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A SURVEY ON LIVER TUMOR DETECTION AND SEGMENTATION METHODS

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ABSTRACT

Liver tumor is a pathological disorder of the human that affects around 50 million people worldwide. The early detection and diagnosis of liver tumor is important for the prevention of liver tumor. Many techniques have been developed for the detection of liver tumor using the abnormal lesion size and shape. This paper reviews various lung tumor detection algorithms and methodologies used for lung tumor diagnosis. The novel methodology for the detection and diagnosis of liver tumor is also proposed in this paper and its experimental results are compared with various methodologies for the detection and diagnosis of liver tumor.

Keywords: liver tumor, segmentation, computed tomography (CT), SVM classifier, diagnosis, medical imaging.

1. INTRODUCTION

Liver cancer is one of the major death factors in the world. Early detection and accurate staging of liver cancer is an important issue in practical radiology. Liver lesions refer to those abnormal tissues that are found in the liver. Liver lesions are a wound or injury in the tissue areas of the body due to damage caused by a wound or disease. These lesions can be identified in a CT scan by a difference in pixel intensity from other regions of the liver. For proper clinical treatment, manual segmentation of this CT scan is difficult and prohibitively time-consuming task. Alternatively, automatic segmentation is a very challenging task, due to several factors, including liver stretch over 150 slices in a CT image, low intensity contrast between lesions and other nearby similar tissues and indefinite shape of the lesions.

Segmentation of liver tumors is an important prerequisite task before any surgical intervention. A precise and accurate analysis of the lesions/tumors allows for accurate staging and evaluation of the available therapies that can be provided to the patient. It can help in deciding the best treatment approach as well as track the progress of the therapy over an interval of time. Also, tumor segmentation plays a vital role in the development of 3D surgical tools that can help and guide the surgeon for the complete removal of the tumor rendering the patient free of the underlying disease.

Accurate and early detection of the tumor is very important for the diagnosis and treatment of the disease. Since CT is one the most commonly used imaging modalities in the diagnosis of liver tumors, segmentation and calculation of volume becomes essential. Various automatic/semiautomatic techniques for liver tumor segmentation have been developed based on strategies which include Bayesian approaches, entropy based segmentations, level set techniques, multi-level thresholds, and region growing techniques.

Several studies have developed various algorithms that can be categorized on the degree of automation–fully automatic and semi-automatic, and based on the segmentation algorithms as:

A. Region based/Contour based Segmentation Methods
B. Thresholding Method
C. Model Based approach
D. Level Based Approach
E. Graph cut

Generally, tumor segmentation methods for a multi-stage segmentation technique comprise of 5 main stages and are explained below:

a) **Liver extraction:** first step in the segmentation is to extract the liver region.

b) **Image de-noising:** performed using a median filter to improve the contrast of the tumors in the liver and to reduce specular noise.

c) **Intensity based region growing:** a semi-automatic step requiring a single point per tumor as a seed. The region growing aims at encompassing regions of similar intensity to segment the tumor.

d) **Localized contouring:** coarse tumor segmentation obtained in step 3 is improved upon using a localized contouring algorithm to improve the detection of the tumor region.

e) **Rendering and volume calculations:** tumor/tumors are rendered in 3-D space to display location, size and extent of the tumor within the liver. Volume calculations are carried out based on the number of voxels comprised within the tumor.

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www.arpnjournals.com

Therefore, we present a fully automatic segmentation algorithm using SVM classifier in this paper. Also, some of the significant approaches used for liver segmentation have been discussed in this work in detail with their methodologies and procedures.

2. REGION BASED SEGMENTATION APPROACH

Region-based segmentation is commonly based on the intensity levels of neighbouring pixels, whereas, contour-based segmentation includes statistical or geometrical active shape model. Both these approaches have their advantages and disadvantages in terms of performance, applicability and computational cost. The region-growing based approaches provide good results on contrast enhanced images. Region-based segmentation schemes attempt to group pixels with similar characteristics into distinct regions. The two approaches in region-based methods are region growing and region splitting. In the region growing method, the estimated sets of the segmentation process are very small initially. The iterative process of region growing must then be applied in order to recover The surfaces of interest in the region growing process, the seed region are expanded to include all homogeneous neighbors and the process is repeated until the segmented region is accurately obtained. In region splitting methods, the evaluation of homogeneity is made on the basis of large sets of image elements.

