Image Denoising Model Based on Wiener Filter and a Novel Wavelet

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Abstract:-The requirement for image improvement and restoration is experienced in numerous down to earth applications. For example, mutilation because of Gaussian noise can be caused by low quality image obtaining, images saw in a noisy situation or noise intrinsic in correspondence channels. In this proposition, image denoising is examined. In the wake of looking into standard image denoising strategies as connected in the spatial, frequency and wavelet domains of the noisy image, the proposal sets out on the undertaking of creating and exploring different avenues regarding new image denoising techniques in view of wiener channel and Bayesian shrinkage govern utilizing wavelet change. Specifically, four new image denoising strategies are proposed. The performance of the denoising results is assessed using PSNR, SSIM and UIQI. It is observed that the proposed model 1 out of four models shows the best results in terms of quantitative and qualitative analysis.

I. INTRODUCTION

A. Image Denoising

Advanced images assume a pivotal part each in regular daily existence applications like satellite TV, attractive reverberation imaging, tomography pictorial portrayal tomography as in zones of investigation and innovation like geological information frameworks and stargazing. Informational indexes gathered by image sensors territory unit generally defiled by noise. Blemished instruments, issues with the data procurement technique, and meddling regular wonders will all corrupt the data of intrigue. Restoration is usually an essential and in this way the initiation to be taken before the images information is broke down [1]. It's important to utilize a proficient denoising method to make up for such learning defilement. Image denoising still remains a test for specialists because of noise evacuation presents ancient rarities and causes obscuring of the images [2]. This theory depicts diverse procedures for noise diminishment (or denoising) giving an understanding as to which calculation ought to be utilized to locate the most dependable gauge of the first image information given its debased form and proposed another versatile 2D-DWT based image denoising strategy utilizing wavelet thresholding and wiener channel. Diverse calculations region unit utilized relying on the noise display.

B. Evolution Of Image Denoising Research

Image Denoising has remained an essential disadvantage inside the field of image processing. The wavelets give a prevalent execution in image denoising in view of properties like meagre condition and multi-resolution structure. With wavelet change increasing quality inside the most recent 20 years various calculations for denoising in wavelet domain were presented. the principle target was moved from the spatial and Fourier domain to the wavelet change domain. As far back as Donoho's wavelet fundamentally based thresholding approach was uncovered in 1995; there was a surge inside the denoising papers being uncovered. despite the fact that Donoho's build wasn't progressive, his ways didn't require trailing or relationship of different scales as arranged by Mallat [3]. In this manner, there was a resuscitated enthusiasm for wavelet methods. It exhibited a simple way to deal with an intense downside. Scientists distributed elective approaches to figure the parameters for the thresholding of wavelet coefficients. Information accommodative limits [6] were acquainted with acknowledge ideal worth of edge. Later endeavors found that significant upgrades in tactile action quality may be acquired by interpretation invariant ways bolstered thresholding of an Undecimated wavelet modify [7]. These thresholding systems were connected to the non-symmetrical wavelet coefficients to downsize ancient rarities. Multiwavelets were conjointly wont to achieve comparative outcomes. Probabilistic models exploitation the measurable properties of the wavelet consistent gave the impression to surpass the thresholding procedures and made progress. As of late, a ton of exertion has been committed to Bayesian denoising in wavelet domain [5]. It turned out to be popular and extra investigation keeps on being uncovered. Tree Structures requesting the riffle coefficients bolstered scale and spatial area. Information versatile changes like free part Analysis (ICA) are investigated for thin shrinkage. The pattern keeps on focusing on exploitation very surprising factual models to demonstrate the measurable types of the wavelets and its surroundings. Future pattern are towards finding extra right different models for the appropriation of non-symmetrical wavelet coefficients.

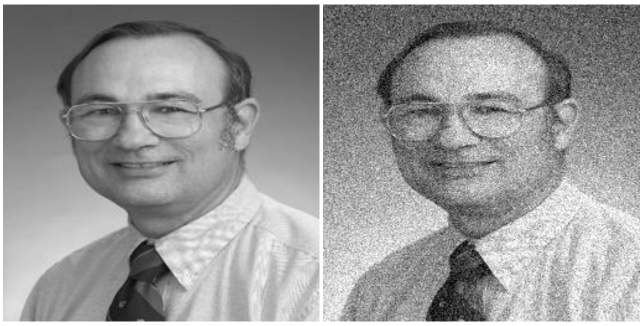
C. Noise

Image noise is arbitrary variety of brilliance or shading data in images, and is typically a part of electronic noise. It can be delivered by the sensor and hardware of a scanner or computerized camera. Image noise can likewise begin in film grain and in the unavoidable shot noise of a perfect photon identifier. Image noise is a bothersome result of image catch that clouds the coveted data [9].

The first significance of "noise" was "undesirable flag"; undesirable electrical vacillations in signals got by AM radios caused capable of being heard acoustic noise ("static"). By relationship, undesirable electrical changes are additionally called "noise" [8].

Image noise can go from relatively subtle bits on an advanced photo taken in great light, to optical and radio galactic images that are for the most part noise, from which a little measure of data can be inferred by complex handling.

Such a noise level would be inadmissible in a photo since it would be outlandish even to decide the subject [10].



