Design and Analysis Performance of Kidney Cyst Detection from Ultrasound Images

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Abstract - The research presents a system which is mainly pointing to the analysis of kidney and its abnormality as a cyst. The main goal of research is classification of ultrasound (US) kidney image as normal kidney or cystic one. The system with trained template is developed and user's sample tests are verified from it. Ultrasound images contain a noise called speckle noise. It is multiplicative noise and it is introduced due to signal modification at the time of capturing an image. US images also suffers by low contrast. These issues are sorted out using filter technique and histogram equalization method. The pre-processed image is segmented using Gradient Vector Flow (GVF) and from it region of interest is identified. 22 features of an image are extracted and these features are trained by feed forward Artificial Neural Network (ANN) to identify the class of kidney (i.e. normal or cyst). In order to analyse the systems functionality, it is tested on a dataset of ultrasound images of two classes. The analysis performance is based on two parameters first is accuracy and second is precision, which results in 87.5% and 100% respectively.

Index terms - US kidney images, Speckle noise, GVF, ANN.

I. INTRODUCTION

The world is increasingly suffering from various kidney diseases. Many of the people do not notice symptoms in its earlier phase but it starts to damage kidney slowly. Hence, early detection and prevention is become need of such patients. Now days many diagnosis techniques are available in the medical field. Every technique has importance according to severity of disease at particular time. But Ultrasound imaging technique is extensively used as an initial evaluation or as primary diagnosis aid. In Ultrasound imaging, image is obtained by passing high frequency sound waves through the human body. The echoes of reflected sound wave are recorded and displayed as a real time visual image. Ultrasound imaging is radiation free and portable. It is also faster, economical; non-invasive which makes this method very popular. Estimation of kidney size and position, and diagnosing structural abnormalities as well as presence of cysts can be done with the help of US images.

Several techniques are applied for identification of organ as well as its abnormalities. Emmanouil Skounakis [1], the author has proposed multifunctional platform focusing on the kidneys and their pathology using "templates" based technique. For that initially specialist clinician has to train the system by giving comment on the kidneys and their abnormalities, then, medical technicians experimentally adjust rules and parameters (templates) for the integrated "automatic recognition framework" to achieve results which are closest to those of the clinicians. These parameters can later be used by non-experts to achieve increased automation in the identification process. The functionality of system was tested on 20 MRI datasets (552 images) and results are most promising as they yield an average accuracy of 97.2% in successfully identifying kidneys and 96.1% of their abnormalities. J. K. Viswanathand, R. Gunasundari [2] these authors have focused on the abnormalities of the kidney which can be identified by ultrasound imaging. The kidney may have structural abnormalities like kidney swelling, change in its position and appearance. Kidney abnormality may also arise due to the formation of stones, cysts, cancerous cells, congenital anomalies, blockage of urine etc. In preprocessing, first image restoration is done to reduce speckle noise then it is applied to Gabor filter for smoothening. Next the resultant image is enhanced using histogram equalization. The preprocessed ultrasound image is segmented using level set segmentation, since it yields better results. To identify the type of abnormality, these energy levels are trained by Multilayer Perceptron (MLP) and Back Propagation (BP) ANN. R. Prevost [3], has presented a method to segment the kidney in 3D contrast-enhanced ultrasound (CEUS) images. This modality has lately benefited of an increasing interest for diagnosis and intervention planning, as it allows visualizing blood flow in real-time harmlessly for the patient. This method is composed of two steps: first, the kidney is automatically localized by a novel robust ellipsoid detector and then, segmentation is obtained through the deformation of this ellipsoid with a model based approach. To cope with low image quality and strong organ variability induced by pathologies, the algorithm allows the user to refine the result by real-time interactions. This method has been validated on a representative clinical database. Prema T. Akkasaligar, SunandaBiradar [4], have aims on classification of medical ultrasound images of kidney as normal and abnormal 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 de-speckled images are used for extraction of potential texture features that provides tissue characteristics of kidney region in ultrasound images. The Gray Level Co-occurrence Matrix (GLCM) features and run length texture features are extracted. Further, authors have used the k-nearest neighbour classifier (k-NN) to classify the images as normal and abnormal kidney images.

