Comparative Analysis of Textural Features Derived from GLCM for Ultrasound Liver Image Classification

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***Abstract*— Comparative analysis of nine textural feature measures derived from gray-level co-occurrence matrix obtained from the region(s) of interest (ROI) among the normal and abnormal anatomical structures that appear in the patient's ultrasound liver images is presented in this paper. Selection of the most robust discriminating features for classification experiment is performed through analysis of each feature classes' separability power. The results analysis shows that cluster prominence, cluster shade, maximum probability, and entropy have high classes' separability power and were selected for the classification of liver ultrasound images into normal liver (NL), primary liver cell carcinoma (PLCC) and hepatocellular carcinoma (HCC) at 0.4, 0.4, 0.2 and 0.6 sensitivity respectively.**

***Keywords*— Liver tissue, Feature extraction, Feature selection.**

I. INTRODUCTION

Applications of medical imaging have received a great attention in medical and healthcare sector. Imaging techniques for computer aided diagnosis of diseases are of various kinds such as magnetic resonance imaging (MRI), single positron emission computerized tomography (SPECT), computerized tomography (CT) and ultrasound. However, ultrasound imaging is widely used technique in the diagnosis of soft tissues, due to its ability to visualize human tissue without deleterious effects [1].

Liver is a large organ in the body that cleans the blood and produces bile which helps the body to deal with the fats we eat. However liver tissue is prone to diseases such as cyst, alcoholic cirrhosis, and carcinoma [2]. Many researchers in different contexts have proved in their findings that early detection and treatment of liver diseases is the only way to reduce the mortality [3, 4]. ltrasound images play an important role to detect anatomical and functional information of liver tissue for diagnosis [5, 6]. Ultrasound are generally complex in nature for physicians and radiologists to be examine by simple visual inspection based on their individual experiences and knowledge, thus computer aided diagnosis system (CAD) is required for supporting the detection and characterization of liver tissue from ultrasound images [7-9]. The aim of liver images characterization is the extraction of set of features from the region(s) of interest (ROI) among the normal and abnormal anatomical structures that appear in the patient's ultrasound images, for ultrasonic liver tissues classification.

The characterization of liver images in this work is based on texture analysis techniques. There exist a considerable number of texture analysis techniques. The most common are first order statistics, grey level co-occurrence matrix and fractal geometry. In this paper, gray-level co-occurrence matrix (GLCM) method is used to extract nine textural features used to categorize the ultrasonic liver images into normal liver (NL), primary liver cell carcinoma (PLCC) and hepatocellular carcinoma (HCC).

However, for a real-time ultrasonic liver image classification problems large number of features are not necessary and thus dimensionality reduction is performed. An approach to dimensionality reduction is feature selection. Without employing feature selection technique many of the extracted features could be either redundant or even irrelevant to the classification task. In this work, selection of the most robust discriminating features to better represent the target concept is performed through analysis of each feature classes' separability power. The results analysis shows that cluster prominence, cluster shade, maximum probability, and entropy have high classes' separability power and were selected for the classification of liver ultrasound images.

The remaining of this paper is organized as follows: Section II presents feature extraction scheme and overview of various image classification methods. The experimental results and conclusion was given in Section III while conclusion was presented in Section IV.

II. TEXTURE ANALYSIS AND CLASSIFICATION METHODS

Our approach to feature extraction and selection in addition to the overview of some image classification methods are presented in this section.

A. Feature Extraction

Feature extraction is a crucial step for any pattern recognition task especially for ultrasonic liver tissues classification. Generally, ultrasound images present various granular structures as texture and the analysis of ultrasound image is analogous to the problem in texture analysis. However textural features are those characteristics such as smoothness, fitness and coarseness of certain pattern associated with the image. There exist a considerable number of texture feature analysis techniques. In this work gray-level co-occurrence matrix (GLCM) is used for the extraction of textural features.

