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Hybrid Filtering Approach for Retrieval of MRI Image

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Abstract
The quality of Magnetic Resonance Images(MRI) are degraded by the various types of noises. In this paper, a Hybrid Multi-resolution filter for denoising the MRI images degraded by the Salt and Pepper noise is proposed and the wavelet transform is used to improve the resolution of the denoised image.. The Hybrid filter consist of three value weighted filter and similarity based filter. In three value weighted filter, a variable local window is applied to find the noisy pixels. By using the noise free pixels in that window, the noisy pixels are reconstructed using three value method. In similarity based filter, a variable local window is applied to reconstruct the noisy pixels. In that window, based on the similarity between the noisy pixel sequence and noise free pixels sequence are used to reconstruct the noisy pixel. At last wavelet transform is used to increase the resolution of the reconstructed image. The experimental results shows that the proposed filter denoises the image and improves the resolution when compared to the existing methods and produces the efficiency of about 98%.

Keywords Image denoising · Hybrid filter · Weighted filter · Similarity filter · Multi-resolution

Introduction

Images are often corrupted by the impulse noise during the formation due to the noisy channel transmission, malfunctioning pixels in camera sensors. Impulse noise is classified into two categories. They are salt and pepper noise and random valued noise. The affect of above said noise is more serious in images. This degrade the quality of an images by corrupting the pixels to the maximum or minimum value. The process of removing impulse noise efficiently is a research task.

This article is part of the Topical Collection on *Image; Signal Processing*

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Various filtering techniques have been to remove the Impulse noise. The efficiency of the various techniques are different. Median filter [1] is the most popular filter used to remove the impulse noise. Few of its variations [2–4] are also used to remove the impulse noise. Median filter replaces all the pixels in an image by the estimated values irrespective of noisy or noise free pixels. Due to this image will be damaged especially in the images with low signal to noise ratio (SNR).

To overcome this, various switching based filters have been proposed. In this class of filters a noise detector is introduced to classify the pixels into noisy and noise free. After the classifications of pixels, filters are used to reconstruct the noisy pixels. Recently proposed switching based filters are, Block based switch median filter [5], switching based clustering algorithm [6], Global Local noise detection based Adaptive Median (GLAM) filter [7], Adaptive decision based denoising algorithm [8]. Efficient edge preserving filter based on fuzzy switching median filter [9], Fast Switching Median (FSM) filter [10], High density noise removal through a modified decision based median filter [11], Convolutional Noise Detection based Switching Median (CNDSM) filter [12],Mixed noise removal using noisy pixel modification technique [13] and Switching based Filter using Non-monotone Adaptive Gradient Method (NAGM) [14]. Noisy pixels are reconstructed using the pixels in the local window. This switching filters have produced better results when compared to Median filter. But the efficiency of the switching filter are reduced when the noise level is high.

Another popular technique used to reconstruct the Salt and Pepper noise is Mean Filter. Both Median and Mean filters performs well when the noise level is below 60%. Various kind of Mean filters are also proposed to remove the impulse noise. They are Switching Adaptive Weighted Mean (SAWM) filter [15], Non-local mean filter [16], decision based non local mean filter [17] and New adaptive weighted mean filter [18].

In mean filters, when the noise density is high the size of the local window should be increased. This produces blurring of an image. The edge details are also not preserved.

The overcome the drawbacks of the median filters, its variations, a Hybrid Multi-resolution filter have been proposed. It consist of three value weighted filter [19] and similarity based filter [20]. Proposed filter produces better results when compared with the existing methods.

In this paper, section II introduces the three value filter, section III introduces similarity filter, section IV discusses about the experimental results and finally we conclude it.

