Diagnosis of Renal Calculus Disease in Medical Ultrasound Images

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***Abstract*— Ultrasound imaging is used as the primary imaging modality for diagnosis of renal calculus. Speckle noise and shadows present in ultrasound images makes the identification of kidney stones very complex and challenging. Therefore despeckling of ultrasound images is carried out as a preprocessing step. The preprocessing of kidney ultrasound images consists of denoising using wavelet thresholding method Wavelet decomposition is performed on despeckled images and wavelet energy features are extracted for different wavelet families. Further, these features are used by feed-forward, backpropagation artificial neural network for classification of kidney ultrasound image as renal calculi image or normal image. Experimental results demonstrate that the approach is suitable and effective.**

***Keywords*— Kidney stone, Despeckling, Ultrasound images, Wavelets, Neural network**

I. Introduction

Computer-aided medical systems have become widespread recently. These systems are useful in assisting the medical experts for diagnosis and treatment. Kidney stone constitutes one of the commonest diseases. A large population in India is suffering from kidney stone disease and minimum one patient out of 1000 patients is in need of hospitalization because of the kidney stone disease. A worldwide survey shows that a large number of premature deaths may happen every year due to kidney failure only. Detection of the presence of kidney stone at earlier stage is much more beneficial in therapy. The diagnosis usually confirmed by different imaging modalities. Computed tomography (CT) is considered to be the best diagnostic way because of its excellent accuracy. However, ultrasound (US) should be considered as the primary imaging technique. It is a harmless, reproducible and less expensive imaging technique, leading to an accurate diagnosis in most cases without the need for radiation. Ultrasound imaging is one of the important and common modes of diagnosis used by medical experts primarily. Analysis of ultrasound image has a major role in many clinical applications. There are various ways to remove the speckle noise namely median filter, Gaussian filter, Weiner filter, Gabor filters [2,3]. Despeckling of ultrasound images is essential for enhancing the image quality. It helps in separating the boundaries of different tissues lying closer. In [4], authors have proposed the linear elastic theory for finding the pressure in fluid for calculating the depth of shock wave scattering. work is carried out on various types of kidney stones by placing them externally in fluid. In [5] authors have worked on MRI images of kidney. They have used a template based technique for diagnosis of kidney diseases such as tumors, cyst and stone. Authors in [6] have proposed a computer aided diagnostic system for segmentation and classification of kidney ultrasound images using seeded region growing algorithm. Poor contrast is one of the major defects found in recorded images. This may be due to improper lighting conditions, aperture size, shutter size, etc. These defects affect the range and gray level of each pixel. In such cases, contrast can be improved by the operation of contrast enhancement [7]. By the literature survey, it can be observed that there is a very less work carried out in the domain of identification of kidney stone in medical ultrasound images.

This paper is organized into four sections. Methodology is discussed in Section II. Section III has discussions about experimental results and section IV represents the conclusion of the proposed work.

II. Methodology

Identification of renal calculi in medical ultrasound images proposed is shown in Fig 1. Different views of ultrasound kidney images like transverse view and longitudinal view are considered for the implementation and study.

A. Speckle Noise Removal

Medical ultrasound images have many virtues but usually contain speckle noise. The speckle noise arises during image acquisition because of existence of background tissues and other effects such as fat content of body and body movements due to respiration. The speckle may adversely affect the detection of lesion [8]. Speckle in ultrasound images results into poorer resolution as compared with different medical imaging modalities such as MRI, CT, etc. Speckle noise is of multiplicative type. Because of speckle noise, image contrast gets reduced. Therefore it is necessary to remove speckle noise and enhance the contrast of kidney medical ultrasound images without modifying major and important characteristics of the image. We have used the wavelet transform and applied multiresolution analysis to partition an image into various frequency "subbands". Speckle noise can be effectively reduced considering the local statistics in these subbands. The major benefit of the wavelet thresholding technique is that the

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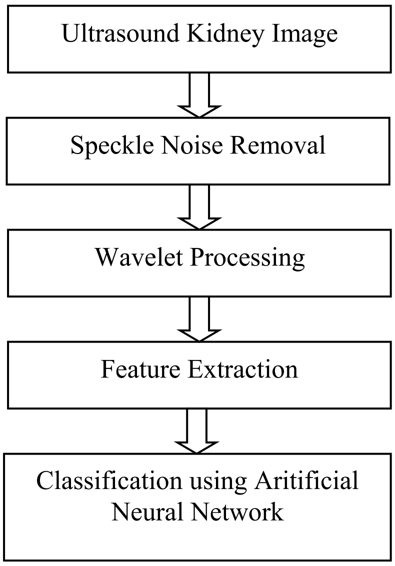


