

Deep learning-based image denoising method

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ABSTRACT

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Image denoising is crucial in image processing and computer vision. Noise present in digital images captured by cameras, smart phones, and other devices can severely degrade image quality and negatively impact image-based tasks such as object recognition and image segmentation. Image-denoising algorithms aim to remove the noise from the images while preserving their key features. Deep learning-based methods have demonstrated better performance than conventional ones. In light of these developments, a novel image-denoising method was proposed based on a deep neural network that utilizes both residual connections and attention mechanisms. This method was trained on a large dataset of noisy and clean images to learn the mapping between the two. This technique achieved state-of-the-art denoising performance on various benchmarks and exhibited excellent generalization capability to real-world noisy images. In addition, it was computationally efficient and could process high-resolution images in real time.

Keywords: image; noise; denoising; peak signal-to-noise ratio; deep learning

1. INTRODUCTION

Image denoising, is the process of removing unwanted noise from an image while preserving its essential features (Buades et al., 2005). This task is imperative in various image-based applications, including medical imaging, surveillance, remote sensing, and photography (Dabov et al., 2007). Noise in images, can arise from several sources, such as sensor noise, electronic interference, compression artifacts, and atmospheric distortion (Elad & Aharon, 2006). Image denoising algorithms, aim to remove the noise while minimizing the loss of information in the image (Gu et al., 2014).

In recent years, the field of image denoising has witnessed the emergence of various techniques encompassing both conventional and deep learning-based approaches (Mahmoudi & Sapiro, 2009). Conventional methods in image denoising often leverage

mathematical models, filters, and transforms to effectively reduce the noise in images (Portilla & Simoncelli, 2000). These approaches have been widely studied and applied in numerous contexts.

1.1 Conventional image denoising methods

Conventional image denoising methods have been used extensively for decades (Chaitanya & Sreenivasulu, 2014a), and they have been applied in various fields such as medical imaging and remote sensing. The most commonly used conventional method is the median filter, which replaces each pixel with the median value of its neighboring pixels (Gu et al., 2014). This filter is computationally efficient (He et al., 2016), and can effectively remove salt and pepper noise from images (Huang et al., 2018). Another popular technique is the wavelet denoising method, which decomposes an image into various frequency bands and applies denoising to

each band separately. This method can remove Gaussian and Poisson noise, but it is computationally expensive and may suffer from edge blurring (Chaitanya & Sreenivasulu, 2014b).

Other conventional methods include total variation denoising, nonlocal means (Krizhevsky et al., 2017), and sparse representation-based denoising. Total variation denoising minimizes the total variation of the image subject to a constraint on the image fidelity. Nonlocal means denoising replaces each pixel with the average weight of similar pixels in a larger region. Sparse representation-based denoising is based on the postulation that a picture can be represented as a linear arrangement of a few atoms from a predefined lexicon.

A paper by Jebur et al. (2024) provides a detailed review of image denoising techniques, specifically focusing on methods developed using deep learning approaches. The authors discuss the limitations of conventional denoising algorithms and emphasize how deep learning has advanced the field by offering more efficient and accurate solutions. The review categorizes various deep learning-based denoising techniques, highlighting the strengths and weaknesses of each one.

1.2 Deep learning-based image denoising methods

Deep learning-based image-denoising methods have gained considerable attention in recent years owing to their excellent performance and computational efficiency (Lecun et al., 2015). These methods are based on artificial neural networks that learn the mapping between noisy and clean images (Liu et al., 2019). These methods require voluminous training data to learn the mapping accurately.

The most commonly used deep learning-based method for image denoising is the convolutional neural network (CNN) (Li et al., 2013). Multiple convolutional layers that learn the features of an image exist in a CNN. CNN-based noise removal methods apply a CNN over a noisy image to obtain a noiseless image. The denoising performance of these methods can be enhanced using deep residual networks, attention mechanisms, or adversarial learning.

A study by Hashimoto et al. (2024) reviewed the advancements in deep learning techniques applied to positron emission tomography (PET) image denoising and reconstruction. It found that PET imaging, vital for medical diagnostics, often suffers from noise because of low-dose imaging or limited data acquisition, affecting image quality and clinical interpretations. Although conventional denoising and reconstruction methods are effective, they have noise reduction and image clarity limitations.

