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AN EVALUATION OF THE STATE-OF-THE-ART BM3D-DOUBLE CONVOLUTIONAL LAYER NEURAL NETWORK (C2L-NET) FOR DENOISING

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Abstract: In this paper, we introduce a method for denoising high-definition images using a block-matching 3D double convolutional neural network (BM3D-C2L-Net). Depending on the weather, HDR photos may exhibit a wide variety of dynamic noise and rain streak patterns. Many researchers have found it difficult to find a solution for removing high density, directed noise patterns from photographs. In order to solve this issue, a convolutional neural network structure with an extra "block" is devised to make sure that inputs from the previous layer are used in the next. To improve the improvement of the image despite the noise, a dual convolution layer structure is adopted. We test the BM3D-C2L network's denoising capabilities on a range of image sequences with varying levels of noise and rain streak patterns. The double convolutional layer approach makes it simple to train a network to remove the directional oriented noise pattern. The suggested denoising network is trained on the TensorFlow open-source platform. According to the experiments, the suggested draining network provides a greater PSNR value than any other existing denoising approach.

Keywords: Convolutional Neural Networks, Denoising, Image processing, TensorFlow, Block Matching Algorithm

1. Introduction

Sounds that are static or based on movement are a major problem with live video or still photography. Real-time image processing employs the proper pre-processing strategy to remove the noise pattern. Due of its importance, pre-processing is employed in numerous disciplines, such as computer vision, video analysis, and image/video processing. Numerous algorithms for removing the noise pattern have been developed in recent years. Time-domain, frequency-domain, and wavelet-domain filtering are all instances of elementary methods. There are a number of methods for removing static noise in the spatial domain, including nonlocal means filters [1], bilateral filters [2], anisotropic diffusion filters [3], and directed filters [4]. The frequency domain technique eliminates noise's effect by modifying the coefficients in that space. Discrete Cosine Transform (DCT), Walsh Transform, and Hadamard Transform are examples of transforms used in frequency-domain filtering.

The wavelet transform is especially useful for eradicating noise artefacts in moving images. Multiple shrinking approaches are presented in [5], [6], and [7] to eliminate the noise impact by adjusting the size and the frequency design. Hard shrinkage [8] and soft shrinkage [9] are also common approaches to enhancing photographs in low light. As with most pre-processing methods, spatial domain and frequent domain based pre-

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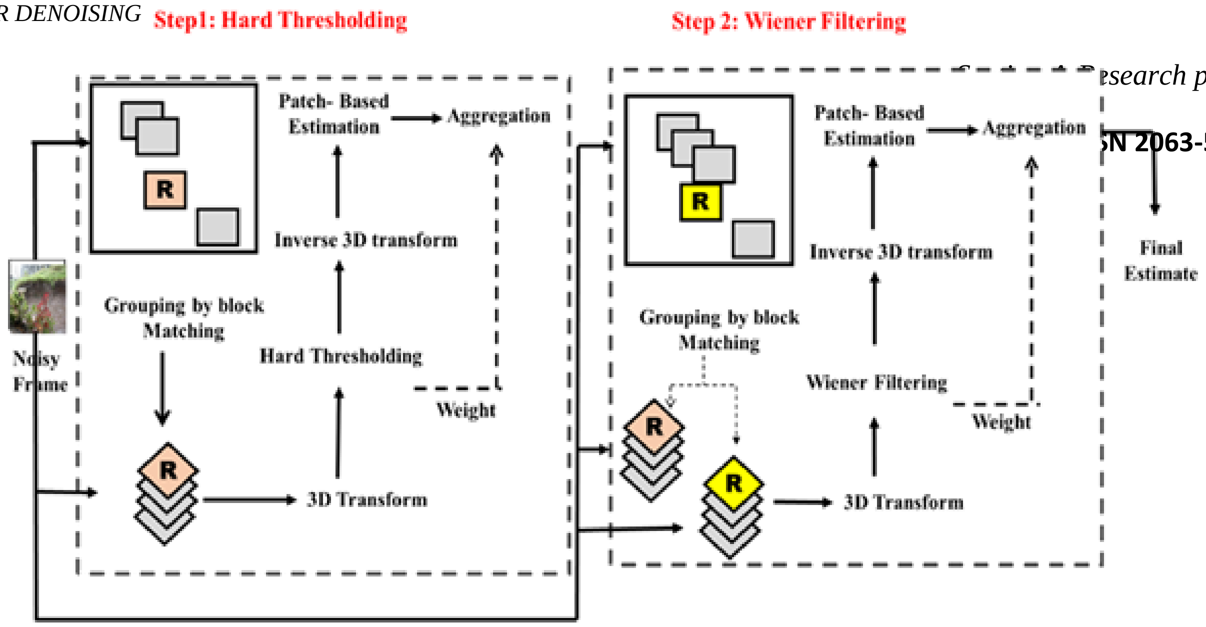

