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"A Comprehensive Review of CNN-Based Image Denoising Algorithms "

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Abstract : Recent advancements in image denoising algorithms utilizing Convolutional Neural Networks (CNN) have demonstrated significant success, surpassing traditional methods in both performance and efficiency. CNN-based approaches offer powerful learning capabilities, enabling them to effectively handle complex noise patterns. This paper provides an overview of both traditional image denoising techniques and CNN-based methods, with a detailed explanation of the fundamentals of image denoising. This serves as a valuable resource for those new to the field of image denoising. Additionally, the paper highlights commonly used datasets in image processing, facilitating better access to resources for image denoising tasks. Finally, the paper offers recommendations for enhancing the performance of CNN-based image denoising techniques and discusses potential future research directions in this area.

Keywords: Convolutional Neu ral Network, Denoising Algorithms, Image Processing, Deep Learning

I. INTRODUCTION

As technology becomes increasingly integrated into all aspects of life, the number of digital images continues to rise [1]. However, the quality of these images varies, making image processing a critical issue [2]. Techniques in image processing encompass tasks such as image denoising, enhancement, and restoration [3]. Image denoising, being a fundamental aspect of image processing, plays a crucial role in ensuring the success of other operations. A clear, high-quality image is essential for achieving optimal results in subsequent processing steps. Understanding the nature of image noise can significantly improve the effectiveness of noise removal [4]. This section covers the basics of noise, including its sources, classifications, and the use of convolutional neural networks (CNNs) in noise reduction.

With the growing number of digital images captured under poor conditions, image denoising techniques have become essential for computer-aided analysis. Today, the task of recovering information from noisy images to produce a clear, clean image has become a critical challenge. Image denoising methods aim to eliminate noise and restore the image's original quality. A key difficulty in this process is effectively differentiating between noise, edges, and textures.

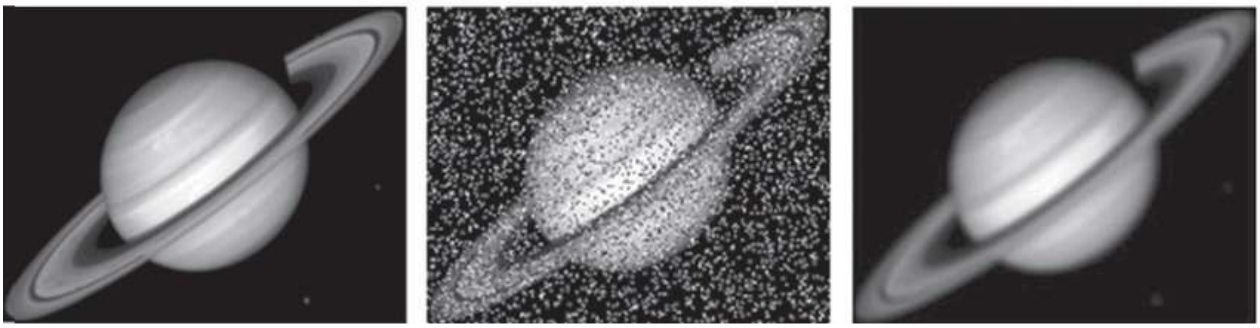

Figure 1 From left to right: original image (without noise), noisy image and the restored image

1.1. SOURCES AND CLASSIFICATION OF NOISE

When creating an image, the goal is to maintain uniform brightness across all areas, except for those parts that form the image itself. However, in practice, various factors that aren't necessary for image formation cause brightness variations. These variations are random and typically lead to a decline in image quality. This randomness is referred to as image noise. In an image, noise appears as excess signals that obscure what we're trying to view, often represented visually as isolated pixel spots. Generally, noise diminishes the clarity of image features, making the image less clear. Noise primarily arises during two stages: image signal acquisition and image signal transmission. The former results from differences in the sensor, such as variations in material or circuit design, while the latter stems from issues in the transmission equipment's performance. Due to the increasing number of digital images captured in poor conditions, image denoising has become an essential tool for computer-aided analysis. Restoring information from noisy images to obtain a clean version is a critical challenge. Image denoising techniques aim to remove noise while preserving important details. One of the main difficulties in this process is distinguishing noise from edges and textures, as all contain high-frequency components. Among the most studied types of noise in literature are additive white Gaussian noise (AWGN) [2], impulse noise [3], quantization noise [4], Poisson noise [5], and speckle noise [6]. AWGN commonly arises in analog circuitry, while impulse, speckle, Poisson, and quantization noise result from faulty manufacturing, bit errors, and inadequate photon counts [7]. Denoising methods have applications in various fields, including medical imaging, remote sensing, military surveillance, biometrics, forensics, industrial automation, and individual recognition. In medical imaging, denoising algorithms are crucial pre-processing steps for removing noise such as speckle, Rician, and quantum noise [8, 9]. In remote sensing, these algorithms help eliminate salt-and-pepper noise and additive white Gaussian noise [10, 11].

