A New Hybrid Technique for Detection of Liver Cancer on Ultrasound Images

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Abstract: ***Liver cancer is the sixth most common malignant tumour in the world. In today's world of lasers, MRI's and high technology, it is very foremost to examine a patient with correct diagnosis. The accurate diagnosis is called the ultimate diagnosis, which is assembled from a list of A diagnosis is very much like a jigsaw puzzle. In this study a new hybrid technique is proposed based on the combination of wavelet and morphological processing. Different Ultrasound images of liver and kidney were taken, and 2 fundamentally different and widely employed image enhancement techniques were applied on these images. The processed images are then analyzed on the basis of Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Energy Factor (PERFL2).***

Keywords: Wavelets, Morphological, Ultrasound

1. Introduction

In this era of technology, every medical discipline attached himself to ultrasound or other medical instruments and benefits itself from this relatively reasonable method that provides a view of the inner organs of the human body without exposing the patient to any radiations [1]. Due to the presence of noisy dots in them, the enhancement of ultrasound images is extremely difficult, especially in case of liver or kidney images whose essential structures are too small to be resolved by large wavelength ultrasound. This type of noise significantly increases the difficulty in discriminating fine details in images during diagnostic analyses. This also elaborates further image processing like edge detection and image segmentation [2].

The detection of focal lesions of varying size and contrast (echo amplitude) from surrounding tissues is a feature of prime importance in the used images. It has been observed that the detection of high-contrast targets is limited by the spatial resolution of the imaging system, whereas, the image speckle limits the detection of features in low-contrast targets [3]. For removing noise and to improve the interpretability or perception of information in images, we proposed an efficient enhancement technique which is combined use of wavelet transform and other morphological operations.

To overcome the limitations of existed techniques such as Shock Filter, Contrast Limited Adaptive Histogram Equalization (CLAHE), spatial filter [4, 5] a new hybrid approach is used. in order to understand the problem of finding information from ultrasound or other type of biomedical images , one have to familiar with the basics of digital image processing especially in case of biomedical images.

2. Enhancement Algorithms

Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. During this process, one or more elements of the image are amended. The choice of elements and the way they are amended are specific to a given task [6]. Enhancement techniques which are commonly used for image analysis and interpretation includes the Spatial filtering, Shock filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), Contrast Stretching, Histogram Equalization, frequency domain filtering, histogram processing, morphological filtering, and wavelet-based filtering [7].

2.1 Wavelet Domain Filtering

Wavelets are mathematical functions that cut up data into different frequency components, and then study all components with a resolution matched to its scale. Wavelet functions are distinguished from other transformations in which they not only dissect signals into their component frequencies, they also deviate the scale at which the component frequencies are examined. So, wavelets as component pieces used to examine a signal which is limited in space. Wavelet transform, due to its splendid localization property, has rapidly become a vital signal and image processing tool for a variety of applications, including denoising and compression [8, 9, 10].

Wavelet denoising attempts to remove the noise present in the signal while preserving the signal attributes, regardless of its frequency content. Wavelet thresholding [8, 9, 10] is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by dispatch coefficients that are insignificant relative to some threshold, and turns out to be easy and effectual, depends heavily on the choice of a thresholding parameter and the choice of this threshold determines, to a great extent the ability of denoising.

2.2 Morphological operations

Morphological operations are based on a form of set of algebra known as mathematical morphology. To examine the geometrical structure of an image, a small pattern, called structuring element, is translated over the image to extract useful information [11]. Morphological image transformations have an intuitive geometrical interpretation, and can be represented by two elementary operators [12] named as erosion and dilation. Mathematically, the dilation of A by B, denoted as A⊕B. Below is an example of dilation process using four and eight neighbors respectively.

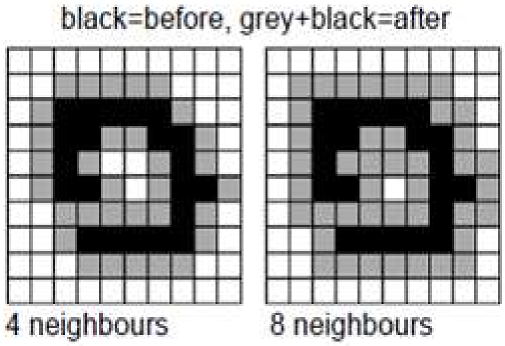

Figure 1: Results after dilation process

Similarly, the erosion of A by B, denoted as AΘB. The result of opening operation is an image in which the bright spots smaller than the structuring elements are removed, while the dark spots are preserved. When we finally subtract this morphologically opened image from the original, we get the so-called top-hat transform. Below is an example of erosion process by using four and eight neighbors respectively.

