Proceedings of the 2013 Federated Conference on
Computer Science and Information Systems pp. 193–198

Automatic computer aided segmentation for liver and hepatic lesions using hybrid segmentations techniques

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***Abstract*—Liver cancer is one of the major death factors in the world. Transplantation and tumor resection are two main therapies in common clinical practice. Both tasks need image assisted planning and quantitative evaluations. An efficient and effective automatic liver segmentation is required for corresponding quantitative evaluations. Computed Tomography (CT) is highly accurate for liver cancer diagnosis. Manual identification of hepatic lesions done by trained physicians is a time-consuming task and can be subjective depending on the skill, expertise and experience of the physician. Computer aided segmentation of CT images would thus be a great step forward to scientific advancement for medical purposes. The sophisticated hybrid system was proposed in this paper which is capable to segment liver from abdominal CT and detect hepatic lesions automatically. The proposed system based on two different datasets and experimental results show that the proposed system robust, fastest and effectively detect the presence of lesions in the liver, count the distinctly identifiable lesions and compute the area of liver affected as tumors lesion, and provided good quality results, which could segment liver and extract lesions from abdominal CT in less than 0.15 s/slice.**

I. Introduction

THE LIVER cancer is one of the most common internal malignancies worldwide and also one of the leading death causes. Early detection and accurate staging of liver cancer is an important issue in practical radiology. Liver lesions are a wound or injury to body tissues. It is the area of tissue that caused damage because a wounding or disease. Liver lesions refer to those abnormal tissues that are found in the liver. In a CT scan these can be identified by a difference in pixel intensity from that of the liver. Manual segmentation of this CT scans are tedious and prohibitively time-consuming for a clinical setting. Automatic segmentation on the other hand, is a very challenging task, due to various factors, such as liver stretch over 150 slices in a CT image, indefinite shape of the lesions and low intensity contrast between lesions and similar to those of nearby tissues. The irregularity in the liver shape and size between the patients and the similarity with other organs of almost same intensity make automatic liver segmentation difficult [1, 2].

Several studies have developed various algorithms that can be categorized on the degree of automation (fully, semi or interactive) and in two approaches: region-based or contour-based. Region-based segmentation is commonly based on intensity of neighbour pixels. While contour-based segmentation includes geometrical or statistical active shape model. Each of these approaches has its advantages and disadvantages in terms of applicability, suitability, performance, and computational cost [3,4].

Particularly, no one who did not consider above characteristics of the abdominal CT image can meet desirable results on liver segmentation. In addition, the traditional method of getting volume of the liver is to perform a by-hand 2D segmentation of parallel cross-sectional CT slices and to multiply all voxels of the stacked slices by their size while the procedure is often time consuming and non-systematic [5].

Therefore, to address the above mentioned problems, we present fully automatic liver segmentation and detection algorithms in abdominal CT images based on a hybrid approach using an adaptive threshold, morphological operators and Connected Component Labelling algorithm (CCL) to segment liver parenchyma from abdominal CT and Watershed algorithm coupled with Region Growing algorithm to extract lesions from liver parenchyma. The hybrid system is proposed to improve the segmentation performance and time consuming compared with the conventional process. The proposed approach starts with search for suitable abdominal liver CT image from DICOM file, and then this suitable image is passed to a filter to enhance and remove noise, and finally passing to segmentation algorithm to segment the whole liver then passed to hybrid segmentation system to extract hepatic lesions.

978-1-4673-4471-5/$25.00

The process of segmentation is done in two phases. The first phase aimed to segment liver parenchyma from abdominal CT, this phase consist of three steps. The first step is to convert CT image into binary image using adaptive threshold that examine the intensity values of the local neighbourhood of each pixel. The second step is to apply multi-scale morphological operators to filter tissues nearby liver, to preserve the liver structure and remove the fragments of other organs. The third step is a CCL algorithm to remove small objects and false positive regions. The second phase aimed to segment and extract lesions from liver parenchyma which is segmented in first phase, in this phase integration between segmentation algorithms was applied to boost and increase the efficiency of segmentation behaviour. Marker-controller watershed algorithm was applied to cluster liver and define ROI, after liver clustered using watershed, an adaptive region growing is integrated with watershed algorithm to increase the performance and accuracy of segmentation. This system was tested on two different datasets. Good results were obtained in terms of quality and less processing time of the segmentation operation.

