Natural Image Deblurring using Recursive Deep Convolutional Neural Network (R-DbCNN) and Second-Generation Wavelets

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Abstract— Deconvolution in blind digital images is a common issue in image enhancement techniques, which basically was a notion of many researches. In this study, spatial varying blind deconvolution is stated and implemented. In addition, image noise removal approach which utilizes the normalized platform of second-generation wavelet transform is applied as pre-processing step. The low and high frequencies are decomposed in this step in order to be extracted. Practically, the main merit of wavelet transform is its efficiency in reduction of data redundancy in digital images. This feature helps a lot in terms of data classification where it is easy to distinguish the signal from its noisy counterpart. The second step, a recursive deep convolutional neural network (R-DbCNN) is implemented to suppress any image blur affected by second-generation wavelet transform to further remove the blur of noisy image. The experimental results depict that the suggested method outperforms recent blur removal techniques for different bluer image types in terms of image quality and time consumption.

Keywords— Image deblurring, second-generation wavelet transforms, image enhancement, convolution neural network, image denoising

I. INTRODUCTION

Dealing with digital image acquiring in most cases needs to take in consideration several factors, such as false in hardware and software platforms which may lead to image blurring and noise. The general form of bluriness can be stated as \( y = x * v + n \), where * represents the convolution factor, \( x \) is the noise-free image, \( v \) is the point spread function labeling the blurriness and \( n \) is the additive white Gaussian noise. As a result, the main aim of digital image deblurring is to get a noise-free image which denoted by \( x \) throughout suppressing both factors \( v \) and \( n \). The techniques which remove blur form digital images are basically classified to two kinds, non-blind and blind deconvolution, according to the case were \( v \) details are well known [1, 2] or unidentified [3, 4]. From theoretical point of view, a many researches have been conducted in order to address this problem, including transformation methods, filtering types techniques, combination methods that contain total variation and Fourier analysis, artificial intelligent techniques that represents by fuzzy, neural networks and Genetic algorithms, to name a few. Filters such as Median filter and Wiener filter which described in [5, 6, 7] are designed in order to remove the additive noise that attacks the natural digital images. Other filters which utilize orthogonal transforms such as hybrid Fourier image noise removal is presented in [8]. This method is mainly proposed to suppress white Gaussian noise from digital images. Because of the pivotal merit of wavelet transform in noise removal applications, techniques which produced in [9, 10] is exploited to removal additive white Gaussian noise. Although peak to signal ratio (PSNR) was high in their methods, the resulted images were over smoothed and its fine details almost missing. Another recent technique based on artificial intelligence is introduced in [11, 12]. In these approaches, multilayers perceptron networks are applied to suppress the Gaussian blur and speckle noise as well. Furthermore, Genetic algorithm was utilized in [13, 14, 15] to suppress the additive noise in [12]. In the same regard, second-generation wavelet transform (SGWs) is utilized in [16, 17] to get rid of the multiplicative noise in natural digital images with the help of semi-soft thresholding and cycle spinning approach. They found that by applying the semi-soft thresholding, the fine texture of the noisy images are kept and noise is mostly removed without any distortion in the image details. This paper basically focuses on different second-generation wavelet transformation types which include Haar, Daubechies, Symlet wavelet families due to its high quality in noise reduction and edge preservations. In the practical part of this study, a new deep recursive neural deconvolution network which denoted by R-DbCNN is proposed in order to apply further deblurring process to make sure the resulted images is clear of noise. Consequently, the proposed technique is implemented by combining the advanced natures of the transformation method (Wavelet) and artificial intelligent method (Convolutional neural network). This study is structured as follows: Section.2 contains a deep discussion about the latest literature review on digital image deblurring and noise removing methods. In Section 3, main details of the proposed technique and its methodology are presented which stated the novel deblurring technique. The experimental results are presented in the Section.4. Lastly, Section.5 summaries the study and depicts the future work of this study.

II. RELATED WORK

Nowadays, in image processing arena, deep learning is mostly implemented in many applications specifically when it comes to computer vision applications. The researches in
the image denoising and deblurring are still seminal and interesting. Techniques based on adapted filters are used in the removal of additive white Gaussian noise; these methods include linear filters [5, 6, 7] and transformation methods [8, 9, 10]. In [11], the authors applied stacked image noise removal based on auto-encoders to paradigm an artificial neural network that contains local noise suppressed model. However, in [18] the technique mixed up sparse coding method with image noise removal auto-encoders in order to reduce the demerits of the method in [11] where they utilized the combination technique to make illumination atmosphere low. They achieved better results than the study in [11] visually and subjectively as the unwanted noise is suppressed. On the other hand, the technique showed poor performance in term of time execution. Dynamic nonlinear approach is introduced by [19]; they utilized the dependent parameters of the digital images in order to attain high visual performance due to the advantage of diffusion model and less steps of the proposed model. In study which conducted by Tim Meinhardt and others [20], they concluded that a noise removal using convolution neural network (CNN) can easily exchange the operator of the regularized proximal of curved energy in minimum mode. It is implemented in order to obtain acceptable performance by utilizing several kernels of blur image deconvolution in well-learned neural network. On the other hand, the techniques based on statistical approaches and neural networks mainly exploited for image noise removal over digital image deblurring. Deeply recursive convolutional network for digital image super-resolution was introduced in [21, 22]. They integrated the supervision recursive with skip networks connection and found that the high deblurring performance can be achieved in classical deep recursive techniques.

