FPGA based Preliminary CAD for Kidney on IoT Enabled Portable Ultrasound Imaging System

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Abstract-Ultrasound imaging has been widely used for preliminary diagnosis as it is non-invasive and has good scope for the doctors to analyze many diseases. Lack of trained sonographers make ultrasound imaging diagnosis time consuming to detect any abnormality. Sometimes the problem cannot exactly be identified which may lead to error in diagnosis. Hence in this paper we present computer aided automatic detection of abnormality in kidney on the ultrasound system itself, to decrease the time for reports and not to depend on the sonographer. We classified the kidney as normal and abnormal case. Segment the kidney region and extract Intensity histogram features and Haralick features from Gray Level Cooccurnace Matrix (GLCM). These features are calculated for a set of large data containing both normal and abnormal cases. Abnormal case includes kidney stone, cyst and bacterial infection. Standard deviation for each parameter is observed, considered only those features with less deviation and implemented on FPGA Kintex board. If the range of mean value is 1.08 to 1.336, skewness is 2.882 to 7.708, Kurtosis is 1.06 to 71.152, Cluster Shade is 72 to 243, Homogeneity is 0.993 to 0.998, the observed kidney image is normal otherwise abnormal.

Keywords—Intensity histogram features, Haralick features, FPGA, cloud, speckle

I. INTRODUCTION

Medical images can be diagnosed through various imaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasonography (US), Intravenous Urography (IVU), Angiography (AG). Each of this modality has distinct advantages and disadvantages in contrast formation, sensitivity, resolution, level of invasive and cost. MRI gives the same information as CT scan in regarding to kidney imaging. However, the contrast material gadolinium present in MRI is associated with Nephrogenic Systemic Fibrosis (NSF) [1], which decreases the kidney functioning. IVU is used to measure kidney size and shape and in the evaluation of pelvis and ureters. The major drawback with this is due to radiation and IV contrast administration, there may be renal failures [2]. CT uses computer processed X-rays to form tomographic image and gives most of the details similar to ultrasound. But this has disadvantage of radiation exposure and usage of contrast dye causes kidney damage. Ultrasonography is a ultrasound based imaging technique for visualizing internal organs structure at real time. Used for both diagnosis and therapeutic procedures with least invasive compared to other procedures [3]. It does not require any radiations and is portable to carry the device to patient bedside. The main advantage of this is its low cost, excellent spatial/contrast resolution, does not use harmful ionizing radiations.

People in India, particularly in rural and remote areas are found struggling to access timely medical treatment. There is lack of qualified personnel in every sector of health service. Telemedicine has come to serve rural populations, where time and the cost of travel constraints their access to the best medical care [4]. In India 70% of population live in rural areas whereas 75% of qualified consultants practice only in urban centres. Hence there is need to bridge the gap between rural and urban centres. Cloud based wireless portable ultrasound imaging system with preliminary Computer Aided Diagnosis (CAD) serves this purpose. The patient data from the remote ultrasound device is stored on the cloud and can be accessed by authenticated doctors from geographically anywhere.

Sonographers who are experts in ultrasound imaging generally may not prefer to go and work in rural areas. Due to lack of experts there is always delay in the process of getting reports in real time, which is not preferable in the case of emergencies. Hence there is necessity for the device to detect the abnormality, that helps the untrained sonographers to take correct decisions. According to Indian council of medical research (ICMR), it is estimated that 77.2 million people are suffering from pre-diabetes, a condition in which the patients have high blood glucose level which is not in diabetes range but having great risk of getting diabetes. Out of 1.27 billion population 65.1 million patients are confirmed diabetes and 17 million diabetes patients are suffering from kidney problems [5]. So there is a need to design a system for preliminary diagnosis of kidney diseases, which is portable and operator independent. The best suited medical imaging modality with these advantages is our proposed IoT enabled ultrasound machine with preliminary CAD. To make the device user independent and detect the abnormality, image processing algorithm are to be ported on the device itself.

We have chosen FPGA based implementation to reduce the time of execution, low cost and for debugging and verification, which is best suited for real time image processing applications. Normal and abnormal cases of kidney were considered to design an algorithm on FPGA for automatic detection of kidney abnormality. Intensity histogram and Haralick features are extracted from the segmented region and trained the system for particular range of values giving normal case and the values not included in this range as abnormal. From the segmented region of test image the features are calculated and compared to those values in the trained set. Xilinx ISE is used to synthesize and process the HDL code on Kintex 7 Field Programmable Gate Arrays (FPGA), a reconfigurable device.

The rest of the paper is organized as follows, Section II describes the system architecture of IoT enabled ultrasound system with preliminary CAD and discusses features to be selected for CAD analysis of kidney. In section III presents the experimental results are presented and our conclusions and future work are given in section IV.

