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Image Analysis of Kidney Using Wavelet Transform

Carmen Mariana Nicolae and Luminita Moraru

Abstract. Ultrasonography is often preferred over other medical imaging modalities because it is noninvasive, portable, and versatile, it does not use ionizing radiations, and it is relatively low-cost. However, the main disadvantage of medical ultrasonography is the poor quality of images, which are affected by multiplicative speckle noise. Speckle occurs especially in images of the liver and kidney whose underlying structures are too small to be resolved by large wavelength ultrasound. The presence of speckle is undesirable since it degrades image quality and it affects the tasks of human interpretation and diagnosis. As a result, speckle filtering is a critical pre-processing step for feature extraction, analysis, and recognition from medical imagery measurements.

For 2-dimensional B-mode ultrasound images, we use an image enhancement algorithm based on filtering and noise reducing procedures from the coarse to fine resolution images that are obtained from the wavelet-transformed data. A comparative study with other despeckling techniques (median and Wiener filtering), employing quantitative indices and visual evaluation, demonstrated that our method achieved superior speckle reduction performance.

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1. Introduction

Medical images are often deteriorated by noise due to various sources of interferences and other phenomena that affect the measurement processes in imaging and acquisition system. Speckle noise is a random mottling of the image with bright and dark spots, which obscures fine details and degrades the detectability of low-contrast lesions. Speckle noise occurrence is often undesirable, since it affects the tasks of human interpretation and diagnosis. On the other hand, its texture carries important information about the tissue being imaged. Speckle filtering is thus a critical preprocessing step in medical ultrasound imagery, provided that the features of interest for diagnosis are not lost. The small differences that may exist between normal and abnormal tissues are confounded by noise and artifacts, often making direct analysis of the acquired images difficult. Image enhancement techniques are mathematical techniques that are aimed at realizing improvement in the quality of a given image. The result is another image that demonstrates certain features in a manner that is better in some sense as compared to their appearance in the original image.

However, sonography is much more operator-dependent, reading ultrasound image requires well-trained and experienced radiologists. Even well-trained experts may have a high inter-observer variation rate; therefore computer-aided improvement is needed to help radiologists in diseases detection and classification. There are many factors which can disturb the ultrasound image, such as: special speculative reflections, refractions, interferences, attenuation, distortions, non-linear propagation etc.

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There is also the tissue movement, its non-homogeneous structure and even the fluid movement at the vessel level.

The objectives of the present study were to compare quantitative and qualitative ultrasound highly improved images by alleviating speckle noise while enhancing anatomical features, so that the images may be comfortable for the diagnosis. For efficient image enhancement we adopt a multi-resolution approach. For speckle reduction, Wiener filtering [10], median filtering [13], and Wavelet transform [6], [15] are used. Median filtering enhances edges and speckle indiscriminately, while Wiener filter manages to remove considerable amounts of speckle but also tends to oversmooth the boundaries of important image features. Throughout the last decade a new approach in US images denoising emerged based on the wavelet transform. Some of the wavelet-based proposed methods for US image despeckling, are the multiscale non-linear processing method by Hao et al. [9], and the Bayesian wavelet method by Achimet et al. [1].

A wavelet-based method is introduced in this paper for efficient speckle suppression in sonographic images of the kidney. The proposed wavelet approach avoids both log and exponential transform, considering the fully developed speckle as additive signal-dependent noise with zero mean. The proposed method throughout the wavelet transform has the capacity to combine the information at different frequency bands and accurately measure the local regularity of image features.

2. Material and Methods

Utilized a generally used computer (Hewlett Packard 2008) and software (MATLAB 7.1, The Math Works, Natick, USA) to analysis the kidney image.

Wavelets are developed in applied mathematics for the analysis of multiscale image structures. Wavelet functions are distinguished from other transformations such as Fourier transform because they not only dissect signals into their component frequencies but also vary the scale at which the component frequencies are analysed. As a result, wavelets are exceptionally suited for applications such as data compression, noise reduction, and singularity detection in signals. The ability to vary the scale of the function as it addresses different frequencies also makes wavelets better suited to signals with spikes or discontinuities than traditional transformations such as the Fourier transforms. The application of wavelets to medical image enhancement has been extensively studied and starts recently to be applied.

