

Simulated evaluation of new switching based median filter for suppressing SPN and RVIN

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Article Info

Article history:

Received Oct 13, 2018

Revised Feb 15, 2019

Accepted Mar 2, 2019

Keywords:

AMF (adaptive median filter)

Digital image processing

NSMF (new switching-based median filtering)

SMF (standard median filtering)

ABSTRACT

In the past two decades, the SPN (salt and pepper noise) suppressing method is worldwide interested researches on computer vision and image processing hence many SPN suppressing methods have been proposed. In general, the primary goal of SPN removal method is the suppressing of SPN in digital images thereby one of the recent effective and powerful SPN suppressing methods is a new switching-based median filtering (NSMF), which is innovated for suppressing high density SPN. Consequently, this paper thoroughly examines its efficiency and constrain of a new switching-based median filtering when this filter is used for contaminated image, which is synthesized by SPN and RVIN (random-value impulsive noise). In these simulations, six well-known images (Lena, Mobile, Pepper, Pentagon, Girl, Resolution) with two impulsive noise classes (SPN and RVIN) are used for measuring the its efficiency and constrain. An evaluation of the efficiency is conducted with many previous methods in forms of subjective and objective indicators.

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1. INTRODUCTION OF NSMF (NEW SWITCHING-BASED MEDIAN FILTERING)

Digital images [1]-[4] are generally contaminated by impulsive noise [5]-[23] due to communicating unsuccess, improper operating of CCD sensor, ADC synchronized erroneous and memory site erroneous hence noise suppressing method is one of the most vital process for sophisticated digital image process [24]-[26] for instant, face identification, license plate identification, remote sensing, etc. Even through the original Median Filter (SMF) [5]-[7] and Adaptive Median Filter (AMF) [14], [27] are known as the practical noise suppressing method [5]-[23] for SPN, one of the recent effective and powerful SPN suppressing methods is a NSMF (new switching-based median filtering) [28], which is proposed for suppressing only SPN, especially high density. From some results [28], it can conclude that NSMF has good efficiency while the NSMF has low computational complexity however there are no research of the NSMF for SPN at all density and random-value impulsive noise. Consequently, this paper thoroughly examines its efficiency and constrain of a novel modified median filtering based switching technique.

2. STATISTICAL THEORY OF NSMF

The NSMF comprises of four modified processes (*Process 1- Process 4*) as showing in Figure 1 instead of three processes (for previous proposed method), namely, detection, estimation, and replacement.

- a) *Process 1*: Detecting the processed pixel as noisy pixel or noiseless pixel. If the processed pixel is 0 or 255 then the processed pixel is classified as contaminated noise otherwise the pixel is noiseless.
- b) *Process 2*: Substituting the processed input pixel by using 1st order linear predictor.
- c) *Process 3*: Estimating the expected original image by using a median filtering based on L-estimators.

d) *Process 4*: Replacing contaminated pixels by the estimated pixels.

