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A Hybrid Image Denoising Technique based on FNLM and Wavelet Thresholding

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ABSTRACT: Image denoising constitutes the first step in image processing domain. In order to solve this frequently occurring problem various methods have been proposed. In this paper a denoising algorithm is proposed which uses the combination of Fast Non-Local means filter (FNLM) and adaptive wavelet thresholding. The performance of FNLM filter deteriorates with the increase of noise amount in the image. This hybrid approach solves this problem. Firstly, the image is denoised by the FNLM filter and then its method noise is obtained. The method noise is subjected to adaptive wavelet thresholding for extracting the image details that were removed by the FNLM filter. These extracted details are added to the output of FNLM filter and a noise free image is recovered with all the edges and image details preserved.

KEYWORDS: adaptive thresholding; method noise; BayesShrink; fast non local means

I. INTRODUCTION

With the increase in use of digital imaging in all the fields, the need of noise free data has increased many folds. Researchers have developed many new ways to prevent the contamination of noise but no method has given absolute results, so there's always a room for denoising. Noise removal is a very delicate process because along with the suppression of noise image details are required to be kept intact. A noisy image can be represented as eq.(1).

$$s(i,j) = o(i,j) + n(i,j) \qquad \text{eq.(1)}$$

Where s(i,j) is the observed image, o(i,j) is the original image and n(i,j) is the noise component affecting the noise with (i,j) representing the pixel value.

II. RELATED WORK

In case the image data is not very crucial, simple spatial filtering can be performed to remove the high frequency noise. Several spatial filtering techniques have been proposed so far such as a mean filter [1] which performs the smoothening operation by convolving the noisy image with a filter mask. Due to the flaw of over smoothening the image mean filter is not very popular. Non linear spatial filters are quite useful in suppressing the noise, such as non local means filter proposed in [2]. It performs weighted averaging based on structural similarity concept [3]. In [4] an improved non-local means (NLM) filter for image denoising is proposed. It first pre-processes the noisy image by Gaussian filter. Then, a moving window at each pixel of the noisy image is chosen as the search window, and meanwhile, an improved calculation method of spatial distance based on the pre-processed image is used for computing the similarity. Finally, combining the improved distance with search window based on the noisy image, the intensity of each pixel is restored as the traditional NLM method proposed in [2].

Although spatial filtering is a very effective noise removal technique it has high computational complexity. This problem is solved by utilizing Frequency domain methods as explained in [5] which convert the convolution in spatial domain to simple multiplication. In the last few years wavelet transform has become a very popular denoising technique because of it multi-resolution and energy compactness properties [5]. In [6] an improved method in the wavelet sub-band domain is proposed. It is based on threshold estimation for each sub-band of the wavelet decomposition of a noisy image. In [7] an adaptive thresholding technique is proposed. The main idea behind this proposal was to do thresholding based on the noise content present in the particular sub band. In [8] a hybrid technique is proposed which combines wavelet and Curvelet transform for denoising.

In this paper a simple hybrid image denoising algorithm is presented. It uses a combination of spatial and transform domain filtering. It implements Fast Non Local means filter for denoising followed by the thresholding of the method noise.

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In section II Non Local means filter proposed by Buades et al. in [2] and Fast Non Local means as proposed in [9] are discussed followed by Wavelet thresholding in section III. Section IV of this paper deals with the proposed methodology. The experimental results and conclusion are presented in section V and VI respectively

III. NON LOCAL MEANS FILTERING

In [2] Buades et al. proposed a denoising algorithm that explores the self similarity property of the natural images for weighted averaging. Unlike mean filtering where the noisy pixel is replaced with the average of the neighborhood window, in NLM filtering the noisy pixel is replaced with the weighted average of the pixels having similar neighborhood.

Given a discrete noisy image $s = \{s(i)|\ i \in I\}$, the denoised value NL[s](i), for a pixel I, is computed as the weighted average of all the similar pixels.

$$\mathrm{NLs}(i) = \sum_{j\epsilon I} w(i,j)s(j) \qquad \text{eq. (2)}$$

Where the family of weights w(i,j) depends upon the similarity between pixel i and j, satisfying the criteria $0 \le w(i,j) \le 1$ and $\sum_q w(i,j) = 1$. The weight calculation is given by eq.(3).

$$w(i,j) = \frac{1}{Z(i)} e^{-\frac{\left\|u(N_i)-u(N_j)\right\|^2}{h^2}} \qquad \text{eq.(3)}$$

The similarity between pixel i and j depends upon the similarity between $v(N_i)$ and $v(N_j)$, representing the intensity gray level vectors of pixel i and j respectively. Here N_k denotes a square neighborhood centered at pixel k, Z(i) is the normalizing constant and h is the degree of filtering.

