Hybrid filtering technique to remove noise of high density from digital images

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***Abstract*—**Noise removal is one of the greatest challenges among the researchers, noise removal algorithms vary with the application areas and the type of images and noises.

The work proposes a novel hybrid filter which is capable of predicting the best filter for every pixel using neural network and choose the best technique to remove noise with 3x3 mask operation. Proposed algorithm first train the neural network for various filters like mean, median, mode, geometrical mean, arithmetic mean and will use to remove noise later on. Later, the proposed method is compared with the existing techniques using the parameters MAE, PSNR, MSE and IEF. The experimental result shows that proposed method gives better performance in comparison with MF, AMF and other existing noise removal algorithms and improves the values of various parameters.

Keywords- *Image De-noising, High density impulse noise, hybrid filter*

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I. INTRODUCTION

Image De-noising is one of the fundamental problems in image processing and computer vision. The major concern in image processing is estimation of pixel values. For example, interpolation or resizing is to estimate plausible pixel values located between known ones while de-noising or de-blurring is to estimate clean pixel values from corrupted ones. Filling missing parts of an image in order to obtain a visually plausible outcome is the problem addressed in three distinct but related fields of study.

Image de-noising is an important image processing task, both as a process itself, and as a component in other processes. Very many ways to de-noise an image or a set of data exists. The main property of a good image de-noising model is that it will remove noise while preserving edges. Traditionally, linear models have been used. One common approach is to use a Gaussian filter, or equivalently solving the heat-equation with the noisy image as input-data, i.e. a linear, 2nd order PDE-model. For some purposes this kind of de-noising is adequate. One big advantage of linear noise removal models is the speed. But a drawback of the linear models is that they are not able to preserve edges in a good manner: edges, which are recognized as discontinuities in the image, are smeared out. Nonlinear models on the other hand can handle edges in a much better way than linear models can. One popular model for nonlinear image de-noising is the Total Variation (TV)-filter, introduced by Rudin, Osher and Fatemi. This filter is very good at preserving edges, but smoothly varying regions in the input image are transformed into piecewise constant regions in the output image.

The rest of the paper is structured as follows. The various existing de-noising filters are given in section II, the proposed algorithm is described in section III. Simulation results are presented in section IV. Finally conclusions are drawn in section V.

II. DE-NOISING FILTERS

1. Median Filtering: The median filter is a non-linear filtering technique which is used to remove noise. In this filtering technique, the pixel is replaced with the median of the neighboring pixels. A window is chosen, which vary for the 1D signal and 2D signals, and the window slides over each pixel value. Some issues with median filter includes that the majority of the computational effort and time is spent on calculating the median of each window. As the filter must process every entry in the signal therefore for large signals, the efficiency of median calculation is a critical in determining how fast the algorithm can run. Also median filter is only effective at low noise densities and fails at higher noise densities.

2. Adaptive Median Filtering: AMF performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter compares each pixel in image to its neighbor pixel to determine if it is a noisy pixel. The size of the window is adaptive in nature. A pixel is labeled as impulse noise if it is different from a majority of its neighbors, as well as not structurally aligned with those pixels. These noise pixels are then replaced by the median value of the pixels in the neighborhood.

Based on two types of image models corrupted by impulse noise, Hwang, Humor, and Richard A. Haddad proposed two new algorithms for adaptive median filters. These algorithms have variable window size for removal of impulses while preserving sharpness.

a) Ranked-order based adaptive median filter (RAMF): RAMF [7] is based on a test for the presence of impulses in the center pixel followed by a test for the presence of residual impulses in the median filter output. The corrupted pixel is detected using minimum, maximum and median values of the pixels in the window under consideration. Then this corrupted pixel is replaced by median value of the window which is obtained by increasing size of the window until it reaches maximum window size, which is not an impulse value.

b) Size based adaptive median filter (SAMF): (SAMF) [7] is based on the detection of the size of the impulse noise. It detects and replaces impulse noise of size 1 or 2 or 3 pixels by median filtering while the pixels which are not detected as noisy are replaced by mean value of the window.

The performance of adaptive median filtering is better than that of median filters at lower noise density levels. However it fails at higher noise densities as the edges are smeared significantly because of large numbers of pixels being replaced by median values.

3. Decision based median filters: These filters checks for the presence of Salt and Pepper noise in images. A pixel is said to be corrupted if its value is either '0' or '255'. To filter only the corrupted pixels different techniques were developed, namely decision based algorithm (DBA), decision based unsymmetric trimmed median filter (DBUTMF) and modified decision based unsymmetric trimmed median filter (MDBUTMF).

