Weber's Law-based Regularization for Blind Image Deblurring

Malik Najmus Saqib
College of Computer Science and Engineering, University of Jeddah, Saudi Arabia
mnajam@uj.edu.sa (corresponding author)

Hussain Dawood
Department of Information Engineering Technology, National Skills University Islamabad, Pakistan | School of Computing, Skyline University College, University City Sharjah, United Arab Emirates
hussain.dawood@nsu.edu.pk

Ahmed Alghamdi
College of Computer Science and Engineering, University of Jeddah, Saudi Arabia
ahmedg@uj.edu.sa

Hassan Dawood
Department of Software Engineering, University of Engineering and Technology, Pakistan
hassan.dawood@uettaxila.edu.pk

Received: 30 October 2023 | Revised: 28 November 2023 | Accepted: 1 December 2023

ABSTRACT

Blind image deblurring aims to recover an output latent image and a blur kernel from a given blurred image. Kernel estimation is a significant step in blind image deblurring and requires a regularization technique to minimize the cost function and the edges of objects to generate a sharp image in a better way. This study proposes a new image regularization technique called Weber's Law Regularization (WLR) based on the Weber law phenomenon. The Weber ratio was used to preserve the edges of small salient objects and to minimize the cost function to obtain a sharp image while minimizing the ringing effect. To validate the WLR, experiments were conducted on benchmark synthetic and real word images and compared with existing state-of-the-art methods. The experimental results showed that WLR can effectively and efficiently deblur images even in the absence of prior knowledge.

Keywords-image deblurring; regularization; Weber's law; Weber's Law Regularization (WLR)

I. INTRODUCTION

Blurring can potentially degrade the quality of an image. In this regard, many techniques have been developed in the field of image processing and computer vision. Motion blur is the most common artifact, which is produced by shaking the camera while capturing an image. Image deblurring is mainly divided into two types: (1) blind image deblurring, where a Point Spread Function (PSF) is not known, and (2) nonblind image deblurring, where a PSF is known. However, the estimation of the PSF or a blur kernel plays a significant role in deblurring the image in both cases. After the estimation of the blur kernel, the sharp image is obtained by using several non-blind deconvolution methods. Blur kernel estimation is further categorized into three types: Variational Bayes (VB)-based methods [1-7], Maximum A Posterior (MAP)- based methods [8-35], and neural network-based frameworks [36-40]. VB methods avoid trivial solutions and are considered to be more robust theoretically. However, since VB-based approaches are computationally expensive, more efficient methods are required for approximation [5]. Naive MAP-based methods may produce trivial solutions. Convolution Neural Networks (CNNs) are used to recover sharp images from blurry images without predicting the blur kernel [36-38]. These methods cannot properly eliminate blur without using the blur kernel and model [39]. Due to certain properties of MAP, VB, and CNN-based methods, this study only considered the first type of deblurring methods.

Salient structures have been used to estimate kernels [8,16, 18-19, 21, 23-25, 41-43]. In [8], two types of filters were used to extract the edges of the salient image, a bilateral filter and a shock filter. In [18-19], an extension of filters was proposed by refining the edges while using data-driven priors. In [21], the informative structures of the edges were selected, while the tiny edges were removed using the relative total variation. In [24], high-level scene-specific priors were detected for the edges of an image. In [16], a Generalized Shrinkage-Thresholding (GST) operator was used to solve the problem of minimizing the lp-norm. In [40], a deep generative network regularization was proposed for blind image deconvolution. Sparse regularizations on image gradients have been successfully applied for kernel estimation [2, 9-13, 15, 26-29, 44]. In [26], the l_1-norm was used to detect the salient edges of objects in a gradient image. The methods proposed in [12-13, 17, 26, 30] produce effective results under certain prior conditions. In [31], the hyper-Laplacian distribution was used to model the image gradients, while the lp-norm was used as a regularization term. In [9], the quality of an image was improved by combining the l_1-norm and a ring-suppressing term. In [11], the l_1/l_2-norm regularization suppressed small and redundant structures, while reweighted norms were also used in [15]. In [10], a new approximation of the l0-norm regularizer based on gradients was proposed. In [18], the normalized color-line prior was used to enhance the edge contrast. In [6], a method was proposed to remove the uniform blur shake of the camera from images. Camera shake blur was estimated from image regions without saturation effects selected by users. However, saturated regions of the recovered image had strong artifacts and ringing artifacts near regions of significant object motion. In [7], a fast motion deblurring method was proposed by introducing a prediction step, using image derivatives instead of original pixel values to accelerate the kernel estimation and the latent image. However, the proposed method may not find the global optimal solution if the image has a strong impact on local regions different from other local regions. In [11], a novel type of image regularization for blind deconvolution based on the normalized sparsity measure was proposed. The ratio of l_1 to l_2 norm was proposed for the high-frequency components of an image. The normalized sparsity measure reduced the cost of sharp images. However, this may not work well for objects with sharp edges in an image, because the $l_1$to l_2 cannot possess this property.

