

A Novel Algorithm for Denoising using Adaptive Thresholding Based Dual Tree Complex Wavelet Transform (DTCWT) on Ultrasound Medical Image

Mr. C. Kumar*¹ and Dr. R. Prakash²

¹*Assistant Professor, Department of Electronics and Communication Engineering, Ganadipathy Tulsi's Jain Engineering College, Vellore, Tamil Nadu, India,

Research Scholar (PT), Anna University, Chennai, Tamil Nadu, India

²Professor, Department of Electrical and Electronics Engineering, Muthayammal Engineering College, Rasipuram, Namakkal District. Tamil Nadu, India

¹. kumar.c_ece@gtec.ac.in; kumar.heldah@gmail.com, ²prakashragu@yahoo.co.in

Article Info

Volume 83

Page Number: 10638 - 10647

Publication Issue:

March - April 2020

Abstract

Noise removal, a crucial step is in systems of digital image processing. Though many algorithms are derived for noise removal there is no single algorithm for all types of noise removal. Discrete wavelet transformation has some disadvantages such as it is computationally intensive, shift variance etc. to resolve this challenge, a research proposal method is designed using dual complex wavelet transform algorithm which is far better than the old methods and produces good results. DWT gives extend to Dual-tree complex wavelet transform (DTCWT). Computation of every signal is done along DTCWT complex transform. Each wavelet implements a threshold value, the coefficient value that are greater than threshold value of the coefficients are stored (Lesser are ignored). Then it is passed to many filters to remove different types of noises. Finally an enhanced image with reduced noise will be obtained. Image with noise could be improvised in quality of visual; it simply changes the coefficients with the help of soft-thresholding method. Noises of additive, Speckle, multiplicative and Gaussian and its factors affect images in ultrasound, which minimize the image quality and effects the human interpretation. So, DTCWT based thresholding approach helps to minimize the noise rate considerably for the provided US image. The experimental result confirms that the proposed approach provides better performance with respect to higher PSNR, SSIM and lower MSE, execution time rather than the previous Fisz transformation and DWT methods.

Keywords; *Ultrasound imaging, Data-driven denoising, soft thresholding, additive noise, multiplicative noise*

Article History

Article Received: 24 July 2019

Revised: 12 September 2019

Accepted: 15 February 2020

Publication: 13 April 2020

I. INTRODUCTION

Currently, medical analysis are widely used along ultrasound Images[1]-[3]. This modality of image processing in field of medical provides familiar imaging technique for diagnostic analysis due to the inherent feature of the noninvasiveness. Other advantages of less expenses, portability and less

time consumption are favored mechanism of Ultrasound imaging in generating images [4]-[6]. Research in this area has gained momentum in the recent past due to the fact that this imaging methodology is preferred by many a clinician/physician for diagnostic imaging though several methodologies are existing like Computerized Tomography technique (CT) and

MRI Techniques (Uses strong magnetic fields). Ever growing curiosity within researchers is getting explored to get benefit of ultrasound imaging [7]-[9] in the low income countries as a commercially available premier diagnostics tool. In Ultrasound imaging the primary factor that is of concern is image quality [10]-[11]. The interpretation and examination of images in ultrasound are hampered seriously via presence of dominant unwanted pixels called speckle. Numerous efforts are in place to augment these imagery in reason of receiving legitimate along with satisfactory data in verdict [12]- [14].

In medical ultrasound imaging, a continual challenge that troubled many radiologists over the years is noise. Noise in ultrasound is integrated into the objects in the image making it difficult to obtain improved image quality for viewing [15]. Denoising is often an indispensable preprocessing step to be performed before exploiting the acquired data [16]. The existence of stain [17] in medical images of ultrasound makes interpretation and diagnosis an uphill task. Thus a large set of despeckling algorithms are proposed for analysis of ultrasound images. Spatial filters [18] reduce the effects of image noise by smoothing, resulting in a major side effect called blur. computational fluid dynamics, partial differential equations of several methodologies influences various new algorithms along methods of level set, and methodologies of entire variation [19], nonlinear isotropic and anisotropic diffusion which claim to preserve the image edges. Filters for removing impulse along with local adaptive filtering for removing white as well as mixed noises are combined to form Mixed algorithms [18] [14] are proposed. Edge detection of high resolution images with different methods of clustering also studied[28]-[32]. Images in medical field are get reduced with noise via digital filters (FIR or IIR), adaptive filtering (wiener filter), linear filtering, and median filtering are proposed in literature extensively and effectively [20]-[21]. Recent literature shows the use of wavelet domain

for effectively de-noising medical images [22]-[23]. in wavelet domain , Soft and hard thresholding has successfully been applied by many researchers for noise elimination. In this work, proposal of adaptive thresholding based DTCWT are done to enhance better denoising images, the soft threshold method is introduced. It helps to minimize the noise rate considerably for the provided US image.

