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Speckle Noise Reduction in B-mode Ultrasound Imaging

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Abstract - Ultrasound is a widely used and safe medical diagnostic technique, due to low cost and capability of forming real time imaging. The usefulness of ultrasound imaging is degraded by the presence of signal dependant noise known as speckle. In this paper we make use of daubechies wavelet transformation, Wiener and employing an adaptive thresholding technique in order to improve the performance of this denosing approach the log transformed observation is separated into two images. The summation of these two images constructs the despeckled image.

Keywords— DWT, US, TGC, MDWT, MRI

I. INTRODUCTION

ULTRASOUND imaging application in medicine and other fields is enormous. It has several advantages over other medical imaging modalities. The use of ultrasound in diagnosis is well established because of its noninvasive nature, low cost, capability of forming real time imaging and continuing improvement in image quality. It is estimated that one out of every four medical diagnostic image studies in the world involves ultrasonic techniques. US waves are characterized by frequency above 20 KHz which is the upper limit of human hearing. In medical US applications, frequencies are used between 500 KHz and 30 MHz B-modeimaging is the most used modality in medical US. An US transducer which is placed onto the patient's skin over the imaged region sends an US pulse which travels along a beam into the tissue. Due to interfaces some of the US energy is reflected back to the transducer which converts it into echo signals. These signals are then sent into amplifiers and signal processing circuits in the imaging machine's hardware to form a 2-D image. This process of sending pulses launched in different directions is repeated in order to examine the whole region in the body. Thus, US imaging involves signals which are obtained by coherent summation of echo signals from scatterers in the tissue.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 radiologists and 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, especially 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. It should be noted that obstetrics is not the only use of ultrasound. Soft tissue imaging of many other parts of the body is conducted with ultrasound. Other scans routinely conducted are cardiac, renal, liver and gallbladder (hepatic). Other common applications include musculo-skeletal imaging of muscles, ligaments and tendons, ophthalmic ultrasound (eye) scans and superficial structures such as testicle, thyroid, salivary glands,testing in the breast, thyroid, liver, kidney, lymph nodes, muscles and joints. Ultrasound scanners have different Doppler-techniques to visualize arteries and veins. The most common is colour doppler or power doppler, but also other techniques like b-flow are used to show bloodflow in an organ. By using pulsed wave doppler or continuous wave doppler bloodflow velocities can be calculated. [1]

II. BASIC IMAGING SYSTEM

The block diagram (Figure 1) shows the elements of a system: transducer, multiplexer, transmitter and its beam-forming apparatus, transmit/receive (T/R) switches, low-noise amplifier, signal- and image-processing display, audio, A/D converter and its driver, the TGC amplifier. At the current state of the art, machines can employ as many as 256 channels (comprising 256 ceramic elements, amplifiers, ADCs, etc.). The probes will have a ceramic element for each channel (up to 256). The elements are made of a *piezoelectric ceramic material such as lead zirconium titanate. In some designs the* pulses ring in bursts of a few cycles each time they get a short transmit pulse of about 100 ns . The excitation pulse amplitudes will be of the order of 100 V. The magnitude of the pulse will determine the amount of energy beamed into the patient. The signals to be transmitted must pass from the power amplifier to ceramics and the received signal from ceramics to the receiver. Since the 100-V Transmit and microvolt-level Receive signal must pass through the same cable, a T/R switch (transmit/receive) and multiplexer (mux) are required to steer the signals. The beam is focused by delaying each of the channels so that the return pulses from the *focal point (or area)* arrive at the processor at the same time (see Figure 3). The machine will establish the focal area as set by the operator. Beam forming is currently done with both analog and digital techniques. The machine will adjust the delay required for focus in calculating the position of the sweep line. It will compute the corresponding pixels of the display by using the delay required by each channel to focus the image. Newer machines have multiple focus zones. The TGC (time gain compensation) amplifier is a crucial link in the ultrasound signal path. It must have the ability to amplify signalsranging from a few microvolts to 1 volt up to one or two volts for the ADC. This gain will be exponentially increased along each transmit/receive sweep line. At the near end of the wedge, the gain will be very low. It will have to process the 1-V return signal right after the 100-V ceramic excitation pulse. As time after the excitation pulse passes, the gain will be swept into very high levels. This must be done while maintaining very low noise to avoid masking low-level signal coming from deep within the body.[2] The operator will adjust the TGC amplifier control to improve the quality of the image. There are many sources of noise that combine at the input of the ADC, including body tissue, gain stages and cable noise. As the last link in the chain, it is important that the ADC itself have low noise. Its noise must not be confused with the surviving signal coming from the other components. Quantization noise is improved by using higher resolution converters. Many ultrasound designers are concerned with harmonic distortion and artifacts at frequencies close to the fundamental. Unlike a state trooper’s Doppler radar, which deals with a large frequency shift when measuring the velocity of a speeding Honda, the Doppler modes of an ultrasound system measuring the velocity of blood in a vein or artery produce a shift of only a few hertz. In the FFT plot, the areas near the base of the fundamental frequency spike must be very quiet and free of spurious signals, often caused by ADC or system clock jitter, so as not to mask out this shift. Linearity of the converter is also important to the quality of Doppler ultrasound. Once the points have been scanned, they must be displayed. Now consider how the machine places the images on the screen. It will calculate the location of a target on the screen based on the time delays from element to element in the row of ceramics in the hand piece. It judges depth based on how long it took the signal to come back from each ceramic element. The pixel values will be read out of memory and modulate the CRT trace. The machine must compute the location of each point and add color. Perhaps it will average several received scans together. Then it will start the CRT sweep at the top of the fan-shaped display.[3]