In [5], a simple modification of the MAP algorithm was proposed, considering the covariance near the latent image with the central pixel x itself. The main drawback of this approach was that it used the standard expectation minimization framework. In [10], an effective method with a generalized l_0-norm regularizer on gradients was proposed, eliminating the need for extra filtering and reducing the number of iterations required for convergence. However, a moderate ringing effect was still present in the recovered images. In [19], before restoring sharp edges, an external dataset was used to learn the patch and estimate the blur kernel. However, this method may be ineffective when there is a difference between the selected patch and the external dataset. In [18], the contrast was increased to obtain sharp edges utilizing the normalized color line prior. Salient structures were predicted by sharp intermediate patches and further used to estimate the blur kernel. However, this method may not be suitable if the patches have more than two primary colors. In [32], l0-regularized priors were used for kernel estimation and to avoid complex filter or explicit edge selection methods. In addition, an alternative minimization method was used to estimate the kernel for convergence in a suitable time. Simplified total variation was used for nonblind deblurring. However, any better nonblind image deblurring method can be used to improve the results. Dark channel priors capture the changes caused by the blurring process and favor clear over blurred images in the deblurring process [44]. However, this can be less effective in the case of clear images that do not have dark pixels. In [45], extreme channel priors, named Bright Channel Priors (BCPs), were considered because the bright parts of clear images will not remain intact after applying the blurring process. The proposed method also used the benefits of bright- and dark-channel image priors. In addition, in [46] the effect of outliers was minimized when estimating the blur kernel, but at the expense of an increased computational cost. In [47], Probability Weighted Moments Regularization (PWMR) was proposed to better estimate the kernel, using probability-weighted moments in the x and y directions. However, probability weight moments can only perform well for small sample sizes. In [48], a Local Maximum Gradient (LMG) prior was proposed, since the maximum value of the gradient in the local patch will be diminished after the blurring process. Additionally, the proposed method exploited the l_1-norm. However, this method was computationally inefficient and did not perform well in the presence of Gaussian noise. In [49], a graph-based technique was proposed for blind image deblurring of a single-image photograph, using the Reweighted Graph Total Variation (RGTV) prior as the weight function. This method was unable to handle the defocus blur when not considering the separation of image parts. In [23], a new learning iterative method for blind deconvolution was proposed, using an extended version of the GST operator to minimize l_p-norms that have negative values of p. A GST parameter was defined iteratively to dynamically select the salient edges and time-varying regularization. GST iteratively sharpens the image, ignoring its local details. In [50], the ratio of the Dark Channel Prior (DCP) to the Brilliant Channel Prior (BCP) was considered. In particular, the two-channel priors were obtained from RGB images and used to create an original sparse channel prior first, and then the learned prior was applied to the BID.

Weber's Law (WL) aims to obtain the size of a small difference having a constant proportion to the actual stimulus, i.e. the value of change. In addition, the image affected by camera shake has a small difference between the original and affected pixel values. Moreover, it is difficult to find such a small difference between the affected and original pixels. This study proposes a novel image regularization method, named Weber's Law Regularization (WLR), for blind image deblurring. According to WL, there is a constant difference between the increment threshold and the background intensity. This property was used to estimate the kernel and obtain the sharp image efficiently and effectively. The main contributions of this study are:

- A novel regularization method is proposed based on the WL phenomenon to minimize a cost function to obtain the sharp image.
- The WLR effectively preserves the small texture of an image that was neglected in previous approaches.
- WLR reduces computational cost.

II. BACKGROUND KNOWLEDGE

WL is extensively used in various image processing and computer vision applications such as to compute image feature descriptors [51], identify impulse noise [52], etc. According to E. Weber, "the size of just noticeable difference is a constant proportion of the original value" [52]. Mathematically, WL is expressed as follows:

$$\frac{\Delta I}{I} = K \tag{1}$$

where I is the original value, ΔI is the noticeable Difference Threshold (DT), and $\Delta I/I$ is Weber's fraction. DT is considered the lowest quantity to change stimulus intensity and vary the sensory experience. Moreover, K specifies that Weber's fraction remains stable irrespective of variations in I. By rearranging (1), $\Delta I= IK$ is obtained, which signifies the linear relationship of the incremental threshold and the background intensity in WL.