This section will explore various existing methods for CNN-based image denoising. We categorize these approaches into two types: (1) CNN denoising for general images and (2) CNN denoising for specific images. The first approach involves using CNN architectures to denoise general images, while the second focuses on using CNN to denoise images with specific characteristics. The first approach is more commonly used in CNN denoising applications compared to the second. General images are those that serve broad purposes and are not focused on specific details (examples of general images can be found in [12]. Convolutional Neural Networks (CNNs) have revolutionized image denoising by leveraging deep learning to learn noise patterns and remove noise effectively. Unlike traditional denoising methods (e.g., Gaussian smoothing, wavelet transforms, or non-local means), CNN-based approaches adaptively extract features and distinguish noise from textures and edges, improving overall denoising performance. CNN-based denoising approaches can be customized for **specific image types**, such as medical images, satellite images, document scans, low-light photography, and hyperspectral images. Unlike general-purpose denoising models, these methods are trained to handle the unique noise characteristics of specific image domains. [9].

1.2. Advancements in Deep Learning for Image Denoising

With the rapid advancement of computer networks, computational power has reached unprecedented levels, providing a strong foundation for deep learning development [13]. Deep learning is now being applied across an expanding range of fields [14]. In the domain of computer vision, image denoising—a fundamental low-level task—has also benefited from deep learning advancements. Numerous state-of-the-art denoising algorithms have emerged, surpassing traditional methods in performance and effectiveness [15].The success of deep learning [16] is largely dependent on data, and the availability of large-scale simulation datasets has facilitated its application in image denoising. This is particularly advantageous for images with complex backgrounds, where traditional algorithms often struggle to produce satisfactory results despite extensive tuning [17]. In contrast, deep learning models can effectively address this challenge by learning from noisy samples, enabling them to reconstruct clean images with minimal manual intervention [18–21].

2. Traditional Denoising Algorithms

Traditional image denoising methods can be broadly classified into **spatial domain** and **transform domain** approaches. **Spatial domain filtering techniques** operate directly on pixel values to reduce noise while attempting to preserve edges and textures.[22] Common methods include **mean filtering**, which replaces each pixel with the average of its neighbors but tends to blur edges, and **Gaussian filtering**, which smooths images using a Gaussian-weighted kernel, effectively reducing high-frequency noise while preserving some details. **Median filtering**, on the other hand, is particularly effective for removing impulse noise (salt-and-pepper noise) by replacing each pixel with the median value of its neighborhood. A more advanced approach, **bilateral filtering**, preserves edges by assigning different weights to neighboring pixels based on their intensity differences, making it useful for image enhancement applications.

In contrast, **transform domain filtering techniques** work by converting images into the frequency domain to selectively remove noise. **Fourier transform-based denoising** separates noise from the useful signal but struggles with non-stationary noise.

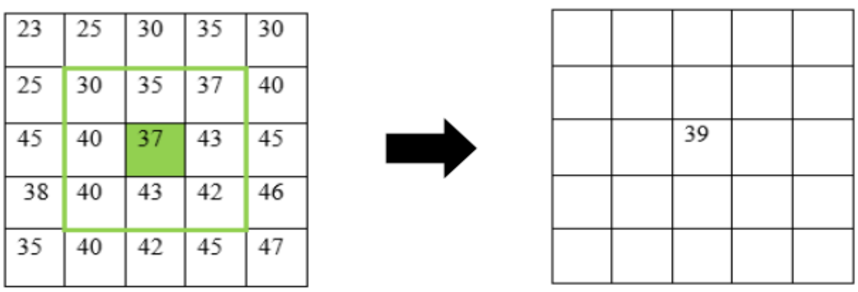

Figure 2 Mean filter calculation method

Wavelet transform-based denoising, such as BayesShrink and VisuShrink, decomposes images into multi-scale wavelet coefficients to filter out noise while preserving edges better than Fourier-based methods. Additionally, **curvelet and contourlet transforms** are designed to capture curved and directional edges, making them useful for applications like medical imaging and astronomical image processing. Beyond filtering methods, **non-local and statistical techniques** have been developed to exploit self-similarity and probabilistic models for improved denoising.

