SURVEY ON LIVER DISEASES IDENTIFICATION BASED ON ULTRASOUND IMAGES

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Abstract : Liver diseases are one of the most popular diseases and cause a large amount of death. Ultrasound is a popularly used medical imaging for liver diseases diagnosis. Detection of the liver diseases is highly important for medical treatment. In this paper, a general comparative analysis is performed based on various available segmentation techniques and classification techniques. This paper analyses the applicability of the techniques in liver diseases identification from Ultrasound images that have been proposed to diagnosis various liver diseases.

***IndexTerms* - Liver diseases, Ultrasound Images, Pre-processing, Segmentation.**

I. INTRODUCTION

Liver is the largest internal organ in the human body, playing a major role in metabolism and serving several vital functions. Liver disease is any disturbance of liver function that causes illness. The liver is responsible for many critical functions within the body and should it become diseased or injured, the loss of those functions can cause significant damage to the body [24]. Liver disease can be inherited or caused by a variety of factors that damage the liver, such as viruses and alcohol use. Obesity is also associated with liver damage. Over time, damage to the liver results in cirrhosis, this can lead to liver failure, a life-threatening condition. Medical image analysis is an important biomedical application which is highly computational in nature and requires the aid of the automated systems. The image analysis techniques are often used to detect the abnormalities in the human bodies through scan images.

Due to the highly varying shape of liver and weak edges between some adjacent organs, liver segmentation becomes a difficult task. The low contrast between the intensities of the liver and its nearby organs hinders the accurate segmentation. The imaging techniques such as Ultrasound (US), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), or Positron Emission Tomography (PET) are the standard instruments for the diagnosis of liver pathologies such as cirrhosis, liver cancer, and fulminant hepatic failure. The Computer Aided Diagnosis (CAD) system consists of Image segmentation and classification. The liver segmentation process is followed by a preprocessing stage. There are several methods for the segmentation of liver. The various approaches used for liver segmentation are based on Threshold, Region of Interest (ROI), Entropy-based thresholding, Otsu thresholding, Iterative isodata thresholding, and Fuzzy C-means (FCM) based thresholding. There are several methods for the segmentation of liver. Many research papers with various different classification methods are Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Back Propagation Neural Network (BPNN). The Section 2 describes the Survey on Image Pre-Processing, Section 3 describes the Survey on Image Segmentation, Section 4 describes the Survey on Image Classification, and finally Section 5 concludes the work.

II. IMAGE PRE-PROCESSING

Image preprocessing is one of the preliminary steps required for getting high accuracy in liver segmentation. The idea of anisotropic diffusion into image processing. Unlike conventional spatial filtering techniques that do not protect region boundaries or small structures, anisotropic diffusion techniques can simultaneously eliminate noise and preserve or even enhance edges [2]. Speckles were removed from images by applying anisotropic diffusion filter. Anisotropic diffusion resembles the process that creates a scale-space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process [3]. Enhance the processed image and remove noise by using a median filter Classification Framework for Diagnosis of Focal [4].

III. IMAGE SEGMENTATION

Segmentation is one of the most significant steps in CAD systems. It is the approach of cutting off an image into different regions. Each region has identical properties like contrast, color, gray level, texture, and brightness[5].The image segmentation is to partition an image into meaningful regions with respect to a particular application. In medical sector, segmenting the liver is difficult since the image includes intensity homogeneities of other organs like kidney, spleen, and pancreas.

There are many segmentation techniques that include Region Growing, Region splitting, Edge based techniques, Threshold based, Level Set method, Statistical model, Active Contour, Clustering algorithm, Histogram based approach and Gray level methods[6]. The Fig 1 shows the various segmentation techniques.

3.1 Region Based Method

Region-based techniques are categorized into two methods one is region growing approach and another region splitting approach. These approaches are based on the similarity among the pixels within a region [7], [8].

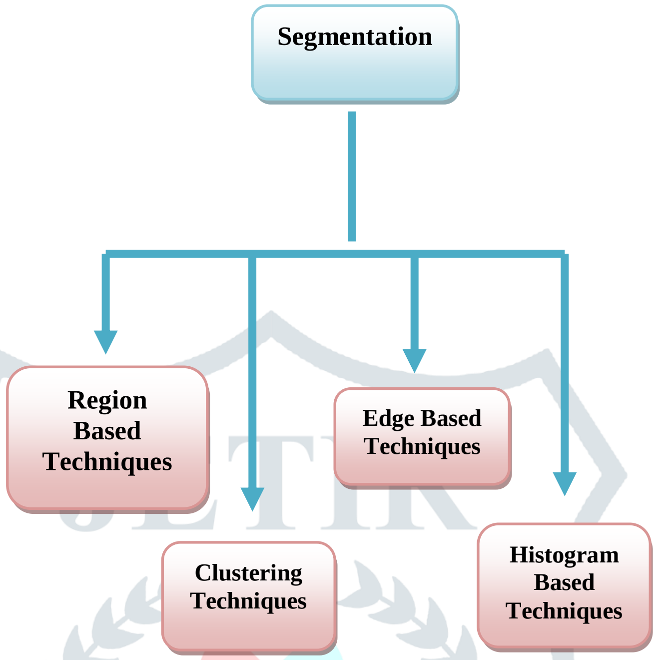

Figure 1: **segmentation techniques**

In the region growing approach, the process starts by selecting a seed region (pixel). The region grows by adding the neighbors' pixels that have the same predefined criteria with the seed, such as intensity or gray level. The process ends when there is no pixel to be added. The advantages of region growing method are that the concept is simple, only small number of seed point is enough to grow region. By using this method we can correctly separate the regions that have the same properties and provide original images with have clear edges [8].

