International Journal of Engineering & Technology, 7 (3.29) (2018) 336-341

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

An efficient image denoising algorithm based on double density dual tree discrete wavelet transform for wireless sensor network

H. Rekha [1] *, P. Samundiswary [1]

[1] *Research Scholar, Department of Electronics Engineering Pondicherry University*
**Corresponding author E-mail: saathvekha16@gmail.com*

Abstract

Generally, the input images are unavoidably corrupted by Gaussian noise during process of sensing, transmitting and retrieval of images over Wireless Sensor Network (WSN). To suppress the noise and enhance the input image quality, the wavelet based image denoising methods has shown better results in the field of WSN. However, these methods affect the quality of the denoised image due to the poor selection of thresholding technique and the number of decomposition levels. In order to overcome the above mentioned problems and to reduce the impact of Gaussian noise over WSN images, this research work concentrated on the hybrid of double density wavelet and DTCWT based wavelet called Double Density Dual Tree Discrete Wavelet Transform(DDDTDWT). The proposed work is discussed in form of two parts. The first part explains about the simple DDDTDWT based image denoising technique. The second part describes about the proposed DDDTDWT with the combination of Fast Non Local Means Filter (FNLMF). Further, to verify the effectiveness of the proposed image denoising algorithms, two thresholding methods such as hard thresholding using median absolute deviation and bivariate thresholding using adaptive method are utilized. Furthermore, the performance comparison of the existing and the proposed image denoising methods developed for WSN are examined through the simulation results using MATLAB.

Keywords: *Image Denoising; Fast Non-Local Means Filter; Double Density Wavelets; Hard Thresholding; Bivariate Thresholding; Wireless Sensor Network.*

1. Introduction

Wireless Sensor Network (WSN) is chosen as one of the best networking technology for many applications including object tracking, tele-medicine and forest monitoring etc. Despite the applications of WSN, there are many design challenges arising from the limited resources of WSN such as image security, acquisition noise, routing techniques and energy consumption [1]. Out of that, due to the usage of large number of low quality camera sensors, the noisy images obtained from the camera sensor cause a severe problem during image analysis which needs to be rectified. Image denoising is one of the most significant pre-processing techniques to suppress the acquisition noise. Some of the noises that frequently affect the images are Additive White Gaussion Noise (AWGN), salt and pepper noise, shot noise etc. Besides, the AWGN noise during image acquisition produces severe problems than that of other noises. The following literature surveys mentioned that, there are lots of image denoising methods developed to reduce the effect of AWGN noise for WSN. These methods are divided into two groups: spatial based and frequency based image denoising methods [4]. In spatial domain, median filter [5], neighbourhood average method [6] and weighted median filter and the center-weight median filter [7], [8] are considered for image denoising. However, these methods have some limitations such as a high computation load and poor image quality. In frequency domain [9], Discrete Fourier Transform (DFT) and Discrete Cosine Transform (DCT) are the most popular transformations that are widely used for image processing applications [10], [11]. But, the drawbacks of DFT and DCT such as high loss of information and low resolution make it unsuitable for real-time image processing of critical applications. Later, Discrete Wavelet Transform (DWT) is broadly used as a image denoising tool than that of DFT and DCT. However, it lack in shift invariant property and poor directionality. Henceforth, to solve the DWT problems, different forms of Complex Wavelet Transforms (CWT) are proposed [12, 13]. Dual-Tree Complex Wavelet Transform (DT-CWT) is one of the most efficient forms of CWT [14]. In 2015, Rachid Sammouda et.al [15] has developed an image denoising algorithm for image based WSN by utilizing the advantages of DTCWT. Here, the image is decomposed in to 3 levels by using DTCWT. Once the image is decomposed in to low and high frequency subband coefficients, hard thresholding is applied to high frequency subband coefficients to reduce the noise level. Recently, Wavelet Thresholding (WT) and its combination with the Bilateral Filter (BF) have shown better results in terms of quantitatively and qualitatively. But, for higher noise levels, the denoised images of BF and its updated version called Fast Bilateral Filter (FBF) are poorly affected by over smoothing and blurring [16]. In the meantime, H. Rekha et al., [17] have tried an attempt on sensor images by combining the FBF and Histogram based Multi-Thresholding (HMT) using harmony search algorithm. However, this method has not shown appreciable results for high noise levels. Therefore, it is essential to propose an effective image denoising algorithm to suppress the Gaussian noise effectively with less computational complexity. In this paper, the proposed method first considers the Double Density Dual Tree Real Discrete Wavelet Transform (DDDTRDWT) and verifies its performance for various standard noisy images. Then, it proposed another denoising method by combining the double density dual tree wavelet transform with Fast Non Local Means Filter (FNLMF) to eradicate the AWGN noise over sensor images. Further, the improvement in denoised image quality can be achieved by analysing the proposed methods with two different threshold techniques such as hard thresholding and bivariate thresholding. Furthermore, the performance comparison of the existing and the proposed image denoising methods in terms of standard metrics such as Peak Signal to Noise Ratio (PSNR), computation time and Normalized Absolute Error (NAE) are taken in to consideration for determining the effectiveness of the proposed wavelet based image denoising algorithms. The rest of the paper is organized as follows: Section 2 presents the detailed descriptions and analysis of existing DTCWT based image compression technique. Section 3 discusses the important blocks of the proposed algorithms. The detailed working principles of the proposed algorithms are clearly depicted in section 4. Simulation results and the performance comparison of the proposed image compression algorithms with the existing techniques are dealt in Section 4. Finally, Section 5 concludes the paper.

