IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 22, 2018, accepted October 31, 2018, date of publication November 9, 2018, date of current version December 7, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2880279

Blind Deblurring via a Novel Recursive Deep CNN Improved by Wavelet Transform

CHAO MIN, (Member, IEEE), GUOQUAN WEN, BINRUI LI, AND FEIFEI FAN
School of Science, Southwest Petroleum University, Chengdu 610500, China

Corresponding author: Chao Min (minchao@swpu.edu.cn)

This work was supported in part by the NSFC of China under Grant 11526173 and Grant 11601451 and in part by the Scientific Research Starting Project of Southwest Petroleum University under Grant 2015QHZ028.

ABSTRACT Blind image deconvolution is an ill-posed problem, which is mainly addressed by the regularization methods. Wavelet transform is an effective denoising method related to regularized inversion. In this paper, wavelet transform is utilized to decompose and extract the low- and high-frequency information of the blurred image, which is taken as the first step of the presented deblurring methods in this paper. However, when the process highlights the approximate portion of the image feature, the blurry image will be smoothed so that the image is distorted. Simultaneously, the overall wavelet transform will result in excessive data redundancy for the image. Thus, in the second step, based upon the recursive convolution neural network, a deep recursive convolutional neural network (R-DbCNN) is designed, which can eliminate or weaken the characteristics of high data redundancy and image smoothness caused by wavelet transform to remove the blur of corrupted image. Comparing with the traditional convolution neural network in image restoration, R-DbCNN has better performance in deblurring with fast training speed. Thereafter, a novel loss function is built to attain the best deblurring effect of the proposed method based on the L_2 regularization term. The experiment results demonstrate that our method has practical applicability for image restoration with different blurs, such as the motion blur, Gaussian blur, and out-of-focus by camera.

INDEX TERMS Blind deblurring, wavelet domain, recursive deblurring convolution neural network.

I. INTRODUCTION

In the process of acquiring images using a digital camera, due to various factors, the natural images might be corrupted by various reasons, including low light, out of focus, motion or underdamping, etc. The common formulation of blurriness is that, the blurred image y is represented by $y = x*v+n$, where $*$ is the convolution operator, x is the underlying truly image, v is the point spread function (PSF) describing the blurriness and n is the noise. Thus, the goal of image deblurring is to obtain the original image x through removing v and n. The deblurring methods can mainly be categorized into two types, the non-blind deconvolution and the blind deconvolution, based on the situation that the details of v are known [1], [2] or unknown [3], [4].

In practical cases, a lot of methods have been proposed for the image deblurring, including Filtering, total variation, Fourier analysis, wavelet and neural network etc. Adaptive median filtering, wiener filtering [5]–[7] are designed to deal with the special noise of single image, like Gaussian noise and additive noise. Based upon orthogonal transforms and sparse representation, a hybrid Fourier denoising method [8] is proposed to deal with Gaussian noise of images. Due to the superiority of wavelet transform in removing image noise, this method [9], [10] is used to process the Gaussian noise and blur, and the results show that the method obtains better Mean Squared Error (MSE) and signal-to-noise ratio (SNR) in terms of noise removal. Along with the development of artificial intelligence, auto-encoders [19], [23], Multi-Layer Perceptron network [16] is applied to remove the Gaussian blur, Motion blur and other blur. In addition, convolutional neural network (CNN) [25], [26] is found to be greatly effective in image restoration, including denoising, and image super resolution. As an unsupervised algorithm, CNN can perform large image processing and remove various noises and blurs while ensuring the effect of the algorithm.

On the other hand, comparing with other basic methods, wavelet transform can cover the entire frequency domain of images, including low and high frequency and greatly reduce the correlation between the extracted features through selecting an appropriate filter [17].

In this paper, several common discrete wavelet transforms are considered for image deblurring, including Haar wavelet, Daubechies wavelet, Symlet wavelet, Coiflet wavelet, Biorthogonal wavelet and ReverseBior wavelet. Meanwhile, to obtain the better deblurring performance, a novel deep recursive deconvolution neural network (R-DbCNN) is applied to further deblur. Thus, the presented method can combine the advantages of both WT and CNN. Moreover, in order to reach the best deblurring efficiency of the method, a novel loss function is proposed to balance the WT and R-DbCNN by using L_2 regularization term. Meanwhile, a procedure of parameter preselection is introduced, in which residual learning (RL), batch-mini (BN) and Stochastic Gradient Descent with Momentum (SGDM) are applied to speed up the training process and boost the deblurring performance.

The main body of the paper is organized as follows: in Section II, a brief survey of the recent related work on image deblurring and denoising is presented. In Section III, the details of our method are separated into two parts and the novel deblurring recursive convolution neural network is focused. In Section IV, the method is applied to deblur the degraded images with various types of blurriness and the results of experiment based on a large dataset show the performance of our method.

II. RELATED WORK

Currently, deep learning is applied increasingly in image processing and computer vision. Until now, the methodology of image deblurring can be categorized into three main strategies.

The first strategy is the traditional methods in image processing, which mainly adopt filtering [5]–[7] (spatial domain), Fourier transform [8], Wavelet transform [9], [10] (time-frequency domain) to recover the corrupted image. Whereas the second strategy adopts the discriminative approaches with image priors [11], [12], including Maximum posterior estimation (MAP), unified probabilistic model with spatial randomness, etc. This kind of methods can obtain good restoration performance on removing some specific blurriness. The third one is to employ the methods of machine learning, which is called ''learn to deblur'' [13]. In this area, many effective and novel ideas are springing up by using neural networks [16], [19], especially the convolution neural network [25], [26].

