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Liver Cancer Tumor Segmentation on ultrasound Images

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***Abstract*-In image analysis the segmentation is the first step. Segmentation is a process of subdivides the image into its constituent parts and objects. The objective of the segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze. In this paper, we propose a full automatic region growing algorithm with texture parameters. The seed point has been automatically selected based on textural features from co-occurrence matrix and run length method. High Pass Filter, Histogram Equalization, Otsu Thresholding and the spatial information of pixels used for segmentation of ultrasound liver cancer tumor images. In this method can reduce the time for manual post processing due to over-segmentation result from ordinary region growing with intensity criteria**

Keywords-Ultrasound Liver Cancer Tumor, High Pass Filter, Region Growing, Segmentation

I. INTRODUCTION

There are more machines and techniques available for identifying the diseases in the inner parts of the human body. Even though to identify for cancer the physician are following the invasive method. But, this method will give more pain to the patients. To overcome this problem we hope our method may help to the radiologist to identify liver cancer tumor. Liver cancer is the fifth most common cancer worldwide in men and eighth in women, and is one of the few cancers still on the rise. Diagnosis by ultrasound imaging is a cost effective approach to ascertain the disease in earlier stage. There are two classes of liver tumors: benign and malignant [2]. The result of image segmentation is a set of regions that collectively cover the entire image. Images pixels are sorted according to classes according sets, which are not specifically connected. Segmentation differs from classification in that the pixels comprising the sets are connected spatially. The sets are then labeled with meaningful designation. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. We describe the segmentation details in section 2, proposed automatic seed point detection 3, final segmentation of liver cancer tumor using Gray space Map & Region growing in section 4 ,section 5 describes the result and discussion and section 6 describes the conclusion.

II. SEGMENTATION

Ultrasound image segmentation is a critical issue in medical image analysis and visualization because these images contain strong speckle noises and attenuation artifacts.Segmentation of medical ultrasound liver cancer tumor images involves three main image-related problems. Ultrasound liver cancer tumor 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 classes so that the intensity of a pixel in the image may not be consistent with any one class [3]. Segmentation of ultrasound liver cancer tumor is more critical because it contains more speckle noise and artifacts.

In the thresholding technique, it considers the gray level and will not consider about spatial information of Pixels and it does not manage well for poor boundary image. Boundary based segmentation is difficult to convert the edge pixel in close to boundary. In the region based segmentation, segmenting the interested region is difficult due the speckle noise. In Active contour method manually we have to select a seed point to segment ultrasound liver cancer tumor image.

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III. AUTOMATIC SEED POINT DETECTION

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. The following diagram shows the flow of the proposed system.

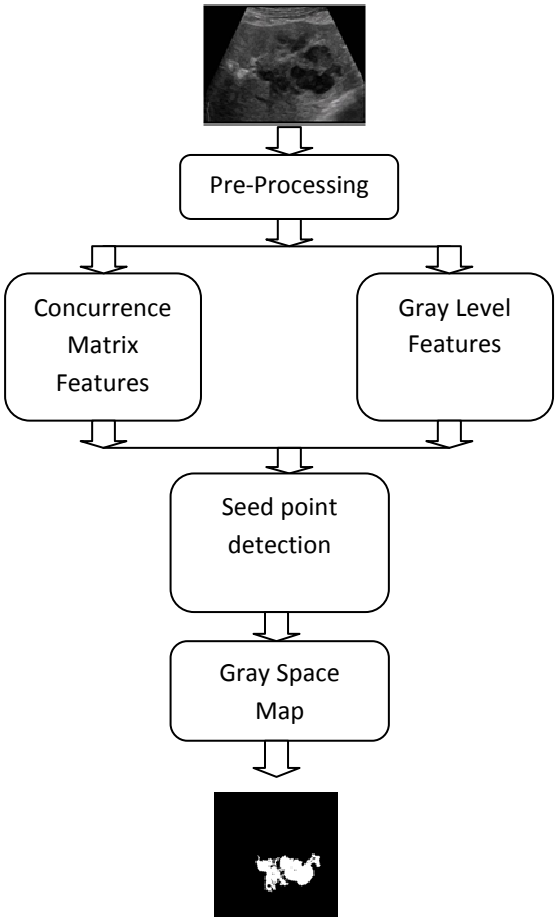

Figure 1. Dataflow Diagram

The proposed system the ultrasound liver cancer tumor image given as input, in the preprocessing technique is used to remove the noise from the image. 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. We describe the method for automatic selection of abnormal liver cancer tumor region from ultrasound image using Co occurrence matrix probability feature and run length method.

A. 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.

$$J = \sum_{i=1}^{G} \sum_{j=1}^{N} (p(i,j))^2 \quad (1)$$

G and N denotes the resolution vector at row and column respectively. P(i,j) 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.

$$S = -\sum_{i=1}^{G} \sum_{j=1}^{N} p(i,j) \log p(i,j) \quad (2)$$

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.

B. 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. p(i,j) denotes the number of runs of length j and gray level i occurring in the image region.

$$\sum_{i=1}^{G} \sum_{j=1}^{N} p(i,j)$$

N represents the number of gray levels (or gray level groups), G represents the number of run length groups.

n_r, the total number of runs in the image.

C. Long Run Emphasis (LRE)

This 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.

$$F1 = 1/n_r \sum_{i=1}^{G} \sum_{j=1}^{N} p(i,j) * j^2 \quad (3)$$

D. Run Length Non-uniformity (RLN)

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

$$F2 = 1/n_r \sum_{i=1}^{G} \left(\sum_{j=1}^{N} p(i,j)\right) 2 \quad (4)$$

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. Gray Space Map & Segmentation

After calculating the seed point automatically, using region growing algorithm segmentation has been taken place.

A. 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. (D is our difference). 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.

Figure 2a. Original image

B. 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 Figure 2(a) shows the histogram equalized image will give the clear view of the abnormal portion of the image (b) shows the filtered image and (c) shows the segmented image.

V. RESULT AND DISCUSSION

After The automatic segmentation of the liver cancer tumor using gray space map on ultrasound images gives the excellent report for all the given images. We have tested for nearly 150 Ultrasound liver cancer tumor images. The Figure 3shows the segmented result for the respective images.

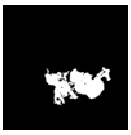

Figure 3. Segmented Image

VI. CONCLUSION

In this work, we propose the Liver Cancer Tumor segmentation method for ultrasound images. First we remove the noise from the image using filter the image using the high pass filter technique. Then we detect the seed point for the given ultrasound liver cancer tumor 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 region growing method. This above mentioned experiment has been tested with nearly 150 ultrasound liver images. So we hope this proposed system can segment abnormal regions of liver cancer tumor boundary accurately. This work will help the physicians to locate the boundary of abnormal regions of liver cancer tumor accurately

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