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HYBRID MODELS FOR DENOISING ULTRASONIC IMAGES

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Abstract: The influence and impact of digital images on modern society is tremendous and is considered as a critical component in variety of application areas including pattern recognition, computer vision, industrial automation and healthcare industries. Medical imaging is concerned with the development of the imaging devices that help to identify different aspects of the tissue and organs based on various properties and reveal new properties of the tissue and internal structure. Examples of such devices / equipments include x-ray devices, CT / MRI scanners, electron microscope, etc. All these devices introduce, an unwanted signal, called noise. This paper considers a special kind of noise introduced by ultra sonographic devices is called 'speckle'. Speckle appears as interference of back-scattered wave from many microscopic diffused reflection. They spread through internal organs and make it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. In this paper, hybrid models are designed for speckle removal by combining anisotropic diffusion based on 4th order PDE with the three conventional linear filters, kaun, lee and frost. Experiments were conducted with various ultrasound images. From the results, it was found that all the three hybrid methods performed denoising operation in a superior fashion and produce images that are of good visual quality.

Keywords: Denoising, ultrasonic images, hybrid models, kaun, lee, frost

INTRODUCTION

Various medical imaging devices like x-ray, CT / MRI scanners and electron microscope produce high-resolution images, which play a vital role in disease diagnosis. Out of these devices, medical sonography (ultrasonography) is an ultrasound-based diagnostic medical imaging technique used to visualize muscles, tendons, and many internal organs, to capture their size, structure and any pathological lesions with real time tomographic images. Ultrasound has been used by sonographers to image the human body for at least 50 years and has become one of the most widely used diagnostic tools in modern medicine. The technology is relatively inexpensive and portable when compared with other techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Ultrasound is also used to visualize fetuses during routine and emergency prenatal care. Such diagnostic applications used during pregnancy are referred to as obstetric sonography. Medical sonography is used in the study of many different systems like cardiology, gastroenterology, gynecology, neurology, obstetrics, urology and cardiovascular systems (Tso and Mather, 2009). Images produced by these devices can be displayed, captured, and broadcast through a computer using a frame grabber to capture and digitize the analog video signal. The captured signal can then be post-processed on the computer itself. Ultrasonogrpahy is widely used by practitioners as they have no long-term side effects and has the added advantage that it is non-intrusive to the patients (Hangiandreou, 2003). The device provides live images, where the operator can select the most useful section for diagnosing thus facilitating quick diagnoses (Sudha *et al*., 2009). However, imperfect acquisition instruments, transmission errors often distort the visual signals obtained. These distortions in ultrasound images are referred as 'Speckle Noise' and are considered as undesirable feature that often lead to incorrect diagnosis.

Speckle is a complex phenomenon and it significantly degrades image quality. Speckle appears interference of back-scattered wave from many microscopic diffused reflection which passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. Thus, it is important that to remove or reduce this noise to the maximum extent before using them (Raman and Himanshu, 2010). The goal of any speckle removal algorithm should be to enhance the corrupted images by maintaining the quality of the image.

In this paper, the applicability of anisotropic diffusion filter, also called Perona–Malik diffusion, to speckle denoise ultrasound images is consider. Anisotropic diffusion filter is a frequently used filtering technique in digital images (Fu *et al*., 2006). Anisotropic diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image (Perona and Malik 1987; 1990; Sapiro, 2001). In spite of its popularity, it faces the following problems.

1. they cause blocky effects in images
2. they destroy structural and spatial neighbourhood information (Pitas and Venetsanopoulos, 1990) and
3. they are slow in reaching a convergence stage.

Attempts made to solve these disadvantages include the development of hybrid varieties (Ling and Bovik, 2002; Rajan and Kaimal, 2006a; 2006b). Eventhough, these hybrid models produce excellent results when compared with stand-alone anisotropic diffusion and other filtering techniques, they come with the defect of removing finer details of an image like edges, sharp corners, thin lines (Hamza *et al*., 1999).

Rajan *et al*. (2009) developed a hybrid method to remove noise from molecular images. The method combined anisotropic diffusion filter with 2D PDE (Partial Differential Equation) with a relaxed median filter (Wang and Zhang, 1999). This method was successful in removing molecular noise and had less blocking and artifacts in the denoised image. However, when applied to speckle noise removal, the noises were not fully removed and it had the serious flaw of slow convergence. The slow convergence is because of 2D PDE used and the failure in noise removal might be because of the relaxed median filter. The relaxed median filter, eventhough is very popular in reducing other types of noises, is not suitable for speckle noise.

