Automated Liver Tumour Detection in Abdominal CT Images

Devendra Joshi¹, Narendra D Londhe²

Abstract—The knowledge of the liver structure, liver surface (boundaries) and lesion localizations is required for segmentation of liver tumour. In this paper we use adaptive thresholding method for segmentation of liver tumour. Our aim is to generate a technique in MATLAB for automatic segmentation. We are using DICOM image and it is further converted to jpeg image for segmentation. These images are adopted from scan centre. Tumour segmentation in CT liver images is a challenging task. CT is the most commonly used imaging technique for the inspection of liver tumour. It helps doctors to acquire the information and provide opinions for liver tumour. Tests are performed on abdominal CT datasets showing promising result. The process of segmentation is done in two parts—first part is to convert a grey scale to binary image. Second part is adaptive thresholding which is done in generated binary mask of CT image.

Index Terms—automatic segmentation, Adaptive thresholding, Boundaries, liver tumour, region splitting and merging.

I. INTRODUCTION

Liver cancer is among the most frequent types of cancerous diseases, showing responsible for the deaths of large number of patients worldwide in every year [1]. Among the predominant cancer types, liver cancer is ranking at the fourth place. The incidence of liver metastases is even higher, as many common cancer types, like lung and breast cancer. The process Computed tomography (CT) images allows good detection rates for most tumour types. The segmentation of liver tumours is challenging due to the small observable changes between healthy tissues and tumours [11]. A normal liver with no tumour, such as liver cancer or liver cirrhosis, shows regular gray values in an abdominal CT image. The gray value of a normal liver ranges between 90 and 92 out of gray values from 0 to 255. However, the tumours of the abnormal liver do not have regular gray values between 90 and 92 [14]. Their gray values are more various and darker than those of normal liver. It is easy to segment the liver with existing methods using both basic place information and distribution information of regular gray values (The liver exists on the left of the abdominal CT image) [9]. To identify tumours from CT images, there is a need for segmentation of tumours. Segmentation subdivides an image into its constituent regions or objects that have similar features according to a set of predefined criteria. Typically, this has been manually done by trained clinicians. The task is time consuming, requiring much effort and can be subjective depending on the experience of the clinician.

A successful treatment depends on an easy and fast preoperative but challenging to understand the complex internal structure of the liver [7]. For any local treatments both surgical and non-surgical, it is necessary to identify and precisely localize the liver surface and its segments, the tumours, the topography of blood vessels, and the spatial relationship between tumours and other structures. Several research groups have developed various algorithms that can be categorized on the degree of automation (fully, semi or interactive) and in two approaches: pixel-based or contour-based. Pixel-based segmentation is commonly based on threshold followed by mathematical morphology or clustering. While contour-based segmentation includes geometrical or statistical active shape model [11]. Therefore, the proposed segmentation method improves the segmentation performance compared with the conventional process based on a regular gray value.

