Analysis of Textural Characteristics Associated with Gray Level Co-occurrence Matrix Statistical Parameters for CT-Scan Images of Liver

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***Abstract*— Liver is the largest organ of body, located in the upper left of abdomen and performs various important functions like clearing toxins from the blood, production of blood proteins and bile to help in digestion. However, liver diseases are one of the leading causes of deaths worldwide. Liver diseases like cysts, hepatitis, tumors need to be detected and diagnose at early stages. In this study we have developed a CAD system which will analyze textural characteristics associated with Gray Level Co-occurrence Matrix (GLCM) statistical parameters for CT Scan DICOM Images of Liver which will be further useful to classify the liver as healthy or diseased.**

***Keywords*— Texture analysis, Statistical parameters, Co-occurrence matrix, Liver abnormalities, Active Contour, snakes, CAD, CT, DICOM**

I. INTRODUCTION

One has to be attentive about liver diseases because of the vital role of liver in physiology of the human body. Primary liver cancer (cancer that starts in the liver) affects approximately 1,000,000 people each year [1].The traditional method used to decide whether liver tissue is normal or abnormal needs specialized radiologists. The decisions made by radiologist are also heavily dependent on their experience which is related to distinguish certain characteristics from the visual interpretation of the image and to compare them by different pathologies. The most useful approach for controlling the growth of diseases to reach at severe condition is to treat these diseases at the early stages. Early treatment requires early diagnosis, which needs an accurate and reliable diagnostic procedure. Hence Medical image processing plays an important role in diagnosis of diseases.

Most systems and organs are placed well within the body and enclosed in protective layers. Investigating or probing such systems typically requires the use of some form of penetrating radiation or invasive procedure. Various medical imaging systems are light microscopy, electron microscopy, X ray imaging, computed tomography (CT), nuclear medicine imaging, ultrasonography and magnetic resonance imaging (MRI). Computed Tomography (CT) is one of the best imaging techniques for soft tissue imaging behind bone structures. A modern multislice CT machine enables the rapid acquisition of precise sets of successive images with very high resolution supporting a more confident diagnosis. CT is often the preferred method for diagnosing many different cancers than ultrasonography, since the image allows a physician to confirm the presence of a tumor and to measure its size, precise location and the extent of the tumor's involvement with other nearby tissue.

Image texture, defined as a function of the spatial variation in pixel intensities(gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. One immediate application of image texture is the recognition of image regions using texture properties. Texture is the most important visual cue in identifying these types of homogeneous regions. This is called texture classification. Liver images have various granular structures called texture. Normal liver usually differs with the disease tone in terms of intensity texture. This variation helps in determining the corresponding disease. Several approaches have been proposed for the analysis of texture in medical images for various diagnostic applications. Approaches to texture analysis are usually categorized into: Structural, Statistical, Model-based and Transform. Statistical Approach is used in this research work. It does not presume in term of primitive but it draws on the general set of statistical tool. It is the most widely used and more generally applied method because of its high accuracy and less computation time.

A Computer-Aided-System (CAD) is a merger of medical imaging and tissue characterization techniques, and is widely used in liver diagnosis. CAD provides computerized aid to the physicians that serve as a second opinion in the detection of abnormalities, quantification of disease progress and differential diagnosis of lesions. A typical CAD system segments the region of interest (ROI) and calculates the features which discriminates the ROI depending upon abnormalities and classifies the ROI as to predefined class. The advantage of CAD systems is that they improve considerably the image based diagnosis, which reduces the necessity of using other methods, such as a needle aspiration biopsy or a surgical biopsy. Moreover, medical imaging is becoming continuously cheaper, faster, and less wasteful.

Many studies have been investigated on computer-aided diagnosis of liver diseases. Various approaches have been proposed, most of them using US B-scan, MR and CT images, based on different image characteristics, such as texture features, calculated from first and second-order gray level statistics, fractal dimension estimators and Gabor Texture. Authors [5] proposed an automated lung segmentation method using watershed transform. Veronica Vasconcelos et al. [7], evaluated the importance of a set of parameters in the classification of lung CT images, such as the size of the ROIs, the quantization level, and textural features used in classification and support vector machine was used as classifier. The result showed the performance of SGLDM and GLRLM is similar and highest for 32 gray levels. Texture analysis of liver CT images based on the Spatial Gray Level Dependence Matrix (SGLDM) has been applied to a Neural Network (NN) for the characterization of hepatic tissue (Hepatoma and Hemangioma) [3]. A CAD to classify liver tissue has been proposed based on different sets of features and using ensembles of neural network classifiers [11]. These techniques helped to reduce the work load of radiologists. These studies were mostly aimed at signifying the usefulness of texture features to detect normal-abnormal class differences and were combined with various classifiers and biomedical images.

