathbf{H}$ (equivalently, the filter $\mathbf{h}$) are estimated by minimizing the cost function

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

where $\mathbb{1}_{S^+}$ is the indicator function of the set S^+,

$$\mathbb{1}_{S^+}(\mathbf{v}) = \begin{cases} 0 & \text{if } \mathbf{v} \in S^+ \\ \infty & \text{if } \mathbf{v} \notin S^+ \end{cases} \tag{2}$$

and the function ϕ represents prior on the image used to promote characteristics that the underlying sharp image is assumed to have. The parameter λ controls the trade-off between data-fidelity term and the regularizer. As shown in previous work [11], good results can be obtained by alternating estimation of the image and the blur kernel (Algorithm 1). Both estimations are performed by using the alternating direction method of multipliers (ADMM, for a detailed explanation about ADMM for imaging inverse problems, see [12] and [11]). In (1), $\phi(\mathbf{x})$ represents a GMM-based image prior. As shown in [13], clean image patches are well modelled by a GMM which can be estimated from a collection of clean image patches using the expectation maximization (EM) algorithm. With a GMM prior for clean patches, the corresponding minimum mean squared error (MMSE) estimator can be obtained in closed-form (for details, see [14]). In contrast to [13], we propose to learn GMM prior from clean images that belong to a specific class.

III. Experiments

The proposed approach was tested on synthetic data and compared with state-of-the-art deblurring algorithms for generic images [11], [5] and the state-of-the-art BID algorithm for text images [7]. Additionally, instead of the proposed class-adapted GMM-based denoiser (PlugGMM), we consider the fixed state-of-the-art block-matching 3D (BM3D) denoiser [15] plugged into ADMM (PlugBM3D). We tested our method on text and face images provided by the author of [16] with five experiments constructed for synthetic data (with Gaussian, linear motion, out-of-focus, uniform, and nonlinear motion kernels, respectively) with different noise levels (Table I, Figure 1, Table II and Figure 2). Results of the experiments performed with BM3D and GMM-based denoisers are visually similar but the PlugGMM method clearly outperform the PlugBM3D method in terms of the ISNR. In all experiments, the parameter λ was hand-tuned for the best results.

IV. Conclusion

We have presented a blind image deblurring method based on the plug-and-play approach with class-adapted image priors (denoisers) based on Gaussian mixture models. Results obtained so far on two specific classes of images (face and text) show that the proposed method outperforms state-of-the-art methods constructed for generic images. Also, experiments performed on synthetic data show that the presented method can be used to recover a variety of blurring filters.

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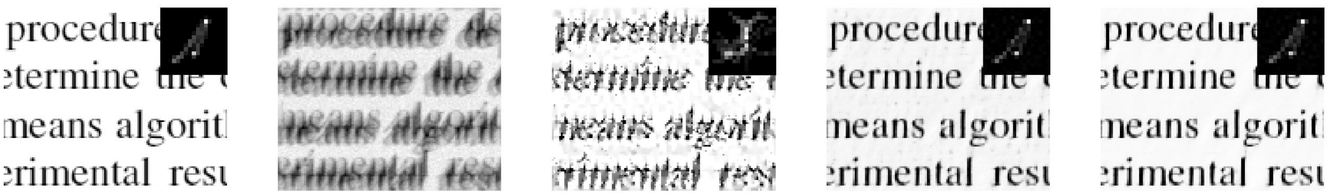
(a) Clean image (b) Blurred image (c) Almeida *et al.* [11] (d) PlugBM3D (e) PlugGMM

Fig. 1: Face image blurred with out-of-focus blur and BSNR = 30 dB: (a) Original image and kernel; (b) Blurred image; (c) Results of [11], ISNR = 3.62; (d) PlugBM3D, ISNR = 4.79; (e) PlugGMM, ISNR = **5.35**.



(a) Clean image (b) Blurred image (c) Pan *et al.* [7] (d) PlugBM3D (e) PlugGMM

Fig. 2: Text image blurred with nonlinear motion blur number 2 from [2] and high noise level (BSNR = 20 dB): (a) Original image and ground truth kernel; (b) Blurred image; (c) Results of [7], ISNR = -2.72; (d) PlugBM3D, ISNR = 9.97; (e) PlugGMM, ISNR = **11.16**.

TABLE I: Results in terms of ISNR of generic methods [11] and [5], our method using the BM3D denoiser, and our method with the class-adapted GMM prior, tested for **text** images (BSNR = 30 dB).

Experiment	1	2	3	4	5
Almeida et al. [11]	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**

TABLE II: Results in terms of ISNR of generic methods [11] and [5], our method using the BM3D denoiser, and our method with the class-adapted GMM prior, tested for **face** images (BSNR = 40 dB).

Experiment	1	2	3	4	5
Almeida et al. [11]	4.31	1.81	2.86	0.85	4.43
Krishnan et al. [5]	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**

Algorithm 1 Blind Image Deblurring Algorithm

Initialization: Set $\hat{\mathbf{x}} = \mathbf{y}$, $\hat{\mathbf{h}}$ to the identity filter, $\lambda > 0$
while stopping criterion is not satisfied **do**
  $\hat{\mathbf{x}} \leftarrow \underset{\mathbf{x}}{\operatorname{argmin}}\ O_\lambda(\mathbf{x}, \hat{\mathbf{h}})$ {estimating $\mathbf{x}$ with $\mathbf{h}$ fixed}
  $\hat{\mathbf{h}} \leftarrow \underset{\mathbf{h}}{\operatorname{argmin}}\ O_\lambda(\hat{\mathbf{x}}, \mathbf{h})$ {estimating $\mathbf{h}$ with $\mathbf{x}$ fixed}
end while

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