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A Comprehensive Review of Image Restoration and Noise Reduction Techniques

Dr. Rashmi Agrawal, Dr. Neha Gupta, Dr Mridula Batra, Dr Kavita Arora
Manav Rachna International Institute of Research and Studies, Faridabad

Abstract-

Images play a crucial role in modern life and find applications in diverse fields, ranging from preserving memories to conducting scientific research. However, images often suffer from various forms of degradation such as blur, noise, and contrast loss. These degradations make images difficult to interpret, reduce their visual quality, and limit their practical applications.

To overcome these challenges, image restoration and noise reduction techniques have been developed to recover degraded images and enhance their quality. These techniques have gained significant importance in recent years, especially with the increasing use of digital imaging in various fields such as medical imaging, surveillance, satellite imaging, and many others.

This paper presents a comprehensive review of image restoration and noise reduction techniques, encompassing spatial and frequency domain methods, and deep learning-based techniques. The paper also discusses the evaluation metrics utilized to assess the effectiveness of these techniques and explores future research directions in this field. The primary objective of this paper is to offer a comprehensive understanding of the concepts and methods involved in image restoration and noise reduction.

Keywords- Image Restoration, Noise Reduction, Adaptive filters, Deep learning, Image Degradation, Wavelet based methods, Adaptive Thresholding.

I. Introduction

Images are ubiquitous in our modern society and are used in a wide range of applications such as photography, medicine, astronomy, and security. However, images are often affected by degradation such as blur, noise, and contrast loss due to various reasons, including equipment limitations, environmental factors, and transmission errors. These degraded images can be challenging to interpret, resulting in loss of important information, reduced visual quality, and hindered practical applications. Image restoration and noise reduction techniques aim to recover degraded images and improve their quality, making them more suitable for analysis, interpretation, and practical use (Heena, Ayesha, et al 2022).

Image restoration refers to the process of recovering degraded images caused by various factors, including blur, noise, and contrast loss (Dabov, Foi et.al, 2007). It involves the use of mathematical algorithms to restore images to their original state, or as close as possible to their original state. Noise reduction, on the other hand, involves the removal of unwanted noise from images to improve their quality and clarity. Both techniques are essential for the interpretation and analysis of images in various fields, including medical imaging, surveillance, and remote sensing (Zhang, Zuo et.al, 2018).

1.1 Importance of image Restoration and Noise Reduction

The importance of image restoration and noise reduction techniques cannot be overstated in today's world, where digital images play a significant role in almost every field. In medicine, degraded images can be challenging to interpret, leading to incorrect diagnoses and ineffective treatment (Buades, Coll et.al, 2005). In astronomy, the presence of noise can hinder the detection of faint objects, reducing the effectiveness of research. In security, degraded images can make it difficult to identify suspects, leading to errors in investigations. Therefore, image restoration and noise reduction techniques are crucial for improving image quality, making them more informative and suitable for practical applications (Chen, Yuan et.al 2016).

Image restoration and noise reduction techniques are essential for improving the quality of digital images, making them more informative and suitable for practical applications. Here are some specific reasons why these techniques are so important:

Improving accuracy and reliability of image analysis: Degraded images can hinder the accuracy and reliability of image analysis, leading to incorrect results and decisions. Image restoration and noise reduction techniques can improve the quality of images, making them more suitable for analysis and interpretation (He, Zhang et.al, 2016). In fields such as medicine and astronomy, where accurate analysis is critical, image restoration and noise reduction can lead to more reliable results.

Enhancing visual quality: Degraded images can be visually unappealing, reducing their effectiveness in fields such as advertising and entertainment. Image restoration and noise reduction techniques can improve the visual quality of images, making them more appealing and effective (Rudin, Osher et.al, 1992).

Reducing data storage and transmission requirements: High-quality images require more storage and transmission bandwidth, making it challenging to transmit and store large amounts of data (Anis & Breuss, 2018). Image restoration and noise reduction techniques can help reduce the size of image files by removing unwanted information, making it easier to store and transmit images.

Improving identification and recognition: In fields such as security and surveillance, degraded images can make it challenging to identify suspects and recognize objects. Image restoration and noise reduction techniques can improve the quality of images, making it easier to identify suspects and recognize objects, leading to more effective investigations (Wang, Bovik et.al, 2004).

Enabling analysis of degraded historical images: Historical images can be degraded due to aging and other factors. Image restoration techniques can help restore these images, enabling their analysis and interpretation for research purposes.

