Experimental and Theoretical Analysis of Wavelet-Based Denoising Filter for Echocardiographic Images

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Abstract --- One of the most significant features of diagnostic echocardiographic images is to reduce speckle noise and make better image quality. In this paper we proposed a simple and effective filter design for image denoising and contrast enhancement based on multiscale wavelet denoising method.

Wavelet threshold algorithms replace wavelet coefficients with small magnitude by zero and keep or shrink the other coefficients. This is basically a local procedure, since wavelet coefficients characterize the local regularity of a function. After we estimate distribution of noise within echocardiographic image, then apply to fitness Wavelet threshold algorithm.

A common way of the estimating the speckle noise level in coherent imaging is to calculate the mean-to-standard-deviation ratio of the pixel intensity, often termed the Equivalent Number of Looks(ENL), over a uniform image area. Unfortunately, we found this measure not very robust mainly because of the difficulty to identify a uniform area in a real image. For this reason, we will only use here the S/MSE ratio and which corresponds to the standard SNR in case of additivie noise.

We have simulated some echocardiographic images by specialized hardware for real-time application;processing of a 512*512 images takes about 1 min.

Our experiments show that the optimal threshold level depends on the spectral content of the image. High spectral content tends to over-estimate the noise standard deviation estimation performed at the finest level of the DWT. As a result, a lower threshold parameter is required to get the optimal S/MSE. The standard WCS theory predicts a threshold that depends on the number of signal samples only.

I. INTRODUCTION

In many different fields, digitized images are replacing conventional analog images as photograph or x-rays. Especially medical image processing is very important for medical field. Developments in medical imaging over the past decade have produced great advances in the flexibility and diagnostic utility of various modalities. As imaging technology advances, more applications in clinical and research settings are propose.

Ultrasound for medical image is a commonly used modality for cardiac imaging since it is noninvasive and real-time and relatively inexpensive method widely used for imaging soft tissue. However, its inherently poor image quality has consistently hampered attempts to automatically evaluate the cardiac function through spatial analysis of the left ventricular endocardial and epicardial boundaries in two dimensional echocardiographic images. The development of a noise reduction filtering for echocardiographic images is very important for the accurate detection of both heart boundary and movement of heart valves. Compared to other medical imaging methods, ultrasound suffers from lower signal to noise ratios, signal dropout, lower contrast, variable intensity of structures and shadowing of structures. Also Echocardiographic images have a high noise content and suffer from poor contrast. Therefore, in the case of echocardiographic images, the edge detection operation can result in a very ambiguous edge map, containing spurious edge points, missing edge points, and genuine edge points which are not part of cardiac borders. Furthermore, the target borders can have complex and highly variable shapes. Extracting the cardiac borders from the edge map can therefore be extremely difficult.

One approach solving these problems is to base wavelet transform on time-frequency domain filtering. Actually wavelet transform methods are multiresolution representations of signal and images. They decompose signals and images into multiscale details. The basis functions used in wavelet transforms are locally supported. Sharp transitions in images are preserved and depicted extremely well in wavelet expansions. This special treatment of edges by wavelet transforms is very attractive in image filtering. Also the Wavelet transform provided an alternative to the classical Short-Time Fourier Transform or Gabor Transform. The self-adjusting window structure of the Wavelet transform results in a time-scale representation that displays the growth of the spectral components of the signal with varying resolutions. The technique was utilized for the detection and spectral analysis of medical image with amount of noise.

In this paper we describe simple and effective techniques for image denoising and contrast enhancement based on the multiscale wavelet edge representation of images.

II. WAVELET METHODS

Morlet laid the foundations for wavelet signal processing. The theory was subsequently developed by Meyer, Daubechies, Mallat and others. The concepts parallel those of multiresolution signal processing.

The main difference between wavelets and traditional harmonic analysis based on the Fourier transform (FT) is that the latter is a decomposition of the signal onto complex sinusoidal basis functions, which are localized in the time domain. Thus any change to an expansion coefficient will manifest itself as a global effect on the signal once the inverse transform is performed. This effect can be overcome by employing the short time Fourier transform (STFT), which first convolve the signal with a window function *w(t)* so that only a portion of the signal is selected for analysis. This achieves a uniform resolution of the analysis throughout the time-frequency plane. The continuous STFT is given by

$$Xstft(w,\tau) = \int_{-00}^{+00} x(t)w(t-\tau)e^{-jwt}\,dt$$

In contrast, a wavelet transform is performed using a single function h(t), which is localized both in time and frequency. This function can be thought of as a band-pass filter. Fine temporal analysis is done with contracted (high frequency) versions of the wavelet, while fine frequency analysis uses dilated versions of the wavelet. This achieves a constant relative bandwidth for the filters. The continuous wavelet transform is given by

