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High Quality Infrared Images with Novel Algorithm for Multi-Noises Removal

Xu Huang, Sheikh Md. Rabiul Islam, Mingyu Liao, and Shutao Li

***Abstract*—Infrared (IR) images have been used extensively for military and civilian purposes, in particular in dark conditions. High quality images are particularly needed in various applications, especially for the security and military environments. But various images, including IR images, almost cannot avoid various noises when they were born as noise sources are distributed almost everywhere. In our paper, in order to obtain a good quality of IR image, it proposes a novel denoising algorithm based on Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) wavelet transform. We also first applied the lifting structure to improve the drawbacks of a traditional wavelet transform. As the normal wavelet transform seems to be restricted and limited a class of opportunities for multi-scale representation of multi-dimensional signals to estimate noises and then remove the noises from original images. The final simulation results show that our proposed algorithm in this paper is much efficient in estimating and reducing noises from the images contaminated by multi noises, such as Gaussian noise, Poisson noise, and impulse (Salt& pepper) noise. Experimental results on several tests for infrared images by using this algorithm are presented, for example under the noise with σ = 0.2 and density = 20% cases, for mean square error (MSE) our method decreasing 83%; peak signal to noise ratio (PSNR) increasing 14% and mean of structural similarity (MSSIM) increasing 67% with the same conditions. Obviously, the results show our proposed algorithm significantly superior to other related methods.**

Index Terms*— IR, MSE, PSNR, MSSIM, Gaussian Noise, Poisson noise, Impulse Noise.

I. INTRODUCTION

It is well known that Infrared (IR) imaging has been used extensively for military and civilian purposes, in particular in dark conditions. Military applications include target acquisition, surveillances and night vision, homing and tracking. On-military IR applications are included thermal efficiency analysis, remote temperature sensing, short-ranged wireless communication, spectroscopy, and weather forecasting. As another example, infrared astronomy uses sensor-equipped telescopes to penetrate dusty regions of space, such as molecular clouds; detect objects such as planets, and to view highly red shifted objects from the early days of the universe [1].

Unfortunately, infrared (IR) images encounter a various number of noises such as: Gaussian, Rician, Poisson, speckle, and impulse (Salt& pepper) noise [2]. Image denoising is a procedure in digital image processing aiming at the removal of noise, which may corrupt an image during its acquisition or transmission, while retaining its quality. This paper is focussing on IR images corrupted by various noises, such as the three major noises, namely Gaussian noise, Poisson noise, and impulse (Salt& pepper) noise. The above noises are frequently encountered in acquisition, transmission storage and processing of IR images. In other words, IR images cannot avoid various noises and if the applications need a good quality of IR images, it has to be denoising. Noise removal is essential in the applications for infrared images. It is also the target that in order to enhance and recover fine details of the images, which may be hidden in the data. As those noises could severely degrade the image's quality and even cause some loss of information about the image's details. The presence of noise not only produces undesirable visual quality but also lowers the visibility of low contrast objects. It is important to know that various noises are with different natures, for example, Poisson noise depends on the intensity of signals, which causes some difficulty for the denoising. Various filters can remove different noises while keeping the image details. Those filtering techniques have been proposed for the applications such as, mean & median filtering [3], generalized trimmed mean filter[4], adaptive median filter [5], generalized morphological filter [6], holomorphic and adaptive order statistic filter [7], wavelet filter [8,9], curvelet filter [10], fuzzy algorithm [11,12], Gaussian filtering [13], and wavelet [21], etc. It is well- known that linear filters could produce serous image blurring so few linear filters are used for complex designs.