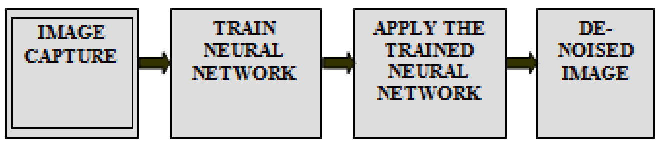
4. Decision Based Algorithm: DBA [10] is a non-linear filter which restores images corrupted by impulse noise. Unlike other nonlinear filters, it first detects the presence of the corrupted pixel based on the decision made using the adaptive median filtering and then if the pixel is corrupted, i.e. it lies between the minimum and maximum values inside the chosen window to be processes, it is replaced with the median value of the neighboring pixels in the window. If the pixel is detected as noise free, then no change is done and the pixel is left unchanged. This filter shows greater peak signal to noise ratio (PSNR) and image enhancement factor (IEF) as compared to other methods such as standard median filter, adaptive median filter. Also, the processing time required for DBA is significantly takes less computation time as compared to AMF and other filters as it uses a fixed length window (3x3). The disadvantage of this filter is that streak occurs at high noise densities due to replacement of the noise pixel with the neighborhood values.

5. Decision based unsymmetric trimmed median filter (DBUTMF): (DBUTMF) [1] Aiswarya, K., V. Jayaraj, and D. Ebenezer proposed a new algorithm for removal of high density salt and pepper noise in images and videos. In this technique, the value to be replaced for the corrupted pixel is calculated by trimmings the impulse values from the current 3x3 window, if they are present. Hence it is an unsymmetric filter as only the impulse values are trimmed to get the median value to replace. DBUTMF has lower computation time as compared to other algorithms. The performance comparison shows that PSNR and IEF values are greater than that for SMF, AMF and DBA. This algorithm does not give better result at very high noise density as at that density level all the pixels are corrupted and hence the trimmed median value cannot be calculated.

6. Modified decision based unsymmetric trimmed median filter (MDBUTMF): The authors proposed a new algorithm, MDBUTMF [6], for restoring gray scale and color images highly corrupted by salt and pepper noise and overcoming the drawback of DBUTMF. As in DBUTMF here also first the corrupted pixel is detected and then one of the below case is applied to that pixel:
Case 1: If the selected window contains noisy pixel (255 or 0) and all the neighboring pixel values are also noisy pixels, then their median value will also be noisy. Hence to avoid this, the mean is calculated of the pixels in the selected window and the noisy pixel is replaced by that value.
Case 2: If the selected window contains noisy pixel (255 or 0) and some of the neighboring pixel values are noisy, then their median value will also be noisy. Hence to remove noise from the image, 1-D array of the selected image region is obtained so that the 0/255 values will be eliminated and after this the median of remaining values is calculated and the noisy pixel value is replaced by this value.
Case 3: If there is no noisy pixel in the selected window, then no changes are done and the pixel value is left unchanged.
This algorithm shows better results than the other filters but the drawback is that it leads to blurring of the image at higher noise densities.

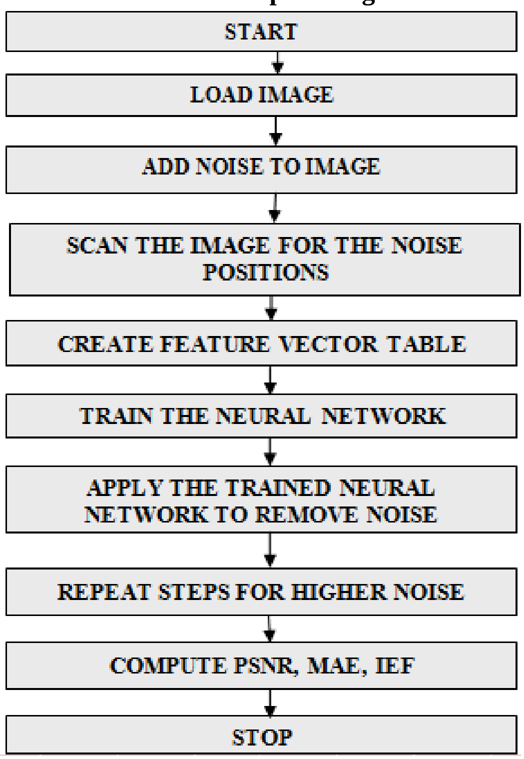
III. PROPOSED METHOD

As various digital images are available, so no acquisition stage is implemented. The image available is added with noise of different noise densities, from 10% to 90%, and then image de-noising is done by applying the proposed algorithm. Firstly, decompose the image and for the noise positions create a feature vector table, computing the min, max, mean and median filter values. Then train the neural network by providing the filter values for the noise. Lastly, apply the neural network to remove noise from the image. Figure show the method adopted to de-noise image.



