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FETAL ULTRASOUND IMAGE DENOISING USING CURVELET TRANSFORM

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Abstract

The random speckle noise in the acquired fetal ultrasound images is caused by the interference of reflected ultrasound wave fronts. The presence of speckle noise will degrade the quality of the image and even hide image details, which in turn affect the process of image segmentation, feature extraction and recognition and most importantly disease diagnosis. The standardization of measurements from the fetal ultrasound images will help the physicians to make correct diagnosis. The accuracy of diagnosis is possible only when the image is noise free. Hence it is very much important to perform filtering of the speckle noise. It is proposed that curvelet transform serves as a better edge preserving filter compared to other speckle reducing anisotropic diffusion filters. Curvelet transform is designed to handle images which involve curves using only a less number of coefficients. Hence a multiscale representation called curvelet transform is applied to enhance the visual quality of the ultrasound images. The experimented results indicate that the proposed curvelet denoising suppresses the noise effectively both in quantitative and visual means by producing high PSNR.

Keywords:

Speckle Noise, Despeckling, Curvelet Transform, Anisotropic Diffusion

1. INTRODUCTION

Ultrasonography has become the most commonly utilized diagnostic imaging modality in obstetrics and gynaecology. The role of an ultrasound imaging is an important one in monitoring the growth of the fetus and estimating the fetal biometrics. Ultrasonography produces the images in real time and is the most widely preferred imaging technique because of its noninvasive, low cost and portable properties. The quality of information from the ultrasound device has been increased in recent years due to the advancement of technology. However, the speckle is a primary source of noise in the clinical ultrasound imaging system and greatly affects the quality of the ultrasound images.

Speckle noise affects all coherent imaging modalities and makes it difficult to perform further processing. It is caused by the constructive and destructive interference of back scattered coherent waves from the transducer at different phases [1]. Speckle is a random multiplicative noise and it affects the extraction and interpretation of fine details in the image. Hence speckle reduction techniques have to be applied to reduce the noise level in ultrasound images as well as enhance the visual quality of images [2]. However, the aim of denoising procedure is to remove the speckle without destroying the clinically significant features.

2. LITERATURE REVIEW

Speckle reduction techniques include single scale spatial filtering (linear, nonlinear, adaptive methods), multiscale spatial filtering (anisotropic diffusion methods) and methods in another domain (wavelet, curvelet) [3]. This work mainly focuses on the performance of different anisotropic diffusion filters which are used for denoising in fetal images. Recent methods of speckle suppression are mainly concentrated towards diffusion and multiscale methods. Anisotropic diffusion [4] is suitable well for suppression of additive noise compared to speckle noise. Yu and Acton [5] proposed speckle reducing anisotropic diffusion filter (SRAD) which is a partial differential equation (PDE) approach to speckle removal. SRAD not only preserves edges, but also enhances edges by inhibiting diffusion across edges and allowing diffusion on either side of the edge. It is adaptive in nature and hard thresholding is not used to alter the process in smooth regions or in regions near edges. The SRAD method uses only a template of four closest neighbours of the pixel under consideration to perform the diffusion process.

The modified Speckle reducing anisotropic diffusion method (MSRAD) proposed by Deepti et.al [6] involves a large sized template of width 5 pixels and has nearly 12 neighbourhood pixels to determine the diffusion term. MSRAD method reduces the speckle without blurring the image and also enhances the contrast of the image providing information about the fine details of the image. The above anisotropic diffusion methods utilize intensity gradient to differentiate the variation caused by speckle noise, but the gradient operator is not effective in identifying edges. Hence, Jinhua Yu et al [7] enhanced the anisotropic diffusion using a different edge detector called Smallest Univalue Segment Assimilating Nucleus (SUSAN). The performance of the above mentioned filters varies with the number of iterations and the initial parameters. The diffusion filters smoothen the edge information. This smoothening factor will cause error in further segmentation and classification process.

Curvelet transform [8] which is a new multiscale directional transform is proposed for the 2D ultrasound images involving curved edges. This method is capable of representing edges and curved shapes effectively. Hence the curvelet denoising method is suitable for the fetal abdominal ultrasound images involving curved structures.