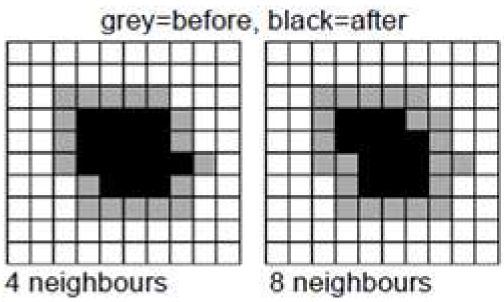

Figure 2: Results after erosion process

3. Experimentation Method

Different original US images of liver and kidney were taken, and 2 fundamentally different and widely employed image enhancement techniques were applied on these images. US images used in this study has been received from a local radiologist. Figure 3 shows the US images of infected Liver and Kidney used for the experimental results.

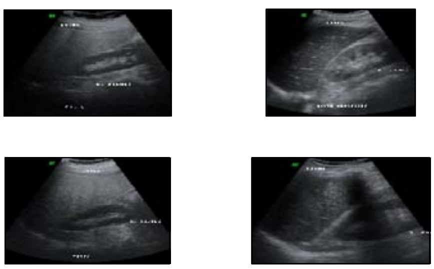

Figure 3: US images of infected Liver and Kidney.

Step one involves the decomposition of image using different wavelets at different levels. Different wavelets work in different way. For example Haar, waveform takes a pixel pair at a time and finds approximation and detail coefficients for each pair. As the level going to increase the number of pixel pairs remained for decomposition will decrease by factor. Debauhies work in same way as haar except the window used for calculating coefficients is increased according to the type used. Below figure 4 is the result after decomposition of Haar at level four.

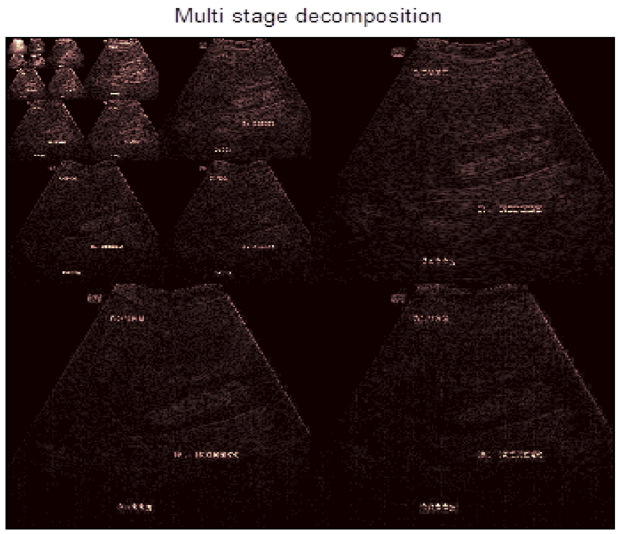

Figure 4: Four level decomposition using haar wavelet

We use 'sym' dwtmode for calculations at boundaries. Dwtmode is discrete wavelet transform extension mode. Dwtmode sets the signal for discrete wavelet and wavelet packet transforms. The extension modes illustrate different ways of handling the problem of border distortion in the analysis. Dwtmode or dwtmode ('status') display the current mode. Dwtmode ('sym') sets the DWT mode to symmetric-padding.

After decomposition, detailed and approximation coefficients are extracted at each level. Approximation coefficients are used at further level for decomposition detailed coefficients are kept for use while reconstruction. As our purpose is to de-noise the image, we applied thresholding to detailed coeffcients to make the noise coefficients null. There are two methods of choosing threshold. One is global and other is adaptive or variable. Global threshold is a single threshold that is applied to all detailed coefficients at all levels while adaptive threshold is uniquely calculated for each detailed coefficient. We used rigrsure method for this.'rigrsure' uses for the soft threshold estimator, a threshold assortment order based on Stein's Unbiased Estimate of Risk. One can evaluate the risk for a particular threshold value (*t*). Minimizing the risks in (*t*) gives a selection of the threshold value.

In step three, reconstruction has been carried out using thresholded detailed coefficients and approximation coefficients. We applied hard and soft thresholding both for global as well as adaptive. Below figure 5 describes outputs when hard and soft thresholding are applied on a signal.

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4. Results and Discussion

Figure 6 shows the original images of ultrasound after denoising step and figure 7 shows the Denoised images using global and variable, hard and soft thresholding.

