

Restoration-Multiple Removing of Noise under Water Images using Multidirectional Filtering Techniques

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Abstract: Image restoration one part is the Denoising which plays important tasks in image processing. Despite the significant research conducted on this topic, the development of efficient denoising methods is still a compelling challenge. Image denoising is an essential requirement of image processing. The images contain strongly oriented harmonics and edge discontinuities. Wavelets, which are localized and multiscaled, do better denoising in single dimension using multiple local thresholding technique. Filter based denoising and reconstruction exhibit higher quality recovery of edges and curvilinear features. This thresholding scheme denoises images embedded in Speckle noise. The experiment shows denoising using Filters such as Wiener, Median, Wavelet Transform, Bayes Shrink and our proposed technique as (median and bayes Shrink wavelet) to outperforms in terms of PSNR(peak signal-to-noise ratio), MSE (mean square Error), Elapsed time and Coc (Coefficient of Correlation), but also in better visual appearance of the resulting images. In this thesis, we will study and investigate the application of using best filters to remove noise using our proposed method Median with Bayes shrink wavelet with soft thresholding for denoising techniques to remove multiple noises from under water images. In this, Gaussian, Poisson, Salt & pepper, Speckle is used for restoration. Our Technique, works best for all types of noises but speckle is better restored as denoised by wavelet based only technique.

Keywords: - Gaussian, Poisson, Salt & Pepper, Speckle noise, Denoising, filters, PSNR, MSE, Coc..

I. INTRODUCTION

The face is our primary focus of attention in social life Image restoration is an art to improve the quality of image via estimating the amount of noises and blur involved in the image. With the passage of time, image gets degraded due to different atmospheric and environmental conditions, so it is required to restore the original image using different image processing algorithms. There is a wide spread application of image restoration in today's world. Application area varies from restoration of old images in museum and radar based image acquisition and restoration.

Underwater photography is the process of taking photographs while under water. It is usually done while scuba diving, but can be done while diving on surface supply, snorkeling, swimming, from a submersible or remotely operated underwater vehicle, or from automated cameras lowered from the surface which causes difficulty in maintain preserved edges or may causes sometime distortion in the form of noise. Another environmental effect is range of visibility. The water is seldom optimally clear, and the dissolved and suspended matter can reduce visibility by both absorption and scattering of light.

Image denoising is a necessary step in image processing applications. In brief, all these algorithms first perform the wavelet transform of the image to denoised, apply some filter to the wavelet coefficients, and finally take the inverse wavelet transform to restore the denoised image. Most popular wavelet-filtering algorithms are based on thresholding.

Wavelet analysis has been demonstrated to be one of the powerful methods for performing image noise reduction. The procedure for noise reduction is applied on the wavelet coefficients obtained after applying the wavelet transform to the image at different scales. The motivation for using the wavelet transform is that it is good for energy compaction since the small and large coefficients are more likely due to noise and important image features, respectively. The small coefficients can be threshold without affecting the significant features of the image. In its most basic form, each coefficient is threshold by comparing against a value, called threshold. If the coefficient is smaller than the threshold, it is set to zero; otherwise it is kept either as it is or modified. The inverse wavelet transform on the resultant image leads to reconstruction of the image with essential characteristics.

Image denoising is a fundamental process in image processing, pattern recognition, and computer vision fields. The main goal of image denoising is to enhance or restore a noisy image and help the other system (or human) to understand it better.

