Three-stage trimmed median-mean filter to remove salt and pepper noise in images

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In this paper, a new three stage trimmed median-mean filter (TSTMMF) has been proposed for denoising the images corrupted by salt and pepper noise (*SPN*). The pixels which are corrupted by *SPN* have been identified and subjected to two stages of trimmed median filtering of different window size. Noise free estimations available from these cascaded stages of filtering, will replace the noisy pixels in an orderly manner. The noisy pixel left over by these stages, if any, would be replaced by the noise free pixel available just prior to the current processing noisy pixel. A simple 3X3 mean-filtering, which is applied as a third stage of denoising if the estimated noise density (*ND*) of given noisy image exceeds a predefined threshold noise density, to enhance the correlation among the denoised samples and hence better denoising performance. Experimental results prove that the proposed TSTMMF has outperformed the recently proposed state-of-the-art-filters available in the literature, in terms the denoising parameters such as peak signal to noise ratio (PSNR), structural similarity index (SSIM), image enhancement factor (IEF), mean absolute error (MAE) and visual representation.

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1. Introduction

DIGITAL images are often corrupted by salt and pepper noise (*SPN*) which is a special of type of impulse noise. Depending upon the noise intensity of *SPN*, a number of pixel values have been altered to its extreme maximum (salt) or extreme minimum (pepper) with equal probability. Standard median filter (SMF) [1] is a simple nonlinear filter developed to filter *SPN* noise in an efficient manner, but only at lower noise densities ($ND < 20\%$). Some variations in median filtering [2-6] such as weighted median filter (WMF) [2], center weighted median filter (CWMF) [3], adaptive center weighted median filter (ACWMF) [4], adaptive median filter (AMF) [5], progressive switching median filtering (PSMF) [6] have been proposed to improve the denoising performance of median filtering as the value of *ND* increases. Among these filters [2-6], AMF could perform very well, as it alters the window sizes adaptively to get noise free pixels. To enhance the speed of denoising along with better denoising performance, switching based filters [7-9] have been developed. Decision based algorithm (DBA) [7] is a simple switching based filter which delivers a very good denoising performance at a faster rate, but only at the medium noise densities (*ND*) up to 60%. New algorithms for recovering images from impulse noise (NARIN) [8] are nothing but improved version of AMF by incorporating switching concept and they perform well at higher densities in a faster rate. Recently proposed adaptive weighted mean filter (AWMF) [9] is a new modified version of AMF, in which *weighed-mean* has been employed instead of *median* to give a good denoising performance for the noise densities (*ND*) up to 90%. Apart from the switching concept, many filtering algorithms have been developed, which estimate the value of noisy pixels by considering the median of noise free pixels only. Simple adaptive median filtering (SAMF) [10] and modified decision based un-symmetric trimmed median filtering (MDBUTMF) [11] fall under this category. Fast switching based median and mean filter (FSMMF) [12] is a very recently developed filter which employs the switching based simple median and trimmed median concepts along with a causal mean to give improved denoising results at a faster rate. Fuzzy based denoising is another area which has been developed recently in which noise adaptive fuzzy switching median (NAFSM) [13] and iterative adaptive fuzzy filter (IAFF) [14] are the two important and significant filters to filter *SPN* at medium and high noise densities respectively. The filters discussed so far could perform well at medium noise densities and their performance is getting degraded along with the longer execution time at higher densities. In this paper, we propose a new optimum filter called as three-stage trimmed median-mean filter (TSTMMF) which could provide an excellent denoising performance for the noise densities (*ND*) up to 95% at a moderate speed of denoising. Using simulation experiments, it is proved that proposed TSTMMF excellently outperforms the state-of-the-art filters considered for experimentation in terms of peak signal to noise ratio (PSNR), structural similarity index (SSIM) [15], image enhancement factor (IEF), mean absolute error (MAE) and visual presentation.

The rest of the paper has been organized as follows. Section II explains the development of our proposed filtering algorithm TSTMMF. Simulation experimental results have been presented in section III and finally the conclusion is drawn in section IV.