(a) (b)

Fig 1:- (a) Original image (b) Noisy image

Types of noise

- *Gaussian noise* - Essential wellsprings of Gaussian noise in advanced pictures emerge amid procurement. The sensor has intrinsic noise because of the level of light and its own particular temperature, and the electronic circuits associated with the sensor infuse their own offer of electronic circuit noise [11-12].
- *Salt-and-pepper noise* - Picture with salt and pepper noise Fat-tail dispersed or "rash" noise is at times called salt-and-pepper noise or spike noise.[7] A picture containing salt-and-pepper noise will have dull pixels in splendid districts and brilliant pixels in dim regions.[8] This kind of noise can be caused by simple to-computerized converter blunders, bit mistakes in transmission, etc.[9][10] It can be for the most part disposed of by utilizing dim edge subtraction, middle sifting and introducing around dim/splendid pixels.
- *Film grain* - The main thing of photographic film is like a subordinate noise, with comparative measurable dissemination to shot noise [15]. If film grains are consistently conveyed (meet number per region), and each grain has an equivalent and free likelihood of creating to a dim silver grain in the wake of retaining photons, at that point the quantity of such dull grains in a zone will be arbitrary with a binomial dispersion. In zones where the likelihood is low, this dispersion will be near the exemplary Poisson dissemination of shot noise. A basic Gaussian dispersion is frequently utilized as a satisfactorily precise model [10].
- *Anisotropic noise* - Some noise sources appear with a noteworthy introduction in pictures. For instance, picture sensors are in some cases subject to push noise or section noise. [15]
- *Periodic noise* - A typical wellspring of intermittent noise in a picture is from electrical or electromechanical obstruction amid the picture catching process.[7] A picture influenced by occasional noise will resemble a rehashing design has been included best of the first picture. In the recurrence area this sort of noise can be viewed as discrete spikes. Critical lessening of this noise can be accomplished by applying indent channels in the recurrence area.

➢ *Sources of noise*

- *In computerized cameras* - Picture on the left has presentation time of >10 seconds in low light. The picture on the benefit has adequate lighting and 0.1 second presentation. In low light, change introduction requires the usage of direct screen speed (i.e. long presentation time), higher get (ISO affectability), or both. On most cameras, slower shade speeds provoke extended salt-and-pepper clamor due to photodiode spillage streams. At the cost of an increasing of read clamor distinction (41% extension in read commotion standard deviation), this salt-and-pepper commotion can be generally shed by dull packaging subtraction. Banding clamor, similar to shadow commotion, can be displayed through illuminating shadows or through shading balance preparing. [6]
- *Impacts of sensor estimate* - The traverse of the picture sensor, or great light assembling locale per pixel sensor, is the greatest determinant of flag levels that choose motion to-commotion proportion and along these lines evident clamor levels, expecting the hole district is relating to sensor region, or that the f-number or focal plane illuminance is held predictable. That is, for a steady f-number, the affectability of a picture scales for the most part with the sensor region, so greater sensors ordinarily make cut down commotion pictures than tinier sensors. By virtue of pictures adequately awesome to be in the shot commotion confined organization, when the picture is scaled to a comparative size on screen, or printed at a comparable size, the pixel check has little impact to perceptible clamor levels – the clamor depends mainly on sensor area, not how this domain is detached into pixels. For pictures at cut down flag levels (higher ISO settings), where examined (clamor floor) is enormous, more pixels inside a given sensor locale will make the picture noisier if the per pixel read commotion is the same [12-15].
- *Sensor fill factor* - The picture sensor has singular photograph destinations to accumulate light from a given region. Not all zones of the sensor are used to assemble light, due to other equipment. A higher fill factor of a sensor makes more light be assembled, thinking about better ISO execution in perspective of sensor measure [12].
- *Sensor heat* - Temperature can likewise affect the measure of commotion delivered by a picture sensor because of spillage. In view of this, it is realized that DSLRs will deliver more commotion amid summer than winter.

D. Background Of Proposed Model

➢ *DWT*

Wavelets may be used in image compression and suppression of noise. The DWT transforms the image from the spatial to the frequency domain [10], [11]. In the proposed methods, the 2D-DWT is applied to analyze the low and high-frequency component in the image. 2D-DWT is used to resolution of approximation expressions. The wavelet function is analyzed in Figure 2 [9-12].

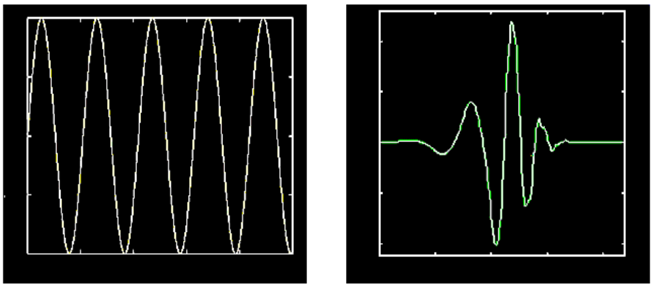


Fig 2:- Comparison of sine wave and daubechies 5 wavelet

In 1976 scientists Croiser, Esteban, and Galand established a technique to decompose the discrete-time signals that sited the foundation for DWT. Few other researchers named Crochiere, Weber, and Flanagan did the similar work of coding the speech signals in the same year. The title of their study is sub-band coding. In 1983, a technique associated to subband coding was explained by Burt and called that technique as pyramidal coding that is also acknowledged as multi-resolution analysis [6-8].

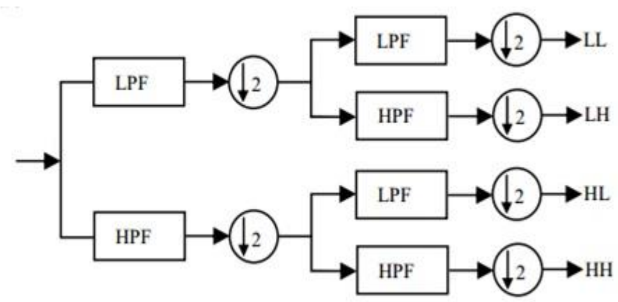


Fig 3:- Wavelet decomposition by filter banks [6]

A low pass and high pass filter are selected in such a way the that they exactlyhalvethe frequency range among themselves. This filter pair is known as analysis filter pair. The low pass filter is implemented at each row to obtain the low-frequency components. The low pass filter is a half-band filter and output data comprise of frequencies in the first half of the original frequency range. Now for the same row of data, high pass filter is implemented, and the high-frequency components can be parted similarly and located on the side of low pass components. The method is implemented on all the rows. The DWT decomposition employed using filter bank is shown in Figure 3.

