A Survey on Image Denoising Techniques

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Abstract:- In the digital era of the world images are vital part of life and media. This survey explores a wide array of image denoising methods, spanning traditional and contemporary approaches. The review encompasses classical filters, statistical methods, and modern machine learning-based algorithms, with a focus on their principles, advantages and limitations. Through a systematic examination of the literature, we categorize the denoising techniques based on their underlying methodologies and applications. Insights are drawn from comparative analyses, highlighting the trade-offs and performance variations across different approaches. Additionally, emerging trends and future directions in image denoising research are discussed. This comprehensive survey serves as a valuable resource for researchers, practitioners, and enthusiasts in understanding of the different image denoising techniques.

***Keywords**:- Wavelet Transformer, Image Denoising, Machine Learning.*

I. INTRODUCTION

Image denoising techniques play a vital role in the field of digital image processing, aiming to enhance the grade of images by reducing unwanted noise and artifacts. Noise, often introduced during image acquisition or transmission, can degrade the visual quality and affect the accuracy of subsequent image analysis tasks. Image denoising techniques employ various algorithms and methods to effectively remove or minimize noise, revealing clearer and more informative images.

Traditional image denoising methods typically involve mathematical operations, statistical analyses, and filter-based approaches. These techniques focus on identifying and suppressing noise while preserving essential image details. Common filters include Gaussian filters, median filters, and bilateral filters, each with its own advantages and limitations.

With the advancements in machine learning and deep learning, there has been a paradigm shift towards data-driven image denoising techniques. Convolutional Neural Networks (CNNs) and other deep learning architectures have demonstrated remarkable performance in denoising tasks. These models learn complex representations from large datasets, enabling them to adaptively filter out noise patterns and generalize well to diverse image types.

One popular approach in deep learning-based image denoising is the use of autoencoders and variational autoencoders. These models are designed to take the input image, convert it into a hidden representation, and then recreate the original image. The goal is to minimize any errors in the recreated image. By learning the underlying structure of clean images during training, these models can effectively denoise new, unseen images.

Another noteworthy technique is the use of generative adversarial networks (GANs) for image denoising. GANs includes a generator and a discriminator, involved in a competitive learning process. The generator tends to produce denoised images, while the discriminator discriminate between clean and denoised images. This hostile training leads to the generation of realistic and high-quality denoised images.

II. LITERATURE SURVEY

In [1], a novel approach called "unprocessing" for raw image denoising which aims to undo the processing steps applied to raw images, allowing for better denoising using learned models.The unprocessing step could lead to better utilization of learned models for raw image denoising.

In [2], deep raw image denoising specifically designed for mobile devices which presents a solution tailored for mobile devices, considering computational constraints. It also addresses the challenges associated with deploying deep denoising models on resource-constrained devices.

In [3], BM3D-AMP, a novel image restoration algorithm based on the BM3D denoising method which integrates the BM3D denoising algorithm into the image recovery process. Demonstrates the effecticacy of the discussed algorithm.Combines denoising techniques with image recovery, potentially improving overall performance.

In [4], a method for learning a deep convolutional neural network (CNN) as a denoiser prior for image restoration having the efficacy of using a deep CNN as a denoiser prior in image restoration tasks. Addresses challenges in learning denoiser priors from data.

In [5], a residual learning framework for deep convolutional neural networks (CNN) to enhance image denoising beyond traditional Gaussian models .Proposes a residual learning approach, where the network learns the residual denoising functions instead of the direct mapping. Also,it is noticed that residual learning can improve the performance of deep CNNs for image denoising tasks.

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In [6], addresses the challenge of blind image denoising, where the noise level is not known in advance, by proposing a convolutional blind denoising model.It Introduces a convolutional blind denoising framework capable of handling real photographs with unknown noise characteristics. Addresses the challenge of real-world denoising where noise characteristics may vary across images. It enlighten applicability of CNN-based denoising methods to real-world scenarios with varying and unknown noise levels.

In [7], the SURE-LET (Stein's unbiased risk estimate learned experts in transform domain) strategy behind image denoising based on learned experts in the transform domain, utilizing Stein's unbiased risk estimate. It focuses on denoising images while preserving important structural information.