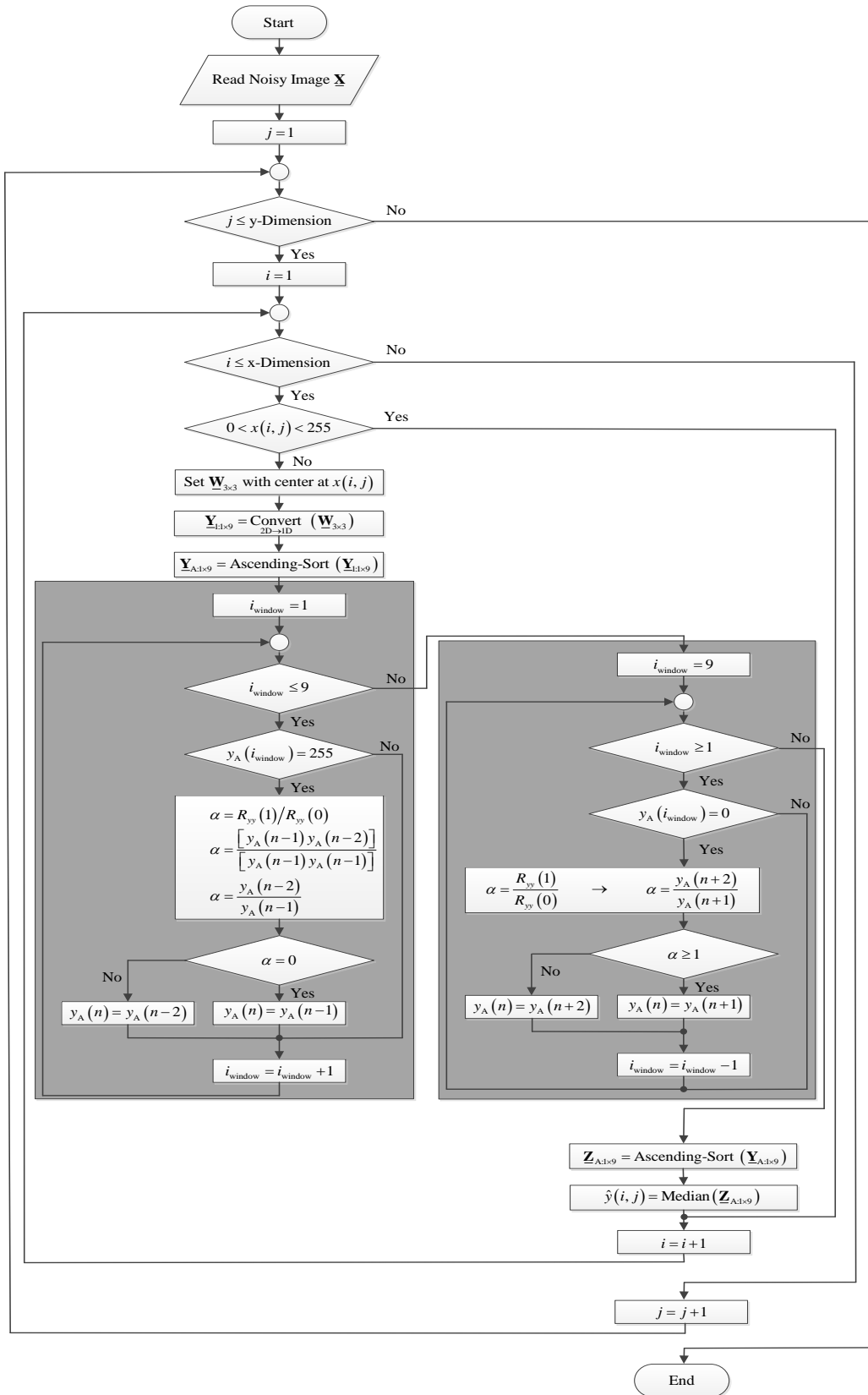


Figure 1. The flowchart of overall method of new switching-based median filtering (NSMF)

2.1. Statistical Theory of Estimating Process

Let $X = \{x_1, x_2, x_3, \dots, x_j, x_{j+1}, x_{j+2}, \dots, x_n\}$ is the original image, which is noiseless, and $Y = \{y_1, y_2, y_3, \dots, y_j, y_{j+1}, y_{j+2}, \dots, y_n\}$ is the contaminated image, which is comprised of a set of noiseless pixels $\{y_1, y_2, y_3, \dots, y_j\}$ and a set of noisy pixels $\{y_{j+1}, y_{j+2}, \dots, y_n\}$. Let $Z = \{y_1, y_2, y_3, \dots, y_j, z_{j+1}, z_{j+2}, \dots, z_n\}$, which is comprised of a set of noiseless pixels $\{y_1, y_2, y_3, \dots, y_j\}$ and a set of substituted pixels for the noisy pixels $\{z_{j+1}, z_{j+2}, \dots, z_n\}$, and z_{med} be the median of Z .

Let $x_i[n]$ is the i^{th} order statistic of the original image and $\hat{x}[n]$ is the expected original image, which can be defined from set of original noiseless pixels ($x_i[n]$). By linear prediction, Finite Impulse Response (FIR) linear predictor of order $(p-1)$ can be statistically defined as:

$$\hat{x}[n+1] = \sum_{k=0}^{p-1} h[k] x[n-k] \quad (1)$$

where $h[k]$ are the prediction filter coefficients.

