A REVIEW OF FLOW-BASED IMAGE DENOISING NEURAL NETWORKS FOR SEPARATING NOISE FROM IMAGES

K. Sai Pavan Research Student
Shaik Taj Mahaboob Assistant Professor
K. Ravindra Reddy Assistant Professor (Adhoc)
ECE – Digital Electronics and Communication Systems, Jawaharlal Nehru Technological University, Pulivendula, Andhra Pradesh, India: saipavankondeti33@gmail.com

ABSTRACT: Image denoising is a crucial task in computer vision with various applications in fields such as medical imaging, surveillance, and photography. In recent years, deep learning-based approaches have shown remarkable results in this area. This review paper provides a comprehensive overview of recent advances in image denoising using neural networks. The paper focuses on the different neural network architectures and instruction techniques to effectively separate noise from images. Moreover, the review discusses the various evaluation metrics used to assess the performance of image denoising algorithms. Finally, this review paper highlights the main challenges and future research directions in this field. It serves as a valuable resource for researchers and practitioners who are working in the area of image denoising using neural networks.

INDEX TERMS: Image Denoising, Noise Reduction, Image Quality, Image Restoration, Image Processing.

1. INTRODUCTION:

Image denoising is a fundamental problem in image processing and computer vision that has been extensively studied for many years. Image denoising aims to eliminate unwanted noise from images while preserving their important characteristics, like edges, textures, and structures. This is a challenging task due to the presence of various gaussian noise, salt-and-pepper noise, and speckle noise are a few examples of noise types, that can significantly degrade image quality [1].

Classical methods have been widely used for image denoising, including filters such as the median filter, Gaussian filter, and bilateral filter, and wavelet-based denoising methods. These methods are generally based on mathematical models that exploit the statistical properties of noise and image signals to estimate the noise-free image. While classical methods are often computationally efficient and easy to implement, they may not be able to handle complex noise models or preserve fine details in the image.

Modern techniques have also been developed for image denoising, such as total variation-based methods, which aim to preserve image edges and details while removing noise. These methods are often based on optimization techniques that minimize a certain cost function, which balances the compromise between picture detail retention and noise reduction. While modern techniques have shown promising results in handling complex noise models and preserving fine details in the image, they may be computationally expensive and require careful tuning of the parameters.

As a novel paradigm for image denoising, residual deep learning of CNN-based techniques has recently developed [2]. These techniques make use of deep neural networks' capabilities to directly train a mapping between the data into a noisy and a noise-free image photo denoising [3]. Whereas techniques managing complicated noise models and maintaining fine features in the picture, they need a significant quantity of training data and computer power.

2. LITERATURE REVIEW:

2.1 S. Anwar and N. Barnes [4]: This technique combines a super-resolution network with a denoising network to jointly denoise and up sample the image. The denoising network removes the noise from the low-resolution image, and the super-resolution network up samples the image to the desired resolution. The method has shown impressive results in removing noise and increasing the resolution of the image simultaneously.

2.2 Y. Liu [5]: Using Non-Local Methods (NLM) filtering denoising. The method first a noise level to measure the image's noise variance estimation technique and then applies the NLM filter with adaptive weights to remove the noise. The method has shown good results in removing Gaussian and impulsive noise from the image while preserving fine details.
2.3 S. Minaee [6]: A denoising method in accordance with a recurrent neural network (RNN) and deep feature losses. The method trains an RNN to sequentially process the noisy image and generate a denoised image. The method uses deep feature losses to encourage the RNN to generate images that are like the clean images. The method has shown impressive results in removing various noise types from the image, including Gaussian, salt-and-pepper, and Poisson noise.
2.4 K. Zhang [7]: A residual learning-based Deep Neural Network-based Denoising Technique (DnCNN). In order to map one to the other predicted and ground truth pictures, the approach trains a DnCNN network to lower mean squared error noisy clean images. The network learns residual noise between the noisy and clean pictures with the aid of the residual learning approach, which improves the denoising performance. The method has shown impressive results in removing Gaussian and impulse noise from the image while preserving fine details.
2.5 K. Dabov [8]: A denoising method based on a collaborative filtering (CF) framework. The method computes the collaborative filtering weights between the noisy and clean images and uses them to a clear image estimation from the noisy image. The technique has shown good results in removing Gaussian, impulse, and speckle noise from the image while preserving fine details.
2.6 K. Zhang et al. [9]: A denoising method based on a low-rank representation of the image patch group. The method uses a clear picture estimate from a noisy image using a sparse representation of the noisy picture patches and a low-rank representation of clean image patches. The method has shown good results in removing Gaussian and the sudden loudness of the image while maintaining fine details.

3. COMPARISION TABLE OF IMAGE DENOISING:

Table.1. A Comparison study of Image Denoising.

