Efficient Noise Removal Based on Non-Local Means Filter and Its Method Noise Wavelet Packet Thresholding

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Abstract— Image denoising includes operation of the image data to yield a visually high quality image and a major process in image processing, pattern recognition, and computer vision fields. The chief aim of image denoising is to re-establish the original image from a noisy image and help the other system (or human) to understand it well. Even though introduces many methods there only reduced visual quality, causing blurring and artifacts in the image. In this project, uses a new technique called wavelet packet transform and adaptive wavelet thresholding to denoise the image and improve visual quality. wavelets based denoising method consist of three steps namely, first to compute the wavelet packet transform, the next step to Remove noise from wavelet coefficients using wavelet packet thresholding and the third step is to reconstruct the enhanced image using inverse wavelet packet transform. Unlike standard wavelet-based methods Wavelet packet transform (WPT) used for image decomposition. The proposed method namely, Fast OWB extraction is a new adaptive thresholding function introduced to improve the denoising efficiency. Hence chooses an adaptive threshold value which is level and subband dependent based on analyzing the sub band coefficients. Estimation of dominant coefficients based on Maximum a posteriori (MAP) estimate to enhance or eliminate the wavelet coefficients. The resultant method yields better peak signal noise ratio with visual image quality measured by universal image quality index compared to standard denoising methods.

Key words: Non-Local Means Filter, Method Noise, Wavelet Packet Thresholding, Bayesshink, Wavelet Packet Transform, Image Quality Index.

I. INTRODUCTION

A primary strategy for communication in the advanced age is transmission of visual data as digital images however the image accomplished after transmission is regularly ruined with noise. The received image needs processing before it used as a part of any applications. Image denoising includes the control of the image information to create a visually high quality image. Image denoising used as a part in the field of photography or publishing where an image some another corrupted needs to enhance before it can print. Wavelet denoising used to eliminate the noise introduced in the image while protecting the image features respect to its frequency content. Wavelet thresholding (shrinking) algorithm was presented by Donoho in 1995 as an intense tool in denoising image degraded by additive white noise. (1)

For original signal many denoising strategies and methodologies (2-13) devise a model for the noise in a suitable subspace where the contrasts between them highlighted taking into account the accompanying observations:(a) the noise and clean signal show distinctive practices in multi-resolution representation, (b) noteworthy geometrical parts of an image (edges) or time structures of a signal (sharp transitions) over-exceed noise data, particularly at low resolutions (14).

For a while, classical signal processing amassed basically in the qualities of signals and on the designing of the time-invariant and space-invariant operator that adjust stationery signal properties. At the same time, the biggest measure of data focused on transients in stationary signals.

As of late, proposed anon-local means (NL means) filter which efficiently uses all the possible self-expectations the image can offer and similarity of local patches to focus the pixel weights. As the patch size decreases to one pixel, the NL means filter gets equal to the BF. The earlier method better cleans the edges without losing an excess of fine structures and details while the later loses details and makes abnormalities on the edges. Further augment the work by controlling the area of every pixel adaptive. All these denoising strategies function admirably with less noise (high SNR) yet neglect to do as such with more noise (low SNR). As both the target pixel and the similar local patches which used to discover the pixel weights are noisy, the estimate of NL means filter gets biased. To cater for this issue of noisy target pixel, adaption of central kernel weight (AKW) to the degree of noise proposed. At the same time, this does not deal with the comparative noisy local patches and particularly at higher noise; the biased estimate degrades/blurs the image by removing a significant part of the image details. To find these issues, an amalgamation of NL means filtering and its method noise thresholding using wavelets proposed for image denoising.

In the literature, a few methods for determination of threshold values and new thresholding systems including fuzzy logic, neural networks, and wavelet packet (WP) reported using Wiener filtering. Researchers may abuse diverse sorts of methods to further enhance denoising.

