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Efficient Edge-preserving Adaptive Image Denoising using Morphological Operations in Wavelet Domain

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Abstract

This paper explores a new image denoising scheme that preserves the image features like edges more efficiently using morphological operation in wavelet domain. It is necessary to reduce the induced noise for further image processing while preserving the image edges which are the important information for visual perception of the image. The edges of image are first detected before applying the wavelet coefficients thresholding. This is achieved by two form of thresholding applied with wavelet coefficients, one for edges region and other for flatten region. Then morphological operations are applied with the thresholded wavelet coefficient of the image and this will further preserve edges from any degradation. In this work, experimental results are compared with state-of-art techniques like bilateral filtering in wavelet domain and block matching and 3D (BM3D) filtering. The efficiency and performance of these denoising methods are compared based on Peak Signal to Noise Ratio (PSNR) and visual perception.

Keywords: Bilateral filtering in wavelet domain, Block matching and 3D filtering, Edge-preserving adaptive thresholding and PSNR.

INTRODUCTION

Generally images get noise during image acquisition and transmission process [5]. In image acquisition using a camera, the amount of noise is induced due to the intensity levels and sensor temperature. The interference in the transmission channel also induces the noise in an image during transmission. This type of noise is additive in nature and is called additive white Gaussian noise (AWGN). The noise in image poses problems for visual quality and automated analysis operations. The process of the noise reduction from the image while retaining the important features is called image denoising [5]. During the image denoising, the important features like edges, textures etc are also disturbed. This degrades the visual quality of the image.

The characteristic of the edges has the great significance for the visual system [4, 6]. So the edge preserving during the image denoising is the necessary preprocessing of the image processing. Due to this, the problem of image denoising and edge preserving continues to attract researchers for computer graphics, and image denoising. The first reason is the wide range of commercial and medical applications and the second is the availability of improved technologies of research.

The AWGN and image edges are always presented by high frequencies. So it is difficult to reduce AWGN from the images without blurring the edges of the image [6-10, 12]. Now question arises that how can edges are preserved during image denoising. For better edges preserving, it is necessary to detect the position and orientation of the edge. The presence and location of edges are a critical task and have so many problems [7]. A true edge detection scheme is a challenging task to the researcher due to the presence of AWGN. An edge may be detected by the intensity changes due the noise where edges do not exist. Another problem is due the edge location shifting by the AWGN. The performance of an edge detector is estimated by locating the true edges in a noisy image.

From two decade there has been a great amount of research on wavelet coefficients thresholding for image denoising [5, 10, 12, 16]. A wavelet is a mathematical function useful in digital image denoising and image compression. For denoising data, techniques based on thresholding of wavelet coefficients are gaining popularity these days.

Many of the existing image denoising schemes in wavelet domain [5] does not select an edge direction before denoising. Some others [10-12] preserve either the small curvature edges or large curvature edges at a time but not both. The edges with angles or large curvature edges are often blurred or rounded by these existing schemes. One major reason of this is that the edge structures (e.g., angles) are hidden in observed image intensities [2], they are not easy to detect. So it is difficult to accommodate these edges in the image denoising process [12]. It is important that edges present in the image should not be missed and that there be no false edge [7]. These issues motivated us to design a novel approach for image denoising. Thus, during the image denoising, the first thing that should be cared about is trying to retain edge information.

A new image denoising method is proposed here: first of all, the noisy image is decomposed using a desired wavelet type.

The standard deviation is calculated using the first level diagonal subband given in eqn (3) and is used to estimate the noise variance for each subband of desired decomposition levels [5]. Then this noise variance is utilised to find the optimal threshold for each subband by Bayesian estimator. Then the edges are detected using the Canny edge detector. The selective thresholding is applied here to avoid the edge over smoothing [10]. For this wavelet coefficients that are detected edges will be protected from the ensuing denoising process. For this two types of threshold are required here, one for edge region and another for flatten region. If a single threshold is applied for both types of the wavelet coefficients, then the edges got over smoothing.

After trimming down the small wavelet coefficients, i.e. after removing the wavelet coefficients from all the detailed coefficients, image reconstruction is performed using the same wavelet function type and version as used at the time of decomposition of the image. The image reconstruction is achieved by finding the inverse DWT (IDWT) of the approximation of first decomposition level and modified detail coefficients of each decomposition level. This process is continued through the same number of decomposition levels as in the decomposition process to obtain the original image.