2. Proposed filter TSTMMF

Let $A(x, y)$ be the noisy image obtained from original gray scale image $O(x, y)$ of size M x N corrupted by SPN with noise density of *ND* (%), where $x = \{1,2, \dots M\}$ and $y = \{1,2, \dots N\}$. The pixels in A can mathematically be modeled as,

$$A(x, y) = O(x, y), \text{ with probability of } 1 - \frac{ND}{100}$$
$$A(x, y) = 0, \text{ with probability of } \frac{ND}{200}$$
$$A(x, y) = 255, \text{ with probability of } \frac{ND}{200}$$

The major objective of given denoising procedure has to remove the SPN noise without affecting the high frequency information and edges. Among the median based filters [2-12] described in section I, the switching based filters, MDBUTMF and SAMF, both employed trimmed median estimation technique which finds the median of noise free pixels in the working window and such estimations are relatively better over the estimations obtained based on simple median. Among the two methods, MDBUTMF requires relatively lesser processing time, but gives relatively a poor estimation with respect to SAMF if all the pixels in the working window $[3X3]$ are corrupted. The method SAMF gives relatively better estimation at higher noise densities, as the algorithm adaptively increases the size of the working window to get a minimum of single noise free pixel for estimation but at the expense of processing time. Moreover, the correlation between the denoised samples is getting decreased in SAMF as the *ND* increases. By performing a careful examination of these methods, we well thought out that if we design a filter with a limited number of working windows of trimmed median estimations along with a simple mean filtering (to enhance the correlation between the samples at higher *ND*), the filter will definitely be giving out an outstanding denoising performance at an optimum speed.

Based on the observations stated above, we propose a simple Three-Stage Trimmed Median-Mean Filter (TSTMMF), in which first and second stages employ the trimmed median filtering with two different working windows ($3X3$ and $5X5$) and a third stage of simple mean filtering ($3X3$). In the first stage, a set of noisy pixels is replaced by median of noise free pixels available in the working window of $3X3$ around each noisy pixel in an orderly manner. If all the pixels in the working window are noisy just proceed to the next noisy pixel without any estimation. A partly denoised intermediate output image obtained from the first stage is passed to the second stage for further estimation. In the second stage, the remaining noisy pixels are replaced by median of noise free pixels available in the working window of $5X5$ around each noisy pixel in an orderly manner. While making the estimations in the second stage, if all the pixels available in the working window are noisy then the estimation for given noisy pixel is same as the just past processed pixel.

Further, if the *ND* increases, estimations and replacements of noisy pixels using first two successive stages, will lead to a fall in correlation between the pixels in the intermediate output image of second stage. To stop decreasing the correlation at higher noise densities, we need to provide a simple $3X3$ mean filtering as a third stage of filtering and hence better denoising performance. Based on vast trial and error based experimentation, we found that the threshold noise density for applying mean filtering in the third stage is determined as $ND = 50\%$. Moreover, if the estimated noise density is less than the threshold noise density, the intermediate output image could be treated as a final denoised image. The algorithm of TSTMMF is presented as follows.

Algorithm

```
1   Estimate ND of given A
2   Initialize W = 3
3   Initialize B = A
4   lpp = B(1,1)
5   for x ← 1 to x ← M
    for y ← 1 to y ← N
    if A(x,y) ∈ [0 , 255]
    Find SNF in W x W
    if (SNF ≠ {})
    B(x,y) = median(SNF)
    elseif (SNF=={}&W==5)
    B(x,y) = lpp
    endif
    lpp = B(x,y)
    endif
    endfor
    endfor
6   if  W < 5
    W= W+2
    A = B
    go to step 3
    endif
7   If ND > 50
    C = 3 x 3 mean(B)
    else
    C = B
    endif
```

<u>*Notation*</u>

ND	*: Noise Density*
W	*: size of working window*
A	*: noisy image*
B	*: intermediate image*
C	*: denoised image*
M x *N*	*: size of image*
(x, y)	*: position of pixel*
SNF	*: set of noise free pixels*
{}	*: empty set*
lpp	*: last processed pixel*

