Automatic Identification of Ultrasound Liver Cancer Tumor Using Support Vector Machine

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***Abstract*-**Ultrasound liver tumor image are naturally have more spackle noise. Automatic identification of ultrasound liver tumor image is a challenging task. In this proposed system, weapproach fully automatic machine learning system for indentifying the liver cancer tumor from ultrasound images. First, we segment the liver image by calculating the textural features from co-occurrence matrix and run length method. This is the best method for segmentation of ultrasound liver cancer tumor images because it is not affected speckle noise and also preserves spatial information. For classification Support Vector machine are a general algorithm based on the risk bounds of statistical learning theory. They have found numerous applications, such as in optical character recognition, object detection,face verification, text categorization and so on. The textural features for different features methods are given as input to the SVM individually. Performance analysis train and test datasets carried out separately using SVM Model. Whenever an ultrasonic liver cancer tumor image is given to the SVM classifier system, the features are calculated, classified, as normal, benign and malignant liver cancer tumor. We hope the result will be helpful to the physician to identify the liver cancer in non invasive method.

***Keywords*-**Segmentation, Support Vector Machine,Ultrasound Liver Cancer Tumor

I. Introduction

IN the medical field computer are now being used virtually in every aspect of modern medicine. Computers are used widely in medical research, where there is a vital need for better microelectronic sensors for data acquisition. Imaging modalities like Ultrasound, MRI (Magnetic Resonance Imaging), CT (Computed Tomography) and PET (Positron Emission Tomography) are widely used techniques for liver cancer tumor diagnosis [1].

Liver cancer tumor is sixth dangerous diseases in the world. Liver diseases are considered seriously because of the liver's vital importance to human beings. There are two classes of liver tumors: benign and malignant [2]. Ultrasound image is a powerful tool for characterizing the state of soft tissues for medical diagnostic purposes. Ultrasound has been extremely valuable in differentiating a simple liver cancer tumor from other liver masses.

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An approach has been made in this research to design a diagnostic classifier system for the identification of liver cancer tumor in ultrasound images using image texture features in non-invasive manner.

Image processing modifies pictures to improve them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method because digital methods are fast, flexible, and precise[3].

So,The proposed system we applied the co-occurrence matrix features and gray level run-length features for identifying the seed point for given ultrasound liver images. After the detection of automated seed point we have to segment the liver image applying the region growing algorithm using gray space map and Otsu algorithm. After segmentation of the image we analyzed calculated texture features parameters to classified, as normal, benign and malignant liver cancer tumor. We explains the image processing procedures, segmentation of image in the section 2, Computation of different image texture features of different feature extraction methods namely first order statistics, run length statistics, wavelet based texture features in section 3, machine learning classifier SVM used for classification of Ultrasound Liver cancer tumor image using texture are describes in the section 4, Trialing resultin section 5 and conclusion in the section 6.

II. Material and Methodology

2.1. Image Preprocessing

An Ultrasound liver cancer tumor images has been taken for this study. The preprocessing step typically is used for reduce the noise and to prepare the ultrasound liver image for further processing such as segmentation and classification.To get a high-pass filter, the general procedure is to apply a low-pass filter to the original image and then subtract this low-frequency image from the original image. The result is then an image containing only high frequencies. Sometimes it is desired to enhance the high frequencies without removing the low frequencies. This is called giving the image a high-frequency *boost*. The preprocessing work could be done for removing the noise of the images. After the removal of noise from the image we applied the histogram to identify the maximum of the intensity value.

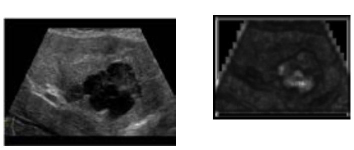
Then we applied the techniques for segmentation of the ultrasound liver cancer tumor.

2.2. Segmentation

Segmentation is played a important role in the image processing. Normally, Segmentation of Ultrasound images are very difficult because it contain more speckle noise. Segmentation of medical images involves three main image-related problems. Images contain *noise* that can alter the intensity of a pixel such that its classification becomes uncertain, images exhibit *intensity no uniformity* where the intensity level of a single tissue class varies gradually over the extent of the image, and images have finite pixel size and are subject to *partial volume averaging* where individual pixel volumes contain a mixture of tissue image may not be consistent with any one class [4].Segmentation of ultrasound liver cancer tumor is more critical because it contains more speckle noise and artifacts. The proposed system we planned to apply the co-occurrence matrix features and gray level run-length features for identifying the seed point for given ultrasound liver images. After the detection of automated seed point we have to segment the liver image applying the region growing algorithm using gray space map and Otsu algorithm for segmenting the ultrasound liver image. These Co occurrence matrix features and the run length also used for the classification of the ultrasound liver cancer tumor images.

2.3.Gray Space Map

The algorithm of region growing is very simple. We compute the seed gray level: U, then look for structures which have the same gray level than the seed overlapping the seed position. At the second iteration, we look for structures having a small gray level difference from the seed. In other words we define a set of gray levels from U-D to U+D. Then we keep those structures which overlap the seed position. At each iteration we increase the difference D by 1. In this way structures which are closed from a spatial AND intensity point of view to the seed are highlighted with higher values [6]. In new image if we far spatially and from an intensity the point of view from the seed, the lower intensity is labeled. The resulted image is Gray Space map of image.