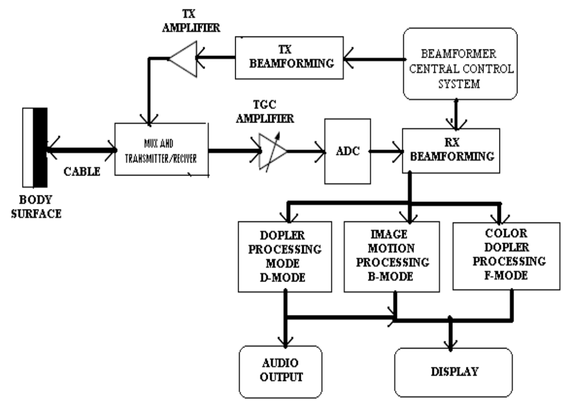

Figure. 1 Block Diagram of Ultrasound imaging system

III. NEED OF DESPECKLING

Speckle in US B-scans is seen as a granular structure which is caused by the constructive and destructive coherent interferences of back scattered echoes from the scatterers that are typically much smaller than the spatial resolution of medical ultrasound system. This phenomenon is common to laser, sonar and synthetic aperture radar imagery (SAR). Speckle pattern is a form of multiplicative noise and it depends on the structure of imaged tissue and various imaging parameters. Speckle degrades the target delectability in B-scan images and reduces the contrast, resolutions which affect the human ability to identify normal and pathological tissue. It also degrades the speed and accuracy of ultrasound image processing tasks such as segmentation and registration.[4] The nature of the speckle pattern can be categorized into one of three classes according to the number of scatterers per resolution cell or the so called scatterer number density (SND), spatial distribution and the characteristics of the imaging system itself. Thus, speckle is considered as the dominant source of noise in ultrasound imaging and should be processed without affecting important image features. The main purposes for speckle reduction in medical ultrasound imaging are: To improve the human interpretation of ultrasound images – speckle reduction makes an ultrasound image cleaner with clearer boundaries. Despeckling is a preprocess step for many ultrasound image processing tasks such as segmentation and registration – speckle reduction improves the speed and accuracy of automatic and semiautomatic segmentation & registration.[5]

