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Information Preserving and Edge Smoothening of Fetal Heart Chamber Using SRDCF with Total Variation

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ABSTRACT

Speckle is an inherent coarse noise that degrades medical ultrasound images. A point is created by the interference of the return wave in the sensor hole. In each resolution cell, several primary scatterers replicate the wave impinging on the sensor. In addition, the obtained images are corrupted by random grain patterns, making image interpretation difficult. Stains may contain useful diagnostic information. The smoothness of spotting depends on the application and knowledge of the doctor. In this work, preprocessing of fetal heart ultrasound images using a Spatially Regularized Discriminative Correlation Filter (SRDCF) with total variation is introduced to preserve fetal heart information and smooth edges. Then qualitatively and quantitatively compare the performance of the proposed filter with conventional methods.

Keywords: *Spatially Regularized Discriminative Correlation Filter, Discriminative Correlation Filter, Total Variation Denoising, Speckle Noise*

INTRODUCTION

Using ultrasound equipment, ultrasound technology allows doctors and other medical professionals to view internal structures such as muscles, joints, blood vessels, and internal organs. Ultrasound creates an acoustic impedance from a two-dimensional cross-section of tissue. Sound waves are composed of pressure waves. 20,000 Hz ultrasound, which is above the range of human hearing, uses its own echo to form an image and is known as an ultrasound device. When using an ultrasound device, different types of images are formed. B-mode imaging techniques are well known for generating acoustic impedance of two-dimensional tissue cross-sections.

Obstetricians and gynecologists have been using two-dimensional ultrasound to monitor fetal development for decades. 2D ultrasound makes this easy, 3D ultrasound creates slightly ghostly images of the fetus, creating echoes like stone carvings, and 4D ultrasound captures movement in the image recording. Ultrasound imaging techniques require experienced and skilled doctors and high-quality equipment.

One of the main drawbacks of ultrasound is the low quality of the image, which destroys the image by creating speckle noise when taking the image.

The smear results from the coherent processing of backscattered signals from multiple targets. Constructive and destructive interference patterns are observed as bright and dark points in the image and are considered spots. In addition, the obtained images are corrupted by random grainy patterns of speckles, making image interpretation difficult. Fully automated segmentation of ultrasound images is required to smooth out speckles while preserving boundaries between different image regions. Healthcare professionals prefer the original, noisy image to a smooth image, as filters can remove the most relevant information. However, developing noise reduction filters that ensure optimal performance without affecting useful information has become a necessary and difficult task.

Related Works

Ultrasound imaging techniques are mainly used for medical diagnosis, but they are spoiled by speckle noise. Speckle noise in ultrasound images should be reduced for better detection. Speckle noise minimization filters are designed to preserve ultrasound image features for medical diagnosis retrieval. Speckle noise filters such as Boolean logic filter, statistical filter, domain filter transforms, and filter based on partial differential equations are analyzed [1]. An effective and efficient denoising technique has been developed for ultrasound images. Different speckle reduction filters are applied to ultrasound images of uterine fibroids. Various hybrid approaches have been implemented to denoise ultrasound images [2].

A hybrid filter was developed to reduce speckles in ultrasound images. Various combinational filters such as Modified Median (Max) and Modified Median (Max), Modified Median (N4 Max), and Modified Speckle Noise cover the very fine details required for the diagnostic median (ND). max) is used to reduce speckle noise [3]. To avoid this problem, a Wiener filter is included in the geometric filter during the iterative process, as the geometric filter preserves the noise. The geometric Wiener filter is improved by using a fuzzy filter called an integrated fuzzy filter [4]. An ultrasound image contains speckle noise with a Rayleigh distribution at four different noise level variations. Various deep-learning networks are used to reduce speckle noise in ultrasound images. The performance of deep learning networks is compared with block-matching and 3D filtering [5]. Two techniques to reduce speckle noise create contrast between the object of interest and the rest of the image. The first fold includes block-based hard thresholding (BHT) and soft thresholding (BST) in the wavelet domain. Since the first fold creates a blur effect, the second fold restores the boundaries and texture of the object [6].

