Classification of Medical Ultrasound Images of Kidney

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ABSTRACT
Ultrasonography is considered to be safest technique in medical imaging and hence is used extensively. Due to the presence of speckle noise and other constraints, establishing the general segmentation scheme for different classes of kidney in ultrasound image is a challenging task. This paper aims at classification of medical ultrasound images of kidney as normal and cystic images. In the proposed method, the acquired images are manually cropped to find the region of interest (ROI) of kidney. The cropped images are pre-processed using three different filters namely Gaussian low-pass filter, median filter and Weiner filter to remove speckle noise. The despeckled images are used for extraction of potential texture features that provide tissue characteristics of kidney region in ultrasound images. The Gray Level Co-occurrence Matrix (GLCM) features and run length texture features are extracted. Further, the k-nearest neighbors classifier (k-NN) is used to classify the images as normal and cystic kidney images. The results obtained show that the Gaussian low-pass filter is more suitable for speckle noise removal. The GLCM extracted features are highly significant in classification of kidney images into normal and cystic. The proposed method has the prospect of implementing a computer-aided diagnosis system for ultrasound kidney images. The experimental results demonstrate the efficacy of the method.

Keywords
US kidney image, Texture features, Gray Level Co-occurrence Matrix, k-NN classifier.

1. INTRODUCTION
The ultrasound (US) imaging uses the faster and more accurate procedures in medical diagnosis. It has several virtues like noninvasive, non-radioactive and inexpensive. US has wide spread applications as a primary diagnostic aid of soft tissue organs and carotid artery [1, 2]. In recent years, the potential use of computer-aided diagnosis in the field of medical image processing in general and kidney images in particular has been the interesting area for rigorous research. But, the quality of the US image depends on combination of many factors originating from the imaging system and the knowledge level or experience of the operator. The US image may contain speckle noise due to loss of proper contact or air gap between transducer and body part. The speckle noise can also be formed during beam forming process or signal processing. The speckle may cause the image to be blurred. Hence despeckling is performed prior to the texture feature extraction. The literature on computer assisted approaches to the US kidney image analysis is scarce.

In [3], authors have proposed an automatic region of interest (ROI) generation for kidney ultrasound images. Firstly, the speckle noise reduction was carried out using median filter, Wiener filter and Gaussian low-pass filter. Then texture analysis was performed by calculating the local entropy of the image, continued with the threshold selection, morphological operations, object windowing, determination of seed point and lastly the ROI generation is carried out after removing unwanted background from the US images. In [4], authors have discussed the texture feature extraction by applying a bank of Gabor filters on test image through a two-sided convolution strategy. The texture model is constructed via estimating the parameters of a set of mixtures of half-planed Gaussians using the expectation-maximization method. Using this texture model, the texture similarities of areas around the segmenting curve are measured, in the inside and outside regions, respectively. In [5], authors have proposed a method based on the scale space representation of the evaluation of multi-scale differential principal curvature features which, can be used to determine and measure the extent of isolation between the features of different kidney categories. In [6], authors have proposed a kidney segmentation algorithm using graph cuts and pixel connectivity. A connectivity term is introduced in the energy function of the standard graph cut via pixel labeling. Each pixel is assigned a different label based on its probabilities to belong to two different segmentation classes. The labeling process is formulated according to Dijkstra's shortest path algorithm. In [7], authors have used active shape model, based on a co-variance matrix adaptation evaluation strategy. The genetic algorithm optimizes the pose and main shape variation models of the kidney leads to accurate segmentation.

In [8], authors have discussed a higher order spline interpolated contour obtained with up-sampling of homogenously distributed coordinates for segmentation of kidney region in different classes of ultrasound images. In [9], authors have used Laws' microtexture energies and maximum a posteriori (MAP) estimation to construct a probabilistic deformable model for kidney segmentation. Using texture image features and MAP estimation, each image pixel is classified as inside or outside the boundary. Texture and shape prioris based method is used for kidney segmentation in ultrasound (US) images. In [10, 11], authors have discussed the US image analysis. It becomes complex due to its data composition which is described in terms of speckle formation. The speckle noise consists of gray-level intensities qualitatively ranging between hyper echoic to hypo echoic domain. Inherently the presence of speckle noise restricts the extraction of content descriptive features that reflects functionality of the kidney US image. The reason is that the interpretation of kidney boundary is difficult even with visual inspection by the experts when the speckle noise becomes apparent. Therefore, most of the work in recent years on US kidney images deals with the segmentation schemes to identify the kidney boundary using various methodologies. In this paper, an attempt is made for automatic classification of ultrasound kidney images into normal and cystic type.

