A Review on various Ultrasound Image Despeckling Techniques

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Abstract

Ultrasound imaging is considered as one of the most widely used imaging modalities owing to its simple and non-invasive nature. However, ultrasound images are usually manifested with speckle noise, that acts as a hindrance in carrying out any further analysis or disease detection by the radiologists. Despeckling of these images is thus a very important phenomenon to carry out further studies by medical experts. It is of utmost importance that ultrasound images be despeckled, keeping in consideration that no information is lost from the images. This paper covers various despeckling techniques that have been designed for ultrasound images, making sure that no information is lost.

Keywords: ultrasound, despeckling, spatial, transformation, multi resolution

1 Introduction

An image can be considered as a matrix of information representing a 3-D world in 2-D form. In medical imaging various techniques such as X-Ray radiography, Ultrasound Imaging, Computed Tomography Scan, Magnetic Resonance Imaging (MRI) are used to create image of human body parts to diagnose and treat the illness. Ultrasound Imaging is corrupted by Speckle noise. Noise irrevocably damages the interpretability of an image. The aim of the paper is to discuss the noise mitigation capabilities of various techniques for Ultrasound Images.

Ultrasound imaging is widely used for imaging soft tissues, structures and also motions of Human Body as it is cost effective and uses non-ionizing radiation. Sonographic Scanners which typically operate in the frequency range of 20 Khz to 18 Mhz are used to take the ultrasound image. The waves generated by the scanners fall on the organs of human body and bounce off making echoes. Using these echoes, an image of the organ is obtained on the screen of the Ultrasound machine. During acquisition of the image, a noise is caused because of the constructive and destructive interference that takes place among the bounced waves causing degradation in the quality of the image obtained. This noise is called Speckle Noise.

The process to mitigate the losses caused by Speckle Noise is called Despeckling. Various methodologies have been proposed by researchers which are applied on the image obtained to reconstruct an image which is free from or has minimum Speckle noise. In the proposed work, the methodologies have been broadly divided into two domains, namely Time Domain and Frequency Domain. In Spatial Domain, broadly there are two classifications, Local Filters and Non-Local Filters. In Transform Domain, there are Fourier Transform, Fast Fourier Transform, Curvelets, Counterlets, Discrete Cosine Transform, Wavelets, Wedgelets, Ripplet, Ridgelets, directionlets, bandlets, directional filter banks, Shearlets. Figure-1 shows the techniques discussed in the paper.



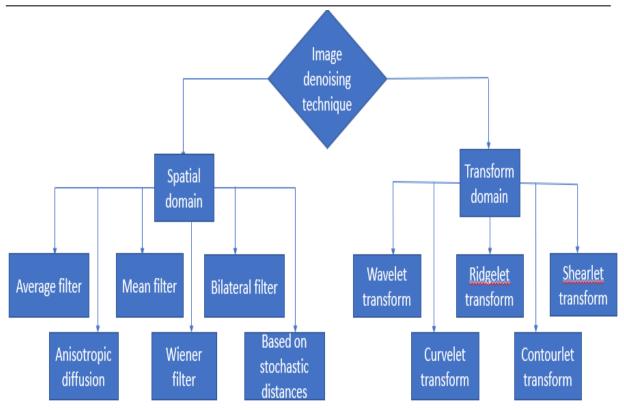


Fig. 1. Denoising techniques discussed in the paper

2 Spatial domain

Local filters use the concept of checking the correlation amongst the neighbouring pixels. Some of the Local filters that are discussed are Mean filter, Weiner Filter, Least Square filter, Bilateral filter, Anisotropic Diffusion filter, SRAD filter, SUSAN-AD filter.

2.1 Average filter

Averaging or the mean filtering is the simplest type of Linear Invariant Filtering. For every pixel an average of the neighboring pixels is calculated as per the pre-defined size of the window. Now each pixel is replaced by the average value. This technique is fast and simple but there is loss of information as image is blurry because of excessive smoothening of edges. A method called Iterative Mean Filter has been proposed in [1]. Author used a fixed size window of 3*3 for noise free pixels calculating mean of gray values for center pixel. Iteration procedure is used to effectively process high density noise. In [2] to meet the real time requirements author has proposed this method where the traditional mean filtering method is combined with block mean filtering method. The proposed method is found to be effective when the image is more complex.