In this paper we present our proposed novel algorithm to denoise the three major noises in IR images and the simulation results show that the noise removal is very successful with the evidences of suppressing the noise while preserving the original image details. The comparisons are made between the outcomes of our novel algorithm with other statistical filters such as, median filter, Weiner filter, Gaussian filter. It is noted that in recent years there has been a fair amount of research on wavelet thresholding for signals and images denoising. For example, Donoho and Johnston [14] proposed hard and soft threshold methods for denoising. The

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detection of coefficients independent threshold given by Donoho and Johnston depends on the noise power and the size of the images. However, in practical application, when one deals with an image would be not the case that the image's size is known and the applicability of such a theoretical result is rather questionable. All the comparison's results strongly support our novel algorithm for denoising IR images.

For denoising IR image, in our algorithm, it has been used that decomposition by Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) lifting scheme [15] to enhance the image quality.

The rest parts of this paper are structured as follows: Section II describes the wavelet logical transform. In Section III we present Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) wavelet transform. In Section IV, threshold and denoising image is discussed. Section V will introduce our proposed novel algorithm for denoising IR images. In Section VI, we present performance of image quality assessment. In Section VIII, the simulation results are demonstrated. Finally in Section IX, a conclusion is presented.

II. MODULES FOR WAVELET TRANSFORM

The lifting scheme based a wavelet transform [4, 5] can be implemented as shown in Fig.1, where the computational complexity is reduced. It has been shown a few modules in this figure. In order to make simpleness, in Fig.1, only the decomposition part of wavelet transform (WT) is depicted as the reconstruction process is just the reverse version in Fig.1. The lifting-based WT consists of three parts, namely splitting, lifting, and scaling modules are shown in Fig.1. The WT itself can be treated as prediction-error decomposition. From Fig.1 we can also find that it provides a complete spatial interpretation of WT. Follow [16, 17], let X denote the input signal and X_{L1} and X_{H1} be the decompose output signals where they are obtained through the following three modules (*A*, *B*, and *C*) of lifting base inverse discrete wavelet transform (IDWT), which can further be described as below:

Module Splitting: In this module, the original signal X is divided into two disjoint parts, i.e., samples $X(2n+1)$ and $X(2n)$ that denotes all odd-indexed and even-indexed samples of X, respectively .

Module Lifting: Lifting consist of three basic steps: Split, Predict, and Updating as shown below. A brief description of these three steps is given below.

(a) Split: In this stage the input signal is divided in to two disjoint sets, the odd ($X[2n+1]$) and the even samples ($X[2n]$). This splitting is also called the Lazy Wavelet transform.

(b) Predict (denotes by P): In this stage the even samples are used to predict the odd coefficients. This predicted value, $P(X[2n])$, is subtracted from the odd coefficients to give error in the prediction.

$$d[n]=X[2n+1]+P(X[2n]) \qquad (1)$$

Here $d[n]$s are also called the detailed coefficients.

Update (denotes by U)*:* In this stage, the even coefficients are combined with $d[n]$ which are passed through an update function, $U(.)$ to give

$$C[n] = X[2n]+U(d[n]) \qquad (2)$$

Module Scaling: A normalization factor is applied to $d(n)$ and $s(n)$, respectively. In the even-indexed part $S(n)$ is multiplied by a normalization factor K_e to produce the wavelet sub band X_{L1}. Similarly in the odd-index part the error signal $d(n)$ is multiplied by K_0 to obtain the wavelet sub band X_{H1}.

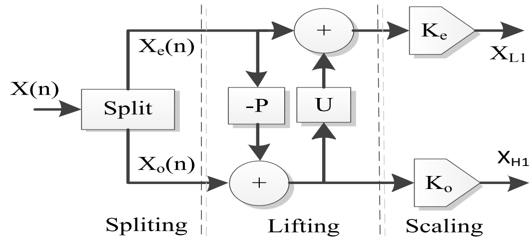

Fig.1: The lifting-based WT.

Above Fig. 1 can be further implemented as Fig. 2, the lifting scheme of the wavelet transform Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) goes through of four steps: two prediction operators and two update operators. Again following [16.17], we described it as follows.