3. Results and Discussion

In this section, the denoising performance of proposed TSTMMF has been studied and compared with the standard state-of-the-art-filters in terms of PSNR, SSIM, IEF, MAE, visual representation and processing time. The standard gray scale images, namely, *Lena.png*, *House.png*, *Mandril.png* and *Peppers.png* of size 512x512 have been considered for our experimentation. Intel®Core™ i5-2320 CPU @ 3GHz, 4 GB RAM equipped with MATLAB 12a is the computing setup employed to perform the denoising experiment. To evaluate the denoising performance of proposed TSTMMF algorithm the standard state-of-the-filtering algorithms, namely, decision based algorithm (DBA) [7], noise adaptive fuzzy switching median (NAFSM) [13], modified decision based un-symmetric trimmed median filtering (MDBUTMF) [11], new algorithms for recovering images from impulse noise (NARIN) [8], simple adaptive median filtering (SAMF) [10] and fast switching based median and mean filter (FSMMF) [12] have been considered.

Table 1. PSNR (dB) values of different filters against proposed TSTMMF at different noise densities(ND)

Image	Noise Density \ Method	10	20	30	40	50	60	70	80	90	95	Average
***Lena.png* 512 x512**	DBA	41.46	37.26	34.53	32.24	30.11	27.97	25.73	23.22	19.82	17.07	28.94
	NAFSM	38.75	35.58	33.70	32.24	31.00	29.83	28.63	27.07	23.55	16.99	29.74
	MDBUTMF	43.09	39.25	36.64	34.45	32.25	30.06	27.61	24.63	20.24	16.78	30.50
	NARIN	41.24	37.00	34.34	32.20	30.41	28.69	26.93	24.98	23.02	21.26	30.01
	SAMF	41.45	37.47	35.23	33.58	32.13	30.69	29.10	27.43	25.09	23.34	31.55
	FSMMF	41.15	37.14	34.42	32.40	30.80	29.56	28.31	26.76	24.14	21.61	30.63
	TSTMMF	42.90	39.17	36.77	34.89	32.57	31.70	30.95	29.80	27.30	24.27	**33.03**
***House.png* 512x512**	DBA	47.11	41.99	38.40	35.49	32.91	30.27	27.37	24.21	20.13	17.10	31.50
	NAFSM	44.65	41.23	38.95	37.29	35.70	34.15	32.32	30.09	24.99	17.01	33.64
	MDBUTMF	51.82	46.37	42.36	38.96	35.90	32.79	29.37	25.27	20.17	16.69	33.97
	NARIN	42.63	41.81	38.83	36.50	34.45	32.37	30.06	27.54	25.02	22.71	33.19
	SAMF	49.49	44.55	41.47	39.14	37.21	35.33	33.14	30.79	27.53	24.79	36.34
	FSMMF	46.99	41.90	38.93	36.73	34.94	33.30	31.49	28.96	24.86	21.61	33.97
	TSTMMF	51.18	45.95	42.66	40.06	39.55	39.34	37.97	35.81	31.66	27.13	**39.13**
***Mandril.png* 512x512**	DBA	36.90	32.97	30.26	28.07	26.07	24.19	22.44	20.62	18.59	17.01	25.71
	NAFSM	32.48	29.41	27.62	26.32	25.26	24.33	23.45	22.49	20.49	16.18	24.80
	MDBUTMF	37.88	34.15	31.61	29.44	27.51	25.62	23.86	22.01	19.80	17.70	26.96
	NARIN	36.79	32.79	30.09	28.04	26.23	24.55	22.95	21.30	19.69	18.59	26.10
	SAMF	35.38	31.42	29.28	27.82	26.57	25.29	23.89	22.58	21.23	20.45	26.39
	FSMMF	36.67	32.81	30.15	28.16	26.61	25.25	24.04	22.74	21.10	19.98	26.75
	TSTMMF	38.02	34.48	32.25	30.49	28.93	26.76	25.99	24.75	22.68	20.89	**28.53**
***Peppers.png* 512 x 512**	DBA	40.38	36.57	33.96	31.79	29.76	27.72	25.42	22.67	19.03	16.13	28.34
	NAFSM	39.48	36.35	34.38	32.81	31.59	30.36	28.99	27.33	23.61	16.86	30.17
	MDBUTMF	41.59	38.05	35.67	33.61	31.68	29.51	26.90	23.74	19.02	15.56	29.53
	NARIN	40.23	36.32	33.77	31.81	30.08	28.49	26.81	24.86	22.85	21.19	29.64
	SAMF	41.16	37.49	35.36	33.71	32.26	30.83	29.44	27.75	25.26	23.06	31.63
	FSMMF	40.16	36.32	33.79	31.94	30.51	29.20	28.03	26.29	23.14	20.47	29.98
	TSTMMF	41.47	37.89	35.71	33.96	32.47	31.37	30.82	29.83	27.55	24.43	**32.55**