Method adopted for Image De-noising

Flowchart for Proposed algorithm



IV. RESULT AND DISCUSSION

The proposed algorithm is tested for different grayscale images and the noise densities are varied from 10% to 90%. The performance of the proposed method is tested at low, medium and high noise densities and is compared with the existing algorithms. The following images 'lena.jpg' and 'boat.bmp' are used to verify the performance of the proposed algorithm.

To confirm the improvement in removing noise from the image, various parameters such as MAE (Mean Absolute Error), PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error), and IEF (Image Enhancement Factor) are used to compare the results of the proposed method and the conventional methods.

PSNR between two images can be expressed as:

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{\mathrm{MAX_f}}{\sqrt{\mathrm{MSE}}}\right)$$

where, $\mathrm{MAX_f}$ is the maximum signal value that exists in the original "known to be good" image.

$$\mathrm{MSE} = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\left|\left|f(i,j) - g(i,j)\right|\right|^2$$

where, f is the original image and g is the uncompressed image. The dimension of the images is mxn.

The MAE is calculated using:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|$$

where f_i is the prediction and y_i the true value.

The IEF is calculated using:

$$\mathrm{IEF} = \frac{\sum_{i,j}(n(i,j) - Y(i,j))^2}{\sum_{i,j}(\hat{Y}(i,j) - Y(i,j))^2}$$

The quality measure of the de-noised images shows that the performance of the proposed algorithm gives better results compared to other algorithms at different noise densities. This is shown in tables below. Comparison of noisy images and original images at different noise densities are shown in figure 4.1 and the comparison of MAE, PSNR and IEF values at different noise densities are shown in figure 4.2, 4.3 and 4.4 respectively.

Table 4.1: Comparison of MAE values of different algorithms

Noise Density in %	MAE VALUES						
	AMF	DBUT MF	MDBUT MF	DBPTG MF	DMF + MDBPTGMF	DMF + MDBUTMF	Proposed
10	4.99	1.57	1.01	1.62	1.97	0.17	0.038902
20	5.53	1.73	1.54	1.81	2.014	0.36	0.075054
30	5.85	1.96	1.83	2.04	2.12	0.62	0.113087
40	6.1	2.37	2.22	2.43	2.16	0.92	0.158268
50	6.49	3.48	3.12	3.22	2.48	1.33	0.202923
60	6.71	6.32	5.9	4.9	2.97	1.89	0.250679
70	7.37	13.92	12.71	8.18	3.8	2.8	0.270535
80	8.59	29.55	21.76	14.08	5.78	4.61	0.315552
90	11.5	57.01	47.98	24.09	14.74	13.21	0.361946

Table 4.2: Comparison of PSNR values of different algorithms

Noise Density in %	PSNR in dB						
	AMF	DBUT MF	MDBUT MF	DBPTG MF	DMF + MDBPTG MF	DMF + MDBUTMF	Proposed
10	28.39	38.2	39.95	38.08	37.19	47.71	52.00721
20	27.55	37.57	38.54	37.47	36.91	44.54	48.83606
30	27.09	36.91	37.33	36.78	36.65	42.01	47.2102
40	26.71	36.06	36.65	36.01	36.34	40.21	45.4434
50	25.9	34.37	34.92	35.01	35.82	39.32	44.28367
60	25.75	32.6	32.94	33.1	34.73	37.02	43.02456
70	24.69	29.85	30.77	32.79	33.65	35.2	42.90916
80	23.22	27.21	28.19	30.96	31.8	33.64	42.13783
90	20.55	25.08	26.09	27.35	29.32	30.95	41.71531

Table 4.3: Comparison of IEF values of different algorithms

Noise Density in %	IEF VALUES						
	AMF	DBUT MF	MDBUT MF	DBPTG MF	DMF + MDBPTG MF	DMF + MDBUT MF	Proposed
10	24.7	417.2	594.9	511.1	277.8	682.1	476.735
20	33.4	361.9	444.5	395.7	307.6	568.4	474.3852
30	47.8	382.1	465.1	368.6	376.7	494.1	484.2664
40	58.8	271.3	323.5	313.3	321.1	388.3	433.3025
50	67.1	126.1	287.5	272.4	291.7	329.1	417.0224
60	43.1	86.6	170.5	197.9	201.4	290.2	371.6472
70	28.1	44.3	98.6	115.9	165.8	198.6	420.0331
80	7.2	19.3	56.7	84.7	90.6	117.1	399.2509
90	1.8	5.2	12.9	18.1	38.9	41.2	412.1622

