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A Study of Responsive Image Denoising Algorithm

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Abstract: The goal of this study is to improve a deep learning-based image denoising algorithm. Image denoising is the process of removing any distortions in an image, and there are several processes available for this purpose. To solve this problem, deep learning is rapidly applied. We present a deep learning convolutional neural network model (CNN) for image denoising in this article. The convolutional neural network is the most accurate and precise solution for image denoising due to its high learning capacity. The architecture of a noise removal convolutional neural network model (CNN) and an image denoising technique based on denoising convolutional neural networks (DnCNN) are improved in this study.

Keywords: *CNN, deep learning, DnCNN, image denoising*

1. Introduction

Noise corrupts the image during transmission and acquisition. The noise in the image is caused by lossy compression, noise sources present in the vicinity of the image capturing equipment, an inaccuracy in the equipment used to capture images, the camera imaging pipeline and faulty memory locations (amplifier noise, quantization noise, and shot noise), scattering, and other adverse atmospheric conditions [1-2]. Denoising an image is a crucial part of image processing that shows how to get rid of image noise. It is the process of estimating an unknown signal using the data of the noise that is accessible. Its goal is to get rid of any noise that may be there, regardless of the signal's frequency content. The ability to eliminate noise while maintaining the integrity of edges is the primary characteristic of an effective denoising model for images [3].

Denoising an image refers to the act of removing noise from an image in order to restore the visibility of the original image. It is challenging, though, because noise, edge, and structure are higher-frequency elements. When attempting to differentiate between the denoised images throughout the process of denoising, it is possible that some information could be lost. In general, during the process of removing noise from noisy images in order to produce high-quality images, one of the primary challenges that exist in the modern world is retrieving crucial information from those images. Denoising an image is a well-known and long-studied problem. In fact, this has been going on for a very long time. Even though it is going to be a difficult and uncertain endeavour.

Deep learning algorithms have received a lot of attention in recent years for image denoising. However, there are significant differences between the various deep learning systems that deal with the process of image denoising. Specifically, the problem of Gaussian noise can be competently addressed by discriminative learning that is based on deep learning. Deep learning-based optimization models are very useful for accurately measuring the background noise. In spite of this, there has been a paucity of relevant research to date that summarizes the many deep learning algorithms for image denoising [4]. Deep learning methodologies have recently emerged as the most effective methods for addressing all of the drawbacks previously mentioned in denoising due to their strong learning ability. Deep learning with convolutional neural networks (CNNs) with adaptable models is the most reasonable deep learning strategy for image applications, particularly image denoising CNNs with adaptable models [5–6].

The Deep Learning Convolutional Neural Networks (CNN) approach treats the issue in image noise removal as a problem of supervised regression and effectively utilizes prior data collected from the external world. A large number of clean-noise images paired together are needed to generate a high level of complexity with multiple layers of network structure constraints. This method places a significant amount of demand on the system's capacity to learn from external past circumstances. Using the convolutional neural network model (CNN) for image denoising offers a number of advantages, the majority of which may be attributed to two specific facets: CNN has a complex hierarchical structure that can efficiently enhance the adaptability and

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efficiency of image feature mining. On the other hand, the regularization technique, the RELU activation functions, the batch standards development process, and other methods are established in the deep learning process to speed up training efficiency and enhance noise reduction performance. This is done to enhance the performance of deep learning overall. CNN can successfully improve image quality.

Deep learning convolutional neural networks (CNN) have recently drawn the attention of a growing number of researchers due to their strong self-learning capacity through a significant amount of information and the lack of requirement for researchers to strongly choose the characteristics; indeed, the researcher only needs to guide learning to accomplish the intended goal. It finds extensive use in the field of image pre-processing, particularly in applications like image super-resolution [7–9].