Three value weighted filter

In this filter, a local variable window that moves from right to left and from top to bottom is applied to estimate the similarity between noise corrupted pixel and un-corrupted pixels. Initially the noise corrupted pixels in that window are calculated as follows,

For a given input noisy image f, the window $W_{x,y}$ is applied. Two extreme values 0 and 255 are excluded for reconstructing the corrupted pixels.

$$f^{'}(p,q) = f(p,q) \text{ if } f(p,q) \neq 0 \text{ and } f(p,q) \neq 255 \quad (1)$$

Maximum and Minimum value pixels in the local window applied to the $X^{'}$ are calculated as,

$$f^{'}_{min} = \min(f^{'}) \quad (2)$$

$$f^{'}_{max} = \max(f^{'}) \quad (3)$$

The non-extreme pixels in the window are classified into maximum and minimum group based on the distance between $f^{'}_{max}$ and $f^{'}_{min}$ as follows

$$d_{max}(p,q) = |f^{'}(p,q) - f^{'}_{max}| \quad (4)$$

$$d_{min}(p,q) = |f^{'}(p,q) - f^{'}_{min}| \quad (5)$$

for maximum group

$$F_{max}(p,q) = \begin{cases} 1, \text{if } d_{max}(p,q) \leq d_{min}(p,q) \\ 0, \text{otherwise} \end{cases} \quad (6)$$

for minimum group

$$F_{min}(p,q) = \begin{cases} 1, \text{if } d_{max}(p,q) > d_{min}(p,q) \\ 0, \text{otherwise} \end{cases} \quad (7)$$

The number of non-extreme pixels in the maximum group and minimum group arecomputed as

$$Nmax = \sum_{m=-s}^{s} \sum_{n=-s}^{s} F_{max}(p,q) \quad (8)$$

$$Nmin = \sum_{m=-s}^{s} \sum_{n=-s}^{s} F_{min}(p,q) \quad (9)$$

Where m, n are dimensions of the window and s is a size of a window.

The ratio of number of maximum pixels and number of non extreme pixels is assigned as a weight of maximum and that can be computed as

$$P_{max}(p,q) = N_{max}/N_{non\ extreme} \quad (10)$$

$N_{non\ extreme}$ is a number of non-extreme pixels in that local window. That can be calculated as

$$N_{nonextreme} = N_{max} + N_{min} \quad (11)$$

The ratio of number of minimum pixels and number of non-extreme pixels is assigned as a weight of minimum and that can be computed as

$$P_{min}(p,q) = N_{min}/N_{non\ extreme} \quad (12)$$

The middle pixel value is computed as,

$$f^{'}_{mid} = P_{max}(p,q).f^{'}_{max} + P_{min}(p,q).f^{'}_{min} \quad (13)$$

After the calculation of middle value the pixels in the local window are again classified into minimum group, middle group and maximum group. To classify the pixels, another difference value d_{mid} is introduced as

$$d_{mid}(p,q) = |f^{'}(p,q) - f^{'}_{mid}| \quad (14)$$

for maximum group

$$F_{max}(p,q) = \begin{cases} 1, \text{if } d_{max}(p,q) < d_{min}(p,q) \text{ and} \\ d_{max}(p,q) < d_{mid}(p,q) \\ 0, \text{otherwise} \end{cases} \quad (15)$$

$$F_{mid}(p,q) = \begin{cases} 1, \text{if } d_{mid}(p,q) \leq d_{max}(p,q) \text{ and} \\ d_{mid}(p,q) \leq d_{min}(p,q) \\ 0, \text{otherwise} \end{cases} \quad (16)$$

$$F_{min}(p,q) = \begin{cases} 1, \text{if } d_{min}(p,q) < d_{max}(p,q) \text{ and} \\ d_{min}(p,q) < d_{mid}(p,q) \\ 0, \text{otherwise} \end{cases} \tag{17}$$

The number of non-extreme pixels in the maximum and minimum group can be find using (8) and (9). The number of non-extreme pixels in the middle group can be computed as

$$\text{Nmid} = \sum_{m=-s}^{s} \sum_{n=-s}^{s} F_{mid}(p,q) \tag{18}$$

The weight of maximum and weight of minimum can be computed using (10) and (12). The weight of middle is computed as

$$P_{mid}\,(p,q) = N_{mid}/N_{non\ extreme} \tag{19}$$

By using the above computed values the corrupted pixel is reconstructed as

$$f\,(p,q) = P_{max}\,(p,q).f'_{max} + P_{mid}\,(p,q).f'_{mid} + P_{min}\,(p,q).f'_{min} \tag{20}$$

Initially the window size is set to 3 × 3. The number of non-extreme pixels calculated by (11) is used to vary the size of the local window. If there is zero non extreme pixel for the window size of 3 × 3, the value of window size is expanded by one. This process is repeated until we find the non-extreme pixel. Maximum window size is set to 7 × 7. If it is not possible to find a non-extreme pixel in a allowed window size, median value of a pixels in a window is assigned as a reconstructed value.

