Graph Cutting Tumor Images

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Abstract—A new proposed method of fully automatic processing frameworks is based on graph-cut active contour algorithms. This paper addresses the problem of segmenting a liver and tumor regions from the abdominal CT images. A predicate is defined for measuring the evidence for a boundary between two regions using a Graph-based representation of the image. The algorithm is applied to image segmentation using two different kinds of local neighborhoods in constructing the graph. Liver and Hepatic Tumor Segmentation can be automatically processed by the graph-cut based method. This system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In preprocessing stage, the CT image process with mean shift filter and statistical thresholding method for reducing processing area with improving detections rate. Second stage is liver segmentation; the liver region has been segmented using the algorithm of the proposed method. The next stage tumor segmentation also followed the same steps. Finally the liver and tumor regions are separately segmented from the computer tomography image.

Keywords—Automatic segmentation; graph-cuts; gradient vector flow (GVF) active contours; hepatic tumors and liver;

I. INTRODUCTION

Hepatocellular carcinoma is common in Asia and metastasis is common in the west. Among the predominant cancer types, liver cancer ranks at fourth place and is rising cause of death in the world. Each year 1 million new patients are diagnosed with primary liver cancer, of which approximately 60% died in 2002. The development of these imaging technologies is the first step towards improvement of diagnosis accuracy and patient quality of life. Computed Tomography (CT) is probably the most widely adopted medical image technology build on X-rays transmission, that allows through image processing techniques to get 2-D cross-section images and then, from a stack of 2-D slices, a 3-D organ reconstruction.

Moreover, CT images, thanks to their high resolution, have been largely used for diagnosis of liver disease and volumetric measurements for medical operation, as in the case of resection or transplantation. Indeed, additional image analysis tools, as 3-D visualization of the patient liver, can help surgeons to plan suitable treatments. Surgical resection of hepatic tumors remains the first choice for curative treatment of primary and secondary liver malignancies. In this work, a new imaging approach and related algorithms for noninvasive diagnosis of liver tumors and subsequent monitoring of therapeutic treatments are presented. A fundamental point is represented by recent advances in image processing techniques, such as medical image segmentation. Indeed, the liver segmentation is an essential step for medical image analysis. In fact, it should be noticed how the segmentation results very often represent an input for 3-D navigation and display systems used for visualization, surgical planning, and radiation therapies.

Despite the multitude of automatic and semiautomatic literature-reported methods for liver segmentation, actual adoption of such approaches still presents several practical difficulties. This causes the usual employment in clinical routine of manual delineations of liver contours and tumors on diagnostic images, with consequent delineation of enormous time and mental efforts for experienced doctors and operators, besides an intrinsic low reproducibility. For that reason, the development of efficient automatic methods is one of the most focused research topics: it can allow increasing radiologists’ productivity, more objective and accurate diagnosis and more reproducible quantitative and qualitative results. In these perspectives, feasibility, in-depth analyses, and assessments of automatic segmentation accuracy and time performances are of paramount importance. To date, still the problem of tissue segmentation is to delimit the image areas representing different anatomies. This remains a challenging task due to the considerable overlap of soft tissues with strong intra-organ variation, to major human anatomical variations in liver shapes and to similar voxel intensities of nearby organs. Furthermore, the detection of liver tumors is challenging because they are not clearly distinguishable from healthy tissues due to the liver itself, being an organ with a high level of vascularization, automatic image processing have a high risk of wrong interpretation in terms of tissue segmentation. For clinical exploitability, the liver tumor segmentation must be able to cope with the variation in shape of tumors and with similar grey intensity of liver parenchyma.