Gray level co-occurrence matrix (GLCM) [10, 11] is a second-order statistics methods, which is based on (local) information about gray levels in pair of pixels. The matrix defined over the image with distribution of co-occurring values of given offset. Let Q be an operator that defines the position of two pixels are relative (offset), and an image f, with L possible intensity levels. Let G be a matrix with element g_{ij} define number of times that pair of pixel with intensities Z_i and Z_j occur in f with specified position in Q $(1 \le i, j \le L)$. Mathematically we have a co-occurrence matrix C which defined over an $n \times m$ image I, offset $(\Delta x, \Delta y)$.

$$C_{\Delta x,\Delta y}(i,j)=\sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, \text{if } (p,q)=i \text{ and } I(p+\Delta x,q+\Delta y)=j\\ 0, \text{otherwise}\end{cases} \quad (1)$$

Haralick [12] described 14 statistic feature measures that can be calculated from the co-occurrence matrix with the intent to describe the texture of the images. In this work we extracted nine of those, homogeneity, correlation, dissimilarity, contrast, clustering shade, clustering prominence, entropy, energy and maximum probability from the region(s) of interest (ROI) of the liver image.

(a) Contrast is a measure of intensity contrast between a pixel and its neighbour over the whole image. For a “constant” image (no variation) contrast is zero.

$$Cont.=\sum_i \sum_j |i-j|^2\, p(i,j) \quad (2)$$

(b) Local homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. For a diagonal GLCM, homogeneity is 1.

$$Homog.=\sum_i \sum_j \frac{1}{1+|i-j|^2}\, p(i,j) \quad (3)$$

(c) Correlation is a measure of how correlated a pixel is to its neighbour over the whole image. It is 1 or -1 for a perfectly positively or negatively correlated image and infinity for a constant image.

$$Correl.=\sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j} \quad (4)$$

where; μ_i and μ_j are the GLCM mean of the first and second components , σ_i and σ_j are the GLCM variances of the first and second components.

(d) Cluster shade and cluster prominence characterises the tendency of clustering of the pixels in the region of interest.

$$Cluster\ Shade=\sum_i \sum_j (i+j-\mu_i-\mu_j)^3\, p(i,j) \quad (5)$$

$$Cluster\ Prom.=\sum_i \sum_j (i+j-\mu_i-\mu_j)^4\, p(i,j) \quad (6)$$

(e) Entropy is a statistical measure of randomness that can be used to characterizes the texture of an image

$$Entropy=\sum_i \sum_j p(i,j)\log p(i,j) \quad (7)$$

(f) Dissimilarity is a measure of distance between pairs of objects (pixels) in the region of interest.

$$Dissimilarity=\sum_i \sum_j |i-j|\, p(i,j) \quad (8)$$

(g) Maximum probability measures the maximum likelihood of producing the pixels of interest.

$$Max.\ Probability=\max.\ p(i,j)\ \ for\ all\ (i,j) \quad (9)$$

(h) Energy provides the sum of squared elements in the GLCM. It has values between 0 and 1.

$$Energy=\sum_{i,j} P(i,j)^2 \quad (10)$$

Selection of a set of appropriate input feature variables is an important issue in the building of a classifier [13]. The purpose of feature variable selection is to find the smallest set of features that can result in satisfactory predictive performance. Because of the curse of dimensionality [14], it is often necessary and beneficial to limit the number of input features in a classifier in order to have a good predictive and less computationally intensive model.

Numerous feature selection methods have been developed in the pattern recognition literature [14], [15]. In this work the best discriminating feature is selected by analyzing the classes’ separability power of each feature.

B. Image Classification Methods

Briefly reviewed of some image classification techniques are given in the following subsection.

1) *k-Nearest Neighbor* [16]**:** *k*- Nearest Neighbor classifier is based on learning by analogy, that is by comparing a given test sample with training samples which are similar to it. The training samples are described by n attributes. Each sample represents a point in $n-$dimensional space. In this way, all of the training samples are stored in an $n-$dimensional pattern space. When given an unknown sample, a *k*-nearest neighbor (*k*-NN) classifier searches the pattern space for the *k* training samples which are closest to the unknown sample. These *k* training samples are the *k*-nearest neighbors of the unknown sample [16, 17]. "Closeness" is defined in terms of a distance metric, such as Euclidean distance. The Euclidean distance between two points or samples $X_1 = (x_{11}, x_{12}, \cdots, x_{1n})$ and $X_2 = (x_{21}, x_{22}, \cdots, x_{2n})$ is computed as;

$$dist.(X_1,\ X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2} \tag{11}$$

The basic steps of the k-NN algorithm are;

- To compute the distances between the new sample and all previous samples, have already been classified into clusters;
- To sort the distances in increasing order and select the *k* samples with the smallest distance values;
- To apply the voting principle. A new sample will be added (classified) to the largest cluster out of *k* selected samples [18].