Next stage is to implement filtering at every column of the intermediary data. On applying 2D-DWT on the imageat level one, it transforms the image into four subband i.e. LL (Approximate Image), HL (Horizontal Noisy Coefficients), LH (Vertical Noisy Coefficients), and HH (Diagonal Noisy Coefficients). In order to obtain the two-level decomposition, once again 2D-DWT is applied on the LL subband and it is further decomposed in the same way, thus generating additional sub-bands. This wavelet decomposition can be performed up to any level. Thus resultant is pyramidal decomposition as shown below in Figure 4 for single level decomposition and Figure 5 for two-level decomposition. In Figure 4, the decomposed subbands are represented by X_n, where X denotes specific decomposed subband and n denotes the level of decomposition, for example LL_2 is aproximate component of the image at decomposition level 2.

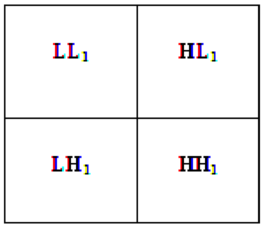


Fig 4:- Single level decomposition

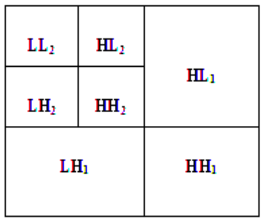


Fig 5:- Two level decomposition

Same as the forward transformation to separate the image data into different classes, a reverse transformation is used to reunite the dissimilar classes of data into a restored image. A pair of high and low pass filter is in use here too. Such filter pair is identified as Synthesis Filter pair. This filtering process is just reverse as it is initiated from the highest level, implement the filter initially column wise and later row-wise, and this continues until this process reaches the first level. The DWT reconstruction employed using filter bank is shown in Figure 6.

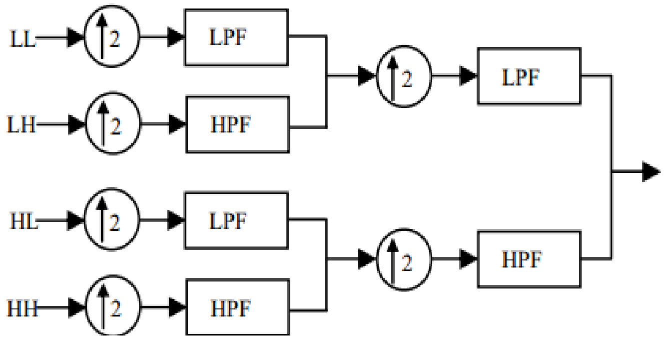


Fig 6:- Wavelet reconstruction using filter banks

The only drawback of 2D-DWT is that on applying DWT on the image, at every level it reduces the size of the image to half of the previous level size as shown in Figure 7. This causes loss of information [5].

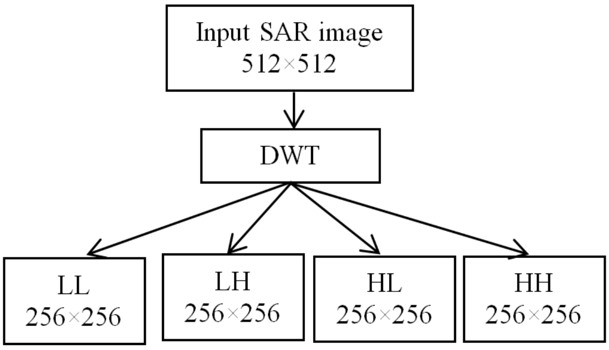


Fig 7:- Frequency band decomposition using DWT

- *Wavelet thresholding using modified Bayesian shrinkage rule*

The threshold λ is evaluated using below equation,

$$\lambda = \left(\frac{{\sigma_n}^2}{\sigma_Y}\right) \tag{1.1}$$

The noise variance is estimated using robust median estimation method (Abramovitch et al. 1998) as follows:

$$\sigma_n^2 = \left[\frac{median(|X(x,y)|)}{0.6754}\right]^2 \tag{1.2}$$

Where, $X(x,y)\epsilon LH_L$, $X(x,y)\epsilon HL_L$ and $X(x,y)\epsilon HH_L$, and L is decomposition level. The standard method works only on the HH_L, but in the proposed work, it is applied to all the detail components (LH_L, HL_L, HH_L). The standard deviation of noise less image (σ_Y) is calculated using:

$$\sigma_Y^2 = max(\sigma_X^2 - \sigma_n^2, 0) \tag{1.3}$$

Where, $\sigma_X^2 = \frac{1}{c}\sum_{i=1}^{c} X_i^2$, and c is the patch size of the input image.

Thresholding can be done either by hard and soft thresholding. The proposed method uses soft thresholding. It is equated as:

$$\hat{Y} := \left\{\begin{cases} 0 & if|X| \le \lambda \\ sign(X)(|X| - \lambda) & if|X| > \lambda \end{cases}\right. \tag{1.4}$$

- *Wiener filter*

The Wiener filter is used for reducing the additive noise in the image. It is based on Fourier iteration. It takes less computational time for filtering the image. It is mainly used for de-blurring [8]. The Wiener filter is used in both spatial and frequency domain filtering. It is more effective in the frequency domain. The disadvantage of Wiener filter is that it cannot reconstruct the image to its original form. It only reduces noise up to a limited extent. It can be used to filter the frequency components but can only suppress noise and is unable to reconstruct the frequency components which are degraded by the noise [4]. The Wiener filtering reduces the overall MSE in the procedure of inverse filtering and noise smoothing. The Wiener filtering is a linear approximation of the original image. The approach is based on a stochastic framework [5].

$$W(f_1, f_2) = \frac{H^*(f_1, f_2)S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)}) \tag{1.5}$$

E. Performance Assessment

PSNR [2] is the most used performance evaluation metric in denoising. Higher the value of PSNR, PSNR should be as high. A high value indicates better results. PSNR is computed by:

$$10\log_{10}\left(\frac{255 \times 255}{MSE}\right) \tag{1.6}$$

SSIM [2] is used measure the similarity between the despeckled image and the reference image. It depends upon three parameters, luminance, contrast and structural. The overall index is a multiplicative combination of the three terms.

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{1.7}$$

The range of SSIM varies from -1 to 1 according to the literature [9].

