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Enhanced Average Filtering Technique for Mitigating Salt and Pepper Noise in High-Resolution Color Images

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ABSTRACT

Digital color images play a crucial role in various critical applications, necessitating the development of effective noise reduction techniques to preserve image quality and characteristics. Salt and pepper noise, in particular, can significantly degrade digital image quality, with the extent of the impact contingent upon image size and noise ratio. Existing methods reliant on arithmetic mean and median filtering have proven inadequate for addressing high noise ratios. In this study, we propose and implement a novel average filter—an enhancement over traditional mean filters—to efficiently mitigate salt and pepper noise, specifically in cases with high noise ratios. Our results demonstrate the superior performance of the proposed filter in terms of preserving image quality and reducing noise, as evidenced by improved maximum auto-correlation factors and peak signal-to-noise ratios.

1. INTRODUCTION

Digital images, comprising a substantial complex [1] of data organized into a three-dimensional matrix, as depicted in Figure 1, allocate the first binary matrix to represent the red color, the second for the green color, and the third for the blue color [2-4].

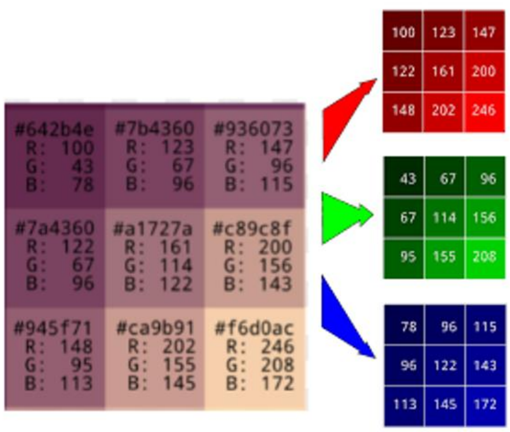


Figure 1. Color image representation

These color digital images find applications in numerous critical domains, potentially serving as carriers of sensitive information [5], necessitating that their properties remain unaltered. However, digital images may be susceptible to various noise types, which can adversely influence the images by altering certain values, subsequently leading to image blurring or changes in their features and characteristics [6].

One prevalent noise type is salt and pepper noise (SAPN) [7, 8], which modifies some image values to 0 or 255. The number of altered values depends on the noise ratio (NR), representing the percentage of noisy values relative to the image size. Alterations in the image values to 0 or 255 are evident in the image histogram [9, 10], as illustrated in Figures 2 and 3, where an increased occurrence of 0s and 255s indicates the image has been affected by SAPN.

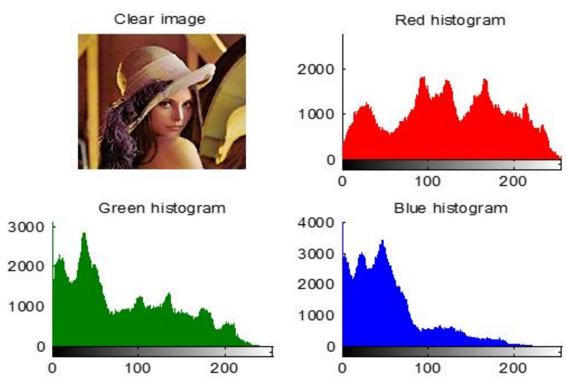


Figure 2. Clear image and histograms

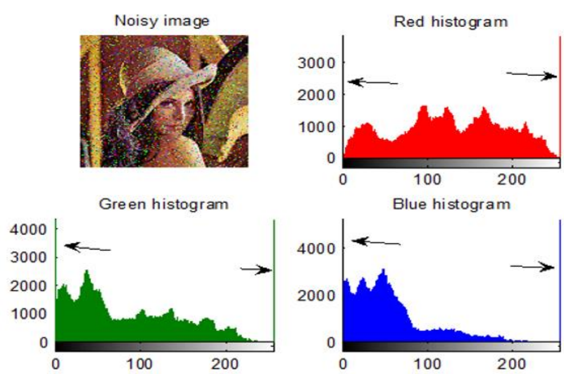


Figure 3. Noisy image and histograms

When digital images are contaminated with noise, it becomes imperative to employ image processing techniques to eliminate or minimize the detrimental effects of noise.

