An Efficient Brute Force Threshold based Method for Image Denoising

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Abstract – *Image denoising may be a well explored topic at intervals the field of image process. Within the past several decades, the progress made in image denoising has benefited from the improved modeling of natural photos. The projected technique makes the utilization of cascading of 3 individual filters, savitzky-golay, median & weiner filters. basically they are used to eliminate impulse noise and Gaussian noise separately, however during this technique as every filter are used simultaneously, impulse noise and Gaussian noise are eliminated at a time. In this the projected Brute Force Threshold algorithmic rule for the image denoising*.

Keywords*: Back projection, image denoising, low-rank approximation (LRA), and patch grouping, self-similarity, singular value decomposition (SVD).*

I. Introduction

Digital pictures play a vital role each in way of life applications like satellite TV, magnetic resonance imaging, pc tomography likewise as in areas of analysis and technology like geographical data systems and astronomy. Information sets collected by image sensors are typically contaminated by noise. Imperfect instruments, issues with the information acquisition method, and interfering natural phenomena will all degrade the information of interest. Moreover, noise may be introduced by transmission error and compression. Thus, denoising is usually a necessary and also the start to be taken before the pictures information is analyzed. It's necessary to use AN efficient denoising technique to complete such information corruption. Image denoising immobile remains a challenge for researchers as a result of noise removal introduces artifact and causes blurring of the pictures.

Denoising could be a basic and wide studied drawback in image process. Varied denoising strategies are planned following different disciplines like statistics, variation theory, etc. Most of those strategies exploit the local correlation of image pixels. Recently, the introduction of NLM opens the floodgate to the exploitation of nonlocal similarities inherent in natural pictures for denoising and different applications [1], [2]. The NLM estimates every pixel by the weighted average of the many pixels within the image, and also the weights are severally evaluated consistent with pair-wise similarity between 2 patches. The advantage of NLM is that it greatly reduces the interference of noise and well preserves the main points like edges and textures within the denoised image.

Digital pictures play a crucial in analysis and technology. It's the most important part within the field of medical science like ultrasound imaging, X-ray imaging, pc tomography and MRI. A really giant portion of digital image process includes image restoration. Image restoration may be a technique of removal or reduction of degradation that are incurred throughout the image capturing. Degradation comes from blurring in addition as noise because of the electronic and photometrical sources. Generally, denoising algorithms is roughly classified into 3 categories: spatial domain ways, transform domain ways and hybrid ways. During acquisition and transmission, pictures are inevitably contaminated by noise. As a necessary and important step to enhance the accuracy of the potential subsequent process, image denoising is very desirable for varied applications, like visual improvement, feature extraction and object recognition.

II. Background

Image denoising features a very wealthy history starting from the mid-70s. An excess of various techniques are planned, a number of that we'll survey later. In recent times, transform-based techniques, particularly in conjunction with machine learning, have gained quality and success in terms of performance. During this paper, we tend to propose a really easy, elegant and effective algorithmic rule that contributes to the paradigm of learning a degree wise variable remodel basis from the crying image pixels by exploiting the non-local self-similarity of the image. Throughout acquisition and transmission, pictures are inevitably contaminated by noise. As a necessary and important step to enhance the accuracy of the possible subsequent process, image denoising is very desirable for various applications, like visual improvement, feature extraction, and object recognition.

Normally pictures are affected by differing kinds of noise. Numerous kinds of noise have their own characteristics and are inherent in pictures in several ways in which. All the kinds of noises may be categorized into 2 models:

- Additive Noise Model
- Multiplicative Noise Model

Additive noise is that the signal that gets added to the first image to get the resultant noisy image. Within the increasing model the noisy image is generated by multiplication of the first image and also the noise signal. The most common noise varieties found in pictures are Gaussian Noise, Salt & Pepper Noise and Speckle Noise.

II.1. Gaussian Noise

It is equally distributed over the signal. Every pixel in noisy image is that the add of true pixel value and a random Gaussian distributed noise value [2]. Gaussian noise is an amplifier noise that is independent at every element and independent of the signal intensity. Gaussian noise is applied math noise that has its probability density operate up to that of the normal distribution. It arises because of electronic circuit noise & sensor noise because of poor illumination or high temperature. It’s a constant power additive noise.