The final output of segmentation in terms of knowledge regarding the exact spatial location and volume of segmented tumors is fundamental information for tumors medical treatments. In recent years, to overcome
the inherent difficulties outlined above, computer-aided diagnosis (CAD) has been vigorously investigated to get more and more accurate liver segmentations. Such research investigations can be categorized into two main approaches: intensity-based and model-based methods. The former combine thresholding and morphological filtering normally resulting in robust approaches even if accurate segmentations need the setting of several parameters depending on processing step, modality, etc. Instead, model-based approaches are currently the main research track, generally based on active contours with level sets or snake, statistical model are also reported. Mahr et al reviewed and compared the various techniques which included region-growing, isocontour, snakes, hierarchical and histogram-based methods, and found that region-growing and snakes (i.e., active contour models), were the most promising for future investigation on liver volumetry determination. In addition, Boykov and Kolmogorov showed the feasibility of liver segmentation by means of graph-cut technique on the liver case. However, all these methods require a manual initialization based on learning database or on user interfaces introducing limitations mainly related to subjectivity and human errors.

In this work, in order to get liver and liver tumors segmentations totally independent from operator’s intervention from contrast enhanced CT volume images, a 3-D initialization method was developed and its reliability was tested through graph-cut and active contour techniques. In our previous work [21], a new method is described for fast segmentation of liver using gradient vector flow (GVF) active contours algorithm from CT volume images. In that work, two different approaches were used for segmentation of liver volume and for related tumors. In this new study, the same segmentation method is applied for liver and for its internal pathological structures. Therefore, the initialization method is further developed making it suitable also for the graph cut algorithm. The aims of this comparative evaluation were: 1) verify the feasibility of two different segmentation approaches and their automation starting from the same adaptive initialization method; 2) apply both segmentation approaches to the liver and to the hepatic tumors employing twice exactly the same initialization method for liver and then for tumor initialization; and 3) comparatively assess the segmentation results concerning liver volumes and tumors with respect to radiologist manual segmentation taken as the ground truth.

II. MATERIALS AND METHODS

For any liver local treatments, it is necessary to identify and localize the liver surface, the tumors, the topography of blood vessel, and the spatial relationship between tumors and structures. To meet these challenges various algorithms have been developed using pixel-based or/and contour-based methods. Currently, two approaches are under investigation. The first one is the active contour approach and the second method is the graph cuts that is one of the current cutting edge technique in image segmentation.

A. Automatic Liver Initialization Method

Model-based segmentation methods usually require a preliminary initialization by operators prior to their application. In this specific case, active contours needs, as an input, a first course outline of the liver while graph-cuts need samples of both liver and background labels. Here, an automatic initialization method is applied to both techniques. First of all, a preprocessing filter needs to be applied to the original volumetric image for noise removal from homogenous areas while keeping clear and sharp edges. The best results were obtained with the mean shift filter most suitable for these purposes. Second, considering the resolution of the processed images, each slice of the filtered volume was divided into 64 squared sub regions, presenting in this way enough pixels for estimations and statistical relevance of regional calculations. Then, for each abdominal sub region, the mean image intensity and its standard deviation were calculated to identify the most homogeneous regions in terms of pixel intensity (i.e., regions with standard deviation lower than 1% of the peak value of corresponding histogram).

Fig. 1. (a) Original image. (b) Manual segmentation made by an expert radiologist. (c) Liver surface initialization for active contour. (d) Liver surface initialization for graph-cut (in white: liver, in gray: background and in black: undetermined voxels). (e) GVF active contour segmentation. (f) Graph-cut segmentation (the plain line represents the liver surface, while the dashed line represents the tumor contour).
Among these latter, the median was selected to be representative of liver regions with corresponding standard deviation. So, as illustrated above, implementing our adaptive threshold technique on this automatically extracted patient-specific data, the images were partitioned and then liver regions identified. Finally, these identified regions were further and more accurately segmented [Fig. 1(b) and (c)], through active contour and graph-cut approaches as described in the following sections.