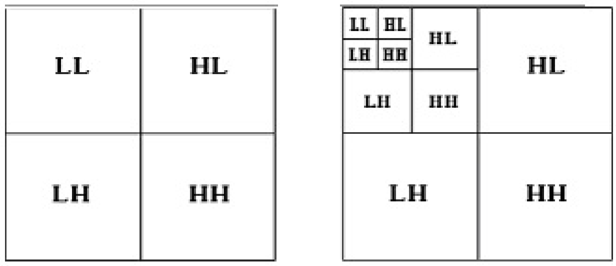
Fig. 1. Block diagram of methodology

image reconstructed after despeckling is lossless in nature [9].We have used soft thresholding technique after finding the wavelet coefficient using discrete wavelet transform (DWT). There are two approaches of thresholding namely, hard and soft thresholding. The hard thresholding denoises by considering the wavelet coefficients of the detailed subbands only without altering the other coefficients of lower resolution. The soft thresholding avoids discontinuities and is more stable than hard thresholding technique [9]. It also avoids the rapid sharp changes of hard thresholding and providing better image recovery.

B. Wavelet Processing

Wavelet is a function of mathematics that partitions a continuous wave into various scale components. Each of these scale components can be assigned with a frequency range and it can be studied with a resolution that matches its scale. A discrete wavelet transform represents a function of wavelets. The wavelets are scaled and translated into a finite-length or fast-decaying oscillating waveforms. Wavelet transform has important applications.

Consider an original image which is represented by a set of sub images of different scales. A two dimensional image is decomposed into four frequency bands, namely, the LL, HL, LH and HH band using wavelet transform, as shown in Fig. 2 (a). The high pass filter is represented by H and L denotes low pass filter. The approximated component (LL) is a result of applying a low pass filter in both row and column directions. The subbands LH, HL, and HH are made high frequency components called detailed images. In further level of decompositions, only LL subband which represents the approximate coefficients is considered for sub division. Fig. 2 (b) shows decomposition at level 3.The energy features of horizontal, vertical, and diagonal details are used as features. There are different families of wavelet filters such as Daubechies, symlets, discrete Meyer, biorthogonal, reverse



(a) (b)

Fig. 2. Wavelet decomposition

biorthogonal and coiflets. The Daubechies wavelets are of orthogonal wavelets family. They define discrete wavelet transform and have a maximal number of vanishing moments. These classes of wavelets use a scaling function that produces an orthogonal multiresolution analysis. There are different orthogonal wavelets such as db1-db20. The index number used as a suffix is a coefficient. The number of vanishing moments is equal to half of the number of coefficients [10]. The polynomial nature of a signal is controlled by vanishing moment. Symlets are the variation of Daubechies wavelets with high symmetry. An orthogonal wavelet is one whose associated wavelet transform is orthogonal. i.e., the inverse wavelet transform is the adjoint of the wavelet transform. If this condition is not true then it is a biorthogonal wavelet. The Meyer wavelet is proposed by Yves Meyer. It is an orthogonal wavelet and infinitely differentiable with infinite support.

C. Multilayer Feed-forward Artificial Neural Network

An artificial neural network (ANN) is a simulator for the central nervous systems or brain organ system of humans. These networks are used to determine the functions that work on a large number of unknown input features. In ANN, artificial nodes called as "neurons" are interconnected to frame a network which looks like a biological network. ANN contains sets of numerical parameters named as adaptive weights that are tuned by a learning algorithm. These adaptive weights are activated during training and prediction. Multilayer ANNs consists of many layers of neurons, are connected together in a feed-forward way. Neuron of each layer is connected with the neurons of the subsequent layer. Many applications use a sigmoid function for activation functionality for the units of these networks. Training of a neural network is choosing one model from the set of different models based on the criteria of minimal cost. The algorithms used for training ANNs are a straightforward application of theory of optimization and estimation using statistics. These algorithms utilize some gradient descent method. Actual gradients are calculated using backpropagation method. This is carried out by taking the derivative of the cost function according to the parameters of network and then varying these parameters in a direction as per the gradient. ANN uses a gradient descent to decreases the mean squared error (MSE) between the output of a network and the required output. These error signals are considered for completion of the weight updates which represent the knowledge gained by the back propagation [11].

