A Review of Nonlinear Image-Denoising Techniques

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***Abstract*—This paper discusses different nonlinear techniques for removing noise from images; i.e., image denoising. These techniques differ in terms of algorithm design, purpose, effectiveness, and efficiency. In this paper, different denoising techniques are described briefly where their advantages and disadvantages are discussed. The performances of these techniques are analyzed and compared according to different implementations using statistical methods. Finally, the paper infers when each denoising method is most effective what type of noise each method can handle effectively.**

Keywords—Denoising filter, Bilateral filter, Anisotropic diffusion, Nonlocal means filter, Median filter, Block-matching 3D transform

I. INTRODUCTION

Image enhancement is one of the most important and challenging fields in digital image processing. Image enhancement techniques, also known as image enhancement filter, include eliminating noise, adjusting colors, and adjusting light intensity.

There are two main purposes for image enhancement filters. The first is filter smoothing, which usually focuses on noise reduction. The other purpose is sharpening the image, by improving its fine details such as lines and edges. These two purposes often contradict one another. For example, smoothing an image may have a blurring effect and could remove fine details. Therefore, a tradeoff between smoothing and sharpening must be realized.

Image noise is an unwanted variation of brightness or color information in an image that degrades its quality. The noise affecting an image may take a random or a nonrandom pattern, depending on the source of that noise. For example, Gaussian noise is usually caused by variations of illumination and temperature during image acquisition, and it is characterized by a probability density function. Variations of this type of noise include white Gaussian and thermal noise. If the noise follows a Rice probability distribution, it is called Rician noise. Illumination problems may also create fog noise, which appears as a white blur shadowing the image. Salt and pepper noise appears as dark and bright spots, and it is often caused by image conversion errors. When noise is significantly related to image orientation, such as row noise or column noise, it is called an anisotropic noise. Speckle or granular noise appears in images acquired using radar, ultrasound, or optical coherence tomography devices due to the effect that different objects have on the image acquisition process.

As there are many types of noise affecting images, there are many techniques used to enhance the quality of these images and remove the noise. To remove the noise, the denoising processes should use one or more techniques, usually known as denoising filters. This paper discusses and compares different nonlinear filters that reduce noise without removing important details from the image such as edges and lines.

A Bilateral Filter (BF) is a nonlinear and non-iterative filter that considers neighboring pixels' geometric closeness and gray level similarities to determine the modified value of the pixel in its neighborhood.

An Anisotropic Diffusion (AD) filter, also known as Perona–Malik diffusion, is a technique that attempts to remove noise by smoothing or blurring the image without degrading significant contents. Similarly, a Median Filter (MF) attempts to preserve significant contents while removing the noise.

A Non-Local Means (NLM) filter is a denoising image-processing algorithm that uses weighted averages computed using all pixel values in the image.

A Wiener filter is an adaptive filter that involves linear estimation of a non-noisy signal sequence using a noisy one. It is successful in removing additive noise when the noise consists of stationary linear random processes with known spectral characteristics, and less effective in general cases [1]. It is a linear filter, but it may be enhanced with a nonlinear extension or combined with nonlinear filters.

A Block-Matching Three-Dimensional (BM3D) filter groups image fragments of the same size based on similarity. The BM3D algorithm was extended to perform decoupled deblurring and denoising.

In the next section, each of the above filters is described briefly with its advantages and disadvantages, and the differences among the filters are highlighted. Then, different variations and implementations of the filters are evaluated using measures that include Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

The MSE for two images, stored in matrices A and B, is computed as in (1):

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A[i,j]-B[i,j]\right)^2 . \tag{1}$$

The Root MSE and Normalized Root MSE are commonly used variations of MSE. In addition, PSNR is a meaningful measure of image quality based on MSE. It is computed as in (2):

$$PSNR = 10\log_{10}\left(MAX^{2} / MSE\right), \qquad (2)$$

where *MAX* is the maximum pixel value of the image, and the PSNR measurement unit is the decibel (dB). SSIM measures the perceived quality of digital images and videos or measures the similarity between two images by focusing on structural information rather than absolute error. It may be used in measuring image quality based on an initial distortion-free image as reference. Lower MSE values and higher PSNR and SSIM values are desired for filtered images since they indicate less noise and better quality.

