A New Hybridization of Bilateral and Wavelet Filters for Noisy De-Noisy Images

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Abstract: In this work we propose, a hybrid noise reduction algorithm that is a combination of a spatial field binary filter and a hybrid wave field threshold function. These two methods are used to stop Gaussian noise. The hybrid filter is a nonlinear filter that deals with spatial averaging of non-uniform edges. We found it to be an effective technique for image reduction. Determining filter parameters for the mixed filter is important to avoid large differences in results, besides the issue of acceleration velocity. This hybrid model, binary filtering, and Wavelet Thresholding have tried standard images, such as normal eyes, MRI, Roya Face, Ultrasound, X-Ray, and Rawa. Different Gaussian noise was added with different standard deviations σ = 10, 20, 35, 40, and 50. The peak-to-noise ratio (PSNR) signal, MSE, VIF, IQI, and the proposed model MSE between pixels were used as quantitative measures of performance of the relative noise reduction algorithms and then were compared to the models.

Keywords: Image Denoising, Wavelet Transform, Wavelet Thresholding, Bilateral Filter

1. Introduction

Computer image processing methods mainly take two categories. First, the space domain processing; that is in the image space of the image processing. The other is the image spatial domain. The frequency domain is used through the orthogonal transformation in various frequency domains. The other way of image processing in the frequency domain. (Such as: Fourier transform, wavelet transform.) It is also based on the actual characteristics of the image, noise and spectral distribution of the demographic characteristics of the law.

Many image filters have been developed to suppress the noise, such as low pass, Wavelet transforms, median filters, etc. (Chambolle, 1998). A fundamentally important property for any filter to possess, but often lacking, is the ability to maximally suppress noise solely without affecting much of the true signal. The bilateral filter is designed to achieve this goal by striking a fine balance between minimizing noise and losing signal. The bilateral filter is a relatively new filter proposed originally to denoise 2D photographic images and has been shown to be very effective in achieving this goal.

Now-a-days an image is synonymous to digital image and is very much essential for daily life applications such as satellite television, medical imaging (magnetic resonance imaging, ultrasound imaging, x-ray imaging), and computed tomography. It is also essential for the researches in the areas of science and technology such as geographical information systems and astronomy.

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The images collected by different type of sensors are generally contaminated by different types of noises (Donoho D. a., 1994). Digital images may be contaminated by different sources of noise. Noise may be generated due to imperfect instruments used in image processing, problems with the data acquisition process, and interference, all of which can degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression also. Different types of noises are introduced by different noise sources (Chang, 1998).

Noise is also channel dependent. Typically, green channel is the least noisy while blue channel is the noisiest channel. That means noise is in general not white. Noise in a digital image has low as well as high frequency components. Though the high-frequency components can easily be removed, it is challenging to eliminate low frequency noise as it is difficult to distinguish between real signal and low-frequency noise. Most of the natural images are assumed to have additive random noise, which is modelled as Gaussian type. Speckle noise is observed in ultrasound images, whereas Rician noise affects MRI images. Thus, denoising is often a necessary and the first step to be considered before the image data is analyzed. It is necessary to apply an efficient denoising technique to compensate for any data corruption. The goal of denoising is to remove the noise while preserving the important image information as much as possible. Linear filtering techniques, such as Wiener filter or match filter, have been used for this purpose for many years. But linear filters may result in some problems, such as blurring the sharp edges, destroying lines and other finer image details. They generally fail to effectively remove heavy tailed noise. Due to these facts, an alternative filtering technique like nonlinear filtering is necessary. Many works (Fan, 2001), (Guo, 1994), ((Hu, 2014), et al. 2014), (Perona, 1990) have been reported on image denoising using nonlinear filters. (Donoho, 1995)

Thresholding algorithm in an orthogonal transform domain, such as subband or wavelet transform, is a nonlinear filter. Subband transform with orthogonal perfect reconstruction filter-banks is an orthogonal transform. It is known that the sub-band filters act as a set of discrete time-based functions in a vector space and the decomposition of signal is just to project the signal onto these base functions. As for a signal with noise, there are some differences between the coefficients of original signal and noise because of their different features (Mallat, 1989), (Misiti, 2007), (Misiti, Wavelets and their Applications, 2013). In general, if an orthogonal transform with high-energy compaction and de-correlation properties is used, most of the energy of the original signal will be compacted into a few high magnitude coefficients. If the image data is corrupted by additive white noise, components that correspond to noise will be distributed among low magnitude high frequency components. Most of the coefficients of noise are of smaller amplitudes. So, it is reasonable to eliminate the noise by comparing all the coefficients with a threshold and cutting off those coefficients with smaller values than the thresholds (Kachouie, 2009), (Liu, 2001), (Motwani, 2004), (Nasersharif, 2004).

In recent years, lots of works have been reported on the use of wavelet transform not only in image processing but also in various fields of signal processing. It has the advantage of using variable size time-windows for different frequency bands. This results in a high frequency resolution in low bands and low frequency resolution in high bands. Consequently, wavelet transform is a powerful tool for modeling non-stationary signals that exhibit slow temporal variations in low frequency and abrupt temporal changes in high frequency (Nowak, 1999).

