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A Novel Wavelet-Based Fuzzy Based Fluorescence Image Denoising Approach With Optimized Variance-Stabilizing Transformations

K. Sampath kumar[1] and C.Arun[2]

[1]Research Scholar of St. Peter's University, Chennai.
[2]Professor, Department of Electronics & Communication Engineering
R.M.K.College of Engineering &Technology, Chennai.
kksam0185@gmail.com

Abstract

Nowadays,Fluorescent protein microscopy imaging is one of themost important tools in biomedical research. However, the resultingimages present a low signal to noise ratio and time intensity decaydue to the photobleaching effect. This phenomenon is a consequenceof the decreasing on the radiation emission efficiency of thetagging protein. This occurs because the fluorophore permanentlyloses its ability to fluoresce, due to photochemical reactions inducedby the incident light. The Poisson multiplicative noise that corruptsthese images, in addition with its quality degradation due to photobleaching,make long time biological observation processes verydifficult.In proposed method a wavelet shrinkage algorithm based on fuzzy logic and the DT-DWTscheme with Anscombe transformtion is used. In particular, intra-scale dependency within wavelet coefficients is modeled using a fuzzyfeature. This model differentiates the important coefficients and the coefficients belong to imagediscontinuity and noisy coefficients. This fuzzy model is used to enhance the wavelet coefficients'information in the shrinkage step which uses the fuzzy membership function to shrink wavelet coefficientsbased on the fuzzy feature. This studyexamine image denoising algorithm in the dual-tree discrete wavelet transform, which is the newshiftable and modified version of discrete wavelet transform. Simulation result shows our approach achieves a substantial improvement in both PSNR and Visual quality.

Keywords: Mixed-Poisson-Gaussian, Poisson–Gaussian unbiased risk estimate, Fluorescence, Anscombe transformation, Image denoising, Dual-tree discrete wavelet transform, Fuzzy membership function.

1. INTRODUCTION

Fluorescence live-cell imaging is generally used to study intracellular molecular dynamics. Inlive cell microscopic imaging there is always exists a compromise between image quality and cell viability. The prerequisite to image rapidly and in numerous dimensions, to capture dynamic intracellular procedures also constrains illumination and exposure regimes and requires fast camera readout. This is in turn results in low signal-to-noise ratio (SNR) fluorescence images with mixed Poisson–Gaussian noise. Under such conditions effective denoising techniques are indispensable and become a critical tool to improve quantitative investigation of these images in order to understand dynamic intracellular processes and their fundamental mechanisms.Low illumination conditions generate arbitrary variations in the photon emission and detection process that manifest as Poisson noise in the captured images [1]. Successful denoising algorithms are consequently indispensable before visualization and analysis of these images.

In this paper main aim of the work is to establish the impact of various standards denoising strategies on fluorescence images [2]. Photon and camera readout noises in general degrade fluorescence images. Thus the stochastic data representation is a Mixed-Poisson-Gaussian (MPG) procedure. Therefore consider strategies which moreover work on the Poisson noise or Gaussianize the Poisson process and then denoise the Gaussianized image [3].For Gaussianizing the images were carriedout to variance stabilizing transform (VST) and applied to Anscombe root transformation$f: z \rightarrow 2\sqrt{z+\frac{3}{8}}$to the data which determination of Gaussianize the noise which is then removed using a conventional denoising algorithm for additive white Gaussian noise, which in our case is Fuzzy-Shrink using DT-DWT, An inverse transformation is used to estimate the signal of interest for denoised signal.

