

Comparative Analysis of an Efficient Image Denoising Method for Wireless Multimedia Sensor Network Images in Transform Domain

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Abstract

In recent years, there has been an increasing research interest in image de-noising due to an emphasis on sparse representation. When sparse representation theory is compared to transform domain-based image de-noising, the former indicates that the images have more information. It contains structural characteristics that are quite similar to the structure of dictionary-based atoms. This structure and the dictionary-based method is highly unsuccessful. However, image representation assumes that the noise lack such a feature. The dual-tree complex wavelet transform incorporates an increase in transform data density to reduce the effects of sparse data. This technique has been developed to decrease the image noise by selecting the best-predicted threshold value derived from wavelet coefficients. For our experiment, Discrete Cosine Transform (DCT) and Complex Wavelet Transform (CWT) are used to examine how the suggested technique compares the conventional DCT and CWT on sets of realistic images. As for image quality measures, DT-CWT has leveraged superior results. In terms of processing time, DT-CWT gave better results with a wider PSNR range. Further, the proposed model is tested with a standard

digital image named Lena and multimedia sensor images for the denoising algorithm. The suggested denoising technique has delivered minimal effect on the MSE value.

Keywords: WMSN, Image denoising methods

1. Introduction

A fully developed wireless multimedia sensor network includes sensor nodes, which are equipped with cameras to collect and distribute images and videos to and from other nodes present in the network. Because camera sensors produce digital pictures and movies that are then altered by noise throughout each of the recording, sending, and retrieving operations, digital images and videos are developed through digital image capturing sensors that provide imperfections [1-4]. The consequence is that poor lighting, change of illumination, fog, rain, and other weather issues make numerous dots visible in a picture. To execute the functions of detection and segmentation, a picture that is clear and noise free is essential. Additionally, many image denoising techniques are used to suppress the noise present in the images with the primary goal of protecting the object in the data without decreasing the quality of overall image [5-9]. Figure 1 shows some standard images for testing various transform methods.

The adoption of a noise reduction technique is required to extract speech from the systems with just one microphone. There are many issues in the sensor module, they are processing delay, signal distortion, and audio signals resulting from external noise are all issues that enhance at the cost of other factors that come from the noisy domain [10]. Furthermore, an improved noise spectrum estimate is required for the SS technique. A voiceless section detector is needed in practice to provide good noise reduction. Also, here a noise reduction technique uses linear prediction to consider the undesirable side effects.



Figure 1. Sample Standard Images

White noise is accurately and rapidly quantified by using the technique shown above since the coefficients of linear predictors converge to produce white noise in the prediction error signal. The efficacy of noise reduction diminishes, however, when the noise is colored [11].

Every pixel in the original picture may be treated separately in the spatial domain, and each has a relationship with its surrounding pixels and associated filter matrix. Although there are several denoising methods for spatial domain image processing, an adaptive median filter for noise suppression is provided [12].