3. MATERIALS AND METHODS

The fetal abdominal ultrasound images are captured by a Wipro GE logic scanning machine with a transducer having a frequency of 3-5MHz. The images are acquired from a plane perpendicular to the long axis of the fetus just below the cross sectional view of the heart. In this plane of section, one or more of the following organs should be visible, umbilical vein in cross section just inside the abdominal wall, fetal stomach, bifurcation of the main portal vein and the gall bladder. The plane is circular with the spine in cross section and ribs not identifiable. The ultrasound images taken for analysis have curved edges. In this paper, the performance comparison is carried out for SRAD, MODSRAD, SUSAN-AD and Curvelet transform based denoising methods.

3.1 SPECKLE REDUCING ANISOTROPIC DIFFUSION (SRAD)

SRAD not only preserves edges, but also enhances edges by inhibiting diffusion across edges and allowing diffusion on either side of the edge. Given the image '*I*' by defining image intensity at the pixel position (*x*, *y*), the instantaneous coefficient of variation $q(x, y; t)$ which serves as the edge detector can be mathematically expressed as,

$$q(x,y;t)=\sqrt{\frac{\left|(1/2)\|\nabla I\|^2-(1/16)\left(\nabla^2 I\right)^2\right|}{\left(I+(1/4)\left(\nabla^2 I\right)\right)^2}} \qquad (1)$$

where, ∇ and ∇^2 are the gradient and laplacian operator respectively. The function exhibits high values at the edges or on high-contrast features and produces low values in homogeneous regions. The speckle scale function $q_0(t)$ effectively controls the amount of smoothing applied to the image by SRAD. Then the initial diffusion threshold q_0 is computed using,

$$q_0=\frac{\sqrt{\mathrm{var}[Y]}}{\bar{Y}} \qquad (2)$$

where, var[Y] and $\bar{Y}$ denotes the intensity variance and mean over a homogenous area. The diffusion threshold $q_0(t)$ with ρ constant is approximated by,

$$q_0(t)=q_0 ex(p-\rho t) \qquad (3)$$

The diffusion coefficient $c(q)$ of the SRAD process is defined as,

$$c(q)=\frac{1}{1+\left[q^2(x,y;t)-q_0^2(t)\right]/\left[q_0^2(t)\left(1+q_0^2(t)\right)\right]} \qquad (4)$$

The relationship between the edge detector $q(x, y; t)$ and $q_0(t)$ decides the performance of SRAD. For SRAD, the diffusion is stopped automatically when the residual error, defined as the mean square error of images between two iterations is smaller than 0.01.

3.2 MODIFIED SPECKLE REDUCING ANISOTROPIC DIFFUSION (MSRAD)

The modified SRAD involves a large sized template of width 5 pixels and has nearly 12 neighbourhood pixels to determine the diffusion term. The diffusion equation is calculated iteratively and is expressed as,

$$I_{i,j}^{t+\Delta t}=I_{i,j}^{t}+\frac{\Delta t}{12}\sum_{p\in\eta_{i,j}}c\left(\left(q_{i,j}^{t}\right)\right)\left(\left(\nabla I_{i,j}^{t}\right)\right) \qquad (5)$$

where, $I_{i,j}^t$ is the digitized sample image at the pixel position (*i*, *j*), $\eta_{i,j}$ is the local neighborhood of pixels and Δt is the time step size. The instantaneous coefficient of variation (ICOV) has now been modified for the 12 neighbourhood pixels and is given by,

$$q_{i,j}^n=\sqrt{\frac{\left|(1/2)\left\|\nabla I_{i,j}^n\right\|^2-\left(1/12^2\right)\left(\nabla^2 I_{i,j}^n\right)^2\right|}{\left(I_{i,j}^n+(1/12)\nabla^2 I_{i,j}^n\right)^2}} \qquad (6)$$

3.3 SUSAN CONTROLLED ANISOTROPIC DIFFUSION (SUSAN-AD)

SUSAN algorithm proposed by Smith et al. [9] associates each pixel with the pixel of similar brightness in the local area. The new feature detectors are based on the minimization of this local image region, and the noise reduction method uses this region as the smoothing neighbourhood. The resulting methods are accurate, noise resistant and fast. It uses circular masks to perform edge detection. The partial differential equation for the SUSAN-AD model is denoted as,

$$\frac{\partial I}{\partial t}=div\left[c(S=div\left[c\left(SUSAN\left(G(\sigma)*I\right)\right).\nabla I\right]\right] \qquad (7)$$

where, $G(\sigma)$ denotes the Gaussian kernel function with a standard deviation σ and *SUSAN*( ) finds the intensity at the edge using the SUSAN edge detector. The diffusion function is also modified in order to preserve edges as,

$$c(q)=\exp\left[-\left(\frac{q}{4k}\right)^2\right] \qquad (8)$$

and the parameter denotes the diffusion threshold used to distinguish noise gradients and edge gradients. The Eq.(7) and Eq.(8) represents the diffusion model of SUSAN-AD.