III. METHODOLOGY

Recently, the main steps in image deblurring utilize convolutional neural networks or techniques based on artificial intelligent in order to accomplish clean digital images that is free of blurring Consequently, in the proposed method, two-way image deblurring algorithm which combines second generation wavelets and CNN is introduced. The pivotal merit of second generation wavelets is that the original energy shows more intensive in very rarer coefficients in the platform domain; energy of the noise does not. Thus, it helps a lot in the issue of separating the original signal from noise. As a result, a recursive CNN is utilized in order to eliminate the artifacts that caused by the redundancy of the second generation wavelets. The suggested technique is depicted in Fig. 1. It is implemented based on combining the merits of SGWs and CNN, so accordingly, it shows a high performance not only in handling different blurs types in comparison with SGWs, but also reflects better deblurring visual quality compared with original CNN. The pivotal step of the suggested technique is that the sharp images mostly contaminated with additive white Gaussian noise AWGN and blur. Thus, it is supposed that the original digital image is corrupted by a spread function with point-wise model v and an AWGN that represented by n, as follows:

\[ y = v * x + n \]  \hspace{1cm} (1)

The symbol y which presented in Eq(1) denotes the blurry image, \( * \) is the convolution process. In order to attain the resulted image x, the deblurring operator is found using the following model:

\[ \hat{y} = \phi(v * x + n) \]  \hspace{1cm} (2)

The model \( \phi(.) \) reflects a nonlinear deblurring factor, and \( \hat{y} \) denotes the deblurring digital image by model \( \phi(.) \). As a consequence, the aim of deblurring process is to minimize the term \( \phi(.) \) with respect to all pixels of the original image x.

A. Degradation of Blur Images based on Wavelet Domain

Basically, SGWs is used to attain more details about the blurry image where it used to suppress the redundancy of the coefficients which resulted from blur and noise factors, the normal blurring images can be found as:

\[ W_N(y) = W_H^x(y) + W_V^x(y) + W_D^x(y) + W_{N-1}^x(y) \]  \hspace{1cm} (3)

where \( W_N(.) \) depicts the traditional wavelets with N levels for blurry images, and \( H, V \) and D reflect the variations along three dimensional wavelet format i.e. columns, rows and diagonals coefficients. Due to inter and intra-correlation of SGWs, \( W_H^x(.) \), \( W_V^x(.) \), \( W_D^x(.) \) and \( W_{N-1}^x(.) \) show high data dependency and redundancy coefficients especially when performing image synthesis which leads to image smoothing.

\begin{center}
\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig1_Novel_structure_of_the_proposed_method.png}
\caption{Novel structure of the proposed method}
\end{figure}
\end{center}
The operator $\odot$ denotes point by point multiplication; $r$ is the redundancy artifacts after deblurred process by SGWs. Supposing $Y$ reflects $W_{Y}(x)$ the following model can be achieved:

$$Y = x \odot r$$  \hspace{1cm} (5)

Second-generation wavelet transformation can successfully make the blurred digital image less smoothing. Thus, the main aim of digital image smoothing is to suppress the effect of additive white Gaussian noise in order to make the original image clearer and its quality is high for R-DbCNN, so that it helps in case of further deblurring of the input image.

### B. Visual artifacts suppression using R-DbCNN training

As depicted in Fig. 2, the detailed structure of the proposed algorithm is shown where the combination of SGWs and R-DbCNN is presented. In this study, the parameters of the traditional wavelets consist of number of levels, types and scales of the chosen wavelet. Thus, supposing the running time of a CNN with $i$ layers is $T_i$, the running time of the proposed technique can be found as: $n \times m \times l \times \sum_{i=1}^{T_i}$ shows a heavy computation source. In order to accelerate task under the ground of deblurring causes, pre-selection parameters are used into the proposed technique. Pre-selection parameter utilizes the SGWs by assuming the lightweight R-DbCNN contains only limited layers, i.e. input, hidden and output layers. In this case, the combining SGWs and lightweight network of R-DbCNN is exploited to pick up suitable parameters to be used in the wavelet domain. Consequently, subjective analysis such as Mean Square Error (MSE), Peak-Signal to Noise Ratio (PSNR), and Structure Similarity Index (SSIM) are exploited in this study in order to assess the combination method. The criterion is to choose the extreme value of particular factors for SGWs in the order of $n$, $m$ and $l$, where $n$, $m$ and $l$ represent the full number of changes in the selected pre-selection of parameter values for order, scale and threshold respectively. Thus, the running time will be critically minimized to $n \times m \times l \times \sum_{i=1}^{T_i}$.