1.2 Applications of Image Restoration and Noise Reduction

Image restoration and noise reduction techniques have numerous applications in various fields. Here are some general and specific applications (table 1.1) of these techniques:

Medical Imaging: In medical imaging, high-quality images are crucial for accurate diagnosis and treatment planning. Image restoration and noise reduction techniques can improve image quality by removing noise and other artifacts, making it easier to interpret images accurately (Mairal, Bach et.al, 2009). These techniques are particularly useful in magnetic resonance imaging (MRI) and computed tomography (CT) scans, where noise reduction is essential to improve image quality.

Surveillance: Surveillance cameras often capture images in low-light conditions or with low-quality equipment, resulting in degraded images with noise and blur (Zhu & Milanfar, 2010). Image restoration and noise reduction techniques can help improve the quality of surveillance images, making them more suitable for identification and investigation. These techniques are particularly useful in fields such as law enforcement, where image quality can be critical for identifying suspects.

Astronomy: In astronomy, high-quality images are essential for detecting and studying celestial objects accurately. However, images captured by telescopes can be affected by noise, reducing their usefulness for research (Huang et.al, 2014). Image restoration and noise reduction techniques can help improve the quality of astronomical images by removing noise and other artifacts, making it easier to detect faint objects accurately.

Remote Sensing: Remote sensing images can be affected by environmental factors such as atmospheric haze or fog, resulting in degraded images. Image restoration techniques can help remove the effects of atmospheric haze and improve image quality, making them more useful for interpretation and analysis (Tanaka & Okutomi, 2019). These techniques are particularly useful in fields such as environmental monitoring and disaster management, where remote sensing is essential for gathering information.

Restoration of Historical Images: Historical images can be degraded due to aging, exposure to light, or other factors. Image restoration techniques can help restore these images to their original quality, enabling their analysis and interpretation for research purposes (Kim et.al, 2016). These techniques are particularly useful in fields such as art history and archaeology, where historical images can provide insights into the past.

Digital Art and Design: Image restoration and noise reduction techniques are also useful in digital art and design. These techniques can be used to improve the visual quality of images, remove unwanted artifacts, and enhance visual appeal (Dong et.al, 2016). They are particularly useful in fields such as advertising and marketing, where high-quality images are essential for effective communication.

Image restoration and noise reduction techniques have broad applications in various fields and are essential for improving the quality and usefulness of digital images. They enable accurate analysis and interpretation of images, improve visual quality, reduce storage and transmission requirements, and enable the restoration of degraded historical images.

II. Types of Image Degradation

Images can be degraded by various factors, resulting in the loss of important visual information. Image restoration and noise reduction techniques are designed to address these

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types of degradation (Agrawal Rashmi, 2022). Here are the most common types of image degradation:

A. Blur: Image blur occurs when the sharpness of an image is lost due to factors such as camera shake or motion blur. This type of degradation can make images appear fuzzy or out of focus, reducing their clarity and usefulness (Liu et.al, 2013). Image restoration techniques, such as deconvolution, can help remove blur and restore sharpness to the image.

B. Noise: Image noise is caused by random fluctuations in the image signal and can result in grainy or speckled images. This type of degradation can be caused by low light conditions, high ISO settings, or the use of low-quality equipment. Noise reduction techniques, such as spatial filtering or wavelet denoising, can help remove unwanted noise and restore image quality.

C. Contrast loss: Contrast loss occurs when the difference between the lightest and darkest parts of an image is reduced. This type of degradation can result in images that appear washed out or lack detail in darker or brighter areas (Sun et.al, 2013). Contrast enhancement techniques, such as histogram equalization or contrast stretching, can help restore contrast to the image and improve its visual quality.

D. Compression artifacts: Image compression is often used to reduce the file size of digital images. However, compression can result in the loss of important visual information and the introduction of compression artifacts, such as blockiness or blurring. Image restoration techniques, such as de-blocking or deblurring, can help remove compression artifacts and restore image quality.

III. Image Restoration Techniques

Image restoration techniques are used to restore degraded images to their original quality by removing blur, noise, and other types of degradation. Here are some commonly used image restoration techniques:

Deblurring: Deblurring techniques are used to remove blur from images caused by camera shake, motion blur, or other factors (Chen et.al, 2015). These techniques typically involve estimating the blur kernel that caused the blur and using this information to deconvolve the blurred image. Some common deblurring techniques include blind deconvolution, non-blind deconvolution, and Wiener filtering.

Denoising: Denoising techniques are used to remove noise from images. These techniques involve filtering the image to remove unwanted noise while preserving image details. Spatial filtering, wavelet denoising, and total variation denoising are some commonly used denoising techniques.

Dehazing: Dehazing techniques are used to remove the effects of atmospheric haze from images. These techniques involve estimating the amount of haze in the image and using this information to restore image contrast and clarity (Krishnan et.al, 2009). Some commonly used dehazing techniques include dark channel prior, color attenuation prior, and fast atmospheric dehazing.