2. Existing DDCWT based image denoising method for WSN

In 2015, Rachid Sammouda et.al [16] has developed an image denoising algorithm for WSN by considering the advantages of DTCWT. For denoising, Rachid et.al has assumed that the image from the camera sensor is affected by AWGN noise which is usually present in the WSN domain. The first step in the model is to convert the color input image from the camera sensor into grayscale image. Then, the image is decomposed into 3 levels by using DTCWT. Followed by the decomposition, filter bank is applied on each row and column of the decomposed image. Once the image is separated into low and high frequency subband coefficients, hard thresholding using optimal threshold value is applied to high frequency subband coefficients. If the value of the each coefficient from the high frequency subband is lesser than that of the optimal threshold value, then the high frequency subband values set as zero, otherwise it remain in the same value. The appropriate optimal threshold value for proper thresholding is calculated by using Median Absolute Deviation (MAD) and length of the wavelet subband coefficient, The optimal threshold value T_j is calculated as follows,

$$T_j = MAD_j \times \sqrt{2 * \log N_j} \tag{1}$$

Where, MAD is a Median Absolute Deviation (MAD) and Nj is the length of the coefficient of each subband. The MAD value of the each coefficient (ω) is calculated by using the following function,

$$MAD_j = \frac{median(|w_{L-1,j}|)}{0.6745} \tag{2}$$

$$\omega_{i,j}Z = \begin{cases} \omega_{i,j}Y \text{ if } |\omega_{i,j}Y| > T \\ 0 \text{ if } |\omega_{i,j}Y| \le T \end{cases} \tag{3}$$

Here, $\omega_{i,j}Y$ is mentioned as input image wavelet coefficient before threshold and $\omega_{i,j}Z$ is represented as wavelet coefficient after threshold. From the above equations, L is used to represent the number of decomposition levels of the input image. By using the optimal threshold value T_j, the hard threshold is applied to the wavelet coefficients. Basically, DTCWT gives texture oriented information in six different directions with limited redundancy. Therefore, some of the fine information from the captured image may lose during image denoising because of the poor selection of number of decomposition levels. Added to that, the selection of optimal threshold using MAD strategy may cause smoothness over image edges for some images.

3. Proposed DDDTCWT based image denoising method

From the above section, it is clear that the selection of number of decomposition levels of the DTCWT determines the quality of the image denoising. However, the appearance of DTCWT in image denoising results in degradation of some image features. Particularly, the image edges are smoothened and the output looks alike blurred at high noise levels. Hence in this section, an attempt has been made to develop an efficient image denoising technique using Double Density Dual Tree Real Discrete Wavelet Transform (DDDTRDWT). Before, understanding the working principle of the proposed model, it is necessary to know about the characteristics of the double density dual tree wavelet, FNLMF and bivariate shrink method which is explained in the following subsection.

a) DDDTCWT

In the field of image processing, Discrete Wavelet Transform (DWT) plays a major role to pre-process the image I(x, y). Particularly for image denoising, the usage of the DWT is to provide the spatial and spectral localization of the image for better image formation. However, the DWT lacks in shift invariance and directional selectivity properties. Hence, to reduce the artifacts of the DWT, another wavelet called double density wavelet is developed by using one scaling function and two distinct wavelets [18]. It is an advanced version of DWT and constructed by using three filter channels i.e one low pass filter and two high pass filters. The properties of the DTCWT and DDDWT are similar in many aspects. But, for design of filters, the DDDWT is considered more flexible than that of DTCWT. Hence, for practical applications, the DDDWTs are preferable than that of DTCWT. Although, the double-density DWT has better functional properties and less computational complexity, but they are lack in spatial orientation. A solution to improve the spatial orientation is done by combining the DDDWT and the DTCWT. The combination is called as Double-Density Dual Tree DWT (DDDTDWT). The output of DDDTDWT based wavelet consists of 16 numbers of sub bands (i.e) one approximation and 15 detailed coefficients compared to that of DTCWT. Because of using more number of sub bands, the decomposition output of DDDTDWT contains more information of the image than that of DTCWT. The basic filter bank design of the DDDTRDWT is portrayed in Figure 1.