Previous comparative analyses work on denoising algorithms was mostly focused on finding the best technique among different denoising strategies handling the same noise type. In contrast, this paper mainly aims at classifying denoising techniques in terms of the noise types they can handle better than others do, where PSNR and SSIM are used to measure the effectiveness of these techniques.

II. DENOISING IMAGE TECHNIQUES

A. Bilateral Filter (BF)

This filter attempts to preserve the sharpness of edges while smoothing the image to reduce the noise. The intensity of each pixel is replaced with a weighted average of intensity values from neighboring pixels. These weights are based on radiometric differences between the pixels such as depth distance and color intensity.

BF is generally more successful than traditional filters in removing noise without degrading edge quality, but its effectiveness depends on the selection of the neighborhood, the intensity of the pixels, and the spatial-domain weights [2,3]. Since achieving an optimal tradeoff between these parameters is a challenging task, this filter often fails to detect fine edges. However, BF is generally effective in denoising medical images [4].

B. Anisotropic Diffusion (AD) Filter

Anisotropic Diffusion (AD) is a technique designed to reduce image confusion without removing important parts of image content such as edges, lines, and small details. It has applications in medical imaging, especially with ultrasound. The anisotropic diffusion process creates a scale space, where an image generates a parameterized set of increasingly blurred images based on a diffusion process.

In color images, the noisy image is preprocessed by finding the technical limits of the colors where each color is treated as a separate part of the image. This step preserves the color border of the image. A detailed description of AD steps with the related equations is available in [5]. Although this technique was effective with color images, it was not effective with black and white images.

Due to the high space complexity of AD in animation, a technique was presented by [6] to save memory space by ignoring animated images and showing only still images or vice versa. This was useful with some applications, but it had limited success in general cases.

C. Non-local means (NLM) filter

NLM is a nonlinear filter widely used in digital image processing to reduce noise. It has many applications, especially in medical and MRI images. It averages the similar pixels (or voxels) in the image based on the intensity distance to regain the single noiseless pixel value.

In contrast, a “local means” filter takes the mean value of a group of pixels surrounding a target pixel to smooth the image, where a “non-local means” filter takes the mean value of all pixels in the image, weighted by how similar these pixels are to the target pixel. This process results in much greater post-filtering clarity and less loss of detail in the image compared with “local mean” algorithms.

Therefore, NLM is a powerful way to reduce noise while preserving the important details in the image. It may be applied to MRI images to contribute to accurate medical diagnosis. It is effective with Gaussian noise, Rician noise, and salt and pepper noise. Even though it produces good results, demonstrated by high PSNR and SSIM values, it involves complex calculations to determine the weights of pixels, requiring a relatively high time complexity. This becomes a more noticeable problem with large images and images that have high noise density. Nevertheless, it requires less execution time compared to other nonlinear filters such as BF and AD [2,7-9].

NLM may be combined with many other denoising techniques as a preprocessing or post-processing step, producing a more powerful filter such as Unbiased NLM (UNLM), Spatially Adaptive NLM (SANLM), and principal component analysis NLM (PCA-NLM) [9].

Examining results from different implementations [2,7-9], this technique appears to be successful in removing noise from images, demonstrated by low MSE and high PSNR values, with excellent visual interpretation indicated by very high SSIM values. See Table I for some detailed values. Execution time was long as expected, but it was less than that of AD and BF.

