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FUZZY SHRINK IMAGE DENOISING USING SMOOTHING SPLINE ESTIMATION

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ABSTRACT

The image data is normally corrupted by additive noise during acquisition. This reduces the accuracy and reliability of any automatic analysis. For this reason, denoising methods are often applied to restore the original image. In proposed method a wavelet shrinkage algorithm based on fuzzy logic and the DT-DWT scheme is used. In particular, intra-scale dependency within wavelet coefficients is modeled using a fuzzy feature. This model differentiates the important coefficients and the coefficients belong to image discontinuity and noisy coefficients. This fuzzy model is used to enhance the wavelet coefficients' information in the shrinkage step which uses the fuzzy membership function to shrink wavelet coefficients based on the fuzzy feature. The effectiveness of image denoising depends upon the estimation of noise variance of noisy image, the noise variance is estimated using smoothing spline Estimation. This study examine image denoising algorithm in the dual-tree discrete wavelet transform, which is the new shiftable and modified version of discrete wavelet transform. Simulation result shows our approach achieves a substantial improvement in both PSNR and Visual quality.

Keywords: Denoising, Fuzzy, DT-DWT, Smoothing Spline Estimation

1. INTRODUCTION

Denoising is essential for image analysis, due to sensor imperfections, transmission channels defects, as well as physical constraints, noise weakens the quality of almost every acquired image. Because of the importance and commonality of preprocessing in most image and video systems, there has been an enormous amount of research dedicated to the subject of noise removal and many different mathematical tools have been proposed. Variable coefficient linear filters (Dugad and Ahuja, 1999; Ojo and Kwaaitaal-Spassova, 2000), adaptive nonlinear filters (Meguro *et al*., 1999; Zlokolica *et al*., 2002), DCT-based solutions (Kim *et al*., 1999), cluster filtering (Wong *et al*., 1995), genetic algorithms (Vertan *et al*., 1997), fuzzy logic (Ling and Tam, 2001; Shutao *et al*., 2000), have all been proposed in the literature.

The main goal of an image denoising algorithm is then to reduce the noise level, while preserving the image features (such as edges, textures). Indeed, in the wavelet domain, the noise is uniformly spread throughout the coefficients, while most of the image information is concentrated in the few largest ones.

The linearity of the wavelet transform, additive noise in the image domain remains additive in the transform domain. If $\gamma_{s,d}(i,j)$ and $x_{s,d}(i,j)$ denote the noisy and the noise-free wavelet coefficients of scale s and orientation d respectively, then model the additive noise in the transform domain as Equation 1:

$$\gamma_{s,d}(i,j) = x_{s,d}(i,j) + {}_{s,d}(i,j) \quad (1)$$

where, $\eta_{s,d}(i,j)$ is the corresponding noise component, additive Gaussian white noise following a normal law defined by a zero mean and a known1 variance, that is $n \sim N(0,\sigma^2)$.

Wavelet threshold is a noise reduction method by transforming a noisy image into the wavelet domain,

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applying threshold in the wavelet domain and inverse transforming that enhanced wavelet coefficients. Most of the related studies are based on a hard or soft threshold of wavelet coefficients.

Wavelets are simply mathematical functions and these functions analyze data according to scale or resolution. They aid in studying a signal at different resolutions or in different windows. (Sendur and Selesnick, 2002) used a bivariate shrinkage function, which models the statistical dependence between a wavelet coefficient and its parent. It needs to estimate the marginal variance of the coefficient in a local neighborhood (Mallat, 1989; Donoho and Johnstone, 1995); and also they proposed De-noising by soft-thresholding (Blu and Luisier, 2007) directly parameterized the denoising process as a sum of elementary nonlinear processes with unknown weights. It need not hypothesize a statistical model for the noiseless image while it minimizes an estimate of the mean squared error between the noiseless image and the denoised one by the SURE. Consequently, it computes the unknown weights by solving a linear system of Equation (Selesnick, 2002) and among the methods in which intra-scale dependency for image denoising have used: (Chen *et al*., 2005) used local mean of neighbor coefficients in wavelet sub-bands as a feature to shrink wavelet coefficients and their method is called NeighShrink; Pizurica and Philips used a probabilistic shrinkage function. Its core is estimating the probability that a given coefficient contains a significant noise-free component. (Siler and Buckley, 2005). They construct successful real-world fuzzy expert systems for problem solving. The characteristics of expert systems neural nets and symbolic reasoning. They also discuss developing a rule-based expert system, fuzzy rule-based systems and tools for learning how to construct fuzzy expert systems.