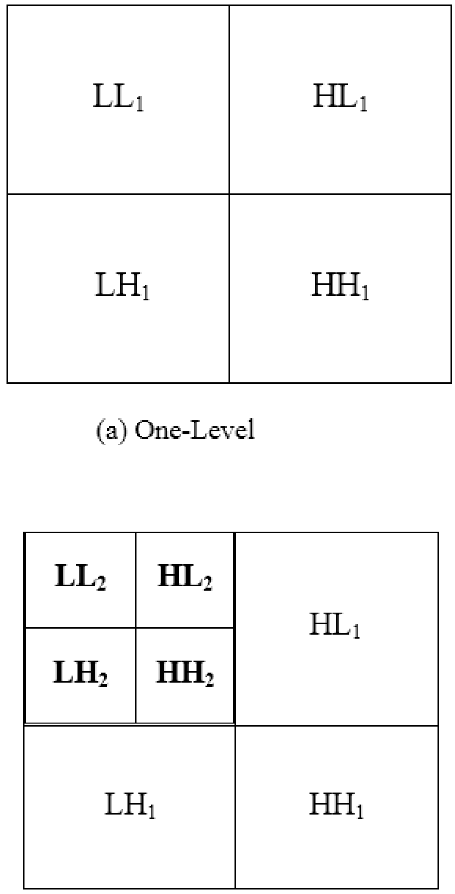
During the image reconstruction, the edges get disturbed due to not well handled. Then the edges can be improved by using morphological operations like opening and closing. Closing smooths the contour of an image and fill small gaps and holes. Opening also smoothes the contour, breaks narrow isthmuses, and eliminates thin protrusions. Removal of small holes and narrow branches can be accomplished by concatenating opening with closing. In this way, the experimental results are improved in the form of PSNR and visual perception. The subjective and objective analyses of results are presented which demonstrate that, compared with previously used edge preserving image denoising methods in wavelet domain; the proposed image denoising method is more efficient.

The paper is organized as follows. Section II provides brief review of the methodologies used with their brief description. Section III provides brief review of two adaptive wavelet-based algorithms and proposed one with their structures. The experimental results analysis of the image with three samples of noise variance (low, medium and high) for each adaptive technique is reviewed in Section IV under subsection i) in tabular form and subsection ii) in visual perception form of different images. In Section V, purposed work is concluded and Section VI is the description of future scope.

MATHODOLOGY

i). Discrete Wavelet Transform (DWT)

In DWT, a noisy image can be decomposed into a sequence of four frequency subbands namely, LL_1, LH_1, HL_1 and HH_1 as shown in Fig. 1 (a). The low pass band (LL_1) of decomposed image represents a coarse approximation image in the lowest resolution, and three detail images in higher bands (LH_1, HL_1 and HH_1) [5. 16]. The next level of DWT is applied to the low frequency subband image LL_1 only and it can be further decomposed into four subbands namely LL_2, LH_2, HL_2, and HH_2 as shown in Fig. 1 (b).



(b) Two-Level

Figure 1: 2D-DWT decomposition

The wavelet decomposition is continued until a desired level (level 4) is reached but it depends more on noise deviation. In DWT, the magnitude of the coefficient varies depending on the decomposition level. The wavelet coefficients become smoother as the level of decomposition increases. Thus the subband HL_2 is smoother than the corresponding subband in the first level (HL_1) and so the threshold value of HL_2 should be smaller than that of HL_1. After forth level, there is no more image details information are found in the decomposition subbands, only severer noise remains.

After the wavelet decomposition is performed on the noisy image, it is needed to do thresholding. The wavelet coefficients thresholding has two parameters: shrinkage rule and shrinkage function. The shrinkage rule is how to calculate the threshold and shrinkage function is how to apply the calculated threshold. Researchers published different ways to estimate the parameters for the thresholding of wavelet coefficients and its application.

ii) Multiscale mathematical morphology

Mathematical Morphology (MM) is a powerful technique in the field of image processing and analysis. MM is an appropriate tool for dealing with spatial features of an image. In morphology, the objects in an image are considered as set of points and operations are defined between two sets: the object and the structuring element (SE) [28,12]. The shape and the size of SE are defined according to the purpose of the associated application. Basic morphological operations are erosion and dilation. Other operation like opening (closing) is sequential combination of erosion (dilation) and dilation (erosion).

