Liver Segmentation of CT Scan Images: A Survey

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***Abstract*—**Liver Cancer is one of the fastest growing cancer in the world. According to a survey the liver cancer ranks as the 11th most commonly occurring cancer. The survey was done on the basis of survival rate. If the person has survived for 5 years then the survival rate is chosen as 5 years. From study it is revealed that every one man among three and every one woman among nine has chance of getting liver cancer in lifetime. This paper gives a comparision study between texture based segmentation and k means algorithm. Various works have been carried out in order to extract liver from ct scan images. Many works claims it to be superior but comparative study is lacking among them.

Keywords*—Texture algorithm, k means algorithm, segmentation*

I. INTRODUCTION

The liver is the largest glandular organ lying on the right side of the abdominal cavity just below the diaphragm. It is an important organ for survival with a wide range of functions like glycogen storage, protein synthesis, hormone production etc.[1].Liver cancer is one of the most diseases for tumour which is also one of the leading death causes. Medical image analysis is an important biomedical application which is highly computational in nature and requires the aid of the automated systems. Analysis of images is necessary in order to detect the internal abnormalities in the human body. By use of Computer Aided Diagnosis (CAD) a robust and accurate segmentation of liver tissue is required. But due to irregularities between the shape of liver and other organs like spleen, heart, spinal cord segmentation is quite difficult.

The liver is the second organ most commonly involved by metastatic disease, being liver cancer one of the leading causes of death worldwide. Tumour volume measurement, accurate staging analysis (tumours features such as site, local, spread distant and involvement with other organs in the body) and early detection are are very important to know so that the doctor can easily detect the disease of which the person is suffering and hence can provide proper medical treatment to the patient. [2-5]

The main difficulties in liver segmentation include ambiguity between liver tissue and tumours boundaries, complexity of tumour surfaces, contrast variability between liver parenchyma, tumours and vessels different tumour size, shape structures/organs with the and location, patient conditions, presence of neighbouring same density/values and possible presence of many small metastases. Due to these multiple difficulties, the analysis of ct scan images become very difficult. The new segmentation techniques should be very fast and robust so that they can provide an accurate and fat segmentation of images so as to analyse [6, 7]

The Computer aided diagnosis system consists of two major steps: (a) Image segmentation & (b) Image classification. The liver segmentation process starts with a preprocessing stage in which the noise is removed if present in am image which would degrade the quality o0f images and proper results will not be obtained then it is followed by the actual segmentation process. Process of segmentation of an images can be either fully automatic or semi automatic. By performing segmentation by semi automatic method user can choose his own area of interest and then the image will be given for computer processing whereas fully automated segmentation method segments without having user intervention. The various approaches used for liver segmentation in this paper are based on Thresholding , Model, Level Set, Region, Active contour, and k mean clustering.

II. SURVEY ON IMAGE PRE-PROCESSING

Image preprocessing is one of the primary steps required for getting accurate segmentation The CT image contains different types of noise which can be either salt and pepper or gaussian noise which reduces the overall accuracy of the images. The preprocessing step includes first converting any given image into gray scale image, and then the filter is applied on it so as to remove the noise present in an image. [1]. Another method includes 3D anisotropic diffusion which can be usede as preprocessing step for removing image noise, and this technique, also, preserves the significant parts of the image, typically edges, lines or other details that are important for the analysis of the image [2]. However, the drawback of this filtering method is that it requires more computational time due to the iterative process. The CT images are smoothed, in order to reduce some noise, using the Curvature Anisotropic Diffusion Image Filter in [3].The Image down sampling, image smoothing and edge detection are performed in [4]. Applying mean filter means to eliminate the staircase edges and smoothen the images. Gaussian functions are applied for image preprocessing to smoothen the image and get the liver likelihood images [5].

III. SURVEY ON IMAGE SEGMENTATION

The image segmentation is to partition an image into desired regions with respect to a particular application. The process of segmentation of liver is difficult since the image includes intensity similarities between different organs like kidney, spleen, and pancreas. Basic segmentation techniques include Region Growing, Threshold based, Level Set, k-means segmentation and texture segmentation.

A. Region based approaches:

Liver surgical planning which involves region based approach has the following steps. In the first step the liver blood vessels are segmented by using a threshold based region growing method. The second step involves the analysis of vessel structures into hepatic vein and portal vein using graph theoretical methods to segment the skeletons of the vessels. In the third step nearest neighbor segment approximation and Laplacian segment approximation are used. By using this methods we can analyse the structure of vessels based on skeletons and information such as vessel diameter and it is malignant or not can be known. [11]. The region-growing based approaches can provide good results on contrast enhanced images.