In image processing system, the acquisition techniques and systems introduce various types of noises and artifacts in the digital image that leads to poor quality image. For example, Magnetic Resonance Imaging (MRI) is the most common tool for diagnosis in medical field and it is often affected by various types of noises during image acquisition process. Besides the noisy image produces undesirable visual quality, it also lowers the visibility of low contrast objects. Hence noise removal is essential in medical imaging applications in order to enhance and recover fine details which are hidden in the data. In many occasions, noise in digital images is found to be additive in nature with uniform power in the whole bandwidth and with Gaussian probability distribution. Such a noise is referred to as Additive White Gaussian Noise (AWGN). It is difficult to suppress AWGN since it corrupts almost all pixels in an image (Kahwachi, 2005).

Many denoising methods have been proposed over the years, such as the Wiener filter, wavelet thresholding (Donoho D. J.-3., 1995), anisotropic filtering, bilateral filtering (Bao, 2003), total variation method (Chang S. Y., 2000), and non-local methods. Among these methods, wavelet thresholding has been reported to be a highly successful method. In wavelet thresholding, a signal is decomposed into approximation (low-frequency) and detail (high-frequency) subbands, and the coefficients in the detail subbands are processed via hard or soft thresholding, (Buades, 2006), (Roy, 2010), (Blbas, 2021). The hard thresholding eliminates (sets to zero) coefficients that are smaller than a threshold while the soft thresholding shrinks the coefficients that are larger than the threshold also. The main task of the wavelet thresholding is selection of the threshold and the effect of denoising depends on the selected threshold: a bigger threshold will throw off the useful information and the noise components at the same time while a smaller threshold cannot eliminate the noise effectively. (Donoho D., 1995) gave a general estimation method of threshold, but the best threshold cannot be found by this method. (Chang S. Y., 2000) have used predictive models to estimate the threshold. It is a spatially adaptive threshold based on context modeling. They also presented data-driven threshold for image denoising in a Bayesian framework (Rudin, 1992).

A wavelet based multiscale products thresholding method which fusing both dyadic wavelets transform and adaptive multiscale product thresholding is proposed. In the multiscale products, edges can be effectively distinguished from noise. Another spatial domain method known as Bilateral Filter (BF) is proposed in. It helps in edge preservation and smoothing. Bilateral filtering smooths images while preserving edges with the nonlinear combination of nearby pixel values. In Multiresolution Bilateral Filtering (Al-Talib, 2019) for Image Denoising, the bilateral filter is combined with wavelet thresholding to provide an image denoising framework, which helps in removing noise in real noisy images. In the hybrid model (Tomasi, 1998) it clearly shows the use of bilateral filters in combination with wavelet thresholding filters on subbands of a decomposed image deteriorates the performance. Additionally, Wavelet Transform decorrelates signals in a well manner, strong intrascale and interscale dependencies between wavelet coefficients exist. The performance of denoising would be significantly improved if such dependencies could be efficiently modeled and exploited. (Donoho D., 1995) classified the wavelet statistical models into intrascale, interscale and hybrid ones (Donoho D. J.-3., 1995).

The bilateral filter was proposed in (Wang, 2002), (Zhang, 2008), (Zhang M. a., Multiresolution bilateral filtering for image denoising, 2008) as an alternative to wavelet thresholding. It applies spatially weighted averaging without smoothing edges. This is achieved by combining two Gaussian filters; one filter works in spatial domain, the other in the intensity domain. Therefore, not only the spatial distance but also the intensity distance is important for the determination of weights. Hence, these types of filters can remove the noise in an image while retaining its edges. However, the filter may not be very efficient in removing any noise in the texture part of the image. It is not being able to remove salt and pepper type of noise. Also, there is no theoretical works on optimization of the parameters of the filters (Egiazarian, et al. 1999), (Omer, 2020).

2. The Main Objectives of the Work Are:

1. To develop a hybrid filter through the hybridization of wavelet thresholding and bilateral filters and to tune the different parameters of the filter to optimize the performance of the filter for denoising different types of images.
2. To tune the parameters of both the wavelet-based filter and bilateral filters to optimize their performance for filtering the same types of images as in step (i).
3. To compare the performance of the filters developed in step (i) with those in step (ii) in denoising different types of images.

Image is an important source of information. People can know the intension of information through the image processing technology. Digital image noise removal involves computer science, mathematical analysis, optical systems, micro-electronics technology, and other fields. That is a very complex edge science. It is already a comprehensive theoretical system. Its practice is widely used in medicine, military, art, agricultural field. The aim of image enhancement was to improve visual image. For the given image application, people can emphasize the overall image or local characteristics. And then make the original image become clear or emphasize certain traits of interest. In this way, it is possible to improve the image quality and rich amount of information. (Saeed, 2017).