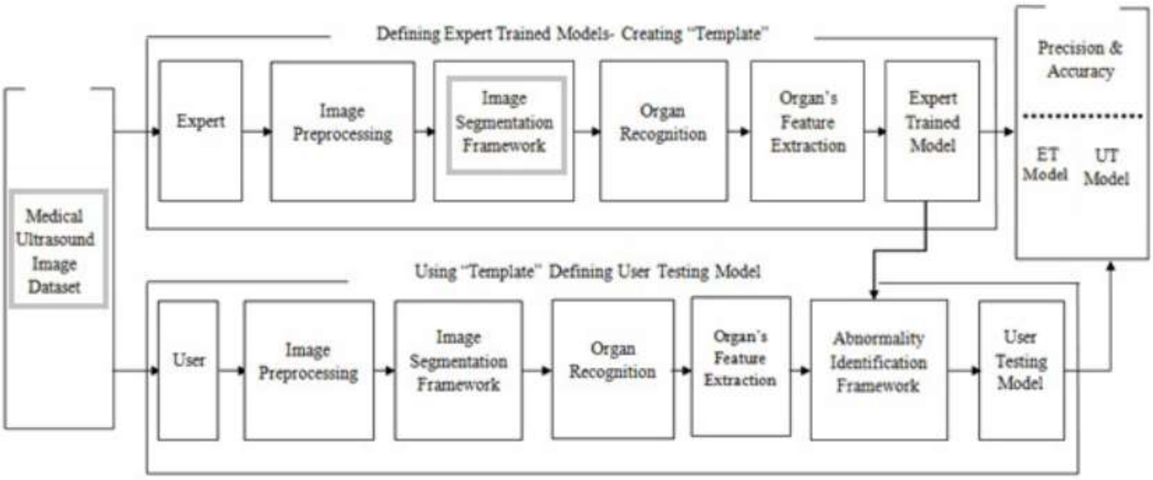


Fig.1. *System Architecture*

This research presents the system which satisfies the following objectives:

1. Identification of abnormalities of kidney using Ultrasound images is essential as a primary step of diagnosis, as it is cost effectivemethod than MRI.
2. The main goal of this research is to classify the normal kidney and cystic kidney from ultrasound kidney images.
3. To determine more accurate classification method.

II.METHODOLOGY

The functionality of the system is carried out with the help of two models:

1. Defining "Expert Trained model" template
2. Defining "User Testing Model" template:

The above specified both templates have to perform following modules:

1. Image Preprocessing

The Ultrasound image contains speckle noise and low contrast which creates difficulty while diagnosing abnormalities if any. The captured image is an echo of sound waves that generated at the time of diagnosis by transducer. To reduce this speckle noise and to enhance contrast, US image should be preprocessed.

i. Reduction of Speckle Noise:

In order to overcome issue of speckle noise, several different filtering methods [6, 7] are used which are also based upon different mathematical models. Here Gaussian low pass filter is used to resolve the issue of speckle noise. It has the bell-shaped distribution.

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}} \qquad (1)$$

where, σ in the equation (1) is the standard deviation of the distribution, and also the degree of smoothing. The larger the value of σ, the filtered image is smoother.

ii. Contrast Enhancement:

Ultrasound images are grey scale images and also have low contrast. To overcome this issue histogram equalization method is used. In whichintensity range of image pixels are transformed in such way that the histogram of the output image and specified histogram get matches. So the goal of histogram equalization algorithm is to find gray level transformation. Histogram equalization redistributes the intensity distributions based on a statistical process that has proven to be really effective.

Algorithm:

- Choose an image 'im' which is original image with low contrast.
- Image is passed as an input to histeq() function which works as follows:
  It enhances the contrast of images by transforming the values in an intensity image so that the histogram of the output image approximately matches a specified histogram (uniform distribution by default).
- To minimize $|c_1(T(k)) - c_0(k)|$where c_0 is the cumulative histogram of A, c_1 is the cumulative sum of hgram for all intensities k, histeq chooses the greyscale transformation T. This minimization is subject to the constraints that T must be monotonic and c1(T(a)) cannot overshoot $c_0(a)$ by more than half the distance between the histogram counts at a. The transformation used by histeq is b = T(a) to map the grey levels in X (or the colormap) to their new values. $c_0(a)$ by more than half the distance between the histogram counts at a.
- The transformation used by histeq is b = T(a) to map the gray levels in X (or the colormap) to their new values.