B. Automatic Tumor Initialization Method

This step was applied only to liver volume, obtained after automatic delineation of liver surface: this latter, applied to original dataset volume, was used as a mask in order to prevent processing overloads and avoid errors related to the presence of surrounding tissues presenting similar gray scale distributions. Additionally, for this purpose, the voxels belonging to the intensity range domain were also removed from the segmented liver volume. This intensity range domain is selected because the data fitted to Gaussian distribution and nearly all (99.7%) of the values lied within three standard deviations of the mean. This choice allowed the correct identification of liver respect to other organs, optimizing the calculation resources and increasing the tumor segmentation accuracy. The histograms of the anatomical structures of liver are showed in Fig. 2.

Fig. 2. Gray-level histograms related to structural components of: (a) segmented liver, (b) histogram of whole liver, (c) zooming of histogram related to tumors, and (d) zooming of histogram related to vessels.

In conclusion, the Gaussian distribution with lowest Hounsfield units (HU) values corresponds to tumor intensities, and then the average tumor intensity value and its standard deviation were extracted from the histogram thanks to a cross-correlation with a Gaussian shaped function. These and were used to identify tumor voxels in the partitioned liver regions that represented the input for the final segmentation step.

C. Patient Datasets

The used CT volume datasets reflect indeed an average quality of the technology and competence and should present a more general meaning in term of final applicability and effectiveness. The only limitation for data selection was related to the image resolution needed for a coherent final result assessment. Then, imaging CT protocols followed the clinical routine in use in each hospital for imaging abdominal cancers with portal vein phase contrast enhancement. Moreover, accordingly with the aim of this paper, final clinical therapies to patients were not influenced by the result of this work. In summary, 25 anonymized CT datasets from corresponding different patients were collected and retrospectively processed by means of previously mentioned algorithms. Image datasets were acquired on six different CT scanners (LightSpeed VCT, HiSpeed NX/I, LightSpeed Pro 16, LightSpeed Plus – General Electric, Emotion 16 – Siemens, Brilliance 16 – Philips). Scanning acquisition parameters were the following: 120–130 kV voltage 250–375 mAs X-ray tube current and an exposure time between 700 and 1070 ms.

D. GVF Active Contour Segmentation Algorithm of Liver and Tumors

Liver domain $L_1$ is defined as the following interval: $L_1 = [\mu_{\text{liver}} - 3\sigma_{\text{liver}}; \mu_{\text{liver}} + 3\sigma_{\text{liver}}]$. The initialization range has been adopted according to the same statistical approach as Automatic tumor Initialization method. On CT scans, the liver shares some of these image intensity values with other nearby tissues. Therefore, the voxels belonging to other tissues were removed from liver volume initialization by automatic 3-D morphological filtering, and as following specified: first, connected components of binary thresholded volume were labeled using an
18-connected neighborhood; then, by referring to the relative sizes of organs, the liver was separated as the biggest labeled region. In fact, liver is the biggest organ of abdominal acquired volume in a great majority of cases. Then, after obtaining that initial raw liver volume, a refined liver surface segmentation was obtained by adapting a 3-D active contour technique enabling inclusion of contextual information into the algorithm. The active contour was based on a type of external force field, GVF, which does not require particular conditions on the shape of initial contour (regularity, smoothness, etc.) allowing correct surface definition of both concave and convex features within an object. Preliminary work was done in order to find the best parameter settings valid for abdominal CT scans, avoiding wrong boundary selections. The GVF was computed as a spatial diffusion of the gradient of an edge map derived from the original image.

**E. Graph-Cut Segmentation Algorithm of Liver and Tumors**

To discriminate liver from background, we set a range threshold equal to $2\sigma$. The initialization rules are as follows:

1. $v$ (voxel) $\in$ liver, if $I(v)$ (image intensity of voxel) $\in$ $L_2$ (liver domain) and $v \in$ BIG
2. $v \in$ Background if $I(v) \in B_2$ (Background domain) or if $I(v) \in L_2$ and $v$ does not belong to BIG (biggest 18 connected component after thresholding)
3. $v \in$ undetermined otherwise.