Many research groups have developed different approaches for liver and tumour segmentation. They all give different types of approaches and algorithms for automatic liver tumour segmentation. Park et al proposed a method that first obtains a segmentation of the liver using intensity histogram transformation and maximum a posteriori classification resulting in a binary mask. After morphological processing of the mask, the tumours are located by defining a statistically optimal gray level threshold within the mask area. Seo proposed a multi-stage automatic hepatic tumour segmentation method [10]. It firstly segments the liver, then; hepatic tumour is segmented by using the optimal threshold value with minimum total probability error. Promising results are shown, even if the approach produce diverse false positives, especially for small tumours. A method by Ciecholewski et al used a contour model to obtain a segmentation of the liver, and then by histogram transformation enhanced the image to find neo plastic lesions at locations of cavities within the healthy liver volume. Jolly et al locates tumours on 2D plains after simple grey level distribution estimation, and the results are combined to obtain final 3D segmentations [9]. Zhao et al developed a region growing algorithm using intensity distributions of the seed ROI provided by users to delineate liver metastases. They also used specific shape constraints to prevent the region growing from leaking into surrounding tissues. Bourquain et al used interactive region-growing method for the vessels and tumours. Among other works that used region growing to detect liver lesions.
In, Arakeri et al. proposed an automatic region growing method that incorporates fuzzy c-means clustering algorithm to find the threshold value and modified region growing algorithm to find seed point automatically [10]. Massopetri and Casciaro firstly, segmented the liver by adopting a statistical model based approach and then apply a wavelet analysis for classifying the tumours [4]. AdaBoost is a supervised learning method, introduced by Freund and Schapire, based on the use of weak learners to construct a strong classifier. This method has been widely used, because it runs fast (when the weak learners are fast) and may be applied in many cases [7]. Chen and Metaxas used Markov Random Field (MRF) estimation coupled with Deformable models for the segmentation of tumours. Lu et al also used the active contour with a manually specified initial contour to obtain the tumour boundary [10]. The problem related to the automatic liver segmentation has been faced already using CT images with the wish to obtain a fast and accurate solution. In that we work to develop a new fully automatic method based on a hybrid approach using adaptive thresholding. The process of segmentation is done in two parts – first part is to create a gray scale image to binary mask of CT image. Second part is thresholding which is done to generated binary mask of CT image. This algorithm was tested on abdomens CT scan images of patient. Good results were obtained in terms of quality and processing time of the segmentation operation.

II. METHOD

The segmentation procedure of liver tumour is proposed by using abdominal CT images. We are using DICOM files for segmentation process. Tumour segmentation in CT liver images is a challenging task. The segmentation of liver tumours is challenging due to the small observable changes between healthy tissues and tumours. A normal liver with no tumour, such as liver cancer or liver cirrhosis, shows regular gray values in an abdominal CT image. The gray value of a normal liver ranges between 90 and 255. However, the tumours of the abnormal liver do not have regular gray values between 90 and 255. CT is the most widely used imaging technique for the detection of liver tumour. It helps doctors to acquire the information and provide opinions for liver tumour. Many research groups have developed different approaches for liver and tumour segmentation. They all give different types of approaches and algorithms for automatic liver tumour segmentation. Here in this paper we used region splitting, adaptive thresholding and merging process for segmentation of liver tumour. Our aim is to generate an automatic technique for automatic segmentation which is much better than other technique. First we have collected CT images from Bhilai scan centre and then take details information about liver tumour in CT images from doctor and radiographer of Bhilai scan centre.

They tell us about lots of knowledge the liver structure, liver surface (boundaries) and lesion localizations or tumour localizations are required for segmentation of liver tumour. First Split image into regions using a binary space partition (BSP) or a quadtree partition. Then next step is to apply adaptive thresholding to split region of CT image. After adaptive thresholding merging of image is done. Hence segmentation of tumour is done.

Liver imaging in patients with a history of known or suspected malignancy is important because the liver is a common site of metastatic spread, especially tumours from the colon, lung, pancreas and stomach, and in patients with chronic liver disease who are at risk for developing hepatocellular carcinoma [18]. Since benign liver lesions are common, liver imaging strategies should incorporate liver lesion detection and characterisation [18]. Survey examination in patients with a known extra-hepatic malignancy to exclude the presence of hepatic and extra-hepatic involvement is normally undertaken with a contrast-enhanced CT examination [18]. When patients with hepatic metastases are being considered for metastasectomy, they undergo a staging examination with contrast-enhanced magnetic resonance imaging (MRI) using tissue-specific contrast agents. Patients with chronic liver disease who are at risk for hepatocellular carcinoma undergo periodic liver screening for focal liver detection, usually with ultrasonography (US) with MRI being used when US is equivocal. Finally, contrast-enhanced MRI with extra-cellular gadolinium chelates is preferred for characterisation of indeterminate hepatic masses with liver biopsy used when tissue diagnosis is needed [18]. Hepatocellular carcinoma (HCC) is the most common primary cancer of the liver and its incidence has increased in Japan and portions of the developing world, arising mainly in patients with chronic liver disease [3]. In both situations, accurate detection of malignant liver disease remains crucial to patient management. However, since benign liver lesions are very common, liver-imaging strategies should incorporate liver lesion characterisation as an equally important goal. Several imaging modalities are now available for detection and characterisation of focal liver lesions [7]. Liver cancer is considered one of the major causes of death in humans [1]. Early detection of tumours is essential for increasing the survival chances of patients. Recent advancements in medical imaging modalities have enabled the acquisition of high-resolution CT datasets, and thus, allowing physicians to identify both small and large tumours by manual visual inspection. Owing to the large number of images in medical datasets, it is difficult to manually analyze all images, and useful diagnostic information may be overlooked. Moreover, the diagnoses are mainly based on the physician’s subjective evaluation and are dependent on the physician’s experience [19].

