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Efficient Denoising by Feature Recovery from Residual Noise in Spatial Domain

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Abstract ***The growth of image processing techniques has lead to limitless applications of imaging in various fields of medical, remote sensing. However, the unpreventable problem of noise contamination arises during the processing of images. As the noise content in an image rises, it becomes difficult to denoise an image while preserving high-frequency edge features as well as low frequency smooth features. Minimal artefacts and better preservation of geometrical details such as edges and texture reflects efficient image reconstruction. Since many State-of-the-art denoising algorithms have been reported in the literature, and there is always a compromise between noise removal and feature preservation. A novel approach for efficient noise removal along with recovery of fine features is being proposed. The idea behind denoising approach is the use of hybridization of spatial domain filters where base layer image and residual image are extracted and processed separately to mitigate the prevalence of artefacts and preserve image content. The performance of the proposed method is evaluated both quantitatively as well as qualitatively, and it is found that the proposed method could outperform existing denoising techniques.***

Keywords: Image Noise Cancellation, Image Denoising, Nonlinear Diffusion, Texture, Spatial Filters, Transforms

I. INTRODUCTION

The inevitable need for rectification of pictorial information for better human visualization and applications motivated the emergence of image processing techniques.

The innumerable applications of imaging in a medical field, remote sensing, weather forecasting, atmospheric study, astronomy, machine vision applications, automated inspection, movement detection, image data compression have led to the remarkable growth of image processing techniques [1]. In the medical field, the segmentation of CT scan images of the human brain is used to locate tumor cells [2]. Mammogram and ultrasonic images can be used to detect formation of cancerous tissues [3]. Remote sensing is considered a substantial technique to investigate areas on earth.

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To determine the rate of growth of vegetation in a region, the direction of river flow, study pollution in a city, industry planning, territory mapping, *etc.*, remote sensing imaging is a comprehensive approach. Image processing techniques allow for automated inspection of the quality of the product to ensure adequate delivery of product [4]. For efficient transmission over a low bandwidth channel, images are compressed. Unfortunately, the most common and inevitable obstacle that occurs during the processing of images is the prevalence of noise that leads to degradation of image visualization [5]. Noise is a discrepancy that causes unpleasant effects by disturbing luminance levels in an image. Hence it is important to reduce the detrimental effects of noise on images so as to make better analysis [6]. The prevalence of noise in images is apparently a natural phenomenon and cannot be avoided [7]. To reduce the undesirable effects of noise, it is important to use an efficient denoising technique that can remove the artefacts, enhance and retain the fine details of an image [8].

The motivation of image denoising is to retain the attributes of image and removal of random noise as much as possible. Due to limitless applications of image processing in various fields, it is essential to ensure the quality of images [9]. Hence, noise reduction is crucial in medical imaging applications in order to restore hidden details in the data.

Today the immense utilization of digital imaging in the medical field, the visualization of digital medical images is of significant concern. The medical images need to be clear, sharp and free from artefacts to attain the best possible diagnosis. The quality of medical images is deteriorated by noise introduced during acquisition and by illumination conditions, thus causing hindrance to effective feature extraction, analysis, recognition, and quantitative measurements. Therefore it is a dominant exercise to eliminate noise from medical images especially digital mammogram, MRI, ultrasound images, *etc.*[3]. The quality of remote sensing images is highly degraded by additive noise that can limit the fidelity of successive processing, such as target detection, classification, and segmentation, *etc.*[10].

The noise in an image may transpire from analog circuitry as electronic noise, photon noise, thermal agitation of ions, coding errors, *etc*,[11]. Blurring is a kind of noise that may occur because of improper camera setting or when the image has been captured from a moving platform [12]. To examine image denoising techniques, it is essential to have prior knowledge of noise models. The selection of a noise reduction algorithm depends greatly on the type of noise introduced in the image. The type of noise is either additive or multiplicative in nature [1, 11, 13, 14].

Gaussian noise: The emergence of noise from amplifiers or sensors used during acquisition is electronic noise and is commonly known as Gaussian noise [1, 11]. Gaussian noise basically disrupts the gray levels in an image and is uniformly distributed over the signal. This type of noise is additive noise and as its power is evenly distributed, so it is called as Additive white Gaussian noise (AWGN).

It is important to have prior knowledge of noise introduced to develop acceptable denoising algorithm. However, AWGN is extremely popular noise in images as it occurs during acquisition and transmission through an analog circuit which is a basic step of any imaging process [13, 14].

The flow of the manuscript is as follows: Section 2 elaborates the importance of image restoration system. Section 3 describes previous studies which have been utilized for comparison in the context of this manuscript. Section 4 describes the proposed algorithm. Section 5 presents results and discussions, and finally, the conclusion is drawn in Section 6.

II. IMAGE RESTORATION SYSTEM

Image restoration system is the procedure of extracting a clean image from an image that has been distorted during either capturing or transmission process [1]. In the area of astronomical imaging due to the frequent variations in the atmospheric index of refraction, ground-based imaging systems are exposed to blurring. In most cases, the noise which is found digital imaging applications is basically a Gaussian noise, which often originates from the electronic components in the imaging system. Also, Image restoration has been proved to play a significant role in the area of medical imaging. It has also been exploited for refining of film-grain noise in mammograms, Chest X-rays and digital angiographic images that remove additive noise in Resonance Imaging (MRI) [15], [16]. Thus image restoration system is of great importance.