B. Threshold based approaches:

In this process the liver is segmented using global thresholding in [1].Morphological operations are applied on images which have similar intensities. This process continues until finally desired segmented area is achieved. This approach has been implemented in threshold value for the whole CT image is a drawback of [6].The region growing based liver segmentation starts from this approach. Thresholding process cannot have fixed threshold value for seed point. The similarity measure of each neighborhood segmentation because the liver intensity differs according pixel with the seed point region is calculated. The pixel with to the patient slice and the CT machine. This segmentation using adaptive threshold technique has been process continues iteratively by comparing all unallocated used in [12]. The advantages of this approach is that different neighboring adjacent pixels of the grown region. The threshold are used for different regions in the image. Further, drawback is that wrong selection of seed point leads to incorrect results for the Neural network based texture analysis of liver tumor from CT segmentation. In fully automatic liver segmentation images uses adaptive threshold method to extract the liver for contrast-enhanced CT images using region growing, first pixels from the CT abdominal image. This is followed by the the seed region is determined based on the priori knowledge morphological operations like closing and opening in order to and to keep the region growing off the heart they separated the heart fragments of other organs adjacent to the liver with the from the liver by means of connecting the bottom of the left same intensity as that of liver [13]. In the automatic and right lung lobes with a surface. Then the liver is separated threshold based on Liver Lesion segmentation in Abdominal from the heart to prevent over segmentation in this region. 2D-CT Images - pre contrast and post contrast images, The drawback of this approach is that if the liver has large intensity of the entire liver region varies with respect to that lesions, this method provides bad result concerning all metrics of the liver lesions and the type of lesion. A minimum of two since the large lesions are under segmented [7]. An adaptive thresholds are needed to segment the liver and lesions from region growing algorithm that learns its homogeneity criterion the abdominal CT images. The mean value of the image is automatically from characteristic of the region to be used to determine LT and another statistical measure i.e. segmented has been proposed in [8].Parameters of the homogeneity criterion are estimated from sample locations in the region .These locations are selected sequentially in a random walk starting at the seed point and the homogeneity criterion is updated continuously. The main advantage of this approach is the automatic detection of seed point. Segmentation of liver Vasculature using Context based voting proposed in [9]. To segment and identifies the liver vasculature using region based features. Quad-Tree (QT) decomposition was used to detect the soft- tissue regions which were determined using the Expectation Minimization (EM) algorithm. Then, an initial liver region was determined using Classification and Regression (C&RT) model and thresholding-based approach was used to detect the liver region from the intensities of the initial regions. Semi automatic method based on 2D region growing with knowledge based constraints proposed in [10]. The seed point and feature vectors are calculated using region growing algorithm. After that applying knowledge based constraints to ensure the size and shape of the segmented regions. The main advantage of this knowledge based constraints to reduce the computational requirements. Analysis of Liver vasculature for standard deviation is used to determine HT to segment the liver and lesion within the liver. Usually, In pre contrast images, the gray level difference in liver and liver lesion is very feeble as compared to post contrast images, which makes the segmentation of lesion difficult. But in this proposed method lesion boundaries can be accurately determined in pre-contrast images. The advantages of this approach is that , it is able to segment lesions of various types and sizes in both pre contrast and post contrast images and also improves radiological analysis and diagnosis [14]. Using histogram threshold tail method to remove the neighboring abdominal organs. After that applying the binary morphological filter to improve the quality of the segmentation of the liver [15]. 3D Anisotropic Diffusion for Liver Segmentation proposed in [2]. Liver volume segmentation using threshold based approaches the peak intensities values are represented as liver regions.

C. Level Set Approach:

The level set method has been successfully used for medical image segmentation. The advantages of the level set approach handle topological changes define the problem in one higher dimension. The main disadvantages of this method is that the result obtained are not proper and also it is a time consuming process [16]. The Segmentation using level set method that evolves according to a speed image that is the result of a scanning technique based dynamic programming implemented by [17]. The main limitations is level set method adjusts this first segmentation using a speed function obtained from a pixel classification algorithm. The accuracy is only sufficient in a small number of cases. In this core of the algorithm is a level set function that has the availability to manage separating and joining liver boundary routinely. The processing of liver level set (LLS) is done in two steps, first preprocesssing and then hybrid energy minimization algorithm. The drawback of this approach is the hybrid energy is reformulate in level set framework in a looping manner, thus allowing to inherent the topology changes from previous image [18]. First attempt to segment the liver using level set is done by introducing an level-set speed function which varied by time to improve the detection sensitivity of weak edges. It is so incorporated prior liver location based on anatomy knowledge inorder to help in the segmentation process. Thus, if a disconnected region occurs in the current slice, a user needs to initialize a circle for each disconnected regions [19].