II. SYSTEM ARCHITECTURE

Cloud based ultrasound system architecture as shown in Fig. 1 can provide medical amenities for people in rural areas by transmitting the ultrasound data to cloud, which can be later accessed by doctors from anywhere across the globe. Computer Aided Diagnosis (CAD), when included in ultrasound device provides a preliminary diagnosis to patient by indicating abnormality and thus providing a faster medication if needed.



Fig. 1: Proposed cloud based ultrasound imaging system with CAD for preliminary diagnosis

Fig. 2 shows the FPGA based CAD implementation of the classifier to determine the abnormality of kidney if any. After acquiring raw image, noise is to be reduced as it can be a major problem for automatic segmentation [6]. Wavelet based pre-processing technique is applied to reduce the noise [7]. Features for further processing are extracted at feature extraction block, out of which only few features are selected at feature selection to confirm any abnormality in the kidney at the classifier. Based on the classifier decision, priority of sending patient data can be changed to high in case of emergency.



Fig. 2: System Architecture on FPGA

We have taken set of normal and abnormal images each and applied our proposed algorithm on these images. Normal and Abnormal case of kidney is shown in Fig. 3.



Fig. 3: a) Normal and b) Abnormal

A. Pre-processing

Ultrasound images are highly affected by speckle noise. Speckles are spatially correlated multiplicative noise [8], which appears as granular like structures in the B-mode ultrasound images. This will delineate the edges, which is a useful information provided for the sonographer to do diagnosis. Speckle suppression helps to segment the images and to detect the contours in an image to finer extent. Denoisng of these speckles is done using threshold wavelet coefficients as shown in Fig. 4 by using the fact that in the wavelet domain image is sparse in nature [9]. All the coefficients of original image will be large and when the original image is added with noise, there will be coefficients having small value. Coefficients having small value correspond to noise and are set to zeros, to eliminate noise. Global threshold is applied according to which values below threshold are set to zero and remaining values are made to start from zeros. Original image is taken and threshold is calculated using global threshold λ given by:

$$\lambda = \sqrt{2 * \log(n)} * s$$

where n is total number of pixels in image given by N*M where N, M are the dimensions of image s is the noise variance.

Discrete Wavelet Transform (DWT) of image is calculated to 3 decomposition levels and threshold is applied to these levels. Inverse Discrete Wavelet Transform (IDWT) is performed on the resultant wavelet coefficients, to obtain the denoised image.



Fig. 4: Denoising using 2 level DWT: dwt2, idwt2

B. Feature Extraction

After Pre-processing, set of images with normal and abnormal classification of kidney were obtained. Manual segmentation is done on images in presence of well trained doctor. Later basic features to characterize kidney are extracted. These features can be grouped into three classes: Adaptive features, Histogram features, Haralick features [10]. Adaptive features include size, location and echo texture. These are termed adaptive as they vary from person to person hence cannot be generalized. For example, latitudinal length of normal kidney varies form 8 cm for short people and 12 cm for tall people, echo texture varies between thin and muscled persons, thin people have dark echo texture and kidney is visible clearly but muscled people have light echo texture making it difficult to categorize the kidney. Comparative study is to be done between two kidneys to determine the change in size of kidney. This method also eliminates false negative of abnormality detection in case of diabetics where kidneys are usually larger in size.

Histogram features include mean, variance, skewness, kurtosis, energy and entropy. Extracting the features based on the histogram gives first order statistical features of an image, which is useful for object recognition and classification. Haralick features include auto correlation, contrast, correlation, cluster prominence, cluster shade, dissimilarity, homogeneity, maximum probability, sum of squares, sum average, sum variance, sum entropy, difference variance, difference entropy,



Fig. 5: (a) Noisy image (b) Denoised image

information measure of correlation, inverse difference moment normalized. These are extracted from co-occurrence matrix Gof dimension N_g (number of gray level) as given below, each element P(i, j) gives the probability of occurrence of gray level i in the specified spatial relationship with gray level j.

$$G = \begin{pmatrix} P(1,1) & \dots & P(1,N_g) \\ \vdots & \ddots & \vdots \\ P(N_g,1) & \dots & P(N_g,N_g) \end{pmatrix}$$
$$\mu_x = \sum_{i=1}^{N_g} i P_x(i), \qquad \mu_y = \sum_{j=1}^{N_g} j P_y(j)$$
$$\sigma^2_x = \sum_{i=1}^{N_g} (P_x(i) - \mu_x)^2, \quad \sigma^2_y = \sum_{j=1}^{N_g} (P_y(j) - \mu_y)^2$$
$$P_x(i) = \sum_{i=1}^{N_g} P(i,j), \qquad P_y(j) = \sum_{j=1}^{N_g} P(i,j),$$
$$P_{x+y}(k) = \sum_{i,j=1}^{N_g} P(i,j)$$

where μ_x , μ_y , σ_x , σ_y are the mean and standard deviation of P_x and P_y . $P_x(i)$, $P_y(j)$ is sum of i^{th} row and j^{th} column respectively.