Proper inverse transformation is primary in order to reduce the bias error which prone position when the nonlinear forward transformation is performed [4]. In [5] developed an algebraic inverse and the asymptotically unbiased inverse that together show the way to a substantial bias at low counts.In this paper, an efficient approach is proposed to determine the impact of various standards of denoising approach on fluorescence images.In this paper, wemodel the intra-scale dependency in wavelet transform domain as afuzzy feature. We always postulate that noise is uncorrelated in thespatial domain; it is also uncorrelated in the wavelet domain. Withrespect to this principle, we use a fuzzy feature for single channelimage denoising to enhance image information in wavelet sub-bands,and then using a fuzzy membership function to shrink waveletcoefficients, accordingly. This feature space distinguishes betweenimportant coefficients, which belong to image discontinuity and noisycoefficients.

The rest of the paper is organized as follows: Section 2 introduces about Poisson noise, variance stabilization, Gaussian and Poisson denoising along with the conventional inverses of the Anscombe transformation. Section 4 discusses the various experiments, and consists of results followed by conclusion in Section 5.

2. THEORY

2.1. Poisson noise

Let z i , where $i = 1, \ldots N$, be the experiential pixel values attained through an image acquisition device. Consider eachz_i to be an autonomous random Poisson variable whose mean $y_i \geq 0$ is the fundamental intensity value to be calculated. The discrete Poisson probability of each $z_i$is

$$E\{zi|yi\}=\frac{\mathrm{yi}^{\mathrm{zi}} e^{-yi}}{\mathrm{zi!}} \quad (1)$$

In addition to that the mean of the Poisson variable z_i and the parameter $y_i$also its variance is as follows:

$$E\{zi|yi\}=yi = var\{zi|yi\} \quad (2)$$

Poisson noise can be defined as

$$\eta i = zi - E\{zi|yi\} \quad (3)$$

Hence, slightly have $E\{\eta i|yi\} = 0$ and $var\{\eta i|yi\} = var\{zi|yi\} = y$.As the variance of noise varies the accurate intensity value varies; Poisson noise is depends on signal. In general the standard deviation of the noise ηi equals$\sqrt{yi}$. Due to this, the effect of Poisson noise increases that is the signal-to-noise ratio decreases as the intensity value decreases.

2.2. Variance stabilization and the Anscombe transformation

The fundamental reason for proposing a VST is to eliminate the dependent data of the noise variance, as a result that it becomes stable for the entire data $z_i, i = 1, \ldots \ldots, N$.Furthermore, if the transformation is also Gaussian noise distribution, to calculate the intensity values y_i with a conventional denoising method considered for preservative white Gaussian noise. Neither exact stabilization nor exact normalization is probable so, put into practice, an approximate or asymptotical results are employed.

Variance stabilizing transformations is the Anscombe transformation is widely used transform is explained in [6].

$$f: z \rightarrow 2\sqrt{z + \frac{3}{8}} \quad (4)$$

Poisson distributed data gives a signal whose noise is asymptotically additive standard normal by applying (4).

The $f(z)$ is a denosing produces a signal D that can be considered as an estimation of $E\{f(z)|y\}$.

3. IMAGE ENHANCEMENT USING FUZZY SHRINK DT-DWT

In this paper, proposed an efficient technique to enhance thefluorescence image using a new wavelet based fuzzy shrink andthresholding method. The following section discusses aboutthe structural design and the use of fuzzy shrink in fluorescenceimage enhancement.Initially, the fluorescence images are transformed topreprocessing process for preliminary enhancement. Then theoutput of preprocessing is given as input to the DT-DWT. Inthis transform, the preprocessing is not used as the initial step,although it is more efficient. Because it enhances the imagecontrast by transforming the pixel distribution as a result theycan conform to uniform distribution. In this proposed work, the input image which consists of noise is called noisy imageis first transformed into wavelet domain. In the waveletdomain there are mainly three processes in which the imagefirst compute the DUAL TREE discrete wavelet transform (DT-DWT),pixel values are converted into wavelet coefficients thendecomposed into six sub bands.