Table 4.4: Comparison of MAE values of different cascade algorithms

Noise Density in %	MAE VALUES				
	DMF+UTMF	DMF+UTMP	DMF + MDBPTGMF	DMF + MDBUTMF	Proposed
10	0.39	0.4	1.97	0.17	0.038902
20	0.87	0.88	2.01	0.36	0.075054
30	1.41	1.41	2.12	0.62	0.113087
40	2.08	2.09	2.16	0.92	0.158268
50	2.87	2.9	2.48	1.33	0.202923
60	3.95	3.93	2.97	1.89	0.250679
70	5.33	5.29	3.8	2.8	0.270535
80	7.22	7.19	5.78	4.61	0.315552
90	15.41	15.11	14.74	13.21	0.361946

Table 4.5: Comparison of PSNR values of different cascade algorithms

Noise Density in %	PSNR VALUES				
	DMF +UTMF	DMF+ UTMP	DMF + MDBPTGMF	DMF + MDBUTMF	Proposed
10	45.37	45.57	37.19	47.71	52.00721
20	42.26	42.37	36.91	44.54	48.83606
30	39.59	39.57	36.65	42.01	47.2102
40	37.34	37.09	36.34	40.21	45.4434
50	35.12	34.95	35.82	39.32	44.28367
60	33.04	33.02	34.73	37.02	43.02456
70	31.05	31.05	33.65	35.2	42.90916
80	28.9	28.97	31.8	33.64	42.13783
90	26.51	26.7	29.32	30.95	41.71531

