A Novel Fully Automated Liver and HCC Tumor Segmentation System Using Morphological Operations

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Abstract. Early detection and diagnosis of Hepatocellular Carcinoma (HCC) is the most discriminating step in liver cancer management. Image processing is primarily used, where fast and accurate Computed Tomography (CT) liver image segmentation is required for effective clinical studies and treatment plans. The purpose of this research is to develop an automated HCC detection and diagnosis system, able to work with HCC lesions from liver CT images, with maximum sensitivity and minimum specificity.

Our proposed system carried out automated segmentation of HCC lesions from 3D liver CT images. First, based on chosen histogram thresholds, we create a mask to predict the segmentation area by exploiting prior knowledge of the location and shape. Next, we obtain a 3D HCC lesion using an appropriate combination of cancer area pixel density calculations, histogram analysis and morphological processing. To demonstrate the feasibility of our approach, we carried out a series of experiments using 31 CT cases, comprised of 18 HCC lesions and 13 non HCC lesions. The acquired CT images (in DICOM format) had 128 channels of 512×512 pixels, each with pixel space varying between 0.54 and 0.85.

Simulation results showed 92.68% accuracy and a false positive incidence of 9.75%. These were also compared and validated against manual segmentation carried out by a radiologist and other widely used image segmentation methods.

Fully automated HCC detection can be efficiently used to aid medical professionals in diagnosing HCC. A limitation of this research is that the performance was evaluated on a small dataset, which does not allow us to confirm robustness of this system. For future work, we will collect additional clinical and CT image data to ensure comprehensive evaluation and clinical validation. We also intend to apply this automated HCC detection and diagnosis system to Positron Emission Tomography (PET) and Magnetic Resonance Imaging

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(MRI) datasets, as well as adapting it for diagnosing different liver diseases using state-of-the-art feature extraction and selection, and machine learning classification techniques.

Keywords: HCC · Lesion · Detection · Segmentation · CT

1 Introduction

Hepatocellular Carcinoma (HCC) is the 5th most common type of cancer and the 2nd highest cause of cancer related deaths [1]. Diagnosis of this condition is made using 3-Dimensional Computed Tomography (CT), a non-invasive diagnostic imaging technique [2] which utilizes both X-rays and computer technology to produce horizontal or axial images (often called slices) of the body. A CT scan demonstrates detailed images of any part of the body, including the bones, muscles, fat, and internal organs. The early detection and diagnosis of HCC, especially small lesions less than 2 cm [3] is a labour intensive operation, requiring repetitive manual intervention. Additionally, HCC lesion detection is a challenging task due to irregular shapes, sizes, densities and the large number of slices to be processed in 3D CT scans. To tackle these challenges we proposed a fully automated, efficient and cost effective intelligent system to detect and diagnose HCC.