Table 2. SSIM (%) values of different filters against proposed TSTMMF at different noise densities (ND)

Image	Noise Density \ Method	10	20	30	40	50	60	70	80	90	95	Average
Lena.png 512 x512	DBA	98.86	97.36	95.51	93.07	89.82	85.41	79.41	70.81	57.56	46.51	81.43
	NAFSM	98.36	96.63	94.80	92.80	90.58	88.02	84.82	80.17	68.31	40.19	83.47
	MDBUTMF	99.03	97.87	96.49	94.75	92.45	89.25	84.47	76.80	62.29	47.78	84.12
	NARIN	98.81	97.18	95.13	92.55	89.46	85.65	80.71	73.90	65.50	59.50	83.84
	SAMF	98.84	97.39	95.75	94.04	91.95	89.41	85.92	81.24	73.79	68.00	87.63
	FSMMF	98.80	97.21	95.16	92.74	90.00	87.14	83.94	79.83	72.62	65.09	86.25
	TSTMMF	99.01	97.87	96.49	94.96	90.64	88.72	87.64	85.64	80.47	72.63	**89.41**
House.png 512x512	DBA	99.72	99.23	98.44	97.21	95.34	92.39	87.86	81.00	70.33	61.67	88.32
	NAFSM	99.14	98.25	97.33	96.35	95.27	93.98	92.04	88.91	77.76	44.71	88.37
	MDBUTMF	99.83	99.54	99.06	98.28	97.01	94.81	91.04	84.24	72.63	62.55	89.90
	NARIN	99.44	99.12	98.34	97.26	95.81	93.73	90.52	85.49	78.80	73.81	91.23
	SAMF	99.69	99.17	98.55	97.85	96.97	95.68	93.40	90.11	84.18	79.40	93.50
	FSMMF	99.69	99.13	98.36	97.36	96.12	94.64	92.56	89.13	82.11	75.33	92.44
	TSTMMF	99.82	99.54	99.14	98.60	98.00	97.71	97.09	95.85	92.15	86.02	**96.39**
Mandril.png 512x512	DBA	98.61	96.56	93.64	89.62	83.92	76.10	66.00	53.01	37.04	27.21	72.17
	NAFSM	96.19	92.11	87.80	83.15	77.94	72.16	65.52	57.38	44.35	26.54	70.31
	MDBUTMF	98.84	97.26	95.10	91.94	87.47	80.80	71.58	58.53	41.46	30.91	75.39
	NARIN	98.58	96.43	93.46	89.65	84.63	78.05	69.41	57.83	43.30	34.66	74.60
	SAMF	98.01	94.99	91.54	87.92	83.68	77.72	68.93	57.75	44.04	36.65	74.12
	FSMMF	98.54	96.47	93.56	89.89	85.64	80.52	74.34	65.41	51.49	40.96	77.68
	TSTMMF	98.88	97.50	95.75	93.66	90.96	81.79	78.74	73.17	61.08	48.34	**81.99**
Peppers.png 512 x 512	DBA	97.93	95.60	92.86	89.67	85.72	80.86	74.42	65.67	52.27	41.45	77.65
	NAFSM	97.78	95.58	93.28	90.84	88.25	85.32	81.78	76.80	65.21	38.86	81.37
	MDBUTMF	98.15	96.15	93.95	91.47	88.61	84.94	79.73	71.66	56.44	43.42	80.45
	NARIN	97.88	95.36	92.33	88.94	85.01	80.54	75.18	68.41	60.29	55.30	79.92
	SAMF	98.12	96.07	93.87	91.45	88.92	85.92	82.46	78.08	71.09	64.99	85.10
	FSMMF	97.87	95.37	92.39	89.10	85.58	81.93	78.44	73.92	66.31	58.69	81.96
	TSTMMF	98.12	96.08	93.84	91.30	88.57	82.74	81.80	80.10	75.62	68.77	**85.69**