Here, Energy function relies on Region term and Boundary term. $I(v)$ stands for the image intensity of voxel, and $BIG$ for the biggest 18-connected component after similar thresholding. 3-D graph-cut method, conversely to active contour technique, is not iterative and is based on global minimization of defined energy function classes on a discrete graph. Energy function and penalties definitions were adapted to the specific liver segmentation purpose.

Then, energy function relies on two main terms: a) a region term (penalties depending on neighborhood context and on voxel labeling) and b) a boundary term (penalties based on adjacent voxels dissimilarity). For region term weights $R_p$, a patient-specific Gaussian model was used for the liver, thus providing a more faithful result than a-posteriori probability of object-labeled voxels. Then, for background, the a-posteriori probability was adapted taken into account all voxels but the ones initialized as liver in order to provide a non-null $R_p$ also to undetermined voxels during initialization.

$$R_p (obj) = \exp \left( - \left( \frac{I_p - \mu_{liver}}{\sigma_{liver}} \right)^2 / (2 \sigma_{liver}^2) \right)$$

$$R_p (bkg) = - \ln Pr (I_p \text{ (obj)})$$

$a$-posteriori probability for $R_p$ (bkg) was evaluated on the histogram of the mean-shift filtered image for the voxels that were not initialized as liver. For boundary term, “directed” edge weights $w_{p,q}$ seem the best solution to encourage cuts from brighter objects to darker background like liver in CT scans, and were defined as follows:

$$w_{p,q} = 1, \text{ if } I_p \leq I_q$$

$$= \exp \left( - \left( \frac{I_p - I_q}{2\sigma^2} \right) \right), \text{ if } I_p > I_q$$

Here $\sigma$, enabled to adjust the range of intensities taken into account to find the edges. Indeed small $\sigma^2$ encouraged edges between voxels with about the same intensities, while for big $\sigma^2$, intensity range was wider enabling contours to evolve with less constraints.

The cost function $E$ can be defined as follows:

$$E = \Sigma w_{p,q} \cdot \delta_{p\neq q} + \Lambda \Sigma R_p(S_p)$$

where $S_p$ and $S_q$ can take the label values {liver or background} in order to find the minimum of $E$ and the corresponding optimal set of segmentation $S_p$ of all voxels. Cost function $E$ and edge weights $w_{p,q}$ were used for the second run of the graph-cut technique, while the region term weights $R_p$ were redefined as follows:

$$R_p (tumor) = \exp \left( - \left( \frac{I_p - \mu_{tumor}}{\sigma_{tumor}} \right)^2 / (2 \sigma_{tumor}^2) \right)$$

$$R_p (liver) = \exp \left( - \left( \frac{I_p - \mu_{liver}}{\sigma_{liver}} \right)^2 / (2 \sigma_{liver}^2) \right)$$

**III. RESULTS AND DISCUSSION**

The automatic segmentation of liver surface and hepatic tumor was executed successfully for all patient datasets with both automatic segmentation techniques; Automatic liver segmentation by active contours algorithm encounters some problems with tumors and vessel positioned just underneath the liver surface. These structures have different intensity values compared to those of liver parenchyma, so that they are initialized as outside of the liver; actually, according to literature, it is a widespread problem of the traditional active contour approaches. On the contrary, automatic liver segmentation by the graph-cut algorithm succeeds to include these tumors (underneath the
surface) inside the liver segmentation. The reason is that the graph-cuts include neighboring contextual information enabling to overstep edges between tumors or vessel and liver parenchyma.