Similarity filter

Image denoising using similarity filter can be classified into Pixel to Pixel Similarity (PPS) filter and Block to Block Similarity (BBS) filter. In pixel to pixel similarity filter, the pixels in the local window (5 × 5) are assigned with the weights depends on the distance between central pixel and the pixels. The pixels in the local window with its weights are used to reconstruct the central pixel. This pixel to pixel similarity filter produces good results when the image has flat regions. The area with edges are blurred in filtering because of the pixel to pixel similarity.

To overcome this drawback, Block to Block similarity filter were introduced. Traditional methods scans overall image to find the similar block with respect to the current processing block. Weights are assigned based on the similarity of the block. Similar blocks with assigned weights are used to reconstruct the central pixel in the current processing window.

This method can produce very good results, but it has some drawbacks. First, scanning the overall image and assigning weights to similar blocks is a time consuming and computationally complex one. Second, blocks with low similarity does not guarantee that the central pixel and edge information are also less similar. So this low similarity blocks may produce blurring of edges.

When the noise level is high, it is difficult to find the blocks with high similarity due to the affect of noise in all pixels in the block. Preservation edge information is more important than the block information. So to preserve edges while denoising, a new approach called Sequence to Sequence Similarity (SSS) filter is proposed. This sequence to sequence similarity filter differs from other two filters by utilizing the information contained by highly similar sequence in the images in different directions.

The sequence to sequence similarity filtering process can be divided into SSS based filtering and smoothing technique. The sequence in the different directions of the pixel at the center of local window and sequence of the surrounding pixels in the same directions are used to compute the sequence to sequence similarity. Based on the similarity of the sequence, weights are assigned to the surrounding pixels. Sequence to sequence similarity is used to find the high similar sequences. High value of similarity indicates the high correlation between the sequences. So it is possible to reconstruct the pixels in a sequence if it is affected by noise. High value of noise makes it difficult to find the high similar sequences.

The directions used to find the sequence are horizontal, vertical, right-oblique and left oblique. For the window size of 4 × 4, centered at the pixel of an image $f_{(4,4)}$ the different directional sequence for the surrounding pixel $f_{(3,2)}$can be calculated as shown in Fig. 1.

The similarity between two sequences can be expressed in terms of mathematical model. Similarity between two sequences $A = [A_1\ A_2\ A_3......A_n]$ and $B = [B_1\ B_2\ B_3.....B_n]$ is given by

$$S(A,B) = \frac{1}{n} * \sqrt{\sum_{i=1}^{n} (A_i - B_i)^2} \tag{21}$$

Where n is number of elements in a,

In SSS based filter two parameters has to be defined. They are, the size of the local window (N) and length of the sequence (K). For the window centered at the position (i,j), the four directional weight of pixel positioned at (k1, k2) are given by

$$W^h{}_{i+k1,j+k2} = S\left(A_{i+k1,j+k2-K:j+k2+K}, A_{i,j-K:j+K}\right) \tag{22}$$

$$W^v{}_{i+k1,j+k2} = S\left(A_{i+k1-K:i+k1-K,j+k2}, A_{i-K:i+K,j}\right) \tag{23}$$

$$W^l{}_{i+k1,j+k2} = S\left(A_{i+k1-K:i+k1+K,j+k2-K:j+k2+K}, A_{i-K:i+K,j-K:j+K}\right) \tag{24}$$

$$W^r{}_{i+k1,j+k2} = S\left(A_{i+k1+K:i+k1-K,j+k2-K:j+k2+K}, A_{i+K:i-K,j-K:j+K}\right) \tag{25}$$