A. THE DISCRIMINATIVE METHODS

The typical method of deblurring and denoising in image processing is the deconvolution method with regularization inversion, but existing methods are difficult to handle some blurriness. Xiao *et al.* [24] proposed a stochastic blind deblurring method, which is an efficient local evaluation for the blurry image and can be quickly implemented by prior. The experiment demonstrates that the framework can produce better result with Peak Signal-to-Noise Ratio (PSNR) values with different image priors, compared with the results obtained by other state-of-the-art blind motion deblurring algorithms, Given a blurry image y and a PSF v (The idea is to find the x by maximizing $p(x|y, v) \propto p(y|x, v)p(x)$), it is ill-posed to model the marginal distribution $p(x)$ with Gaussian likelihood of images, so Krishnan *et al.* [29] and Levin *et al.* [30] assume that the gradients of training yield the hyper Laplacian distribution. In order to get satisfactory results, the above methods must have enough assumptions. In addition, FoE [23] models $p(x)$ by combining a Bayesian minimum mean squared error estimate (MMSE) with a fixed framework. The experiment turns out those most existing discriminative methods with deconvolution are designed to specially deal with the AWG noise [31]. However, the methods can bring other artifacts resulting in removing more difficultly when making the image sharper. There are some methods that can remove the colored noise, such as BM3D [32] and others (e.g. [33]). From the results of experiments, all of them have achieved good deblurring performance on their test samples. To deal with the blurriness, Escande *et al.* [34] used the variation method (EM) with a Gaussian likelihood. An auxiliary variable combining with the Richardson-Lucy method is applied in [35] to image deblurring, which can obtain restoration performance for various blurs.

B. THE METHODS BASED ON MACHINE LEARNING

In [16], Schuler *et al.* successfully applied the multi-layers perceptron (MLP) combing with Fourier domain for non-blind image deblurring, which can be adapted to remove the studied blurriness, e.g. motion blur and Gaussian blur. Elad *et al.* [18] draw on a K-SVD algorithm to obtain a dictionary describing the image content effectively for image denoising. In [19], Lore *et al.* apply the stacked denoising auto-encoders (SDA) to construct a neural network with a local denoising criterion. Then in [20], the methods combining the sparse coding with denoising auto-encoders are utilized to model low illumination environment. Comparing with linear sparse coding, the methods obtain the better performance in removing Gauss white Noise; however, the methods rely heavily on supervised training and can only remove the noise, which have appeared in the training process. Chen and Pock [21] proposed a dynamic nonlinear reaction diffusion model with time-dependent parameters. The method lead to the best performance on common test datasets for the tested applications while it preserves the structural simplicity of diffusion models and takes only a small number of diffusion steps.

C. THE METHODS BASED ON DEEP LEARNING

Image deconvolution is achieved through deep convolutional neural network image restoration. Jain and Seung [25] applied the deep convolutional neural networks (CNNs) to natural image denoising and demonstrated that CNNs can obtain similar or even better result than the previous model. Then Xu *et al.* [14] adopt the improved deep convolution neural network to capture the characteristics of

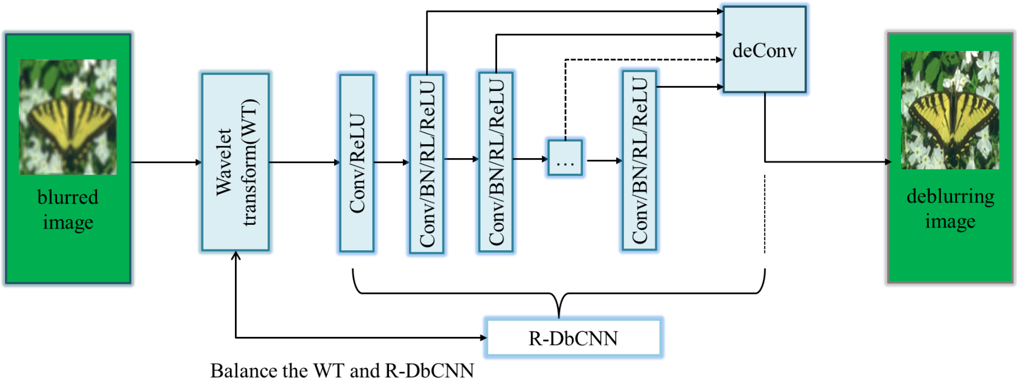


FIGURE 1. The novel structure of the method.

degradation by establishing a separable structure. Comparing with other methods, it obtains the better visual effects. In [15], Zeiler *et al.* proposed a novel deep convolutional neural network (CNN) by reconstructing the clean image, including denoising and motion deblurring. The proposed network combines multiresolution decomposition with residual learning, which outperforms total variation-regularized iterative reconstruction with the more realistic and speeds up the rebuilt procedure of the clearer image. In [26], Zhang *et al.* proposed another fast and effective denoising convolutional neural network and apply it to solve the inverse problems of image deconvolution for Gauss noise. Meinhardt *et al.* [27] embraced a denoising convolution neural network to replace the regularized proximal operator of convex energy minimization algorithms, which can obtain good performance by using different blur kernels (e.g. Gaussian blur and motion blur) in image deconvolution for learned network. However, these methods are basically used for image denoising instead of deblurring. Deep CNN is effective for extracting image characteristics. Different CNN structure involving with batch normalization and residual learning [22], [39] obtain the good performance in image processing, which can not only speed up the training process, but also improve the performance. In [28], Kim *et al.* proposed a deeply-recursive convolutional network for image super-resolution, which incorporate recursive supervision with skip-connection, it obtain good performance comparing with other classical methods.

III. METHODOLOGY

In recent studies of image deblurring, most methods apply the convolutional neural networks or regularization methods directly to perform the case studies on blurred/clean image pairs. Therefore, based on the basic idea of [14], a two-step deblurring method combining wavelet transform and CNN is employed for image deblurring in this paper. Wavelet transform can capture detail spatial features (e.g. noise information) of blurred images and make the blurry images smoother, which take positive effect on obtaining global information of blurred image in time-frequency domain [26]. However, there exist some side-effects in this method, which are the new artifacts and high redundancy caused by wavelet transform. Thus a recursive CNN is adopted to remove the generated artifacts and reduce the redundancy. The result of deblurring efficiency proves the validity of the proposed recursive deblurring CNN. The main structure of the presented method is shown in Figure 2.