In Ramanjot Kaur *et al.* 2011, an enhanced k-means clustering algorithm is implemented for liver segmentation in which the given dataset is classified into certain number of clusters and each cluster is provided with a centroid. Then, morphological opening was applied on the output of k-means clustering algorithm for better segmentation of cyst area in liver the image. Another method for liver tumor segmentation used Fuzzy C means (FCM) clustering algorithm [Nandha Gopal and Karnan, 2010] which was not very effective with noisy or outlying points and with clusters of unequal sample sizes and different volume. Hence, an alternative FCM (AFCM) clustering algorithm was developed to overcome these problems. AFCM is a segmentation algorithm that is based on clustering similar pixels in an iterative way, by adjusting the cluster centers for every iteration.

3. THRESHOLD BASED APPROACH

Adaptive thresholding Technique, Global thresholding, local adaptive thresholding are used to separate the desirable foreground image objects from the background based on the difference in pixel intensities of the regions in the liver. Global thresholding [Choudhary *et al.* 2008] employs fixed threshold methodology for all pixels in the image and therefore works only if the intensity histogram of the input image contains neatly separated peaks corresponding to the desired object and background. Hence, it cannot deal with images containing, a strong illumination gradient. Alternatively, local adaptive thresholding chooses a unique threshold for each pixel depending upon the intensity values in its mean of local neighbourhood, thereby allowing thresholding of an image with global intensity histogram containing no distinctive peaks. Adaptive thresholding is more sophisticated and accommodate changing lighting conditions in the image. This approach is used for finding the local threshold to statistically examine the intensity values of the local neighbourhood of each pixel. This method is simple, fast and less computationally intensive and produces good results for CT liver images.

4. MODEL BASED AND LEVEL BASED APPROACH

A two-stage algorithm developed by Saddi *et al.* 2007, performed the segmentation of the liver by first estimating the pose and global shape properties based on low dimensional space scanned training set and then performing a template matching algorithm to recover local deformations. The method is semi-automatic requiring a single seed point in the initialization phase. A rule-based technique using Cognitive Network Technology was proposed for the liver segmentation by Schmidt *et al.* 2007. Their technique used pixel classification by a semantic knowledge based method and their results showed a mean overlap error of 16% in the liver segmentation process.

Another method for liver segmentation was developed by integrating a multiple seed point k-means clustering process and the active contours algorithm. The implementation strategy is illustrated in Figure-1.

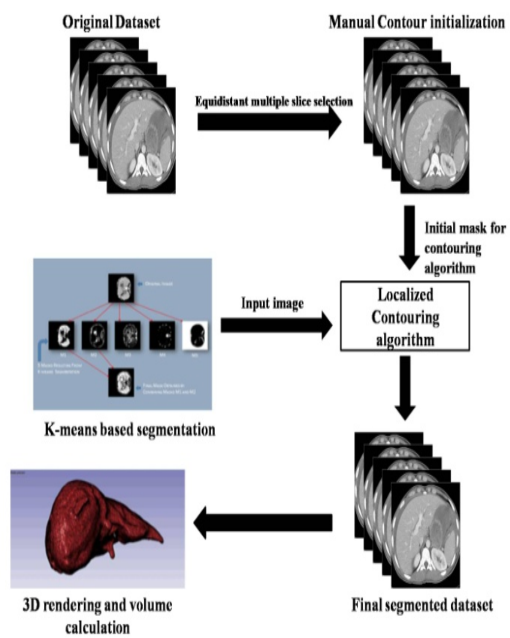

Figure-1. K-means based algorithm for 3D liver segmentation.

ARPN Journal of Engineering and Applied Sciences

The novelty in this algorithm is in the manner the modified k-means based segmentation is used in combination with a localized contouring algorithm. The k-means segmentation approach requires the identification of five separate regions of the input CT images, and developed a new localized contouring algorithm based on local region thresholding defined in a small region around a point of interest. Pixels in an image obtained by CT scanning are displayed in terms of relative radio density in Hounsfield units (HU), instead of representing in their gray level intensity values. The HU value will be used to identify the liver tissues in the CT images. Typically the liver window is defined between –40 HU and 180 HU.

