

Adaptive Technique for Salt and Pepper Noise Removal through Functional Link Artificial Neural Network



Sunita Sarangi, Suchitra Sarangi

Abstract: In this paper, an adaptive method for removing salt and pepper noise from images is proposed. A second order difference operator is used to locate the corrupted pixels in images by comparing with a threshold, which is selected adaptively using the image properties. A functional link artificial neural network (FLANN) based method is proposed to set a threshold for each corrupted image for identification of noisy pixels using recursive zero attracting least mean square (RZALMS) as the updating algorithm. Median filter is used to eliminate noise from the detected pixel locations.

Keywords: Adaptive threshold, Median Filter, Reweighted zero Attracting LMS, Salt and Pepper noise.

I. INTRODUCTION

Denoising of images is a crucial step in the analysis of images. Many image processing applications require noise removal as preprocessing step. Several variations of median and mean filter have been proposed for denoising of images effectively. Ching-Ta Lu et al [9] proposed directional weighted median filter for suppressing background noise while preserving the complete information of an image. Another variation of median filter is proposed by Vikas Gupta et al [2] which use adaptive dual threshold technique for noise removal that gives better performance as compared to standard median filter. V. R. Vijaykumar et al [4] also proposed a technique of filtering salt and pepper noise using median – mean filter which can preserve details in image up to a noise intensity of 90%. Subhojit Sarker et al [10] combine median filter with mean filter for eliminating noise from images which provides better quantitative measures in terms of PSNR. Xuming Zhang et al [3] proposed that a combination of an adaptive weighted mean filter and directional difference based noise detector can outperform existing methods in noise detection and image restoration. An adaptive statistics estimation filter is suggested by V. Jayaraj et al [5] which gives superior results in noise reduction in comparison with standard filters while consuming less

computational time. Xiaotian Wang et al [6] presented an iterative nonlocal means filter for removal noise which is robust to the detection procedure. Kenny Kal Vin Toh et al [8] adaptive fuzzy switching median filter which is able to detect and remove noise having less processing time.

In this paper, an efficient image denoising algorithm is proposed in which second order difference operator and median filter is used for salt and pepper noise removal. The second order difference operator identifies the noisy pixels using a threshold which is computed adaptively by FLANN. FLANN trained by RZALMS as back propagation algorithm calculates the threshold using properties of noisy image. After detecting the noisy pixel locations, filtering is done through standard median filter.

The proposed method detects the noisy pixels and only those detected pixels are applied filtering while keeping other pixels unchanged. Experimental results demonstrate that the proposed model is superior to other standard filtering methods.

The remaining part of the paper is organized as follows. The methodology involved in salt and pepper noise reduction in images is described in section 2. The detailed process involved in adaptive estimation of threshold is described section 3. The simulation and comparison results are given in section 4. Finally the concluding remarks are presented in section 5.

II. METHODOLOGY

The proposed method detects the locations of noisy pixels using a second order difference operator which uses a threshold. The efficiency of noise removal from images depends on the efficient detection of threshold. The detailed procedure of adaptive threshold selection by FLANN using properties of noisy image such as mean and variance is described in the following section. After computing threshold median filtering is applied to noisy locations for removal of noise.

Consider I^N as the noisy version of original image, I of sizes $M \times N$. The intermediate output obtained after processing I^N in horizontal direction is again processed in vertical direction using thresholds computed by FLANN.

For a pixel located at (m, n) :

$$\hat{I}^N(m, n) = \begin{cases} I^N_{m,n}, & D_{m,n} = 1 \\ O_{m,n}, & D_{m,n} = 0 \end{cases} \quad (1)$$

Where $O_{m,n} = \text{median}\{I^N_{m-p,n-q}, (p, q) \in W\}$ and W is a window of size 3×3 .