The convolutional neural network model for noise removal is known as DnCNN. To forecast the residual image rather than output the denoised image instantly, the improved denoising convolutional neural network (DnCNN) is designed, which represents the difference between both the latent clean image and the noisy observations. In other words, the improved denoising convolutional neural network (DnCNN) will implicitly get rid of the latent clean image using the operations that take place in the hidden layers of the network. DnCNN eliminates the latent clean images using hidden layer procedures [10]. Convolution is a process used to extract an image's feature information, which can include edges, lines, and other characteristics. The output layer is the final layer in the network topology and features full connectivity between all of its components. In order to lessen the impact of noise, the technique for image reconstruction known as convolutional networks was applied in this investigation. Moreover, residual learning was added to the model training process. Following the completion of the residual learning phase, a noise image is produced. The process of training is simpler, the results are superior, and the convolutional network-based method of image denoising requires fewer network layers because this image has less information than a clean image. Also, it has the potential to assist in accelerating the convergence process of the networks and increase noise removal capabilities [11].

2. Literature Review

Gupta, Kanika et al. (2021) [12] introduced various neural network models that have improved denoising of different types of photos, but there are still issues with parameter choice and data set size. There are no set standards for parameter setting in the model because the best settings are found experimentally.

Ashly Roy et al. (2021) [13] investigated image denoising using machine learning and deep learning. This paper examines a CNN method for image denoising that employs the LeNet architecture. They also demonstrated the use of machine learning in image denoising to determine which type of learning is most effective at removing distortions. Machine learning makes use of a variety of different techniques, including naive bayes, support vector machines, random forests, decision trees, and k-nearest neighbors. When deep learning algorithms and machine learning algorithms are correlated, an accurate image denoising solution can be generated. With an accuracy of 92.59%, Naive Bayes surpassed all of the other models.

A. Roy et al. (2021) [14] presented a variety of image denoising models that are based on deep CNN. These models provided the best denoised image as an output in terms of accuracy and performance in image denoising in comparison to other models that are not based on CNN. They began by focusing on a select few techniques that were utilized in the architecture for the process of picture denoising. These techniques included dilated convolutions, residual learning, attention mechanism, receptive field, and bath renormalization. The following section, the third one, will provide an explanation of the complex architecture of the CNN models that are employed the most frequently. Then, depending on the PSNR value, they looked at the experimental findings of these models. On the tested datasets, BRDNET and ADNET show promising results for picture denoising, with BRDNET coming out on top. The models were tested and trained using different datasets.

Zhou S. et al. (2019) [15] introduced an innovative multi-view image of denoising approach that is based on the convolutional neural networks (MVCNN). In stacks of 3-D focus images (3DFIS), multiple-view images are organised in a manner that takes into account the discrepancies between the views. In addition, the residual learning and batch normalisation procedures are implemented within the MVCNN that was proposed in order to enhance the performance of the denoising, as well as the speed of the training process. According to studies, the suggested CNN-based technique is a very efficient and effective method to denoise Gaussian in multi-view images. In contrast, the most cutting-edge single image and multi-view denoising techniques.

Zhang, Fu, et al. (2018) [16] presented a method for image cleaning that make the use of deep convolutional neural networks. The proposed deep convolutional neural network (DCNN), in contrast to other cutting-edge learning approaches, makes an accurate prediction of the noisy image when a messed-up image is fed into network. After that, the latent clean images are obtained by isolating the predicted noisy images from the dirty images. They piloted various tests for investigate the properties of developed DCNN. They found that the performance of the recommended denoising method improved with increasing network depth. Additionally, the proposed denoising techniques can simultaneously suppress numerous noises of various noise levels using a single model. The outcomes of the comparative testing support the recommended method's strong denoising capabilities and show that it offers a better solution to image denoising.

Kai Zhang et al. (2017) [17] conducted a research on the development of feed-forward denoising utilizing a convolutional neural network. The two applications that make the most use of this technology are known as residual learning and batch normalization. The training can be completed much more quickly as a result. This method has an effect on the training of one of the DnCNN models. Like DE blocking for JPEG images with Gaussian denoising.

3. Research Methodology

DnCNN denoising method

Training a task-specific convolutional neural network model involves two steps: 1) build the network; 2) train the model.