2.2 Weiner filter

Weiner filter are based on an assumption that the spectral properties of the Original signal and the noise are known. In this technique, the linear estimation of the sequence of desired signal is calculated from the other related sequence. Weiner filter does the linear restoration mapping. In [3] author has proposed a method in which noisy image is operated upon by discrete wavelet transform. Quadtree decomposition and 4th order wiener filter are applied on detailed region and on each variable size block, respectively. In [4] author proposed a method which is a combination of weiner filter, multiscale approach and new fast bilateral filter. Firstly, laplacian pyramid in used obtain multi-scale of image. Then, for initial filtering weiner filter is used which is followed by new fast bilateral filter finally to remove the artifact wavelet decomposition anistropic filter was used.

2.3 Bilateral filter

Bilateral filter is an example of non-linear and non-iterative method. It is a combination of range and domain filters. Initially the processing of the Bilateral Filter was slow because of the exponential increment in the computational complexity it had. Trigonometric range Kernels were introduced by Chaudhary et al. in place of Euclidean Spatial Distance which reduced the computational complexity[5]. It preserves the information related to boundaries and sharp edges and filters out the noise from the reference pixels. This technique has a drawback that the real gray levels of the image get largely affected by noise as the range filter is not efficient there. This phenomenon is called Propagation of Noise (PON).

In [6] author has proposed Rayleigh-maximum-likelihood bilateral filter to enhance ultra sound image by removing noise and suppressing spackle. Pixel is classified as noise, spackle or noise free by using sorted quadrant median vector. bilateral filter is used to remove noise and Rayleigh maximum likelihood filter is used to suppress the speckles.

In [7] fast bilateral filter and Neighshrinksure filter are used, in wavelet domain, for low pass components i,e approximation band corfficients, and high pass components i.e, datail band coefficients, respectively. In [8] author proposes a 3-phases and 3-step denoising filter. In phase 1 is computation of coefficients of variation (CoV) from noise image. Phase 2 has a three step denoising filter compresing of fuzzy logic, adaptive bilateral filter and weighted adaptive bilateral filter. Phase 3 is evaluation of output images using fuzzy logic approach. In [9] proposes improved adaptive weiner filter (AWF). It has 3 phases and 3 denoising filters. Phase 1 is computation of coefficients of variation and application of fuzzy c-means (FCM) for fuzzy classification of image regions. In phase 2 hybrid of 3 denoising filters , namely, fast bilateral filter, improved adaptive wiener filter and wavelet filter are applied on homogenous, detailed and edge regions, respectively. Phase 3 is evaluation of output images using fuzzy logic approach.

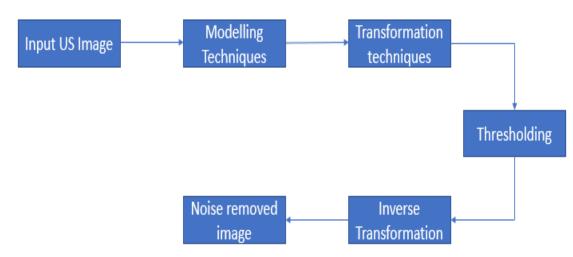
2.4 Speckle reducing anisotropic diffusion

Speckle reducing anisotropic diffusion (SRAD) is a Edge Sensitive speckle reducing technique. In the conventional anisotropic diffusion techniques, the log compressed image data is used [10]. The work proposed by Yogijan Yu et al. proposes a non linear Anisotropic diffusion technique which directly processes the data without compressing it logarithmically. It uses Instantaneous Coefficient of Variation (ICoV). The author has validated his claims by testing the approach on synthetic as well as real linear Ultrasonic images. In [11] modified multiscale anisotropic diffusion technique has been proposed by Bedi et al. for speckle reduction.

In [12] Smith et al. proposed SUSAN algo. In this algorithm, a circular mask which is a circular area has a centre pixel called as nucleus. The brightness of each pixel lying in the mask is compared with that of the nucleus. For the pixels which have same or similar brightness, the area of mask is defined as Univalue Segment Assimilating Nucleus (USAN). When the nucleus is lying on the flat surface of the image, the USAN is maximum. When the nucleus is lying in the corner of the image, the USAN is minimum. In the work [13] by Jihhua Yu et al., they proposed a SUSAN controlled Anisotropic Diffusion (SUSAN-AD). To improve the performance of the adaptive diffusion threshold estimation and automatic diffusion termination criteria are used. SUSAN-AD has performed better than several existing methods.