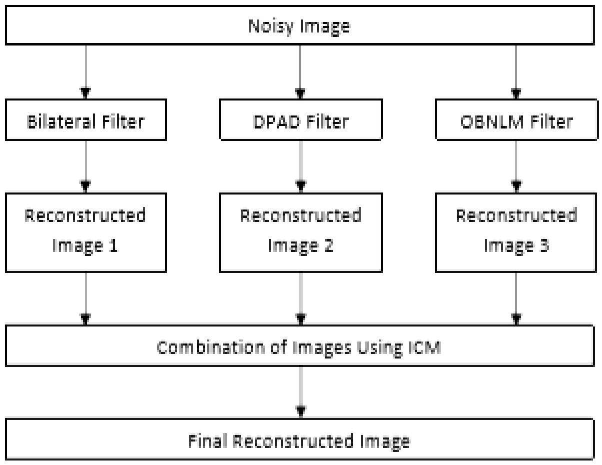

Fig. 1. Flowchart of denoising method presented by [10].

Reference [10] presented a way to reduce noise in the images taken by ultrasonic waves by combining different technologies together to produce an image-denoising filter. Three filters used in this method are BF, Detail Preserving AD (DPAD) and Optimized Bayesian NLM (OBNLM) which are used for speckle denoising of homogeneous, detail, and edge regions respectively. These three filters are combined using an Intensity Classifier Map (ICM). The flowchart of this denoising method is shown in Fig. 1.

D. Median Filter (MF)

A Median Filter (MF) is a nonlinear digital denoising and smoothing filter that replaces the value of each pixel in the image by the median of the values of its neighbors. It is often used as a preprocessing step with other image processing algorithms. Nonetheless, it preserves fine image details only in special cases, and it is inefficient with images of small size or high noise density [1]. Furthermore, it is relatively expensive in terms of time complexity [11].

The basic model of this filter is the Standard Median Filter (SMF). The Adaptive Median Filter (AMF) [11,12] is an improvement over SMF that can be used with windows of different sizes. AMF compares each pixel to its neighbors based on a threshold, where the threshold and the size of the neighborhood are adjustable parameters. If a pixel appears different from its neighbors according to the specified parameters, it is classified as a noise pixel and replaced by the median of the non-noise pixels in the neighborhood. Classification of pixels as noise or non-noise is critical to the performance of this filter.

AMF is inefficient with images having high noise densities, where fine details and edges do not appear clearly after filtering [11,12]. The main reason for this problem is the undeliberate replacement of non-noise pixels during the denoising process. To enhance AMF further, [12] presented a Proposed AMF (PAMF) that uses pixels from outside the neighbors' window in computing the median value. This method increased efficiency of noise removal in images with high-density noise.

In a different attempt to handle higher noise density, [11] developed a decision-based image-denoising algorithm. However, this algorithm replaced too many pixels, including some original non-noise pixels, in images of higher noise density. This over-replacement produced an undesired streaking effect. To overcome this drawback, they developed a Modified Decision-Based Unsymmetric Trimmed Median Filter (MDBUTMF), which produced better results at higher noise densities.

Reference [1] combined MF, Wiener filter, and BF to produce one special filter that was able to remove mixed noise better than using any of these filters alone.

E. Block-Matching 3D (BM3D) Transform Filter

In block matching, a fragment is added to a group if its dissimilarity with a reference fragment for that group falls below a specified threshold. Block matching is typically used to group similar blocks across different frames of a digital video. However, it may be used to group macroblocks within a single frame where each group of image fragments is stacked together to form a 3D cylinder-like shape. In a Block-Matching Three-Dimensional (BM3D) transform filter, image fragments are grouped together based on similarity, where the image fragments have the same size and are not necessarily disjoint.

Reference [13] divided the noisy image into several sub-images depending on the noise ratio, and then used a BM3D filter on the sub-images. They combined sliding-window transform processing with BM3D and Wiener filtering to produce a better filter that maintains good visual quality even for relatively high levels of noise. This combined filter was able to preserve fine details while removing high-density white Gaussian noise. For salt and pepper noise, a different technique was developed by [14], but it was only tested with low-density noise.

