Texture Feature Analysis for Different Resolution Level of Kidney Ultrasound Images

Wan Nur Hafsha Wan Kairuddin, Wan Mahani Hafizah Wan Mahmud

Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Malaysia.

Corresponding author: wannahani@uthm.edu.my

Abstract. Image feature extraction is a technique to identify the characteristic of the image. The objective of this work is to discover the texture features that best describe a tissue characteristic of a healthy kidney from ultrasound (US) image. Three ultrasound machines that have different specifications are used in order to get a different quality (different resolution) of the image. Initially, the acquired images are pre-processed to de-noise the speckle to ensure the image preserve the pixels in a region of interest (ROI) for further extraction. Gaussian Low-pass Filter is chosen as the filtering method in this work. 150 of enhanced images then are segmented by creating a foreground and background of image where the mask is created to eliminate some unwanted intensity values. Statistical based texture features method is used namely Intensity Histogram (IH), Gray-Level Co-Occurance Matrix (GLCM) and Gray-level run-length matrix (GLRLM). This method is depends on the spatial distribution of intensity values or gray levels in the kidney region. By using One-Way ANOVA in SPSS, the result indicated that three features (Contrast, Difference Variance and Inverse Difference Moment Normalized) from GLCM are not statistically significant; this concludes that these three features describe a healthy kidney characteristic regardless of the ultrasound image quality.

1. Introduction

Medical imaging is medical diagnostic technologies that use images for diagnosis purposes. Ultrasound imaging is one of the imaging modalities that is widely used because inexpensive, ease of use, noninvasive nature, real time imaging and most portable if compared to other imaging modalities like magnetic resonance (MR), Computed Tomography (CT) and positron emission tomography (PET). But on the downside, the ultrasound images has low image quality as always corrupted by the speckle noise mainly caused by improper contact or air gap between transducer and the body part. Noise is the random variation in signal amplitude measurements of detected echoes and causes brightness fluctuations in the ultrasound image [1]. Hence, in order to maintain a high quality image for an accurate image processing output, the enhancement process is needed to de-noise the speckle. Image enhancement is the first process for any application of image processing where it plays an important role to minimize the noise in the image for further image analysis without eliminating the important features and edges of the images. These will help in extracting some important features of the image for image classification.

The purpose of this work is to extract texture features of healthy kidney which in future can be used to classify the healthy kidney and the abnormal kidney characteristics. Texture of an image can be defined as a feature that contains important characteristic of that image. Texture is represented by the
2. Material and Methods

This study may be divided into few steps as stated in the flowchart in Figure 1. The project started with the image acquisition, and continued with processing the image including image cropping, image enhancement, image segmentation, feature extraction as well as feature selection. All image processing steps were performed using MATLAB software. Each step was elaborated in the next subsections.

Figure 1: Flowchart of the study

2.1 Image Acquisition
The work starts with acquiring a B-mode of healthy kidney images. These images are gathered from volunteer students and staff from Faculty of Electrical & Electronics, Universiti Tun Hussein Onn Malaysia (UTHM) with no reported kidney diseases. 150 images from three US machines are gathered
(50 images for each machines), where three machines were used to acquire images on the same subjects. The images were taken from USB port of each machine in the .bmp format with the original size of 716x537. All possible setting including frequency, gain, depth, and dynamic range were set at the same range. The convex probe transducer is set to frequency of 3.75MHz while the ultrasound machine frequency is set to 6MHz. The US machines used in this work are: Toshiba Nemio XG (SSA-580A), GE Healthcare (LOGIQ P5) and Philips (HDII XE).

These three US machines are compared by using three technologies that have the most impact on US image quality. They are Tissue Harmonics Imaging (THI), Compound Imaging and Speckle Reduction Imaging. The difference technologies used for each machine giving variation of the image quality.

THI is a technology that having a function of the harmonic imaging used to reduce artifacts and noise by sending and receiving signals at two different frequencies [7]. This will help to improve image quality because the body tissue will reflects sound at twice the frequency that was initially sent. With that, a clean image with reduce artifacts can be produced.

Speckle Reduction Imaging works by evaluating the image on a pixel-by-pixel basis where it can identify tissue, so that it can reduce the speckle noise that occurs in the ultrasound image. This technology uses some algorithm to identify weak and strong signals. The weak signal will be removed while the strong signals will be enhanced. A better and clear image can be produced.

Compound imaging is a technique that combines multiple images from different angle to be a single image. The ultrasound sends signals at multiple angles, so that the tissues can be seen at the different angles. This can help to reduce artifacts in the image and produce a clearer image. All of the images are then cropped to ROI before performing the enhancement for each of the image. The ultrasound images of healthy kidney from the three different ultrasound machines used are shown in Figure 2 (a) – (c). Each machine provides a different resolution of images depending on the technologies used for each machine.