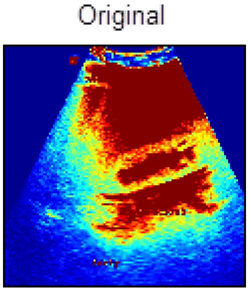

Figure 6: original image

The degradation introduced in watermarked image with respect to original one is determined by using Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) metrics and are given in the Eq. 1 and Eq. 2 respectively:
PSNR=10log10*(R^2/MSE)………… Eq. 1

MSE=I, J [test1(i, j) – denoised(i, j)]2/ i*j ……………………………… Eq. 2

Where R is the maximum fluctuation of intensity in the input image data type. For example, if image has double precision floating point data type then R is 1 and if input image has an 8 bit unsigned integer data type R is 255; and where I and J are number of rows and number of columns in both the test and de-noised image. Other parameter used for comparing the results is energy retained scores PERFL2.

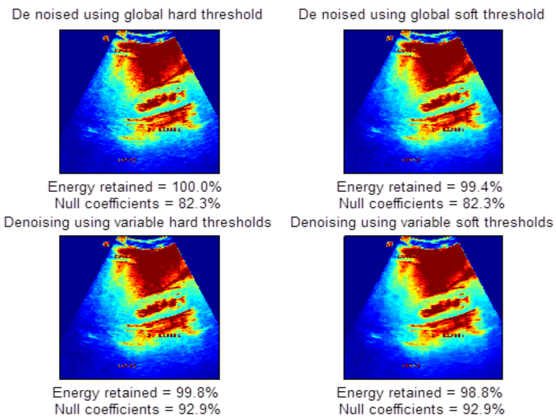

Figure 7: Denoised image using global and variable hard and soft thresholding

PERFL2 = 100 * (vector-norm of WP-cfs of XD / vector-norm of WP-cfs of X)^2. If X is a one-dimensional signal and 'wname' an orthogonal wavelet and PERFL2 is turn down to

$$\frac{100\|XD\|^2}{\|X\|^2}$$

In next step some morphological operations are applied and effected organs are marked with a color. We used dilation and erosion techniques to achieve the output results. Below figure 8 is the resulted output of effected kidney marked as blue using haar waveform.

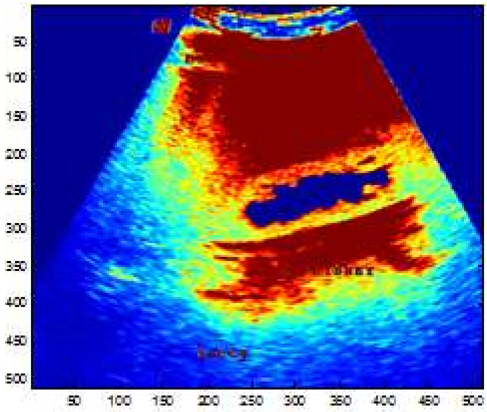

Figure 8: Effected kidney marked as blue

4.1 Performance Analysis

Below are the graphs for all wavelets at level 4. MSE, PSNR and PERFL2 energy score is considered in following graphs.

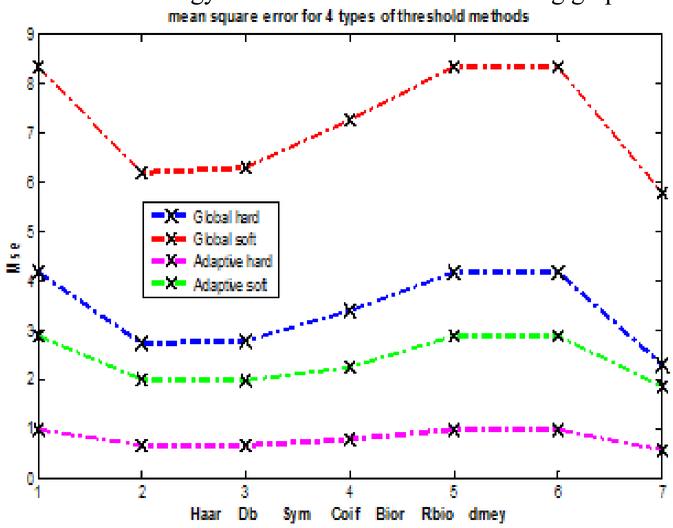

Figure 9: MSE values for using different types of wavelets and using global and adaptive thresholds