Our method combines the advantages of wavelet transform and CNN, so that it can help not only handle different blurs, but also get better deblurring performance comparing with traditional CNN. Then the presented method is in line with proposed methods in [9], [10], [25], and [26], but different from the methods in [14] and [28].

Firstly, for the sharp images, they are always corrupted by noise and blur. It is assumed that the sharp image x is degraded by a point spread function v (PSF) and an additive noise n (e.g. white Gaussian noise, AWG), which is as follows:

$$y = v * x + n \tag{1}$$

where y is the blurry image, $*$ represents the convolution operator.

To obtain the sharp image x, the deblurring model is given by

$$\hat{y} = \psi(x * v + n) \tag{2}$$

where $\psi[.]$ represents a nonlinear deblurring operator, and $\hat{y}$ is the restored image by algorithm $\psi[.]$. Then the goal of deblurring is minimizing the difference between $\hat{y}$ and the clear image x with respect to all pixels.

A. THE BLUR DEGRADATION WITH WAVELET TRANSFORM

The goal of this step is to obtain more information of blurry image by choosing an appropriate wavelet basis. By using the wavelet transform, deblurring images are transformed into

$$W_N(y) = W^H(y) + W^V(y) + W^D(y) + W_{N-1}(y) \tag{3}$$

where W_N (.) represents the wavelet transform with order decomposition N for blurry images, and H, V, D correspond to variations along columns, rows and diagonals, respectively.

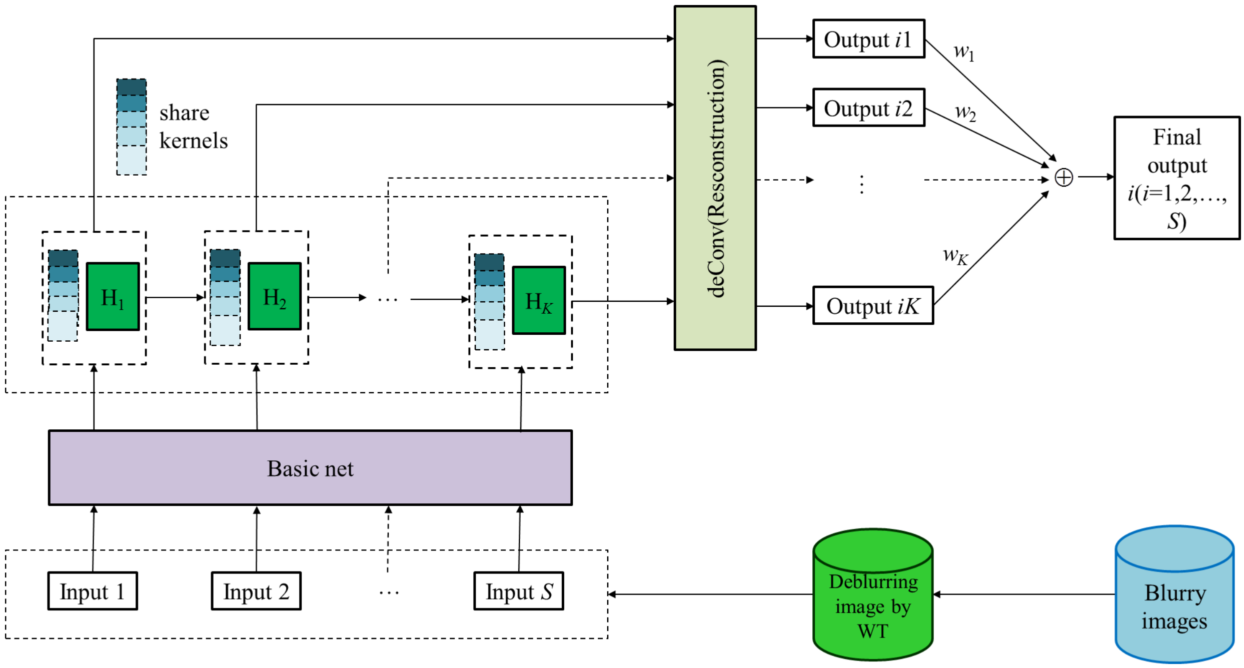


FIGURE 2. **The structure of the presented method.**

In addition, because of the mutual interdependence and relevance, $W^H(\cdot)$, $W^V(\cdot)$, $W^D(\cdot)$ and $W_{N-1}(.)$ have high data redundancy when performing image reconstruction. Thus the blur degradation by wavelet transform can be obtained by

$$\begin{aligned} W_N(y) &= W_N(x * \mathrm{v} + n) \\ &= W^H(x * \mathrm{v} + n) + W^V(x * \mathrm{v} + n) \\ &\quad + W^D(x * \mathrm{v} + n) + W_{N-1}(y) \\ &= W_{N-1}^{HVD}(X * \mathrm{R}) \\ &= \mathrm{x} \odot r \end{aligned} \tag{4}$$

where $\odot$ represents element-wise multiplication, r stands for the extra artifacts after deblurred by wavelet transform.

Denote $W_N(y)$ by Y, (4) can be simplified into the following equation.

$$Y = x \odot r \tag{5}$$

Wavelet transform can effectively smooth the blurred image. The purpose of image smoothing is to eliminate the influence of noise to improve the quality of input images for R-DbCNN, which is helpful for further deblurring the blurred image.

B. ARTIFACT REMOVAL BY TRAINING R-DBCNN

As shown in Figure 2, the training time of the proposed method is related to the training time of the WT and R-DbCNN. In this paper, the parameters of WT include the order, scale and threshold (N, M and L denote the total number of the changes of the value of order, scale and threshold, respectively). When assuming the training time of a CNN with i layers is T_i, the training time of the method combing WT and simple recursive CNN is $N \times M \times L \times \sum_{i=1}^{K} T_i$, resulting in a high computation cost. To accelerate this process under the premise of deblurring effect, the parameter pre-selection and the parameter sharing are added into the procedure of our method.

