Blur Removal in Natural Digital Images Using Self-Reference Generative Networks

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***Abstract*—The blur detection in a single image is considered as a pivotal issue in digital image processing applications, especially when the blurring is spatially-varying. This study introduces self-reference generative network (SR-GN) algorithm in order to deblur a digital natural blurred image. The proposed method divides the contaminated image into two main parts, which are the clear part and blur parts. The blur parts which caused by the shadowy channel are less sparse while the other parts have some dark patches, which can be cleaned by avenging them. In addition, due to the global performance of the proposed algorithm on public database, multicomponent loss function is utilized in order to perform further classification to the original patches of the blurred image to distinguish it from the contaminated counterparts as the experimental results demonstrated. The experimental results show that the proposed technique has an improvement in visual quality, and objective results as well in comparison to related advanced blur removal algorithms.**

***Index Terms*—Classifications; Deblurring; Generative Networks; Image Restoration; Noise Removal; Restoration.**

I. INTRODUCTION

Two pivotal reasons that may cause of blurring in digital images are motion and defocus while taking the pictures. As a result, Deblurring plays the main role in the arena of image enhancement and restoration [1]. The problem of blurring becomes increasingly vital as many digital images are snapped by hand-held digital cameras, mostly using smart phones [2].

The present study focuses on blind deblurring of a single local blurred image by the self-reference generative networks (SR-GN). Many techniques that utilized machine learning and artificial and the generative adversarial networks GANs have been implemented [3-6]. Theoretically, GANs, Generator and Discriminator can easily effect on the Generator in order to produce an output that can fool the Discriminator. Consequently, using the setting of the input in the Generator as a blurred image, the network then generates a latent blur-less image that can be classified as pure image. Practically, in this paper, self-reference deblurring a generative network is proposed, which presented as SR-GN.

The proposed method is implemented according to Wasserstein GANs [7], and the deblurring image is produced by referring to the pure parts of the contaminated image. Furthermore, due to the lack of quality deblurring image which the up mentioned methods sowed, the digital image edges and ridges must be reconstructed during every single iteration before the following step takes place. In addition, in order to reduce locality in blurring edges, a coarse-to-fine technique should be exploited during the interchanging optimization procedure. All the demerits which indicated earlier make the deblurring processes complicated. Furthermore, most existing techniques are aimed only for random hand-drawn blur types. On the other hand, in real time conditions, the blur model could be known in most cases. From this point of view, self-reference generative network (SR-GN) procedure in the existing methods can be simplified, and the quality of the deblurring algorithm can be increased by solving the optimization problem.

The essential contributions of this study are stated in two contributions. Firstly, a novel algorithm is introduced, and a multi-component loss function is implemented as well in order to achieve high visual quality images compared to state-of-the-art blur removing methods. Secondly, by utilizing separating approach and combining model to differentiate the information of varied parts of the tested images during the process of the restoration, as a result, high-quality image is achieved in terms of qualitative assessments as the peak signal to noise ration PSNR and structural similarity model SSIM.

II. RELATED WORKS

A. Blur-Removal in Digital Images

All image blur-removal is an essential step in digital image processing and its applications such as image registration and computer vision. Single based techniques are designed according to the blur cue which is mined from a single digital image. In this regard, the formula of the blur model can be written as follows [8].

$$A = \mathrm{b} \otimes \mathrm{S} + N \tag{1}$$

where: b = Unknown blur-kernel
S = Latent sharp digital image
N = Additive noise
$\otimes$ = Convolution

The issue of deblurring is seminal research and still active in clean and pure images and videos, so the challenge is that it is burden task to get an original clear picture from blurred image [8]. As a pivotal point in deblurring digital images, the kernel or the point-spread function (PSF) one of them at least should be known [9], the image restoration and blur removal are categorized into non-blind and blind blur removal methods [10].

