Comparative Analysis of Anisotropic Diffusion and Non Local Means on Ultrasound Images

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Abstract

Applications of Ultrasound in examining physical health of patient are continuously expanding over last few decades. Ultrasound imaging has assisted doctors in the diagnosis of medical health of patient in obstetrics, cardiology, gynaecology, musculoskeletal, urology and others. It has proved to be very promising and considerably advantageous over other imaging methods because of its features like non-invasive nature, use of non-ionizing radiation, portability, rapidity in performance, ease and cheap availability, real time imaging capability, high patient acceptability. Despite many advantages, it suffers from Speckle noise which results in affecting image resolution and contrast making an adverse impact on the diagnostic capability of the imaging modality. In this paper, we attempt to remove speckle noise from musculoskeletal ultrasound image for shoulder application using Anisotropic Diffusion and Non-Local Means (NLM) method. The quantitative analysis of the result is done using measurement indexes such as peak signal to noise ratio (PSNR), signal to noise ratio (SNR) and root mean square error (RMSE), whereas, visual inspection is carried out for qualitative analysis.

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1 Introduction

Ultrasound imaging has assisted radiologist and physicians in observing anatomy of human body since past few decades. Ultrasound was developed during the Second World War and since then is assisting for various applications on water, air and earth in various forms. Ultrasound as a medical imaging modality evolved about half a century ago and considered to be great invention because of its unique and advantageous features over all other existing medical imaging modalities. It offers several superior features such as use of non-ionizing radiation, real time imaging, portability, high patient acceptability, ease of use and is economical. Despite many advantages, ultrasound images contain noise known as ‘Speckle’ which corrupts the image resolution and contrast making interpretation of physical structure lying underneath, extremely difficult for physicians. Various phenomena like image acquisition and imperfections in machine design contribute to the existing resolution and contrast in ultrasound images. Despeckling of ultrasound images is considered to be of utmost important to make it a viable and suitable option for use as imaging modality. As a result, several efforts have been made by research community to despeckle the image as well as to improve the system design to help diagnostics.

Speckle noise in ultrasound image is introduced because of the coherence nature of imaging modality, the interference of back scattered signals from each resolution and sub-resolution cell towards receiver or transducer. The backscattered waves undergo constructive or destructive interference in a random manner spoiling image in a random granular pattern, termed as Speckle. Due to the acquisition process the speckle noise in ultrasound is multiplicative in nature which is directly proportional to grey level in any area and is statistically independent from signal.

The statistics of the speckle noise was first proposed by Goodman [1], where he modeled the statistical representation of speckle formation in laser. With study about statistical features in ultrasound imaging it was concluded that speckle in ultrasound images is multiplicative in nature following a different statistical distribution [22], [23], [24], [25] naming Rayleigh, Rician, Nakagami, K- distribution depending on the scatterer density and scatterer size of the tissue being imaged.

Noise in ultrasound images introduced has both multiplicative as well as additive nature making it more difficult to separate signals and denoise image. The multiplicative noise introduced due to the coherency feature whereas additive noise comes from the system properties. In the past few decades, efforts have been made to post process ultrasound images taken from system and remove noise from ultrasound images for better interpretation and diagnosis.

In this paper we have discussed in detail comparison about two despeckling method 1) Anisotropic diffusion method 2) Non Local Means Method. Anisotropic Diffusion Method [13], [14], [15] is successfully used to remove speckle noise from ultrasound images, whereas nonlocal means method [16] initially used for additive noise is recently introduced to despeckle ultrasound images [17]. The qualitative and quantitative comparison for two methods is also provided.

2 Speckle Noise

2.1 Model for Speckle Noise

The generalized model for speckle noise as proposed in [2] is given by:

$$g(n, m) = f(n, m) \times u(n, m) + \xi(n, m) \quad (1)$$

where, g, f, u and ξ are observed envelope image, original image, multiplicative noise and additive components respectively. The model has been successfully used both in Synthetic Aperture Radar as well as Ultrasound Imaging.