2) *Bayes Classifier* [19-21]: The Bayes classifier is applied to investigate the feasibility of classifying texture image, since from the statistical viewpoint, it represents the optimum measure of performance. The Bayesian decision rule classifies an observation to the class that has the highest a posteriori probability among the classes. One of the ways to represent a pattern classifier is in terms of a set of discriminant functions $g_i(X),\ i = 1, \cdots, K$ where K denote total number of classes. The classifier is to assign a feature vector X to class ω_i if $g_i(X) > g_j(X)$ for all $j \neq i$. Let us assume that the distribution of feature vectors X within the *i*th class $P(X|\omega_i)$ is a multivariate normal distribution with mean vector μ_i and covariance matrix C_i and the a priori probabilities are equal for all classes. Under such an assumption, the discriminant functions can be defined as;

$$g_i(X) = -\frac{1}{2}(X - \mu_i)^T C_i^{-1} (X - \mu_i) - \frac{1}{2}\log|C_i| + \log P(\omega_i) \tag{12}$$

3) *Support Vector Machine* [22]**:** SVMs are primarily two-class classifiers that have been shown to be an attractive and more systematic approach to learn linear or non-linear decision boundaries [23, 24]. The classifier constructs an optimal separating hyper-plane between the classes in the dataset by maximizing the distance of either class from the hyper-plane using the Gaussian radial basis kernel. This is equivalent to performing structural risk minimization to achieve good generalization [23, 24]. Finding the optimal hyper-plane implies solving a constrained optimization problem using quadratic programming.

The dimensionality of the feature space is determined by the number of support vectors extracted from the training data. The SVM can locate all the support vectors, which exclusively determine the decision boundaries. To estimate the misclassification rate (risk), the so called leave-one-out procedure is used. It removes one of training samples, performs training using the remaining training samples, and tests the removed sample with the newly derived hyper-plane. It repeats this process for all of the samples, and the total number of errors becomes the estimation of the risk [25].

III. RESULTS AND DISCUSSION

The ultrasound image datasets used in the experiment are provided by St.Gregory's specialist clinic and ultrasound diagnostic service, Yemetu, Ibadan. The data samples which was scanned with HP Deskjet F2400 at both vertical and horizontal resolution of 200dpi with a bit depth of 24 were acquired in off-line mode from a Shimedzu 350XL ultrasound machine. Ninety samples of ultrasound liver images are used in the experiments. Out of these samples 18 are normal, 42 primary liver cell carcinoma (PLCC) and 30 hepatocellular carcinoma (HCC) images. First all images are registered into the database through intensity based image registration method. Nine textural features derived from gray level co-occurrence matrix are extracted from the region of interests (ROIs) among the normal and abnormal ultrasound images. The between classes distance of the extracted features was computed to selects the best discriminant features for the the classification of liver ultrasound images for every three class cases shown in Fig. 1 to 3.

The input data set is divided into two equal halves for training and the testing as presented in Table 1. The result of the experiment is shown in Table 2. Based on the available data and the experiments conducted, it was found from the result presented in Table 2 and Figure 4 that, cluster prominence, cluster shade, maximum probability and entropy have high classes' separability power than other features and are then selected as the best discriminant features for the the classification of liver ultrasound images for the three class cases at 0.4, 0.4, 0.2 and 0.6 sensitivity respectively.

TABLE 1

DISTRIBUTION OF SAMPLES IN TRAINING AND TESTING SETS

	Training	**Testing**
PLCC	21	21
HCC	15	15
Normal	9	9

TABLE 2
PERFORMANCE EVALUATION FOR NORMAL, HCC AND PLCC LIVER FOR *K*-NN CLASSIFIER WITH *K* = 7.