The reminder of this paper is ordered as follows. Section II discusses the previous work on liver segmentation. Details of the proposed methods and datasets are given in Section III. The proposed system is presented in Section IV. Section V shows the experimental results and analysis. Finally, Conclusion and future work are discussed in Section VI.

II. Previous Work

Several researchers have focused their attention on the use of threshold to segment liver. Massoptier and Casciaro [6] used adaptive thresholding to detect livers and refined the segmentations by graph cut. Campadelli et al. [7] detected livers by using heart segmentation information and then used adaptive thresholding and morphology as an alternative to graph cut to segment livers. Masumoto et al. [8] utilized conventional thresholding in multi-phase images to delineate the liver. Rusko et al. [9] mainly used region-growing with various pre-processing and post-processing steps to segment liver. Extracting regions of interest (ROIs) requires a sharpening filter to stress the regions edges [10]. Kumar and Moni [11] proposed their thresholding and morphological operator based algorithm to segment liver from abdominal CT image slices. Susomboon et al. [12] proposed a hybrid approach consisted of intensity based partition, region-based texture classification, connected component analysis and thresholding for liver segmentation. Massieh et al. [13] 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. However, their approach is very time consuming. In contrast with active shape models, Seghers et al. [14] incorporated both local intensity and local shape models for liver segmentation. Wan Nural and Hans Burkhardt [15] used Integration of Morphology and Graph-based Techniques for liver segmentation. Abdalla et al. [16], proposed new combined approach level set and watershed approach for CT liver segmentation to separate the liver from other organs and obtained overall accuracy of 92%. Shweta and Sumit [17] proposed level set segmentation technique using Variational Level Set Formulation techniques without initialization with various filtering methods. It was found that maximum filter provided the best results on the samples of the segmentation of CT images.

Jeongjin et al. [18] applied two steps of seeded region growing onto level-set speed images to define liver region. Ruchaneewan etal. [19] used intensity-based partition and region-based texture to segment liver. Abdalla et al. [10] Proposed for segment and isolate the liver region of interest using a region growing segmentation approach, and achieved highest performance for contrast stretching filter.

III. Martials and Methods

CT scanning is a diagnostic imaging procedure that uses X-rays in order to present cross-sectional images ("slices") of the body. The proposed system will be work on two different datasets: First dataset has divided into seven categories depends on the tumour type of benign (Cyst (CY), Hemangioma (HG), Hepatic adenoma (HA), and Focal nodular hyperplasia (FNH)) or malignant (hepatocellular carcinoma (HCC), Cholangiocarcinoma (CC), and Metastases (MS)), each of these categories have more than fifteen patients, each patient has more than one hundred slices, and each patient has more than one phases of CT scan (arterial, delayed, portal venous, non-contrast), also this dataset has a report diagnosis for each patient. All images are in JPEG Format selected from DICOM file and have Dimensions 630 x 630 with horizontal and vertical resolution of 72 DPI and bit depth 24 bit. All CT images captured from Radiopaedia web site [19].

For the second dataset, the data is acquired on a GE Discovery ST with the breathing trace provided by a Varian RPM system, and processed by a Varian 4D workstation. Information found in series description DICOM tag [0008,103E], T=0% is end-inhale and T=50% end-exhale. Livers and liver tumours CT images are manually segmented by five expert radiologists. These datasets are provided by Dr. Kevin Cleary at the Imaging Science and Information Systems (ISIS) Center from the Georgetown University Medical Centre [20].