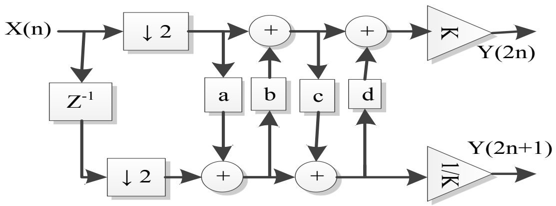

Fig.2: Split, Predict and Update Steps of forward CDF 9/7 wavelet using Lifting scheme: Lifting implementation of the analysis side of the CDF 9/7 filter bank

For lifting implementation, Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) pair can be factorized into a sequence of primal and dual lifting. The most efficient factorization of the polyphase matrix for the 9/7 filter can be shown as follows [18]:

$$P(Z)=\begin{bmatrix}1 & a(1+Z^{-1})\\ 0 & 1\end{bmatrix}\bullet\begin{bmatrix}1 & 0\\ b(1+Z) & 1\end{bmatrix}\bullet\begin{bmatrix}1 & c(1+Z^{-1})\\ 0 & 1\end{bmatrix}\bullet \qquad (3)$$

$$\bullet\begin{bmatrix}1 & 0\\ d(1+Z) & 1\end{bmatrix}\bullet\begin{bmatrix}K & 0\\ 0 & 1/K\end{bmatrix}$$

The following equation describes the four "lifting" steps and the two "Scaling" steps, where the numbers a, b, c, d, K are irrational values as shown below, with experience approximations.

a = -1.586134342,
b = -0.0529801185,
c = 0.8829110762,
d= 0.4435068522,
K= 1.149604398.

where a, b, c, d and K are filter coefficients.

Instead of using equation 3, we update the four lifting steps by using finite impulse response (FIR) wavelet transform with same parameters shown in [16, 18]:

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$$\begin{aligned} Y(2n+1) &\leftarrow X(2n+1)+\{a\times[X(2n)+X(2n+2)]\} \\ Y(2n) &\leftarrow X(2n)+\{b\times[Y(2n-1)+Y(2n+1)]\} \\ Y(2n+1) &\leftarrow Y(2n+1)+\{c\times[Y(2n)+Y(2n+2)]\} \\ Y(2n) &\leftarrow Y(2n)+\{d\times[Y(2n-1)+Y(2n+1)]\} \end{aligned} \tag{4}$$

$$\begin{aligned} Y(2n+1) &\leftarrow -K\times Y(2n+1) \\ Y(2n) &\leftarrow (1/K)\times Y(2n) \end{aligned} \tag{5}$$

The synthesis side of the filter bank simply inverts the scaling, and reverses the sequence of the lifting and update steps. Fig.3 shows the synthesis side of the filter bank using lifting.

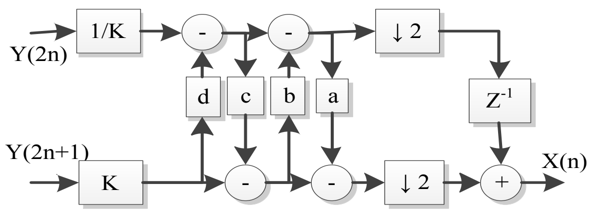

Fig.3: Lifting implementation of the synthesis side of the Cohen-Daubechies-Feauveau (CDF 9/7) filter bank.

III. DENOISING IMAGE & THRESHOLD

The objective of wavelet based denoising process is to estimate the original image $x(i, j)$ by discarding the corrupted noise $e(i, j)$ from the function $f(i, j)$::

$$f(i,j)=x(i,j)+e(i,j) \tag{6}$$

The model analysis for the noisy image is the superposition of the image $x(i, j)$ and a Gaussian zero mean white noise with a variance of σ^2. The threshold value is computed according to the model of the signal of interest to be estimated $x(i, j)$ the corrupted noise $e(i, j)$. One has to estimate, via the medium absolute deviation (MAD), the universal "VisuShrink" threshold [14] as below:

$$Thr=\sigma\sqrt{2\cdot\log(N)} \tag{7}$$

The noise variance is estimated by the mean absolute deviation (MAD) which is given by

$$\sigma_n^2=\left(\frac{\mathrm{MAD}(|C_{i,j}|)}{0.6754}\right)^2 \tag{8}$$

where $c_{i,j}$ is the wavelet coefficients of the noisy image.