II.2. Salt & Pepper Noise

The salt-and-pepper noise is additionally referred to as shot noise, impulse noise or spike noise. a picture containing salt-and pepper noise can have dark pixels in bright regions and bright pixels in dark regions. It is caused by dead pixels, analogue-to-digital convertor errors, and bit errors in transmission [3]. It’s only 2 potential values, a high value and a low price. The likelihood of every is usually less than 0.1.

II.3. Thresholding

In cases where a feature with intermediate image values needs to be separated from a darker background and brighter features, the histogram would show three modes. The intermediate mode can be separated with two thresholds T1 and T2, where T1 < T2. The image with the thresholded feature is then converted into a binary mask: and the between-class variance σ_B^2 can be defined by

$$\begin{aligned}\sigma_B^2 &= P_1(T)\,|\mu_1|^2 + P_2(T)\,|\mu_2(T)-\mu_1|^2 \\ &= P_1(T)P_2(T)\,|\mu_1(T)-\mu_2(T)|^2\end{aligned} \quad (1)$$

$$I_T(x,y) = \begin{cases} 0 & for\ I(x,y) < T_1 \\ 1 & for\ T_1 \le I(x,y) \le T_2 \\ 0 & for\ I(x,y) > T_2 \end{cases} \quad (2)$$

With multiple thresholds, computational efficiency is reduced, as a (n – 1)-dimensional space needs to be searched exhaustively for the combination of thresholds that minimizes ct^. Furthermore, the search for multiple thresholds becomes less stable with increasing n and less credible thresholds. For the most common cases, n = 2 and n = 3, the method remains robust.

III. Proposed method

Image Denoising has remained a basic drawback within the field of image process. Wavelets provide a superior performance in image denoising because of properties like sparsity and multi resolution structure. With wavelet transform gaining quality within the last 20 years numerous algorithms for denoising in wavelet domain were introduced.

The planned flow diagram shown in fig.1.In this flow diagram first of all takes an input image so add noise. once the method applying savitzky-golay filter to a group of digital image points for the aim of smoothing the information, that is, to increase the signal/noise ratio while not greatly distorting the signal. Then applying median filter on noisy image to perform some kind of noise reduction on a picture or signal and used to remove noise. Once the method of applying DWT so applying Brute Force Threshold algorithmic rule to Finding an optimized value (λ) for threshold could be a major drawback. A small modification in optimum threshold worth destroys some necessary image details that will cause blur and artifacts. So, optimum threshold value ought to be identified, that is adaptive to different sub band characteristics.

Here we tend to plan a Brute Force Thresholding technique which supplies an efficient threshold value for noise to induce high value of PSNR. Threshold follows a similar thought as in basic electronics, Brute force Threshold is given five times the maximum pixel intensity, which can be 127 in most of the pictures. Brute force thresholding forever outclass different existing thresholding techniques in terms of higher results. Any method is checking the result. Once the method of decomposition, during this we tend to are initial level decomposition of image. Then we tend to are replacing the low pixel of image so apply direction dependent and smoothing filter to smooth the image. Any method is applying IDWT on the noise remove image. Once applying IDWT then we tend to get output results.

