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Image Enhancement through Noise Suppression using Nonlinear Parameterized Adaptive Recursive Model

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ABSTRACT

Quality of the image is corrupted by noise in many cases so that it is difficult to extract the useful information. Noise corrupts the image during sensing with malfunctioning cameras, storing in faulty memory locations or sending through a noisy channel. The main objective of this paper is to develop a faster and better algorithm for suppressing salt and pepper noise from noisy images. This paper proposes a method for image enhancement through noise suppression using a Nonlinear Parameterized Adaptive Recursive Model in spatial domain. The proposed method provides good results subjectively and objectively for both gray scale and true color images. The proposed method is useful for interactive image processing applications as it has a family of possible denoisy images for a noisy image.

Keywords **- Digital Image Processing (DIP), Image Enhancement (IE), Parameterized Adaptive Recursive (PAR), Parameterized Gradient Intercept (PGI), and Peak Signal to Noise Ratio (PSNR).**

I. INTRODUCTION

One of the common types of noise with which images are corrupted is salt and pepper noise. Image denoising basically improves visual quality by providing clear images for human observer and/or for machine in automatic processing techniques. Image enhancement operations can be done in spatial domain and/or frequency domain. Image enhancement in spatial domain means modifying the image pixels directly. We reviewed about enhancement techniques for gray scale images in spatial domain and implemented using MATLAB [1]. These techniques have been extended successfully to true color images also in [2]. Image enhancement process gives better visual quality either by improving the contrast or suppressing the noise. Image enhancement through contrast improvement can be done by using Linear Parameterized Gradient Intercept (PGI) model. This paper proposes a method for image enhancement through noise suppression using a Nonlinear Parameterized Adaptive Recursive (PAR) model in spatial domain.

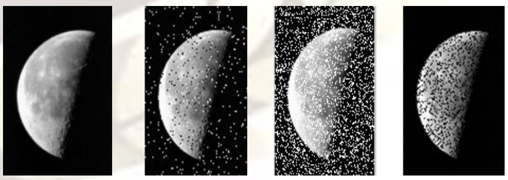
II. RELATED WORK

Let f(x,y) be a digital image of size MxN with pixel values in the range [0, L-1], $f_n(x,y)$ be its noisy image corrupted by salt and pepper noise and g(x,y) be its denoisy image in which noise is suppressed. Noisy pixels in $f_n(x,y)$ can take the values of either minimum value or maximum value in the given dynamic range.

$$f_n(x,y) = \begin{cases} 0 \\ L-1 \\ f(x,y) \end{cases} \qquad (1)$$

Spatial filtering operation involves moving the centre of a square mask from pixel to pixel over the entire image. In nonlinear filters enhanced image g(x,y) at (x,y) is not linearly related to pixels in the neighborhood of input image. For each neighborhood, find pixel value based on the type of nonlinear filter and then map with the central pixel. Generally the size of the window is odd. The two basic filters are Maximum and Minimum filters [3]. Max filter locates brightest point in an image so that it removes pepper noise only where as Min filter locates darkest point in an image so that it removes salt noise only.

$$g(x,y) = max\ [f_n(x,y)]$$
$$g(x,y) = min\ [f_n(x,y)]$$



a b c d

Fig. 1: a) moon image corrupted with salt & pepper noise (1%), results of b) max c) min d) median filters
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Median filters are popular in signal processing as well as in image processing [4]. Basic Median Filter (BMF) removes both salt and pepper noise simultaneously as it locates the median of the pixels.

$$g(x,y) = bmed\ [f_n(x,y)]$$

Even though basic median filters add less blur, but fails to remove salt and pepper noise for boarder pixels of the noisy image. To avoid this ensquare the noisy image by padding zeros before median filtering which are to be removed after filtering. Conventional non linear median filters are classified as:

- Traditional Median Filter (TME)
- Recursive Median Filter (RMF)
- Adaptive Median Filter (AHE)

TMF takes the window size as 3x3. RMF takes the output image as the input image for next iterative filtering; it is also known as multrate median filter. When compared to TMF, RMF has more computational time. AMF takes the window size as adaptive. Window size increases as intensity of noise to be suppressed increases [5] and it increases computational time when compared to TMF and RMF. All the three filters TMF, RMF, and AMF perform filtering operation to noisy image irrespective of whether the pixel is noisy or not.

$g(x,y) = tmed[f_n(x,y)]$
$g(x,y) = rmed[f_n(x,y)]$
$g(x,y) = amed[f_n(x,y)]$

Hence it is necessary to find a new median filter that performs filtering operation to only noisy pixels intentionally with smallest computational time and large peak signal to noise ratio.