A. Pre-Processing

The main objective of image pre-processing is to enhance, smoothness, remove noise that caused by defects of CT scanner, improve quality and emphasizes certain features of an image so that it makes segmentation or recognition easier and more effective. Filtering is a key pre-processing technique used for various effects including contrast stretching, sharpening and smoothing. In this paper, the effective filtering techniques were evaluated and analysed to modify, smooth the image and to enhance the efficiency of proposed algorithm. Pre-processing of Liver CT's are typically aimed at either improvement of the overall visibility of features or enhancement of a specific sign of malignancy also morphological operators based algorithm is sensitive to noise, for these reasons pre-processing and filters is very important for liver images.

B. Liver segmentation methods

Segmentation of the liver and hepatic lesions from abdominal CT image is difficult. Therefore, a system is developed to extract liver and lesions automatically with sophisticated hybrid technique. To achieve the segmentation process, the following methods was proposed:

1) 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 each region. Global thresholding uses a fixed threshold 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 subject(s) and background(s). Hence, it cannot deal with images containing, a strong illumination gradient. Local adaptive thresholding, on the other hand, selects an individual threshold for each pixel based on the range of intensity values in its mean of local neighbourhood. This allows for thresholding of an image whose global intensity histogram doesn't contain 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.

2) Morphological Operator-based Algorithm

A morphological processing is an obvious choice to refine the segmentation. The main idea of morphological operators is to detect the object forms or shapes from the images based on a set of pre-defined structuring elements. Usually a set of structuring elements (SE) is based on the prior knowledge, and then some morphological operators apply structuring elements to images [21]. Dilation and erosion are the two main morphological processing. Dilation expands objects by a structuring element, filling holes, and connecting disjoint regions. Erosion deletes the small region by a structuring element. Morphological operations based algorithm has several advantages. First it does not need any specific initialization, which makes it possible to design the fully-automatic algorithms. Second it focuses less on the structure of the object of interest. Therefore, it can work well on the liver whose structure varies between different persons.

3) Connected Component Labeling algorithm(CCL)

CCL works by scanning a binary image pixel by pixel (from top to bottom and left to right) in order to identify connected pixel regions [22]. The result of applying an adaptive threshold is a collection of different regions, applying morphological operators to preserve the liver structure and remove the fragments of other organs, but still some regions not interested to be liver will be removed by post-processing approach CCL. The largest region extracted by using CCL, it is used to label the separate regions in CT, yielding a new labelled image. In general, this algorithm is useful to find non-connected objects in images.

C. Lesions segmentation methods

In this phase we used two different methods to extract lesions. Watershed algorithm as edge-based image Segmentation and Region Growing (RG) algorithm as region-based image Segmentation.

1) Watershed Algorithm

Separating lesions from liver image is one of the more difficult processing operations. The watershed transform is often applied to this problem. Watershed image segmentation can be regarded as an image in three dimensions (two spatial coordinates versus intensity). We will use three types of point which "minimum", "catchment basin", and "watershed line" to express a topographic interpretation. Watershed algorithm has an advantage that it is fast speed. While disadvantages of this algorithm is over-segmentation results, to solve this problem used marker-controlled for watershed Segmentation.

The watershed marker finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low. Segmentation using the watershed marker works better if you can identify, or "mark," foreground objects and background locations. Marker-controlled watershed segmentation follows this basic procedure:

1. Use a smoothing filter to pre-process the original image, then the action can minimize the large numbers of small spatial details.

2. Compute a segmentation function. This is an image whose dark regions are the objects you are trying to segment.

3. Compute foreground markers. These are connected blobs of pixels within each of the objects.

4. Compute background markers. These are pixels that are not part of any object.

5. Modify the segmentation function so that it only has minima at the foreground and background marker locations.

6. Compute the watershed transform of the modified segmentation function.

2) Region Growing Algorithm

The region growing (RG) algorithm is one of the simplest region-based segmentation methods. It performs a segmentation of an image with examine the neighboring pixels of a set of points, known as seed points, and determine whether the pixels could be classified to the cluster of seed point or not [22].The advantages of this algorithm is simplest, can correctly separate the regions of same properties, give good shape matching of its results. The algorithm procedure is as follows.