1) PARAMETER PRE-SELECTION

Parameter pre-selection is mainly aiming at the wavelet transform process. Assuming that the lightweight R-DbCNN has only a few layers, wavelet combining a lightweight network of R-DbCNN is utilized to select parameters for wavelet transform. Subsequently, Mean Square Error (MSE), Peak-Signal to Noise Ratio (PSNR), and Structure Similarity (SSIM) are used as the criteria for selecting wavelet transform parameters.

After parameter pre-selection, the maximum value of the selected parameters for WT are n, m and l, where $n \ll N$, $m \ll M$ and $l \ll L$. Thus the training time will be greatly reduced to $n \times m \times l \times \sum_{i=1}^{K} T_i$.

2) PARAMETER SHARING

Parameter sharing is aiming at R-DbCNN to speed up the training process, which is accomplished by weight sharing and partial connections. For a fixed input picture, the training time of the method with parameters sharing will turn into $n \times m \times l \times (T_K + T*)$, where $T*$ represent the training time of basic net in Figure 2 and

$$n \times m \times l \times (T_K + T*) \ll n \times m \times l \times \sum_{i=1}^{K} T_i.$$

Simultaneously, the performance of the method with training time of $n \times m \times l \times (T_K + T*)$ is approximate to the method of image restoration in [28], whose training time is $n \times m \times l \times \sum_{i=1}^{K} T_i$.

After parameter pre-selection and parameter sharing, our method can not only accelerate the training process greatly, but also maintain the good performance of CNN in image restoration. In Section IV, the specific details will be shown in the results.

3) THE STRUCTURE OF R-DBCNN

According to the equation (5), the R-DbCNN is trained to minimize the mean-squared-error between the clean images x and deblurring images Y further. So in this step a loss function L_θ of R-DbCNN is established firstly, which can be separated in three parts.

For the outputs of wavelet transform, the loss function is defined as.

$$L_{\theta_1}(Y_i, x_i) = \arg\min_{\theta_1}\left(\frac{1}{2S}\sum_{i\in S}\|Y_i - x_i\|^2\right) \tag{6}$$

where θ_1 is the parameters for wavelet transform, S is the number of blurry images.

For the output of R-DbCNN, the loss function is defined as

$$L_{\theta_2}\left(\hat{Y}_i, x_i\right) = \arg\min_{\theta_2}\left(\frac{1}{2S}\sum_{i\in S}\left\|\hat{Y}_i - x_i\right\|^2\right) \tag{7}$$

where $\hat{Y}_i$ denotes the outputs of R-DbCNN, and θ_2 is the parameters for R-DbCNN.

In order to avoid overfitting, a L_2 regularization term is added.

$$J(\theta_1, \theta_2) = \frac{\lambda}{2S}(\|\theta_1\|_2^2 + \|\theta_2\|_2^2) \tag{8}$$

where λ is the regularization coefficient, and θ_1, θ_2 represent the parameters for wavelet and R-DbCNN respectively.

Then under the premise of getting a very good deblurring effect, the balance loss function is

$$L_\theta = \sum_{i=1}^{S}\gamma L_{\theta_1}(Y_i, x_i) + (1-\gamma)L_{\theta_2}\left(\hat{Y}_i, x_i\right) + J(\theta_1, \theta_2) \tag{9}$$

Where γ represents the balance parameter with respect to deblurring images of the Y_i and $\hat{Y}_i$. It means that the better the deblurring effect of wavelet is controlled, the better the deblurring effect of the R-DbCNN is achieved, then we should find a balance tip.

In the training process of R-DbCNN, residual learning is applied to help reduce internal covariate shift, where batch normalization is applied to speed up the residual learning process.

As shown in Figure 2, the structure of R-DbCNN consists of three parts: basic sub-networks, hidden layers and reconstruction layers. The basic net is applied to extract initial features from the image deblurred by wavelet transform. The hidden layers are applied to obtain the final features for reconstruction, which is similar to traditional convolution neural network. Once hidden layer finishes its work, the reconstruction layer is utilized to generate the final output image. The detail of three parts of R-DbCNN is listed below.

(a) For the basic nets, the input images' size should be $50\times50\times c$;

(b) For the hidden layers $1 \sim K$, 64 channels of the patch images with size 3×3 are taken, and the batch normalization is applied to avoid training overfitting. Meanwhile, the stride and padding of convolutions operator are [1 1] and [1 1];

(c) For the output layer, channels are utilized to reconstruct the image by minimizing the MSE of blurry/clear images.

Here c represents the number of image channels (i.e. $c = 1$ for gray image and $c = 3$ for color image). In the R-DbCNN, in order to avoid the dead neuron, the activation function adopts Rectified Linear units in the network, which is

$$ReLU(x) = max(0, x) \tag{10}$$

where x is the number of pixels of the image.

Then for the basic net, the specific algorithm is

$$\begin{aligned} H_{-d}(x_i) &= x_i; \\ H_j(x) &= ReLU(W_{j-1} * H_{j-1} + b_{j-1}), \\ j &= -(d-1), -(d-2), \ldots, 0 \\ \hat{x}_{i0} &= H_0(x_i) \end{aligned} \tag{11}$$

Here, x_i is the number of pixels of the i-th input image. W_j and b_j are the weights and basis with kernels at Layer j for basic net. H_0 is the output of basic net.