III. LITERATURE REVIEW

Numerous techniques that attempt to minimize the consequences of noise have been evolved to show considerable performance with minimal artefacts and better PSNR (Peak Signal-to-Noise Ratio) of the processed image [17]. However, as the extent of noise increases their performance eventually degrades [2]. The well-known denoising algorithms are classified as spatial domain and transform domain. The spatial domain can be further local or non-local [18]. Earlier spatial domain linear filters such as Gaussian filter was inherently used as denoising filters, but it was incapable of preserving attributes of images. Besides this, blurring was accomplished by Gaussian filtering at high noise levels [19]. The consequences of blurring were easily removed with the help of median filter[20]. Similarly, the anisotropic filtering was introduced to avoid blurring effects with an idea to smoothen the image only in an orthogonal direction to gradient function such that only low frequency regions were smoothed without disturbing high-frequency edge information.

Another local filtering based smallest univalve segment assimilating nucleus (SUSAN) filter was designed on that fact that center pixel is replaced by the mean of all local neighborhood pixel having a same spatial region as central pixel [21]. Similarly, the development of steering kernel regression (SKR) allows edge-preserving by the fact that pixel centered near the edge will have an effect of a pixel on the same side of edge but not the edge pixels [22]. MSKR desires to upgrade SKR by optimizing metric Q and making the algorithm more adaptable [23].

A non-local filter such as bilateral filter improves Gaussian and median filter by taking into consideration intensity similarity rather than only spatial similarity. The idea behind filtering is so appealing that combines intensity or gray levels based spatial closeness as well as photometric closeness [24]. The non-local filters are more robust and have better edge preserving capability.

A wavelet transform is a most vigorous and extensively used transform in the context of removing Gaussian noise [25]. Due to its multi-resolution analysis and property to breaks image signal into a different band of frequencies, it is regarded as the strongest image processing tool for various tasks, noise reduction and image compression [2]. Most commonly known linear filter in wavelet domain is wiener filter [2], [26], [27]. Although Weiner filter provides excellent performance in terms of MSE for Gaussian corruption, the visualization is much annoying.

Another approach to denoising in the wavelet domain is non-linear thresholding technique. The thresholding based methods were devised to abolish redundant coefficients while preserving high-intensity coefficients. Threshold estimation is much involving task. Various thresholding techniques vary in threshold selection. The VisuShrink presented by Donoho and Johnstone makes use of universal threshold (UT) whose value is specified as $\sigma\sqrt{2logN}$, where σ is the noise variance, and N is no of pixels in an image [28]. The non-adaptive choice of threshold gives better visualization but results in over smoothed signal and loss of details in an image. On the other hand, Sureshrink is based adaptive thresholding algorithm in which different threshold is computed for each sub-band due to which loss of information while using a universal threshold is minimized. Hence the results obtained by Sureshrink are considerably sharp images with reduced [29].

In this section, we also briefly explore existing efforts made on noise removal whose results are compared with the results of our proposed technique. Block-matching 3D filtering (BM3D) inspired by non-local grouping is the most appealing and distinctive state of the art algorithm for attenuating Additive White Gaussian Noise (AWGN) [30]. In order to sharpen edges and other details along with denoising, Dabov k. combined BM3D denoising technique with an alpha-rooting approach known as BM3D-SH3D [31]. In this process, noise attenuation was achieved by the two-step process. First, the 3D transformation of a group is realized by block matching (*i.e.* similar blocks are placed together in form of a stack to form a 3D array) and then collaborating filtering of each group is performed by shrinkage. Second, sharpening of an image is obtained by applying alpha-rooting on hard threshold 3D transformed spectrum.

Anisotropic diffusion filtering (ADF) proposed by Perona and Malik [1990] has been appreciably utilized in the event of solving a partial differential equation based image denoising while preserving the edge information [19].

However, as the noise level exceeds three percent of the maximum image intensity, it significantly tends to blur edges. Numerous efforts have been made either to improve it or to extend it. Ritwik Kumar has contributed a variety of diffusion-based filtering methods.

Two linear diffusion based filtering techniques are assorted, one is heat equation solved using implicit Euler method (DF(A)) and another is heat equation solved using explicit method (DF(B)) [32]. VisuSoft is another most fundamental technique in the wavelet domain. Visusoft acquires non-adaptive universal in which the coefficient value is left unchanged if it is greater than threshold otherwise it is equal to a difference of threshold and coefficient value. Due to the loss of image data and it sometimes introduced errors and biased [33].

Robust bilateral filter: The major constraint concerned with the process of denoising is the introduction of artefacts and blurring effect. A bilateral filter which is a spatial domain non-linear filter has been developed in the context of denoising and has feature and details preserving properties. Bilateral filtering algorithm takes into consideration both the spatial and the intensity information between a pixel and its neighbors in order to smooth the corrupted images [24]. It replaces intensity value at each point in an image by the weighted mean of intensity values from spatially nearby pixels that depend on Euclidean distance of pixels as well as range differences. The range filtering is significant to preserve edges. The Robust bilateral filter has been designed as a modification of standard bilateral filter by establishing a box filter (Chaudhary *et al.*) [34]. The box filter is used to introduce a small amount of blurring in order to eliminate noise avoiding excessive blurring of edges. More often, it performs above a certain noise level as at low noise, box filter will introduce more blurring in an image than noise reduction.

Guided filter: The guided filter is detailed enhancement filter that automatically limited smoothing at edges which were devised by Kaiming He. It transfers attributes of guidance image that may be input image or different impression of an input image. The outputz_i at any pixel *i* is the result of multiplication of each pixel in the input image 1 and the weight generated using guidance image G for that particular pixel.

$$z_i = \sum_j w_{ij}(G)*I_j \qquad \ldots(4)$$

where *i* and *j* are pixel indexes.

The guided filter is considered a decent algorithm in terms of quality in diverse applications such as image denoising, image enhancement, haze removal, HDR compression, image matting and joint upsampling. The filter may result in halos near edges. But due to low complexity and efficiency, it is useful in many application[35].

