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Implementation of Pixel Likeness Weighted Frame (Plwf) Filter Technique Based Digital Image Denoising for DSP Applications

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ABSTRACT: ***Digital images are often corrupted by contaminated display and information quality noise. Images can be corrupted at any stage during which they are acquired and transmitted through the media. Image denoising is a basic function designed to eliminate noise from naturally corrupted images. This work proposes a fixed-point discrete wavelet transform (DWT) architecture that uses a nonlinearly modified pixel-like weighted frame (PLWF) technique to denoise the high-throughput of adaptive white Gaussian white noise (AWGN) images. The linearized state to be based on the neighboring pixel unity is that the state model noise is used to improve the peak signal to the sound rate (PSNR). The proposed architecture is employed in two different stages - consistent and conditional sorting output selection unit. The detailed result of the proposed architecture shows the size and display quality of any state-of-the-art performance and some recently introduced work. For further evaluation of the denoising capability, the algorithm is compared to some state-of-the-art algorithms and experimental results on simulated sound images and captured images of low-light noise especially large image processes Low noise light picked up by the test results. The performance of the proposed method is compared to wavelet thresholds, bilateral filters, non-local averaging filters, and bilateral multi-resolution filters. The study found that the draft production plan is smaller than the wavelet threshold, the bilateral filter, and the non-local means of filtering and larger superior/similar to the method, visual quality, PSNR and image index noise bilateral multi-resolution filter quality.***

Keywords: ***Discrete Wavelet Transform, Adaptive White Gaussian Noise, Pixel Likeness Weighted Frame, Peak Signal to Noise Ratio, denoising***

I. INTRODUCTION

Noise can be generated during image capture and broadcast operations. Impulse noise, Gaussian noise and balanced noise are three important noises. Impulse noise is shown in a random distribution of pixels of bright and dark noise. The only real factor in viewing this image is corruption, but it seriously affects the visual effect of the image. Therefore, impulse noise cancellation is very important for computer vision analysis and image processing.

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A linear operation from the addition of the noise n(X, Y) or the multiplication of the signal s(X, Y) is shown in Figure 1.. Once the damaged image w (x, y) is obtained, it is subjected to obtain the denoised image z (x, y) [1] using denoising technique. This work is different from the point of view of many denoising techniques and has noise diffusion to use linear or nonlinear filtering methods to reduce noise

Frequency intelligence details are easily confused with higher frequency noise and they are in the high frequency components of the image. Therefore, it is very important to effectively filter the image details and the random noise of the filter.

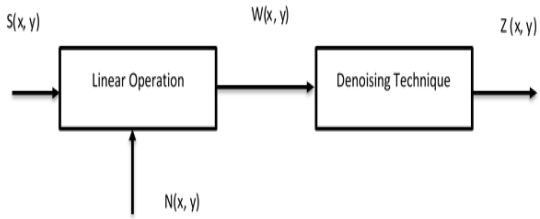

Figure 1. Image Denoising Concept

The median filter is a nonlinear filter that is widely used for digital image processing to reduce performance and impulse noise capacity because it has good characteristics of edging [2].The existing median and bilateral method are good for noise reduction effects but its complex time is not desirable. Therefore, a new image denoising algorithm using pixel pictographic weighted frame filtering techniques for noise removal has been introduced in this work. Based on the noise detection result, and the image selection pixel pictogram weighted frame filter, the algorithm adaptively eliminates impulsive blends in different fields. Using multiple simple classical filters, denoising conclusions on PLWF outputs are more than many states of art.

II. LITERATURE SURVEY

Image acquisition and transmission, noise is inevitable, reducing image quality, so denoising images is very important. The image denoising mechanism has been separated by the denoising outer domain noise reduction and frequency fields. The some of the existing filtering methods are wiener filter, median filter, mean filter, Fourier transform, Laplace transforms, and wavelet transforms [3-5]. he series of wavelet multi-scale tools are based on ripple theory to filter out effective such as curve let [6], direction let [7], let the noise in [8], and shear wave [9].In recent years different types of denoising methods are developed such as Non-local Average denoising [10], in [11] discuss the Gaussian mixture Model denoising, in [12]

discuss the dictionary learning denoising [12] and sparse representation based denoising is presented at [13]. In addition, K-singular value decomposition (K-SVD) [15] is the most widely used for image denoising, and the K-SVD is basically a sparse based representation of noise reduction method, which is apparently in [16, 17]. However, the iteration of K-SVD is dealing with large data. So the K-SVD algorithm, which not only breaks that sparse coefficient structure, but also overcomes the imperfections of learning simple dictionaries, Can be applied to a variety of sparse representations [18] with less complexity and fast computational capacity [19-20].