IV. DISCRETE WAVELET

Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (also called father wavelet) which generates an orthogonal multiresolution analysis. In general the Daubechies wavelets are chosen to have the highest number *A* of vanishing moments, (this does not imply the best smoothness) for given support width *N=2A*, and among the 2^{A-1} possible solutions the one is chosen whose scaling filter has extremal phase. The wavelet transform is also easy to put into practice using the fast wavelet transform. Daubechies wavelets are widely used in solving a broad range of problems, e.g. self-similarity properties of a signal or fractal problems, signal discontinuities, etc. The Daubechies wavelets are not defined in terms of the resulting scaling and wavelet function M-band wavelet transform is a generalization of dyadic wavelet transform and can generally represent signals better than it. In M-band wavelet system there is one scaling function and *M*-1 wavelets instead of one scaling and one wavelet function in dyadic wavelet system. This means that the expansion of a signal in terms of the M-band wavelet transform involves dilations and translations of *M* basis functions rather than two functions [3]. Note that in dyadic wavelet system, *M* is 2 hence the name 2-band wavelets. In this paper we will consider M-band wavelet systems in which $M = 3$, 4 or 8. Similar to dyadic case, coefficients of MDWT can be calculated through a filter bank which consists of analysis and synthesis filters. For 1-D signals, MDWT filter bank employs *M* analysis filters for each level of decomposition that are one scaling filter 0 *h* and *M*-1 wavelet filters. Now we have down sampling with sampling rate *M* rather than 2 in discrete wavelet transform filter bank. The decomposed signal can be reconstructed through the synthesis part of the filter bank which consists of synthesis filters and up sampling with rate *M*. We can easily exploit one dimensional MDWT for decomposing an image in a separable manner. By applying 2-D MDWT to an image, *M*2 subbands are obtained.

H_0H_0	H_1H_0	H_2H_0	H_3H_0
H_0H_1	H_1H_1	H_2H_1	H_3H_1
H_0H_2	H_1H_2	H_2H_2	H_3H_2
H_0H_3	H_1H_3	H_2H_3	H_3H_3

Figure. 2 Subband regions obtained from one level decomposition of a sample image using 4-band wavelet transform.

Fig. 2 illustrates subband regions obtained from one level decomposition of an image using 4- band wavelet transform. The subband located at the top left corner is a low-passed version of the original image and is called approximation. Other subbands are called details. The procedure of decomposing can be iterated on the approximation subband.[6-8]

V. THRESHOLDING

Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. During the thresholding process, individual pixels in an image are marked as “object” pixels if their value is greater than some threshold value (assuming an object to be brighter than the background) and as “background” pixels otherwise. This convention is known as *threshold above*. Variants include *threshold below*, which is opposite of threshold above; *threshold inside*, where a pixel is labeled "object" if its value is between two thresholds; and *threshold outside*, which is the opposite of threshold inside. Typically, an object pixel is given a value of “1” while a background pixel is given a value of “0.” Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's label'. The key parameter in the thresholding process is the choice of the threshold value (or *values*, as mentioned earlier). Several different methods for choosing a threshold exist; users can manually choose a threshold value, or a thresholding algorithm can compute a value automatically, which is known as *automatic thresholding* A simple method would be to choose the mean or median value, the rationale being that if the object pixels are brighter than the background, they should also be brighter than the average. In a noiseless image with uniform background and object values, the mean or median will work well as the threshold, however, this will generally not be the case. A more sophisticated approach might be to create a histogram of the image pixel intensities and use the valley point as the threshold. The histogram approach assumes that there is some average value for the background and object pixels, but that the actual pixel values have some variation around these average values. However, this may be computationally expensive, and image histograms may not have clearly defined valley points, often making the selection of an accurate threshold difficult. One method that is relatively simple, does not require much specific knowledge of the image, and is robust against image noise, is the following iterative method An initial threshold (T) is chosen, this can be done randomly or according to any other method desired. The image is segmented into object and background pixels as described above, creating two sets: G_1 = {f(m,n):f(m,n)>T} (object pixels) G_2 = {f(m,n):f(m,n) $\leq$T} (background pixels) (note, f(m,n) is the value of the pixel located in the m^{th} column, n^{th} row) .The average of each set is computed. m_1 = average value of G_1 m_2 = average value of G_2.A new threshold is created that is the average of m_1 and m_2 .T' = (m_1 + m_2)/2.Go back to step two, now using the new threshold computed in step four, keep repeating until the new threshold matches the one before it (i.e. until convergence has been reached).[9]

