A Novel Image Denoising with Wavelet and Adaptive Filtering Integration

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Abstract - Image denoising technique is utilized to find the best estimation of the original image given by its corresponding noisy image. There are numerous image denoising methods are presents. Selection of a specific image denoising method is depends upon the requirement and noise presents in image. Among various denoising schemes, wavelet and adaptive filtering methods have drawn much attention in the image processing application. Moreover, most of the image denoising schemes deals with Gaussian noise model. Various existing spatial-domain and transform-domain image denoising filters are studied and their filtering performances are compared to choose appropriate method and develop an efficient algorithm for novel image denoising. In this work a novel image denoising approach has been proposed with wavelet and adaptive filtering integration scheme. Implementation of proposed approach has complete and on Matlab and Simulated on Simulink. To determine the performance of proposed algorithm results are compared with existing algorithm.

Keywords - Image Denoising, Adaptive Filtering, and Wavelet image denoising, PSNR, SSIM.

I. INTRODUCTION

A digital image is composed of set of pixels which is defined as a two dimensional function, where and are spatial coordinates. The value of at any particular pair of coordinates is called the gray level or intensity of the image at that location. The image becomes a digital image when and the values of are all finite, discrete quantities. These values of are generally referred to as pixels. Pixel values in images can be noisy. Noise in images is mainly caused by sensors during acquisition, environments (e.g. poor illumination) or during transmissions. No matter how good the image acquisition devices are, an image improvement is always sought-after to improve their range of applications in various fields. The process of estimating the original image by reducing the noises from noise-contaminated image is referred to as image denoising in image processing. Image denoising is a very important task in image processing as a process itself or as an element of other image processing tasks.

Image denoising is a well-studied field and yet it's still one of the most active research areas in image processing and computer vision. It's a pre-requisite for many image processing tasks such as image segmentation, image restoration, object recognition, image classification, and image registration, where estimating the true signal is crucial to accomplish desirable results.

The form of the noise can be additive, which is generally independent of image data, or multiplicative, which is dependent on image data.

The formula for additive noise is

$$Z(x) = y(x) + \eta(x), \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1.1)$$

whereas the formula for multiplicative noise is

$$Z(x) = y(x) \times \eta\ (x) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . (1.2)$$

Here, x represents the location of pixels, $y(x)$ is the original signal, while $\eta\ (x)$ denotes the noise introduced to form the corrupted image Z(x).

Most of the images are assumed to be contaminated by additive random noise and can be modeled by a Gaussian distribution. Hence, this type of noise is referred to as Additive White Gaussian Noise (AWGN). AWGN is also probably the simplest and most commonly used model in the image denoising literature. As AWGN is random in nature and it corrupts almost all areas of images, it is challenging to remove AWGN from images. It becomes increasingly difficult to preserve the small details of an image as the error level increases.

This work presents a few improvements over the previous method for reducing the effect of noises. Noise models are of particular importance in image denoising as most denoising methods work well with a particular noise model. Probabilistic models best reflect the randomness of the noise within images. In image denoising applications, parametric models (with few parameters) of the probability density function (PDF) are most commonly used.

II. SYSTEM MODEL

a. Wavelet

Wavelet domain filters essentially employs Wavelet Transform (WT) and hence are named so. Fig. 3.4 shows the block schematic of a wavelet-domain filter. Here, the filtering operation is performed in the wavelet-domain. A brief introduction to wavelet transform is presented here.

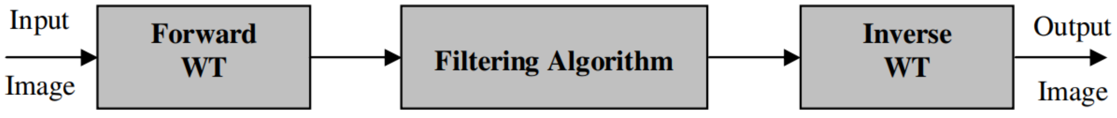


Figure 2.1 a wavelet domain filter.

