iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 4 Issue: X Month of publication: October 2016

DOI:

Volume 4 Issue X, October 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Comparison and Study of Different Image Denoising Techniques

Nijisha P
Department of Applied Electronics and Communication System
Cochin College of Engineering and Technology, Kerala

Abstract: Image denoising is a technique which removes out noise which is added in the original image. Noise reduction is an important part of image processing systems. An image is always affected by noise. Image quality may get disturbed while capturing, processing and storing the image. Noise is nothing but the real world signals and which are not part of the original signal. Removal of noise is an important step in the image restoration process, and remains a challenging problem in spite of the sophistication of recent research. Image denoising involves the manipulation of the image data to produce a visually high quality image. This report presents a comparison of three image denoising methods, all minimizing the variation of an image – Dual-tree complex DWT,Surelet denoising method and Bayes estimate denoise method. These algorithms are compared based on their assumptions and shortcomings using a methodology that examines the Peak signal-to-noise ratio (PSNR), Mean Square Error (MSE) ,Structural Similarity Index (SSIM) and overall quality of the denoised image.
Keywords: PSNR,MSE, SSIM and denoising

I. INTRODUCTION

Digital images are most suitable way of transmitting visual information from one place to another thus it is very useful, both in applications like television magnetic resonance imaging computer tomography and in field of science and technology such as geographical information system and astronomy. The devices like image sensors assemble the sets of data which is frequently contaminated by noise due to device failures. Also noise can lead due to communication errors and compression. Hence before image data is inspected and processed reduction of noise compulsory. Thus a technique is required to imitate the original image [1]. A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained [2]. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus [3]. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contribute to the degradation.

II. RELATED WORKS

In [5] Kaibing Zhang , Xinbo Gao , Dacheng Tao and Xuelong Li states a general model for the SR problem assumes that an LR image y is generated from the corresponding HR image X through a sequence of degradation factors including (i) a blur operation H, (ii) a down-sampling step represented by S, and (iii) an additive zero-mean white and Gaussian noise. Therefore, the goal of single image SR reconstruction is solving the inverse problem to estimate the underlying HR image X using only one observation y. However, due to blurring, down-sampling, and noising, one LR image may correspond with many different HR images, so the SR problem is severely undetermined. In such a case, it is crucial important to incorporate a certain effective prior knowledge (denoted as a regularization term) into the reconstruction process. Given a regularization term, the maximum a posterior probability (MAP) estimation. In [6] Chen Huang , Xiaoqing Ding , Chi Fang states that a Single image super-resolution (SR) methods can be broadly categorized into three classes: interpolation-based methods, reconstruction-based meth- ods , and example-based methods . The reconstruction-based methods often incorporate prior knowledge to regularize the ill-posed problem. For example, Zhang et al. assembled the Steering Kernel Regression (SKR)-based local prior and Nonlocal Means (NLM)- based nonlocal prior. The example-based methods strongly rely on the chosen dictionary for satisfactory results. This paper focuses on learning good image priors and robust dictionaries for SR reconstruction. Among the extensively studied natural image priors, we choose to exploit the local structural regularity prior and nonlocal self-similarity prior in a coherent framework. In [7], This paper addresses the problem of generating a super resolution (SR) image from a single low-resolution input image. We approach this problem from the perspective of compressed sensing. The low-resolution image is viewed as down sampled version of a high-resolution image, whose patches are assumed to have a sparse representation with respect to an over-complete dictionary of prototype signalatoms. The principle of compressed sensing ensures that under mild conditions, the sparse representation can be correctly recovered from the down sampled signal. We will demonstrate the effectiveness of sparsity as a prior for regularizing the otherwise ill-posed super-resolution problem. We further show that a small set of randomly chosen raw patches from training images of similar statistical nature to the input image generally serve as a good dictionary, in the sense that the computed representation is sparse and the recovered high-resolution image is competitive or even superior in quality to images produced by other SR methods. In [8] The growing interest in image scaling is mainly due to the availability of digital imaging devices such as, digital cameras, digital camcorders, 3G mobile handsets, high definition monitors etc. Scaling a digital image is a demanding and very important area of research. Image scaling is an important image processing operation applied in diverse areas in computer graphics. Image scaling can be especially useful when one needs to reduce image file size for email and web documents or increase image size for printing, GIS observation, medical diagnostic etc. With the recent advances in imaging technology, digital images have become an important component of media distribution. In addition, a variety of displays can be used for image viewing, ranging from high-resolution computer monitors to TV screens and low-resolution mobile devices. This paper is focused on different image scaling techniques with intent that review to be useful to researchers and practitioners interested in image Scaling. This paper [9] addresses the problem of generating a High-resolution (HR) image from a single Low-resolution (LR) image. We propose the super-resolution reconstruction approach based on sparse representation and low-rank matrix completion. The approach represents images in forms of sparse and rearranges image regions into the low dimension construction matrices of low rank. High-frequency details of image are restored using the sparse representation which is recovered from the down-sampled images. For paths at the same position of multiple pictures which are obtained by several super resolution reconstructions are highly correlated, they are arranged to be a matrix of low-rank which can be completed exactly from corrupted entries. Experiment results demonstrate that the proposed method significantly improves the PSNR and visual quality of reconstructed high-resolution images.