C. Feature Selection

Histogram features gives five important features of image which includes mean, skewness, kurtosis, variance and entropy. Similarly from GLCM, 16 harlick features are calculated for all the available set of images. Out of these mean, skewness, kurtosis are selected from histogram features and cluster shade feature is selected from Haralick features [10], further standard deviation of each metric is calculated separately for all images and those with lower deviation are further selected to increase the parameter length to train classifier. We found that homogeneity, maximum probability, correlation, sum average and sum of squares has the least deviation compared to the other features. Finally these 9 optimized features are considered for further classification rather than considering all the features. These features can be calculated as follows [11]

$$Mean, \mu = \frac{1}{MN} \sum_{i,j} I(i,j) \tag{1}$$

$$Kurtosis = \frac{1}{MN} \sum_{i,j} \frac{\left(I(i,j) - \mu\right)^4}{\sigma^4}$$
(2)

$$Skewness = \frac{1}{MN} \sum_{i,j} \frac{(I(i,j) - \mu)^3}{\sigma^3}$$
(3)

$$correlation = \sum_{i,j=1}^{N_g} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \sigma_y}$$
(4)

$$sum \ avg = \sum_{i=1}^{2N_g} iP_{x+y}(i)$$
 (5)

$$max \ prob. = \sum_{i,j=1}^{N_g} \max(P(i,j)) \tag{6}$$

cluster shade =
$$\sum_{i,j} (i+j-\mu_x-\mu_y)^3 P(i,j)$$
(7)

$$homogeneity = \sum_{i,j} \frac{P(i,j)}{1+|i-j|}$$
(8)

sum of squares =
$$\sum_{i,j} (i - \mu_x)^2 P(i,j)$$
(9)

where I(i, j) is the intensity value at i^{th} row and j^{th} column.

S1.No	Feature	Desired Range
1	Length	8-12 cm
2	Sum Average	0.414-4.182
3	Mean	1.08-1.336
4	Skewness	2.822-7.708
5	Kurtosis	11.06-71.152
6	Correlation	0.971-0.987
7	Cluster Shade	72-243
8	Homogenity	0.993-0.998
9	Maximum Probabilty	0.840-0.969
10	Sum of Squares	0.828-10.756

TABLE I: Desired range of features extracted from normal kidney

D. Classifier

The classifier is initially trained with features having desired range as mentioned in Table I. Since length is an adaptive feature it has to be trained every time depending on the patient, for example in the case of diabetics the size of kidney will be more than 12 cm but this case is to be identified as normal. Intensity and Haralick features need not be changed as they are fixed. Steps involved in the CAD analysis are shown in Algorithm 1.

Depending on the patients condition, longitudinal length of normal kidney is considered as threshold. Later 10 features extracted from feature selection block which includes length of kidney are fed as inputs to classifier block. The intervals are then compared with threshold values and if any feature exceeds the threshold limit then classifier decides that the kidney is abnormal and sends the data to cloud with high priority requesting doctor for immediate diagnosis. If all the features are in desired range then data is sent to cloud, without any priority and doctor can go through reports whenever possible.

III. EXPERIMENTAL ANALYSIS

Ultrasound kidney images of normal and abnormal cases are gathered from a diagnostic centre, Hyderabad, India. The proposed CAD for kidney has been implemented on FPGA platform Kintex 7 board. Images acquired form ultrasound imaging system have noise in them, hence images were preprocessed using wavelet based denoising technique discussed above to reduce the noise in images. Fig. 5 shows the noisy image and denoised image obtained after applying global threshold. Histogram and Haralick features are calculated to classify the kidney depending on range of feature values. Fig. 6 indicates the plot of true negatives calculated for different parameter length. Since true negative is constant, from parameter length 8, 9 and 10, we have considered parameter length of 10 which includes longitudinal length of kidney that

Algorithm 1 Automatic Kidney Classification

Initial: Set Threshold values

Set *abnormal_count=*0;

- 1: **procedure** DECISION MAKER(*Extracted Features*)
- 2: **Comment:** Calculate mean, skewness, krutosis, correlation, cluster shade, homogeneity, maximum probability, sum of squares, sum average intervals.
- 3: Calculate *length of normal kidney*;
- 4: Set length.threshold = length of normal kidney;
- 5: Calculate *Data.length_interval*;
- 6: **if** $Data.length \neq length.threshold$ **then**
- Decide the kidney is abnormal; 7: 8: Send data with high priority; Calculate Data.mean_interval; 9: 10: Calculate Data.skewness_interval; Calculate Data.krutosis interval; 11: 12: Calculate Data.correlation interval; Calculate Data.clustershade interval; 13: Calculate Data.homogeneity_interval; 14: Calculate Data.maximumprobability_interval; 15: 16: Calculate Data.sumofsquares_interval; 17: Calculate Data.sumaverage_interval; if Data exceeds Threshold then 18: Transmit the data immediately; 19: Set *abnormal_count*=1; 20·
- 21: else

22.