Median filter: To overcome the consequence of over blurring introduced by mean filters, a median filter has been proposed. Median filters are found to manifest excellent performance in case of random noise without dropping the spatial resolution. The isolated lines or pixels can be efficiently eliminated while reserving high-frequency information such as edges and texture [20].

The processing of the image by a median filter is by running window with a specified radius over the image. The neighborhood pixels around the target pixel are sorted and the value of a central pixel is restored by the median value obtained from pixels contained in the window [1]. Let R_{xy} be the set of coordinates of rectangular window of subimage of size $m \times n$ that is centered at (x,y), let $d(x,y)$ be the input corrupted image and $\hat{g}$ be the restored image then

$$\hat{g}(x,y) = median_{\{R,t\}\in R_{xy}}\{d(R,t)\} \quad \ldots(5)$$

The radius of filter greatly depends on the noise level. Low radius is ineffective in eliminating large noise clusters. However, as the radius of the filter is increased, the quality of image degrades. There is a trade-off between noise reduction and visual quality of the image.

IV. PROPOSED WORK

In this section, we discuss the detailed steps of the proposed denoising algorithm. The prime motive of the present work is to eliminate residual noise while preserving the edges, textures, and contours. As the noise dosage increases in the image, it becomes difficult to obtain an estimate of original image because at high noise levels most of the denoising algorithms tend to eliminate high-frequency edge information and also features details in an image due to which quality of the reconstructed image is poor, and thus the PSNR reduces.

The proposed scheme aims at removing Gaussian noise by employing the combination of RBF, median filter and guided filter. A Novel technique in which residual noise at the output of RBF is eliminated and features that are eliminated by RBF are retained. The proposed algorithm is shown in Fig 1 and is explained as:

Step 1: First the noisy image is passed onto RBF filter whose Gaussian kernel is taken as 20 and space kernel is taken as 4. The RBF filter is smoothing filter while preserving edge details and is used as a preliminary filter for removal of noise and artefacts [34]. The output of RBF is a denoised image in which some of the noise coefficients remain and some of the features of the image are lost as the high-frequency details of the image are perceived as noise pixels by the RBF filter.

Step 2: The residual image is obtained after subtracting the output of the RBF filter from the noisy image and the base layer is obtained after subtracting a residual image from the output of the RBF filter. The residual image contains noise as well as detail-features that were eliminated by the RBF filter whereas the base layer contains low contrast edge details that define the overall shape of the image.

Step 3: The residual image is filtered using the median filter. The non-linear median filter is broadly used for noise reduction. The radius of the median filter depends on noise which is optimally taken as 2. Thus median filter will remove the residual noise and preserve edges and textures [20].

Step 4: The base image is enhanced using the guided filter. The guided filter is detailed enhancement filter that automatically limited smoothing at edges is edge preserving [35]. The radius of the guided filter is chosen as 1 that will enhance the low contrast details, reduce noise and preserve edges.

Step 5: As The filtered residual image contain edge information and enhanced base image contain feature details and textures. Therefore filtered residual and enhanced base image are linearly combined to obtain the final denoised image that will contain features and edge-details of an original image.

Further, the proposed algorithm has been refined using Butterworth high pass [1]. A Butterworth high pass filter is basically an image sharpening filter that attenuates low frequency details and allows high-frequency edge information to pass through it. Application of Butterworth high pass filter to an image will result in high pass image which is then added to the input of Butterworth HPF to obtain a sharpened image. The order of filter controls the level of sharpening. The importance of using a Butterworth filter is that it allows a gradual transition from the stop band to pass bank to avoid the ringing effect. The block diagram for the proposed technique using Butterworth HPF is shown in Fig 2.

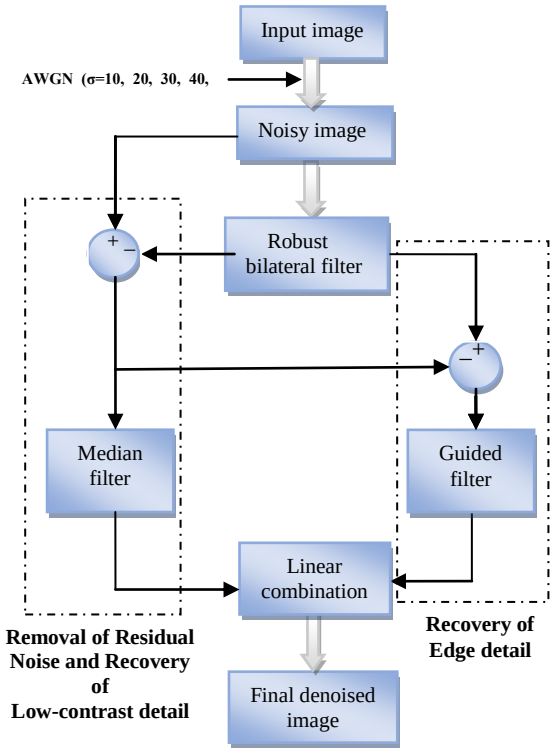

Fig 1. Block diagram of proposed algorithm 1

Performance metrics: Since different kinds of noise degrade the Quality of an image. Hence, the determination of image quality has been taken as an important aspect of image processing. To evaluate the quality of an image, there are many techniques are available, among which pixel-based difference measure
which includes PSNR (peak signal-to-noise ratio) and MSE (mean-square-error) are the most common techniques [36]. PSNR is the mathematical measure, whereas MSE is the cumulative squared error between the initial noiseless image and the denoised image. The quality of the denoised image depends upon the PSNR value, and it is measured in decibels. PSNR is calculated as:

$$PSNR = 10log_{10}(\frac{R^2}{MSE}) \qquad \dots (6)$$

Here R is maximum variation in input image data type.