UIQI [3] is written as a product of three components: the first component is used to measures the degree of linear correlation, second component measures closeness of mean luminance and the third component measures how similar the contrasts of the images are. The range of the three components is in [0, 1]. Therefore, the final range of the UIQI is in between [0, 1].

$$Q = \frac{\sigma_{xy}}{\sigma_x\sigma_y} \cdot \frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2} \cdot \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2} \tag{1.8}$$

F. Problem Statement And Objectives

There are various sources of the noises that corrupt the quality of the digital image due to which the feature extraction and image analysis becomes the difficult task to perform. The brings the concept of denoising the images first and then perform feature extraction and image analysis. The image denoising is the pre-processing task to remove the noise. The kind of noise that corrupts the digital images are Gaussian noise. This thesis proposes a denoising model for removal of Gaussian noise from the image.

II. LITERATURE SURVEY

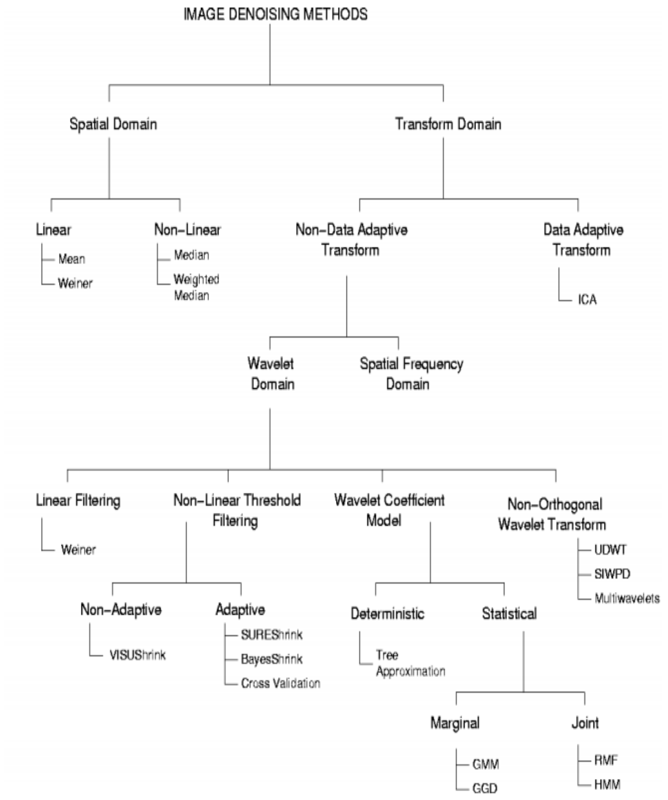


Fig 8:- Classification of image denoising techniques

A. *Spatial Filtering*

A regular strategy to oust commotion from picture data is to use spatial channels. Spatial channels can be furthermore requested into non-straight and direct channels.

- *Non-Linear Filters*

With non-straight channels, the commotion is cleared without any undertakings to explicitly recognize it. Spatial channels use a low pass sifting on social affairs of pixels with the doubt that the commotion has the higher area of repeat go. Generally spatial channels empty clamor to a sensible degree yet at the cost of darkening pictures which consequently makes the edges in pictures imperceptible. Recently, a grouping of nonlinear center create channels, for instance, weighted center [8], rank adjusted rank decision [9], and free center [10] have been delivered to beat this weakness.

- *Linear Filters*

A mean channel is the perfect direct channel for Gaussian clamor in the sentiment of mean square screw up. Direct channels excessively tend, making it impossible to darken sharp edges, obliterate lines and other fine picture unobtrusive components, and perform ineffectually inside seeing sign subordinate commotion. Wiener procedure executes spatial smoothing and its model eccentrics control contrast with picking the window measure. To beat the deficiency of the Wiener sifting, Donoho and Johnstone proposed the wavelet-based restoration plan in [12, 13].

B. *Transform Domain Filtering*

The change region separating techniques can be subdivided by the choice of the introduce limits. The introduce limits can be furthermore appointed data adaptable and non-flexible. Non-adaptable changes are discussed first since they are more acclaimed.

- *Spatial-Frequency Filtering*

Spatial-recurrence separating insinuates usage of low pass channels using FFT. In recurrence smoothing techniques [11] the removal of the commotion is refined by illustrating a recurrence space channel. These methodologies are dreary and depend upon the cut-off recurrence and the channel work direct. Furthermore, they may convey fake frequencies in the arranged image.

- *Wavelet space*

Separating activities in the wavelet space can be subdivided into straight and nonlinear strategies.

➢ *Straight Filters*

These filters yield perfect results when the flag corruption can be shown as a Gaussian method and the precision demonstrate is the mean square goof (MSE) [14, 15]. Regardless, sketching out a channel in light of this assumption as frequently as conceivable results in a sifted picture that is more apparently disillusioning than the principal uproarious flag, in spite of the way that the separating activity adequately diminishes the MSE. In [6] a wavelet-territory spatially flexible FIR Wiener sifting for picture denoising is proposed where wiener separating is performed simply inside each scale and intrascale sifting isn't allowed.

➢ *Non-Linear Threshold Filtering*

The most important region in restoration using WT is non-straight coefficient thresholding based systems. The framework abuses sparsity property of the wavelet change and the way that the Wavelet Transform maps dull sound the flag zone to foundation clamor the change space. Thusly, while flag essentialness ends up being more pressed into less coefficients in the change space, commotion imperativeness does not. It is these imperatives decide that engages the division of flag from clamor. The strategy in which little coefficients are emptied while others are left immaculate is called Hard Thresholding [5]. Regardless, the system produces deceiving blips, generally called old rarities, in the pictures due to unsuccessful undertakings of removing bearably far reaching commotion coefficients. To crush the negative signs of hard thresholding, wavelet change using delicate thresholding was in like manner displayed in [5]. In this arrangement, coefficients over the edge are shrunk by the preeminent estimation of the edge itself. Like delicate thresholding, distinctive systems of applying limits are semi-delicate thresholding and Garrote thresholding [6]. By far most of the wavelet shrinkage composing relies upon procedures for picking the perfect edge which can be flexible or non-adaptable to the picture.

- *Non-Adaptive limits*

VISUShrink [12] is non-versatile all inclusive limit, which depends just on number of information focuses. It has asymptotic proportionality recommending best execution regarding MSE when the quantity of pixels achieves vastness. VISUShrink is known to yield excessively smoothed pictures since its edge decision can be outlandishly substantial because of its reliance on the quantity of pixels in the picture.