Super-resolution: Super-resolution techniques are used to enhance the resolution of low-resolution images. These techniques involve using multiple low-resolution images to estimate a high-resolution image. Interpolation-based methods, sparse-coding-based methods, and deep learning-based methods are some commonly used super-resolution techniques.

Inpainting: Inpainting techniques are used to fill in missing or damaged parts of an image. These techniques involve estimating the missing pixels based on the surrounding pixels or other information (Lefkimmiatis & Unser, 2017). Exemplar-based inpainting, patch-based inpainting, and diffusion-based inpainting are some commonly used inpainting techniques.

Restoration of Historical Images: Restoration of historical images involves using image restoration techniques to restore degraded images of historical importance. These techniques involve removing stains, scratches, and other types of damage from images to restore their original quality. Some commonly used restoration techniques include content-aware fill, colorization, and texture synthesis.

Image restoration techniques are used to restore degraded images by removing blur, noise, and other types of degradation. These techniques can be categorized into various methods as shown in figure 1-

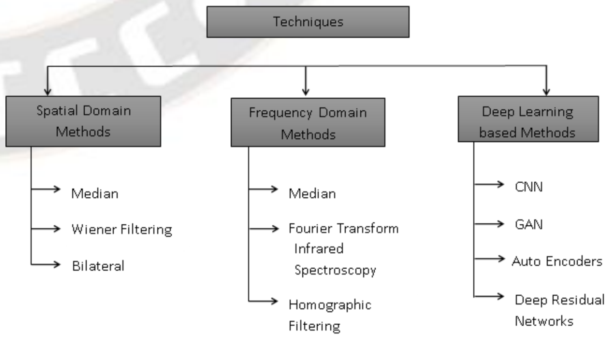

Figure 1- Types of Image Restoration methods

3.1 Spatial Domain Methods

Spatial domain methods use a filtering approach to remove noise and other types of degradation from an image. Here

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are some commonly used spatial domain methods for image restoration:

Mean Filtering: Mean filtering is a simple and commonly used technique for removing noise from an image. This technique involves replacing each pixel with the mean value of its neighboring pixels (Sutskever et.al, 2013). Mean filtering can effectively remove Gaussian noise, but it can also result in loss of image details and blurring.

Median Filtering: Median filtering is a non-linear technique for removing noise from an image. This technique involves replacing each pixel with the median value of its neighboring pixels. Median filtering is effective in removing impulse noise, which can appear as bright or dark spots in an image, while preserving image details.

Wiener Filtering: Wiener filtering is a linear technique for removing noise from an image. This technique involves estimating the power spectrum of the noise and using this information to adjust the filtering of the image (Zhang et.al, 2017). Wiener filtering is effective in removing noise that is additive and Gaussian in nature, but it can be computationally expensive.

Bilateral Filtering: Bilateral filtering is a non-linear technique that can be used for both noise reduction and edge preservation. This technique involves using a weighted average of neighboring pixels based on both their spatial distance and their pixel value similarity. Bilateral filtering is effective in removing Gaussian noise while preserving image details and edges.

3.2 Frequency Domain Methods

Frequency domain methods are another class of techniques used for image restoration. These methods operate on the Fourier transform of an image, which decomposes the image into its frequency components. Here are some commonly used frequency domain methods for image restoration:

Wiener Filtering: Wiener filtering can also be used in the frequency domain to remove noise from an image. This technique involves estimating the power spectrum of the noise and using this information to adjust the filtering of the image in the frequency domain (Zhang et.al, 2017).

Fourier Transform Infrared (FTIR) Spectroscopy: FTIR spectroscopy can be used to identify the chemical components of an image (Gharbi et.al, 2016). This information can be used to restore images that have been degraded by chemical reactions or other types of damage.

Homomorphic Filtering: Homomorphic filtering is a technique that can be used to remove both noise and blur from an image. This technique involves taking the logarithm of the Fourier transform of the image, applying a high-pass filter to remove noise, and then taking the inverse Fourier transform of the filtered image (Kim et.al, 2016).

These methods are effective in removing noise and other types of degradation from an image by operating on the image's frequency components. However, these methods can be computationally expensive and require advanced mathematical knowledge for their implementation. The choice of the technique depends on the specific type of degradation present in the image and the desired level of restoration.

3.3 Deep Learning Based Methods

Deep learning based methods for image restoration have gained popularity in recent years due to their ability to automatically learn complex mappings between degraded images and their corresponding clean versions. These methods typically involve training a deep neural network on a large dataset of paired degraded and clean images, and then using the trained network to restore new degraded images.