The paper is organized into four sections. Section 2 gives the proposed methodology containing details on speckle noise removal, texture feature extraction using GLCM and classification with the k-nearest neighbors classifier. Section 3 describes about experimental results obtained. Section 4 deals with conclusion of the work carried out.

2. METHODOLOGY

In this paper, we have proposed the classification of digital ultrasound image of kidney into cystic and normal kidney image. The various views of ultrasound kidney images are considered for the study. The image set consists of normal and cystic US kidney images. The Fig.1 shows the methodology of proposed algorithm.

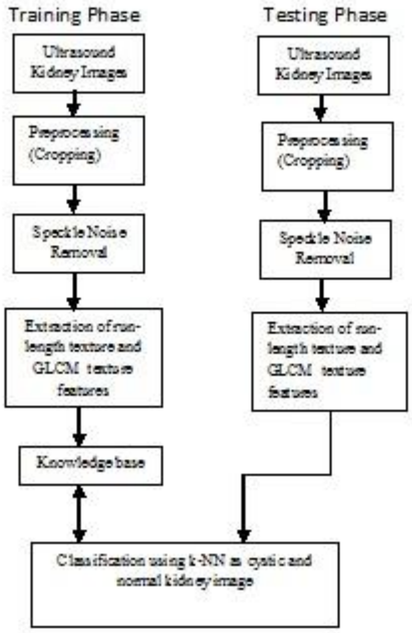


Fig. 1: Block diagram of the proposed methodology

The methodology consists of following modules:

i. Speckle noise removal

ii. Texture feature extraction.

iii. k-NN classifier.

2.1 Speckle Noise Removal

It is very necessary to remove speckle noise from US images without loss of pixel information in the original images. The filtering techniques used for despeckling US kidney images are discussed as follows [12].

i. Gaussian Low-pass Filter

In Gaussian filtering, the smoother cutoff process is used rather cutting the frequency coefficients abruptly. It also takes advantage of the fact that the discrete fourier transform (DFT) of a Gaussian function is also a Gaussian function. The Gaussian low-pass filter varies frequency components that are further away from the image center. So, the filter is more effective in speckle noise reduction of US images.

ii. Median Filter

The median filter is one of the nonlinear filter types. The filtering is performed by replacing the median of the gray values of pixels into its original gray level of a pixel in a specific neighborhood. The speckle noise as well as salt and pepper noise can be reduced by using the median filter. The neighborhoods' spatial extent and the number of pixels involved in the median calculation decides to what extent the noise can be reduced.

iii. Wiener Filter

The Wiener filtering is a linear type of filter. It helps in inverting the blur. Wiener filter removes additive noise. It optimally minimizes the overall mean square error in the process of inverse filtering and noise smoothing.

2.2 Feature Extraction

An image texture is a set of metrics, calculated in image processing, designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image. Texture is one of the important characteristics used in identifying objects or images [13].

The gray-level co-occurrence matrix (GLCM) is also known as the gray-level spatial dependence matrix. It uses a statistical method for examining the texture, considering the spatial relationship of pixels. The GLCM functions are used for finding texture properties of an image by calculating the frequency of occurrence of pixel pairs with specific values and in a specified spatial relationship. The GLCM can be calculated on square matrix of relative frequencies in which two neighboring pixels separated by distance d at orientation q occur in the image, at two different gray levels. This results into a square matrix having the size of the largest pixel value in the image. It enables the representation of the relative frequency distributions of gray levels and describes the frequency of how often one gray level will appear in a specified spatial. The GLCM features –contrast, correlation, energy and homogeneity are calculated. The contrast measures the intensity contrast between a pixel and its neighbor on the entire image. The correlation is used to find a measure of how a pixel is correlated to its neighbor over the whole image. The energy is using the homogeneous region from non-homogeneous regions. It is expected to be high if the frequency of repeated pixel pairs is high. The normalized co-occurrence matrix is denoted by total number of the occurrence of two neighboring pixels between gray-intensity at vertical direction and angle. The homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. The steps involved in the process of feature extraction are represented by Algorithm1.

Algorithm 1: Textural Feature Extraction
Input: Medical ultrasound kidney image.
Output: 23 texture features.
Start
Step 1: Crop the medical US image of kidney to obtain ROI of kidney.
Step 2: Apply log transform to cropped image.
Step 3: Perform despeckling of log transformed image using speckle removal filters.