II. PROBLEM DEFINITION

Transiting ultrasonic waves to the body from probes is common in US Medical imaging system. On propagation, several tissues get function and get reflect back on scattering towards transducers. Electrical impulses are attained from the echoes that provide radio-frequency (RF) signals and in turn extract the density and echo strength on creating US images. The amplitude values and the scatters locations produce US image. Post processing of signals RF is displayed. Suppression of high-frequency carrier is enveloped by demodulation step process. The perception from human visual is not enough with attained signal as the dynamic range.

III. NOISES IN US IMAGES

Multiplicative Noise

Need to recognize the sufficient noise model, is a significant challenge in establishing the novel methods for denoising ultrasound images. After demodulation step, Gaussian noise is not present anywhere in magnitude distribution. Like imaging of SAR, models of multiplicative noise are growing. For successful US imaging, in addition to filters of Anisotropic diffusion several filters are developed in these model. speckle noise statistics are included in account of SRAD (speckle-reducing-anisotropic-diffusion) [24], with OSRAD (Oriented Version) [25], in addition with currently filters for memory-driven [26].

Speckle noises

Speckle noises are the most common issue here, which is produced by the non-homogenous structure

of the tissues. Details as well as edge definitions in ultrasound images, gets degraded due to this noise.

Additive Noise

The log compression leads to the final Ultrasound image visualized on the scanner isn't considered in the Multiplicative noise models. A easy resolution are focused on removing of various signal and noise removal. Hence, the multiplicative-noise model is transformed towards an additive signal-independent noise model, in the logarithmic compression step:

$$v=u+\varepsilon \quad (1)$$

Where v is the observation factor, u is the unknown image value and ε is a random noise component.

Wavelet-based strategies manages these kind of model contingent upon the idea of ε . For instance: consider that "is a zero-mean Gaussian white noise" which leads AWGN models that perfectly suits the classical wavelet thresholding approaches. In [27] indicated that under model (1) and logarithmic transformations, the wavelet coefficients of the noise-component have non-Gaussian statistics, which is explained by some alpha stable distributions & Wavelet thresholding customized for such a situation.

Gaussian noise

Gaussian noise (speckle noise's model) computes the mean and SD accordingly with PSNR from image of ultrasound, with help of the proposed linear model for Gaussian noise estimation and removal. Insufficient performance of most de-speckling algorithms happens in the white Gaussian noise due to the additive noise. Factors like noises of sensor, electronic circuit that maximize noise of Gaussian as either bad light or maximum temperature.

Salt & pepper noise

Transmission of data causing Errors is termed as Salt and pepper noise. In single case, data dropout noise appears on simple single cases and value are

set to 0 or nearer 0.

IV. PROPOSED METHODOLOGY

The quality of image is improved by denoising method to filter noise significantly. Noises like Gaussian, pepper salt, additive and multiplicative are handled significantly through method proposed.

A. Dual tree complex wavelet transform(DTCWT)

The primary subsections of 2D dual tree wavelet are complex transform of 2D wavelet addition with transform of real 2D wavelet. The image data are crucially denoised safely by discarding noisy data. transform of Real Dual tree complex wavelet are expandable twice as transform of complex Dual tree complex wavelet are four times expandable [3]. Upper and lower complex wavelet transform are considered as real or authentic and imaginary part complex wavelet transform accordingly. Both authentic and complex wavelets will give wavelets in six different directions. Image fusion is one of the important advantages of DTCWT. Figure 1 is the block diagram of 3 levels DTCWT. two sampled separable 2D DWT support applying of Real 2D dual tree wavelet transform in parallel and four sampled separable 2D DWT in parallel support complex 2D wavelet transform. But both are using wavelets in six different directions. The addition and subtraction of every pair are computed along its sub bands