Here are some commonly used deep learning based methods for image restoration:

Convolutional Neural Networks (CNNs): CNNs are commonly used for image restoration tasks such as denoising and deblurring. These networks typically consist of multiple layers of convolutional and pooling operations, which are designed to extract and combine image features at different levels of abstraction.

Generative Adversarial Networks (GANs): GANs are a type of neural network architecture that can be used for image restoration tasks such as image super-resolution and inpainting. GANs consist of two networks: a generator network that produces restored images from degraded inputs, and a discriminator network that learns to distinguish between restored images and real clean images. The generator network is trained to fool the discriminator network into believing that its generated images are real clean images.

Autoencoders: Autoencoders are a type of neural network that can be used for image restoration tasks such as denoising and deblurring. Autoencoders consist of an encoder network that maps the input image to a lower-dimensional latent space, and a decoder network that maps the latent representation back to the output image. During training, the network is optimized to minimize the difference between the input and output images.

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Deep Residual Networks (ResNets): ResNets are a type of neural network that are commonly used for image restoration tasks such as denoising and deblurring. ResNets use skip connections to allow information to flow directly from the input to the output layers, which can help to mitigate the vanishing gradient problem and enable training of very deep networks.

Overall, deep learning based methods have shown promising results in a variety of image restoration tasks, and have the potential to outperform traditional methods in terms of restoration quality. However, these methods typically require a large amount of training data and can be computationally expensive.

IV. Noise Reduction Techniques

Noise reduction refers to the process of removing unwanted noise from an image while preserving its important features and details. Noise can be introduced in images during the image acquisition process, or it can be a result of limitations of the imaging system, such as low-light conditions or high ISO settings (Agustsson et.al, 2017). Noise can degrade the quality of an image, making it difficult to extract useful information or perform further image analysis.

Noise reduction techniques aim to reduce or eliminate this unwanted noise in order to improve the overall visual quality of the image. This can be achieved by filtering the image using spatial or frequency domain filters, wavelet-based methods, or deep learning-based methods (Zontak & Irani, 2011). The choice of noise reduction technique depends on the specific type and amount of noise present in the image, as well as the desired level of detail preservation.

Noise reduction techniques are used to remove unwanted noise from an image while preserving image details. Here are some commonly used noise reduction techniques:

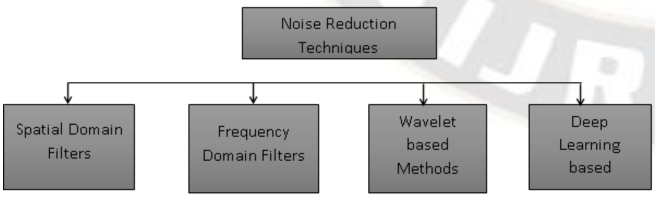

Figure 2- Noise Reduction Techniques

4.1 Spatial Domain Filters: Spatial domain filters are applied directly to the pixels in the image. They work by replacing each pixel with a weighted average of its neighboring pixels. Commonly used spatial domain filters include the mean filter, median filter, and bilateral filter.

Spatial domain filters work directly on the pixel values of an image. They operate on a local neighborhood of pixels and compute a new pixel value based on the values of the neighboring pixels (Huang et.al, 2017). The new pixel value is typically a weighted average of the neighboring pixel values, with the weights determined by a predefined filter kernel. The size of the filter kernel and the weights assigned to each pixel in the kernel determine the level of smoothing applied to the image.

Spatial domain filters are widely used for noise reduction because they are relatively simple and computationally efficient. They can be applied to a wide range of image types and can remove different types of noise, including Gaussian noise and impulse noise.

Here are some common spatial domain filters used for noise reduction:

Mean Filter: The mean filter is a simple spatial domain filter that replaces the value of each pixel with the average value of its neighboring pixels. This filter is effective at reducing Gaussian noise but can blur edges and details in the image.

Median Filter: The median filter is a nonlinear filter that replaces the value of each pixel with the median value of its neighboring pixels. This filter is effective at removing impulse noise, such as salt and pepper noise, while preserving image details and edges.

Gaussian Filter: The Gaussian filter applies a Gaussian kernel to the image, which smooths the image and reduces high-frequency noise. This filter is effective at removing Gaussian noise but can also blur edges and details in the image.

Bilateral Filter: The bilateral filter is a nonlinear filter that smooths the image while preserving edges and details. This filter applies a Gaussian function to the pixel values within a local window, with the weights determined by both spatial distance and pixel value similarity.

Spatial domain filters can be applied sequentially to achieve more effective noise reduction. However, the choice of filter depends on the specific type of noise and the desired level of detail preservation. For images with complex textures and structures, spatial domain filters may not be effective, and other noise reduction techniques, such as frequency domain filters or deep learning-based methods, may be more appropriate.