Table 3. Image Enhancement Factor (IEF) values of different filters against proposed TSTMMF at different noise densities (ND)

Image	Noise Density \ Method	10	20	30	40	50	60	70	80	90	95	Average
Lena.png 512 x512	DBA	400.62	304.00	243.01	190.99	146.24	107.31	74.79	47.89	24.68	13.83	155.34
	NAFSM	213.42	206.68	200.74	191.35	179.60	164.64	145.77	116.27	58.24	13.56	149.03
	MDBUTMF	582.64	480.86	394.34	317.62	239.56	173.75	115.37	66.26	27.18	12.93	241.05
	NARIN	380.37	286.82	232.45	189.46	156.74	126.76	98.52	71.82	51.45	36.25	163.06
	SAMF	398.94	319.10	285.37	260.54	233.17	200.85	162.25	126.65	83.04	58.58	212.85
	FSMMF	372.27	295.37	236.57	198.47	171.78	154.59	135.49	108.35	66.61	39.36	177.89
	TSTMMF	556.83	471.74	406.83	351.78	259.92	253.36	248.75	218.41	137.96	72.51	**297.81**
House.png 512x512	DBA	1556.37	961.60	627.81	428.21	295.65	192.80	115.70	63.97	28.08	14.75	428.49
	NAFSM	881.88	803.51	712.15	648.44	562.50	472.05	362.15	247.52	85.97	14.42	479.06
	MDBUTMF	4586.92	2626.73	1565.06	951.32	588.49	344.97	183.12	81.68	28.35	13.45	1097.01
	NARIN	568.29	919.46	693.98	540.35	420.68	313.17	214.55	137.62	86.63	53.72	394.84
	SAMF	2716.48	1730.82	1278.10	993.83	797.69	618.90	437.70	291.24	154.21	86.57	910.55
	FSMMF	1509.54	938.88	710.32	568.50	472.09	387.73	298.93	190.76	83.42	41.70	520.19
	TSTMMF	4004.44	2391.17	1683.45	1227.84	1401.15	1560.04	1330.91	924.34	399.97	148.60	**1507.19**
Mandril.png 512x512	DBA	134.49	108.69	87.35	70.23	55.58	43.22	33.75	25.32	17.87	13.10	58.96
	NAFSM	48.66	47.89	47.58	46.99	46.10	44.71	42.55	38.93	27.69	10.82	40.19
	MDBUTMF	167.80	142.92	119.17	96.60	77.34	60.12	46.71	34.91	23.56	15.37	78.45
	NARIN	131.03	104.31	84.08	69.83	57.71	46.99	37.93	29.60	22.98	18.88	60.33
	SAMF	95.04	76.21	69.79	66.47	62.26	55.56	47.16	39.77	32.80	28.91	57.40
	FSMMF	128.26	104.76	85.24	71.84	62.84	55.26	48.68	41.25	31.83	25.98	65.60
	TSTMMF	174.62	154.25	138.43	123.04	107.28	78.02	76.43	65.66	45.73	32.01	**99.55**
Peppers.png 512 x 512	DBA	324.45	268.46	220.85	179.13	140.27	105.12	72.27	43.79	21.35	11.55	138.72
	NAFSM	263.75	254.69	243.52	226.79	213.42	192.71	164.26	128.17	61.27	13.66	176.22
	MDBUTMF	428.21	378.31	327.89	271.89	217.80	158.55	101.63	56.08	21.27	10.13	197.18
	NARIN	313.78	253.30	211.30	179.99	151.05	125.33	99.48	72.60	51.44	37.02	149.53
	SAMF	387.18	332.32	305.45	278.20	248.33	215.06	182.17	140.78	89.42	56.84	223.57
	FSMMF	308.82	253.01	212.66	185.46	166.60	147.71	131.19	100.97	54.92	31.39	159.27
	TSTMMF	414.87	363.97	330.57	294.40	260.76	243.23	249.99	227.18	151.83	77.97	**261.48**