Wavelet transform , due to its localization property, has become an indispensable signal and image processing tool for a variety of applications, including compression and denoising. A wavelet is a mathematical function used to decompose a given function or continuous-time signal into different frequency components and study each component with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies (known as daughter wavelets) of a finite length or fast decaying oscillating waveform (known as mother wavelet). Wavelet transforms are classified into continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

The continuous wavelet transform (CWT) has received significant attention for its ability to perform a time-scale analysis of signals. On the other hand, the discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of wavelet scales and translations obeying some definite rules. In other words, this transform decomposes the signals into mutually orthogonal set of wavelets. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets.

b. Adaptive Filtering

An adaptive filter does a better job of denoising images compared to the averaging filter. The fundamental difference between the mean filter and the adaptive filter lies in the fact that the weight matrix varies after each iteration in the adaptive filter while it remains constant throughout the iterations in the mean filter. Adaptive filters are capable of denoising non-stationary images, that is, images that have abrupt changes in intensity. Such filters are known for their ability in automatically tracking an unknown circumstance or when a signal is variable with little a priori knowledge about the signal to be processed. In general, an adaptive filter iteratively adjusts its parameters during scanning the image to match the image generating mechanism. This mechanism is more significant in practical images, which tend to be non-stationary.

Compared to other adaptive filters, the Least Mean Square (LMS) adaptive filter is known for its simplicity in computation and implementation. The basic model is a linear combination of a stationary low-pass image and a non-stationary high-pass component through a weighting function [Li93]. Thus, the function provides a compromise between resolution of genuine features and suppression of noise.

A median filter belongs to the class of nonlinear filters unlike the mean filter. The median filter also follows the moving window principle similar to the mean filter. A 3 x 3, 5 x 5, or 7 x 7 kernel of pixels is scanned over pixel matrix of the entire image. The median of the pixel values in the window is computed, and the center pixel of the window is replaced with the computed median. Median filtering is done by, first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

III. PROPOSED METHODOLOGY

A novels algorithm for image denoising has been proposed in this work. The Implementation and simulation of proposed work has done on Matlab Simulink. Wavelets are mathematical functions that analyze data according to scale or resolution. They aid in studying a signal in different windows or at different resolutions. For instance, if the signal is viewed in a large window, gross features can be noticed, but if viewed in a small window, only small features can be noticed. From the properties of wavelet and behavior, it plays a major role in image compression and image denoising. Wavelet coefficients calculated by a wavelet transform represent change in the time series at a particular resolution. By considering the time series at various resolutions, it is then possible to filter out noise. The process flow of proposed algorithm has given in Figure 3.2. The steps involved in the synthesis of proposed work have given as follows.

Step 1: Start
Initialize Matlab simulation environment.
Step 2: Select Input Image
Select input test image to be denoised using propsed algorithm.
Step 3: Load Selected Input Image
Load selected input test image in Matlab Simulation environment.
Step 4: Extract File Name from Path
Extract image file name from the path
Step 5: Add Noise
Add different level of noise in test image for experiment purpose.
Step 6: Apply Condition

If i=10:20:90 then process to next step else process to step no 8.
Step 7: Denoise with HAAR wavelet Filter
Denoise image with HAAR wavelet filter using following steps.

