Denoising Algorithm Based on Anisotropic Diffusion with Vector Median Filtering

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Abstract:- **Traditional noise removal techniques couldn't well achieve the trade -off between preserving feature information and removing noise .This project proposed an improved Anisotropic Diffusion (AD) to improve their performance when dealing with multimodal noises in an image. To achieve this goal here propose the inclusion of Vector Median Filtering (VMF) into the formulation of anisotropic diffusion. The main contributions associated with this work are located in the inclusion of a multi-scale edge detector into the formulation of the Perona-Malik (PM) anisotropic diffusion scheme and in the implementation of a new noise removal framework that is able to restore digital images that are corrupted by Gaussian, impulse and photon noise. This noise removal scheme is quantitatively evaluated using standard metrics such as Peak Signal to Noise Ratio (PSNR), edge preservation index.**

Keywords: - Anisotropic Diffusion, Vector Median Filtering, multi-scale edge detector, edge preservation index.

I. INTRODUCTION

Images are frequently corrupted due to the presence of noise and loss of sharpness, during image transmission or acquisition. In the development of noise reduction algorithms basic knowledge about noise distribution is essential (where the most common are the Gaussian distributed and the impulse noise) and the main efforts were focused on the development of optimal strategies that addressed accurate image restoration for one particular noise model. Gaussian Noise is very commonly encountered in image acquisition, and it is characterized by adding a value from a zero-mean Gaussian distribution to each image pixel. The goal of denoising of an image is to remove the noise and to retain the important signal features as much as possible for sharpness enhancement.

Image noise is random variation of brightness or color information in images. Image is often contaminated by noise in the process of transmission, acquisition and storage, which results in the image degradation of the visual quality. The performance of imaging sensor is affected by variety of factors, such as by the quality of sensing elements themselves and environmental conditions during image acquisition. Images are corrupted during transmission due to interference in the channel used for transmission. It can be produced by the sensor and digital camera or circuitry of a scanner . Noise can originate in film grain and in the unavoidable photon noise of an ideal photon detector. Image noise is classified as Gaussian noise, Salt and Pepper noise, Quantization noise, Photon noise, and Film grain noise.

II. RELATED WORKS

One of the well-known algorithms for image denoising is anisotropic diffusion. Diffusion algorithms remove noise from an image by modifying the image via a partial differential equation. This method able to preserve the edges during denoising, but is not able to produce accurate result on different noises. Other denoising method is median filtering. This method specially designed to eliminate different types of noises but this denoising process has week feature preservation.

Nonlinear anisotropic diffusion filtering algorithm for multiscale edge enhancement has been explained in [8] by Stephen L. Keeling. This work is to develop nonlinear anisotropic diffusion filters which sharpen edges over a wide range of slope scales and which reduce noise while conserving feature boundaries. To this end, it has been found that while a greater diffusivity decay rate will create sharper edges in a narrower range of edge slopes, a more gradual diffusivity decay rate will sharpen edges over a wider range of edge slopes.

The basic concept of robustifying vector median filter has been explained in [7] by Samuel Morillas.et.al. This method describes two methods for impulse noise reduction in color images that outperform the vector median filter from the noise reduction capability point of view. But this process has week feature preservation. VMF attempts to minimize the distances between the intensities of the pixels situated within a predefined neighborhood.

III. PROPOSED METHOD

Many noise reduction schemes are decision-based median filters. This indicates that the noise pixels are first detected and are replaced by the median output or its variants. These techniques are very good because the uncorrupted pixels in a corrupted image will not be modified. The replacement methods in these noise reduction schemes cannot preserve the features of the images. Some other methods preserve edges during noise reduction but it has problem in detecting noisy patches.

In this regard, here propose the implementation of multi level smoothing algorithm for three types of noises. The first method able to preserve the edges during noise reduction, but is not able to produce accurate result on different noises. The second method specially designed to eliminate different types of noises but the noise reduction process has week feature preservation. The first method is Multi Scale -Anisotropic Diffusion (MS-AD) [4] and the second method is Vector Median Filtering [5] (VMF). Combining both methods will avoid the drawbacks of either one of them. The aims of this method are to correct images corrupted by multi modal noises and preserve edges in the image.