Motivated by the work of Rajan *et* al. (2009), the present research work proposes to combine anisotropic diffusion filter with conventional speckle noise denoising filters, namely, Kaun, Lee and Frost. Normally, the anisotropic functions are based on 2^{nd} order PDE (Partial Differential Equation) functions. In the present research work, a fourth order PDE is used with the conventional basic anisotropic model. The combination of anisotropic diffusion function with 4^{th} order PDE and conventional despeckling filter is proposed to reduce the speckle noise from ultrasonic images, which while denoising, preserves the edges, avoids staircase artifacts and converges in a fast manner.

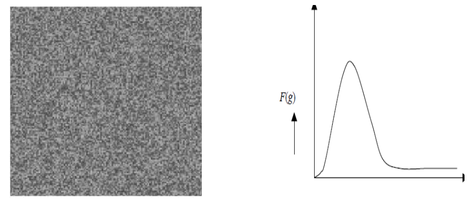
The paper is organized as below. Section 1 provided a brief overview to the topic under discussion. The second section gives an overview to Speckle noise. Section 3 explains the concepts of the techniques used in the proposed hybrid models. Section 4 presents the proposed methodology and the results of experiments conducted are presented in Section 5. Section 6 presents a short conclusion with future research directions.

SPECKLE NOISE

Speckle is a random, deterministic, interference pattern in an image formed with coherent radiation of a medium containing many sub-resolution scatterers. Speckle has a negative impact on ultrasound imaging. The presence of speckle noise in images shows a reduction of lesion detectability of approximately a factor of eight. This radical reduction in contrast resolution is responsible for the poorer effective resolution of ultrasound compared to x-ray and MRI. Presence of speckle noise prevents Automatic Target Recognition (ATR) and texture analysis algorithm to perform efficiently and gives the image a grainy appearance. Hence, despeckling is considered as a critical pre-processing step in medical imaging systems. Speckle noise follows a gamma distribution and is given as in Equation (1).

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{-\frac{g}{a}} \qquad (1)$$

where variance is a^{α} and g is the gray level. On an image, speckle noise (with variance 0.05) looks as shown in Figure 1a and the corresponding gamma distribution is given in Figure 1b.



(a) Speckle Noise **(b)Gamma Distribution**

Figure 1 : Noise and Distribution

Mathematically, a speckle noise can be represented by the Equation 2.

$$S' = FS \qquad (2)$$

where S' (=s_1', s_2', …) is the speckled image, F (=f_1, f_2, …) is the noise free image and S (=s_1, s_2, …) is the speckle noise introduced. The corrupted pixels are either set to the maximum value, which is something like a snow in image or have single bits flipped over. These noisy data can be reduced or removed using specially designed filters and are discussed in the next section.

ROPOSED HYBRID FILTERS

This paper proposes a new variant of base model, which replaces the median filter with a filter that is more suitable to remove speckle noise. The filters considered to replace median filters are (i) Kaun filter, (ii) Lee filter and (iii) Frost filter. All the three filters selected have been successfully exploited to remove speckle noise. The disadvantage of using it directly on ultrasonic images is that it produces artifacts as a side effect after removal. In order to improve anisotropic diffusion filter, traditional speckle noise removal filters and RHM model, anisotropic diffusion filter is modified to use a 4^{th} order PDE, followed by any one of the three speckle noise removal techniques. Thus, three new hybrid models are proposed, as listed below and Figure 2 shows the methodology adopted. The techniques and algorithms used are explained in this section.