- *Versatile Thresholds*

Beyond any doubt Shrink [12] uses a cross type of the general edge and performs better than visuShrink. Bayes Shrink [7, 8] limits the Bayes Risk Estimator work tolerating Generalized Gaussian before and in like manner yielding data adaptable edge. Bayes Shrink beats SURE Shrink most by far of the conditions The assumption that one can perceive commotion from the flag only in light of coefficient sizes is manhandled when clamor levels are higher than flag degrees. Under this high clamor condition, the spatial design of neighboring wavelet coefficients can accept a fundamental part in commotion flag orders. Signs tend to shape essential features (e.g. straight lines, twists), while noisy coefficients habitually disperse self-assertively.

➢ *Non-symmetrical Wavelet Transforms*

UDWT is used for crumbling the flag to give ostensibly better plan. Since UDWT is move invariant it avoids visual knick-knacks, for instance, pseudo-Gibbs ponder. In spite of the way that the adjustment in occurs is considerably higher, use of UDWT incorporates a broad overhead of computations along these lines making it less achievable. Then using Minimum Description Length standard the Best Basis Function was found which yielded humblest code length required for depiction of the given data. Then, thresholding was associated with denoise the data. Despite UDWT, usage of Multi-wavelets is researched which furthermore enhances the execution yet also extends the computation multifaceted nature. The Multi-wavelets are gained by applying more than one mother work to given dataset. Multi-wavelets have properties, for instance, short help, symmetry, and the specifically higher demand of vanishing minutes. This blend of move invariance and Multi-wavelets is realized in [2] which give pervasive results for the Lena picture in setting of MSE.

➢ *Wavelet Coefficient Model*

This technique revolves around abusing the multi-resolution property of WT. This strategy perceives cozy relationship of flag at different resolutions by watching the flag crosswise over various resolutions. This procedure produces unfathomable yield anyway is computationally considerably more staggering and exorbitant.

- *Deterministic*

The Deterministic technique for showing incorporates influencing tree to structure of wavelet coefficients with each level in the tree addressing each size of change and center points addressing the wavelet coefficients. This approach is gotten in [3]. The perfect tree gauge demonstrates a different leveled explanation of wavelet decay. Wavelet coefficients of singularities have huge wavelet coefficients that hang on along the branches of tree. In case it is rowdy coefficient, for instance spuriousblip, by then such solid closeness will miss.

- *Quantifiable Modeling of Wavelet Coefficients*

This approach revolves around some furthermore charming and drawing in properties of the Wavelet Transform, for instance, multi scale association between's the wavelet coefficients, close-by connection between'sneighborhood coefficients et cetera. This approach has an inborn goal of romanticizing the right showing of picture data with usage of Wavelet Transform. A good review of genuine properties of wavelet coefficients can be found in [6] and [7]. The going with two frameworks manhandle the quantifiable properties of the wavelet coefficients in perspective of a probabilistic model.

- *Minimal Probabilistic Model*

Different investigators have made homogeneous neighborhood probability models for pictures in the wavelet territory. Specifically, the fringe courses of wavelet coefficients are exceedingly kurtotic, and commonly have a stamped peak at zero and considerable tails. The Gaussian mix appear (GMM) [8] and the summed up Gaussian spread (GGD) [9] are normally used to show the wavelet coefficients scattering. Notwithstanding the way that GGD is more exact, GMM is more clear to use. In [3], makers proposed a system in which the wavelet coefficients are believed to be prohibitively self-sufficient zero-mean Gaussian sporadic variables, with changes showed as vaguely scattered, significantly related self-assertive elements. An estimated Maximum A Posteriori (MAP) Probability direct is used to assess fringe before scattering of wavelet coefficient variances. Each one of these systems said above require a commotion assess, which may be difficult to secure in rational applications. Simoncelli and Adelson [3] used a two parameter summed up Laplacian assignment for the wavelet coefficients of the picture, which is assessed from the uproarious recognitions. Chang et al. [4] proposed the usage of flexible wavelet thresholding for picture denoising, by showing the wavelet coefficients as a summed up Gaussian sporadic variable, whose parameters are assessed locally (i.e., inside a given neighbourhood).

- *Joint Probabilistic Model*

Concealed Markov Models (HMM) [5] models are capable in getting between scale conditions, while Random Markov Field [6] models are more profitable to get intrascale connections. The association between's coefficients at same scale yet staying in an adjacent neighborhood are shown by Chain Model where the connection between's coefficients over the chain is exhibited by Markov Trees. In [1], a model is depicted in which each region of wavelet coefficients is portrayed as a Gaussian scale mix (GSM) which is a consequence of a Gaussian subjective vector, and a self-ruling concealed unpredictable scalar multiplier. Strela et al. [2] delineated the joint densities of gatherings of wavelet coefficients as a Gaussian scale mix, and developed a most extraordinary likelihood respond in due order regarding assessing critical wavelet coefficients from the tumultuous recognitions. An inconvenience of HMT is the computational weights of the planning sort out. Remembering the true objective to overcome this computational issue, an unraveled HMT, named as HMT [7], was proposed.

- *Data-Adaptive Transforms*

The ICA methodology was adequately executed in [8, 9] in denoising Non-Gaussian data. One exceptional benefit of using ICA is its doubt of flag to be Non-Gaussian which serves to restore pictures with Non-Gaussian and also Gaussian course. Drawbacks of ICA based procedures when diverged from wavelet based techniques are the computational cost since it uses a sliding window and it requires trial of commotion free data or if nothing else two picture edges of a comparative scene. In a couple of utilizations, it might be difficult to procure the clamorfree getting readydata [5 - 7].

III. PROPOSED MODEL

A. *Proposed Algorithm*

Input image: Noisy image.

Output image: Denoised image.

Step 1: Apply 2D-DWT on the noisy image, I. Image I is transformed into four parts i.e. approximate-A, horizontal-H, vertical-V, and diagonal-D.