Concatenation of dilation and erosion in different orders result in more high level operations, including *closing* and *opening*. The closing operation is a dilation followed by erosion as given below:

$$(A \bullet B) = (A \oplus B)\ \Theta B = \{z \mid (B)z \cap A \neq \emptyset\} \qquad (1)$$

Holes in the foreground those are smaller than SE will be filled. It smoothes the contour, fuses narrow breaks and long thin gulfs, and eliminates small holes.

The opening operation is erosion followed by dilation as given below:

$$(A \circ B) = (A \Theta B) \oplus B = \cup\{(B)z \mid (B)z \subseteq A\} \qquad (2)$$

In opening operation, the structures that are smaller than the structure element will disappear and larger structures will remain. It smoothes the contour, breaks narrow isthmuses, and eliminates thin protrusions

The shape of the structuring element *B* plays a crucial role in extracting features or objects of given shape from the image. However, for a categorical extraction of features or objects from the image based on shape and size we must incorporate a second attribute to the SE which is its *scale*. A morphological operation with a scalable SE can extract features based not only on shape but also on size. Also features of identical shape but of different size are now treated. Removal of narrow branches and improving the presence of edges can be accomplished by concatenating opening with closing.

ADAPTIVE THRESHOLDING FOR IMAGE DENOISING

This section covers the details regarding the adaptive algorithms of image denoising along with their theory. The wavelet coefficients thresholding techniques discussed here are bilateral filter in wavelet domain, BM3D filtering and edge-preserving adaptive thresholding. For the considered images, the noise level can be estimated from the highest frequency coefficients. A robust estimate of noise variance uses the median absolute value of the wavelet coefficients of HH_1 [5], which is insensitive to isolated outliers of potentially high amplitudes. The universal threshold value is calculated from the diagonal subband (HH_1) of first decomposition level and is applied for all desired levels [3]. It is given as:

$$\hat{\sigma}_{noise} = \frac{median(|HH_1|)}{0.6745} \qquad (3)$$

where $\hat{\sigma}_{noise}$ noise is the estimated noise deviation. The processed image may be overly smoothened due to the larger threshold value so that sufficient information preservation is not possible and the image gets blurred. So an adaptive thresholding is required for image features preservation especially edges. For this, an adaptive threshold is calculated for each subband at each level separately.

i). Bilateral Filtering using Wavelets

A bilateral filter is a nonlinear, edge-preserving and noise reducing smoothing filter [14]. When filtering noise using a Gaussian filter there is a problem of edge blurring between areas of different shades or colors. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. These weights are based on a Gaussian distribution depending on the spatial distance and on the intensity of the pixels. This preserves sharp edges by systematically looping through each pixel and adjusting weights to the adjacent pixels accordingly. The mathematical formula is as follows:

$$\tilde{I}(x) = \frac{1}{\mathrm{C}} \sum_{y \in N(x)} \mathrm{e}^{\frac{-\|\mathrm{y}-\mathrm{x}\|^2}{2\sigma_{\mathrm{d}}^2}}\ \mathrm{e}^{\frac{-|\mathrm{I}(\mathrm{y})-\mathrm{I}(\mathrm{x})|^2}{2\sigma_{\mathrm{r}}^2}}\ \mathrm{I}(\mathrm{y}) \qquad (4)$$

where

$$C = \sum_{y \in N(x)} \mathrm{e}^{\frac{-\|\mathrm{y}-\mathrm{x}\|^2}{2\sigma_{\mathrm{d}}^2}}\ \mathrm{e}^{\frac{-|\mathrm{I}(\mathrm{y})-\mathrm{I}(\mathrm{x})|^2}{2\sigma_{\mathrm{r}}^2}}$$

There are two parameters that control the behavior of the bilateral filter. Referring to eqn. (4), σ_d and σ_r characterize the spatial and intensity domain behaviors, respectively. In case of image denoising applications, these parameter values must be selected optimal. To understand the relationship among σ_d , σ_r and the noise standard deviation σ_n , the following experiments were done. Zero-mean white Gaussian noise was added to some standard test images and the bilateral filter was applied for different values of the parameters σ_d and σ_r.