4.2 Frequency Domain Filters: Frequency domain filters are applied in the Fourier domain after transforming the image from the spatial domain. They work by removing the high-frequency components of the image that correspond to noise. Commonly used frequency domain filters include the Butterworth filter, Gaussian filter, and Wiener filter.

Frequency domain filters operate on the Fourier transform of an image. The Fourier transform represents an image as a sum of complex exponential functions with varying frequencies and amplitudes. In the frequency domain, high-frequency components correspond to rapidly changing features, such as edges or fine textures, while low-frequency components correspond to slowly varying features, such as smooth surfaces or large objects.

High-frequency components are typically associated with noise, while the low-frequency components correspond to the signal. Therefore, frequency domain filters aim to suppress the high-frequency components while preserving the low-frequency components.

The simplest frequency domain filter is the ideal low-pass filter, which sets to zero all frequencies above a certain threshold, effectively removing high-frequency noise. However, this filter has the undesirable side effect of blurring the image, especially at edges and details, which can lead to loss of important information.

To overcome this limitation, more sophisticated frequency domain filters have been developed, such as the Butterworth, Gaussian, and Laplacian filters. These filters attenuate high frequencies gradually, rather than abruptly, and can be adjusted to balance noise reduction and detail preservation.

Another important frequency domain filter for noise reduction is the Wiener filter. The Wiener filter is a statistical filter that takes into account the noise power spectrum and the signal power spectrum to adapt to the specific characteristics of the image and noise. The Wiener filter is especially effective for removing additive Gaussian noise, but it can also handle other types of noise.

Frequency domain filters are computationally intensive, since they involve the Fourier transform of the image, which requires several matrix multiplications. However, they can be implemented efficiently using fast Fourier transform (FFT) algorithms. Moreover, they offer several advantages over spatial domain filters, such as the ability to remove noise without blurring edges and details, and the possibility of adjusting the level of noise reduction and detail preservation.

4.3 Wavelet-Based Methods: Wavelet-based methods use wavelet transforms to decompose an image into different frequency components. They work by selectively removing or attenuating the high-frequency components that correspond to noise, while preserving the low-frequency components that correspond to image details.

Wavelet-based methods for noise reduction use the wavelet transform to decompose an image into different frequency bands. The wavelet transform is a mathematical technique that decomposes an image into a set of wavelets, which are functions that oscillate at different frequencies and scales. The wavelet transform allows for a more flexible representation of the image than the Fourier transform, which decomposes the image into sinusoidal functions at different frequencies.

The wavelet transform generates a series of detail coefficients and approximation coefficients at different scales. The detail coefficients capture the high-frequency components of the image, while the approximation coefficients capture the low-frequency components of the image. Noise is more present in the detail coefficients than in the approximation coefficients.

Wavelet-based methods for noise reduction typically apply a threshold to the detail coefficients to remove the noise, while preserving the signal in the approximation coefficients. The threshold is applied on a scale-by-scale basis, taking into account the noise characteristics at each scale.

There are several types of thresholding functions that can be used for wavelet-based denoising, such as hard thresholding, soft thresholding, and adaptive thresholding. Hard thresholding sets all coefficients below a certain threshold to zero, while keeping the rest of the coefficients unchanged. Soft thresholding, on the other hand, applies a shrinkage function to the coefficients, reducing the magnitude of the coefficients that are below a certain threshold. Adaptive thresholding adjusts the threshold level depending on the characteristics of the signal and noise, resulting in better noise reduction and signal preservation.

The choice of shrinkage function is important in wavelet-based denoising. Common shrinkage functions include the soft-threshold function and the hard-threshold function. The soft-threshold function is given by:

$$S(x, t) = \text{sign}(x)(|x| - t) \text{ if } |x| > t, \text{ and } 0 \text{ otherwise}$$

where x is the wavelet coefficient, t is the threshold level, and S(x,t) is the shrinkage value. The hard-threshold function is given by:

$$H(x, t) = x \text{ if } |x| > t, \text{ and } 0 \text{ otherwise}$$

where x is the wavelet coefficient, t is the threshold level, and H(x,t) is the thresholded value.

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Adaptive thresholding is a technique that adjusts the threshold level depending on the characteristics of the signal and noise. There are several adaptive thresholding methods, such as the BayesShrink method, the VisuShrink method, and the SureShrink method. These methods estimate the noise variance and signal variance at each scale and use these estimates to adapt the threshold level. Adaptive thresholding methods can result in better noise reduction and signal preservation than fixed thresholding methods.