III. WEBER'S LAW REGULARIZATION (WLR)

To estimate the blur kernel, most techniques neglected the small textures of an image that over-smoothened it. However, ignoring small textures may also eliminate the salient regions of an image. WL provides the relationship between the central pixel and the pixels in a compact neighborhood. In this study, the value of each pixel in the sliding window was calculated. Let x_c be the central pixel in the sliding window, and two filters f_c and f_n, as defined in [52], for the central and neighboring pixels in the sliding window, respectively. Additionally, the central pixel, x_c represents the fraction of two filters obtained by convolving the f_c and f_n with the current sliding window S_w. After convolving the f_c and f_n with S_w, p_c and p_n are obtained, respectively. Equation (2) computes the differences between the central and neighboring pixels within the sliding window S_w by convolving the filter f_n with S_w.

$$p_n = \sum_{i=1}^{n} \Delta x = \sum_{i-1}^{n} (S_{wi} - x_c), \tag{2}$$

where:

$$S_w = \begin{bmatrix} x_0 & x_1 & x_2 \\ x_3 & x_c & x_4 \\ x_5 & x_6 & x_7 \end{bmatrix},\ f_n = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix},$$

$$\text{and } f_c = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

where n is the total number of neighbors in the sliding window, and S_{wi} (i=1, 2, ..., n) denotes the i^{th} neighbor of x_c. Then, p_n and p_c are combined to compute the ratio of differences to the intensity of the central pixel in the sliding window. Therefore, the *WLR* value of the current sliding window (central pixel) is given by:

$$WLR = \arctan\left[\frac{p_n+\varepsilon}{p_c+\gamma}\right] \tag{3}$$

where ε controls the difference between neighbors and γ is added to not allow the value of the central pixel to be zero. However, the value of *WLR* may abruptly increase or decrease as the input becomes larger or smaller. Therefore, the arctan function is used to control the value of *WLR* from being too large or too small due to its simplicity. Other functions may be used instead of the arctan function. As the fraction p_n/p_c can give some negative values, the logarithm function cannot be used. Discriminative information can be effectively preserved if pixel intensities in the neighborhood are less than the central pixel.

$$WLR = \begin{cases} < 0,\ if\ x_c > s_{wi} \\ > 0,\ if\ \ x_c < s_{wi} \end{cases}$$

Otherwise, the central pixel in the sliding window is lighter than the neighboring pixels.

IV. PROPOSED ALGORITHM

Blind image deblurring models can be described as:

$$v = ku + N \tag{4}$$

where v is the blurred image, k is the unknown blurring matrix, u is the sharp image, and N is the Gaussian noise, which is i.i.d. The main purpose is to blindly estimate the blur matrix k, which will be used to deblur the image. The complete proposed algorithm for image de-blurring is shown in Algorithm 1.

```
Algorithm 1
Input: Blurred image v, Maximum kernel size kmax
Output: Estimated Kernel k, deblurred image u
1. Apply derivative filter to blurry input image v
   and get a high-frequency image a
2.Blind Estimation of blur matrix k. Update the
   sharp high-frequency image by using (6)
   Update the blurry matrix k
   Continue this step until the fine level is
   obtained
3.Use matrix k to deblur v and get the sharp image
   u
```

A. Blind Kernel Estimation

Kernel estimation plays a significant role in image deblurring. The estimation of the kernel in high frequency provides a better estimation compared to the estimation in the normal image [11]. The high frequencies of noisy and blurred images are used as a prior for kernel estimation. The high frequencies of the noisy and blurry image are obtained by (5). The following filters are used to obtain the high-frequency image:

$$\nabla_x = [\,1, -1];\ \ \nabla_y = [\,1, -1]^T \tag{5}$$

After convolving the aforementioned filter with blurry input image v, the following is obtained:

$$a = [\,\nabla_{xv},\ \nabla_{yv}]$$

For spatially invariant blurring, the cost function can be modeled as:

$$WLR = arctan\left[\frac{p_n+\varepsilon}{p_c+\gamma}\right]$$

$$\min_{x,k} \lambda \| x \otimes k - a \|_2^2 + W + \beta \| k \|_1 \tag{6}$$

where k is the unknown blurring kernel with the constraint that $k \geq 0$ and $\sum ki = 1$, x is the unknown sharp image in the frequency domain, $\otimes$ is a 2D convolution operator, and W is the proposed regularization term based on the WL phenomenon:

$$W = \sum \frac{WLR_x}{WLR_y} \quad (7)$$

where:

$WLR_x = WLR(\nabla_x)$ and $WLR_y = WLR(\nabla_y)$

The blur is normally caused by the interaction of the horizontal with the vertical axis or can be a motion on one axis. The proposed regularization method based on the WL phenomenon is shown in (7), indicating that the Weber ratio provides a small distance among the pixels in an image. The first term in (6) shows the likelihood relationship among the kernel, the high-frequency image x, and the unknown sharp image. In (6), the second term shows the novel regularization term proposed in WLR. The third term in (6) is added to remove the noise from the kernel. The constant weights λ and β are used to control the strength of the kernel and the regularization terms. The compact relationship between the central and the neighboring pixels within the sliding window is given by WLR_x and WLR_y, which are obtained by applying a derivative filter along the horizontal and vertical directions. To find a better estimation of the blur kernel, the fraction of WLR_x and WLR_y is computed, and then the summation of the fraction term is used as the regularization term.

Equation (6) is highly non-convex. By initializing the initial kernel k and the high-frequency image x, the problem of high no-convexity can be solved by switching between x and k [6]. The cost function in (6) can be divided into two parts for updating x and k:

$$\min_x \lambda \|xK - a\|_2^2 + W \quad (8)$$

where K is the blurring matrix and:

$$\min_k \lambda \|x \otimes k - a\|_2^2 + \beta \|k\|_1 \quad (9)$$

In each iteration, the Iterative Shrinkage-Thresholding Algorithm (ISTA) [53] was used to update the values in the sharp image using the following parameters: To update x, the regularization parameter λ was set to 20, and the threshold value t was taken as 0.001. Moreover, the observed image a and the maximum iterations N, both inner and outer, were taken as 2 each. The following algorithm was used to update x and the ISTA algorithm was also used for the inner iteration.

```
Algorithm 2: updating x
For l = 1: M
λ' = λ||x'||2
     x^(l+1) =ISTA(k, λ', x^l, t, N)
     The ISTA algorithm is as follows
     for I = 1: N
          c = a-tk^T(x^i - a)
          x^(i+1) = S_tλ(c)
     end for N
end for M
Updated image x^M
```

where S represents the soft shrinkage operation on a vector, and k is the blurring matrix k. ISTA involves the simple multiplication of the blurring matrix k with the sharpening image x, followed by the shrinkage operation computed component-wise. Each component of the input vector is reduced/shrinked to zero by using the soft shrinkage operator S given by:

$$S_x(x)_i = max(|x_i| - \alpha, 0) sign(x_i) \quad (10)$$

After updating x, kernel k is estimated by using the unconstrained Iterative Re-weighted Least Squares (IRLS) method [11]. IRLS is just used for one iteration, in which the weights are computed from the previous updated k. At the finest level, the estimated kernel may have a few values that are negligible or so small that they are normalized to 0. These values may appear likely due to noise. Some previous studies also have used similar blind de-convolution techniques [6]. For a multi-scale estimation of the kernel, a coarse-to-fine pyramid of image resolutions was used to overcome the problem of estimating the large kernel.

B. Image Deblurring

After kernel estimation, different nonblind deconvolution methods can be used to recover the sharp image at the finest level [10, 23, 30]. Richardson-Lucy (RL) is the most used method for non-blind image deconvolution. However, if the estimated kernel is not estimated correctly, then RL can produce ringing effect in the deconvolved image. To avoid this problem, fast image deconvolution was used with hyper-laplacian priors after kernel estimation, which is fast and robust against small kernel errors [30].

$$\min_x \lambda \|x \otimes k - y\|_2^2 + \|\nabla_x\|_b + \|\nabla_y\|_b \quad (11)$$

where ∇_x and ∇_y are the same derivative filters used in (5). The above cost function is solved by lp-type regularization. The values of λ and b were 3000 and 0.8, respectively, as in [11].

V. EXPERIMENTAL RESULTS AND DISCUSSION

Real-world and synthetic images were used to compare the performance of the proposed WLR method and state-of-the-art deblurring methods, such as those in [2, 5-6, 8, 10-11, 13, 19, 20-21, 23, 25, 27, 44, 47, 54]. Two quantitative measures were used to evaluate performance.

A. Synthetic Data

A standard benchmark dataset [12] was used to validate the effectiveness of the proposed method. This dataset consists of four 255×255 images and eight different blur kernels with sizes varying from 13×13 to 27×27. After convolution, there were 32 images in total. Blurred images, ground-truth images, and ground-truth kernels were also provided. The parameter settings in [11] were followed by using the same nonblind deconvolution algorithm to evaluate the estimated kernels. It was seen that the kernel estimated by WLR produced better results compared to other methods. The experimental results showed that the kernel estimated using WLR effectively preserves the edges of an object compared to various state-of-the-art methods [5-6, 7-14, 18, 21, 44]. Table I shows a detailed comparison of WLR with other methods in terms of PSNR, SSIM, and computational time, showing that the proposed method outperformed the others in terms of optimal error ratios.