Fan *et al.* (2008). A Lifting-Based Wavelet Domain Wiener Filter (LBWDMF) in image enhancement is proposed. Lifting schemes have emerged as a powerful method for implementing bi-orthogonal wavelet filters. The method transforms an image into the wavelet domain using lifting-based wavelet filters and then applies a Wiener filter in the wavelet domain and finally transforms the result into the spatial domain. LBWDMF not only helps in reducing the number of computations but also achieves lossy to lossless performance with finite precision.

Then the wavelet coefficient is multiplied with the probability (Pizurica and Philips, 2006; Schulte *et al*., 2007) introduced a fuzzy version of probabilistic shrinkage method. Its core is shrinkage based on local mean of wavelet coefficients and some fuzzy rules (Schulte *et al*., 2006). Many other techniques have combined inter-and intra-scale dependencies. For example, denoising methods based on Gaussian Scale Mixture models, often employ the neighboring coefficients on the same and adjacent scales (Portilla *et al*., 2003). Local contextual HMT models have been developed, which capture both inter-scale and intra-scale information (Fan and Xia, 2001a; 2001b).

Nonparametric and parametric estimator in multiresponse semi parametric regression model can be obtained by using weighted penalized least square. More specific, estimator for nonparametric component is partial spline function. Especially, if nonparametric component hold some assumption, then the kind of spline function is polynomial natural spline. This estimator depends on smoothing parameter and these imply that the predicted values also depend on smoothing parameter. However, the optimal smoothing parameter can be chosen by using G criteria. (Wibowo *et al*., 2012).

Diana *et al*. (2013).The smoothing spline in semi parametric additive regression model with Bayesian approach is a development of Bayesian smoothing spline for nonparametric component by assuming improper Gaussian distribution for prior distribution in nonparametric components and multivariate normal distribution for parametric components. In this study, they obtain parameter estimators for parametric component and smoothing spline estimators for the nonparametric component in semiparametric additive regression model and develop a smoothing parameters selection method simultaneously using Generalized Maximum Likelihood (GML) and confidence intervals for the parameters of the parametric component and the smoothing spline functions of the nonparametric component using Bayesian approach. By computing each posterior mean and posterior variance of parametric component parameters and smoothing spline functions, confidence intervals can be constructed for the parametric component parameters and confidence interval smoothing spline functions for nonparametric components in semiparametric additive regression models.

Khmag *et al*. (2014) Exposes that a newly developed method based on the wavelet transform (semi-soft thresholding) there is a practical guidance on its use. Cycle Spinning technique is implemented in order to enhance the quality of the denoised estimates. The restoration of images are preserving high frequency.

In the implementation of the proposed algorithm, first the noisy image is transformed into the wavelet domain by DT-DWT scheme called Dual Tree -DWT based wavelet filter. Second, in the Transformation wavelet domain intra-scale dependency within wavelet coefficients is modeled using a fuzzy feature and Smoothing Spline Noise Estimation is carried out over high frequency sub-band images. Third, the sub-band images are given for denoising purpose where Fuzzy shrinkage is used for removing the noise, then inversely transformed to the spatial domain, to produce the final enhanced image. Section 2 describes the proposed model and some simulation results are illustrated in section 3. Finally, the conclusions are drawn in section 4.

2. IMAGE DENOISING USING FUZZY SHRINK AND DT-DWT

The block diagram is shown in the **Fig. 1**. In proposed method a wavelet shrinkage algorithm based on fuzzy logic and the DT-DWT scheme is used. In particular, the model of intra-scale dependency within wavelet coefficients by using a fuzzy feature. This model differentiate the important coefficients and the coefficients belong to image discontinuity and noisy coefficients. In this study by using fuzzy feature to enhance the wavelet coefficients' information in the shrinkage step which uses the fuzzy membership function to shrink wavelet coefficients based on the fuzzy feature. The effectiveness of image denoising depends upon the estimation of noise variance of the noisy image and it is estimated using smoothing spline estimation.