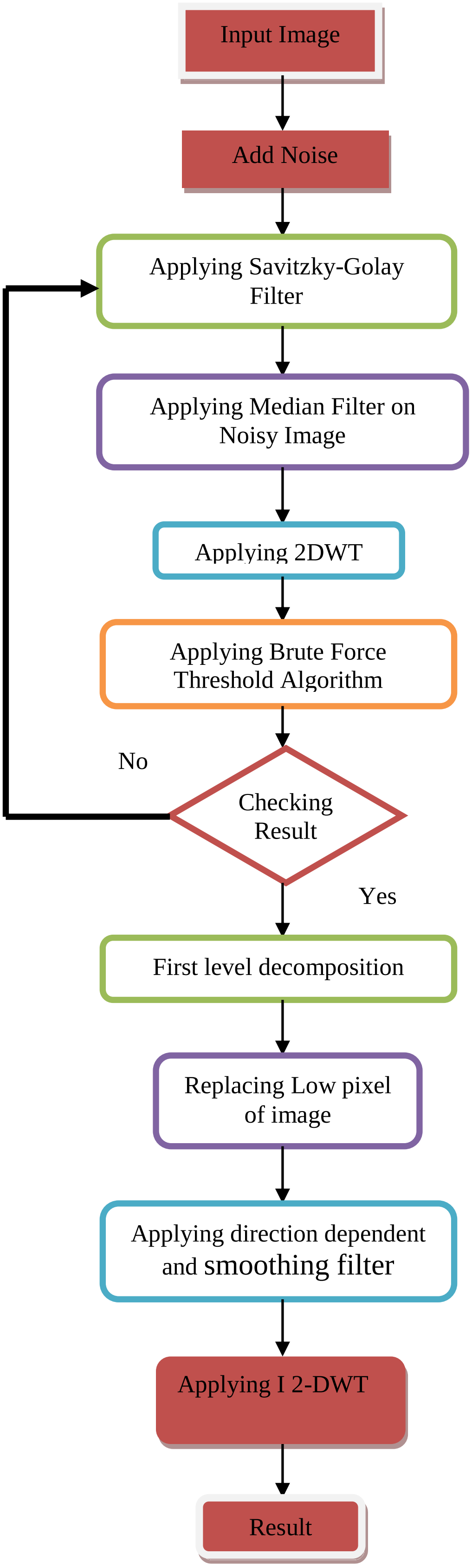

Fig.1 flow of proposed method

III.1. Median Filter

Median filtering follows this basic prescription. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images A(x) and B(x):

Median [A(x) + B(x)] ≠ median [A (x)] + median [B (x)]

These filters smooth's the data while keeping the small and sharp details. The median is just the middle value of all the values of the pixels in the neighborhood. Note that this is not the same as the average (or mean); instead, the median has half the values in the neighborhood larger and half smaller. The median is a stronger "central indicator" than the average. In particular, the median is hardly affected by a small number of discrepant values among the pixels in the neighborhood. Consequently, median filtering is very effective at removing various kinds of noise. Figure 2 illustrates an example of median filtering.

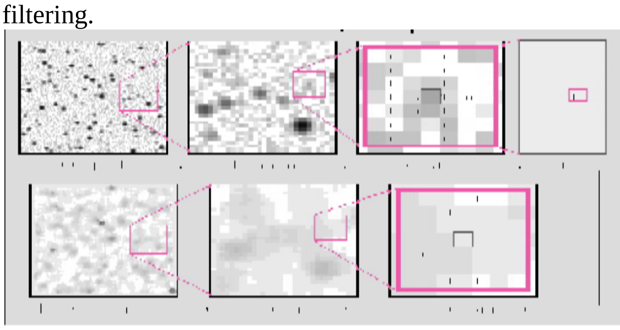

Fig.2 example of median filter

III.2. Brute Force Threshold Algorithm

Finding an optimized value (λ) for threshold may be a major drawback. A little modification in optimum threshold value destroys some necessary image details which will cause blur and artifacts. So, optimum threshold value ought to be found out, that is adaptive to different sub band characteristics. Here we tend to plan a Brute Force Thresholding technique which supplies AN efficient threshold value for noise to induce high value of PSNR. Threshold follows a similar concept as in basic electronics, Brute force Threshold is given five times the most pixel intensity, which can be 127 in most of the pictures. Brute force thresholding always outclass different existing thresholding techniques in terms of higher results.

Algorithm for brute force thresholding is given

- Input wavelet sub band.
- Find maximum (max) and minimum (min) value of sub band coefficients.
- loop through (threshold=min to max) and execute desired algorithm

• save the results in array for each loop such that F= [threshold, result]
• When loop completed, select the (threshold) that gives best result.

