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A REVIEW ON IMAGE DENOISING TECHNIQUES

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ABSTRACT

With the explosion in the number of digital images taken every day, the demand for more accurate and visually pleasing images is increasing. However, the images captured by modern cameras are inevitably degraded by noise, which leads to deteriorated visual image quality. Therefore, work is required to reduce noise without losing image features (edges, corners, and other sharp structures). So far, researchers have already proposed various methods for decreasing noise. Each method has its own advantages and disadvantages. In this paper, we summarize some important research in the field of imagedenoising. First, we give the formulation of the image denoising problem, and then we present several image denoising techniques. In addition, we discuss the characteristics of these techniques. Finally, we provide several promising directions for future research.

The removal of noise from original signals remains a formidable challenge in various fields, prompting researchers to explore diverse algorithms with distinct assumptions, advantages, and limitations. This paper offers a thorough review of significant advancements in the realm of image denoising. Following a concise introduction, prevalent approaches are systematically classified into distinct groups, providing readers with a comprehensive overview of various algorithms and theiranalyses. The paper delves into the intricacies of each method, shedding light on their efficacy and contextualizing their applications. Furthermore, insights into the current state of image denoising techniques are presented, offering a glimpse into potential future trends in the field. By synthesizing existing knowledge and identifying emerging directions, this review serves as a valuable resource for researchers, practitioners, and enthusiasts working in image processing and computer vision.

Addressing diverse noise densities in image denoising, this paper explores the efficacy of Wavelet-based Methods and Fourier Transform, recognizing theirdistinctive frequency domain localizations. While FourierTransform concentrates solely on frequency, WaveletTransform localizes noise in both frequency and spatial domains. Despite their merits, both methods lack data adaptiveness. Introducing Independent Component Analysis (ICA), a higher-order statistical tool known for its intrinsic data adaptiveness, this paper reviews significant work in image denoising.

We systematically classify popular approaches into distinct groups, emphasizing the comparative analysis ofWavelet-based Methods, Fourier Transform, and ICA. The paper scrutinizes their performances across various parameters, including noise densities and adaptability. Through this comprehensive evaluation, we aim to identify the most effective technique for image denoising.The findings contribute valuable insights to the field, guiding researchers and practitioners towards optimal denoising strategies. The conclusion consolidates the comparative results, offering a decisive recommendationfor the superior image denoising method based on the analysis of Wavelet-based Methods, Fourier Transform, and ICA.

1. INTRODUCTION

Image denoising remains a formidable challenge in the realm of image processing, as the removal of noise often introduces undesirable artifacts and blurs the underlying image. Researchers continually strive to develop methodologies that strike a balance between effectively suppressing noise and preserving crucial image features. This paper explores various image denoising techniques,aiming to provide insights into the selection of algorithmsthat offer reliable estimates of the original image data from its degraded versions.

In the pursuit of noise reduction, researchers have devised methodologies classified into spatial and transformation fields. Spatial field methods involve data operations directly on the original image, manipulating its grey values through techniques such as the neighbourhood average method, Wiener filter, and center value filter. Understanding the statistical properties of noise and the distribution of frequency spectra has been instrumental inthe development of these techniques.

The overarching goal of image denoising techniques is to retain vital image features while efficiently suppressing noise. This pursuit has evolved from traditional methods relying on filters and statistical approaches to more contemporary techniques that leverage advanced algorithms, machine learning, and deep learning models. These modern approaches have significantly enhanced the ability to address complex noise patterns while preserving fine

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details in images. Throughout this paper, we will delve into specific image denoising methodologies, providing a comprehensive exploration of their underlying mechanisms and illustrating practical applications. The subsequent discussions aim to empower researchers, engineers, and practitioners in the field of image processing with a nuanced understanding of evolving image denoising techniques. As the demand for high-quality images continues to rise across diverse industries, the implementation of effective image denoising techniques becomes increasingly vital. This overview serves as a valuable resource for navigating the diverse landscape of image denoising algorithms, from classical mathematicalprinciples to cutting-edge machine learning and deeplearning models.