Step 4: Perform histogram equalization on despeckled image(P).
Step 5: Find the run length features namely, Mean, Variance, Range, Energy, Homogeneity, Maximum Probability, Inverse Difference Moment (IDM) using the Eqs. (1) - (7).

$$Energy = \sum_{x,y} P^2(x,y) \tag{1}$$

$$Homogeneity = \sum x \sum y\ (P(x, y)] / (1 + |x-y|\ )) \tag{2}$$

$$Maximum\ probability = max(P(x,y)) \tag{3}$$

$$\begin{matrix} Inverse\,difference \\ moment \end{matrix} = \sum_{x,y;x \neq y} \frac{P^{\lambda}(x,y)}{|x-y|^k} \tag{4}$$

Where $\mu_x, \mu_y, \sigma_x, \sigma_y$ are standard deviations defined by,

$$\mu_x = \sum_x x \sum_y P(x,y) \quad (5)$$

$$\mu_y = \sum_y y \sum_x P(x,y)$$

(6)

$$\sigma_x = \sum_x (x-\mu_x)^2 \sum_y P(x,y) \quad (7)$$

Step 6: Store the values obtained to in Step 5 as a feature vector.

Step 7: Find gray-level co-occurrence matrices in four directions i.e. for the directions of 0°, 45°,90°,135° and a distance 1 for the image obtained in Step 4.

Step 8: For each matrix calculate contrast, correlation, energy and homogeneity separately using Eqs (1), (2), (8) and (9).

$$Contrast = \sum_{xy} |x-y|^2 P(x,y) \quad (8)$$

$$Correlation = \sum_{xy} \frac{(x-\mu)(y-\mu)P(x,y)}{\sigma^2} \quad (9)$$

where, μ = weighted pixel average and σ = weighted pixel variance.

Step 9: Store the combined feature vector by using the feature sets in Step 5 and Step 8.

Stop.

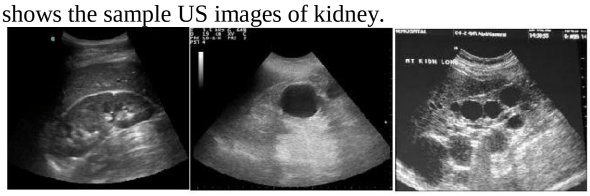
2.3 k-Nearest Neighbors Classifier

The **k-Nearest Neighbors algorithm** (or **k-NN**) is a non-parametric method used for classification in machine learning. The input for the classifier consists of few closest training examples in the feature space. The output obtained from k-NN classifier is a class membership to the nearest in the knowledge base. The classification is carried out on the basis of a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small) then the object is simply assigned to the class of that single nearest neighbor. The training stage of the algorithm is made up of only storing the feature vectors and class labels for the training image samples. The training examples are vectors in a multidimensional feature space, each with a class label.

The classification phase requires a user-defined constant k and an unlabeled feature vector (a query for test). The sample image to be tested is classified by assigning the label which is most frequent among the k training samples and nearest to the query point. The k-NN does not use the training data points explicitly for generalization. The training phase is pretty fast as there is no explicit training. But, the entire training data is needed during the testing phase in contrast to other techniques like Support Vector Machine (SVM) where training can discard all non support vectors without any problem. k-NN makes the decision based on the entire training data set. As the explicit training consumes system time, this becomes an added advantage of k-NN.

3. EXPERIMENTAL RESULTS AND DISCUSSION

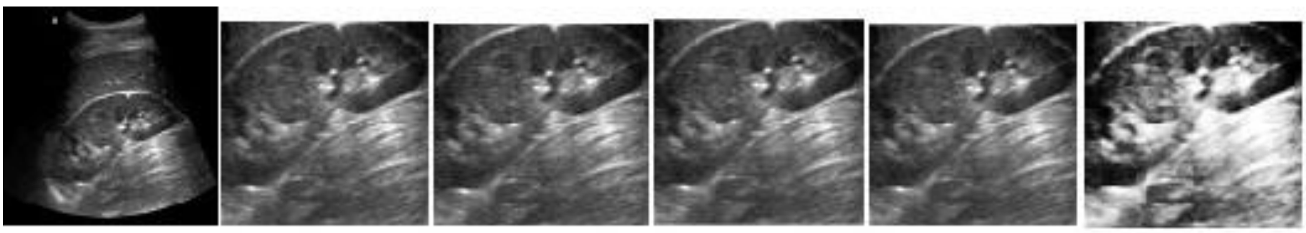
The experimentation is carried out on medical ultrasound images of kidney. The algorithm is implemented on Intel core i5 processor with 10GB RAM using MATLAB 7.11. The datasets D1 and D2 of US images of kidney are prepared in consultation with medical experts namely, radiologist and nephrologist for the present study of classification of kidney images. The images in D1 set are captured by the instrument GE LOGIQ 3 Expert system with 5 MHz transducer frequency, in JPEG format. The images in D2 set are obtained from publicly available websites [www.radiologyinfo.com; www.ultrasoundimages.com]. The data set D1 consists of 08 US kidney images with the size 512X512. The data set D2 consists of 44 US kidney images of different sizes. In total, the data sets contain 25 normal (healthy) kidney images, 19 cystic kidney images and 08 polycystic kidney images. Out of total 44 images, 26 images are used as a training set and the remaining 18 images are used for testing. Testing set additionally consists of 17 images from training set. The Fig.2 shows the sample US images of kidney.