Step 1: Function [dist, loc]= Brute_Force(T,n)
Step 2: best_so_far_dist = 0
Step 3: best_so_far_ioc = NaN
Step 4: For p =1 to |T|-n+1
Step 5: nearest_neighbor_dist = infinity
Step 6: For q= 1 to |T|-n+1
Step 7: IF |p-q| $\geq$ n
Step 8: IF Dist $\left(t_p ....,t_{p+n-1},\ t_q ....,t_{q+n-1}\right)$
Step 9: nearest_neighbor_dist = Dist

$$\left(t_p ....,t_{p+n-1},\ t_q ....,t_{q+n-1}\right)$$

Step 10: End
Step 11: End
Step 12: End
Step 13: IF nearest_neighbor_dist> best_so_far_dist
Step 14: best_so_far_dist = nearest_neighbor_dist
Step 15: best_so_far_ioc = p
Step 16: End
Step 17: End
Step 18: Return [best_so_far_dist, best_so_far_ioc]

IV. Result

Brute Force Threshold Algorithm is used in the proposed system then we get the better results that are denoising image are as shown in below:

Fig.3 Original image

This fig.3 shows the original image. In this proposed method we take the input image for proposed work.

Fig.4 noisy image

This fig. 4 shows the noisy image. This input image adds the noise that is known as speckled image.

Fig.5 Savitzky-Golay Filtered image

This fig.5 shows the Savitzky-Golay Filtered image. The speckled image is filtered by the use of Savitzky-Golay Filter.

Fig.6 median Filtered image

This fig.6 shows the median filtered image. The Savitzky golay filtered image is also filtered by the median filter. Then we get this image.

Fig.7 De-noised image

This fig.7 shows the de-noised image. The input image filtered by the use of different filters then filtereing the noise that is remove the speckle noise after get the de-specked image that is output image.

MSE & PSNR:

As a performance measure for image distortion due to hidding of message, the well-known peak-signal-to noise ratio (PSNR), which is categorized under difference distortion metrics, can be applied to stego images. In the MSE calculation the total squared difference among the real signal and there build one is averaged over the overall signal. Mathematically,

$$MSE = \frac{1}{N}\sum_{i=0}^{N-1}(\hat{x}_i - \hat{x}_i)^2$$

Where $\hat{x}_i$ is the rebuild value of x_i . N is the number of pixels. The mean square error is generally utilized because of its convenience. A calculation of MSE in decibels on alogarithmic level is the Peak Signal-to-Noise Ratio (PSNR), which is a famous specific objective calculation of the lossy codec. We utilize the PSNR as the empirical measurement for compression algorithms throughout this thesis. It is explained as follows:

Peak Signal-to- Noise Ratio (PSNR), which is a famous specific objective calculation of the lossy codec. We utilize the PSNR as the empirical measurement for compression algorithms throughout this thesis. It is explained as follows

$$PSNR = 10\log\frac{MAX^2}{\frac{1}{W\times h}\sum_{i=1}^{W}\sum_{j=1}^{h}(o(i,j)-c(i-j))^2}$$

$$PSNR = 10\log\frac{I^2}{MSE}$$

where w and h are the breadth and height of the image severally, o is the original image data, and c is the compressed image data. MAX is the maximum value that a pixel.

Table 1 Comparison table

Image	Noise level	Base Paper		Proposed	
		PSNR	SSIM	PSNR	SSIM
Barbara	10	35.43	0.9847	54.8942	0.7425
	20	32.23	0.9696	54.4897	0.7336
	30	30.21	0.9550	54.2928	0.7408
	40	28.74	0.9409	54.1663	0.7382
	50	27.50	0.9269	54.1007	0.7380

This table shows the comparison of base paper value and proposed PSNR and SSIM value at different noise level.

V. Conclusion

In this paper image denoising using combination of techniques has been mentioned. Within the analysis introduced wavelet transform and wiener filter for image denoising. During this work, used the image format and adding 3 noises (impulse noise, Gaussian noise, blurredness) and apply the noisy image to the advanced filter. During this projected Brute Force Threshold algorithmic rule for image denoising. During this paper, comparison of PSNR and SSIM value of previous technique and projected technique. Once the PSNR value is high therefore image quality is better.

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