The $h[k]$ is statistically defined by the Wiener-Hopf [5] equation as

$$R_x[k] h[k] = r_x[k] \quad (2)$$

where $R_x[k]$ is an autocorrelation matrix, $h[k]$ is predictor coefficient vector, and $r_x[k]$ is autocorrelation vector. The autocorrelation $R_x[k]$ can be statistically defined as

$$E[x[l-k]x[n-k]] = R_x[k-1] \quad (3)$$

where $k=0$ to $(p-1)$ and $l=0$ to $(p-1)$

By Auto Regressive Moving Average (ARMA) in time domain, the causal Infinite Impulse Response (IIR) predictor is given by $H[z] = z(1-1/Q[z])$, which can be statistically defined as

$$\hat{x}[n+1] = \sum_{k=0}^{N-1} a_k \hat{x}[n-k] + \sum_{k=0}^{N-1} b_k \hat{x}[n-k] \quad (4)$$

Let $\hat{x}[n]$ is an expected original image from one or more noiseless pixels and $\hat{x}[n] = d[k]$

$$E[\hat{x}[n]x[n+1]] = E[d[n]x[n+1]] = \hat{r}d[k] \quad (5)$$

2.2. Statistical Theory of Replacing Process

If the processed input pixel is 0 or 255 then the pixel is defined as a noisy pixel and is replace by the replacing process, which comprises of 10 processing step as following:

- 1) *Processing Step 1*: Setting the 3×3 window with center at the processed pixel $x(i, j)$.
- 2) *Processing Step 2*: If $0 < x(i, j) < 255$ then the processed input pixel is classified as noiseless pixel and it is left unchanged and, then, the processed pixel $x(i, j)$ moves to the next position.
- 3) *Processing Step 3*: If $x(i, j) = 0$ or $x(i, j) = 255$ then the processed input pixel is classified as noisy pixel and go to *Processing Step 4*.
- 4) *Processing Step 4*: Converting the 3×3 window (2D) to the vector Y_A (1D)
- 5) *Processing Step 5*: Sorting to the vector Y_A (1D) in ascending order
- 6) *Processing Step 6*: If $x[n] = 255$ then replacing $x[n]$ from left to right by following equation

$$x[n] = \alpha \cdot x[n-1] \text{ with } \alpha = (R_{xx}[1]/R_{xx}[0]), 0 < \alpha < 1 \quad (6)$$

$$R_{xx}[1] = x[n-1] \cdot x[n-2] \quad (7)$$

$$R_{xx}[0] = x[n-1] \cdot x[n-1] \quad (8)$$

If $\alpha = 0$ then $x[n] = x[n-1]$

- a) *Processing Step 7*: If $x[n] = 0$ then replacing $x[n]$ from right to left by following equation

$$x[n] = \alpha \cdot x[n+1] \text{ with } \alpha = (R_{xx}[1]/R_{xx}[0]), 0 < \alpha < 1 \quad (9)$$

$$R_{xx}[1] = x[n+1] \cdot x[n+2] \quad (10)$$

$$R_{xx}[0] = x[n+1] \cdot x[n+1] \quad (11)$$

If $\alpha \geq 1$ then $x[n] = x[n+1]$

- b) *Processing Step 8*: Estimating the vector Z_A (1D) by the predicted value, Sort the vector Z_A (1D), and Determine the median value.
 c) *Processing Step 9*: Replace the processed pixel $x(i, j)$ with its median value.
 d) *Processing Step 10*: Reprocess the Processing Steps 1 to Processing Steps 3 until the entire image is processed completely.

3. ILLUSTRATION OF NSMF

In this NSMF calculation example, the processed pixel intensity is 255 therefore the processed pixel is noisy and the processed pixel is suppressed by NSMF as shown in Figure 2. From the NSMF process, the denoised pixel is suppressed and the output pixel is replaced to be "200".

4. SIMULATION OUTCOMES

In this simulation section under both SPN and RVIN, six tested images (Lena (256x256), Mobile (704x480), Pepper (256x256), Pentagon (512x512), Girl-Tiffany (256x256) and Resolution (128x128)) are employed to analytically simulate the upper bound of NSMF efficiency. This simulation analyses the noise suppressing efficiency of the NSMF by first applying the SPN and the RVIN on tested images. Subsequently, the NSMF processes for suppressing the noisy images, which are used to compute the PSNR with the known original images. From the simulation outcomes in Table 1 for SPN (salt&pepper noise), the NSMF algorithms have the better quality outcomes than SMF (Standard Median Filter) and GMF (Gaussian Mean Filter) at all cases however the NSMF algorithms have the better quality outcomes than AMF for high noise density.