Another selection is parameters sharing, it is the use of R-DbCNN in sharing process of R-DbCNN, and it can be concluded by two main factors, weight sharing and partial connections, which used in order to speed up the training processes. Practically, the training time which used for the neural network will be $n \times m \times l \times (\frac{T_i}{T^*})$, where $T^*$ denotes the training time of main network as depicted in Fig. 2 and $n \times m \times l \times (\frac{T_i}{T^*})$, $<< n \times m \times l \times \sum_{i=1}^{T_i}$.

Concurrently, the achievement of the technique with the specific training time of $n \times m \times l \times (\frac{T_i}{T^*})$, is similar to the algorithm with training time study which done in [23]. For the resulted wavelet domain, the loss function is organized as follows:

$$L_0(x, y) = \arg \min_{x} \sum_{i=1}^{S} ||I_i - x_i ||^2$$  \hspace{1cm} (6)

where $\emptyset$ is the wavelet parameters and $S$ represents the number of noisy and blurry images. The proposed method exploits Stochastic Gradient Descent Momentum (SGDM) to update the current parameters.

### IV. EXPERIMENTAL RESULTS

#### A. Data of the experiments

This part is used to assess the proposed noise removal and deblurring technique efficiency. In this section, a set of 300 clear/blurry/noisy images from several sources [3, 20, 24] are utilized. Fig. 3 and 4 depict samples of standard images along with different state of art deblurring methods. In order to achieve digital images with low computational time for the proposed deblurring technique, the benchmark image size of the tested image is chosen to be in size 512 x 512. In the same regard, to examine and train the achievements of the suggested deblurring algorithm, the established noise freer/blurry images are exploited to train the proposed platform.

#### B. Training of the network and its parameter selection

In every step of the proposed method, the procedure factors are designed as follows: the SGWs parameters: according to wavelet type, level and characteristics, so the
suitable parameters are designed according as Orthogonal, Daubechies and Symmetrical wavelets for deblurring processes in this study. On the other hand, the parameters of SGWs decomposition basically consider three main factors, containing analysis order \( u \), scale parameter \( s \) and lastly semi-soft threshold value \( p \). Practically, the parameters set to a reliable value, where \( u = 3 \), \( s = [1, 2] \); \( p = [12.20, 22.34] \). In addition, the main factors of the Neural Network for R-DbCNN, depth of the model is chosen to be 18, and the basic depth net is 6, the hidden layers is 15 \((K=15)\) and only one output layer. In the case of SGDM, the selected weight is used in decay format, momentum and learning rate are 0.01, 0.0001 and 0.8, correspondingly, and mini-batch size is 32.

C. Assessments comparison

In this part, in order to achieve the best performance of the proposed algorithm, firstly, the SGWs procedure is used due to its facilities for the suggested deblurring algorithm. In addition, it is important to control the suitable running times of R-DbCNN, followed by the appropriate factors of SGWs and R-DbCNN. Taking the different wavelet with proper factors, different R-DbCNNs with varying epochs are trained, which is aim to obtain the proper epoch. Table I shows the deblurring performance of the proposed method that consisting of SGWs and several deblurring techniques, which is basically depicted by three pivotal digital image subjective assessments indicators: Peak-Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structure Similarity Index (SSIM). The main aim of the comparison is to compare the proposed method with recent deblurring techniques, 40 contaminated digital images were exploited in order to test the deblurring performance of every algorithm. Then Coiflet wavelet combing R-DbCNN is used and the performance of the comparisons is presented in Table I. Due to space limitations, we cannot present the full results of the 40 tested images.