For the hidden layers H_j $(j = 1, 2, \ldots, K)$, the output is as follows

$$H_j(x_i) = ReLU(W_{j-1} * H_{j-1}(\hat{x}_{i0}) + b_{j-1}) \tag{12}$$

$$\hat{x}_{ij} = H_j(x_i) \tag{13}$$

For the final output of R-DbCNN, it yields the solution

$$\hat{Y}_i = \sum_{j=1}^{K} w_{ij}\hat{x}_{ij}, \quad i = 1, 2, \ldots, S \tag{14}$$

where w_{ij} is the weight of the j-th hidden layer of the i-th deblurring image $\hat{x}_{ij}$ is the i-th deblurring image by j-th hidden layer. The weight w_{ij} is yielding the solution

$$w_{ij} = \frac{w_{ij}^{PSNR} - w_{ij}^{MSE} + w_{ij}^{SSIM}}{\sum_{j=1}^{K}\left(w_{ij}^{PSNR} - w_{ij}^{MSE} + w_{ij}^{SSIM}\right)} \tag{15}$$

where

$$\begin{aligned} w_{ij}^{PSNR} &= PSNR_{ij}\Big/\sum_{j=1}^{K} PSNR_{ij}, \\ w_{ij}^{PSNR} &= MSE_{ij}\Big/\sum_{j=1}^{K} MSE_{ij}, \\ w_{ij}^{SSIM} &= SSIM_{ij}\Big/\sum_{j=1}^{K} SSIM_{ij} \end{aligned}$$

and PSNR_{ij}, MSE_{ij} and SSIM_{ij} is the Peak Signal to Noise Ratio, Mean Square Error, and Structure Similarity between $\hat{x}_{ij}$ and clear image x_i, respectively.

In this paper, the method uses Stochastic Gradient Descent with Momentum (SGDM) to update the parameters.

For the hidden layer, other detail of structure for R-DbCNN is shown in Figure 3, in which residual learning (RL), batch-mini (BN) are applied to speed up the training and boost the deblurring performance.

TABLE 1. Comparison of deblurring performance between our method and other methods.

Blurriness	Motion blur	Gaussian blur	Other blur	All blur
IQA	PSNR/MSE/SSIM	PSNR/MSE/SSIM	PSNR/MSE/SSIM	Average PSNR/MSE/SSIM
BM3D	26.49/145.91/0.7066	27.96/104.01/0.7050	27.57/113.78/0.7066	27.34/119.97/0.7062
Lucy-Richardson	27.21/123.62/0.7251	28.03/102.35/0.7276	27.62/112.48/0.7294	27.62/112.48/7260
MLP[16]	28.78/86.12/0.7562	28.88/84.15/0.7595	27.87/106.19/0.7604	28.51/91.64/0.7576
SSDA[19]	28.89/83.96/0.7731	29.01/81.67/0.7721	28.56/90.59/0.7725	28.82/85.35/0.7735
DCNN[14]	29.42/74.32/0.7877	29.25/77.280.7869	28.39/94.21/0.7842	29.02/81.49/0.7846
TRND[21]	29.39/74.83/0.7964	29.56/71.96/0.7982	29.10/79.99/0.7928	29.35/75.52/0.7941
DnCNN[22]	30.54/72.29/0.8024	29.79/68.25/0.8054	**29.62**/**70.97**/0.8076	29.65/70.48/0.8046
Ours	**30.94/65.93/0.8053**	**29.88/66.85/0.8052**	29.52/72.62/**0.8093**	**29.78/68.40/0.8065**

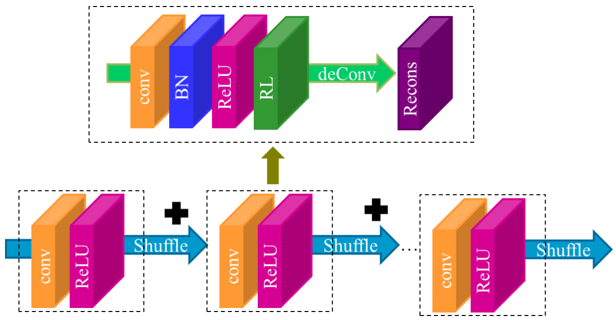


FIGURE 3. The specific architecture of the R-DbCNN. (The Recons represent the image reconstruction).

IV. EXPERIMENTS

A. DATA OF THE EXPERIMENTS

In this section, to evaluate the performance of our deblurring method for blurry images, we rebuilt a set of 500 clear/blurry image pairs via multiple sources, e.g. representative images from previous work [3], [13], [36], some images from GOPRO dataset or several classical images. The blurriness of blurry images (gray image and color image) can be mainly categorized into three types, which are Gaussian blur, motion blur and other kind of blur. Figure 4 shows some sample images for the three types of blur image. To make these images computationally feasible for our deblurring algorithms, they are cut into patches with the size of 64.

Simultaneously, in order to train and test the deblurring performance of the proposed method, these clear/blurry pair images are utilized to train the model.

B. PARAMETER SETTING AND NETWORK TRAINING

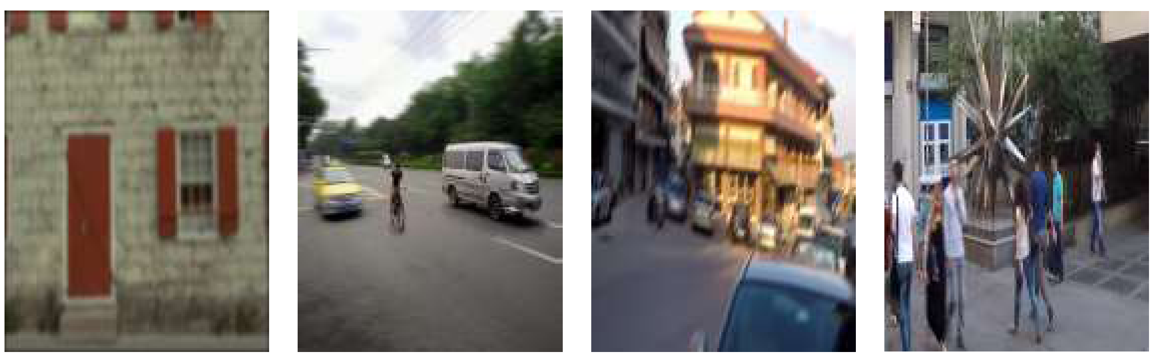
For each step described in Section III, the parameter setting is as follows:

1) PARAMETERS OF WAVELET TRANSFORM

Different wavelet transforms have particular characteristics, which are suitable for different problems. According to whether the wavelet basis of the wavelet transform is discrete, orthogonal or tightly supported, Haar, Daubechies, Symlet, Coiflet and Biorthogonal wavelet are applied for deblurring in this paper. For the parameters of wavelet decomposition and reconstruction, we mainly consider three parameters, including decomposition order u, scale vector s and threshold vector p. Among them, in order to avoid the image after processing is too smooth, the parameters should be adjusted to a reasonable value. In this paper, we have $u = 2$, $s = [12]$ and $p = [10.28, 24.08]$.