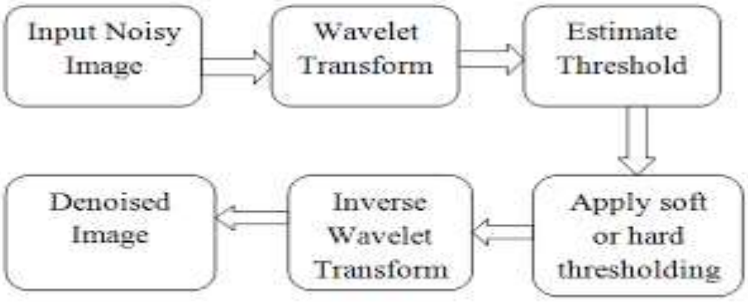

Figure 5 Principle of the wavelet denoising process

Non-Local Means (NLM) filtering compares similar patches across the image and replaces noisy pixels with weighted averages of similar patches, making it highly effective for Gaussian noise removal, though computationally expensive[23]. Mean value filtering, also referred to as **arithmetic mean filtering** [24], smooths an image by replacing each pixel's value with the **average of its neighboring pixels**, as illustrated in Figure 3. While this method helps in reducing noise, it comes with significant drawbacks. It tends to **blur image details, reduce sharpness, and lower contrast**, making it less effective for preserving fine textures and edges. Additionally, its performance in removing noise is limited, often failing to distinguish between actual image structures and unwanted noise.

Despite their effectiveness, traditional denoising methods suffer from several limitations. Many filtering techniques **blur edges and textures**, resulting in a loss of fine details. Methods like **NLM and BM3D are computationally expensive**, making them impractical for real-time applications. Additionally, these methods often require **manual tuning of parameters** and struggle with **complex, real-world noise variations**. Due to these challenges, modern deep learning-based denoising techniques have emerged as a superior alternative, offering **better noise suppression, edge preservation, and automation** without the need for extensive parameter tuning.

3. Convolutional Neural Network-Based Approach for Image Denoising

3.1. Introduction to CNN

CNN is a neural network that emulates the human brain's neural system and serves as a form of machine learning. Other network architectures, such as Generative Adversarial Networks (GAN) and Recurrent Neural Networks (RNN) [25, 26], also exhibit different types of connectivity. They function similarly to the human brain, enabling them to make basic decisions. Since its introduction, CNN has been extensively applied in image processing, delivering effective solutions to various challenges in the field [27, 28]. The convolutional layer primarily extracts feature information from input images, allowing the computer to recognize semantic content. The pooling layer reduces feature dimensionality by compressing parameters, enhancing computational efficiency without compromising recognition accuracy, thereby improving model performance [29]. The fully connected layer is mainly responsible for classification, integrating extracted local features into a comprehensive global representation.

3.2. CNN Architecture for Denoising

Convolutional Neural Networks (CNNs) have demonstrated remarkable effectiveness in image denoising by learning complex patterns and structures in noisy images. A typical CNN-based denoising architecture consists of multiple layers designed to extract, refine, and reconstruct image features while reducing noise. The process begins with an input layer that receives the noisy image, followed by convolutional layers that apply learnable filters to capture essential spatial features. Activation functions, such as ReLU, introduce non-linearity, allowing the network to learn complex mappings between noisy and clean images. Some architectures incorporate batch normalization to stabilize training and improve convergence. While pooling layers are commonly used in CNNs to reduce spatial dimensions, they are sometimes omitted in denoising models to preserve fine details. Advanced architectures often employ residual learning, where the model learns the difference between noisy and clean images, enhancing denoising performance. In certain cases, fully connected layers refine the extracted features before reconstruction. The final output layer generates a clean, denoised image of the same dimensions as the input, often using a sigmoid or identity activation function for pixel-wise restoration. Popular CNN-based denoising models include Denoising Convolutional Autoencoders (DCAE), which use an encoder-decoder structure, DnCNN, which incorporates batch normalization and residual learning for high-performance denoising, and FFDNet, which utilizes downsampling and multi-scale feature extraction for improved efficiency. These CNN-based models effectively remove various types of noise, such as Gaussian noise, salt-and-pepper noise, and speckle noise, making them highly valuable in image processing applications.