![B-mode ultrasound images](image1.png)

2.2 Image Cropping
Cropping is an operation, which is performed on acquired images to accentuate the ROI and to remove all the unwanted artifacts such as written labels and background noise from them. Image cropping is
needed to speed up further image processing. In this work, manual cropping is used where the image is cut in a rectangular shape which consist only the ROI with the size of 240x120. The example of image that has been cropped is as in Figure 3.

![Figure 3: Image cropping consisting ROI](image)

2.3 Image Enhancement
All the 150 images are filtered using Gaussian Low-pass Filter. Gaussian filtering is a frequency domain filtering. 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. The result after image enhancement using Gaussian low-pass filter is as in Figure 4 (a)-(c).

![Figure 4: Image enhancement output using (a) Toshiba Nemio XG (SSA-580A), (b) GE Healthcare (LOGIQ P5) and (c) Philips (HDII XE).](image)

2.4 Image Segmentation
Segmentation is a method to subdivide the kidney region into its constituent regions or object. The main purpose of the segmentation process is to get more information in the region of interest in an image which helps in getting correct features of the image. The segmentation will provide a boundary over a kidney image. In this work, manual contouring is used to segment the kidney edge. The image is segment into foreground and background where the mask is created in order to erase pieces of a binary image that are not attached to the object surrounded by the boundary. The complicated background that is outside ROI will be masked. This process will eliminate unwanted intensity values which are outside the contour (edge) of the kidney image. It is to avoid the calculation of these unwanted intensities that will be incorporated during extraction of feature parameters. Figure 5 shows the output of image segmentation process where 5(a) shows the manual contouring of kidney image while 5(b) shows the example of the blackmasked image that will be used for the later process.
Figure 5: Output of image segmentation process; (a) manual contouring of kidney image, (b) Blackmasked image

2.5 Feature Extraction

Three statistical feature extractions namely Intensity Histogram (IH), Gray-Level Run Length Matrix (GLRLM) and Gray-Level co-Occurrence Matrix (GLCM) are used to extract the features of the kidney. Each type of features is described as follows:

2.5.1 Intensity Histogram Features. The intensity-level histogram is a function showing the number of pixels in the whole image, which have this intensity. The 8-bit gray scale image is having 256 possible intensity values. The parameters in the following statistical formulas are $p$ that represents the pixel intensity, $p(i)$ represents the pixel intensity at i value and N represents total number of pixels.

\[
p(i) = \frac{\text{Number of pixels with grey level } i}{N}
\]

Five individual features under this feature extraction technique IH has been used including Mean, Standard Deviation, Skewness, Kurtosis and Entropy.

2.5.2 GLRLM Features. Grey-level run-length matrix (GLRLM) is a matrix from which the texture features can be extracted for texture analysis. The GLRLM method is a way of extracting higher order statistical texture features. A gray level run can be described as a line of pixels in a certain direction with the same intensity value. The number of such pixels defines the gray level run length and the number of occurrences is called the run length value. Here a run length is considered to be a number of neighbouring pixels that possess the same grey intensity in a particular direction. In this work only seven GLRLM features will be extracted and these parameters are Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray level non-uniformity (GLN), Run length non-uniformity (RLN), Run Percentage (RP), Low Gray Level Run Emphasis (LGLRE), and High Gray Level Run Emphasis (LGLRE).

2.5.3 GLCM Features. GLCM is also known as spatial gray level dependency matrices. It is one of the most widely used second-order statistical tools for extracting texture information from images. 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 specific spatial relationship. GLCM can be formed in a four direction, $0^\circ$, $45^\circ$, $90^\circ$ and $135^\circ$. In this work, only one direction of $0^\circ$ is consider to get the GLCM features of the images with distance is set to 1 from the pixel of interest. A total of 20 GLCM features are extracted including Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shades, Dissimilarity, Energy, Entropy, Homogeneity, Maximum Probability, Sum of Squares, Sum Average, Sum Variance, Sum Entropy, Difference Variance, Difference Entropy, Information measures of Correlation-1, Information measures of Correlation-2, Inverse Difference Normalized, and Inverse Difference Moment Normalized.
2.6 Feature Selection
Feature selection is the most important part in this work. Feature selection will conclude the texture features for a healthy kidney from US images. Feature selection techniques are applied to choose as many image parameters as possible to identify the image characteristic in the kidney region. This will select few of those extracted features which are most significant and describe the kidney characteristic the best.

