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Parameter Assumption for Blind and Non-Blind Deblurring in Image Processing

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ABSTRACT: Image deblurring (ID) is an ill-posed problem typically addressed by using regularization, or prior knowledge, on the unknown image (and also on the blur operator, in the blind case). ID is often formulated as an optimization problem, where the objective function includes a data term encouraging the estimated image (and blur, in blind ID) to explain well the observed data (typically, the squared norm of a residual) plus a regularizer that penalizes solutions deemed undesirable. In this paper, we propose new criteria for adjusting the regularization parameter and/or the number of iterations of ID algorithms.

A method for blind image deblurring is presented. The method only makes weak assumptions about the blurring filter and is able to undo a wide variety of blurring degradations. To overcome the ill-posedness of the blind image deblurring problem, the method includes a learning technique which initially focuses on the main edges of the image and gradually takes details into account. A new image prior, which includes a new edge detector, is used. The method is able to handle unconstrained blurs, but also allows the use of constraints or of prior information on the blurring filter, as well as the use of filters defined in a parametric manner. Furthermore, it works in both single-frame and multiframe scenarios. The use of constrained blur models appropriate to the problem at hand, and/or of multiframe scenarios, generally improves the deblurring results. Tests performed on monochrome and color images, with various synthetic and real-life degradations, without and with noise, in single-frame and multiframe scenarios, showed good results, both in subjective terms and in terms of the increase of signal to noise ratio (ISNR) measure. In comparisons with other state of the art methods, our method yields better results, and shows to be applicable to a much wider range of blurs. We propose new criteria for adjusting the regularization parameter and/or the number of iterations of ID algorithms.

I. INTRODUCTION

Image deblurring methods can be divided into two classes: *nonblind*, in which we assume the blurring operator to be known, and *blind*, in which we assume that the blurring operator is unknown. The method that this paper describes here belongs to the latter class.

A. Motivation

The application range of nonblind methods is much narrower than the one of blind methods: in most situations of practical interest the blurring filter's impulse response, also called point spread function (PSF), is not known with good accuracy. Since nonblind deblurring methods are very sensitive to mismatches between the PSF used by the method and the true blurring PSF, a poor knowledge of the blurring PSF normally leads to poor deblurring results.

Image deblurring (ID) is an inverse problem where the observed image is modeled as the convolution of a sharp image with a blur filter, possibly plus some noise (often assumed spectrally white and Gaussian). With applications in many areas (*e.g.*, astronomy, photography, surveillance, remote sensing, medical imaging), research on ID can be divided into non-blind ID (NBID), in which the blur filter is assumed known, and (more realistic) blind ID (BID), in which both the image and the blur filter are (totally or partially) unknown. Automatic image deblurring is an objective of great practical interest for the enhancement of images in photo and video cameras in astronomy in remote sensing in tomography in other biomedical imaging techniques etc. [2].

Despite its narrower applicability, NBID is already a challenging problem to which a large amount of research has been (and still is) devoted, mainly due to the ill-conditioned nature of the blur operator: the observed image does not uniquely and stably determine the underlying original image. If this problem is serious with a known blur, it is much worse if there is even a slight mismatch between the assumed blur and true one.

Most of the NBID methods overcome this difficulty through the use of an image regularizer, or prior, the weight of which has to be tuned or adapted [8], [13], [14], [15]. Most state-of-the-art regularizers exploit the sparsity1 of the high frequency/edge components of images; this is the rationale underlying wavelet/frame-based methods and total variation (TV) regularization [21].

In blind image deblurring (BID), not only the degradation operator is ill-conditioned, but the problem also is, inherently, severely ill-posed: there is an infinite number of solutions (original image + blurring filter) that are compatible with the degraded image. For an overview of BID methods, see [22] and [23]. Most previously published blind deblurring methods are very limited, since they do not allow the use of a generic PSF. Most of them are based, instead, on PSF models with a small number of parameters [24]–[28]. For example, to model an out-of-focus blur, they normally use a circle with uniform intensity, having as single parameter the circle's radius [24]. Similarly, to model a motion blur, they normally use a straight-line segment with uniform intensity, the only parameters being length and slope [24]–[26]. These approaches are very limited, because such models rarely fit actual blurring PSFs well. For example, the out-of-focus blurring PSF generally is more complex than a simple uniform circle, and the camera motion that causes a motion blur generally is much more complex than a uniform, straight-line motion. And, as was emphasized above, even a slight mismatch between the deblurring PSF and the blurring PSF strongly degrades the quality of the deblurred image.