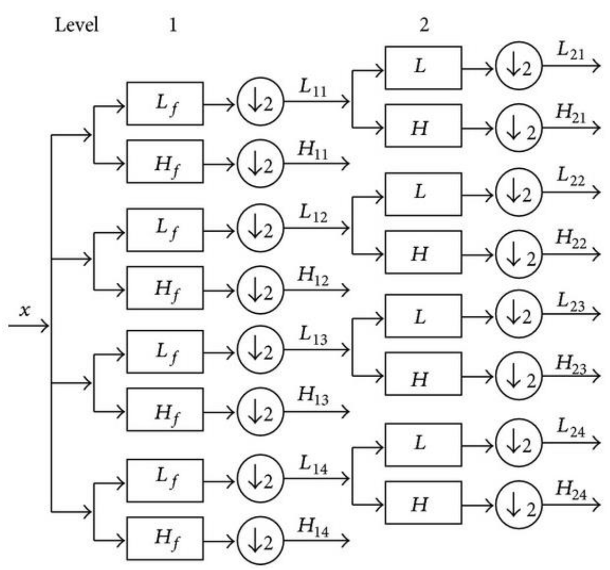


Fig. 2: 2d-Double Density Dual Tree Discrete Wavelet Transform Filter Bank [16].

b) Bivariate Shrink Method

The bivariate shrink model is derived from Bayesian estimation theory. It is a non-Gaussian bivariate probability distribution function to model the statistics of wavelet coefficients of natural images. It is one of the simple non-linear threshold functions using Maximum a postriori (MAP) for wavelet denoising. It depends on both the wavelet coefficient and its parent coefficient, to improve the denoised output. By using the bivariate shrink expression, threshold is calculated for wavelet coefficients.

$$\sigma = \max\left(\overline{\sigma_y^2} - \overline{\sigma_n^2}, 0\right) \tag{4}$$

where σy2 is a variance of noisy image coefficient and σn2 is a noise variance which is calculated by using the following formula,

$$\overline{\sigma_n^2} = \frac{median(|y_i|)}{0.6745} \tag{5}$$

c) Fast Non Local Means Filter (FNLMF)

$$u(s) = \frac{1}{z(s)} \sum_{t \in N(s)} w(s,t) v(t) \tag{6}$$

Where w(s,t) are non-negative weights, Z(s) is a normalization constant and N (s) corresponds to a set of neighbouring sites of s. N (·) will be referred to as the searching window. The weight w(s, t) measures the similarity between two square patches cantered, respectively, at sites s and t, and it is defined as follows,

$$w(s,t) = gh\left(\sum_{\delta \epsilon \Delta} G_\sigma(\delta)\left(v(s+\delta) - v(t+\delta)\right)^2\right) \tag{7}$$

Where Gσ is a Gaussian kernel of variance σ 2, gh: IR+ → IR+ is a continuous non-increasing function with gh (0) = 1 and limx→+α gh(x) = 0, and Δ (Δ = [-p, p]) represents the discrete patch region containing the neighbouring sites δ. The parameter h is used to control the amount of filtering. As from eq. (5), the weight computation w(s, t) is by far the most time consuming part when generating the restored image u. This can be avoided by replacing the Gaussian kernel by the constant without noticeable differences. The modified weight equation is given below,

$$w(s,t) = gh\left(Sd_x(s+p) - Sd_x(s-p)\right) \tag{8}$$

Where Sdx as defined from the following equation corresponds to the discrete integration of the squared difference of the image v and its translation vector dx.

4. Working principle

To understand the working principle of the proposed double density wavelet based image denoising method and its improved version, it is assumed that the input image is corrupted by Gaussian noise which is usually difficult to eliminate. The following subsections clearly explain about the proposed image denoising methods.

a) Proposed Image Denoising Model-1

The working principle of the proposed DDDTRDWT based image denoising method is shown in Figure 2. From the flowchart, it is observed that the noisy input image is first applied in to the series of DDDTRDWT filter bank for performing the decomposition. After decomposition, numbers of sub bands are generated by using the combination of approximation and detailed coefficients. Further, the approximate coefficients are alone considered for the next level of computation. In this method, the DDDTRDWTs provide better output image than that of DTCWT because of using more number of sub bands. Once the decomposition process is completed, next necessary step is to remove the Gaussian noise by applying the thresholding algorithm on each sub-band. The hard thresholding using MAD function or bivariate thresholding using adaptive method is applied on each subband coefficient excluding the approximate coefficient. Therefore, all the high frequency subband coefficients are thresholded to reduce the noise. Finally, the inverse transform of the wavelet coefficient takes place to get the better denoised image.