Figure. 1 Flow diagram of BM3D Denoising Network

processing offers little to help contaminated high-definition photos in any visual application. When applied to photos that have been degraded by salt-and-pepper and Gaussian noises, the basic filtering process yields moderate improvements. Improved denoising of pictures and video sequences has been proposed using learning-based algorithms to address the problems with the current filtering approach.

Dictionary learning [10, 11], as well as deep learning [13, 14], are two well-known examples of learning-based denoising approaches. Image denoising can be improved by using these methods that are based on learning. In recent years, a great number of deep learning algorithms for the identification of pictures, the compression of images, and the denoising of images have been reported [15], [16], [17], and [18]. Utilizing a batch group normalisation and learning strategy in conjunction with a deep convolutional neural network (DnCNN) for denoising applications allows for excellent results to be obtained. Nevertheless, training such a deep network is necessary in order to achieve accurate denoising of real-time images. It is essential to pay close attention to the network initialization, the adjustment of the number of layers, and the modulation of the filter size when developing deep networks. In [19], [20], and [21], the author proposed a network architecture that was based on cutting-edge learning methods. This was done in order to address the difficulties of network initialization and learning rate. In general, the more layers a network possesses, the more difficult it is to train a network [22, 23]. This is because the learning process becomes more complex as more layers are added. The reduction of artefacts Dong et al. proposed the use of convolutional neural networks, sometimes known as AR-CNNs, to clean up JPEG images by artificially suppressing artefacts. To be more specific, AR-CNN is a fully convolutional neural network that consists of 4 layers. Both the number of filters and the size of the filters are subject to change throughout each of the four convolutional layers. The AR-CNN is able to increase the quality of an image and extract valuable features from it when a low-level noise reduction is given to the image. This denoise network is not capable of restoring HD photographs that have been corrupted by noise.

The deep convolutional network has been integrated with the Block matching 3D (BM3D) filtering method because of its popularity in the denoising application. Non-local techniques, such as patch groups and wavelet shrinkage operations, are utilised in this filtering strategy. Within the core architecture of BM3D-Net [24], a total of five layers are accessible for use during the training of the network. The proposed network architecture employs a double convolution procedure on the input side to give superior enhancement of noisy images as compared to the existing BM3D-net architecture based denoising approach.

- Here's a quick rundown of the main benefits you may expect from our planned work:

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- A reliable Advanced BM3D-Double Convolutional Layer Neural Network(BM3D-C^{2}L-Net) Structure is proposed for quality enhancement of single image.
- The proposed Denoising Network is also designed to eliminate the various directional oriented rain streaks pattern
- Tensor flow, an open-source software tool, is used for both training and validating the suggested method.

The paper is structured as follows: Section 2 provides an overview of the BM3D Filtering Process, while Section 3 delves into the tensor flow specifications. In Section 4, we go into the specifics of the proposed denoising network's architecture. In Section 5 we present the experimental findings and discuss them. Section 6 presents the final conclusion and the potential reach of the planned network.