PSNR measures the peak error, and its value approaches infinity as the MSE approaches zero. Thus large PSNR value corresponds to better-denoised image whereas the lower PSNR corresponds to high numerical differences between the images. Similarly, if calculated MSE is lower, better is the denoised image. MSE is calculated as:

$$MSE = \frac{\sum_{L,M}[I^1(l,m)-I^2(l,m)]^2}{L*M} \qquad \dots (7)$$

where M and L define the no. of columns and rows of the input image respectively [37]. Structural Similarity Index (SSIM) has also been considered which is a perception-based model that considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close which carry important information about the structure of the objects in the visual scene.

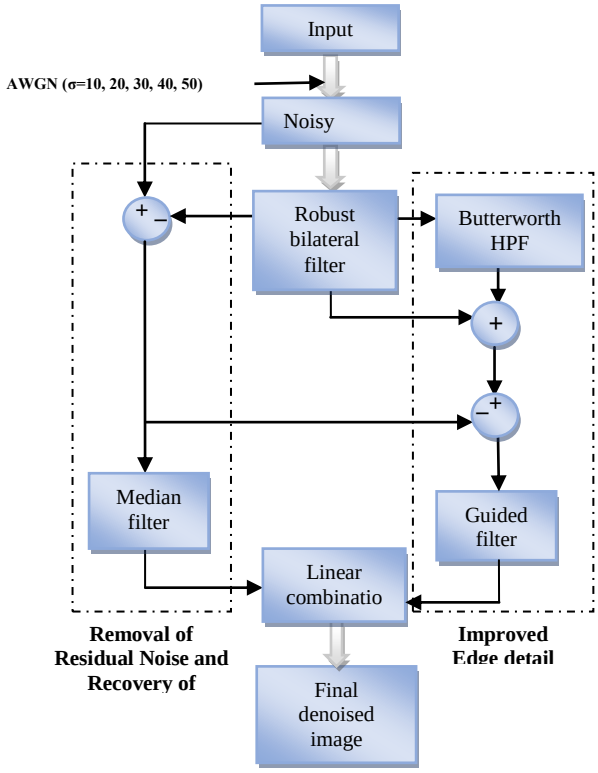

Fig 2. Block diagram of proposed algorithm 2

V. RESULTS AND DISCUSSION

In this section, the execution of the proposed denoising algorithm on size 256*256 grayscale images has been examined. We have taken three kinds of the dataset, *i.e.* Remote sensing image, medical image, and natural image. Different kind of images, *i.e.* house image, MRI (magnetic resonance image) and PAN (panchromatic) image has been taken to justify the adaptability of the proposed denoising algorithm.

Standard test images are adulterated by zero mean Additive white Gaussian noise at standard deviation σ=10, 20, 30, 40 and 50. Fig 3 and Figure 4 shows test images and noisy images respectively. The proposed algorithm has been implemented in MATLAB. The performance metric used is PSNR as well as visual quality. The proposed algorithm has been quantified at different noise intensities.

At different noise realizations, the performance of the proposed algorithm is compared with the promising denoising methods namely, *i.e.*, BM3D-SH3D, Diffusion filtering assortments: DF(A), DF(B), Visusoft and MF. The choice of filter parameter selection mainly depends on noise content in an image. However, constant parameters have been used to evaluate the results of these filters.

For a category of diffusion filters, the finite contrast parameter value α is chosen to be 0.5, and no of iterations is taken as 10 for optimality as an increase in iteration results in blurring rather than preserving image details. The radius of the median filter is taken as 4. Default parameters are taken for BM3D whereas for sharpening alpha is taken as two [30][31].

Fig 3. Input Images to evaluate denoising techniques: (a) MRI (b) House and (c) PAN