After applying wavelettransform small coefficients are subjected by noise, whilecoefficients with a large absolute value carry more signalinformation than noise. Replacing the smallest, noisycoefficients by zero and a backwards wavelet transform on theresult may lead to a reconstruction with the essential signalcharacteristics and with less noise. For thresholding threeobservations and assumptions:

1. The decorrelating property of a wavelet trans-form creates a sparse signal: most untouched coefficients are zero or close to zero.
2. Noise is spread out equally over all coefficients.
3. The noise level is not too high, so that can recognize the signal and the signal wavelet coefficients.

So, choosing of threshold level is an important task thecoefficients having magnitude greater than threshold areconsidered as signal of interest and keep the same or modifiedaccording to type of threshold selected and other coefficientsbecome zero. The image is reconstructed from the modifiedcoefficients. This process is also known as the inverse discretewavelet transforms (IDWT). Selection of threshold is animportant point of interest.Care should be taken so as to preserve the edges of thedenoised image. There will be various methods for waveletthresholding, which depend on the choice of a threshold value.To choose the threshold value using fuzzy shrink rule, finallyall the images are summed to low sub-band at the next to finerscale. The process is repeated until the image is reconstructed,at last get enhanced fluorescence image.

3.1 Denoising and Thresholding

Here the denoising is done through Fuzzy shrinkage rule. Inimage denoising, where a trade-off between noise suppressionand the maintenance of actual image discontinuity must bemade, solutions are required to detect important image detailsand accordingly adapt the degree of noise smoothing. Withrespect to this principle, use a fuzzy feature for single channelimage denoising to enhance image information in waveletsub-bands and then using a fuzzy membership function toshrink wavelet coefficients, accordingly.

3.2 Fuzzy Feature

Here, want to give large weights to neighboring coefficientswith similar magnitude, and a small weight to neighboringcoefficients with dissimilar magnitude. The larger coefficientsare produced by noises which are always isolated orunconnected, but edge coefficients are clustered andpersistent. It is well known that the more adjacent points aremore similar in magnitude. So use a fuzzy function $m(l,k)$ofmagnitude similarity and a fuzzy function$s(l,k)$ of spatialsimilarity, which is defined as:

$$m(l,k) = \exp\left(-\left(\frac{Y_{s,d}(i,j) - Y_{sd}(i+1,j+k)}{Thr}\right)^2\right)$$

Where $Y_{s,d}(i,j)$ and $Y_{sd}(i+1,j+k)$ are central coefficientand neighbor coefficients in the wavelet sub-bands,respectively. $Thr = c \times \hat{\sigma}_n, 3 \leq c \leq 4, \hat{\sigma}_n$ is estimated noisevariance, and N is the number of coefficients in the localwindow $k \in [-K, \dots, K]$, and $l \in [-L, \dots, L]$ .According the two fuzzy functions can get adaptive weight$w(l,k)$for each neighboring coefficient:

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

Using the adaptive weights, obtain the fuzzy feature foreach coefficient in the wavelet sub-bands as follows:

$$f(i,j) = \frac{\sum_{I=-L}^{L}\sum_{K=-K}^{K} W(l,k) \times |Y_{sd}(i+1,j+k)|}{\sum_{I=-L}^{L}\sum_{K=-K}^{K} W(l,k)}$$

3.3 Fuzzy Shrinkage Rule

The second step is want to give large weights to neighboringcoefficients with similar magnitude, and a small weight toneighboring coefficients with dissimilar magnitude. The nextstep in the wavelet denoising procedure usually consists ofshrinking the wavelet coefficients: the coefficients thatcontain primarily noise should be reduced to tiny values,while the ones containing a significant noise-free componentshould be reduced less. Here, use a fuzzy rule based on thefuzzy feature for shrinking the wavelet coefficients. Fuzzylogic was proposed [7], and has application in alarge number of fields. The fuzzy sets and fuzzy rules formthe knowledge base of a fuzzy rule-based reasoning system.Fuzzy rules are linguistic IF-THEN constructions that havethe general form “IF A THEN B”, where A and B are(collections of) propositions containing linguistic variables.The variable A is called the premise or antecedent and B is theconsequence of the rule [8]. After finding the fuzzy feature,will form Linguistic IF-THEN rules for shrinking waveletcoefficients as follows:

IF the fuzzy feature$f(i,j)$ is large THEN shrinkage ofwavelet coefficients $Y_{s,d}(i,j)$is small.