3.4 CURVELET TRANSFORM DENOISING (CT)

The curvelet analysis is based on wavelet analysis, but this is more suitable for images with curved structures. The process of curvelet denoising is initiated by transforming the speckle affected image into a new space. In the new space, the curvelet coefficients where the signal to noise ratio is high are retained and those with low signal to ratio are reduced. The manipulated coefficients are converted back to the original space to obtain the despeckled image [10]-[13]. The curvelet decomposition involves the following steps,

1) Subband decomposition: The image *f* is decomposed into subbands and is represented as,

$$f\rightarrow\left(\mathrm{P}_0\, f,\Delta_1 f,\Delta_2 f,\Delta_3 f\ldots\right) \qquad (9)$$

2) Smooth partitioning: Each subband is smoothly partitioned into a block of an appropriate scale.

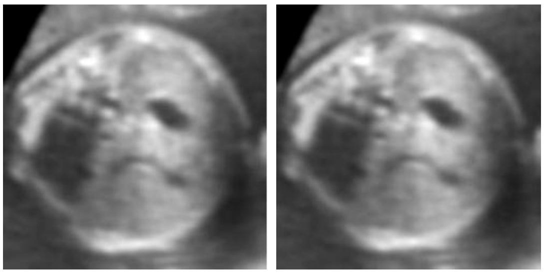
   Renormalization: The resulting block is renormalized to a unit scale.

3) Ridgelet Analysis: Finally, each block is analysed using the digital ridgelet transform. The curvelet coefficients are analysed to eliminate the noisy coefficients by setting a threshold. The process is repeated in the reverse order to perform inverse curvelet transform [14]. The curvelet

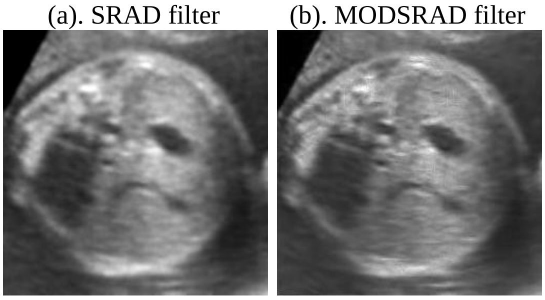
transform requires only the lesser number of nonzero coefficients for the image reconstruction.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The fetal abdominal ultrasound images taken for denoising analysis is processed in the MATLAB environment. The fetal images at different gestational ages are tested using the various anisotropic diffusion filters and the curvelet transform. The speckle noise variance is set at different values such as 0.01, 0.02, 0.04 and 0.06. The resultant images are analyzed both in visual means and qualitatively. The despeckled images are shown in the Fig.1.



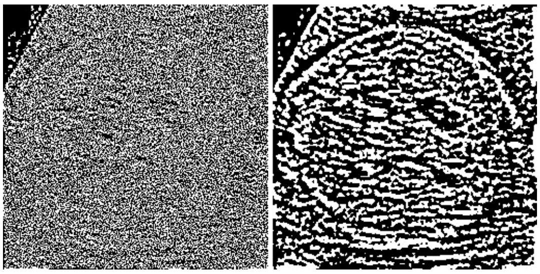
(a). SRAD filter (b). MODSRAD filter



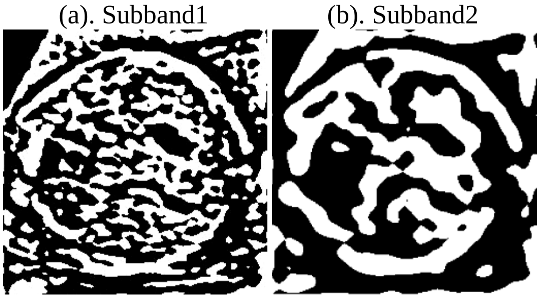
(c). SUSAN AD filter (d). CT filter

Fig.1. Despeckled fetal ultrasound images for different filters

The curvelet denoising is performed by decomposing the input ultrasound image into subbands. The ridgelet analysis is further performed only on the individual blocks in the subbands.