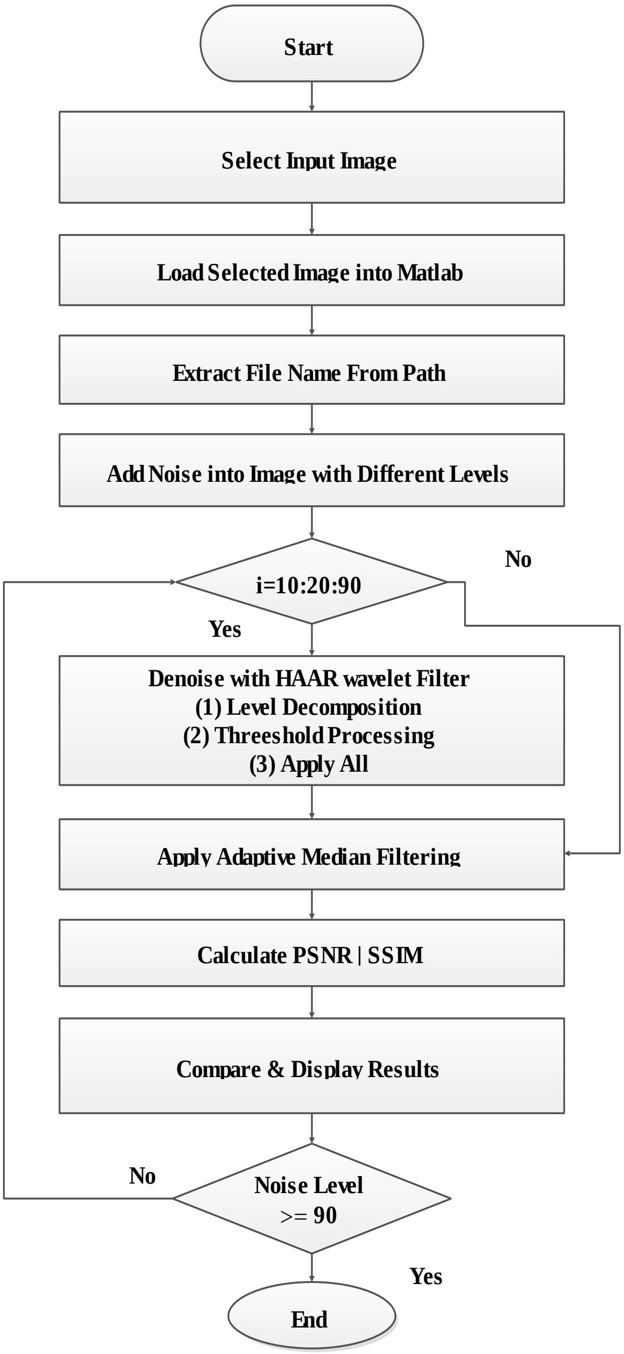


Figure 3.1 Process Flow of proposed work.

(1) Level decomposition

(2) Threeshold Processing

(3) Apply All

Step 8: Apply Adaptive Median Filtering
Apply adaptive median filtering to denoised image.
Step 9: calculate PSNR and SSIM
Calculate values of peak signal to noise ratio and The Structural SIMilarity (SSIM) index.
Step 10: Compare and Display Results
Compare obtained results with existing results based on PSNR and SSIM values from base work. and display it.
Step 11: Check Condition
If noise level of filtered image is more than 90, forward it to previous condition step no 6 and if noise level is less than 90 end process.
Step 12 End Process.

IV. SIMULATION RESULTS

The simulation of proposed work has completed on Matalb Simulink simulation environment for image processing. It is important to be able to somehow quantify and measure the effectiveness of the filters. This is especially important when trying to determine optimal parameters for each filter and each sequence. There are of course many ways to do this. The number of options available is also different depending on whether a clean reference sequence is available or not. If no reference sequence is available then one usually resorts to measuring subjectively, i.e. one simply looks at the images and decides if the result is good or not.

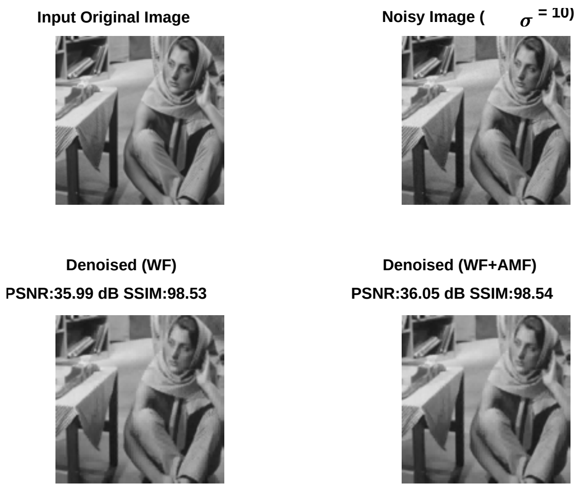


Fig. 4.1 Result with Wavelet and Wavelet + AMF of PSNR and SSIM for Barbara image on σ = 10.

The problem of finding good quality metrics is very difficult, and a research field in its own right. There exist many error measures. Two very common are mean square error (MSE) and peak signal to noise ratio (PSNR). These are popular because of their simplicity of implementation. Another common quality metric is structural similarity index (SSIM), which also takes structural similarities into consideration. a greyscale Barbara image has taken for experiment and result analysis . Effectiveness of proposed algorithm for different noise level has given in Figure 4.1 to Figure 4.5 and comparison of proposed work with existing work has given in Table 1.