Speckle reduction techniques are classified into three groups: (1) filtering techniques [12], [8]; (2) wavelet domain techniques [11], [7]; and (3) compounding approaches [2].

Most filters are traditional techniques in spatial domain and can be categorized as linear (mean filter) and nonlinear filters. The mean filter [3] replaces each pixel by the average value of the intensities in its neighborhood. It can locally reduce the variance and is easy to implement. It has the effect of smoothing and blurring the image, and is optimal for additive Gaussian noise in the sense of mean square error. Speckled image is a multiplicative model with non-Gaussian noise, and therefore, the simple mean filter is not effective in this case. Order-statistic filters are particularly effective in reducing noise whose probability density function has significant tail. The median filter [12], [3] is a special case of order-statistic filters. It preserves the edge sharpness and produces less blurring than mean filter. Specially, it is effective when image is affected by impulsive noise. Several researchers have experimented with adaptive median filters which outperform the median filters [18], [5]. An adaptive weighted median filter was developed to achieve maximum speckle reduction in uniform areas and to preserve the edges and features [4]. However, this algorithm uses an operator which can cause difficulties in enhancing image features such as line segments. To overcome this drawback, [4] applied a bank of oriented one-dimensional median filters and retained at each point the largest value among all the filter bank outputs. The directional median filter suppresses speckle noise while retaining the structure of the image, particularly, the thin bright streaks.

The discrete wavelet transform (DWT) translates the image into an approximation sub-band consisting of the scale coefficients and a set of detail sub-bands at different orientations and resolution scales composed of the wavelet coefficients [16], [20]. DWT provides an appropriate basis for separating the noise from an image. As the wavelet transform is good at energy compaction, the small coefficients more likely represent noise, and large coefficients represent important image features. The coefficients representing features tend to persist across the scales and form spatially connected clusters within each sub-band. These properties make DWT attractive for denoising. From the structural computation point of view, wavelet denoising involves three stages: (1) calculate the discrete wavelet transform; (2) remove noise by changing the wavelet coefficients; and (3) apply the inverse wavelet transform (IDWT) to construct the despeckled image.

An investigation to choose the best filter solutions for ultrasound images was performed here. Some of the filters existing in Matlab-7.1 software were tested. The criterion used to determine the best filter was the one which optimizes the signal to noise ratio in a broad spectrum of spatial frequencies.

3. Experimental Results

We have been used several methods for removing speckle. First of them is the classical Wiener filter that is not adequate, since it is designed mainly for additive noise suppression. To address this issue, Jain [10] developed a homomorphic approach, which by taking the logarithm of the image, converts the multiplicative into additive noise, and consequently applies the Wiener filter. Also, the adaptive weighted median filter, introduced in [4], can effectively suppress speckle but it fails to preserve many useful details, being merely a low-pass filter.

Figure 1 shows experimental results for a 5 MHz kidney image captured from a convex probe. The images used for the analysis are acquired from scanning systems namely, SLE-401 curvilinear probe with transducer frequency of 5 MHz. Transducers in the range of 6 - 10 MHz are able to detect renal calculi as small as 3 mm. The protection of the renal calculus is based on the presence a of highly echogenic focus with posterior acoustic shadowing of the stone. The main disadvantages of ultrasound are poor visualization of calcifications or obstructing stones in the ureter and lack of assessment of renal function. In order to obtain speckle images, we degraded the original test image by multiplying it with unit-mean random fields. We controlled the correlation length of the speckle by appropriately setting the size of the kernel used to introduce correlation to the underlying Gaussian noise. In practice uncorrelatedness of the noise could be achieved by decimating the image to the theoretical resolution limit of the imaging device. Thus, a short-term correlation obtained with a kernel of size three was sufficient to model reality.