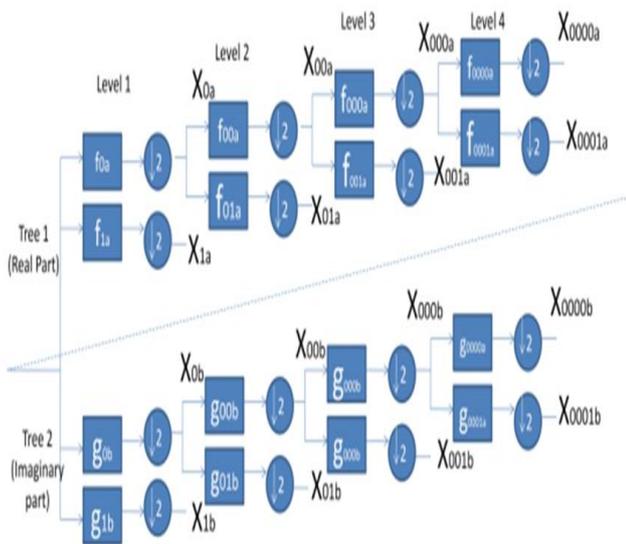


Fig 1. Analysis phase of DTCWT

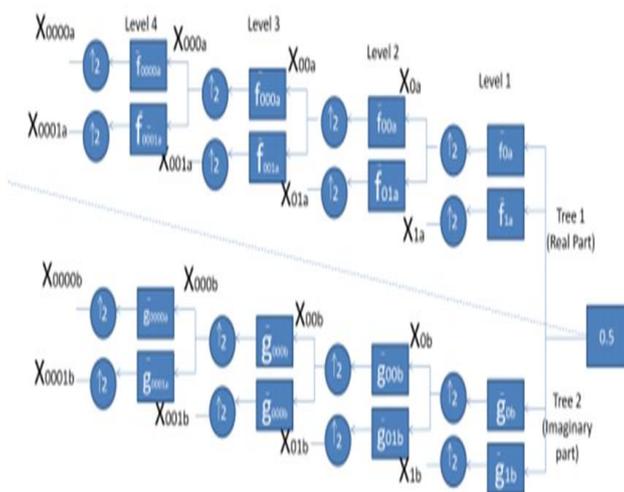


Fig 2. Synthesis phase of DTCWT

Local adaptive image denoising. Input and output are taken from image and binary image respectively. Usually there are some dissimilarity in images of noisy and clear along pixel value holding value of threshold. If the values are lesser than the threshold value then it is removed. Likewise smaller threshold values are eliminated, to yield better image. In wavelet thresholding, image can be decomposed into high frequency and the sub bands of low frequency and are approximated through hard and soft thresholding [4].

B. Proposed Algorithm for denoising

Improving the image quality for visualisation and analysis by eliminating the bad factors to recover the useful information from the degraded image is important [5]. The proposed DTCWT used to remove noise in an image is as follows:

Step 1: examine source image

Step 2: Apply hybrid median filtering in noisy image

2.1 3 X3 sub masks are used

2.2 median value determines incoming pixel value

2.3 remove multi-type of noises

Step 3: Read enhanced image.

Step 4: Apply wavelet transform with dual tree complex

4.1 calculate forward dual tree DWT

4.2 At the analysis stage, a Hilbert transformer is applied both real and imaginary part of wavelet transform.

4.3 on renovation stage, renovated real and imaginary trees are added up to outputs and in the another direction subtract results from results of signals image.

4.4 calculate the magnitude of complex co-efficient

4.5 calculate the inverse wavelet transform

Step 5: Apply local adaptive thresholding technique

5.1 level adaptive threshold selection

5.2 on value of threshold is greater than pixel value replace black pixel and on value of threshold is lesser than pixel value replace white pixel

Step 6: Extract a denoised image as output

In this research, a hybrid median filter has been implemented in the original image to produce enhanced image. Multi-type noise can be reduced at

this level. Dual tree complex wavelet transform are formed along enhanced image. In formulation the DTCWT is complex pair of real and imaginary discrete wavelet transform trees [6]. Finally, enhanced image is applied with local adaptive image denoising method. achromatic plane influence HVS on any changes unlike chromatic plane [7]. Analysis and synthesis filters are well discussed by Kingsbury provide a perfect reconstruction analysis and synthesis filter banks for image denoising with critically-sampled for discrete wavelet shrinkage [8].