Currently, many image denoising mechanisms have gone from standard noise distortion [21-22], but it is usually not known in practice. Therefore, the noise level is created in the noise reduction community [23]. The Bayesian compression algorithm [25] is used to determine the autocorrelation analysis activity in the Denoise and the standard noise distortion range to find the right value. Usually the Bayesian algorithm noise distribution consists of a sideband filter [26], in this sideband filter has been divided into two types [27-29].

However, most of the above mentioned algorithms seem to be the image uniform, in [30-31] discuss the PCA noise estimation based on the data patch ,The standard noise distortion image attachment is calculated as a minimum eigenvalue with patch covariance matrix. The results show that the system has the problems of all of the above techniques for image denoising. So another mobile strategy has already predicted this research. This work reveals how to find image denoising in different ways. In this work, instead of proposing a merger is collecting new request strategies correctly than ever before.

III. MATERIALS AND METHOD

In several sensible cases of image methodology, complete a full image is available. This circumstance is thought as results of the blind condition. Many de-noising ways generally require a precise of noise supply as a required filter parameter. Therefore, the noise estimation within the domain is to use the r variance to rate the noise distribution specified in the prediction ways. However, it can be found that the median mean deviation variant or noise transfer gives more results than estimating the noise variance. Therefore, in this research work, a pixel-like weighted frame filter (PLWF) technique is proposed to improve image denoising performance.

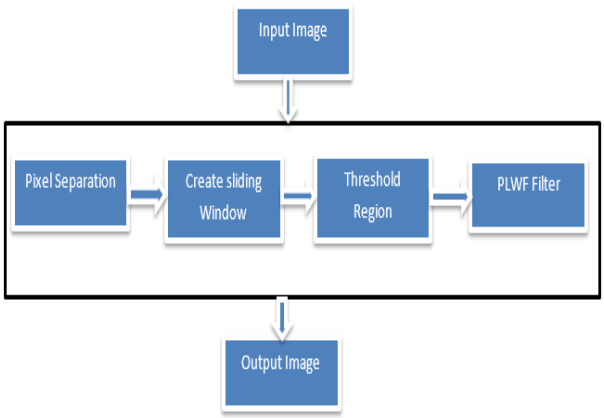

Figure.1.Block Diagram of Proposed system

The block diagram of a proposed method is shown in Figure.1, it comprises three states like pixel separation, sliding window creation, and filtering. The standard deviation has emphasized a great difference. The more significant the faster squaring values are the average distance between each unit. The big difference will cause below to calculate the over or below estimation noise. The average perfection can make a lot of computation and therefore the average difference is the use of this area. Keeping this perspective, researchers have used voice coding to make the choice of a pixel optical filter, and in the pixel peak it's been supplanted as opposed to supposition.

3.1 PIXEL LIKENESS WEIGHTED FRAME FILTER (PLWF) ALGORITHM

A filter called Pixel Likeness Weighted Frame Filter (PLWF) is developed to suppress the Gaussian noise effectively. In this first filter, locate a local Pixel Difference (LPD) by pixel values near the value of the pixel and also calculate the weight of every pixel has been connected to LPD. The filtered value is the order in which the original pixel values of the pixels are assigned to each current pixel. The noise reduction in pixels is observed at the optimal weight for the noise value with the current pixel, such as a PLWF filter solution. Thanks to the PLWF filter, both the high pass and low pass filter gain effects. The noise variance of the filter is effectively reduced, with all of its neighbors behaving like a low pass filter to smooth the area by giving equal weights to the pixels. This, in turn, replaces only the high frequency noise signal in place of all noise signals.