2.1. Dual Tree Discrete Wavelet Transform

Nevertheless, DWT(Selesnick *et al*., 2005) suffers from five fundamental, those are oscillations, aliasing, shift-variance, poor directionality and absence of phase information. Shift invariance and directional selectivity are essential to the quality of wavelet based image denoising results. Because of the down-sampling operation in the DWT Filter Bank (FB), it is shift-variance and will cause some visual artifacts (such as Gibbs phenomena) in thresholding- based denoising (Zhang and Bao, 2003). In addition, if the directional selectivity of a FB is defined as the ability to extract directional features into separate images, then the 2-D DWT has very poor directional selectivity because 2-D DWT has four sub-images, which are usually referred to as LL, LH, HL and HH images. Many solutions to the shift-variance and lack of directionality of the DWT have been suggested in the literature. A simple approach to shift-variance is to remove the decimation blocks in the FB, so that there is no aliasing in the output sub-band signals. In this case, the sub-bands signals are perfectly shift-invariant high-dimensional signals more effectively (undecimated discrete wavelet transform). The new properties resulting from the use of this highly redundant transformation have been obtained at the expense of the loss of orthogonality, a considerably more intensive memory usage and a higher computational cost than that of the original DWT. In this study, examine our image Denoising algorithm in the Dual-Tree DWT (DTDWT), which provides both shiftable sub-bands and good directional selectivity and low redundancy (Kingsbury, 2001; 2000; Selesnick, 2002). Kingsbury found that the low pass filters of one DWT interpolate midway between the low pass filters of the second DWT when dual-tree DWT is nearly shift-invariant.

The dual-tree can be executed as critically-sampled separable two dimensional Discrete Wavelet Transforms (DWTs) operating in parallel. The two trees may have the filters that process the time-reverse of each other, those are the analysis and reconstruction filters. The new filters are shorter than before and the new transform still satisfies the shift invariant property and good directional selectivity in multiple dimensions

2.2. Denoising and Thresholding

Here the denoising is done through Fuzzy shrinkage rule. In image denoising, fuzzy model is used to enhance image information in wavelet sub-bands and then using a fuzzy membership function to shrink wavelet coefficients, accordingly. This feature space distinguishes between important coefficients, which belong to image discontinuity and noisy coefficient.

2.2.1. Fuzzy Model

Give large weights to neighboring coefficients with similar magnitude and a small weight to neighboring coefficients with dissimilar magnitude. The larger coefficients, which are produced by noise, are always isolated or unconnected, but edge coefficients are clustered and persistent. It is well known that the more adjacent points are more similar in magnitude. So use a fuzzy function m(l, k) of magnitude similarity and a fuzzy function s(l, k) of spatial similarity, which is defined as (Saeedi *et al*., 2010) Equation 2 and 3:

$$m(l,k) = \exp\left(-\left(\frac{Y_{s,d}(i,j) - Y_{s,d}(i+l, j+k)}{Thr}\right)^2\right) \quad (2)$$

$$s(l,k) = \exp\left(-\left(\frac{l^2+k^2}{N}\right)\right) \quad (3)$$

where, $Y_{s,d}(i,j)$ and $Y_{s,d}(i+l, j+k)$ are central coefficient and neighbor coefficients in the wavelet sub-bands, respectively. $Thr = c\times\hat{\sigma}_n,\ 3\le c\le 4, \hat{\sigma}_n$ is estimated noise variance and N is the number of coefficients in the local window $k\in[-K\ldots K]$ and $l\in[-L\ldots L]$.

According the two fuzzy functions, can get adaptive weight w(l, k) for each neighboring coefficient Equation 4:

$$w(l,k) = m(l,k)\times s(l,k) \quad (4)$$

Using the adaptive weights w(l, k), obtain the fuzzy feature for each coefficient in the wavelet sub-bands as follows Equation 5:

$$f(i,j) = \frac{\sum_{I=-L}^{L}\sum_{K=-K}^{K} W(l,k)\times\left|Y_{s,d}(i+l, j+k)\right|}{\sum_{I=-L}^{L}\sum_{K=-K}^{K} W(l,k)} \quad (5)$$

2.2.2. Noise Variance Estimation

Noise estimation and image denoising are in general chicken and egg problems. The underlying signal must be known to estimate the noise level, which could be estimated using a denoising algorithm; most probably some denoising algorithms depend on knowing the noise level.