The quality of the method used to remove any noise including SAPN can be measured by mean square error (MSE) [11, 12] or peak signal to noise ratio (PSNR) [13, 14], these quality parameters can be calculated between the clean image and the de-noised image, a method is considered good method if is satisfies the requirements shown in Table 1, while the values of MSE and PSNR can be calculated using Eq. (1) and Eq. (2).

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

$$PSNR = 20\log_{10}\left(\frac{Max_f}{\sqrt{MSE}}\right) \tag{2}$$

where, f is the clean image, g is the de-noised image.

Table 1. Quality parameters requirements

Quality parameter	Image	Clean image	De-noised
MSE	Clean image	0	Very small
PSNR	De-noised image	Very high	infinite

Image padding means expanding the image matrix row wise and column wise in a symmetric way using a padding factor (PF) referencing to the expansion such as shown in Figure 4.

Digital color image can be de-noised by filtering each color using digital filter, the de-noised colors then to be combined to form a de-noised color image as shown in Figures 5 and 6 [15].

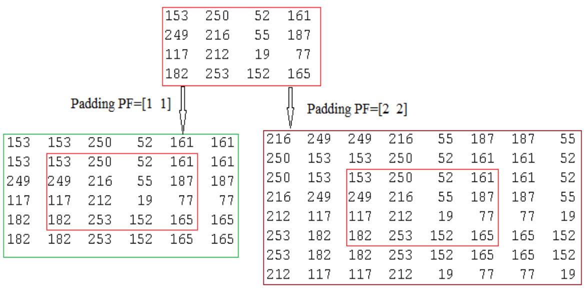


Figure 4. Image (matrix) padding

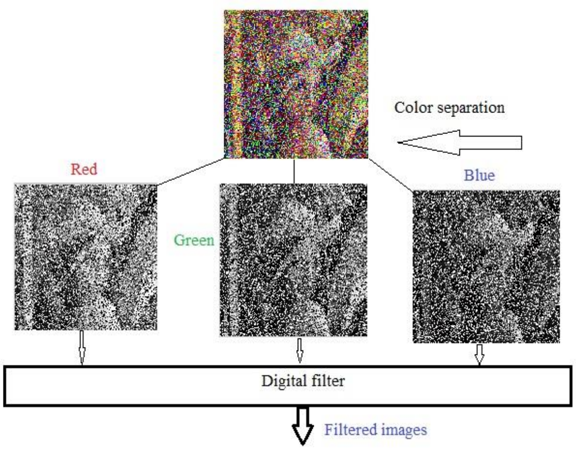


Figure 5. Color image filtering

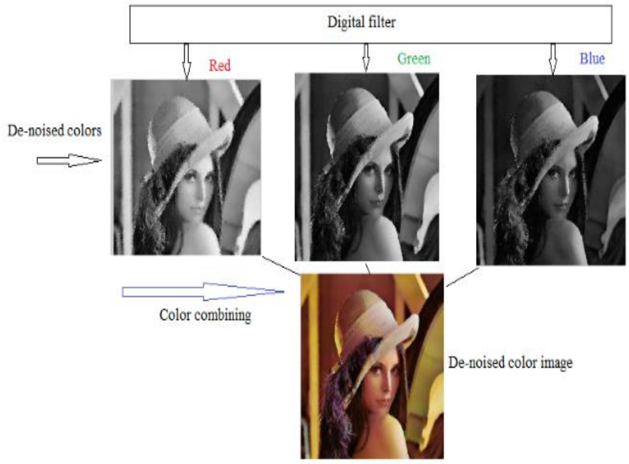


Figure 6. Combining de-noised colors

2. RELATED WORKS

Many methods are used to get rid of the SAPN noise of salt and spice or to mitigate its negative effects on the digital color image [16, 17], the percentage of noise removal varies from one method to another. The matter here depends on the size of the image and the percentage of noise that hit the image (noise ratio: NR) [18, 19].

The majority of the methods used depend on the arithmetic mean or median method, which often fails to deal with noise if its rate is too high (more than 70%).

Average filter is a pixel operation and it can be implemented applying convolution between the kernel and associated pixels in the image as shown in Figure 7, while median filter replaces the pixel value with the median value covered by the kernel.