A new algorithm based on speckle-reducing anisotropic diffusion (SRAD) filtering, symmetry-based discrete wavelet transform (DWT), gradient-driven image filtering (GDGIF), and weighted-driven image filtering (WGIF) is used to improve noise elimination. This algorithm produces effective speckle noise elimination and edge preservation [7]. Removing additive noise is as simple as compared to multiplicative noise. Bacterial foraging optimization (BFO) cascaded with a wavelet transform and a Wiener filter in a homomorphic framework was implemented to remove speckle noise. Noise identification and removal is achieved by wavelet packet decomposition and a Wiener filter used in preprocessing. The BFO algorithm reduces the errors between the speckled image and the output image without speckles from the homomorphic image [8]. The output of the filter is estimated as the weighted average of pixels connected by paths.[9] A suitable anti-speckling filter will preserve the edges and preserve the features of the images. Capable of Edge preservation is measured using the beta metric and structure reservation is quantified using the Image Quality Index[10]. Ultrasound Fetal heart chamber images were pre-processed with the total variation method. Furthermore, the Term Frequency – Inverse Document Frequency (TF-IDF) technique is used for feature extraction[11].

Edge limiting and preservation filters respond to noise components, and insufficient noise reduction in smooth areas and background areas. Existing filters smooth the edges and fail to highlight the edges. Effective stain removal requires an accurate statistical model of the ultrasound signals. The selection of the despeckling filter and the speckle model plays a critical role in the design of the denoising process and varies from application to application. In this proposed method, spatially regularized discriminant correlation with a total deviation filter removes speckles and preserves the information content of regions of interest.

Speckle Noise

There are two different noise models, additive and multiplicative. In general, ultrasound medical images are affected by a multiplicative noise called speckle noise. Speckle is grainy noise that exists naturally and degrades the quality of ultrasound images. The speckle noise model is shown as

$$g(x, y) = f(x, y) * u(x, y) + \eta(x, y) \quad (1)$$

Where g(x, y) is the observed image, f(x, y) is the noise-free image, u(x, y) is the multiplicative component, and is the additive speckle noise component. The x and y coordinates indicate the axial and lateral indices of the image samples in the spatial domain. Speckle noise with different variance values is added to fetal heart ultrasound images to test the performance of the image-denoising algorithm.

To verify the functionality of the proposed scheme, a speckle noise with a variance of 0.02 to 0.08 is added. A noise deviation greater than 0.1 results in a degraded image that is completely corrupted by noise. The block diagram of the proposed SRDCF with the total variation filtering technique is shown in Figure 1.

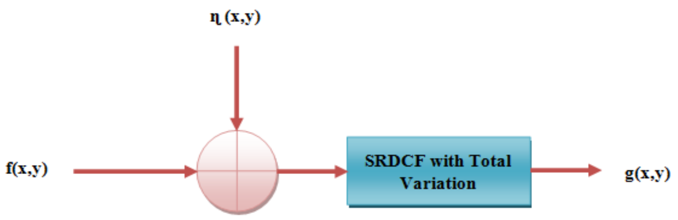


FIG 1: Block diagram of SRDCF with Total Variation denoising method

Discriminative Correlation Filter(DCF)

The discriminant correlation filter (DCF) is a supervised linear regressor learning system. DCF uses circular correlation attributes for efficient training and detection. DCF has two main advantages. DCF takes advantage of the limited training data by implicitly including all the shifted powers of the given samples. Also, the computational effort of training and detection is reduced in the Fourier domain using FFT. Due to circular correlation, the standard DCF relies on the periodic assumption of sample training and detection. Correlation filters capture the advantage of specific features in the Fourier domain, allowing for their efficient estimation.

Spatially Regularized Discriminative Correlation Filter(SRDCF)

The spatial regularization component is formulated to treat correlation filter coefficients depending on their spatial location. The SRDCF formulation allows correlation filters to learn a much larger set of negative training samples without damaging the positive samples. SRDCF uses a spatial weight function to penalize the magnitude of the correlation filter coefficients and uses the Gauss-Seidel method to solve transition and boundary problems. In addition, the SRDCF formulated in the spatial domain is first transformed into the Fourier domain to obtain the complex equation, and then the complex equation is transformed into a real value to using the Gauss-Seidel method. The proposed SRDCF method uses the circulating structure of the train samples in the spatial domain and the regularization matrix in the Fourier domain. SRDCF is modeled using convolution instead of correlation.

The convolutional filter f is learned from a set of training samples$\{(x_k, y_k)\}_{k=1}^{t}$. The samples $x_k \in R^{dXMXN}$consist of a d-channel feature map with MXN spatial size obtained by patching the training image. Let x_k^l represents the lth feature layer of x_k.y_k is the optimal convolution output corresponding to training sample x_k.