V. RESULT AND DISCUSSION

We assume an cancer tumor Ultrasound liver images for our research work. The proposed research work is implemented using MATLAB. Initially, US database images are tested and trained. In training process, 10 normal images and 10 disease images. The main dataset samples are collected from <https://sonographic tendencies.wordpress.com/2017/07/30/hepatic-steatosis-fatty-liver/>. Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) are categorical types

MSE

Computation of input image on median value of squared intensity as well image of output as represented in (1) of pixels.

$$MSE = \frac{1}{NM} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [e((m,n))]^2 \quad (13)$$

Images of deformed in addition to source image are differentiated by $e(m,n)$

PSNR

image quality is measured depending upon the two images' pixel space represents Signal-to-noise ratio [3]. quality of reconstructed image against source image offer SNR measure as given in (2)

$$PSNR = 10 \log s^2 / MSE \quad (14)$$

In an 8-bit image, s is assigned 255. The PSNR with base of SNR holds maximum possible value and pixel values.

SSIM (Structural Similarity Index Metric)

On value equal or nearer zero, the unstable results are produced by Universal image quality index Q. several sized windows of image are measured by SSIM index. windows x and y are measured as with unique size $N \times N$ is:

SSIM

$$(x,y) = \frac{(2\mu_x + \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (15)$$

average values are μ_x , μ_y , and variance σ_x^2 , σ_y^2 for x and y respectively. The covariance σ_{xy} weak denominator are stabilised by two variables $c_2 = [(k_2 L)]^2$ and $c_1 = [(k_1 L)]^2$ pixel values as range dynamically range with k_1 is 0.01 and k_2 is 0.03 is set for default.

Dataset Description

figure 3 represents data input of the ultrasonic image.

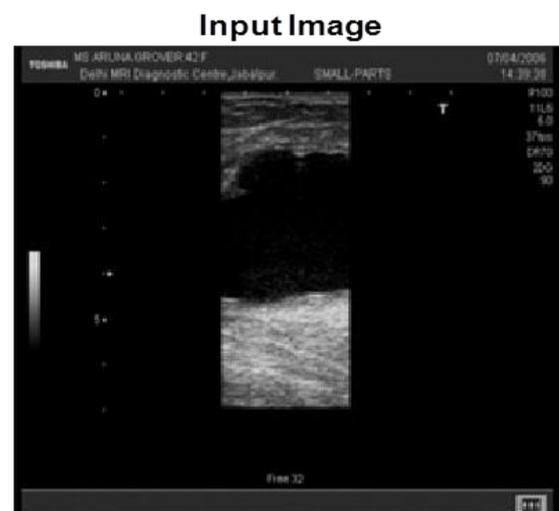


Figure 3: Image of Input Dataset

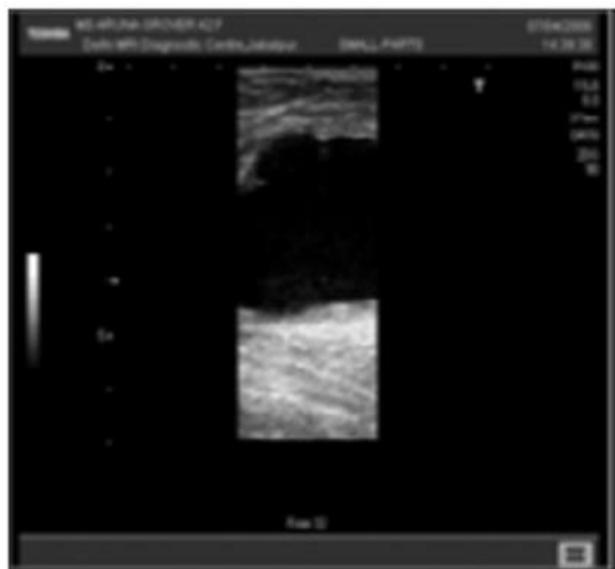


Figure 4 DTCWT Image

the resultant image is represented in Figure 4 along adaptive thresholding based Dual tree complex wavelet transform approach