1. 4^{th} Order PDE based Anisotropic Diffusion Filter + Kaun Filter (ADFK Model)
2. 4^{th} Order PDE based Anisotropic Diffusion Filter + Lee Filter (ADFL Model)
3. 4^{th} Order PDE based Anisotropic Diffusion Filter + Frost Filter (ADFF Model)

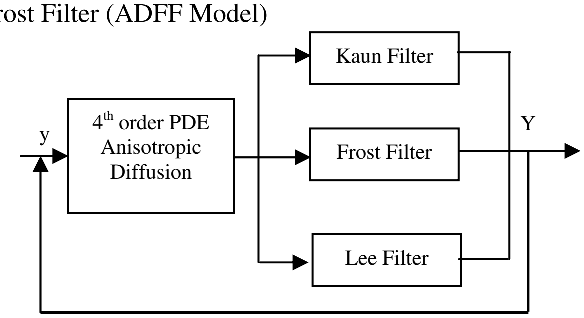


Figure 2: Proposed ASDF

A. Anisotropic diffusion

In anisotropic diffusion, the main motto is to encourage smoothening with in the region in preference to the smoothening across the edges. This is achieved by setting the conduction coefficient as 1 within the region and as 0 near edges, however, the main problem involved in this is the detection of the presence and absence of edges. This is done by analyzing the conduction coefficient as a function of magnitude of the gradient. A general expression (Acton *et al*., 2003) for anisotropic diffusion can be written by Equation (3).

$$\frac{\partial I}{\partial t} = \mathrm{div}(F) + \beta(I_0 - I) \qquad (3)$$

where, I is the input image, I_0 is the initial image and $I_0=I(x,0)$. F is the diffusion flux and β is a data attachment coefficient. If β = 0, particular cases of equation are:

1) The heat diffusion equation $F = \nabla I$ which is equivalent to Gaussian convolution.
2) The non linear probability density function (PDF) with $F= c(|\nabla I|) \times \nabla I$. where ∇ is the gradient operator, div is the divergence operator, || denotes the magnitude and diffusion coefficient c (x) is given by:

   $$c(x) = \frac{1}{1+\left(x/k^2\right)} \text{ and } c(x) = \exp\left[-\left(x/k^2\right)\right] \qquad (4)$$

   where, k is the edge magnitude parameter. In this anisotropic diffusion method, for finding edges as a step discontinuity, gradient magnitude is used.

If $|\nabla I|>>k$, then $c(|\nabla I|) \rightarrow 0$, an all pass filter is used; if $|\nabla I| << k$, then, $c(|\nabla I|) \rightarrow 1$, isotropic diffusion is achieved. Discrete form of (4) is given by

$$I_d^{t+\nabla t} = I_d^t + \frac{\nabla t}{|\eta_s|}\sum_{q\in\eta} c\left(\nabla_{d,q}^t\right)\nabla I_{d,q}^t \qquad (5)$$

where, I_d^t is discretely sampled image, s denotes the pixel position in a discrete (2-D) grid, and ∇t is the time step, $\overline{\eta_s}$ represents the spatial resolution of pixel d, $|\overline{\eta_s}|$ is the number of pixels in the window, and $\nabla I_{d,q}^t = I_q^t - I_d^t$, for every $q \in \overline{\eta_s}$. The above equations show that the anisotropic diffusion allows the smoothening of homogenous regions and prohibits smoothening the near edges, thus, preserving the edges.

B. Speckle Reducing Anisotropic Diffusion (SRAD)

Anisotropic Diffusion is a nonlinear smoothing filter (Grieg *et al*., 1992). It uses a variable conductance term, to control the contrast of the edges that influence the diffusion. This filter has the ability to preserve edges, while smoothing the rest of the image to reduce noise (Sun and Song, 2007). The anisotropic diffusion has been used in several researchers in image restoration (Min and Xiangchu, 2007) and image recovery (Torkamani-Azar and Tait, 1996). SRAD (Yu and Acton, 2002) is an edge-sensitive Partial Differential Equation (PDE) anisotropic diffusion approach to reduce speckle noise in images. The anisotropic filtering in SRAD simplifies image features to improve image segmentation by smoothening the image in homogeneous area while preserving and enhances the edges. It reduces blocking artifacts by deleting small edges amplified by homomorphic filtering. SRAD equation is given by the Equation (6).

$$\mathrm{SRAD}(U') = ut+1 = ut + \frac{\Delta t}{4}\,\mathrm{div}(g(\mathrm{ICOV}(u')) \times \nabla u') \qquad (6)$$

where t is the diffusion time index, Δt is the time step responsible for the convergence rate of the diffusion process (normally in the range 0.05 to 0.25), g(**.**) is the diffusion function and is given by Equations (7) and (8).

$$G(\mathrm{ICOV}(u'))=e-(P) \qquad (7)$$

$$P = \frac{\left(\frac{\mathrm{ICOV}(u')}{q^t}\right)^2 - 1}{1+(q^t)^2} \qquad (8)$$

where q' is the measure of speckle coefficient of variation in a homogenous region of the image. The performance of SRAD is superior to the traditional anisotropic diffusion filters. However, SRAD has the disadvantage that the diffusion time increases with the image features and it is already known that when diffusion time increases the image quality of the denoised image decreases.