In the latter case, the model can be further simplified by disregarding the additive noise term. The image obtained without the application of system processing techniques, changes the resultant image model to:

$$g(n, m) = f(n, m) \times u(n, m) \quad (2)$$

An alternative model for speckle noise has been proposed in [3] wherein it is considered only as the additive noise, the amplitude of which is proportional to the square of the true image. The model is given by:

$$g(x) = x + u\sqrt{x} \quad (3)$$

where, $g(x)$ is the observed signal, x is the original signal without noise, u is the noise which is dependent of the observed signal.

The paper focuses on the B-Scan images taken from ultrasound machine focusing musculoskeletal application for shoulder images. In section (II), a

brief discussion on the speckle reduction methods is provided combined with detail discussion for anisotropic diffusion and non-local means method, followed by, the description of materials and methods in section (III), discussion and conclusion about the findings are shown and summarized in section (IV) and section (V) respectively.

2.2 Speckle Reduction Methods

Speckle degrades information in the image and that too, to the extent, that it becomes difficult for medical practitioner to form a comprehensive understanding of tissues or bones for proper diagnosis.

Several researchers have studied this phenomena and attempted to improve the quality of images using different denoising methods like, mean filter, median filter, adaptive mean filters such as Kuan [4] and Lee [5], both filter have same characteristic and operate by computing the different combination of coefficient of variation of noised image and coefficient of variation of noise, in general operates on center pixel intensity and average pixel intensity of filter window, where filter forms a balance between averaging image in homogeneous region and applying identity filter elsewhere.

Frost [6], this filter also works on principle of averaging homogeneous region and all pass filter in other non-homogeneous sections. The difference lies in filter window which in this case is an exponentially shaped kernel that can form average filter or all pass filter on an adaptive basis. The response of the filter varies again with the coefficient of variation of noise and coefficient of variation of noised image.

Wavelet based speckle reduction methods are classified into Homomorphic and Non-Homomorphic wavelet filtering. In homomorphic method [7], [8], [9] multiplicative noise in ultrasound image is converted into additive noise by taking logarithmic transform in first step, followed by wavelet decomposition and modification of wavelet coefficients in second step, then inverse wavelet and exponential transform is performed to get back the reconstructed image. Whereas in non-homomorphic method [20], [21] it is considered that converting the multiplicative noise to additive noise results in loss of many statistical properties of the image and inappropriate performance of despeckling method [18], therefore in this method despeckling is performed without taking into account any noise model and the method can adapt itself to many different noise models present in medical images. In [12], we have analyzed ultrasound images using wavelets decomposition up to second level and

performed qualitative as well as quantitative analysis using different measurement indexes.

Total variation denoising method is used to remove noise from an image model by solving minimization problem. The noise model for ultrasound image is formed and based on noise model regularization term and data fidelity terms are defined so as to despeckle the image. In [10], [11] the minimization problem is solved using novel Split- Bregman algorithm based on Zhang-Burger-Bresson-Osher's non local graph method.

The detailed discussion for anisotropic diffusion and Nonlocal means method is given in following section.

2.3 Anisotropic Diffusion Filtering

Anisotropic Diffusion filtering is a nonlinear filtering method coined by Perona and Malik [13] in the year 1990 for removing the additive Gaussian noise from images. In this method, partial differential equation (PDE) has been introduced for smoothing the image keeping track of homogeneous region and region containing edges in images. The nonlinear PDE for smoothing image introduced by Perona and Malik is:

$$\begin{cases} \frac{\partial I}{\partial t} = \text{div}[c(|\nabla I|) \cdot \nabla I] \\ I(t=0) = I_0 \end{cases} \quad (4)$$

where div is the divergence operator, $|\nabla I|$ is the gradient magnitude of the image I , $c(|\nabla I|)$ is the diffusivity function or the diffusion coefficient, I_0 is the original image. Perona and Malik [13] suggested two different functions for diffusion coefficients:

$$c(x) = \frac{1}{1 + (x/k)^2} \quad (5)$$

or,

$$c(x) = \exp[-(x/k)^2] \quad (6)$$

where k (set either manually or using noise estimator) is the parameter controlling the level of diffusion between edges and homogeneous region in images, optimum value should be chosen to avoid over or under smoothing. If $x \gg k$, then $c(x) \rightarrow 0$, we use all-pass filter, where as if $x \ll k$, then $c(x) \rightarrow 1$, we use isotropic diffusion (Gaussian filtering). It is also suggested by [14], that anisotropic diffusion discussed above works well for additive noise where as

in the presence of speckle noise, instead of delineating the image enhances speckle.

In [15], Yu and Acton proposed new anisotropic diffusion model to smooth speckle images where output image $I(x, y; t)$ is computed using the following differential equation:

$$\frac{\partial I(x, y; t)}{\partial t} = \text{div}[c(q)\nabla I(x, y; t)] \quad (7)$$

$$I(x, y; 0) = I_0(x, y), \quad (8)$$

$$\partial I(x, y; t)/\partial n|_{\partial\Omega} = 0 \quad (9)$$

where, t represents diffusion time, $\partial\Omega$ denotes borders of Ω , n is outer normal to $\partial\Omega$, their diffusion coefficient $c(q)$ is written as

$$c(q) = \frac{1}{1 + [q^2(x, y; t) - q_0^2(t)]/[q_0^2(t)(1 + q_0^2(t))]} \quad (10)$$

or,

$$c(q) = \exp\{-[q^2(x, y; t) - q_0^2(t)]/[q_0^2(t)(1 + q_0^2(t))]\} \quad (11)$$

where $q(x, y; t)$ is the instantaneous coefficient of variation at position (x, y) and is given by:

$$q(x, y; t) = \sqrt{\frac{(1/2)(\nabla I/I)^2 - (1/4^2)(\nabla^2 I/I)^2}{[1 + (1/4)(\nabla^2 I/I)]^2}} \quad (12)$$

The function $q(x, y; t)$, instantaneous coefficient of variation combines normalized Laplacian operator and normalized gradient operator to detect edges from the speckled images. At the edges, Laplacian term shows zero crossing whereas gradient gives higher values allowing detection of edges in bright as well as dark regions. The function takes higher values at edges or high contrast regions, whereas, low values in homogeneous regions.

2.4 Non Local Means (NLM)

The local smoothing or frequency domain filter takes advantage of regularized geometrical configuration in images, while neglecting details and fine structures preservation. Due to regularity assumption, fine structures like edges

and other details are smoothed in images leading to information loss. In [16], Antoni Buades introduced non-local means (NLM) algorithm which takes advantage of redundant features in natural image. Redundant features refer to the similar patches in image which very often are present in natural images. Mathematically, NLM algorithm is described as, for a given noisy image $u(x)$, denoised value for pixel can be written as,

$$u'(x) = \frac{1}{C(x)} \sum_{x' \in \Omega_s} w(x, x') f(x') \quad (13)$$

Where $C(x)$ is the normalizing factor and $w(x, x')$ is the weight determined by the similarity level of different patches around x, x' . The weight $w(x, x')$ is computed using

$$w(x, x') = \exp(-\|P(x) - P(x')\|_{2,a}^2 / h^2) \quad (14)$$

where, $P(x)$ denotes the square patch centered around pixel x , h is filtering parameter and $\|\bullet\|_{2,a}$ is a Gaussian weighted Euclidean distance whose value is determined by amount of similarity between patches from different neighborhood. Higher the similarity, more will be $w(x, x')$.