3. Wavelet Filter

Image denoising algorithm consists of few steps; consider an input signal X(t)and noisy signal n(t). Add these components to get noisy data y(t) i.e.

$$y(t) = x(t) + n(t) \quad [1]$$

Here the noise can be Gaussian, Poisson's, speckle and Salt and pepper, then apply wavelet transform to get w(t).

$$y(t) \xrightarrow{Wavelet\,Transform} w(t) \quad [2]$$

Modify the wavelet coefficient w(t) using different threshold algorithm and take inverse wavelet transform to get denoising image x^(t).

$$w(t) \xrightarrow{Inverse\,Wavelet\,Transform} \hat{X}(t) \quad [3]$$

The system is expressed in Figure (1).

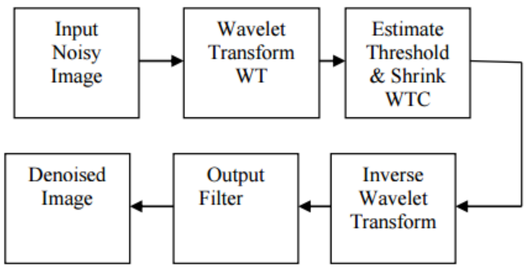

Figure 1: Block diagram of image denoising using wavelet transform

Image quality was expressed using signal to noise ratio of denoised image (Daubechies, 1990).

3.1 Wavelet Decomposition

A wavelet is simply a small wave, which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary or time varying phenomena. Generally, in signal processing, the way of representing a signal should be such that the task of extracting certain properties of the signal is important for specific application, like denoising. Also, the building blocks required for processing and representing a signal with a given accuracy, are as few as possible for faster computation. Another important aspect in signal processing especially, image processing, are the detail features, which are dependent on different scales of resolution. Multi-resolution representation as in wavelet decomposition enables one to analyze different details at different resolution scales (Blbas, 2021).

The wavelet decomposition process involves three basic steps as follows:

a linear forward wavelet transforms

nonlinear thresholding step and

a linear inverse wavelet transforms

3.2 Wavelet Representation of Image

Let $f = \{f_{ij}, i, j = 1,2, \ldots M\}$ denote the M × M matrix of the original image and M is some integer power of 2. During transmission the image f is corrupted by white Gaussian noise with independent and identically distributed (i.i.d) zero mean, and standard deviation σ i.e. $n_{ij} \sim N(0, \sigma^2)$. So, the noisy image received at the receiver end is $g_{ij} = f_{ij} + \sigma n_{ij}$. The goal is to estimate the signal f from noisy observations g_{ij} such that Mean Squared Error (MSE) is minimum and Peak Signal to Noise Ratio (PSNR) is maximum as well as image quality index (IQI) is also maximum within its range [0,1]. Let W and W–1 denote the two-dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then Y = W.g represents the matrix of wavelet coefficients of g having four subbands (LL, LH, HL and HH). The sub-bands HHk, HLk, and LHk are called details, where k is the scale varying from 1, 2 … J and J is the total number of decompositions. The size of the subband at scale k is N/2k × N/2k. The subband LLJ is the low-resolution residue. The wavelet thresholding denoising method processes each coefficient of Y from the detail subbands with a soft threshold function to obtain $\hat{X}$ (Kahwachi W. a., 2006).

The denoised estimate is inverse transform $\hat{f} = W^{-1}\hat{X}$

3.3 Wavelet Thresholding

It has been observed that in many signals' energy is mostly concentrated in a small number of dimensions and the coefficients of these dimensions are relatively large compared to other dimensions or to any other signal (specially, noise) that has its energy spread over a large number of coefficients. Hence, in wavelet thresholding, each coefficient is thresholded (set to zero) by comparing against a threshold to eliminate noise, while preserving important information of the original signal.

Usually two types of thresholding techniques are used:

3.3.1 Hard Thresholding

The hard thresholding operator is defined as

$$D\ (U, \lambda) = U \text{ for all } |U| > \lambda = 0 \text{ otherwise} \quad [4]$$

Hard threshold is a "keep or kill" procedure and is more intuitively appealing.

3.3.2 Soft Thresholding

The soft thresholding operator is defined as

$$D\ (U, \lambda) = 0 \text{ for all } |U| \leq \lambda = \text{sgn}(U)\ (|U| - \lambda) \text{ otherwise} \quad [5]$$

Soft thresholding shrinks the magnitudes of the coefficients above the threshold in absolute value and this method is used as the thresholding technique in this paper.

Determination of the value of the threshold is crucial as larger value may result into loss of information while smaller one may allow noise to continue.

The thresholding techniques have some underlying disadvantages. For instance, the estimated wavelet coefficients by the hard thresholding method are not continuous at the threshold ë which may lead to the oscillation of the reconstructed signal. In the soft thresholding case, there are deviations between image coefficients and thresholded coefficients which directly influence the accuracy of the reconstructed signal. Retention of the edges is also a problem here. Different edge detection algorithm is used to extract the contour feature of cell images. Bilateral filter may help to achieve the target of edge retention.