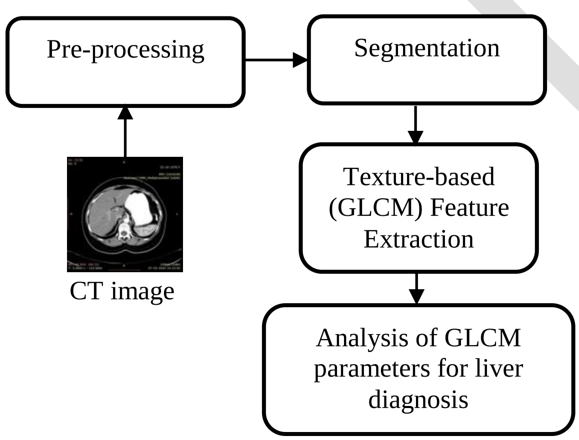

Fig. 1 Block Diagram

In this study, method for segmentation of liver and feature extraction is suggested. Analysis of statistical parameters calculated from GLCM is done which will help in classification and recognition of five hepatic tissues: healthy, hepatic cyst, hepatic abscess, fatty liver and hepatocellular carcinoma. The block diagram of the study is shown in figure 1.

II. METHODOLOGY

A. Image Acquisition

Computed tomography (CT) is one of the most common and robust imaging techniques for the detection of liver lesions. Abdominal CT images in DICOM format with a spatial resolution of 512×512 pixels and 8-bit gray-level taken for various patients and healthy individuals collected from hospital were used. The diagnosed hepatic lesions from patients with cyst, abscess, fatty liver and hepatocellular carcinoma are validated by radiologist. A total of 78 ROIs were sampled and analyzed according to values of statistical parameters.

Table I. Distribution of Ct image Database

Type	No. of images
Normal	36
Fatty	10
Abscess	8
Cyst	12
Hepatocellular Carcinoma	12

B. Liver Segmentation

An active contour is an energy minimizing spline that detects specified features within an image. It is a flexible curve (or surface) which can be dynamically adapted to required edges or objects in the image. The user must suggest an initial contour which is quite close to the intended shape. The contour will then be attracted to features in the image extracted by internal energy creating an attractor (ROI) image. The algorithm can deal with weak image boundaries and low contrast images but the accuracy of this method depends on the initial points of the contour. The basic snake model is a controlled continuity spline under the influence of image force and external constraint forces. The internal spline forces serve to impose a piecewise smoothness constraint. The image forces push the snake toward salient image features like lines, edges, and subjective contours. The external constraint forces are responsible for putting the snake near the desired local minimum. These forces can, for example, come from a user interface, automatic attentional mechanisms, or high-level interpretations. Representing the position of a snake parametrically by v(s) = (x(s), y(s)), we can write its energy functional as:

$$E_{snake}^{*} = \int E_{snake}(v(s))\,ds$$

$$= \int [\, E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))\,]\,ds$$

where E_{int} represent the internal energy of the spline due to bending, E_{image} gives rise to the image forces, and E_{con} gives rise to the external constraint forces.

C. *Feature Extraction Based on Gray-Level Co-Occurrence Matrix*

GLCM describes the frequency of one gray tone appearing in a specified spatial linear relationship with another gray tone, within the area under investigation [2]. GLCM are normally defined for a fixed distance and direction, so pixel pairs are defined by a distance and direction which can be represented by a displacement vector d = (dx, dy), where dx represents the number of pixels moved along the x-axis, and dy represents the number of pixels moved along the y-axis of the image slices. To compute features for the ROI, the normalized co-occurrence matrices are calculated in four directions (0, 45, 90, and 135).

GLCM gives fourteen statistical GLCM parameters [1] out of which six parameters are relevant [4] to describe the properties of texture. The six parameters are as follows:

1. *Contrast:* It is a measure of the amount of local variation in an image.

$$\text{Contrast} = \sum_i^m \sum_j^n (i-j)^2 \mathrm{P}[i,j]$$

2. *Entropy:* It measures he randomness of a gray-level distribution. The Entropy is expected to be high if the gray levels are distributed randomly throughout the image.

$$\text{Entropy} = -\sum_i^m \sum_j^n P[i,j] \log P[i,j]$$

3. *Energy:* It measures the uniformity of texture of area under consideration. Energy is maximum when the image patch under consideration is texturally uniform.