According to [17], applying NLM directly on the speckle noise or ultrasound images will not yield better results because of the multiplicative nature of speckle contained in the images. Speckle in ultrasound images is different from additive noise, therefore using square patches yields ringing artifacts, noise named halo. In eq(15), $S(\tau)$ gives definition to different shaped patches like disks and pies which could effectively deal with speckle noise compared to square patches which were introduced initially. The author in [18] suggested Gaussianizing speckle noise in ultrasound images, before using non local means-multi shape normal patches (NLM-MSPA). The measurement between the pixels in Eq. (14) is reformulated as:

$$w_s^2(x, x') = \sum_{\tau \in \Omega} S(\tau) (f(x + \tau) - f(x' + \tau))^2 \quad (15)$$

where, S gives definition to the patch considered which could be, for instance it can be written as:

$$S(\tau) = \begin{cases} 1, & \text{if } \|\tau\|_{\infty} \leq \frac{p-1}{2} \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

This makes patch as standard square patch of size of $p \times p$ and the distance being measured as Euclidean norm.

Two issues prevail when it comes to taking into consideration arbitrary patches for distance measure between pixels, first is to choose the shape among the existing ones and second is to combine the estimator so as to give a combined result from every estimate. To solve first problem Stein proposition [26] unbiased estimate for risk estimation for pixel x is considered and shape based norm defined in Eq(15) has been modified to following derivative expression

$$\frac{\partial w(x, x')}{\partial \varepsilon(x')} = \frac{\left(S(0) \left[f(x) - f(x') \right] + S(x - x') \left[f(x) - f(2x - x') \right] \right)}{h^2} \quad (17)$$

where S defines shape of K^{th} estimator. The second concern is dealt with statistical method of exponentially weighted aggregation (EWA) [27], where several estimators are combined using weighted average, giving higher weights to estimators with low risks.

3 Material and Methods

Ultrasound images were taken from a healthy shoulder of ten different volunteers after all subjects gave their informed consent before participation and the procedures were approved by the local ethics committee. The experimental setup was designed so as to acquire best possible image with maximum comfort of subject. Figure 1 provides the setup configuration.

Despeckling was done using anisotropic diffusion and nonlocal means algorithm. For rigorous study, 70 different images from ten subjects were involved and quantitative parameters were recorded for each image to establish concrete foundation for results. In anisotropic method, the function used for denoising is taken from Eq. 5, and number of iterations was set to 10. In

Figure 1 Experimental setup for Data Acquisition

the NLM method, square patches were taken and weight is calculated using Euclidean distance formula introduced in Eq. (14).

In order to quantitatively compare the performance, three different measurement indexes such as peak signal to noise ratio (PSNR), root mean square error (RMSE) and signal to noise ratio (SNR) [19] have been used. The PSNR is calculated using:

$$PSNR = 10 \cdot \log_{10} \left(\frac{M^2}{E\phi_i^j(x)[x - \hat{x}]^2} \right) \quad (18)$$

where, M is the peak pixel amplitude, x represents pixel amplitude in the original image, and $\hat{x}$ is the corresponding pixel in reconstructed image. The greater the PSNR better is the result.

MSE is measure of error between the filtered or denoised image and original image. The greater the value poorer is the result.

$$RMSE = \frac{1}{MN} \sum_{x=1}^M \sum_{y=1}^N [I(x, y) - \hat{I}(x, y)]^2 \quad (19)$$

where, $I(x, y)$ is the original image and $\hat{I}(x, y)$ is the denoised image and MN is the size of image.

Third measure indexes introduced for quantitative analysis was signal to noise ratio (SNR). SNR value is calculated using the formulae

$$SNR = \frac{\mu}{\sigma} \quad (20)$$

where, μ is the mean calculated over the resultant image taken into consideration and σ is the standard deviation of the image.

4 Results and Discussion

Figure 2 shows the original image in first column, followed by same image processed using anisotropic diffusion in second column and non-local means algorithm in the third column.