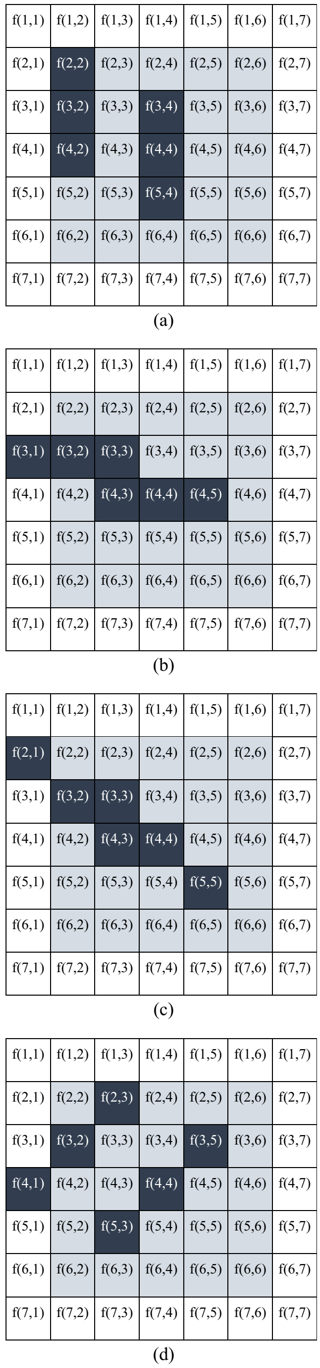


Fig. 1 Example of finding different directional sequences (a) Vertical (b) Horizontal (c) left-oblique (d) right-oblique

The overall weight of the pixel at (k1,k2) can be computed as,

$$W^{C}_{i+k1,j+k2} = \left(W^{h}_{i+k1,j+k2} + W^{v}_{i+k1,j+k2} + W^{l}_{i+k1,j+k2} + W^{r}_{i+k1,j+k2}\right)/\sqrt{k_1^2+k_2^2} \tag{26}$$

After computing overall weight of all the pixels in a window, the central noisy pixel can be reconstructed as

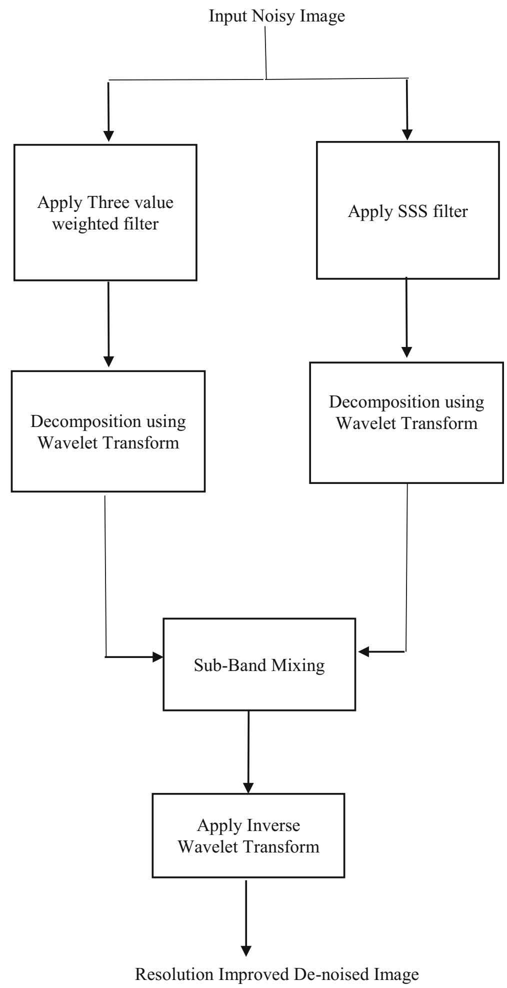


Fig. 2 Architectural diagram of proposed methodology

$$\mathrm{Ci, j} = \sum_{k1=-N}^{N} \sum_{k2=-N}^{N} \left(A_{i+k1,j+k2} * W^{C}_{i+k1,j+k2}\right) \tag{27}$$