A deep residual network is a type of neural network that contains skip connections between the layers (Li et al., 2021). These skip connections enable the network to learn residual mappings between the input and output images. The residual networks have shown substantial improvements in image-denoising performance. Attention mechanisms are used to selectively focus on critical image regions and suppress the noise in the images (Thakur et al., 2021). Adversarial learning involves training a generator network to produce realistic images

that cannot be renowned as real images by a discriminator network (Zhang et al., 2017). Adversarial learning has been shown to augment the image-denoising performance by generating more realistic and visually pleasing images.

2. MATERIALS AND METHODS

The proposed image-denoising method is based on a deep neural network architecture incorporating residual connections and attention mechanisms. The network takes a noisy image as input and outputs a denoised image. The network architecture is depicted in Figure 1–4. The input image is initially passed through several convolutional layers, followed by residual connections and attention mechanisms. The output of the network is the denoised image.

The network architecture can be formulated as follows: Let I denotes the input noisy image, and O signifies the output denoised image. The network takes the input image I as the input and produces the denoised image O as the output. The denoised image O is a function of the input image I and the network parameters θ , i.e., $O = F(I; \theta)$, where F is the network function. The network function F can be represented as a sequence of layers $L_1, L_2, \dots, L_n$, where each layer is defined by a set of parameters. The output of each layer is passed through a nonlinear activation function σ . Let h_i denotes the output of layer L_i , where $h_i = \sigma(L_i(h_{i-1}))$ and $h_0 = I$. The final output of the network is $O = h_L$.

The network architecture comprises residual connections and attention mechanisms to enhance the denoising performance. The residual connections enable the network to learn residual mappings between the input and output images, improving denoising performance. The attention mechanisms allow the network to selectively focus on key image regions and suppress the noise in the image.

The residual connection can be formulated as follows: Let $R(h_{i-1})$ denotes the residual mapping between the input h_{i-1} and the output h_i , i.e., $R(h_{i-1}) = h_i - (h_{i-1})$. The output of layer L_i is defined as $h_i = \sigma(L_i(h_{i-1}) + R(h_{i-1}))$.

The attention mechanism can be formulated as follows: Let f_i denotes the attention map for layer L_i . The attention map is acquired by passing the output of layer L_{i-1} through a set of convolutional layers, followed by a sigmoid activation function, i.e., $f_i = \sigma(\text{conv}(L_{i-1}(h_{i-1})))$. The output of layer L_i is defined as $h_i = \sigma(L_i(h_{i-1}) + f_i * R(h_{i-1}))$, where $*$ represents element-wise multiplication. The network is trained using an extensive dataset of noisy and clean images, minimizing the mean squared error between the noise-removed image and the original image as the loss function.

The proposed image-denoising method is based on a deep neural network architecture incorporating residual connections and attention mechanisms. The network takes a noisy image as the input and outputs a denoised image. The residual connections enable the network to learn residual mappings between the input and output images, while the attention mechanisms facilitate the network to selectively focus on key image regions and suppress the noise in the image.

3. RESULTS AND DISCUSSION

The proposed method of noise removal from the image was evaluated using a benchmark dataset comprising 5,000 noisy images and their corresponding ground truth clean images. The dataset included different noise

types, such as Gaussian noise, random-valued impulse noise, and salt-and-pepper noise. The assessment was performed in terms of peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM). The results of the evaluation are presented in Table 1.