3.2 PIXEL LIKENESS WEIGHTED FRAME FILTER (PLWF) ALGORITHM FOR DENOISING

The first step in the PLWF method is to find out if the B_{ij} noise pixel value is input noise or not. As shown in Figure 2, the noise reduction is done by the denoising model. The adjacent pixels are $B_i - 1j, B_i + 1, j, B_i j - 1$, $B_i j + 1$,, that is, after the pixel values of the current pixel B_{ij} of the past wavelet frame are compared with the pixels in parallel P_{ij}

	P_{ij}	

a) Wavelet Frame

	$B_i j - 1$	
$B_i - 1j$	B_{ij}	$B_i + 1j$
	$B_i j + 1$	

b) PLWF Frame

Figure 2. Deduction of denoising

The connection between the noise pixel value B_{ij} and the original pixel value will be reflected by the LPD. This correlation between the pixel differences of corrupted pixels is small, and any filtered values are assigned to each current pixel in the f_{ij} command assuming that the original pixel's original pixel values are adjacent.

The noise pixel value for each uncorrupted pixel is added to the height of the original pixel value. In this case, the filtered value f_{ij} has been generated with a low LPD and a weighted mean squared error (WMSE), and equation (4) is used to calculate the WMSE. The following equations (1) and (2) are used to calculate the weight of W_{ij} for each pixel.

$$W_{ij} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i)\,[|P_{ij}-B_{ij}|]*f_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i)\,[|P_{ij}-B_{ij}|]} \ldots (1)$$

Where

$$g(i) = \begin{cases} 2^{\left(\left[\frac{T}{8}-\frac{i}{8}\right]\right)} & i<T \\ 0 & else \end{cases} \ldots (2)$$

P_{ij} = Current pixel value

B_{ij} = Noisy pixel value

f_{ij}= Filtered value.

PLWF is obtained from the filtered solution equation (5), which is observed with the noise value of the current pixel, which reduces noise. Thanks to the PLWF filter, both the high pass and low pass filter gain effects. In the smooth region, the filter effectively reduces the noise variance with all its neighbors by giving equal weights. Therefore, in this region, the proposed filter maintains the same behavior and edge information of the low pass filter. In high-texture areas, the current pixel using edge information exploits the pixel value difference between this filter and its LPD. Due to this advantage, the PLWF filter attenuates the characteristics of the discontinuous high channel and the intensity of the edge is maintained by the pixel assigning a small weight. In addition, it reduces all noise signals, not high frequency signals. From the quantitative measurements given in the image, the value PSNR is obtained from the equation. (3), at least using WMSE

$$PSNR = 10log_{10}\left[\frac{255^2}{WMSE}\right]dB \ldots (3)$$

$$Minimize\ WMSE = \sum_{i=1}^{M}\sum_{i=1}^{N} W_{ij}(B_{ij}-Y_{ij})^2 \ldots (4)$$

Where Y_{ij} is the PLWF filter solution given by the following equation.

$$Y_{ij} = \frac{\sum_{i=1}^{M}\sum_{i=1}^{N} W_{ij}B_{ij}}{\sum_{i=1}^{M}\sum_{i=1}^{N} W_{ij}} \ldots (5)$$

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3.3 PIXEL LIKENESS WEIGHTED FRAME FILTER STEPS

Input: Pixel value B_{ij}

Output: Denoised pixel B_{ij}

1. The current pixel value of B_{ij} comparison is adjacent to pixels b $b_i - 1j, B_i + 1j, B_{ij} - 1$, $B_{ij} + 1$ and co-located pixel P_{ij} in the previous wavelet frame.
2. Calculate the threshold $T = \sigma\sqrt{2(logn^2)}$, Where σ is the noise variance of the contaminated picture which can be calculated using $\sigma^2 = \frac{PLWF(|X_{ij}|)}{0.6745}$, B_{ji} belongs to each sub band
3. All differences between B_{ij} and $B_i - 1j, B_i + 1j, B_{ij} - 1$, $B_{ij} + 1$ are more than T, then noise marked as corrupt pixel B_{ij}
4. Calculate the filter value defined by B_{ij} for each filter value f_{ij}

$$f_{ij} = \frac{B_i-1j+B_i+1j+B_{ij}-1+B_{ij}+1}{4}$$

5. B_{ij} is related to the noise pixel value between your original pixel values. If it is small, then its filter value f_{ij} is assigned
6. By using the calculated weight W_{ij} for each pixel

$$W_{ij} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i)\,\left[\left|P_{ij}-B_{ij}\right|\right]*f_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i)\,\left[\left|P_{ij}-B_{ij}\right|\right]}$$

