Computer Aided Abnormality Detection for Kidney on FPGA Based IoT Enabled Portable Ultrasound Imaging System


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Graphical abstract

Abstract

Purpose: Ultrasound scanning has been widely used for preliminary diagnosis as it is non-invasive and has good scope for the doctors to analyze many diseases. Due to lack of trained radiologists in remote areas, tele-radiology is used to diagnose the scanned ultrasound data. Availability of online radiographers and having communication facility for the portable ultrasound are issues in tele-radiology for using ultrasound scanning in remote health-care. In these situations, Computer Aided Diagnosis (CAD) will be beneficial in diagnosing the patients with minimal manual intervention.

Methods: We proposed FPGA based CAD algorithm for abnormality detection of kidney in ultrasound images. The proposed algorithm works in the following way: as a pre-processing, an ultrasound image is denoised and region of interest of kidney in ultrasound image is segmented. Intensity histogram features and Haralick features are extracted from the segmented kidney region. Based on extracted features, the classification algorithm is implemented in two stages. In first stage, a Look Up Table (LUT) based approach is used to differentiate between normal and abnormal kidney images. In second stage, after confirming the abnormality, Support Vector Machine (SVM) with Multi-Layer Perceptron (MLP) classifier trained with extracted features is used to further classify the presence of stone or cyst in kidney. The proposed algorithm is implemented on a FPGA based Xilinx Kintex-7 board.

Results: The proposed algorithm gave an accuracy of 98.14%, sensitivity of 100% and specificity of 96.82% in detecting the exact abnormality present in kidney ultrasound images.

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Conclusion: The proposed algorithm and its hardware implementation will be beneficial for diagnosing the kidney in absence of radiologists and internet connectivity.

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Keywords: Intensity histogram features; Haralick features; FPGA; Cloud; Speckle; SVM kernel

1. Introduction

Ultrasound imaging, also called sonography, involves exposing part of the body to high frequency sound waves to produce pictures of inside the body. Compared to Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Intra-venous Urography (IVU) and Angiography (AG), Ultrasound-ography (US) is advantageous and widely used imaging technology worldwide. US offers real-time, cheaper, safest and least invasive imaging technology for doing diagnosis and therapeutic procedures [1]. Ultrasound scanning can image organs like liver, gallbladder, spleen, pancreas, kidneys, bladder, uterus, ovaries, and fetus in pregnant patients. Ultrasound image is immediately visible on a video display screen and radiologist will freeze those images which are important for diagnosis. Telemedicine has come to serve rural populations, where time and the cost of travel constraints their access to the best medical care [2]. In India, 70% of population live in rural areas whereas 75% of qualified consultants practice only in urban centers. Hence there is need to bridge the gap between rural and urban centers. Cloud based wireless portable ultrasound imaging system with preliminary Computer Aided Diagnosis (CAD) serves this purpose. In cloud based diagnosis, the patient data is transferred to cloud, where doctors from anywhere can access and diagnose the data. Having connectivity all the time for a device is a major concern for portable ultrasound device. CAD algorithms on the device are very beneficial in such circumstances in detecting the abnormalities with/without manual intervention. This makes technician to alert the patient regarding his/her condition and also alerts the doctor that there is presence of abnormality and should examine with care.

Tele-radiology using Internet of Things (IoT) enabled ultrasound scanning system can be applied in regions where there is lack of radiologists. Due to lack of medical experts there is always delay in the process of getting reports, which is not preferred in emergency. Hence there is necessity for a device to detect the abnormality that helps the untrained radiologist to take correct decisions in treating the patients at point of care. According to Indian council of medical research (ICMR), out of 1.27 billion population, 65.1 million patients are confirmed diabetes and 17 million diabetes patients are suffering from kidney problems [3]. 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 IoT enabled portable ultrasound system based on a single Field Programmable Gate Array (FPGA) designed for point-of-care applications [4]. FPGA supports high data rates compared to GPU and DSP processors, which is required for implementing complex beamforming algorithms [4]. Implementation of CAD algorithms on FPGA provides the flexibility of integrating the CAD algorithm as an extra module in existing FPGA based portable ultrasound system architecture such that the algorithm will work in real-time.