TABLE I. COMPARISON OF DIFFERENT METHODS ON SYNTHETIC IMAGE DATASET [12] USING DIFFERENT PARAMETERS

Method/ Image	PSNR	SSIM	Time (s)	Error ratio
Known k	32.32	0.9385	---	1.0000
[8]	28.87	0.8845	2.3942	1.4082
[10]	29.41	0.9000	2.9371	1.4071
[11]	28.22	0.8586	10.1178	2.1369
[12]	28.73	0.8916	80.5917	1.5531
[14]	30.1332	0.9119	12.7206	1.2198
[19]	30.60	0.9190	192.5495	1.2234
[44]	30.87	0.9203	28.37	1.1934
[47]	30.14	0.9122	25.1276	1.2271
[54]	30.32	0.9034	10.11	1.23
WLR	30.37	0.9123	7.3562	1.2693

B. Real-World Images

Real-world standard benchmark images were also used to evaluate the performance of the proposed WLR regularization method and compare it with [2, 5-6, 8, 21, 10-11, 13-14, 19-20, 23, 25, 27, 44], using the same parameters for all real-world images. The proposed method effectively restored the image edges compared to the other methods, as it provided less ringing effects and better texture preservation in the zoomed part of the image. The methods from [2, 6, 11, 14, 21] over-smoothened the image while ignoring the small textures, while the proposed method preserved the small salient regions. WLR was effective in preserving the edges and provided sharper images than the other methods. WLR can capture the compact relationship between the pixels in the sliding window. The methods in [23, 44] over-smoothed the images eliminating small textures. Moreover, they only considered the prominent textures from the image and ignored the local information of the patches. The method in [23] also gave high contrast and a strong ringing effect. WLR reduced the ringing effect and preserved the underlying edge details. This is most likely because WLR incorporates even the smallest information of the objects. The image recovered by the method in [25] has a strong blurring effect. The image recovered by the method in [13] had an increased contrast and was brighter. The method proposed in [11] uses the fraction l_1/l_2 as a regularization term. The difference of each point from all other points was computed with this type of fraction and resulted in an increased computational cost. Furthermore, the relationship in the local sliding window was not considered.

VI. CONCLUSION

This study proposed a new regularization method based on Weber's law for blind image deconvolution. The Weber law tends to minimize the cost function. In addition, the proposed regularization method produced sharp images effectively and efficiently. To validate the effectiveness of WLR, experiments were conducted on both synthetic and real-world images. The experimental results showed the effectiveness of the WLR compared to other state-of-the-art blind image deblurring methods. WLR was found to be efficient and effective for the analysis of real-world images even though sometimes it did not perform that well for synthetic images. In the future, the WLR may be incorporated with a neural network to estimate the kernel.

ACKNOWLEDGMENT

This work was funded by the University of Jeddah, Saudi Arabia, under grant No. (UJ-23-DR-98). The authors thank the University of Jeddah for its technical and financial support.

REFERENCES

[1] S. D. Babacan, R. Molina, M. N. Do, and A. K. Katsaggelos, "Bayesian Blind Deconvolution with General Sparse Image Priors," in *Computer Vision – ECCV 2012*, Florence, Italy, 2012, pp. 341–355, https://doi.org/10.1007/978-3-642-33783-3_25.

[2] D. Wipf and H. Zhang, "Analysis of Bayesian Blind Deconvolution," in *Energy Minimization Methods in Computer Vision and Pattern Recognition*, Lund, Sweden, 2013, pp. 40–53, https://doi.org/10.1007/978-3-642-40395-8_4.

[3] S. D. Babacan, R. Molina, and A. K. Katsaggelos, "Variational Bayesian Blind Deconvolution Using a Total Variation Prior," *IEEE Transactions on Image Processing*, vol. 18, no. 1, pp. 12–26, Jan. 2009, https://doi.org/10.1109/TIP.2008.2007354.

[4] D. Wipf and H. Zhang, "Revisiting Bayesian Blind Deconvolution," *Journal of Machine Learning Research*, vol. 15, no. 111, pp. 3775–3814, 2014.

[5] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, "Efficient marginal likelihood optimization in blind deconvolution," in *CVPR 2011*, Colorado Springs, CO, USA, Jun. 2011, pp. 2657–2664, https://doi.org/10.1109/CVPR.2011.5995308.