The DnCNN structure

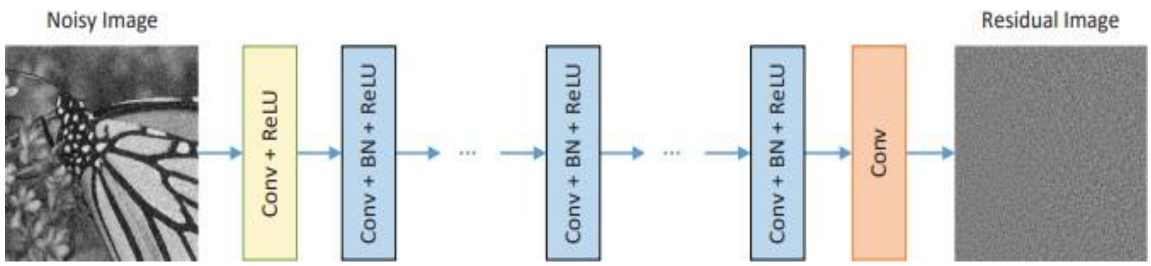

Fig. 1: DnCNN network structure

Figure 1 presents an overview of the fundamental structure of DnCNN used for image denoising. The network is made up of 10 layers of convolutional processing. Rectified Linear Unit Activation (ReLU) is used to activate everything on the layer stack other than the output layer. When multiple layers of convolution are stacked on top of one another, a problem called an "internal covariate shift" can occur. This issue can be remedied by applying batch normalization, also known as BN, to all of the hidden convolution layers. Learning the residual image is done in place of learning the clean image. In order to improve performance, the residual learning strategy, in which the noise residual (noise) is eliminated from the noisy image, has been implemented. On the other hand, the DnCNN's most significant drawback is that it requires a large number of model parameters to be specified.

5.

Steps of an Algorithm

1. The original, noisy image is convolutionally convolved to obtain a feature map, which is subsequently deconvolutionally calculated to obtain a reconstructed image;
2. The residual image is produced by subtracting the rebuilt image from the noisy real image;
3. calculate an initial difference between the residual picture from step 2 and the residual image after noise removal;
4. Training ends when the entire number of iterations is reached; else repeat 1-3.

DnCNN Algorithm

Required: y noisy signal

Required: σ noise standard deviation

Required: T noise threshold

CNN: Conv+BN+ReLU

If C (Θ) ≅ 0

Model is trained

else

Retrain model for next epoch

return $\hat{x} = y - R(y)$ residual learning

4. Results and Analysis

Testing and Training Data: This training set of Gaussian noise removal with known and unknown levels of noise consists of 400 grayscale images with a 180 by 180 pixel resolution. The approach described in this research was learned using a noise level of between 0 and 55 for the training set. The images of Gaussian noise with intensities of 15, 25, and 50 were selected for the purpose of this paper. This was done so that the reduction of noise effect of this technique could be verified using a known noise level. Every patch block has a width of 30 pixels and a depth of 30 pixels as well.

To train a single (DnCNN) blind Gaussian denoising model, we fixed the range of the noise levels to be between 0-55, and we made the patch size 50 by 50 pixels. Clipping 128 times 3000 patches is used to train the model.

We created test images for all competing approaches using two popular datasets. The first one is a testing dataset that has 68 natural images that were taken from the Berkeley segmentation dataset (BSD68), and the second one has 12 standard test images that are displayed in Figure 2. All images are heavily used to evaluate the Gaussian denoising algorithm and are not included in the training dataset.

Parameter setting and network training: The DnCNN network depth is set at 10 to account for noise reduction and convergence effectiveness. The first nine levels consist of a convolution layer and a deconvolution layer, and level ten is occupied by the last, fully connected layer. A small batch of 128 image blocks is used to train the updated loss function over 50 iterative cycles.

Fig. 2: 12 standard test images.