2 State of the Art

Fast and accurate CT liver image segmentation is very important in detection, diagnosis, clinical studies and treatment planning of HCC. Our main objective is to develop an automatic HCC segmentation system that can accurately detect and segment HCC from liver CT images. Canny Edge Detector [4] was introduced to approximate and optimize the edge-searching problem. In order to make the edges more prominent, two-dimensional Gaussian, Magnitude and Direction of the gradient are computed at each pixel level [4] presenting a new algorithm for segmentation of intensity images. This is robust, rapid, and free of tuning parameters but requires the input of a number of seeds, either individual pixels or regions, which will control the formation of regions into which the image is segmented. Region Growing [5] was used firstly to obtain homogeneous seeds via histogram analysis. The histogram of each band was analyzed to obtain a set of representative pixel values, then seeds generated with all the image pixels with representative grey values. Secondly, a modified seeded region growing algorithm was applied to perform the segmentation. This algorithm made use of instance based learning as similarity criteria. K-means clustering [5] and a priori knowledge to find and identify liver and non-liver pixels, which were use "object" and "background" seeds, respectively. Optimizing Fast Fuzzy C-Means [6] by utilizing the Particle Swarm Optimization method (PSOFFCM) [7] which showed higher values for jaccard index and dice coefficient on Liver CT images, and higher similarity with the ground truth presented. Furthermore to evaluate performance, ANOVA analysis and PSOFFCM were also applied, showing better results in terms of box and whisker plots. Different approaches to automatic liver tumour detection and semi-automatic segmentation from CT liver images were also proposed [4] by utilizing the kernel based extreme learning machine but it showed promising segmentation and detection performance in CT scans of 7 patients with total 20 tumours. An automated segmentation technique was also presented [8]. Their work was based on the liver region and likelihood intensity range of CT image data (determined by the histogram analysis, cell density and morphological operations). Graph Cut [9] was applied to detect and segment hepatic tumours using shape and enhancement constrains. Furthermore, tumour Burdon was computed from the segmented liver and tumour. The paper also reported that image registration computation was very expensive, with running time for one case between 50–60 min, including approximately 30–35 min for the initial liver segmentation, 20–25 min for liver segmentation correction and a couple of additional minutes for tumour analysis. The region growing [10] method applied, that automatically segments the liver by combining more phases of the contrast-enhanced CT examination. Also, morphological analysis and geometric feature methods were applied [11] to segment liver lesions automatically, but with inconclusive results. From previous literature it can be seen that there are very few methods which can automatically detect and segment liver tumours accurately. Furthermore, many studies were restricted to specific types of lesion or required certain types of images, some of which were slow in computation. In light of the above issues, there is a great requirement for a robust, state of art and fully automated system that can accurately detect and segment liver and HCC lesion.

3 Proposed Method

3.1 Automatic HCC Detection System

The aim of our research is to develop a robust, real time, and computationally efficient automated liver HCC detection and segmentation system. The proposed system consists of two steps: automatic liver segmentation and automatic HCC lesion detection, as shown in Figure 1. The novelty of the proposed fully automated liver and its lesion segmentation system is: (a) we have introduced a fully automated liver and lesion segmentation based on morphological operations with 3-D CT scan images, (b) the proposed system is fully integrated with the segmentation of the liver and its lesion, (c) it requires minimal computational power, (d) is cost effective, (e) it reduces the work load for the clinical experts, and (f) it can be configured with ease in clinical laboratories for further evaluation.

3.2 Automatic Liver and Lesion Segmentation

Automatic liver and lesion segmentation was carried out as follows:

(a) Applied masking and prediction to visualize maximum area of liver.
(b) Define and calculate liver area based on the shape and prior knowledge.
(c) Morphological operations, as in [12], are carried out to segment the liver from rest of organs [13], which are removed by morphological erosion and result in an isolated liver region.