III. Proposed method

The relation between noisy image and denoisy image for the proposed method is

$$g(x,y) = imed[f_n(x,y)]$$

where imed means Intentional median filter that performs filtering to noisy pixels intentionally. Let A be the window size that is adaptive and R be the Recursive order that is iteration number. A and/or R can be varied for suppressing the salt and pepper noise This filter has less computational time (t_c) and high Peak Signal to Noise Ratio (PSNR) as it performs filtering to only noisy pixels of noisy image. The proposed nonlinear method is given the name **P**arameterized **A**daptive **R**ecursive (PGI) model', as a family of possible denoisy images can be obtained for achieving effective noise suppression.

IV. PAR Algorithm

The following are the in proposed non linear Parameterized Adaptive Recursive (PAR) algorithm simulation for gray scale and true color images.

Gray scale image:

1. Consider a noise less image f(x,y).
2. f_n(x, y) is a noisy image of f(x,y).
3. Select appropriate values of A and R.
4. Ensquare noisy image with (A-1)/2 zeros to get f_p(x,y)
5. If $0<f_p(x,y) < L-1$, go to next pixel.
6. Perform imed filtering to get g_p(x,y).
7. If g_p(x,y) is noisy, vary A and/or R.
8. If A varies go to 4th step otherwise go to 5th step.
9. Remove the ensqured zeros in g_p(x,y) to get denoisy image g(x,y).

True Color image:

1. Consider a noise less image f(x,y).
2. f_n(x,y) is a noisy image of f(x,y).
3. Extract r,g,b components from f_n(x,y)
4. Select appropriate values of A and R.
5. Ensquare noisy rgb images with (A-1)/2 zeros to get their padded images.
6. If $0<r_p(x,y) < L-1$, go to next pixel. Perform imed filtering to r_p(x,y).
7. If $0<g_p(x,y) < L-1$, go to next pixel. Perform imed filtering to g_p(x,y).
8. If $0<b_p(x,y) < L-1$, go to next pixel. Perform imed filtering to b_p(x,y).
9. Get color image g_p(x,y) from r_p,g_p,b_p.
10. If g_p(x,y) is noisy, vary A and/or R .
11. If A varies go to 5th step otherwise go to 6th step.
12. Remove the ensqured zeros in g_p(x,y) to get denoisy image g(x,y).

V. Results

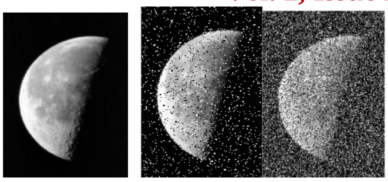
The PAR model performance can be compared to that of TMF, RMF and AMF methods by denoising 'moon', 'man', and 'Lena' images corrupted via salt and pepper noise at various noise intensities. The amount of noise suppression can be judged not only by visual inspection of the resultant images, but also by evaluating the Peak Signal to Noise Ratio (PSNR) using mean square error (mse) and computational time (t_c) for each method [6]. The subjective results and objective results [7] [8] are shown in the following figures and tables respectively.

Peak Signal to Noise Ratio(dB):

$$PSNR = 20log_{10}\left[\frac{L-1}{\sqrt{mse}}\right]$$ where

mean square error:

$$mse = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j) - g(i,j)]^2$$


(a) (b) (c)

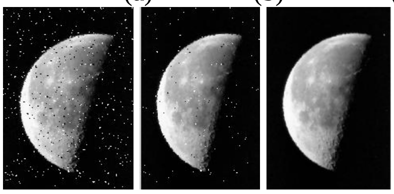
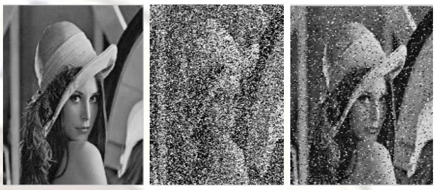

(d) (e) (f)

Fig. 2: (a) moon image (b) its noisy image
(c) TMF (d) RMF (e) AMF (f) PAR


(a) (b) (c)


(d) (e) (f)

Fig. 3: (a) man image (b) its noisy image
(c) TMF (d) RMF (e) AMF (f) PAR


(a) (b) (c)

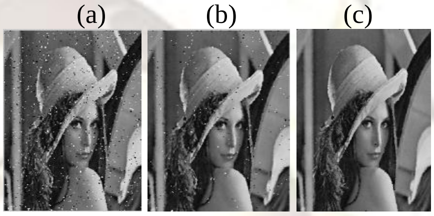

(d) (e) (f)