C. Fourth Order PDEs and Anisotropic Diffusion

Recently, non-linear fourth order PDES are used effectively in the field of noise reduction (Greer and Bertozzi, 2004; Lysaker *et al*., 2003; Wei, 1999). The reason behind this is they are faster in denoising and create a richer set of functional behaviour that can be exploited during image enhancement. The L2-curvature gradient flow method of You and Kaveh (2000) is used and is given in Equation (9).

$$\frac{\partial u}{\partial t} = -\nabla^2[c(|\nabla_u^2|)\nabla_u^2] \qquad (9)$$

where $\nabla^2 u$ is the Laplacian of the image u. Since the Laplacian of an image at a pixel is zero if the image is planar in its neighborhood, the PDE attempt to remove noise and preserve edges by approximating an observed image with a piecewise planar image. The desirable diffusion coefficient c(**.**) should be such that Equation (9) diffuses more in smooth areas and less around less intensity transitions, so that small variations in image intensity such as noise and unwanted texture are smoothed and edges are preserved. Another objective for the selection of c(**.**) is to incur backward diffusion around intensity transitions so that edges are sharpened and to assure forward diffusion in smooth areas for noise removal.

Several diffusivity functions can be used (Mrazek *et al*., 2003). Some of them are Linear diffusivity, Charbonnier diffusivity, Weickert diffusivity, TV diffusivity, BFB diffusivity and Perona-Malik diffusivity. The present study uses Perona-Malik diffusivity as given in Equation (10).

$$c(s) = \frac{1}{1+\left(\frac{s}{k}\right)^2} = \exp\left[-\left(\frac{s}{k}\right)^2\right]_{s=0} \qquad (10)$$

The Equation (9) was associated with the following energy functional

$$E(u) = \int_\Omega f(|\nabla^2 u|)\,dx\,dy \qquad (10)$$

where Ω is the image support and ∇^2 denotes Laplacian operator. Since $f(|\nabla^2 u|)$ is an increasing function of $|\nabla^2 u|$, its global minimum is at $|\nabla^2{}_u|=0$. Consequently, the global minimum of E(u) occurs when

$$|\nabla^2 u| \equiv 0 \text{ for all } (x,y) \in \Omega \qquad (11)$$

A planar image obviously satisfies (Rajan and Kaimal, 2006a), hence is a global minimum of *E(u).* Planar images are the only global minimum of E(u) if f "(s) ≥ 0 for all s ≥ 0 because the cost functional E(u) is convex under this condition (Rajan and Kaimal, 2006b). Therefore, the evolution of Equation (9) is a process in which the image is smoothed more and more until it becomes a planar image. But in the case of second order anisotropic diffusion, *f*"(s) may not be greater than zero for all *s,* which results in a stepping blocking artifact effect in the resultant image.

D. Speckle Filters

Several researchers have contributed techniques to resolve the despeckling problem. The main challenge is that the process of denoising is irreversible and therefore must be very careful while removing noise regions. Accidental removal of important regions should be avoidedAmong the standard filters, Lee Filter, Frost Filter (Frost *et al*., 1982), Median Filter and Kaun Filter (Kaun *et al*., 1985) have been successfully applied to the problem of speckle reduction and are discussed in this section.

Each filter discussed in this section, has a unique reduction approach which is applied to a kernel (square-moving window) and filtering is based on the statistical relationship that exists between the central pixel and its surrounding pixels (Figure 3). The typical size of the kernel has to be odd ranging from 3 x 3 to 33 x 33. The kernel size has to be chosen carefully, as a large size will be computationally expensive and important information might be lost due to over smoothing. Similarly, speckle reduction cannot be applied to a very small kernel. Most of the works use a 3 x 3 or 7 x 7 kernel size.

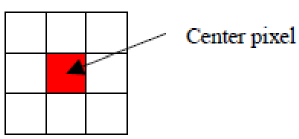


Figure 3 : 3 x 3 Kernal

Filtering is based on either local statistical data or on the estimation of local noise variance of the kernel. The variance thus obtained is then used to determine the amount of smoothening needed for each speckle image. The noise variance determined from the local filter window is more applicable if the intensity of an area is constant or flat while ENL is suitable if there are difficulties determining if an area of the image is flat.