III. PROPOSED WORK

A. *Wavelet Transforms and Denoising*

1) *Wavelet Transform Domain:* A Fourier Transform (FT) is only able to retrieve the global frequency content of a signal, the time information is lost. A multi-resolution analysis becomes possible by using wavelet analysis. The Wavelet Transform (WT) retrieves frequency and time content of a signal. The basic types of wavelet transform are namely, i) Continuous Wavelet Transform (CoWT) ii) Discrete Wavelet Transform (DWT) iii) Complex Wavelet Transform (CWT). A multi-resolution analysis is not possible with Fourier Transform (FT) and Short Time Fourier Transform (STFT) and hence there is a restriction to apply these tools in image processing systems; particularly in image denoising applications. The multi-resolution analysis becomes possible by using wavelet analysis. A Continuous Wavelet Transform (CoWT) is calculated analogous to the Fourier transform (FT), by the convolution between the signal and analysis function. The Discrete Wavelet Transform uses filter banks to perform the wavelet analysis. Image denoising means usually compute the soft threshold in such a way that information present in image is preserved. A block schematic of Wavelet based image denoising technique is shown in Fig. 3.5. Here the basic steps of wavelet based image denoising are given below. 1. Decompose corrupted image by noise using wavelet transform. 2. Compute threshold in wavelet domain and apply to noisy coefficients.
2) *Discrete Wavelet Transform (DWT) – Principles:* Wavelets are mathematical functions that analyze data according to scale or resolution [13]. They aid in studying a signal in different windows or at different resolutions. For instance, if the signal is viewed in a large window, gross features can be noticed, but if viewed in a small window, only small features can be noticed. Wavelets provide some advantages over Fourier transforms. For example, they do a good job in approximating signals with sharp spikes or signals having discontinuities.Wavelets can also model speech, music, video and non-stationary stochastic signals. Wavelets can be used in applications such as image compression, turbulence, human vision, radar, earthquake prediction, etc. [13].The term “wavelets” is used to refer to a set of orthonormal basis functions generated by dilation and translation of scaling function φ and a mother wavelet ψ [14]. The finite scale multi resolution representation of a discrete function can be called as a discrete wavelet transform [15]. DWT is a fast linear operation on a data vector, whose

Volume 4 Issue X, October 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

length is an integer power of 2. This transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix. The wavelet basis or function, unlike sines and cosines as in Fourier transform, is quite localized in space. But similar to sines and cosines, individual wavelet functions are localized in frequency.