III. RESULTS

A comparison was made between the nonlinear denoising filters discussed in this paper. The comparison was based on different implementations where PSNR and SSIM values were considered when they were provided by the references. The data for this comparison are summarized in Table I. Recall that higher PSNR and SSIM values indicate better denoising performance. The following points can be determined from the table and the previous discussions:

- BF is better suited for Rician noise than Gaussian noise, and it is generally better for filtering medical images than other filters.
- Speckle noise is difficult to remove and denoising it generally produces less effective results than removing Gaussian, Rician, and salt and pepper noise types.
- Denoising Speckle noise is more effective with AD than with other filters, but AD may be combined with other filters to enhance its performance.
- NLM is effective with different types of noise, and it requires less execution time than BF and AD. Many variations of this filter were designed to increase its effectiveness and time efficiency.
- MF is better suited for removing salt and pepper noise, where variations of this filter were designed to enhance its performance. However, BM3D outperformed MF at low-density noise removal.
- BM3D is better suited for removing white Gaussian noise, even with high noise standard deviation (σ).

To realize the effectiveness of the discussed filters further, their best PSNR and SSIM values obtained with low noise density are illustrated in Fig. 2 and Fig. 3, respectively, where "Combo" is a combination of BF, AD, and NLM filters. As seen in the figures, combining BF, AD, and NLM filters did not result in values outperforming those of the individual filters. The combination produced medium results, ranging between the best and worst values obtained with each of these three filters individually.

Overall, when comparing the six filters illustrated in Fig. 2 and Fig. 3, it can be observed that a filter outperforming another one in terms of PSNR may not outperform it in terms of SSIM, and vice versa. Consequently, the choice of filter could be affected by the users' goals and the applications utilizing the filter. For example, the effects of picture format and contents on MF performance in removing salt-and-pepper noise were discussed by [15]. Alternatively, [16] focused on modifying the AMF to suit natural images, and [17,18] studied the effectiveness of different filters in denoising specific types of medical images.

IV. CONCLUSIONS AND FUTURE WORK

Different image denoising techniques were discussed with their advantages and disadvantages. Different implementations of these techniques were presented and compared. The results of the comparison showed that each method is suited for a different type of noise, where these methods may be modified or combined to produce better denoising results. In addition, some methods outperform others in specific applications such as medical image denoising.

For future work, filters can be improved to enhance denoising quality and decrease space and time complexity. Different filters may be combined and tested with special denoising applications including medical, security camera, satellite, and space-telescope images and videos.

A different but related future research idea could utilize denoising filter properties to enhance image encryption. As seen in [19-24], the objectives of a successful image encryption include achieving higher MSE values and lower PSNR and SSIM values because that would indicate more noise and better encryption. Since this involves the opposite of the denoising objectives, inverting denoising procedures to increase noise using a reversible procedure should benefit the encryption process. However, it is unlikely for this to be a lossless procedure, and a tradeoff must be made between loss of details and effective encryption.