In the contemporary landscape of digital imagery, the roleof images extends far beyond our daily lives, encompassing critical applications in satellite television, medical imaging (such as magnetic resonance imaging and computer tomography), geographical information systems, and astronomy. However, the inherent complexity of image acquisition processes, imperfect instruments, and the influence of various natural phenomena contribute to the contamination of image datasets with noise. Additionally, factors like transmission errors and compression further exacerbate this issue, necessitating the application of robust denoising techniques as an essential initial step in the analysis of image data. The challenge of image denoising persists due to the inherent risks associated with noise removal, including the introduction of artifacts and the potential for image blurring. This paper seeks to address this challenge by presenting a detailed exploration of diverse methodologies for noise reduction, providing insights intothe selection of algorithms that yield the most reliable estimates of original image data from its degraded versions.

Noise in images can originate from various sources, including capturing instruments, data transmission media, image quantization, and discrete sources of radiation. Different noise models are employed based on the natureof the noise, with additive random noise, commonly modeled as Gaussian, being prevalent in natural images. This paper focuses specifically on noise removal techniques tailored for natural images, considering the distinctive challenges posed by different types of noise, such as speckle noise in ultrasound images and Rician noise in MRI images.

The evolution of image denoising research reflects a shiftfrom traditional spatial and Fourier domain methods to the prominence of the Wavelet Transform domain in the last two decades. Wavelets, renowned for their sparsity and multiresolution structure, have demonstrated superior performance in image denoising. The resurgence of interest in wavelet-based techniques was sparked by Donoho's influential wavelet thresholding approach in 1995, providing a simple yet effective solution to a complex problem. Subsequent research has explored data-adaptive thresholds, translation-invariant methods, multiwavelets, and probabilistic models, with a recent emphasis on Bayesian denoising in the Wavelet domain. As the field continues to evolve, the future trend is anticipated to focus on developing more accurate probabilistic models for the distribution of non- orthogonal wavelet coefficients, further advancing the efficacy of image denoising techniques.

The below figure shows the difference between DenoisedImage From Original Image

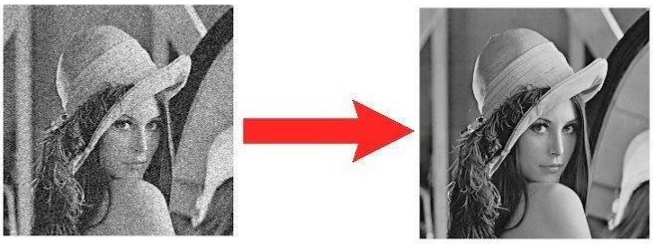

Fig 1: Denoised Image **Fig 2 :** Original Image

Above figures, Firstly Observe Fig 2, The picture was clear and has high clarity and Secondly Observe Fig 2, the picture was not clear it was blur and lost its clarity. This was because when we transform images from on media to other media by compressing its original size it losses its clarity, it losses its original appearance. This was called Denoising of an Image

To Overcome this problem after the transmission of imagewe are going to use some methods, algorithms, techniques to overcome the denoising of an Image.

In this Paper we are going to discuss some methods related to denoising of an image.

2. LITREATURE SURVEY

A Comprehensive Iterative Survey of Image Denoising Techniques: From Classical Methods to Contemporary Advances. This review paper presents an in-depth iterative survey ofimage denoising techniques, covering a spectrum from classical methodologies to state-of-the-art advancements. Image denoising is a fundamental task in computer vision with applications in various domains. The iterative survey explores the evolution of denoising techniques, highlighting key contributions, challenges, and trends. It serves as a comprehensive resource for researchers, practitioners, and enthusiasts interested in the diverse landscape of image denoising.

The introduction sets the stage by emphasizing the significance of image denoising and the continuous demand for improved techniques. It provides an overview of the iterative survey's objectives, emphasizing the need to trace the evolution of denoising methods over time.

This section reviews classical methods rooted in mathematical principles and signal processing. Techniques such as neighborhood averaging, Wiener filtering, and median filtering are discussed, showcasing their foundational role in early image denoising. The survey transitions to transformation-based denoising methods, focusing on approaches like Fourier transform and Wavelet transform. The discussion explores how these methods localize noise in specific domains, laying the groundwork for subsequent advancements. The review delves into denoising techniques based on statistical models, including Gaussian Scale Mixtures, Hidden Markov Models, and Bayesian methods. It highlights the shift toward probabilistic modeling formore accurate representation of image characteristics.