B. *Image denoising techniques*

1) *The Dual-Tree DWT*: By introducing Complex wavelet transforms (CWT) concept, we can achieve Dual-Tree Complex DWT system. Kingsbury's complex Dual-Tree DWT is based on (approximate) Hilbert pairs of wavelets [17]. Kingsbury found that the Dual-Tree DWT is nearly shift-invariant when the lowpass filters of one DWT interpolate midway between the lowpass filters of the second DWT [18]. The Dual-Tree Complex DWT can be implemented using two critically-sampled DWTs in parallel as shown in the Fig. 3. This transform gives 2N DWT coefficients for an N-point signal. Hence this transform is known as 2-times expansive. Here the filters are designed in such a way that the subband signals of the upper DWT can be interpreted as the real part of a CWT and subbands signals of the lower DWT can be interpreted as the imaginary part. For specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. In this manner, the designed DTCWT is nearly shift-invariant than the critically-sampled DWT [19]-[22]. The DTCWT gives wavelets in six distinct directions. In each direction, there are two wavelets. In each direction, one of the two wavelets can be interpreted as the real part and the other wavelet can be interpreted as the imaginary part of a complex-valued two dimensional (2D) wavelet. The DTCWT is implemented as four critically sampled separable 2D DWTs operating in parallel. However, different filter sets are used along the rows and columns [19]-[22]. Fig. 3.7 indicates that a flowchart of Dual-Tree Complex DWT. This illustrates the steps of implementation of DTCWT.

2) *Surelet denoising:* Image denoising based on the image-domain minimization of an estimate of the mean squared error-Stein's Unbaised Risk Estimate(SURE). Unlike. most existing denoising algorithms, using the SURE makes it needless to hypothesize a statistical model for the noiseless image. The nonlinear processing is performed in a transformed domain—typically, an undecimated discrete wavelet transform, but we also address non orthonormal transforms—this minimization is performed in the image domain. Indeed, we demonstrate that, when the transform is a "tight" frame (an undecimated wavelet transform using orthonormal filters), separate subband minimization yields substantially worse results. In order for our approach to be viable, we add another principle, that the denoising process can be expressed as a linear combination of elementary denoising processes—linear expansion of thresholds (LET). Armed with the SURE and LET principles, we show that a denoising algorithm merely amounts to solving a linear system of equations which is obviously fast and efficient. Quite remarkably, the very competitive results obtained by performing a simple threshold (image-domain SURE optimized) on the undecimated Haar wavelet coefficients show that the SURE-LET principle has a huge potential[23]. Surelet denoise removes addtitive gaussian white noise using the inter-scale sure-let principle in the framework of an Orthonormal Wavelet Transform (OWT) only. This approach is made possible by the existence of an excellent unbiased estimate of the mean squared error (MSE) between the noiseless image and its denoised version- Stein's unbiased risk estimate (SURE). If we evaluate denoising performances by comparing PSNRs, then this MSE is precisely the quantity that we want to minimize. Similar to the MSE, the SURE takes the form of a quadratic expression in terms of the denoised image. This may consists in reformulating the denoising problem as the search for the denoising process that will minimize the SURE—in the image domain. In practice, the process is completely characterized by a set of parameters. Now, to take full advantage of the quadratic nature of the SURE, we choose to consider only denoising processes that can be expressed as a linear combination of "elementary" denoising processes—linear expansion of thresholds (LET). This "SURE-LET" stategy is computationally very efficient because minimizing the SURE for the unknown weights gives rise to a mere linear system of equations, which in turn allows to consider processes described by quite a few parameters. There is, however, a tradeoff between the sharpness of the description of the process which increases with the number of parameters, and the predictability of the MSE estimate, which is inversely related to the number of parameters. We have already applied our approach within a non ,redundant, orthonormal wavelet framework, and showed that a simple thresholding function that takes interscale dependences into account is very efficient, both in terms of computation time and image denoising quality [24] The best-known use of the SURE in image denoising is Donoho's Sure Shrink algorithm [25] in which a soft-threshold is applied to the orthonormal wavelet coefficients, and where the threshold parameter is optimized separately in each subband through the minimization of the SURE. Otherwise, the approach that is most closely related to SURE-LET—but for a multichannel image denoising application—is the contribution by Pesquet and his collaborators which perform separate in-band minimization of the SURE applied to a denoising process that contains both nonlinear and linear