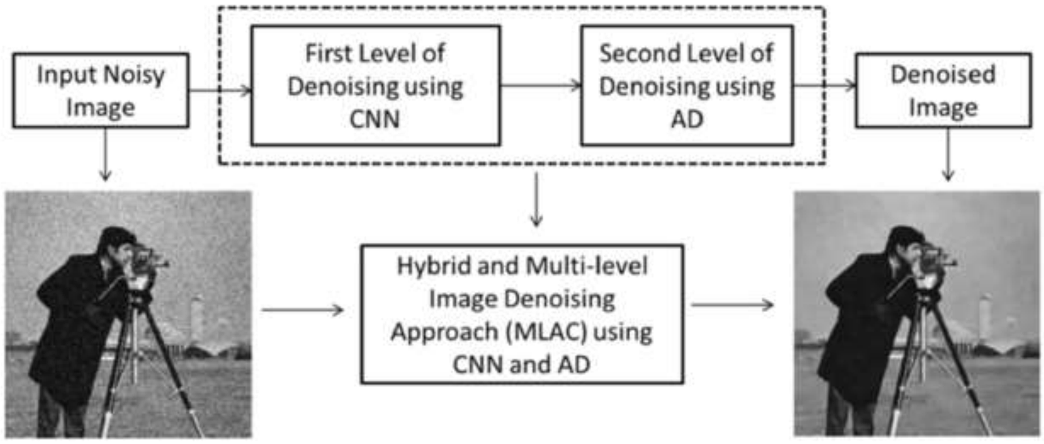

FIGURE 4 CNN ARCHITECTURE FOR DENOISING

LeNet, introduced by Yann LeCun et al., was one of the earliest convolutional neural network (CNN) architectures, primarily designed for handwritten digit recognition [30]. The network consists of seven layers, excluding the input layer, and follows a structured approach of convolution, subsampling (pooling), and fully connected layers. It begins with an input layer that processes grayscale images of size 32×32 pixels, allowing valid convolutions without border loss. The first convolutional layer (C1) applies six 5×5 filters, producing six feature maps of size 28×28, capturing essential patterns such as edges and textures. This is followed by the first subsampling (pooling) layer (S2), which performs 2×2 average pooling, reducing the feature maps to 14×14 and enhancing computational efficiency. The second convolutional layer (C3) then applies 16 filters of size 5×5, generating 16 feature maps of size 10×10, further extracting higher-level image features. The second pooling layer (S4) again applies 2×2 average pooling, reducing the feature maps to 5×5. Next, the convolutional layer C5, which is fully connected to the previous layer, applies 120 filters of size 5×5, mapping each feature map to a single neuron. This is followed by a fully connected layer (F6) with 84 neurons, which refines feature representations and introduces non-linearity. Finally, the output layer consists of 10 neurons using a softmax activation function, classifying images into one of the 10 digit classes (0–9). LeNet is computationally efficient and was foundational in demonstrating the power of CNNs in image recognition, paving the way for modern deep learning architectures.

Layer	Type	Feature Maps	Size
Input	Grayscale Image	1	32×32
C1	Convolutional	6	28×28
S2	Subsampling (Pooling)	6	14×14
C3	Convolutional	16	10×10
S4	Subsampling (Pooling)	16	5×5
C5	Fully Connected Convolutional	120	1×1
F6	Fully Connected	84	1×1
Output	Fully Connected (Softmax)	10	1×1

Figure 5 Summary of LeNet Architecture

As neural networks grow in depth and width, they often suffer from issues such as vanishing gradients, exploding gradients, and overfitting, which hinder training efficiency and model performance. To address these challenges, He et al. [31] introduced ResNet, a deep learning architecture that enables networks to reach greater depths without degradation. The key innovation in ResNet is the incorporation of residual blocks, which facilitate efficient training by allowing the network to learn residual mappings instead of direct feature transformations. A residual block, as illustrated in Figure 10, captures the difference between observed and estimated values, ensuring that deeper models do not perform worse than their shallower counterparts. By leveraging residual connections, ResNet effectively mitigates network degradation, enhances gradient flow, and improves overall model performance.

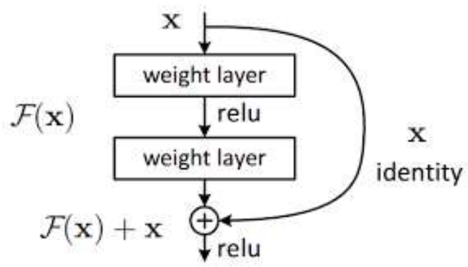

Figure 6 Structure of the residual block

3.3. TYPICAL CNN DENOISING MODEL

The Denoising Convolutional Neural Network (DnCNN) is a straightforward yet effective network model proposed by Zhang et al. [32] for image denoising. As a feed-forward network, DnCNN is designed with a simple architecture that maintains low memory overhead while delivering strong performance. The model is trained using additive noise, where the noise-free image is denoted as C, the noisy image as N, and the noise as V. The relationship between the noisy image and the original clean image can be expressed as:

N=C+VN = C + VN=C+V

By learning the residual noise instead of directly reconstructing the clean image, DnCNN efficiently removes noise while preserving fine details, making it a widely used approach in image denoising tasks. The goal of the denoising model is to extract the clean image **C** from the noisy image **N**. As shown in Figure 11, DnCNN adopts a deeper neural network than previous denoising methods, enabling it to capture more complex noise patterns. It uses the ReLU activation function, while batch normalization is incorporated to accelerate convergence, enhance stability, and reduce the risk of gradient vanishing. The model follows a residual learning approach, where the hidden layers isolate noise from the input image. By extracting this residual noise and subtracting it from the noisy image, DnCNN effectively restores a clean image while preserving essential details.