(a) (b)

Figure1: (a) Original Image (b) Gray Space Map Image

2.4. Region Growing Segmentation

First we find the maximum area variation in which means that from this intensity to 0 we are sure that this is not the ROI. Second we cut the histogram from MAX to 0. Then, we have to find the threshold from MAX to the highest intensity which separates the uncertainty area from the ROI. This is simply done using the well-known Otsu thresholding method [7]. This is a parameter free thresholding technique which maximizes the inter-class variance. It is interesting to observe that the Otsu method is more accurate in cutting into two classes. Otsu also takes care to get compact clusters using the inter-class variance. In Fig.2 we can see the segmented image.

(a) (b) (c)

Figure 2: (a) Histogram Equalized Image (b) High Pass FilteredImage (c) Segmented image

III. Texture Feature Extraction Methods

Texture feature extraction is the procedure of generating descriptions of a textured surface in terms of measurable parameters. The extracted features represent the relevant properties of the surface, and may be used with a classifier. The following textural features groups are used in the proposedsystem,First order statistics (Histogram), Secondorder statistics, Run - length matrices and Waveletfeatures.

3.1 First Order Statistics

In this method, the features are derived from the gray level histogram. The digital image can be represented as a two-dimensional array in the computer. For the digital images, 8 bits are sufficient and the gray-level values range from 0 to 255.Lower values are attributed to darker pixels, and higher values to brighter pixels. Therefore 0 represents the black and white represents the 255.

3.2.Co-occurrence Matrix Feature

A Co-Occurrence Matrix (COM) is square matrices of relative frequencies P (i, j, d, q) with which two neighboring pixels separated by distance d at orientation q occur in the image, one with gray level i and the other with gray level j[4]. Therefore, a square matrix that has the size of the largest pixel value in the image and presents the relative frequency distributions of gray levels and describe how often one gray level will appear in a specified spatial. In our project 2 textural features were calculated from the COM for direction h values of 0° and a distance d of 1.

In this work the co-occurrence features energy and entropy which can easily differentiate non-homogeneous region from homogeneous region are considered. Energy is called Angular Second Moment. It is a measure the homogeneousness of the image and can be calculated from the normalized COM.Energy is expected to be high if the occurrence of repeated pixel pairs is high.

It denotes the normalized co-occurrence matrix by total number of the occurrence of two neighboring pixels between I gray-intensity at vertical direction and angle Θ.

Entropy gives a measure of complexity of the image. Complex textures tend to have higher entropy if the gray levels are distributed randomly through out of the image. These two parameters can identify seed pixel from the abnormal region of the ultrasound liver cancer tumor images. Some times for some cases the normal liver region also can appear be a homogeneous. So to avoid that situation by calculating the run length features.

3.3.Gray Level Run-Length Features

In ultrasound liver images, there are run-length features calculated from run –length matrix that are capable of capturing the texture primitives' properties for different structures in 2D image data, such as the homogeneous texture structure of the image. It denotes the number of runs of length and gray level occurring in the image region. LongRunEmphasis *(LRE)* feature measures distribution of long runs. The LRE is highly dependent on the occurrence of ling runs and is expected large for coarse structural textures.RunLengthNon-uniformity *(RLN)*measures the the task of assigning a set of objects into groups (called clusters) so that the objects in the same cluster are more similar to each other than to those in other clusters. Clustering is a main task of explorative data mining, and a common technique for statistical data analysis used in many fields, including machine learning. Using K-means clustering classified the ultrasound liver cancer image as Normal, Benign, and Malignant.

V. RESULTS

We describethe performance of the SVM classifier to identification of liver cancer tumor from different textural features method used for segmentation and classification. The texture features are extracted from the high intensity value using Otsu'sthresholding method. SVM used as a classifier.

TABLE 1
FEATURES FOR SELECTION

Features	Normal Feature value	Benign Feature value	Malignant Feature value
Mean	1.505170e+002	6.724342e+001	6.939077e+001
Std Deviation	4.612701e+001	8.253612e+001	9.329760e+001
Skewness	5.799401e-001	5.403425e-001	6.899625e-001
Entrophy	3.887	6.2381	7.0855
Varience	0.0135	240.441	267.280

This classifier offers the better results in identifying the malignant liver tumor from the normal. In some cases the benign tumors are misclassified as a normal liver. The intensity value of the normal liver and begin may be same. The overall accuracy of classification value 96.72% approximately for the ultrasound liver images.

VI.CONCLUSION

This paper proposes the automatic identification of ultrasound liver cancer tumor using SVM classifier. . First we detect the seed point for the given ultrasound liver image automatically using features of co-occurrence matrix and run length method. Second, we segment the ultrasound liver images using of gray space map and Otsu method. Finally using SVM classifier we classified the ultrasound liver cancer tumor image as normal, benign and malignant. We hope this

similarity of the length of the runs throughout the image. The RLE is expected small if the run lengths are alike throughout the image.

These run length features will check the selected seed point of the image which is calculated from the co-occurrence matrix is belongs to affected region of the liver image or not.

IV. SVM CLASSIFIER

Support Vector Machine (SVM) performs the robust non-linear classification with kernel trick. SVM is independent of the dimensionality of the feature space and that the results obtained are very accurate. It outperforms other classifiers even with small numbers of available training samples. SVM is a supervised learning method and is used for one class and n class classification problems [5].Cluster analysis or clustering

system will help the physician to diagnose the liver cancer with non invasive method.

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