(a) (b) (c)

Fig. 2. *Kidney Images as*
(a) Original Image, ***(b)*** Filtered Image ***(c)***Enhanced Image

- Result of implementation after applying Gaussian filter to an original image is as shown in Fig 2(a). An Ultrasound (US) image is passed to Gaussian Filter to reduce speckle noise and output is the filtered image shown in Fig 2(b), which is passed for enhancement and resultant image is with high contrast as shown in Fig 2(c).

2. Image Segmentation Framework

In the image processing, segmentation is the process of separating a digital image into multiple parts which helps to analyse an image more efficiently and easily. At present, the segmentation method is widely used in the clinical application of ultrasound imaging systems. Preprocessed image is input for segmentation. The active contour model is the traditional snake model which is popular in applications like edge detection, shape recognition, object tracking etc.

In the present research, Gradient vector flow (GVF) snake is an extension of the well-known method snakes or active contours. The difference between traditional snakes and GVF snakes consists in that the latter converge to boundary concavities and they do not need to be initialized close to the boundary [10].

The original snake v is a two dimensional dynamic contour defined parametrically as v(s) = [x(s), y(s)], where s ∈ [0, 1] that minimizes the energy function:

$$E = \int_0^1 E_{int}\big(v(s)\big) + E_{image}\big(v(s)\big) + E_{con}\big(v(s)\big)ds \qquad (2)$$

Where E_{int} represents the energy of the contour due to bending, the E_{image} represents the energy due the intensity of the image and E_{con} is a constraint energy established by a high-level process or the user.

- First step is to find the edge Map. In order to get the GVF field, it needs to extract the edge map function f (x, y) from the image I (x, y).

- Second step is to find the GVF field,$g(x, y) = (u(x, y) + v(x, y)$, is defined as the equilibrium solution that minimizes the energy function.

- Third step is after obtaining the GVF field g(x, y) and substituting as the energy constraint Econ on equation (2), the snake can be computed iteratively.

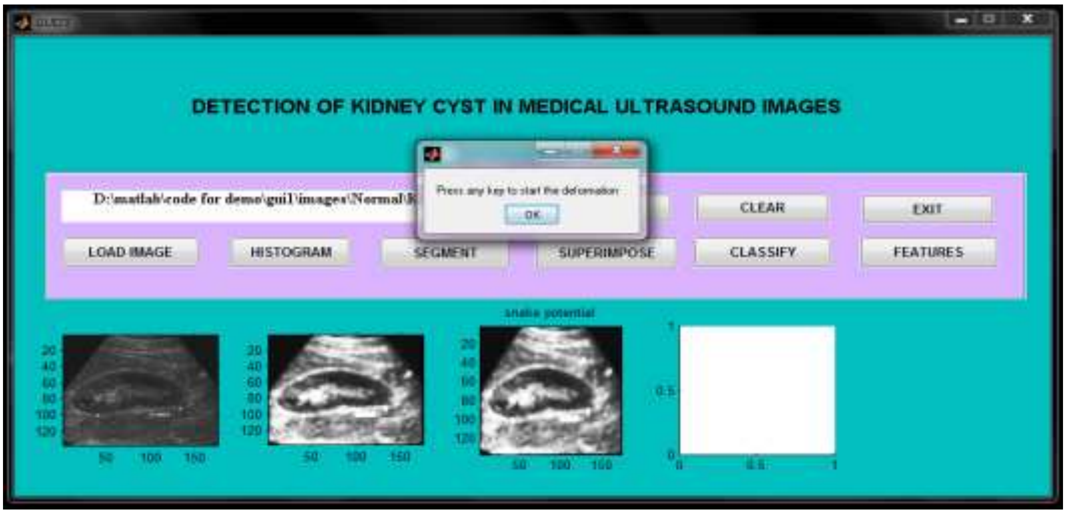
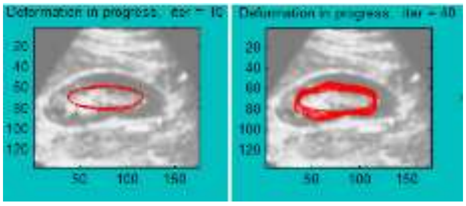