Table 4. Mean Absolute Error (MAE) values of different filters against proposed TSTMMF at different noise densities (ND)

Image	Noise Density \ Method	10	20	30	40	50	60	70	80	90	95	Average
Lena.png 512 x512	DBA	0.40	0.88	1.44	2.11	2.94	4.04	5.55	7.96	13.05	19.94	5.83
	NAFSM	0.50	1.03	1.58	2.16	2.77	3.45	4.22	5.24	7.47	15.52	4.39
	MDBUTMF	0.35	0.75	1.21	1.75	2.43	3.33	4.65	7.02	13.53	25.00	6.00
	NARIN	0.41	0.91	1.50	2.18	2.97	3.91	5.09	6.71	8.89	10.88	4.34
	SAMF	0.39	0.86	1.37	1.90	2.49	3.18	4.06	5.22	7.18	9.13	3.58
	FSMMF	0.41	0.91	1.49	2.15	2.88	3.64	4.52	5.73	8.21	11.78	4.17
	TSTMMF	0.35	0.76	1.20	1.70	3.20	3.85	4.11	4.57	5.83	8.07	**3.36**
House.png 512x512	DBA	0.16	0.38	0.69	1.10	1.64	2.42	3.60	5.60	10.04	16.06	4.17
	NAFSM	0.26	0.54	0.85	1.18	1.54	1.96	2.47	3.19	4.98	13.23	3.02
	MDBUTMF	0.11	0.27	0.51	0.84	1.31	2.00	3.11	5.27	10.88	19.87	4.42
	NARIN	0.18	0.41	0.72	1.09	1.55	2.13	2.91	4.07	5.72	7.37	2.61
	SAMF	0.15	0.36	0.62	0.91	1.25	1.67	2.31	3.17	4.73	6.42	2.16
	FSMMF	0.16	0.41	0.71	1.07	1.49	1.98	2.62	3.64	6.07	9.43	2.76
	TSTMMF	0.12	0.28	0.48	0.74	1.26	1.51	1.71	2.08	3.10	4.84	**1.61**
Mandril.png 512x512	DBA	0.77	1.70	2.84	4.20	5.91	8.05	10.74	14.35	19.81	25.13	9.35
	NAFSM	1.32	2.66	3.99	5.36	6.78	8.25	9.84	11.70	14.95	22.97	8.78
	MDBUTMF	0.68	1.49	2.45	3.63	5.07	6.95	9.29	12.56	18.00	24.95	8.51
	NARIN	0.78	1.74	2.91	4.26	5.88	7.81	10.16	13.19	17.04	19.82	8.36
	SAMF	0.89	2.04	3.24	4.44	5.73	7.30	9.31	11.69	14.70	16.74	7.61
	FSMMF	0.79	1.73	2.89	4.22	5.67	7.31	9.10	11.36	14.81	17.78	7.57
	TSTMMF	0.67	1.44	2.28	3.22	4.31	7.71	8.39	9.61	12.31	15.46	**6.54**
Peppers.png 512 x 512	DBA	0.45	0.97	1.56	2.25	3.11	4.20	5.77	8.36	14.14	22.12	6.29
	NAFSM	0.50	1.00	1.52	2.08	2.66	3.31	4.08	5.11	7.38	15.60	4.32
	MDBUTMF	0.42	0.88	1.38	1.96	2.66	3.59	5.05	7.76	15.65	28.21	6.76
	NARIN	0.46	1.00	1.63	2.33	3.14	4.07	5.24	6.82	8.99	10.88	4.46
	SAMF	0.43	0.90	1.39	1.92	2.51	3.18	3.97	5.04	6.95	9.21	3.55
	FSMMF	0.47	1.00	1.62	2.32	3.08	3.92	4.83	6.21	9.35	13.75	4.66
	TSTMMF	0.43	0.89	1.39	1.94	2.55	4.47	4.68	5.07	6.14	8.22	**3.58**