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The decision index, $D_{m,n}$ decides whether to apply median filtering or leave the pixel unchanged. The following steps are involved in the determination of $D_{m,n}$.

i) A test window, I^{NT} of size 3×5 generated from I^N as

$$I^{NT} = \begin{pmatrix} I_{m-1,n-2}^N & I_{m-1,n-1}^N & I_{m-1,n}^N & I_{m-1,n+1}^N & I_{m-1,n+2}^N \\ I_{m,n-2}^N & I_{m,n-1}^N & I_{m,n}^N & I_{m,n+1}^N & I_{m,n+2}^N \\ I_{m+1,n-2}^N & I_{m+1,n-1}^N & I_{m+1,n}^N & I_{m+1,n+1}^N & I_{m+1,n+2}^N \end{pmatrix} \quad (2)$$

ii) A difference matrix $I^{N(1f)}$ is calculated from I^{NT} as

$$I^{N(1f)} = \begin{pmatrix} I_{m-1,n-1}^{N(1f)} & I_{m-1,n}^{N(1f)} & I_{m-1,n+1}^{N(1f)} & I_{m-1,n+2}^{N(1f)} \\ I_{m,n-1}^{N(1f)} & I_{m,n}^{N(1f)} & I_{m,n+1}^{N(1f)} & I_{m,n+2}^{N(1f)} \\ I_{m+1,n-1}^{N(1f)} & I_{m+1,n}^{N(1f)} & I_{m+1,n+1}^{N(1f)} & I_{m+1,n+2}^{N(1f)} \end{pmatrix} \quad (3)$$

Where, $I_{m+p,n+q}^{N(1f)} = I_{m+p,n+q}^{NT} - I_{m+p,n+q-1}^{NT}$ $p = -1, 0, 1$ and $q = -1, 0, 1, 2$

iii) Another difference matrix $I^{N(2f)}$ is calculated from $I^{N(1f)}$ as given below

$$I^{N(2f)} = \begin{pmatrix} I_{m-1,n-1}^{N(2f)} & I_{m-1,n}^{N(2f)} & I_{m-1,n+1}^{N(2f)} \\ I_{m,n-1}^{N(2f)} & I_{m,n}^{N(2f)} & I_{m,n+1}^{N(2f)} \\ I_{m+1,n-1}^{N(2f)} & I_{m+1,n}^{N(2f)} & I_{m+1,n+1}^{N(2f)} \end{pmatrix} \quad (4)$$

Where $I_{m+p,n+q}^{N(2f)} = I_{m+p,n+q}^{N(1f)} - I_{m+p,n+q-1}^{N(1f)}$, $p = -1, 0, 1$ and $q = -1, 0, 1$.

iv) $D_{m,n}$ for pixel located at (m,n) is computed as

$$D_{m,n} = \begin{cases} 0, & \text{if } |I_{m,n}^{N(2f)}| > T1 \\ 1, & \text{otherwise} \end{cases} \quad (5)$$

The threshold, $T1$ is calculated by FLANN.

v) After computing decision index, equation (1) is used for filtering a pixel located at (m, n) .

vi) All the steps from (i) to (v) are repeated by shifting I^{NT} from left to right and top to bottom in I^N .

vii) The transpose of the output, obtained after completing step (vi) is taken and then the steps from (i) to (vi) are repeated for this output with another threshold $T2$ computed from FLANN.

III. ADAPTIVE THRESHOLD ESTIMATION USING FLANN

The structure of FLANN used for adaptive estimation of thresholds is shown in fig.1. The input to the FLANN is given by

$$x = [M, V] \quad (6)$$

Where M is the mean and V is the variance of noisy image. The input is expanded using trigonometric basis functions as given in equation (8).

$$X(n) = \{M, \sin(\pi M), \sin(50\pi M), \cos(\pi M), \cos(50\pi M), V, \sin(\pi V), \sin(50\pi V), \cos(\pi V), \cos(50\pi V)\} \quad (7)$$

The weight vector, $W(n)$ between input and output layers is given by

$$W(n) = [w_1(n), w_2(n), \dots, w_{10}(n)] \quad (8)$$

By comparing $Y(n)$ with the desired output, $D(n)$, the error $E(n)$ is computed.

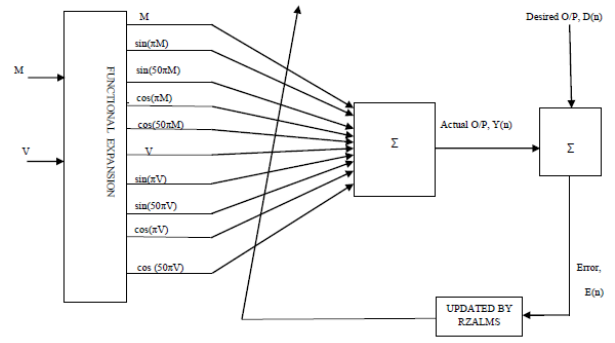


Fig. 1: FLANN structure for threshold estimation

$$E(n) = D(n) - W^T(n)X(n) \quad (9)$$

$W(n)$ is updated using Reweighted Zero Attracting Least Mean Square (RZALMS) algorithm [11] as given below:

$$W(n+1) = W(n) - \rho \frac{\text{sgn}\{W(n)\}}{1 + \varepsilon|W(n)|} + \mu u * E(n) * X(n) \quad (10)$$

Where μ is the step size which is taken to be 0.05 whereas 0.0005 and 10 are taken as values for ρ and ε , which were chosen empirically.