23:

24:

- Set *length.threshold* parameter;
- $abnormal_count = 0;$
- end if
- 25: **else**
- 26: Decide the patient is normal;
- 27: Transmit the data;
- 28: end if
- 29: end procedure



Fig. 6: True negative for variable parameter length

is variable depending on person so as to detect abnormality efficiently. If the calculated parameters like mean, skewness, kurtosis, correlation, cluster shade etc, lie in the desired range as given in Table. I then kidney is considered to be normal otherwise it is classified as abnormal.

Positive and Negative values are calculated to validate the proposed system based on various parameter lengths. Fig. 7 shows the relation between precision, negative predictive value, specificity and sensitivity for parameter length of 4 and Fig. 8 shows the above mentioned relation for parameter length of

10. To classify the kidney image, proposed CAD algorithm was ported on FPGA and indicates normal or abnormal with text N or A respectively. This text is included on displayed image as shown in Fig 9 and Fig 10.



Fig. 7: Relation between positive and negative predictive values for parameter length = 4



Fig. 8: Relation between positive and negative predictive values for parameter length = 10



Fig. 9: Normal case being detected on FPGA



Fig. 10: Abnormal case being detected on FPGA

IV. CONCLUSION

This paper has proposed a fully-automated kidney abnormality detection system based on wavelet based noise removal, automated feature selection and supervised classification. Experimental results show that the designed classifier validates the abnormality without any error. Providing such information helps sonographers to suggest immediate precaution and also monitor disease progression. Thus the proposed technique aids prelimianry CAD for kidney on IoT enabled portable ultrasound systems.

In this paper we classified kidney images as normal and abnormal. As a future work, we would like to extend our algorithm to further classify as cyst, stone, and bacterial infection if its abnormal. Secondly, we are looking at Support Vector Machine (SVM) implemention on FPGA for classifying kidney. Robustness of our algorithm is to be checked using large set of data.

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REFERENCES

- High, Whitney A., et al. "Gadolinium is detectable within the tissue of patients with nephrogenic systemic fibrosis." Journal of the American Academy of Dermatology 56.1 (2007): 21-26.
- [2] Murphy, Sean W., BRENDAD J. BARRETT, and Patrick S. Parfrey. "Contrast nephropathy." Journal of the American Society of Nephrology 11.1 (2000): 177-182.
- [3] Mack, Michael J. "Minimally invasive and robotic surgery." Jama 285.5 (2001): 568-572.
- [4] Wootton, Richard, John Craig, and Victor Patterson. Introduction to telemedicine. Royal Society of Medicine Press, 2006.
- [5] "More than 77 million people in India have pre-diabetes," The Hindu, Coimbatore, January 27, 2014.
- [6] Tanzila Rahman, Mohammad Shorif Uddin."Speckle Noise Reduction and Segmentation of Kidney Regions From Ultrasound Image." Informatics, Electronics and Vision (ICIEV), 2013 International Conference on IEEE, 2013.
- [7] Wei, Dong, Umesh Rajashekar, and Alan C. Bovik "3.4 Wavelet Denoising for Image Enhancement."
- [8] Wang, Fan, et al."Synthetic aperture radar image segementation using fuzzy label field-based triplet Markov fileds model." (2014).
- [9] Hitesh, Ami shah "Research Paper On Reducion Of Speckle Noise In Ultrasound Imaging Using Wavelet And Contourlet Transform", Journal of Information, Knowledge and Research in Electronics and Communication Engineering, Nov 12, Volume-02, Issue-02.
- [10] Hafizah, Wan Mahani, Eko Supriyanto, and Jasmy Yunus. "Feature extraction of kidney ultrasound images based on intensity histogram and gray level co-occurrence matrix." Modelling Symposium (AMS), 2012 Sixth Asia. IEEE, 2012.
- [11] Eleyan, Alaa, and Hasan Demirel. "Co-occurrence matrix and its statistical features as a new approach for face recognition." Turkish Journal of Electrical Engineering and Computer Sciences 19.1 (2011): 97-107.