From the simulation outcomes in Table 2 for RVIN, the NSMF algorithms have the better quality outcomes than SMF (Standard Median Filter), GMF (Gaussian Mean Filter) and AMF at all cases. However, the NSMF algorithms have the worst quality outcomes than AMF for all noise density in Resolution image because this image pixel intensity are "0" or "255".

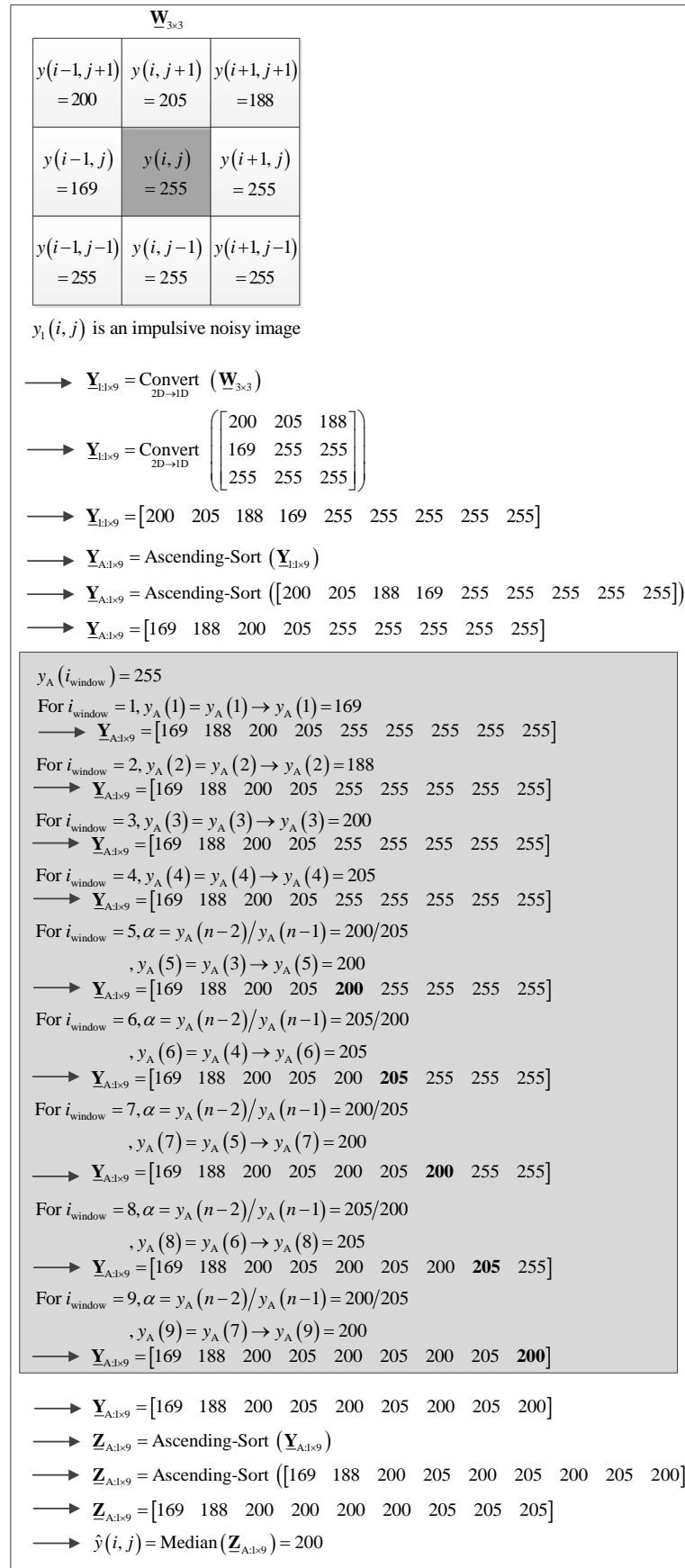


Figure 2. The example of overall calculation of new switching-based median filtering (NSMF)