2. Overview of The BM3D Filtering Process

The block matching 3-D denoising is a popular denoising process to remove the redundant information available in an image. The BM3D process consists of three important process like patch grouping, 3D wavelet shrinkage operation and patch group aggregation. Figure 1. shows the two important steps of BM3D denoising process. Initially, noisy image is applied to hard thresholding process. The hard threshold output image is further enhanced using Wiener filtering stage to eliminate the high density noise pattern and rain streaks.

A. Groping process

The input noisy image is divided into n x n image blocks and similar blocks (patches) are identified to create the 3D array patches. From this step, similar patches are grouped together to form a 3D array.

B. Filtering Process

The 3D array patches are applied to 3D transformation process to obtain the filter coefficients. The filter coefficient is thresholded by weight value based on noisy image strength. After the threshold process, inverse transformation process is applied to obtain the reference estimate of image.

C. Patch Aggregation

In this step all the reference estimates are aggregated to get the final enhanced estimate of original image.

3. Introduction to Tensor Flow

Google's Tensor Flow is a widely used open-source machine-learning software package. It's possible to use Tensor Flow with any CPU or GPU. Here, deep learning methods are tested using a computational graph. Algorithms can be represented by this data flow diagram, which contains four critical nodes. Specifically, we're talking about sessions, variables, tensors, and operations. When these four criteria are met, the deep learning algorithm is considered to have been properly trained. Data flow graph nodes are referred to as operations. When describing a deep learning algorithm, a larger number of nodes is used to illustrate the method's structure. The Data flow from one operation to another is called as Tensors. The tensor flow is assign a special character to computational graph for performing stochastic gradient operation. This special character is named as variables. The execution of sequential operation of DL algorithm is called as sessions. The memory management and resource allocation is important task of sessions.

Table 1. gives the details about recent version and commit id of Tensor flow open source tools used in this paper.

Table 1. Tensor flow Community Parameter

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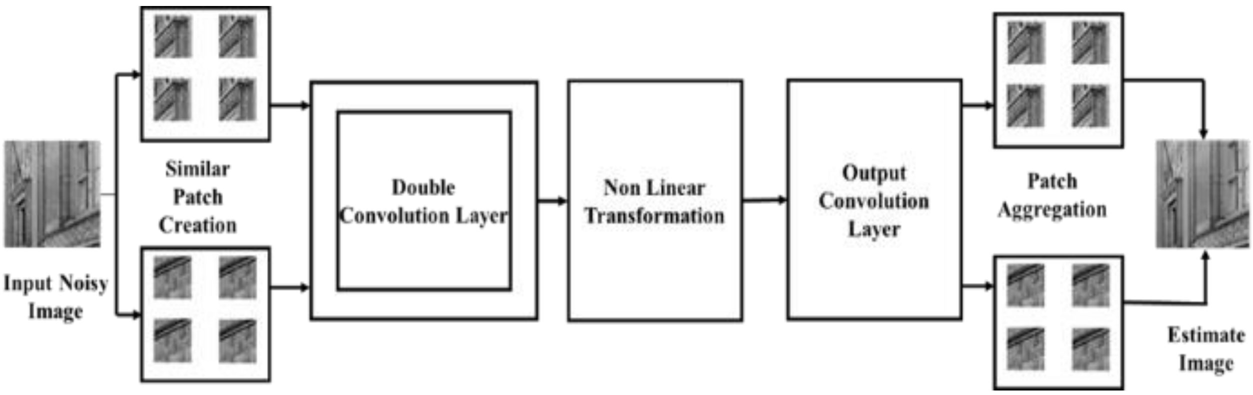
Open source Software	**Recent Version**	**Github Commit ID**	**CuDNN**
Tensorflow [16]	1.10	90209af	V7.2

The important features of Tensor flow open source tool are listed in Table 2. All real time image processing algorithm is implemented in tensor flow using Python packages.