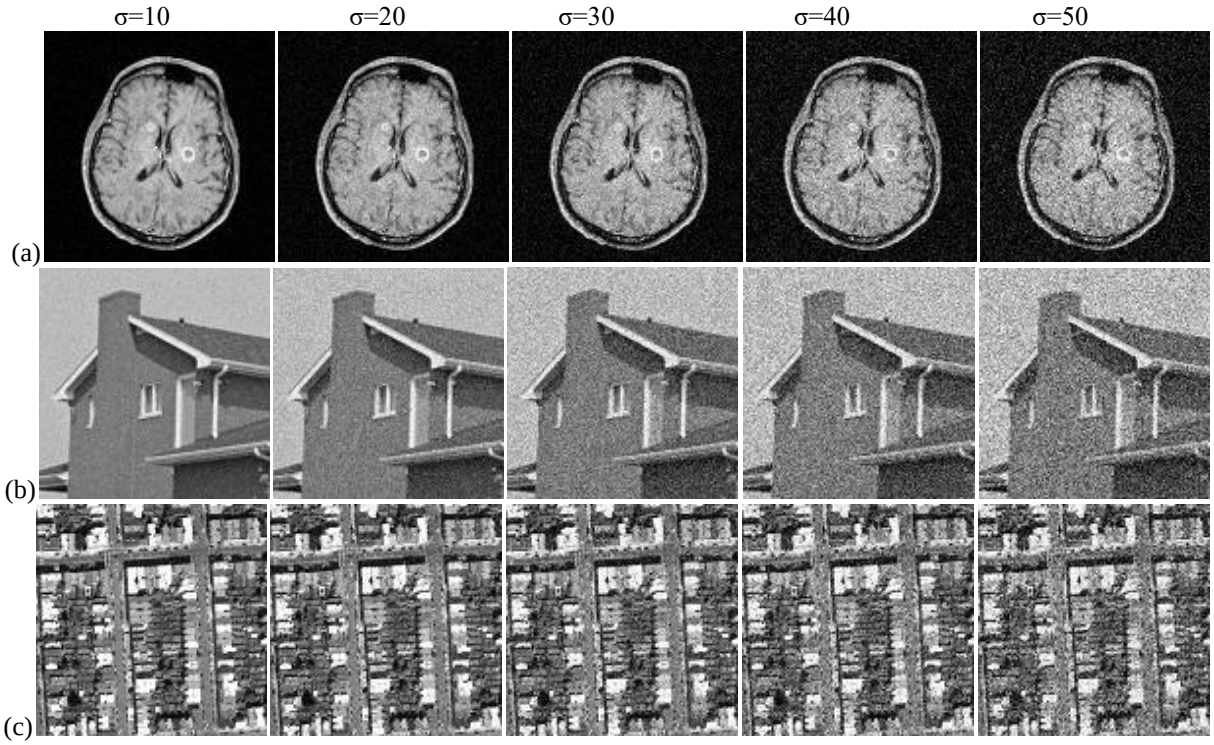

Fig 4. Image contaminated with different noise intensity: (a) MRI, (b) House, (c) PAN.

The visual results of different techniques for each input image at different noise realizations are shown in figures 5, 6, 7, 8, 9, and 10 respectively.

The aim of the proposed technique is to remove the residual noise and preserve the details of an image. Techniques that have been already implemented in the literature were not able to preserve sharp contours and feature details at high noise levels. Also, some of the residual noise is retained in the output images due to which images are not easily perceptible. With varying noise intensity, the proposed technique manifests excellent performance than the existing techniques. Although there is no direct approach to state visual quality of an image, visibility of present artefacts and preservation of edge details are two measures to be often used.

Since our method works on both residual removal as well as edge preservation separately, we expect it to be vigorous to noise. Addition to this our method stresses to preserve smooth features. It can be observed, that the visual quality of our method is competitive to all existing techniques for all type of images and our results are easily perceptible. For BM3D-SH3D some extent of noise is retained during the filtering process thus degrading visual quality. Diffusion-based filters DF(A) and DF(B) are affected by blurring. Hence the sharp features such as edges and contour are not easily perceptible. Similarly, in the case of Vi-soft due to the non-adaptive universal threshold as the noise concentration increases, high-intensity details or peaks are attenuated which cause blurring effect. The implementation of the median filter is uniform on an image due to which both the noisy pixels as well as the good undisturbed pixels are modified which results in residual noise and loss of image content [1], [38].

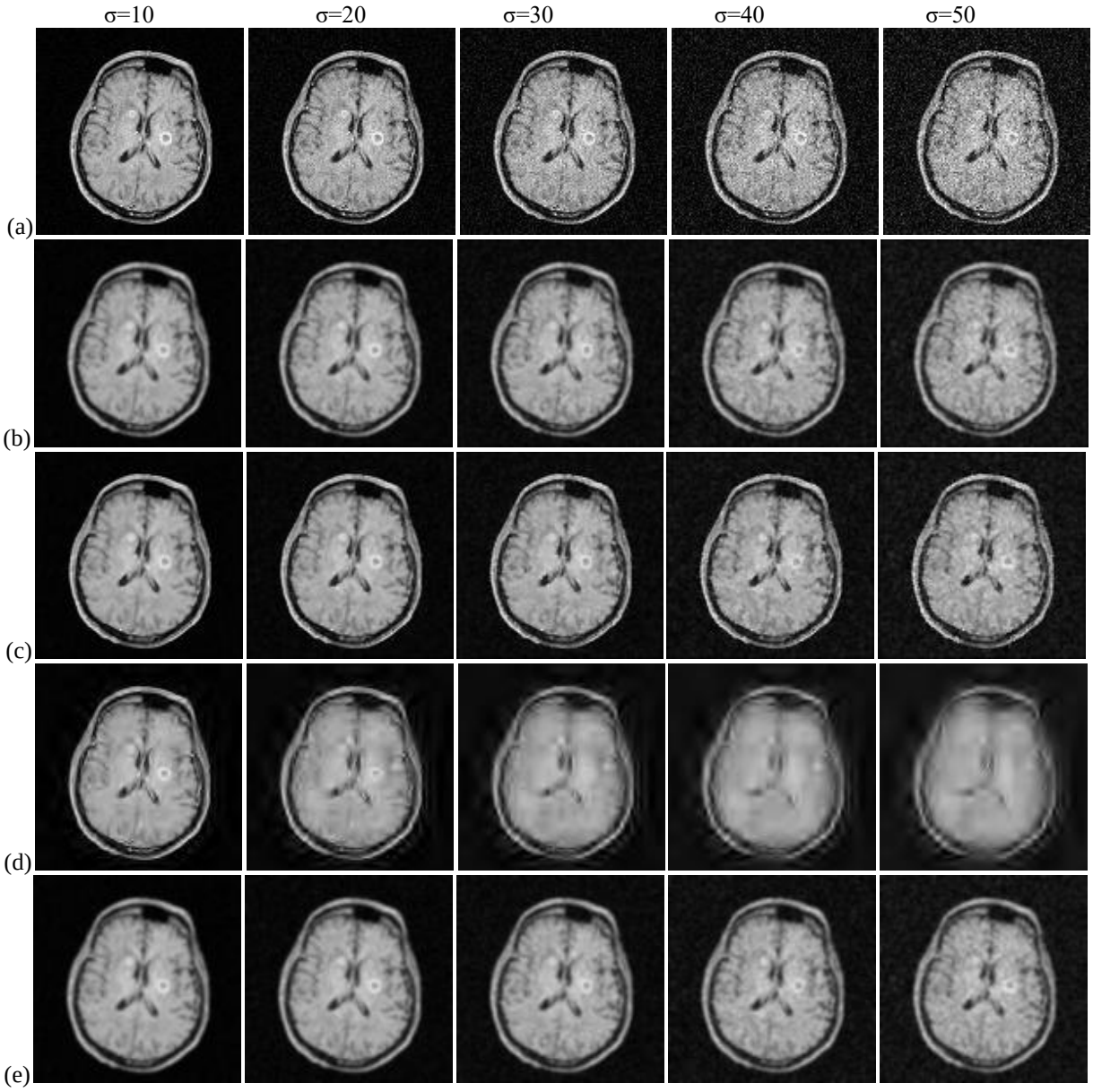

Figure 5. Denoised visual results for MRI image obtained by (a) BM3D-SH3D (b) DF(A) (c) DF(B) (d) Vi-soft (e) MF