2.2.3. Smoothing Spline Estimation with Dual Tree Wavelet Transform

In this study introduce a robust and efficient noise variation estimation scheme based on the wavelet transform and smoothing spline estimation (Feng *et al.*, 2010). Consider the following regression model Equation 6:

$$\begin{aligned} & y_i = x_i^T\beta + \varepsilon_i, i = 1,\ldots,n \\ & or \quad y_i = f(t_i) + \varepsilon_i, t_i = \frac{i}{n}, i = 1,\ldots,n \end{aligned} \quad (6)$$

To assume that f is a smooth function of $t\in[0,1]$.

Define the following infinite dimensional space (Wahba, 1975) $W_2(per)$ = {f: f and f' are absolutely continuous Equation 7:

$$f(0) = f(1), f'(0) = f'(1), \int_0^1 \left(f''(t)\right)^2 dt < \infty \quad (7)$$

A smoothing spline estimate of f is the minimize of the following penalized least square Equation 8:

$$\underset{f\varepsilon W_{2(per)}}{\text{Min}} \left\{\frac{1}{n}\sum_{i=1}^{n}\left\|y_i - f(t_i)\right\| + \lambda\int_0^1 \left\|f''(t)dt\right\|\right\} \quad (8)$$

The first part measures the goodness-of-fit, the second part is a penalty to the roughness of the estimate and $\lambda(0\le\lambda\le\infty)$ is the so called smoothing parameter Equation 9.

Define the following space Equation 9:

$$M_\infty = \text{span}\left\{1, \sqrt{2}\sin 2\pi vt, \sqrt{2}\cos 2\pi vt,\ v = 1,\ldots,\alpha\right\} \quad (9)$$

where, the order α is unknown and need to be selected in {0,1,….,N}. In this study, choose α = 2. In the infinite dimensional space, the following exact solution for in which substitute $W_2(per)$ with M_∞ holds:

$$\hat{f}_\lambda(t) = \beta_1 + \sum_{v=1}^{\infty}(\beta_{2v}\sqrt{2}\sin 2\pi vt + \beta_{2v+1}\sqrt{2}\cos 2\pi vt$$

Let $\hat{f}_\lambda(t) = (\hat{f}_\lambda(t_1),\ldots, \hat{f}_\lambda(t_n))^T$ and then rehearsing in the matrix form Equation10:

$$\hat{f}_\lambda = X_\infty\beta_\infty = \frac{1}{n}X_\infty D X_\infty^T y = H(\lambda)y \quad (10)$$

where, $y = (y_1,\ldots,y_n)T$, $\beta_a = (\beta_1,\ldots, \beta_{2a+1})^T$ Equation 11:

$$X_\alpha = \begin{bmatrix} 1\sqrt{2}\sin 2\pi t_1 & \sqrt{2}\cos 2\pi t_1 .. & \sqrt{2}\sin 2\pi\alpha t_1 & \sqrt{2}\cos 2\propto \pi t_1 \\ 1\sqrt{2}\sin 2\pi t_2 & \sqrt{2}\cos 2\pi t_2 .. & \sqrt{2}\sin 2\pi\alpha t_2 & \sqrt{2}\cos 2\alpha\pi t_2 \\ ; \quad ; & ;; \quad .. & ;; & ;; \\ 1\sqrt{2}\sin 2\pi t_n & \sqrt{2}\cos 2\pi t_n \cdot\cdot & \sqrt{2}\sin 2\pi\propto t_n & \sqrt{2}\cos 2\propto \pi t_n \end{bmatrix}$$

$$\begin{aligned} & D = diag(1, 1/\left(1+\lambda(2\pi)^4\right), 1/\left(1+\lambda(2\pi)^4\right)\ldots, \\ & 1/(1+\lambda(2\pi\alpha)^4), 1/(1+\lambda(2\pi\alpha)^4)) \end{aligned} \quad (11)$$

The Generalized Cross-Validation (GCV) criterion proposed in (Allen, 1974) will be adopted to provide the optimal smoothing parameter λ Equation 12:

$$GCV(\lambda) = \frac{\frac{1}{n}\sum_{i=1}^{n} y_i - \hat{f}_\lambda(t_i)^2}{1 - \frac{trH(\lambda)^2}{n}} \quad (12)$$