In region splitting approach, the process begins with the whole image as a seed. Then the seed is split into a number of subregions, usually four subregions. Thus, the process is repeated using each subregion as a seed. The process ends when there are no regions of the partition. Then, merge any adjacent regions that have similar properties, such as intensity or gray-level. The region-growing based approaches can provide good results on contrast enhanced images [6].

3.2 Clustering Method

A cluster is a collection of similar pixels that are dissimilar to the pixels in the other clusters [9]. Clustering techniques perform clustering either by partitioning or by grouping pixels. In partitioning type, it begins with the whole image and divide it into successively smaller clusters. Whereas, in the grouping type, it begins with each element as a unique cluster and merge these individual clusters to obtain larger clusters.

We can divide clustering techniques to supervised clustering and unsupervised clustering. Supervised clustering technique needs the interaction of humans to determine the clustering criteria, but in unsupervised clustering technique, the clustering criteria is determined by itself. The most significant clustering algorithms some are, k-means, fuzzy c-means, and particle swarm optimization. Bayesian classification [1], automatically extracts the liver from medical images. It utilizes adaptive parameters according to the characteristics of a particular patient (the new slice) to accommodate patient-specific liver features during segmentation.

3.3 Edge-based Method

One of the most common techniques for image segmentation that is used for detecting the discontinuities in intensity value is the edge-based technique [7], [10]. It is based on a sudden change in intensity level at the region's boundaries of images. The edge in an image can be defined as the border between two regions that differ in the level of intensity [11]. These edges are used to determine the size of objects and separate objects from the background. To locate the different points in the image where the intensity naturally changes, edge detectors should be used.

In order to detect an edge in the image, two main methods can be used. These methods are a search-based method and zero-crossing based method. In search-based method, it first calculates the gradient magnitude using first order derivative expression. Therefore, it searches for local directional maxima of the gradient magnitude using the gradient direction.

In zero-crossing based method, it first searches for a zero crossings in the second derivative of the image. It can detect edges by locating the zeros in the second derivative of when the first derivative is at a maximum, the second derivative is zero. This method is also known as Laplacian based edge detection. The problem of edge-based segmentation technique is that it does not work well when there are many edges in the image.

3.4 Histogram based Method

Fully automatic liver segmentation use histogram tail threshold algorithm to segment the liver region by eliminating neighbouring abdominal organs of the liver, such as the pancreas, spleen, and kidneys [12]. In Otsu's method using threshold the histogram using maximum, minimum, median intensity of ROI is used to detect the location of the liver from the Region of Interest.

IV. CLASSIFICATION

Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: training and testing. In the initial training phase, characteristic properties of typical image features are isolated and based on these a unique description of each classification category i.e. training class is created. In the subsequent testing phase, these feature space partition are used to classify image features. Sensitivity is the conditional probability of detecting a disease while there is a liver disease. Specificity is the conditional probability of detecting as a normal liver while the liver is indeed a normal.

The classification of image is done using Artificial neural networks have proven themselves as proficient classifiers and are particularly well suited for classification. The performance of the classifier is evaluated by calculating accuracy, selectivity and specificity from the obtained confusion matrix. Multi-SVM classifier classifies the ROI of the liver images into four classes which are Cyst, Hem, HCC, or a normal image. The goal of SVM classifier is to obtain the optimum hyperplane that separates the different classes [13].

In the training phase, the weights and bias vector are computed using a minimizing cost function. The criterion used by SVM is based on margin maximization between the two data classes. The margin is the distance between the hyperplanes bounding each class. By maximizing the margin, search for the classification function that can most safely separate the classes of normal from the infected tissue [14]. Table 1 shows comparative analysis of various classification techniques.

Table 1: Comparative analysis of various classification techniques

Author	Classifier Techniques	Performance
Tarek M. Hassan (2015)	Multi SVM	96.50%
	KNN	93.60%
	Bayes	95.20%
Andreia Andrade (2012)	ANN	65.27 %
	SVM	66.41%
	KNN	69.08%
Ali.A.Sakr (2014)	Multi-SVM	96.11%
	KNN	93.30%
Fayyaz ul Amir Afsar Minhas (2011)	SVM	95.00%

V. CONCLUSION

It has been observed from the survey that classification of liver diseases is more precise in CT imaging model, but with compared to US imaging modal however CT imaging is costlier. US images force a few troubles to analyze the structure of the liver and then further analyzing texture is a challenge but US imaging is cost effective. Ultrasound scan wavelet-based techniques for feature extraction show good accuracy according to study. The outcomes may enhance by applying combination of texture feature extraction methods and classifiers.

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