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Scene Text Deblurring Using Adaptive Version of Non Uniform Deblurring

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ABSTRACT:

Typical blur from camera shake often deviates from the standard uniform convolutional assumption, in part because of problematic rotations which create greater blurring away from some unknown center point. Consequently, successful blind deconvolution for removing shake artifacts requires the estimation of a spatially varying or non-uniform blur operator. Using ideas from Bayesian inference and convex analysis, this paper derives a simple non-uniform blind deblurring algorithm with a spatially-adaptive image penalty.

Through an implicit normalization process, these penalties automatically adjust its shape based on the estimated degree of local blur and image structure such that regions with large blur or few prominent edges are discounted. Remaining regions with modest blur and revealing edges therefore dominate on average without explicitly incorporating structure selection heuristics. The algorithm can be implemented using an optimization strategy that is virtually tuning-parameter free and simpler than existing methods, and likely can be applied in other settings such as dictionary learning. Detailed theoretical analysis and empirical comparisons on real images serve as validation.

Introduction:

Image blur is an undesirable degradation that often accompanies the image formation process and may arise, for example, because of camera shake during acquisition. Blind image deblurring strategies aim to recover a sharp image from only a blurry, compromised observation. Extensive efforts have been devoted to the uniform blur (shift-invariant) case, which can be described with the convolutional model $y = k * x + n$, where x is the unknown sharp image, y is the observed blurry image, k is the unknown blur kernel (or point spread function), and n is a zero-mean Gaussian noise term [6, 21, 17, 5, 28, 14, 1, 27, 29]. Unfortunately, many real-world photographs contain blur effects that vary across the image plane, such as when unknown [18, 8, 22, 12] and admits an efficient implementation called efficient filter flow (EFF) [10]. The downside with this type of model is that geometric relationships between the blur kernels of different regions derived from the the physical motion path of the camera are ignored. In contrast, to explicitly account for camera motion, the projective motion path (PMP) model [23] treats a blurry image as the weighted summation of projectively transformed sharp images, leading to the revised observation model.

$$\mathbf{y} = \sum_j w_j \mathbf{P}_j \mathbf{x} + \mathbf{n},$$

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wherePj is the j-th projection or homography operator (a combination of rotations and translations) and wj is the corresponding combination weight representing the proportion of time spent at that particular camera pose during exposure. The uniform convolutional model can be obtained by restricting the general projection operators {Pj} to be translations. In this regard, (1) represents a more general model that has been used in many recent non-uniform deblurring efforts [23, 25, 7, 11, 4]. PMP also retains the bilinear property of uniform convolution, meaning that

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} = \mathbf{D}\mathbf{w} + \mathbf{n},$$

$$p(\mathbf{y}|\mathbf{x},\mathbf{w}) \propto \exp\left[-\frac{1}{2\lambda}\|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2\right]$$

Where λ denotes the noise variance. Maximum likelihood estimation of x and w using (3) is clearly ill-posed and so further regularization is required to constrain the solution space. For this purpose we adopt the Gaussian prior p(x) ∼ N (x; 0,Γ), where Γ diag[γ] with γ = [γ1,...,γm] T a vector of m hyperparameter variances, one for each element of x = [x 1,...,xm] T. While presently γ is unknown, if we first marginalize over the unknown x, we can estimate it jointly along with the blur parameters w and the unknown noise variance λ. This type II maximum likelihood procedure has been advocated in the context of sparse estimation, where the goal is to learn vectors with mostly zero-valued coefficients [24, 26]. The final sharp image can then be recovered using the estimated kernel and noise level along with standard non-blind deblurring algorithms (e.g., [15]). Mathematically, the proposed estimation scheme requires that we solve

$$\max_{\gamma,\mathbf{w},\lambda\geq 0} \int p(\mathbf{y}|\mathbf{x},\mathbf{w})p(\mathbf{x})d\mathbf{x} \equiv \min_{\gamma,\mathbf{w},\lambda\geq 0} \mathbf{y}^T\left(\mathbf{H}\Gamma\mathbf{H}^T + \lambda\mathbf{I}\right)^{-1}\mathbf{y} + \log\left|\mathbf{H}\Gamma\mathbf{H}^T + \lambda\mathbf{I}\right|,$$

where a − log transformation has been included for convenience. Clearly (4) does not resemble the traditional blind non-uniform deblurring script, where estimation proceeds using the more transparent penalized regression model

$$\min_{\mathbf{x};\mathbf{w}\geq 0} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2 + \alpha \sum_i g(x_i) + \beta \sum_j h(w_j)$$

and α and β are user-defined trade-off parameters, g is an image penalty which typically favors sparsity, and h is usually assumed to be quadratic.