Table 1. Denoising Performance Result of SPN

SPN	PSNR (dB)					
	Tested Images	Noise Density	Observed Image	Denoising Algorithm		
				SMF	GMF	AMF
Lena (256x256)	10	15.6564	30.7076	19.3812	35.3032	31.3470
	20	12.6389	27.6257	16.3208	32.1558	30.2476
	30	10.8971	23.6811	14.5829	27.9141	29.6058
	40	9.6481	19.0080	13.2479	23.7903	28.5528
	50	8.6553	15.4758	12.2146	20.5725	27.0119
	60	7.7813	13.6792	11.2939	18.4727	25.7010
	70	7.1697	11.0400	10.6509	17.0517	25.2202
	80	6.5846	8.8975	10.0057	16.5452	23.6491
	90	6.0604	7.1223	9.4356	17.1346	21.7870
Mobile (704x480)	10	15.1637	21.3601	18.4448	25.0280	21.5039
	20	12.0780	20.1976	15.4276	23.8172	20.8137
	30	10.3465	18.3435	13.6485	21.7980	20.1805
	40	9.0919	16.1073	12.3414	19.5320	19.6503
	50	8.1216	13.4726	11.3057	17.3015	19.0300
	60	7.3397	12.6259	10.4380	15.9416	17.8327
	70	6.6636	10.2402	9.6946	14.5107	16.9717
	80	6.1003	8.1954	9.0778	13.6481	16.5924
	90	5.5706	6.4911	8.4680	13.1971	15.5046
Pepper (256x256)	10	15.3798	30.6116	19.0677	36.0391	32.0762
	20	12.3593	26.5888	15.9804	31.6485	30.3296
	30	10.6242	22.0663	14.1748	26.7650	29.3512
	40	9.3998	18.4321	12.9076	23.4995	28.4487
	50	7.9930	14.8506	11.8117	20.2203	26.6461
	60	7.6189	12.0128	10.9563	18.3003	24.8222
	70	6.9246	9.7704	10.2039	16.8667	24.1151
	80	6.3710	8.0166	9.5853	16.3827	22.7764
	90	5.8582	6.5767	9.0214	16.7617	20.8912
Pentagon (512x512)	10	15.7999	28.7784	19.5038	32.8245	29.2477
	20	12.7934	26.5128	16.5198	30.5509	28.4111
	30	11.0668	22.8646	14.7790	27.1212	27.8224
	40	9.8125	18.9056	13.5122	23.3677	27.0890
	50	8.8227	15.4225	12.5108	20.4567	25.9327
	60	8.0450	12.6240	11.7138	18.3989	24.7612
	70	7.3650	10.3040	10.9953	17.0422	24.2225
	80	6.7914	8.4840	10.4099	16.4737	22.9866
	90	6.2778	6.9876	9.8698	16.8647	21.4828
Girl-Tiffany (256x256)	10	13.6890	31.5583	17.2530	36.8900	32.9954
	20	10.6567	25.5153	13.9593	32.0377	30.9499
	30	8.8677	20.7738	11.9599	27.6911	29.1071
	40	7.5798	16.5146	10.4543	23.3733	28.6836
	50	6.5712	13.0319	9.2367	20.1711	27.6182
	60	5.8609	10.4981	8.3590	18.5314	26.9544
	70	5.1311	8.0463	7.4271	17.1068	25.7710
	80	4.5674	6.2520	6.6881	16.7480	24.2522
	90	4.0573	4.7465	5.9986	17.1560	22.3078
Resolution (128x128)	10	13.4819	17.9425	16.3688	18.3302	12.9262
	20	10.1271	16.2124	13.0706	17.1273	12.8794
	30	8.4430	14.4548	11.1807	15.7907	12.4083
	40	7.3308	12.6223	9.9457	14.7904	11.6991
	50	6.2938	10.4851	8.7005	13.8816	10.6690
	60	5.4436	8.5925	7.6865	14.0392	10.2361
	70	4.6795	6.6295	6.7002	12.6150	10.4634
	80	4.1940	5.3585	6.0922	10.9746	9.7668
	90	3.7113	4.2234	5.4638	9.3116	8.4931