A) Multimodal noise model

The degraded image can be mathematically expressed by the following formulation

$$I(x,y) = F(x,y) * h(x,y) + \eta(x,y) \qquad (1)$$

Where I(x,y) is the degraded image, F(x,y) is the original image, η(x,y) is the noisy function, h(x,y) is the spatial representation of the degradation function ,. The noise model consists of three types of noise, Gaussian noise, Impulse noise and Photon noise. The image formation process can be expressed as follows

$$I(x,y) = \begin{cases} F(x,y) + \mathrm{N}(0,\sigma) \\ \sup_{(x,y)\in\Gamma} F(x,y) \\ \inf_{(x,y)\in\Gamma} F(x,y) \\ F(x,y) * h + N(\lambda t, \lambda t) \end{cases} \qquad (2)$$

where N (0, σ) is the Gaussian noise with zero mean and standard deviation σ, α is the probability of impulse noise, inf and sup are the infimum and supremum functions and λ is the photon rate respectively, and Γ is the R^2 image domain . The strength of the noise component in an image is controlled by two uncorrelated parameters, α and σ.

B) Anisotropic Diffusion (AD)

The noise reduction techniques based on anisotropic diffusion equations, the Perona–Malik (PM) [6] equation provides a better algorithm for image segmentation, edge detection, noise removal, and image enhancement. The basic idea behind the PM algorithm is

$$\partial I(x,y,t)/\partial t = div[D(|\nabla I(x,y,t)|)\nabla I(x,y,t)] \qquad (3)$$

where I (x, y) is the image at time t, *div*(.) represents the divergence operating, ∇I (x, y, t) is the gradient of the image, and *D*(∇I (x, y)) represents the diffusion coefficient denoted as *D*(*s*) . In this model, the diffusion coefficient D(*s*) is a nonnegative monotonous decreasing function. A typical choice is as follows

$$D(|\nabla I(x,y,t)|) = e^{-(|\nabla I(x,y,t)|/c)^2}$$

$$(4)$$

$$D(|\nabla I(x,y,t)|) = \frac{1}{1 + (|\nabla I(x,y,t)|/c)^2}$$

Where c is the diffusion parameter that controls the strength of the filtering process.

C) Multi Scale Edge Detectors

The structure tensor is calculated for each pixel at the specified scale k in the image as follows

$$M_k(x,y) = \sum\left[\nabla f(x,y)\nabla f(x,y)^T\right] \qquad (5)$$

The next step contains the eigenvector decomposition of the matrix M_k(x, y) to determine the Eigen values λ_1^k and λ_2^k , $\lambda_1^k >> \lambda_2^k$ and $\lambda_1^k >> 0$, then the pixel is an edge and the multi-scale edge response is calculated as follows

$$E(x,y) = \int_{k\in[0,s]} sqrt(\lambda_1^{\,k})dk \qquad (6)$$

Where λ_1^k is the Eigen value.

$$\lambda_1^k = \max\{eig[M_k(x,y)]\} \qquad (7)$$

D) Vector Median Filtering

VMF minimize the distances between the intensities of the pixels situated within a predefined neighborhood in order to implement impulse noise suppression. VMF calculate the distances between the intensity values of the pixels situated in a neighborhood ψ around the central pixels (x, y) as follows

$$L_{(x,y)\in\Psi} = \sum_{(m,n)\in\psi} \|I(p,q) - I(m,n)\| \qquad (8)$$

where $\|.\|$ defines the L_2 norm

VMF performs the ordering of the L_{pq} values in increasing order and the intensity of the central pixels of the neighborhood ψ, I(x, y), is replaced by the intensity of the pixel that has minimum value in the $\{L_{pq}(p,q)\in\psi\}$ set.

$$I(x,y) = I(\arg_{(p,q)} \min(L_{pq})) \qquad (9)$$

E) Combination of MS-AD and VMF noise removal techniques

In the proposed noise removal scheme the impulse noise estimator (N_e) [8] has been implemented as follows

$$N_e = \left\| I(x_c, y_c) - \frac{1}{size(\Omega) - 1} \sum_{(x,y)\in\Omega\setminus(x_c,y_c)} I(x,y) \right\| \qquad (10)$$

Where size(Ω) denotes the cardinality of the neighborhood ψ and (x_c, y_c) defines the coordinate of the centre of the neighborhood Ω. The noise estimator [5] is calculated for each pixel in the image and if the value of N_e is higher than a predefined threshold j ($N_e \geq j$) then the pixel is assumed to be corrupted by multimodal noise.

In this method, the output of the noise estimator gives the decision rule that selects the noise removal technique that is applied to each pixel in the image. If the value of noise estimator Ne calculated for the pixel (x, y) is higher than the predefined threshold value j, then the value of the pixel will be updated using the VMF filtering scheme. Otherwise, this will be updated using the MultiScale-AD approach. The value of the threshold parameter j should be set in the interval [140, 250].