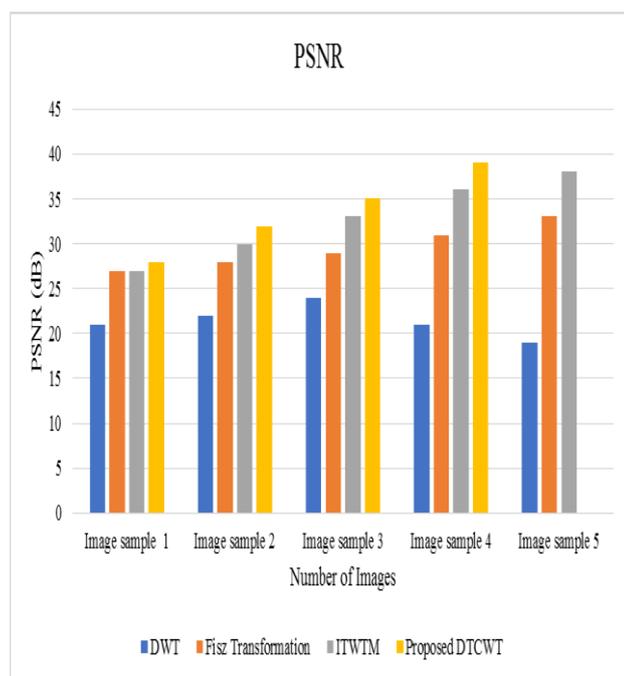


Figure 5 PSNR Comparison

The PSNR comparison results among the proposed DTCWT, and ITWTM, existing DWT and Fisz transformation were given in Fig:3. PSNR value is maximum in proposed method against existing approaches. From the experimental results, it confirmed that proposed DTCWT acquire high

PSNR pointing the good reconstructed image

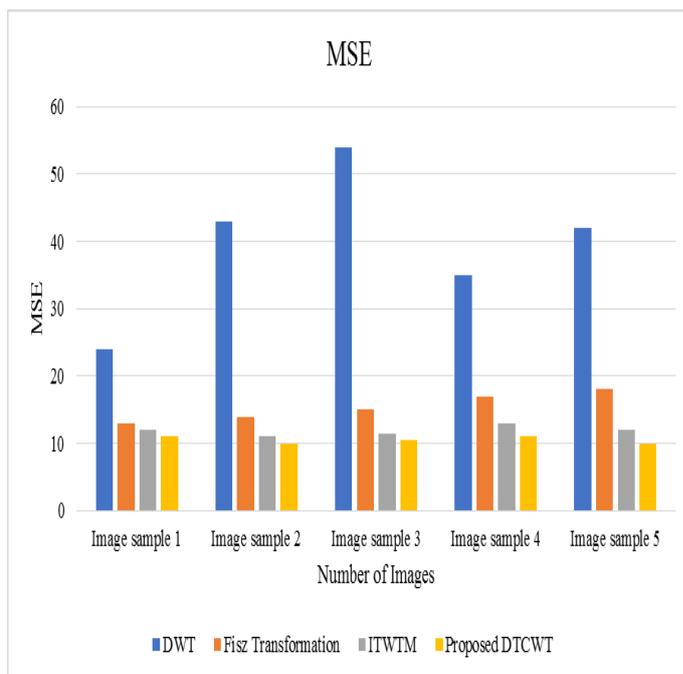


Figure 6 MSE comparison

The MSE performance comparison results among the proposed DTCWT, and ITWTM, existing DWT and Fisz transformation is given in fig.6. It explains that the proposed method has less value of MSE. From the experimental output, it is confirmed that the proposed DTCWT acquire less MSE pointing the good reconstructed image. The significance of the proposed work lies in the probability of reducing the rates for which the image quality remains acceptable.