(a). Subband1 (b). Subband2



(c). Subband3 (d). Subband4

Fig.2. Subband decomposition of the ultrasound image

The Fig.2 shows the different subbands obtained by applying curvelet transform. The denoising process will be effective if the subband details are clearly analyzed. The curved edges in the ultrasound image are preserved while using curvelet denoising.

The quality of the processed image has to be analyzed to evaluate the performance of the despeckling algorithm. The quality assessment parameters [15] used in this work are MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio), SC (Structural content) and NAE (Normalized Absolute Error).

4.1 MEAN SQUARE ERROR

The Mean Square Error is the most common parameter to assess the image quality. If X and Y of size $M \times N$, represents the despeckled image and clinical input image respectively, then the MSE is defined as,

$$\mathrm{MSE} = \frac{1}{\mathrm{MN}} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[X(i,j) - Y(i,j) \right]^2 \qquad (10)$$

The image quality is interpreted as low when the MSE value is high.

4.2 PEAK SIGNAL TO NOISE RATIO

PSNR is the most widely used quality metric and higher its value indicates the better denoising algorithm. It measures the ratio of peak signal in the image to noise and also the difference between images. This is calculated using,

$$PSNR = 10 \log_{10} \frac{255^2}{MSE} \qquad (11)$$

The value 255 indicates the highest intensity value in the image.

4.3 STRUCTURAL CONTENT

The large value of SC means that the despeckled image is a poor quality. SC is defined as follows,

$$\mathrm{SC} = \frac{\sum_{i=1}^{\mathrm{M}} \sum_{j=1}^{N} \left| X(i,j) \right|^2}{\sum_{i=1}^{\mathrm{M}} \sum_{j=1}^{N} \left| Y(i,j) \right|^2} \qquad (12)$$

4.4 NORMALIZED ABSOLUTE ERROR

The large value of NAE means that image is poor quality. NAE is defined as,

$$\mathrm{SC} = \frac{\sum_{i=1}^{\mathrm{M}} \sum_{j=1}^{N} \left| X(i,j) - Y(i,j) \right|}{\sum_{i=1}^{\mathrm{M}} \sum_{j=1}^{N} \left(\left| Xi,j \right| \right)} \qquad (13)$$

The above mentioned parameters are calculated for the ultrasound images by setting different values for noise variance. The Table.1 shows the variation of PSNR for different despeckling filters.

Table.1. Comparison of PSNR values

FILTER TYPE	var 0.01	var 0.02	var 0.04	var 0.06
SRAD	74.1165	72.0911	69.756	68.206
MODSRAD	74.9	73.25	69.98	68.5
SUSAN	75.4246	73.5	69.9895	68.8576
CT	77.1286	74.1232	71.0256	69.2259

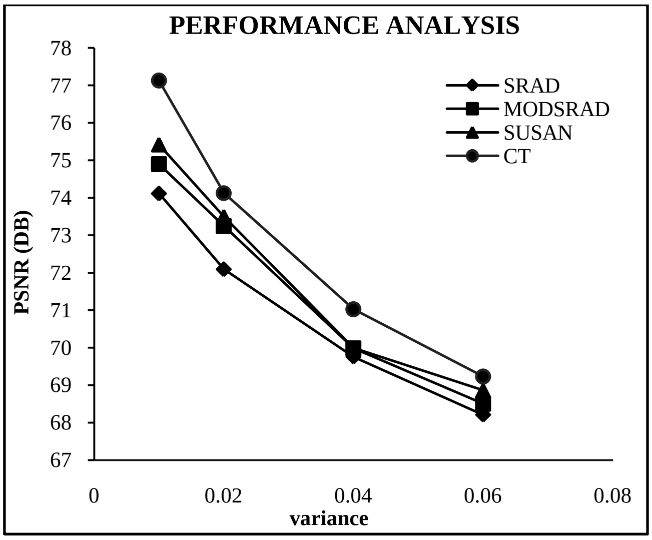


Fig.3. Plot of PSNR values for different filters

The value of PSNR is high for curvelet denoising compared to other filters. It is observed from the plots that the value of MSE, SC and NAE are less for curvelet denoising. By observing the charts, it is noted that the noise is reduced greatly using curvelet denoising.