$$\text{Energy} = \sum_i^m \sum_j^n P^2[i,j]$$

4. *Homogeneity:* It measures the local homogeneity of a pixel pair. The Homogeneity is expected to be large if the gray levels of each pixel pair are similar

$$\text{Homogeneity} = \sum_i^m \sum_j^n \frac{P[i,j]}{1+|i-j|}$$

5. *Variance:* Variance tells us how spread out the distribution of gray levels is. The Variance is expected to be large if the gray levels of the image are spread out greatly.

$$\text{Variance} = \frac{1}{2} \sum_i^m \sum_j^n (1-\mu)^2 P[i,j] + (j-\mu)^2 j P[i,j]$$

6. *Correlation:* Provides a correlation between the two pixels in the pixel pair. The Correlation is expected to be high if the gray levels of the pixel pairs are highly correlated.

$$\text{Correlation} = \sum_i^m \sum_j^n \frac{(i-\mu)(j-\mu)P[i,j]}{\sigma^2}$$

III. ALGORITHM

In our study, algorithm is implemented on MATLAB R2015a.

A. *Pre-processing:*

1. Smoothing is performed on original image to remove noise which is present in CT image. The un-sharping filtering method was used for enhancing edges and contrast enhancement. The alpha value needed for this filtering method was experimentally calculated and optimal results obtained at $\alpha = 0.1$.

B. *Segmentation of liver using Active Contour Method*

1. User need to select initial points near to the real contour on the smoothed image.
2. Using the initial points, spline is created
3. Energy from edges, lines and images forces the spline is attracted to the boundary of liver.
4. The value of spline which detected boundary of liver is used to separate the liver from the background image.

C. *Feature Extraction of GLCM*

1. GLCM is calculated for segmented liver symmetrically at 0, 45, 90, and 135 degrees at distance 0 pixel. GLCM of 32-bit is calculated as it provides sufficient information and does not increase the computational complexity.
2. Contrast, Correlation, Energy, Homogeneity, Entropy and Variance are measured from GLCM for 0, 45, 90, 135 degrees. Total number of 24 features is extracted.
3. Average of all six parameters at four degrees is calculated. Therefore we have only six features for a particular ROI.

IV. RESULTS AND DISCUSSION

The study consists of two solutions: Segmentation and analysis of parameters based on feature extraction. Segmentation of liver is successfully done using Active contour method. Figure 2 shows original CT image and the liver segmented from original image is shown in figure 3.

Fig. 2 Original CT image

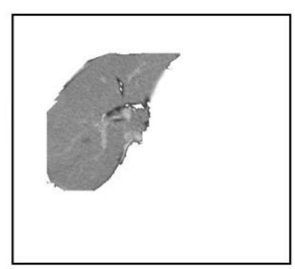

Fig. 3 Extracted liver

On analysis of features obtained from feature extraction stage, three features: Contrast, Energy, and Variance were significantly different between healthy and four diseased: fatty liver, cyst, abscess, and HCC patients. The average value for contrast, energy and variance features is shown in table II

Table II. Average value of features

Type of Liver	Contrast	energy	Variance
Normal	2.47	0.64	10.63 × 10E6
Fatty	2.49	0.56	7.76 × 10E6
HCC	2.61	0.51	8.13 × 10E6
Cyst	4.01	0.49	7.39 × 10E6
Abscess	2.67	0.53	15.31 × 10E6

Discrimination of normal and diseased (fatty liver, cyst, abscess, HCC) images for different textural features are analysed using box-plot. The box-plot for three features namely contrast, entropy and variance are shown in fig 4, fig 5 and fig 6 respectively.