D. k means algorithm:

This paper describes a new 3-D liver segmentation method in support of the selective internal radiation treatment asa treatment for liver tumors. Here segmentation is done by coupling a modified k-means segmentation method with a a contouring algorithm. By using this segmentation process, five separate regions are identified on the CT Scan images. This segmentation provides provide fast and accurate liver segmentation and 3-D rendering also delineating tumor region(s), all with mini-mal user interaction.[11]

The k-means clustering is a traditional clustering technique that tries to partition the given dataset points into various clusters whose means are similar [2], [16]. In this process , the CT slices are portioned into five regions whose mean intensity levels can be given either by the user or preset. After segmentation the regions obtained are liver, surrounding organs, peripheral muscles, ribs/spinal cord, and the outside of the body. It was observed that using five regions yielded the best results. If the value for clustering is changed then it was found at fewer regions resulted in poor separation between the liver and surrounding organs whereas using a larger number of regions affected the accuracy of the segmentation. For the modified k-means segmentation the different regions are selected by users selection of points. The user selected points act as the seeds for each of the five masks. The selection of the seeds, rather yielded much better segmentation results. To obtain results free of inaccuracy a logical intersection of three independent segmentation runs are employed. Also the "online update mode" that calculates the sum of the distances with the movement of every pixel is used to obtain higher accuracies at the cost of processing time. This study demonstrated the development of a robust and accurate method for the segmentation of the liver from CT images for the purpose of volume calculations. The algorithm is independent of the dataset-properties namely structure, size, po-sition, and intensity distribution of the liver region due mainly to the novel hybrid segmentation method that coupled the modified k-means algorithm with a newly established contouring method that relied on radio density of the CT images. The experiment results reported in this study display very high accuracies of 98.27% in agreement with manual expert analysis. Also when user intervention was reduced then highly accurate results with only 4% to 5% of the dataset initialized by the user, was obtained. The proposed algorithm is also designed so as to make it compatible for parallel processing. Also, SIRT relies on the calculation of the tumor to liver volume ratio for the calculation of the radioactive dose to the patient. Accurate volume calculation specific to each patient's anatomy would help in the calculation of the absolute correct dose to deliver to that patient. This would reduce the risk for excess dosing that may damage healthy surrounding liver tissue or reduce the risk of under dosing and the potential relapsing of the tumor.

This paper a a comparative study between two common image segmentation methods for liver CT and breast MRI medical images is presented. The two algorithms are K-means clustering and normalized cuts. All results were compared using different techniques so as to obtain better accuracy for medical images. Obtained experimental results show that the overall accuracy offered by the employed K-means technique is high compared to the well-known normalized cuts segmentation approach. Not only the color feature, shape and texture can be also considered when applying K-means clustering. For future work, considering the usage of the multi-objective concept in order to add additional features to improve K-means clustering algorithm. Moreover, the research work is being extended to analyze the affected part of the examined organ[12]

E. Texture based technique:

Texture feature extraction identifies and selects a set of distinguishing and sufficient features to clsassify a texture. Texture features is an important and most commonly used step in the CAD systems. The process involves by use of a ROI which is cropped from the automatically segmented tumor to extract texture features. In this paper an unsupervised texture segmentation technique using multi-channel filtering has been proposed. Advantage of this method is that it can use simple statistics of gray values in the filtered images as texture features. This simplicity is due to direct result of decomposition of original image into several filtered images with limited information. The main issues involved in this approach are: 1) functional characterization of the channels and its types, 2) extraction of accurate and desired texture features from the filtered images, 3) the relationship between the channels, and 4) integration of texture features from different channels to produce a reliable segmentation dimensionally. The algorithm is more general and is applicable to a large number of texture classes. There is no post-processing required on the segmented images. The results could be improved by using spatial relationship among the pixels. The segmentation of the feature images has been realized by applying fuzzy clustering. The accuracy of the segmentation results also depends on the clustering technique employed. In future, this task can be essentially improved by applying more sophisticated clustering and classification techniques[6]. In order to assess the potential of various texture features in the classification of hepatic lesions from CT images the following steps were preformed: i) five sets of texture features were estimated, ii) if the dimensionality of the features set was greater than a predefined threshold, a Genetic Algorithm (GA) based feature selection method was applied, iii) each of the initial and reduced feature sets was fed to a NN classifier, and iv) the area under Receiver Operating Characteristic (ROC) curves (zA) was calculated.[9]. This paper describes an unsupervised segmentation of textured images. Local texture properties are extracted using local linear transforms that have been optimized for maximal texture discrimination. Local statistics are estimated at the output of an equivalent filter bank by means of a non- linear transformation followed by an iterative Gaussian smoothing algorithm. Reduction technique is then applied to the data and is deter- mined by simultaneously diagonalizing scatter matrices evaluated at different spatial resolutions. This approach provides a good approximation of Fisher's multiple linear discriminants and has the advantage of requiring no upriori knowledge.

IV. CONCLUSION

In this paper different works, its merits and demerits of various automated techniques for Liver segmentation is discussed in detail.As, per the dataset and the requirement of analysis any method out of thme can be used The suitability of the techniques for various applications is also illustrated in this survey. Different new hybrid approaches may be developed through the ideas conveyed in this paper.

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