The Spatially Regularized Discriminative Correlation Filter (SRDCF) is obtained from the convex problem

$$\min_{f} \sum_{k=1}^{l} \alpha_k \|S_f(x_k) - y_k\|^2 + \sum_{l=1}^{d} \|\omega \odot f^l\|^2 \quad (2)$$

The required filter f consists of one M × N convolution filter flipper feature layer. Where $\alpha_k$is the weight of all training sample x_k, ω denotes spatial regularization, which is a function with a Gaussian shape and having smaller values in the centre area and higher values in the marginal area,$S_f(x_k)$ is the convolution function, and ⊙ denotes the element-wise multiplication.

$$S_f(x_k) = \sum_{l=1}^{d} x_k^l * f^l \quad (3)$$

Where, * denotes circular convolution. Equation (2) is transformed into a Fourier domain by using Parseval's theorem and convolution property.

$$\min_{\hat{f}} \sum_{k=1}^{t} \alpha_k \left\|\sum_{l=1}^{d} \hat{x}_k^l \odot \hat{f}^l - \hat{y}_k\right\|^2 + \sum_{l=1}^{d} \left\|\frac{\hat{w}}{MN} * \hat{f}^l\right\|^2 \quad (4)$$

Where, the hat indicates the Discrete Fourier Transform (DFT) of a variable. Variables in Equation (4) are vectorized and convolution is changed into matrix multiplication.

$$\min_{\hat{f}} \sum_{k=1}^{t} \alpha_k \left\|\sum_{l=1}^{d} D(\hat{x}_k^l)\hat{f}^l - \hat{y}_k\right\|^2 + \sum_{l=1}^{d} \left\|\frac{C(\hat{w})}{MN} \hat{f}^l\right\|^2 \quad (5)$$

The resultant is a complex convex problem, since the DFT of a real value function is Hermitian symmetric. Hence, the convex problem is altered into a real-valued function by a unitary matrix $B \in R^{MNXMN}$

$$\min_{\tilde{f}} \sum_{k=1}^{t} \alpha_k \left\|\sum_{l=1}^{d} D_k^l \tilde{f}^l - \tilde{y}_k^l\right\|^2 + \sum_{l=1}^{d} \left\|C\tilde{f}^l\right\|^2 \quad (6)$$

Each and every layer of convolution filters and training data are concatenated. The method of SRDCF is similar to standard DCF-based trackers,

$$S_f(z) = \mathcal{F}^{-1}\left\{\sum_{l=1}^{d} \hat{z}^l \odot \hat{f}^l\right\} \quad (7)$$

Where, F-1 denotes the inverse DFT.

Total Variation Denoising

The total denoising of variations is referred to as total variation regularization. This process is often used in digital image processing to remove noise. It works on the principle that signals with excessive and possibly spurious detail have a high total variance, while the integral of the signal's absolute gradient is high. Thus, by reducing the total variance of the signal, it approximates the original signal and removes unwanted details while preserving important details such as edges. Thus, total deviation denoising is extremely effective at preserving edges while smoothing out noise in flat areas, even at low signal-to-noise ratios.

For a one-dimensional digital signal yn total variation is defined as

$$V(y) = \sum_n |y_{n+1} - y_n| \quad (8)$$

Let the input signal is xn, the total variation aims to find an approximation yn, that has lesser total variation than xn. and is close to xn. One measure of closeness is the sum of square errors.

$$E(x, y) = \frac{1}{2}\sum_n (x_n - y_n)^2 \quad (9)$$

Hence the total variation denoising problem amounts to minimizing the following discrete functional over the signal yn,

$$E(X, Y) + \lambda V(Y) \quad (10)$$

Convex optimization is used to minimize, as this is a convex function, and find the solution yn. The regularization parameter λ is important in the denoising process.

Total variation norm defined as for two-dimension signals y,

$$V(y) = \sum_{i,j} \sqrt{\left|y_{i+1,j} - y_{i,j}\right|^2 + \left|y_{i,j+1} - y_{i,j}\right|^2} \quad (11)$$

Proposed SRDCF with Total Variation Method

The proposed Spatially Regularized Discriminative Correlation Filter (SRDCF) with Total Variation Denoising workflow process is shown below in Figure 2. The acquired fetal heart images are added with speckle noise and involved in this proposed denoise process. A regularization term is introduced for the weight of each training sample. The noise images are transformed from the spatial domain to the frequency domain to combine all layers of training data and convolutional filters.