The non-blind blur removal methods are generally depending on the hypothesis that the kernel of blur image is given. In addition, the most common techniques are based on the deconvolution process in order to attain the correct estimation of original digital image. As a consequence, if the kernel is not given, then the problem is considered as blind blur removal and right estimation and algorithm should be implemented. In this case, it is important to seek for an assessment of the original (blur-less) image S and the blur kernel k. Most of the traditional techniques mainly designed according to the thermo of maximum posterior probability (MAP) that in most cases is a burden to the processor of the system due to its complicated calculations and statistical formulas as mentioned in [11].

Conventional blind blur removing algorithms is classified into parameter techniques such as the study introduced by Fergus [12] and iterative-based methods such as the technique in [13].

On the other hand, methods which basically designed according to specific parameters take effect only on some certain fuzzy techniques, but the demerit of this method is that it shows low quality of deblurring images due to the poor distinguish of the blur kernel from the free- blur image and also it suffers from calculation burden due to many iteration processes. Recently, most of kernel-free blind blur-removal techniques are designed according to be worked by utilizing deep learning and artificial intelligent network, studies lie [14], [15], and [16] are the best example of these methods. The main advantage of these techniques is that they do not need much complicated calculations and its execution time is fair compared to the up mentioned techniques. Different methods that combine the learning networks and external control mechanisms is designed and introduced in order to control the learning process like Collaborative Generation Correction Modules (GCM) [8].

In addition, Kupyn in [17] utilized generative conditional adversarial networks (cGAN) from the super resolution image in order to come up with novel image deblurring method that give results better than the study in [17].

B. Self-Reference Generative Networks for Blur Removal

In this regard, the Generator and the Discriminator have competed against each other in order to distinguish the noise from the original signal. The Generator will mislead the Discriminator by adding and generating redundant samples from noises, while the Discriminator will try to make classification process in order to split the generated samples from the original samples. As a result, reducing the Jensen-Shannon (JS) deviation between the original signal and the distributions model is highly demanded [3]. The pivotal objective function of this formula is stated as follows:

$$\min_G \max_D V(G,D) = E_{x\sim p_r(x)}[\log D(x)] + E_{x^*\sim p_g(x^*)}[\log(1-D(x^*))] \tag{2}$$

where: D = Discriminator
G = Generator
Pr = Original data distribution
Pg = Model distribution

Let assume that b is the input signal, then $x *= G(b)$, and Pb represents the distribution of the original input. Additionally, in the case of generative network for image blur removing, the input signal of the Generator is stated as a blurred or additive white Gaussian noise image, which generates an original clear digital image in order to fool the Discriminator. In study which originated by [7] JS divergence can easily cause problems of mode collapse and effect on the vanishing gradients. In [18], with addition to a gradient penalty, machine learning can be used as similar as regularization processes in order to solve these shortcomings by applying the following formula:

$$\gamma \mathrm{E}_{x^*\sim p_g(x^*)}[(\|\nabla_x - D(x^*)\|_2 - 1)^2] \tag{3}$$

While in the study of Arjovsky [18] they designed it by utilizing the Wasserstein-1 or named Earth-Mover distance in order to replace JS divergence in [7] which called WGN. The objective function for this is as follows:

$$\min_G \max_{D\in L_1} \mathrm{E}_{x\sim p_r(x)}[D(x)] - \mathrm{E}_{x^*\sim p_g(x^*)}[D(x^*)] \tag{4}$$

L_1 is the set of *1−Lipschitz* functions. In order to have Lipschitz constraint b in WGN, the weight can be clipped to be $|c|$.

III. The Proposed Self-Reference Generative Network

The main objective of this study is to retrieve the original input image *b* by making the produced image L closer to the sharp image *S*. In order to do so for the blurred image; demanding for a powerful tool that improves the existing techniques which mainly deal with the full input image instead of dealing with sub-blocks of the tested image [19, 20]. In this case, the operation ensures the full tested image. However, the variance and association between several degradation sub-parts of the same image will be ignored.