Features	Con	Dis	Ent	En	Hom	MP	CS	CP
Spec.	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Sens.	0.0	0.0	0.6	0.0	0.0	0.2	0.4	0.4
FPR	NaN	NaN	1.0	NaN	NaN	1.0	1.0	1.0
FNR	0.88	0.88	0.95	0.88	0.88	0.9	0.93	0.93

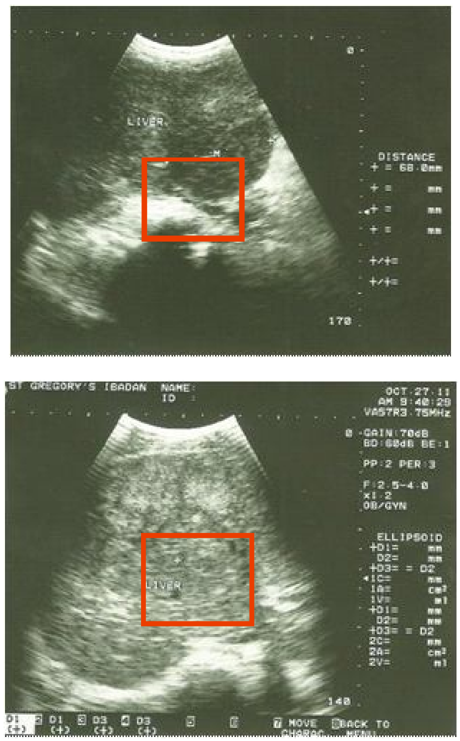
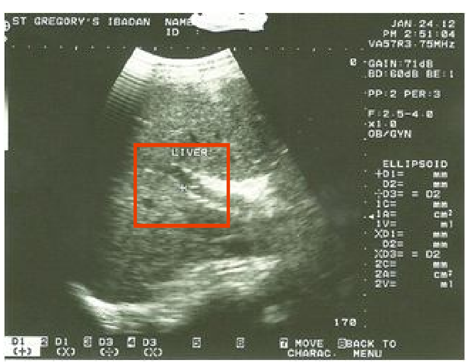


Fig. 1 Hepatocellular Carcinoma (HCC) Liver



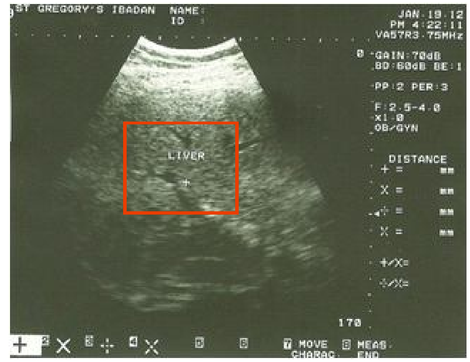


Fig. 2 Primary Liver Cell Carcinoma (PLCC) Liver

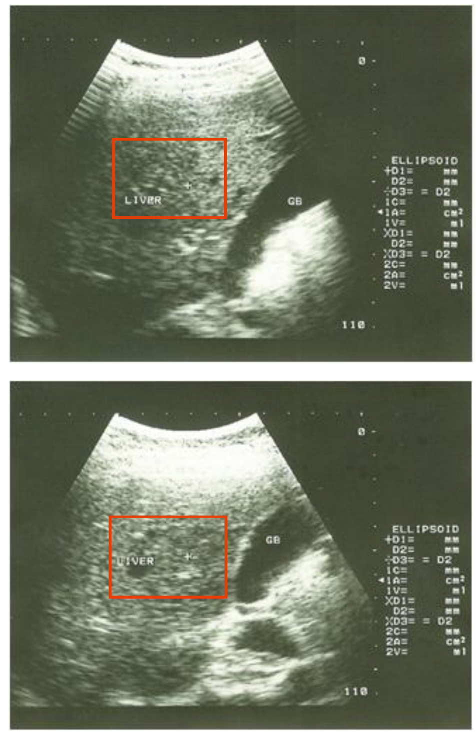


Fig. 3 Normal Liver

IV. CONCLUSION

In this paper, nine textural features derived from gray level co-occurrence matrix were extracted from the region of interests (ROIs) among the normal and abnormal ultrasound liver images. Results analysis of between classes value of each feature shows that cluster prominence, cluster shade, maximum probability, and entropy are the best discriminating features selected for the classification of liver ultrasound images and for diagnosing liver diseases based on the following diagnostic indices; False-Positive Rate, False-Negative Rate, Specificity and Sensitivity .