With application not only in ID, but also in other inverse problems, several optimization techniques have been proposed to handle sparsity-inducing regularizers. A popular class of such techniques belongs to the class of iterative shrinkage/thresholding (IST) algorithms and their recent accelerated versions [7], [8]. The iterative nature of these methods requires, in addition to the regularization parameter, the choice of an adequate stopping criterion; often, there is a delicate interplay between these two choices.

B. Objectives

The Objectives can be enlisted as follows:

- To design an algorithm that provides a solution for blind and nonblind images.
- To design an algorithm which provides perfect whiteness criteria function.
- To provide an optimal deblurring algorithm.
- To provide a proper solution for real time blur images for example moving object problem and moving camera problem**.**

II. LITERATURE SURVEY

Recently, research issues at the various intersections have been studied extensively. The related work done and summary and discussion is given among those research issues.

A. Related work done

In blind image deblurring (BID), not only the degradation operator is ill-conditioned, but the problem also is, inherently, severely ill-posed: there are an infinite number of solutions (original image + blurring filter) that are compatible with the degraded image. For an overview of BID methods, see [22] and [23].

Most previously published blind deblurring methods are very limited, since they do not allow the use of a generic PSF. Most of them are based, instead, on PSF models with a small number of parameters [24]–[28]. For example, to model an out-of-focus blur, they normally use a circle with uniform intensity, having as single parameter the circle's radius [24]. Similarly, to model a motion blur, they normally use a straight-line segment with uniform intensity, the only parameters being length and slope [24–28]. These approaches are very limited, because such models rarely fit actual blurring PSFs well. For example, the out-of-focus blurring PSF generally is more complex than a simple uniform circle, and the camera motion that causes a motion blur generally is much more complex than a uniform, straight-line motion. And, as was emphasized above, even a slight mismatch between the deblurring PSF and the blurring PSF strongly degrades the quality of the deblurred image.

A recent work [28] manages to estimate the blur under the variational Bayesian approach. However, this method models the blur by means of a Gaussian filter, which is completely defined by a single parameter (the Gaussian's variance), and is a very weak model for real-life blurs.

References [12] and [13] present a method called APEX. Although this method covers some blurs which can be found in real-life, it is limited to blurring PSFs modeled by a symmetrical Lévy distribution with just two parameters. The authors presented an experimental comparison of our method with APEX. Some methods have been proposed, which impose no strong restrictions on the blurring filter [2], [14]–[17]. These methods typically impose priors over the blurring filter, and do not seem to be able to handle a wide variety of blurs and scenes.

The total variation (TV) is used to regularize the blurring filters. Besides being used for space-invariant blurs, the method described in [2] was also applied with success in a synthetic image with a space-variant blur. The method recently presented in [9] is much less restrictive than parameterized ones and yields good results, but is only designed for motion blurs. An interesting method for blind deblurring of color images was proposed in [39]. This method appears not to pose any strong restrictions on the blurring filter. In the cited paper, several experimental results on synthetic blurs are shown, but little information is provided about them. From the information that is given, it appears that the blurring filters that were used in the experiments were either circularly symmetric (including simulated out-of-focus blurs), or corresponded to straight-line motion blurs. There seems to be no reason for the method not to be able to successfully deal with other kinds of blurs, however. The blurring PSFs that are shown in that paper appear to have a maximum size of about 55 pixels (or a length of 3 pixels, in the case of the motion blur). The improvements in signal to noise ratio (ISNR) seem to be between 2 and 4 dB for the circularly symmetric blurs, and of 7 dB for the motion blur. In some cases, one has access to more than one degraded image from the same original scene, a fact which can be used to reduce the ill-posedness of the problem. There are also solutions like the ones presented in [2], which cannot be considered completely blind, since they require the use of additional data for preliminary training. Contrary to previously published blind deconvolution methods such as those mentioned above, the method that we propose only makes a weak assumption on the blurring PSF: it must have a limited support. The method also assumes that the leading (most important) edges of the original image, before the blur, are sharp and sparse, as happens in most natural images. To the authors' knowledge, this is the first method to be proposed, which is able to yield results of good quality in such a wide range of situations.