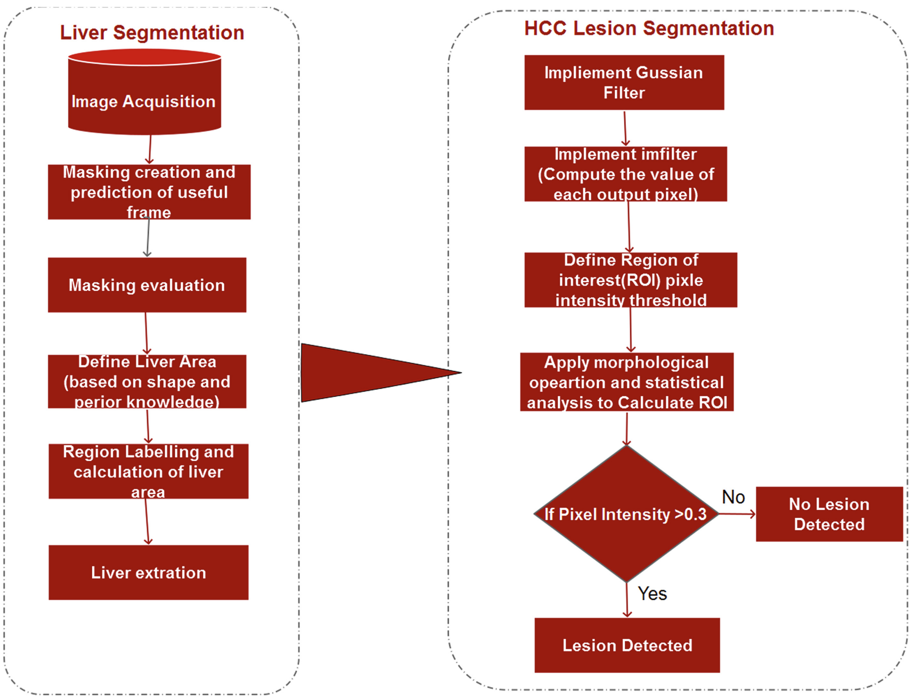

Fig. 1. Proposed system

(d) Applied Gaussian filter [10] to remove noise and preserve the edges.
(e) Defined pixel intensity threshold value using trial and error to find out the normal image surface and lesion surface.
(f) In its final state use histogram analysis, and other morphological operations, to detect HCC lesion.

Specifically, the following steps were followed for automatic liver segmentation from an abdominal CT image:

- First acquired and loaded all frames of the abdominal CT image
- Applied masking to predict the useful frame (where all organs clearly shown)
- Converted matrix image into an intensity image by scaling it between 0 and 1
- Found and determined threshold value of image pixel using a trial and error approach as in [5].

  (a) If image pixel intensity > 0.3 then threshold $= 1$, otherwise 0

- Applied morphological operations, following [5, 10, 14] listed below:

  (a) Applied disk structuring element to include true pixels and exclude false areas in the morphological computation, within a radius of 2 cm
  (b) Applied Erode function to erode the image
  (c) Removed other organs surrounding liver using the bwareaopen function.