Where

M and N = Width and height of the image B_{ij} and $g(i) = \begin{cases} 2^{\left(\left[\frac{T}{8}-\frac{i}{8}\right]\right)} & i<T \\ 0 & else \end{cases}$

P_{ij} = Current pixel value

B_{ij} = Noisy pixel value

f_{ij}= Filtered value.

7. The LPD value is reduced using a least squares method f_{ij} to produce a filtered value.
8. Minimizing WMSE for generating filtered values, where

$$WMSE = \sum_{i=1}^{M}\sum_{i=1}^{N} W_{ij}(B_{ij}-Y_{ij})^2$$

9. Calculate PLWF Filtration Solution by Using Equation (6)

$$Y_{ij} = \frac{\sum_{i=1}^{M}\sum_{i=1}^{N} W_{ij}B_{ij}}{\sum_{i=1}^{M}\sum_{i=1}^{N} W_{ij}} \text{ and } PSNR = 10log_{10}\left[\frac{255^2}{WMSE}\right] \ldots (6)$$

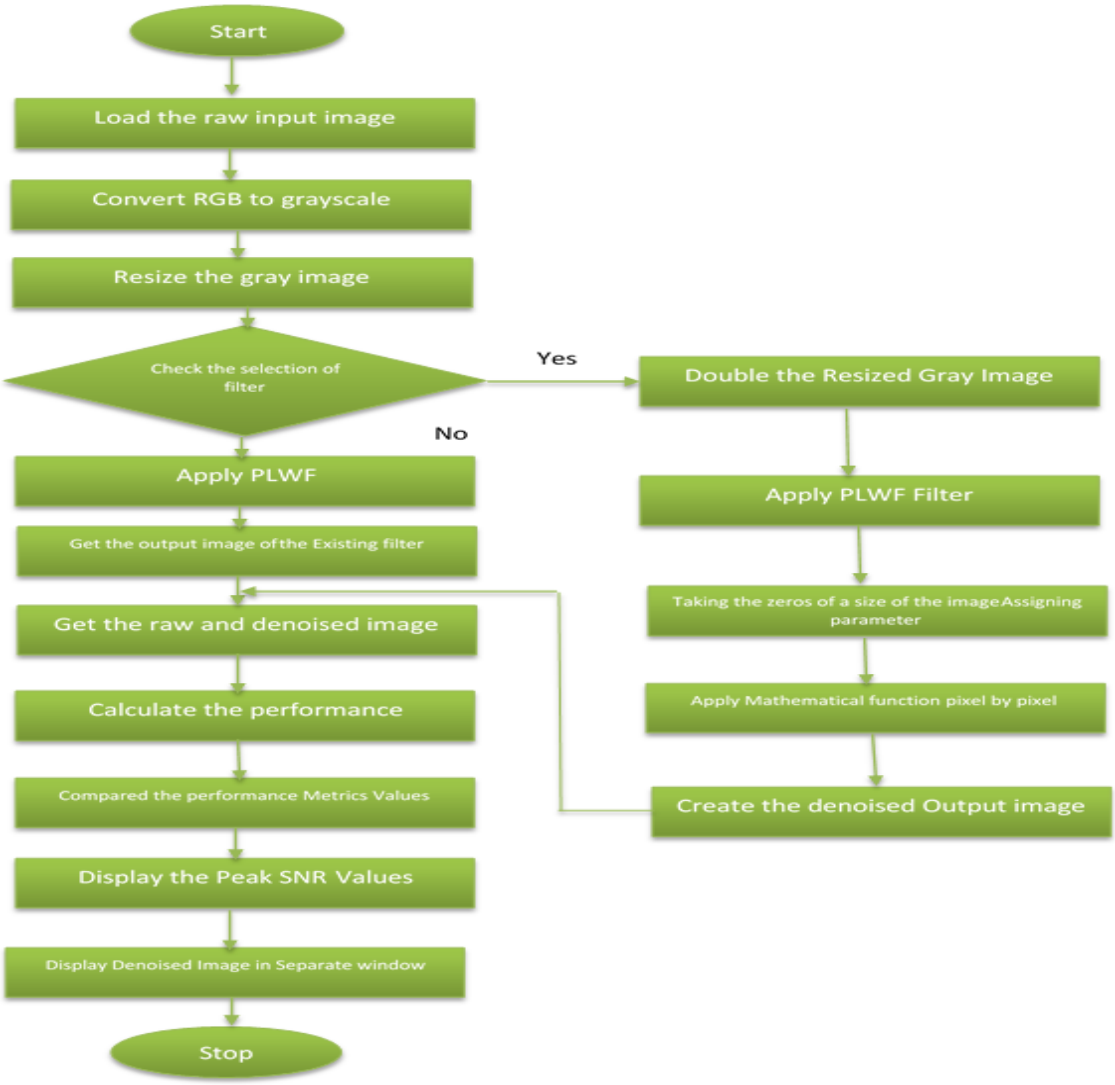

Figure2: Flowchart of the proposed system

The figure above shows a flow chart of the proposed system. In addition, it is obvious that the details of the image are presumed in the case of rules, within the preservation and distinction, so the level, so far, better countermeasures.

IV. RESULTS AND DISCUSSION