In addition to self-attention, in the proposed GAN we also incorporate recent insights which related to network conditioning to increase GAN performance. In tradition GAN as described by [26], it showed that well-conditioned generators tend to show high quality images. In the proposed work, we introduce enforcing good conditioning of GAN generators by utilizing the spectral normalization algorithm that has in previous works applied only to the discriminator. Moreover, the amount of calculation and the complexity of the technique will be increased. Consequently, a reliable and robust method is introduced in this paper, where it adds self-reference process to the generative network for blur removal of local noisy sub-images, named SR-GN blur removal method. More automatically, for the two or more consecutive parts, when the pure reference parts are not minimized, and the contaminated sub-image is clear enough, the deblurring steps will show high quality results with fair computional time.

A. Proposed Loss Function

The main goal of the loss function is to combine the loss model LWGN and the aggregation of the content losses L content of different sub-image z, the content loss denotes the variance between a selected pre-trained network feature maps of the sharp and resulted images. Based on the study in [17], the suggested technique is showed its high efficiency results to generate an original image, since the tested image and its fine textures and small details are taken under consideration. The loss function formulas are stated as follows:

$$L = L_{WGAN} + \sum_{z} \gamma_z L^z_{content} \tag{5}$$

$$L_{WGAN} = \sum_{m=1}^{M} -D_{\theta G}(D_{\theta G}(B)) \tag{6}$$

$$L^z_{content} \frac{1}{w^z_{ij} h^z_{ij}} \sum_{x=1}^{w^z_{ij}} \sum_{y=1}^{h^z_{ij}} (\emptyset_{ij}(S^z)_{x,y} - \emptyset_{ij}(D_{\theta G}(B^z))_{x,y})^2 \tag{7}$$

where: z = Label of image
$\emptyset_{ij}$ = Feature maps
w_{ij} = Dimensions of feature maps
h_{ij} = Dimension of feature maps
i^{th} = Pooling layer
j^{th} = Convolution layer with the label in the pretrained network

The i^{th} and j^{th} both are equal to 3 by initial value as the study in [11] mentioned. Furthermore, the general and default situation is when the tested digital image is incompletely blurred, and some image details are still clear.

B. Structure of the Proposed Network

As mentioned in the study in [11] where blind motion blur removing technique is used with GAN network, the details structure of Discriminator network is determined by c-GAN in [17], the proposed Generator network is shown as Figure 1. Furthermore, the diagram of SR-GN is depicted in Figure 2.

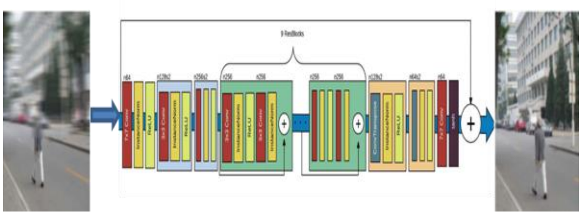


Figure 1: The proposed self-reference generative network SR-GN

IV. Experiments and Analysis

Keras at Tensorflow background is utilized in order to implement the proposed model. In addition, the experimental processes are conducted by dividing them into two main categories. The group was conducted on the artificial sub-blurred digital images while the other group was done using original sub-blurred digital images. The first patch of the tested images is used in order to reveal the necessity and reliability of the proposed technique. On the other hand, the second group is utilized to confirm the global and effectiveness of the proposed blur-removal method. The proposed SR-Deblurrng-GAN is used in each sub-group and compared with the method for deblurring that introduced in [11].

