Survey – Start with Image Denoising

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Abstract: - Denoising is a noise reduction technique for a signal that remains a problematic task for researchers. Although several works have been published on algorithms, each of these methods has its advantages and limitations. This work presents a state-of-the-art of some of the major works developed in the field of image noise reduction, as well as a new direction in the categorization of MR image debriefing techniques. The categorization of the different image models used in medical image processing serves as the basis for our classification. This study includes recent improvements in deep learning-based debriefing methods as well as important traditional MR image denoising methods. The major issues and their scope for improvement are also addressed. In addition, many other evaluation indices are considered for fair comparison. This study may encourage researchers to continue their work in this area. The work begins with an introduction, then presents some of the most widely used approaches in their classification sets and an overview of many algorithms and analyses is provided. Possible future perspectives and trends in noise reduction are also presented here.

Key-Words: - Digital images, Magnetic resonance imaging, biomedical image denoising, wavelet transformation, un-decimatedwavelet transformation, noise reduction images.

Received: April 16, 2024. Revised: November 19, 2024. Accepted: March 9, 2025. Published: April 17, 2025.

1 Introduction

Digital images play a crucial role in everyday life where they are used in applications such as satellite TV, magnetic resonance imaging, computer tomography and other areas of research and technology, including geographic information systems (GIS) alongside astronomy and other scientific fields. The datasets collected by the image sensors are normally noisy. Faulty tools interfere with the data acquisition procedure and interfering naturalphenomena can all decrease the levels of the data of interest, [1]. Another way to introduce noise is transmission errors and compression. For this reason, denoising is sometimes considered essential and the initial step to be taken before data images are studied. The application of an effective denoising method to compensate for data corruption at hand has become a necessity. Breaking down images continues to be a challenge for researchers because noise suppression brings artifacts and blurs images.

Medical image denoising is a critical step in the processing of medical images, as it aims to improve the quality and clarity of images obtained from various medical imaging modalities such as X-rays, CT scans, MRI, ultrasound, and more. Denoising techniques are employed to remove or reduce unwanted noise, artifacts, and disturbances from these images, which can otherwise hinder accurate diagnosis and analysis by healthcare professionals.

The basic steps in image processing include improvement, recording, segmentation, object recognition, etc. Many methods have been reported for each step. One of the key steps in the improvement is denoising.

Image noise modeling is primarily affected by capture instruments, data carriers, image quantification and discrete radiation sources. A variety of algorithms are used with respect to the noise model. It is supposed that most natural images have an unintended noise modeled like a Gaussian, [2].

The practical applications of image denoising surveys are broad and can be beneficial in several fields, including: Medical Imaging, Surveillance and Security, Astronomy, Photography, Remote Sensing, Computer Vision, Art Restoration, Industrial Inspection, Forensics, Video Conferencing and Streaming, Enhancing Low-Quality Historical Images, Self-Driving Cars, Image Compression.

2 Mathematical Noise Models

Here are several mathematical noise models commonly used in various fields along with their formulas:

1. White Noise:
White noise is a random signal with a constant power spectral density, meaning it has equal power at all frequencies within a specified bandwidth.
Formula:

$$X(t)=\text{constant} \quad (1)$$

2. Gaussian Noise: Gaussian noise follows a Gaussian or normal distribution, characterized by a bell-shaped probability density function.
Formula: The probability density function (PDF) of a Gaussian random variable X with mean μ and variance σ^2 is given by:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(x-\mu)^2}{2\sigma^2}) \quad (2)$$

3. Pink Noise (1/f Noise):
Pink noise has a power spectral density inversely proportional to the frequency, resulting in decreasing power as frequency increases.
Formula:

$$S(f) = \frac{1}{f^\alpha} \quad (3)$$

4. Brownian Noise (Brown Noise):
Brownian noise has a power spectral density inversely proportional to the square of the frequency, resulting in a more rapid decrease in power as frequency increases compared to pink noise.
Formula:

$$S(f) = \frac{1}{f^2} \quad (4)$$

5. Impulse Noise: Impulse noise consists of sudden, short-duration spikes or impulses that can occur randomly in a signal.
Formula: The effect of impulse noise can be represented as x(t)=s(t)+n(t), where x(t) is the noisy signal, s(t) is the clean signal, and n(t) represents the impulses (noise) added to the signal.