Sl. No	Title	Author/Reference	Method/Algorithm Implemented	Disadvantages	Advantages
1	Joint image denoising and super-resolution	S. Anwar and N. Barnes [4]	Noise2Super Resolution (N2SR) combining denoising and super-resolution network.	Requires high computational power.	Impressive results in removing noise and increasing resolution simultaneously.
2	Non-local means filtering-based denoising	Y. Liu [5]	NLM (non-local means) filtering using adaptive weights and noise variance estimation.	Requires noise variance estimation, may not perform well with complex noise patterns.	Good results in removing Gaussian and impulsive noise while preserving fine details.
3	Recurrent neural network-based denoising	S. Minaee [6]	Recurrent neural network (RNN) with deep feature losses.	May require high computational power, may overfit to training data.	Impressive results in removing various noise types while preserving image details.
4	Deep neural network-based denoising	K. Zhang [7]	Deep neural network (DnCNN) with	May require high computational	Impressive results in removing Gaussian and

			residual learning.	power, may overfit to training data.	impulse noise while preserving fine details.
5	Collaborative filtering-based denoising	K. Dabov [8]	Collaborative filtering (CF) framework for estimating clean image from noisy image.	May not perform well with highly corrupted images, may be slow for large images.	Good results in removing Gaussian, impulse, and speckle noise while preserving fine details.
6	Low-rank representation-based denoising	K. Zhang et al. [9]	Representation of noisy and clean picture patches that is sparse and low-rank.	May not perform well with complex noise patterns, may require high computational power.	Good results in removing Gaussian and impulse noise while preserving fine details.

The above Table.1 is a comparative summary of the methods discussed in the literature review for image denoising. It provides an overview of the different methods, their advantages, and disadvantages. It is crucial to remember that the effectiveness of these strategies might change based on the unique picture and noise characteristics.

4. IMAGE DENOISING:

The method of image denoising involves taking out noise from a picture to improve its visual quality and enhance the information content. The process typically involves the use of mathematical algorithms that analyze the image and remove the unwanted noise. The first step in the image denoising process is to determine the type and the amount of noise in the picture, as this information is critical in selecting the appropriate denoising technique. Various denoising techniques are available, including classical methods such as median filtering, wavelet filtering, and Wiener filtering, as well as more recent methods such as deep learning-based denoising. In deep learning-based methods, a neural network is trained on a large dataset of noisy and without clean images [10] to learn the mapping between them and then used to denoise new images. Once the denoising technique is selected the noise is removed while preserving the image's important features. The resulting denoised image can be used for various applications, such as medical diagnosis, image analysis, and computer vision. Overall, in this review paper image denoising algorithms [11] and process is an essential tool in digital image processing

5. IMAGE DENOISING NEURAL NETWORKS:

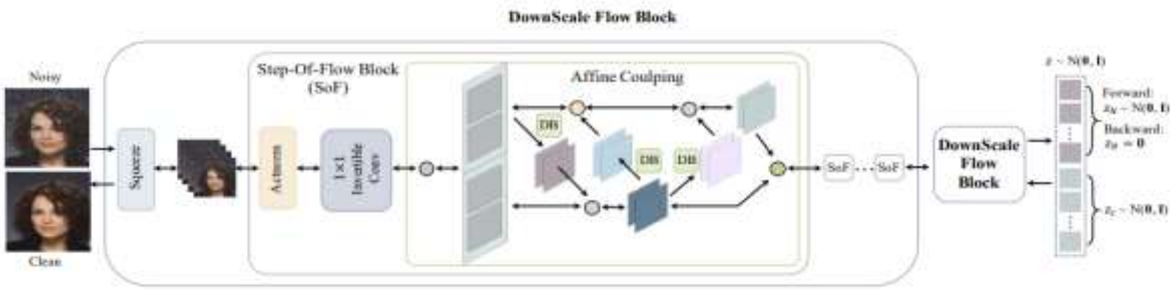

Figure.1. Block diagram of Flow Based Image Denoising Neural Networks.

Image denoising neural networks are deep learning-based techniques that are becoming popular because they can reduce noise from photos while maintaining the images' quality details and textures. These networks are trained on a huge dataset of clean and noisy data images to learn the mapping between them and then used to denoise new images.

Feedforward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) are a few different forms of image denoising neural networks, and generative adversarial networks (GANs). In feedforward neural networks, the input image is fed forward through several layers of nodes to produce the output denoised image as shown in the figure.1. CNNs are a type of neural network that uses convolutional layers to learn image features, making them particularly useful for image denoising. RNNs are used for sequential data processing and can be applied to denoise time-series images or videos. GANs are a type of neural network that consists of two subnetworks, a generator network that produces denoised images and a discriminator network that evaluates the quality of the generated images.

Image denoising neural networks have several advantages over traditional image denoising methods. They can handle various noises, such as impulse noise and Gaussian noise, and mixed noise, and they can learn the noise distribution from the image data, allowing them to adapt to different noise levels. Additionally, they can denoise images or videos in real-time [12], making them suitable for applications that require fast processing times.