Normally, two algorithms are popular for a threshold, i.e. a *hard* and soft threshold algorithm can be shown as [14]:

$$\left.\begin{aligned} T_{soft}&=\mathrm{sgn}(x)\cdot(|x|\,Thr) \\ T_{hard}&=x\cdot 1(|x|>Thr) \end{aligned}\right\} \tag{9}$$

Our original IR image can be reconstructed from the threshold wavelet, whose detail coefficients show a denoised (smoothed) version of the original image.

IV. PROPOSED ALGORITHM FOR DENOISING

Now based on above preparation described in sections II to IV, we can now proposes a novel denoising algorithm based on Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7) wavelet transform. We first applied the lifting structure to improve the drawbacks of a traditional wavelet transform.

Our novel ***denoising algorithm*** can be summarized as below:

1. Perform CDF9/7 wavelet transform to the noisy image; from the decomposition process the coefficients are extracted.
2. Estimate the noise variance for each noisy image pixel equation (8).
3. The threshold T for the wavelet coefficients of noisy image is calculated using equation (9).
4. If the wavelet coefficients are greater than threshold, that coefficients are remained unchanged. If they are less, they are suppressed.
5. Further comparing for denoising image; apply kernel mask size 3x3 of median filtering, Gaussian filtering and wiener filtering individually .Keep scaling (low pass) coefficients s unchanged.
6. Then all the resultant coefficients are reconstructed by applying inverses CDF 9/7 wavelet transform, which results in deionised image.

In the following section, we shall demonstrate that our denoising algorithm enables a very noisy infrared image corrupted by three major noises namely, Gaussian noise, Poisson noise, and impulse (slat & pepper) noise to become a smooth and clean image. In order to make comparisons with (6) our novel algorithm, we also apply the popular classical wavelet denoising schemes, such as median filter, Wiener filter with known variance, the universal threshold and 'soft' & 'hard' strategy, at level 3 for denoising the same image as that our method used.

V. QUANTITATIVE ANALYSIS FOR IR IMAGES

The mean square error (MSE) between the original and denoised image is used for quantitative analysis of an IR image. It is easily defined for two $M\times N$ grayscale images I and K, where I is the original image and K is the noisy image or processed image, which can be given as:

$$\mathrm{MSE}=\frac{1}{M\times N}\sum_{i=1}^{i=M}\sum_{j=1}^{j=N}[I(i,j)-K(i,j)]^2 \tag{10}$$

The Peak Signal to Noise Ratio (PSNR) is also the most commonly used as a measure of quality of reconstruction. The PSNR are identified using the following formulate:

$$\mathrm{PSNR}=10\log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) \tag{11}$$

Apart from the PSNR assessment, the mean of absolute error (MAE) has also been used too in this analysis to characterize the filter's detail preservation behaviour, which can be defined as:

$$\mathrm{MAE}=\frac{1}{M\times N}\sum_{i=1}^{i=M}\sum_{j=1}^{j=N}[I(i,j)-K(i,j)] \tag{12}$$

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Usually an image is encoded on 8 bits. It is represented by 256 grey levels, which vary between 0 and 255, the extent of image dynamics is 255 in our analysis.