The method uses a new prior which depends on the image's edges, and which favors images with sparse edges. This prior leads to a regularizing term which generalizes the well known total variation (TV), in its discrete form. The estimation is guided to a good solution by first concentrating on the main edges of the image, and progressively dealing with smaller and/or fainter details. Though the method allows the use of a very generic PSF, it can also take into account prior information on the blurring PSF, if available. If a parameterized model of the PSF is known, the method allows the estimation of the model's parameters. Although initially developed for the single-frame scenario, the method can also be used in multiframe cases, benefiting from the existence of the additional information from the multiple frames [5].

The performance and the robustness of the method were tested in various experiments, with synthetic and real-life degradations, without and with constraints on the blurring filter, without and with noise, using monochrome and color images, and under the single-frame the multiframe paradigms.

The quality of the results was evaluated both visually and in terms of ISNR. Detailed comparisons with two other methods available in the literature [2], [12] were performed, and show that the proposed method yields significantly better results than these other methods.

In an attempt to encompass less restrictive blurs, a fuzzy technique that uses several prespecified PSF models [29]. However, this method assumes that the PSF is zero-phase and, furthermore, depends on the existence of a good initial estimate of the PSF.

It is compared that method with two other methods from the literature: APEX [12], [13] and the method from [2] (which shall call YK method). These were the only two methods for which it was able to obtain implementations.

The APEX method [12] is quite fast, but is limited to blurs which belong to the Levy family. This is a family with just two parameters, in which all functions have circular symmetry, and which encompasses the Gaussians. The method has two regularizing parameters (and), whose values have set to those recommended by the author. The method has two further parameters (designated by and, respectively). For the used values 2.00, 2.25, 2.50, 7.75, 8.00, which cover the recommended interval. Parameter can be varied between 1 and 0, corresponding to the blurred image, and to a "completely deblurred" one. The used the values 1, 0.75, 0.5, 0.25, and 0. For synthetic blurs, the ISNR values were computed for all combinations of values of the best combination was selected. For real-life blurred photos, the best pair was chosen by visual inspection, since no ISNR values could be computed.

The YK method does not constrain the blur PSF, but assumes that it is piecewise smooth (and, from the comments made in [2], one can see that the method has some bias toward piecewise constant PSFs). The method has four parameters that must be manually chosen. It started by trying the values used in [2] but, with the blurred images, this produced results with very strong oscillatory artifacts. After several tests, they chose the following values, which seemed to produce the results with fewest artifacts: 1 and 2000 for the regularizing parameters of the image and of the PSF, respectively; 0.1 and 0.001 for the threshold parameters of the diffusion coefficients of the image and of the PSF, respectively. It should note that there tests were severely limited by the fact that the deblurring of each image, with this method, took about 12 h. Besides preventing us from doing a more extensive search of parameter values, this also prevented us from testing the method on noisy synthetic degradations [5]. *B. Summary and discussion* Extensive work has been done in the field of image which processing describes the proposed method and presents the new prior for images. Here, a very brief overview of some of these research works has been presented.

Deblurring method: The deblurring method is based on two simple facts:

• In a natural image, leading edges are sparse.

• Edges of a blurred image are less sparse than those of a sharp image because they occupy a wider area.

Due to these facts, a prior which tends to make the detected edges sparser will tend to make the image sharper, while preventing it from becoming unnatural (i.e., from presenting noise or artifacts) [3].

Edge Detector: In order to be able to apply a prior over the image edges, an edge detector was developed. This edge detector showed to yield better deblurring results than those obtained using detectors. The edge detector is based on a set of filters obtained, from a base filter, through successive rotations [3], [4].

Image Prior: The prior that we use for images assumes that edges are sparse, and that edge intensities at different pixels are independent from one another (which obviously is a large simplification, but still leads to good results) [2][4].

Border Effects: Since, in the first iterations of the method, the image estimates only contain the main image edges, the optimal filter estimates, at this stage, would not (even approximately) have a limited support [1] [4].

Color and Hyperspectral Images: The method that is proposed can also address color and hyperspectral images. A color image is a multichannel image which typically has three channels (red, green and blue). A hyperspectral image takes this concept much further, usually containing more than one hundred channels, which correspond to different frequency bands [3].

Quality measures: The measure that was used for evaluating the quality of the results of blind deblurring tests was the increase in signal to noise addressed by adopting a regularizer expressing prior information about the image x and considering an objective function of the form ratio (ISNR), similarly to what is commonly done in nonblind deblurring. [1], [3], [4].