- **Lee Filter**

The Lee filter uses the least-squares approach to estimate the true signal strength of the center cell in the filter window from the measured value in that cell, the local mean brightness of all cells in the window, and a gain factor is calculated from the local variance and the noise standard deviation. The filter assumes a Gaussian (normal) distribution for the noise values, and calculates the local noise standard deviation for each filter window. The Lee filter calculation produces an output value close to the local mean for uniform areas and a value close to the original input value in higher contrast regions. Lee filters are more affective in uniform areas and can maintain edges and other fine detail. The Lee filter has no user-defined parameters. The mathematical background of the lee filter is given below.

The Lee filter is based on the approach where smoothing is performed when the variance over an area is low or constant, otherwise, that is, if the variance is high (e.g. near edges), smoothing will not be performed. The Lee filter assumes that the speckle noise is multiplicative and can be approximated by a linear model given in Equation (12).

$$Img(i,j) = Im + W * (Cp - Im) \qquad (12)$$

where Img(i,j) is the color value of the pixel at indices i and j after filtering. If there is no smoothing, the filter will output only the mean intensity value of the filter window Im. Otherwise, the difference between Cp (center pixel) and Im is calculated and multiplied with a weighting function W given in Equation (13) and then summed with Im.

$$W = \sigma^2/(\sigma^2 + \rho^2) \qquad (13)$$

where σ^2 is the variance of the pixels values within the filter window given in Equation (3.15), N is the size of the filter window and Xj is the pixel value within the filter window at indices j.

$$\sigma^2 = \left[\frac{1}{N} \sum_{j=0}^{N-1} (X_j)^2 \right] \qquad (14)$$

The parameter ρ is the additive noise variance of the image given in Equation (15), M is the size of the image and Yj is the value of each pixel in the image.

$$\rho^2 = \left[\frac{1}{M} \sum_{i=0}^{N-1} (Y_i)^2 \right] \qquad (15)$$

The main disadvantage of Lee filter is that it tends to ignore speckle noise in the areas closest to edges and lines.

- **Frost Filter**

The Frost filter is an adaptive radar filter that incorporates the local image statistics in the filtering process, assuming a negative exponential distribution for the speckle noise. The filter performs a weighted average of the cell values in the filter window, with the weights for each cell being determined from the local statistics to minimize the mean square error of the signal estimate. The filter weight for a cell is a negative exponential function of the noise standard deviation (calculated locally for each filter window) and also decreases with distance from the center cell. The center cells are weighted more heavily as the variance in the filter window increases. The filter therefore smoothes more in homogeneous areas, but provides a signal estimate closer to the observed value of the center cell in heterogeneous areas. The Frost filter has no user-defined parameters. The mathematics behind Frost filter is given below.

A Frost filter adapts to the noise variance within the filter window by applying exponentially weighting factors M as given in Equation (16). These weighting factors decrease as the variance within the filter windows reduces.

$$M_n = \exp(-(DAMP*(S/IM)\text{^}2) * T) \qquad (16)$$

In the Equation, DAMP is a factor that determines the extent of the exponential damping for the image. The larger the damping value, the heavier is the damping effect. Typically the value is set to 1. S is the standard deviation of the filter window, Im is the mean value within the window and T is the absolute value of the pixel distance between the center pixel to its surrounding pixels in the filter window. The value of the filtered pixel is replaced with a value calculated from weighted sum of each pixel value Pn and the weights of each pixel Mn in the filter window over the total weighted value of the image as given in Equation (17).

$$Img(i,j) = \Sigma Pn*Mn / \Sigma Mn \quad (17)$$

The parameters in the Frost filter are adjusted according to the local variance in each area. Low variances causes extensive smoothing and high variance, smoothing is normal and edges are also retained.

- **Median Filter**

This filter first sorts the surrounding pixels values in the window to an orderly set and replaces the center pixel within the define window with the middle value in the set. Median filtering is a non-linear filtering technique that works best with impulse noise (salt and pepper noise) whilst retaining sharp edges in the image. The main disadvantage of the median filter is the additional computation time needed to sort the intensity value of each set.