II. LITERATURE SURVEY

Anamika Maurya,(2014), here author describes about image restoration which estimate the original image from the degraded data by using Different types of image restoration techniques like wiener filter, inverse filter, regularized filter, Richardson –Lucy algorithm, neural network approach, wavelet based approach, blind de-convolution are described and strength and weakness of each approach are identified. **Biswa Ranjan Mohapatra (2014)**, author presents here that Image restoration is an art to improve the quality of image via estimating the amount of noises and blur involved in the image. This paper gives a review of different image restoration techniques used. But primarily image restoration is done

mostly using Weiner filter, Richardson-Lucy Blind Deconvolution algorithm, Inverse and Pseudo-inverse filter. **Sarabjeet Kaur (2014)**, In this paper, author writes brief introduction of digital image processing related to image restoration, different types of noises are introduced and different methods which are used to remove noise are described with different parameters performed on medical images. Parameters like Contour plots, Histogram equalization, MSE, PSNR, max difference, average difference, normalized cross correlation, normalized absolute error, structure content are performed to be measured. Salt n pepper noise can be better removed by median filter. The performance of clahe and histogram filter is not better as compare to median, adaptive and linear filter. **Seema, Meenakshi Garg (2014)**, here the concept of removing the noises by using the various types of filters and techniques are proposed. A new method based on discrete wavelet transforms using the bayes-shrink method results were compared with median and wiener filter. In this, proposed technique work with two noises, namely Salt &Pepper and Gaussian noise, that were simultaneously reduced from a single image successfully and results were found to be better than wiener and median filters due to better PSNR ratio and Coc value. Results revealed that the proposed method was very efficiently able to remove noise from ultrasound gray scale images then others. **P. Sureka (2013)**, here author described that Image restoration technique which restore the degraded face images such as faxed images, scanned passport photos and printed images by removing noise in the image. The degradations include half toning, dithering and security watermarks. An iterative image restoration scheme is used to restore the severely degraded face images which improve the recognition performance and the quality of the restored image. Here performed the Viola and Jones face detection algorithm which is to localize the spatial extent of the face and determine its boundary. In next step, geometric normalization is applied to both original and degraded images. It holds two processes namely automatic eye detection and affine transformation that matches the images in the database and constructs the canonical faces. Low pass filtering is done using Wiener filter which reduces the noise in the image and the invariant wavelet transform reduces artifacts. Then, the quality of the image is checked using some of the quality metrics and it is restored if the quality is good. Image identification before and after restoration is achieved using certain classification tools and methods. The proposed method of restoration methodology consists of iterative method to restore the noisy images and that is compared with the high resolution counterparts. Their proposed work uses neural network classifier to recognize the image which is restored with that of the original image. Experimental results show that the face recognition is achieved better in neural network classifier than that of k-nearest neighbor classifier used in the existing model. One of the possible improvements could be made is the use of super-resolution algorithm which helps to know about the prior on the spatial distribution of the image gradient for frontal face images. Another future work to be done is the better classification of the degraded face images which will improve the integrity of the overall restoration technique.

III. METHDOLOGY

Algorithm of proposed method: discrete wavelet transforms with Bayes shrink technique and median filter

algorithm: In this work, the algorithm via the wavelet shrinkage technique is as follows [5] [20]:

Step 1: Load an original image.

Step 2: Noise is added to the standard image read in above step using the any type noise such as Poisson, Gaussian, Salt & Pepper and Speckle which produce image $J(x, y)$. Noises added additive & multiplicative noise to the image according to the following formula:

$$J(x, y) = I(x, y) + n * I(x, y)$$

Step 3: Second step is followed again to another type of noise for denoising.

Step 4: Select the Wavelet Thresholding method with Soft Threshold technique to denoise the noisy image on which logarithmic transform is performed firstly. $\log J(x, y) = \log I(x, y) + \log \eta(x, y)$

Step 5: Decomposition level on which the log transformed image using wavelet transform is to be performed is selected by default second.

Step 6: Applied Median filter. Now apply the DWT of the noisy image $J(x, y)$ up to 2 levels ($L=2$) to obtain seven sub bands and 1 Levels ($L=1$) to obtain 4 sub bands. These four and seven sub-bands are:

- LL1: Approximation of original image.
- LH1: Horizontal Coefficient of image at level1.
- HL1: Vertical Coefficient of image at level1.
- LH1: Diagonal Coefficient of image at level1.
- LH2: horizontal Coefficient of image at level2.
- HL2: Vertical Coefficient of image at level2.
- LH2: Diagonal Coefficient of image at level2.