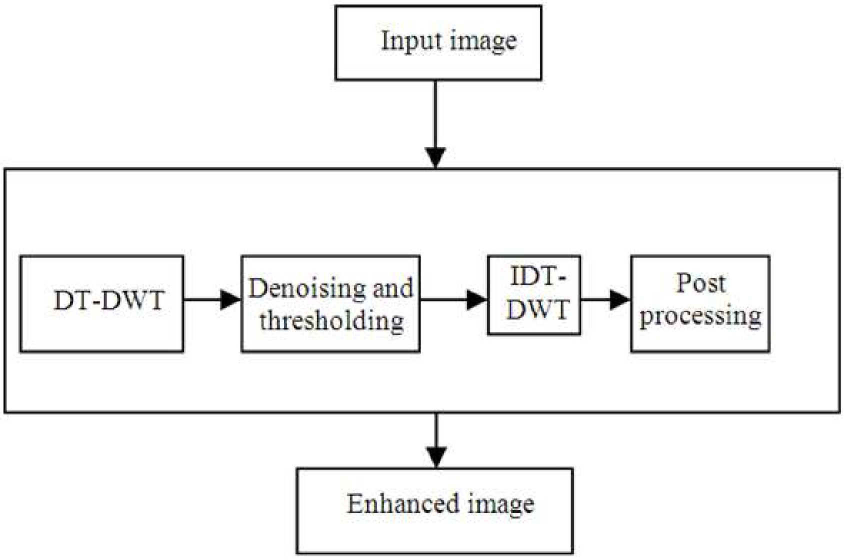

Fig. 1. Block diagram of proposed model

where, n is the number of the wavelet coefficients. Then get the $\hat{f}_\lambda(t)\, and\, \hat{\sigma}$.

Algorithm for Smoothing Spline estimated with wavelet transform.
Input: The noised image Processing:

Step 1 = Decompose the noised image into sub bands using wavelet transform;
Step 2 = Extract the coefficient vector y_i from high frequency band of DT-DWT wavelet;
Step 3 = Perform the smoothing spline estimate
Step 4 = Utilize generalized cross validation criterion to get minimization of the GCV score and the noise variance
Output = The estimated noise variance

2.2.3. Fuzzy Shrinkage Rule

The study of rules may use the B-spline curve, which is a mapping on the vector x and is named because of its B-shape. The parameters T_1 and T_2 locate the extremes of the sloped portion of the curve as given by (Saeedi *et al*., 2010):

$$\mu(x) = \begin{cases} 0 & x \le T_1 \\ 2\left(\dfrac{x - T_1}{T_2 - T_1}\right)^2 & T_1 \le x \le \dfrac{T_1 + T_2}{2} \\ 1 - 2\left(T_2 - \dfrac{x}{T_2 - T_1}\right)^2 & \dfrac{T_1 + T_2}{2} \le x \le T_2 \\ 1 & x \le T_2 \end{cases}$$

Finally, the estimated noise-free signal is obtained using the following formula Equation 13:

$$\hat{x}_{s,d}(i,j) = \mu(f(i,j)) \times Y_{s,d}(i,j) \tag{13}$$

For building fuzzy membership function, two thresholds (T_1 and T_2), must be determined. In this we found out that T_1 and T_2 are related with the $\hat{\sigma}_n$ which is the estimated noise variance. Here found out that T_1 and T_2 have nonlinear relation with the $\hat{\sigma}_n$. In each different noise variance they obtained best values for T_1 and T_2 Equation 14 and 15.

$$T_1\, K_1 \times \hat{\sigma}_n \tag{14}$$

$$T_2\, K_2 \times \hat{\sigma}_n \tag{15}$$

By using trial and error method, arrived k_1 and k_2 values is $0.22<k_1<0.8$ and $1.44<k_2<1.8$

$\hat{\sigma}_n$ is the noise variance using Smoothing Spline Estimation. Indeed, this method is a simple fuzzy IF THEN rule, which assigns smaller local window and smaller level of decomposition when the estimated noise variance is small and vice versa then the denoising output of the image is given to the inverse of the DWT for the reconstruction of the image. Then the image is sent for post processing process.