Figure 4.2 Result with Wavelet and Wavelet + AMF of PSNR and SSIM for Barbara image on σ = 30

Figure 4.3 Result with Wavelet and Wavelet + AMF of PSNR and SSIM for Barbara image on σ = 50

Figure 4.4 Result with Wavelet and Wavelet + AMF of PSNR and SSIM for Barbara image on σ = 70

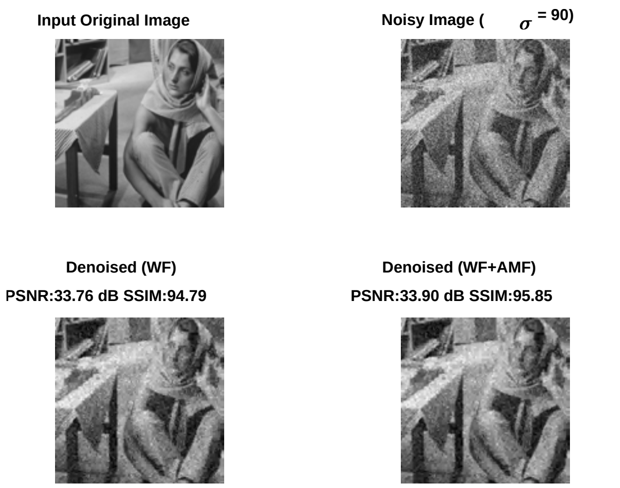


Figure 4.5 Result with Wavelet and Wavelet + AMF of PSNR and SSIM for Barbara image on σ = 90.

Table 1: Performance Comparison of PSNR and SSIM for Noise Standard Deviation σ = 30

Images	***Peak Signal to Noise Ratio (PSNR) in dB***		***Structural Similarity Index (SSIM)***	
	Previous NLM-SVB	***Proposed Hybrid (WF+ AMF)***	***Previous NLM-SVB***	***Proposed Hybrid(WF+ AMF)***
Cameraman	27.70	37.95	82.48	96.74
House	30.53	38.58	81.54	99.55
Barbara	27.94	35.58	81.35	98.31
Couple	27.29	36.00	73.85	97.95
Man	28.1	36.47	75.85	98.94
Boat	27.94	36.33	76.19	98.71

A brief result analysis based on graphical representation has given in Figure 4.6 Performance Comparison with Previous Method for PSNR with Noise Standard Deviation σ = 30. Performance Comparison with Previous Method for SSIM with Noise Standard Deviation σ = 30 has given in figure 4.7.

PSNR and SSIM Values for Different Test Images on Noise Standard Deviation σ = 10, 30, 50, 70 and 90 has given in Table 2. In Figure 4.8 PSNR and SSIM Values for

Different Test Images on Noise Standard Deviation σ = 10, 30, 50, 70 and 90 has given and In Figure 4.9 Figure 4.9 (a) PSNR and (b) SSIM Comparison of Man image for Noise standard deviation σ = 10, 30, 50, 70 and 90 has given. Comparison of PSNR and SSIM with HAAR, COIFLET and SYMLET wavelet filters has given in Table 3.