The basic work flow of the proposed denoising algorithm is described by using the following steps:

- A two level decomposition is applied to the input noisy image using DDDTRDWT
- After decomposition, the optimal threshold value of each subband is measured by using either Hard Thresholding (HT) or Bivariate Thresholding (BT).
- All high frequency subbands less than that of the optimal threshold value are set to zero. Otherwise, retain in the same value
- Finally, Inverse DDDTRDWT is applied on the wavelet coefficients to obtain the denoised output image.

The effectiveness of the proposed algorithm is determined by calculating the performance metrics such as PSNR, MSE, NAE and computation time through simulation.

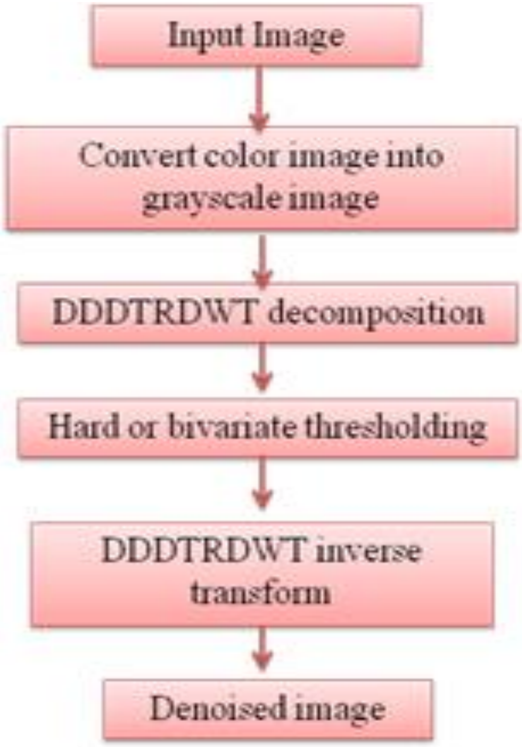


Fig. 2: Proposed Image Denoising Using DDDTRDWT.

b) Proposed Image Denoising Model-2

From the above mentioned proposed DDDTRDWT based image denoising method, there is a possibility of missing some of the original information during thresholding. Hence, to improve the effectiveness of the proposed double density wavelet based image denoising further, the FNLMF is appended with the proposed DDDTRDWT method. The incorporation of the FNLMF and DDDTRDWT is clearly depicted in Figure 3. It is illustrated through the figure that, the Gaussian noise corrupted image is first applied into the FNLMF filter section to reduce the noise level by reducing the redundancy.

Then, the difference between the corrupted input image and the FNLMF filter output image is fed into the wavelet section for thresholding i.e. the double density dual tree wavelet first decompose the difference image into [2] levels. After that, the thresholding is done on decomposed coefficients by using the selected thresholding method. Finally, the quality of the denoised image is enhanced by adding the reconstructed output of threshold wavelet coefficients with the smoothed output of the FNLMF.

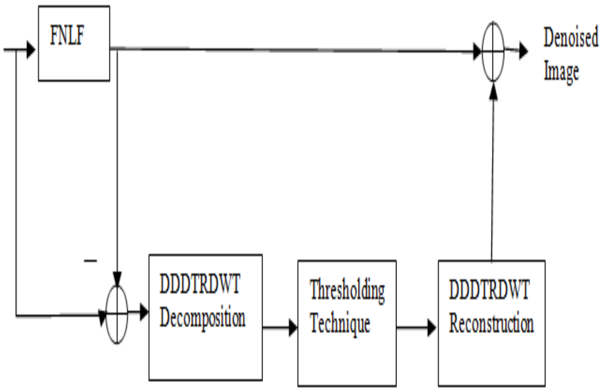
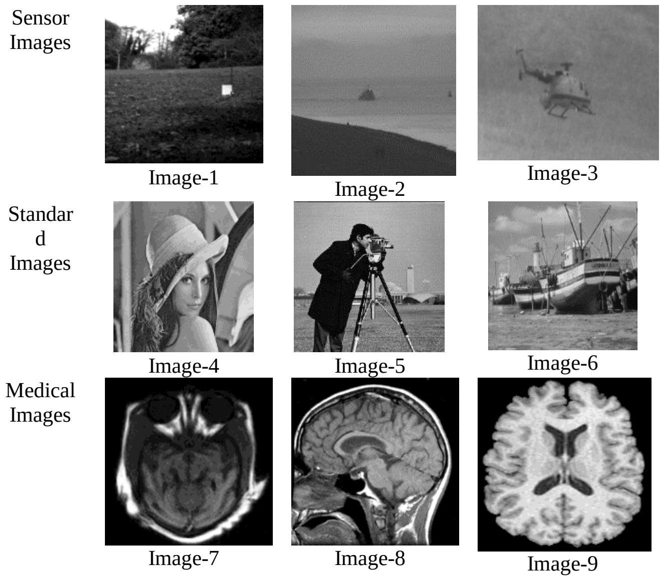


Fig. 3: Proposed Image Denoising using DDDTRDWT with FNLMF.