2.3. Post Processing

Processing is a result of modification in the spatial correlation between wavelet coefficients (often caused by zeroing of small neighboring coefficients) or using DWT, which is shift invariance and will cause some visual artifacts in thresholding based denoising. For this reason, use a fuzzy filter on the results of our fuzzy-shrink algorithm to reduce artifacts to some extent. First, use a window of size (2L+1)×(2K+1) centered at (i, j) to filter the current image pixel at position (i,j). Next, calculate the similarity of neighboring pixels to the center pixel using following formula (Saeedi *et al*., 2010) Equation 16:

$$m(l,k) = \exp\left(-\left(\frac{\hat{x}(i,j) - \hat{x}(i+1, j+1)}{thr}\right)^2\right) \quad (16)$$

where, $\hat{x}(i,j)$ *and* $\hat{x}(i+l, j+k)$ are central pixel and neighbor pixels in the denoised image, respectively. N is the number of pixels in the local window k∈[-K…K] and l∈[-L…L] and Thr 0<1.

According the fuzzy feature, get adaptive weight for each neighboring coefficient Equation 17:

$$w(l,k) = m(l,k) \times s(l,k) \quad (17)$$

where, s(l,k) is obtained using Equation (3).

Finally, the output of post-processing step is determined as follows Equation 18:

$$\tilde{x}(i,j,c) = \frac{\sum_{I=-L}^{L}\sum_{K=-K}^{K} w(l,k) \times \tilde{x}(i+1, j+k, c)}{\sum_{i=-L}^{L}\sum_{k=-K}^{k} w(l,k)} \quad (18)$$

where, $\hat{x}$ is the denoised image, which is obtained via our fuzzy-shrink algorithm. After the post processing process the enhanced image is obtained as a result.

3. SIMULATION RESULT

The simulation result that can be obtained as shown in the figure. When the input image is the Original image is shown in the **Fig. 2a** the noise is added with it is shown in the **Fig. 2b**. Then the image undergo denoising process in which the noise is removed, then for the reconstruction of the image inverse wavelet transform is performed,finally get the enhanced image as shown in the **Fig. 2c**.

The objectively measured the results by the Peak Signal-to-Noise Ratio (PSNR) in decibels (dB), which is defined Equation 19:

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{\text{MSE}}\right) \quad (19)$$

Where:

$$\text{MSE} = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\hat{x}(i,j) - x(i,j)\right)^2$$

Where:

x(i,j) = The original image
$\hat{x}$(i, j) = The estimated noise-free signal and
M×N = The number of pixels

Table 1 shows comparison of PSNR Value for various fuzzy membership function **Table 2** shows comparison of PSNR Value for various denoising methods. Proposed method with B Spline method having better PSNR Value for Barbara Image.

(a) (b) (c)

Fig. 2. (a) Original image (b) noisy image (c) enhanced image

Table 1. Comparison of PSNR value for various membership function

	σ = 10	σ = 15	σ = 20
Various methods	PSNR	PSNR	PSNR
S Shaped	32.99	32.79	32.24
Triangular shaped	32.79	31.20	32.54
Z Shaped	30.56	29.98	29.54
B Spline	34.01	33.79	32.56

Table 2. Comparison of PSNR value for various denoising methods with proposed method

Various methods	σ = 5	σ = 10	σ = 15	σ = 20	σ = 25	σ = 30	σ = 50
HMT (DWT)	31.62	28.18	26.20	25.05	24.27	23.80	22.54
NeighShrink (DWT)	32.69	29.04	26.87	25.24	24.02	23.33	21.91
ProbShrink (DWT)	36.00	31.57	29.65	28.06	27.01	26.15	23.63
Sure-let (DWT)	36.71	32.18	29.66	27.98	26.76	25.83	23.70
BLS-GSM non-redundant	36.63	32.29	29.88	28.24	27.05	26.14	23.82
Fuzzy-shrink (DWT)	36.72	32.58	30.21	28.68	27.48	26.57	23.93
Bi-shrink (DT-DWT)	36.75	33.17	30.85	29.13	27.74	26.47	22.88
BLS-GSM best redundant	37.62	33.66	31.31	30.22	28.40	27.38	24.70
Fuzzy-shrink (DT-DWT)	37.81	33.96	31.72	30.31	29.04	28.04	25.38
Proposed 2D-DWT	36.67	34.01	33.79	32.56	31.58	30.14	27.83

4. CONCLUSION

This study proposes a wavelet shrinkage algorithm using fuzzy model for intra-scale dependency and then, shrinkage wavelet coefficients with corresponding fuzzy membership function, for image denoising. This method use the DT-DWT for wavelet analysis, because it is shift-invariant and has more directional sub-bands compared to the DWT. In other words, proposing a new method for shrinking wavelet coefficients in the second step of the wavelet-based image denoising for the image and the noise is estimated using smoothing spline noise estimation is the novelty of the paper. The comparison of the denoising results obtained in our algorithm is the best state-of-the-art methods, demonstrate that the performance of our approach, which shows the better PSNRs output. In addition, the visual quality of our denoised images exhibits the fewest number of artifacts and preserves most of edges compared to other methods.

