Automatic Couinaud Liver Segmentation Using CT Images

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ABSTRACT: This paper presents an algorithm to segment the liver structures on computed tomography (CT) images according to the Couinaud orientation. Our method firstly separates the liver from the rest of the image. Then it segments the hepatic and portal vessel trees inside the liver area using a region growing technique combined with hysteresis thresholding. Finally, the method estimates the planes that best fit each of the three branches of the segmented hepatic veins and the plane that best fits the portal vein. These planes define the subdivision of the liver in the Couinaud segments. An experimental evaluation based on real CT images demonstrated that the outcome of the proposed method is generally consistent with a visual segmentation.

1 INTRODUCTION

Current computed tomography scanners allow for non-invasive high resolution imaging of the human body. A major challenge accompanying this improvement is dealing with the enormous amount of data generated in the form of image sequences.

By and large the CT data analysis is performed visually by a radiologist. This is a time consuming task, whose accuracy depends essentially on the experience of the analyst (Kakinuma et al., 1999; Li et al., 2002). Digital Image Processing techniques can be used to develop methods that automatically perform many of the tasks involved in the CT analysis, improving productivity and the overall accuracy.

The segmentation process is particularly arduous in abdominal CT images because different organs frequently share the same intensity value range and are often near to each other anatomically. Many techniques have been proposed in the literature for the analysis of abdominal CT scans. They can be roughly divided in two main groups: model driven and data driven approaches (Masutani et al, 2005).

Model driven techniques (e.g. Lamecker et al (2004) and Soler et al (2000)) use pre-defined models to segment the desired object from the available images. This kind of technique basically searches the images for instances that fit a given model described in terms of object characteristics such as position, texture and spatial relation to other objects.

Data driven techniques (e.g. Kim et al. (2000) and Fujimoto et al (2001) try to emulate the human capacity to identify objects using some similarity information present on image data, automatically detecting and classifying objects and features in images. Many of them use known techniques such as region growing and thresholding, combined with some heuristic knowledge about the aimed object.

Other important issue consists in segmenting vessels. Inside the liver, the contrast can be insufficient to distinguish minimally the veins from the liver parenchyma. Another problem is that the portal and hepatic veins can be erroneously connected leading to identification as a single object. Kirbas et al (2004) presented a review of vessel extraction, in which many of the available techniques for this purpose can be found.

This paper proposes a data driven algorithm for 3D segmentation of the liver structures based on CT image sequences using the Couinaud orientation (Couinaud, 1957), which is presently used as reference in liver surgical procedures.

The following sections describe our approach in greater detail. Section 2 discusses the details of our segmentation methods, section 3 reports some results, and the main conclusions are presented in section 4.

2 THE 3D SEGMENTATION METHOD

The segmentation method consists of four main steps:

a) segmentation of organs and muscle tissues from the rest of the image based on a dual thresholding
b) segmentation of the liver using heuristic related to anatomy, such as liver position and relative density of liver’s tissue.

c) segmentation of the hepatic and portal vessels in the liver by a region growing technique combined with hysteresis thresholding inspired in Canny’s Edge Detector (Canny et al., 1986).

d) Estimation of the planes that define the subdivision of the liver in the eight Couinaud segments.

Each step is described in details in the next subsections.

2.1 Segmentation of organs and muscle tissue

Organs and muscles tissue are the main presence in abdominal images. Typical gray values of these tissues occur around the maximum (CM) of the gray value histogram for the whole CT sequence.

Figure 1 shows the histogram of a sample CT exam, the range of intensities corresponding to organs and muscles and the lower and upper limits TL and TH defining this range.

Let CM be the maximum CT histogram count, TM the corresponding intensity value, and CL and CH the counts corresponding respectively to TL and TH. It has been observed in our experiments that the ratios RL=CL/CM and RH=CH/CM do not significantly change from CT exam to CT exam. In fact these ratios lied around RL=0.6 and RH=0.2 through all our experiments.

This regularity suggests the following procedure to select the lower and higher threshold values:

a) Compute and smooth the histogram of the whole CT exam;

b) Detect the maximum histogram count CM;

c) Multiply CM by the constant factors RL and RH, and obtain the count values CL and CH.

d) Search the smoothed histogram for the intensity values TL and TH closest to TM corresponding to CL and CH, such that TL<TM and TH>TM.

Figure 2-a show a CT image in which the pixels with gray levels falling in this range are shown in white. These pixels form connected components that will be used in the later segmentation steps.

2.2 Segmentation of the liver

The next step consists in segmenting the liver. Generally the liver appears as homogeneous areas on CT slices, i.e. its intensities are restricted to a narrow gray value interval. This can be observed in Figure 1, where the histogram of the pixels belonging to the liver is drawn in red over the histogram of the whole CT sequence shown in blue.

Our method determines the extreme values of this interval in the following way:

One image of the CT set where the liver is present is selected as the main sample and passed as a parameter to the algorithm. Then, the largest connected component of this slice located on the upper-left side of the image (right side of the human body), is identified and its mean value on the original image is computed.

Using the pixels of organs and muscle tissue previously segmented, a new gray level range is defined following a similar procedure of the subsection 2.1. The histogram count value corresponding to the liver mean value is used as the maximum count value and the range limits are calculated using as limiting ratios the value 0.8 for both cases. The threshold values obtained this way are applied to the regions selected in the previous step. Figure 2-b shows the collection of objects obtained in this fashion in CT slice of figure 1-a. Notice that the kidneys and the muscles were for the most part discarded.