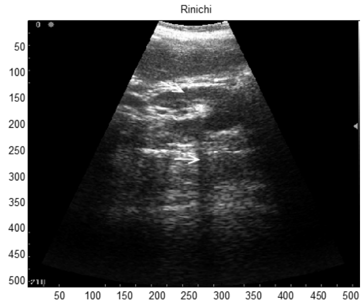

FIGURE 1. Conventional ultrasonography shows a poorly defined low echoic multiple kidney stones (renal calculi). Renal ultrasound demonstrates echogenic focus with an associated acoustical shadow. Such a small stones is easy to be hampered and overlooked by artifacts and speckles.

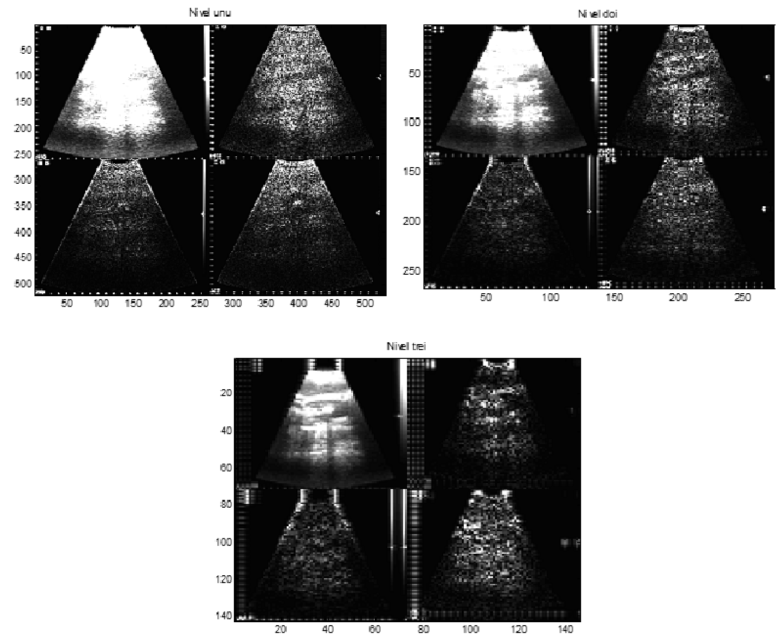

FIGURE 2. Three different levels of simulated speckle noise: image degraded (upper left corner) with simulated speckle noise and details.

We considered three different levels of simulated speckle noise (fig. 2 a-c). In the result from Wiener filtering in Figure 3, speckle is reduced well and structures are enhanced. But some details are lost and some are over-enhanced. Meanwhile, in the result given by Median filtering in Figure 4, speckle is reduced relatively well, but structures are blurred and some visible artifacts are introduced.

Also, both images in Figures 3 and 4 look artificial. Fig. 5 shows that the wavelet transform performs like a feature detector, retaining the features that are clearly

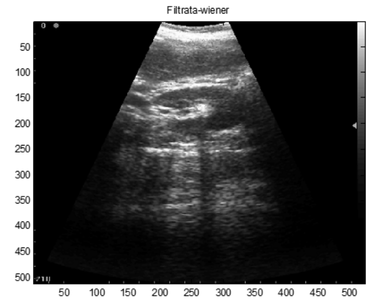

FIGURE 3. Denoised image by the Wiener filtering (area with over-enhanced structure).

FIGURE 4. Denoised image by the Median filtering (blurred structure area).

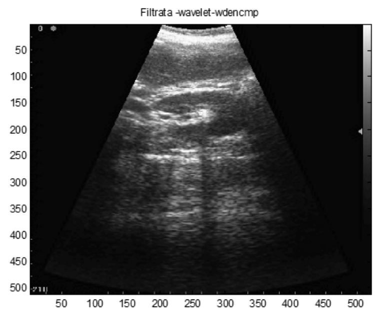

FIGURE 5. Denoised image by the Wavelet filtering The proposed method.

distinguishable in the speckled data but cutting out anything which is assumed to be constituted by noise.