In fact, the fuzzy feature indicates how coefficients in thenoisy sub-band should be shrunk. Fuzzy membership function(MF) is a curve that defines how each point in the input spaceis mapped to a membership value (or degree of membership)between 0 and 1.MF is often given the designation of μ. Theinput space is sometimes referred to as the universe ofdiscourse, a fancy name for a simple concept. The onlycondition a membership function must really satisfy is that itmust vary between 0 and 1. The function itself can bearbitrary curves whose shape can be define as a function thatsuits us from the point of view of simplicity, convenience,speed and efficiency. MF is built from several basic functionssuch as: piece-wise linear functions, the sigmoid curve,quadratic curve, the Gaussian distribution function and cubicpolynomial curves.

A cubic B-spline is a piecewise cubic polynomial that istwice continuously differentiable. This B-spline using here isthe second order B-spline membership function and thegeneral equation for unity is termed as

$$\sum_{i=-m}^{N} B_{i,m}(x) = 1, x_0 \leq x \leq x_n$$

where m=0,1,2,3….Generally, the B-spline basis functions with order higher than1 are not a normal fuzzy set, in the other words, the maximumvalue of the B-spline membership function does not reach 1.Usually fuzzy systems theory requires that the membershipfunctions are normal, this can be resolved by multiplying theB-spline basis functions by a positive number so that itsmaximum value is 1. In this paper using B-spline curve to geta smooth joint need to control the position and the curvature atthe end points of the curve segments. These curves are highlyflexible in nature than the S curves.Here, the B-spline curve is using in which is a mapping on thevector x, and is named because of its B-shape. Theparameters T1 and T2 locate the extremes of the slopedportion of the curve as given by:

$$\mu(x) = \begin{cases} 0 & x \leq T_1 \\ 2X\left(\frac{x-T_1}{T_2-T_1}\right)^2 & T_1 \leq x \leq \frac{T_1+T_2}{2} \\ 1-2\left(T_2-\frac{x}{T_2-T_1}\right)^2 & \frac{T_1+T_2 \leq x \leq T_2}{2} \\ 1 & x \geq T_2 \end{cases}$$

Here, also drawn an S shaped curve [8] by using themapping on the vector x, and is named because of its Sshape.By using the above parameters of the T1 and T2 thespline based curve also drawn with the B-Spline curve.Finally, the estimated noise-free signal is obtained using thefollowing formula:

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

For building fuzzy membership function, two thresholds (T1and T2), must be determined. Hence, found out that T1 andT2 are related with the $\hat{\sigma}_n$ which is the estimated noisevariance. In order to find these relations, we have done someexperiments using test images. We found out that T1 and T2have nonlinear relation with the $\hat{\sigma}_n$. For achieving thenonlinear relation, have to test the noise reduction algorithmwith the different noisy images. In each different noisevariance, the result obtained best values for T1 and T2.

$$T_1 = K_1 \times \hat{\sigma}_n$$

$$T_2 = K_2 \times \hat{\sigma}_n$$

Where k_1 and the $k_2$are the constant values. $\hat{\sigma}_n$ is the noise variance using median estimator.

$$\hat{\sigma}_n = \frac{1}{\mathrm{N}-1}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{x_i}-\bar{\mathrm{x}})^2$$

Where$\mathrm{x_i}$is the selected pixels,$\bar{\mathrm{x}}$ is the centered pixels andthe N is the order of samples using this noise variance of theimage is calculated.