5. REFERENCES

Allen, D., 1974. The relationship between variable selection and data augmentation and a method for prediction. Technometrics, 16: 125-127. DOI: 10.1080/00401706.1974.10489157

Blu, T., F. Luisier, 2007. The SURE-LET approach to image denoising. IEEE Trans. Image Process., 16: 2778-2786. DOI: 10.1109/TIP.2007.906002

Chen, G.Y., T.D. Bui and A. Krzyzak, 2005. Image denoising with neighbour dependency and customized wavelet and threshold. Patt. Recog., 38: 115-124. DOI: 10.1016/j.patcog.2004.05.009

Diana, R., I.N. Budiantara, Purhadi and S. Darmesto, 2013. Smoothing spline in semiparametric additive regression model with Bayesian approach. J. Math. Stat.,9:161-168.

Donoho, D.L. and I.M. Johnstone, 1995. Adapting to unknown smoothness via wavelet shrinkage. J. Am. Stat. Assoc., 90: 1200-1224. DOI: 10.1080/01621459.1995.10476626

Donoho, D.L. and I.M. Johnstone, 1995. De-noising by soft-thresholding. IEEE Trans. Inform. Theory, 41: 613-27. DOI: 10.1109/18.382009

Dugad, R. and N. Ahuja, 1999. Video denoising by combining Kalman and Wiener estimates. Procedins of the International Conference on Image Processing, (CIP' 99), IEEE Xplore Press, pp: 152-156. DOI: 10.1109/ICIP.1999.819568

Fan, G. and X. Xia, 2001a. Image denoising using local contextual hidden Markov model in the wavelet domain. IEEE Signal Process. Lett., 8: 125-128. DOI: 10.1109/97.917691

Fan, G. and X. Xia, 2001b. Improved hidden Markov models in the wavelet-domain. IEEE Trans. Signal Process., 40: 115-120. DOI: 10.1109/78.890351

Fan, W., Z. Ge and Y. Wang, 2008. Adaptive wiener filter based on fast DT-DWT wavelet transform for image enhancement. Proceedings of the 7th World Congress on Intelligent Control and Automation Jun. 25-27, Chongqing, China.

Feng, W.Q., S.M. Li and K.L. Zheng, 2010. A non-local bilateral filter for image Denoising. Proceedings of the International Conference on Apperceiving Computing and Intelligence Analysis, Dec. 17-19, IEEE Xplore Press, Chengdu, pp: 253-257. DOI: 10.1109/ICACIA.2010.5709895

Khmag, A., A.R. Ramli, S.A.R. Al-Haddad and S.J.B. Hashim, 2014. Additive and multiplicative noise removal based on adaptive wavelet transformation using cycle spinning. Am. J. Applied Sci., 11: 316-328.

Kim, S.D., S.K. Jang, M.J. Kim and J.B. Ra, 1999. Efficient block-based coding of noise images by combining pre-filtering and DCT. Proc. IEEE Int. Symp. Circuits Syst., 4: 37-40. 10.1109/ISCAS.1999.779937

Kingsbury, N., 2001. Complex wavelets for shift invariant analysis and filtering of signals. J. Appl. Computat. Harmonic Anal., 10: 234-253. DOI: 10.1006/acha.2000.0343

Kingsbury, N.G., 2000. A dual-tree complex wavelet transform with improved orthogonality and symmetry properties. Proceedings of the International Conference on Image Processing, Sept. 10-13, IEEE Xplore Press, Vancouver, BC, Canada, pp: 375-378. DOI: 10.1109/ICIP.2000.899397

Ling, W. and P.K.S. Tam, 2001. Video denoising using fuzzy-connectedness principles. Proceedings of the 2001 International Symposium on Intelligent Multimedia Video, Speech Processing, (VSP' 01), IEEE Xplore Press, Hong Kong, DOI: 10.1109/ISIMP.2001.925450

Mallat, S., 1989. A theory for multiresolution signal decomposition: The wavelet representation. IEEE Trans. Pattern Anal. Mach. Intell., 11: 674-693. DOI: 10.1109/34.192463