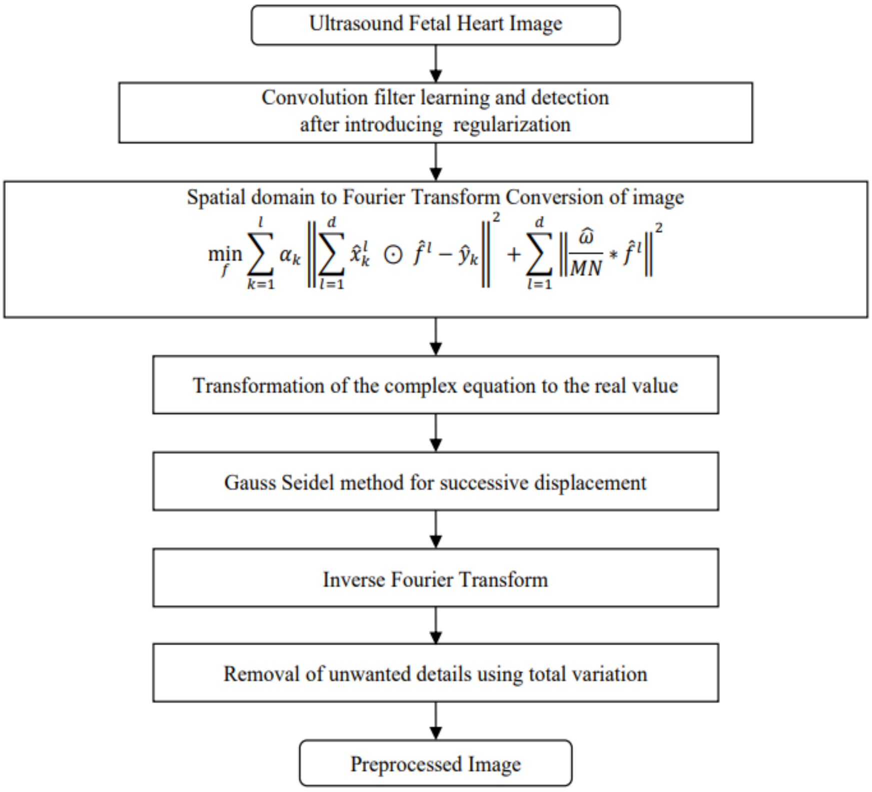


FIG 2: Workflow process of SRDCF with total variation denoising method

Gauss Seidal iterative method with computational complexity is used for successive displacement. Then inverse transform of the Fourier transform is applied. Finally, total variation denoising is employed for removing highly varied details.

RESULTS AND DISCUSSION

Second-trimester fetal cardiac ultrasound images used in this work were gathered from Mediscan Systems, Chennai, and also from online data. The fetal heart ultrasound image database consists of 50 numbers of normal images, 18 numbers of AVSD abnormal images, 18 VSD abnormal images, and 14 numbers of abnormal Ebstein images. Ultrasound images containing speckle noise were subjected to different speckle reduction techniques such as Wiener and Wavelet to analyze the performance of the proposed SRDCF with the total variation filter.

Wiener is a spatial domain filter and Wavelet filter is a frequency domain filter. The most reliable measure of quality is visual appearance. Additionally, objective measures called Peak Signal to Noise Ratio (PSNR), and Mean Square Error (MSE), Equivalent Number of Views

(ENL) are quality measures used to assess the response of denoising filters. High values of PSNR, ENL, and the smallest MSE value are considered to be a sign of effective enhancement. The performance metrics MSE, PSNR, and ENL in the spatial domain are

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{255}{\sqrt{\mathrm{MSE}}}\right) \qquad (12)$$

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (13)$$

$$\mathrm{ENL} = \left(\frac{\mu}{\sigma}\right)^2$$
(14)

The PSNR, MSE, and ENL are obtained for the proposed SRDCF with total variation, Wavelet, and Wiener filter. The response is obtained for the proposed SRDCF with total variation, The variance of noise level is varied from 0.02 to 0.08 for the input images of Wavelet and Wiener Filter. Moreover, the PSNR, MSE, and ENL for fetal heart ultrasound images are calculated for Mediscan and online datasets and also tabulated from Tables 1 to 4. The improved performance of the SRDCF produces better visibility and good quality at all noise level variances.