IV. EXPERIMENTAL RESULTS

The tests were conducted on different images of size 256×256. All images were corrupted by multimodal noises and the performance of the proposed filtering scheme is quantitatively evaluated using the Peak Signal to Noise Ratio (PSNR).

$$PSNR = 10\log_{10}\frac{\max_{(x,y)\in\Gamma}(I(x,y))^2}{(1/size(\Gamma))\int\limits_{(x,y)\in\Gamma}\|O(x,y)-I(x,y)\|^2\,dxdy} \quad (11)$$

where O(x, y) defines the pixel intensities of the original image O and I(x, y) are the pixel intensities resulting after the data smoothing algorithms were applied to the image that was corrupted by multimodal noise, $\Gamma \subset R^2$ is the image domain,. The edge preservation index (E_{pi}) is

$$E_{pi} = \frac{\Lambda(O-\overline{O}, I-\overline{I})}{\sqrt{\Lambda(O-\overline{O}, O-\overline{O})\Lambda(I-\overline{I}, I-\overline{I})}} \quad (12)$$

where I define the image resulting from smoothing process, O is the original image, $\overline{O}$ and $\overline{I}$ are the mean intensity values calculated from images O and I, respectively and $\Lambda(q,r) = \sum_{(x,y)\in\Gamma} q(x,y)r(x,y)$. The E_{pi} value is normalized in the interval [0, 1] and a value closer to one indicates accurate edge preservation attained by the data smoothing algorithm.

The experimental tests reported results when the performance of the MS-AD VMF algorithm has been compared against those offered by the MS-AD and VMF techniques. The first set of experiments was conducted on test images corrupted by Gaussian and impulse noise and evaluated using PSNR metric and E_{pi} value. The second set of experiments was conducted on test images corrupted by Gaussian, impulse and photon noise and evaluated using PSNR metric and E_{pi} value. The results indicate that the MS-AD VMF image restoration strategy outperforms the VMF and MS-AD noise removal methods because of its ability to locally adapt to the characteristics of image noise.

In Figure 1, (a) shows the original image, (b) shows test Image corrupted by Gaussian noise, Impulse noise and Photon noise, (c) shows the result of MS-AD method,(d) shows the result of VMF method, and (e) shows the result of the proposed MS- AD VMF image restoration method. This technique outperforms the VMF and MS-AD noise removal techniques.

V. CONCLUSIONS

The multi-phase noise removing scheme that is able to restore digital images corrupted by multimodal noise has been implemented. The inclusion of VMF into the formulation of AD produced a more robust noise removal scheme that is able to eliminate different types of noises and also preserve feature. This noise reduction scheme was quantitatively evaluated using standard parameters such as PSNR, Epi and its performance has also been assessed when applied to different images. PSNR value of MS-AD VMF method is higher than that of MS-AD and VMF methods. E_{pi} value closer to 1 indicates that accurate edge preservation was attained by this data smoothing algorithm.

The future works will focus on the development of more accurate models that can be applied to detect the pixels that are corrupted by non-Gaussian distributed noise and additional work will be concerned with the removal of noises in a color image.


a b


c d

e

Figure 1 Experimental Results in Presence of Gaussian, Impulse Noise and Photon Noise - Cameraman Image

a. Original Image
b. Test Image Corrupted by Gaussian Noise (N(0, 20)), Impulse Noise

(α- 0.2) and Photon Noise

c. MS-AD Image
d. VMF Image
e. MS-AD VMF Image

Table 1 Quantitative Results in Presence of Gaussian, Impulse Noise and Photon Noise

IMAGES	METHODS	NOISE LEVEL	PSNR in dB	E_{pi}
Lena.jpg	Without any filter	N(0,20) & α=0.2	11.87	0.8376
	MS-AD		16.51	0.8700
	VMF		19.81	0.8928
	MS-AD-VMF		24.97	0.8943
Eagle.jpg	Without any filter	N(0,20) & α=0.2	11.83	0.7698
	MS-AD		16.57	0.7942
	VMF		19.45	0.8064
	MS-AD-VMF		24.52	0.8899
Cameraman.tif	Without any filter	N(0,20) & α=0.2	11.81	0.7818
	MS-AD		16.57	0.8309
	VMF		19.32	0.8411
	MS-AD-VMF		24.35	0.9500
Sample picture.jpg	Without any filter	N(0,20) & α=0.2	12.02	0.8056
	MS-AD		15.88	0.8602
	VMF		19.92	0.8604
	MS-AD-VMF		25.92	0.8816

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