Fig. 4: (a) lena image (b) its noisy image
(c) TMF (d) RMF (e) AMF (f) PAR

Table 1: PAR with A=3x3 and R=1

moon	Peak Signal to noise ratio(PSNR) in dB					Computational time(t_c) in sec			
Noise	original	TMF	RMF	AMF	PAR	TMF	RMF	AMF	PAR
1%	71.8879	88.2499	86.9051	84.5980	102.982	0.641379	1.750565	1.532068	0.327906
2%	68.9359	88.1451	86.8390	84.5437	102.047	0.986047	1.127265	0.848692	0.176841
3%	66.9403	87.9242	86.7148	84.4668	99.8731	0.619397	1.086479	0.844120	0.182955
4%	65.8178	87.6334	86.5594	84.3782	98.4010	1.027188	1.932597	0.829071	0.187080
5%	64.8458	87.3782	86.3532	84.2720	96.3917	1.024819	1.972571	0.829510	0.193336
6%	63.9540	87.4719	86.4644	84.3716	97.1399	1.040213	1.766819	0.839590	0.198213
7%	63.3633	86.8564	86.2426	84.1749	94.0129	1.032107	1.379749	1.264724	0.364163
8%	62.7959	87.0398	86.2489	84.1800	95.2316	0.670125	1.397606	1.449867	0.211592
9%	62.3314	85.6578	85.9629	83.9327	91.9331	0.874176	1.194209	1.531124	0.401457
10%	61.8304	86.4173	85.8962	83.9262	93.0883	1.031289	1.985404	1.518034	0.394458
15%	60.0491	82.7356	85.1096	83.3789	86.9625	1.024806	1.472294	1.211419	0.422902
man	Peak Signal to noise ratio(PSNR) in dB					Computational time(t_c) in sec			
Noise	original	TMF	RMF	AMF	PAR	TMF	RMF	AMF	PAR
1%	72.9729	75.2620	74.5479	71.8971	91.9110	0.465621	0.817768	0.647978	0.229135
2%	70.2048	75.0749	74.4417	71.8773	88.0165	0.470731	0.534591	0.358457	0.127704
3%	68.3899	75.0059	74.3486	71.7734	87.2399	0.467395	0.516493	0.352795	0.129465
4%	67.3774	74.8128	74.2282	71.7341	85.6522	0.356191	0.441168	0.361248	0.140169
5%	66.2259	74.7996	74.2467	71.7322	85.3066	0.465621	0.817768	0.647978	0.229135
6%	65.5385	74.7025	74.1162	71.6912	84.2274	0.446105	0.791191	0.643829	0.141598
7%	64.5123	74.4254	74.0210	71.6982	83.2134	0.308469	0.456706	0.356191	0.181945
8%	64.1291	74.3088	73.8908	71.6211	82.4474	0.446290	0.831637	0.676935	0.258502
9%	63.6780	74.3475	73.9081	71.5414	82.3300	0.446537	0.791778	0.645244	0.252389
10%	63.2956	74.2503	73.8747	71.5449	81.3961	0.439644	0.633756	0.370175	0.182324
15%	61.4314	72.9385	72.9871	70.9088	78.3979	0.475231	0.897457	0.762771	0.400670
lena	Peak Signal to noise ratio(PSNR) in dB					Computational time(t_c) in sec			

Noise	original	TMF	RMF	AMF	PAR	TMF	RMF	AMF	PAR
1%	73.2662	81.6908	80.6739	77.9050	98.3812	0.783882	1.427921	1.206299	0.199016
2%	70.3006	81.4515	80.5436	77.8573	94.9613	1.346975	2.627292	1.876503	0.195304
3%	68.5254	81.4484	80.5258	77.8407	93.8591	1.348196	1.877713	1.097273	0.220291
4%	67.2724	81.2782	80.4000	77.8001	92.4139	1.127996	1.772741	1.509762	0.297181
5%	66.3444	81.0136	80.2123	77.6920	90.8765	1.345799	1.430941	1.142487	0.219161
6%	65.4632	80.6328	79.9597	77.6291	89.2288	0.933597	1.480969	1.171644	0.228449
7%	64.8577	80.5908	79.9500	77.5355	89.3241	0.795420	1.480972	1.127244	0.244122
8%	64.2377	80.3903	79.8478	77.4767	88.2361	0.808637	1.448732	1.114924	0.307932
9%	63.7699	80.3059	79.7953	77.4894	88.0021	1.058009	1.453477	1.137083	0.246914
10%	63.2941	80.1247	79.6954	77.3470	87.2905	0.806836	2.051770	2.018655	0.447694
15%	61.5218	78.6778	79.0772	76.9254	83.6966	1.343149	2.653474	1.387617	0.519028