In literature, complete ultrasound signal processing algorithms are realized on programmable platforms like FPGA, DSP and media processors [4], [5], [6]. CAD on ultrasound images using FPGA platform has been proposed in the literature and some of them are listed below. In [7], stone in kidney ultrasound images is detected using ANN via level set segmentation and the algorithm is implemented on vertex-2 pro FPGA. An FPGA and DSP based ultrasound system for tumor detection in soft tissues was implemented in [8]. In [9], FPGA based CAD system was developed for automatic detection of microcalcifications. We proposed FPGA based CAD for normal and abnormal classification of kidney ultrasound images in [10], where intensity histogram and Haralick features are extracted from the segmented region. The range of values for each feature is noted for normal case. If the values lie out of this range then the image is classified as abnormal case. Here, stone and cyst are considered as abnormality cases. The selected features for abnormality detection are motivated from findings of [11].

In this paper, we further extended to classify abnormal images into cyst and stone. From [10], selected feature values of kidney images with cyst and stone are having very small difference and cannot find unique range of values to classify the image. Supervised classifiers can work effectively in these conditions; SVM classifier with same set of selected features for normal/abnormal classification are used to classify image as cyst or stone in kidney. To evaluate the performance of different kernels in SVM for classifying the abnormality, the SVM classifier is tested with linear, polynomial, Radial Basis Function (RBF) and MLP kernels. The performance of each kernel is reported in experimental analysis section. Compared to other kernels, MLP kernel performed better in classifying the abnormal kidney images. Therefore, SVM with MLP kernel is chosen to implement on FPGA platform. Xilinx ISE is used to synthesize and process the HDL code on Kintex-7 FPGA board.

The rest of the paper is organized as follows, section 2 describes the system architecture of IoT enabled ultrasound system with preliminary CAD. Section 3 discusses proposed CAD analysis for kidney. Section 4 presents the experimental analysis and section 5 concludes the paper.

2. System architecture

Fig. 1 shows IoT enabled portable ultrasound system architecture. This provides 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 for doing diagnosis. Ultrasound imaging system consists of data acquisition, signal conditioning and image reconstruction blocks. CAD, when included in ultrasound device provides a preliminary diagnosis to patient by indicating abnormality in the organ thus providing a faster medication.

For our analysis, we considered US images consisting of normal, cyst and stone cases in kidney. Fig. 2 shows workflow of proposed CAD on FPGA. After classification, all images are stored in cloud and doctors can access those images by providing their own login id and password.

3. Proposed CAD for kidney US images

Block diagram for FPGA based CAD implementation of the classifier for detecting the abnormality of kidney is shown in Fig. 3. After acquiring raw image, noise is to be reduced as it can be a major problem for segmentation [12]. Wavelet based pre-processing technique is applied to reduce the noise [13]. From denoised image, kidney region is segmented and features for further processing are extracted, out of which only few features are selected at feature selection to confirm abnormality present in the kidney [10].

3.1. Pre-processing

If any abnormal case is detected, then SVM classifier is used to detect cyst or stone in kidney. Based on the classifier decision, priority of sending patient data can be changed to high in case of emergency. Normal and Abnormal case of kidney with cyst and stone are marked with circle as shown in Fig. 4.

Reduction of speckle noise is one of the operation which increases the quality of ultrasound images by retaining the important features of image. Speckle noise is deterministic and random in ultrasound image which is spatially correlated and multiplicative in nature [14]. Reducing the speckle noise in image will improve the contour of organ in US images and easier to segment. Denoising of speckles is done using threshold wavelet coefficients as shown in Fig. 5 by using the fact that in the wavelet domain image is sparse in nature [15].

Original image has coefficients with large value and when noise is added to it, there will be coefficients having small value.
Coefficients having small value are set to zero, since these values belong to added noise. Global threshold value is selected such that values below it are set to zero and values greater than threshold are set to start from zero. Global threshold value $\lambda$ is given by:

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

where $n$ is total number of pixels in image given by $N \times M$ where $N, M$ are the dimensions of image, $s$ is the noise variance. Discrete Wavelet Transform (DWT) of image is calculated for three 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. Noisy and denoised image obtained after applying global threshold is shown in Fig. 6(a) and Fig. 6(b) respectively.

3.2. Segmentation

To do CAD on any organ, firstly we have to extract region of interest for an organ in an image, this is similar to separating the foreground (organ region) from background (region not useful for diagnosis) region from an image. Due to nonrigid nature of kidney in ultrasound images and scanning artifacts like acoustic shadowing, low contrast and low signal to noise ratio, we manually segmented the region of interest from kidney ultrasound images. For doing manual segmentation, a graphical user interface is created for extracting the region of interest of kidney. We manually marked points along the contour of kidney and cubic spline interpolation is performed between the points to get smooth contour [16]. Normal case of kidney ultrasound image is shown in Fig. 7(a) with segmented points marked along contour, segmented region of kidney is shown in Fig. 7(b). Fig. 7(c) shows ultrasound image with stone in kidney, corresponding segmented region is shown in Fig. 7(d).