Meguro, M., A. Taguchi and N. Hamada, 1999. Data-dependent weighted median filtering with robust motion information for image sequence restoration. IEICE Trans. Fund., 2: 424-428. DOI: 10.1109/ICIP.1999.822931

Ojo, O. and T. Kwaaitaal-Spassova, 2000. An algorithm for integrated noise reduction and sharpness enhancement, IEEE Trans. Consum. Electron. 46: 474-480. DOI: 10.1109/30.883396

Pizurica, A. and W. Philips, 2006. Estimating the probability of the presence of a signal of interest in multiresolution single and multiband image denoising. IEEE Trans. Image Process., DOI: 10.1109/TIP.2005.863698

Portilla, J., V. Strela, M. Wainwright and E. Simoncelli, 2003. Image denoising using Gaussian scale mixtures in the wavelet domain. IEEE Trans. Image Process., 12: 1338-1351. DOI: 10.1109/TIP.2003.818640

Saeedi, J., M.H. Moradi and K. Faez, 2010. A new wavelet-based fuzzy single and multi-channel image denoising. Image Vision Computing, 28: 1611-1623. DOI: 10.1016/j.imavis.2010.04.004

Schulte, S., B. Huysmans, A. Pizurica, E.E. Kerrel and W. Philips, 2006. A new fuzzy-based wavelet shrinkage image denoising technique. Proceedings of the 8th International Conference, Sept. 18-21, Antwerp, Belgium, pp: 12-23. DOI: 10.1007/11864349_2

Schulte, S., V.D. Witte and E.E. Kerre, 2007. A fuzzy noise reduction method for color images. IEEE Trans. Image Process., 16: 1425-1436. DOI: 10.1109/TIP.2007.904960

Selesnick, I.W., 2002. The design of approximate Hilbert transform pairs of wavelet bases. IEEE Trans. Signal Process., 50: 1144-1152. DOI: 10.1109/78.995070

Selesnick, I.W., R.G. Baraniuk and N.G. Kingsbury, 2005. The dual-tree complex wavelet transform. IEEE Signal Process. Mag., 22: 124-152. DOI: 10.1109/MSP.2005.1550194

Sendur, L. and I.W. Selesnick, 2002. Bivariate shrinkage with local variance estimation. IEEE Signal Proc. Lett., 9: 438-441. DOI: 10.1109/LSP.2002.806054

Shutao, L., W. Yaonan, Z. Changfan and M. Jianxu, 2000. Fuzzy filter based on neural network and its applications to image restoration. Proc. IEEE Int. Conf. Signal Process., 2: 1133-1138. DOI: 10.1109/ICOSP.2000.891739

Siler, W. and J.J. Buckley, 2005. Fuzzy Expert Systems and Fuzzy Reasoning. 1st Edn., John Wiley and Sons, ISBN-10: 0471698490, pp: 350.

Velaga, S. and S. Kovvada, 2012. Efficient techniques for denoising of highly corrupted impulse noise images. Int. J. Soft Comput. Eng., 2: 255-258.

Vertan, C., C.I. Vertan and V. Buzuloiu, 1997. Reduced computation genetic algorithm for noise removal. Proceedings of the 6th International Conference on Image Processing and Its Applications, Jul. 14-17. IEEE Xplore Press, Dublin, pp: 313-316. DOI: 10.1049/cp:19970906

Wahba, O., 1975. Smoothing noisy data with spline functions. Numer. Math., 24: 383-393. DOI: 10.1007/BF01437407

Wibowo, W., S. Haryatmi and I.N. Budiantara, 2012. On multiresponse semiparametric regression model. J. Math. Stat., 8: 489-499.

Wong, Y.F., E. Viscito and E. Linzer, 1995. Preprocessing of video signals for MPEG coding by clustering filter. Proc. IEEE Int. Conf. Image Process., 2: 2129-2133. DOI: 10.1109/ICIP.1995.537431

Zhang, L. and P. Bao, 2003. Hybrid inter and intra-wavelet scale image restoration. Patt. Recog., 36: 1737-1746. DOI: 10.1016/S0031-3203(02)00350-3

Zlokolica, W., D. Philips, V.D. Ville, 2002. A new nonlinear filter for video processing, Proc. IEEE Benelux Signal Process. Symp., 2: 221-224.