Fig. 3. *GUI for detection of kidney cyst*



(a) (b)

Fig. 4. *Segmentation of Kidney Images*
(a) After 10 iterations, ***(b)*** After 40 iteration

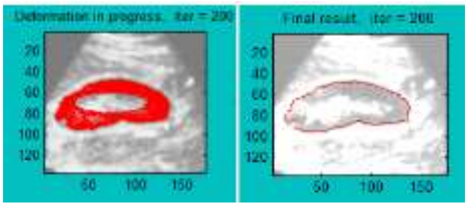


Fig. 5. *Segmentation of Kidney Images*
(a) After 200 iterations, ***(b)*** Final Result

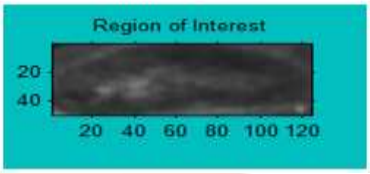


Fig. 6.*Identified ROI Image*

3. Organ's Feature Extraction

As shown in Table 1, the GLCM texture features are extracted and following notations are used:

N_g is the number of gray levels used.
μ is the mean value of P.
μ_x, μ_y, σ_x and σ_y are the means and standard deviations of P_x and P_y.
P_x is the i^{th} entry in the marginal-probability matrix obtained by summing the rows of P(i,j).

Table 1. GLCM Features

Feature Index	**Feature**	**Formula**
F1	Autocorrelation	$F1 = \sum_i \sum_j (i \times j)\, P(i,j)$
F2	Contrast	$F2 = \sum_n n^2 \left\{ \sum_i \sum_j P(i,j) \right\}$
F3	Correlation	$F3 = \frac{\sum_i \sum_j (i \times j) P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
F4	Cluster prominence	$F4 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^4 P(i,j)$
F5	Cluster shade	$F5 = \sum_i \sum_j (i + j - \mu_x - \mu_y)^3 P(i,j)$
F6	Dissimilarity	$F6 = \sum_{i,j} \lvert i - j \rvert P(i,j)$
F7	Energy	$F7 = \sum_i \sum_j P(i,j)^2$

F8	Entropy	$F8 = -\sum_i \sum_j P(i,j)\, log(P(i,j))$
F9	Homogeneity	$F9 = \sum_i \sum_j \frac{1}{1+(i-j)^2} P(i,j)$
F10	Maximum probability	$F10 = \max_{i,j} P(i,j)$
F11	Sum of squares/ variance	$F11 = \sum_i \sum_j (1-\mu)^2 P(i,j)$
F12	Sum of average	$F12 = \sum_{i=2}^{2N_g} i \times P_{x+y}(i)$
F13	Sum of Variance	$F13 = \sum_{i=2}^{2N_g} \left(1 - \left(\sum_{i=2}^{2N_g} iP_{x+y}(i)\right)\right)^2 g_{x+y}(i)$
F14	Sum of entropy	$F14 = -\sum_{i=2}^{2N_g} P_{x+y}(i)\, log\{P_{x+y}(i)\}$
F15	Difference in variance	$\mathrm{F15} = \mathrm{Variance}(\mathrm{P}_{x-y})$
F16	Difference in entropy	$\mathrm{F16} = -\sum_{i=0}^{N_g-1} \mathrm{P}_{x-y}(\mathrm{i}) \log\{\mathrm{P}_{x-y}(\mathrm{i})\}$
F17	Information measure of correlation	$\mathrm{F17} = \frac{\mathrm{HXY} - \mathrm{HXY1}}{\max\{\mathrm{HX}, \mathrm{HY}\}}$
F18	Inverse difference moment normalized	$\mathrm{F18} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{P(i,j)}{1+(i-j)^2} i$

For the generated region of kidney (as shown in Fig 6), needs to extract the texture features. For the extraction of features first it is needed to create grey level co-occurrence matrix (GLCM) by calculating how often a pixel with gray-level (grayscale intensity) value i occurs horizontally adjacent to a pixel with the value j [8].