TABLE I. PSNR AND SSIM VALUES FOR DIFFERENT IMPLEMENTATIONS OF BF, AD, NLM, MF, AND BM3D FILTERS

Reference	FILTER	NOISE TYPE	PSNR	SSIM
[2]	BF	Rician	5% Noise ⇒ 20.86 30% Noise ⇒ 14.96	5% Noise ⇒ 0.5488 30% Noise ⇒0.1535
		Gaussian	5% Noise ⇒ 16.45 30% Noise ⇒ 10.88	5% Noise ⇒ 0.1914 30% Noise ⇒ 0.1448
[2]	AD	Rician	5% Noise ⇒ 24.49 30% Noise ⇒ 13.62	5% Noise ⇒ 0.5000 30% Noise ⇒ 0.0662
		Gaussian	5% Noise ⇒ 15.54 30% Noise ⇒ 9.96	5% Noise ⇒ 0.1115 30% Noise ⇒ 0.447
[5]	AD	Speckle	Unavailable	0.8441
[6]	AD	Speckle	Unavailable	0.8814
[10]	AD	Speckle	23.9120	0.528
[7]	NLM	Rician	9% Noise ⇒ 29.26 11% Noise ⇒26.04 15% Noise ⇒25.65	9% Noise ⇒ 0.87 11% Noise ⇒ 0.876 15% Noise ⇒ 0.765
[8]	NLM – UNLM	Rician	6% Noise ⇒28.04 9% Noise ⇒ 24.27 12% Noise ⇒21.904 15% Noise ⇒19.95	6% Noise ⇒ 1.00 9% Noise ⇒ 0.9978 12% Noise ⇒ 0.961 15% Noise ⇒ 0.9929
[2]	NLM	Rician	5% Noise ⇒ 29.02 30% Noise ⇒ 14.30	5% Noise ⇒ 0.6365 30% Noise ⇒ 0.1906
		Gaussian	5% Noise ⇒ 23.28 30% Noise ⇒ 11.62	5% Noise ⇒ 0.887 30% Noise ⇒ 0.3584
[9]	NLM PCA-NLM NLM – SANLM	Mixed (Rician, Gaussian, Thermal, Fog, Salt and Pepper)	42.2083 42.7771 43.09	0.9486 0.9597 0.9701
[10]	Combined (BF + AD + NLM)	Speckle	27.1234	0.6767
[1]	MF	Mixed (Gaussian, Salt and Pepper, Speckle)	18.50	0.8441
[11]	MF – SMF	Salt and Pepper	10% Noise ⇒ 28.49 90% Noise ⇒ 6.57	Unavailable
	MF – AMF		10% Noise ⇒ 21.98 90% Noise ⇒ 8.06	
	MF – MDBUTMF		10% Noise ⇒ 38.12 90% Noise ⇒ 17.98	
[12]	MF – SMF	Salt and Pepper	30% Noise ⇒ 21.08 70% Noise ⇒ 9.52	Unavailable
	MF – AMF		30% Noise ⇒ 26.54 70% Noise ⇒ 17.60	
	MF – PAMF		30% Noise ⇒ 28.65 70% Noise ⇒ 20.81	
[13]	Combined (BM3D + Wiener)	White Gaussian	Noise σ = 5 ⇒ 38.63 Noise σ = 100 ⇒ 26.04	Unavailable
[14]	BM3D – PBM3D	Salt and Pepper	48 (approximated)	4% Noise ⇒ 0.61 5% Noise ⇒ 0.54 10% Noise ⇒ 0.47

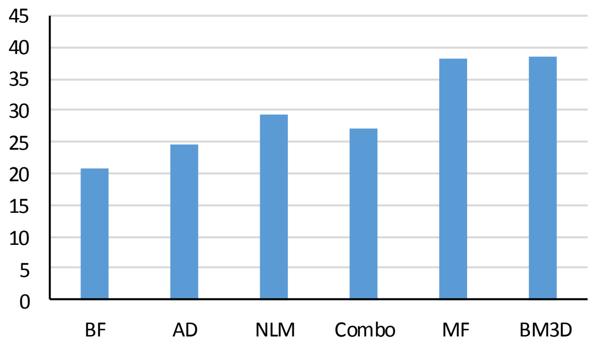

Fig. 2. PSNR values obtained after using different filters.

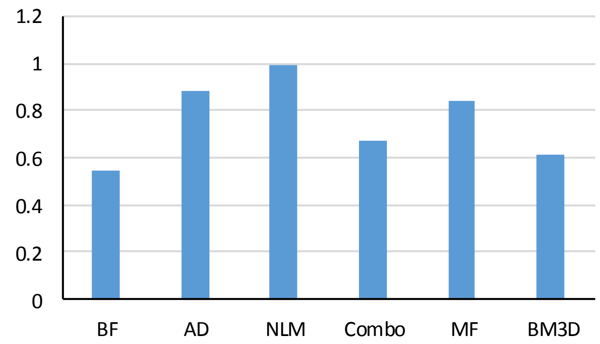

Fig. 3. SSIM values obtained after using different filters.

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