IV. RESULT AND DISCUSSION

The proposed method was designed and tested with different standard images using MATLAB R2016a. Fig. 2 shows the outputs of the proposed algorithm for three standard images for a noise density of 30%.

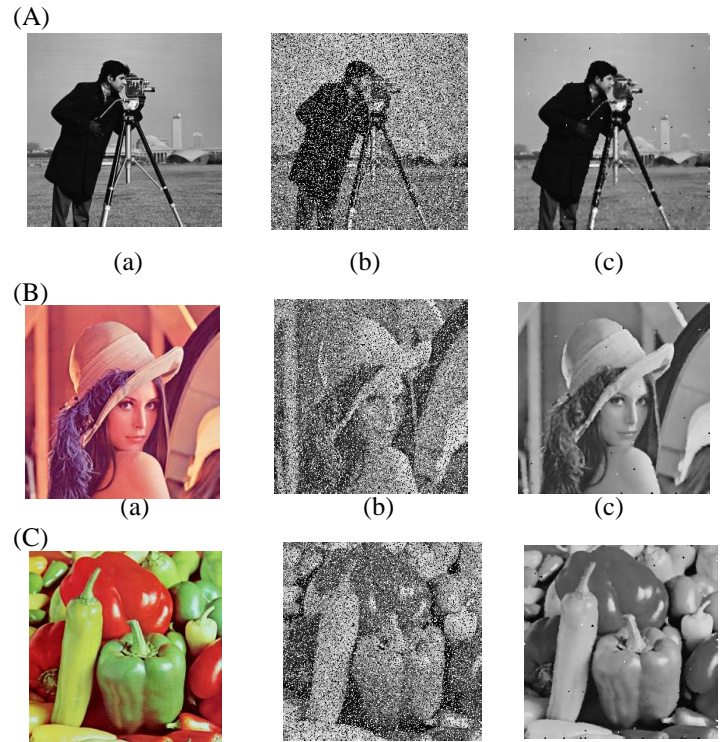


Fig. 2: Outputs of the proposed system for images corrupted with 30% noise density (A) Cameraman, (B) Lena and (C) Pepper where (a) original image, (b) noisy image and (c) output image

A comparison was made between different adaptive algorithms like Least Mean Square (LMS), Normalized LMS (NLMS) and RZALMS algorithms to be used for updating the weights of $W(n)$ in estimating thresholds. Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Mean Absolute Error (MAE) and Structural Similarity Index Measure (SSIM) are the performance measures used for comparison between different adaptive algorithms.

$$PSNR = 10 \log_{10} \left(\frac{255^2}{\frac{1}{MN} \sum_i \sum_j (I_{i,j} - X_{i,j})^2} \right) \quad (11)$$

$$MSE = \frac{1}{MN} \sum_i \sum_j (I_{i,j} - X_{i,j})^2 \quad (12)$$

$$MAE = \frac{1}{MN} \sum_i \sum_j (I_{i,j} - X_{i,j}) \quad (13)$$

The SSIM index [12] is also used for comparison between the outputs obtained using different adaptive algorithms which values are in between 0 to 1. A zero value indicates no correlation between the input and output images whereas one indicates equality between the input and output images. Hence, more the index closer to 1 better is the output. Also an output with high value of PSNR and at the same time having less MSE and MAE will be considered as better result.

The tables I to IV show the comparison between adaptive algorithms using PSNR, MSE, MAE and SSIM as the quantitative measures taking Lena as the input image at varying noise density. It was found that the outputs obtained using the threshold which is estimated by RZALMS algorithm are superior in terms of performance measures as compared to other two adaptive algorithms.