6. Autoregressive (AR) Model: The autoregressive model is a time series model where each observation is modeled as a linear combination of previous observations and a random error term.
Formula: An autoregressive model of order p is defined as:

$$X(t) = c + \sum_{i=!}^{p} a_i X(t-i) + \varepsilon(t) \quad (5)$$

where X(t) is the value of the time series at time t, c is a constant, a_i are the autoregressive parameters, ε(t) is a white noise term representing random error at time t, and p is the order of the autoregressive model.

7. Colored Noise: Colored noise refers to noise with a non-constant power spectral density, meaning it has different power levels at different frequencies. Formulas for colored noise can vary depending on the specific spectral characteristics. Examples include pink noise and brown noise, which have been mentioned above. Images can contain noise, an extra element that interferes with a pure signal and is caused by numerous physical events, [3], [4]. High levels of noise may not only affect how humans see images but also degrade the effectiveness of image identification systems. We discuss thenoise models used throughout the studies in thissection.

3 Evolution of Denoising Image Research

One major barrier to image processingcontinuesto be the field of picture denoising. Wavelets' strengths—such as their rarity and multi- resolution structure—have beendemonstrated to translate into higher image denoising performance. Over the past twodecades, a wide range of algorithms (WT) have been developed as wavelet transformation (WT) has grown inpopularity. This is how focus moved to the domain (WT) from the Space and Fourier domain. Massive progress has been made in the release papers since the Donoho wavelet-based threshold technique was first with m being the mean of distribution, σ^2 its variance, and $-\infty < x < \infty$.

Quantization Noise
Quantization noise is most often associated with quality drop occurring due to converting continuous signal into digital format. It can be modeled as a noise sampled uniformly from distribution with specified range from 0 to q.

Salt & Pepper Noise
Salt & pepper noise can be used to model distortions introduced while transmit- ting data through noisy channel, resulting in loss of information in a number of pixels. We can modelsalt & pepper noise by altering n-th pixelwith probability specified as:

$$P(X_n = x_n) = 1 - p, \quad (6)$$

The idea presented in [5] was not novel, but contrary to [6], claimed approaches do not have to connect or follow the maximum and minimum for wavelets between the various scales. This hasrevived the attention paid to wavelet-based denoising techniques since, they established a simple method to a complex problem.

The aforementioned thresholding techniques were applied to the non-orthogonal wavelet coefficients, [7], [8], to help reduce artifacts. Multi-wavelets were used to find similar results, while probabilistic models, [9], using the statistical properties of the wavelet coefficient tended to outperform thresholding techniques and to obtain more terrain. In recent times, much work has been devoted to Bayesian denoising in the field of wavelets, [10], [11]. Hidden Markov patterns and Gaussian scale mixtures have gained renown as research continues to be published. Several adaptive datatransformations have been studied, including the analysis of independent components (ICA). The trend remains to pay attention to the use of various statistical prototypes to model thestatistical assets of wavelet coefficients and its neighbors. Future work to find clearer probabilistic models for the provision of non- orthogonal wavelet coefficients.

The field of denoising image research, including medical image denoising, has seen significant evolution and progress over the years. Here's a brief overview of the key milestones anddevelopments in the evolution of denoising image research:

✓ Classical Filtering Techniques (Pre-1990s):
Early denoising methods relied on classical filters such as Gaussian filters, mean filters, and median filters. These methods were simple and computationally efficient but often lacked the ability to preserve fine details in images.

✓ Wavelet Transform (1990s):
The 1990s saw the emergence of wavelet- based denoising techniques. Wavelet transforms allowed for multi-resolution analysis of images, making it possible to remove noise while preserving important image features.

✓ Non-Local Means (NLM) and Variants (2000s):
In the 2000s, the Non-Local Means (NLM) algorithm was introduced. NLM and its variants proved to be effective in denoising by considering similarities between image patches. These methods offered improved noise reduction and better preservation of image details.

✓ Sparse Representations (Late 2000s):
Sparse representation-based methods gained popularity. These techniques exploited the idea that images can be sparsely represented in a suitable transform domain (e.g., wavelets or dictionaries), making it possible to separate noise from the signal.

✓ Dictionary Learning (2010s):
Dictionary learning methods, such as K- SVD and the use of over-complete dictionaries, became prevalent. These techniques allowed for better modeling of image structures and more effective denoising.