The performance evaluation of the proposed noise reduction technique and the existing denoising method are discussed in this section. All simulations were completed at MATLAB 2017A and the draft production plan was found to be superior to the existing noise reduction techniques for noise, MSE, PSNR and correlation coefficients.

Table 1: Details on Dataset

Parameter	Data Set	No of images	Tool Used
Details	Natural images and raw images	100	Matlab 2017 a.

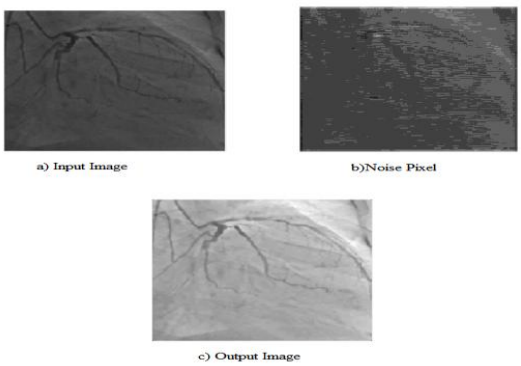

Figure. 3. Simulation results of Coronary heart image

The simulation results of the coronary heart image suggesting pixel-like weighted frame (PLWF) techniques are shown in Figure 3. The denoising method proposed here has advantages over other visual qualities and is shown in figure.3.

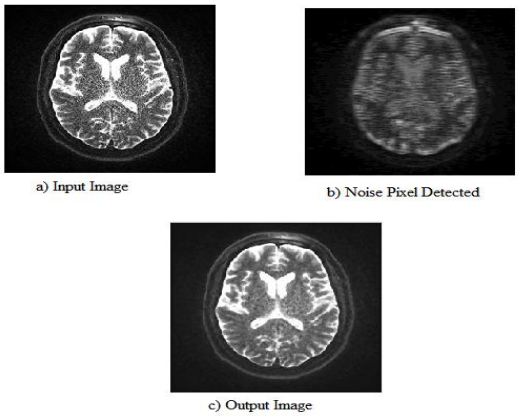

Figure. 4. Simulation results of MRI Brain image

The simulation results of the proposed MRI brain image of the pixel pictogram weighted frame (PLWF) technique are shown in figure.4. The denoising method proposed here has better visual quality than others and is shown in figure.4.