4. LEVEL BASED METHOD

Level set based methods prevent the extraction of muscles as a part of the liver for accurate liver segmentation. Smeets *et al.* 2008, demonstrated the development of a level-set algorithm based on statistical pixel classification with supervised learning for the segmentation of lesions. The algorithm was tested on 10 datasets provided an average volumetric difference of about 17.8%. Jimenez-Carretero *et al.* 2011, and Jeongjin *et al.* 2007, demonstrated the development of a multi-resolution 3D level set technique coupled with adaptive curvature technique for the classification of the pixels into tumor and background (Jimenez-Carretero *et al.* 2011). The technique demonstrated promising results for detection of elongated tumors avoiding internal leakages to close structures.

Choudhary *et al.* 2008, demonstrated a semi-automatic technique using an initial Watershed algorithm followed by minimum entropy-based region growing technique and level set smoothing [Choudhary *et al.* 2008]. The technique was tested on 10 datasets rendering a mean volumetric error of 22.58%.

5. GRAPH CUT BASED APPROACH

A novel approach that applies global optimal tree-metrics graph cuts algorithm on multi-phase contrast enhanced contrast enhanced MRI for liver tumor segmentation is proposed in Fang et al., 2012. Primarily, a feature set is extracted from multi-phase contrast enhanced MRI data and color-space mapping is used to reveal spatial-temporal information invisible in MRI intensity images. Then, an efficient tree-metrics graph cut algorithm is applied on multi-phase contrast enhanced MRI data to obtain global optimal labeling using an unsupervised structure. Finally, tree-pruning method is used to reduce the number of available labels for liver tumor segmentation. The algorithm takes three inputs, namely, 1) a multi-phase contrast enhanced MRI liver image, 2) a tree of labels, and 3) a smoothness parameter $\lambda \geq 0$. Then a tree of labels is generated with agglomerative clustering based on the extracted dynamic features. The steps followed in their algorithm, are detailed below.

5.1. Tree generation

The closest pairs of clusters in the feature space are repeatedly merged. For multi-phase contrast enhanced MRI liver image, agglomerative hierarchical clustering is performed on the pseudo-color mapped image in phases, and k-nearest neighbors (measured in Euclidean distance) are used as the candidate clusters and merged. Approximate nearest neighbors are used when the number of clusters are very large. The process is repeated until the maximum variance becomes greater than two times of the minimum variance.

5.2. Sweep algorithm

The tree of labels generated from the multi-phase contrast enhanced MRI pseudocolor mapped image represents the tree-metrics distance function d. Then, the algorithm is applied to the multi-phase contrast enhanced MRI liver image, with the tree of labels and a smoothness parameter $\lambda \geq 0$. The algorithm minimizes the cost function for a distance d and labeling f:

$$Q(f) = \sum_{v \in V} d\big(c(v), f(v)\big) + \lambda \sum_{(u,v) \in E} d\big(f(u), f(v)\big) \tag{1}$$

Graph cuts were used to optimize the objective function Q (f) in Equation (1), and tree-metric distance was used to measure the cost in both the data term and the smoothness term. The advantage of using tree-metrics graph cuts is the global optimality and the efficiency which is higher compared with conventional graph cuts. Their algorithm computes the globally optimal labeling f for the cost function Q(f) in Equation (1) in O(log(k)(g(n)+k)) time for ‘k’ labels and ‘n’ voxels, where g(n) is the running time of the min-cut algorithm on graph with n nodes.

5.3. Tree cutting

The labeling returned by the segmentation algorithm is usually more than the required number of segments in the multi-phase contrast enhanced MRI liver image. To reduce the number of labels, the binary tree of labels is “cut” at depth d; for each node at depth d (where the root node is depth 0), their child subtrees now map to the same label as their ancestor node at depth d). By cutting the tree at depth d, we are left with N labels, where $N = \sum_{n=0}^{d} 2^n$. Finally, these labels provide the accurate boundary of the tumor, which help the radiologists to analyze the exact region of the tumor in the liver.

6. PROPOSED METHOD

The block diagram of proposed liver tumor segmentation and detection algorithm is shown in Figure-2. The proposed method employs a pre-processing step, feature extraction and SVM classification of liver tumor region.

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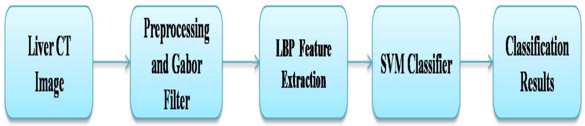

Figure-2. Block diagram of proposed liver tumor detection technique.