✓ Deep Learning (Late 2010s - Present):
The advent of deep learning, particularly convolutional neural networks (CNNs), has revolutionized image denoising. Deep learning models have demonstrated outstanding performance in denoising tasks, both for natural images and medical images. Architectures like U-Net and variations of CNNs have been applied to denoise medical images with impressive results.

✓ Generative Adversarial Networks (GANs):
GANs have also been employed in image denoising. The generator-discriminator architecture of GANs can be used to generate clean images from noisy inputs, resulting in high-quality denoised images.

✓ Transfer Learning and Pre-trained Models:
Transfer learning, using pre-trained models on large datasets, has become a common practice.Fine-tuning these models on medical image denoising tasks has led to state-of-the-art results.

✓ Evaluation Metrics and Benchmarks:
The development of standardized evaluation metrics such as PSNR, SSIM, and perceptual metrics has facilitated the comparison of denoising algorithms. Benchmark datasets for medical image denoising have also been created to assess and compare the performance of different methods.

✓ Real-time and Hardware Acceleration:
Research has focused on real-time denoising and hardware acceleration, particularly for applications where speed is critical, such as in medical imaging during surgeries or real-timediagnostics.

✓ Adaptive and Data-Driven Approaches:
Researchers have explored adaptive and data-driven approaches, where denoising parameters are determined dynamically based on the characteristics of the input data.

The evolution of denoising image research has been marked by a transition from classical methods to data-driven and deep learning techniques, resulting in substantial improvements in denoising quality and speed. As technology continues to advance, we can expect further innovations and refinements in the field of image denoising, benefiting various applications, including medical imaging.

4 Denoising Algorithms Classification

Denoising algorithms can be classified into several categories based on their underlying principles and methodologies. Here's a classification of denoising algorithms:

4.1 Filter-Based Methods

Linear Filters: These methods include Gaussian filters, mean filters, and median filters.They apply a fixed linear operation to the noisy image to reduce noise. Gaussian filters are effective for Gaussian noise, while median filters are robust to impulse noise.

Linear filters such as the Wiener filter in the wavelet domain give optimal results when the signal corruption can be modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE), [12], [13]. However, designing a filter based on this assumption frequently results in a filtered image that is more visually unpleasant than the original noisy signal, even if the filtering operation succeeds in reducing the MSE. In [14], a wavelet domain spatially adaptive FIR Wiener filtering for image denoising is proposed where Wiener filtering is performed only within each scale and intra scale filtering is not allowed.

4.2 Transform-Based Methods

Wavelet Transform: Wavelet-based denoising decomposes an image into different frequency components and selectively removes noise at various scales. Common techniques include wavelet thresholding and wavelet shrinkage.

Nonlinear Threshold Filtering: The most studied area in denoising using wavelet transform is nonlinear coefficient threshold-based methods. The procedure exploits the sparsity property of the wavelet transform and the fact that the wavelet transform maps white noise in the signal domain to white noise in the transform domain. So while the signal energy becomes more concentrated into fewer coefficients in the transform domain, the noise energy does not. It is this important principle that allows us to separate the signal from the noise. The procedure in which small coefficients are removed while others are left intact is called hardthresholding. But the process generates spurious blips, better known as artifacts, in images following failed attempts to remove moderately high noise coefficients. To overcome the disadvantages of hard thresholding, wavelet transform using soft thresholding was alsointroduced. In this scheme, the coefficients above the threshold arereduced by the absolute value of the threshold itself. Similar to soft thresholding, other thresholding techniques are semi-soft thresholding and Garrote thresholding, [15].

Fourier Transform: Fourier domain denoising methods operate in the frequency domain to remove noise and enhance signal components.

The papers collectively suggest that Fourier Transform-based methods can be effective for denoising and enhancing signal components. [10], compares Fourier and wavelet analysis and highlights that Fourier analysis is suitable forsignals with frequency-localized features. [11] proposes a denoising method based on the fractional Fourier transform, which shows better performance compared to conventional Fourier transform-based methods. [16] presents an improved speech denoising algorithm based on the discrete fractional Fourier transform, demonstrating its ability to eliminate noise and enhance the original speech signal. [17] proposes a hybrid method that combines frequency domainfilters and Fourier transformations for denoising digital images. These findings support the use of Fourier domain denoising methods for noise removal and signal enhancement.

5 Statistical Methods

Maximum Likelihood Estimation (MLE): MLE-based denoising models the noise statistics and estimates the clean image by maximizing the likelihood of the observed noisydata.