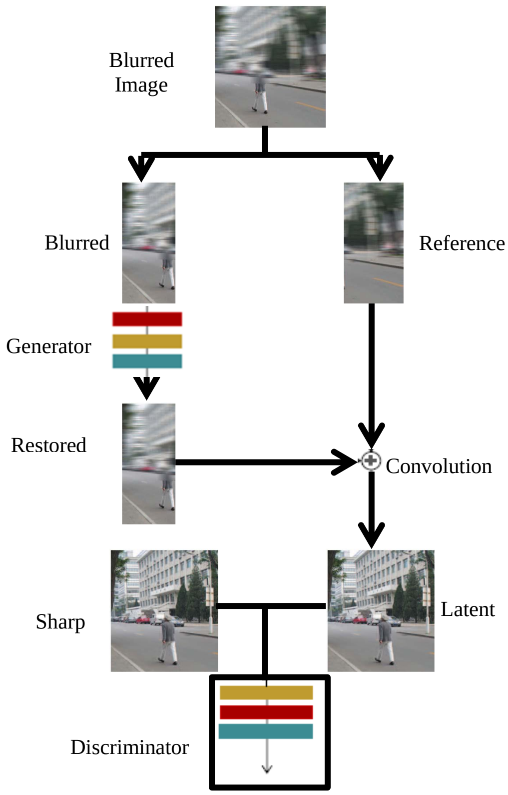


Figure 2: Block diagram of the proposed SR-GN circuit

A. Experiment on Artificial Partial Blurred Images

Dataset of the digital images were 1800 and it was taken from GoPro [15], those images have been picked up in order to train the generative network. In the practical part, for the tested images in the artificial blurred group, collected clear images are used as ground truth tests and those images are basically sub-blurred by two types of blur kernels additive Gaussian blur kernel in OpenCV and the designed motion blur as well.

The additive Gaussian Kernel size which used as ground truth images are 70×70, while motion blur kernel is chosen as the study in [11]. Figure 3 depicted one of the sub-blurred patches.

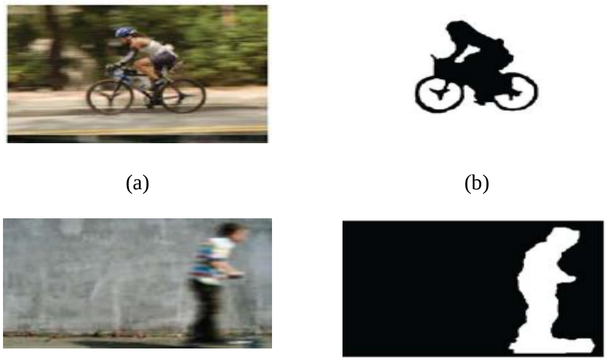
(a) (b)

Figure 3: (a) Original image, and (b) image contaminated with Gaussian blurring

B. Experiment on Natural Partial Blurred Images

As BDD dataset shows [26], some digital images with partial blurring which stated as ground truth with fuzzy textures are utilized to be included in our experimental tests. The blur-removal results which obtained from two main groups are depicted in Figure 4. The proposed method SR-GN depicts high image quality in the pictures which contaminated partially and fully with blurring especially when it comes to the fuzzy parts.

In our method, we used Ground Truth digital images in order to present a fair evaluation to the proposed technique. The GoPro dataset [11] is use as Ground Truth tests and consists of multiple blur and clean digital images, the blur images are considered as local blur digital images. Figure 5 shows the main results of a pair of blur and clean images which are deblurred as real sharp images. From practical point of view, the fuzzy textures and parts using the proposed algorithm is clearly improved as depicted in Figure 5.



(a) (b) (c) (d)

Figure 4: (a) and (c) are the original images; (b) and (d) are the Ground Truth of blur boundary images

Figure 5: The first row represents the original digital images with specific sensitive blurred parts. The second row shows the blur removal results of the proposed SR-GN

The PSNR and SSIM of several blur removal techniques are depicted in Table 1. The larger the PSNR, the better the denoising performance. Similarly, the larger SSIM, the higher image similarity of the original image and denoised image.