3.4 Bilateral Filter

The bilateral filter was proposed in as an alternative to wavelet thresholding for image denoising. It applies spatial weighted averaging without smoothing edges. This is achieved by combining two Gaussian filters; one filter works in spatial domain; the other filter works in intensity domain. Therefore, not only the spatial distance but also the intensity distance is important for the determination of weights. At a pixel location x, the output of a bilateral filter can be formulated as follows:

$$\tilde{I}(x) = \frac{1}{c} \sum\nolimits_{y \in N(x)} e^{\frac{-\|y-x\|^2}{2\sigma_s^2}} e^{\frac{-|I(y)-\tilde{I}(x)|^2}{2\sigma_r^2}} I(y) \quad [6]$$

where σ_s and σ_r are parameters controlling the fall-off of weights in spatial and intensity domains, N(x) is a spatial neighborhood of pixel I(x), and C is the normalization constant:

$$c = \sum\nolimits_{y \in N(x)} e^{\frac{-\|y-x\|^2}{2\sigma_s^2}} e^{\frac{-|I(y)-\tilde{I}(x)|^2}{2\sigma_r^2}} \quad [7]$$

One weakness of the bilateral filter is not being able to remove salt-and-pepper type of noise. A second drawback of the bilateral filter is its single resolution nature. Unlike the wavelet filter, the bilateral filter may not access to the different frequency components of a signal. Although it is effective in removing high-frequency noise, the bilateral filter fails to remove low-frequency noise. Another issue with the bilateral filter is that there is no theoretical work on the optimal values of the parameters, σ_s and σ_r.

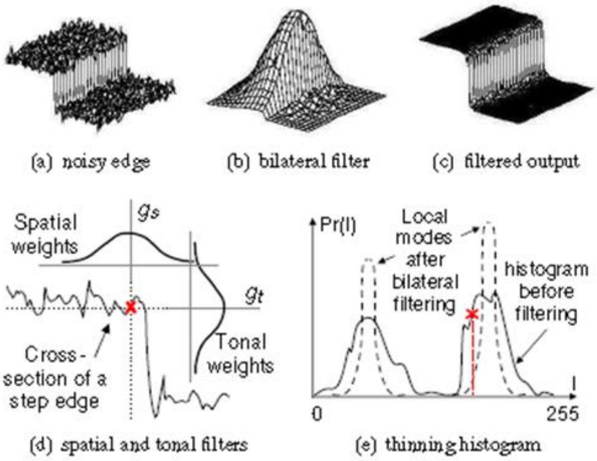

Figure 2: Bilateral filtering as a mode seeking process

3.5 Measurement of Performance

The performance of the denoising technique is judged by using the objective criteria.

For objective measurement, Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) are used here and (MES between pixel). Good PSNR does not imply that the visual quality of the image is good. To overcome this problem Image Quality Index (IQI) is considered as the second parameter for judging the quality of denoised images. (Chang S. Y., 2000).

MSE may be defined by equation (8).

$$MSE = \frac{1}{M}\sum_{i=1}^{M}(g_i - f_i)^2 \qquad [8]$$

Where M is the number of elements in the image.

The PSNR may be defined by equation (9) as given below:

$$PSNR = 10log_{10}\left(\frac{(2^n - 1)^2}{MSE}\right) \qquad [9]$$

Where n is the number of bits per symbol.

The MSE between pixels may be defined by eqn. (8) as given below:

$$MSE_{between\ pixels} = \sum_{i=1}^{n-1}\left(\frac{(e_{i+1}-e_i)}{(e_{i+1}+e_i)}\right)^2 \Big/ n-1 \qquad [10]$$

Where e_i is the pixel of image, and i=1, 2, 3,…, n-1.

The Image Quality Index (IQI), Q, is proposed by (Wang, 2002) as a product of three different factors: loss of correlation, luminance distortion, and contrast distortion and is defined as (Wang, 2002)

$$Q = \frac{\sigma_{fg}}{\sigma_f \sigma_g} \cdot \frac{2\bar{f}\bar{g}}{\bar{f}^2+\bar{g}^2} \cdot \frac{2\sigma_f \sigma_g}{\sigma_f^2+\sigma_g^2} \quad [11]$$

Where

$$\bar{f} = \frac{1}{M}\sum_{i=1}^{M} f_i \qquad \bar{g} = \frac{1}{M}\sum_{i=1}^{M} g_i$$

$$\sigma_f^2 = \frac{1}{M-1}\sum_{i=1}^{M}(f_i - \bar{f})^2 \qquad \sigma_g^2 = \frac{1}{M-1}\sum_{i=1}^{M}(g_i - \bar{g})^2$$

$$\sigma_{fg} = \frac{1}{M-1}\sum_{i=1}^{M}(f_i - \bar{f})(g_i - \bar{g})$$

The first component of equation (11) is the correlation coefficient between f and g, which measures the degree of linear correlation between f and g and its dynamic range is [-1,1]. The second component, with a value range of [0,1], measures how close the mean luminance is between f and g. σ_f and σ_g can be viewed as estimate of the contrast of f and g, so the third component with a value range of [0,1] measures how similar the contrasts of the images are.