Maximum likelihood (ML) estimation is a method of calculating parameters from the probability distribution of a finite Gaussian model. This is the value that maximizes the likelihood function in parameter space. The method calculates the amount of noise by subtracting two successive acquisitions of the same object. This reduces the bias effects that appear in conventional ML estimation.

Bayesian Methods: Bayesian denoising uses a probabilistic framework to estimate the clean image and the noise distribution, taking into account prior information about the image and noise.

Adaptive threshold SURE Shrink, [17], uses a hybrid of the universal threshold and the SURE threshold [Stein's Unbeased Risk Estimator] and performs better than VISU Shrink. Bayes Shrink, [18], [19], minimizes the Bayes risk estimation function by assuming a generalized Gaussian prior and thus producing an adaptive data threshold. Bayes Shrink outperforms SURE Shrink most of the time. Cross-validation, [20], replaces the wavelet coefficient with the weighted average of the neighborhood coefficients to minimize the generalized cross- validation (GCV) function providing an optimal threshold for each coefficient.

6 Non-Local Methods

Non-Local Means (NLM): NLM compares similar patches within an image and uses their information to denoise a target patch. This method is effective in preserving image details.

In recent years, many researchers have presented a study on MR image denoising techniques, [21], in their study classified denoising methods into three groups based on filtering approach, transformation approach and statistical approach. The authors discussed the filtering approach in detail. However, little discussion is made of the other two approaches. Moreover, recent techniques on deep learning-based schemes are also not included in the study. Furthermore, very few evaluation metrics areused when comparing different denoising techniques. [22] presented a survey of denoising techniques using only the non-local mean filtering (NLM) approach. They did not consider any other approach in their study. [23] presented a survey on denoising approaches for multi-parametric MR images of the prostate, i.e., diffusion-weighted and T2- weighted MR images with Gaussian noise. Their study focused only on the filtering approach to denoising. Additionally, their investigation is terms of logic gate count and visual quality. [24] proposes a bounded BM3D scheme that restricts block matching search within the region of the template block, resulting in better visual performance and increased PSNR for heavily noisy images. [25] introduces a novel approach that combines sliding-window transform processing with block matching and 3D filtering, achieving state-of-the-art denoising performance. However, there is insufficient information available for [26] to draw any conclusions about its findings related to the research question.

7 Sparse Representation Methods

Sparse Coding: Sparse representation- based denoising methods exploit the sparsity of image patches in a suitable dictionary. Algorithms like K-SVD and the use of over- complete dictionaries are common.

The papers collectively suggest that sparse representation methods are effective for image denoising. [27] proposes a method using a mixed overcomplete dictionary and matching pursuit algorithm, which effectively reduces noise in more application specific. [28] presented a survey of denoising techniques based on noise models. The authors considered only the Gaussian and Rician noise model, which is a very common noise in MR images. Furthermore, they mainly discussed spatial filtering and wavelet domain filtering approaches to denoising with a single performance metric for comparison. The authors did not consider any other approaches ormeasures for a fair comparison.

Block-Matching 3D (BM3D): BM3D groups similar patches in both spatial and spectral domains to collaboratively denoise the image.

The papers collectively suggest that block matching 3D denoising is an effective approach for image denoising. [29] combines orthogonal matching pursuit and sparse representation theory to denoise low signal-to-noise ratio images, achieving better noise removal while preserving useful information. [30] introduces amulti-stage framework for denoising, capturing multiscale image features and achieving denoised images with superior visual quality.

[31] proposes a non-local denoising method based on sparse representation, improving image structure and achieving better image reconstruction. These findings collectively demonstrate the effectiveness of sparse representation methods for image denoising, [32].

8 Deep Learning-Based Methods

Convolutional Neural Networks (CNNs): CNNs have been highly successful in image denoising. Architectures like U-Net and variants of CNNs are trained to map noisy images to clean images.

Image denoising is a basic problem in image processing, some papers suggest that Convolutional Neural Networks (CNNs) can be effective for image denoising, highlights the use of CNNs along with Autoencoders for image denoising, showing promising results on the MNIST dataset. [33] introduces symmetric gated connections in deep CNNs, which improve feature learning and image denoising.