[6] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," in *ACM SIGGRAPH 2006 Papers*, Boston, MA, USA, Apr. 2006, pp. 787–794, https://doi.org/10.1145/1179352.1141956.

[7] L. Guo, X.-L. Zhao, X. M. Gu, Y. L. Zhao, Y. B. Zheng, and T. Z. Huang, "Three-dimensional fractional total variation regularized tensor optimized model for image deblurring," *Applied Mathematics and Computation*, vol. 404, Art. no. 126224, Sep. 2021, https://doi.org/10.1016/j.amc.2021.126224.

[8] S. Cho and S. Lee, "Fast motion deblurring," in *ACM SIGGRAPH Asia 2009 papers*, Yokohama, Japan, Sep. 2009, pp. 1–8, https://doi.org/10.1145/1661412.1618491.

[9] Q. Shan, J. Jia, and A. Agarwala, "High-quality motion deblurring from a single image," *ACM Transactions on Graphics*, vol. 27, no. 3, pp. 1–10, May 2008, https://doi.org/10.1145/1360612.1360672.

[10] L. Xu, S. Zheng, and J. Jia, "Unnatural L0 Sparse Representation for Natural Image Deblurring," in *2013 IEEE Conference on Computer Vision and Pattern Recognition*, Portland, OR, USA, Jun. 2013, pp. 1107–1114, https://doi.org/10.1109/CVPR.2013.147.

[11] D. Krishnan, T. Tay, and R. Fergus, "Blind deconvolution using a normalized sparsity measure," in *CVPR 2011*, Colorado Springs, CO, USA, Jun. 2011, pp. 233–240, https://doi.org/10.1109/CVPR.2011.5995521.

[12] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, "Understanding and evaluating blind deconvolution algorithms," in *2009 IEEE Conference on Computer Vision and Pattern Recognition*, Miami, FL, USA, Jun. 2009, pp. 1964–1971, https://doi.org/10.1109/CVPR.2009.5206815.

[13] D. Perrone and P. Favaro, "Total Variation Blind Deconvolution: The Devil Is in the Details," in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA, Jun. 2014, pp. 2909–2916, https://doi.org/10.1109/CVPR.2014.372.

[14] T. Yue, S. Cho, J. Wang, and Q. Dai, "Hybrid Image Deblurring by Fusing Edge and Power Spectrum Information," in *Computer Vision – ECCV 2014*, Zurich, Switzerland, 2014, pp. 79–93, https://doi.org/10.1007/978-3-319-10584-0_6.

[15] D. Krishnan, J. Bruna, and R. Fergus, "Blind Deconvolution with Non-local Sparsity Reweighting." arXiv, Jun. 16, 2014, https://doi.org/10.48550/arXiv.1311.4029.

[16] W. Zuo, D. Ren, S. Gu, L. Lin, and L. Zhang, "Discriminative learning of iteration-wise priors for blind deconvolution," in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*,

Boston, MA, USA, Jun. 2015, pp. 3232–3240, https://doi.org/10.1109/CVPR.2015.7298943.

[17] L. Li, J. Pan, W. S. Lai, C. Gao, N. Sang, and M.-H. Yang, "Learning a Discriminative Prior for Blind Image Deblurring," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, USA, Jun. 2018, pp. 6616–6625, https://doi.org/10.1109/CVPR.2018.00692.

[18] W. S. Lai, J. J. Ding, Y. Y. Lin, and Y. Y. Chuang, "Blur kernel estimation using normalized color-line priors," in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, USA, Jun. 2015, pp. 64–72, https://doi.org/10.1109/CVPR.2015.7298601.

[19] L. Sun, S. Cho, J. Wang, and J. Hays, "Edge-based blur kernel estimation using patch priors," in *IEEE International Conference on Computational Photography (ICCP)*, Cambridge, MA, USA, Apr. 2013, pp. 1–8, https://doi.org/10.1109/ICCPhot.2013.6528301.

[20] J. Pan, Z. Hu, Z. Su, and M. H. Yang, "Deblurring Face Images with Exemplars," in *Computer Vision – ECCV 2014*, Zurich, Switzerland, 2014, pp. 47–62, https://doi.org/10.1007/978-3-319-10584-0_4.

[21] L. Xu and J. Jia, "Two-Phase Kernel Estimation for Robust Motion Deblurring," in *Computer Vision – ECCV 2010*, Heraklion, Greece, 2010, pp. 157–170, https://doi.org/10.1007/978-3-642-15549-9_12.