$$Xwt(a,b) = \frac{1}{\sqrt{a}}\int_{-00}^{+00} h^*(\frac{t-b}{a})x(t)dt$$

The multiresoultion wavelet model is applied which shows that the difference of boundary information between two successive resolutions can be computed by decomposing the signal in a wavelet orthonormal basis. This concept of multresolution which gives different information of an image at two different resolutions is particularly useful to texture discrimination in medical imaging. The main advantages of wavelet processing are the basis functions provide localization in both time and frequency domains, fast discrete wavelet transform algorithms are available, it naturally leads to multi-resolution analysis and wavelet filters for specific application can be designed. The disadvantages are the discrete wavelet transform is not translation invarient. The ability or need to select wavelet basis functions for specific applications can be seen as a disadvantage when compared to the Fourier transform, which uses the same basis functions for all applications.

III. SPECKLE NOISE REMOVAL

The physical principle of ultrasound is the emission and reception of high frequency (high speed) sound waves. As ultrasonic waves travel through tissue they reflect at those boundaries where tissue density changes. The energy of the reflected wave is proportional to the differences in the sound impedance of tissue types.

A major disadvantage with ultrasound imaging is the presence of noise, which perturbs feature location and creates artifacts. Methods are needed to suppress this noise without introducing additional artifacts or losing image features. Ultrasound images and volumes contain speckle patterns, which are the result of interference between multiple independent scattering beams and the main reflected signal. This speckle is characteristic of many coherent radiation imaging methods including ultrasound, infrared and laser imaging and synthetic aperture radar (SAR). Its properties have been studied extensively.

A number of methods exist for the removal of speckle. Adaptive low-pass filtering, adaptive median filtering, Crimmins' geometric filter and others manage to remove substantial amounts of speckle, but also tend to over smooth features. Previously, median filters and other filters have been applied to noisy data, but this approach provides no means for detecting noise or filtering locally. Here, an algorithm is introduced that uses wavelet based multiresolution analysis to more effectively remove noise from image data. The time and frequency localization properties of wavelets often allow noise detection in wavelet bands where the signal energy is small, especially when noise is wideband and short duration as impulsive spikes. These properties also allow greater preservation of the desired signal since the data can be processed locally in time and frequency using wavelets.

Donoho and Johnstone have developed a “wavelet shrinkage” algorithm that uses soft thresholding in fine resolution wavelet bands to eliminate Gaussian noise. The soft thresholding technique sets to zero small wavelet coefficients corresponding to Gaussian noise while retaining the larger coefficients corresponding to signal features. The basic idea is that if the signal component is in fact zero, then with high probability the combination of zero signal plus noise should not exceed the threshold level. Given the wavelet coefficients for each scale level, the noisy coefficients can be identified using a variety of criteria. That is a priori knowledge about the noise, visual inspection, application of threshold criterion, or statistical detection. In simplest case, the noise is isolated in frequency. In this case, while the noise could be eliminated through direct application of an appropriate filter to the noisy segment of data, the filter design parameters and the time period over which to apply the filter can be very difficult to determine from the unprocessed data. The noise is often much easier to identify in the wavelet bands, however, and, having performed noise detection using wavelets, noise suppression is achieved simply by changing to zero the values of the noisy wavelet coefficients and reconstructing, thereby eliminating the need for filter design parameters.

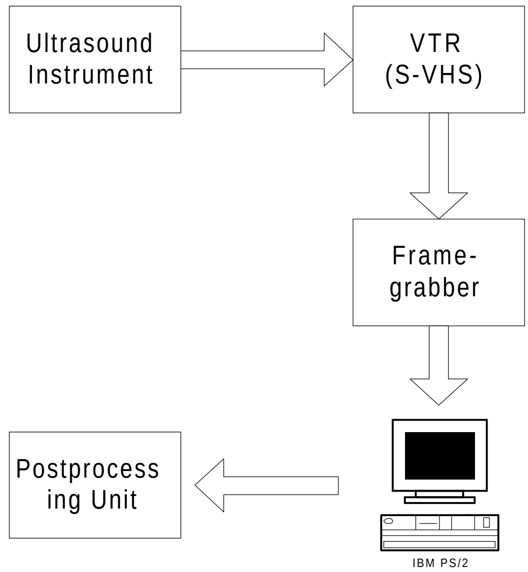
The wavelet transform domain noise filteration technique we are developing is based on the fact that sharp edges have large signal over many wavelet scales, and noise dies out swiftly with increasing scale. Our approach to filtering noise from echocardiograpic images relies on the variations in scale of the wavelet transform data of the signal, but rather than detecting edges directly on the wavelet transform data with a complicated algorithm. Also we use the direct multiplication of wavelet transform data at adjacent scales to distinguish important edges from noise and accomplish the task of removing noise from signals.