III. PROPOSED WORK

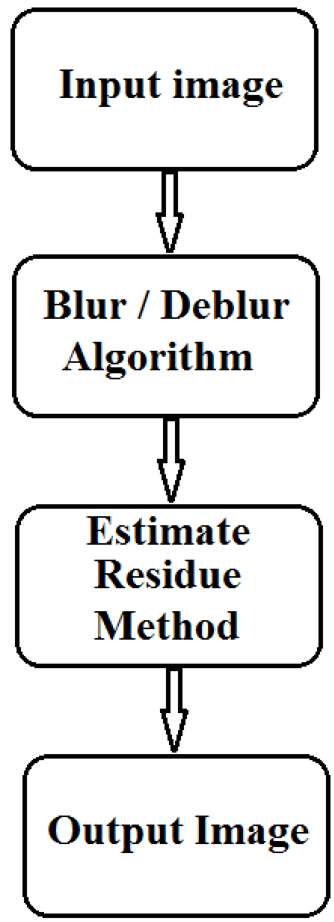

Fig. 1. Residue of image by using Blur/Deblur method.

The formulation of blind and non-blind ID is briefly reviewed as follows:

A. Image Deconvolution/Deblurring

In ID problems, the degraded image is usually modeled as:

$$y = h \ast x + n \qquad \ldots(1)$$

where y is the degraded image, x is the (unknown) original image, n is noise, and h is the point spread function (PSF) of the blur operator (assumed to be known in NBID and unknown in BID) and $\ast$ denotes convolution. Both BID (finding x and h, from y) and NBID (finding x, from y and h) are normally

$$C_\lambda(x,h) = \frac{1}{2}\,\|y - h * x\|_2^2 + \lambda\,\Phi(x); \qquad \dots(2)$$

the first term in is the classical data fidelity term that results from assuming that the noise n is white and Gaussian, $\Phi(x)$ is a regularization function embodying the prior information about x, and λ is the regularization parameter. Typically, too large values of λ lead to over-regularized images (e.g., over smoothed or cartoon-like), while too small values of λ lead to under-regularized images dominated by the influence of the noise. An adequate choice of the regularization parameter λ is thus clearly crucial to obtain a good image estimate.

B. Non-blind Deblurring

In NBID, h is assumed to be known and the cost function (2) is minimized with respect to x, given some choice of the regularization parameter λ. Many optimization methods for ID minimize the cost function (2) iteratively [8], [9], [21] computing the image estimate at iteration t + 1 as a function of the previous estimate x_t, the available data (y and h), and the regularization parameter λ:

$x_{k+1} = f(x_k, y, h, \lambda)$. …(3)

Besides requiring a good estimate for the regularization parameter λ, these iterative approaches also need stopping criteria, which considerably influence the final results.

C. Blind Deblurring

In BID, both the image x and the filter h are unknown. A BID problem suffers from an obvious lack of data, since there are many pairs (x, h) that explain equally well the observed data y. Most BID methods circumvent this difficulty by adding to (2) a regularizer on the blur filter and, usually, by alternatingly estimating the image and the blur filter. A regularizer on the blur naturally involves an additional regularization parameter, also requiring adjustment, while the alternating estimation of the image and the filter requires good initialization (since the underlying objective (2) is non-convex) and a good criterion to stop the iterative process. The recent method in [2], [3] yields good results without regularization on the blur filter, i.e., using a cost function with the form of (2). That method uses an iterative algorithm to minimize (2), by starting with a strong regularization (large λ), and gradually decreasing it.

D. The Whiteness Criteria

The proposed criteria for selecting the regularization parameter and the stopping iteration are based on measures of the fitness of the image estimate $\widehat{x}$ and the blur estimate $\widehat{h}$ (in NBID, *h* is known, thus $\widehat{h} = h$) to the degradation model (1), by analyzing the estimated residual image:

$$r = y - \widehat{h} * \widehat{x}. \qquad (4)$$

Algorithm: For Blind and non-blind images

```
Set λ to the initial value; choose α < 1.
Set x̂ = y
repeat
    ĥ ← arg min_h C_λ(x̂, h)
    x̂ ← arg min_x C_λ(x, ĥ)
    λ ← α λ
until stopping criterion is satisfied
```

The characteristics of the residual *r* are then compared with those assumed for the noise *n* in the degradation model (1). In particular, the noise *n* is assumed to be spectrally white (uncorrelated), thus a measure of the whiteness of the residual *r* is used to assess the adequacy of the estimates $(\widehat{x}, \widehat{h})$ to the model. This is a quite generic assumption, valid for most real situation. Our approach differs from other methods based on residual statistics, such as those in [17], [1], in that those methods do not use spectral properties of the residual, but other statistics, such as variance and other moments.