WP transform (WPT) implemented alongside optimal wavelet basis (OWB) for image decomposition demonstrated in Fig. 1. At that point, for every wavelet sub band, an adaptive threshold value assessed taking into account on analyzing the sub band's statistical parameters.

The proposed algorithm of the denoised image both having low mean square lapse (MSE) and improved Signal quality. Wavelet transform has wide acknowledgement as an important tool for common signal and image processing tasks in light of the way that the wavelets are localized in both time and frequency domains.

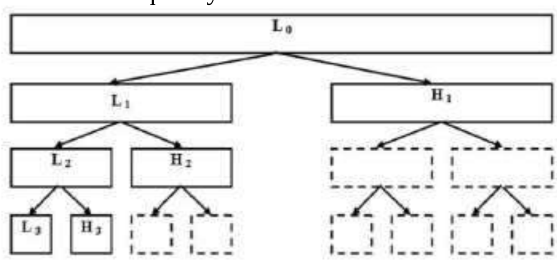

Fig. 1. WP decomposition.

II. NL MEANS FILTER

The goal of image denoising is to remove the noise while holding the imperative image features like edges, details however much as could reasonably be expected. Linear filter convolve the image with a steady matrix to acquire a linear combination of neighbor-hood values and generally used for noise elimination as a part in vicinity of additive noise. This creates a blurred and smoothed image with poor feature localization and inadequate noise suppression.

The issue with these filters is that contrasting just gray level values around a given pixel is not all that robust when these values are noisy. Further, the Neighborhood filters make artificial shocks. In a decade ago stretched out neighborhood filters to a more extensive class which they called it as non-local means (NL means). This is with the supposition that the image has a broad measure of self-likeness and is used to discover the pixel weights for filtering the noisy image. The most similar pixels to a given pixel have no reason near to it. Think about the periodic patterns or the lengthened edges which show up in many images. It is there-fore licit to scan an inconceivable part of the image looking for all the pixels that really resemble the pixel denoised. The similarity assessed by looking at an entire window around every pixel, not simply the pixel value. Denoising is then done by processing the average gray value of these most taking after pixels. Since the image pixels are exceptionally correlated while noise is ordinarily independently and undistinguishable distributed, averaging of these pixels results about noise cancellation and yields a pixel that is like its original value.

III. WP AND OWB

In wavelet packet transform, the optimal basis of the input signal chosen by optimizing a capacity known as "cost function" in every sub band. The cost functions will focus the cost value for every node and its children node in the obtained full binary tree. The algorithm begins with evaluating the cost values from the deepest level nodes. On the off-chance that the sum of the cost values for two children nodes is lower than the cost estimation of their parent node, then the children's acknowledged, else, they eliminated.

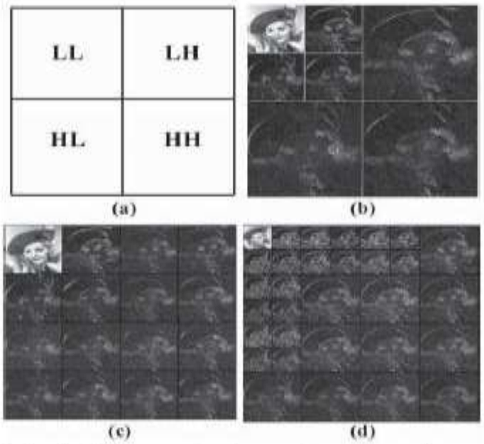

Fig. 2. Results of different wavelet decompositions. (a) Image decomposition scheme. (b) Traditional DWT. (c) WP decomposition. (d) Obtained OWB.