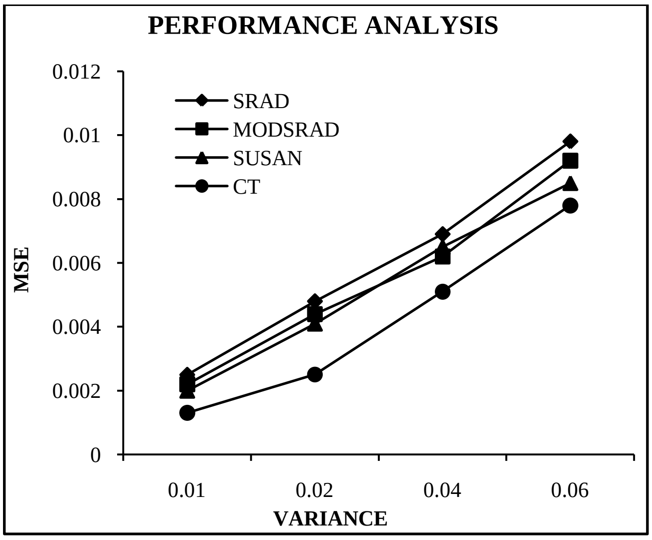


Fig.4. Plot of MSE values for different filters

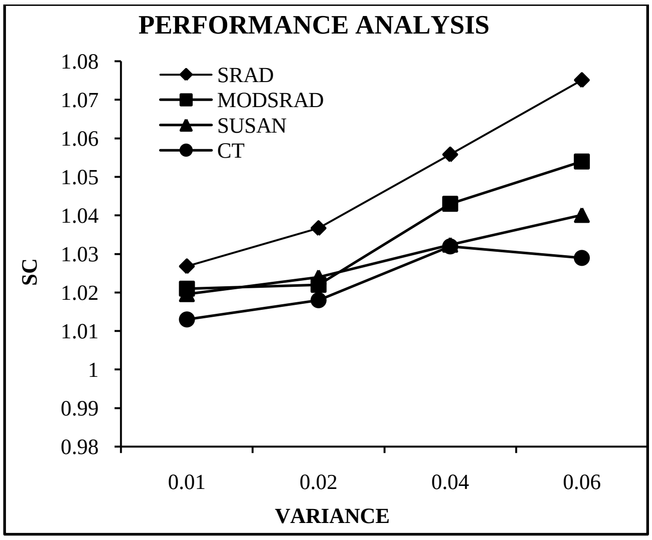


Fig.5. Plot of SC values for different filters

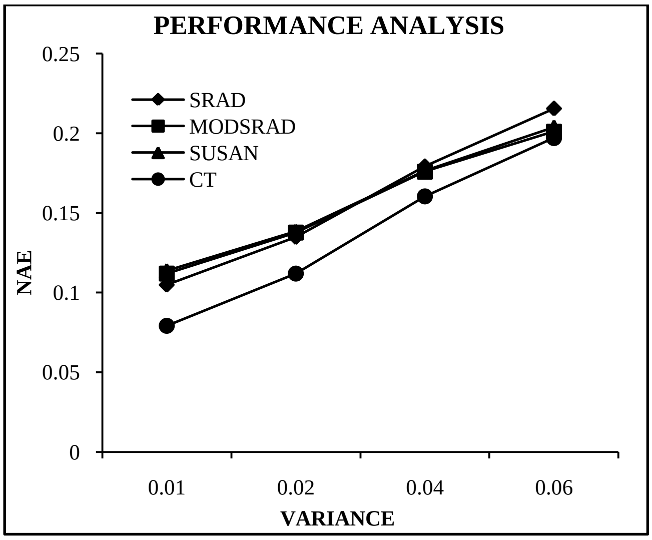


Fig.6. Plot of NAE values for different filters

5. CONCLUSION

The obtained results indicate that the curvelet transform performs efficient despeckling for the images involving curved structures. The visual quality of the image is also enhanced and the measured quality metrics show that the curvelet transform method has high PSNR and low SC, NAE and MSE values. Thus, for fetal abdominal ultrasound images which has curved edges, the curvelet denoising method is the suitable one for further processing.

The curved edges in the fetal abdominal ultrasound images are preserved after curvelet denoising which helps to estimate the fetal biometrics effectively. The accurate determination of the fetal biometric parameters helps in the monitoring of fetal growth and early diagnosis of fetal malformations.

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