Figure 4.1: Comparison of Image with noise and De-noise Image

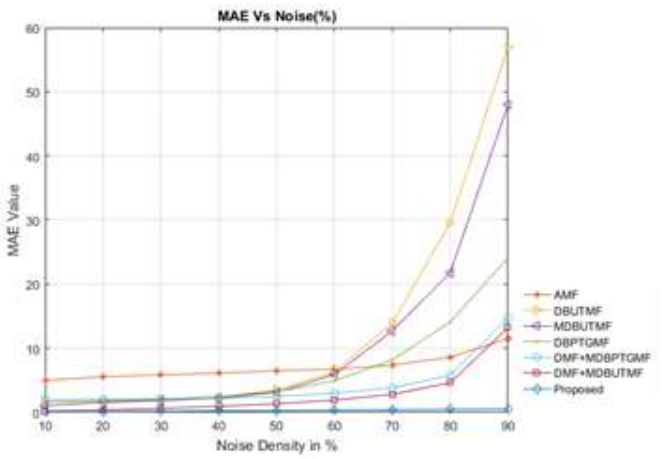


Figure 4.2: Comparison of MAE at different noise densities

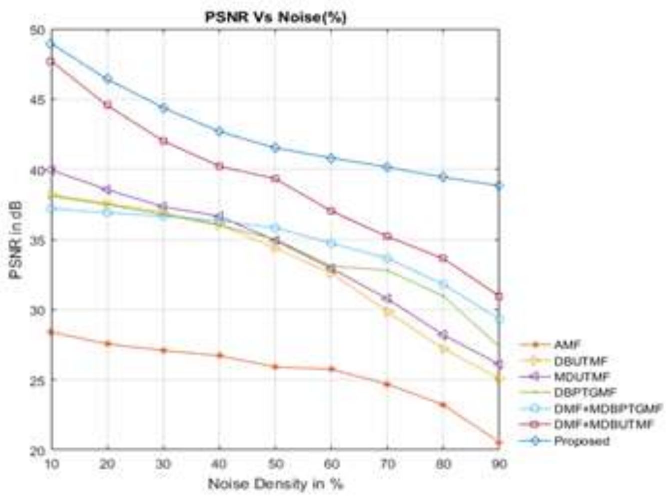


Figure 4.3: Comparison of PSNR at different noise densities

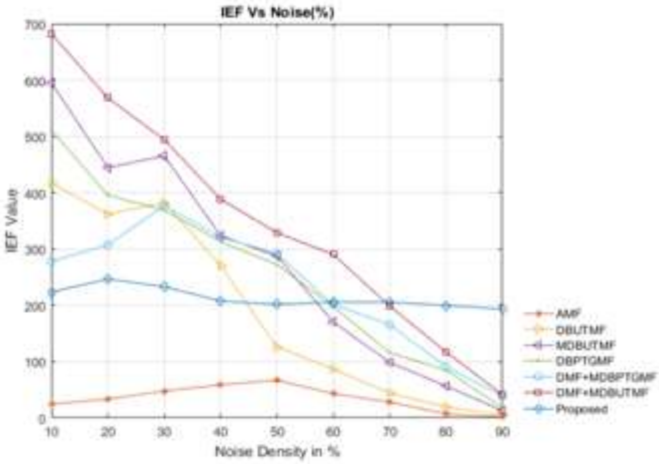


Figure 4.4: Comparison of IEF at different noise densities

Figure 4.1.1: Image with noise density=10

Figure 4.1.2: Image with noise density=20

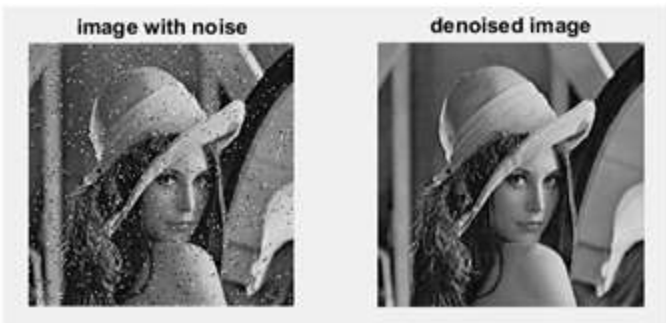


Figure 4.1.3: Image with noise density=30

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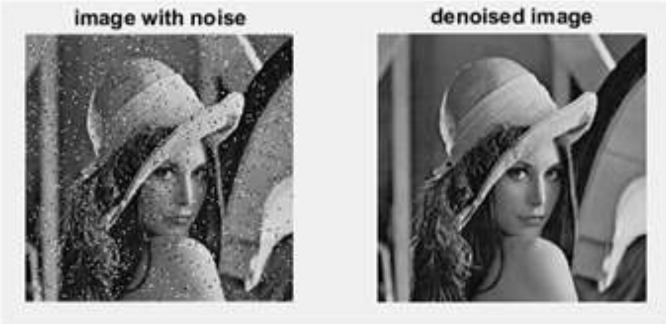

Figure 4.1.4: Image with noise density=40

Figure 4.1.5: Image with noise density=50

Figure 4.1.6: Image with noise density=60

Figure 4.1.7: Image with noise density=70

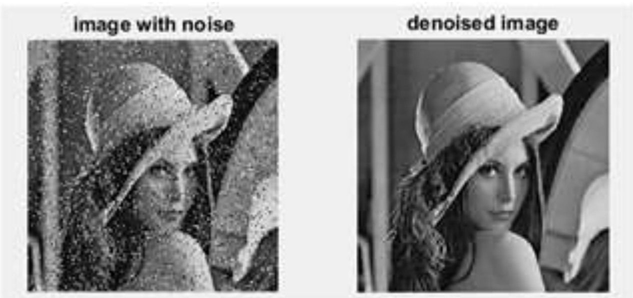

Figure 4.1.8: Image with noise density=80

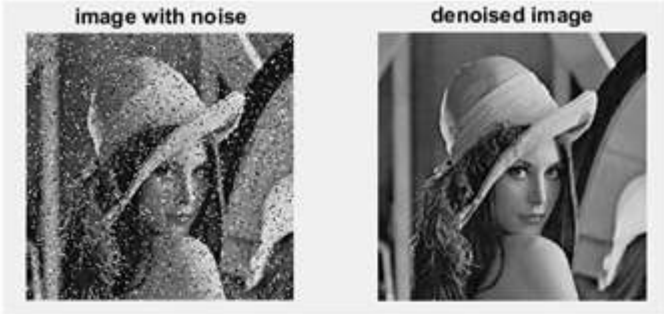

Figure 4.1.9: Image with noise density=90

V. CONCLUSION

The Work Has Briefly Overviewed The Method For Image De-Noising Using Neural Network. A Novel Hybrid Filter Is Implemented Which Is Capable Of Predicting The Best Filter For Every Pixel Using Neural Network And Choose The Best Technique To Remove Noise With 3x3 Mask Operation. The Proposed Algorithm First Trains The Neural Network For Various Filters Like Mean, Median, Mode, Geometrical Mean, Arithmetic Mean And Then Use To Remove Noise Later On. The Experimental Result Shows That Proposed Method Gives Better Performance In Comparison With Mf, Amf And Other Existing Noise Removal Algorithms And Improves The Values Of Various Parameters. The Performance Of The Algorithm Has Been Tested At Low, Medium And High Noise Densities.

The proposed work had concluded that:
a) The proposed hybrid filter is efficient in removing high density noise from a digital image.
b) The proposed algorithm gives better results of images and their parameters.

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