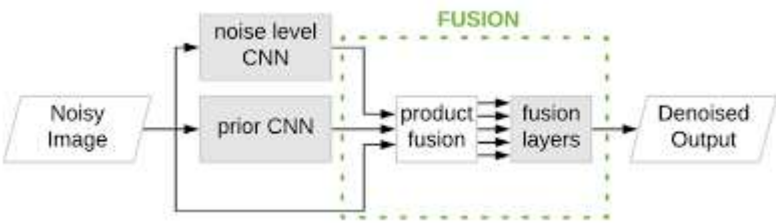

Figure 7 DnCNN model denoising process

FFDNet, proposed by Zhang et al. [33], is a well-regarded model in the field of image denoising. The success of CNNs in image processing is largely attributed to their strong modeling capabilities, efficient network training, and optimization techniques. However, many denoising models are trained on fixed noise levels, making them highly effective for specific noise intensities but less adaptable to varying noise conditions. FFDNet addresses this limitation by incorporating noise level mapping, allowing the model's parameters to dynamically adjust based on the noise intensity. When the noise level is high, denoised images often lose fine details due to excessive smoothing. To counter this, FFDNet improves image quality by using an orthogonal initialization method for convolutional filters. Unlike DnCNN, FFDNet employs depth-to-space and space-to-depth transformations, performing an additional up-sampling operation. If the original input image size is **H × W × C**, after down-sampling, it is divided into four smaller images of size **(H/2) × (W/2) × 4C**. Here, **W** and **H** represent the image's width and height, while **C** denotes the number of channels. This technique reduces network parameters, expands the receptive field, and enhances overall model performance.

3.4. Methods for Improving the Performance of CNN Image Denoising

To achieve better denoising results, several optimization techniques can be applied.

1. **Data Augmentation**
   Data augmentation enhances the quality and diversity of training data without altering its core information. Before feeding images into the model, various preprocessing and augmentation techniques are applied. Common transformations include rotation, translation, scaling, and cropping. Additionally, modifications such as color adjustments or adding artificial noise can be introduced. These techniques help the model learn a broader range of features from complex images, ultimately improving its performance and robustness.
2. **Loss Function Optimization**
   Selecting an appropriate loss function plays a crucial role in model performance. Implementing hybrid loss functions or exploring alternatives such as adversarial loss and perceptual loss can enhance the denoising capability of the model. By optimizing the loss function, the model can achieve better noise reduction and overall performance improvements.
3. **Integration of New Techniques**
   Incorporating advanced techniques into the CNN model can further enhance its effectiveness. Methods such as self-attention mechanisms and residual modules have already demonstrated significant success in image denoising. Exploring and integrating additional innovative techniques will contribute to the ongoing advancement of image processing and denoising models.

   Enhancing the performance of a network model requires developing deeper, wider, and more efficient architectures. Improving denoising capabilities can be achieved by incorporating additional network branches. Since various image processing tasks are inherently interconnected, architectures designed for other tasks can be adapted and integrated into image denoising models. By leveraging and combining these advancements, the field of image denoising can continue to evolve and improve.

4. Conclusion

This paper presents a comprehensive overview of image denoising, covering fundamental concepts and the evolution of denoising techniques, from traditional algorithms to neural network-based approaches [34]. However, this study primarily focuses on theoretical aspects and does not include experimental data, which will be explored in future research. Over the past few decades, significant advancements have been made in image denoising, leading to continuous improvements in noise reduction techniques. Despite these achievements, the pursuit of better denoising algorithms remains ongoing. Several challenges still need to be addressed. For instance, in complex scenarios, existing denoising methods struggle to fully utilize their capabilities and often fail to preserve fine details. Additionally, no single algorithm can effectively handle mixed types of noise, as most approaches are optimized for specific noise patterns. Moreover, deep learning-based denoising models require substantial computational resources, making large-scale data processing both time-consuming and costly. Addressing these limitations will be crucial for the future development of image denoising and broader advancements in image processing.

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