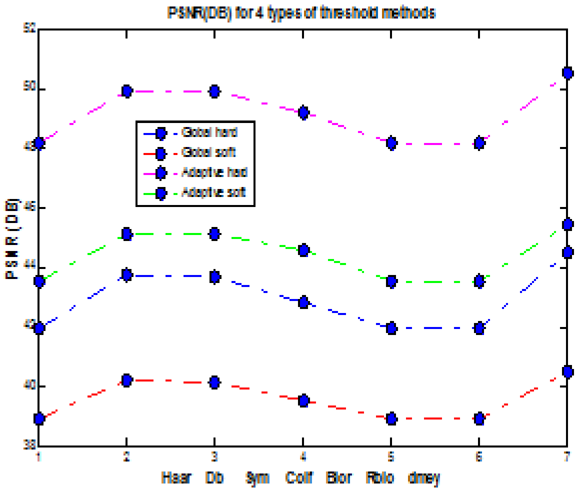

Figure 10: PSNR values for using different types of wavelets and using global and adaptive thresholds

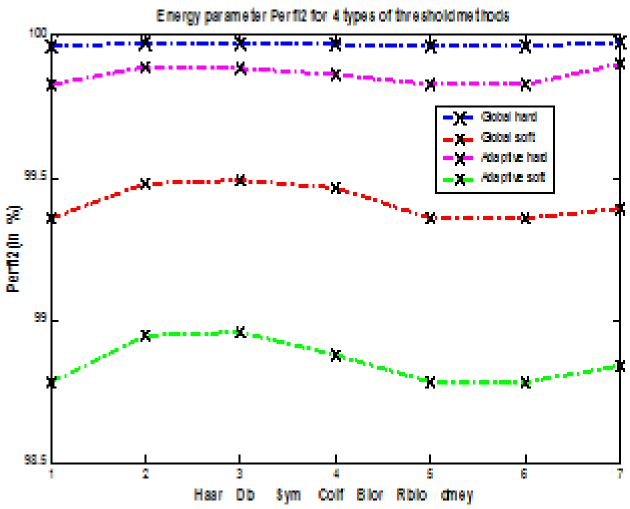

Figure 11: PerfL2 (energy content preserved in output image)

In this proposed algorithm we have compared the results for all the wavelets i.e. haar, db, sym, bior etc.The wavelet domain filter is essentially a spatially varying filter that automatically adjusts itself to the local signal and noise structure. One of the key features of the wavelet transform is that it provides information about how the frequency contents of the signal vary overtime. The approach of wavelet denoising is simple and effective as compared to other filtering techniques.

The DWT method is based on the assumption that the amplitude of spectra of signal is different from that of the noise spectra. In the experiment, soft thresholding has been used over hard thresholding because it gives more Visually pleasant images compared with those hard thresholding: As the latter is discontinuous and yields abrupt artifacts in the recapture images, especially when the noise energy is remarkable. This can be seen in the figure 12 below.

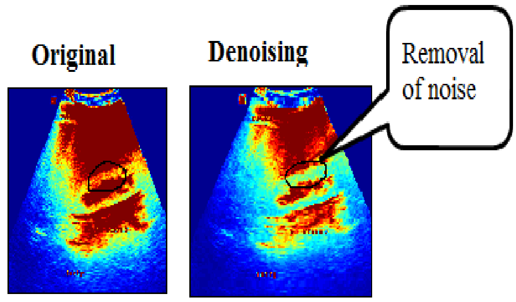

Figure 12: Shows removal of high frequency noise components using wavelets.

As seen from plots in figure 10 and 11, it has been find out that Debauchees wavelet give better results in terms of PSNR as well as energy factor PerfL2. Therefore we applied morphological operations using DB4 wavelet. Dilation and erosion operations of morphological domain are used to highlight infected parts in the image. Below figure 13 is output in case of infected kidney as pointed by the radiologist from where images have been taken.

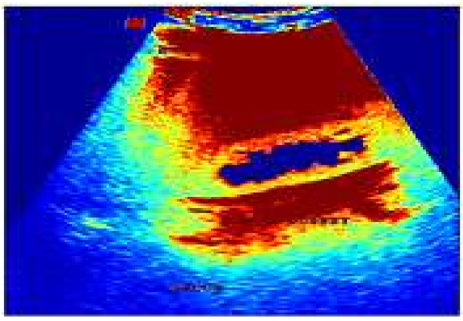

Figure 13: Infected portion has been marked in blue.

5. Conclusion

In this work, we propose a comparative analysis of the performance of different wavelet functions in order to provide a useful guideline for applying wavelet de-noising in medical field. The simulation tests have been carried out using images with different organs, noise levels, and transducer frequency. Medical image quality for each wavelet function has been evaluated using three different metrics: Mean square error, the classical peak signal to-noise ratio and the energy content preservation in the filtered image. After that morphological operations have been applied to mark out the infected portion in the image.

6. Future Scope

The drawback of our work is that we used images for kidney and liver diagnosis and as it depends on special type of disease only. In future, work can be expanded by taking images from different infected organs of the body.

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