$$PSNR = 10\ log \frac{255^2 MN}{\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j) - f_{0(i,j)}]^2} \tag{8}$$

$$SSIM = u_f \frac{(2u_f u_{f_0} + c_1)(2\sigma_{ff_0} + c_2)}{({u_f}^2 + {u_{f_0}}^2 + c_1)({\sigma_f}^2 + {\sigma_{f_0}}^2 + c_2)} \tag{9}$$

where:
$f\ (i,j)$ = Pixels of noisy image
$f_{0(i,j)}$ = Pixels of original images
M = Number of rows of the image
N = Number of columns of the image
u_f = Mean value of image f
u_{f_0} = Mean value of image f_0
${\sigma_f}^2$ = Variance
${\sigma_{f_0}}^2$ = Variance
σ_{ff_0} = Co-variance
c_1 = Constant
c_2 = Constant
c_1 = $(0.01L)^2$
c_2 = $(0.03L)^2$
L = Dynamic range of pixel values [27]

It is clearly noticed that the proposed SR-GN technique achieves the highest PSNR and SSIM [24] compared to methods in [11] and [25], and the suggested network increases the SSIM for the full blur-removal digital images. From practical viewpoint, the proposed technique is feasible to improve the deblurring image quality of local blurred images as well.

V. Conclusion

The proposed SR-GN technique with high blur removal is suggested to solve the problem of blur and noisy of natural digital images. This method has a unique multi-component loss function that used for local and full blurred images as showed in the results compared to state-of-the-art blur removal techniques results. Furthermore, many applications can be used in the arena of deblurring digital images such as local in-painting and local-image translation. The main advantage of SR-GN technique is that it does not need any heuristic edge choice steps or complex handling methods in kernel evaluation. As a future work, the proposed algorithm can be used to deal with blur satellite images if the multilayers network is studied to deal with each band of the hyper-image as an individual image.

Table 1
PSNR and SSIM of SR-GN Compared to Several Deblurring Methods

Noise Type	Metric Type	Proposed Method		Ref [11]		Ref [25]	
		Reference Part	Complete Part	Reference Part	Complete Part	Reference Part	Complete Part
Additive Gaussian	PSNR	36.17	29.27	33.42	31.68	35.76	29.82
	SSIM	0.998	0.992	0.991	0.988	0.996	0.991
Motion	PSNR	33.89	27.18	31.27	29.41	32.60	28.47
	SSIM	0.991	0.988	0.986	0.982	0.987	0.865

References

[1] P. Yanwei, H. Zhu, X. Li and X. Li, “Classifying discriminative features for blur detection”, *IEEE transactions on cybernetics*, vol. 46, no. 10, pp. 2220-2227, 2015.
[2] P. Jinshan, D. Sun, H. Pfister and M. Yang, “Blind image deblurring using dark channel prior ”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 10, pp. 2315 – 2328, 2018.
[3] C. Ledig, L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, “Photo-

Realistic Single Image Super-Resolution Using a Generative Adversarial Network, *" In IEEE Conference on Computer Vision and Pattern Recognition (*CVPR), pp. 105-114. 2017.

[4] X. Hu, X. Liu, Z. Wang, X. Li, W. Peng and G. Cheng, "ESRGAN: RTSRGAN: Real-Time Super-Resolution Generative Adversarial Networks," *Seventh International Conference on Advanced Cloud and Big Data* (CBD), 2019.

[5] D. Ugur, and G. Unal, "Patch-based image inpainting with generative adversarial networks," *arXiv preprint arXiv*, 2018.

[6] L. Avisek, A.Jain, D. Nadendla and P. Biswas, "Improved Techniques for GAN based Facial Inpainting," *arXiv preprint arXiv*, 2018.

[7] A. Khmag and N. Kamarudin, "Clustring-based natural image denoising using dictionary learning approach in wavelet domain," *Soft computing,* vol. 23, no.17, pp.8013-8027, 2019.

[8] R. Liu, Y. He and S. Cheng, "Learning Collaborative Generation Correction Modules for Blind Image Deblurring and Beyond" *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), 2018.