Multi-resolution analysis has been proven to be an important tool for eliminating noise in the images; it is possible to distinguish between noise and image information better at one resolution level than another [14] [16]. Therefore, the bilateral filter in a multi resolution framework is considered here. The image is decomposed into its frequency sub-bands with wavelet decomposition as given above. Bilateral filtering works in approximation sub-bands and wavelet thresholding on the detail sub-bands. Unlike the standard single-level bilateral filtering, this multi resolution bilateral filtering has the potential of eliminating low-frequency noise components. This new image denoising framework combines bilateral filtering and wavelet thresholding [16]. The experiment results will be given in the table. The bilateral filtering reduced the noise, and smoothed features in the image, but the distinct edges are preserved [21].

ii). Block Matching and 3D Filtering

The block-matching and 3-D filtering (BM3D) algorithm is currently one of the most powerful and effective image denoising procedures. It exploits a specific nonlocal image modelling through grouping and collaborative filtering. In doing so, BM3D relies both on nonlocal and local characteristics of natural images, namely the abundance of mutually similar patches and the fact that image data is locally highly correlated.

The blocking imposes a localization of the image on small pieces where simpler models may fit the observations. It has been demonstrated that a higher scarcity of the signal representation and a lower complexity of the model can be achieved using joint 3D groupwise instead of 2D blockwise transforms. This joint 3D transform dramatically improves the effectiveness of image spectrum approximation.

iii). Proposed scheme: Efficient Edge-preserving based on Morphological Operations

As the decomposition level increases, the signal-to-noise ratio (SNR) of the subband usually become smaller i.e. the noise is higher [13]. For example, the subband LH_3 has higher noise than the corresponding subband in the previous level LH_2 which appears in the edges more, so the threshold value for edges region of LH_3 should be estimated high to remove more coefficients than the one for LH_2.

In this paper, an adaptive image denoising scheme is suggested, which can preserve each edge structures well. In this scheme, edge pixels are detected in the image by the Canny edge detector which is superior edge detector in noisy images [6]. To improve the image denoising, two thresholds are used within a subband of each decomposion level. A threshold is calculated and applied for flatten region of each subband of different levels based on Bayesian estimator as usual and a lower threshold is used for edges region as the noise appears less in these regions. In this way, an edge-dependent thresholding scheme is used to threshold the wavelet coefficients of the edges within that subband for preserving them. So the wavelet coefficients are thresholded adaptively according to their local statistics.

After wavelet thresholding, many details features (edges and texture) of an image are disturbed more which are more significant for the image quality. Now a need to restore these arises for further image processing operations. This can be achieved by applying the morphological operations to the reconstructed image.

EXPERIMENTAL RESULTS AND ANALYSIS

Proposed scheme has been implemented in MATLAB. Difference density images of size 512x512 are considered for experiment purpose. The results are analysed subjectively by visual perception and objectively by PSNR for different values of noise variance.

i). Objective Evaluation

All the schemes implemented are compared by finding PSNR in dB using wavelet types ‘db3’ and ‘db8’, as they are more suitable in image denoising. Following table illustrates the comparison among bilateral filtering in wavelet domain, BM3D filtering and efficient edge-preserving adaptive thresholding on the basis of PSNR values for the images of different structure. Further, output PSNR have been compared and analyzed for these thresholding schemes at different noise variance from .001 to .009 respectively (low, medium and high), as shown ahead in Table 1. The scheme which results in higher PSNR value is better denoising approach compared those having lower PSNR values as given in this table.

Table I: PSNR values for difference images with different values of noise variance