The details of data set are given below in table and figure of data set is shown:
Fig.1. Test CT Images of (a) patient 1, (b) patient 2, (c) patient 3 and (d) patient 4 from Bhilai scan centre

TABLE I
DETAILS OF THE PATIENTS AND THEIR DIAGNOSIS

<table>
<thead>
<tr>
<th>Patient No.</th>
<th>Age</th>
<th>sex</th>
<th>CT Scan</th>
<th>Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36</td>
<td>M</td>
<td>CT Scan Whole Abdomen (Plain and Contrast Study)</td>
<td>Medial limb of right adrenal gland appears thickened.</td>
</tr>
<tr>
<td>2</td>
<td>56</td>
<td>F</td>
<td>CT Scan Whole Abdomen (Plain and Contrast Study)</td>
<td>Mild hepatomegaly with two large hypodense peripherally enhancing SOL in liver.</td>
</tr>
<tr>
<td>3</td>
<td>61</td>
<td>M</td>
<td>CT Scan Whole Abdomen (Plain and Contrast Study)</td>
<td>Evidence of III defined mass with irregular margins showing non-enhancing necrotic in left lobe of liver.</td>
</tr>
<tr>
<td>4</td>
<td>72</td>
<td>M</td>
<td>CT Scan Whole Abdomen (Plain and Contrast Study)</td>
<td>Hypodense soft tissue mass showing irregular enhancing margins is noted in right lobe of liver.</td>
</tr>
</tbody>
</table>

III. REGION SPLITTING AND MERGING

The split-and-merge algorithm is composed by two steps. First, the method subdivides the entire image into smaller regions following a dissimilarity criterion.

To divide the image, different strategies can be adopted such as a quad tree partition (where each region is subdivided into four equal regions) and a binary space partition (BSP) (where an optimal partition is selected to divide the region). Second, the neighbour regions obtained from the splitting step are merged if they verify a similarity criterion. These similarity and dissimilarity criteria can be based on an intensity range, gradient, contrast, region statistics, or texture. The combination of splitting and merging steps allows for the segmentation of arbitrary shapes, which are not constrained to vertical or horizontal lines, as occurs if only the splitting step is considered [16].

Region splitting and merging subdivide an image initially into a set of arbitrary, disjoint regions and then merge and/or split the regions in an attempt to satisfy the necessary conditions.

Let R represent entire image region and select a predicate P

1) Split into four disjoint quadrants any region Rᵢ for which P (Rᵢ) = FALSE
2) Merge any adjacent regions Rⱼ and Rₖ for which P (Rⱼ ∪ Rₖ) = TRUE
3) Stop when no further merging or splitting is possible

Several variations of this theme are possible ex:

<table>
<thead>
<tr>
<th>R1</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>R3</td>
<td>R4</td>
</tr>
<tr>
<td>R4</td>
<td></td>
</tr>
</tbody>
</table>

Fig.2. partitioned image

Define P (Rᵢ) = TRUE if at least 80% of the pixels in Rᵢ have the property |Zᵢ - Mᵢ| ≤ 2σᵢ.

If P (Rᵢ) = TRUE, the value of all the pixels in Rᵢ are set equal to Mᵢ.

Splitting and merging are done using the algorithm on the previous transparency [16].

Properties based on mean and standard deviation attempt to quantify the texture of a region [16].

Texture segmentation is based on using measures of texture for the predicates P (Rᵢ) [16].