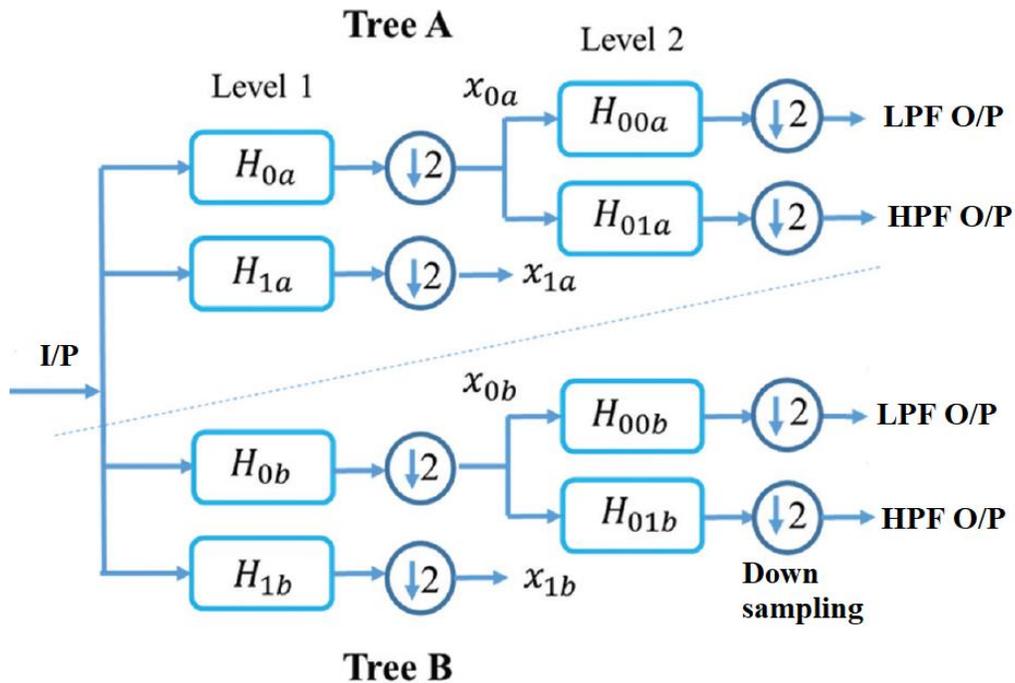


Figure 2. Dual Tree Complex Wavelet Transform (DT-CWT)

While these approaches have certain disadvantages, such as a high computational cost, nevertheless they are very effective. Furthermore, recent techniques have attempted to integrate the median filter with impulse detection in order to make up for the median filter's limitations. However, the performance of the impulse detector must be maintained. Other methods, such as mean-based filters, may be used in place of heavy computation when it exists. Recently, several fuzzy logic techniques have been suggested for picture noise reduction.

Even if DWT was utilized, it has several challenges. This data is affected by a lack of shift-invariance, insufficient directional information, and a lack of phase information. Applying the Stationary Wavelet Transform (SWT) throughout the course of the last year has helped to eliminate

the challenge of shift variation. However, SWT may boost the power of wavelet-based picture denoising significantly but it is computationally costly due to its higher redundancy [13].

Research Gap

Complex Wavelet Transforms (CWTs) have been recently used to address DWT issues by utilizing a variety of mathematical methods. Many studies have claimed Dual-Tree Complex Wavelet Transform (DT-CWT) as one of the most efficient versions of CWT. It provides six-dimensional texture information with a lower degree of redundancy. An effective image denoising technique for wireless multimedia sensor network applications use the DT-CWT for performing real-time image processing. The proposed approach has two novel features. The first solution is to use Structural Similarity Index Measure (SSIM) as a fidelity term instead of the reconstruction error. This recommendation is made because it correlates to anatomical similarities in the human visual system (HVS), which makes it more likely to result in better outcomes.

2. Organization of the Research

The remaining part of this research article is organized as follows: section 3 discusses about the existing research works on the efficient image denoising methods. Section 4 discusses about the proposed work for image denoising methods. Section 5 presents the obtained results as well as their discussion. The conclusion and future tasks of the wireless sensor network research will be discussed in the final section of this research article.

3. Preliminaries

In order to decrease background noise, Zhang and Xie's de-noising technique employs DCT and sparse representation. An over-complete vocabulary learnt from the noisy image may be used to efficiently characterise the image's content in this manner. However, the dictionary

includes a significant number of meaningless atoms, which reduces the effectiveness of picture sparse representation, wherein the number of these atoms present in the dictionary is decreasing [14].

It was also suggested by Zhang et al. to use adaptive sparse representation for de-noising. By using the K-SVD technique, an over-complete vocabulary has been learned from the test picture. This process is susceptible to noise, and when there is a significant amount of noise is present in the picture, the rebuilt image may fluctuate [15].

Zhou and Luo proposed a novel technique for acquiring over-complete vocabulary, which they dubbed the K-LMS (K-Least Mean Square). Adopting the LMS decomposition method produces step lengths that are inflexible and stiff may result in an unusually high number of steady-state errors [16].

Generally, three main algorithms were used in the construction of an artificial immune system, which comprised negative selection, clonal selection, and immune networks. A superior approach to decrease data quantities is presented by the theory of the immune network system, which is more suited for image pattern recognition. This method uses the IN algorithm for pattern recognition, which gives the capability to quickly identify internal data representation and as a result a reduction in data size can be achieved by utilizing memory cell representation [17].