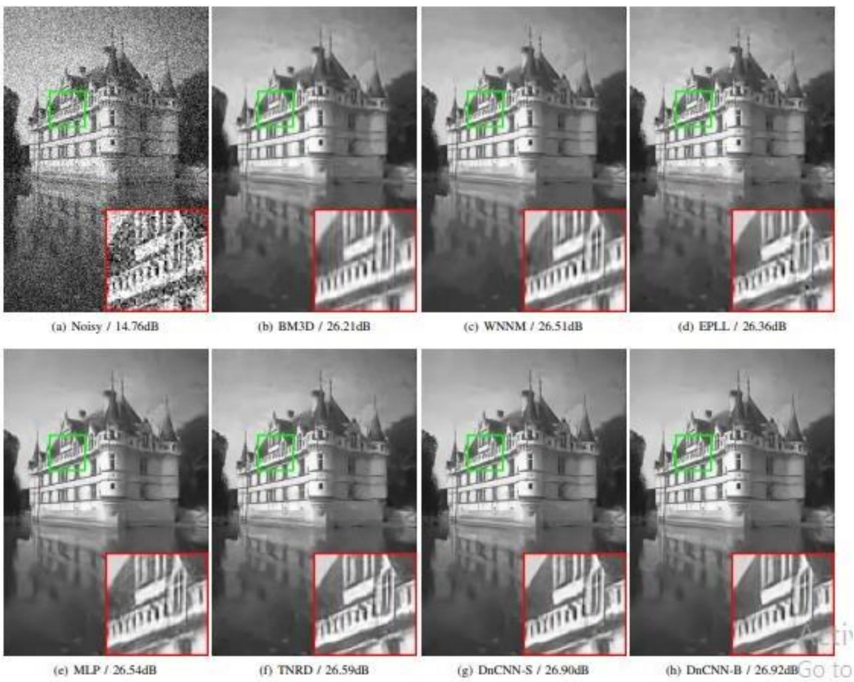

Fig. 3: Results of denoising one BSD68 image at level 50 of noise

The deep residual method, the SGD gradient optimization method, and the updated DnCNN loss function are all used in this particular research project.

Fig. 4 shows the variance in the PSNR value over the course of the model's training as a function of the iteration cycle.

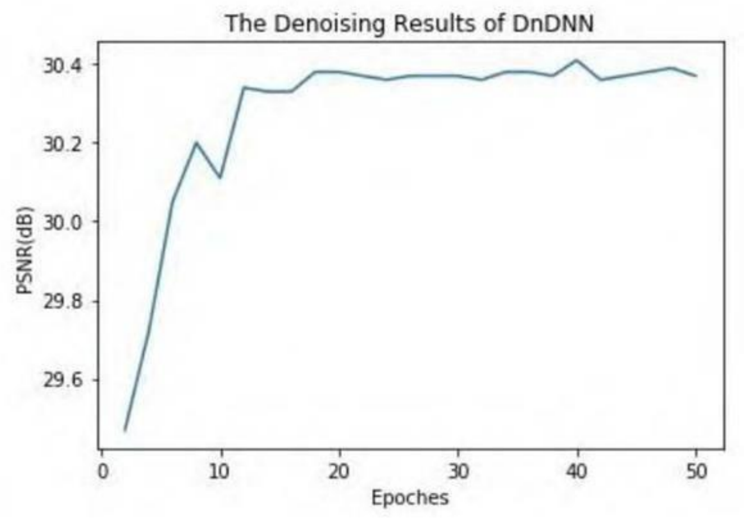

Fig. 4: DnCNN model-based training for removing Gaussian noise: Convergence Impact Diagram

5. Conclusion

Image denoising is becoming an increasingly common use for deep learning algorithms. The objective of this article is to present a method for image denoising that makes use of a convolutional denoising neural network as its basis. The algorithm is based on the structure of the first deep residual learning network, which incorporates the addition of a convolution layer. The utilization of convolution improves the quality and efficacy of noisy image residual learning, and loss function optimization has the additional impact of accelerating the training convergence speed while simultaneously improving the level of noise reduction effect. The fact that the DnCNN technique presented in this work has an excellent capability to cope with unknown noise levels represents a significant distinction from the discriminant model that was trained for specified image noise levels. The algorithm used in this work, which is referred to as DnCNN, has a substantially longer convergence time than the technique that is discussed in this research.

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