Step1. Start with a number of clusters and seed points which have been identified from watershed algorithm, cluster called C_1, C_2,...., C_n. And the positions of initial seed points is set as P_1, P_2,....., P_n.

Step2. To compute the difference of pixel value of the initial seed point pi and its neighboring points, if the difference is smaller than the threshold criterion that define, the neighboring point could be classified into C_i, where i = 1, 2,....,n.

Step3. Recompute the boundary of C_i and set those boundary points as new seed points pi (s). In addition, the mean pixel values of C_i have to be recomputed, respectively.

Step4. Repeat Step 2 and 3 until all pixels in image have been allocated to a suitable cluster.

The mean drawback of RG is initial seed-points. The initial seed-points problem means the different sets of initial seed points cause different segmentation results. This problem reduces the stability of segmentation results from the same image. Furthermore, how many seed points should be initially decided is an important issue because various images have individually suitable segmentation number. These problems will be handled in this paper by integrated RG with watershed algorithm.

IV. Proposed System

The proposed fully automatic technique and methods to segment liver structure and lesions from abdominal CT divided into two phases liver structure segmentation and lesions segmentation. The first phase of liver parenchyma segmentation from abdominal CT is comprised of five fundamental building steps as seen in Figure 1. The first step searches for suitable slices in CT DICOM file because liver intensity distribution is different between slices. Liver parenchyma is the largest abdominal object in middle slices. These slices are suitable for segmentation and give high accuracy.

Pre-processing step: In this step pre-processing algorithm is used before the segmentation phase to enhance contrast, remove noise and emphasize certain features that affect segmentation algorithms and morphology operators.

Adaptive threshold step: In this step CT image is converted into binary image using adaptive threshold method that examines the intensity values of the local neighbourhood of each pixel.

Morphological Operators step: After the CT image is converted into binary image using adaptive threshold, morphological operators will be applied to filter tissues nearby liver, to preserve the liver structure and remove the fragments of other organs.

Connected Component Labeling phase: CCL algorithm is used to remove small objects, false positive regions and focused on liver parenchyma.

The second phase of liver lesions segmentation and extraction aimed to integrate between watershed algorithm and RG to boost and increase the performance of segmentation. Watershed used to segment liver into different regions and solving the problem of over-segmentation using watershed marker. RG used to improve watershed segmentation using the clusters and centroid point for each cluster in watershed as seed point for RG.

V. Experimental Results

Hybrid system was used to segment liver structure from abdominal CT. The reason to do these hybrid methods was that