The proposed criterion consists in selecting the regularization parameter and/or final iteration of the algorithm that maximize one of the whiteness measures introduced below.

If this measure exhibits a clear peak as a function of the regularization parameter and/or the iteration number, we adopt an oriented search scheme and stop the method as soon as the measure of whiteness starts to decrease. This is the case in the BID algorithm mentioned in the previous section. Also in NBID, if optimizing only with respect to λ, an efficient strategy is to sweep a range of values, using the estimate at each value to initialize the algorithm at the next value; this process is known *warm-starting*, and may yield large computational savings [1]. In our NBID experiments, when optimizing with respect to λ and/or the number of iterations, and since the goal is to assess the ability of the proposed criteria to select these quantities, with no concern for computational efficiency, we simply consider a grid of values and return the image estimate yielding the maximum residual whiteness.

E. Measures of whiteness

The first step of the method is to normalize the residual image to zero mean and unit variance; for simplicity of notation, let this normalized residual still be denoted as r.

$$r \leftarrow \frac{r - \overline{r}}{\sqrt{\mathrm{var}(r)}},$$

Where, $\overline{r}$ r and var(r) are, respectively, the sample mean and sample variance of r. The autocorrelation (and auto-variance, since the mean is zero) of the normalized residual r, at 2D lag (m; n), is estimated by

$$R_{rr}(m,n) = \sum_{i,j} r(i,j)\, r(i-m, j-n), \qquad (4)$$

Where, the sum extends over the whole image. The auto-covariance of a spectrally white image is a delta function at the origin, δ (m, n). A possible measure of whiteness of r is thus the distance between the estimated autocorrelation Rrr(m, n) and the ideal delta function. Considering a window of (2L + 1) X (2L + 1) pixels, the first measure of whiteness that is considered is simply the energy of R_{rr}(m; n) outside the origin,

$$M_R(r) = -\sum_{\substack{(m,n)=(-L,-L)\\(m,n)\neq(0,0)}}^{L,L} \Big(R_{rr}(m,n)\Big)^2, \qquad (5)$$

Where, the minus sign is used so that MR(r) is larger for whiter residuals. In the experiments reported below, they have used L = 4.

Considering that the auto-covariance has more significant values for smaller lags, it makes sense to give more weight to these terms. Based on that, a weighted version of the measure in (5) was also considered,

$$M_{RW}(r) = -\sum_{\substack{(m,n)=(-L,-L)\\(m,n)\neq(0,0)}}^{L,L} W(m,n)\Big(R_{rr}(m,n)\Big)^2, \quad (6)$$

Where, W(m; n) is a matrix of weights. In the experiments, they have used a Gaussian weighting. Let S_{rr}(ω 1; ω 2) denote the power spectral density of r, at 2D spatial frequency (ω1; ω 2),

$$S_{rr}(\omega_1, \omega_2) = \mathcal{F}(R_{rr}), \qquad (7)$$

Where, $\mathcal{F}$ is the two-dimensional discrete Fourier transform (2D-DFT). In agreement with the fact that the autocorrelation of a white signal is a delta function, a white signal has a flat power spectral density. To measure the flatness of S_{rr}, the authors measure its Shannon entropy, after adequate normalization; recall that the maximum entropy is achieved by a flat distribution. The resulting measure of whiteness is denoted as MH(r). The stopping criterion consists in stopping the BID algorithm when the whiteness measure used (MR(r), MRW(r), or MH(r)) starts decreasing. To avoid a premature stopping (of course, we have no guarantee that the whiteness measure does not oscillate), we actually run the algorithm until the whiteness measure decreases considerably, and then return the image estimate obtained at the iteration at which the maximum whiteness was observed [2].