Table 2: Performance Metrics of MSE in Image De-noising Implementations in Coronary heart image

Noise level	MSE			
	DCT	**DWT**	**IPC**	**PLWF**
10%	0.0255	0.0240	0.0226	0.0215
20%	0.0407	0.0373	0.0358	0.0341
30%	0.0542	0.0517	0.0504	0.0490
40%	0.0685	0.0674	0.0659	0.0517
50%	0.0825	0.0813	0.0800	0.0745
60%	0.0967	0.0993	0.0977	0.0943
70%	0.1124	0.1129	0.1114	0.1010
80%	0.1268	0.1251	0.1236	0.1018
90%	0.1450	0.1417	0.1402	0.1432

Table 2 shows the comparison features - parameters as follows for the MSE values of the various noise levels of the photographer image. In this proposed PLWF denoising method has better visual quality than another conventional method against MSE. To evaluate the accuracy of order noise reduction and expansion protection, the criteria for image quality evaluation are necessary.

The criteria chosen in this work is PSNR and MSE can be used to find image quality and filter performance. The lower the value of MSE, the lower the error. The PSNR can be calculated using the following formula

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (7)$$

Where,

$$MSE = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N} \quad (8)$$

M and N = number of rows and columns in the original image R = Maximum fluctuation in the input image data type.

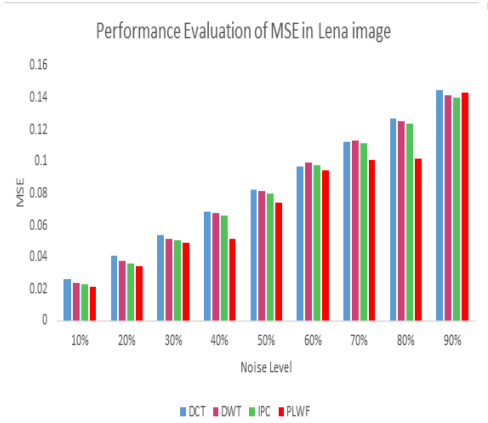

Figure 5.Performance Evaluation of PSNR in Coronary heart Images

T Table 2 and Figure 5.5 show comparative features - parameters such as MSE values for different methods at various noise levels. In this proposed denoising method has better visual quality than , for example, the proposed PLWF method achieve the best result of 0.1432 against 90% noise level and 0.0215 against 10% of the noise level.

Table 3. Performance Evaluation of PSNR in Lean Image

Noise level	PSNR			
	DCT	**DWT**	**IPC**	**PLWF**
10%	42.3985	42.4668	46.4668	48.62
20%	40.0847	42.4210	44.4210	45.63
30%	38.8475	40.9640	42.9640	44.51
40%	37.7734	39.7824	41.7824	43.23
50%	36.7083	38.8617	40.8617	42.15
60%	36.0803	38.2725	40.2725	43.12
70%	34.5792	36.5408	39.5408	41.02
80%	34.9765	36.1228	39.1228	410.3
90%	34.5502	36.5558	38.5558	40.15

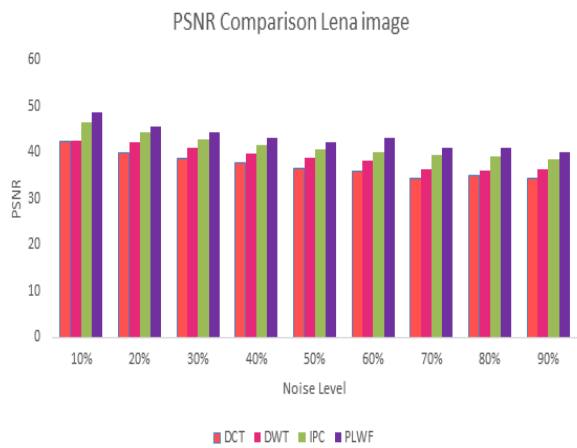

Figure 6. Comparison of PSNR performance under different noise densities of coronary heart images

Table 3 and Figure 6 show comparative features - parameters such as PSNR values at various noise levels. In this proposed denoising method has better visual quality than another conventional method, for example, the proposed PLWF method achieve the best result of 40.15 against 90% noise level and 48.62 against 10% of the noise level.