Table 2: PAR with A=5x5, R=1

noise	man			lena			moon		
	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)
	original	PAR		original	PAR		original	PAR	
20%	60.1658	76.9413	0.256909	60.2746	82.2778	0.389064	58.7836	89.0324	0.492115
25%	59.2671	75.1825	0.311380	59.3213	80.6297	0.558315	57.8732	87.5534	0.558653
30%	58.4806	73.9469	0.336833	58.5169	79.6115	0.639958	57.0150	86.1888	0.617659
35%	57.7546	73.2172	0.321584	57.8512	77.9215	0.758368	56.3454	84.0130	0.708721
40%	57.2126	71.8646	0.370316	57.2570	76.8099	0.736357	55.8032	80.4632	0.746626
45%	56.6507	70.6853	0.417965	56.7460	75.1590	0.876449	55.2857	77.8477	0.808748
50%	56.2012	69.3684	0.398131	56.2973	73.0698	1.208033	54.7845	73.9453	0.883556

Table 3: PAR with A=3x3, R=2

noise	man			lena			moon		
	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)
	original	PAR		original	PAR		original	PAR	
20%	60.1729	77.5374	0.212003	60.2884	83.4089	0.596601	58.8356	88.6831	0.494937
25%	59.1772	76.0083	0.264658	59.3072	81.3329	0.656560	57.8115	86.6944	0.560937
30%	58.4083	74.7935	0.280478	58.5306	80.0484	0.663698	57.0275	83.3302	0.600394
35%	57.7256	73.3495	0.300292	57.8809	78.1108	0.702574	56.3749	80.8284	0.635808
40%	57.1515	72.2548	0.325453	57.2660	75.7313	0.856761	55.7823	77.2082	0.698804
45%	56.6849	70.2748	0.335666	56.7507	73.2266	0.933612	55.2891	73.7953	0.738639
50%	56.2090	68.8002	0.355427	56.3046	71.0515	1.036821	54.8248	70.7248	0.791942

Table.4: PAR with A=7x7, R=1

noise	man			lena			moon		
	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)
	original	PAR		original	PAR		original	PAR	
40%	57.2017	71.2969	0.338442	57.2570	76.3700	1.253990	55.7933	83.7996	0.685859
45%	56.6798	70.5076	0.382829	56.7482	75.4585	1.444316	55.2735	82.3272	0.738154
50%	56.1962	69.7654	0.384500	56.2852	74.3819	1.586536	54.8157	80.7431	0.826666
60%	55.4277	67.7207	0.468871	55.4916	71.8831	1.827057	54.0193	75.1285	1.066149
65%	55.1063	66.5360	0.581749	55.1605	70.0561	1.938304	53.6567	71.2500	1.066649
70%	54.7458	64.7566	0.622745	54.8263	67.2351	2.049575	53.3351	67.2335	1.126386

Table 5: PAR with A=5x5, R=2

noise	man			lena			moon		
	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)
	original	PAR		original	PAR		original	PAR	
40%	57.2272	72.6545	0.378422	57.2560	78.0028	0.625861	55.8007	83.9712	0.854334

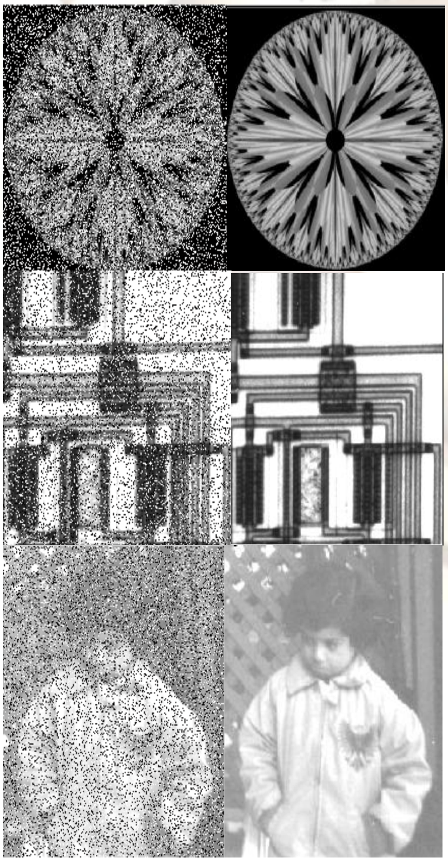
45%	56.6821	71.7125	0.398884	56.7489	76.7343	0.750781	55.2599	83.0245	0.915027
50%	56.2359	70.7891	0.425310	56.2861	75.7569	0.806194	54.8305	81.6153	0.988651
60%	55.4278	68.7709	0.478199	55.4937	73.3114	0.921761	54.0193	77.3863	1.135095
65%	55.0559	67.7534	0.538365	55.1545	71.5768	1.070117	53.6743	74.2393	1.215601
70%	54.7326	66.0329	0.566301	54.8264	69.3428	1.758960	53.3515	70.3490	1.350219

