IETE 46th Mid Term Symposium "Impact of Technology on Skill Development" MTS- 2015
Special Issue of International Journal of Electronics, Communication & Soft Computing Science and Engineering, ISSN: 2277-9477

Classification of Liver Disease: A Review

Vishakha V. Hambire **Dr. S.R. Ganorkar**

***Abstract*— Liver disease is progressive, asymptotic and potentially fatal. The classification stratergy of the chronic Liver disease is proposed in this paper. Classification of liver disease using the USG of Liver is based on the k-nearest neighbuor classifier. The well established classification srtatergy of liver disease differential diagnosis is built up. The classifier classifies the Liver in three stages. The performance of the proposed technique reliable evolution that can improve the information in classification of Liver disease.**

***Index Terms*—Liver cirrhosis, Conrtast Enhancement, Descrete wavelet transform.**

I. Introduction

Chronic liver disease (CLD) is a significant cause of morbidity and mortality in developed countries. It is generally caused by viral hepatitis, alcohol abuse and metabolic disorders.These results in hepatocytes damage, the consequence of which may be liver fibrosis, cirrhosis, hepatocellular carcinoma.

Typically, The initial stages of CLD are usually asymptomatic such as steatosis or hepatitis. Hepatitis is the inflammation of the liver, which results in liver cell damage and destruction. It is caused by hepatitis viruses, which can have several types, or by other factors. CLD is established with the presence of hepatitis which can evolve to the end-stage of every CLD - cirrhosis. In the cirrhosis stage there are two phases a compensated one (asymptomatic) followed by the development of liver dysfunction,i.e. decompensated cirrhosis.

Liver biopsy is an important step in the evaluation and staging of CLD. Nevertheless, due to it's invasive nature and the improved accuracy of noninvasive tests, its importance have diminished. In particularly, ultrasound (US) as proven to be an very much useful diagnostic procedure for CLD.

Ultrasound is commonly used initial examination for diagnosis of diffuse liver diseases because of its non radioactive, non-invasive and inexpensive nature. Cirrhosis is a diffused disease, most commonly seen as a precursor to the development of hepatocellular carcinoma. Experienced radiologists differentiate normal liver from cirrhotic liver by observing the echotexture which is mostly homogeneous with medium echogenicity in case of normal liver. The diagnosis of cirrhotic liver is carried out by observing the degree of nodularity present in the heterogeneous echotexture. Variation in size and shape of liver is observed depending upon severity of the liver cirrhosis. The right lobe is mostly affected by cirrhosis .

II. Related Work

In the review study presented in [1] it is shown that echogenicity, texture characterization and surface morphology of the liver parenchyma are effective features to diagnose the CLD. However, the evaluation of these features is normally affected by the subjective assessment of the human operator. This factor may lead to significant errors in the diagnosis and staging of CLD, since US liver images can show great variability. Therefore, new objective feature extraction and classification methodologies in a Computer Assisted Diagnosis framework are needed.

An experimental study was performed in [2] aiming at to discriminate the liver fibrosis from ultrasound images. They computed fractal features, entropy measures and cooccurrence information from ultrasound images to characterize the liver parenchyma form a textural point of view and the classification results by using a Fisher linear classifier.

Other important work described in [3] shows the ability of the Wavelet coefficients, also computed from US images, to characterize the diffuse liver disease. Their goal was to discriminate normal, steatotic and cirrhotic conditions. A comparison results by using other classes of features, such as co-occurrence information, Fourier descriptors and fractal measures, show that the wavelet based classifier outperforms the classifiers based on the other features.

In addition, the study in [4] proposes a quantitative tissue characterization to increase the usefulness of US for evaluating the diffuse liver disease. In [5] it is referred that the pulse echo data from different grain types contain distinguishable statistical regularities.