A rapid road categorization and orientation estimate technique was reported by Z. Zhu, et al. to utilize Omni-view pictures and neural networks. Face identification is efficiently handled by utilizing a learning-based approach for super-resolved face pictures, which incorporates a PCA-based previous model [18].

Kingsbury developed the DT-CWT approach to properly reconstruct it by providing the benefits of complex wavelets. It exhibits a very distinct directionality in two and higher dimensions and is only weakly invariant in terms of shifts [19].

4. Proposed Methodology

The input images are collected from the multimedia sensor output image and also it performs image registration and preprocessing to obtain the better PSNR and SSIM values. Following the hard threshold function procedure (shown in figure 4), analysis and synthesis filter banks are employed to deconstruct and rebuild the image features.

4.1 Design of DT-CWT

This is an expansion of DWT that adds key characteristics of the wavelet. From the perspective of using real-valued filter coefficients, the software utilizes an analytic filter to conduct the wavelet analysis. Figure 4 shows overall proposed framework. This solution alleviates the issues associated with DWT at the expense of reduced redundancy and sparse effects [20]. With DWT, three directional sub-bands are created for each pixel for displaying picture characteristics that are oriented at 90, 45, and 0 degrees (x). Figure 3 shows DT-CWT real and imaginary part orientation angle of the coefficient location.

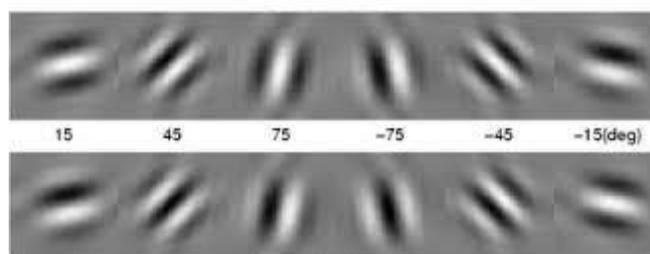


Figure 3. DT-CWT Real & Imaginary Part Orientation

4.2 Computation in DT-CWT

The DT-CWT of an image may be computed by individually applying the filter bank to the two dimensions and then extend the result to the whole picture. One or more trees (such as trees a, b, c, and d) are required for analysis, while several trees (such as trees a, b, c, and d) are required for synthesis, which has shown in the figure 2. Also soft threshold is taking place in the proposed work. The wavelet co-efficient gets adjusted with soft threshold value [21, 22].

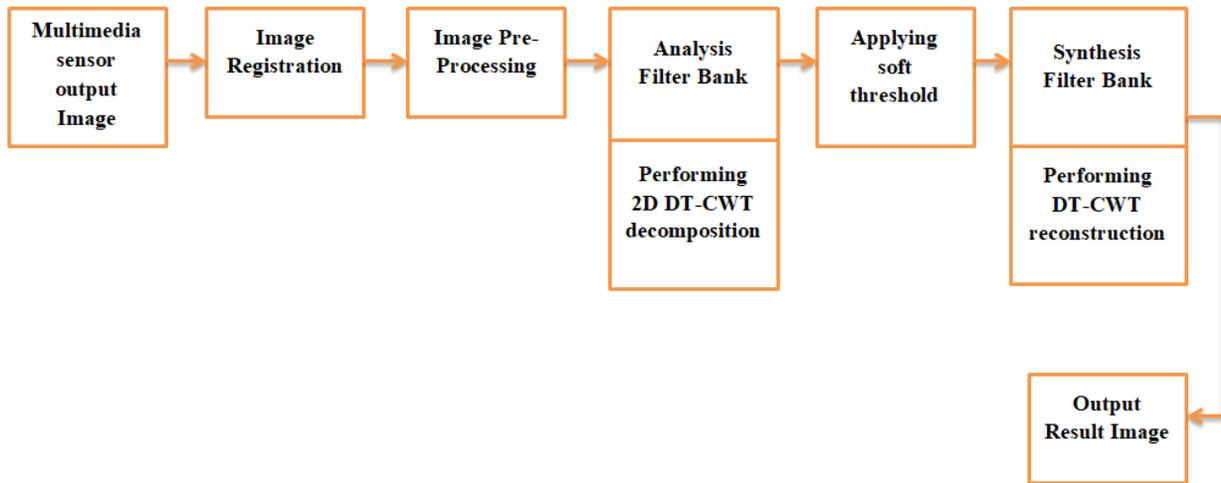


Figure 4. Overall Proposed Framework

4.3 Down sampling process

This process decomposes the signal of the input picture by using two separable 2D DWT branches (*a*) and (*b*) in parallel. For each filtering step, there is a down sampling operation followed by a DT-CWT tree application to rows (*x*) and subsequently to columns (*y*) [23-25]. It is defined with a combination of imaginary part as follows;