In the pre-processing step, the image contrast is improved for well differentiation of the liver from its surrounding tissues with similar intensity levels. The noise removal and enhancement of contrast are done using median filter and the fine details of the image are further improved. Then, morphological operations are applied to further improve the tumor region segmentation accuracy by extracting the image components from the binary image to extract the region shape, i.e., edges. Morphological opening and closing are the two functions in morphological operations.

6.1. Morphological opening and closing

After converting the image into binary, a few morphological operations are applied on the converted binary image. The morphological operators separate the tumor part of the image which has the highest intensity than other regions of the image. For the Liver CT image, we need the image in Multi Resolution mode, i.e., Frequency vs. Time. Hence, we use Gabor Wavelet Transform instead of FT to obtain the multi resolution liver image. The frequency and orientation representations of Gabor filters are identical to those of the human visual system and are particularly suitable for differentiation and texture representation. The Gabor kernels used in 2D Gabor filter modulated by a sinusoidal plane wave are defined as follows:

$$\psi_{\mu,v} = \frac{k_{\mu,v}^2}{\sigma^2}\exp\left(-\frac{k_{\mu,v}^2 z^2}{2\sigma^2}\right) \times \left[\exp\left(ik_{\mu,v} z\right) - \exp\left(-\frac{\sigma^2}{2}\right)\right] \quad (2)$$

where, μ & υ are the orientation and scale of the Gabor kernels, respectively, z=(x,y), and $k_{\mu,v}$ is the wave vector.

6.2. Feature extraction and tumor classification

The Local Binary Pattern features for a set of images are extracted and the SVM classifier is trained with these features in the training mode. Then, the performance analysis of Dysplastic cell segmentation is done with the following parameters:

- Sensitivity [Se=TP/(TP+FN)]
- Specificity [Sp=TN/(TN+FP)]
- Positive predictive value [Ppv=TP/(TP+FP)]
- Negative predictive value [Npv=TN/(TN+FN)]
- Accuracy [Acc=(TP+TN)/(TP+FN+TN+FP)]

where, TP denotes true positive, FP denotes false positive, FN is false negative and TN is true negative. TP refers to the correctly identified tumor pixels, TN refers to the wrongly identified tumor pixels, FP refers to the correctly identified non- tumor pixels and FN refers to the wrongly identified non- tumor pixels.

6.3. Experimental results

Table 1 illustrates the performance evaluation of the proposed tumor detection algorithm in terms of the performance evaluation parameters. The average accuracy achieved is 95% for malignant tumor region in accordance with ground truth images.

Table-1. Performance evaluation of proposed algorithm.

Test Images	Sensi tivity	Specifi city	Positive Predic tive value	Negative Predictiv e value	Accuracy
Dataset 1	0.4621	0.9947	0.7369	0.9831	0.9783
Dataset 2	0.4398	0.9709	0.3544	0.9795	0.9523

The source liver image, preprocessed image, feature extracted image, and the tumor segmented image are all shown in Figure-3.

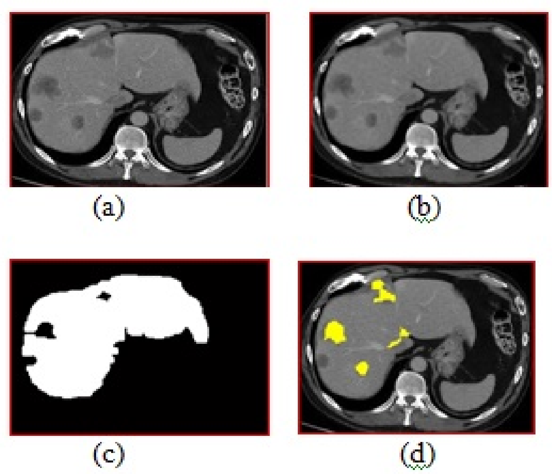

Figure-3. (a) Liver CT image; (b) Preprocessed image; (c) Feature Extracted image; (d) Tumor regions segmented image.

7. CONCLUSIONS

This paper describes various algorithms and methodologies for the detection and diagnosis of liver tumor in human body. Most of the previous methodologies have focused their work based on the shape and size of the abnormal lesions in the liver area. The features and higher level classifiers were not focused. In this paper, a novel methodology for the detection and diagnosis of liver tumor based on hierarchical feature set and classifier is proposed for the detection of liver tumor.

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