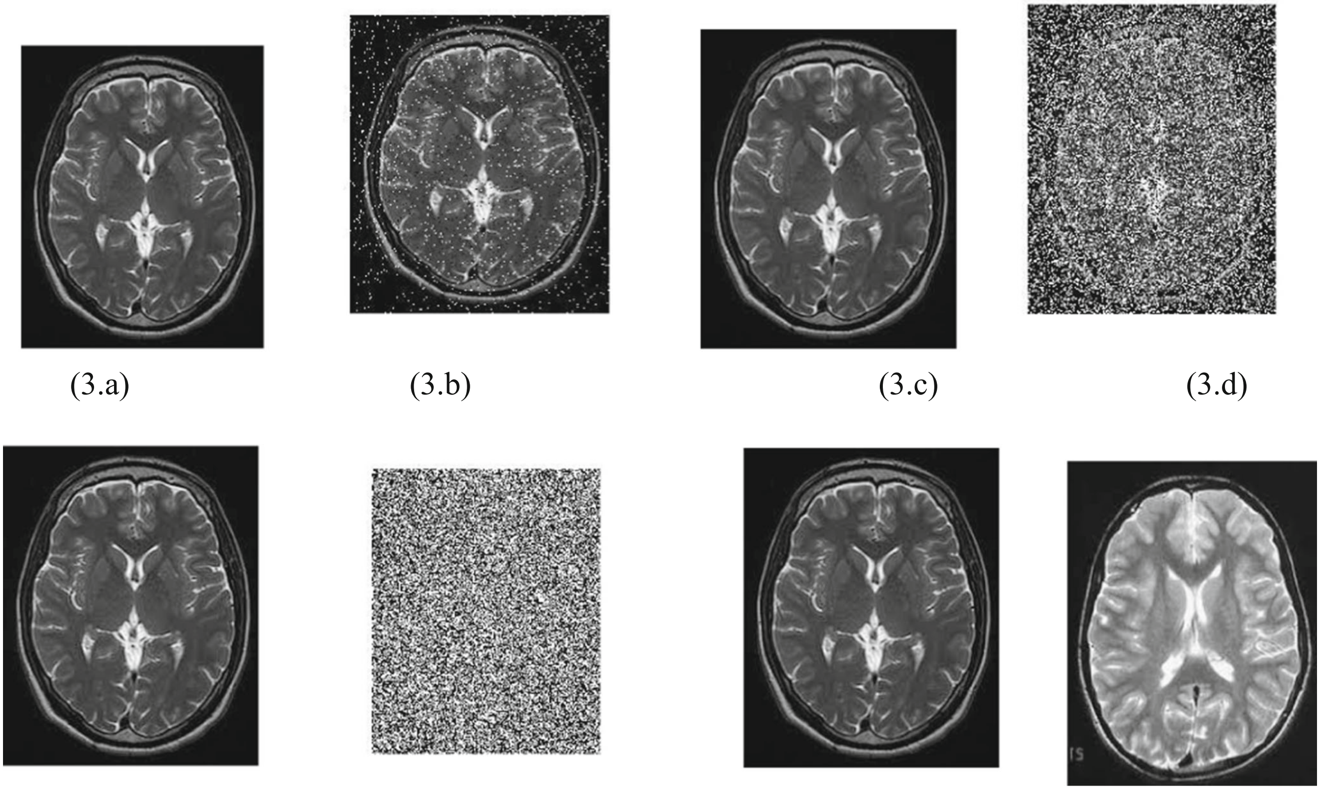
By sliding the window from left to right and top to bottom, all the noisy pixels are reconstructed using the above prescribed method. After denoising the image, the smoothing process is applied with window size of M and it is described as

$$\mathrm{Di, j} = \sum_{k1=-M}^{M} \sum_{k2=-M}^{M} \left(C_{i+k1,j+k2} * \omega^{D}_{i+k1,j+k2}\right) \tag{28}$$

$$\text{Where } \omega^{D}_{i+k1,j+k2} = e^{-\left(\frac{A_{i+k1,j+k2}-A_{i,j}}{\alpha}\right)^2} \tag{29}$$

is the level of noise. The length of the sequence corresponds to the similarity between the sequences. If we have high length of sequence, it could be used to identify high similar sequences.