A. Liver Segmentation Accuracy

Both automatic techniques provided highly accurate liver surface segmentation with respect to the manual segmentation defined as the gold standard. Indeed, both algorithms reached quite similar good values for all comparative metrics defined in Table I. GVF active contour and graph-cut algorithms produced a liver volume with a high level of overlapping given by an average DSC of 96.17% ± 0.87 and of 95.49 ± 0.66, respectively. Active contours reached therefore a slightly better average DSC, but on nine cases over 25 (36%) graph-cuts produced a liver surface segmentation with a higher DSC than active contours. FPR and FNR misclassification ratios were balanced with contemporary low values for both automatic approaches. The algorithm based on GVF active contours generated fairly equal false alarm rate (FPR = 3.87% ± 0.98) and undetection rate (FNR = 3.87± 0.98). In addition, over the set of 25 cases, the average Distance – Error was equal to 2.38mm ±0.41for GVF active contour method, while it was fairly better for graph-cut method with a value of 2.19 mm ± 0.59. Furthermore, for all these three metrics the paired -test provided a great result statistically significant with a 95% confidence interval.

<table>
<thead>
<tr>
<th>TABLE I COMPARISON OF LIVER SURFACE SEGMENTATION</th>
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<td>Performance parameters</td>
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<td>DSC</td>
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<td>FNR</td>
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<td>FPR</td>
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<td>DISTANCE ERROR</td>
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A. Tumor Segmentation Accuracy

Among the 52 hepatic tumors diagnosed in 25 patients, graph-cut algorithm detected 48 tumors leading to a detection rate of 92.31%, while GVF active contours only detected 44 tumors for a detection rate of 84.62%. The differences between results produced by the two automatic algorithms were emphasized by three metrics. Regarding the volume overlapping of hepatic tumors, graph-cut algorithm provided an average DSC of 88.65% ± 3.01, while GVF active contour method reached a lower average DSC equal to 87.10% ± 2.99. In terms of misclassification, graph-cut algorithm presented again a lower average FPR than active contours (6.10% ± 2.52 versus 8.99% ± 3.95). However, the undetection rate was in favor of active contour algorithm since its average FNR reached the value of 8.97% ± 2.26, while graph-cuts obtained an average FNR of 9.89% ± 2.93. Again, for all these three metrics the paired T–test provided a great result statistically significant with a least 90% confidence interval.

<table>
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<th>TABLE II PROCESSING TIME</th>
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<td>Processing Steps</td>
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<td>Initialization</td>
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<td>Tumor Segmentation</td>
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<td>Total</td>
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The graph-cut technique is also able to deal with lots of initially undetermined voxels. In addition, concerning the graph-cut algorithm, any misclassification during the initialization process should be prevented in order to have proper region term weights for the background. Therefore, liver domains and were set to obtain optimal results for both methods. In comparison with the average 78 s/slice needed for manual liver segmentation, the processing time (10.9 s/slice in Table II) reached by the implemented automatic version of graph-cuts presented in this work demonstrates the important potential time saving for this operation. In addition, the implemented graph-cut technique produces accurate segmentation results always faster than the implemented GVF active contour algorithm.

V. CONCLUSION

In conclusion, this study presented the implementation of two fully automatic liver and tumors segmentation techniques and their comparative assessment. The described adaptive initialization method enabled fully automatic liver surface segmentation with both GVF active contour and graph-cut techniques, demonstrating the feasibility of two different approaches. The comparative assessment showed that the graph-cut method provided superior results in terms of accuracy and did not present the described main limitations related to the GVF method. The proposed image processing method will improve computerized CT-based 3-D visualizations enabling noninvasive diagnosis of hepatic tumors. The described imaging approach might be valuable also for monitoring of postoperative outcomes through CT-volumetric assessments. Processing time is an important feature for any computer-aided diagnosis system, especially in the intra-operative phase.

FUTURE WORK

Future focus will be given towards time reduction needed for the image prefiltering also by employing more powerful computers. In addition, the satisfactory results obtained in tumor delineations may be exploited for future improvement regarding the detection of cysts. Major focus will be on combination of Geodesic Graph cut method with existing Graph cut method to improve performance efficiency in segmentation of liver and hepatic tumor.

REFERENCES