A simple procedure extracts the liver from the remaining objects. Starting on the main sample it is executed on the next adjacent slice upward and downward in the CT image set till all slices have been processed. It consists in three main steps:

a) Select the biggest object in the collection;

b) If its centroid is in the upper left quadrant of the CT image, go to step c, otherwise discard.
this object from the collection and go back to step a;
c) If the selected object is connected to another object of an adjacent slice previously classified as liver, classify it as liver, otherwise discard the object from the collection and go back to step a;
Clearly the first iteration does not pass through step c and the object selected in step b is set as liver directly.

2.3 Segmentation of Hepatic and Portal Veins

This section describes our adaptive method inspired on the Canny Edge Detector (Canny et al., 1986) to segment the portal and hepatic vessel trees from the segmented liver.

Initially we select a threshold VH, such that the intensities above it identify unambiguously the vessels. A second threshold VL (VL<VH) is further selected such that intensities below it clearly indicate liver parenchyma. Figure 3 shows these limits and the liver histogram in red.

These two threshold values define three ranges of pixel intensities, namely:
- the strong vessel range, defined by intensities above VH,
- the weak vessel range, comprising intensities between VL and VH, and
- the liver tissue range, covering intensities below VL.

The construction of the vessel tree is performed by a region growing approach consisting of the following basic steps:
a) Build the weak vessel object set defined by the pixels with values above VL.
b) Build the strong vessel object set defined by the pixels with values above VH.
c) Take the strong vessel set computed in the preceding step as the initial vessel tree estimate.
d) Add to the vessel tree estimate all objects of the weak vessel set connected to it.
e) Repeat the previous step using the current vessel tree estimated until it stops growing.

Experiments using the above explained procedure have shown that the selection of the threshold values VL and VH is a key issue for an accurate segmentation. Appropriate values for these parameters change from image to image depending on the contrast and average brightness level.

We searched appropriate values for VL and VH manually through many experiments using different CT sequences. We observed that the histogram counts for the manually selected values stayed at a roughly constant ratio to the intensity corresponding to the maximum count.

Considering NM the maximum liver histogram count, and NL and NH the counts corresponding respectively to VL and VH , the ratios rl=NL/NM and rh=NH/NM do not significantly change from CT exam to CT exam. These ratios were determined experimentally as rl=0.5 and rh=0.2.

This regularity suggests the following procedure to select the lower and higher threshold values:
a) Compute and smooth the histogram of the image region inside the liver;
b) Detect the maximum histogram count NM and the corresponding intensity VM.
c) Multiply NM by the ratios rl and rh, and obtain the count values NL and NH.
d) Search the smoothed histogram for the intensity values VL and VH corresponding to NL and NH, whereby both VL and VH are greater than VM.

Figure 4 shows an example of the results produced by the proposed method. The hepatic vein is shown in red and the portal vein in blue, for two different slices.

2.4 Segmentation of Couinaud regions

The Couinaud paradigm divides the liver into eight independent segments each one having its own vascular inflow, outflow, and biliary drainage. Because of this division into self-contained units, each can be removed without damaging those remaining.
Our method estimates the subdivision of the liver in the eight Couinaud segments, by fitting planes to the portal vein, and to each of the hepatic vein branches. To separate the three main branches of the hepatic vein we apply the k-means algorithm on the 3 dimensional coordinates of the pixels identified in the preceding step as belonging to the hepatic vein. It is assumed that there are three clusters. A restriction for singleton value is imposed so as to guarantee that no cluster will be empty. This leads to three different objects corresponding to each branch of the hepatic vein.

Then, a least squares based procedure determines the four planes that best fit the points of each branch of the hepatic vein and the portal vein segmented before. These planes divide the liver in the Couinaud segments. Figure 5 shows the Couinaud segments in different colors obtained by this procedure on a sample CT sequence. Figure 5-a shows one CT slice with the hepatic vein in red and the portal vein in blue, and figure 5-b shows another CT slice with the derived segments in different colors.

3 RESULTS

A software prototype implementing the proposed method has been built for validation purpose. Based on the VTK library (Schroeder et al., 1998) the prototype also implements both the surface and volumetric visualization of the structures segmented. It receives as input the segmented structures of each image slice and the thickness of the CT slices available in the DICOM image file header.

Figure 6 shows our segmentation results through a 3D surface model generated by our prototype. In figure 6-a liver, the hepatic vein and the portal vein are shown respectively in gray, blue and red. Figure 6-b shows the Couinaud segments in different colors with the hepatic and portal veins also present. It can be shown that the segments are divided according to the veins orientation, as proposed.

Experiments performed on seven different CT sequences have shown that the results produced by the proposed method are consistent with the visual perception.

4 CONCLUSION

This work proposes an algorithm to segment the liver in computer tomography (CT) images according to the Couinaud classification.

Experiments conducted on 7 CT series confirm that the proposed method produces a result consistent with the visual analysis. The method has the potential of becoming a useful tool in various applications. It can be used to generate 3D liver representations to aid visual diagnostic and surgery planning. Shape attributes other than volume may also be measured from the 3D model and explored in Computer Aided Diagnostic environments.

The assessment of segmentation accuracy is a major concern for the continuation of this work. This is one of the next steps planned for the continuation of this research.
5 REFERENCES