![Fig.3. Several achievements of different deblurring methods (a) Blur-free, (b) blurred image, (c) [25], (d) [21], (e)BM3D, (f) [26], (g) Proposed method](image)

<table>
<thead>
<tr>
<th>Technique</th>
<th>Motion Type</th>
<th>Gaussian Type</th>
<th>Traditional Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>[25]</td>
<td>74.32/29.42/0.7877</td>
<td>77.28/29.25/0.7869</td>
<td>94.21/28.39/0.7842</td>
</tr>
<tr>
<td>[21]</td>
<td>86.12/28.78/0.7562</td>
<td>84.15/28.88/0.7595</td>
<td>106.19/27.87/0.7604</td>
</tr>
<tr>
<td>[26]</td>
<td>65.93/30.94/0.8053</td>
<td>66.85/29.88/0.8052</td>
<td>72.62/29.52/0.8093</td>
</tr>
<tr>
<td>BM3D</td>
<td>145.91/26.49/0.7066</td>
<td>104.01/27.94/0.7050</td>
<td>113.78/27.57/0.7066</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>62.19/31.12/0.8665</td>
<td>60.87/29.94/0.8505</td>
<td>65.98/30.06/0.8231</td>
</tr>
</tbody>
</table>

**TABLE I. COMPARISON OF ACHIEVEMENTS OF DIFFERENT DEBLURRING TECHNIQUES IN TERMS OF MSE/PSNR/SSIM**

| Objective Assessments: MSE/PSNR/SSIM | | |
|-------------------------------------|------------------|
| Bold values reflect the high values in each technique in the comparison study | | |

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Methods such as Block-Matching and 3D filtering (BM3D) [27] and Lucy Richardson show the original images in single noisy format which indicate that the up mentioned techniques work without training processes compared with conventional techniques. From objective assessment point of view, PSNR and MSE are used to assess the proposed method. On the other hand, SSIM is chosen to be a subjective assessment technique to assess the suggested method. Table I tabulated the outcomes of PSNR, MSE and SSIM in average format for several recent blur-less techniques. Compared with other methods, the proposed technique reflects the greater PSNR, the lower MSE, and SSIM with values close to the maximum value 1. Practically, 40 blurry images of size 512×512 were utilized in order to prove the deblurring achievements of several techniques. As showed in Table I, it is clear to notice that the deblurring methods which represented by Lucy-Richardson and BM3D show poor performance compared to other methods. Additionally, technique in [25] (MLP) has optimal performance only in case where blurriness level is trained on. However, it may show low results in the blurriness have not trained. Compared to auto-encoders technique, SSDA [26] accomplished poorly as a visual quality appearance than other methods. On the other hand, the achievement of BM3D [27] show better performance in images with less textures and fine details compared to complicated images, but still the resulted images of the proposed method more pleasant. Furthermore, both [26] and the proposed method generate novel convolutional neural networks for deblurring of digital natural images.

Furthermore, Fig. 3 and 4 depict the deblurring effect of the proposed technique and several state of the art deblurring techniques.

A. Running time comparison

In this part, the running time of the proposed method and several deblurring techniques is calculated as represented in Table II. As Table II depicts, the comparison of the proposed method with several deblurring methods shows that the proposed technique takes the shortest time to train the conventional network. Furthermore, in comparison with BM3D and study in [25], the proposed algorithm spent less time for training process, and as an objective analysis, it shows high visual quality and deblurring performance. The technique in [26] showed the longer where it performed the deblurring results in 120, 113 and 128 seconds in different deblurring techniques, Motion Gaussian and other blur techniques respectively. To sum up, the proposed algorithm is more efficient (less time consuming) compared with state of the art deblurring methods under investigation where the processing is very efficient using our hardware and software configurations, deblurring each image has taken an average time of 33 seconds, so that the proposed algorithm has the high performance objectively, subjectively and less time consuming of the execution time.

**Table II. Several Results of Running Times in Seconds for Several Deblurring Techniques**

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Technique</th>
<th>[25]</th>
<th>[21]</th>
<th>[26]</th>
<th>BM3D</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motion Blur</td>
<td>87</td>
<td>67</td>
<td>120</td>
<td>37</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td>Gaussian Blur</td>
<td>92</td>
<td>81</td>
<td>113</td>
<td>41</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>Other Blur</td>
<td>94</td>
<td>102</td>
<td>128</td>
<td>51</td>
<td>40</td>
<td></td>
</tr>
</tbody>
</table>
V. CONCLUSION

This paper combines second-generation wavelet transformation which implemented based on recursive deep noise blur removal with convolutional neural network to attain digital image deblurring technique. In addition, the proposed deblurring method incorporates with deep learning procedure to distinct the PSFs and additive white Gaussian noise from the contaminated digital images. Furthermore, the sub-image normalization and residual learning are utilized to make the training steps faster and increase the deblurring achievements. Compared with best blur removing methods, the proposed technique gains a better result in comparison with BM3D, MLP, SSDA and conventional neural network in visual quality and time consuming metrics. The proposed method presents a clear benefit that according to learning prospect, which reflects that the processes do not depend on designing or selecting features, where the deep learning of artificial neural network solves automatically with these issues. As future work, many types of wavelets can be applied in order to improve the fine details of the complicated scenes and also several types of digital images such as medical and satellite images. At the same time, the structure of R-DbCNN can be also changed in the future study so that the combination method can show an improved image denoising with the premise of super running time and training speed.

REFERENCES