Step 2: Apply wiener filter (W) on (A) for proposed model 1, on (H) for proposed model 2, on (V) for proposed model 3 and on (D) for proposed model 4 using Eq. 1.5.

Step 3: Apply wavelet thresholding (WT) on (H), (V), and (D) for proposed model 1, on (A), (V), and (D) for proposed model 2, on (A), (H), and (D) for proposed model 3 and on (A), (H), and (V) for proposed model 4 using below steps:

- Noise variance estimation using Eq. 1.2.
- Threshold calculation using Eq. 1.1.
- Apply soft thresholding using Eq. 1.3 and 1.4.

Step 4: Apply IDWT on the enhanced A, H, V and D.

Step 5: The final outcome of IDWT is the denoised image.

B. *Proposed Models*

- *Proposed model 1*

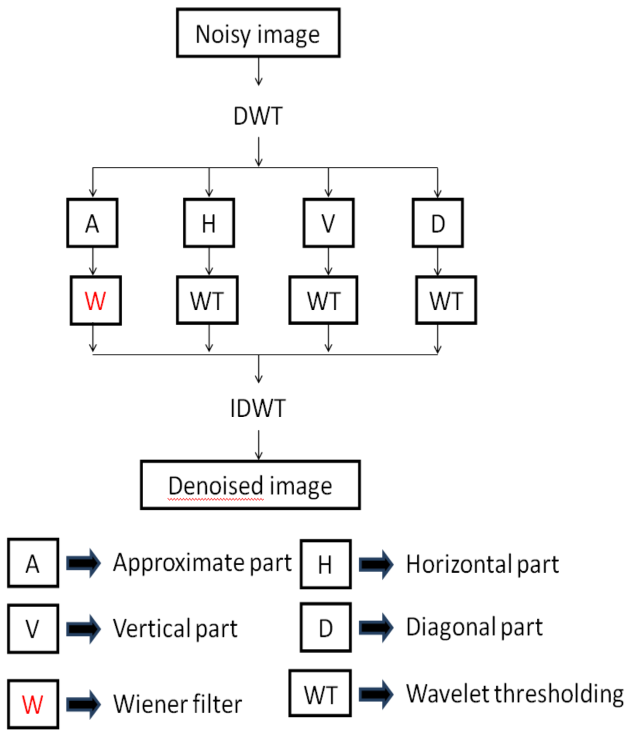


Fig 9:- Block diagram of proposed model 1

- *Proposed model 2*

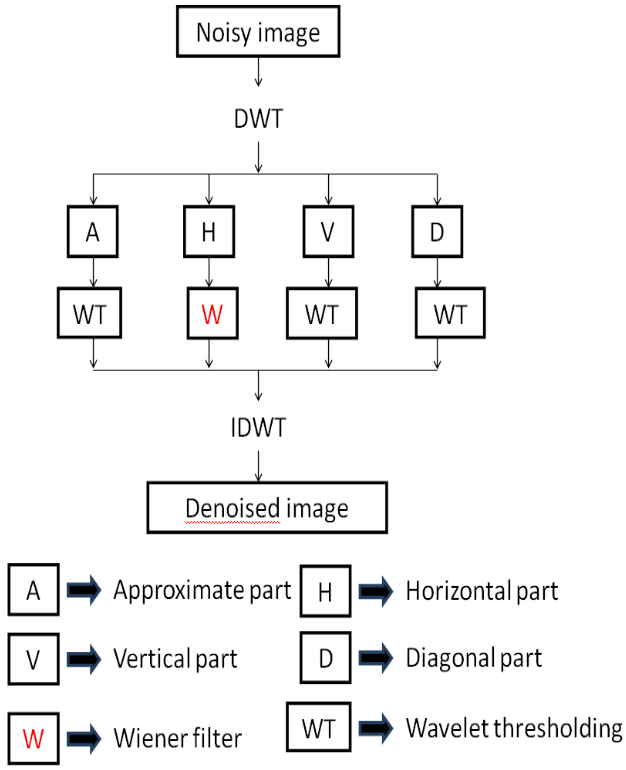


Fig 10:- Block diagram of proposed model 2

- *Proposed model 3*

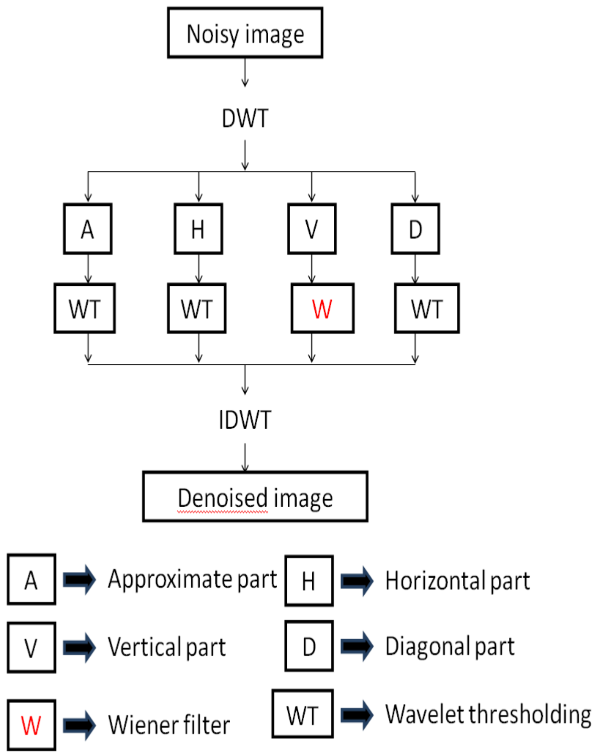


Fig 11:- Block diagram of proposed model 3

- *Proposed model 4*

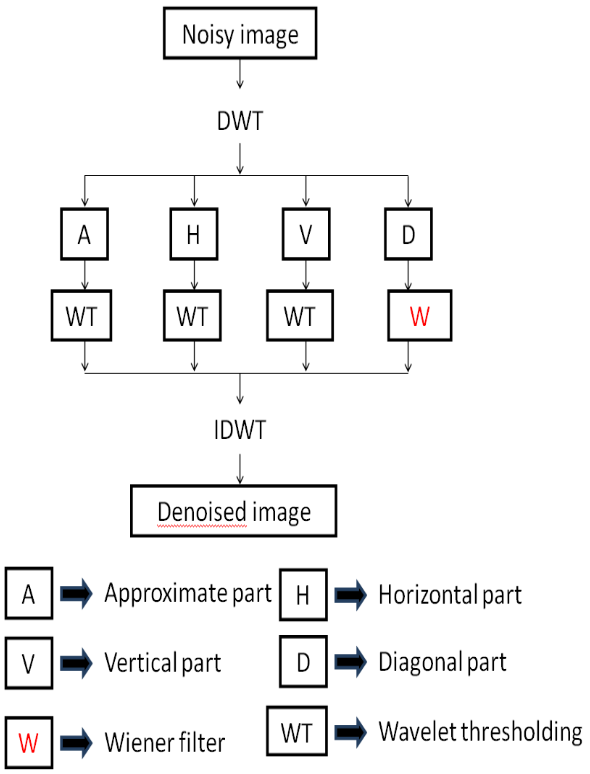


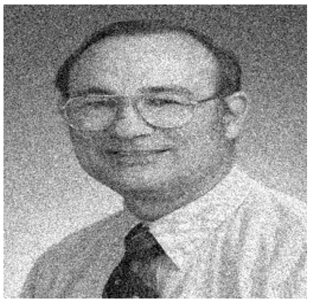
Fig 12:- Block diagram of proposed model 4

IV. RESULTS AND ANALYSIS

The experimental testing is performed on digital images. The proposed model is specifically designed for digital images. The parameters used for analysing the quality of denoised image are PSNR, SSIM and UIQI. The results are also analysed quantitatively, qualitatively and graphically. The experiment is conducted on several digital images but the results are shown on images in the Figure 13. The Figure 14. shows the noisy images over which the results are shown at noise variance (σ) = 20.

(a)

Fig 13:- Original Images

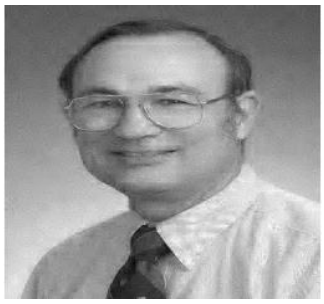


(a)

Fig 14:- Noisy images at σ = 20.

A. *Qualitative Analysis*

The Figure 15. shows the denoised images at the noise variance = 20. The denoised images are cleaner and smoother. The edges are well preserved and there is preservation of texture in the heterogeneous part of the image. There is bit of over smoothening can be observed in the denoised image as in the Figure 15. But the overall result of the proposed model 1 is better than other works. The Figure 15. shows the denoised results using proposed model 1.