5. simulation results and discussions

The effectiveness of the existing DTCWT and the proposed DDDTRDWT based image denoising algorithms are examined by conducting the simulations. The simulations are carried out with the help of MATLAB R2014b programming environment. As a matter of fact, this work mainly concentrates on the denoised image quality and the time taken to compute the image denoising algorithms. In addition, the performance metrics such as MSE, PSNR and NAE which are explained in the subsequent section are analysed to determine the denoised image quality.
Various bench mark images from the standard data set and the sensor images from Berkeley data set [19] are considered for simulation. For demonstration purpose, the input images shown in Figure 4 are artificially corrupted by AWGN noise for different noise levels 10, 20, 30 and 40 respectively. Before the simulation, the parameters of the FNLMF should be assigned. To obtain a better denoised output, the parameter values used in simulation are listed in Table 1. The number of decomposition levels used for DTCWT is [3] and for DDDTRDWT is [2].

Table 1: Parameters of FNLMF

Parameter	Value
Patch radius (f)	10
Searching range (t)	2

a) Quantitative Analysis

In order to understand the quantitative analysis of the existing DTCWT based image denoising algorithm for WSN, it is tested with different image sets such as sensor images, standard images and medical images are shown in Figure 4.
Moreover, the performance metrics such as NAE, PSNR and computation time are also calculated to evaluate the effectiveness of the denoising algorithm on various images. Table 2 showcases the simulation results of the existing DTCWT based image denoising at different noise levels.

Table 2: Quantitative Analysis of the Existing DTCWT Based

Input Images	Performance Metrics	Noise Level (σ)			
		10	20	30	40
	NAE	0.0620	0.084	0.0917	0.105
Image-1	MSE	33.55	60.39	96.24	148.7
	PSNR(dB)	32.87	30.32	28.29	26.41
	NAE	0.047	0.087	0.125	0.161
Image-2	MSE	26.80	88.09	180.31	214.86
	PSNR(dB)	33.85	28.68	25.57	23.376
	NAE	0.0303	0.0571	0.081	0.098
Image-3	MSE	22.39	80.22	176.75	208.01
	PSNR(dB)	34.64	29.087	25.67	23.23
	NAE	0.0326	0.0457	0.0601	0.0632
Image-4	MSE	31.245	67.85	97.62	128.62
	PSNR(dB)	33.18	29.85	28.248	27.038
	NAE	0.035	0.0515	0.0658	0.080
Image-5	MSE	42.3	89.44	138.25	195.15
	PSNR(dB)	31.86	28.80	26.78	25.22
	NAE	0.039	0.051	0.063	0.075
Image-6	MSE	43.24	72.45	109.2	154.4
	PSNR(dB)	31.77	29.53	27.73	26.24
	NAE	0.059	0.087	0.121	0.147
Image-7	MSE	17.02	43.66	89.02	158.05
	PSNR(dB)	35.85	31.72	28.59	26.14
	NAE	0.0575	0.0968	0.132	0.158
Image-8	MSE	40.02	110.25	201.33	290.75
	PSNR(dB)	32.11	27.69	25.11	23.50
	NAE	0.035	0.065	0.089	0.107
Image-9	MSE	28.032	94.13	194.28	256.77
	PSNR(dB)	33.65	28.39	25.29	24.03

Table 3: Quantitative Analysis of the Proposed DDDTRDWT Based Image Denoising Algorithm with HT and BT