2) PARAMETERS OF NEURAL NETWORK

For the R-DbCNN, the network depth is set as 15, in which the depth of basic net is 4, the depth of hidden layers is 10 ($K = 10$) and the depth of output layer is 1. The final loss function of R-DbCNN is the (11), in which the balance parameter is 0.1. Moreover, the weights are initialized by the



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

FIGURE 4. Sample images with the different blur in our dataset. (a) Gaussian blur. (b) Motion blur. (c) Other blur. (d) Other blur.

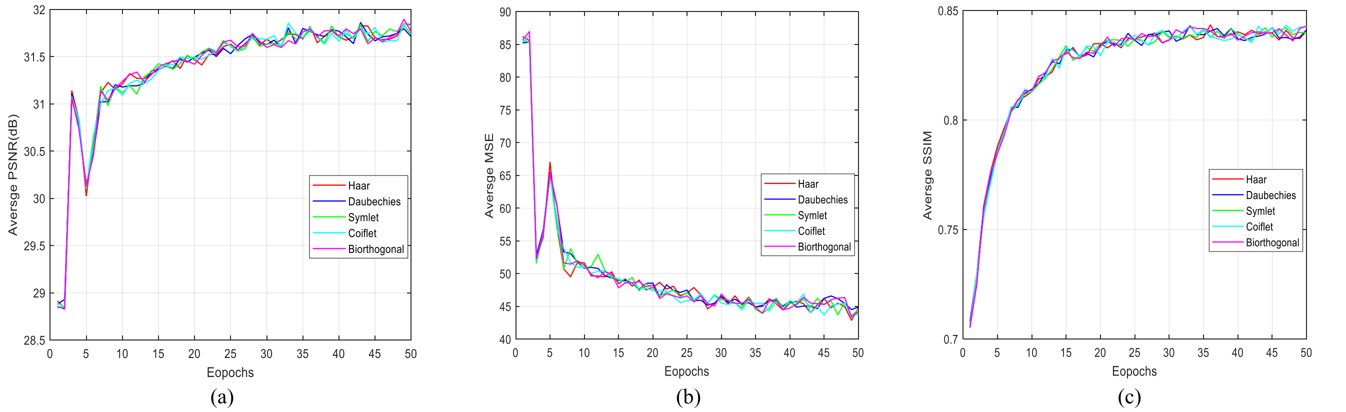


FIGURE 5. Average PSNR/MSE/SSIM following epoch change for different wavelet combining R-DbCNN. (a) Average PSNR. (b) Average MSE. (c) Average SSIM.

TABLE 2. Comparison of the IQA for different image kernel with multiple deblurring methods.

Blur	Motion blur			Gaussian blur			Other blur
Kernel	θ=10	θ = 15	θ = 20	α =15	α = 25	α = 50	/
IQA	PSNR/MSE/SSIM	PSNR/MSE/SSIM	PSNR/MSE/SSIM	PSNR/MSE/SSIM	PSNR/MSE/SSIM	PSNR/MSE/SSIM	PSNR/MSE/SSIM
BM3D	24.23/245.52/0.7121	23.25/307.67/0.7115	22.95/329.67/0.7034	24.34/245.52/0.7094	24.12/251.81/0.7071	23.84/268.58/0.7042	23.67/279.09/0.7062
Lucy-Richardson	24.97/207.05/0.7273	24.03/257.09/0.7262	23.63/281.89/0.7244	24.75/217.81/0.7357	24.54/228.60/0.7316	24.15/250.08/0.7254	24.18/247.98/7260
MLP [16]	28.77/86.31/0.7595	28.59/89.97/0.7577	28.01/102.82/0.7554	29.36/75.35/0.7643	29.03/81.30/0.7512	28.69/87.92/0.7577	28.51/91.64/0.7576
SSDA [19]	29.64/70.64/0.7765	28.93/83.19/0.7749	28.13/100.02/0.7723	29.51/72.79/0.7762	29.22/77.82/0.7733	28.83/85.13/0.7712	28.82/85.35/0.7735
DCNN [14]	30.51/57.82/0.7903	29.70/69.68/0.7882	28.79/85.92/0.7861	29.89/66.69/0.7900	29.43/74.14/0.7881	28.94/83.00/0.7852	29.02/81.49/0.7846
TRND [21]	30.75/54.71/0.7992	29.72/69.36/0.7975	28.95/82.81/0.7951	30.07/63.99/0.8023	29.75/68.88/0.8009	29.23/77.64/0.7961	29.35/75.52/0.7941
DnCNN [22]	31.62/44.78/0.8061	30.88/53.10/0.8047	30.14/62.96/0.8013	30.41/59.17/0.8092	29.96/65.63/0.8077	29.41/74.49/0.8033	29.65/70.48/0.8046
Our	**32.03/40.75/0.8094**	**31.46/46.46/0.8077**	**30.32/60.41/0.8039**	**30.53/57.55/0.8083**	**30.18/62.39/0.8065**	**29.45/73.80/0.8023**	**29.78/68.40/0.8065**

method in [37] and the networks employ Stochastic Gradient Descent with Momentum (SGDM) to update parameters of R-DbCNN. For the SGDM, its weight decay, momentum and learning rate are 0.001, 0.00001 and 0.9, respectively. The size of mini-batch is 64.

C. COMPARISON

In addition, to achieve the best performance of our method, firstly, we should know which wavelets are more suitable for the proposed deblurring method, and determine the appropriate epochs in R-DbCNN, followed by the parameters of wavelet transform and R-DbCNN.