Table 4: Smoothing Index against Coronary heart Image

Tested Image with Noise Ratio	Original	Stabilized	Increased
MRI BRAIN+ 90%	6.906	15.6108	8.7048
MRI BRAIN+ 80%	8.841	10.9184796	2.0774796
MRI BRAIN+ 70%	11.69	14.920128	3.230128

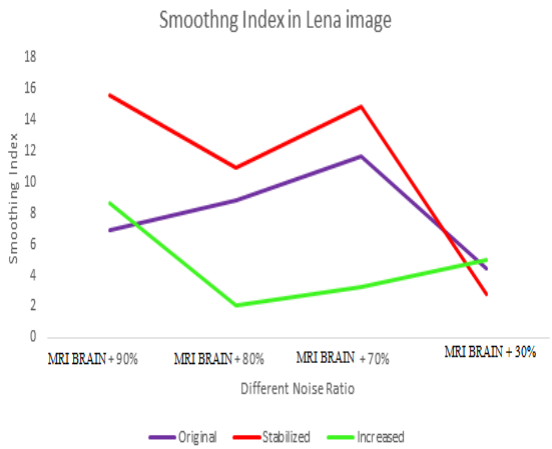

Figure.7 Smoothing Index Analysis in Coronary heart Image

The above table 4 and Figure 7 depicted the smoothing index measure for proposed digital denoising system against different noise ratio in Coronary heart image, as compared with the result of original smoothing index the stabilized smoothing index value was high. Therefore, the denoised images using the PLWF algorithm appear smoother and more comfortable for viewing.

Table 5: MSE performance indicators for image denoising of MRI brain images

Noise level	*MSE*			
	DCT	**DWT**	**IPC**	**PLWF**
10%	0.0356	0.0341	0.03102	0.0290
20%	0.0456	0.0396	0.0342	0.0310
30%	0.0569	0.0520	0.0490	0.0454
40%	0.0690	0.0671	0.0571	0.0501
50%	0.0912	0.0871	0.0789	0.0710
60%	0.0998	0.0961	0.0940	0.0892
70%	0.1135	0.1129	0.1012	0.0946
80%	0.1360	0.1251	0.1017	0.0912
90%	0.1561	0.1502	0.1402	0.1120

Table 5 shows the comparison features - the parameters of the MSE values of the various noise levels of the MRI image as follows. In this proposed PLWF denoising method has better visual quality than another conventional method against MSE.

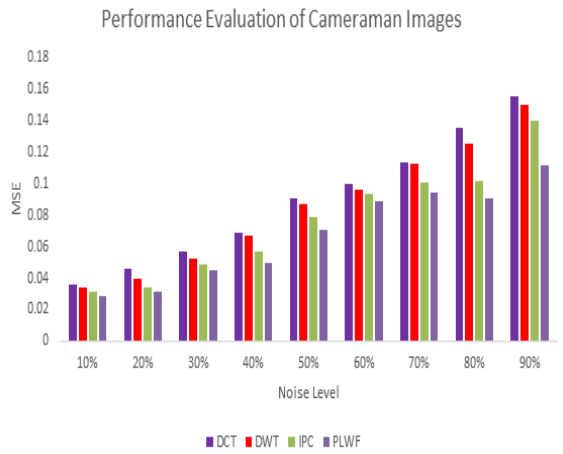

Figure 8 Performance Evaluation of PSNR in camera Images

Table 5 and Figure 8. Show comparative features - parameters such as MSE values for brain MRI images in different ways of noise levels. In this proposed denoising method has better visual quality than , for example, the proposed PLWF method achieve the best result of 0.1120 against 90% noise level and 0.0290 against 10% of the noise level.

Table 6. Performance Evaluation of PSNR in MRI Brain Image

Noise level	*PSNR*			
	DCT	DWT	IPC	PLWF
10%	41.230	42.532	44.064	45.584
20%	40.301	41.603	42.163	43.683
30%	38.632	39.934	40.494	42.014
40%	38.023	39.325	39.885	41.405
50%	37.861	39.163	39.723	41.243
60%	36.245	37.547	38.107	39.627
70%	35.021	36.323	36.883	38.403
80%	34.860	36.162	36.722	38.242
90%	34.190	35.412	36.052	37.572

Table 6 shows the comparison of feature-parameters, such as method PSNR values at various noise levels. In this proposed denoising method has better visual quality than another conventional method.