Thus, Q can be rewritten as

$$Q = \frac{4\sigma_{fg}\bar{f}\bar{g}}{(\sigma_f^2 + \sigma_g^2)(\bar{f}^2 + \bar{g}^2)} \quad [12]$$

The dynamic range of Q is [-1,1]. The best value 1 is achieved, if and only if, gi=fi for i=1,2,…,M. the lowest value of -1 occurs when $g_i = 2\bar{f} - f_i$ for all i=1,2,…,M.

4. Proposed Approach

In this work a new model is proposed by hybridizing bilateral and wavelet-based principles for image denoising. The performance of the model is compared with wavelet based denoising method, bilateral filtering-based image denoising method by using MATLAB R2013a programs.

While working with the models, the parameters w, σ_d and σ_r of bilateral filters are varied over a wide range of values as there is no explicit rules that can guide the tuning of these parameters. And the threshold value for the wavelet-based filter is also varied.

In this thesis we use of a set of image and image are diverse and, in many areas, synonymous to digital image and is very much essential for daily life applications such as satellite television, medical imaging (magnetic resonance imaging, ultrasound imaging, x-ray imaging), computer tomography. The images collected by different type of sensors are generally contaminated by different types of noises.

4.1 Hybrid Filter Framework

Proposed method is the newly designed hybridized one as shown in figure (3). In this model a new hybrid method is developed based on previous ones. Hybrid means a thing made by combining two different elements. Same as meaning, hybrid threshold is developed. Hybrid threshold is a combination of bilateral and Wavelet filters. Bilateral filter i.e. smoothing denoised or non-adaptive smoothing and Wavelet filter i.e. adaptive threshold.

The image is denoised first with bilateral filter followed by decomposition into four subbands using db8 filters. In the next level the wavelet based soft thresholding is applied on all the subbands. The results obtained after thresholding are then used to reconstruct the image. In the last level, again bilateral filter is applied to get the final denoised image.

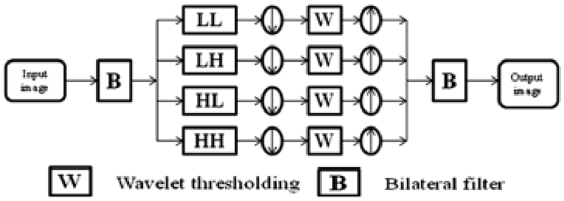

Figure 3: The proposed Hybrid Model

In the hybrid work, two techniques namely, wavelet thresholding and bilateral filters are combined to form a hybrid denoising model. These techniques are used to suppress the Gaussian noise. The figure (4) shows the proposed method for denoising.

1. Gaussian noise is estimated.
2. Perform multi-scale decomposition of the image corrupted by Gaussian noise using hybrid method.
3. For each step, compute the scale parameter.
4. for each sub-band.
   A. Compute the standard deviation.
   B. Compute sigma s and sigma r.
   C. Apply soft thresholding to the noisy coefficients.
6. The denoised image obtained from hybridizing bilateral and wavelet method is again processed for reducing Gaussian noise.
7. The denoised output produced by hybrid method still contains some Characteristics that distinguish the picture.
8. To reduce those images and to preserve fine details the Bilateral filtering and detail thresholding are applied.
9. Finally the denoised image is obtained.

Figure 4: Proposed methods for denoising Gaussian noise

Bilateral and wavelet filter have made quite a splash in the field of image processing. Proposed model is the newly designed hybridized one as shown in figure 1. In this model, the image is denoised first using bilateral filters. In the second level the wavelet based soft thresholding is applied on all the sub-bands. In recent level has been denoised image by using bilateral filter. It is used for suppressing the Gaussian noise. Resultant coefficients are used for image reconstruction with bilateral filter. The results obtained after thresholding are then used to reconstruct the image. In the last level, bilateral filter is used to remove impulse noise present in the image during transformation. The final denoised image is obtained.

The advantage of hybrid denoising is possible to remove the noise with little loss of details. The Hybrid denoises only the Gaussian type of noise. So, when multiple noise present in the image it will remove only Gaussian the remaining noise are unremoved. So, for removing the remaining noise and to preserve the fine details Bilateral and detail thresholding filters are applied. The hybrid filter can denoise the large window size. The proposed method consists of the following process

5. Results and Discussions

Experiments using Bilateral Filtering (BF),Wavelet Thresholding (WT), and hybrid model (B+W+B) are conducted on a set of standard benchmark (monochrome) images such as normal image by using the proposed denoising algorithm namely σs=2, σr=(0.1, 0.5, 1, 10, inf) window size N=512 × 512, and ratio of Gaussian noise for standard division (10), MRI image by using the proposed denoising algorithm namely σs=6, σr=(0.1, 0.5, 1, 10, inf), window size N=512 × 512, and ratio of Gaussian noise for standard division (20), X-Ray image by using the proposed denoising algorithm namely σs=18, σr=(0.1, 0.5, 1, 10, inf), window size N=512 × 512, and ratio of Gaussian noise for standard division (30), ultrasound image by using the proposed denoising algorithm namely σs=54, σr=(0.1, 0.5, 1, 10, inf), window size N=512 × 512, and ratio of Gaussian noise for standard division (40), Roya face image by using the proposed denoising algorithm namely σs=162, σr=(0.1, 0.5, 1, 10, inf), window size N=512 × 512, and ratio of Gaussian noise for standard division (50). However, the results obtained with Gaussian noise added images are shown in Figure (5.2).