[9] A. Khmag, S. Al Haddad, A. Ramlee, N. Kamarudin and F. Malallah, "Natural image noise removal using nonlocal means and hidden Markov models in transform domain," *The visual Computer,* vol. 34, no. 12, pp. 1661-1675, 2017.

[10] A. Khmag and N. Kamarudin, "Natural Image Deblurring using Recursive Deep Convolutional Neural Network (R-DbCNN) and Second-Generation Wavelets," *The IEEE International Conference on Signal and Image Processing Applications* (IEEE ICSIPA), 2019.

[11] O. Kupyn, V. Budzan and M. Mykhailych, "DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks," *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), pp. 8183-8192, 2018.

[12] A. Khmag, AR. Ramli, SJ. Hashim and S. Al Haddad, "Additive noise reduction in natural images using second generation wavelet transform hidden Markov models,"*IEEJ Transactions on electrical and electronic engineering,* vol.11, no.3, pp.339-347, 2016.

[13] L. Yuan, J. Sun, L. Quan, and H.-Y. Shum, "Image deblurring with blurred/noisy image pairs," *in Proc. ACM SIGGRAPH,* San Diego, CA, USA, pp. 1-es, 2007.

[14] J. Pan, D. Sun and H. Pfister, "Blind Image Deblurring Using Dark Channel Prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.40, no.10, pp. 2315 – 2328, 2018.

[15] J. Sun, W. Cao, Z. Xu and J. Ponce, "Learning a convolutional neural network for non-uniform motion blur removal," *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), pp. 769-777, 2015.

[16] S. Nah, T. H. Kim and K. M. Lee, "Deep Multi-scale Convolutional Neural Network for Dynamic Scene Deblurring," *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), pp. 257-265, 2017.

[17] T. M. Nimisha, A. K. Singh and A. N. Rajagopalan, "Blur-Invariant Deep Learning for Blind-Deblurring," *in IEEE International Conference on Computer Vision* (ICCV), pp. 4762-4770, 2017.

[18] J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde- Farley, S. Ozair, A. Courville and Y. Bengio, "Generative Adversarial Nets," *in Advances in Neural Information Processing Systems*, vol. 27, pp. 1-9, 2014.

[19] Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville, "Improved Training of Wasserstein GANs," *In Advances in neural information processing systems*, pp. 5767-5777, 2017.

[20] X. Tao, H. Gao and Y. Wang, "Scale-recurrent Network for Deep Image Deblurring," *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), 2018.

[21] Y. Bahat, N. Efrat and M. Irani, "Non-uniform Blind Deblurring by Reblurring," *IEEE International Conference on Computer Vision* (ICCV), 3306-3314, 2017.

[22] F. Yu, W. Xian, Y. Chen, F. Liu, M. Liao, V. Madhavan and T. Darrell, "BDD100K: A Diverse Driving Video Database with Scalable Annotation Tooling," *arXiv*, 2018.

[23] K. Purohit, A. Shah and A. Rajagopalan, "Learning Based Single Image Blur Detection and Segmentation," *25th IEEE International Conference on Image Processing* (ICIP), pp.2202-2206, 2018.

[24] Y. Chen, T. Wunderli, "Adaptive total variation for image restoration in BV space," Journal of Math. Anal. App, vol. 272, pp. 117 – 137, 2002.

[25] Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600-612, 2004.

[26] G. Guiliang and Z. Kai, "Local Blurred Natural Image Restoration Based on Self-Reference Deblurring Generative Adversarial Networks," *IEEE International Conference on Signal and Image Processing Applications* (IEEE ICSIPA 2019), pp. 231-235, 2019.

[27] A. Odena, J. Buckman, C. Olsson, T. B. Brown, C. Olah, C. Raffel, and I. Goodfellow, "Is generator conditioning causally related to GAN performance?," pp. 43-56, 2018.