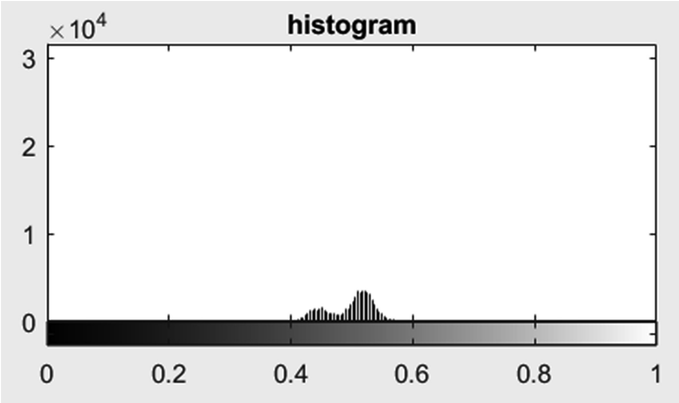

Fig. 2. Image histogram analysis for liver and lesion segmentation

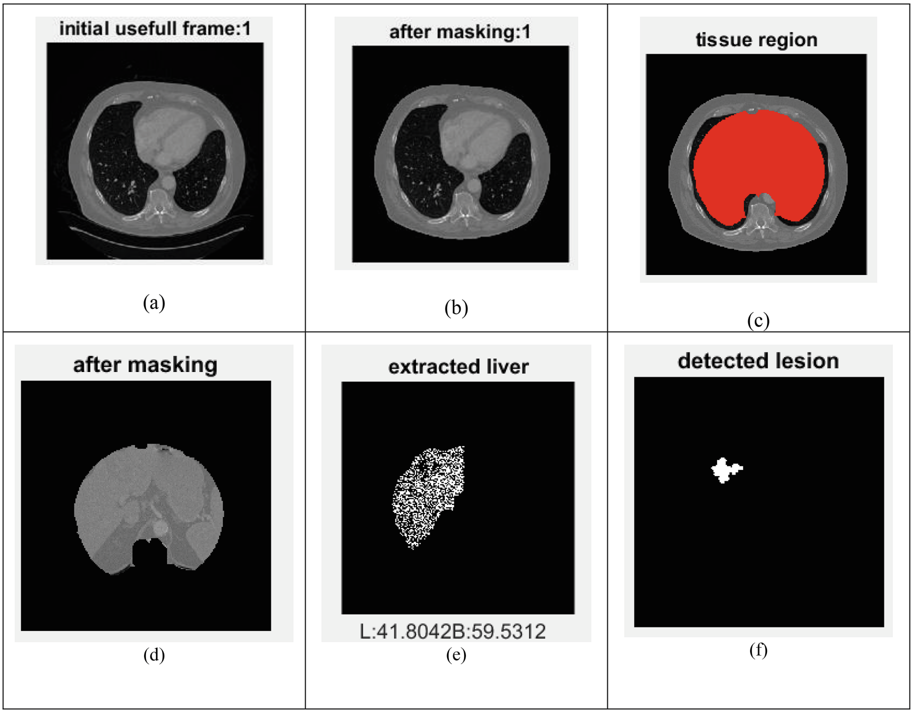

Fig. 3. Liver and lesion segmentation using metrological operations

(d) Used imdilate function to add pixels to the boundaries of objects in image
(e) Filled a hole of background pixels that cannot be reached by filling in the background from the edge of the image.

(f) Calculated average mask to determine the Region of Interest area(RIO)- cancer area
(g) Applied the histogram to show the liver area pixels in Fig. 2
(h) Finally showed the liver area in the window shown in Fig. 3
Applied rotationally symmetric Gaussian low pass filter of hsize 5 with standard deviation sigma = 5 to remove noise, and preserve high frequency edges. Mathematically Gaussian Filter can expressed in following equation [15]

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} \mathrm{EXP}\left(-\left(\mathrm{x}^2 + \mathrm{y}^2\right)/2\sigma^2\right) \tag{1}$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis and σ^2 represent the variance which determine the amount of smoothing.

- Applied threshold if ROI image pixel intensity >0.3.
- Applied morphological operations to find the threshold value and if ROI = 1 and row array is empty, then calculate the area of lesion by using the formula below: Pixel intensity = MAX(row) – Min(row) and Max(column) – Min(column) then calculation of array dimension = (row) If Pixel Intensity >0.3 then detected lesion else no lesion detection.

4 Comparative Studies

We compared proposed segmentation method with other widely used segmentation method, namely region growing, but results are compromised and computational performance is very low as shown in Fig. 4.