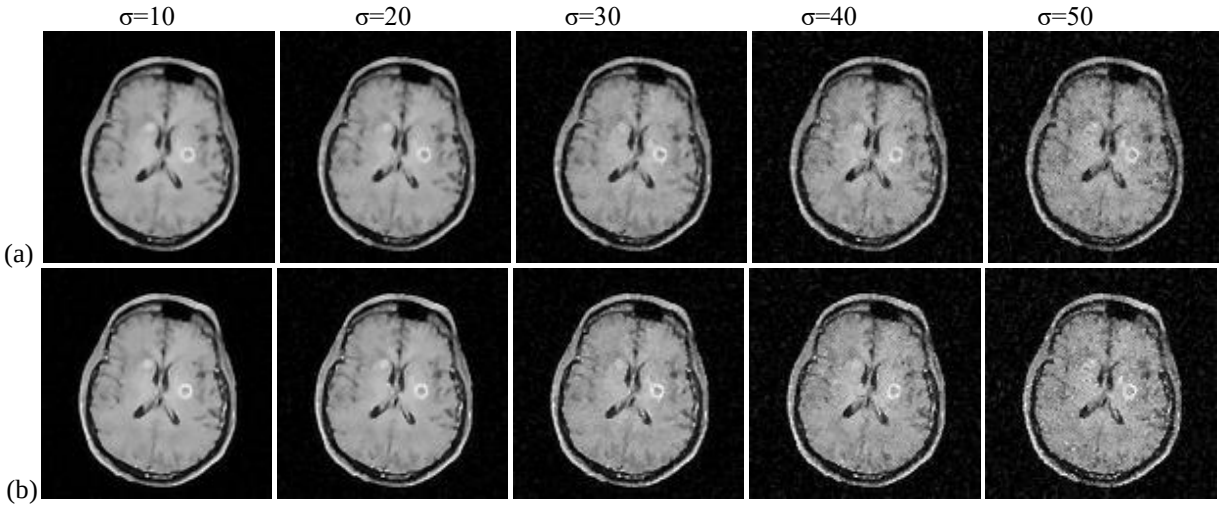

Figure 6. Denoised visual results for MRI image obtained by (a) Proposed Algorithm 1 (b) Proposed algorithm 2

Figure 7. Denoised visual results for House image obtained by (a) BM3D-SH3D (b) DF(A) (c) DF(B) (d) Vi-soft (e) MF

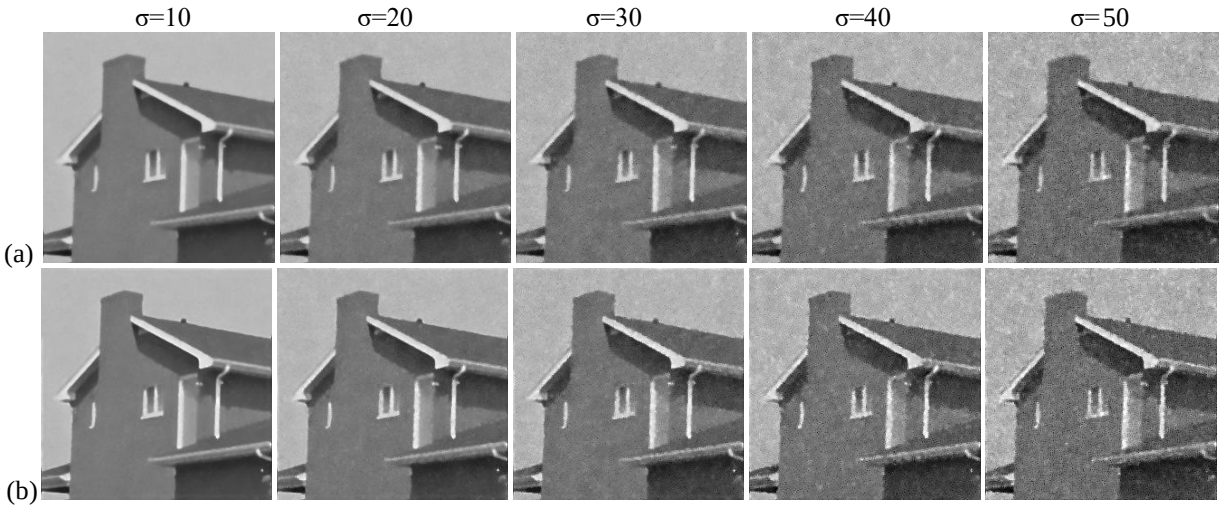

Figure 8. Denoised visual results for House image obtained by (a) Proposed Algorithm 1 (b) Proposed algorithm 2