The noisy images have been simulated by adding Salt and Pepper noise with the standard images mentioned with various $ND \in [10,20,30,40,50,60,70,80,90,95]$ and have been denoised using the proposed TSTMMF and different algorithm mentioned. The denoising parameters such as PSNR, SSIM, IEF and MAE have been calculated and tabulated as the Table 1, Table 2, Table 3 and Table 4 respectively. From these tables, it can be found that proposed TSTMMF outperforms the state-of-the-art methods, decision based algorithm (DBA) [7], noise adaptive fuzzy switching median (NAFSM) [13], new algorithms for recovering images from impulse noise (NARIN) [8], simple adaptive median filtering (SAMF) [10] and fast switching based median and mean filter (FSMMF) [12] in terms of PSNR, SSIM, IEF and MAE at all the noise densities considered. Though the method, (MDBUTMF) [11] equally perform with TSTMMF at lower noise densities ($ND < 50\%$), it fails to maintain the performance at higher noise densities. The proposed TSTMMF maintains its superior performance at higher noise densities and hence it outperforms MDBUTMF at $ND > 50\%$.

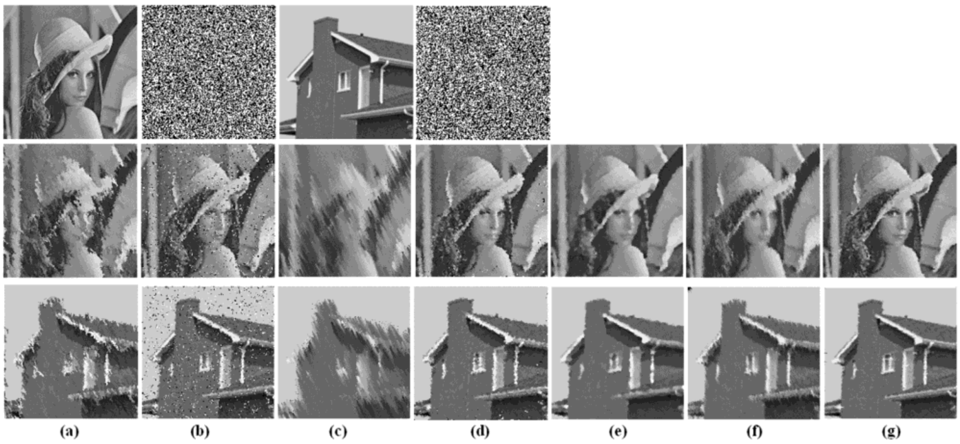


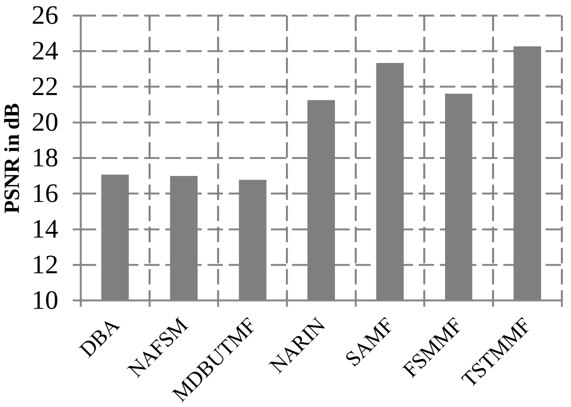
Fig. 1 Illustration of visual presentation of different denoising methods. Top Row: (a) Lena.png (512x512) image, (b) Noisy Lena.png (ND=95%), (c) House.png (512x512) image, (d) Noisy House.png (ND=95%) Middle and Bottom Rows: Denoised images using the methods of (a) DBA [7], (b) NAFSM [13], (c) MDBUTMF [11], (d) NARIN [8], (e) SAMF [10], (f) FSMMF [12] and (g) proposed TSTMMF

Moreover, comparing the proposed TSTMMF exclusively against SAMF makes a sense as it stands second in terms of the average values of PSNR, SSIM, IEF and MAE with respect to TSTMMF. From Table 1 and Table 3, it can be found that that proposed TSTMMF outperforms SAMF in terms of PSNR and IEF at all the densities for all the noisy images considered. Similarly, from Table 2 and Table 4, it is proved that the TSTMMF performs better over SAMF in terms of SSIM and MAE except for very few cases. Furthermore, TSTMMF outperforms SAMF in terms of SSIM and MAE on an average.