IV. METHOD NOISE AND THRESHOLDING

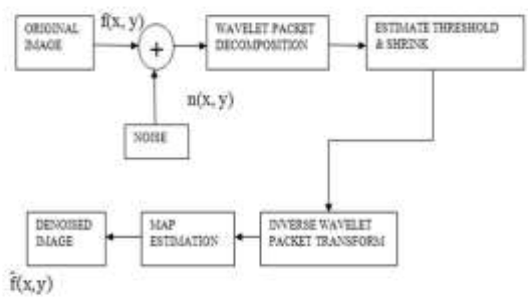

Fig. 3: Proposed Image Denoising Frame Work

Fig.3 demonstrates the proposed technique for Denoising. Application of NL means filter on the noisy image removes the noise and cleans the edges without losing an excess of fine structures and details. Despite that the NL means filter is exceptionally successful in removing the noise at high SNR (with less noise) however as the noise builds, its execution break down. This is because the similar patches used to discover the pixel weights are additionally noisy. To capture what removed from the noisy image by the NL means filter, the meaning of the method noise re-imagined as the distinction between the noisy image and its denoised image.

$$MN = I - I_F \tag{1}$$

Where $I = A + Z$ a noisy image obtained by corrupting the original image A by a white Gaussian noise Z and I_F is the output of NL means filter for an input image I .

At low SNR, the NL means filter not only removes the noise but at the same time it blurs the image thereby removing much of the image details. Consequently, the method noise will consists of noise as well as image details along with some edges. Hence, the method noise MN can be considered as a combination of image details D and a white Gaussian noise N and is written as

$$MN = D + N \tag{2}$$

Now the problem is to estimate the detail image D , which has only the original image features and edges/sharp boundaries that are removed by NL means filter, as accurately as possible according to some criteria and is added with the NL means filtered image I_F to get better denoised image with details. In wavelet domain, can be represented as

$$Y = W + N_W \tag{3}$$

Where Y is the noisy wavelet coefficient (method noise), W is the true wavelet coefficient (detail image) and N_W is independent Gaussian noise.

In wavelet domain, the goal is to estimate the true wavelet coefficient W from Y by thres holding Y with a proper value of threshold which minimizes MSE so that it can retain the original image features and edges or sharp boundaries very well in the final denoised image. The estimate of the true wavelet coefficient is represented as W and its wavelet reconstruction gives an estimate of detail image D . The summation of this detail image D with the

NL means filtered image I_F give the denoised image B, certainly have more image details and edges as compared with NL means filtered image I_F.

The wavelet thresholding adds energy to the proposed technique as noise components eliminated better in detail sub-bands of method noise. The adaptive method for selecting a threshold developed by Donoho and Johnstone minimizes the Stein unbiased risk estimator (SURE) which has been known as the SureShrink wavelet thresholding method. The adaptivity of SureShrink accomplish by picking distinct thresholds for every sub-band of every level of the wavelet tree using an effective recursive procedure. In a decade ago, there has been a fair amount of research on threshold value choice for image denoising. Among them, proposed a BayesShrink technique which infers a threshold in a Bayesian system expecting a generalized Gaussian distribution for the wavelet coefficients. This system has a superior MSE performance than SureShrink, and henceforth, it is used as a part of the proposed strategy to threshold the method noise wavelet coefficients.

BayesShrink is likewise an adaptive, data-driven thresholding method through soft-thresholding which infers the threshold in a Bayesian system, accepting a generalized Gaussian distribution. This method is adaptive to every sub-band because it relies upon data-driven estimates of the parameters.

V. RESULTS AND DISCUSSION

The performance of the proposed image denoising algorithm calculated using quantitative performance measures such as peak signal noise ratio (PSNR) using universal image quality index. The PSNR is given by

$$PSNR(X,\hat{X}) = 10\log_{10}\left(\frac{255^2}{MSE}\right)dB \quad (4)$$

Where X *is* the original image and $\hat{X}$ *is* the denoised image and the MSE between the original and denoised images is given as,

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X(i,j) - \hat{X}(i,j))^2 \quad (5)$$

Where, M and N are the width and height of the image. Experiments were carried out on various standard grayscale images of size 512 × 512 which are shown in Fig.4. The input images are corrupted by a simulated Gaussian white noise with zero mean and five different standard deviations $\sigma \in [10, 20, 30]$. The denoising process has been performed on these five noisy realizations. In these experiments, images contaminated by Gaussian white noise at different standard deviations $\sigma = 5, 10, 15, 20, 30$ used. Daubechies wavelet with eight vanishing moments (Db8) is used to decompose the input image into wavelet levels shown in Fig.5.