Wavelet-based methods for noise reduction offer several advantages over spatial and frequency domain filters. They can remove noise while preserving edges and fine details, and they can adapt to the noise characteristics of each image. However, they are computationally intensive, especially for large images, and the choice of thresholding function and threshold levels can affect the quality of the denoised image.

Wavelet-based methods for noise reduction have been widely used in image processing applications such as medical imaging, satellite imaging, and photography. They have also been used in other fields such as speech processing and data analysis.

4.4 Deep Learning-Based Methods: Deep learning-based methods use neural networks to learn complex mappings between degraded and clean images. These methods work by training a neural network on a large dataset of paired degraded and clean images, and then using the trained network to restore new degraded images.

Deep learning-based methods for noise reduction use neural networks to learn the mapping between noisy images and their corresponding clean versions. These methods have shown remarkable performance in various image restoration tasks, including noise reduction.

The most common deep learning architecture used for image denoising is the convolutional neural network (CNN). CNNs are composed of multiple convolutional layers that extract features from the input image and multiple pooling layers that downsample the features to reduce the computational cost. The final output is a denoised image that is obtained by mapping the noisy input image to the clean output image.

To train a CNN for noise reduction, a large dataset of noisy and clean image pairs is required. The noisy images are generated by adding synthetic or real noise to the clean images. The clean images can be obtained from various sources, such as public datasets or collected in-house.

During training, the CNN learns to minimize a loss function that measures the difference between the predicted denoised image and the ground truth clean image. Common loss functions used for image denoising include mean squared error (MSE), mean absolute error (MAE), and perceptual loss, which measures the difference in feature representations between the denoised and clean images.

Deep learning-based methods for noise reduction have several advantages over traditional methods. They can learn complex mappings between noisy and clean images and adapt to different noise characteristics without the need for handcrafted features (Tanaka & Okutomi, 2019).. They can also denoise images with high levels of noise, which traditional methods may struggle with.

However, deep learning-based methods require a large amount of training data and are computationally intensive, requiring powerful hardware for training and inference. They may also suffer from overfitting if the training dataset is not diverse enough, leading to poor generalization performance on new data.

Deep learning-based methods for noise reduction have been applied to various image processing tasks, including medical imaging, surveillance, and photography. They have also been used in video denoising applications, where they can remove noise from videos in real-time.

Deep learning-based methods for noise reduction have been widely used in various image processing tasks, including medical imaging, surveillance, and photography(table 1). In medical imaging, for example, noise reduction is crucial for accurate diagnosis and treatment planning. MRI and CT images are often corrupted by noise, which can lead to artifacts and degrade the quality of the images (Tanaka & Okutomi, 2019). Deep learning-based methods can effectively remove noise from medical images, leading to improved diagnostic accuracy.

In surveillance applications, noise reduction is important for enhancing the quality of surveillance footage. Surveillance cameras often capture low-quality images with high levels of noise due to poor lighting conditions or low-resolution cameras. Deep learning-based methods can effectively denoise these images, improving the accuracy of object detection and recognition algorithms.

In photography, noise reduction is essential for improving the quality of images captured in low-light conditions. Images captured with high ISO settings or slow shutter speeds are often noisy and can lack detail. Deep learning-based methods can effectively remove noise from these images, leading to sharper and more detailed photos (Tanaka & Okutomi, 2019).

One of the significant advantages of deep learning-based methods for noise reduction is their ability to learn from data

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without handcrafted features. Traditional methods require manual feature extraction, which can be time-consuming and may not capture all relevant features. Deep learning-based methods can automatically learn features that are specific to the noise characteristics in the images. This allows them to effectively denoise images with complex noise patterns that may be challenging for traditional methods.