Indeed, this method is a simple fuzzy IFTHEN rule, whichassigns smaller local window and smaller level ofdecomposition when the estimated noise variance is small,and vice versa then the denoising output of the image is givento the inverse of the DWT for the reconstruction of the image.Then the image is sent for post processing process.

3.4. Post Processing

Processing is usually result from a modification of the spatialcorrelation between wavelet coefficients (often caused byzeroing of small neighboring coefficients) or by using DWT.DWT is shift invariance and will cause some visual artifactsin thresholding based denoising. For this reason, the fuzzyfilter is used on the results of the proposed fuzzy-shrinkalgorithm to reduce artifacts to some extent. First, use awindow of size (2 L+1) × (2 K+1) centered at(i, j) to filter thecurrent image pixel at position (i, j). Next, the similarity ofneighboring pixels to the center pixel is calculated. Adaptive weight $w(l, k)$ for each neighboringcoefficient is calculated. Finally, theoutput of post-processing step is determined as follows:

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

Where,$\hat{x}$ is the denoised image, which can be obtained usingproposed fuzzy-shrink algorithm. After the post processingprocess the enhanced leaf image is obtained as a result.

4. EXPERIMENTS

The experiments mainly consist of following steps as the forward Anscombe transformation to noisy images, and then denoise the transformed image with Fuzzy-

Shrink using DT-DWT [9], lastly the inverse transform is applied to get a final enhanced image. Evaluate the performance by peak signal-to-noise ratio (PSNR). The PSNR is calculated as

$$10\log_{10}\left(\frac{max(yi)^2}{\sum_i((\hat{yi}-yi)^2|N)}\right)$$

Where N is the total number of pixels in the image.

The test images taken for the experiment is shown in **Figure 1a, 1b and 1c** and the performance of the proposed approach is evaluated in terms of PSNR.

Table II shows the results using Fuzzy-Shrink using DT-DWT. The plots of the PSNR values obtained using BLS_GSM and Fuzzy-Shrink using DT-DWTshows that DT-DWT provides higher SNR for low count image when the sigma value is low. As the sigma value increases there is a steep fall in the signal to noise ratio. For higher count images, the ISNR is less in Fuzzy-Shrink using DT-DWTwhen compared with the BLS-GSM technique. The results are tabulated in Table.1.