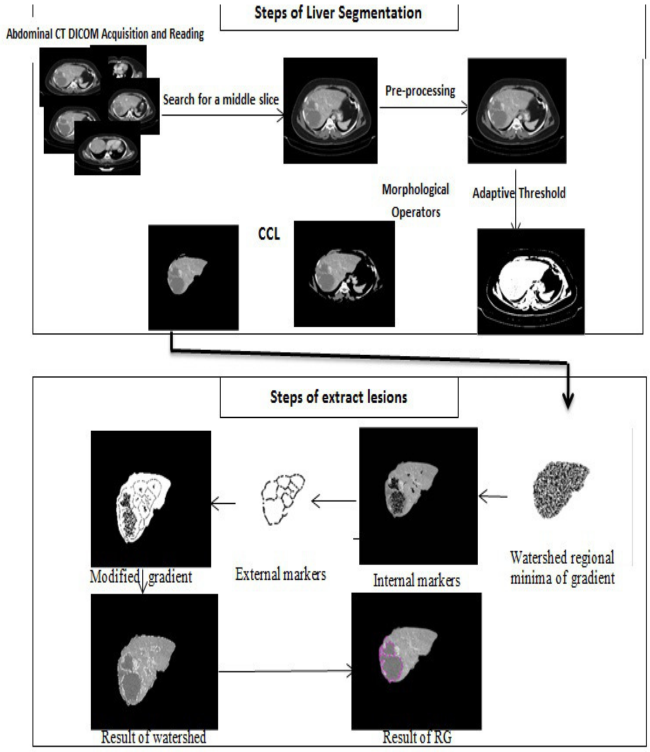

Fig. 1. Architecture of the proposed automatic liver segmentation approach

each method as such has problems, which the other method does not have. The proposed hybrid system divided into two phases. In the first phase suitable abdominal CT slice image of a patient with liver lesions was selected from DICOM file. Liver parenchyma is the largest abdominal object in middle slices as shown in Figure 2(a). Pre-processing median filter is used to enhance, remove noise and emphasize certain features that affect segmentation algorithms and morphology operators with 3x3 window as shown in Figure 2(b). After pre-processing stage, the hybrid segmentation based on adaptive threshold algorithm is applied on enhanced abdominal CT as shown in Figure 2(c). The adaptive threshold used the mean of the local intensity distribution to decide whether a pixel belongs to an organ of interest based on its neighboring features. Output is a binary image with the mean of local threshold. This mean of the local area is not suitable as a threshold, because the range of intensity values within a local neighborhood is very small and their mean is close to the value of the center pixel. The quality of adaptive threshold was improved by using static coefficient factor for all slices to increase performance. This method is simple, fast, less computationally intensive and produces good results for all slices.

After applying adaptive threshold, the morphological erosion and dilation operator with the shape and size of structuring element (SE) was used to shrink and remove small regions and extract liver from abdominal CT as shown in Figure 2(d). The experimental results show that the best shape

TABLE I
COMPARISON WITH EXISTING WORK ON LIVER SEGMENTATION

Author	Yearn	Patients	Slices	accuracy
Jeongjin et al. [18]	2007	20	—	0.70
Ruchaneewan et al.[12]	2007	20	30	0.86
Toshiyuki et al. [23]	2008	28	159	0.89
Abdalla et al. [10]	2012	—	26	0.84
Abdalla Z. et al. [16]	2012	4	27	0.92
Proposed	2013	112	860	0.93

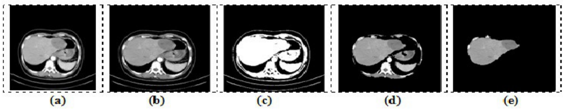

Fig. 2. Results liver segmentation on different patient's slices, a) The original suitable Slice, b) pre-processing median filter, c) Automatic adaptive threshold for each slice, d) Operators Dilation and erosion Morphology, e) The final results for ROI selected by CCL

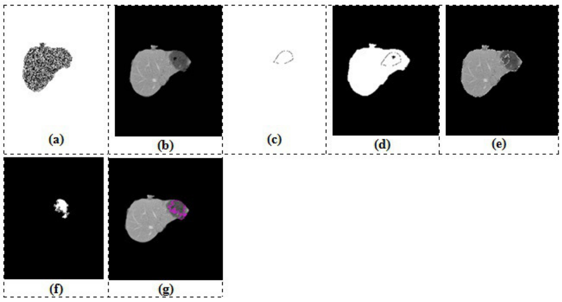

Fig. 3. Results of lesions segmentation, a) Watershed over-segmentation result, b) Internal Markers, c) External Markers, d) Modified watershed, e) Output watershed segmentation, f) Automatic seeded point for RG, g) Final result from RG segmentation