To quantify the denoising performance of the algorithm we employed the follow parameters defined as:

MSE (Mean Square Error)

TABLE 1. Quantitative image enhancement parameters obtained using three denoising methods

	Signal to noise ratio SNR	Peak signal to noise ratio PSNR (dB)	Mean absolute error MAE
Wiener Filtering	24.9139	37.9368	1.6884
Median Filtering	18.5880	31.6108	2.0958
Wavelet filtering proposed method	29.8734	42.8963	1.1022

$$MDE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j) - f'(i,j)]^2 \tag{1}$$

$PSNR$(Peak Signal to Noise Ratio)

$$MDE = 10log\frac{(2^n - 1)^2}{MSE} \tag{2}$$

MAE (Mean Absolute Error)

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j) - f'(i,j)]^2 \tag{3}$$

where original image $f(i,j)$ and denoising image $f'(i,j)$ have resolution MxN pixels.

The results of these experiments are shown in Table1. Such quantitative studies elicit objective results that would not depend on investigators. Depending on the original image, the test value and evaluation are not always correlated with the impression of quality of a subjective observation. The evaluation deals with the PSNR and MAE coefficients of image and SNR. Higher values of SNR imply higher image enhancement. Therefore, this technique better depicts tissue and lesion boundaries, and thus provides more realistic images of tissues and lesions. Moreover, signal-to-noise ratio improvements obtained by wavelet filtering, enhance contrast resolution and may improve lesion conspicuity, and therefore, diagnostic confidence.

Experimental results showed that the proposed method outperformed the median filter by 47,4% and the Wiener filter by 34,7% in terms of the mean absolute error parameter. The numerical values of these quantitative parameters indicated the good feature preservation performance of the algorithm, as desired for better diagnosis in medical image processing.

The visual evaluation is made. The experts suggested that the results produced by the proposed method and the Weiner filter are approximately same from clinical point of view. The performance of median filter is poor than the proposed method from clinical point of view. But from the speckle removal capability point of view, the proposed method performs better than other two methods. It can also be observed from the numeric values of MAE and SNR given in Table 1.

Our study has three advantages. First, we used larger-size 2D data compared (the sample data might represent the entire kidney). Second, the results were expressed numerically, meaning that they are convincingly objective. Third, the method used in the patient study requires no invasive technique and acquisition of the ultrasound data can be done in very short order. On the other hand, our method has a weak point in that the qualitative analysis of the processing ultrasound image requires well-trained and experienced radiologists. So our method can certainly stand further improvement.

4. Conclusion

As diagnosing tool, the conventional ultrasound is a simple method bringing useful information but largely dependent on the examiner. We present an ultrasound image enhancement algorithm based on the wavelet transform. In ultrasound images, the speckle energy is comparable to the signal energy in a wide range of frequency bands. So it is not easy to discriminate speckle from the signal only using magnitude statistics of wavelet coefficients in the decomposed image. In the proposed algorithm, to discriminate speckle from the signal, we obtain the structural information from the wavelet decomposed image. The experimental results show that the proposed algorithm considerably improves the subjective image quality without generating any noticeable artifact, and provides better performance compared with the existing enhancement schemes. Our algorithm was tested and found to be effective for an exact matching of the signal and noise distributions at different scales and orientations. Computerized analysis of the US data objectifies the examination and makes easier and more accurate the early diagnosis of certain diseases which usually provide similar US images. It represents a virtual biopsy, offering a more precise monitoring of the disease evolution, by avoiding as much as possible the harmfulness of invasive diagnostic methods.

Finally, we note that our algorithm could be easily adapted for the purpose of denoising other types of biomedical images.

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(Carmen Mariana Nicolae, Luminita Moraru) Physics Department, University of Galati, 47 Domneasca St., 800008 Galati, Romania
E-mail address: mariana_carmen_nicolae@yahoo.com, luminita.moraru@ugal.ro