Following [19], we also defined the *structural similarity index (SSIM)* for estimating the quality of IR images, specifically for the ones compressed by Cohen-Daubechies-Feauveau wavelets with the low-pass filters of the length 9 and 7 (CDF 9/7), based on the hypothesis that the human visual system (HVS). Following [6], the similarity index compares the brightness, contrast and structure between each pair of vectors, where the structural similarity index (SSIM) between two signals x and y can be given by the following expression:

$$\mathrm{SSIM}(x,y) = l(x,y)c(x,y)s(x,y) \tag{13}$$

Here $l(x, y)$ is luminance; $c\ (x, y)$ is contrast and $s\ (x, y)$ is structural similarity. For an application, we require a single overall measurement of the whole image quality that is given by the following formula:

$$\mathrm{MSSIM}(x,y) = \frac{1}{M}\sum_{i=1}^{M}\mathrm{SSIM}(x_i, y_i) \tag{14}$$

Where X and Y are respectively the reference and denoised images, x_i and y_i are the contents of images at the i^{th} local window. M is the total number of local windows in image. The MSSIM (Mean Structural Similarity Index) values demonstrate greater reliability with the visual quality.

VI. RESULT & DISCUSSION

In this section we present some simulation result performed on the IR image and implemented in MATLAB to the performance of our proposed denoising algorithm with wavelet filter method for denoising IR image. For this reason, we have chosen an infrared (IR) image size 500X500 encoded on 8 bits per pixel, recorded by means of an infrared (IR) image (Fig.4 (a)). This image is taken from the database [20].

Median filtering is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighbourhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the *median* of the neighbourhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called *outliers*). Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

The Gaussian outputs a "weighted average" of each pixel's neighbourhood, with the average weighted more towards the value of the central pixels. This is in contrast to the mean filter's uniformly weighted average. Because of this, a Gaussian provides gentler smoothing and preserves edges better than a similarly sized mean filter.

Both filters attenuate high frequencies more than low frequencies, but the mean filter exhibits oscillations in its frequency response. The Gaussian on the other hand shows no oscillations. In fact, the shape of the frequency response curve is itself (half a) Gaussian. So by choosing an appropriately sized Gaussian filter we can be fairly confident about what range of spatial frequencies are still present in the image after filtering, which is not the case of the mean filter.

The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework.

Tables I, II, III & IV showed the values of image quality assessments comparison of values of MAE, MSE, PSNR and MSSIM show that our proposed algorithm has the best performance for the IR image corrupted together with Gaussian noise, Poisson noise and impulse noise (Salt& pepper). All the Tables represent the MAE, MSE, PSNR and MSSIM values at the noise variance σ = 0.025, 0.1, and 0.2 for the Gaussian noise; with noise density = 2.5%, 10% and 20% for impulse (salt & pepper) noise; Best result was written in bold font, which shows our algorithm denoising algorithm has excellent performance on IR image at different type of noises. It is also noted that the outcomes depend on the lower value of noise variance for Gaussian noise, noise density for impulse noise, and noise the entire image for Poisson noise. Providing visually pleasing output for the image is imperative, since the quality of image is subjective to human eye.

TABLE.I COMPARISON OF MSE, VALUES FOR DIFFERENT WAVELET FILTERS AT IR IMAGE CORRUPTED BY GAUSSIAN, POISSON & IMPULSE NOISE (SALT& PEPPER).

Filter algorithm	**Noise variance=0.025 Noise density=2.5%**	**Noise variance=0.1 Noise density=10%**	**Noise variance=0.2 Noise density=20%**
	MSE	MSE	MSE
Noisy image	0.6386	0.6768	0.6450
Proposed algorithm	**0.5243**	**0.5256**	**0.5363**
Wiener filter	0.5482	0.5392	0.5569
Gaussian filter	0.5620	0.5592	0.5444
Hard threshold	0.5668	0.5551	0.6092
Soft threshold	0.5541	0.5649	0.5866

We have also made comparison with the Median filtering, Wiener filtering with known variance, *hard* and *soft* threshold, the best possible linear filtering. The PSNR results are shown in Table II. The image quality can be shown by Fig. 4, Fig. 5 and Fig. 6, which are taken from the Table I, II, III.