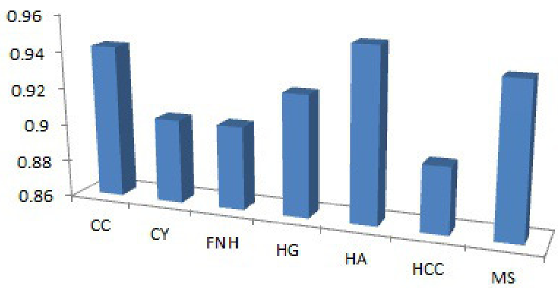

Fig. 4. Segmentation accuracy of livers with hepatic lesions

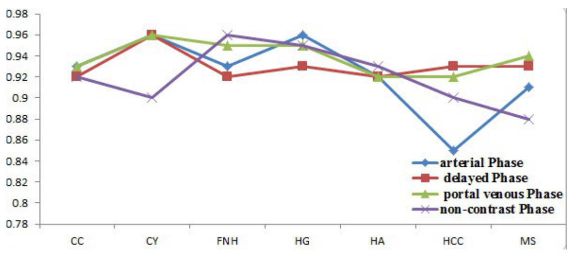

Fig. 5. Segmentation accuracy of abdominal CT phases for hepatic lesions

is diamond with SE size value 4. The shape and size of SE is decided after analyzing many Liver CT's. After applying morphological operators, post-processing CCL is applied on adaptive threshold with 8-connected objects to search for the largest connected region, remove false positive regions and focus on the ROI as shown in Figure 2(e).

In the second phase, after liver parenchyma segmentation passed to watershed to segment liver into distinct regions. Watershed approach combines the edge detection and region growing approaches, producing more stable results and connected boundaries. The main idea in watershed approach is to check whether one point belongs to one minimal, then it merges the point to it. Otherwise, the pixel is considered a boundary between the two minimal. This is done in a binary image using the morphological dilation. A huge number of potential minima of small objects in an image lead to over-segmenting problem. A smoothing filter should be used to eliminate that huge number. The simulation result of this algorithm has an advantage that it is fast speed. At the same time, it has a critical over-segmented problem, to solve this problem we use internal and external marker control to segment objects with closed contours, expressing the boundaries as ridges. Then pass this segmented liver to RG. The RG algorithm is used to improve watershed segmentation using the centroid point for each segmented region from watershed as seed point for RG. The region growing method had basically three problems, the rugged border, seeded point very difficult to assign it automatically for ROI and the leakage problem, but when combined with watershed gives accurate results as shown in Figure 3. The performance and accuracy of the proposed system was evaluated by Similarity Index technique (SI) between automated segmented images and manual segmented images.

The proposed hybrid system applied on 112 patients from different datasets with different hepatic lesions. The overall accuracy obtained is 0.93 for livers segmentation, and the proposed system applied on 860 abdominal CT slices achieved overall accuracy result 0.90. The proposed approach also gives acceptable accuracy of livers segmented with hepatic lesions are 0.94, 0.91, 0.91, 0.93, 0.95, 0.90, and 0.94 for CC, CY, FNH, HG, HA, HCC, and MS respectively as shown in Figure 4. In Figure 5, the proposed system also measures the segmentation accuracy of abdominal CT phases (arterial, delayed, portal venous, and non-contrast) for hepatic lesions. The better segmentation accuracy was achieved in portal venous phase, while arterial phase gives non accurate results in Hepatocelleour Carcinoma. This is because the nature of livers tissue which are ambiguous in this phase.

Comparing the results of proposed system with other previous work on CT liver segmentation from abdominal CT as shown in Table 1. The proposed approach is fast, precise, robust and provides good quality results and there is no meaningful loss of information, which could segment liver and extract lesions from abdominal CT in less than 0.15 s/slice when implemented in Matlab on PC Intel Core I5, 2.5GHz with 4GBytes of RAM.

VI. Conclusion and Future Work

The presented system for segmentation and liver lesions extraction is able to reliably segment and extract the lesions in the used patient database. Liver segmentation is a complicated process which consists of many steps for segmentation process. Integration between edge-based segmentation and region-based segmentation methods give more reliable and trust segmentation. The experimental results show that it is a robust proposed algorithm and obtained 93% of good extraction for liver from abdominal CT.

In conclusion, our results suggest that ensemble segmentation is effective in segmentation of livers and liver lesions, boosting and increasing the performance of weak segmentation processes.

In future work, we plan to assess the performance using a large dataset to evaluate generalization performance of the algorithm that includes a number of parameters in the feature measurement process, which means it might sensitive to size and characteristics of lesions.

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