3.3. Feature extraction

Manual segmentation is done on the set of normal and abnormal images in presence of well trained doctor. Features required to characterize kidney are extracted from segmented region. These features can be categorized into three classes: Adaptive features, Histogram features and Haralick features [11]. Some features are adaptive that include size, location and echo texture. The term adaptive means these features vary from person to person and hence cannot be generalized. For example, 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, longitudinal length of normal kidney varies from 8 cm for short people and 12 cm for tall people 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 diabetes where kidneys are usually larger in size. Intensity histogram features include mean, variance, skewness, kurtosis, energy and entropy.

Feature extraction based on the histogram gives first order statistical features of an image, which is useful for organ recognition and classification. Haralick features also called as Gray Level Co-occurrence Matrix (GLCM) features are rotational invariant features which include auto correlation, contrast, cluster prominence, correlation, cluster shade, homogeneity, dissimilarity, maximum probability, sum average, sum of squares, sum variance, difference variance, sum entropy, difference entropy, information measure of correlation and inverse difference moment normalized [17]. These are extracted from co-occurrence matrix $G$ of 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 $j$.

$$G = \begin{pmatrix} P(1, 1) & \cdots & P(1, N_g) \\ \vdots & \ddots & \vdots \\ P(N_g, 1) & \cdots & P(N_g, N_g) \end{pmatrix}$$

$$\mu_x = \sum_{i=1}^{N_g} i P_x(i), \quad \mu_y = \sum_{j=1}^{N_g} j P_y(j)$$

$$\sigma^2_x = \sum_{i=1}^{N_g} (P_x(i) - \mu_x)^2, \quad \sigma^2_y = \sum_{j=1}^{N_g} (P_y(j) - \mu_y)^2$$
\[ P_x(i) = \sum_{i=1}^{N_x} P(i, j), \quad P_y(j) = \sum_{j=1}^{N_y} P(i, j), \]

\[ P_{x+y}(k) = \sum_{i,j=1}^{N_x} P(i, j) \]

where \( \mu_x, \mu_y, \sigma_x, \sigma_y \) 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.

### 3.4. Feature selection

Histogram features gives intensity distribution of an image, which includes mean, skewness, kurtosis, variance and entropy. Similarly from Haralick features, 16 features are computed from region of interest. Out of these mean, skewness, kurtosis are selected from histogram features and cluster shade feature is selected from Haralick features [18], 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 have 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 are computed in the following way.

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

\[
\text{Kurtosis} = \frac{1}{MN} \sum_{i,j} \frac{(I(i, j) - \mu)^4}{\sigma^4} \tag{2}
\]

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

\[
\text{correlation} = \frac{\sum_{i,j=1}^{N_x} [i \times j] \times P(i, j) - \mu_x \times \mu_y}{\sigma_x \sigma_y} \tag{4}
\]

\[
\text{sum avg} = \sum_{i=1}^{N_x} i P_{x+y}(i) \tag{5}
\]

\[
\text{max prob.} = \sum_{i,j=1}^{N_x} \max(P(i, j)) \tag{6}
\]

\[
\text{cluster shade} = \sum_{i,j} (i + j - \mu_x - \mu_y) \times P(i, j) \tag{7}
\]

\[
\text{homogeneity} = \sum_{i,j} P(i, j) \times \frac{1}{1 + |i-j|} \tag{8}
\]

\[
\text{sum of squares} = \sum_{i,j} (i - \mu_x)^2 \times P(i, j) \tag{9}
\]

where \( I(i, j) \) is the image intensity value at \( i \)th row and \( j \)th column.

### 3.5. Normal/abnormal classification of kidney

The classifier is initially loaded with features having desired range as mentioned in Table 1. 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 patient’s condition, longitudinal length of normal kidney is considered as threshold. Later 9 features extracted from feature selection block and 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. After confirming the image has abnormality, the image has to be further classified as cyst and stone using supervised SVM classifier.

### 3.6. SVM classifier

Support vector machines (SVM) are set of supervised learning methods used for classification, regression and outlier’s detection. SVM models are designed based on learning algorithms that help in analyzing data and recognizing patterns. If classification is easier in a high-dimensional feature space, we would like to build a maximal margin hyperplane in that space as shown in Fig. 8. We choose the hyper plane such that the distance from hyper plane to nearest support vectors on both sides is maximized.