$$(h_x + jg_x)(h_y + jg_y) = (h_xh_y + g_xg_y) + j(h_xg_y + g_xh_y)$$

5. Results & Discussion

This section displays the results of the proposed image denoising application that was created by running DT-CWT on a group of indoor-outdoor scenes. We also demonstrate the effectiveness of the proposed approach by comparing it to DCT and CWT when applied to the same collection of pictures.



Figure 5. Obtained Results by Various Algorithms

The result of suggested method is shown in Figure 5A. The output of DWT, DCT, CWT, first level, and second level transforms are shown in Figure 5B, E, F, G, and H. The ground truth picture in Figure 5D is used to calculate the performance measures of different methods. Figure 5C depicts a noisy view of the Lena. Our suggested method, DT-CWT, demonstrates the existence of sparse free effects in the Lena image, as shown in Figure 5D.



Figure 6. Multimedia Sensor Image Reconstruction

Figure 6 shows multimedia sensor image reconstruction with our proposed work. Our proposed work has suppressed the sparse effect in the noise representing the effect. Our proposed work performs well in sparse suppression.

Table 1. Calculation of Performance Metrics

S.No	Transform Domain	PSNR	MSE	SSIM	Average processing Time (sec)
1	CWT	21.41	0.167	0.661	2.4892
2	DCT	24.57	0.093	0.840	6.3353
3	Proposed DT-CWT	32.98	0.004	0.912	3.8138

Three picture quality measures are used to quantify the suggested denoising method's performance: the Peak Signal-to-Noise Ratio (PSNR), and the Mean Square Error (MSE) and

structure similarity index (SSIM). Denoised and original scene pictures are used to calculate image quality measures.

$$PSNR = 10 * \log \left(\frac{255^2}{MSE} \right)$$

$$MSE = \frac{1}{M * N} \sum_{i=1}^N \sum_{j=1}^M [I(i, j) - \hat{I}(i, j)]^2$$

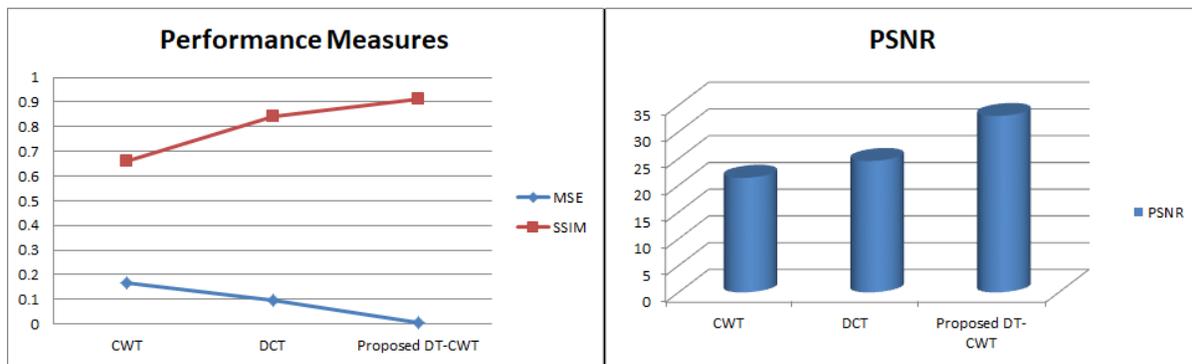


Figure 7. Overall Performance Measures

Figure 7 shows overall performance measures of the proposed work. SSIM is a novel method for assessing picture quality. Brightness, contrast, and structure are all measured when determining the picture quality. According to the SSIM, it may be characterized as follows:

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

SSIM is more aligned with the properties of the human visual system, which include brightness, contrast, and structure. It is in the range of 0 to 1. The pictures are more similar in structure, when it is closer to 1. The proposed algorithm proves SSIM value is nearer to 1 than

other techniques. Various image denoising techniques used in real-time image processing applications need processing time to be a critical measurement especially sensor output images. It may be computed on the same hardware setup described above by executing the programs of various picture denoising techniques in MATLAB R2012a.