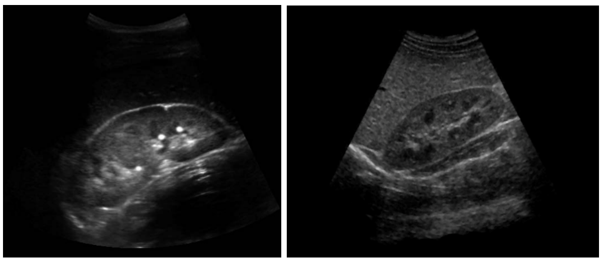
The knowledge base obtained as a result of training phase can be used successfully to classify the unknown input.

III. EXPERIMENTAL RESULTS

Implementation of the proposed methodology is carried out using Intel core i5 system with 4 GB RAM and 2.50 GHz processor. The algorithms are implemented in MATLAB 7.14 software. The image dataset consists of medical ultrasound images of kidney of different sizes and orientations. The images in the dataset are acquired from ultrasound machine with 3.5MHz transducer. All the images are of varying size and converted in jpeg format. The dataset also includes US images of kidney, collected from publically available websites such as http://www.ultrasoundimages.com and http://www.sonoworld.com. The experimentation is carried out on an image set consisting of 19 normal ultrasound images without kidney stones and 13 ultrasound images of kidney with stones. The sample input ultrasound images of kidney are shown in Fig. 3((a) and (b)). Fig. 3(a) shows normal medical kidney ultrasound image. Fig. 3(b) is an example of medical ultrasound image of kidney having multiple stones. Preprocessing of medical ultrasound images of kidney includes speckle noise removal using wavelet thresholding method. We have used level 3, bior6.8 family of wavelet filter. Soft thresholding is performed on obtained wavelet subbands.

The preprocessed medical ultrasound image of kidney is passed through wavelet analysis. A preprocessed image is partitioned into four subbands, approximation subband, horizontal details subband, vertical detail subband and diagonal detail subband (or LL, HL, LH and HH bands) using wavelet transform. The decomposition applied for preprocessed image of Fig. 3(b) is shown in Fig. 4.

Fig 4. shows first level wavelet decomposition of Fig. 3(b) using Daubechies wavelet filter. We have used different wavelet families such as Daubechies (db10), symlets and biorthogonal. The energy features of approximation subband and detailed (horizontal, vertical and diagonal) components are used as features for classification purpose. Energy feature is the measure of uniformity distribution of the intensity level. The higher value of energy indicates the distribution to a small number of intensity levels. Energy can be defined as in (1). In (1), I(x,y) denotes the wavelet coefficient value at the position (x,y). We have calculated energy features for sub bands and experimented with different wavelet families such as symlet,



(a) (b)

Fig. 3. Sample input medical ultrasound images of kidney

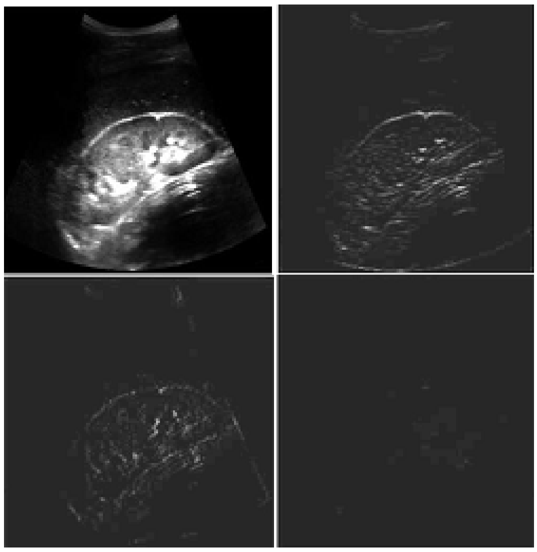


Fig. 4. Wavelet decomposition at level 1

$$\boldsymbol{Energy} = \sum_{x,y} \boldsymbol{I}^2(x,y) \quad (1)$$

Daubechies and biorthogonal for different levels from level 1 to level 4 and extracted energy features. We get 4 features for level 1, 7 features at level 2 (3 energy features from level 1 and 4 energy features from level 2), 10 features at level 3 (3 features at level 1, 3 features at level 2 and 4 features at level 3) and 13 features at level 4 (3 features at level 1, 3 features at level 2, 3 features at level 3 and 4 features at level 4). These features are used by a feed-forward, multilayer backpropagation ANN.