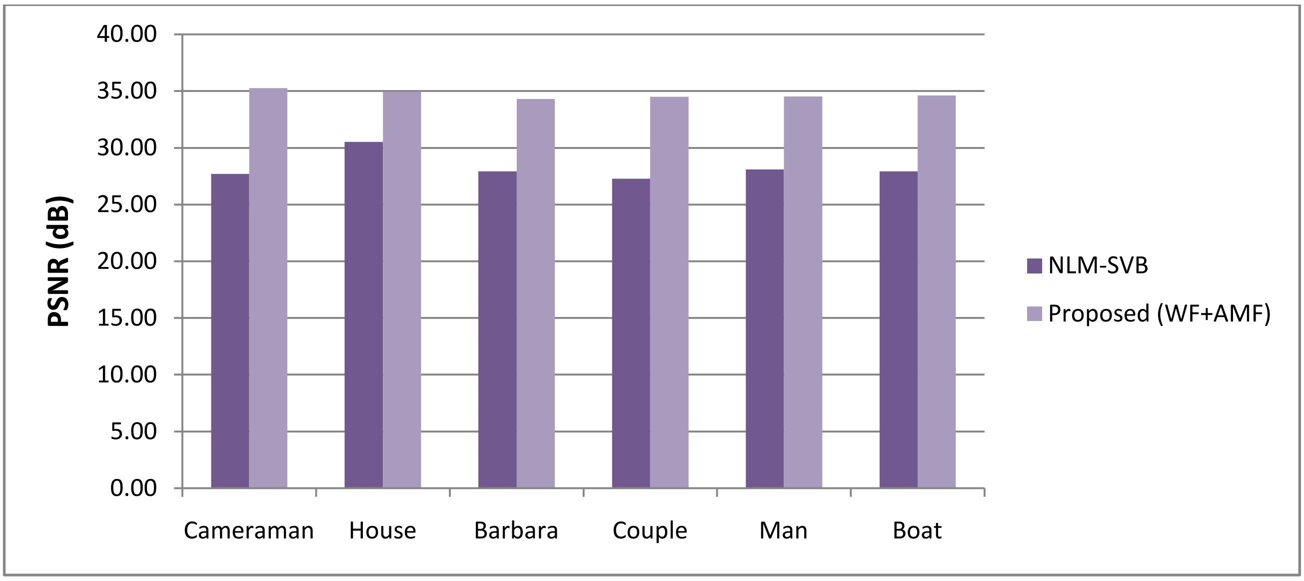
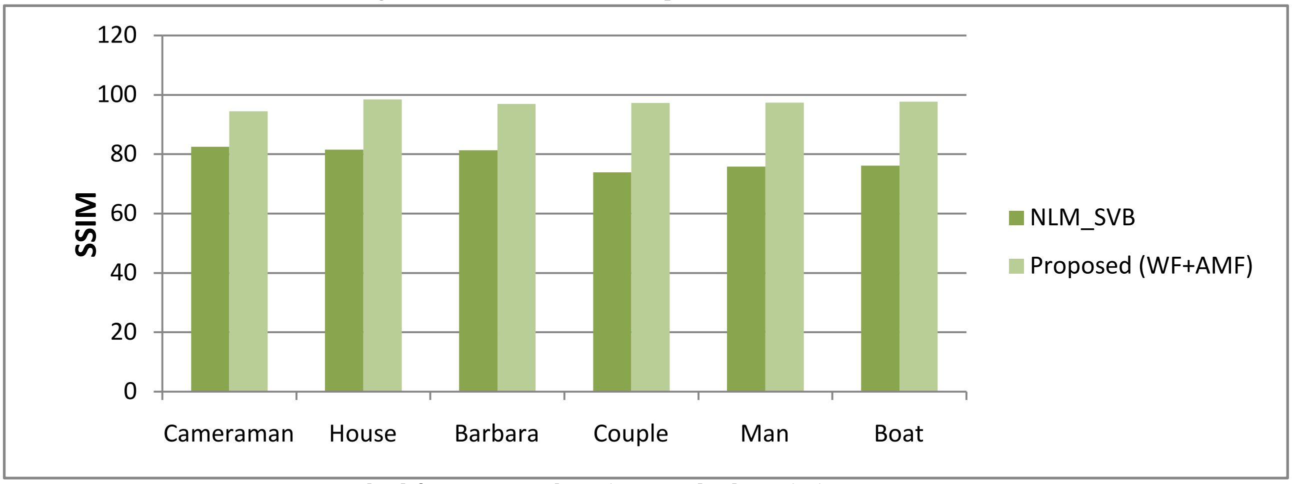


Figure 4.6 Performance Comparison with Previous Method for PSNR with Noise Standard Deviation σ = 30.