Input Images	Performance Metrics	Noise Level (σ)							
		10		20		30		40	
		HT	BT	HT	BT	HT	BT	HT	BT
	NAE	0.055	0.045	0.075	0.061	0.080	0.076	0.095	0.090
Image-1	MSE	25.82	16.15	40.15	34.31	63.05	50.83	90.2	75.54
	PSNR(dB)	34.15	35.82	31.45	32.86	30.45	31.21	29.26	29.95
	NAE	0.036	0.017	0.0502	0.026	0.069	0.036	0.087	0.05
Image-2	MSE	18.40	11.55	44.85	25.41	76.23	43.71	84.21	58.51
	PSNR(dB)	35.16	37.50	31.38	34.08	29.67	31.72	28.04	30.45
	NAE	0.025	0.0206	0.043	0.027	0.060	0.035	0.0761	0.043
Image-3	MSE	14.30	10.89	45.09	20.22	85.21	41.29	129.55	68.9
	PSNR(dB)	36.57	37.76	31.80	35.29	28.98	33.18	27.11	31.48
	NAE	0.0281	0.0265	0.042	0.035	0.052	0.042	0.060	0.047
Image-4	MSE	20.93	19.67	46.39	35.56	81.99	51.12	102.71	69.39
	PSNR(dB)	34.86	34.98	31.46	32.92	28.99	30.99	28.15	29.72
	NAE	0.0305	0.028	0.0429	0.039	0.059	0.056	0.073	0.067
Image-5	MSE	28.14	22.69	61.03	53.18	86.02	82.95	111.68	109.7
	PSNR(dB)	33.69	34.56	31.07	30.98	28.94	29.02	27.74	27.85
	NAE	0.0354	0.0338	0.045	0.042	0.053	0.047	0.061	0.056
Image-6	MSE	36.54	31.95	60.38	49.78	84.94	64.38	92.85	81.9
	PSNR(dB)	32.81	32.96	30.32	31.33	28.83	30.15	27.91	29.02
	NAE	0.0486	0.045	0.078	0.072	0.118	0.094	0.121	0.11
Image-7	MSE	14.39	11.02	30.90	20.37	66.12	39.90	85.03	67.71
	PSNR(dB)	37.11	37.35	33.23	34.28	29.93	31.99	28.87	30.22
	NAE	0.0529	0.0493	0.076	0.066	0.091	0.079	0.102	0.093
Image-8	MSE	31.77	24.96	68.09	57.61	100.47	90.24	148.47	109.5
	PSNR(dB)	33.11	33.95	30.60	31.37	27.32	28.46	26.87	27.04
	NAE	0.0261	0.025	0.047	0.041	0.060	0.052	0.088	0.061
Image-9	MSE	13.47	11.58	50.49	41.21	89.40	65.56	113.51	86.2
	PSNR(dB)	35.56	37.49	31.59	32.37	28.94	30.18	27.87	28.80

Table 4: Quantitative Analysis of the Proposed DDDTRDWT Combined with FNLMF Based Image Denoising Algorithm with HT and BT

Input Image	Performance Metrics	Noise Level (σ)							
		10		20		30		40	
		HT	BT	HT	BT	HT	BT	HT	BT
	NAE	0.0513	0.0404	0.070	0.060	0.078	0.074	0.090	0.089
Image-1	MSE	20.93	13.73	35.16	32.26	59.88	47.44	82.40	66.31
	PSNR(dB)	34.82	36.75	33.07	34.29	31.18	32.36	29.59	30.79
	NAE	0.0196	0.014	0.037	0.024	0.0454	0.0328	0.069	0.042
Image-2	MSE	9.99	8.28	29.35	15.46	44.51	28.54	82.71	41.99
	PSNR(dB)	38.10	40.12	33.45	36.24	31.18	33.87	28.95	31.90
	NAE	0.021	0.012	0.034	0.023	0.049	0.032	0.065	0.036
Image-3	MSE	10.77	9.18	29.06	14.25	59.95	32.46	103.5	56.10
	PSNR(dB)	37.81	38.36	33.49	36.59	30.35	33.96	27.98	32.86
	NAE	0.027	0.0258	0.038	0.034	0.051	0.0416	0.062	0.045
Image-4	MSE	18.67	15.13	38.32	29.11	66.00	53.01	82.76	60.53
	PSNR(dB)	35.27	36.54	32.29	33.21	29.82	31.46	28.79	30.08
	NAE	0.0274	0.024	0.0415	0.0348	0.056	0.044	0.064	0.054
Image-5	MSE	25.16	19.74	48.50	42.22	80.23	62.40	100.92	80.43
	PSNR(dB)	34.12	35.97	32.27	33.25	29.00	30.18	28.09	29.71
	NAE	0.032	0.030	0.039	0.033	0.045	0.041	0.052	0.049
Image-6	MSE	32.52	26.25	46.77	33.33	64.65	50.45	84.39	70.68
	PSNR(dB)	33.10	34.03	31.43	32.90	30.02	31.10	28.89	29.63
	NAE	0.046	0.043	0.07	0.058	0.09	0.081	0.12	0.10
Image-7	MSE	10.02	9.25	23.49	17.31	40.13	35.24	71.23	64.27
	PSNR(dB)	38.12	38.46	34.42	36.27	32.09	32.94	29.60	30.78
	NAE	0.0421	0.0375	0.059	0.057	0.0891	0.0861	0.092	0.088
Image-8	MSE	24.56	19.49	42.48	38.80	90.49	84.83	108.11	93.21
	PSNR(dB)	34.227	35.16	31.84	32.24	28.56	29.84	27.17	28.41
	NAE	0.0258	0.023	0.044	0.036	0.059	0.051	0.074	0.067
Image-9	MSE	11.68	9.03	42.39	37.12	78.58	61.26	92.03	84.63
	PSNR(dB)	37.14	38.02	31.85	33.64	29.17	30.89	28.04	29.97