From Figure 2, it can be seen that, anisotropic diffusion gives the smoother image with 10 iterations which on increasing number of iteration becomes blurry and loose important details for diagnosis, on the other hand nonlocal means technique preserves the important details in image at same time maintaining sharpness in image resulting in better contrast. In image 1, having a

Figure 2 Results obtained with Anisotropic Diffusion and Non local means method on shoulder ultrasound images.

closer look provides necessary interpretation about two techniques discussed. Yellow arrow, indicated in both processed image shows blurriness at edges

in anisotropic diffusion method whereas sharpness using nonlocal means method, red arrow shown in homogeneous region gives details about the smooth structure inside the healthy tendon of a subject which is more prominent and sharp after using nonlocal means method. The visual results from all images considered are in compliance with [17]. The blurriness in the image processed by anisotropic diffusion increases as we increase the number of iterations, which makes homogeneous regions smooth at the same time hides important details. NLM algorithm takes into account redundancy in the patches and iterations are not required for smoothing, therefore the smoothing of homogeneous regions and sharpness in edges, the better patches and weight calculation leads to more optimum results.

The PSNR, SNR and RMSE values obtained for the ultrasound image despeckling using the anisotropic diffusion and nonlocal means algorithm are shown in Table 1.

It can be seen that the average PSNR value for non-local means method is 35.2844 whereas for anisotropic diffusion it is computed as 32.8985 which is well below NLM method. Also, the computed average RMSE value for NLM method is 0.1721 whereas that for anisotropic diffusion method is 0.2279. The SNR value computed for every image shows significant increase in the signal to noise ratio in case of NLM method as compared to anisotropic Diffusion. Taking into account the statistical relevance provided by all three measurement metric of anisotropic diffusion and its compliance with visual interpretation, it is clear that NLM algorithm performs well for ultrasound images as compared to anisotropic diffusion method.

Table 1 Comparison Results for despeckling

Methods	ANISOTROPIC DIFF. (ITER-10,FN-1)			NON LOCAL MEANS (NLM)		
	PSNR	SNR	RMSE	PSNR	SNR	RMSE
Images						
Image 1	30.2541	1.3915	0.0303	34.0893	1.58	0.01951
Image 2	31.7288	1.2468	0.0259	34.5822	1.29	0.01865
Image 3	33.3226	1.32	0.0215	35.4642	1.346	0.01685
Image 4	33.7039	1.2841	0.0206	35.6655	1.34	0.01647
Image 5	33.9778	1.2606	0.0200	35.8742	1.3125	0.01607
Image 6	33.1249	1.44	0.0220	35.4796	1.4933	0.01682
Image 7	33.7199	1.31	0.0206	35.6103	1.325	0.01657
Image 8	32.9876	1.2887	0.0224	35.1445	1.327	0.01748
Image 9	33.3162	1.203	0.0215	35.6129	1.2284	0.01657
Image 10	32.8491	1.0644	0.0227	35.3206	1.11	0.01713

The trend for the variation in values of PSNR, SNR and RMSE is also shown in graphical form in Figure 3 for better understanding.

In Figure 3, it can be clearly seen that values for PSNR and SNR is greater for every image in NLM method than for anisotropic diffusion method, and value for root mean square error is smaller for every image for NLM method

(a) Root Mean Square Error(RMSE)

(b) Peak Signal to Noise Ratio(PSNR)

(c) Signal to Noise Ratio(SNR)

Figure 3 Graphical representation of Measurement indexes.

compared to that for anisotropic diffusion method. In general, it can be deduced that the results obtained are in compliance with the analytical discussion as well as in accordance with [17]. Further work in direction of qualitative analysis will be carried out in future taking into account necessity and needs of medical practitioners.

5 Conclusion

The findings from the study on anisotropic diffusion and NLM methods, it can be concluded that NLM method is superior and yields better results for ultrasound image despeckling both qualitatively and quantitatively. Further work involving radiologist and clinicians will be carried out to validate results qualitatively and focus on enhancing the NLM algorithm with various variants so as to provide more accurate results for better diagnosis and understanding.

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