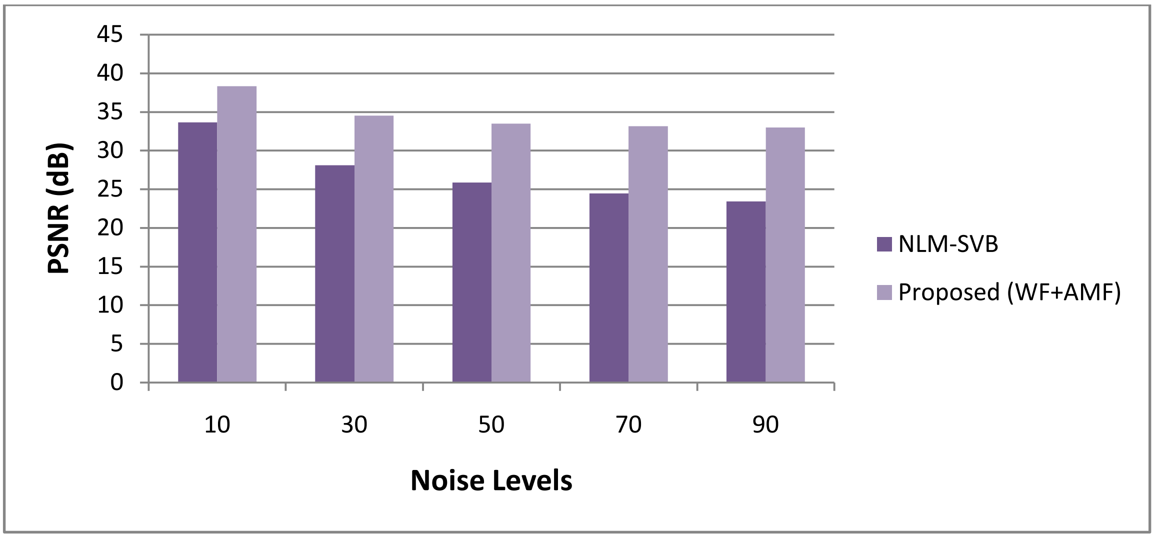
Figure 4.7 Performance Comparison with Previous Me



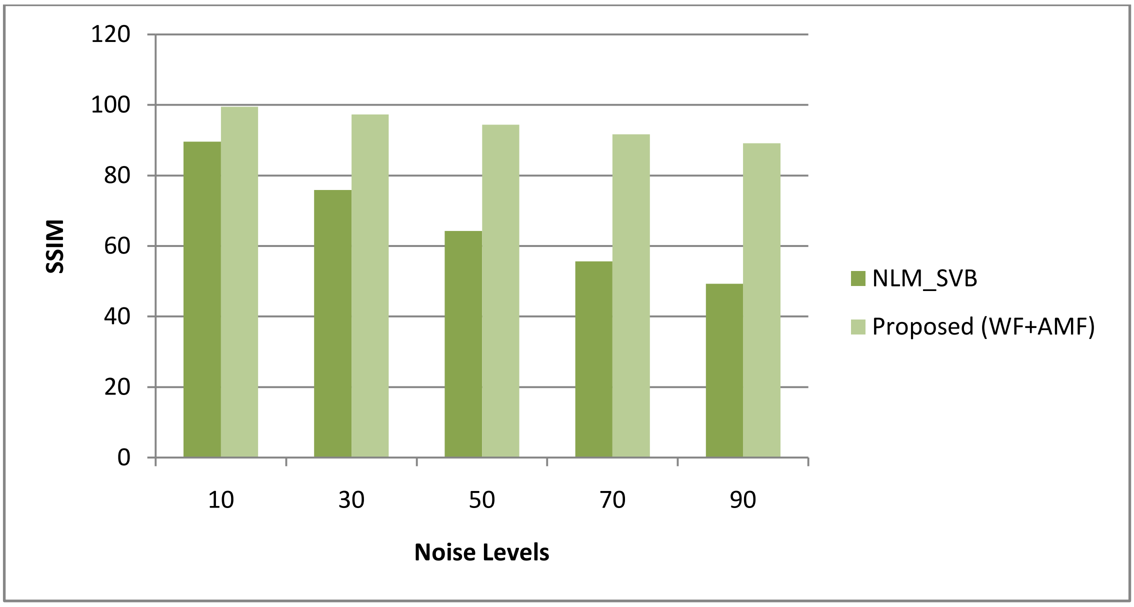
thod for SSIM with Noise Standard Deviation σ = 30.