Despite the differing appearances however, (4) has some advantageous properties with respect to deconvolution problems. In particular, it is devoid of tuning parameters and it possesses more favorable minimization conditions. For example, consider the simplified non-uniform deblurring situation where the true x has a single non-zero element and H is defined such that each column indexed by i is independently parameterized with finite support symmetric around pixel i. Moreover, assume this support matches the true support of the unknown blur operator. Then we have the following: Lemma 1 Given the idealized non-uniform deblurring problem described above, the cost function (4) will be characterized by a unique minimizing solution that correctly locates the nonzero element in x and the corresponding true blur kernel at this location. No possible problem in the form of (5), with g(x) = |x| p, h(w) = wq, and {p, q} arbitrary non-negative scalars, can achieve a similar result (there will always exist either multiple different minimizing solutions or an global minima that does not produce the correct solution).

This result, which can be generalized with additional effort, can be shown by expanding on some of the derivations in [26]. Although obviously the conditions upon which Lemma 1 is based are extremely idealized, it is nonetheless emblematic of the potential of the underlying cost function to avoid local minima, etc., and [26] contains complementary results in the case where H is fixed. While optimizing (4) is possible using various general techniques such as the EM algorithm, it is computationally expensive in part because of the high-dimensional determinants involved with realistic-sized images. Consequently we are presently considering various specially-tailored optimization schemes for future work. But for the present purposes, we instead minimize a convenient upper bound allowing us to circumvent such computational issues. Specifically, using Hadamard's

$$\begin{aligned}\log\left|\mathbf{H}\Gamma\mathbf{H}^T + \lambda\mathbf{I}\right| &= n\log\lambda + \log|\Gamma| + \log\left|\lambda^{-1}\mathbf{H}^T\mathbf{H} + \Gamma^{-1}\right| \\ &\leq n\log\lambda + \log|\Gamma| + \log\left|\lambda^{-1}\mathrm{diag}\left[\mathbf{H}^T\mathbf{H}\right] + \Gamma^{-1}\right| \\ &= \sum_i \log\left(\lambda + \gamma_i\|\bar{\mathbf{w}}_i\|_2^2\right) + (n-m)\log\lambda,\end{aligned}$$

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$$\min_{\mathbf{x};\mathbf{w}\geq 0,\lambda\geq 0} \frac{1}{\lambda}\|\mathbf{y}-\mathbf{H}\mathbf{x}\|_2^2 + \sum_i \psi(|x_i|\|\bar{\mathbf{w}}_i\|_2, \lambda) + (n-m)\log\lambda, \quad \text{with}$$

$$\psi(u,\lambda) \triangleq \frac{2u}{u+\sqrt{4\lambda+u^2}} + \log\left(2\lambda + u^2 + u\sqrt{4\lambda+u^2}\right) \quad u \geq 0.$$

The optimization from (7) closely resembles a standard penalized regression (or equivalently MAP) problem used for blind deblurring. The primary distinction is the penalty term ψ, which jointly regularizes x, w, and λ as discussed Section 4. The supplementary file derives a simple majorization minimization algorithm for solving (7) along with additional implementational details. The underlying procedure is related to variational Bayesian (VB) models from [1, 16, 20]; however, these models are based on a completely different mean-field approximation and a uniform blur assumption, and they do not learn the noise parameter. Additionally, the analysis provided with these VB models is limited by relatively less transparent underlying cost functions. 4

Model Properties:

The proposed blind deblurring strategy involves simply minimizing (7); no additional steps for tradeoff parameter selection or structure/salient-edge detection are required unlike other state-of-the-art approaches. This section will examine theoretical properties of (7) that ultimately allow such a simple algorithm to succeed. First, we will demonstrate a form of intrinsic column normalization that facilitates the balanced sparse estimation of the unknown latent image and implicitly de-emphasizes regions with large blur and few dominate edges. Later we describe an appealing form of noise dependent shape adaptation that helps in avoiding local minima. While there are multiple, complementary perspectives for interpreting the behavior of this algorithm, more detailed analyses, as well as extensions to other types of underdetermined inverse problems such as dictionary learning, will be deferred to a later publication. Column-Normalized Sparse Estimation Using the simple reparameterization zixiw¯ i2 it follows that (7) is exactly equivalent to solving

$$\min_{\mathbf{z};\mathbf{w}\geq 0,\lambda\geq 0} \frac{1}{\lambda}\|\mathbf{y}-\tilde{\mathbf{H}}\mathbf{z}\|_2^2 + \sum_i \psi(|z_i|, \lambda) + (n-m)\log\lambda,$$

This will indeed result in normalized columns and a properly balanced data-fit term, these raw norms will now appear in the penalty function g, giving the equivalent objective

$$\min_{\mathbf{z};\mathbf{w}\geq 0} \|\mathbf{y}-\tilde{\mathbf{H}}\mathbf{z}\|_2^2 + \alpha\sum_i g\left(z_i\|\bar{\mathbf{w}}_i\|_2^{-1}\right) + \beta\sum_j h(w_j).$$

Noise-Dependent, Parameter-Free Homotopy Continuation Column normalization can be viewed as a principled first step towards solving challenging sparse estimation problems. However, when non-convex sparse regularizers are used for the image penalty, e.g., p norms with p < 1, then local minima can be a significant problem. The rationalization for using such potentially problematic non-convexity is as follows; more details can be found in [17, 27]. When applied to a sharp image, any blur operator will necessarily contribute two opposing effects: (i) It reduces a measure of the image sparsity, which normally increases the penalty i |yi| p, and (ii) It broadly reduces the overall image variance, which actually reduces i |yi| p. Additionally, the greater the degree of blur, the more effect (ii) will begin to overshadow (i). Note that we can always apply greater and greater blur to any sharp image x such that the variance of the resulting blurry y is arbitrarily small. This then produces an arbitrarily small p norm, which implies that i |yi| p < i |xi| p, meaning that the penalty actually favors the blurry image over the sharp one. In a practical sense though, the amount of blur that can be tolerated before this undesirable preference for y over x occurs is much larger as p approaches zero. This is because the more concave the image penalty becomes (as a function of coefficient magnitudes), the less sensitive it is to image variance and the more sensitive it is to image sparsity. In fact the scale-invariant special case.

Definition

Let u be a strictly increasing function on [a, b]. The function ν is concave relative to u on the interval [a, b] if and only if

$$\nu(y) \leq \nu(x) + \frac{\nu'(x)}{u'(x)}\left[u(y)-u(x)\right] \; holds \; \forall x, y \in [a, b].$$

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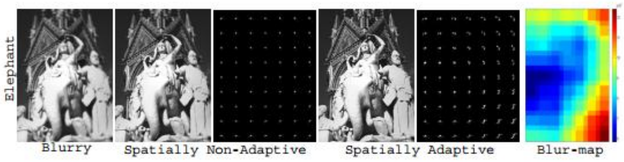
We will use ν ≺ u to denote that ν is concave relative to u on [0, ∞). This can be understood as a natural generalization of the traditional notion of a concavity, in that a concave function is equivalently concave relative to a linear function per Definition 1. In general, if ν ≺ u, then when ν and u are set to have the same functional value and the same slope at any given point (i.e., by an affine transformation of u), then ν lies completely under u. In the context of homotopy continuation, an ideal candidate penalty would be one for which g(x; θ 1) ≺ g(x; θ2) whenever θ1 ≤ θ2. This would ensure that greater sparsity-inducing concavity is introduced as θ is reduced. We now demonstrate that ψ(|z|, λ) is such a function, with λ occupying the role of θ. This dependency on the noise parameter is unlike other continuation methods and ultimately leads to several attractive attributes.