In the previous work done, Wan Mahani Hafizah et al. [5] the features selection is done by finding the difference of features value between the group of normal kidney, bacterial infection kidney, cystic disease (CD) and kidney stones. The features with higher different value from different group of kidney are choosing as the features to classify the different classes of kidney. K.Bomman Raja et al. [2, 8] used statistical analysis, student t-Test which measures the significance of features values in distinguishing kidney disorders. Karthik Kalyan et al. [9] performed the feature selections that have high significance using Waikato Environment for Knowledge Analysis (WEKA) software that gives variety of feature selection options.

In this study, features selection technique used is statistical analysis using Statistical Package for the Social Sciences (SPSS). The potential of these features in identifying the category is verified statistically by evaluating ‘p’ value. It measures how compatible the data collected are with the null hypothesis.

Null hypothesis  
Ho: All means feature are equal  
Ho:μmachine1=μmachine2= μmachine3

Alternative hypothesis  
H1: At least one mean feature is different  
H1:μmachine1≠ μmachine2 ≠ μmachine3

The analysis One-way ANOVA is used to do this statistical analysis. It is used to determine whether there are any significant differences between the means of two or more independent (unrelated) groups. To conclude that the feature parameters are same for all the three classes of US machines the p value must be > 0.05. This tells that the mean values are not statistically significant where we cannot reject the H0. This shows that the feature parameters has no different for each classes of US machine. So that the conclusion can be made, that for feature parameters that are not statistically significant or when the value of p>0.05 are the feature parameters for the healthy kidney.

3. Results and Analysis
The result for intensity histogram (IH), Grey-level run-length matrix (GLRLM) and Gray-Level co-Ocurrence Matrix (GLCM) features are as in Table 1, 2 and 3 respectively.

| Table 1. Result for IH features |
|--------------------------------|
| Features                  | p-value |
|---------------------------|---------|
| Mean                      | .000    |
| Standard Deviation        | .000    |
| Skewness                  | .000    |
| Kurtosis                  | .000    |
| Entropy                   | .000    |
Table 2. Result for GLRLM features

| Features                               | p-value |
|----------------------------------------|---------|
| Short Run Emphasis (SRE)               | .000    |
| Long Run Emphasis (LRE)                | .000    |
| Gray level non-uniformity (GLN)        | .000    |
| Run length non-uniformity (RLN)        | .000    |
| Run Percentage (RP)                    | .000    |
| Low Gray Level Run Emphasis (LGLRE)    | .000    |
| High Gray Level Run Emphasis (LGLRE)   | .000    |

Table 3. Result for GLCM features

| Features                               | p-value |
|----------------------------------------|---------|
| Autocorrelation                        | .000    |
| **Contrast**                           | .284    |
| Correlation                            | .000    |
| Cluster Prominence                     | .000    |
| Cluster Shade                          | .000    |
| Dissimilarity                          | .000    |
| Energy                                 | .000    |
| Entropy                                | .000    |
| Homogeneity                            | .000    |
| Maximum Probability                    | .001    |
| Sum of Squares                         | .000    |
| Sum Average                            | .000    |
| Sum Variance                           | .000    |
| Sum Entropy                            | .001    |
| **Difference Variance**                | .563    |
| Difference Entropy                     | .000    |
| Information measures of Correlation-1  | .000    |
| Information measures of Correlation-2  | .000    |
| Inverse Difference Normalized          | .000    |
| **Inverse Difference Moment Normalized** | .212   |

For Table 1, the result from statistical analysis shows that for all the 5 features used in IH having significance value, p<0.05. For Table 2, the result from statistical analysis shows that for all the 7 features used in GLRLM having p value, p<0.05. The results show that all the image features are
different for the three types of US machine used. For Table 3, the result from statistical analysis shows that from 20 GLCM features extracted, three features having p value, p>0.05. They are Contrast with p value of 0.284, Difference Variance with p value of 0.563 and Inverse Difference Moment Normalized with p value of 0.212. Other features having p value, p<0.05.

Based on the result, since p-value is higher than 0.05, it shows that the images contain features that has no significant differences (image compared are statistically same). All tested images from three different ultrasound machines have almost the same value of three features including Contrast, Difference Variance and Inverse Difference Moment Normalized. Therefore, according to the result, it can tell us that regardless of having different image quality, these three features can be used to acknowledge that the images are the healthy kidney images.

4. Conclusion
As conclusion, this particular study indicated that three features (Contrast, Difference Variance and Inverse Difference Moment Normalized) from GLCM are not statistically significant (p>0.05). This concludes that these three features describe healthy kidney characteristics regardless of the ultrasound image quality. The outcome of this study is important as it may be used for the development of computer aided diagnosis (CAD) system for kidney ultrasound images. Developing the CAD system that is reliable and applicable should be unanimous and not just for one type of ultrasound machine only. Thus, this study concludes that it is possible to develop the CAD system for kidney ultrasound images which can be based on three features mentioned earlier.

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