(a)

Fig 15:- Denoised images using proposed model 1.

- *Quantiative Analysis*

The Table 1, 2, and 3 shows the quantitative analysis of the denoised image of the Figure 13. (a) using PSNR, SSIM, and UIQI. As per Table 1, 2, and 3, it can be observed that proposed model 1 shows the best results when the wiener filter is applied at the approximate part of the image. Apart from proposed model 1, the soft thresholding method also shows better results in terms of PSNR and SSIM. In terms of UIQI, the proposed model 1 shows the best results.

		PSNR				
Image	Noise Variance	4	10	20	30	40
Figure 13. (a)	Median filter	23.55	21.56	20.87	17.78	17.01
	Wiener filter	25.67	24.33	22.56	20.22	17.67
	Soft Thresholding	27.68	25.50	23.04	**21.10**	19.03
	Hard Thresholding	27.56	25.01	22.92	20.02	18.67
	Proposed model 1	**27.62**	**25.98**	**23.45**	21.03	**19.34**
	Proposed model 2	26.45	25.45	22.67	20.87	17.75
	Proposed model 3	26.64	24.64	23.60	19.80	18.54
	Proposed model 4	25.46	23.65	22.40	20.18	18.12

Table 1. PSNR of denoised images

		SSIM				
Image	Noise Variance	4	10	20	30	40
Figure 13. (a)	Median filter	0.79	0.77	0.73	0.71	0.67
	Wiener filter	0.82	0.79	0.75	0.71	0.70
	Soft thresholding	**0.88**	0.82	0.80	0.75	0.77
	Hard thresholding	0.85	0.81	0.75	0.76	0.71
	Proposed model 1	0.87	**0.85**	**0.81**	**0.80**	**0.79**
	Proposed model 2	0.81	0.78	0.77	0.74	0.71
	Proposed model 3	0.80	0.78	0.74	0.71	0.68
	Proposed model 4	0.79	0.77	0.71	0.67	0.65

Table 2. SSIM of denoised images

		UIQI				
Image	Noise Variance	4	10	20	30	40
Figure 13. (a)	Median filter	0.79	0.77	0.75	0.71	0.69
	Wiener filter	0.82	0.79	0.77	0.74	0.71
	Soft Thresholding	0.86	0.83	0.81	0.77	0.70
	Hard Thresholding	0.85	0.82	0.79	0.75	0.71
	Proposed model 1	**0.88**	**0.87**	**0.85**	**0.81**	**0.79**
	Proposed model 2	0.82	0.81	0.79	0.75	0.77
	Proposed model 3	0.81	0.79	0.77	0.75	0.74
	Proposed model 4	0.80	0.79	0.77	0.71	0.72

Table 3. UIQI of denoised images

B. Graphical Analysis

The Figure 16 to 4.18 graphically analyses the PSNR, SSIM and UIQI values of the denoised images at various noise variances for the better understanding and analysis of the denoising results.