[34] proposes a fully symmetric convolutional-deconvolutional neural network (FSCN) that achieves superior denoising performance compared to existing algorithms, evaluates the performance of a convolutional neural network for image denoising

and measures its impact on classification accuracy. Overall, these papers demonstrate the potential of CNNs for image denoising tasks.

Generative Adversarial Networks: Some works applies a generative adversarial network with a deep convolutional densenet framework, utilizing Wasserstein- GAN as the loss function to improve image quality. presents a GAN- based image denoising method that utilizes heterogeneous losses, including a structural loss, and adapts the strength of the loss based on input patches. These papers collectively demonstrate the effectiveness of GANs in image denoising, showcasing improvements in denoising performance, image quality, and preservation of structural information.

9 Hybrid Methods

Some denoising methods combine multiple techniques from different categories to improve performance. For example, combining wavelet denoising with CNN-based denoising or incorporating non-local information into deep learning models.
The papers collectively suggest that hybrid methods combining different denoising techniques can be effective for image denoising. Some works proposes an hybrid wavelet-fractal denoising method that achieves comparable results to other efficient denoising methods, some works presents an hybrid framework that incorporates region division and utilizes

(GANs): GANs consist of a generator and discriminator network. The generator learns to produce clean images from noisy inputs, while the discriminator helps improve the generator's output quality.
The block-matching with 3D transform domain collaborative filtering (BM3D) achieves very good performance in image denoising. However, BM3D becomes ineffective when an image is heavily contaminated by noise.

We present proposed neural networks architecture together with employed training procedure, those explore the use of Generative Adversarial Networks (GANs) for image denoising. Some works proposes a new GAN with a generator network that produces denoised images, showing superiority over other denoising methods. [35] introduces a denoising model based on a generative countermeasure different denoising methods based on the characteristics of the patches, resulting in better denoising performance, especially in preserving textures and edges. [36] proposes a hybrid denoising technique that combines wavelet-based shrinkage in the transform domain with non-local means in the spatial domain, showing improved denoising performance. [37] introduces a hybrid image fusion algorithm using DDCT andPCA, which demonstrates superior denoising results compared to traditional filters. Overall, these papers highlight the potential of hybrid methods for image denoising.

10 Adaptive Methods

Adaptive denoising methods adjust denoising parameters based on the characteristics of the input data. They may use local statistics or machine learning to determine the optimal denoising strategy for each image region.

These papers proposes an efficient adaptive methods for image denoising, and propose different adaptive methods for image denoising.

[38] presents an adaptive spatial filtering method that combines adaptive filtering with multi-frame averaging filtering to improve denoising performance. [39] introduces an adaptive method based on wavelet transformand ridgelet transform, which shows superiority in processing point and line singularities. [40] suggests an adaptive smoothing method that uses discontinuity measures to iteratively convolute the input image with a weighted smoothing mask. [41] proposes a pointwise adaptive approach that relies on an adaptivechoice of a smoothing window based on the distance to the closest boundary and thesmoothness properties of the image. Overall, them suitable for use in medical imaging, video processing, and other applications where lowlatency is essential.

The present point offers a new **approach** to **image denoising** based on the idea of real time; it suggests that real-time and hardware- accelerated methods for image denoising are feasible and effective. [42] introduces a fast denoising method that aligns and fuses a burst of noisy images, achieving comparable denoising quality to previous work but with significantly faster processing. [43] presents an algorithm for real-time video denoising on mobile platforms, demonstrating comparable quality to offline methods but with orders of magnitude faster processing. [44] proposes a non-parametric ADMM algorithm for image denoising, which automatically learns parameters and achieves fast convergence speedand high restoration quality. [45] presents a new block-based image denoising method that improves compute speed and restoration quality, particularly for large-scale problems. These findings collectively suggest that real-time and hardware-accelerated methods can effectively denoise images with improved efficiency.

11 Evaluation-Based Methods

Some denoising methods use perceptual quality metrics as part of the denoising process to ensure that the denoised image is visually pleasing. The procedure for noise reduction is discussed in these papers provide different adaptive methods for image denoising, each with its own advantages and improvements over existing methods.

12 Real-Time and Hardware-Accelerated Methods

Denoising algorithms designed for real- time applications or hardware acceleration are optimized for speed and efficiency, making various methods for image denoising. [46] and [47] proposes a hybrid image fusion algorithm using DDCT and PCA, which was found to be superior to traditional denoising filters. [48] and [49] introduces a finite element solving method for image denoising, which showed better restoration effects compared to traditional finite difference methods. [50] provides a literature review of image denoising methods, highlighting the classification of methods into local and non- local, as well as spatial and frequency domain approaches. [51] presents a new block-based image denoising method that improves computational speed and image restoration quality.