It is observed through the Table 2 that the NAE value of the existing technique show better results for low noise levels of 10 and 20 compared to that of the high noise levels. But, it is
not appreciable for medical images (image 7, 8 and 9). It fails to preserve the original content of the medical image information and cause artifacts. In addition, the PSNR value of the denoised output images are also decreased below the moderate level with high noise conditions which clearly depicts that there is some loss of information. Hence, an attempt has been made in this work by replacing the DTCWT with DDDTRDWT. The performance of the double density wavelet over noisy images is verified by simulating the proposed DDDTRDWT with hard thresholding and bivariate thresholding for different noise levels which is listed in Table 3. From the table, it is noted that the quantitative metrics such as PSNR, NAE of the DDDTRDWT with BT for different set of images, shows better results compared to that of the HT combination. It is worth mentioning that, the DDDTRDWT with BT achieves better PSNR value than that of the existing and modified DTCWT based image denoising method for higher noise levels.

Further, the performance of the proposed DDDTRDWT is improved by combining the DDDTRDWT with the denoising filter FNLMF. In order to improve the performance of the hybrid of DDDTRDWT and FNLMF, Hard Thresholding (HT) and Bivariate Thresholding (BT) methods are used and they are tested for different set of images. For a quantitative analysis, the computation time is also important to analyse the efficiency of the proposed image denoising methods. The average computation time of the existing and the proposed wavelet based image denoising methods are given in the Table 5.

Table 5: Average Computation Time of the Existing and the Proposed Wavelet Based Image Denoising Algorithms

Image Denoising Methods	Average Computation Time (sec)
Existing DTCWT+HT	0.189
Proposed DDDTRDWT+HT	0.20
Proposed DDDTRDWT+BT	0.216
Proposed DDDTRDWT+FNLMF+HT	0.385
Proposed DDDTRDWT+FNLMF+BT	0.467

It is noticed through the table that the computation time of the proposed DDDTRDWT with FNLMF and BT is slightly higher than that of the existing DTCWT based image denoising method which is a tolerable value. However, the
other performance metrics such as PSNR, NAE and MSE supports the effectiveness of the proposed image denoising method for WSN. From the simulation results of sample input images considered for this research work, the average performance of the proposed DDDTRDWT based image denoising method is improved approximately by 10.5 % in terms of PSNR, 28.81 % of reduction in NAE than that of the existing DTCWT based image denoising. Further, the improvement in PSNR by approximately 5.64 % and also reduction in the image quality metric NAE approximately by 17.97 % is achieved by combining the DDDTRDWT with FNLMF and BT based image denoising. However, the average computation time of the proposed DDDTRDWT image denoising method is approximately by 11.72% higher than that of the existing DTCWT method which is tolerable for WSN. It is confirmed from the above performance comparison results that the image quality of the proposed DDDTRDWT with FNLMF and BT in terms of PSNR and NAE is superior to the image quality of the existing and the modified DTCWT with FNLMF and BT.

6. Conclusion

In this paper, two wavelet based image denoising methods are developed to reduce the impact of AWGN noise and enhance the quality of the noisy input images. The first proposed method namely DDDTRDWT is developed for denoising the AWGN noise. The second proposed method merges the DDDTRDWT with FNLMF to provide a better image quality and reduce the loss of original image information. Further, two different thresholding techniques such as hard thresholding and bivariate thresholding are included with the proposed methods in order to improve the quality of the denoised image. The performances of the proposed image denoising methods are analysed through MATLAB simulation in terms of following metrics such as MSE, PSNR, NAE and computation time. It is observed through the simulation results that the proposed methods achieves better results in terms of quantitatively and qualitatively than that of the existing DTCWT based image denoising method. In particular, the proposed DDDTRDWT with FNLMF and BT achieves better simulation results than that of the other methods. Hence, it is clear from the quantitative analysis, the proposed DDDTRDWT with FNLMF and BT based image denoising is suitable

References

[1] Mohsen Nasri, Abdelhamid Helali, Halim Sghaier and Hassen Maaref, "Adaptive Image Transfer for Wireless Sensor Networks (WSNs)", Proceedings of International Conference on Design & Technology of Integrated Systems in Nanoscale Era, Hammamet, Tunisia, pp.1-7, 23-25 March 2010.

[2] Paras Jain and Vipin Tyagi, “A Survey of Edge Preserving Image Denoising Methods”, Information Systems Frontiers (Springer), Vol.18, pp.159-170, February 2016.

[3] Xu Lin and Fu Anqi, “Research on Energy Conservation Method of the Image Compression Coding Based on Wavelet Transform for WVSNs”, Proceedings of 7th Chinese Control and Decision Conference (CCDC), Qingdao, China, pp.1425-1430, 23-25 May 2015.