VI. FORMULATION OF PROBLEM

For speckle noise reduction, first we need to model the noise. presented as $f\ x\ y)=g(x,y)\varepsilon m(x,y)+\varepsilon a(x,y)\backslash$ where $g(x,y)$is the noise free image to be recovered, $f(x,y)$ is the noisy image.In order to convert multiplicative noise to additive one we apply the logarithmic transform to both sides of Now, each of the standard noise suppression techniques can be used on this logarithmically transformed image $f\ l$ in order to reduce speckle noise. After doing denoising procedure, by applying the inverse of logarithmic transform a denoised version of the noisy observationis obtained this is known as homomorphic filtering. Now Obtain the RMSE between the denoised image and the original image which is given by:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(u_{ij}-\tilde{u}_{ij})2}{MxN}}$$

After this Obtain PSNR from the RMSE which is used to measure the difference between two images and it is defined by the equation:

$$\text{PSNR} = 20 \log_{10(255/\text{RMSE})\ \text{db}}$$

VII. BASIC FILTERING SYSTEM

Basic filter system consists of wiener filter, wavelet transformation technique and thresholding technique. Our experiments showed that by combining Wiener filtering and thresholding in MDWT domain, better results can be obtained in comparison to using each of these methods (i.e. homomorphic Wiener filtering or homomorphic M-band wavelet filtering) individually. Our proposed algorithm is as follows in Fig. 3): take the logarithmic transform of the observation image which yields another image, generate two images S1 and S2 from *F1* using Wiener filter. Image S1 is the output of Wiener filter and S2 is obtained by subtracting image S1 from F2. Now decompose each of images S1 and S2 into J scales using 2-dimensional MDWT. Then perform an adaptive denoising method on coefficients of images S1 and S2 to suppress the noise. Now apply the inverse of MDWT to these denoised images which yields M1 and M2 the denoised versions of S1 and S2. After this add M1 and M2 . Now apply the inverse of logarithmic transform to the resulted image so as to obtain the final despeckled image which is G1.

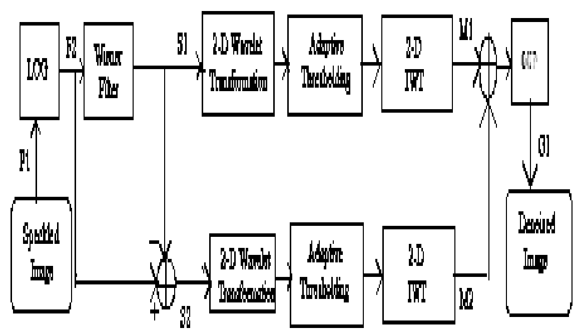

Figure. 3 Basic filtering system

VIII. RESULTS

Basically we increase the PSNR ratio of given image.We calculate the RMSE and PSNR for the medical ultra sound image and compare the meadian filter with the wiener filter the RMSE for the filter image is 0.01 and PSNR ratio is 20db. But our method using winner filtering the RMSE 0.006 and PSNR ratio is 24 db. All images are shown in fig. 4,5,6.

Figure 4: Original image

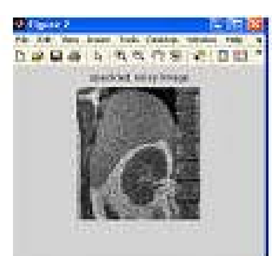

Figure5: Speckled image

Figure6: Despeckled image

IX. CONCLUSION

In this paper we proposed a homomorphic approach for despeckling of ultrasound images in which a combination of Wiener filter and thresholding in discrete M-band wavelet transform domain is used. Three are the main processing stages of our approach. First, similarly to several multiresolution techniques the logarithm of the image is obtained. This step guarantees that the speckle is transformed from multiplicative into additive. In the second step, two images are obtained using Wiener filter: the first image is the output of Wiener filter and the second one is subtraction of this image from log transformed observation. In the third step, both of shows that how the tested methods act on a realistic ultrasound image corrupted with speckle noise. We can easily observe that our proposed method outperforms other ones both in terms of S/mse and visual quality of denoised images. From this figure it is evident that median filter, homomorphic Wiener filter, and these two images are denoised using an adaptive noise reduction method (e.g. *BayesShrink* which we used in this paper). In the final step, the two denoised images are added together and exp-function is then applied to the resulted image. We have presented our experimental results both in terms of quantitative criterions and by illustrating realistic ultrasound images intended for visual comparison. Results show that our algorithm is more effective than other tested methods.

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