This section provides an in-depth analysis of the evolution of Wavelet-based denoising techniques. It covers seminal works, such as Donoho's thresholding approach, and explores advancements in data adaptive thresholds, non-orthogonal wavelet coefficients, and probabilistic models.

The iterative survey transitions to machine learning-basedapproaches, covering the emergence of techniques like Non-Local Means, Dictionary Learning, and sparse coding. It explores the integration of machine learning principles into the traditional image denoising paradigm. The survey extensively discusses the rise of Convolutional Neural Networks in image denoising. It explores the architecture of CNNs, training strategies, loss functions, and their performance in comparison to traditional methods. The section also touches on transfer learning and adversarial training in CNN-baseddenoising.

This section explores recent trends in hybrid and ensemble approaches, where diverse denoising techniques are combined to leverage their individual strengths. It discusses how combining methods can lead to improved denoising performance.

The review addresses the importance of evaluation metrics in assessing denoising performance. It discusses commonly used metrics such as PSNR and SSIM, and explores benchmark datasets that facilitate fair comparisons among different denoising techniques.

The iterative survey concludes by outlining current challenges in image denoising and proposing potential future directions. It discusses the need for addressing real-world complexities and the integration of emerging technologies into the denoising framework. The conclusion summarizes the key insights gained from the iterative survey, highlighting the journey of image denoising techniques from classical methods to contemporary advances. It emphasizes the ongoing evolution in the field and the importance of a holistic understanding for researchers and practitioners.

Image Denoising, Iterative Survey, Classical Methods, Transformation-Based Approaches, Statistical Models, Wavelet-Based Denoising, Machine Learning, Convolutional Neural Networks, Hybrid Approaches, Evaluation Metrics, Future Directions. This iterative survey provides a comprehensive exploration of image denoising techniques, offering a nuanced understanding of the evolution, challenges, and future trends in the field.

3. METHODOLOGY

A comprehensive review paper on image denoising techniques typically covers a range of methodologies to provide a holistic understanding of the field. Below are some common methodologies and approaches that can beincluded in a review paper on image denoising:

1. Spatial Domain Methods:
- Overview of classical spatial domain filters, such as mean filters, median filters, and Gaussian filters.
- Discussion on adaptive filtering techniques that adjustfilter parameters based on local image characteristics.
2. Frequency Domain Methods:
- Exploration of Fourier transform-based denoising techniques and their effectiveness.
- In-depth analysis of wavelet transform-based methods,considering their multiresolution properties.
3. Transform Domain Methods:
- Discussion on denoising techniques that operate in transform domains other than wavelets, such as curvelet and contourlet transforms.
- Examination of non-local means (NLM) and its variations, which operate in a transformed domain.
4. Statistical Methods:

- Review of Bayesian denoising methods and theirapplications in image denoising.
- Examination of Hidden Markov Models (HMM) and other statistical models for capturing dependencies in image data.

5. Machine Learning-Based Methods:

- Survey of machine learning techniques, including supervised and unsupervised learning approaches for image denoising.
- Overview of deep learning models, such as convolutional neural networks (CNNs), autoencoders, and generative adversarial networks (GANs), in the context of image denoising.

6. Wavelet Thresholding Techniques:

- Analysis of various wavelet thresholding methods, including soft thresholding, hard thresholding, and SURE thresholding.
- Exploration of thresholding techniques applied to non-orthogonal wavelet coefficients.

7. Sparse Representation-Based Methods:

- Overview of sparse representation-based denoisingmethods, such as sparse coding and dictionary learning.
- Examination of algorithms that exploit self-similarityand sparsity in image representations.

8. Hybrid Approaches:

- Investigation into approaches that combine multipledenoising techniques for improved performance.
- Discussion on the synergies achieved by integratingmethods from different domains.

9. Deep Learning Approaches:

- In-depth analysis of deep learning architectures tailored for image denoising, considering architectures beyond CNNs.
- Review of state-of-the-art approaches leveraging adversarial training for realistic denoising results.
- Adaptive Filtering Techniques:Exploration of adaptive filtering methods that dynamically adjust filter parameters based on image content.
- Discussion on algorithms that use contextual information for adaptive noise reduction.