The construction depends on inner products, we will have to evaluate inner products in the feature space. This can be computationally intractable, if the dimensions become too large. Using of kernel function that lives in low dimensions, but behaves like an inner product in high dimensions [19,20]. In training phase, SVM tries to build a model that best separates the features of two different classes. SVM uses an optimization method to identify support vectors \( S_i \), weights \( W_i \), and bias \( B \) that are used to classify vectors \( X \) according to the following equation:

\[
Y = \sum_i W_i K(S_i, X) + B \tag{10}
\]
Algorithm 1 Automatic kidney classification.

Initial: Set threshold values
Set abnormal_count = 0;

1: procedure DECISION MAKER(Extracted Features)
2:  Comment: Calculate mean, skewness, kurtosis, 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
7:      Decide the kidney is abnormal;
8:      Send data with high priority;
9:      Calculate Data.mean_interval;
10:     Calculate Data.skewness_interval;
11:     Calculate Data.kurtosis_interval;
12:     Calculate Data.correlation_interval;
13:     Calculate Data.cluster_shade_interval;
14:     Calculate Data.homogeneity_interval;
15:     Calculate Data.maximum_probability_interval;
16:     Calculate Data.sum of squares_interval;
17:     Calculate Data.sum average_interval;
18:     if Data exceeds Threshold then
19:         Transmit the data immediately;
20:         Set abnormal_count = 1;
21:         Apply SVM Classifier:
22:            if classifier_output = 0 then
23:                Cyst is present in Kidney;
24:                else
25:                    Stone is present in Kidney;
26:                end if
27:            else
28:                Set length.threshold parameter;
29:                abnormal_count = 0;
30:            end if
31:        else
32:            Decide the patient is normal;
33:            Transmit the data;
34:        end if
35:     end procedure

Fig. 8. SVM classifier hyperplane separation.

where $K$ is a kernel function. Different kernel functions like linear, polynomial, radial basis, multilayer perception are used with SVM classifier [20]. In the case of a linear kernel, $K$ is the dot product. If $Y \geq 0$, then X is classified as a member of the first group, else it is classified as a member of the second group. The different kernels used in SVM classifier are:

3.6.1. **Linear SVM**

If $D$ be the training data of both normal and abnormal images with a set of $n$ images, it can be represented in the form

$$D = \{(x_i, y_i)|x_i \in \mathbb{R}^p, y_i \in \{-1, 1\}\}_{i=1}^n$$

where $y_i$ is either 1 or $-1$, indicating the class to which $x_i$ belongs. $x_i$ is a two dimensional vector, of which $x_{1}$ is data set of normal images and $x_{2}$ is data set of abnormal images. Linear kernel finds hyperplane to classify the images having $y_i = 1$ and $y_i = -1$.

3.6.2. **Polynomial kernel**

Polynomial kernel is defined as

$$k(x, y) = (x^T y + c)^d$$

where $x$ and $y$ are vectors in the input space, i.e., vectors of features computed from training and test samples. $d$ is set to 3 and $c$ is set to 0 as we computed results for homogeneous kernel.

3.6.3. **Radial basis function kernel**

Radial basis function kernel is a Gaussian kernel. It has two samples $x$ and $x'$, representing feature vectors of given input image. It is defined as

$$k(x, x') = \exp\left(\frac{||x - x'||^2}{2\sigma^2}\right)$$

$||x - x'||^2$ is the squared Euclidean distance between feature vectors. $\sigma$ is variance of Gaussian kernel and is set to 1 in our case.

3.6.4. **Multi-layer perceptron**

Multi-Layer Perceptron resemble like neural network and also called as hyperbolic tangent kernel. It combines several single layer perceptron’s. Each single layer perceptron uses a sigmoid shaped transfer function like the logistic or hyperbolic tangent function:

$$k(x, x') = \tanh(\rho(x, x'), \delta)$$

The simplest algorithm for training a multilayer perceptron is the backpropagation algorithm, which is as follows:

1. Select small random weights $w$.
2. Until halting condition:
   (a) Select a random training example.
   (b) Calculate the output of the hidden layer.
   (c) Calculate the output of the output layer.
   (d) Calculate error for output layer.
   (e) Calculate error for hidden layer.
   (f) Update weights.