The proposed algorithm helps to preserve the edges in the best way while suppressing the noise. The application of Bilateral Filter and multiscale product wavelet technique enhances the performance. Hence this hybrid method is recommended as a well competent and efficient model for denoising any type of images.

The wavelet transforms employ hybrid least asymmetric compactly supported wavelet. We shall use the Peak Signal to Noise Ratio (PSNR), MSE, IQI, and proposed model MSE between pixels, as our quantitative measure of the relative denoising algorithms performance. In this experiment, we have compared the proposed denoising algorithm with the conventional bilateral filter, and Wavelet thresholding filter. Bilateral and thresholding are frequency domain based denoising algorithms using 4- Level wavelet transform decomposition. The bilateral filter is a spatial domain based denoising algorithm. While, the proposed denoising algorithm uses both spatial and frequency domain as shown in figure (5.1) with single-level wavelet transform decomposition. The PSNR and others model for various denoising algorithms are recorded in tables for a set of images.

The data are collected from an average of ten runs. The best denoising algorithm among others in terms of PSNR, MSE, IQI and MSE between pixels' values are highlighted in bold font for each test image. Referring to the results in following Tables, we can clearly see that the proposed denoising algorithm outperforms other denoising algorithms most of the time in terms of individual values. It outperforms other denoising algorithms all the time in terms of average value over the whole scope of noise levels and images under test.

Also, we can see that bilateral and wavelet filter achieves competitive image denoising performance. However, bilateral and wavelet filters require much processing time compared with the proposed denoising algorithm. This is due to the fact that search hybrid filter or optimal window size and threshold value for every wavelet sub band by minimizing MSE unbiased risk estimate which is a time-consuming process especially for large size images. As an example, the average execution time of ten runs, shows that bilateral filter requires about 27.352 Minute for denoising image of size 512×512 while the proposed denoising algorithm did better results with about just 49.508 Minute. Thus, we can deduce that the proposed denoising algorithm provides both good performance and low computation cost.

5.1 Denoising Images Corrupted with White Gaussian Noise

For hybrid function, the effect of the parameters was examined over a wide range of image degradations and the optimum value for parameters was searched that maximizes the Peak Signal to Noise Ratio (PSNR, IQI, MSE, and MSE between pixels) between the original and denoised image. Were the MSE between pixels from (Normal, MRI, Roya Face, Ultrasound, X-Ray) images are (0.4163, 0.9728, 0.0037, 0.005 and 0.9861) respectively

The results are reported in figure (5.2). From this figure, it's clear that the spatial bilateral filter parameters namely σ_s, σ_r and N were examined extensively over a wide range of image degradations. Results show that, for the proposed denoising algorithm, these parameters can be set easily and accurately for denoising a wide range of images over a wide range of noise levels under test. Results also show that the parameter σ_r has higher effect on denoising performance as compared with the σ_s, and N and it has a linear relationship with the noise standard deviation, the following shows the original and noise image, and shows the results of denoising images from the model of denoising.

Extensive optimization has been carried out for the selection of optimum value for σ_r and σ_s related to σ_n.