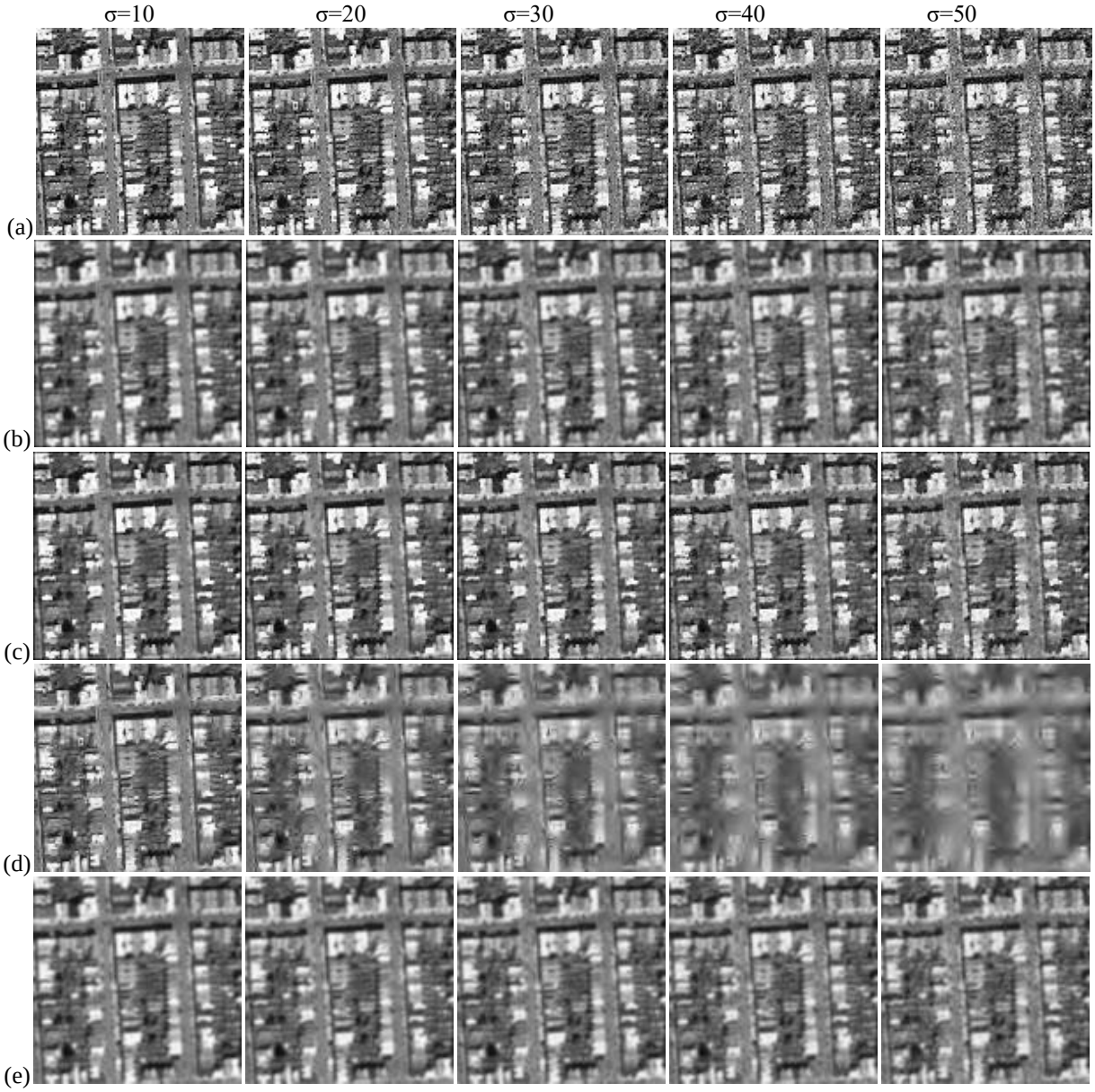

Figure 9. Denoised visual results for PAN image obtained by (a) BM3D-SH3D (b) DF(A) (c) DF(B) (d) Vi-soft (e) MF

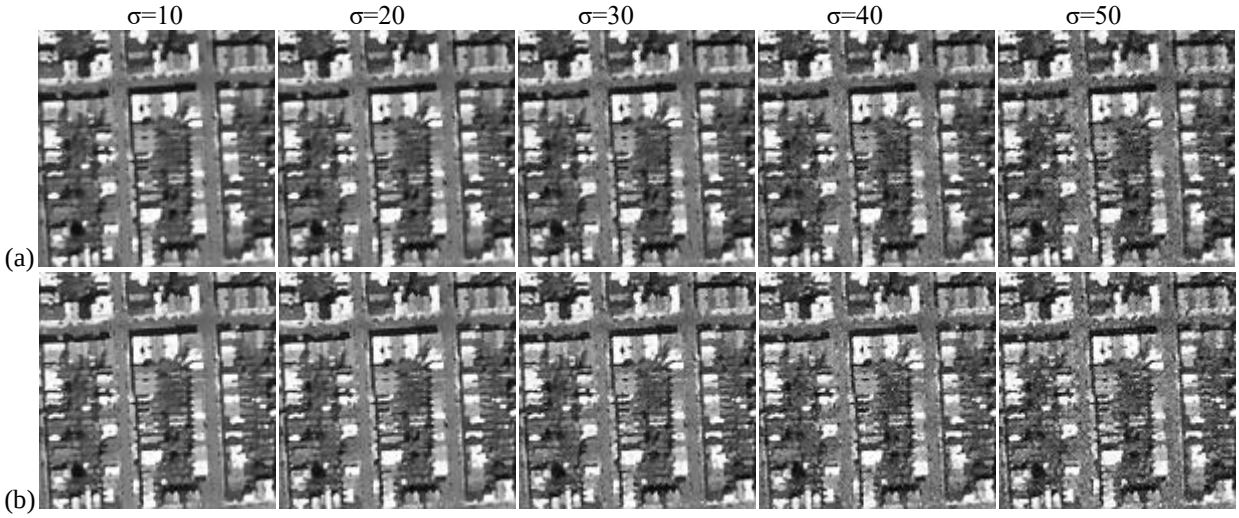

Figure 10. Denoised visual results for PAN image obtained by (a) Proposed Algorithm 1 (b) Proposed algorithm 2

In the proposed technique, the improvisation of hybridization has lead to the removal of residual noise and the preservation of image content. The preliminary filter such as robust bilateral filter failed to preserve image content and also remove all noise coefficients. Thus by subtracting the pre-filtered output from a noisy image, we obtained the residual image that contains feature details. On the other hand, by eliminating residual image from a pre-filtered output, we obtained a base image that contained edge details.