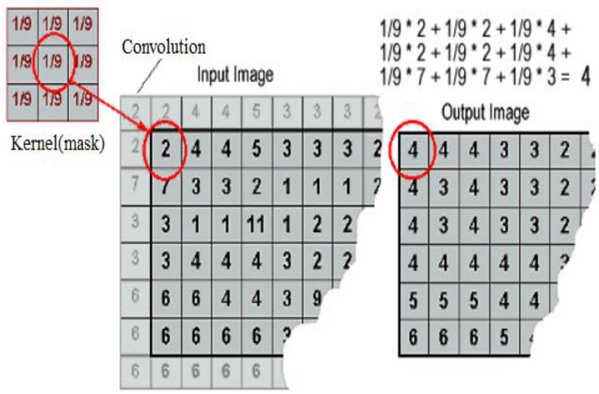


Figure 7. Average filtering

To demonstrate the effectiveness of the proposed filter will be compared with the standard median and average filters, it will be also compared with other six famous methods based on average and median filters used to reduce the negative effects on SAPN. These methods are: switching median (SM) filter [20], the directional weighted median (DWM) filter [21], the modified directional weighted median (MDWM) filter , the modified directional weighted (MDW) filter , Two stage filter (TSF) , and the three-values-weighted (TVW) filter [22], among these filters the most effective filters are TVW TSF filters, these filters gave good value for PSNR when NR has a small value, but increasing NR will rapidly decrease the value of PSNR making then inefficient.

3. THE PROPOSED FILTER

The proposed filter is based on average filter, and it can be easily implemented to treat each color matrix in the digital color image (see Figures 5 and 6).

The proposed filter requires the following matrices to handle the SAPN affected the color image [23]:

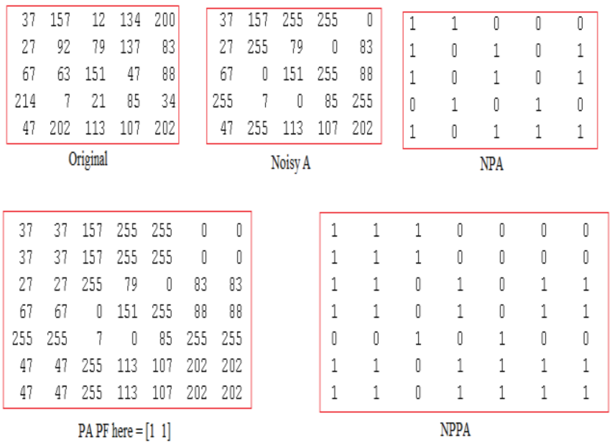
Noisy matrix A for each color channel.

Noise pointing matrix NPA with values 0s and 1s, one means that the associated pixel in A is not noisy, while zero mean that the associated pixel in A is a noisy pixel (with value 0 or 255).

Padded matrix PA for each color, the padding factor must equal the window used for filtering, here we use PF equal [24, 25] to allow us to create a window of size 15 by 15.

Noise pointing matrix NPPA for the padding matrix PA.

Figure 8 shows an example of these matrices:



Original

37	157	12	134	200
27	92	79	137	83
67	63	151	47	88
214	7	21	85	34
47	202	113	107	202

Noisy A

37	157	255	255	0
27	255	79	0	83
67	0	151	255	88
255	7	0	85	255
47	255	113	107	202

NPA

1	1	0	0	0
1	0	1	0	1
1	0	1	0	1
0	1	0	1	0
1	0	1	1	1

PA PF here = [1 1]

37	37	157	255	255	0	0
37	37	157	255	255	0	0
27	27	255	79	0	83	83
67	67	0	151	255	88	88
255	255	7	0	85	255	255
47	47	255	113	107	202	202
47	47	255	113	107	202	202

NPPA

1	1	1	0	0	0	0
1	1	1	0	0	0	0
1	1	0	1	0	1	1
1	1	0	1	0	1	1
0	0	1	0	1	0	0
1	1	0	1	1	1	1
1	1	0	1	1	1	1

Figure 8. Required matrices

The proposed filter can be implemented applying the following steps:

For each noisy color matrix A calculate the matrix NPA.

For each color matrix A create a padding matrix PA.

For each PA calculate the matrix NPPA.

For each pixel in A, if the associated pixel in NPA=1 keep this pixel in A without changing and proceed to the next pixel, otherwise proceed to the next step.

Create windows for the pixel in PA and NPPA.

If the sum of elements of the window in NPPA equal zero keep the pixel in A without changing and proceed to next pixel in A, otherwise proceed to the next step.