TABLE.II COMPARISON OF PSNR VALUES FOR DIFFERENT WAVELET FILTERS AT IR IMAGE CORRUPTED BY GAUSSIAN, POISSON & IMPULSE NOISE (SALT& PEPPER).

Filter algorithm	**Noise variance=0.025 Noise density=2.5%**	**Noise variance=0.1 Noise density=10%**	**Noise variance=0.2 Noise density=20%**
	PSNR (dB)	PSNR (dB)	PSNR (dB)
Noisy image	50.8169	50.5268	50.0398
Proposed algorithm	**58.9323**	**57.9205**	**56.8472**
Wiener filter	50.8994	50.8150	50.6803
Gaussian filter	50.9501	50.8965	50.7779
Hard threshold	51.0769	50.7651	50.2749
Soft threshold	51.7922	50.0226	53.7919

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TABLE.III COMPARISON OF MSSIM VALUES FOR DIFFERENT WAVELET FILTERS AT IR IMAGE CORRUPTED BY GAUSSIAN, POISSON & IMPULSE NOISE (SALT& PEPPER).

Filter algorithm	Noise variance=0.025 Noise density=2.5%	Noise variance=0.1 Noise density=10%	Noise variance=0.2 Noise density=20%
	MSSIM	MSSIM	MSSIM
Noisy image	0.2632	0.1981	0.1521
Proposed algorithm	**0.3940**	**0.2848**	**0.2232**
Wiener filter	0.2875	0.2386	0.2043
Gaussian filter	0.3131	0.2554	0.2183
Hard threshold	0.1881	0.1609	0.1321
Soft threshold	0.2909	0.2199	0.2202

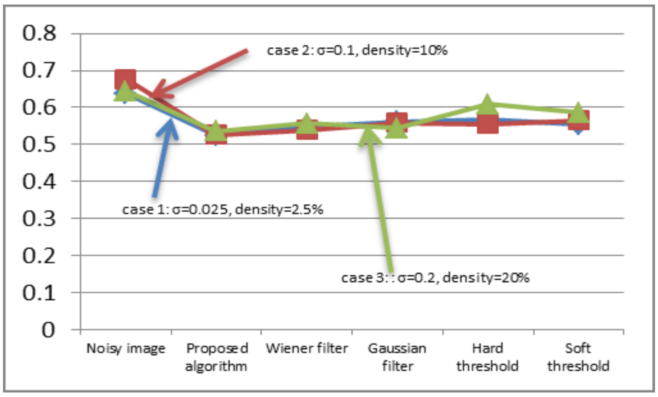

Fig.4: Comparisons of MSE values for different wavelet filters at IR image corrupted by Gaussian, Poisson and impulse noise. It is obviously the proposed algorithm has the minimum MSE in all the three different cases.

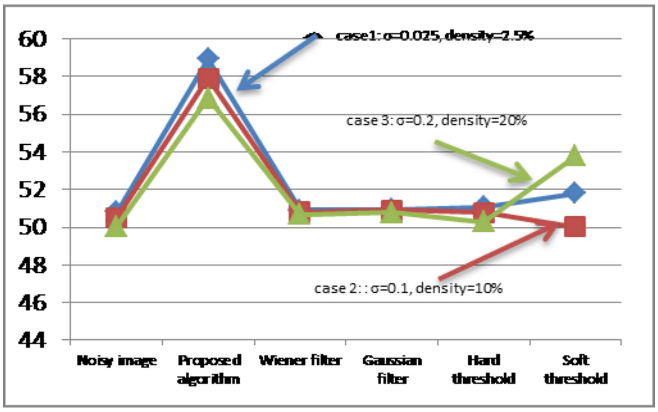

Fig.5 Comparisons of PSNR values for different wavelet filters at IR image corrupted by Gaussian, Poisson and impulse noise. It is clearly shows the proposed algorithm has the maximum PSN in all the three different cases.