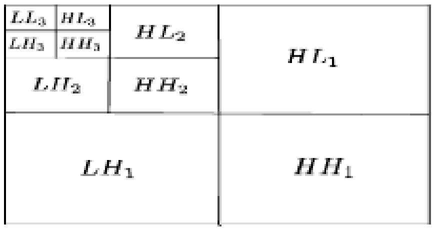

Fig. 5: Schematic Representation of Image Decomposition Using Db8

All images we use in our experiments obtained from several different sources.Fig.6, represents the image added with Gaussian noise. The image quality measured by visual inspection as there is no generally accepted objective way to judge the image quality of a denoised image. There are two criteria that used widely in the literature: (1) visibility of the artifacts and (2) preservation of edge details.

Fig.6 Cameraman Image Is Added With Gaussian Noise

The application of NL means filter removes the details to some extent and blurs the image at low SNR as the similar local patches used to find pixel weights are noisy. NL-means Filter Fig.7 has more details.

Fig. 7: Non-Local Means Filtered Image

With increasing noise, the NL-means filter blurs the image detail reflected in terms of method Noise. The image details present in the method noise of NL means filter added to NL-means filtered output after wavelet packet thresholding its Method noise.

In the decomposition process, the entire image divided into several sub bands. The sub band is also called as sub images. This paper uses DWT and WPT along with OWB for decomposing the input images. Fig. 8, 9 shows the decomposition process. The cost value of this process recursively repeated up to the tree's root.

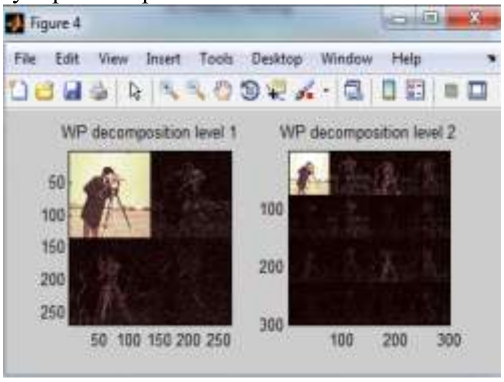

Fig.8 WP Decomposition Level 1& 2 Image

Figure shows cost function may find the cost value for each node and its children in the obtained full binary tree. Figure originally known as Optimal Sub band Tree Structuring (SB-TS) also called Wavelet Packet Decomposition (WPD) (sometimes known as just Wavelet Packets or Sub band Tree) is a wavelet transform where the discrete-time (sampled) signal passed through more filters than the discrete wavelet transform (DWT)

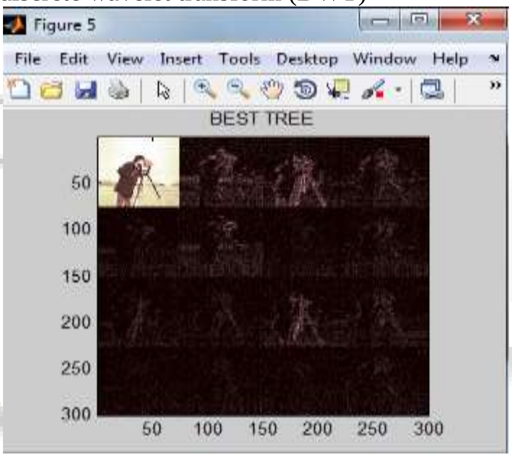

Fig. 9: Wavelet Packet Best Tree Image

Images produced by Non Local means square filtering combined with Method noise thresholding. Reconstruction with wavelet packet transform shows piecewise smooth effects. The images generated by this method present much higher visual quality. It shows the smallest MSE and provides an edge-preserving image Reconstruction and the PSNR rate is high. The UIQI rate is higher compared with other methods.