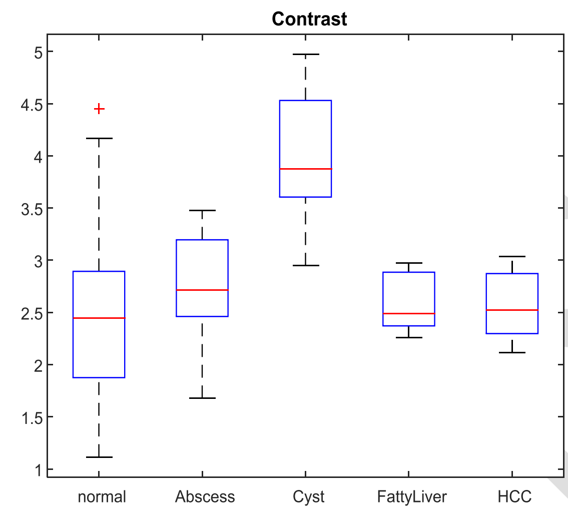

Fig. 3: Performance Analysis of Textural Feature: Contrast

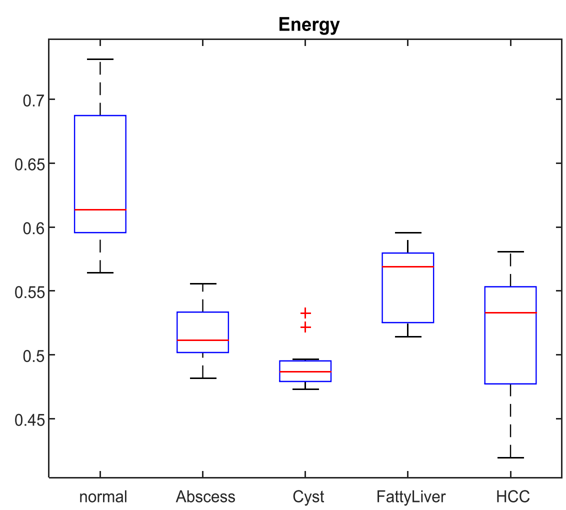

Fig. 4: Performance Analysis of Textural Feature: Energy

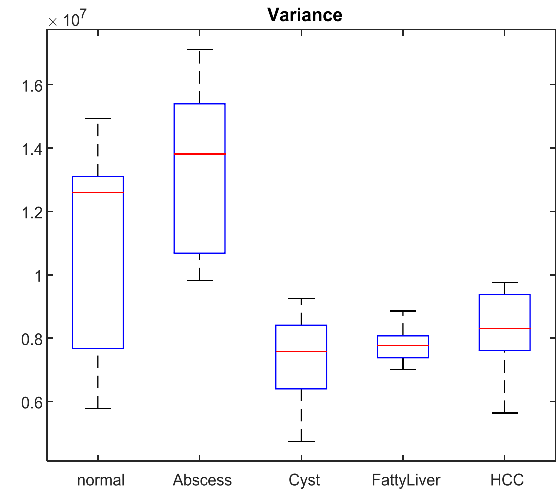

Fig. 5: Performance Analysis of Textural Feature: Variance

A. Results for variation in features:

1. Energy measures textural uniformity, hence Energy obtained in abnormal cases is less as compared to normal cases. Value of Energy is highest in normal liver.
2. Contrast is a measure of the amount of local variation in an image. As this study is performed on non-enhanced images, contrast feature obtained is almost same in normal, fatty liver and HCC cases. HCC tumor is more easily visible in enhanced images such portal, venous phases, etc. Cysts are thin-walled fluid like structure with bile-like watery fluid, hence cyst have more local variation in gray-levels and contrast feature obtained is highest in cysts cases.
3. Variance tells us how spread out the distribution of gray levels is. Abscess is thick-walled, dark colored, radio-opaque containing generally fluid made up of dead cells, white blood cells, bacteria present in liver. Hence the mass is denser and hence more gray level spreading is observed and variance feature obtained is highest in case of abscess liver. In other abnormal cases, variance feature is less compared to normal case of liver.

The variation in contrast, energy and variance features in different diseases compared to healthy liver is shown in table III.

Table III. Variation in features compared to healthy liver

Type of Liver	Variation in Features		
	Contrast	energy	Variance
Fatty	Almost same	Decreases	Decreases
HCC	Increases	Decreases	Decreases
Cyst	Increases	Decreases	Decreases
Abscess	Increases	Decreases	Increases

V. Conclusion

The results obtained show that applying smoothing filter on original image and by proper combination of image parameters best results are obtained for segmentation of liver. It has also been observed that accuracy of segmentation depends on selection of initial points of contour. The results obtained from feature extraction phase show that an optimal solution can be obtained using six texture features. Significant variation in values of three features viz. Contrast, Energy and Variance is observed for normal and abnormal livers.

VI. Future Work

The feature set calculated will be used for designing a classifier which will aim at classification of four diseased livers: Hepatic Cyst, Fatty Liver, Hepatic Abscess and Hepatocellular Carcinoma. Abnormality analysis of other abdominal organs viz. Gall bladder, spleen, Kidneys etc. can also be done using same methodology.

Only CT scan images of abdomen are studied in this work. Images of other body parts can also be considered. In addition, other images like MRI, Ultrasound, X ray images etc. can also be taken and effects of various parameters can be studied on them. The proposed system can be extended for other types of images or for other classes of liver diseases and other organs, provided that the feature vectors are re-evaluated. The findings of this work may also suggest a much easier hardware implementation of tissue analysis functions to be provided in image acquisition machines like CT scanners in the future. This can be helpful for teaching and for fresher to improve their diagnostic accuracy.

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