TABLE 1: MSE, PSNR and ENL for speckle noise variance of 0.02

Image ID	Wavelet Filter			Wiener Filter			SRDCF with Total Variation		
	MSE	PSNR	ENL	MSE	PSNR	ENL	MSE	PSNR	ENL
MSN0011	29.57	33.42	0.92	13.09	36.95	0.94	8.97	38.60	0.97
MSN0097	26.41	33.91	0.70	12.09	37.30	0.72	9.75	38.24	0.75
MSN0023	21.88	34.73	0.46	11.58	37.49	0.47	8.81	38.68	0.48
MSA0069	18.26	35.52	0.49	11.75	37.43	0.35	8.69	38.74	0.36
MSA0009	19.14	35.31	0.35	9.48	38.36	0.50	8.53	38.82	0.53
ITA0005	28.54	33.57	1.27	21.69	34.76	1.39	26.77	33.85	1.46
Average	23.96	34.41	0.698	13.28	37.04	0.728	11.92	37.82	0.758

TABLE 2: MSE, PSNR and ENL for speckle noise variance of 0.04

Image ID	Wavelet Filter			Wiener Filter			SRDCF with Total Variation		
	MSE	PSNR	ENL	MSE	PSNR	ENL	MSE	PSNR	ENL
MSN0011	40.24	32.08	0.88	19.97	35.12	0.93	13.09	36.87	0.97
MSN0097	35.64	32.61	0.68	18.66	35.56	0.72	13.76	36.75	0.75
MSN0023	27.91	33.67	0.45	17.34	35.74	0.46	12.17	37.28	0.48
MSA0069	25.47	34.06	0.50	13.81	36.72	0.50	11.23	37.62	0.50
MSA0009	24.34	34.26	0.35	16.36	35.99	0.35	12.00	37.33	0.40
ITA0005	38.79	32.24	1.22	26.16	33.95	1.37	27.52	33.73	1.46
Average	32.07	33.15	0.68	18.72	35.51	0.72	14.96	36.59	0.76

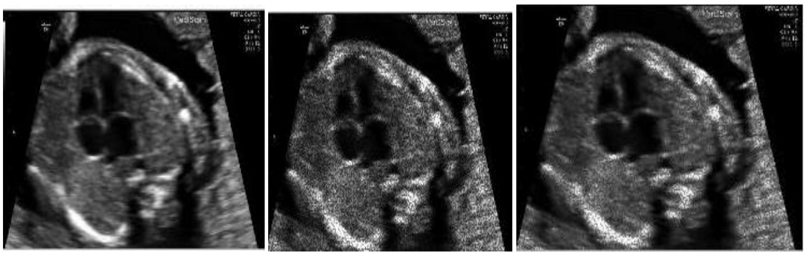
TABLE 3: MSE, PSNR and ENL for speckle noise variance of 0.06

Image ID	Wavelet Filter			Wiener Filter			SRDCF with Total Variation		
	MSE	PSNR	ENL	MSE	PSNR	ENL	MSE	PSNR	ENL
MSN0011	46.11	31.49	0.86	24.43	34.25	0.92	17.02	35.82	0.97
MSN0097	40.99	32.00	0.67	22.03	34.70	0.71	17.08	35.81	0.75
MSN0023	31.42	38.16	0.44	20.67	34.98	0.46	14.79	36.43	0.48
MSA0069	29.98	33.36	0.47	16.45	35.97	0.50	13.12	36.95	0.53
MSA0009	27.29	33.77	0.33	18.76	35.39	0.35	14.38	36.55	0.39
ITA0005	44.88	31.61	1.18	29.52	33.42	1.35	29.72	33.30	1.45
Average	36.78	33.39	0.66	21.97	34.78	0.71	17.69	35.81	0.76

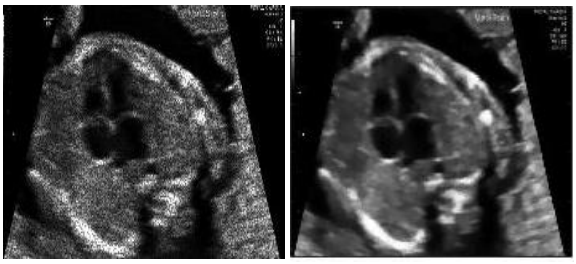
TABLE 4: MSE, PSNR and ENL for speckle noise variance of 0.08