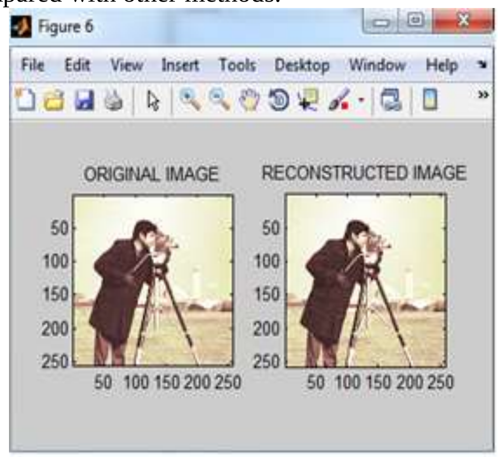

Fig. 10: Reconstructed Image after Method Noise

Fig. 10 shows the final reconstructed image. This shows the higher visual quality, higher resolution and no artifacts. The thresholding function, necessary in the enhancement and/or elimination of the wavelet coefficients, is obtained using Bayesian maximum a posteriori (MAP) estimate. Fig.11, 12, 13, 14 shows the MAP estimation of Original image i.e., Cameraman image, Gaussian noise added image, NL-means filter image and the reconstructed image from Method noise wavelet packet Thresholding.

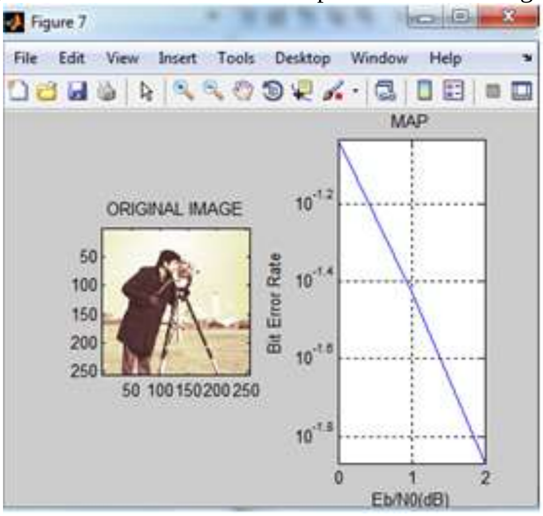

Fig. 11: MAP Estimation of Cameraman Image

MAP is to enhance or eliminate the wavelet coefficient which is smaller than the threshold value. Estimation of the various image based on the signal to noise ratio and Bit error rate coordinate axis. The thresholding function, essential in the upgrade and/or elimination of the wavelet coefficients, obtained using Bayesian maximum a posteriori (MAP) estimate. At that point, the optimal linear interpolation between every coefficient and the mean value of the comparing sub band used to calculate the changed version of dominant coefficients.