6. Conclusion

Thus, the suggested model outperformed other methods in terms of PSNR and SSIM. Additionally, our test picture is becoming sparse as a result of the multimedia sensor output. The suggested approach is utilized to reduce the noise caused by the temperature of sensor devices. Other techniques have failed to produce a sparse-free effect from the input pictures resulting in a blurring impact on the rebuilt images. The visual results in the future will be further enhanced with PSNR measurements. Additionally, the two-dimensional DT-CWT method may improve the efficiency of noisy images that are processed by sensor network devices can indicate its efficacy in reducing the images through wireless sensor devices. Additionally, the pictures from the sensor network may be utilized as a preprocessing step to optimize the operations. While this study used real-world time images to validate the proposed technique, future work will include further validation by utilizing the images obtained through wireless multimedia sensor networks that are connected to other devices. In the transform domain, these images have a significant degree of sparse impurity [26-29].

References

- [1] Warriar, Prasanth M., B. R. Manju, and Rajkumar P. Sreedharan. "A Survey of Pre-processing Techniques Using Wavelets and Empirical-Mode Decomposition on Biomedical Signals." In *Inventive Communication and Computational Technologies*, pp. 993-1002. Springer, Singapore, 2020.

- [2] Manoharan, J. Samuel. "A Novel User Layer Cloud Security Model based on Chaotic Arnold Transformation using Fingerprint Biometric Traits." *Journal of Innovative Image Processing (JIIP)* 3, no. 01 (2021): 36-51.
- [3] Mamta, P., and S. V. A. V. Prasad. "Identification of Insomnia Based on Discrete Wavelet Transform Using Time Domain and Nonlinear Features." In *Computational Vision and Bio-Inspired Computing*, pp. 121-133. Springer, Singapore, 2021.
- [4] Bose, Subash Chandra, Murugesh Veerasamy, Azath Mubarakali, Ninoslav Marina, and Elena Hadzieva. "Analysis of Feature Extraction Algorithm Using Two Dimensional Discrete Wavelet Transforms in Mammograms to Detect Microcalcifications." In *International Conference On Computational Vision and Bio Inspired Computing*, pp. 26-39. Springer, Cham, 2019.
- [5] Vaneeta, M., V. Sangeetha, and S. Swapna Kumar. "Efficient Two-Layer Image Protection with Wavelet Transform Compression." In *Innovative Data Communication Technologies and Application*, pp. 433-448. Springer, Singapore, 2021.
- [6] Duraipandian, M. "Adaptive Algorithms for Signature Wavelet recognition in the Musical Sounds." *Journal of Soft Computing Paradigm (JSCP)* 2, no. 02 (2020): 120-129.
- [7] D. L. Donoho, "De-noising by soft thresholding," *IEEE Transactions on Information Theory*, vol. 41, no. 3, pp. 613–627, 1995.
- [8] Adam, Edriss Eisa Babikir. "Evaluation of Fingerprint Liveness Detection by Machine Learning Approach-A Systematic View." *Journal of ISMAC* 3, no. 01 (2021): 16-30.
- [9] L. S, endur and I. W. Selesnick, "Bivariate shrinkage with local variance estimation," *IEEE Signal Processing Letters*, vol. 9, no. 12, pp. 438–441, 2002.
- [10] Sungeetha, Akey, and Rajesh Sharma. "Design an Early Detection and Classification for Diabetic Retinopathy by Deep Feature Extraction based Convolution Neural Network." *Journal of Trends in Computer Science and Smart technology (TCSST)* 3, no. 02 (2021): 81-94.