After denoising an images using three value filter and similarity filter, wavelet transform is used to improve the resolution of an images. The wavelet transformation is used to decompose the image into different sub-bands based frequency



(3.a) (3.b) (3.c) (3.d)

(3.e) (3.f) (3.g) (3.h)

Fig. 3 (3.a) original rice image (3.b) image with noise density of 0.05 (3.c) restored image (3.d) image with noise density of 0.5 (3.e) restored image (3.f) image with noise density of 0.9 (3.g) restored image (3.h) resolution improved image

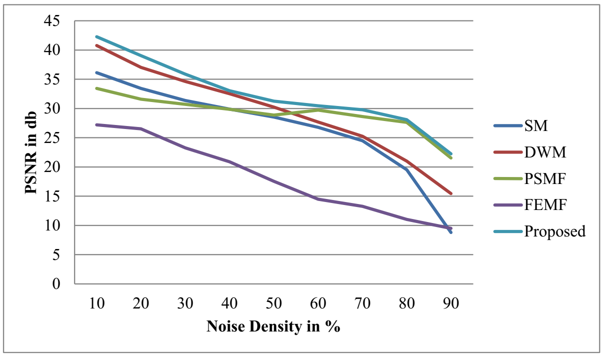
content of the pixels. By decomposing the denoised images and combining the different sub-bands, images with different resolution can be obtained. Figure 2 shows the architectural diagram of proposed methodology.

The proposed algorithm can be described as follows.

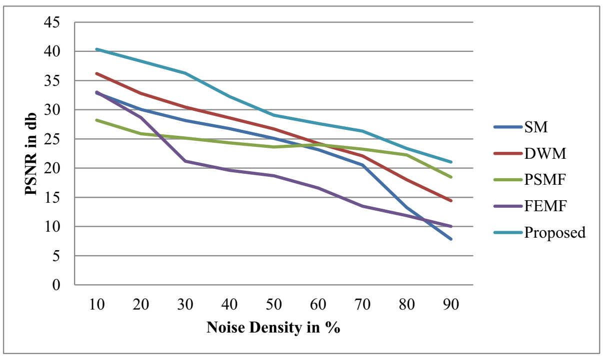
Step 1: input the image with impulse noise.
Step 2: denoise the image using three value filter.