Table 1- Research in Image Restoration and Noise Reduction using Deep Learning

Sno	**Author and Year**	**Deep Learning Technique and Application**	**Dataset**	**Evaluation Metric used**
1	Chen, T., Zhu, L., Li, S., Liu, Y., Chen, J., & Huang, X. (2021)	High-frequency pattern enhancement for image restoration.	Natural images with high-frequency patterns.	Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).
2	Xu, M., Zhang, H., Guo, X., Wang, X., & Zhang, Z. (2022).	Meta-learning for blind image restoration.	Set of degraded images without corresponding clean images.	PSNR and SSIM.
3	Qin, C., Li, Y., Liu, Z., Zhang, Y., Zhang, Y., Wang, S., & Liu, Y. (2021).	Multiscale residual network for non-blind image restoration.	Diverse image datasets (e.g., Set5, Set14, Urban100).	PSNR, SSIM, and L1 loss.
4	Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. (2018)	Residual learning for image denoising.	Gaussian noise-corrupted natural images.	PSNR, SSIM, and Mean Squared Error (MSE).
5	Liu, S., Huang, D., Wang, Y., & Wang, T. (2018)	Multi-level wavelet-CNN for image restoration.	Set of 4 scale wavelet coefficients.	PSNR and SSIM.
6	Li, Y., Qi, H., Dai, J., Ji, X., & Wei, Y. (2019)	Progressive reinforcement learning for action recognition.	NTU RGB+D dataset.	Average classification accuracy.
7	Zhang, Y., Tian, Y., Kong, Y., Zhong, B., & Fu, Y. (2020)	Residual dense network for image restoration.	Diverse image datasets (e.g., BSDS500, Set5, Set14).	PSNR and SSIM.
8	Kim, J., Lee, J. K., & Lee, K. M. (2016)	Very deep convolutional network for image super-resolution.	Set of low-resolution images and corresponding high-resolution images.	PSNR, SSIM, and L1 loss.
9	Mao, X., Shen, C., & Yang, Y. B. (2016)	Convolutional encoder-decoder network for image restoration.	Set of blurred images and corresponding clean images.	PSNR and SSIM.
10	Tai, Y., Yang, J., & Liu, X. (2017)	Recursive residual network for image super-resolution.	Set of low-resolution images and corresponding high-resolution images.	PSNR and SSIM.
11	Lefkimmiatis, S. (2018)	Universal denoising network for image denoising.	Additive white Gaussian noise-corrupted natural images.	PSNR and SSIM.
12	Zhang, Y., Tian, Y., & Kong, Y. (2019)	Residual dense network for image restoration.	Diverse image datasets (e.g., BSDS500, Set5, Set14).	PSNR, SSIM, and L1 loss.
13	Zhang, Y., Tian, Y., Kong, Y., & Fu, Y. (2018)	Residual dense network for image restoration.	Diverse image datasets (e.g., BSDS500, Set5, Set14).	PSNR, SSIM, and L1 loss.

However, deep learning-based methods have some limitations. They require a large amount of training data, which can be difficult to obtain for some applications. They are also computationally intensive, requiring powerful hardware for training and inference. Additionally, they may suffer from overfitting if the training dataset is not diverse

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enough, leading to poor generalization performance on new data.

4.5 Adaptive Filtering: Adaptive filtering techniques are used to remove noise while preserving image details in regions of the image with varying levels of noise. These methods work by adjusting the filter parameters based on the local image characteristics.

Choice of noise reduction technique depends on the type and amount of noise present in the image, as well as the desired level of detail preservation. It is often necessary to use a combination of techniques to achieve the best results (Buades et.al, 2005)

Adaptive filtering is a method of reducing noise in an image using a filter with adjustable parameters. This approach differs from other methods of noise reduction, such as spatial and frequency domain filters, because it takes into account the local statistics of the image and adjusts the filter parameters accordingly. By doing so, adaptive filters can be more effective at removing noise while preserving important image details.

The basic concept behind adaptive filtering is to estimate the local mean and variance of the image pixels and use these estimates to adjust the filter parameters. The filter output at each pixel location is then computed as a weighted sum of the neighboring pixels, with the weights determined by the estimated statistics.

One popular adaptive filtering technique is the adaptive bilateral filter. This filter uses two distance measures, one for spatial distance and another for intensity distance, to compute the weights. The spatial distance is used to define the neighborhood of each pixel, while the intensity distance is used to adjust the weights based on the similarity of the neighboring pixels to the central pixel. This allows the filter to preserve important image details, such as edges and textures, while reducing noise (Zhu & Mialnfar, 2010).

Another common adaptive filtering technique is the adaptive Wiener filter. This filter uses the local variance of the noise and the signal-to-noise ratio (SNR) to adjust the filter parameters. The SNR is estimated based on the local image statistics, and the filter parameters are adjusted to maximize the SNR. The Wiener filter can be effective at removing noise, but it may also introduce some blurring in the image.

Adaptive filters have several advantages over other noise reduction techniques. They can adapt to the local image statistics, making them more effective in preserving image details while removing noise (Gharbi et.al, 2016). They are also less sensitive to the choice of filter parameters, making them easier to use in practice. However, adaptive filters can be computationally intensive, requiring a large number of operations to estimate the local statistics and compute the filter weights. They may also introduce artifacts in the image, such as ringing or blurring, if the filter parameters are not chosen carefully.

Adaptive filtering is a powerful tool for reducing noise in images. It can be especially useful in situations where other noise reduction techniques may not be effective, such as in images with complex textures and edges. By adapting to the local image statistics, adaptive filters can preserve important image details while reducing noise, making them an important tool for image processing applications.