Table I: Comparison between different adaptive algorithms using PSNR

Noise density (%)	LMS	NLMS	RZALMS
10	30.1848	30.2948	30.7160
20	27.7768	28.4756	28.6524
30	25.8753	26.0773	26.3013
40	23.0411	23.0865	23.3595
50	19.2708	19.4026	19.7787
60	15.3853	15.4170	15.7993
70	11.7704	11.8415	12.1802
80	9.2361	9.2413	9.2395
90	7.0475	7.0804	7.1317

Table II: Comparison between different adaptive algorithms using MSE

Noise density (%)	LMS	NLMS	RZALMS
10	12.5067	12.1149	11.9825
20	14.6349	14.5844	14.1929
30	16.7855	16.4119	16.3342
40	19.7033	19.4876	19.5356
50	24.9468	24.3866	23.8197
60	34.2034	33.0167	32.5873
70	49.8688	47.7276	46.8925
80	69.0857	67.7543	66.1762
90	95.3029	95.2592	94.8065

Table III: Comparison between different adaptive algorithms using MAE

Noise density (%)	LMS	NLMS	RZALMS
10	1.5937	1.5496	1.5376
20	1.8587	1.8480	1.8037
30	2.1946	2.1688	2.1177
40	2.8562	2.8376	2.7422
50	4.6595	4.4975	4.1934
60	8.6754	8.4955	7.9018
70	17.5933	16.4317	15.7650
80	28.9395	28.3832	27.8335
90	45.4577	45.1337	44.8744

Table IV: Comparison between different adaptive algorithms using SSIM

Noise density (%)	LMS	NLMS	RZALMS
10	0.9131	0.9125	0.9164
20	0.8842	0.8912	0.8929
30	0.8533	0.8466	0.8554
40	0.7722	0.7675	0.7758
50	0.6039	0.6120	0.6250
60	0.3581	0.3557	0.3783
70	0.1551	0.1543	0.1724
80	0.0641	0.0610	0.0706
90	0.0238	0.0249	0.0244

The proposed technique is also compared with other standard filters like Mean, Median and Gaussian including the adaptive methods like LMS and NLMS for different images at 60% noise density and the corresponding PSNR values are given in table V. From the table it is found that the proposed method using FLANN and RZALMS algorithm provides better output in all the cases except for onion image.

Table V: comparison results for different images at 60% noise density

Method s	camera man	rice	saturn	greens	Football	Onion
Mean	14.6862	16.1587	12.1069	13.3809	14.9443	15.4824
Median	14.3280	15.1673	13.9590	13.6015	14.9801	15.1723
Gaussian	11.3085	11.9874	9.4699	10.5618	11.2739	11.5731
LMS	17.8160	19.3389	19.0629	16.2990	19.6292	20.5344
NLMS	17.7443	19.3011	19.1156	16.4505	20.4555	20.2856
Proposed	18.0087	19.4226	19.5544	16.7243	20.5517	20.1842

The graph in fig. 3 shows the variation of PSNR (dB) with noise density for Lena image obtained from the proposed approach and other standard filters. It has been observed that at low level of noise densities, the median filter provides better results where as at high level of noise densities, the proposed method results are superior to other methods.

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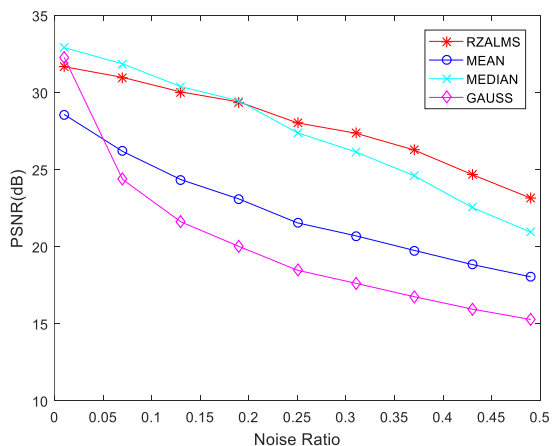


Fig. 3: Variation of PSNR (dB) at different noise density for Lena image

V. CONCLUSION

The paper proposes an approach for denoising of images using an adaptive threshold based second order difference operator method. According to the image properties, the threshold is computed adaptively using FLANN and RZALMS algorithm. The proposed technique is also compared with other adaptive algorithm based methods and standard filters in terms of PSNR, MSE, MAE and SSIM as the performance measures and it was found that the proposed model outputs exceeds other methods.

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