Noise variance σ_n^2	*lena*				*perrot*		
	Wavelet Type	Bilateral Filter using Wavelet	Block matching and 3D filtering	Efficient Edge-preserving Image Denoising	Bilateral Filter using Wavelet	Block matching and 3D filtering	Efficient Edge-preserving Image Denoising
.001	db3	35.4127	35.5636	35.8821	34.3634	33.3758	34.1189
	db8	34.6102	34.5632	35.3610	33.6370	33.4727	34.8707
.002	db3	33.4323	33.2932	33.7381	32.8792	32.7731	33.0134
	db8	32.8851	32.6944	33.5361	32.4362	31.9607	32.6932
.003	db3	32.0541	31.9643	32.3764	31.8126	31.7720	32.2773
	db8	31.4313	31.3026	31.6381	30.8972	30. 5106	31.5829
.004	db3	29.7861	29.7365	30.3752	29.1767	28.9535	29.6903
	db8	29.3739	29.2123	30.0147	28.7254	28.6058	28.9974
.005	db3	28.7543	28.5568	28.9687	27.5242	27.5915	27.8646
	db8	28.5861	28.3365	28.7752	27.4791	26.9392	27.6352
.006	db3	27.7869	27.0537	27.9104	26.6506	26.3245	26.7760
	db8	27.2538	26.9568	27.5987	26.3037	26.1534	26.4175
.007	db3	25.3625	25.1730	25.7395	24.6222	24.4721	24.9624
	db8	25.5479	25.3210	25.5624	24.8915	24.8935	25.3633
.008	db3	24.5531	24.6265	24.8216	23.0414	23.5372	23.8426
	db8	24.2315	24.1126	24.6931	23.2723	24.3547	24.6372
.009	db3	23.5210	23.2428	23.7256	22.7502	22.8782	23.6571
	db8	23.2031	23.1753	23.6274	22.8109	22.9346	23.5235
	peppers				*child*		
.001	db3	34.9095	34.6170	35.9034	34.5810	34.4093	35.0143
	db8	34.4467	34.3002	34.6752	34.5437	34.4323	34.6108
.002	db3	32.5436	32.2653	32.9391	32.6904	32.1125	32.9136
	db8	32.4436	32.2075	31.6326	31.9706	31.7660	32.1731
.003	db3	30.2357	30.8817	30.5274	30.8856	30.6524	30.8988
	db8	30.5579	30.1896	29.9903	30.4351	30.1256	30.7820
.004	db3	28.6533	28.3900	28. 8875	28.8766	26.3205	28.5208
	db8	28.5374	28.1469	28.8607	28.2654	28.0481	28.3669
.005	db3	26.5785	26.4909	26.9827	26.3692	26.2744	26.6137
	db8	26.2961	26.3913	26.8710	26.2459	26.0237	26.5472
.006	db3	25.8549	25.6027	26.0365	25.7175	25.5769	25.0967
	db8	25.8797	25.5116	26.0023	25.2478	25.8231	25.8934
.007	db3	24.9035	24.8528	25.2376	24.7423	24.3789	25.1136
	db8	24.7236	24.4876	25.0205	24.4931	24.3010	24.9303
.008	db3	23.5210	23.1048	23.9256	23.7502	23.3782	23.6571
	db8	23.0201	23.1753	23.5274	22.8109	22.7660	23.3719
.009	db3	22.1210	22.0076	22.7261	22.2385	22.0705	22.5126
	db8	21.8201	21.7233	22.2383	21.8924	21.8346	22.1235

ii). Subjective Evaluation

The different grayscale images of size 512x512 are used as test images with different noise densities. The kind of noise is AWGN with variance from 0.001 to 0.009 for each denoising scheme with proposed one. Here three level of noise shows the low, medium, high value of variance respectively. The result shows that the proposed scheme performs better edge preserving image denoising using morphological operations and gives better results in terms of PSNR as given in the table and visual perception as shown in denoised images.

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a). for child image using Db3.

i) Noise Variance=.003, Value of PSNR=32.3764

Original image *Noisy image* *Denoised image*

ii). Noise Variance=.005, Value of PSNR=28.9687

Original image *Noisy image* *Denoised image*

iii). Noise Variance=.007, Value of PSNR=25.9395

Original image *Noisy image* *Denoised image*

b). for child image using Db3.

i). Noise Variance=.003, Value of PSNR=30.8988

Original image *Noisy image* *Denoised image* *ii). Noise Variance=.005, Value of PSNR=26.6137*

Original image *Noisy image* *Denoised image*

iii). Noise Variance=.007, Value of PSNR=25.1137

Original image *Noisy image* *Denoised image*

V. PERFORMANCE ANALYSIS

The proposed method is compared to adaptive thresholding methods to assess the denoising effectiveness. The values amongst bilateral filtering in wavelet domain, BM3D filtering and proposed efficient edge preserving image denoising are plotted with PSNR values at x- axis and PSNR at y-axis. Three graphs are plotted for all level of noise variance from **low** to **high** that is from 0.001, to 0.009.