At first we apply median filtering to echocardiographic image. A median filter operation on an image removes long tailed noise such as negative exponential and salt and pepper type noise from image with a minimum blurring of the image. The median filter is defined as the median of all pixels within a local region of an image. The median filter performs much better than the arithmetic mean filter in removing salt and pepper noise from an image and in preserving the spatial details contained within the image. This method is particularly effective when the noise pattern consists of strong, spikelike components and the characteristic to be preserved is edge sharpness.

IV. EXPERIMENTAL RESULTS

We acquired data using transducer at medical ultrasound instrument and record those data. Also image data digitized using framegrabber. (Figure.1)

Figure 1. System Block diagram acquiring Images



Compared to proposed filter, we apply Wiener filtration to same image. The Wiener filter, also Known as the Least Mean Square filter, is given by the following expression;

H(u,v) is the degradation function(* indicates complex conjugate) and G(u,v) is the degraded image. The functions Sf(u,v) and Sn(u,v) are the power spectra of the original image (prior to degradation) and the noise. The wiener filter assumes the noise and power spectra of the object a priori. At very low SNR, the wiener filter tends to close its high-frequency passing band.

The wavelet decomposition and noise reduction algorithm were coded in MATLAB and C++. Then

$$F(u,v) = \left[\frac{H(u,v)^*}{\left|H(u,v)\right|^2 + [Sn(u,v)/Sf(u,v)]} \right] G(u,v)$$

it applied to five examples in order to demonstrate the effectiveness of the method. A three-level discrete wavelet decomposition was performed on the echocardiographic image and local thresholding was applied to the wavelet coefficients on the three finest scale levels. Then to detect and eliminate the speckle noise locally at each scale level before reconstructing. Measures that have been proposed to determine the amount of speckle present within an image include the contrast to speckle noise ratio (CSR) of Patterson and Foster, introduced as an attempt to quantify the ability of an observer to perceive anechoic areas against a background of speckle. It measures the image contrast of cylindrical voids in a random scattering medium relative to the contrast fluctuation due to speckle and is given by

$$CRS = \frac{x_o - x_i}{\sqrt{\sigma_0^2 + \sigma_i^2}}$$

Where Xi, and square sigma i respectively, are the average signal value and the variance inside the void and Xo and square sigma o are those outside the region. Then we calculate the CRS in order to compare proposed filtering method to wiener filtering. Those results are presented Table.1.

Some examples of image processing are presented.

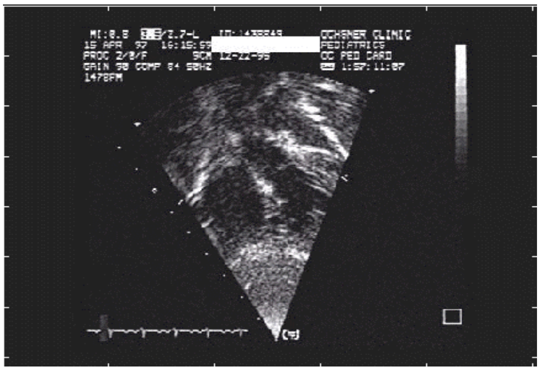


Figure 2. Original image (Echocardiographic image)

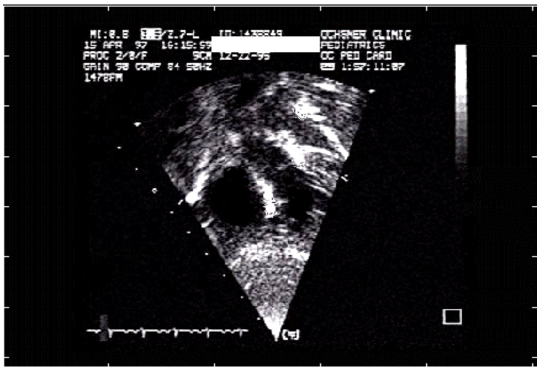


Figure 3. Result of proposed filtering

V. CONCLUSION

In this paper, we apply a nonlinear wavelet algorithm to echocardiographic images in order to enhance the detection of these boundaries. The proposed wavelet filter is superior to the Wiener filter because of its edge and feature-sensitive selectivity in passing certain high-frequency data.

We have tested the technique on several real ultrasound medical images. It is found that the technique can reduce noise contents in signals and images at most edges. Artifacts that arose from the filtration are very small and local. We have compared the performance of the technique to that of the wiener filter and found it to be superior.

Table 1. CSR of both Wiener and proposed filter

Image type	Wiener Filtering	Proposed Algorithm
Test image # 1	4.712	4.932
Test image # 2	6.041	7.442
Test image # 3	6.569	8.017
Test image # 4	4.832	5.677
Test image # 5	5.008	6.320

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