[4] Arafat Senturk and Resul Kara, “An Analysis of Image Compression Techniques in Wireless Multimedia Sensor Networks”, Tehnicki Vjesnik-Technical Gazette, Vol.23, No.6, pp.1863-1869, 2016.

[5] Muhammed Adeel Javaid, “Wireless Sensor Networks: Software Architecture”, Social Science Research Network (SSRN) Journal, pp.1-9, January 2014.

[6] Bulent Tavil, Kemal Bicakei, Ruken Zilan, Jose M. Barcelo- Ordinas, “A Survey of Visual Sensor Network Platforms”, Multimedia Tools Applications, Vol. 60, Issue.3, pp. 689-726, October 2012.

[7] Guojun Wang, MdZakirul Alam Bhuiyan, Jiannong Cao, Jie Wu, “Detecting Movements of a Target using Face Tracking in Wireless Sensor Networks”, IEEE Transactions on Parallel and Distributed Systems, Vol. 25, No. 4, pp. 939-949, April 2014.

[8] Kerem Irgan, Cem Unsalan, Sebnem Baydere, “Low-Cost Prioritization of Image Blocks in Wireless Sensor Networks for Border Surveillance”, Journal of Network and Computer Applications, Vol.38, pp. 54-64, February 2014.

[9] Hadi S. Aghdasi, Maghsoud Abbaspour, “Energy Efficient Area Coverage by Evolutionary Camera Node Scheduling Algorithms in Visual Sensor Networks”, soft Computing: A Fusion of Foundations, methodologies and Applications (Springer), Vol.20, Issue.3, pp. 1191-1202, March 2016.

[10] Alice Abraham, Narendra Kumar G, “Cross Layer Optimized Transmission for an Energy Efficient Wireless Image Sensor Network”, International Journal of Computer Science Issues (IJCSI), Vol. 10, Issue 2, No. 2, pp. 31-38, March 2013.

[11] Rohit Verma, Jahid Ali, “A Comparative Study of Various Types of Image Noise and Efficient Noise Removal Techniques”, International Journal of Advanced research in Computer Science and Software Engineering, Vol. 3, Issue 10, pp. 617-622, October 2013.

[12] Jing Tian, Weiyu Yu and Lihong Ma, “Ant Shrink: Ant colony optimization for Image Shrinkage”, Pattern Recognition Letters, Vol.31, Issue.13, pp.1751-1758, October 2010.

[13] X.Wang, X. Ou, B.-W. Chen, and M. Kim, “Image Denoising Based on Improved Wavelet Threshold Function for Wireless Camera Networks and Transmissions,” International Journal of Distributed Sensor Networks, Vol. 2015, No.23, pp.1-7, January 2015.

[14] I.W.Selesnick, R. G. Baraniuk, and N. G. Kingsbury, “The Dual-Tree Complex Wavelet Transform,” IEEE Signal Processing Magazine, Vol. 22, Issue.6, pp.123–151, November 2005.

[15] C.Vimala and P.Aruna Priya, “Degraded Image Enhancement through Double Density Dual Tree Discrete Wavelet Transform”, Indian Journal of Science and Technology, Vol.9, No.28, pp.1-4, July 2016.

[16] Pallavi L.Patil and V.B.Raskar, "Image Denoising with wavelet thresholding method for different level of decomposition", International Journal of Engineering Research and General Science, Vol.3, Issue.3, pp.1092-1099, May-June 2015.

[17] B.K.Shreyamsha Kumar, "Image Denoising based on non-local means filter and its method noise thresholding", Signal, Image and Video Processing, Vol.7, Issue.6, pp.1211-1227, November 2013.

[18] Rachid Sammouda, Abdul Malik S.Al-Salman, Abdul Gumaei and Nejmeddine Tagoug, “An Efficient Image Denoising Method for Wireless Multimedia Sensor Networks Based on DT-CWT”, International Journal of Distributed Sensor Networks, Vol.2015, pp.1-13, January 2015.

[19] Varun P.Gopi, M.Pavithran, et.al, "Undecimated Double Density Dual Tree Wavelet Transform based Image Denoising using a Subband Adaptive Threshold", Proceedings of International Conference on Issues and Challenges in Intelligent Computing Techniques, Ghaziabad, India, pp.743-748, 7-8 February 2014.

[20] H. Rekha, P .Samundiswary, “Double Density Wavelet with Fast Bilateral Filter based Image Denoising for WMSN”, Proceedings of 9th International Conference on Advanced Computing, Chennai, India, pp.315-319, 14-16 December 2017.

[21] Ali Rekabdar, Omid Khayat, Noushin Khatib and Mina Aminghafari, " Using Bivariate Gaussian Distribution for Image Denoising in the 2D Complex Wavelet Domain", Proceedings of 6th Iranian Machine Vision and Image Processing, Isfahan, Iran, pp.1-6, 27-28 October 2010.