Table 1. Comparative analysis of PSNR for MRI, House, and PAN image for different denoising algorithms.

Image	Denoising algorithms	Noise levels					
		σ=10	σ=20	σ=30	σ=40	σ=50	Mean value
MRI	BM3D-SH3D	29.51	23.53	20.05	17.63	15.81	21.31
	DF(A)	25.33	24.57	23.65	22.51	21.46	23.50
	DF(B)	23.08	22.64	22.07	21.33	20.56	21.94
	Vi-soft	26.14	22.76	20.82	19.48	21.53	22.15
	MF	24.35	23.74	22.96	21.98	21.04	22.81
	Proposed Algorithm 1	27.24	26.19	24.66	23.15	21.56	24.56
	Proposed Algorithm 2	28.25	26.99	25.16	23.32	21.51	25.05
HOUSE	BM3D-SH3D	28.10	22.10	18.65	16.29	14.55	19.93
	DF(A)	24.66	24.47	24.13	23.73	23.28	24.05
	DF(B)	22.17	22.12	22.00	21.82	21.63	21.95
	vi-soft	28.05	25.23	23.67	22.45	21.64	24.21
	MF	27.80	27.48	26.93	26.39	25.70	26.86
	Proposed Algorithm 1	29.12	27.15	24.75	22.60	20.80	24.88
	Proposed Algorithm 2	29.67	27.70	25.19	22.89	21.12	25.31
PAN	BM3D-SH3D	28.31	22.40	19.01	16.67	14.93	20.26
	DF(A)	17.12	17.02	16.91	16.76	16.60	16.88
	DF(B)	15.67	15.62	15.55	15.46	15.36	15.53
	vi-soft	19.79	16.85	15.45	14.60	14.03	16.14
	MF	18.13	18.01	17.84	17.63	17.39	16.71
	Proposed Algorithm 1	16.98	16.77	16.37	15.88	15.52	16.30
	Proposed Algorithm 2	17.38	17.14	16.68	16.08	15.56	16.57

Table 2. Comparative analysis of Structure Similarity Index Metric (SSIM) values.

Image	Denoising algorithms	Noise levels				
		σ=10	σ=20	σ=30	σ=40	σ=50
MRI	BM3D-SH3D	0.522057	0.329754	0.245156	0.193875	0.158521
	DF(A)	0.519168	0.404272	0.363926	0.333712	0.317685
	DF(B)	0.570145	0.447097	0.398552	0.359572	0.335210
	vi-soft	0.527813	0.343195	0.256589	0.210314	0.185253
	MF	0.482852	0.374831	0.340089	0.315147	0.302286
	Proposed Algorithm 1	0.737996	0.584617	0.471236	0.367795	0.300628
	Proposed Algorithm 2	0.733627	0.580852	0.461200	0.353712	0.283792
HOUSE	BM3D-SH3D	0.588154	0.330094	0.218742	0.159158	0.122517
	DF(A)	0.764594	0.734193	0.688522	0.644325	0.602980
	DF(B)	0.792689	0.753037	0.694967	0.636948	0.583458
	vi-soft	0.784264	0.726379	0.690513	0.667779	0.648251
	MF	0.796534	0.773623	0.737550	0.701563	0.668150
	Proposed Algorithm 1	0.786899	0.683342	0.524674	0.390654	0.312015
	Proposed Algorithm 2	0.782703	0.680663	0.520695	0.382260	0.302220
PAN	BM3D-SH3D	0.942233	0.832461	0.720404	0.620376	0.535506
	DF(A)	0.467541	0.461399	0.452433	0.441356	0.430922
	DF(B)	0.625741	0.611849	0.592648	0.570469	0.549172
	vi-soft	0.665854	0.423147	0.288993	0.210925	0.164840
	MF	0.415287	0.410361	0.403126	0.393663	0.385369
	Proposed Algorithm 1	0.418555	0.404898	0.379674	0.354608	0.347006
	Proposed Algorithm 2	0.469826	0.453295	0.424874	0.453295	0.469826

Further, the residual image and base image are separately filtered and enhanced respectively. Now the resultant image obtained by linear combination of these images is free from residual noise and also contain feature and edge details.

The comparative analysis of PSNR and SSIM for different denoising algorithms at different noise realizations is shown in table 1 and table 2 respectively.

Since, for PAN images, PSNR values of proposed methods are comparable to existing techniques at moderate to high noise power levels. At high noise power levels, the PSNR of BM3D-SH3D and MF exceeds the proposed technique. Although BM3D-SH3D reveals high PSNR at low noise levels, its performance drastically decreases with increase in noise intensity.

On the other hand, our method can show consistent performance at different noise realizations.

VI. CONCLUSION AND FUTURE SCOPE

We have presented a hybrid approach using spatial domain filters to denoise an image while preserving image content. The performance of our proposed technique is examined by evaluating MSE and PSNR. Experiments show that the application of our method to remove residual noise and content preservation is best for denoising medical images. However, our method gives considerable results for natural image and remote sensing image. Moreover, the visualization of our method is identified by fewer artefacts and is more perceptible. We have also tried to refine our proposed algorithm in order to sharpen high-frequency edge information and improve visualization. The results of the refined algorithm show a considerable increase in PSNR.

Further, the performance of our method can be improved for images that contain more detailing by varying filter parameters or by replacing the median filter by some other suitable filter.

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