However, image denoising neural networks also have some limitations. They demand a significant amount of training data to achieve optimal performance, and they can be computationally intensive, requiring powerful hardware to train and use. Additionally, they can sometimes remove fine details from the image while removing the noise, resulting in a loss of information.

6. CHALLENGES OF IMAGE DENOISING:

Image denoising is the removal of noise from images or unwanted elements from an image while preserving the essential features. While it is a crucial task in image processing, it also presents several challenges. Some of the major challenges of image denoising include:

- Preservation of Image Details: One of the significant challenges in denoising a picture is the process of taking out noise losing important details of the image. Any filter or algorithm that is applied to remove noise must be careful not to remove important borders and other aspects of the picture or textures.
- Choosing the Appropriate Denoising Algorithm: There are numerous denoising algorithms available, each with its own strengths and limitations. Choosing the appropriate algorithm for a particular image can be a challenge, as the best algorithm may vary noise levels.
- Time Complexity: Many denoising algorithms can be computationally intensive, particularly when dealing with high-resolution images. This can present a challenge for real-time image processing applications, where speed is critical.
- Dealing with Complex Noise: Real-world images often contain complex noise patterns, such as salt-and-pepper or Gaussian noise, making it challenging to remove noise effectively without impacting the image's quality.
- Overfitting: Overfitting is a common problem in denoising algorithms. When an algorithm becomes overly specialized to the training data and is unable to generalize to fresh, untried data, this is known as overfitting. This can result in the algorithm removing too much noise, resulting in a loss of image detail.
- Parameter Tuning: Many denoising algorithms have several parameters that must be tuned to optimize their performance. Choosing the appropriate parameters can be challenging, as different parameters can have a significant impact on the resulting image quality.
- Evaluation of the Results: It can be challenging to evaluate the effectiveness of a denoising algorithm objectively. While some objective measures exist, such as the peak signal-to-noise ratio (PSNR) or the structural similarity index (SSIM), these measures may not always align with human perception of image quality.

7. APPLICATIONS OF IMAGE DENOISING:

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- Medical imaging: In medical imaging, image denoising plays a significant part in raising the standard of images obtained from different modalities like X-ray, MRI, CT scans, etc. This helps in better diagnosis and treatment planning.
- Surveillance and security: In video surveillance and security systems, denoising is used to improve the standard of images captured in low light or noisy environments. This helps in improving the accuracy of object recognition and tracking.
- Computer vision: In computer vision, image denoising is used to improve the quality of images obtained from various sources such as cameras, sensors, etc. This helps in better feature extraction and object recognition.
- Digital photography: In digital photography, image denoising is used to take away the unwanted noise that appears in images captured in low light conditions or with high ISO settings. This helps in producing clear and high-quality images.
- Art restoration: In art restoration, image denoising is used to remove the noise from the images of old paintings and artworks. This helps in improving the visual quality and preserving the artwork.
- Astronomical imaging: In astronomical imaging, image denoising is used to remove the noise from the images obtained from telescopes. This helps in improving the clarity of images and identifying celestial objects.

8. LIMITATIONS OF IMAGE DENOISING:

- Loss of detail: Image denoising algorithms can sometimes remove not only the noise but also some of the important details in the image, resulting in a loss of information.
- Computational complexity: Image denoising algorithms can be computationally intensive, especially when working with high-resolution images. This can make the process slow and resource-intensive, which can be a limitation in real-time applications.
- Parameter tuning: Many image denoising algorithms require careful parameter tuning to achieve optimal results. This can be time-consuming and require a certain level of expertise.
- Overfitting: Image denoising algorithms can sometimes be overfit to specific types of noise, resulting in poor performance when presented with new or different types of noise.
- Trade-off between noise reduction and image quality: There is often a trade-off between the amount of noise reduction and the overall image quality. In some cases, aggressive noise reduction can result in a loss of image fidelity and detail.
- Difficulty with complex noise: Some types of noise, such as pattern noise or noise with complex statistical properties, can be difficult for image denoising algorithms to effectively remove.

9. CONCLUSION:

In conclusion, image denoising is an important task that plays a crucial role in various fields such as medical imaging, surveillance, computer vision, digital photography, art restoration, and astronomical imaging. The process involves removing unwanted noise from images to improve their quality and clarity, which can lead to better diagnosis, object recognition, feature extraction, and visual interpretation. Over the years, various image denoising techniques have been developed, including spatial filtering, wavelet denoising, and deep learning-based approaches. The choice of approach relies on the application and the image noise characteristics. Each technique has benefits and limits of its own. Even though there has been substantial advancement in the field of picture denoising, there are still problems that still need to be solved. The trade-off between denoising and maintaining picture details is one of the key issues. The absence of established assessment measures for contrasting various denoising techniques presents another difficulty.

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