2.5 Based on stochastic distances

In [14] proposed method, the author has measured the Kolmogorov-Smirnov distance to evaluate similarity between the pixels. The distance is measured between the Cummilative Distribution Function (CDF) to get more effective estimation of statistical distribution a 3*3 neighborhood system is considered for each pixel and these are jointly exploited to get the CDF. In [15] paper author has tried to improve the performance of BM3D algorithm which used Euclidean distance. New stochastic distances are measured in the proposed work between the patches using Fisher-Tippett distribution to improve despeckling of log compressed ultrasound images.



3 Transform Domain

Fig. 2. Pictorial representation of steps involved in transform domain techniques

3.1 Wavelet transform Technique

In Wavelet Transform the data is decomposed into various segments based on frequency components. Then coefficients of each segment are manipulated as per the need. In [16] Randhawa et al have decomposed an image into two main categories, Approximate region and detailed region, based on frequency. The low frequency components are segmented into Detailed region. The proposed method is tested for Orthogonal and biorthogonal filters. The mother wavelet used is Symlet8.

This [17] approach uses Monogenic wavelet transform (MWT) and Bayesian transform. The coefficients of MWT for noise free signal are modelled as Laplace mixture distribution and coefficients of MWT for speckle noise signal are modelled as Rayleigh distribution. Then for despeckling Bayesian minimum mean square estimator is used.

In [18] CauchyShrinkageGMAP shrinkage function is used to provide solution of maximum a posteriori (MAP) estimator. Cauchy prior is used for modelling the wavelet coefficients.

3.2 Curvelet transform Technique

Curvelet is an extension of wavelet transform. It is an optimal adaptive representation up to a large extent. It is used for multi-scale object representation. In [19] Devarapu et al. have proposed a Curvelet based Denoising Algorithm for Ultrasound Images. The results obtained indicate a better edge preservation in comparison to the Adaptive filters and SRAD techniques. Objects which have discontinuities across the curves are best suited case for Curvelet transform. In [20] curvelet transform is used to despeckle Intravascular ultrasound (IVUS) images. Performance of the Curvelet and wavelet is also compared in the work.

3.3 Ridgelet Transform Technique

In [21] introduced the Ridgelet transform. It is an extension of Wavelet transform defined in Radial directions and constant times. Ridgelet tries to address those expects which became shortcomings of Wavelet. Ridgelets are more appropriate for line and edge singularities. Ridgelet is effective for sparse directional analysis.

Adaptive Digital Ridgelet (ADR) algorithm has been proposed by Huang et al. in [22]. It adaptively deals with line and curve information. ADR is shown to be outperforming conventional Curvelet and Ridgelet. PSNR values have increased significantly and MER values have reduced fairly.

3.4 Contourlet transform Technique

Intrinsic geometrical structure of an image is of utmost importance across the applications. M.N.Do in [23] has proposed an extension of wavelet transform called contourlet transform. Contourlet is a twodimensional transform developed in discrete domain, unlike the other approaches where construction starts in continuous domain and then discretization of sample data is done. Non-separable filter banks are used to construct a discrete domain for expansion in multiple resolutions and directions. In [24] additive speckle noise is decomposed using non-subsampled contourlet domain transform. Then despeckling of decomposed image is done by cross-guided bilateral filter.

Discrete Contourlet Transform has filter bank with fast iterations. For N pixels the filter bank algorithm requires N order operations. A framework of directional multiresolution

analysis is used to establish link between associated continuous-domain and the discrete continuous transform. Some numerical experiments are also performed to show potential of the transform.

3.5 Shearlet Transform Technique

A new text tool for multidimensional representation system was described by Labate et.al. [25] called Shearlet. It is an extension of wavelet transform. The author said to have introduced the tool to extend the approach to higher dimensions and multiresolution construction, and not just limited to locations, shapes, scales and direction. This suited well for fast numerical implementation. A combination of Dilation, Translation and Shear transforms provided this useful tool. This tool shows mathematical and geometrical properties, including anisotropy, localisations, directionality.