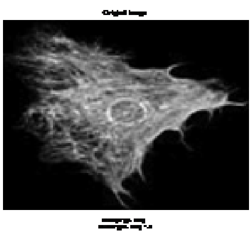
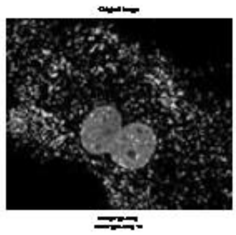
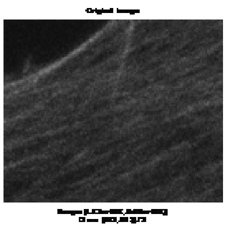
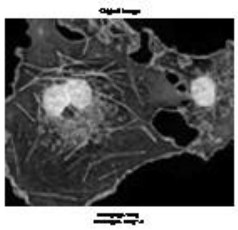
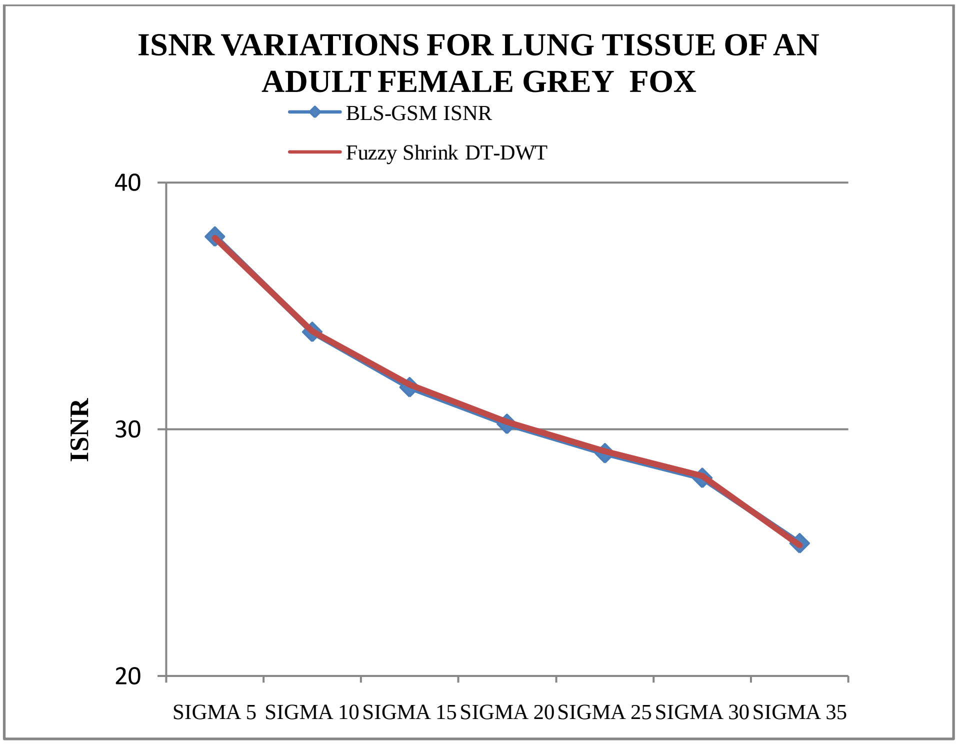
 Lung tissue of an adult female grey fox	 Embryonic Albino Swiss mouse fibroblast Cells
 Image of Phalloidin staining	 Transformed African Green Monkey kidney Fibroblast Cells

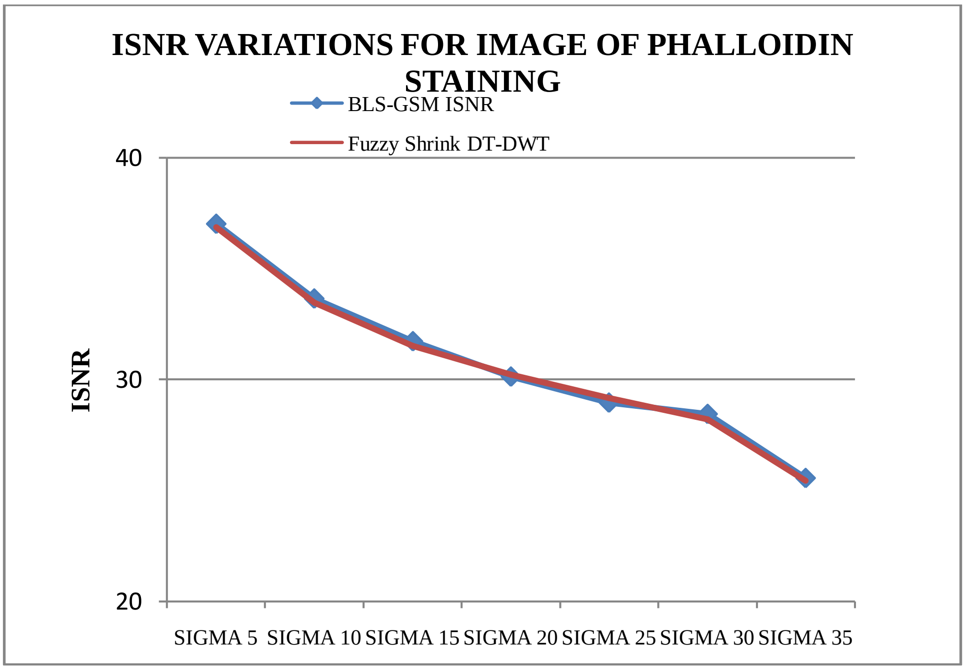
Figure 1: The Four Test Images used in the Experiments