The denoising result obtained using NLM filter is quite good but the processing time of this algorithm is quite high. It takes M^2*n^2 calculations for processing the value of a single pixel, where M denotes the size of search window and n denotes the size of the image. to solve this problem Fast Non Local Means(FNLM) filter was developed. Not only the processing time is less but the visual quality is also improved.

The concept behind the development of FNLM filter as described in [10] is the rejection of dissimilar windows. This rejection is done by assigning zero weights to those windows which do not satisfy the pre-decided similarity threshold value. A predefined mean and variance threshold is selected then the mean and variance of all the patches that lie in the search window are compared to it. In case it does not satisfy the condition the weight is assigned zero value. If $\left|\mu_i - \mu_j\right| \le \Delta_\mu$ or $|\sigma_i - \sigma_j| \le \Delta_\sigma$ the window is considered to be similar. Where μ_i and σ_i are the mean and variance respectively, of the image to be denoised, μ_j and σ_j mean and variance respectively of the concerned window and Δ_μ and Δ_σ are the threshold values.

IV. WAVELET THRESHOLDING

Properties like sparseness, energy compactness, clustering etc. as described in [11] make wavelet thresholding an important tool for image denoising. The noisy image is transformed into wavelet domain that leads to the decomposition of the noisy image into sub-bands as shown in Fig.1. In sub-bands the coefficients with smaller value are more affected by noise. So a proper threshold value is chosen for the modification of the corrupted coefficients. There are many methods to estimate the threshold such as SureShrink, VisuShrink, BayesShrink [13]. The choice of the threshold estimation method depends upon the requirement. Once a proper threshold is estimated the noisy wavelet coefficients are discarded and only the required coefficients are kept intact and then inverse wavelet transform is applied on the modified coefficients to get the denoised image.

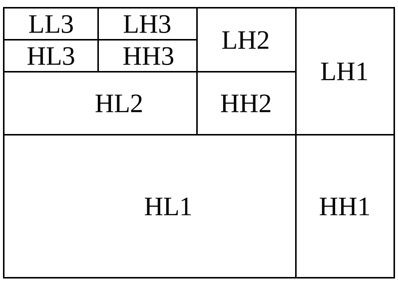

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Fig. 1. Two level discrete wavelet transform on 2D data

The sub bands HHk, HLk, LHk, k= 1,2…… ,j in Fig.1. are details, where k is the scale with j as the largest scale in decomposition. Thresholding is applied to the detail coefficients to remove unwanted coefficients as it is assumed that noise occupies the higher frequencies.

A. VisuShrink

Also known as the universal threshold method this technique estimates a universal threshold 'δ' for all sub-bands, which is proportional to the standard deviation of noise.

$$\delta = \sigma\sqrt{2\log n} \qquad \text{eq.(4)}$$

In eq.(4) σ is the standard deviation of the noise and n is the number of signal samples.

B. SureShrink Algorithm

In this technique threshold is determined for each sub-band by minimizing Stein's Unbiased Risk Estimate (SURE) for those coefficients. The goal of SureShrink is to minimize mean square error. SureShrink threshold $\delta*$ is defined mathematically in eq.(5).

$$\delta^* = \min\left(\delta, \sigma\sqrt{2\log n}\right) \qquad \text{eq. (5)}$$

Where, δ denotes the threshold value that minimizes Stein's Unbiased Risk Estimate. σ is the standard deviation of noise and n is the size of the sample image.

C. BayesShrink

This is the adaptive thresholding technique in which a separate threshold is decided for every sub-band as explained in eq.(6).

$$\delta_B = \frac{\sigma_n^2}{\sigma_s} \qquad \text{eq.(6)}$$

If σ_s is zero, it is set to a predefined value described in eq.(7).

$$\sqrt{\max\left(\sigma_y\right)^2 - (\sigma_n)^2, 0} \qquad \text{eq.(7)}$$

$$\sigma_y = \frac{1}{N}\left(\sum(W_n^2)\right) \qquad \text{eq.(8)}$$

Where, σ_n^2 is the noise variance estimated from sub band HH1 as $\text{median}(|W_n|/0.6745)$. W_n is the wavelet coefficients after subtracting mean and σ_s is the standard deviation of the signal without noise.