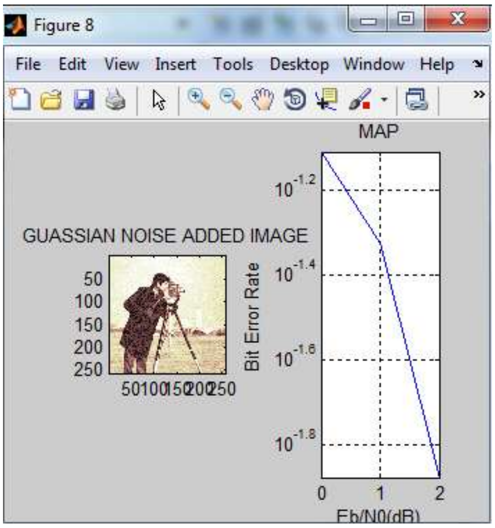

Fig. 12: MAP Estimation of Gaussian Noise Added Image

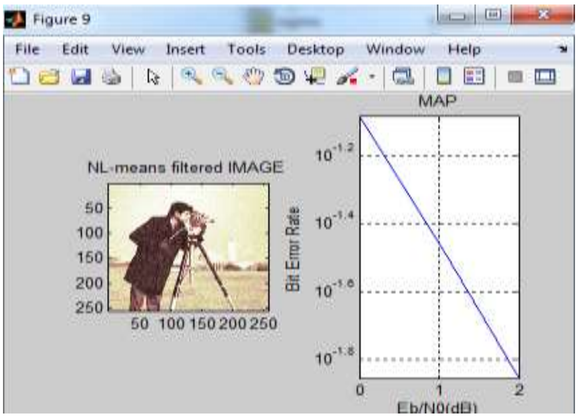

Fig. 13: MAP Estimation of NL-Means Filtering

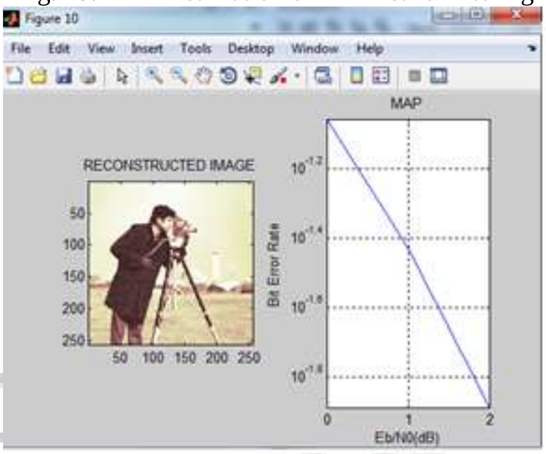

Fig. 14: MAP Estimation of Method Noise Wavelet Packet Thresholding Image

In the used thresholding function based on a maximum a posteriori estimate, the modified version of dominant coefficients assessed by optimal linear interpolation between every coefficient and the mean value of the corresponding sub band. In this paper, a statistical optimization process along adaptive and subband-dependable approach connected to both the thresholding function and wavelet transform, so as to propel the denoising further. It observed that the denoised images by NLFMT using sym8, coif5 and DCHWT have practically identical visual qualities.

Fig. 15: Denoised Images By Method Noise Wavelet Packet Thresholding With Global, Hard, And Soft Thresholding

Fig.15 shows the various denoised images compared with the proposed method It is known that performance of the WPT-based denoising method depends on the type of wavelet used. In order to analyze the effect of the same on the proposed NLFMT method, different wavelets like db8, sym8, db16, coif5, bior6.8 and DCHWT used to decompose the method noise.

PSNR of the denoised images by NLFMT with different wavelets are tabulated in Table 1. The bolded values in these tables show the highest PSNR and IQI of the denoised images by different wavelets. It is observed from the Table 1 that the DCHWT decomposition provides highest PSNR in most of the cases, and in other cases, it provided by bior6.8 and coif5. It observed that, in most of the cases the denoised image with high PSNR will have higher IQI and vice versa.

σ	10	20	30	10	20	30
Input image	Camera man 512 × 512			Barbara 512 × 512		
db8	35.41	31.62	29.44	35.18	29.96	26.88
sym8	35.41	31.65	29.46	35.14	29.94	26.88
db16	35.40	31.61	29.42	35.21	29.97	26.93
coif5	35.47	31.67	29.49	35.29	30.09	27.05
bior6.8	35.60	31.49	29.11	35.54	30.09	26.93
DCHWT	35.47	31.68	29.48	35.41	30.14	27.09
Input image	Boat 512 × 512			Baboon 512 × 512		
db8	33.47	29.60	27.32	33.47	26.94	24.13
sym8	33.43	29.63	27.33	33.51	26.93	24.13
db16	33.44	29.59	27.29	33.55	27.01	24.17
coif5	33.56	29.71	27.42	33.71	27.05	24.20
bior6.8	33.89	29.76	27.26	34.23	27.46	24.33
DCHWT	33.50	29.69	27.38	33.65	27.08	24.26