Find the average of the elements of the window in PA excluding the values 0 and 255.

Replace the pixel value in A with the obtained average [26].

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The proposed improved average filter IAVF was implemented using matlab; several images with various sizes were implemented applying SAPN with various values of SAPN noise ratios, Table 2 shows the information used in the process of implementation, while Figures 9-14 shows some output examples of the implementation.

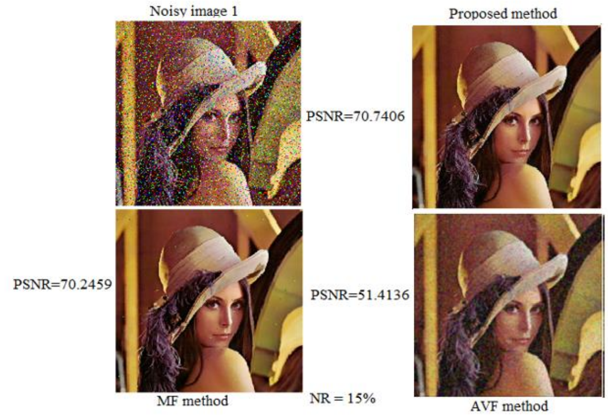


Figure 9. Medium size image NR=15%

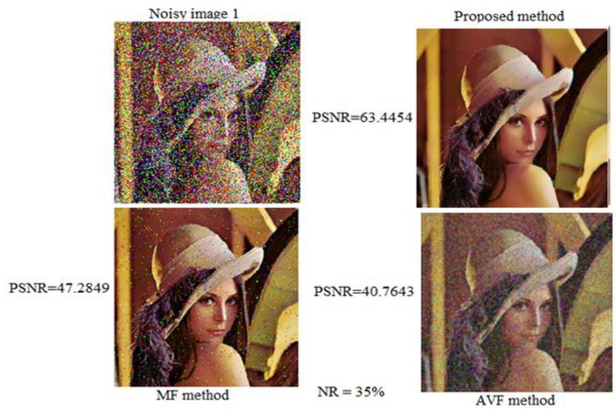


Figure 10. Medium size image NR=35%

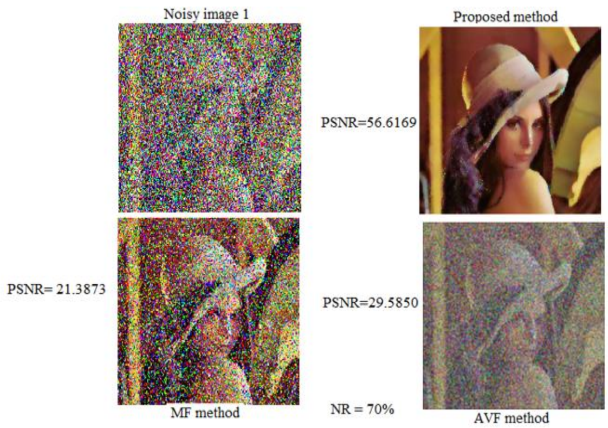


Figure 11. Medium size image NR=70%

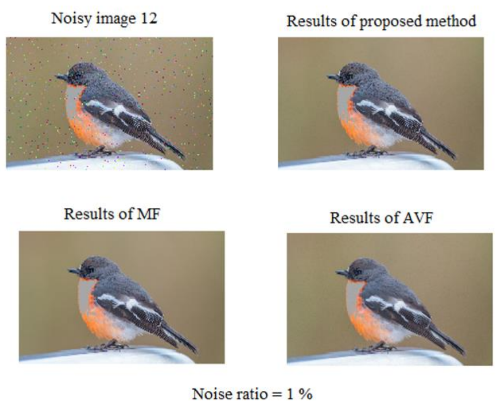


Figure 12. Big size image NR=1%

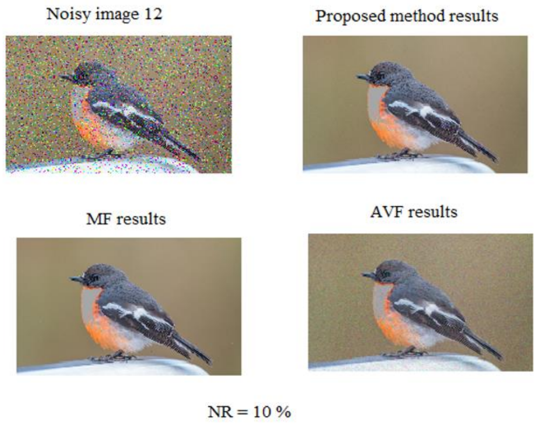


Figure 13. Big size image NR=10%

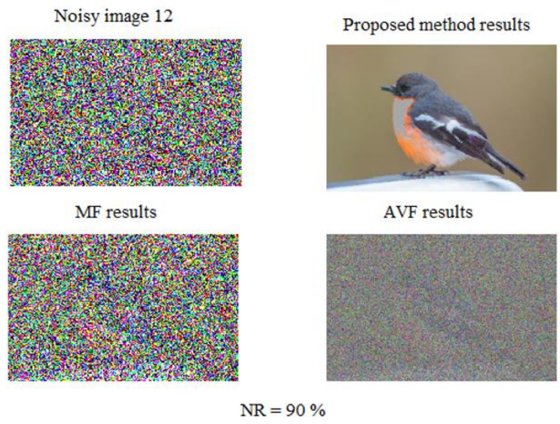


Figure 14. Big size image NR=90%

The images in Table 2 were affected by SAPN with various values of NR, the obtained noisy images were treated using average, median and the proposed filters, Table 3 shows the obtained results using average filter, Table 4 shows the obtained results using median filter, while Table 5 shows the obtained results using the proposed method.

Table 2. Used images information (red: big size, green: medium size, blue: small size)

Image number	Size(byte)	Noise ratio (%)			
		10	1	0.1	0.01
		Number of affected bytes (noisy bytes)			
1	786432	78643	7864	786	78
2	150849	15084	1508	150	15
3	77976	7797	779	77	7
4	518400	51840	5184	518	51
5	5140800	514080	51408	5140	514
6	4326210	432621	43262	4326	432
7	122265	12226	1222	122	12
8	151353	15135	1513	151	15
9	1890000	1890000	1890000	1890000	1890000
10	6119256	6119256	6119256	6119256	6119256

Table 3. Obtained results using average filter