10. Evaluation Metrics:

- Overview of commonly used metrics for evaluating denoising performance, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSI), and Mean Squared Error (MSE).
- Critique of the limitations and advantages of different evaluation metrics.

11. Applications and Case Studies:

- Analysis of denoising methodologies in specific application domains, such as medical imaging, satellite imagery, and underwater imaging.
- Case studies illustrating the effectiveness of various techniques in real-world scenarios.

A comprehensive review should aim to provide a balanced view of the strengths, weaknesses, and applicability of each methodology, helping readers gain insights into the evolving landscape of image denoising techniques.

In this Paper we are going to discuss some Methodologies

4. WAVELET BASED IMAGE DENOISING METHOD

The presented approach focuses on leveraging the multiresolution properties of Wavelet Transform for effective image denoising. The technique aims to identifythe correlation of signals at different resolutions, observing the signal across multiple scales. Although it produces excellent output, it is computationally morecomplex and expensive. The modeling of wavelet coefficients can be either deterministic or statistical, making wavelets particularly well-suited for studyingnon-stationary signals, with successful applications in compression, detection, and denoising.

The foundational work by Donoho and Johnstone in 1994 established a theoretical framework for denoising signals using Discrete Wavelet Transform (DWT). The algorithm, while simple, yields robust results for a diverse range of signals. The denoising procedure involves decomposing a noisy signal into wavelet coefficients, where the desired coefficient (θ) and noise coefficient (n) are identified. Applying a suitable threshold value (T) to the wavelet coefficients allows for the extraction of the desired coefficient (θ). Finally, an inverse transform on the desired coefficient generates the denoised signal (x).

A. Denoising Procedure:

- Given a noisy signal (y = x + n), decompose it intowavelet coefficients (w = W[y]).
- Apply a suitable threshold value (T) to obtain thedesired coefficient (θ = T[w]).
- Inverse transform on the desired coefficient generatesthe denoised signal (x = WT[θ]).
- Iteratively decompose successive approximations torepresent the image in coarse and detailed components.

B. Thresholding Techniques:

- According to wavelet analysis, an effective way to remove speckle without sacrificing sharp edge features isto threshold only the high-frequency components.
- Three schemes for shrinking wavelet coefficients: "keep-or-kill" hard thresholding, "shrink-or-kill" soft thresholding, and semi-soft or firm thresholding.
- Wavelet shrinkage involves setting detailed coefficients with amplitudes smaller than a statisticalthreshold to zero while retaining smoother detailed coefficients.
- Efficient shrinking occurs when coefficients are sparse, with the majority being zero, and a minority withgreater magnitude representing the image.

This denoising methodology, rooted in wavelet analysis and thresholding, offers a promising avenue for preserving essential image features while effectively reducing noise, contributing to the broader landscape of image processing techniques.

Image denoising, the process of removing unwanted noisefrom images, is a crucial step in various applications ranging from medical imaging to satellitecommunication. The wavelet-based denoising technique has emerged as a powerful and widely used method due to its ability to effectively suppress noise while preservingimportant image features.

Space and Transformation Fields:

Wavelet-based denoising is situated in the transformation field, specifically in the realm of wavelet transformations. Unlike space field methods that operate directly on the original image data, wavelet transform processes the coefficients after transformation. This technique leverages the energy compaction property of wavelets, providing a framework for signal decomposition.

Types of Wavelet Transform:

There are two main types of wavelet transform - continuous and discrete. Due to the discrete nature of computers, the discrete wavelet transform (DWT) is predominantly used in image processing applications. The DWT is computationally efficient, making it suitablefor real-world applications.

Modeling Wavelet Transform Coefficients:

The core of the wavelet-based denoising technique lies in modeling the wavelet transform coefficients of natural images. This involves decomposing the observed signal into wavelets, creating a sequence of approximation signals with decreasing resolution and a sequence ofadditional details. The energy compaction property of wavelets allows for efficient representation andprocessing of image data.