3.7. **Database acquisition**

We acquired images using Siemens Acuson S2000 ultrasound machine with the help of radiologist by taking patients approval on patient consent form. 508 patients including male and female gender are involved in the data collection procedure. The patients are in the age group of 14 to 60 years. Logarithmically compressed kidney images are acquired from the machine. The database consists of 250 normal, 138 stone and 120 cyst.
kidney images. The condition of kidneys are analyzed and confirmed from the radiologist, which is used as a ground truth in training and testing the algorithm.

4. Experimental analysis

The proposed CAD for preliminary diagnosis of kidney has been implemented on kintex-7 FPGA board. For normal and abnormal classification of the image, 150 normal and 150 abnormal image features are analyzed, 100 normal and 100 abnormal images are used for testing the LUT approach. To detect the cyst or stone in an abnormal kidney image, SVM classifier is trained with 75 cyst and 75 stone kidney images and tested with 45 cyst and 63 stone images. Ultrasound images are effected by speckle noise, hence wavelet based denoising technique is used to reduce speckles. Noisy image and denoised image obtained after applying global threshold are shown in Fig. 6. Kidney region is segmented from the denoised image as shown in Fig. 7. To avoid artifacts from non-kidney images, features are extracted from segmented image. From segmented region, 6 intensity histogram and 16 Haralick features are extracted, out of which only 9 are selected based on standard deviation. Length of a kidney, mean, skewness, kurtosis, correlation, cluster shade, homogeneity, sum of average, sum of squares and maximum probability are selected. If the range of values lie in the desired range as given in Table 1 then kidney is considered to be normal otherwise it is classified as abnormal. Fig. 9 indicates the plot of true negatives resulted in LUT approach 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 is variable depending on person so as to detect abnormality efficiently. The accuracy of LUT algorithm increased with increase in parameter length. The classification efficiency of LUT approach for parameter length of 4 in classifying normal and abnormal kidney cases is shown in Fig. 10, the algorithm resulted with an accuracy of 86%. The LUT approach classified with an accuracy of 100% for parameter length 10 as shown in Fig. 11. Xilinx Simulink model used to implement LUT approach on FPGA with those 10 features is shown in Fig. 12. The algorithm displays text N for normal, A for abnormal case as shown in Fig. 13 and Fig. 14 respectively.

If the kidney is classified as abnormal, then we further classify abnormal kidney as cyst or stone. SVM classifier with same set of features (used for classifying normal and abnormal) are
used for detecting the kidney abnormality. SVM classifier is tested with 108 images (45 cyst and 63 stone images). The results are analyzed by plotting the confusion matrix for each SVM kernel. Linear, RBF, polynomial and MLP kernels are used with SVM and confusion matrix for each kernel are shown in Fig. 15, Fig. 16, Fig. 17 and Fig. 18 respectively. From Table 2 we can conclude that among linear, RBF, polynomial and MLP kernels, MLP resulted with highest accuracy of 98.14% while polynomial kernel has least accuracy with 41.66%. Xilinx simulink model [21] for SVM classifier to detect cyst or stone in kidney image is shown in Fig. 19. If the cyst is present in a kidney then it indicates with text C and for stone with text S on displayed image as shown in Fig. 20 and Fig. 21 respectively.

5. Conclusion

In this paper we proposed an algorithm for abnormality detection of kidney ultrasound images on FPGA based IoT enabled ultrasound system. This includes wavelet based noise

![Table 2: Accuracy using different kernels in SVM classifier.](image)

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>66.67</td>
</tr>
<tr>
<td>RBF</td>
<td>58.33</td>
</tr>
<tr>
<td>Polynomial</td>
<td>41.66</td>
</tr>
<tr>
<td>MLP</td>
<td>98.14</td>
</tr>
</tbody>
</table>

![Fig. 19. Simulink model for cyst/stone classification on FPGA.](image)

![Fig. 20. Abnormal case with cyst being detected on FPGA.](image)

![Fig. 21. Abnormal case with stone being detected on FPGA.](image)
removal and segmentation of kidney region, feature extraction and selection, and supervised classification. Experimental results show that the designed LUT based classifier, classifies normal and abnormal images without any error. Detected abnormality is further classified as cyst or stone in kidney using SVM classifier. Various kernels are used with SVM classifier out of which multi-layer perceptron kernel gave an accuracy of 98.14% in classifying whether abnormal images correspond to cyst or stone. Providing such information helps radiologist to suggest immediate precaution and also monitor disease progression.

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