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RESEARCH ARTICLE

IN-DEPTH EXPLORATION AND COMPARATIVE ASSESSMENT OF CUTTING-EDGE ALGORITHMS FOR IMPULSE NOISE ATTENUATION IN CORRUPTED VISUAL DATA

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Abstract – Image denoising is a vital process in image pre-processing, particularly for applications focused on image-based objectives. This process, which occurs during image acquisition and transmission, is crucial for enhancing image quality to facilitate subsequent analysis by medical image processing algorithms. Given its importance in improving medical images, image denoising has become a prominent research focus. This paper explores the latest advancements in denoising techniques specifically tailored for magnetic resonance imaging (MRI), offering a detailed examination of their publication details, underlying methodologies, strengths, limitations, and accuracy metrics, including peak signal-to-noise ratio (PSNR). The study provides a thorough review of contemporary denoising strategies proposed by researchers such as Taherkhani et al., Zhang et al., Yuan et al., and Chen et al., among others, presenting an in-depth survey of current denoising algorithms. Understanding these methods is critical for selecting robust denoising techniques capable of mitigating artifacts like salt-and-pepper noise, which is essential for effective medical image segmentation. This paper aims to provide valuable insights into denoising methodologies, thereby advancing MRI image processing in the medical domain.

Keywords *–Image Denoising, Magnetic Resonance Imaging (MRI), Medical Image Processing, Peak Signal-to-Noise Ratio (PSNR), Noise Reduction Algorithms.*

1. INTRODUCTION

Image denoising entails the reduction of noise in digital images, which can originate from various sources such as sensor limitations, transmission errors, or environmental factors [1]. A common type of noise is 'Salt and Pepper noise,' characterized by the presence of randomly distributed bright and dark pixels, resembling grains of salt and pepper, hence its name. Also known as impulse noise, Salt and Pepper noise can be introduced through multiple mechanisms, including transmission errors in digital images, electrical interference during image acquisition, or defects in image sensors [2]. This type of noise can significantly degrade image quality and impair its visual integrity. The noisy pixels appear as outliers in comparison to the surrounding pixels, resulting in a disruptive effect on the overall image [3]. Therefore, it is essential to remove or mitigate Salt and Pepper noise to restore the image to its original quality.

Various techniques are available for mitigating salt and pepper noise in images. A widely used method is the median filter, which substitutes each noisy pixel with the median value of its neighboring pixels. This technique is effective in reducing salt and pepper noise while preserving the image's edges and details. Another advanced method is the adaptive median filter, which dynamically adjusts the window size of the median filter according to the noise characteristics. This adaptability enhances the filter's performance in handling images with varying levels of noise [4].

Other noise reduction techniques include mean filtering, Gaussian filtering, and bilateral filtering. These approaches apply spatial filters to smooth out noise while striving to maintain essential image features. In addition to these conventional methods, more sophisticated techniques leveraging machine learning and deep learning—such as convolutional neural networks (CNNs)—have emerged for addressing salt and pepper noise [5]. These advanced methods utilize artificial intelligence to improve the image restoration process.

The choice of an effective noise removal technique is influenced by the specific characteristics of the noise, the desired degree of noise reduction, and the need to balance noise suppression with the preservation of image details.

Frequently, multiple methods must be tested to identify the optimal solution for a given image. This paper offers a comprehensive survey of image denoising methodologies, aiming to explore and assess these various approaches

2. LITERATURE REVIEW ON DENOISING TECHNIQUES

This survey paper examines eleven research studies focused on image denoising with an emphasis on salt and pepper noise. It includes detailed information such as author details, objectives, the principal algorithm used, descriptions of supporting algorithms, database names, and a comprehensive analysis of the merits and limitations of each study.

Taherkhani et al. [6] developed an algorithm utilizing Radial Basis Functions (RBFs) interpolation to estimate the intensities of corrupted pixels based on their neighboring pixels. This approach begins by estimating the intensity values of noisy pixels in the corrupted image using RBFs, followed by a smoothing process. The algorithm was tested on four standard 8-bit grayscale images: ‘Boat,’ ‘Peppers,’ ‘Gold Hill,’ and ‘Barbara.’ A key advantage of this method is its ability to restore images with enhanced visual quality, better edge definition, and preserved texture details. Additionally, the algorithm does not require parameter tuning through trial and error to achieve optimal results. However, a notable drawback is its ineffectiveness in addressing Gaussian and Speckle noise. Furthermore, excessive smoothing may lead to blurring, which can adversely affect texture areas.

Zhang et al. [7] introduced a data-driven algorithm for impulse noise removal using an Iterative Scheme-Inspired Network (ISIN). This network shifts the primary effort from the online optimization phase to a preliminary offline training stage, allowing it to be applied to new data using the learned parameters. The Berkeley Segmentation Dataset was utilized for testing. The advantage of this network lies in its efficient noise reduction capability through a straightforward iterative scheme. However, a drawback is that excessive smoothing may cause blurring in texture areas. Additionally, the network does not address the handling of multiple datasets.