In [26] Bedi et al. have proposed a method of despeckling of ultrasound Image in Non-Sub Sampled domain using Modified Anisotropic Diffusion Model. The author uses a combination of Non-sub sampled Shearlet Transform and Anisotropic diffusion model in the proposed technique. In [27], a despeckling method based on non-subsampled shearlet and guided filter is proposed. First, the noisy image is decomposed into high frequency subband and low frequency subband using nonsubsampled Laplacian pyramid filter. Then improved thresholding shrinkage algorithm is used to perform thresholding on high frequency subband shearlet coefficients. Guided filter is used to process the low frequency subband shearlet coefficients.

Discrete Shearlet Transform is given by Wang-Q Lim in [28]. Discrete Shearlet Transform (DST) is efficient in presenting mutliscale directional aspects of data. Performance of DST is evaluated on image denoising and approximation applications. The implementation of the transform is done in discrete framework and analysed in multiple resolutions. In [29] author has proposed a pseudo-polar fast fourier transform based despeckling technique using discrete shearlet transform for medical ultrasound images.

4 Thresholding

Thresholding is the process of segmenting an image into regions based on threshold value. The coefficients obtained from the applied transformation technique are modified according to the value. Broadly it is divided into three parts:

- 1. Global Thresholding: When thresholding operation is depending only on grey scale value.
- 2. Local thresholding: When the neighborhood properties are also considered in the operation.
- 3. Dynamic/Adaptive thresholding: When the thresholding value depends on pixel coordinates also.

5 Conclusion

In this work, honest effort has been made to enlist and classify all the types of image denoising techniques. The techniques have been broadly divided into two categories namely spatial domain and transformation domain. Though it is impossible to mention all the techniques but sincere efforts have been made to enlist the basic image denoising techniques existing till date

References

- Thanh, Dang Ngoc Hoang, and Serdar Engínoğlu. "An iterative mean filter for image denoising." IEEE Access 7 (2019): 167847-167859
- [2] Weizheng, Xu, Xiao Chenqi, Jia Zhengru, and Han Yueping. "Digital Image Denoising Method Based on Mean Filter." In 2020 International Conference on Computer Engineering and Application (ICCEA), pp. 857-859. IEEE, 2020.
- [3] Dagher, Issam, and Catherine Taleb. "Image denoising using fourth order wiener filter with wavelet quadtree decomposition." Journal of Electrical and Computer Engineering 2014 (2014).
- [4] Ilesanmi, Ademola E., Oluwagbenga P. Idowu, Utairat Chaumrattanakul, and Stanislav S. Makhanov. "Multiscale hybrid algorithm for pre-processing of ultrasound images." Biomedical Signal Processing and Control 66 (2021): 102396.
- [5] Chaudhury, Kunal Narayan, Daniel Sage, and Michael Unser. "Fast \$ O (1) \$ bilateral filtering using trigonometric range kernels." IEEE transactions on image processing 20, no. 12 (2011): 3376-3382
- [6] Li, Haiyan, Jun Wu, Aimin Miao, Pengfei Yu, Jianhua Chen, and Yufeng Zhang. "Rayleigh-maximum likelihood bilateral filter for ultrasound image enhancement." Biomedical engineering online 16, no. 1 (2017): 1-22.
- [7] Garg, Amit, and Vineet Khandelwal. "Despeckling of medical ultrasound images using fast bilateral filter and neighshrinksure filter in wavelet domain." In Advances in Signal Processing and Communication, pp. 271-280. Springer, Singapore, 2019.
- [8] Salehi, Hadi, and Javad Vahidi. "An Ultrasound Image Despeckling Method Based on Weighted Adaptive Bilateral Filter." International Journal of Image and Graphics 20, no. 03 (2020): 2050020.
- [9] Salehi, Hadi, and Javad Vahidi. "A Novel Hybrid Filter for Image Despeckling Based On Improved Adaptive Wiener Filter, Bilateral Filter and Wavelet Filter." International Journal of Image and Graphics (2021): 2150036.
- [10] Yu, Yongjian, and Scott T. Acton. "Speckle reducing anisotropic diffusion." IEEE Transactions on image processing 11, no. 11 (2002): 1260-1270.
- [11] Bedi, Anterpreet Kaur, Ramesh Kumar Sunkaria, and Deepti Mittal. "Ultrasound Image Despeckling and Enhancement using Modified Multiscale AnisotropicDiffusion Model in Non-Subsampled Shearlet Domain." The Computer Journal (2019).
- [12] Smith, Stephen M., and J. Michael Brady. "SUSAN- a new approach to low level image processing." International journal of computer vision 23, no. 1 (1997): 45-78.
- [13] Yu, Jinhua, Jinglu Tan, and Yuanyuan Wang. "Ultrasound speckle reduction by a SUSAN-controlled anisotropic diffusion method." Pattern recognition 43, no. 9 (2010): 3083-3092.
- Baselice, Fabio. "Ultrasound image despeckling based on statistical similarity." Ultrasound in medicine & biology 43, no. 9 (2017): 2065-2078.
- [15] Santos, Cid AN, Diego LN Martins, and Nelson DA Mascarenhas. "Ultrasound image despeckling using stochastic distance-based BM3D." IEEE Transactions on Image Processing 26, no. 6 (2017): 2632-2643.
- [16] Randhawa, Simarjot Kaur, Ramesh Kumar Sunkaria, and Emjee Puthooran. "Despeckling of ultrasound images using novel adaptive wavelet thresholding function." Multidimensional Systems and Signal Processing 30, no. 3 (2019): 1545-1561.
- [17] Gai, Shan, Boyu Zhang, Cihui Yang, and Lei Yu. "Speckle noise reduction in medical ultrasound image using monogenic wavelet and Laplace mixture distribution." Digital Signal Processing 72 (2018): 192- 207.
- [18] Kim, Kyong-Il & Bahng, Soon-Ic & Choe, Ryong- Nam. (2020). Despeckling Method of Ultrasound Images Using Closed Form Shrinkage Function based on Cauchy Distribution in Wavelet Domain. International Journal of Wavelets, Multiresolution and Information Processing. 18.10.1142/ S0219691320500265
- [19] Devarapu, K. Venkatrayudu, Subrahmanyam Murala, and Vinod Kumar. "Denoising of ultrasound images using curvelet transform." In 2010 *The 2nd* International Conference on Computer and Automation Engineering (ICCAE), vol. 3, pp. 447-451. IEEE, 2010.