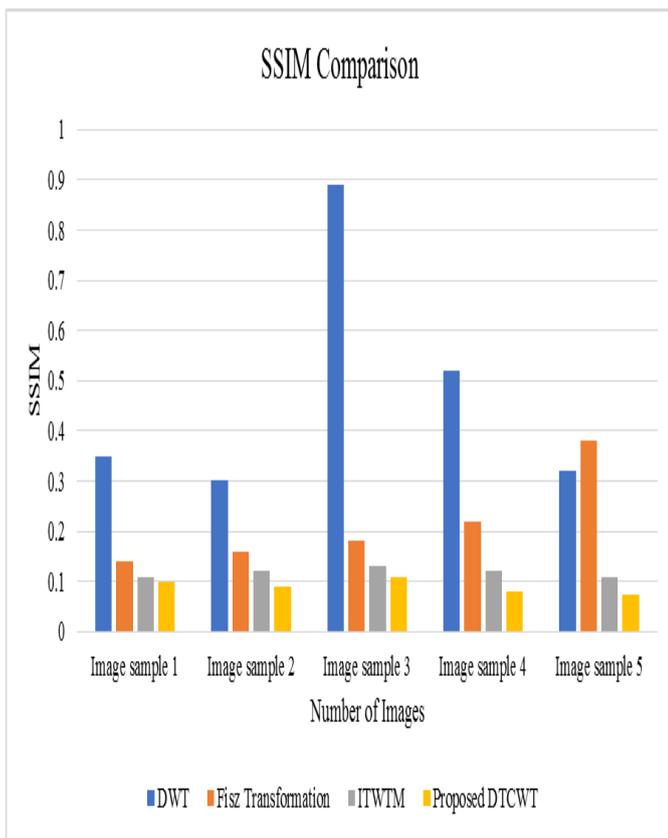


Figure 7 SSIM Comparison

The SSIM performance comparison results between proposed algorithm, and ITWTM, existing DWT and Fisz transformation is given in Fig 7, where the proposed method has high and good value of SSIM. From the experimental output it is confirmed that the proposed DTCWT acquire better SSIM value when compared with the existing methods. The reason behind this is that the proposed quincunx transform has the least redundancy.

VI. CONCLUSION

This proposal research develops algorithm for image denoising algorithm which proves in efficient than older algorithms. This method is combination of hybrid filtering over a noisy image, applies DTCWT filter banks over enhanced image and finally applying local adaptive thresholding over the image samples. The proposed method is applied on enhanced image, hence proved to have less amount of noise and able to achieve better improvements in the PSNR values. This method preserves edges in an image and maintains the visual quality of an image.

The expanded wing proves apt noise model for enforcing the real data. The noise is eliminates considerably and it performs higher with respect to PSNR, SSIM and lower MSE, execution time for entire value of noise level. Hence it gives better US denoising performance when compared with the previous approaches. Future enhancement must focus on adaptive signals methods along higher sparsity.

REFERENCES

- [1] Soloperto G, Francesco Conversano, Greco A , Casciaro E, Andrea Ragusa, Leporatti S, A. LayEkuakille, S. Casciaro, "Multiparametric Evaluation of the Acoustic Behaviour of Halloysite Nanotubes for Medical Echographic Image Enhancement," IEEE Trans., on Inst., & Measur., vol. 63, Issue.6, 2014, pp. 1423 – 1430.
- [2] Lasso A , Tamas Heffter , Adam Rankin , Csaba Pinter , Tamas Ungi , Gabor Fichtinger, "PLUS: open-source toolkit for ultrasound-guided intervention systems", IEEE Trans., on Biomed., Engg., vol.61, Issue.10 , 2014, pp. 2527 - 2537
- [3] Tanya Chernyakova , Yonina C. Eldar "Fourier-domain beamforming: the path to compressed ultrasound imaging", IEEE_Trans., on Ultrasonics, Ferroelectrics and Frequency Control, vol.61, Issue.8, 2014, pp.1252-1267.
- [4] Tanter, M., Fink, M., "Ultrafast imaging in biomedical ultrasound," IEEE_Trans., on Ultrasonics, Ferroelectrics & Freq., Control , vol.61, no.1, 2014, pp.102-119.
- [5] Francesco Conversano , A Greco , Ernesto Casciaro , Andrea Ragusa , Aimé Lay-Ekuakille , S Casciar "Harmonic Ultrasound Imaging of Nanosized Contrast Agents for Multimodal Molecular Diagnoses", IEEE_Trans., on Instr., & Measur., volu.61, Issue.7, 2012, pp.1848- 1856
- [6] Tim Idzenga , Evghenii Gaburov , W Vermin , Menssen J, Chris L. De Korte, "Fast 2-D