Image ID	Wavelet Filter			Wiener Filter			SRDCF with Total Variation		
	MSE	PSNR	ENL	MSE	PSNR	ENL	MSE	PSNR	ENL
MSN0011	49.24	31.21	0.84	27.02	33.81	0.91	19.26	35.28	0.98
MSN0097	44.44	31.65	0.65	24.61	34.22	0.70	19.57	35.21	0.75
MSN0023	33.74	32.85	0.43	22.76	34.56	0.45	16.63	35.92	0.48
MSA0069	33.45	32.80	0.46	18.73	35.41	0.49	15.09	36.34	0.53
MSA0009	29.38	33.45	0.33	20.44	35.03	0.34	16.19	36.04	0.37
ITA0005	50.66	31.08	1.11	34.01	32.81	1.31	31.78	33.10	1.44
Average	40.15	32.17	0.64	24.59	34.31	0.70	19.75	35.32	0.758

The performance of the proposed SRDCF with total variation for speckle noise is superior to the other filters with the same as that of an image suffering from different noise variance. The proposed SRDCF with total variation method provides better results when compared to other methods in visual appearance and parametric measures such as PSNR, MSE and ENL.



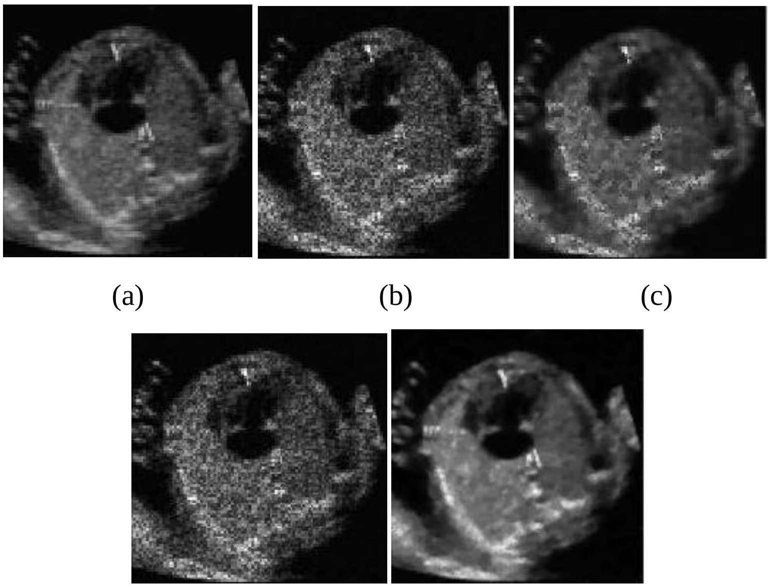
(a) (b) (c)



(d) (e)

FIG 3: (a) Ultrasound Fetal heart image named MSN0011 of Mediscan normal dataset (b) Corrupted Image (Speckle noise σ2 =0.08) (c) Noise removed Image using Wiener Filter (d) Denoised Image using Wavelet Filter (e) Response of Proposed SRDCF with Total Variation Algorithm

Initially, the ultrasound fetal heart image MSN 0011 is taken as primary support to begin the analysis. Figure 3(a) shows a normal fetal heart ultrasound image MSN 0011 of size 512 × 512 and a known quantity of Speckle noise with variance 0.08 is added to Figure 3(a) and is shown in Figure 3(b). The enhanced image, after removing the Speckle contamination using the spatial domain filters such as Wiener is shown in Figure 3(c). The response of the wavelet filter is shown in Figure 3(d). The proposed SRDCF with total variation technique is shown in Figure 3(e). The resultant image by the proposed SRDCF with total variation method clearly shows the four chambers with neighboring regions, whereas the other methods introduce the dullness in details of some regions and also the multiplicative noise is not fully removed.



(a) (b) (c)

(d) (e)

FIG 4: (a) Ultrasound Fetal heart image named ITA0005 of the online dataset (b) Corrupted Image (Speckle noise σ2 =0.08) (c) Noise Removed Image using Wiener Filter (d) Denoised Image using Wavelet Filter (e) Response of Proposed SRDCF with Total Variation Algorithm

Further analysis is continued with the two-chambered online ultrasound fetal heart image labeled as ITA0005 as shown in Figure 4(a). This image is also degraded with a speckle noise variance of 0.08, as shown in Figure 4(b). On examining this image, the spatial and frequency domain filters fail to clear the multiplicative noise present in the image that is shown in Figures 4(c) and (d) respectively.