Step 7: Now, Calculate σ noise variance of the corrupted image using sigmahat [3].

$$\sigma = \frac{\text{Median } |Y_{i,j}|}{0.6745}, Y_{i,j} \in \text{subband HH1}$$

Wavelet based method commonly used the highest frequency sub band of the decomposition. In the DWT of the image, the HH1 sub band contains mainly noise. For estimating the noise level we use the above equation proposed by Donoho [19], [5], which is also known as robust median estimator.

Step 8: For each level in sub bands, compute the scale parameter K using the below formula [3].

$$K = \sqrt{\log(L_k)}$$

Step 9: For each sub-band (except the low pass residual). Compute the standard deviation σ_x using the below formula [1].

$$\hat{\sigma}_x = \sqrt{\max(\hat{\sigma}_y^2 - \hat{\sigma}^2, 0)}$$

Step 10: T Compute threshold T_N using below formula [1]

$$T_N = K \frac{\sigma^2}{\sigma_x}$$

if sub-band variance U : is greater than noise variance, otherwise set T_N to maximum coefficient of the sub band.

Step 11: Apply soft thresholding to the noisy coefficients.

$$\sigma_x = \sqrt{\max\left(\frac{\sum X(i,j)^2}{\text{length}(X)} - \sigma^2, 0\right)}$$

$$Th2 = \begin{cases} \sigma_x = 0 & \max(abs(X)) \\ else & \sigma^2/\sigma_x \end{cases}$$

From both above calculated threshold we take the average of the threshold value.

Th = Th2;

Step 12: After the decomposed image coefficients are threshold using the above threshold technique, denoised image is reconstructed as $I_R(x, y)$ using inverse wavelet transforms- IDWT.

Now apply the filter based on statistics estimated from a local neighborhood around each pixel. Filter reconstructed image $I_R(x, y)$ according to following formula:

$$I(x, y) = \mu + \frac{(\sigma^2 - v^2)(I_S(x, y) - \mu)}{\sigma^2}$$

Where, μ is the local mean, σ^2 the variance in 3×3 neighborhoods around each pixel and v^2 is the average of all estimated variances of each pixel in the neighborhood.

Step 13: Take exponent of the image obtained in above step and obtained the denoised image.

Step 14: Now we get the restoration image after denoised and image with decomposition level and shows the performance with various parameters such as MSE, Coc, Elapsed Time and PSNR.

IV. RESULTS

The GUI part is designed for image Restoration with various methods such as Bayes shrink, Median, Weiner, Wavelet and our proposed method (median + Bayes shrink wavelet) with choosing threshold techniques such as Soft threshold using for Denoising underwater images. MATLAB graphical user interface development environment provides a set of tools for creating graphical user interfaces (GUIs). These tools simplify the process of lying out and programming GUIs to solve the our problem of Restoration of Images while using various types of noises which are to be removed as unwanted noise. Noise types, using Poisson, Gaussian, Speckle and Salt & Pepper as applying more than once.

DESIGN AND IMPLEMENTATION

Below figure 4.1 shows the GUI part in which all details are selected and displayed as one window but selecting different types of button and selection options to get output as image restoration using denoising.

Figure 4.8: Resultant images with various methods

Above figure 4.8, shows the images as original with resultant noisy and denoised restored image.