After selecting the threshold δ, hard, soft or trim thresholding can be performed as described in eq.(9), (10) and (11) respectively [12].

$$X = \begin{Bmatrix} \text{sign (Y)} \ \forall\ |Y| \geq \delta \\ \text{else } 0 \end{Bmatrix} \qquad \text{eq.(9)}$$

$$X = \begin{Bmatrix} \text{sign (Y)}.\left(|Y| - \delta\right) \ \forall\ |Y| \geq \delta \\ \text{else } 0 \end{Bmatrix} \qquad \text{eq.(10)}$$

$$X = \begin{Bmatrix} \text{sign (Y)}.\frac{|Y|^a - \delta^a}{|Y|^a} \ \forall\ |Y| \geq \delta \\ \text{else } 0 \end{Bmatrix} \qquad \text{eq.(11)}$$

Where Y is the noisy input coefficient and X is the modified coefficient.

V. PROPOSED METHOD

The FNLM filtering and Wavelet thresholding when used alone has some disadvantages such as FNLM over smoothens the image and wavelet thresholding loses the edge details. So a combination of both techniques is proposed that preserves both the inner image details and the boundary details.

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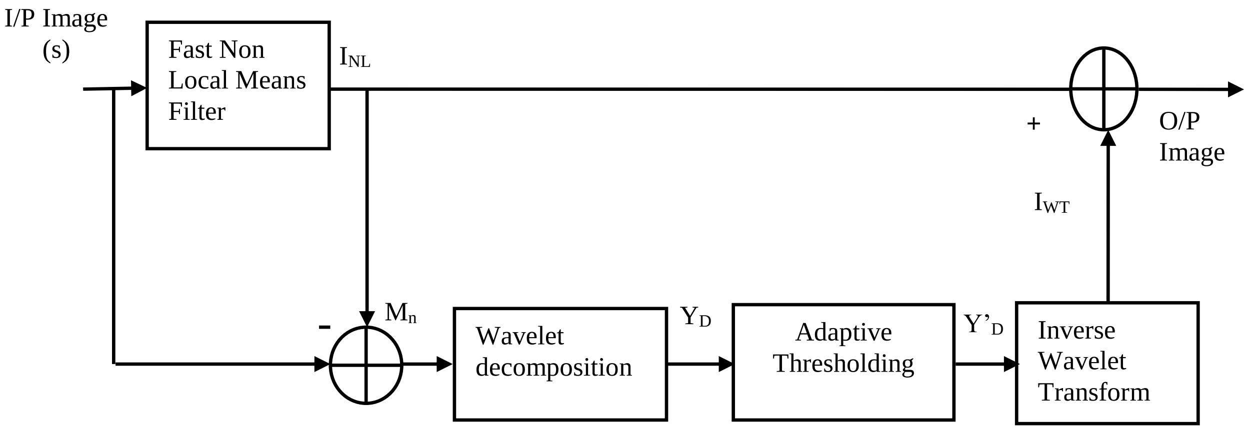

Fig. 2 Block diagram of the proposed method

VI. Simulation Results

Fig.2. is the lock diagram of the proposed denoising algorithm. In which the first step is to denoise the degraded Image 's' by using Fast NLM filter followed by Method Noise computation. The concept of method noise was introduced by Buades et al. [14].

$$M_n = s - I_{NL} \qquad \text{eq.(12)}$$

Here, s is the noisy image and I_{NL} is the output of Fast NLM filter as shown in Fig. 2. Method Noise M_n is considered to be a mixture of Gaussian Noise and detailed image components. The next step is to differentiate detailed image from Gaussian noise and it is achieved by applying Wavelet Transform on Method noise. In wavelet domain method noise is represented as eq.(13).

$$Y_D = Y'_D + N \qquad \text{eq.(13)}$$

Here, Y_D is the noisy wavelet coefficient of method noise. Y'_D detailed image coefficients and N is the noise coefficients.

After the computation of Y_D, the detailed image coefficients Y'_D are estimated. It is done by applying BayesShrink thresholding on the noisy wavelet coefficient. It minimizes mean square error and gives accurate detailed image coefficients Y'_D with original image features and sharp boundaries. Later Inverse wavelet transform is applied on the modified wavelet coefficients to get an estimate of detailed image I_{WT}. The final step consists of the summation of detailed image I_{WT} to the output of FNLM filter I_{NL}. The output obtained after the final step resembles the actual image. The boundaries and image details both are retained.

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VII. SIMULATION RESULTS

In order to analyse the proposed algorithm it is tested on natural gray scale test images. Then the proposed algorithm is compared to the existing NLM and FNLM filter in terms of PSNR value.