Yuan et al. [8] proposed a model in the domain of regularization-based image processing featuring a novel sparse optimization technique known as l0TV-PADMM. This approach addresses the Total Variation (TV)-based restoration problem with `l0-norm data fidelity. Test images of size 512×512 were utilized in this model, and the entire implementation is conducted in MATLAB. The model's advantage lies in its improved handling of image denoising and deblurring in the presence of impulse noise. However, a limitation of this technique is its inefficiency with high-resolution images. Additionally, since the model is not implemented in C++, it exhibits slower performance.

Chen et al. [9] putforth an adaptive sequentially weighted median filter (ASWMF) designed for images affected by impulse noise. This method incorporates a noise detector that utilizes the 3σ principle of normal distribution alongside local intensity statistics. The ASWMF applies a sequentially weighted median filter with an adaptive neighborhood size, where the weights are determined based on the spatial distances from the central noisy pixel. The input datasets for testing include SET12, BSD68, and medical images. The advantage of the ASWMF lies in its superior performance compared to state-of-the-art filters in managing impulse noise, as well as its significantly reduced computational time. However, the filter faces challenges in real-time denoising applications and, being implemented in MATLAB rather than C++, exhibits slower processing speed.

Sonali et al. [10] presented a noise removal and contrast enhancement algorithm specifically for fundus images. This technique integrates various filters with the Contrast Limited Adaptive Histogram Equalization (CLAHE) method to address both denoising and enhancement issues in color fundus images. Initially, the fundus RGB image is decomposed into its red, green, and blue channels. Different filtering techniques, along with CLAHE, are applied to each channel to reduce noise and enhance contrast. The processed channels are then combined to produce an improved RGB fundus image. The technique uses RGB fundus images of size 605 x 700 from the STARE database for simulation. The advantages of this method include effective noise removal and contrast enhancement in fundus images, with performance metrics surpassing those of state-of-the-art methods. However, the technique is limited to the medical domain and specifically designed for fundus images. Additionally, it does not address the needs of color medical images outside this scope.

Jin et.al. [11] developed an Image Recovery Method (IRM) leveraging deep convolutional neural networks for the removal of impulse noise. This denoising framework employs two deep CNNs: a classifier network and a regression network. The classifier network is trained to identify noisy pixels within an image, while the regression network is designed to reconstruct the denoised image. The input images used for testing include Lena, Cameraman, Barbara, and Boat. The primary advantage of this method is its superior denoising performance. However, it is hindered by its high running time and increased computational complexity.

Zhang et al. [12] put forth an Exemplar-Based Image De-Noising Algorithm (EIDA) that demonstrates significant potential for image restoration. The method incorporates a parameterized surrogate of the l0 norm to address both low-rank and sparse constraints, with analytic solutions provided for the associated optimization problems. The algorithm is evaluated using Lansel’s benchmark dataset, focusing on grayscale images. The key advantage of EIDA is its superior performance in image restoration. However, the algorithm has limitations, including its applicability to only a single dataset and reduced efficiency with other types of images.

Sheela et al. [13] presented an Adaptive Switching Modified Decision-Based Unsymmetric Trimmed Median Filter (ASMDBUTMF) designed for noise reduction in grayscale MRI images affected by salt and pepper noise. This method adaptively selects overlapping windows for the noise reduction process, specifically targeting medical MRI images to minimize noise. The advantage of this technique is its potential use as a preprocessing step for scanning machines, enhancing robustness in noisy environments. However, the method is limited to MRI images and does not perform effectively with other types of images. Additionally, it does not address the removal of random noise types.

Li et al. [14] presented a method called the Densely Connected Network for Impulse Noise Removal (DNINR), which employs convolutional neural networks (CNNs) to learn pixel-distribution features from noisy images. This method is based on advanced non-linear learning and residual learning principles. The test images used include Barbara, Baboon, Boat, C-man, and Foreman. The primary advantage of DNINR is its superior performance in preserving edges and suppressing noise. However, the method encounters limitations when dealing with non-Gaussian noises, such as Poisson and Rician noise, and it suffers from high computational complexity.

Wang et al. [15] presented a method for detecting noise points in images using Fractional Differential Gradient (FDG), with an enhanced image denoising algorithm based on fractional integration. The method is evaluated using grayscale images, such as Lena. The advantage of this model is its effective noise removal while preserving image edge details. However, the model's performance is limited when applied to other types of images and is assessed with a relatively small number of test images.

Liu et al. [16] put forth a nonlinear Spline Adaptive Filter based on the Robust Geman-McClure Estimator (SAF-RGM). This algorithm employs a cost function derived from the Geman-McClure estimator and processes signals generated by a Gaussian process. The advantage of this filter is its superior stability in the presence of impulsive noise. However, the technique is characterized by high time consumption and significant computational complexity.

Golam Muktadir Mukti et al. [17] present a Mat Lab-based Noise Removal Technique (MNRT) for removing salt and pepper noise from brain MR image. The goodness of this technique is that this weighted median filter provides high quality images by removing salt and pepper noises. The drawback of this technique is that it loses its efficiency while working with the kernel size above three.