Table 1 PSNR (db) comparison of different algorithms with different noise level

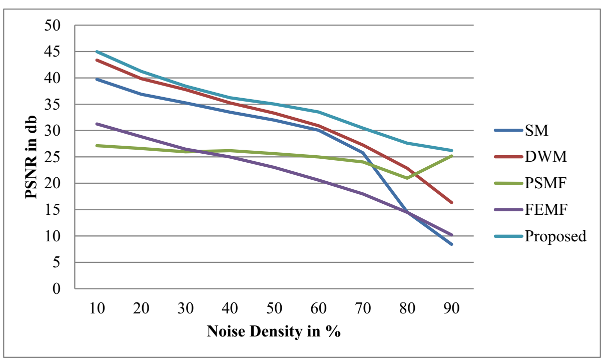
Image	Filter	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
sectional view of brain	SM	36.12	33.42	31.36	29.88	28.54	26.76	24.47	19.52	8.80
	DWM	40.78	37.02	34.63	32.51	30.23	27.69	25.23	21.00	15.45
	PSMF	33.42	31.58	30.72	29.87	28.88	29.72	28.61	27.16	21.54
	FEMF	27.21	26.51	23.25	20.89	17.54	15.47	13.26	11.02	9.48
	Proposed	42.28	39.05	35.88	33.03	31.25	30.46	29.78	28.09	22.25
Lateral view of brain	SM	32.84	30.05	28.15	26.76	25.08	23.16	20.54	13.25	7.83
	DWM	36.19	32.81	30.44	28.61	26.70	24.25	22.10	18.0	14.42
	PSMF	28.22	25.89	25.15	24.34	23.61	24.02	23.25	22.26	18.46
	FEMF	33.01	28.66	21.17	19.62	18.69	16.58	13.47	11.86	10.01
	Proposed	40.36	38.32	36.25	32.25	29.05	27.65	26.35	23.35	21.05
upper view of hands	SM	39.72	36.90	35.26	33.48	31.98	30.05	25.79	14.55	8.42
	DWM	43.39	39.85	37.76	35.27	33.32	30.92	27.26	22.85	16.33
	PSMF	27.15	26.60	25.98	26.19	25.64	25.00	24.06	20.98	25.20
	FEMF	31.25	28.84	26.47	24.98	23.02	20.58	17.98	14.48	10.19
	Proposed	44.98	41.23	38.45	36.24	35.02	33.54	30.47	27.61	26.21
Spine	SM	37.08	34.47	31.98	28.51	26.04	23.41	18.56	12.74	8.52
	DWM	38.25	33.02	29.98	26.52	22.01	21.02	20.63	18.75	15.64
	PSMF	25.55	24.99	24.38	24.67	24.05	23.31	22.28	18.91	17.92
	FEMF	30.22	27.25	24.89	23.45	22.82	18.45	12.03	8.05	1.34
	Proposed	39.08	35.62	32.05	29.47	26.20	24.03	22.56	19.91	18.56



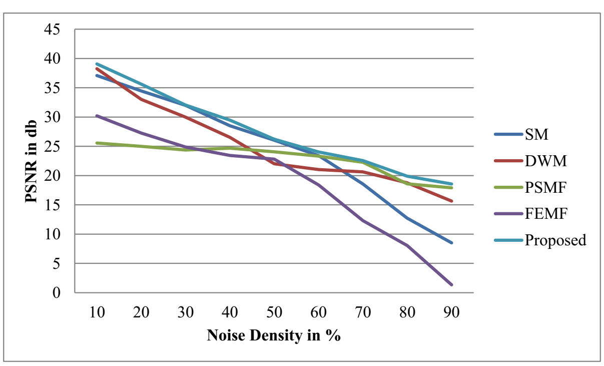
(a)



(b)

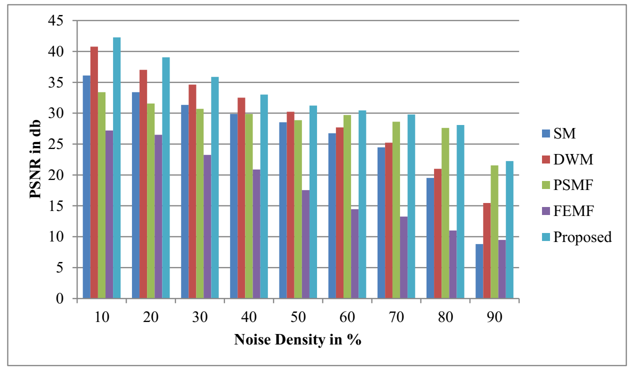


(c)

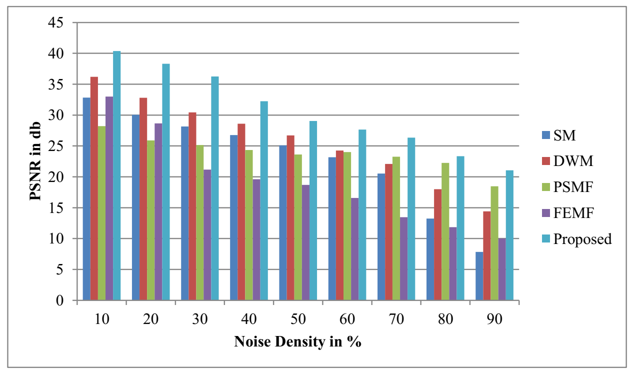


(d)