Table 2: PSNR and SSIM Values for Different Test Images on Noise Standard Deviation σ = 10, 30, 50, 70 and 90

σ	**Barbara**		**Boat**		**Cameraman**		**Couple**		**House**	
	PSNR	***SSIM***	***PSNR***	***SSIM***	***PSNR***	***SSIM***	***PSNR***	***SSIM***	***PSNR***	***SSIM***
10	36.03	98.55	36.96	99.01	39.33	98.44	36.54	98.23	40.91	99.75
30	35.58	98.31	36.33	98.71	37.95	96.74	36	97.95	38.58	99.55
50	34.94	97.71	35.41	98.13	36.35	94.62	35.1	97.41	36.54	99.13
70	34.36	96.88	34.66	97.37	35.43	92.18	34.44	96.72	35.27	98.57
90	33.83	95.66	34.11	96.34	34.81	91.18	33.95	95.95	34.44	97.89

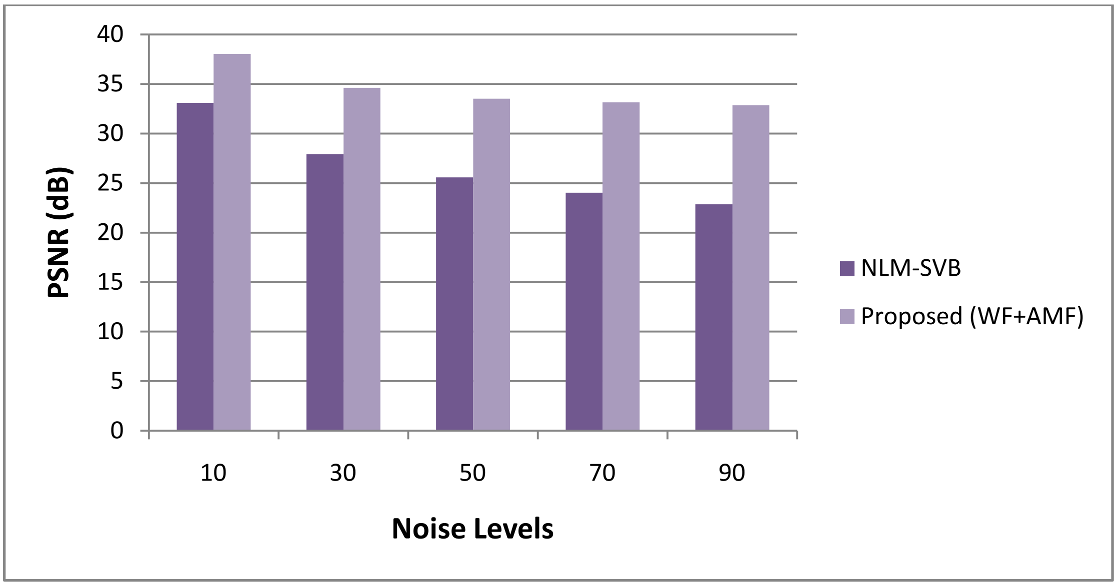


(a)