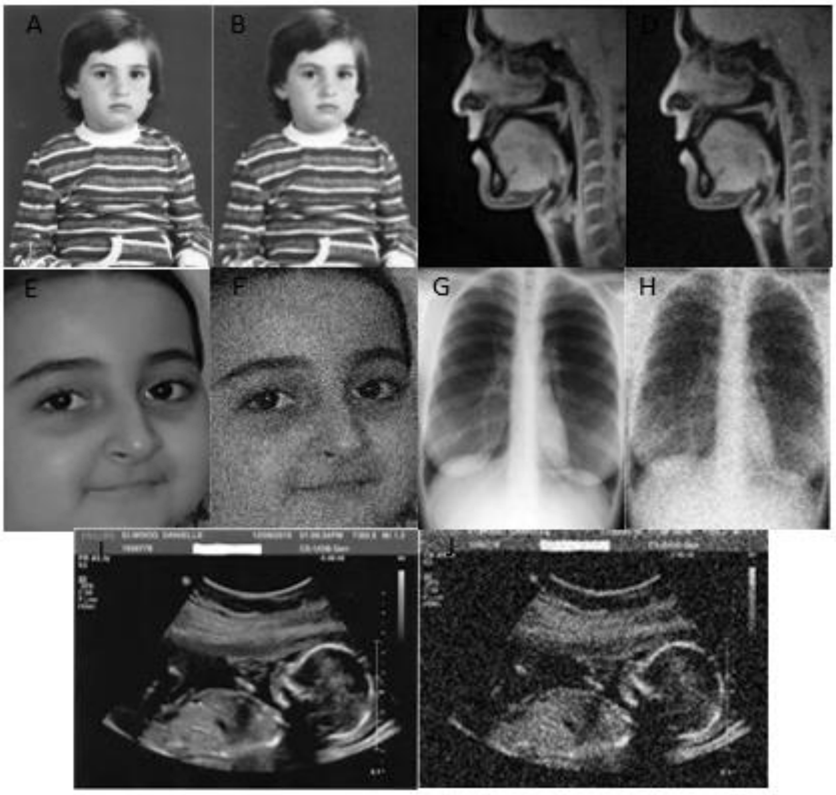

Figure 5: Original and Noise Images A) Original Normal image. B) Noise image (Std. 10). C) Original MRI image D) Noise image (std. 20). E) original Roya face image. F) noise image (std. 30). G) Original X-Ray image. H) Noise image (std. 40). I) Original Ultrasound image. J) Noise image (std. 50)

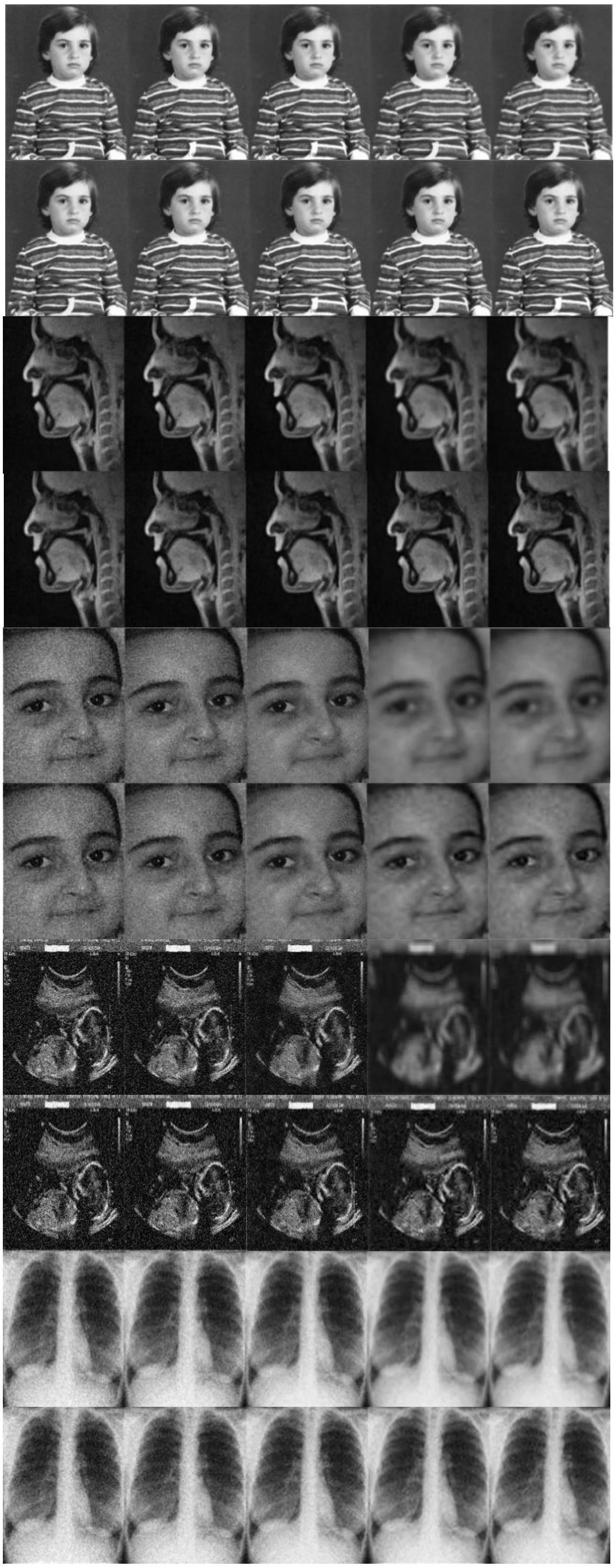

Figure 5.1 shows the original and noisy normal images considered in our experiments each of size 512 × 512.