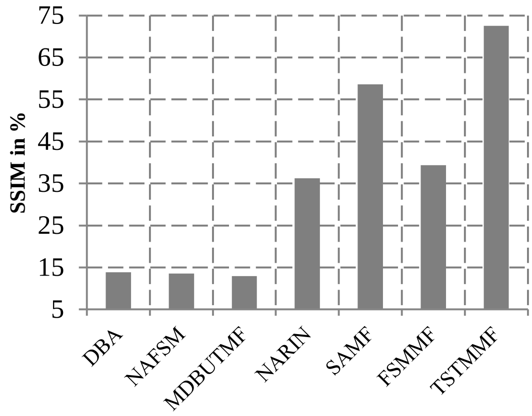
Hence the proposed TSTMMF gives the best average of PSNR, SSIM, IEF and MAE over all other state-of-the-art methods considered.

In order to check the performance of TSTMMF in terms of visual presentation a noisy *Lena.png* and *House.png* images with *ND* = 95% have been denoised using different denoising methods and the results have been illustrated in Fig. 1. From the results shown in Fig. 1, it can be understood that the proposed filter outperforms different state-of-the-art denoising methods in terms of edge preservation and good visual appearance. Fig. 2 shows the respective values of PSNR, SSIM, IEF and processing time required by different filtering methods to obtain the denoised image from noisy *lena.png* image at *ND*=95%. It can be seen that the proposed TSTMMF outperforms the filters by all the parameters of denoising.

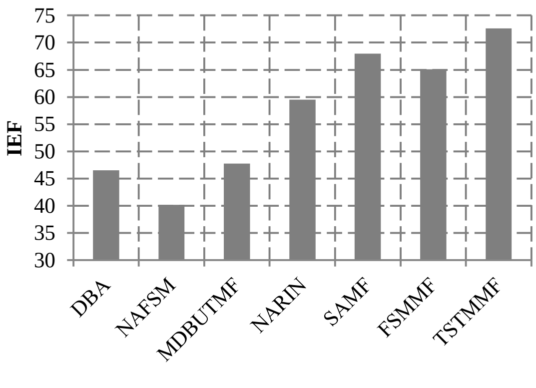
The time taken by DBA [7], MDBUTMF [11] and FSMMF [12] relatively less compared to that of proposed TSTMMF but the denoising performance of these filters is relatively less to that of TSTMMF. It can also be seen that the proposed TSTMMF takes the time which is very much less than that of the SAMF [10] which stands second among the filtering methods in terms of PSNR, SSIM, IEF and MAE on an average.



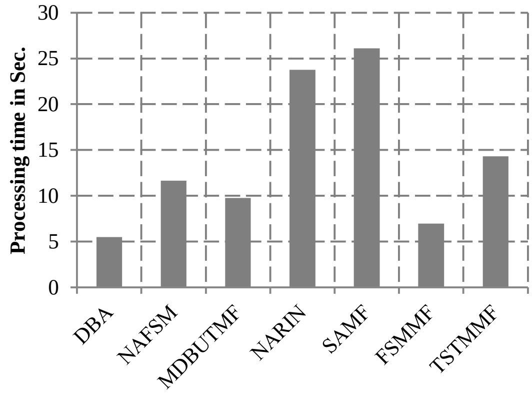
(a)



(b)



(c)



(d)

Fig. 2. Illustration showing denoising results of different denoising methods for corrupted Lena.png (512x512) with ND = 95% (a) PSNR results in dB (b) SSIM results in % (c) IEF results (d) Processing time required in Seconds

4. Conclusion

In this paper, a new estimation technique has been proposed to remove SNP noise in an efficient manner using two stages of trimmed median and a single stage of mean filtering. It has been proved that the proposed TSTMMF filter gives an outstanding performance of denoising in terms of PSNR, SSIM, IEF, MAE and visual appearance at an optimum speed over many of the state-of-the-art filters considered. Moreover, it is proved that the proposed filter gives progressively increasing difference in denoising performance over the compared filters, as the noise density increases and hence proposed TSTMMF works very well for the noise densities up to 95%.

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