Table 4.1: Comparing Gaussian & (Salt & Pepper) Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Sr. No.	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	14.754	11.717	13.370	1.64	1.74	1.68	0.75	0.67	0.80	0.04	0.05	0.05

Sr. No.	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	15.088	11.545	13.832	1.63	1.75	1.67	0.7	0.6	0.79	0.04	0.06	0.04
Median	56.67	23.46	43.05	20.5	24.4	21.7	0.9	0.9	0.93	0.03	0.03	0.03
Wavelet	11.412	59.90	10.619	17.5	20.3	17.87	0.8	0.8	0.84	0.11	0.11	0.12
Bayes Shrink	19.733	20.569	21.515	15.1	14.9	14.80	0.6	0.5	0.71	0.09	0.10	0.10
Proposed	54.92	21.26	40.80	25.7	29.8	27.02	1.2	1.2	1.24	0.07	0.07	0.08

Table 4.2: Comparing Gaussian & Speckle Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Sr. No.	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	22.248	19.427	26.644	14.6	15.2	13.8	0.63	0.50	0.58	0.04	0.04	0.04
Median	44.697	44.024	56.252	11.6	11.6	10.6	0.55	0.43	0.50	0.03	0.03	0.04
Wavelet	15.142	11.180	18.896	16.3	17.6	15.3	0.71	0.63	0.68	0.11	0.12	0.12
Bayes Shrink	28.424	28.175	36.088	13.5	13.6	12.5	0.57	0.505	0.53	0.09	0.09	0.09
Proposed	34.811	38.336	48.332	17.7	17.2	16.2	0.89	0.77	0.83	0.06	0.07	0.06

Table 4.3: Comparing Poisson & (Salt & Pepper) Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Sr. No.	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	14.754	11.717	13.370	1.64	1.74	1.68	0.75	0.67	0.80	0.04	0.05	0.05

Proposed	50 8.5	19 4.8	39 0.5	2 6.0	3 0.2	2 7.2	1 2.2	0 9.1	0 9.3	0 9.4	0 0.3	0 0.4	0 0.7
Bayes Shrink	19 52.7	22 15.3	21 27.2	1 5.2	1 4.6	1 4.8	0 6.9	0 8.1	0 8.4	0 0.13	0 0.13	0 0.13	0 0.13
Wavelet	11 15.8	59 9.0	10 46.2	1 7.6	2 0.3	1 7.9	0 8.1	0 8.1	0 8.4	0 0.13	0 0.13	0 0.13	0 0.13
Median	51 0.6	21 2.6	40 7.9	2 1.0	2 4.8	2 2.0	0 9.1	0 9.3	0 9.4	0 0.3	0 0.4	0 0.4	0 0.7

Table 4.4: Comparing Poisson & Speckle Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Proposed	91 3.1	57 9.5	88 7.1	23 .5	25 .4	23 .6	1 14	1 12	1 17	0 07	0 09	0 09
Bayes Shrink	27 17.9	23 90.1	27 56.8	13 .7	14 .3	13 .7	0 56	0 51	0 61	0 10	0 12	0 11
Wavelet	16 67.6	10 22.7	15 78.3	15 .9	18 .0	16 .1	0 72	0 69	0 77	0 15	0 16	0 15
Median	11 07.2	67 3.1	10 20.5	17 .6	19 .8	18 .0	0 82	0 81	0 86	0 04	0 04	0 06

Table 4.6: Comparing (Salt & Pepper) & Speckle Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Sr. No	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	22 44.2	19 38.2	26 88.2	1 4.6	1 5.2	1 3.8	0 6.3	0.5 0	0 5.8	0 6.6	0 5.5	0 4
Median	45 25.3	43 66.3	56 33.4	1 1.5	1 1.7	1 0.6	0 2.2	0.4 2	0 4.9	0 4.9	0 3.3	0 5
Wavelet	15 12.9	10 88.6	19 01.1	1 6.3	1 7.7	1 5.3	0 7.1	0.6 4	0 6.8	0 6.8	0 1.3	0 1.3
Bayes Shrink	28 67.8	28 14.6	35 90.5	1 3.5	1 3.6	1 2.5	0 5.7	0.5 0	0 5.3	0 0	0 0	0 0
Proposed	35 21.6	38 33.1	47 95.7	1 7.6	1 7.2	1 6.3	0 8.7	0.7 4	0 8.2	0 0.7	0 0.7	0 9