Table 1: The new hybrid denoising algorithm performance vs conventional bilateral filter, wavelet thresholding, and hybrid filter denoising

Std. Noise	Sigma S	Sigma R	PSNR Hybrid Filter	PSNR Bilateral Filter	(IQI) Hybrid Filter	(IQI) Bilateral Filter	MSE between pixels Bilateral Filter	MSE between pixels Hybrid Filter	MSE Bilateral Filter	MSE Hybrid Filter
10	2	0.1	28.219	28.219	0.990	0.990	0.758	0.758	0.098	0.098
		0.5	29.077	29.083	0.990	0.990	0.758	0.758	0.080	0.080
		1	30.762	31.025	0.991	0.991	0.303	0.357	0.051	0.055
		10	32.900	27.799	0.993	0.977	0.000	0.006	0.108	0.033
		Inf.	32.561	25.156	0.993	0.961	0.000	0.018	0.198	0.036
20	6	0.1	22.906	22.911	0.943	0.943	0.973	0.973	0.333	0.333
		0.5	24.006	24.052	0.953	0.953	0.973	0.973	0.256	0.259
		1	26.690	26.814	0.969	0.969	0.973	0.973	0.135	0.139
		10	34.533	31.863	0.995	0.993	0.000	0.092	0.042	0.023
		Inf.	34.531	31.561	0.995	0.993	0.000	0.095	0.045	0.023
30	18	0.1	18.715	18.715	0.836	0.836	0.005	0.005	0.874	0.874
		0.5	20.232	20.248	0.859	0.863	0.005	0.005	0.614	0.616
		1	23.685	23.743	0.916	0.915	0.005	0.005	0.275	0.278
		10	30.652	28.847	0.984	0.983	0.000	0.000	0.085	0.056
		Inf.	30.728	28.874	0.983	0.982	0.000	0.000	0.084	0.055
40	54	0.1	17.454	17.456	0.845	0.846	0.005	0.005	1.168	1.169
		0.5	18.292	18.368	0.863	0.866	0.005	0.005	0.947	0.964
		1	20.280	20.508	0.905	0.910	0.005	0.005	0.578	0.610
		10	23.490	19.472	0.967	0.931	0.000	0.002	0.734	0.291
		Inf.	23.337	19.116	0.967	0.925	0.000	0.002	0.797	0.302
50	162	0.1	15.022	15.023	0.878	0.878	0.863	0.863	2.046	2.046
		0.5	16.359	16.393	0.900	0.901	0.863	0.863	1.492	1.504
		1	19.762	19.901	0.944	0.945	0.863	0.863	0.665	0.687
		10	29.162	29.833	0.993	0.994	0.000	0.000	0.068	0.079
		Inf.	29.127	29.802	0.994	0.994	0.000	0.000	0.068	0.080

6. Conclusions and Future Works

In this work, a new hybrid denoising algorithm was proposed. The performance of the proposed algorithm was compared with conventional bilateral filter, wavelet thresholding, and hybrid filter denoising .

The subjective and objective quality of the proposed denoising algorithm reveals that it outperforms all other denoising algorithm under test and can deal with both low and high frequency noise components effectively.

The performance of proposed denoising model can further be improved by adaptively tuning the bilateral filter parameters (σ_s and σ_r) over the image based on the spatial noise levels.

As a result of these experiments in the previous chapter, we can reach the following

7. Conclusions

1. Clearly, with the hybrid filter, the strong noise is eliminated most effectively.
2. For the gray-scale images, method denoised-bilateral filtering and detail thresholding will still keep some random noises in the texture which can be clearly observed, while bilateral filter can remove the noises in the texture very well. However, original bilateral filter has a stronger intensity parameter σ_r than it will lose some details in the texture. With wavelet thresholding, bilateral filter can eliminate the noises in the high frequency components without obvious influence on the texture.
3. Wavelet thresholding is not effective for the real noisy images. The reason to explain this can be inferred that because wavelet thresholding is based on the robust median estimation, the real noise doesn't have the same property as the standard Gaussian random noise so that it could not be estimated correctly.
4. Bilateral filter can use any type of wavelet thresholding method, as long as this method is effective. Compared with the proposed method, although the bilateral and wavelet filter has good performance for the slight noisy image, but when it comes to the strong noisy image, using same parameters, the proposed method has the best output performance.
5. When we transfer the color space, we can use the advantage of Hybrid filter more effectively. Because human visual system is more sensitive to the red and green color noises, we can use higher level decomposition. According to the observation, for those noises in the color, like the red and green color noises on the Roya face and hair, only the Hybrid filter can work with the most effect.
6. We compare our algorithm with bilateral filter, which is considered as the most effective recent image denoising method. From Figures (5.10, 5.12, 5.14, 5.16, 5.18, 5.20, …, 5.90, 5.92), we can find that some obvious noises remained, while hybrid filter can avoid. Therefore, our proposed method has the best efficiency in the denoising works for real noisy image.

The key factor in the performance of the proposed method is the application of the bilateral filter. It helped eliminating the coarse-grain noise in images. The wavelet thresholding adds power the proposed method as salt-and-pepper type of noise components cannot be eliminated with the bilateral filter.

This technique is computationally faster and gives better results. Some aspects that were analyzed in this paper may be useful for other denoising schemes, objective criteria for evaluating noise suppression performance of different significance measures. Our new threshold function is better as compare to other threshold function. Some function gives better edge perseverance, background information, contrast stretching, in spatial domain. In future we can use same threshold function for medical images as well as texture images to get denoised image with improved performance parameter.

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