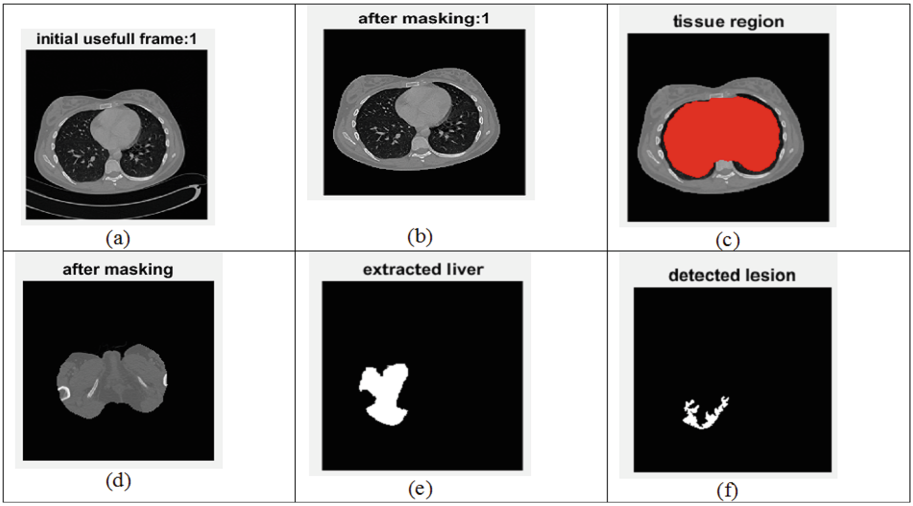

Fig. 4. Liver and lesion segmentation results using region growing method

5 Results and Discussion

A total of 31 CT images were obtained from Crosshouse Hospital, Glasgow, UK. The images were in the DICOM format, and had 128 channels of 512 $\times$ 512 pixels, each with pixel space varying between 0.54 and 0.85. A Liver and its lesion segmentation process, from a patient's abdominal CT scan, is shown in Fig. 3(a) shows the initial most suitable frame, by use of a masking method. Figure 3(b) shows bone masking along with elliptical masking. Figure 3(c) shows the tissue region. Figure 3(d) shows the shape of the abdomen in the frame. Figure 3(e) shows the extracted liver. Figure 3 (f) shows the detected lesion and its segmentation. Figure 2 is a histogram showing a liver lesion's minimum and maximum intensity, which aids in correctly and automatically identifying a lesion and its region. We performed morphological erosion on the abdominal CT, which removed the organs around the liver [4] and isolated it, as shown in Fig. 3(e). Gaussian filtering was then used to remove noise, preserve high frequency edges and determine pixel intensity threshold values. If the pixel intensity >0.3, then a lesion is present and has been detected, as shown in Fig. 3(f). The results showed successful automated liver and lesion segmentation in each frame of the 31 cases. We have compared the performance of our proposed automatic segmentation system, against manual segmentation by a radiologist for the same cases, as shown in Table 1, and obtained 92.68% accuracy. The false positive incidence was only 9.75%. Further, we also compared proposed method with widely used segment method region growing shown in Fig. 4 but results were compromising and computation performance very low. In Fig. 4 (e) showed, the region growing method was not correctly detected and segmented liver and lesion.

5.1 Performance Measure

The proposed automated segmentation was carried out on all data sets and compared with lesions identified manually by a radiologist and other widely used image segmentation method for the same data. The True Positives (TP), False Positives (FP) and False Negatives (FN) were then computed as follows [10]:

- For each manually detected lesion, we assessed if there was any intersection with the automated system lesion and checked whether it was intersection with any automatic detect lesion. If there was intersection, the TP was increased, otherwise the FN was increased.
- For each large manually detected lesion, we also assessed if there was no intersection with automated system lesion. If this manual lesion was intersected by more than one (automated), only one is considered as a TP, whilst the rest contribute to FP. Table 1 and Figs. 5 and 6 shows the TP and FP for results obtained from both automated system, and manual lesions, for the 31 cases.
- The results show that all lesions from the 31 cases were identified correctly by our proposed automated system, with an accuracy of 92.68%.

Table 1. Manual V/S automatic segmentation performance evaluation

Case	No of lesions	Manual lesion		Automatic lesion	
		TP	FP	TP	FP
1	2	2	0	1	0
2	2	2	0	2	0
3	1	1	0	0	1
4	1	1	0	1	0
5	0	0	0	0	0
6	1	1	0	1	0
7	0	0	0	0	1
8	1	1	0	1	0
9	1	1	0	1	0
10	0	0	0	1	0
9	1	1	0	1	0
10	2	2	0	1	0
11	2	2	0	1	0
12	2	2	0	1	0
13	0	0	0	1	0
14	2	2	0	2	0
15	1	1	0	1	1
16	2	1	0	1	0
17	2	2	0	2	0
18	1	1	0	1	0
19	2	2	0	2	0
20	2	2	0	2	0
21	1	1	0	1	0
22	2	2	0	1	0
23	1	1	0	1	0
24	2	2	0	2	0
25	2	2	0	1	0
26	1	1	0	1	0
27	0	1	0	1	0
28	2	1	1	1	0
29	1	1	0	1	0
30	1	1	0	1	1
31	1	1	0	1	0
Total	42	41	1	38	4