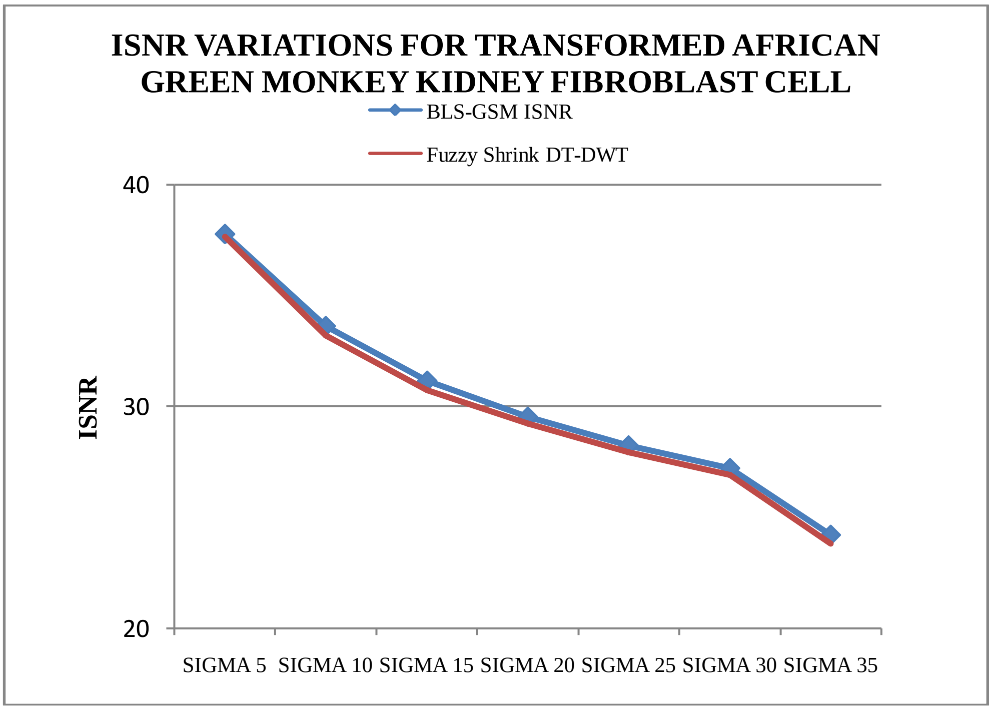
Table 1: Test Results using Fuzzy-Shrink using DT-DWT