- **Kaun Filter**

The Kaun Adaptive Noise Smoothing filter uses a minimum mean square error calculation to estimate the value of the true signal for the center cell in the filter window from the local statistics. It is similar in approach to the Lee filter, but makes simplifying assumptions in the calculations. The Adaptive Noise Filter calculates the signal estimate from the local mean and variance, and the noise standard deviation (assumed to be constant for the entire image); it assumes a Gaussian (normal) distribution for the speckle noise. Kaun filter has no user defined parameters. The equations used during denoising while using Kaun filter is described below.

The Kaun filter is considered to be more superior than the Lee filter. It does not make an approximation on the noise variance within the filter window. The Kaun filter simply models the multiplicative model of speckle into an additive linear form as in Equation (18), but it relies on the ENL from a medical image to determine a different weighting function W given in Equation (3.19) to perform the filtering.

$$W = (1 \text{ x } Cu/Ci)/(1 + Cu) \quad (18)$$

The weighting function is computed from the estimated noise variation coefficient of the image, Cu given in Equation (19)

$$C_u = \sqrt{\frac{1}{ENL}} \quad (19)$$

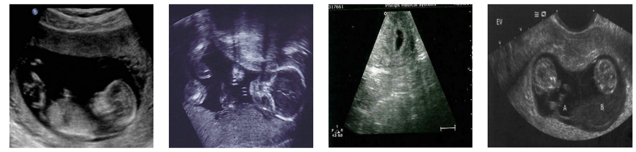
and Ci is the variation coefficient of the image given in Equation (20).

$$Ci = S/Im \quad (20)$$

where S is the standard deviation in filter window and Im is mean intensity value within the window. The only limitation with Kuan filter is that the ENL parameter is needed for computation

EXPERIMENTAL RESULTS

To evaluate the proposed models, eight performance metrics were used. They are, Noise Mean Value, Noise Standard Deviation, Mean Square Difference, Equivalent Number of Looks, Deflection Ratio and Figure of Merit, Peak Signal to Noise Ratio (PSNR) and Denoising time. The explanation of the first six parameters are given in Mastriani and Giraldez (2006). Four ultasound images were selected for testing the proposed models. All the proposed models were executed on a Pentium IV machine with 512 MB RAM and were developed in MATLAB 7.3. The test original images used are given in Figure 4 and 20% speckle noise was introduced in all these images. The performance of the proposed hybrid models, namely, ADFK, ADFL and ADFF models were judged by comparing the result with the conventional models. The models chosen for comparison are median filter, Kaun Filter, Lee Filter, Frost Filter, SRAD filter and SRAD + Median Filter (Base Model).



US 1 **US 2** **US 3** **US 4**

Figure 4 : Original Images

A. Noise Mean Value

The Noise Mean Value was calculated for all the test images, before and after filtering, for all filters and the results obtained are shown in Table 1.

Table 1 : Noise Mean Value

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	90.0890	91.8464	90.1470	91.2387
Median	88.4311	88.7546	88.4643	87.9920
Kaun	87.8221	88.1112	88.3481	88.5734
Lee	87.8474	88.3232	88.7772	88.9121
Frost	87.6463	89.3245	87.7465	87.5245
SRAD	89.8475	90.3232	88.9932	88.7395
Base	88.4311	87.1112	88.1320	88.9023
ADFK	84.4567	85.3488	84.9001	85.0999
ADFL	84.9782	85.4921	84.9102	84.7377
ADFF	84.3245	85.0032	84.0902	84.1293

From the Noise Mean Values projected in Table 1, it is clear that all the three proposed hybrid models produce better results than the conventional models. To evaluate the overall model performance, the average value of the four models were calculated. From the Table, it can be seen that among the ten models, ADFF produce better results in all the four images. This was followed by ADFL and ADFK.

B. Noise Standard Deviation (NSD)

The noise standard deviation obtained for the four test noisy images are projected in Table 2.

Table 2 : Noise Standard Deviation (NSD)

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	43.9961	43.8271	43.9230	43.8977
Median	42.5373	41.9920	42.5331	42.6792
Kaun	40.8363	40.3774	40.0094	40.0094
Lee	40.7465	40.6453	40.4231	40.2291
Frost	40.8645	40.0094	40.9921	40.5671
SRAD	32.6884	32.9122	32.5992	32.7912
Base	32.8978	32.8688	32.9812	32.9991
ADFK	31.9212	31.6673	31.9806	31.7892
ADFL	31.8664	31.3338	31.7884	31.6732
ADFF	31.7102	31.7449	31.8929	31.6412

From the results, it could be seen that the ADFF filter again outperforms all the other proposed models and the conventional models. This result is at par with the results of Table 2, which shows that the NSD results are consistent.