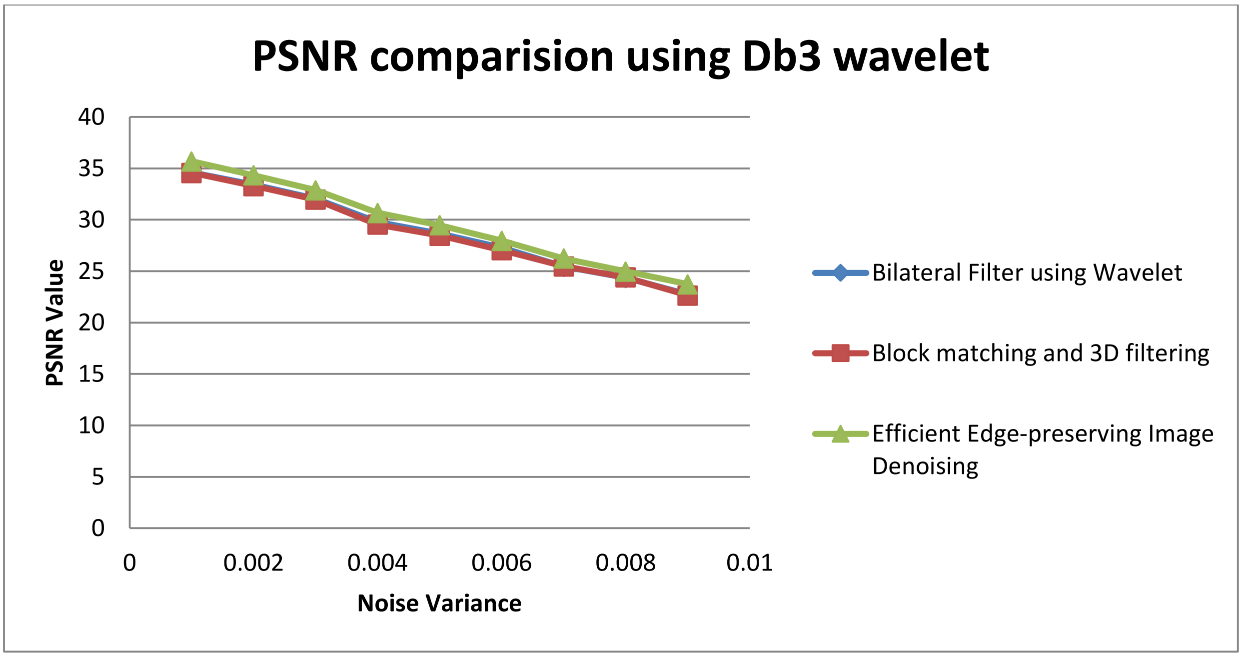

Figure 2: PSNR performance graphs for test image.

In the performance of the proposed method the major factor is the application of selective thresholding on subbands and further improving the edges using morphological operations. It helped in preserving edge details in images. This adds power to the proposed method as noise components can be eliminated better in detail as compared to traditional subbands thresholding.

CONCLUSION

Wavelet analysis is widely used in many applications because it provides localization in both time and frequency domain therefore leads to avoid the loss of information. When an image is corrupted with AWGN, the wavelet shrinkage denoising has proved to be nearly optimal. All these methods are adaptive in nature. Each of these methods is compared in terms of the PSNR values and visual perception.

Morphological operations can be used for smoothing or edge detection or extraction of other features. The concatenating opening with closing can improve the experimental results. Experimental results show that edges are being successfully preserved as offers superior performance than traditional sub band adaptive thresholding both in terms of PSNR and visual perception.

FUTURE WORK

In the experimental analysis given above, it is tried to determine the best adaptive method which preserve the image edges more. The drawbacks of bilateral filtering and subband-adaptive thresholding can be eliminated by using edge-preserving adaptive wavelet coefficients thresholding method. Such adaptivity can improve the wavelet coefficients thresholding performance because it allows additional local information of the image (such as the identification of smoothen or edge regions) to be incorporated into the algorithm. The edge-preserving adaptive thresholding will be extended to various other wavelet families such as Symlets, and Coiflets depending upon the number of vanishing points. This thresholding scheme will also be extended to undecimated DWT (UDWT) domain, which yield better results than the orthogonal wavelet transform. This would likely improve the denoising performance. Similar bodies of research work may be conducted for other kinds of non-gray scale (color) images.

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