Volume 4 Issue X, October 2016
ISSN: 2321-9653

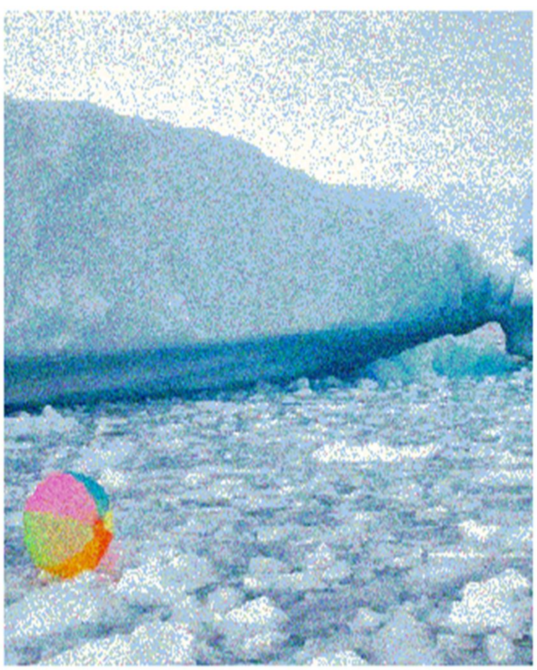
parameters.

SURE-LET for redundant or nonorthonormal transforms lies in the fact that this minimization is performed in the image domain. While it is true that, due to some Parseval-like MSE conservation, image domain MSE/SURE minimization is equivalent to separate in-band MSE/SURE minimization whenever the analysis transformation is—nonredundant—orthonormal [26], this is grossly wrong as soon as the transformation is, either redundant (even when it is a "tight frame") or non orthonormal. This is actually the observation made by those who apply soft-thresholding to an undecimated wavelet transform: the Sure Shrink threshold determination yields substantially worse results than an empirical choice. Unfortunately, this may lead practitioners to wrongly conclude that the SURE approach is unsuitable for redundant transforms, whereas a correct diagnosis should be that it is the independent subband approach that is flawed.

3) *Bayesian Estimation:* Speckle is an inherent characteristic of images acquired with any imaging technique that is based on detection of coherent waves, for example synthetic aperture radar (SAR), ultrasound, coherent optical imaging, etc. Speckle carries information about both the structure of the imaged object as well as a noise component, and the latter is responsible for the grainy appearance of the images. Optical coherence tomography (OCT) is an imaging technique capable of noncontact, high resolution (few micrometers), 3D imaging of the structure of optically semitransparent objects, including biological tissue. Bayesian estimation process is used to optimize the removal of Poisson noise. Bayesian estimation is a framework for the formulation of statistical inference problems. In the prediction or estimation of a random process from a related observation signal, the Bayesian philosophy is based on combining the evidence contained in the signal with prior knowledge of the probability distribution of the process. Bayesian methodology includes the classical estimators such as maximum a posteriori (MAP), maximum-likelihood (ML), minimum mean square error (MMSE) and minimum mean absolute value of error (MAVE) as special cases. The hidden Markov model, widely used in statistical signal processing, is an example of a Bayesian model. Bayesian inference is based on minimization of the so-called Baye's risk function, which includes a posterior model of the unknown parameters given the observation and a cost-of-error function.

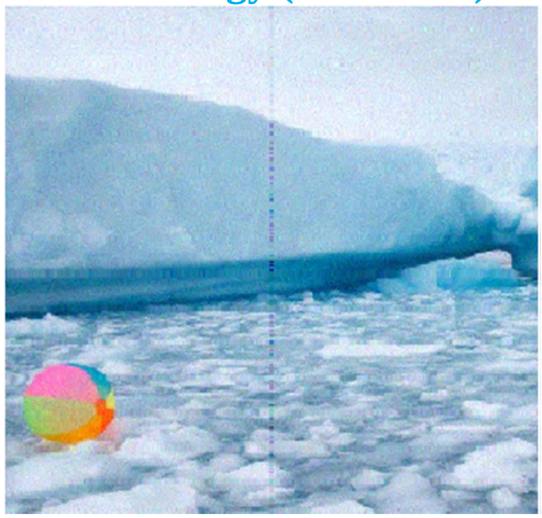
IV. RESULT AND OBSERVATION

In this section we will discuss the obtained results of our experiments. Tool required for the experimentation is MATLAB with Image Processing toolbox. We used images to enumerate the performance of the algorithms. Our dataset includes standard test images selected from the image database. We will evaluate the data for the image.We compare our denoised images by three parameters PSNR ,MSE and SSIM. Fig 4.1 shows the denoising results of the test image with different methods.