After clicking FEATURES button, features get extracted and stored as matrix (GLCM.mat) of 22 x 1 which is saved as Excel file.

For each samples of different class image, above features are computed and stored in the data base feature vector as GLCM features. Therefore these features are used at the time of classification stage.

4. Abnormality Identification Framework

After successful extraction of all features of some number of images it is considered as Expert Trained Model and remaining number of images are considered as User Testing Model. So we can elaborate it as follow:

Expert Trained Model (Template): Texture features need to extract from the segmented images. Then extracted features of various images need to maintain as record which will be considered as an Expert Trained Model. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, i.e. training class, is created.

User Testing Model: After feature extraction of image, these features will be given as input to Abnormality Identification Framework to classify the kidney ultrasound images as normal kidney or cystic kidney. Result will be considered as User Testing Model.

This identification framework classify dataset using ANN feed forward neural network.

Feed-forward neural networks, where the data flow from input to output units is strictly feed-forward. The data processing can extend over multiple (layers of) units, but no feedback connections are present, that is, connections extending from outputs of units to inputs of units in the same layer or previous layers.

As shown in Fig 7 and Fig 8 ANN builds network in order to train specified number of samples and this trained network is then used against test sample for classification which results in identification of abnormality i.e. cyst in an Ultrasound image.

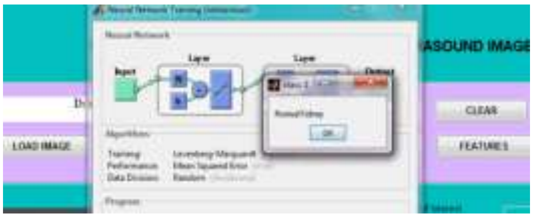


Fig. 7.*Test sample detected as Normal Kidney (i. e. Y=1)*

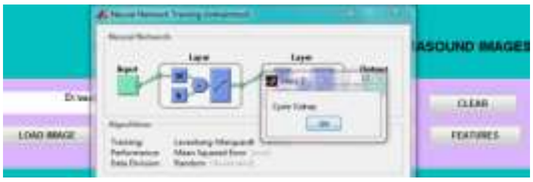


Fig. 8.*Test sample detected as Cystic Kidney (i. e. Y=0)*

III.RESULTS AND DISCUSSION

- *Training Phase:*

In this phase, 22 extracted GLCM features are of 70% images of the total number of images i.e. (18 out of 26 total images) are considered as knowledge database.

- *Testing Phase:*

In this phase, image get classified using knowledge database which is trained in Training Phase. In order to find out accuracy and precision of test images, 8 sample images are considered and following table shows details.

Table 2 Experimental Results

Data set	**D1**
Accuracy	87%
Precision	100%
Type I Error (FAR)*	12.5%
Type I Error (FRR)**	0%

**Type I Error:* It is the incorrect rejections of a true null hypothesis (a "false positive"). It occurs when the null hypothesis is true, but is rejected. Type I error is the (false) detection of an effect that is not present, i.e. image is detected as normal, but it is a cystic.

***Type II Error:* It is incorrectly retaining a false null hypothesis (a "false negative"). It occurs when the null hypothesis is false, but erroneously fails to be rejected. Type II error is the failure to detect an effect that is present, i.e. image is detected as cystic, but is a normal.

The Table 2 shows the percentage of accurate classification for a dataset is 87%. However, the false acceptance rate (FAR) is 12.5% and false rejection rate (FRR) is 0%

Table 3 shows an order to find out accuracy and precision, features of dataset sample considered in following ratio:

Table 3 Analysis of dataset with 4 types Train-Test Ratio

Train-Test Sample Ratio	**TP**	**TN**	**FP**	**FN**	**Accuracy (%)**	**Precision (%)**
80-20	2	2	0	0	100	100
70-30	4	3	0	1	87.5	100
60-40	5	3	2	0	80	71
50-50	4	5	2	1	75	65

The work has carried out for normal and cystic kidney ultrasound images. It can beextend for other kind of abnormalities like kidney stone as well as other organs of humanbody like liver, lungs etc. In this work for classification feed forward method is used, theother classification methods can be applied for the same.

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