Table 2. Properties of Tensorflow

Property	***Tensor flow***
License	Apache2.0
Language	C++, Python
API's	Python, C++,JAVA,GO
Core	C++
CPU	Yes
Multi-threaded CPU	Eigen
GPU	Yes
Multi-GPU	Most flexible
Nvidia cuDNN	Yes
Quick deploy. On standard models	Yes
Auto. Gradient	Yes
Models	InceptionV3, ResNet-50,

4. The Proposed BM3D-C^{2}L Convolutional Neural Network Architecture



In this part, we detail the proposed deep BM3D-C2L architecture and the methods required in using this design to denoise the tainted photos. The design of the proposed BM3D -C2L network for picture denoising is depicted in Figure 2. Extraction, Dual Convolution, Non-Linear Transform, Output Convolution, and Aggregation are the five core layers that make up this network. All five-layer having their own role to enhance the noise affected image. The corrupted high definition images is considered as I with the size of M x N.The Y_l is considered as output of the l^{th} layer in BM3D-C^{2}L structure.

A. Extraction layer

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In this layer construction of patch group for similar block objects in an input noisy images. For each pixel p in an input image and its corresponding patch is denoted as C_p. The similar patches C_p are grouped Figure.2

Figure 2: Proposed Denoising Block Diagram

together to form a patch group denoted as S_{C_p}. This patch group extraction process is executed in all pixels in the noisy images. The patch group extraction process of input image I, $\in R^{MXN}$ is denoted as,

$$y_{1,p} = M_P . I \quad (1)$$

Where M_P is a matrix defined by a corresponding patch group with size of M x N. All extracted similar patch groups are grouped together to form a matrix Y_l. The Y_l is the output of the first extraction layer. The output of first layer is sent to next layer for further process.

B. Double convolution layer

This layer is responsible to perform 3D wavelet shrinkage of patch groups identified from the first layer. In this proposed architecture two convolution layer is used to get better denoising of input image compared to other existing single convolution layer deep network. The first convolution layer performs the convolution of patch group $y_{1,p}$ with the transform matrix T_1

$$y_{2',p} = T_1 . y_{1,p} \quad (2)$$

The Second Convolutional layer perform another convolutional operation using $y_{2',p}$ and Orthogonal transform matrix T_2. The output of this additional convolutional layer is defined as

$$y_{2,p} = T_2 . y_{2',p} \quad (3)$$

Then the second convolutional layer is used to eliminate the sharp edges present in the HD images. The dominance of the directional noise pattern is eliminated through this convolution layer. This layer performs the convolution with shifted version of similar patch groups obtained from extraction layer. The double convolution layer results $y_{2,p}$ is passed to next layer. In frequency domain the output of this layer is given by

$$Y_{2,i} = T_{2,i} . Y_{2'} \quad (4)$$

C. Nonlinear Transform layer

This layer performs the nonlinear transform with the output of the previous double convolution layer.

$$Y_{3,i} = \phi(Y_{2,i}, T_{2,i}) \quad (5)$$

Where ϕ denotes the nonlinear transform.

$$\phi(t, T_{2,i}) = \sum_{j=1}^{M} t_{ij} . \exp(|t - \mu_j|^2 / \sigma_j^2) \quad (6)$$

From the Equation (6), t_{ij} defines the learning weights of the layer. μ_j defines the average of the transform matrix. σ_j defines the standard deviation of the transform. For given the (μ_j, σ_j), non-liner transform is applied to previous layer output $Y_{2,i}$. The selection of the learning weight is adaptive in this proposed network. Hence learning weight is taken between 0.1 and 0.01 based on the type of images.

D. Output Convolutional Layer

This layer is performing an inverse wavelet transform in 3D domain. The output of this layer is defined as,

$$Y_{4,i} = T_{3,i} * Y_3 \quad , i = 1, 2, ...n \quad (7)$$

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Where $T_{3,i}$ is transform basis vector with size 1x1xn and Y_3 is the output of the non-linear transform layer.

5. Results and Discussion

The proposed convolutional network is trained to perform enhancement of noisy images using Tensorflow open source tool. Recent days, there are more numbers of test images available for research purpose includes monochrome test images and RGB test images. The table 3 presents the specification of test images used in this proposed method. Totally 5 test images are used to evaluate the denoising performance of BM3D-C^{2}L network.