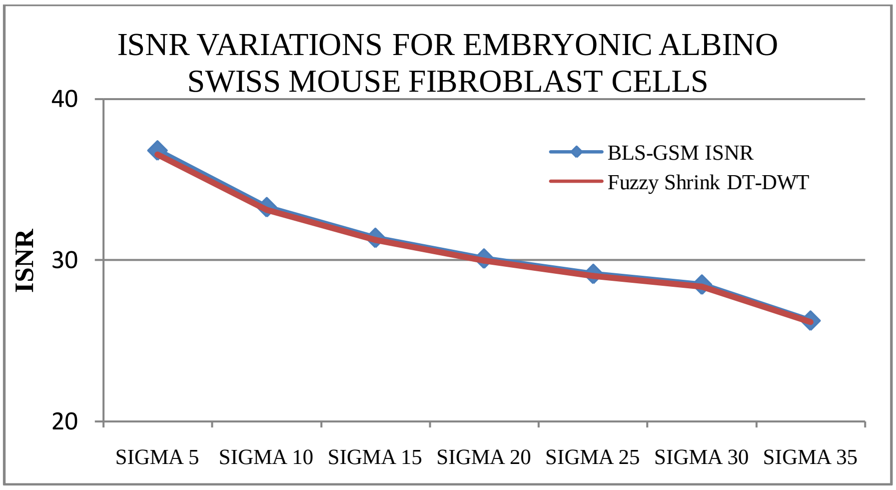
IMAGES	FIGURE 1(a)		FIGURE 1(b)		FIGURE 1(c)		FIGURE 1(d)	
σ_n	ISNR WITH ASYMPTOTIC INVERSE	ISNR WITH FUZZY-SHRINK USING DT-DWT	ISNR WITH ASYMPTOTIC INVERSE	ISNR WITH FUZZY-SHRINK USING DT-DWT	ISNR WITH ASYMPTOTIC INVERSE	ISNR WITH FUZZY-SHRINK USING DT-DWT	ISNR WITH ASYMPTOTIC INVERSE	ISNR WITH FUZZY-SHRINK USING DT-DWT
5	37.81	37.75	37.02	36.89	37.77	37.65	36.82	36.56
10	33.96	33.99	33.67	33.49	33.63	33.21	33.29	33.14
15	31.72	31.81	31.75	31.53	31.17	30.75	31.37	31.25
20	30.22	30.31	30.13	30.24	29.55	29.24	30.11	29.96
25	29.04	29.11	28.96	29.18	28.26	27.96	29.16	29.03
30	28.04	28.11	28.46	28.21	27.22	26.91	28.47	28.35
35	25.38	25.31	25.56	25.45	24.21	23.83	26.23	26.15

Result Plot Variations




ISNR VARIATIONS FOR IMAGE OF PHALLOIDIN STAINING
BLS-GSM ISNR
Fuzzy Shrink DT-DWT
ISNR
40
30
20
SIGMA 5 SIGMA 10 SIGMA 15 SIGMA 20 SIGMA 25 SIGMA 30 SIGMA 35


ISNR VARIATIONS FOR TRANSFORMED AFRICAN GREEN MONKEY KIDNEY FIBROBLAST CELL
BLS-GSM ISNR
Fuzzy Shrink DT-DWT
ISNR
40
30
20
SIGMA 5 SIGMA 10 SIGMA 15 SIGMA 20 SIGMA 25 SIGMA 30 SIGMA 35



5. CONCLUSION

In this paper, we use a new wavelet-based multi-channel image denoising using intra-scale dependency as a fuzzy feature, and inter-channel relation to improve wavelet coefficients' information at the shrinkage step. We use the DT-DWT for wavelet analysis, because it is shift invariant, and has more directional sub-bandscompared to the DWT. In other words, proposing a new method for shrinking waveletcoefficients in the second step of the wavelet-based image denoising is the mainnovelty of this paper. The comparison of the denoising results obtained with our algorithm, and with thebest state-of-the-art methods, demonstrate the performance of our fuzzy approach,which gave the best output PSNRs for most of the images. In addition, the visualquality of our denoised images exhibits the fewest number of artifacts and preservesmost of edges compared to other methods.

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Author's Information

K. Sampath Kumar received the B.E degree in Electrical and Electronics Engineering from Bharathiyar University, Tamil Nadu, and India. He received his M.E degree in Applied Electronics from Anna University, Chennai., India. He spent nearly 9 years as a teaching faculty in Electronics and Communication Engineering Department of Anna University Affiliated Colleges. Currently he is working as Assistant Professor in Sree Sastha College of Engineering and pursuing PhD in the department of Electrical and Electronics Engineering at St Peters University, Chennai. His research area is Digital Image Processing.

Dr.Arun Chokkalingam received his B.E degree in Electronic and Communication Engineering from Bharathidasan University, Trichy, India. He received his M.E and Ph.D. degree in VLSI design from Anna University, Chennai, India. He spent nearly 10 years as a teaching faculty in Electronics and Communication Engineering Department at Anna University Affiliated Colleges. His main research is on Channel Coding algorithms, VLSI Architecture, Mobile Communication and Signal Processing. He has published over 30 articles in reputed journals.