In this paper, different wavelets with appropriate parameters, different R-DbCNNs with changing epochs are trained, which is aiming at obtaining the suitable epoch. Figure 5 shows the deblurring performance of different wavelet combining different epoch of R-DbCNN, which is mainly represented by three image quality assessment (IQA) indicators: PSNR, MSE and SSIM. According to the trend of the value of PSNR, MSE and SSIM followed with the different epochs, the deblurring performance of different wavelet combing R-DbCNN is almost getting better and better. Simultaneously, different wavelets have very litte difference in deblurring performance when R-DbCNN has different epochs. When the value of epoch is 50, the proposed method almost show the best deblurring performance. From the trend of IQA, the deblurring effect of Coiflet wavelet is more stable, so in this paper the Coiflet wavelet is applied in the first step.

1) COMPARISON OF OUR METHOD WITH OTHER METHODS

In addition, to test and compare the deblurring performance of our method and other methods, 30 blurred images were used to test the deblurring performance of each method, and the comparison results are shown in Table 1, where Other Blur contains the out-of-focus and shake etc. caused by camera.

For the deblurring method BM3D and Lucy-Richardson, the input images are the single blurry image, which means the above methods do not need to be trained comparing with other methods.

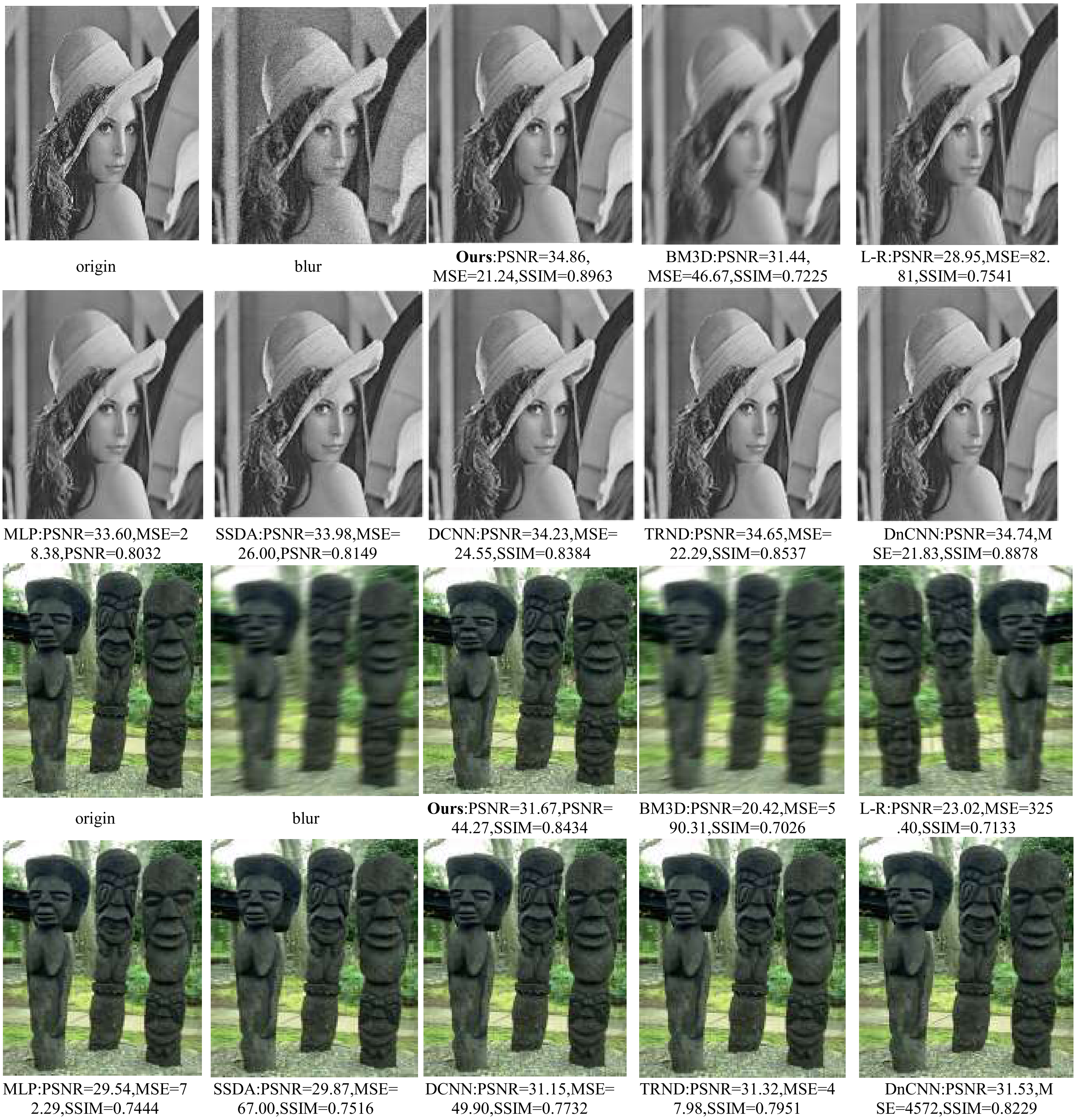


FIGURE 6. **Deblurring performance of different methods.**

PSNR and MSE are objective criteria for evaluating image quality, and SSIM is a subjective indicator for measuring the similarity of two images. Table 1 lists the results of average PSNR, MSE and SSIM for different deblurring methods. Compared with other methods, our method has the higher PSNR, the lower MSE, and the SSIM that is closer to 1.

A thorough testing was infeasible on the all blurry images of our dataset due to the running times. In this section, 30 blurry images were applied to demonstrate the deblurring performance of the methods. In Table 1 the deblurring performance calculated by multiple methods on the 30 testing blurry images are summarized, in which the images size is $512 \times 512 \times c$. As the benchmark scenarios, the deblurring method of Lucy-Richardson and BM3D are obviously weaker than other methods. In the additional materials in [14] (MLP), it shows that the method is optimal only for the blurriness level which has been trained on, but it may have obtained relatively poor results in the blurriness that did not existing before. As a typical auto-encoders algorithm, SSDA [19] does not perform better than other methods. At the same

TABLE 3. Comparison of the running time for deblurring method with different types.