Donoho and Johnstone proposed a simple wavelet –based denoising scheme called VISU SHIRINK. This method uses a single universal threshold for all scales and resulting estimate is not clearly smooth for the denoising image. Although the resulting estimate is smooth, inconsistency may exist between the estimate and the original signal. This situation can be significantly improved by replacing the median filtering and Gaussian filtering a pleasant visual appearance.

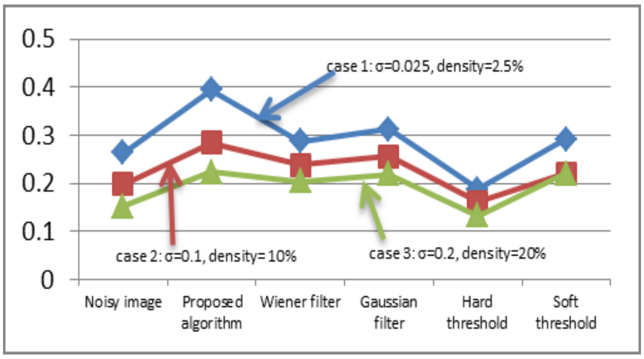

Fig.6 Comparisons of MSSIM values for different wavelet filters at IR image corrupted by Gaussian, Poisson and impulse noise. It is clearly shows the proposed algorithm has the maximum MSSIM in all the three different cases.

VII. CONCLUSION

In this paper, a simple effective and efficient wavelet based denoising algorithm is first proposed. It is extended from our previous research [21] to address the issue of image recovery from an IR image corrupted with three major IR image's noises, i.e. Gaussian noise, Poisson noise & impulse noise. The evaluation of the results supports the conclusion that method has significantly better result than others. For example, referring the tables, under the noise with $\sigma = 0.2$ and density = 20% cases, for MSE our method decreasing 83%; PSNR increasing 14% and MSSIM increasing 67% under the same conditions. The proposed algorithm introduced better results provide smoothness and better edge preservation at the same time of subband coefficients. The result has shown that the noise removal significantly depends on the minimum value of σ and noise density for different filter such as median filter, Gaussian filter, Wiener filter and soft and hard thresholding as expected. It is further suggested that the proposed threshold may be implemented to the compression framework, which may further improve the denoising performance.

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REFERENCES

[1] G. O. Young, "Synthetic structure of industrial plastics (Book style with paper title and editor)," in *Plastics*, 2nd ed. vol. 3, J. Peters, Ed. New York: McGraw-Hill, 1964, pp. 15–64.

[2] Amit Sahu, Vandana Shandilya "Infrared Image Enhancement Using Wavelet Transform" Computer Engineering and Intelligent Systems ISSN 2222-1719 (Paper) ISSN 2222-2863 (Online) Vol 3, No.3, 2012.

[3] P. Gravel, G. Beaudoin, and J. A. De Guise, "A Method for Modeling Noise in Medical Images," *IEEE Trans. MedicalImaging.*, vol. 23, no. 10, pp.1221–1231, Oct. 2004.

[4] Abreu, M. Lightstone, S.K. Mitra and K. Arakawa, "A New Efficient Approach for the Removal of Impulse Noise from Highly Corrupted Images," *IEEE Trans. Image Processing,* vol. 5, no. 6,pp. 1012–1025, June. 1996.

[5] Y. B. Rytsar and I. B. Ivasenko, "Application of (alpha, beta) trimmed mean filtering for removal of additive noise from

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images,"*Optoelectronic and Hybrid Optical/Digital Systems for ImageProcessing.*, Proc SPIE 3238, pp.45–52, 1997.

[6] Sawant, H.Zeman, D. Muratone, S. Samant and F. DiBianca,"Adaptive median filter algorithm to remove impulse noise in x-ray and CT images and speckle in ultrasound images," *in Medical Imaging 99.*, Proc SPIE 3661, pp.1263–1274, 1999.