[22] Y. Zhou and N. Komodakis, "A MAP-Estimation Framework for Blind Deblurring Using High-Level Edge Priors," in *Computer Vision – ECCV 2014*, Zurich, Switzerland, 2014, pp. 142–157, https://doi.org/10.1007/978-3-319-10605-2_10.

[23] W. Zuo, D. Ren, D. Zhang, S. Gu, and L. Zhang, "Learning Iteration-wise Generalized Shrinkage–Thresholding Operators for Blind Deconvolution," *IEEE Transactions on Image Processing*, vol. 25, no. 4, pp. 1751–1764, Apr. 2016, https://doi.org/10.1109/TIP.2016.2531905.

[24] U. Schmidt, C. Rother, S. Nowozin, J. Jancsary, and S. Roth, "Discriminative Non-blind Deblurring," in *2013 IEEE Conference on Computer Vision and Pattern Recognition*, Portland, OR, USA, Jun. 2013, pp. 604–611, https://doi.org/10.1109/CVPR.2013.84.

[25] T. Michaeli and M. Irani, "Blind Deblurring Using Internal Patch Recurrence," in *Computer Vision – ECCV 2014*, Zurich, Switzerland, 2014, pp. 783–798, https://doi.org/10.1007/978-3-319-10578-9_51.

[26] T. F. Chan and C. K. Wong, "Total variation blind deconvolution," *IEEE Transactions on Image Processing*, vol. 7, no. 3, pp. 370–375, Mar. 1998, https://doi.org/10.1109/83.661187.

[27] L. Zhong, S. Cho, D. Metaxas, S. Paris, and J. Wang, "Handling Noise in Single Image Deblurring Using Directional Filters," in *2013 IEEE Conference on Computer Vision and Pattern Recognition*, Portland, OR, USA, Jun. 2013, pp. 612–619, https://doi.org/10.1109/CVPR.2013.85.

[28] H. Zhang, J. Yang, Y. Zhang, and T. S. Huang, "Sparse representation based blind image deblurring," in *2011 IEEE International Conference on Multimedia and Expo*, Barcelona, Spain, Jul. 2011, pp. 1–6, https://doi.org/10.1109/ICME.2011.6012035.

[29] H. Li, Y. Zhang, H. Zhang, Y. Zhu, and J. Sun, "Blind image deblurring based on sparse prior of dictionary pair," in *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*, Tsukuba, Japan, Aug. 2012, pp. 3054–3057.

[30] X. Tao, H. Gao, X. Shen, J. Wang, and J. Jia, "Scale-Recurrent Network for Deep Image Deblurring," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Salt Lake City, UT, USA, Jun. 2018, pp. 8174–8182, https://doi.org/10.1109/CVPR.2018.00853.

[31] D. Krishnan and R. Fergus, "Fast Image Deconvolution using Hyper-Laplacian Priors," in *Advances in Neural Information Processing Systems*, 2009, vol. 22.

[32] J. Li and W. Lu, "Blind image motion deblurring with L0-regularized priors," *Journal of Visual Communication and Image Representation*, vol. 40, pp. 14–23, Oct. 2016, https://doi.org/10.1016/j.jvcir.2016.06.003.

[33] G. Marti, B. Ma, and H.-A. Loeliger, "Why Maximum-A-Posteriori Blind Image Deblurring Works After All," in *2021 29th European Signal Processing Conference (EUSIPCO)*, Dublin, Ireland, Dec. 2021, pp. 666–670, https://doi.org/10.23919/EUSIPCO54536.2021.9615985.

[34] J. Dong, S. Roth, and B. Schiele, "Learning Spatially-Variant MAP Models for Non-blind Image Deblurring," in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA, Jun. 2021, pp. 4884–4893, https://doi.org/10.1109/CVPR46437.2021.00485.

[35] C. Li, "A Survey on Image Deblurring." arXiv, Jan. 30, 2022, https://doi.org/10.48550/arXiv.2202.07456.

[36] F. J. Tsai, Y. T. Peng, Y. Y. Lin, C. C. Tsai, and C. W. Lin, "Stripformer: Strip Transformer for Fast Image Deblurring," in *Computer Vision – ECCV 2022*, Tel Aviv, Israel, 2022, pp. 146–162, https://doi.org/10.1007/978-3-031-19800-7_9.

[37] Z. Wang, X. Cun, J. Bao, W. Zhou, J. Liu, and H. Li, "Uformer: A General U-Shaped Transformer for Image Restoration," in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, New Orleans, LA, USA, Jun. 2022, pp. 17662–17672, https://doi.org/10.1109/CVPR52688.2022.01716.