In the study presented in [6] a set of features from speckle and despeckled speckled image fields, computed from US images, to detect chronic liver disease. The commonest features described in literature for the diagnosis of diffuse liver diseases include first order statistics, co-occurrence matrices, wavelet transform, attenuation and backscattering parameters.

In [7] mean and standard deviation texture descriptors (TDs) evaluated from various subband feature images obtained by 2D-DWT, 2D-WPT and 2D-GWT are considered for classification of normal and cirrhotic liver. It is well known that classifier designs which use regularisation like support vector machines are less prone to over fitting and obtain good generalisation performance to a certain extent even without feature space dimensionality reduction. For the this work SVM classifier is chosen for classification of normal and cirrhotic liver.

III. Methodology

It is common practice to have the preprocessing of US images before it has been extracted and classified.

A. *Preprocessing of Ultrasound image of liver*

The input inage has to be preprocessed because images are corrupted by a type of multiplicative noise, that may contain useful information about the tissues that can be used in the medical diagnosis. The preprocessing is done with the contrast enhancement, discrete wavelet transform .

Contrast Enhancement

Contrast is the visual property of an object that separates it from other objects in an image. The contrast of objects against

Journal Impact Factor-2.02
Indexed by- ProQuest, DOAJ and many International Bodies.

the background of an image is important for two functions: identifying an object and later tracking it. In order to have discernible objects that can each be properly recorded and tracked, correct contrast levels must be utilized to distinguish one object from another.

Contrast enhancements improve the perceptibility of objects in the scene by enhancing the brightness difference between objects and their backgrounds. Contrast enhancements are typically performed as a contrast stretch followed by a tonal enhancement, although these could both be performed in one step. A contrast stretch improves the brightness differences uniformly across the dynamic range of the image, whereas tonal enhancements improve the brightness differences in the shadow (dark), midtone (grays), or highlight (bright) regions at the expense of the brightness differences in the other regions.

Discrete wavelet transform

The *Wavelet Transform* (WT) provides multiscale features from the US images. The decomposition is performed according to a sequence of low pass (*G*) and high-pass, (*H*), filtering operations followed by down-sampling the results, ↓2. This method generates a pyramidal representation of the original image with decreasing resolution comprising a lower resolution low-pass component (approximation component) (LL), and three high-pass components (detailed components) along the horizontal (HL), vertical (LH), and diagonal directions (HH). An example of a multiscaleWT analysis using a US liver image is provided in Fig. 3. High-pass components (*H*) contain image detailed information at different resolution scales along three directions, while low-pass versions (*L*) contain the approximation component.

Liver tissue characterization based on WT multiresolution analysis has been performed in several works. This approach is effective in the morphological characterization of the image from the approximation fields and at the same time in a textural characterization at several resolution scales from the detailed fields.

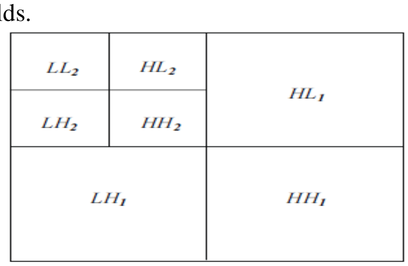


Fig. 1 wavelet pyramidal decomposition of images.

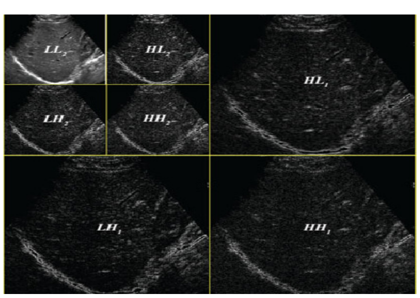


Fig.2 Wavelet pyramidal decomposition example from a US liver image

Classification

Instance-based classifiers such as the kNN classifier operate on the premises that classification of unknown instances can be done by relating the unknown to the known according to some distance/similarity function. The intuition is that two instances far apart in the instance space defined by the appropriate distance function are less likely than two closely situated instances to belong to the same class.