C. Mean Square Difference (MSD)

The Mean Square Difference (MSD) obtained for all the three proposed models and the selected six conventional filter models are shown in Table 3.

Table 3 : Mean Square Difference (MSD)

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	798.4422	732.8777	724.0867	749.8947
Median	797.8754	733.1891	726.9232	749.8964
Kaun	797.9193	782.3323	727.3122	720.7694
Lee	698. 8832	683. 1033	675.1129	621.9328
Frost	661. 2210	683. 0054	628.0098	620.7473
SRAD	762.9872	783.1987	775.8934	722.0909
Base	563.0003	554.6344	576.3985	588.1299
ADFK	560.3834	553.6632	577.1002	567.3876
ADFL	533.2256	533.1921	566.9854	560.7479
ADFF	522.8319	521.8882	549.3651	538.2821

The results again projected that the ADFF model is the best in removing the speckle noise from the input image.

D. Equivalent Numbers of Looks (ENL)

The effective equivalent number of looks is a statistics of the speckle in an image. The ENL for the various test images is presented in Table 4.

Table 4 : Equivalent Numbers of Looks (ENL)

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	11.093	11.983	11.121	11.392
Median	13.980	13.746	14.938	15.035
Kaun	15.752	16.962	17.838	17.424
Lee	17.652	16.868	16.847	16.573
Frost	15.643	16.345	16.533	15.939
SRAD	20.010	19.228	26.789	20.309
Base	21.960	23.274	22.864	21.953
ADFK	37.212	37.893	37.123	38.049
ADFL	37.009	36.098	36.846	37.909
ADFF	38.302	39.088	38.984	39.088

As seen from the table, ADFF hybrid model performed better at denoising while comparing the other models. This was followed by ADFK and ADFL. Among the conventional filters, Base model, SRAD and Lee filter produced better results.

E. Deflection Ratio (DR)

The deflection ratios obtained are tabulated in Table 5. Again the results projected indicate that the ADFF model is the best among proposed and conventional filters.

Table 5 : Deflection Ratio (DR)

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	2.56E-15	2.57E-15	2.40E-16	2.49E-15
Median	2.57E-16	1.05E-16	1.58E-16	1.03E-16
Kaun	3.27E-16	3.92E-16	4.00E-16	4.39E-16
Lee	3.84E-16	4.42E-16	4.12E-16	4.19E-16
Frost	3.86E-16	4.85E-16	3.27E-16	3.61E-16
SRAD	4.40E-15	4.14E-15	4.12E-15	4.36E-15
Base	5.99E-15	5.30E-15	5.76E-15	5.98E-15
ADFK	7.86E-15	7.74E-15	7.27E-15	7.80E-15
ADFL	6.74E-15	6.27E-15	6.23E-15	6.90E-15
ADFF	8.59E-15	8.99E-15	9.14E-15	9.33E-15

The results obtained portray the fact that, in terms of Deflection ratio (DR), the denoised image of ADFF model has the minimum deflection from the noisy image. As with other performance metrics, the next highest performance was produced by ADFL and ADFK.

F. Pratt's Figure Of Merit (FOM)

The Pratt's Figure Of Merit (FOM) obtained are shown in Table 6.

Table 6 : Figure Of Merit (FOM)

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	0.3027	0.3072	0.3026	0.3002
Median	0.4004	0.4212	0.4120	0.4099
Kaun	0.4217	0.4223	0.4214	0.4229
Lee	0.4228	0.4112	0.4223	0.4632
Frost	0.4213	0.4213	0.4312	0.4344
SRAD	0.7257	0.6841	0.6958	0.7193
Base	0.7399	0.7001	0.7199	0.7200
ADFK	0.7690	0.7653	0.7652	0.7610
ADFL	0.7490	0.7209	0.7363	0.7437
ADFF	0.7990	0.7892	0.7877	0.7813

By the nearing value to unity achieved for the proposed model, it is clear that the proposed model is successful in removing maximum speckle noise from the noisy image. The results projected in Table shows that the ADFF, ADFK and ADFL having an average FOM value of 0.7893, 0.7374 and 0.7651 respectively, produces better FOM than all the other models.