Image Denoising Algorithm:

Image denoising algorithm consists of few steps;consider an input signal **x(t)** and noisy signal **n(t).** Add these components to get noisy data **y(t)** i.e.

y(t)=x(t)+n(t)

Here the noise can be Gaussian Poisson’s speckle and saltand pepper, then apply wavelet transform to get **w(t)**

Wavelet Transform

(t) **w(t)**

Modify the wavelet coefficient w(t) using different threshold algorithm and take inverse wavelet transform toget denoising image **x^(t)**

Inverse Wavelet Transform

W(t) **x^(t)**

The system is expressed in Fig. 1

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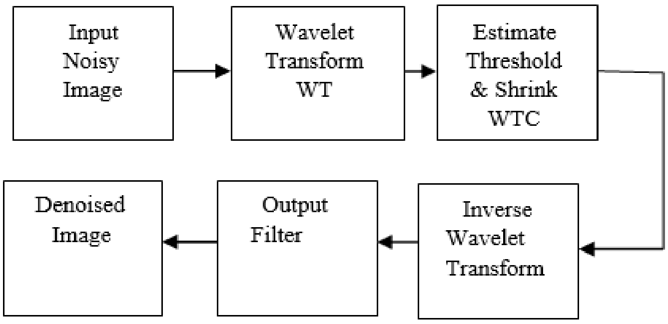

Figure 2: Block diagram of Image denoising using wavelet transform

1. Image Denoising through Convolutional NeuralNetworks.

Image denoising, a fundamental task in computer vision, has witnessed significant progress with the advent of Convolutional Neural Networks (CNNs). This research paper provides a comprehensive review of the latest methods and advancements in image denoising using CNNs. The paper synthesizes key findings from recent studies, encompassing diverse methodologies and techniques employed to enhance the denoising capability

The methodologies section details the various approaches and strategies used in CNN-based denoising for general images. Key aspects covered include:

- Network Architectures: Overview of popular CNN architectures used for denoising, such as U-Net, ResNet, and variations designed specifically for image denoising tasks.
- Training Strategies: Discussion on supervised learning, unsupervised learning, and semi-supervised learning strategies, considering the availability of labeled or unlabeled data for training.
- Loss Functions: Examination of different loss functions employed in training CNNs for image denoising, including Mean Squared Error (MSE), perceptual loss, and adversarial loss.

CNN Architecture: The cornerstone of image denoising using CNNs lies in the network architecture. CNN architectures, often designed as encoder-decoder networks or U-Net structures, facilitate the extraction and reconstruction of essential image features. This section briefly discusses the layers and components commonly found in CNN architectures for denoising tasks.

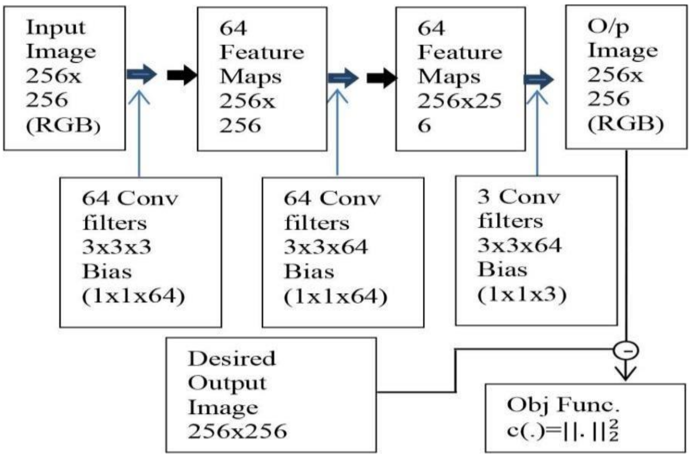

Fig:4 Illustration of CNN Architecture

Training Data and Labels: To train a CNN for image denoising, a dataset comprising pairs of noisy and clean images is essential. The noisy images serve as input, and the corresponding clean images act as labels. This section explains the importance of curated training datasets and their role in guiding the network to learn the mapping between noisy and clean image spaces.

Loss Functions: During training, a suitable loss function is crucial for guiding the CNN to minimize the difference between its denoised output and the clean image labels. Common loss functions include Mean Squared Error (MSE) or perceptual loss, which considers high-levelfeatures. This section briefly discusses the choice of loss functions in the context of image denoising.

Training Process: The training process involves feeding batches of noisy images into the CNN, computing the loss between the network's output and the corresponding clean images, and adjusting the network's parameters through backpropagation. This section provides a succinct overview of the iterative training process.