The choice of denoising algorithm depends on factors such as the type of noise present in the image, the desired level of denoising, computational resources available, and the specific application. In medical imaging, for instance, selecting an appropriate denoising method is crucial to preserving diagnostic information while reducing noise. To fulfil the needs of diverse imaging tasks and enhance their performance, researchers are still working to create and improve such algorithms.

13 Conclusion

Together, the publications cited in this one offer an overview of methods for denoising medical images. They draw attention to the difficulties caused by noise distortion in medical images as well as the significance of denoising in this area of image analysis. The papers include a range of denoising techniques, such as curvelet and wavelet transforms, classification algorithms, and optimisation strategies. These methods aim to eliminate noise while maintaining major details in the image. The analysis of denoising techniques and the exploration of picture denoising have been enlightening and informative. We now have a thorough understanding of the area, its methods, and its importance in a range of applications thanks to the survey that was completed. Several important conclusions can be derived from this:

The preprocessing stage of image denoising is essential in a number of domains, such as computer vision, medical imaging, and remote sensing. Images become better when noise is removed, which makes them better for analysis and interpretation.

Various Techniques: The results of our survey showed that there are many different ways to denoise images, ranging from more conventional approaches like Gaussian filtering to more recent deep learning strategies. Every approach has advantages and disadvantages based on the particular use and noise properties.

Dominance of Deep Learning: Deep learning-based techniques have become more well-known recently as a result of their outstanding results in a variety of denoising tasks. Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) have become highly effective techniques for picture denoising.

Difficulties: Although there has been progress, image denoising still has issues in managing intricate noise patterns, maintaining minute features, and adjusting for variances in real-world data. The field's study is still motivated by these obstacles.

Uses: There are many uses for image denoising, such as sharpening medical images for diagnosis, enhancing photographs for photography, and supporting objects that are frequently measured using metrics like Root Mean Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR). All things considered, these studies highlight how important image denoising is to improving the precision and quality of medical images. improving satellite pictures for Earth observation, and computer vision recognition.

Ethical Considerations: With the development of image denoising technology, it is important to take into account ethical issues like privacy issues and the possible abuse of denoising algorithms for picture manipulation or change.

To sum up, image denoising is an important topic with lots of room for creativity and real-world uses. We may anticipate more advanced and practical methods to appear as technology develops, hence enhancing the quality of photos across a range of fields. An excellent basis for comprehending the state of image denoising now and its probable future directions has been provided by this survey.

14 Perspectives

Image denoising has a bright future. Research is probably going to concentrate on creating denoising algorithms that are more resilient and adaptable, investigating new architectures, and tackling special specific to the domain issues.

Here are some suggestions for additional study in this field: Investigate and create cutting-edge deep learning architectures intended for picture denoising. Examine the application of transfer learning strategies to modify learned models for denoising applications. Create denoising models that are suited for particular image domains or kinds, such as photographs taken in low light, via satellite, underwater, or for medical purposes. Examine applying GANs to image denoising. Examine denoising techniques created especially for non-photorealistic images, including styled or digitally created artwork. To gain a deeper understanding of the characteristics of noise in different kinds of images, investigate noise modelling and characterization methods. To expedite the denoising process and increase its viability in real-time applications, investigate hardware acceleration approaches such as the use of specialised hardware like GPUs, TPUs, or bespoke accelerators. Create denoising approaches that can efficiently reduce image noise while protecting data that is important to privacy. Assess the resistance that denoising models are to hostile assaults. Examine interactive denoising techniques that allow users to influence the denoising process by offering comments. Provide real-time or low-latency denoising algorithms that can be used for mobile devices for real-time image enhancement or video denoising. Produce and uphold evaluation standards and benchmark datasets that faithfully capture the difficulties associated with denoising in the actual world. Examine ways to improve the readability and transparency of denoising models, particularly for major uses where decision arguments are essential.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The author wrote, reviewed and edited the content as needed and the author has not utilised artificial intelligence (AI) tools. The author takes full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

From the drafting of the problem to the final conclusions and solution, the author participated in every step of the current investigation.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The author has no conflicts of interest to declare.