IV. INPUT OUTPUT SPECIFICATION & DISCUSSION

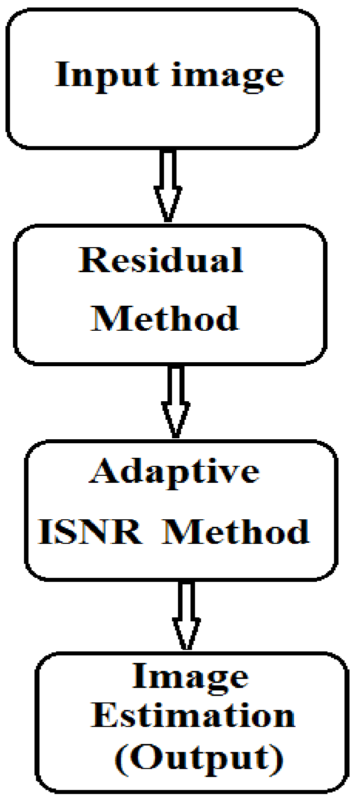

Fig. 2. Adaptive method for whiteness measurement.

The above shown Adaptive method for whiteness measurement can be explained with examples as follows:

A. Input images

Fig. 3. Type of Input Image with residual value = 5.

B. Processing images

The images below can be obtained during the working of residual method.

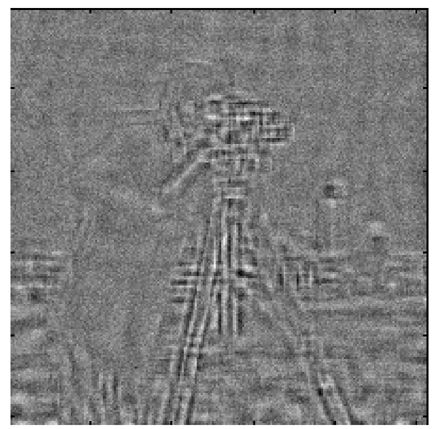

Fig. 4. Type of Image with residual value = 17.

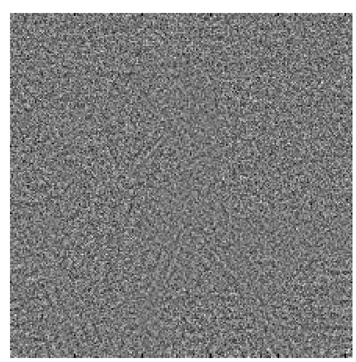

Fig. 5. Type of Image with residual value = 23.

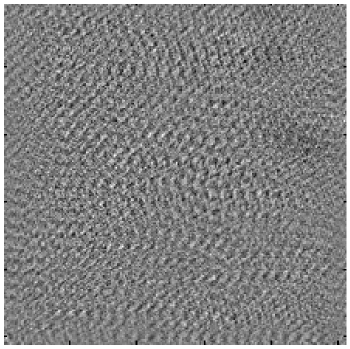

Fig. 6. Type of Image with residual value = 30.

C. Output Images

The images below can be assumed that they can be obtained after the working of residual method and the Adaptive ISNR method. Some Adaptive ISNR methods are as follows:

GSURE method: The well known SURE (Stein's unbiased risk estimate) is an unbiased estimator of the MSE achieved by an (almost arbitrary) estimator of an unknown vector observed under additive white Gaussian noise. SURE have been directly applied to tune the regularizing parameter of linear and nonlinear denoising methods.

PD-SURE: The predicted SURE (PD-SURE) is a SURE-based unbiased estimator of the predicted-MSE (mean square error on the data domain).

Monte-Carlo estimation of the divergence: The difficulty in using SURE-based measures (SURE, GSURE or PD-SURE) resides in computation/approximating the divergence term, as it involves derivatives of a function defined via an optimization problem [1].

Fig. 7. Estimated output Image with ISNR value = 24.

Fig. 8. Estimated output Image with ISNR value = 23.

CONCLUSION

We have presented a method for blind and non-blind image deblurring. The method differs from most other existing methods by only imposing weak restrictions on the blurring filter, being able to recover images which have suffered a wide range of degradations. Good estimates of both the image and the blurring operator are reached by initially considering the main image edges, and progressively handling smaller and/or fainter ones. The method uses an image prior that favors images with sparse edges, and which incorporates an edge detector that was specially developed for this application. The method can handle both unconstrained blurs and constrained or parametric ones, and it can deal with both single-frame and multiframe scenarios. Thus the algorithm can be designed which provides a solution for blind and nonblind images which provides perfect whiteness criteria function and provide a proper solution for real time blur images. Also there can be a solution for the moving object or moving camera blur image problems.

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