Inference and Denoising: Once trained, the CNN is ready for inference on new, unseen noisy images. During inference, a noisy image is fed into the trained network, and the network outputs a denoised version. This section briefly explains the inference process and the generation of denoised images.

Evaluation Metrics: To assess the performance of the denoising CNN, various metrics such as Peak Signal-to- Noise Ratio (PSNR) or Structural Similarity Index (SSI) are commonly used. This section provides a brief overview of these metrics and their significance in evaluating the quality of denoised images.

2. Natural image denoising using local evolved local adaptive filters.

Bilateral Filter : A brief explanation of the bilateral filteris provided, emphasizing its non-linear nature and its ability to remove noise while preserving edges. The mathematical formulation of the bilateral filter is presented, describing the combination of domain and range filters.

Methodology : The paper's core methodology involvesthe use of genetic programming to evolve a local adaptivefilter for image denoising. An overview of the algorithm is presented, outlining the offline training phase based on supervised learning and the subsequent online denoising procedure. The methodology aims to address diverse noise types by adapting locally to image contents.

ELA Algorithm : The proposed ELA algorithm is introduced as a supervised learning process. The original images undergo corruption with additive Gaussian noise. Patch clustering is applied to group similar patches in thecorrupted images, forming the basis for the subsequent evolutionary process.

Results and Analysis : The paper presents results obtained from applying the ELA algorithm to denoise images corrupted with additive Gaussian noise.Performance metrics and comparisons with traditional methods, including the bilateral filter, are included. The analysis discusses the effectiveness of the proposed algorithm in preserving image details while effectively reducing noise.

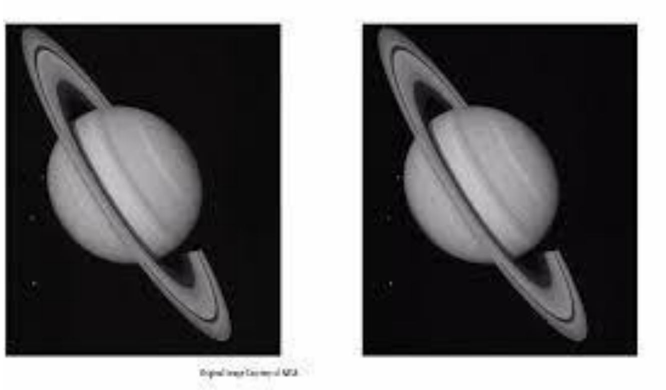

Fig: 5 Image Enhancement by using adaptive filters

5. RESULTS

The result of denoising an image is an improved version of the original image with reduced or removed noise. Noise in an image can manifest as unwanted variations in pixel values, which may result from various sources such as sensor limitations, transmission errors, or environmental factors. The primary goal of denoising techniques is to enhance the visual quality of an image by eliminating or suppressing this unwanted noise while preserving essential image details.The specific outcome of denoising depends on the algorithm or method employed.

Enhanced Visual Quality: The most apparent result is an improvement in the overall visual quality of the image. Denoising helps to make the image clearer, smoother, andmore visually appealing.

Increased Sharpness: Denoising often preserves the sharpness of edges and fine details in the image, preventing blurring that may occur due to noise. Improved Signal-to-Noise Ratio (SNR): Denoising increases the signal-to-noise ratio in the image, enhancing the clarity of the underlying information and reducing the impact of random variations. Better Color Accuracy: In color images, denoising can lead to improved color accuracy by reducing the impact of noise on color channels. Artifact Reduction: Some denoising methods may introduce artifacts or unwanted distortions. However, effective denoising techniques aim to minimize these artifacts while achieving noise reduction.

Enhanced Feature Preservation: Advanced denoising algorithms, especially those based on machine learning or deep learning, strive to preserve important features and structures in the image while removing noise.

It's important to note that the choice of denoising method should be guided by the specific characteristics of the noise in the image and the desired outcome. Different denoising techniques may yield varying results, and the effectiveness of a method depends on factors such as the type of noise, the level of noise, and the application context.