Table 4.5: Comparing (Salt & Pepper) & (Salt & Pepper) Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Sr. No	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	24 95.8	20 54.8	30 42.3	14 .1	15 .0	13 .2	0 55	0 43	0 50	0 04	0 04	0 04
Median	55 67.0	53 31.3	70 67.6	10 .6	10 .8	9 63	0 44	0 34	0 39	0 04	0 03	0 04
Wavelet	17 47.8	11 81.8	22 84.4	15 .7	17 .4	14 .5	0 65	0 56	0 60	0 12	0 12	0 12
Bayes Shrink	34 29.8	30 28.6	42 95.8	12 .7	13 .3	11 .8	0 47	0 46	0 45	0 10	0 10	0 10
Proposed	44 53.1	47 79.1	61 68.8	16 .6	16 .3	15 .2	0 78	0 66	0 72	0 07	0 07	0 07

Table 4.7 Comparing Speckle & Speckle Noises by PSNR, Elapsed Time, Coc and MSE using Decomposition Level 2 and Noise Level =0.02

Sr. No	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	21 78.9	17 03.9	20 59.9	14 .7	15 .8	14 .9	0 63	0 55	0 68	0 05	0 05	0 08

Sr. No	MSE			PSNR			Coc			Elapsed Time		
	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3	Image1	Image2	Image3
Wiener	22 68.6	19 86.9	26 42.3	14 .5	15 .1	13 .9	0 63	0 49	0 59	0 04	0 0	0 04
Median	44 99.5	45 86.1	55 20.5	11 .5	11 .5	1 0.7	0.5 3	0 40	0 50	0 04	0 03	0 04

Wavelet	14 98. 0	11 17. 7	19 08 .4	16 .3	17 .6	1 5. 3	0.7 1	0. 62	0. 6 8	0.1 2	0 . . 1 1 2 2	0 . . 1 1 2 2
Bayes Shrink	28 72. 4	27 92. 9	35 60 .5	13 .5	13 .6	1 2. 6	0.5 7	0. 50	0. 5 4	0.1 0	0 . . 0 1 9 0	0 . . 0 1 0 0
Proposed	34 96. 0	40 56. 4	47 16 .1	17 .6	17 .0	1 6. 3	0.8 8	0. 72	0. 8 3	0.0 7	0 . . 0 0 7 7	0 . . 0 0 0 0

From above tables 4.1 and 4.7 describes the parameters followed for comparison of various noises which can be denoised for restoration of an image. Gaussian, Poisson, Salt & Pepper Noise are having PSNR and Coc high and MSE low for our proposed method, but using speckle noise is not good as to be good for removing noise as wavelet technique alone can work best for restoring image. PSNR and Coc should be high and MSE should be less in quality of image.

V. CONCLUSION

In our work, soft thresholding methods is implemented with denoising filters such as to restore images with different noise levels. As seen from the results that our proposed method (Median +Bayes Shrink wavelet) Soft thresholding is an effective method of denoising noisy images. We first tested on noisy versions of the standard 2-D images. Then we implemented Soft thresholding to remove noise from images which shows good results. The MSE, PSNR and Coc values are calculated for different types of noises at levels 0 to 10 for any type of image (512 x 512) even for 3-D images. PSNR, Coc and MSE are used for comparison which shows that our proposed technique for Gaussian, Poisson and Salt & Pepper noise are best to be removed but Speckle noise is removed better with wavelet soft threshold technique for restoring image.

VI. FUTURE SCOPE

In this work, Bayes shrink wavelet with median filter is implemented with soft techniques; Further, this work can be enhanced for better noise removal efficiency by adding more restoration techniques like VISU Shrink, SURE Shrink, Stationary Wavelet Transform (SWT) and normal Shrink thresholding techniques. Also, more wavelet decomposition levels can be used for better PSNR values. Instead of Soft, we can use in future with Hard Threshold technique.

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