Table 3. Test Image Dataset

S.NO	***Test Image***	***Size***
1	Building	256x256
2	Barbara	512X512
3	House	256x256
4	Rain Fall (Rain)	512X512
5	Vinegar	256x256

Experiments are run on a 2.50 GHz Intel i5 -2450M Core CPU equipped with an NVidia Geforce CUDA graphics card and 4 GB of RAM. The 256x256 and 512x512 versions of the standard test image can both be successfully executed on this hardware setup. The effectiveness of the proposed denoising network is assessed using test photos with varying degrees of noise. In this analysis, we take into account noise levels of 15, 25, 35, and 50. When comparing results for a variety of noise levels, the proposed technique performs better. To train the suggested network, a 10x10 pixel patch size is taken into account. The efficiency of the denoising network is also impacted by the choice of patch size.
Table 4 shows how different denoising networks perform in comparison to the one we suggest for photos with a noise level of 15. Due to poor image capture, the photographs suffer from a low noise level. All known basic methods and learning methods make short work of removing such low-level noise from high-definition photos. Results reported in table 4 show that the PSNR variation of all test images is quite low. For images with minimal noise contamination, the suggested denoising network yields optimal results.

Table 4. PSNR Results for Noise Level 15

Test Image	***BM3D***	***TNRD***	***DnCNN***	***BM3D-Net***	***Proposed Net***
Building	31.91	32.01	32.61	32.73	**32.85**
Barbara	33.07	32.11	32.60	**33.08**	33.05
House	34.93	32.19	32.61	32.42	**32.75**
Rain Fall	32.69	32.99	33.04	**33.10**	32.95
Vinegar	30.25	31.25	30.85	32.42	**32.47**

Further the investigation of the proposed method is extended for image affected with different noise level. Table 5 presents comparative performance values of image corrupted with noise level 25. The proposed network outperforms in all test image compared to other denoising network. For House and Vineger images, proposed network provides the better results due to their simplicity of network structure and type of noise pattern.

Table 5. PSNR Results for Noise Level 25

Test Image	***BM3D***	***TNRD***	***DnCNN***	***BM3D-Net***	***Proposed Net***
Building	29.45	29.85	30.25	31.45	31.69

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Barbara	31.65	30.52	32.05	31.25	31.45
House	32.85	31.44	32.95	32.97	32.55
Rain Fall	29.90	29.85	29.78	29.95	29.97
Vinegar	28.42	28.35	28.47	28.77	28.65

The reconstructed output images for the proposed denoising network is shown in Figure 3. and Figure 4. The output image is presented for images with noise level 35. The proposed network performs well on both dynamic noise as well as rain streaks pattern. On observing the Figure 3(b) to Figure 3(e), when noise strength is more, proposed network performs superior than the DNCNN and other BM3D algorithm. The PSNR value is also improved by 2% to 12 % compared to other traditional denoising method.

Table 6 presents the comparative results of various denoising network with proposed denoising network for images with noise level 50. When the noise level of images increases, denoising of such a high level images are very difficult. Even more denoising methods are available in present days, the proposed method performs well on high noise affected images.

Table 6. PSNR Results for Noise Level 50

Test Image	***BM3D***	***TNRD***	***DnCNN***	***BM3D-Net***	***Proposed Net***
Building	29.45	29.85	30.25	31.45	31.69
Barbara	31.65	30.52	32.05	31.25	31.45
House	32.85	31.44	32.95	32.97	32.55
Rain Fall	29.90	29.85	29.78	29.95	29.97
Vinegar	28.42	28.35	28.47	28.77	28.65

The proposed method is also tested for rain streaks affected images. The rain streaks are basically directional oriented pattern. on observing the Figure 4(a), rain streaks are having different intensity value on original color image in various direction. Rain streaks are eliminated in proposed denoising network as shown in Figure 4 (e) compared to other denoising frameworks. Hence proposed network provides good PSNR improvement for rain streaks affected image.