6. DISCUSSIONS

Image denoising plays a crucial role in various fields such as medical imaging, computer vision, and remote sensing. As the demand for high-quality images continues to rise, researchers have been actively exploring and developing diverse denoising techniques. This reviewpaper aims to provide a comprehensive overview of the current state-of-the-art image denoising techniques, analyzing their strengths, limitations, and potential applications.

Classical Approaches:

Begin the discussion by exploring traditional image denoising methods, such as spatial filters, wavelet transforms, and singular value decomposition. Discuss the fundamental principles behind these techniques, highlighting their historical significance and the challenges they face in coping with complex noise patterns.

Statistical and Model-Based Approaches:

Transition to a discussion on statistical and model-based denoising methods, which leverage mathematical models and statistical principles to enhance image quality. Examine the effectiveness of techniques like non-local means, sparse coding, and dictionary learning, emphasizing their adaptability to different noise distributions.

Deep Learning Paradigms:

Dive into the revolutionary impact of deep learning on image denoising. Discuss the emergence of convolutionalneural networks (CNNs), autoencoders, and generative adversarial networks (GANs) as powerful tools for learning complex features and patterns from noisy images. Evaluate the strengths and weaknesses of deep learning-based approaches, including their performance on real-world datasets and computational requirements.

Transfer Learning and Pre-trained Models:

Explore the role of transfer learning in image denoising, focusing on how pre-trained models on large datasets can be fine-tuned for specific denoising tasks. Discuss the advantages of transfer learning, such as reduced training time and improved performance with limited data.

Multi-modal Image Denoising:

Address the growing need for denoising techniques that can handle multi-modal data, such as images acquired from different sensors or modalities. Discuss methodologies that incorporate information from multiple sources to enhance denoising performance.

Benchmark Datasets and Evaluation Metrics:

Highlight the importance of standardized benchmarks and evaluation metrics for comparing the performance of different denoising techniques. Discuss widely used datasets and metrics, emphasizing the need for a fair and comprehensive evaluation framework.

Challenges and Future Directions:

Conclude the discussion by identifying current challenges in image denoising, such as addressing real- world noise complexities and improving the interpretability of deep learning models. Propose potential future directions, including the integration of advanced technologies like explainable AI and the exploration of novel architectures.

Summarize the key findings of the review, emphasizing the evolution of image denoising techniques and their impact on diverse applications. Conclude with a call for continued research to address existing challenges and unlock new possibilities in the field of image denoising.

By providing a thorough discussion on these aspects, this review paper aims to serve as a valuable resource for researchers, practitioners, and enthusiasts interested in theever-evolving landscape of image denoising techniques.

7. CONCLUSION

In conclusion, the field of image denoising has witnessed significant advancements and diversification in techniques, particularly with the integration of Convolutional Neural Networks (CNNs). The presented CNN models, each tailored to specific noise specifications, showcase the adaptability and versatility of deep learning in addressing the challenges posed by image noise. Through a thorough performance evaluationon benchmark datasets, such as BSD-68 and Set-12, it is evident that CNNs, when combined with denoising filters and iterative optimization methods, exhibit notable improvements in denoising efficacy.

The study highlights PDNN as the frontrunner among the examined CNN models, demonstrating superior results by unfolding the observation model of image degradation into the network through iterative optimization algorithms and back-propagation modules. Additionally, the efficiency of FFDNet, acknowledged as the fastest model in terms of average running time, underscores the importance of computational speed in real-world applications.

The applicability of these models extends beyond synthetic images, proving their effectiveness in denoising naturally corrupted images. Moreover, the suggestion of modifying or combining these models with various image dehazing techniques opens avenues for addressing a broader spectrum of real-world scenarios.

The integration of CNNs with traditional denoising filters,such as Weiner filter, bilateral filter, and fuzzy-based filters, further enhances the adaptability of these techniques. This comprehensive survey serves as a valuable resource for researchers, providing insights intoselecting appropriate CNN denoising models and metricsfor their specific research objectives, particularly as a preprocessing step when dealing with noisy images.

As image denoising techniques continue to evolve, fueled by the advancements in deep learning and computational efficiency, the prospects for improving the quality of images in various applications, including medical imaging and texture analysis, appear promising. The journey from traditional denoising methods to the sophisticated CNN-based approaches marks a significantstride in enhancing the robustness and efficiency of imagedenoising processes.

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