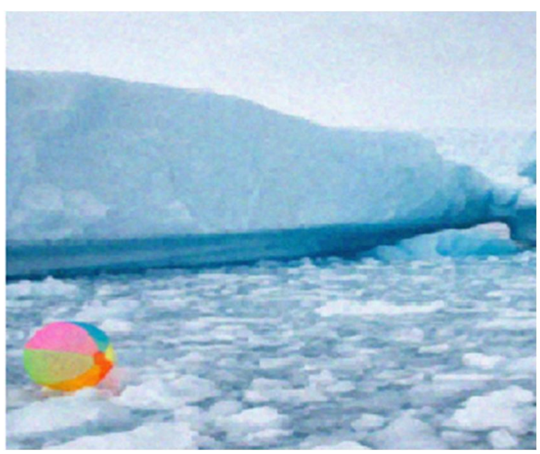
(a)

Volume 4 Issue X, October 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)



(b)

(c)



(d)

Fig 4.1 The denoised results of image snow hill by different schemes. (a) Noisy image (b) Dual tree DWT (c) SURELET method (d) Bayesian estimation

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

V. COMPARISON TABLE

Comparison of PSNR (Peak Signal to Noise ratio) ,MSE (Mean Square Error) and SSIM (Structural Similarity Index) using Dual tree DWT ,Surelet and Baye's Estimator shown in fig

PARAMETERS	DUAL TREE DWT	SURE LET	BAYESIAN
PSNR	28.2902	32.3645	30.5254
MSE	0.0385028	0.0240866	0.0297667
SSIM	0.907938	0.972959	0.951244

Fig 4.2 Comparison of PSNR, MSE and SSIM

The paper emphasizes on the PSNR, MSE and SSIM for various noises using Dual tree DWT,SURE LET and Bayesian Estimator. The Results shows that SURELET denoise Optimizes the addtitive gaussian white noise using the inter-scale sure-let principle in the framework of an Orthonormal Wavelet Transform (OWT) only. removal as its Peak Signal to Noise ratio (PSNR) is maximum and least Mean square error (MSE) and maximum Structural Similarity Index (SSIM). The PSNR for speckle noise is maximum and the MSE is minimum and also SSIM is maximum. Our experimental results demonstrated that SURELET denoise has the highest PSNR and SSIM measures The simulation results reveal that wavelet based SURELET denoise method outperforms other methods.

VI. CONCLUSION

In this paper, the important property of a good image denoising model should completely remove noise as far as possible as well as preserve edges. comparison of various Wavelets at different decomposition levels has been done in this paper. A comparison of various wavelet based methods has also been carried out to denoise the image. The paper emphasizes on the PSNR, MSE and SSIM for various noises using Dual tree DWT, SURE LET and Bayesian Estimator. The Results shows that SURELET denoise Optimizes the addtitive gaussian white noise using the inter-scale sure-let principle in the framework of an Orthonormal Wavelet Transform (OWT) only. removal as its Peak Signal to Noise ratio (PSNR) is maximum and least Mean square error (MSE) and maximum Structural Similarity Index (SSIM). The PSNR for speckle noise is maximum and the MSE is minimum and also SSIM is maximum. Our experimental results demonstrated that SURELET denoise has the highest PSNR and SSIM measures The simulation results reveal that wavelet based SURELET denoise method outperforms other methods .