Image #	Noise ratio (%)								
	0.01	0.05	0.09	0.1	0.5	0.9	1	10	90
1	63.9534	63.9105	63.8832	63.8602	63.5132	63.1309	63.0262	55.1981	25.1905
2	40.6415	40.6333	40.6341	40.6293	40.5731	40.5143	40.5089	38.9630	22.4865
3	41.6844	41.6821	41.6713	41.6703	41.6052	41.5280	41.5065	39.4654	19.8335
4	54.0148	53.9988	53.9825	53.9865	53.8177	53.6739	53.6310	49.6932	25.4532
5	59.9166	59.6873	59.4639	59.4055	59.6920	59.4563	59.4133	54.1166	27.8780
6	58.7167	58.5143	58.3004	58.2514	58.5045	58.3021	58.2476	53.4165	28.0321
7	50.4226	50.3477	50.2586	50.2674	50.3428	50.2724	50.2648	48.2217	30.7044
8	43.9255	43.8691	43.7998	43.7770	43.8720	43.7948	43.7908	41.9568	23.3383
9	60.4492	60.1608	59.8962	59.8149	60.1548	59.8737	59.7974	53.3023	24.6386
10	72.2529	71.6170	71.0292	70.8572	71.6129	71.0192	70.8789	61.5967	35.1886
Average	**54.5978**	**54.4421**	**54.2919**	**54.2520**	**54.3688**	**54.1566**	**54.1065**	**49.5930**	**26.2744**

Table 4. Obtained results using median filter

Image #	Noise ratio (%)								
	0.01	0.05	.09	0.1	0.5	0.9	1	10	90
1	79.2454	79.2295	79.2147	79.2080	79.0288	78.9385	78.8910	74.1821	13.6426
2	47.8472	47.8484	47.8444	47.8501	47.7977	47.7399	47.7491	46.1467	12.6418
3	49.9809	49.9797	49.9685	49.9749	49.9312	49.9573	49.9326	47.7742	11.5148
4	65.8640	65.8533	65.8516	65.8438	65.7753	65.7010	65.6803	63.2402	13.6936
5	70.5522	70.4801	70.4108	70.3908	70.4801	70.4047	70.3956	68.0833	14.3430
6	70.8078	70.7512	70.6942	70.6833	70.7454	70.7011	70.6819	68.2409	14.3841
7	56.3462	56.3246	56.3165	56.3039	56.3244	56.2684	56.3071	55.1921	14.9485
8	49.6842	49.6739	49.6285	49.5975	49.6667	49.6306	49.6287	48.3074	12.8966
9	79.3720	79.0746	78.8061	78.6975	79.0435	78.7545	78.6301	71.7700	13.4585
10	85.4126	85.3313	85.2504	85.1826	85.3137	85.2443	85.2032	81.1049	15.6708
Average	**65.5112**	**65.4547**	**65.3986**	**65.3732**	**65.4107**	**65.3340**	**65.3100**	**62.4042**	**13.7194**