XuYan et al. [18] developed Unsupervised Image De-noising algorithm based on Generative Adversarial Networks (UIDGAN). The model employs perceptual loss and cycle-consistency loss to ensure consistency of content information which is considered it to be its shinning side. The drawback of this method is that it considers many parameters which in turn increases its complexity and processing time.

3. DISCUSSION AND ANNALYSIS

Table 1 reports the considered research papers about their author's name, publication, published year, and the core method that is implemented. The core method column indicates that the Densely Connected Network, Fractional Differential Gradient and Geman-McClure technologies dominated in the recent noise removal algorithm.

Table 1. Representation of publication information and core technology used

Author name	Publication	Year	Methodology Used
Taherkhani et al.	IET	2017	RBF
Zhang et al.	SPRINGER	2018	ISIN
Yuan et al.	IEEE	2018	*l*0*TV*-PADMM
Chen et al.	IEEE	2019	ASWMF
Sonali et al.	ELSEVIER	2019	CLAHE
Jin et.al.	ELSEVIER	2019	IRM
Zhang et al.	IEEE	2020	EIDA
Sheela et al.	ELSEVIER	2020	ASMDBUTMF
Li et al.	SPRINGER	2020	DNINR
Wang et al.	ELSEVIER	2020	FDG
Liu et al.	IEEE	2020	SAF-RGM
Mukti et al	IJRES	2022	MNRT
XuYan et al	JTPES	2024	UIDGAN

Table 2. Description of the merits and demerits of the reviewed methods

Method	Advantage	Disadvantage
Taherkhani et al. [6]	Higher visual quality	Gaussian and Speckle noises
Zhang et al. [7]	Noise reduction with the simple iterative scheme	Not tested for multiple datasets
Yuan et al. [8]	Problem of de-blurring is addressed in a better manner	Not efficient for high resolution images
Chen et al. [9]	Low computational time	Not supportive for applied for real time de-noising
Sonali et al. [10]	Remove noises and enhance contrast in fundus images	color medical images is not addressed
Jin et.al. [11]	Better denoising performance	Higher computational complexity.
Zhang et al. [12]	Image restoration is better	Not supportive for other type of images
Sheela et al. [13]	shows better Better robustness	Random noises cannot be removed
Li et al. [14]	Better performance on edge preservation and noise suppression	Non-Gaussian noises like Poisson noise and Rician noise cannot be supported
Wang et al. [15]	Preserves the details of image edges in a better manner	Evaluated only by the minimum quantity of test images.

Liu et al. [16]	Better performance against impulsive noise	High time consumption and high computational complexity.
Mukti et al. [17]	It provides high quality images by removing salt and pepper noises	It loses its efficiency while working with the kernel size above three
XuYan et al. [18]	The consistency of content information is maintained	It considers many parameters which in turn increases its complexity

Table 2 discusses the advantages and disadvantages of considered research papers. This analysis reveals that the recent advantages of the researches on denoising are detail preservation and edge structure preservation. Also, the recent papers in denoising field suffers based on the demerits like high computational complexity and incapable in high resolution images.

Table 3. PSNR analysis for 50% of noise pollution

Methods	PSNR (in db)
[6]	26.91
[7]	26.81
[8]	26.93
[9]	27.19
[10]	27.22
[11]	27.08
[12]	27.51
[13]	27.18
[14]	28.20
[15]	28.41
[16]	28.53
[17]	29.83
[18]	30.22

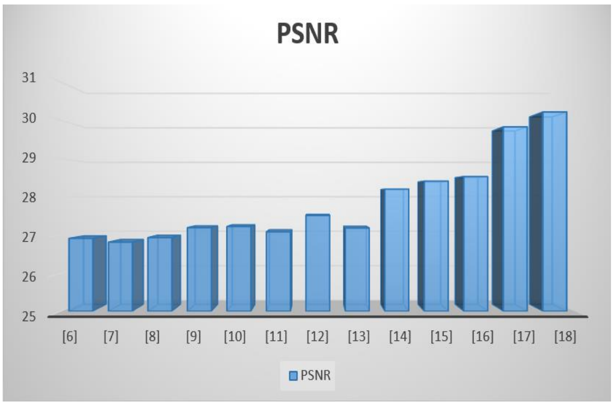

Figure 1. Representation of PSNR for 50% of noise corruption**.**

Table 3 and Figure 1 focus on the peak signal to noise ratio (PSNR) of the research papers on denoising. The authors Wang et al. and Liu et al. designed the two effective methods on requiring impulse noises which are proved by the PSNR results.

4. CONCLUSION

This survey paper examines recent advancements in noise reduction techniques, with a focus on various impulse noise suppression strategies. It provides an in-depth analysis of eleven denoising methods to elucidate the underlying principles of existing approaches. The research findings indicate that the methods developed by Wang et al. and Liu et al. demonstrate superior denoising performance, particularly in terms of PSNR. In contrast, the denoising technique proposed by Taherkhani et al. is found to be less effective compared to other methods. A thorough understanding of the noise characteristics and the degree of image degradation is crucial for selecting the most suitable filters and algorithms.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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