REFERENCES

[1] Rafael C. Gonzalez, Richard E. Woods, and Steven L. Eddins, Digital Image Processing , 2nd ed. Englewood Cliffs, NJ: Prentice- Hall, 2002.
[2] Castleman Kenneth R, Digital Image Processing, Prentice Hall, New Jersey, 1979.
[3] Reginald L. Lagendijk, Jan Biemond, Iterative Identification and Restoration of Images, Kulwer Academic, Boston, 1991.
[4] Kenneth, "Digital Image Processing", Prentice Hall, New Jersey, R. 1979
[5] Kaibing Zhang , Xinbo Gao , Dacheng Tao and Xuelong Li "Image Super Resolution Via Non Local Steering Kernel Regression Regularization" IEEE Trans. Image Process., vol. 21, no. 11, pp. 4544 4556, Jul. 2012.
[6] Chen Huang , Xiaoqing Ding , Chi Fang "Single-Image Super-Resolution via Adaptive Joint Kernel Regression" International Journal of Computer Applications, November 2012.
[7] Jianchao Yang , John Wright , Yi Ma , Thomas Huang "Image Super-Resolution as Sparse Representation of Raw Image Patches" International Journal of Computer Applications june 2000.
[8] Prof. PankajS. Parsania and Dr. Paresh V.Virparia "A Review: Image Interpolation Techniques for Image Scaling "International Journal of Innovative Research in Computer and Communication Engineering, 12 December 2014,
[9] Guodong Jing, Yunhui Shi and Baocai Yin " Image Super-resolution Reconstruction Based on Sparse Representation and Low-rank Matrix Completion" Journal of Information & Computational Science, November 1, 2012
[10] Umbaugh, Computer Vision and Image Processing, Prentice Hall PTR, New Jersey, S. E. 1998
[11] Gagnon, L. "Wavelet Filtering of Speckle Noise- ome Numerical Results, Proceedings of the Conference Vision Interface", Trois-Reveres.1999
[12] Goodman, J. W. " Some fundamental properties of Speckle", J. Opt. Soc. Am., 66, pp. 1145–1150. 1976
[13] Amara Graps, "An Introduction to Wavelets," IEEE Computational Science and Engineering, summer 1995, Vol 2, No. 2.

Volume 4 Issue X, October 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

[14] Anestis Antoniadis, Jeremie Bigot,“Wavelet Estimators in Nonparametric Regression: A Comparative Simulation Study,” Journal of Statistical Software, Vol 6, I 06, 2001

[15] Matlab6.1.”Wavelettool”,http://www.mathworks.com/access/helpdesk/help/toolbox/wavelet.shtml

[16] Tim Edwards, “Discrete Wavelet Transforms: Theory and Implementation,” Discrete Wavelet Transforms, Stanford University, Draft #2, June 4, 1992

[17] I. W. Selesnick, The design of approximate Hilbert transform pairs of wavelet bases,‖ IEEE Transaction on Signal Processing, vol. 50, no. 5, pp. 1144–1152, May 2002.

[18] I. W. Selesnick, ―Hilbert transform pairs of wavelet bases,‖ IEEE Signal Process. Letter, vol. 8, no. 6, pp. 170–173 Jun. 2001.

[19] I.W. Selesnick, R.G.Baraniuk, and N.G. Kingsbury, ―The dual-tree complex wavelet transform—A coherent framework for multiscale signal and image processing,‖ IEEE Signal Procesin. Mag., vol. 22, no. 6, pp. 123–151, Nov. 2005.

[20] Shan Lal, Mahesh Chandra, Gopal Krishna Upadhyay, Deep Gupta, ―Removal of Additive Gaussian Noise by Complex Double Density Dual Tree Discrete Wavelet Transform” MIT International Journal of Electronics and Communication Engineering, Vol. 1, No. 1, pp. 8-16 Jan 2011.

[21] Devanand Bhonsle and Sandeepa Dewangan ―Comparative Study of dual-tree complex wavelet transform and double density complex wavelet transform for Image Denoising Using Wavelet-Domain‖ International Journal of Scientific and Research Publications, vol. 2, Issue 7, pp. 1-5,July 2012.