Table 5. Obtained results using proposed filter

Image #	Noise ratio (%)								
	0.01	**0.05**	**0.09**	**0.1**	**0.5**	**0.9**	**1**	**10**	**90**
1	86.0603	85.9774	85.8723	85.8078	84.8377	84.0839	83.9584	73.6927	52.6878
2	57.8396	57.8084	57.7680	57.7384	57.4140	57.0803	57.0568	51.6260	35.0671
3	62.4053	62.3890	62.3421	62.3598	61.9407	61.5077	61.6018	55.8142	39.0132
4	64.6684	64.5900	64.5543	64.5003	63.8659	63.2072	63.1146	54.4312	34.6863
5	89.4311	89.2581	89.0924	89.0195	87.5907	86.2315	85.9489	72.8829	51.6630
6	64.1402	63.9167	63.6673	63.6326	61.7919	60.3661	60.0223	72.2553	50.8216
7	76.7373	76.6060	76.5546	76.5892	76.0429	75.3060	75.1050	66.7665	47.7812
8	62.4850	62.4469	62.4303	62.4338	61.9816	61.4940	61.4636	54.8965	37.5070
9	60.1336	60.1153	60.0885	60.0753	59.9093	59.7525	59.7242	56.7553	43.5426
10	104.8383	104.6647	104.5129	104.4959	102.9296	101.5029	101.2205	88.0379	66.6155
Average	**72.8739**	**72.7773**	**72.6883**	**72.6653**	**71.8304**	**71.0532**	**70.9216**	**64.7159**	**45.9385**

From the practical results obtained, we can see the following:

The extent of the negative impact of noise depends on the size of the image. The smaller the image size, the greater the effect of noise and the distorted image becomes.

Median filter gave better results than average filter when NR less than 50%.

Average and median filters cannot get rid of the effect of noise if the noise ratio is high (more than 70%).

The proposed method reduces the effects of SAPN even if the value of PSNR is high.

For any image with any size and for any noise ratio value the proposed method improves the value of PSNR, thus improves the quality of the de-noised image, this is seen in Figure 15.

The results of the proposed method were compared with the results of the filters in studies [1-6], and the proposed method gave a significant enhancement of PSNR for any image and any NR value.

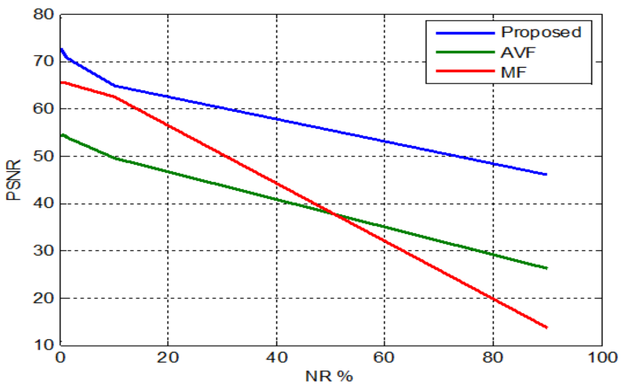


Figure 15. Results comparisons

5. CONCLUSION

A new method has been proposed to get rid of salt and pepper noise in the digital color image, and this method is simplified, easy to implement, and highly efficient by giving images with high efficiency, regardless of the image size or the value of the noise ratio. The proposed filter has been implemented in practice, and the practical results obtained show the extent of the improvement that was obtained in the image in which the noise was processed.

The practical results of the proposed filter were compared with the practical results of other filters such as the median filter, the arithmetic mean filter and other filters. The comparison showed that the proposed filter gives better results for PSNR and that the proposed filter can be used efficiently even if the noise ratio is high.

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