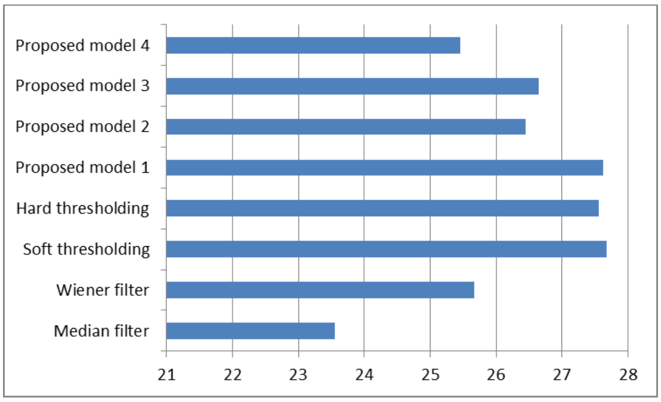


Fig 16:- PSNR of denoised image at σ = 4

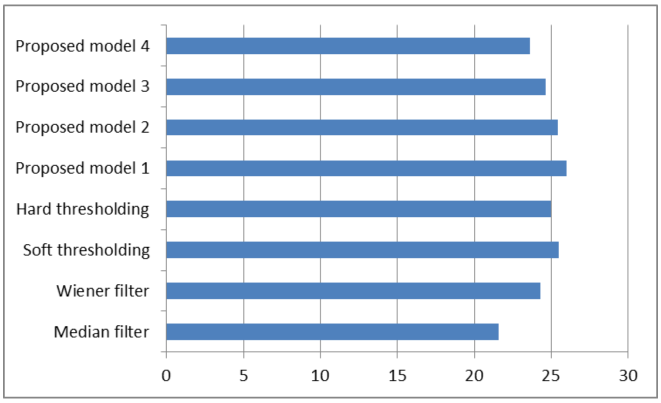


Fig 17:- PSNR of denoised image at σ = 10

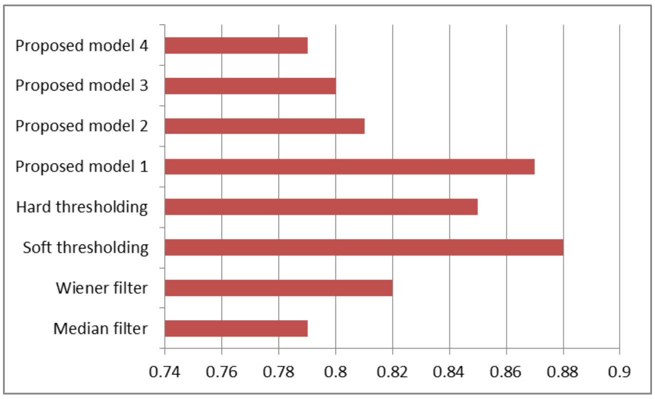


Fig 18:- SSIM of denoised image at σ = 4

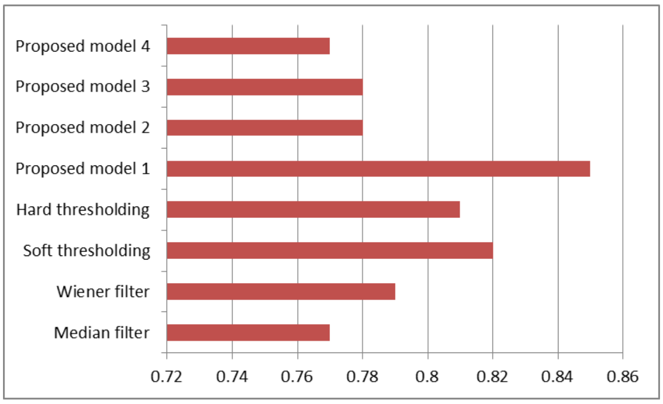


Fig 19:- SSIM of denoised image at σ = 10

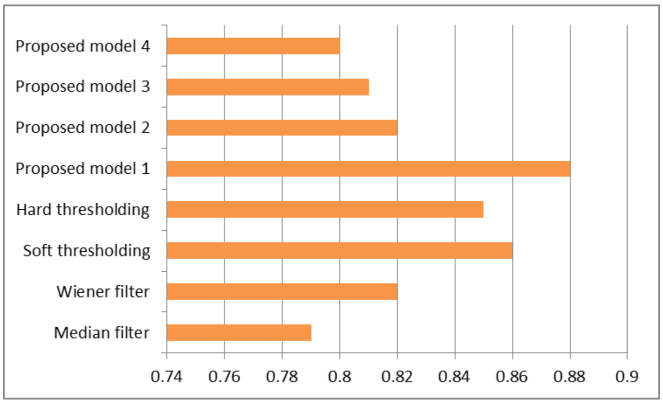


Fig 20:- UIQI of denoised image at σ = 4

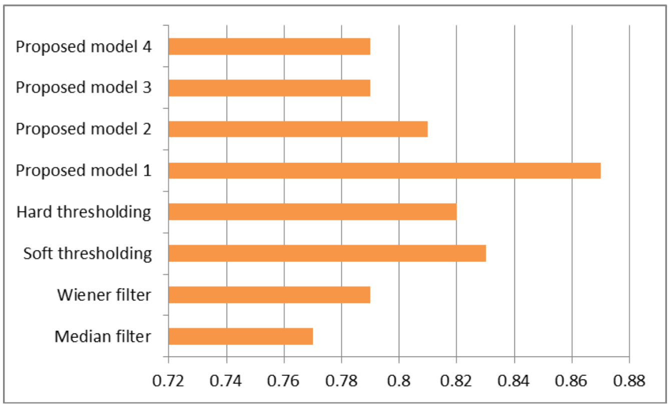


Fig 21:- UIQI of denoised image at σ = 10

V. CONCLUSION

This thesis proposed four denoising model for removal of noise from the digital image. The proposed model proposes four different uses of the wiener filter on the DWT. It is applied on each part one by one and in the rest part, the wavelet thresholding using modified Bayesian shrinkage rule is performed. Out of four proposed models, the proposed model 1 shows that the best results where the wiener filter is applied at the appropriate part of the images. It explains that the best use of any kind of filter in DWT is to apply at the approximate part of the image. The denoising results are compared with standard denoising methods and it is concluded that the proposed model 1 shows the best results in terms of PSNR, SSIM and UIQI.

VI. FUTURE SCOPE

There are various directions that can enhance the denoising result. A more enhanced and improved filter can be used. The concept of the method noise thresholding can enhance the denoising results. The field of image denoising is a never ending research field.

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