(a) (b)

Fig. 3 (a) Original image 1 (b) Original image 2

Fig.3 shows the two original test images used for analysing the proposed method. These are the natural gray scale images which are corrupted with Gaussian noise to check the efficiency of the proposed algorithm.

Table 1: Comparison of Traditional NLM filter, FNLM filter with the proposed denoising algorithm in terms of PSNR

Image(256*256)	PSNR		
σ_n = 10	NLM	FNLM	Proposed method
Image 1	35.41	78.6434	80.1981
Image 2	33.56	78.0069	80.1131
σ_n = 15			
Image 1	33.45	75.1574	78.6810
Image 2	32.81	76.9073	80.0415
σ_n=20			
Image 1	32.15	75.8870	76.7745
Image 2	31.64	77.5365	77.6614

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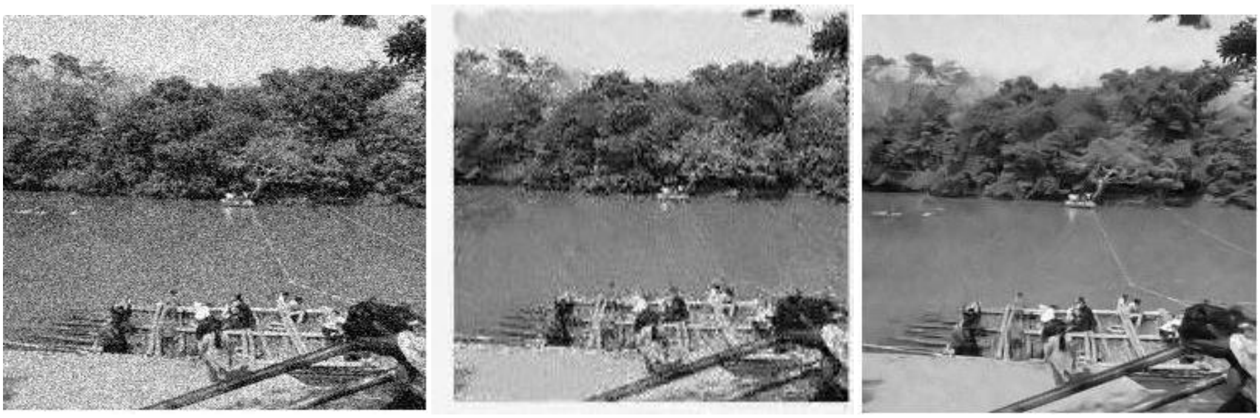
Table 1 illustrates the comparison of the traditional NLM filter, Fast Non Local Means filter with the proposed algorithm. It proves that the proposed algorithm outperforms the existing techniques in terms of PSNR.

(a) (b) (c)

Fig. 4 (a) Noisy image'1' σ_n=10 (b) Output of traditional NLM filter and (c) output of the proposed method.

Fig.4 illustrates Noisy image '1' corrupted with Gaussian noise having Standard deviation '10'and the results when it is subjected to traditional NLM filter and proposed algorithm.



(a) (b) (c)

Fig. 5 (a) Noisy image '2' σ_n=10 (b) Output of NLM filter and (c) output of the proposed method.

Fig.5 illustrates Noisy image '2' corrupted with Gaussian noise having Standard deviation '10'and the results when it is subjected to traditional NLM filter and proposed algorithm.

The processing time of the proposed method is very less as compared to the traditional techniques. This algorithm gives better output in comparatively less time.

VIII. CONCLUSION AND FUTURE SCOPE

In this work an effective image denoising technique is proposed using the two most commonly used filters, Fast non Local means algorithm in combination with wavelet thresholding. However popular these techniques may be individually there were some inherent flaws in them. By combining these filters those flaws are suppressed and a better and strong denoising mechanism is developed. It takes less processing time and gives an output with high PSNR and better visual quality. The noisy image is first subjected to the FNLM filter which removes maximum amount of noise but along with that some image details are also lost. It is then followed by wavelet thresholding which restores the image details by extracting the lost content from the method noise of Fast NLM filter, thus giving an output which is

not only noise free but also with its contents preserved. The results show that the proposed method is better than the existing technique irrespective of the image size, noise content the proposed algorithm gives a consistent output with all the image details and edges preserved. This method replicates the input image in case it was noise free. It means this algorithm is quite effective and can efficiently separate noise from signal without losing the image details.
This algorithm is designed for gray scale images it can be modified for denoising colored images.

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