Theorem 1 If λ1 < λ2, then ψ(u, λ1) ≺ ψ(u, λ2) for u ≥ 0. Additionally, in the limit as λ → 0, then i ψ(|zi|, λ) converges to the 0 norm (up to an inconsequential scaling and translation). Conversely, as λ becomes large, i ψ(|zi|, λ) converges to 2z1/ √ λ. The proof has been deferred to the supplementary file. The relevance of this result can be understood as follows. First, at the beginning of the optimization process λ will be large both because of initialization and because we have not yet found a relatively sparse z and associated w such that y can be well-approximated; hence the estimated λ should not be small. Based on Theorem 1, in this regime (8) approaches

$$\min_{\mathbf{z}} \|\mathbf{y} - \tilde{\mathbf{H}}\mathbf{z}\|_2^2 + 2\sqrt{\lambda}\|\mathbf{z}\|_1$$



Effectiveness of spatially-adaptive sparsity. From left to right: the blurry image,

The deblurred image and estimated local kernels without spatially-adaptive column normalization, the analogous results with this normalization and its spatially-varying impact on image estimation, and the associated map of w¯ i−1 2 , which reflects the degree of estimated. local blurring. Later as the estimation proceeds and w and z are refined, λ will be reduced which in turn necessarily increases the relative concavity of the penalty ψ per Theorem 1. However, the added concavity will now be welcome for resolving increasingly fine details uncovered by a lower noise variance and the concomitant boosted importance of the data fidelity term, especially since many of these uncovered details may reside near increasingly blurry regions of the image and we need to avoid unwanted noblur solutions.

Eventually the penalty can even approach the non-uniform blind deblurring using real-world images from previously published papers (note that source code is not available for conducting more widespread evaluations with most algorithms). The supplementary file contains a number of additional comparisons, including assessments with a benchmark uniform blind deblurring dataset where ground truth is available.

Overall, our algorithm consistently performs comparably or better on all of these respective images. Experimental specifics of our implementation (e.g., regarding the non-blind deblurring step, projection operators, etc.) are also contained in the supplementary file for space considerations. Comparison with Harmeling et al. [8] and Hirsch et al. [9]: Results are based on three test images provided in [8].

Figure 2 displays deblurring comparisons based on the Butchershop and Vintage-car images. In both cases, the proposed algorithm reveals more fine details than the other methods, despite its simplicity and lack of salient structure selection heuristics or trade-off parameters.

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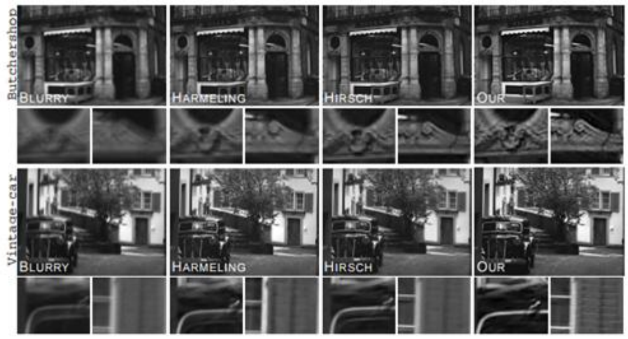

Non-uniform deblurring results.Comparison with Harmeling [8] and Hirsch [9] on real-world images. (better viewed electronically with zooming)

Non-uniform deblurring results.Comparison with Whyte [25], Gupta [7], and Joshi [13] on real-world images. (better viewed electronically with zooming)

CONCLUSION:

This paper presents a strikingly simple yet effective method for non-uniform camera shake removal based upon a principled, transparent cost function that is open to analysis and further extensions/refinements. For example, it can be combined with the model from [29] to perform joint multi-image alignment, denoising, and deblurring.

Both theoretical and empirical evidence are provided demonstrating the efficacy of the blur-dependent, spatially-adaptive sparse regularization which emerges from our model. The framework also suggests exploring other related cost functions that, while deviating from the original probabilistic script, nonetheless share similar properties. One such simple example is a penalty of the formm i log(√ λ + |xi|w¯ i2);

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