The process of region splitting and merging is proposed or designed. According to the following criteria:

1) The method should be robust against partially weak edges and noisy homogenous region in object.
2) The method should be robust against different object border orientation and position.
3) The method should be robust in small geometrical translations of the images at instance of registration error.
4) The method should be computationally efficient in the number of split and merge operations.
IV. ADAPTIVE THRESHOLDING

Thresholding is called adaptive thresholding when a different threshold is used for different regions in the image. This may also be known as local or dynamic thresholding (Shapiro, et al. 2001:89). Adaptive Thresholding subdivide original image into small areas and utilize a different threshold to segment each sub images. Since the threshold used for each pixel depends on the location of the pixel in terms of the sub images, this type of thresholding is adaptive. An approach to handling situations in which single value thresholding will not work is to divide an image into sub images and threshold these individually. Since the threshold for each pixel depends on its location within an image this technique is said to adaptive.

We use the adaptive thresholding for segmentation of liver tumour in CT images. Threshold process convert CT image in to binary image. The process of adaptive thresholding is as follows:

1) Adaptive Thresholding divide original CT image into subimages.
2) Utilize a different threshold to segment each subimages.
3) Difficulties occur in subdivision and subsequent threshold estimation.

Image Segmentation for subimages without boundaries, variance < 75, so when variance < 100, subimages treated as a single composite image or subimages with boundaries, variance > 100, so when variance > 100, subimages treated separately. In both these cases T is obtained automatically with T0 midway between the minimum and maximum gray level. This process will automatically generate segmented region using gray level.

V. BOUNDARIES

Trace region boundaries in binary image. B = boundaries traces the exterior boundaries of objects, as well as boundaries of holes inside these objects, in the binary image BW. Boundaries are descends into the outermost objects (parents) and traces their children (objects completely enclosed by the parents). B must be a binary image where nonzero pixels belong to an object and 0 pixels constitute the background.

The following figure will show the process of segmentation in abdominal CT images:

VI. RESULTS

We start the process of segmentation of liver tumour in CT images. We adopt the CT images in form of DICOM images and we convert images in jpeg file. Then the next step is to use the selected jpeg image for tumour segmentation. The process of segmentation is done in two parts –first part is to convert a gray scale to binary image. Second part is adaptive thresholding which is done in generated binary mask of CT image. Adaptive Thresholding divide original CT image into subimages. It uses a different threshold value to segment each subimages. This process will automatically generate segmented region using gray level. After thresholding, tumour is segmented from CT image. Tumour is segmented then boundaries are made in segmented region.

The thresholding method has been applied to the abdominal CT images. Each case consists of slice images and the size of each slice is 512x512 pixels with 1 byte/pixel. For experiment, radiologists and physicians have judged whether the segmentation results are correct. Fig a, b, c and d shows the process of segmentation.
We propose an effective method to segment the tumour in abdominal CT images. In this study, we use the thresholding in each slice for the segmentation of tumour. Therefore, this method effectively segments the tumour when applied to the abdominal CT images which is difficult to segment the tumour accurately. This segmentation method can be applied to not only the abnormal liver tumour with liver cirrhosis or liver cancer but also the normal liver. The proposed segmentation method improves the segmentation performance compared with the conventional process based on a regular gray value. The presented system for segmentation of liver tumour is able to reliably segment the tumour in the used patient database. Successive training of several classifiers using additional probability features proved useful, as did the proposed standardization method. For satisfying tumour detection, however, false positive rates have to be further reduced. An integration of multiple contrast phases into the classification process might also be helpful when adapting the system for the segmentation of hyper dense tumour. Furthermore, this work can be extended in order to differentiate internal liver tissues like the parenchyma, the tumour lesions, and the vessel tree. The same kind of approach, in fact, can be employed to classify the three types of tissues.

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REFERENCES


**BIOGRAPHIES**

**Devendra Joshi** was born in Bhilai in India, on April 19, 1986. He graduated from Govt. Engg. College, Raipur, Chhattisgarh in 2009 and student of M.Tech Computer Technology at National Institute of Technology Raipur, India. His areas of interest are image processing, medical image processing.

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