The purpose of the k Nearest Neighbours (kNN) algorithm is to use a database in which the data points are separated into several separate classes to predict the classification of a new sample point.

The non-parametric kNN classifier is tested in this study. It classifies a test sample to a class according to the majority of the training neighbors in the feature space by using the minimum Euclidean distance criterion . The algorithm for the *nearest neighbor rule* is summarized as follows ; Given an unknown feature vector *x* and a is the distance measure, then:

• Out of the set of *N* training vectors, identify the *k* nearest neighbors, regardless of class label.

• Out of these *k* samples, identify the number os vectors, *ki*, that belong to class w*i*, i=1, 2, ..., M.

• Assigning *x* to the class w*i* with the maximum number *ki* of samples.

B. Dataset

For this experimental study a dataset is built up. A total of 70 US images from 70 patients has been collected for the work. A real dataset is collected from the patients from radiology department ,SKN medical college,Pune.

Radiology experts confirmed the presence of cirrhosis by assessment criteria including:

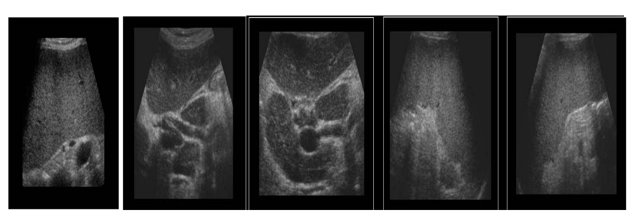
1 Visual inspection of sonographic features according to their expertise.

2 Follow-up the clinical history of the patient and other associated finding.

IV. EXPERIMENTAL RESULTS

In this section, results from the real data, as described in previous section are presented to validate the proposed method. All the results are obtained with the Matlab for pattern recognition. All the results shown below are for the preprocessing. For this first contrast enhancement is done on the input US image. Contrast enhancements improve the perceptibility of objects in the scene by enhancing the brightness difference between objects and their backgrounds.

Then later discrete wavelet transform is applied to that image.Then after taking DWT, the approximate component subjected to classifier i.e k mean, which segments the image with respect to the Euclidian distance. The results generated are of the same.



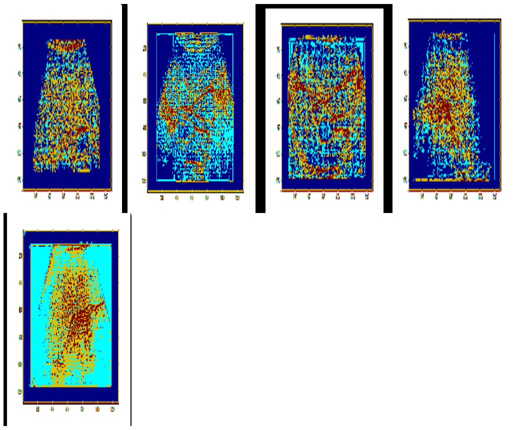


Fig. 3. Input US image of Liver and its corresponding results.

Above results are generated from the preprocessing procedures. The red shows third level liver disease. Yellow shows second level,while blue shows first level liver disease.

CONCLUSION

In the work of the proposed technique demonstrate the classification strategy for the liver disease based on the USG of liver. The method undergoes preprocessing and then the classification. The main goal of method is to provide a useful diagnosis tool which may reduce, but does not replace, liver biopsy and it is useful for the doctors for the second openion.
In future work, the proposed multifeature approach will be expanded to incorporate more textural and morphological features. Moreover future work will also investigate classifier combination techniques as well as other classifier such as Neural Networks, SVM classifier.

ACKNOWLEDGMENT

I would like to thank my respected Guide Dr. S. R. Ganorkar for his encouragement and support. I gratefully acknowledge him for imparting me the valuable basic knowledge of Digital Image Processing. I am also thankful to the department of Electronics and telecommunication Engineering, Sinhgad College of Engineering, Pune for providing us infrastructure facilities and moral support.

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