G. Peak Signal to Noise Ratio (PSNR)

PSNR is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of denoising algorithm. The PSNR values obtained during experimentation is projected in Table 7.

Table 7 : PSNR (dB)

Filter Model	US 1	US 2	US 3	US 4
Original-Noisy Image	33	32	36	34
Median	31	32	33	32
Kaun	30	31	30	31
Lee	30	30	38	29
Frost	40	29	34	26
SRAD	39	29	34	30

Base	39	36	39	37
ADFK	44	42	41	42
ADFL	43	41	40	40
ADFF	45	45	45	46

The high PSNR obtained gives the understanding that the visual quality of the denoised image is good. According to Venkatesan *et al*. (2008), an improved denoising algorithm is recognized by a high PSNR or a lower MSE. In agreement with this, the results of the proposed systems with high PSNR prove that they are an improved version over existing methods. Similarly, according to the report of Schneier and Abdel-Mottaleb (1996), a PSNR value in the range 30-40 indicates that the resultant image is a very good match to the original image. In accordance with this report, the results of all the three the proposed hybrid algorithms produce PSNR values in the range 40-46dB proving that it is an enhanced version when compared with the conventional algorithms.

H. Despeckling Time

Table 8 shows the time taken by the proposed and conventional filters to perform the denoising operation.

Table 8 : Despeckling time (seconds)

Filter Model	US 1	US 2	US 3	US 4
Median	0.18	0.15	0.178	0.16
Kaun	0.19	0.17	0.08	0.18
Lee	0.20	0.21	0.20	0.21
Frost	0.17	0.17	0.16	0.17
SRAD	0.18	0.18	0.17	0.18
Base	0.19	0.19	0.19	0.19
ADFK	0.14	0.15	0.13	0.14
ADFL	0.16	0.15	0.16	0.15
ADFF	0.12	0.11	0.11	0.11

While considering the execution time, the ADFF model was the quickest in despeckling the noisy image, which was followed by ADFK and ADFL. This clearly shows that the introduction of 4th order PDE based anisotropic diffusion function combined with knau, lee and frost filters converges quickly, which consequently speeds up the despeckling process.

According to Müldner *et al*. (2005), PSNR and speed are the two most important performance factors of any denoising algorithm. From the results, it is evident that the speed of the proposed denoising algorithms are faster when compared to the standard algorithms and therefore makes it an attractive option for several advanced applications in the field of medical imaging.

The visual comparison of the denoised image produced by the various conventional and proposed filters is shown in Figure 5 for image UC 1. Similar quality was observed with all other test images also.

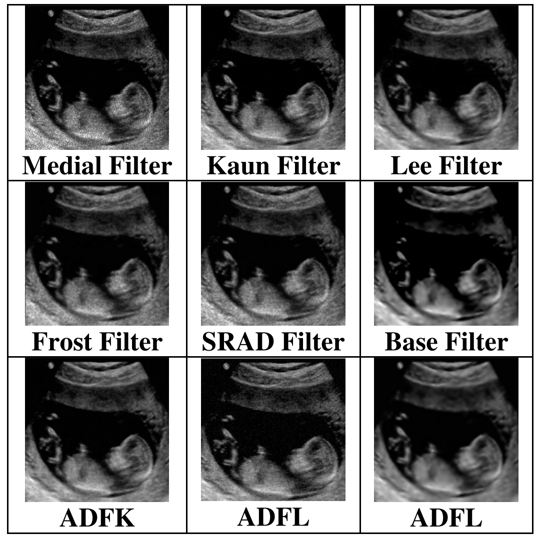


Figure 5 : Visual comparison of UC 1

CONCLUSION

Thus, the various results of the experiments conducted clearly indicate that the images produced by the proposed despeckling algorithm are of good visual quality and therefore can be applied to most of the image medical processing systems. The three hybrid models can be combined with wavelet shrinkage function to improve the convergence time. The three shrinkage functions, VisuShrink, BayesShrink and PureShrink can be applied and the performance can be compared. The present work focused on producing despeckling algorithms which reduces the noise from the noisy image. The work has not considered the memory efficiency and computation complexity, which can be analyzed in future.

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