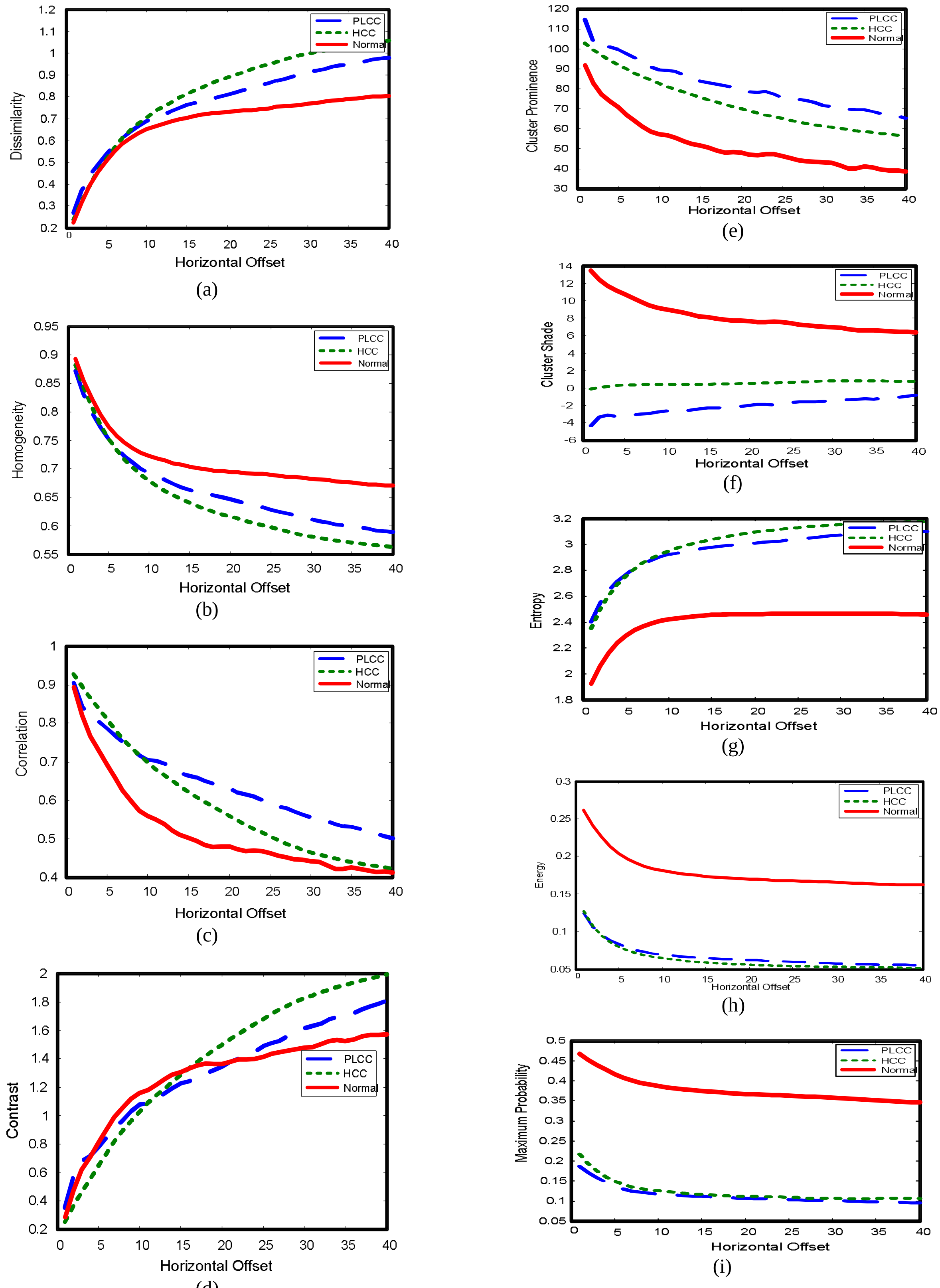


Fig.4 Analysis of saparabilty power of each feature classes'

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