(a) (b) (c)

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(d) (e)

Figure.3 Performance result for noise level 35 (a) Original noise image (b) BM3D (c) DNCNN (d) BM3D-Net (e) Proposed Net

(a) (b) (c)

(d) (e)

Fig.4. Visual results for rain streaks affected color image (a) Original noise color image (b) BM3D (c) DNCNN (d) BM3D-Net (e) Proposed Net

Figure 5. shows the PSNR comparison of various denoising network for noise level 25 . From the graph, it is observed that 1% to 4 % PSNR value improved in proposed deep learning denoising network.

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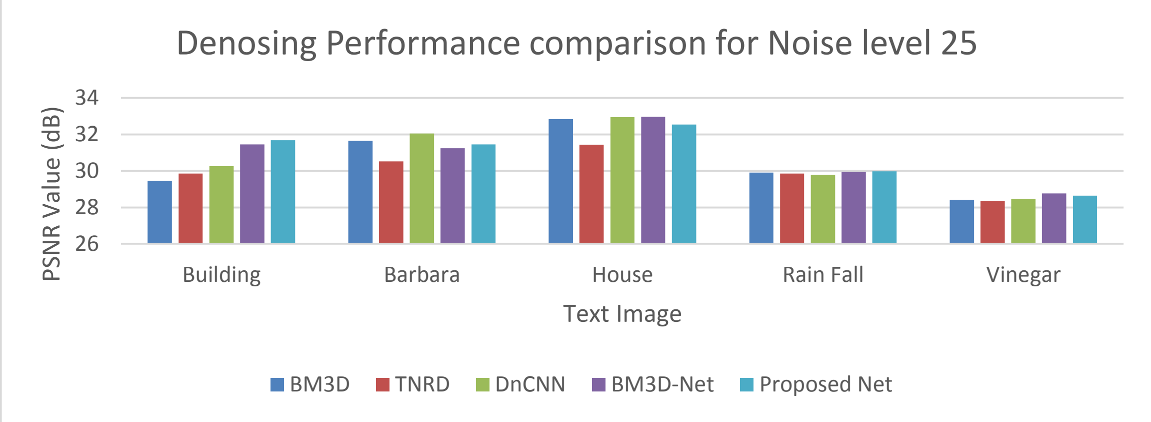

Figure.5. PSNR Comparision of Various Denosing Algorithm

Table 7 displays the mean PSNR value obtained from a number of different test photos. Table 7 shows that the proposed denoising framework excels at reducing noise with increasing levels of intensity from 15 to 35 to 50.

Table 7. Average PSNR Value comparison

Noise level (σ)	*BM3D*	*TNRD*	*DnCNN*	*BM3D-Net*	*Proposed Net*
15	32.57	32.11	32.342	32.75	32.814
25	30.454	30.002	30.7	30.878	30.95
35	28.778	28.684	28.886	29.078	29.068
50	26.776	26.846	26.776	26.878	27.062

6. Conclusion

In this paper, we present a unique BM3D-C2L network for denoising a single image of rain. A double convolutional layer serves as the foundation of the suggested network, allowing for powerful augmentation to be carried out. In-depth quantitative examination of the proposed denoising framework shows that it is superior to other existing deep learning algorithms at restoring detail to distorted images. The suggested convolution denoising network can be filtered and its performance evaluated using the tensor flow open source tool. To evaluate the denoising capabilities of the deep learning denoising system, experiments are run with varying degrees of background noise. Regardless matter how severely the photos have been distorted by noise or rain streaks, the experimental findings show that high PSNR may be achieved. The effectiveness of the proposed denoising technique will be evaluated in the future using 4K image and video sequences.

7. Conflicts of Interest

According to the guideline, we are uploading manuscript.doc. We feel that our paper addresses interesting and important issues in the field of Image processing. We are sure that this paper is suitable to be published in your prestigious journal and therefore we are submitting our results of hard work with lots of hope.

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We have no conflicts of interest to disclose.

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