[38] O. Kupyn, T. Martyniuk, J. Wu, and Z. Wang, "DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better," presented at the 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Oct. 2019, pp. 8877–8886, https://doi.org/10.1109/ICCV.2019.00897.

[39] L. Chen *et al.*, "Deep Richardson–Lucy Deconvolution for Low-Light Image Deblurring," *International Journal of Computer Vision*, Sep. 2023, https://doi.org/10.1007/s11263-023-01877-9.

[40] M. Asim, F. Shamshad, and A. Ahmed, "Blind Image Deconvolution Using Deep Generative Priors," *IEEE Transactions on Computational Imaging*, vol. 6, pp. 1493–1506, 2020, https://doi.org/10.1109/TCI.2020.3032671.

[41] S. Alqethami, B. Almtanni, W. Alzhrani, and M. Alghamdi, "Disease Detection in Apple Leaves Using Image Processing Techniques," *Engineering, Technology & Applied Science Research*, vol. 12, no. 2, pp. 8335–8341, Apr. 2022, https://doi.org/10.48084/etasr.4721.

[42] P. Matlani and M. Shrivastava, "An Efficient Algorithm Proposed For Smoke Detection in Video Using Hybrid Feature Selection Techniques," *Engineering, Technology & Applied Science Research*, vol. 9, no. 2, pp. 3939–3944, Apr. 2019, https://doi.org/10.48084/etasr.2571.

[43] A. Khalfa, M. Sahed, E. Kenane, and N. Amardjia, "A Novel Blind Image Source Separation Using Hybrid Firefly Particle Swarm Optimization Algorithm," *Engineering, Technology & Applied Science Research*, vol. 12, no. 6, pp. 9680–9686, Dec. 2022, https://doi.org/10.48084/etasr.5255.

[44] J. Pan, D. Sun, H. Pfister, and M.-H. Yang, "Deblurring Images via Dark Channel Prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 10, pp. 2315–2328, Jul. 2018, https://doi.org/10.1109/TPAMI.2017.2753804.

[45] Y. Yan, W. Ren, Y. Guo, R. Wang, and X. Cao, "Image Deblurring via Extreme Channels Prior," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, USA, Jul. 2017, pp. 6978–6986, https://doi.org/10.1109/CVPR.2017.738.

[46] J. Dong, J. Pan, Z. Su, and M. H. Yang, "Blind Image Deblurring with Outlier Handling," in *2017 IEEE International Conference on Computer Vision (ICCV)*, Venice, Italy, Jul. 2017, pp. 2497–2505, https://doi.org/10.1109/ICCV.2017.271.

[47] H. Dawood *et al.*, "Probability weighted moments regularization based blind image De-blurring," *Multimedia Tools and Applications*, vol. 79, no. 7, pp. 4483–4498, Feb. 2020, https://doi.org/10.1007/s11042-019-7520-9.

[48] L. Chen, F. Fang, T. Wang, and G. Zhang, "Blind Image Deblurring With Local Maximum Gradient Prior," in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, Jun. 2019, pp. 1742–1750, https://doi.org/10.1109/CVPR.2019.00184.

[49] Y. Bai, G. Cheung, X. Liu, and W. Gao, "Graph-Based Blind Image Deblurring From a Single Photograph," *IEEE Transactions on Image Processing*, vol. 28, no. 3, pp. 1404–1418, Mar. 2019, https://doi.org/10.1109/TIP.2018.2874290.

[50] D. Yang, X. Wu, and H. Yin, "Blind Image Deblurring via a Novel Sparse Channel Prior," *Mathematics*, vol. 10, no. 8, Art. no. 1238, Jan. 2022, https://doi.org/10.3390/math10081238.

[51] J. Chen *et al.*, "WLD: A Robust Local Image Descriptor," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 9, pp. 1705–1720, Sep. 2010, https://doi.org/10.1109/TPAMI.2009.155.

[52] H. Dawood, H. Dawood, and P. Guo, "Removal of high-intensity impulse noise by Weber's law Noise Identifier," *Pattern Recognition Letters*, vol. 49, pp. 121–130, Nov. 2014, https://doi.org/10.1016/j.patrec.2014.06.016.

[53] A. Beck and M. Teboulle, "A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems," *SIAM Journal on Imaging Sciences*, vol. 2, no. 1, pp. 183–202, Jan. 2009, https://doi.org/10.1137/080716542.

[54] N. Bibi and H. Dawood, "SEBR: Scharr Edge-Based Regularization Method for Blind Image Deblurring," *Arabian Journal for Science and Engineering*, Jun. 2023, https://doi.org/10.1007/s13369-023-07986-4.