[7] Z. Chunhui, X. Qingbin, N. Wei, "Study on the noise attenuation characteristics of generalized morphological filters," *in Medical Imaging98,* Proc SPIE, vol. 3545, pp. 236–239, 1998.

[8] D. Runtao, and A. Venetsanopoulos, "Generalized homomorphic and adaptive order statistic filters for the removal of impulsive and signal dependent noise," *IEEE Trans. Circuits and Systems.*, vol.34, no. 8, pp. 948–955, Aug. 2003.

[9] K. Karthikeyan, and C. Chandrasekar, "Speckle Noise Reduction of Medical Ultrasound Images using Bayesshrink Wavelet Threshold," *International Journal of Computer Applications.*, vol.22, no. 9, pp. 8–14, May. 2011.

[10] L. Wang, J. Lu, Y. Li, T. Yahagi, and T. Okamoto, "Noise reduction using wavelet with application to medical X-ray image,"*International* Conference on Industrial Technology., vol. 20, pp.33–38, Dec. 2005.

[11] Y. Cheng, Y. Li, D. Xue, "Image Denoising Method Based on Curvelet Cycle Spinning," *International Conference on WirelessCommunications, Networking and Mobile Computing.*, vol. 13, pp.1–3, Oct. 2008.

[12] F. Russo, F. Ramponi, "A Fuzzy Filter for Images Corrupted By Impulse Noise," *IEEE Trans. Image Processing,* vol. 3, no. 6, pp.168–170, June. 2000.

[13] K. Anisha, and M. Wilscy, "Impulse Noise Removal From Medical Images Using Fuzzy Genetic Algorithm," *The InternationalJournal of Multimedia & Its Applications.* vol. 3, no. 4, pp. 93-106,Nov. 2011.

[14] Peter Kovesi, "Fast Almost-Gaussian Filtering" 2010 International Conference on Digital Image Computing: Techniques and Applications (DICTA), Page(s): 121 - 125 1-3 Dec. 2010.

[15] Donoho DL. De-noising by soft-thresholding, IEEE Trans.Inform.Theory 1995;41(3):612-627.

[16] COHEN, A.; DAUBECHIES, I.; FEAUVEAU, J. C. *Biorthogonal Bases of Compactly Supported Wavelets*. Comm. Pure and Appl. Math., vol. 45, 1992, pp. 485-560.

[17] M. Beladgham, A. Bessaid, A. Moulay-Lakhdar, M. Ben Aissa , A. Bassou, "MRI image compression using biorthogonal CDF Wavelet based on lifting scheme and SPIHT coding" ,Quatrième Conférence Internationale sur le Génie Electrique CIGE'10, 03-04 Novembre 2010, Université de Bechar, Algérie.

[18] Mohammed Beladgham, Abdelhafid Bessaid,Abdelmounaim Moulay Lakhdar, Abdelmalik Taleb-Ahmed, "Improving Quality of Medical Image Compression Using Biorthogonal CDF Wavelet Based on Lifting Scheme and SPIHT Coding", SERBIAN JOURNAL OF ELECTRICATL ENGINEERING Vol. 8, No. 2, May 2011, 163-179

[19] Ingrid Daubechies, W. Sweldens: Factoring Wavelet Transforms into Lifting Steps, Journal of Fourier Analysis and Applications, Vol.4, No. 3, May 1998, pp. 247 – 269.

[20] Zhou Wang, Alan C. Bovik,Hamid R. Sheikh, Eero P. Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 4, APRIL 2004

[21] Sheikh Md. Rabiul Islam, Xu Huang, and Dharmendra Sharma, "ECG signal corrupted by EGN and Poission noise," IEEE ISCIT 2012, Gold Coast Australia, 2-5 Oct. 2012. Pp-107.

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