In [8], focuses on image denoising using sparse and redundant representations over learned dictionaries. Demonstrates a method based on sparse coding and learned dictionaries for image denoising.Emphasizes the importance of sparse representations in capturing essential image features during denoising.Pioneers the use of learned dictionaries and sparse representations for image denoising, contributing to the broader field of sparse signal processing.

In [9], a sparsity-based approach to image denoising by combining dictionary learning and structural clustering. Demonstrates a method that leverages both dictionary learning and structural clustering to enhance the denoising process.

In [10], WINNet, an invertible neural network for image denoising. Draws inspiration from wavelet transforms to enhance denoising performance.Incorporates multi-resolution analysis and sparse representations inspired by wavelet techniques.Ensures invertibility in the neural network, allowing accurate reconstruction of the original image.Advances image denoising technology by combining invertible neural networks with wavelet-inspired insights.Potential applications in medical imaging, remote sensing, and computer vision.

III. FUTURE SCOPE

The future scope for image denoising is promising and involves several key areas of exploration. This includes the integration of deep learning techniques, such as CNNs and GANs, for more sophisticated denoising models. The development of end-to-end learning systems and the exploration of adversarial training aim to enhance model robustness. Future research may focus on dynamic noise modeling, adaptive to different noise patterns in real-time, and the extension of denoising techniques to handle multimodal and multispectral imaging data. Real-time and hardware implementation for applications like video streaming and surveillance, as well as domain-specific denoising models for various imaging domains, are also areas of interest. Exploring explainable AI, self-supervised learning, and the fusion of classical and deep learning approaches, along with standardized benchmarking, will contribute to the continuous advancement of image denoising technologies.

IV. CONCLUSION

Subsequently, an analysis was conducted on 10 scholarly articles, and the salient findings were encapsulated in the literature review. The research delved into identifying gaps within the extant knowledge, considering the articulation of the problem statement and its corresponding objectives. Additionally, a meticulously crafted activity regimen was delineated. The developed system is engineered to cater to the requirements of the ultimate end user.

REFERENCES

[1]. T. Brooks, B. Mildenhall, T. Xue, J. Chen, D. Sharlet, and J. T. Barron, “Unprocessing images for learned raw denoising,” in Proc.IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2019,pp. 11036–11045.

[2]. Y. Wang, H. Huang, Q. Xu, J. Liu, Y. Liu, and J. Wang, “Practical deep raw image denoising on mobile devices,” in Proc. Eur. Conf. Comput.Vis. (ECCV), Aug. 2020, pp. 1–16.

[3]. C. A. Metzler, A. Maleki, and R. G. Baraniuk, “BM3D-AMP: A new image recovery algorithm based on BM3D denoising,” in Proc. IEEE Int. Conf. Image Process. (ICIP), Sep. 2015, pp. 3116–3120.

[4]. K. Zhang, W. Zuo, S. Gu, and L. Zhang, “Learning deep CNN denoiser prior for image restoration,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 3929–3938.

[5]. K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, “Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising,”IEEE Trans. Image Process., vol. 26, no. 7, pp. 3142–3155, Jul. 2017.

[6]. S. Guo, Z. Yan, K. Zhang, W. Zuo, and L. Zhang, “Toward convolutional blind denoising of real photographs,” in Proc. IEEE/CVF Conf. Comput.Vis. Pattern Recognit. (CVPR), Jun. 2019, pp. 1712–1722.

[7]. T. Blu and F. Luisier, “The SURE-LET approach to image denoising,”IEEE Trans. Image Process., vol. 16, no. 11, pp. 2778–2786, Nov. 2007.

[8]. M. Elad and M. Aharon, “Image denoising via sparse and redundant representations over learned dictionaries,” IEEE Trans. Image Process.,vol. 15, no. 12, pp. 3736–3745, Dec. 2006.

[9]. W. Dong, X. Li, L. Zhang, and G. Shi, “Sparsity-based image denoising via dictionary learning and structural clustering,” in Proc. CVPR,Jun. 2011, pp. 457–464.

[10]. WINNet: Wavelet-Inspired Invertible Network for Image Denoising Jun-Jie Huang , Member, IEEE, and Pier Luigi Dragotti , Fellow, IEEE. IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 31, 2022.