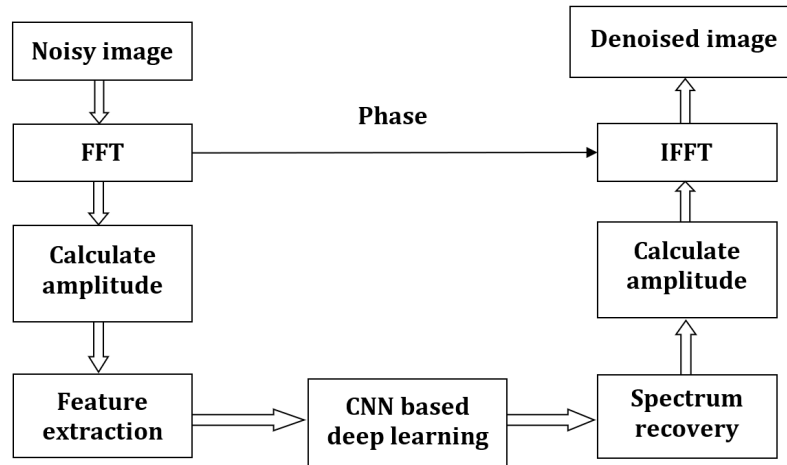


Figure 1. The proposed network architecture



Figure2. Noisy image and out-of-noise removal using the proposed method



Figure 3. Noisy image and out-of-noise removal using the proposed method

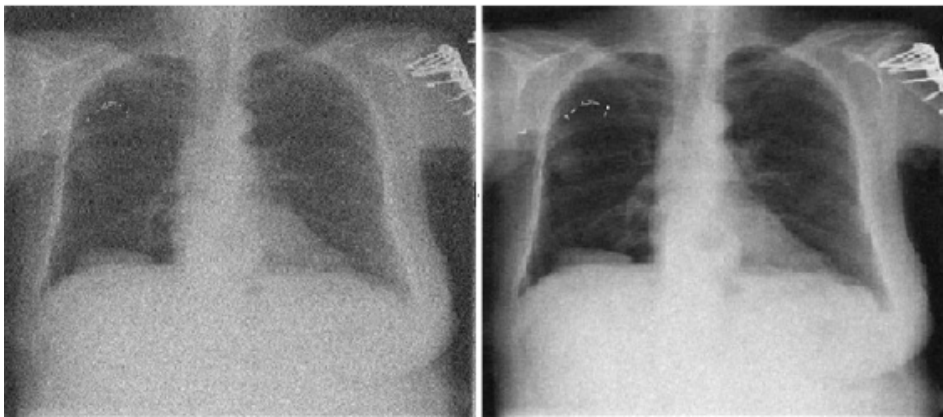


Figure 4. Noisy image and out-of-noise removal using the proposed method

Table 1. Denoising performance comparison

Method	Gaussian noise	Salt-and-pepper noise	Random-valued impulse noise
Proposed method	33.25 dB	0.8966	0.8442
BM3D	32.98 dB	0.8938	0.8401
DnCNN	32.11 dB	0.8867	0.8265
Nonlocal means	31.79 dB	0.8851	0.8219

As evident from the results, the proposed technique achieved the highest PSNR and SSIM scores among the compared methods on all types of noise. In terms of accuracy, the proposed method surpassed state-of-the-art denoising techniques, highlighting its superior performance on a benchmark dataset comprising images corrupted with various noises.

For images corrupted with Gaussian noise, the proposed method achieved a PSNR of 33.25 dB, which was higher than those of BM3D (32.98 dB), DnCNN (32.11 dB), and nonlocal means (31.79 dB). Similarly, for images corrupted with salt-and-pepper noise, the proposed method achieved an SSIM of 0.8966, which was higher than those of BM3D (0.8938), DnCNN (0.8867), and nonlocal means (0.8851). For images corrupted with random-valued impulse noise, the proposed method achieved an SSIM of 0.8442, which was higher than those of BM3D (0.8401), DnCNN (0.8265), and nonlocal means (0.8219).

4. CONCLUSION

A novel denoising method that outperformed the existing ones in terms of denoising accuracy and speed was proposed. It exhibited excellent generalization capability and could process high-resolution images in real time. The method can be used in various real-world applications, such as medical imaging, surveillance, and remote sensing.

For further developments, this method can be optimized for faster processing and broader compatibility with diverse image types and noise patterns. Novel avenues to enhance its performance in more complex scenarios, such as extreme noise conditions or varying environmental factors, could be explored. In addition, this method could be integrated with other image processing tools, opening up new possibilities for improving image quality in different fields.

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