Method		DnCNN [22]	Normal Recursive DbCNN [28]	R-DbCNN
Training Time (50 epoch)		10.1h	36.5h	17.3h
IQA (testin-g)	motion blur	PSNR=30.54, MSE=72.29, SSIM=0.8024	PSNR=31.05, MSE=51.06, SSIM=0.8055	PSNR=30.94, MSE=65.93 SSIM=0.8053
	Gaussian blur	PSNR=29.79, MSE=68.25 SSIM=0.8053	PSNR=29.84, MSE=67.47, SSIM=0.8061	PSNR=29.79, MSE=68.25, SSIM=0.8054
	other blur	PSNR=29.62, MSE=70.79, SSIM=0.8076	PSNR=29.57, MSE=71.79, SSIM=0.8110	PSNR=29.52, MSE=72.62, SSIM=0.8093

time, the performance of TRND [21] is also weaker than DnCNN [22]. Although both DCNN and DnCNN create new convolutional neural networks for image deblurring, the deblurring performance of DCNN [14] is not good, and the deblurring performance of DnCNN [22] is still outperformed by our method. Compared with other methods, our method can obtain better a PSNR for about 0.4 $\sim$ 4dB, a better MSE for about 7 $\sim$ 8 and a better SSIM for about 0.001 $\sim$ 0.1, which means our method can restore the original details of the image better. To sum up, our approach is superior to other methods. Figure 6 shows the deblurring effect of some different methods.

2) COMPARISON FOR DEBLURRING EFFECTS AT DIFFERENT NOISE LEVELS WITH R-DBCNN

To further verify the validity of the method, we have artificially constructed some blurred images involving Gaussian blur and motion blur. Here, different levels of noise in Gaussian blur and in Motion blur are considered in artificial blurry image, and the other blur are not influenced by noise levels etc. The analysis of results will be introduced in Table 2.

Compared with other methods, including discriminative methods (BM3D, Lucy-Richardson), machining learning methods (MLP) and deep learning methods (SSDA,CNN etc.), our method can still get best performance in the IQA, when the blurry images correspond to the different noise levels for Gaussian blur and the degrees of the motion blur. From the perspective of IQA (PSNR, MSE and SSIM), it shows that the proposed method can not only effectively remove the blur, but also restore the details of the original image better. In addition, the method can obtain good deblurring performance for blur images with other blur.

3) COMPARISON OF RUNNING TIME FOR DIFFERENT CNN IN IMAGE DEBLURRING

In the third section, we have explained the reason why our method uses recursive convolutional neural networks for image deblurring. The specific results with different CNN are shown in Table 3.

Compared with DnCNN, our method needs to spend more time to train the network, but it can effectively improve the deblurring performance which is indicated in PSNR, MSE and SSIM. At the same time, compared with Normal Recursive DbCNN, our method spend less time to train, which still has good deblurring performance. Overall, the training process of R-DbCNN does not take too much time to ensure the deblurring performance.

V. CONCLUSION

In this paper, the method combining the wavelet transform with recursive deep deblurring convolutional neural network was proposed for image deblurring, in which the traditional image deblurring method is incorporated with deep learning to separate the PSFs and noise from the blurry image by the first step. In addition, the batch normalization and residual learning are employed to speed up the training process and boost the deblurring performance. On the basis of traditional discriminative models which specific models are trained for particular blurry types and noise levels, our method has the capacity to handle the non-blind blurriness for a variety of different types, including the Gaussian blur, Motion blur and other blur, by combining the wavelet transform with convolution neural network. This method can get better results, compared with other methods in image restoration such as BM3D, MLP, SSDA and DnCNN. In Section IV, the results showed that the method achieve a better performance in image deblurring without expensive computing cost. Meanwhile, the method in this paper has a clear benefit that this method is based on learning, i.e. it does not need to design or select features, or determine a useful transform domain. The deep learning neural network can automatically deal with these tasks. Another benefit related to deep learning is that it can handle different types of noise or blur. Finally, by directly learning the mapping from corrupted/clean pairs, we can handle different types of artifacts introduced by direct deconvolution without being limited to removing colored noise.

However, this paper does not explore in detail how the wavelet transform affects the convolutional neural network. Meanwhile, there are many variations of wavelet transform, but we only discussed the traditional wavelet transform. These are the further research of our work. Moreover, we can discuss the optimization of R-DbCNN to obtain better image restoration effect under the premise of faster training speed.

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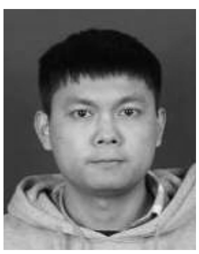
CHAO MIN (M'08) was born in Xindu, Chengdu, China, in 1982. He received the M.S. degree in pure mathematics and the Ph.D. degree in operations and control theory from Sichuan University, Chengdu, in 2007 and 2013, respectively. He is currently an Associate Professor with the School of Sciences, Southwest Petroleum University, China. His research interests include uncertainty theory and its application, especially in petroleum engineering and image processing. He was a recipient of the Scientific and Technological Progress Award (First Class) of the China National Association for Automation in Petroleum and Chemical Industry in 2015 and the Scientific and Technological Progress Award (First Class) of the Ministry of Education of China in 2015.



GUOQUAN WEN was born in Yibin, Sichuan, China, in 1994. He received the bachelor's and master's degrees from Southwest Petroleum University, where he is currently pursuing the degree. He has published two articles in total. His research interests are image processing and data mining.

BINRUI LI was born in Yangquan, Shanxi, China, in 1992. He is currently pursuing the master's degree with Southwest Petroleum University. He has published two articles in total. His research interests are evolutionary optimization and data mining.

FEIFEI FAN was born in Nanchong, Sichuan, China, in 1994. She is currently pursuing the degree in applied mathematics with Southwest Petroleum University. Her research interest is the theory of optimization.