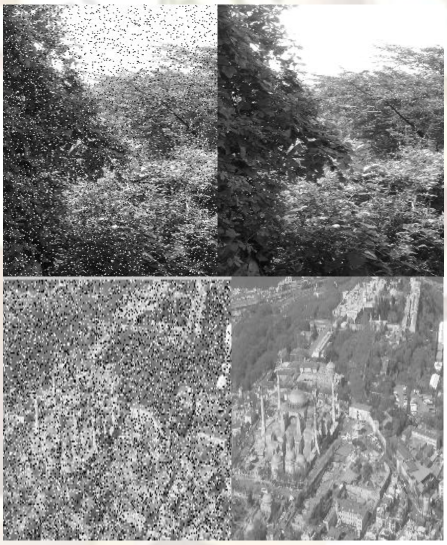
Table 6: PAR with A=7x7, R=2

noise	man			lena			moon		
	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)
	original	PAR		original	PAR		original	PAR	
65%	55.0870	67.5795	0.618415	55.1545	72.3188	1.930700	53.6929	77.9063	1.318531
70%	54.7620	66.7559	0.630611	54.8322	71.1277	2.625542	53.3238	76.4218	1.578933
75%	54.4519	65.6758	0.667128	54.5485	69.7392	2.714258	53.0577	72.7955	2.012724
80%	54.2016	63.9912	0.742045	54.2546	67.1673	3.093635	52.7800	67.7975	2.024871
85%	53.9297	61.5501	0.893274	53.9837	63.1480	3.511625	52.4917	62.9549	2.070514
90%	53.6731	58.8501	0.994462	53.7368	59.4628	3.708699	52.2665	58.5628	2.278872

Table 7: PAR with A=9x9, R=2

noise	man			lena			moon		
	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)	PSNR(dB)		t_c(sec)
	original	PAR		original	PAR		original	PAR	
80%	54.1746	64.5431	0.590783	54.2612	68.5338	2.413934	52.7756	73.2324	1.532866
85%	53.9007	62.4971	0.717572	53.9912	65.7602	2.707727	52.4968	66.3769	1.793030
90%	53.6671	59.5949	0.776945	53.7355	61.3481	3.034454	52.2692	60.9609	2.599874





(a) (b)

Fig. 5: (a) Noisy gray scale images
(b) PAR model Denoisy images

(a) (b)

Fig. 6: (a) Noisy true color images
(b) PAR model Denoisy images

Table 8: PAR model for different Gray Scale and True Color images from different fields.

Gray scale Image	A	R	True Color Image	A	R
fractal	3x3	2	moon	5x5	1
circuit	5x5	1	lena	3x3	2
pout	5x5	2	pepper	7x7	2
bush	3x3	2	birds	5x5	2
city	5x5	3	tower	3x3	2

V. Discussions

Visual inspection of results indicate that, the three filters TMF, RMF, and AMF perform filtering to noisy images corrupted by noise intensity of up to 15% where as proposed PAR model performs intentional median filtering with highest Peak Signal to Noise Ratio (PSNR) at lowest computational time.

The three existing conventional median filters fail to produce clear pictures for noisy images having noise intensity above 15% where as proposed PAR model works well. The reason is, on increasing window size (A) or recursive order(R), conventional methods round the corners and add the blur in denoisy image.

The proposed non linear model works well by providing a set of denoisy images for a noisy image on changing A and/or G. The limitation in the proposed model is small improvement in PSNR for suppressing high level noise intensities and also it suppresses only Salt and Pepper noise.

VI. Conclusions

Image enhancement through noise suppression using nonlinear parameterized adaptive recursive model in spatial domain has been successfully implemented using MATLAB. This paper considers images from different fields and choice of A and R depend on the type of the noisy image. Results show that PAR algorithm is faster and better when compared to TMF, RMF, and AMF methods. Proposed model can be used as a tool for Photo editing software like Photoshop or any existing image processing software by attaching two sliding bars for A and R. The PAR model can be used for suppressing high level salt and pepper noise or other types of noises with slight changes in algorithm. Future scope will be the development of an algorithm for image enhancement when an image is corrupted by both poor contrast and noise by using parameterized hybrid model.

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