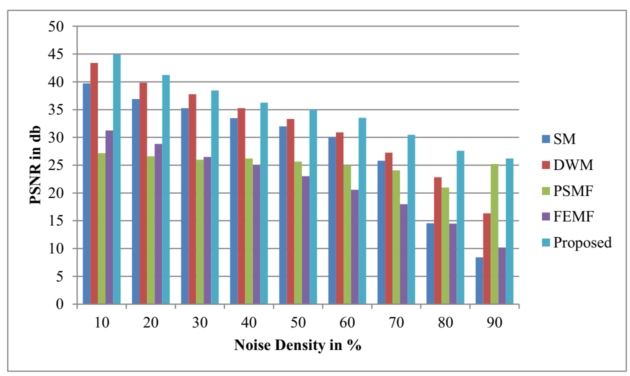
Fig. 4 (4.i&m) PSNR comparison of sectional view of brain Image (4.j&n) PSNR comparison of Lateral view of brain Image (4.k&o) PSNR comparison of upper view of hands Image (4.l&p) PSNR comparison of Spine Image



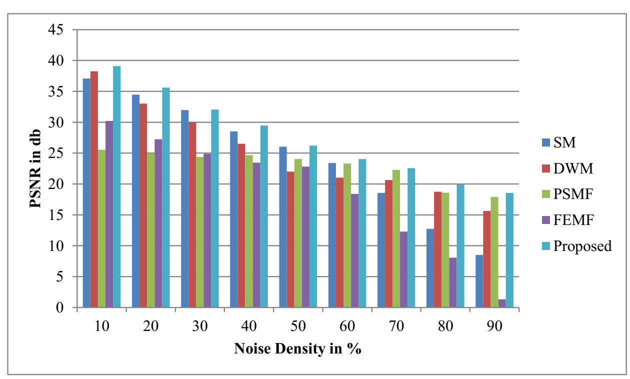
(e)



(f)



(g)



(h)

Fig. 4 (continued)

Step 3: denoise the image using similarity filter.
Step 4: decompose the denoised images.
Step 5: combine the different sub- bands of denoised images to improve resolution.
Step 6: take inverse transform of the sub-band mixed image to get resolution improved image.

Experimental results

The proposed hybrid multi-resolution filter can be used to denoise the gray scale images that are degraded by the salt and pepper noise while increasing the resolution of the restored images. This algorithm is applied on some MRI images like 'sectional view of brain', 'Lateral view of brain', 'upper view of hands', 'spinet' with the noise density level of 10% to 90% to measure the efficiency of it and their experimental results are shown in Fig. 3. The switch median filter (SM), Directional weighted median filter.

(DWM), Progressive switching median filter (PSMF), Fast and Efficient median filter (FEMF) are also implemented for comparison of results.

The quantitative analysis includes the comparison parameters called Peak Signal to Noise Ratio (PSNR) and it is given by

$$\mathrm{PSNR}\ (\mathrm{db}) = 10.\log_{10}\frac{MAX}{}MSE \tag{30}$$

Where MAX is the maximum gray value in an image (255), MSE is mean square error which is given by

$$\mathrm{MSE} = \frac{1}{M.N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left|x_{i,j}-y_{i,j}\right|^2 \tag{31}$$

M and N are size of an images, x is input image, y is a restored image.

Table 1 and Fig. 4 represents the comparison of proposed algorithm with other algorithms. When the noise level is low (10%- 50%), the proposed algorithm produces the restored image more similar to the original image. And also edges are preserved well. When the noise level increases, the proposed algorithm performs well when compared to other techniques. Visual comparison shows that the resolution of the restored image is also increased.

Conclusion

In this paper, a hybrid multi-resolution filter for image denoising is proposed. It consist of similarity filter and three value weighted filter. The experimental results shows that the proposed hybrid filter efficiently removes the Salt & Pepper noise present in an image while noise density level is high and produces high PNSR value when compared to existing methods. It also shows that the resolution of the denoised is also got increased. This is achieved by wavelet sub-band mixing technique. Images with different resolution can also be obtained by using this technique.

Compliance with Ethical Standards

Research Involving Human Participants and/or Animals - Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent No humans are involved.

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