- ultrasound strain imaging: the benefits of using a GPU”, *IEEE Transa., on Ultrasonics, Ferroelect., & Freq Control*, vol.61, Issue.1, 2014, pp.207-213.
- [7] F Conversano , E Casciaro , R Franchini , S Casciaro , A Lay-Ekuakille “Fully Automatic 3D Segmentation Measurements of Human Liver Vessels from Contrast-Enhanced CT”, *IEEE Intern., Sym., on MeMea*, June, 11-12, 2014, Lisbon, Portugal.
- [8] Sylvia Rueda , S Fathima , Caroline L Knight , Mohammad Yaqub , Aris T Papageorghiou , Bahbibah Rahmatullah , Alessandro Foi , Matteo Maggioni , A Pepe , Jussi Tohka , Richard V Stebbing , John E McManigle , Anca Ciurte , Xavier B , M B Cuadra , Changming Sun , Gennady V Ponomarev , Mikhail S Gelfand , Marat D Kazanov , Ching-Wei Wang , Hsiang-Chou Chen , Chun-Wei Peng , Chu-Mei Hung , J A Noble, “Evaluation and Comparison of Current Fetal Ultrasound Image Segmentation Methods for Biometric Measurements: A Grand Challenge”, *IEEE Transa., on Med., Imag.*, vol.33, Issue.4, 2014, pp.797-813.
- [9] Y H Chen , Y M Lin , Kuan-Yu Ho , A Y Wu , P C Li, “Low-Complexity Motion-Compensated Beamforming Algorithm and Architecture for Synthetic Transmit Aperture in Ultrasound Imaging”, *IEEE Transa., on Signal Proce.*, vol.62, Issue.4, 2014, pp.840-851.
- [10] A Fenster , D B Downey “3-D ultrasound imaging a review”, *IEEE Engg., in Medi., & Biology Mag.*, volume.15, Issue.6, 2013, pp.41-51
- [11] K J Parker, M M Doyley, D J Rubens “Imaging the elastic properties of tissue: the 20 year perspective”, *Physics in Medicine & Biology*, Volume 56, Number 1, 2011.
- [12] C P Loizou , C S Pattichis , C I Christodoulou , RSH Istepanian , M Pantziaris , A Nicolaides, “Comparative evaluation of despeckle filtering in ultrasound imaging of the carotid artery”, *IEEE Trans., on Ultrasonics, Ferroelectrics & Freq Control*, vol. 52, Issue.10, 2005, pp.1653–1669.
- [13] N Torbati, A Ayatollahi, A Kermani, “An efficient neural network based method for medical image segmentation”, *Computers in Biology and Medicine – Elsevier*, volume. 44, no. 1, 2014, pp.76-87.
- [14] CP Loizou , Pattichis CS, Christodoulou CI, RSH Istepanian , M Pantziaris , A Nicolaides “Comparative evaluation of despeckle filtering in ultrasound imaging of the carotid artery”, *IEEE Transa., on Ultrasonics, Ferroelectrics and Freq., Control*, vol.52, Issue.10, 2005, pp.1653-1669.
- [15] Michailovich O V, Tannenbaum A, “Despeckling of medical ultrasound images”, *IEEE Transa., on Ultrasonics, Ferroelectrics, & Freq., Control*, vol.54, no.3, 2007, pp. 530 – 538.
- [16] Eduardo T Cost, R G Dantas a “Ultrasound speckle reduction using modified gabor filters”, *IEEE Transa., on Ultrasonics, Ferroelectrics & Freq., Control*, vol.54, Issue.3, 2007, pp.530-538.
- [17] J L Mateo, A Fernández-Caballero, “Finding out general tendencies in speckle noise reduction in ultrasound images”, *Elsevier Expert Systems with Applications*, vol.36, no. 4, 2009, pp.7786-7707.
- [18] C Munteanu ., Morales, F.C., J R Alzola, “Speckle Reduction Through Interactive Evolution of a General Order Statistics Filter for Clinical Ultrasound Imaging”, *IEEE Transa., on Biomed., Engg.*, vol.55, Issue.1, 2008, pp.365-369.
- [19] P Coupe, Hellier, P., Kervrann, C., C Barillot, “Nonlocal Means-Based Speckle Filtering for Ultrasound Images”, *Image Processing, IEEE Transactions*, vol.18, no.10, 2009, pp.2221:2229.
- [20] Smital, L., M Víte., J Kozumplík., Provazník I, “Adaptive Wavelet Wiener Filtering of ECG Signals”, *IEEE Transac., on Biomed., Eng.*, 10645