Table 1: PSNR of The Denoised Images By Non-Local Means Filter Method Noise With Different Wavelets By Wavelet Packet Soft Thresholding

σ	10	20	30	10	20	30
Input image	Cameraman 512 × 512			Barbara 512 × 512		
db8	0.9957	0.9907	0.9850	0.9944	0.9829	0.9689
sym8	0.9957	0.9907	0.9852	0.9944	0.9830	0.9691
db16	0.9957	0.9906	0.9852	0.9945	0.9833	0.9702
coif5	0.9957	0.9906	0.9853	0.9945	0.9836	0.9707
bior6.8	0.9956	0.9899	0.9833	0.9947	0.9838	0.9706
DCHWT	0.9957	0.9907	0.9852	0.9946	0.9836	0.9706
Input image	Boat 512 × 512			Baboon 512 × 512		
db8	0.9933	0.9857	0.9778	0.9909	0.9678	0.9447
sym8	0.9931	0.9857	0.9780	0.9910	0.9676	0.9448
db16	0.9934	0.9858	0.9776	0.9910	0.9676	0.9445
coif5	0.9935	0.9863	0.9786	0.9913	0.9683	0.9450
bior6.8	0.9942	0.9860	0.9756	0.9923	0.9709	0.9463
DCHWT	0.9935	0.9862	0.9786	0.9912	0.9685	0.9459

Table 2: IQI of the Denoised Images by Non-Local Means Filter Method Noise with Different Wavelets by Wavelet Packet Soft Thresholding

The bolded values in these tables show the highest PSNR and IQI of the denoised images by different wavelets. In Table 2, for most of the cases, coif5 provides highest IQI, and in other cases, it is by DCHWT and bior6.8. In this case, higher PSNR and IQI correspond to a better visual quality. It is known that the performance of the WT-based denoising method depends on the type of wavelet used.

In order to analyze the effect of the same on the proposed NLFMT method, different wavelets like db8, sym8, db16, coif5, bior6.8 and DCHWT used to decompose the method noise. PSNR and IQI of the denoised images by NLFMT with different wavelets are tabulated in Tables 1 and 2, respectively. NL means is better than BF and WT at lower σ and at higher σ either BF or WT scores over NL means filter. From Table 4, it is noticed that almost all the

IQI values for different methods are greater than 0.9 and approaching 1. This means, when the IQI approaches 1 the denoised image is close to the original image. It is observed from Table 4 that, NLFMT has highest IQI than that of other methods for images like Barbara (σ=10, 20), Lena (σ = 10, 20), boat (σ = 10, 20).

VI. Conclusion

In this paper, amalgamation of NL means filter and its method noise wavelet packet thresholding using wavelet has proposed. Performance of the proposed methods compared with WT-based approach, Global Thresholding, Soft thresholding and hard thresholding. Through experiments conducted on standard images, it was found that the proposed method has improved the results of WT approach, BF, NL means filter and MRBF with slight increase in performance in terms of method noise, visual quality, PSNR and reduced MSE. Performance of the proposed method can be improved by using NL means filter and Method noise Thresholding. The results indicated that the proposed method outperforms all but one of the methods and is categorically more visually pleasant than all of the other methods. In addition, the computational cost of the proposed method is moderate. So it is suitable for many image processing applications, such as medical image analyzing systems, noisy texture analyzing systems, display systems, and digital multimedia broadcasting. Further, it is possible to improve the results by using shift invariant wavelet transform and better sub band denoising techniques for method noise decomposition and thresholding. These issues and the detailed analysis of parameter choice for the proposed framework as well as application of other nonlinear filters instead of NL means filter are left as future work and will inspire further research toward understanding and eliminating noise in real images.

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