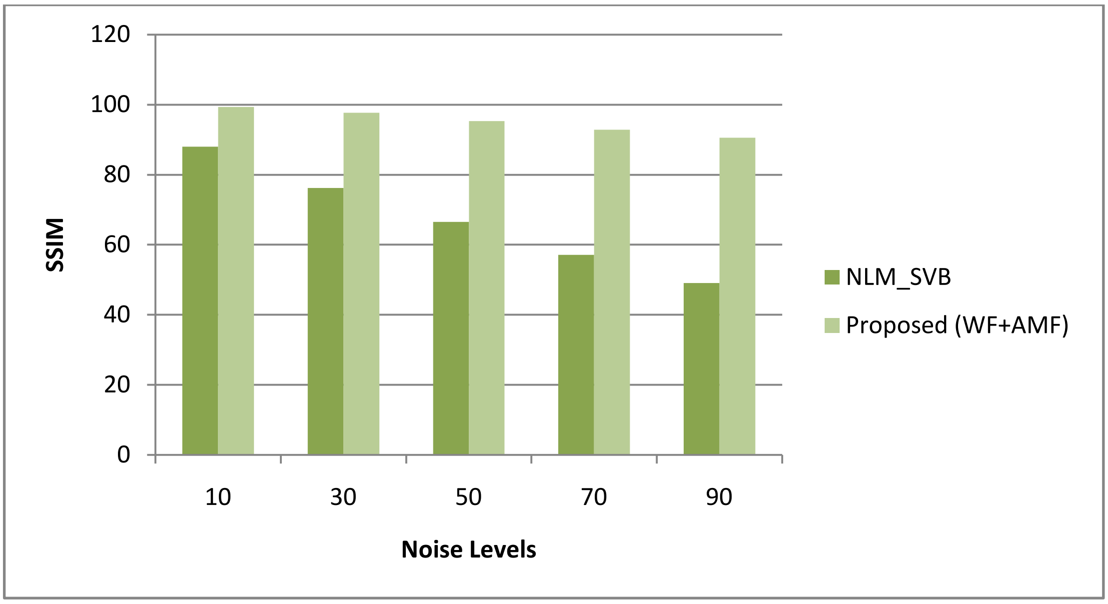


(b)

Figure 4.8. (a) PSNR and (b) SSIM Comparison of Man image for Noise standard deviation σ = 10, 30, 50, 70 and 90 .



(a)



(b)

Figure 4.9 (a) PSNR and (b) SSIM Comparison of Man image for Noise standard deviation σ = 10, 30, 50, 70 and 90 .

Table 3: Comparison of PSNR and SSIM with haar, coiflet and symlet wavelet filters

Noise Standard Deviation (σ)	*PSNR*			*SSIM*		
	Haar	*Coiflet*	*Symlet*	*Haar*	*Coiflet*	*Symlet*
barbara						
10	36.03	36.45	36.46	98.55	98.74	98.77
30	35.58	35.87	35.91	98.31	98.47	98.48
50	34.94	35.17	35.05	97.71	97.89	97.79
70	34.36	34.52	34.36	96.88	97.02	96.76
90	33.83	33.99	33.86	95.66	95.89	95.68
boat						
10	36.96	37.23	37.25	99.01	99.13	99.14
30	36.33	36.58	36.57	98.71	98.82	98.81
50	35.41	35.57	35.42	98.13	98.26	98.11
70	34.66	34.82	34.66	97.37	97.48	97.17
90	34.11	34.18	34.02	96.34	96.47	96.15
cameraman						
10	39.33	39.84	39.79	98.44	98.41	98.16
30	37.95	38.35	38.16	96.74	97.03	96.58
50	36.35	36.65	36.36	94.62	95.05	94.38
70	35.43	35.63	35.39	92.18	93.09	92.46
90	34.81	35.01	34.63	91.18	91.7	90.61
couple						
10	36.54	36.74	36.76	98.23	98.35	98.37
30	36	36.17	36.05	97.95	98.09	98.02
50	35.1	35.28	35.12	97.41	97.53	97.49
70	34.44	34.6	34.45	96.72	96.95	96.63
90	33.95	34.06	34.01	95.95	96.21	95.79
house						
10	40.91	42.55	42.82	99.75	99.83	99.85

30	38.58	39.09	38.78	99.55	99.62	99.6
50	36.54	36.88	36.48	99.13	99.24	99.16
70	35.27	35.51	35.18	98.57	98.69	98.52
90	34.44	34.67	34.41	97.89	97.99	97.78
man						
10	37.12	37.45	37.49	99.17	99.28	99.29
30	36.47	36.71	36.56	98.94	99.03	99.01
50	35.44	35.59	35.46	98.38	98.44	98.38
70	34.73	34.82	34.64	97.61	97.67	97.43
90	34.13	34.22	34.16	96.43	96.66	96.25

V. CONCLUSION AND FUTURE SCOPES

A novel image denoising algorithm has been implemented in this work based on a novel image denoising with wavelet and adaptive filtering integration approach. From the experimental and mathematical results it can be concluded that for adaptive Gaussian noise, the proposed algorithm is optimal compared to existing algorithm for a greyscale image. The proposed algorithm produces optimal SNR for the output image compared to the existing work for same image. The wavelet and adaptive filtering integration proves to be better than the existing. When the noise characteristics of the image are unknown, denoising by wavelet and adaptive filtering integration analysis has proved to be the best method. It does a good job in denoising images that are highly irregular and are corrupted with noise that has a complex nature. In future the proposed work can be implemented for color image for more complex noises.

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