- [20] Lazrag, Hassen, and Med Saber Naceur. "Despeckling of intravascular ultrasound images using curvelet transform." In 2012 6th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT), pp. 365-369. IEEE, 2012.
- [21] Candès, Emmanuel J., and David L. Donoho. "Ridgelets: A key to higher-dimensional intermittency?." Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences 357, no. 1760 (1999): 2495-2509.
- [22] Huang, Qiangui, Boya Hao, and Sheng Chang. "Adaptive digital ridgelet transform and its application in image denoising." Digital Signal Processing 52 (2016): 45-54.
- [23] Do, Minh N., and Martin Vetterli. "The contourlet transform: an efficient directional multiresolution image representation." IEEE Transactions on image processing 14, no. 12 (2005): 2091-2106.
- [24] Joel, Thapasimuthan, and Rajagopal Sivakumar. "Nonsubsampled contourlet transform with cross- guided bilateral filter for despeckling of medical ultrasound images." International Journal of Imaging Systems and Technology (2020).
- [25] Guo, Kanghui, Demetrio Labate, Wang-Q. Lim, Guido Weiss, and Edward Wilson. "Wavelets with composite dilations and their MRA properties." Applied and Computational Harmonic Analysis 20, no. 2 (2006): 202-236.
- [26] Bedi, Anterpreet Kaur, Ramesh Kumar Sunkaria, and Deepti Mittal. "Enhancement of ultrasound images using modified anisotropic diffusion model in non- subsampled shearlet domain." In 2017 International Conference on Computing, Communication and Automation (ICCCA), pp. 1119-1124. IEEE, 2017.
- [27] Zhang, Ju, and Yun Cheng. "Nonsubsampled Shearlet and Guided Filter Based Despeckling Method for Medical Ultrasound Images." In Despeckling Methods for Medical Ultrasound Images, pp. 123-142. Springer, Singapore, 2020.
- [28] Lim, Wang-Q. "The discrete shearlet transform: A new directional transform and compactly supported shearlet frames." IEEE Transactions on image processing 19, no. 5 (2010): 1166-1180.
- [29] Abazari, Reza, and Mehrdad Lakestani. "Fourier based discrete shearlet transform for speckle noise reduction in medical ultrasound images." Current Medical Imaging 14, no. 3 (2018): 477-483