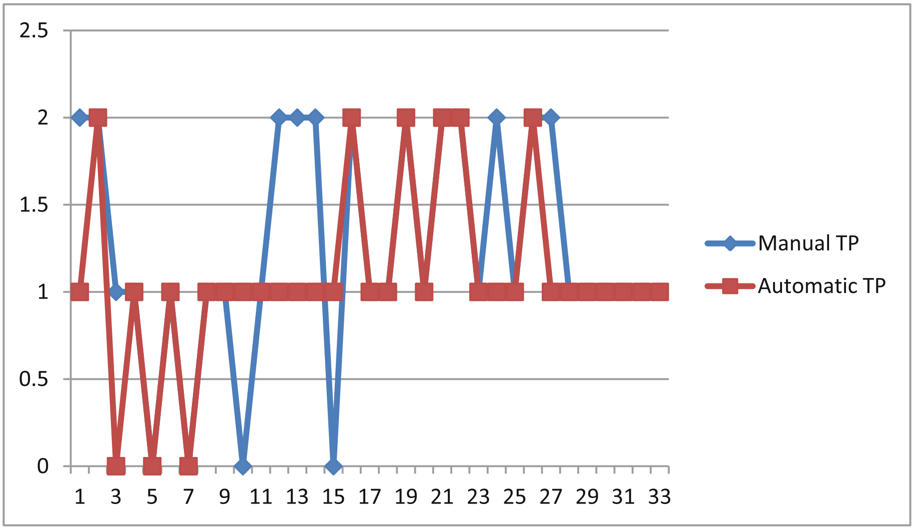

Fig. 5. Manual segmentation True Positive (TP) V/S Automatic Segmentation (TP) comparisons

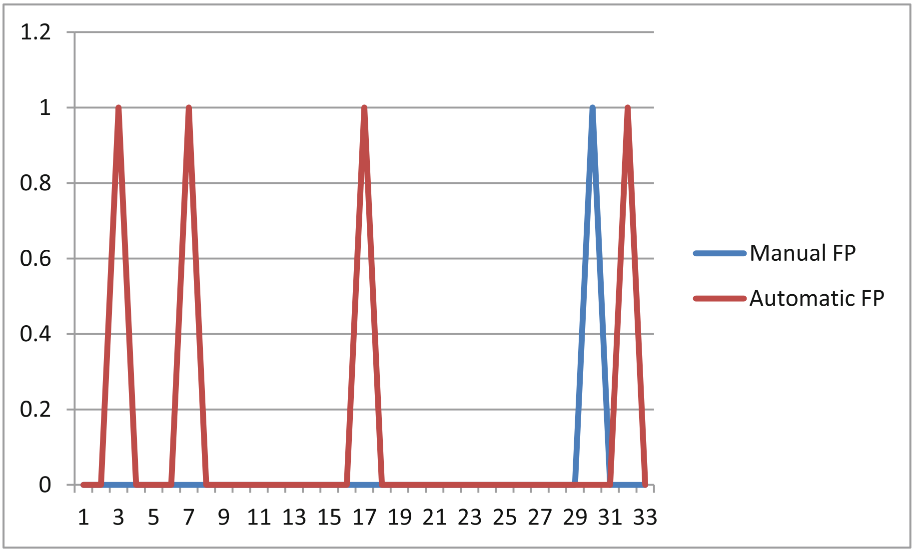

Fig. 6. Manual segmentation FP Positive (FP) V/S Automatic Segmentation (FP) comparisons

6 Conclusion

The proposed research presents a fully automated liver and lesion segmentation system, using morphological operations, for abdominal CT scans. The obtained results suggest that fully automated HCC detection can be efficiently used to aid medical professionals in diagnosing HCC. It has been shown that morphological operations require less computational power when compared to other conventional image segmentation algorithms. A limitation of this research is that the performance was evaluated on a small dataset, which does not allow us to evaluate robustness. For future work, we will collect additional clinical and CT image data to ensure comprehensive evaluation and clinical validation.

We also intend to apply this automated HCC detection and diagnosis system to Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) datasets, as well as adapting it for diagnosing different liver diseases using state-of-the-art feature extraction and se lection, and machine learning classification techniques.

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