Table 2. Denoising Performance Result of RVIN

RVIN Tested Images	PSNR (dB)					
	Noise Density	Observed Image	Denoising Algorithm			
			SMF	GMF	AMF	NSMF
Lena (256x256)	10	19.7193	31.1555	23.2638	28.4992	31.2960
	20	16.6527	29.7106	20.1102	23.1270	29.9009
	30	14.9222	27.5271	18.2831	20.1302	28.0652
	40	13.6990	24.9693	16.9480	18.0338	27.2951
	50	12.6883	22.3406	15.8415	16.3540	25.9716
	60	11.8913	19.7498	14.9352	14.9043	24.2453
	70	11.2184	17.7591	14.1493	13.7787	22.5265
	80	10.6422	16.0345	13.4958	12.8356	20.3198
	90	10.1515	14.5334	12.9029	12.0228	17.8884
Mobile (704x480)	10	18.4574	21.4778	21.1512	22.6605	21.5601
	20	15.5151	20.8069	18.3393	19.7674	20.9019
	30	13.7727	19.7265	16.5214	17.4115	19.8296
	40	12.5299	18.5715	15.1796	15.6813	18.7463
	50	11.5304	17.1060	14.0526	14.1777	18.0061
	60	10.7497	15.5745	13.1263	12.9999	16.9705
	70	10.0875	14.2337	12.3371	11.9870	15.7658
	80	9.4794	12.9625	11.5980	11.0907	14.4949
	90	8.9565	11.8224	10.9422	10.2919	13.1973
Pepper (256x256)	10	19.1143	31.4270	22.6205	27.4518	31.9058
	20	16.0921	28.8665	19.4820	22.3782	29.7204
	30	14.3745	26.5900	17.6137	19.4227	27.4882
	40	13.1825	23.3362	16.2549	17.2699	26.3846
	50	12.2029	20.7731	15.1438	15.6064	24.5452
	60	11.3328	18.2128	14.0998	14.0825	22.4280
	70	10.7068	16.2565	13.3352	13.0203	20.1256
	80	10.1086	14.5768	12.5873	12.0629	17.5477
	90	9.6144	13.2495	11.9859	11.2712	15.6818
Pentagon (512x512)	10	20.2113	29.1520	23.6997	28.2423	29.2203
	20	17.2386	28.0433	20.7616	23.8125	28.2529
	30	15.4355	26.6678	18.9263	20.7887	26.9234
	40	14.1860	24.9238	17.6449	18.7135	26.0936
	50	13.2544	22.9472	16.6548	17.1075	25.3502
	60	12.4342	20.9049	15.7838	15.7400	24.1241
	70	11.7829	19.0652	15.0817	14.6359	23.1046
	80	11.1849	17.3449	14.4326	13.6558	21.7975
	90	10.6746	15.8671	13.8673	12.8241	20.4014
Girl-Tiffany (256x256)	10	16.4414	31.6049	19.9110	25.1339	28.3519
	20	13.4343	28.1774	16.5639	19.5720	28.4094
	30	11.6674	23.8175	14.5342	16.4549	28.0443
	40	10.3946	19.8213	12.9626	14.1248	26.7023
	50	9.4483	16.7201	11.7613	12.3869	24.4072
	60	8.6223	14.0847	10.6637	10.9357	20.5217
	70	7.9734	12.1107	9.8004	9.8160	16.6627
	80	7.3939	10.4710	8.9936	8.7676	13.1380
	90	6.8638	9.1560	8.2609	7.9151	10.6609
Resolution (128x128)	10	17.7992	18.6254	20.1134	18.3074	10.6040
	20	14.6190	17.9190	17.1729	17.4171	11.3422
	30	12.7370	17.1231	15.3050	16.7349	11.3862
	40	11.3691	16.2456	13.8148	15.5071	11.7564
	50	10.5048	15.5229	12.8678	14.4871	11.8203
	60	9.7510	14.3607	11.9178	13.3621	12.0505
	70	9.1026	13.6671	11.1682	12.3620	12.2006
	80	8.4955	12.3904	10.4038	11.1211	12.4048
	90	8.0315	11.6735	9.8152	10.2316	12.3036

5. CONCLUSION

This in-depth research assesses the efficiency of the noise suppressed method based on NSMF under two impulsive noise classes (SPN and RVIN). These simulations employ on six well-known images (Lena, Mobile, Pepper, Pentagon, Girl, Resolution) under two impulsive noise classes for assessing the highest suppressed images in term of PSNR. Many previous noise suppressed methods, such as SMF (Standard Median Filter), GMF (Gaussian Mean Filter) and AMF, are used to assess the analogy efficiency. From simulation outcomes, the NSMF has a good PSNR for high noise density and this filter can work well for RVIN.

ACKNOWLEDGEMENTS

The research project was funded by Assumption University.

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