- [11] Elad, M., M.Aharon. Image Denoising via Learned Dictionaries and Sparse Representation. – IEEE Conference on Computer Vision and Pattern Recognition, 2006, pp. 895-900.
- [12] Sungheetha, Akey, and Rajesh Sharma. "3D Image Processing using Machine Learning based Input Processing for Man-Machine Interaction." Journal of Innovative Image Processing (JIIP) 3, no. 01 (2021): 1-6.
- [13] I. Ha, M. Djuraev, and B. Ahn, "An energy-efficient data collection method for wireless multimedia sensor networks," International Journal of Distributed Sensor Networks, vol. 2014, Article ID 698452, 8 pages, 2014.
- [14] Zhang, F., K. Xie. A Novel Image Denoising Method Based on DCT Basis and Sparse Representation. – In: Proc. of Cross Strait Quad-Regional Radio Science and Wireless Technology Conference, 2011, pp. 26-30.
- [15] Zhang, Q., Y. Fu, L. C. Li, J. Y. Yang. A Millimeter-Wave Image Denoising Method Based On Adaptive Sparse Representation. – In: Proc. of International Conference on Computational Problem-Solving, 2011, pp. 652-655.
- [16] Zhou, Z., L. M. Luo. Research on Image Denoising Algorithm Based on Adaptive Overcomplete Sparse Representation Theories. – Journal of Convergence and Information Technology, Vol. 7, 2012, No 16, pp. 315-321.
- [17] Kuang, Y., L. Zhang, Z. Yi. An Adaptive Rank-Sparsity K-SVD Algorithm for Image Sequence Denoising. – Pattern Recognition Letters, Vol. 45, 2014, No 1, pp. 46-54.
- [18] Z. Zhu, S. Yang, G. Xu, X. Lin, D. Shi, "Fast Road Classification and Orientation Estimation Using Omni-View Images and Neural Networks," IEEE Trans. Image Processing, Vol. 7, No. 8, pp. 1182-1197.
- [19] N. G. Kingsbury, "Complex wavelets for shift invariant analysis and filtering of signals," Applied and Computational Harmonic Analysis, vol. 10, no. 3, pp. 234-253, 2001.
- [20] Smitha, T. V. "A Study on Various Mesh Generation Techniques used for Engineering Applications." Journal of Innovative Image Processing 3, no. 2 (2021): 75-84.

- [21] M. S. Alhilal, A. Soudani, and A. Al-Dhelaan, "Image-based object identification for efficient event-driven sensing in wireless multimedia sensor networks," *International Journal of Distributed Sensor Networks*, vol. 2015, Article ID 850869, 11 pages, 2015.
- [22] Dhaya, R. "Analysis of Adaptive Image Retrieval by Transition Kalman Filter Approach based on Intensity Parameter." *Journal of Innovative Image Processing (JIIP)* 3, no. 01 (2021): 7-20.
- [23] T.-C. Lin, "A new adaptive center weighted median filter for suppressing impulsive noise in images," *Information Sciences*, vol. 177, no. 4, pp. 1073–1087, 2007.
- [24] Vijayakumar, T., Mr R. Vinothkanna, and M. Duraipandian. "Fusion based Feature Extraction Analysis of ECG Signal Interpretation–A Systematic Approach." *Journal of Artificial Intelligence* 3, no. 01 (2021): 1-16.
- [25] T. Chen and H. R. Wu, "Adaptive impulse detection using center-weighted median filters," *IEEE Signal Processing Letters*, vol. 8, no. 1, pp. 1–3, 2001.
- [26] Palani, U., Mrs D. Vasanthi, and Ms S. Rabiya Begam. "Enhancement of Medical Image Fusion Using Image Processing." *Journal of Innovative Image Processing (JIIP)* 2, no. 04 (2020): 165-174.
- [27] Manoharan, Samuel. "A Dual tree complex wavelet transform construction and its application to image denoising." *International Journal of Image Processing (IJIP)* 3, no. 6 (2010): 293.
- [28] Balasubramaniam, Vivekanadam. "Artificial Intelligence Algorithm with SVM Classification using Dermoscopic Images for Melanoma Diagnosis." *Journal of Artificial Intelligence and Capsule Networks* 3, no. 1 (2021): 34-42.
- [29] Manoharan, Samuel. "Early diagnosis of Lung Cancer with Probability of Malignancy Calculation and Automatic Segmentation of Lung CT scan Images." *Journal of Innovative Image Processing (JIIP)* 2, no. 04 (2020): 175-186.

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