- vol.60, Issue.2, 2013, pp.437-445.
- [21] G Andria, F Attivissimo, Cavone G, N Giaquinto, A M L Lanzolla, "Linear filtering of 2-D wavelet coefficients for denoising ultrasound medical images," Elsevier : Measur., vol. 45, no.7, 2012, pp.1792-1800.
- [22] N Gupta, M.N.S Swam, Plotkin E, "Despeckling of medical ultrasound images using data and rate adaptive lossy compression", IEEE Trans., on Med., Imag., vol.24, Issue.6, 2004, pp.743-754.
- [23] Yong Yue; M M Croitoru, A Bidani; J.B Zwischenberger, Clark John W., "Nonlinear multiscale wavelet diffusion for speckle suppression and edge enhancement in ultrasound images", IEEE Trans., on Med., Imag., vol.25, Issue.3, 2006, pp.297-311.
- [24] Y Yu and S. T. Acton, "Speckle reducing anisotropic diffusion." IEEE Transa. Image Processing., vol. 11, Issue. 11, pp. 1260–1270, 2002.
- [25] Krissian K, Westin C F., Kikinis R, Vosburgh K G., "Oriented speckle reducing anisotropic diffusion," Image Process., IEEE Transaction vol. 16, pp. 1412 – 1424, 2007.
- [26] Ramos G L, V S Ferrero G, Martin-Fernandez M, Alberola-Lopez C, Image Process., IEEE Trans., vol. 24, Issue. 1, pp. 345–358.
- [27] Achim, Bezerianos A, and Tsakalides P, "Novel Bayesian multiscale method for speckle removal in medical ultrasound images." IEEE Trans. Medical Imaging, volume. 20, Issue. 8, pp. 772–783, 2001.
- [28] Dhivya, R and Prakash, R., "Edge Detection of Satellite Images Using the Ant Colony Optimization", Journal of Advance Research in Dynamical & Control Systems, Vol. 10, 10-Sp., Issue, 2018, Pages: 1673-1681
- [29] Dhivya, R and Prakash, R., "Stripe Noise Separation and Removal in Remote Sensing Images", Journal of Computational and Theoretical Nanoscience, ISSN:1546-1963 Vol. 15, No.9, Pages: 2724–2728, 10, September 1, 2018
- [30] Dhivya R and R Prakash, Edge detection of satellite image using fuzzy logic., Springer, Cluster Computing, ISSN1386-7857, 9 December 2016, Pages: 1-8
- [31] Dhivya R and R Prakash, Edge Detection Based on Fuzzy Logic and Huffman Coding on Remote Sensing Images, International Jour., of Printing, Packaging and Allied Sciences, ISSN 2320-4387, Vol. 4, No. 4, Pages: 2369-2377, 2016.
- [32] Dhivya, R and Prakash, R., A Paper on Edge Detection in Images using Fuzzy K Means Clustering Approach, International Jour., of Engg., and Computer Science, ISSN: 2319-7242 Vol. 5, No.11, Nov. 2016, Page No. 18848-18852

AUTHOR PROFILE



Mr. C. KUMAR received his bachelor of Engineering degree from Priyadarshini Engg., College, Vaniyambadi affiliated to Anna University, Chennai. Tamilnadu, India in 2005 and the Master of Engineering degree from Thanthai Periyar Govt., Inst., of Technology affiliated to Anna University, India, in 2008. He is working as Assistant Professor in the dept., of Electronics & Communication Engg., at Ganadipathy Tulsi's Jain Engg., College, Vellore, Tamilnadu, India. Now he pursuing doctoral scholar at Centre for Research, Anna University, Chennai, India. The research work is under the supervision of Dr. R. Prakash, at Centre for Research & development, Muthayammal Engg., College, (Autonomous) Rasipuram, Namakkal Dist, Tamil Nadu, India. His area of interest includes Medical images analysis, Image processing, Signal processing and computer Networking.



Dr. R. Prakash, he received the Bachelor of Engineering degree from GCT (Government College of Technology) Coimbatore,

Tamilnadu, India, by the year 2000 and he received Master of Technology degree from the College of Engineering, Thiruvananthapuram, Kerala, India, year 2003. He received his doctorate in the department of Electrical and Electronics Engg., from Anna University, Chennai, India, by the year 2012. He received many funded projects from Govt of India. Now he is working in Department of Electrical and Electronics Engg., as Professor at Muthayammal Engineering College, (Autonomous) Rasipuram, Namakkal District, Tamil Nadu, India . He has authored over Fifty research Publication in journals and many publication in national and international conferences. His area of interest includes Fuzzy logic, adaptive control, control system and neural network