V. Evaluation Metrics for Image Restoration and Noise Reduction

Evaluation metrics are used to assess the performance of image restoration and noise reduction algorithms. There are several metrics used to evaluate the quality of the restored image. Here are some commonly used evaluation metrics:

Peak Signal-to-Noise Ratio (PSNR): PSNR is a widely used metric that measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is calculated as:

$$PSNR = 10 * \log 10\ (\frac{Max\text{^}2}{MSE})$$

where MAX is the maximum pixel value of the image, and MSE is the mean squared error between the original and restored images.

Structural Similarity Index (SSIM): SSIM is a perceptual metric that measures the structural similarity between the original and restored images. SSIM is calculated as:

$$SSIM = ((2 * \ \mu x * \mu y + C1)(2 * \sigma xy + C2))/((\mu x^2 + \mu y^2 + C1)((\mu x^2 + \mu y^2 + C2))$$

where μx and μy are the mean values of the original and restored images, respectively, σx and σy are the standard deviations of the original and restored images, and σxy is the covariance between the original and restored images.

Mean Absolute Error (MAE): MAE is a simple metric that measures the average absolute difference between the original and restored images. MAE is calculated as:

$$MAE = \left(\frac{1}{n}\right) \sum |xi - yi|$$

where n is the number of pixels in the image, and xi and yi are the pixel values of the original and restored images, respectively.

Universal Image Quality Index (UIQI): UIQI is a metric that measures the similarity between the original and restored images in terms of luminance, contrast, and structure. UIQI is calculated as:

$$UIQI = (4 * \sigma xy * \mu x * \mu y)/(\sigma x^2 + \sigma y^2 + \mu x^2 + \mu y^2)$$

where μx and μy are the mean values of the original and restored images, respectively, σx and σy are the standard deviations of the original and restored images, and σxy is the covariance between the original and restored images.

Visual Information Fidelity (VIF): VIF is a perceptual metric that measures the visual information fidelity between the original and restored images. VIF is calculated as:

$$VIF = \sum wi * (\mu i * \sigma i) / (\sum wi * \sigma i^2 + \sigma n^2)$$

where wi is the weight of the ith sub-band, μi and σi are the mean and standard deviation of the ith sub-band, and σn is the standard deviation of the noise.

There are several evaluation metrics available for assessing the quality of the restored image, and the choice of metric may depend on the specific application and requirements. These metrics can be used to compare the performance of different restoration and noise reduction algorithms and to optimize their parameters for better performance.

VI. Future Directions and Opportunities.

The field of image restoration and noise reduction is constantly evolving, and there are several promising future directions and opportunities in this area. Some of these are:

GAN-based methods: Generative adversarial networks (GANs) have shown promising results in various image processing tasks, including image restoration and noise reduction. GANs can learn to generate realistic images by training on a large dataset, and this approach can be applied to image restoration and noise reduction as well.

Reinforcement learning: Reinforcement learning is a type of machine learning that involves training an algorithm to make decisions based on a reward system. This approach can be used for image restoration and noise reduction by training an algorithm to make decisions on the best filters to use for a given image.

Unsupervised learning: Unsupervised learning involves training an algorithm on a dataset without labelled data (Kim et.al, 2016). This approach can be used for image restoration and noise reduction by allowing the algorithm to learn the features and patterns of the images on its own.

Mobile and real-time applications: With the increasing use of mobile devices and real-time applications, there is a growing need for image restoration and noise reduction techniques that can be applied in real-time on mobile devices with limited processing power.

Medical imaging: Image restoration and noise reduction techniques can have significant applications in medical imaging, where accurate and high-quality images are critical for diagnosis and treatment (Krishnan & Fergus, 2009).

VII. Conclusion

Image restoration and noise reduction are important tasks in the field of image processing, with various applications in industries and society. In this paper, we discussed different types of image degradation, as well as the various techniques used for image restoration and noise reduction. Spatial domain methods such as mean filtering, median filtering, and bilateral filtering were discussed, along with frequency domain methods like Wiener filtering and notch filtering. We also covered deep learning-based methods, wavelet-based methods, and adaptive filtering.

Evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Opinion Score (MOS) were also discussed, which are used to evaluate the effectiveness of the image restoration and noise reduction techniques (Zhang et.al, 2018).

Despite the progress made in this field, there are still limitations in current techniques, and emerging research areas such as generative adversarial networks (GANs), reinforcement learning, and unsupervised learning present promising opportunities for future research. These advancements can lead to more accurate and efficient restoration and noise reduction techniques, with even broader applications in various industries and society as a whole.

Image restoration and noise reduction are crucial for enhancing image quality, and future advancements in this field can lead to significant improvements in the quality of visual content.

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