The proposed SRDCF with total variation technique produces a very bright and apparent two-chamber image shown in Figure 4(e), which is qualitatively and quantitatively compared to other methods. The result of the proposed method proves that qualitatively and quantitatively enhanced output for both datasets.

CONCLUSION

The potential and the strength of the proposed ultrasound fetal heart image and Hydrops Fetalis-Pericardial Effusion image enhancement, denoising using SRDCF with total variation is demonstrated and proved through a series of numerical experiments. The main focus here is to enhance the edges, preserve the information and denoise the ultrasound images through the proposed SRDCF with the total variation method. It has been observed from experimentation that the proposed SRDCF with a total variation method is subject to removing the noise in ultrasound images. The proposed SRDCF with the total variation method is comparable to and better than other approaches for preprocessing ultrasound images.

REFERENCES

1. Karthikeyan, T. Manikandan, V. Nandalal, J. L. Mazher Iqbal and J. J. Babu, "A Survey on Despeckling Filters for Speckle Noise Removal in Ultrasound Images," 2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2019, pp. 605-609, doi: 10.1109/ICECA.2019.8822052.
2. Kaitheri Thacharedath Dilna and Duraisamy Jude Hemanth Novel image enhancement approaches for despeckling in ultrasound images for fibroid

detection in human uterus De Gruyter Open Computer Science 2021; 11: 399–410.https://doi.org/10.1515/comp-2020-0140.

3. C. S. Nageswari and K. H. Prabha, "Despeckle process in ultrasound fetal image using hybrid spatial filters," 2013 International Conference on Green Computing, Communication and Conservation of Energy (ICGCE), Chennai, India, 2013, pp. 174-179, doi: 10.1109/ICGCE.2013.6823423.
4. Nagashettappa Biradar,1 M. L. Dewal,1 and Manoj Kumar Rohit,"Edge Preserved Speckle Noise Reduction Using Integrated Fuzzy Filters" ,International Scholarly Research Notices, vol. 2014, Article ID 876434, 11 pages, 2014. https://doi.org/10.1155/2014/876434.
5. Onur Karaoğlu et al, Hasan Şakir Bilge, İhsan Uluer,"Removal of speckle noises from ultrasound images using five different deep learning networks", Engineering Science and Technology,,Vol ,2022,101030,0986,https://doi.org/10.1016/j.jestch.2021.06.010.
6. P.V.V. Kishore, K.L. Mallika, M.V.D. Prasad, K.L. Narayana, "Denoising Ultrasound Medical Images with Selective Fusion in Wavelet Domain",Procedia Computer Science,Volume 58,2015,Pages 129-139,ISSN 1877-0509,https://doi.org/10.1016/j.procs.2015.08.040
7. Hyunho Choi and Jechang Jeong, "Despeckling Algorithm for Removing Speckle Noise from Ultrasound Images" Symmetry 2020, 12, 938; doi:10.3390/sym12060938.
8. Rajeshwar Dass,"Speckle Noise Reduction of Ultrasound Images Using BFO Cascaded with Wiener Filter and Discrete Wavelet Transform in Homomorphic Region", Procedia Computer Science,Vol 132,2018, 1543-1551,ISSN 1877-0509,https://doi.org/10.1016/j.procs.2018.05.118
9. Szczepański M, Radlak K. Digital Path Approach Despeckle Filter for Ultrasound Imaging and Video. J Healthc Eng. 2017;2017:9271251. doi: 10.1155/2017/9271251. Epub 2017 Oct 8. PMID: 29118965; PMCID: PMC5651154.
10. Kriti, J. Virmani, and R. Agarwal, ‘‘Assessment of despeckle filtering algorithms for segmentation of breast tumours from ultrasound images’’, Biocybern. Biomed. Eng., vol. 39, no. 1, pp. 100–121, Jan. 2019, doi: 10.1016/j.bbe.2018.10.002.
11. C. Shobana Nageswari, M.N. Vimal Kumarb, N. Vini Antony Grace and J. Thiyagarajan,‘‘Tunicate swarm-based grey wolf algorithm for fetal heart chamber segmentation and classification: a heuristic-based optimal feature selection concept’’,Journal of Intelligent & Fuzzy Systems 44 (2023) 1029–1041,DOI:10.3233/JIFS-221654.