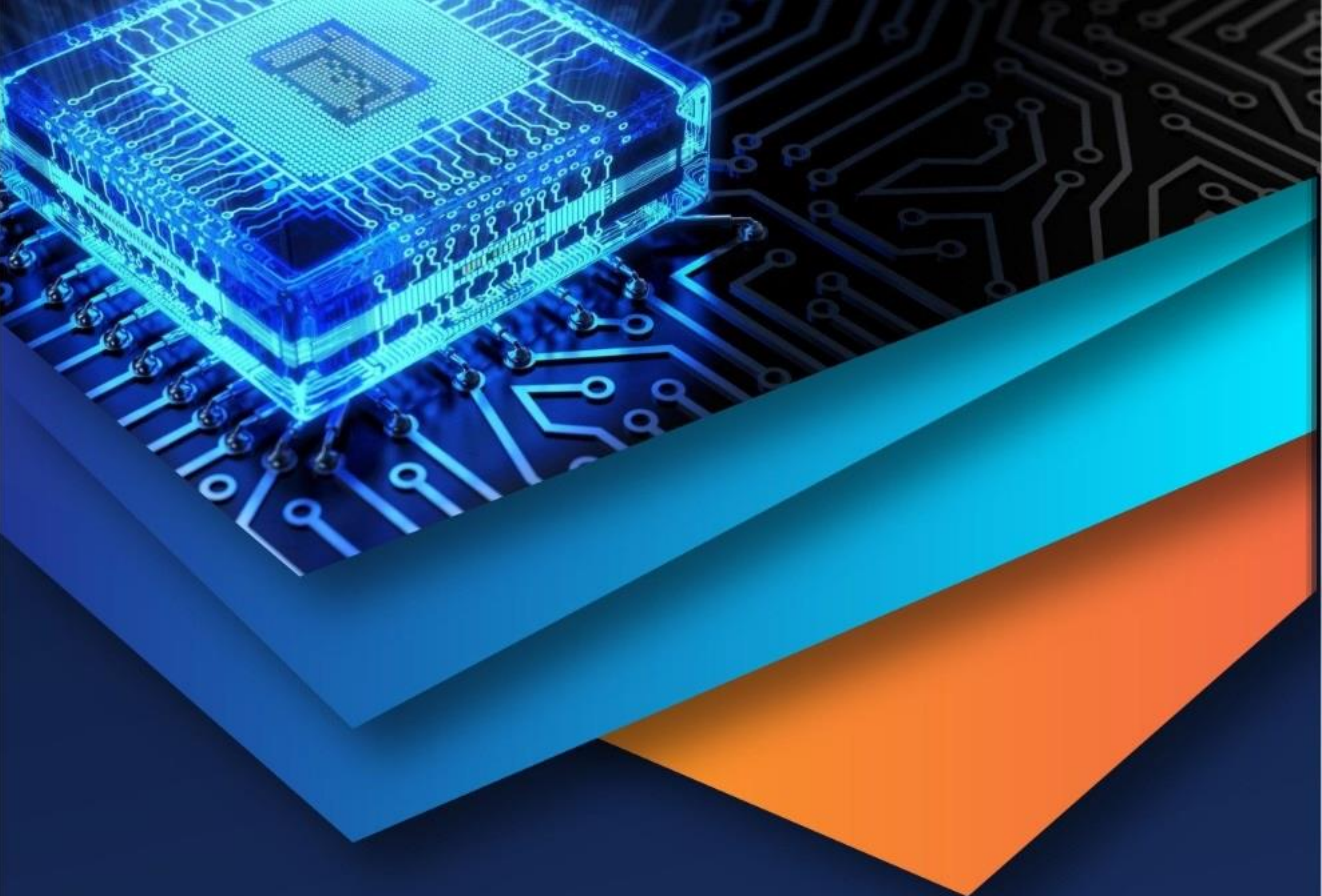
[22] I. Bayram and I. W. Selesnick, ―A simple construction for the M-band dual-tree complex wavelet transform,‖ in Proc. 12th IEEE DSP Workshop, pp. 596–601, 2006.

[23] Thierry Blu, Senior Member, IEEE, and Florian Luisier The SURE-LET Approach To Image Denoising- IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 16, NO. 11, NOVEMBER 2007

[24] F. Luisier, T. Blu, and M. Unser, “A new SURE approach to image denoising: Inter-scale orthonormal wavelet thresholding,” IEEE Trans. Image Process., vol. 16, no. 3, pp. 593–606, Mar. 2007.

[25] D. L. Donoho and I. M. Johnstone, “Adapting to unknown smoothness via wavelet shrinkage,” J. Amer. Statist. Assoc., vol. 90, no. 432, pp. 1200–1224, Dec. 1995.

[26] F. Luisier, T. Blu, and M. Unser, “A new SURE approach to image denoising: Inter-scale orthonormal wavelet thresholding,” IEEE Trans. Image Process., vol. 16, no. 3, pp. 593–606, Mar. 2007.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)