The feed-forward, multilayer backpropagation ANN is used for classification of medical ultrasound images of kidney. 20 images from the dataset are used for training phase. Wavelet energy features are calculated and further classification is performed. Testing is done on all the 32 images in the image dataset. Classification accuracy percentage is calculated by taking the ratio of correctly identified image samples and the total number of samples in testing dataset as in (2).

$$\%\,\boldsymbol{Accuracy} = \frac{\boldsymbol{Correctly\ recognized\ samples}}{\boldsymbol{Total\ number\ of\ samples}} \times \mathbf{100} \quad (2)$$

The percentages of classification accuracy for symlet (sym4) wavelet family at different levels are tabulated in Table I. The percentages of classification accuracy for Daubechies (db10) wavelet family at different levels are tabulated in Table II. The Table III shows the percentages of classification accuracy for biorthogonal (bior3.8) wavelet family at different levels. From Table I, II and III, it is found that the optimal level for wavelet decomposition is level 3, as it gives more accuracy.

TABLE I. CLASSIFICATION ACCURACY FOR THE SYMLET WAVELET

Decomposition Level	Normal Image	Renal Calculi Image
1	47.36%	15.38%
2	0%	100%
3	57.89%	100%
4	52.63%	0%

TABLE II. CLASSIFICATION ACCURACY FOR THE DAUBECHIES WAVELET

Decomposition Level	Normal Image	Renal Calculi Image
1	15.79%	15.38%
2	0%	100%
3	57.89%	100%
4	78.95%	53.84%

TABLE III. CLASSIFICATION ACCURACY FOR THE BIOORHTOGONALWAVELET

Decomposition Level	Normal Image	Renal Calculi Image
1	47.36%	15.38%
2	0%	100%
3	57.89%	100%
4	52.63%	0%

TABLE IV. ENERGY FEATURES FOR DAUBACHES AND BIORTOGONAL WAVELETS AT LEVEL3

Energy Feature	Value	Energy Feature	Value
Ea for db10 at level 3	96.3167	Ea for bior3.8 at level 3	91.4080
Eh for db10 at level 3	0.2628	Eh for bior3.8 at level 3	0.1191
Ev for db10 at level 3	0.7989	Ev for bior3.8 at level 3	1.5011
Ed for db10 at level 3	1.4360	Ed for bior3.8 at level 3	4.0070
Eh for db10 at level 2	0.0508	Eh for bior3.8 at level 2	0.0393
Ev for db10 at level 2	0.1890	Ev for bior3.8 at level 2	0.3268
Ed for db10 at level 2	0.5252	Ed for bior3.8 at level 2	1.7607
Eh for db10 at level 1	0.0180	Eh for bior3.8 at level 1	0.0038
Ev for db10 at level 1	0.1032	Ev for bior3.8 at level 1	0.1114
Ed for db10 at level 1	0.2993	Ed for bior3.8 at level 1	0.7229

We have also experimented with combined energy features of the two wavelet families at different levels. We have considered three combinations such as Daubechies - biorthogonal, biorthogonal - symlet and Daubechies –symlet. Feature values for a sample medical ultrasound image of kidney for db10 and bior 3.8 at level 3 are tabulated in Table IV. There are 20 features altogether. In Table IV, the legends Ea, Eh, Ev and Ed indicate energy of approximate, horizontal, vertical and diagonal components respectively, Classification accuracy obtained is shown in Table V. Classification accuracy for each of these features set are shown in Table V, Table VI and Table VII. Classification accuracy calculated considering all the images of normal and kidney stone images is 93.75%. Table VI shows the classification accuracy considering the energy features of biorthogonal and symlets filters from level 1 to level 4. In this case level 4 is found to be more accurate. Overall accuracy considering entire set of images is 96.88%. This demonstrates the performance of the proposed method and is better compared to the methods already existing [12].

We have considered Type I error (or False Acceptance Ratio) and Type II error (or False Rejection Ratio) also as performance parameters. False Acceptance Ratio (FAR) is calculated as the percentage of recognition of ultrasound images of kidney without stones as images with stones. False Rejection Ratio (FRR) is the percentage of recognition of ultrasound images of kidney with stones as images without stones. FAR and FRR for the module containing combined energy features of Daubechies and biorthogonal wavelets at level 3 is found to be 0% and 10% respectively. FAR and FRR for the module containing combined energy features of biorthogonal and symlet wavelets at level 4 is 5.26% and 0% respectively.

IV. CONCLUSION

We have proposed wavelet based method for classifying medical ultrasound images of kidney. In preprocessing stage, despeckling is carried out. Despeckling of ultrasound images is carried out using wavelet thresholding method. The proposed method shows a total accuracy of 96.88% and can be used effectively in clinical applications for the purpose of image analysis by medical experts.

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