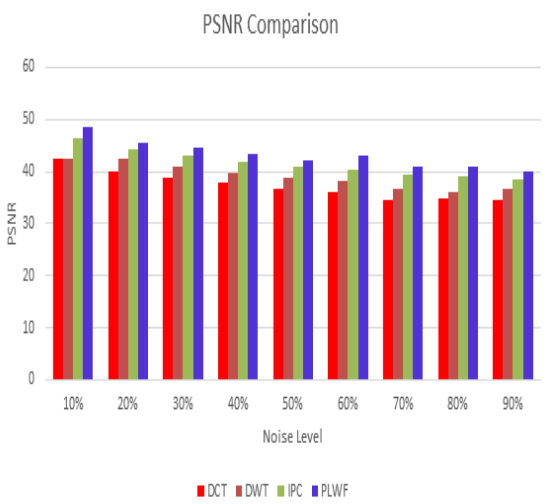

Figure 9 Comparison of PSNR performance in under different noise densities of brain MRI images

Table 6 and Figure 9 shows comparative features - parameters such as PSNR values at various noise levels. In this proposed denoising method has better visual quality than , for example, the proposed PLWF method achieve the best result of 37.572 against 90% noise level and 45.584 against 10% of the noise level.

Table 7. Smoothing Index against MRI Brain Image

Tested Image with Noise Ratio	Original	Stabilized	Increased
Cameraman + 90%	6.906	15.6108	8.7048
Cameraman+ 80%	8.841	10.9184796	2.0774796
Cameraman + 70%	11.69	14.920128	3.230128

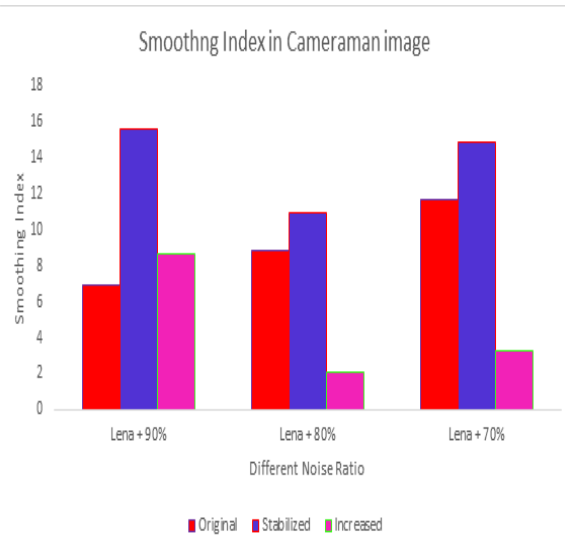

Figure.10 Smoothing Index in MRI Brain Image

The above table 7 and Figure 10 depicted the smoothing index measure for proposed digital denoising system against different noise ratio in MRI Brain image, as compared with the result of original smoothing index the stabilized smoothing index value was high. Therefore, the denoised images using the PLWF algorithm appear smoother and more comfortable for viewing.

V. CONCLUSION

In this research work, modified Pixel Likeness Weighted Frame (PLWF) technique based wavelet thresholding method is proposed for image denoising. The thresholding method of the image denoising method based on wavelet transform is applied to estimate each image based on or based on each subband of the image. The traditional threshold method estimates each subband independently. The existing threshold proposed in this research work guarantees the optimal level of wavelet decomposition and finds an extension of the marginal correction at this threshold. Within a prescribed range, the threshold is varied, and the respective decomposition level of the wavelet is also sought based on a weighting method of the pixel representation of the frame.

PLWF has been used to very efficiently search for values such as optimal thresholds and decomposition levels for wavelet parameters, as these two are the most important parameters of wavelet denoising techniques. In addition to other algorithms, such as DCT, DWT, IPC and the proposed PLWF-based threshold processing techniques have also been implemented with algorithms. The results obtained show that the proposed method effectively suppresses Gaussian noise with low, medium and high density. Experimental results show that the new threshold method based on wavelet transform produces better recovery results in terms of signal-to-noise ratio and visual effects.

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