(a) (b) (c)

Fig.2: a) Normal kidney image b) Cystic kidney image c) Polycystic kidney image

Initially, US images of kidney are manually cropped to obtain ROI of kidney in consultation with medical expert. The log transform is performed on cropped images for converting multiplicative speckle noise into additive noise. Further, the different speckle noise reduction techniques namely, Gaussian low-pass filter, median filter and Wiener filter are performed. The Fig. 3 shows the cropped and despeckled images using different filters. From Fig. 3, it is observed that optimal despeckling is found in Gaussian low-pass filter. The size of neighborhood vector 3X3 and empirically determined, standard deviation sigma of 0.3 is used in Gaussian low-pass filter. After despeckling US image, the histogram equalization is applied to identify the maximum of the intensity value. The Fig. 3(f) shows the image after histogram equalization. Further using GLCM 16 texture features are calculated.



(a) (b) (c) (d) (e) (f)

Fig. 3: (a) Original US image (b) Cropped image (c) Gaussian low-pass filtered image (d) Median filtered image (e) Wiener filtered image (f) Histogram equalized image

Four textural features namely, contrast, correlation, energy and homogeneity are calculated for each of the four different directions of 0°, 45°,90°,135° and a distance of 1. From the histogram equalized image, 7 run-length matrix features namely, mean, variance, range, energy, homogeneity, maximum probability and inverse difference moment are found. Finally, combined feature vector consists of 23 features.

The k-NN classifier is used to classify the medical US kidney image into normal and cystic kidney image. Euclidean distance of 3(k=3) is used in our experimentation. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. The working of k-NN can be merely divided into training and testing phase. But, there is no explicit training phase in k-NN.

• Training Phase

During the training phase, we compute the all the 23 features (run length texture features and texture features obtained from GLCM). A class labeling is done for the training image set in consultation with the medical expert. It is stored as a knowledge base.

• **Testing Phase**

During the testing phase, we compute both run length and GLCM texture features for the image to be classified. The k-NN classifier classifies the test image as normal kidney or cystic kidney image using knowledge base.

Table1. Experimental Results for Classification Percentage of the Proposed Method

Data sets	**D1**	**D2**
Classification Accuracy Rate	84%	87.5%
Type I Error (FAR)*	9.52%	20%
Type II Error (FRR)**	21.7%	0%

***Type I Error:** Image is detected as cystic, but is not a cystic.
****Type II Error:** Image is not detected as cystic, but is a cystic.

From experimentation, it is found that the average classification percentages for normal and cystic kidneys are 89% and 80% respectively, when both D1 and D2 are taken into account. The Table1 shows the comparison of experimental results of the proposed method. The percentage of accurate classification for data sets D1 and D2 is 84% and 87.5% respectively. However, the false acceptance rate (FAR) is 9.52% and 20% for data sets D1 and D2 respectively and false rejection rate (FRR) is 21.7% and 0% for data sets D1 and D2 respectively.

The results of the proposed method are compared with the method discussed in [3]. In [3], Authors have proposed the automatic ROI of kidney, assuming that all the kidney images were taken with the kidney is almost at the centre of the image. But, we have considered various views of US images of kidney, having the kidney organ at different positions like left, right, top and centre of US image. Further GLCM and run-length texture features are extracted from the cropped images. Then k-NN classifier is used for classification.

4. CONCLUSION

In this paper, a method for classification of ultrasound kidney images as normal and cystic kidney images is proposed. Despeckling of US images is tested using three different filters like Gaussian low-pass filter, median filter and Wiener filter. The results show that Gaussian low-pass filter is optimal. The texture is one of the important characteristics used in identifying objects or images. So, run length textural features and texture features extracted from GLCM, used for k-NN classifier. The proposed method shows that the average classification percentages for normal and cystic kidneys are 92% and 85% respectively. From the literature review it is observed that, most of the methods are concentrated on segmentation only. We have extended segmentation method to texture feature extraction and classification. The proposed scheme explores various possibilities in implementing specific computer aided diagnosis system for US kidney images.

5. ACKNOWLEDGMENTS

The authors are thankful to Dr. Vinay Kundaragi, Nephrologist, Sanjeevini Hospital, Bijapur for rendering manual segmentation of images. The authors are also thankful to Prema Scan Centre, Bijapur for providing the image dataset. The authors are also thankful to the reviewers for their valuable suggestions.

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