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Geo-cutting Liver Tumor

Christo Ananth*
Associate Professor,ECE,Francis Xavier Engineering College,
Tirunelveli -627003,India

***Abstract*— The issue of intuitive frontal area/foundation division in still pictures is of awesome down to earth significance in picture altering. They maintain a strategic distance from the limit length predisposition of chart cut strategies and results in expanded affectability to seed situation. Another proposed technique for completely programmed handling structures is given taking into account Graph-cut and Geodesic Graph cut calculations. This paper addresses the issue of dividing liver and tumor locales from the stomach CT pictures. The absence of edge displaying in geodesic or comparable methodologies confines their capacity to exactly restrict object limits, something at which chart cut strategies by and large exceed expectations. A predicate is characterized for measuring the confirmation for a limit between two locales utilizing Geodesic Graph-based representation of the picture. The calculation is connected to picture division utilizing two various types of nearby neighborhoods in building the chart. Liver and hepatic tumor division can be naturally prepared by the Geodesic chart cut based strategy. This framework has focused on finding a quick and intuitive division strategy for liver and tumor division. In the pre-handling stage, Mean movement channel is connected to CT picture process and factual thresholding technique is connected for diminishing preparing zone with enhancing discoveries rate. In the Second stage, the liver area has been divided utilizing the calculation of the proposed strategy. Next, the tumor district has been portioned utilizing Geodesic Graph cut strategy. Results demonstrate that the proposed strategy is less inclined to shortcutting than run of the mill diagram cut techniques while being less delicate to seed position and preferable at edge restriction over geodesic strategies. This prompts expanded division exactness and decreased exertion with respect to the client. At long last Segmented Liver and Tumor Regions were appeared from the stomach Computed Tomographic picture.**

***Keywords*— Automatic Segmentation; Interactive Segmentation; Graph cuts; Geodesic Graph cuts; Hepatic tumor and liver;**

I. INTRODUCTION

Development of Medical diagnosis imaging technologies is the first step towards improvement of diagnosis accuracy and patient quality of life. With increasing use of Computed topography (CT) and Magnetic resonance (MR) imaging for diagnosis, treatment planning and clinical studies, it has become almost compulsory to use computers to assist radiological experts in clinical diagnosis and treatment planning. Surgical resection of hepatic tumors remains the first choice for treatment of primary and secondary liver malignancies. The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. By interactive image segmentation, the user outlines the region of interest and algorithms are applied so that the path best fits the edge of the image. Automatic image segmentation has become a prominent objective in image analysis and computer vision. A geodesic framework was developed for fast interactive image which used Geodesics-based algorithm for (interactive) natural image. Narrow band trimap was quickly generated from a few scribbles. It better handles objects that cross each other in video temporal domain, but it produced poor performance when the distributions overlap. Moreover there is no regularization term in the model. Christo Ananth et al. [1] proposed a method in which the minimization is per-formed in a sequential manner by the fusion move algorithm that uses the QPBO min-cut algorithm. Multi-shape GCs are proven to be more beneficial than single-shape GCs. Hence, the segmentation methods are validated by calculating statistical measures. The false positive (FP) is reduced and sensitivity and specificity improved by multiple MTANN.

Christo Ananth et al. [2] proposed a system, this system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In the pre-processing stage, Mean shift filter is applied to CT image process and statistical thresholding method is applied for reducing processing area with improving detections rate. In the Second stage, the liver region has been segmented using the algorithm of the proposed method. Next, the tumor region has been segmented using Geodesic Graph cut method. Results show that the proposed method is less prone to shortcutting than typical graph cut methods while being less sensitive to seed placement and better at edge localization than geodesic methods. This leads to increased segmentation accuracy and reduced effort on the part of the user. Finally Segmented Liver and Tumor Regions were shown from the abdominal Computed Tomographic image.Geo-cuts method models gradient flows of contours and surfaces. The approach was flexible with respect to distance metrics on the space of contours/surfaces. But the approach

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was mainly theoretical. Moreover the distance map can be determined only with precision of 0.5 and time steps remains to be controlled.

Christo Ananth et al. [3] proposed a system, in which a predicate is defined for measuring the evidence for a boundary between two regions using Geodesic 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 Geodesic graph-cut based method. This system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In the preprocessing stage, the CT image process is carried over 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.

General framework encompassing graph cuts, random walker, shortest-path segmentation and watersheds approach was also developed which uses energy minimization algorithm. However it is not applicable to large systems and it is not a fast and an effective approach. Random Walker approach for general image segmentation was based on small set of pre-labeled pixels. It is robust to weak object boundaries and it takes account of user's pre-labelling choices. But it consumes enormous large computation time and it is only an Initial solution for an iterative matrix solver. Christo Ananth et al. [4] proposed a system in which 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. Christo Ananth et al. [5] proposed a system in which an automatic anatomy segmentation method is proposed which effectively combines the Active Appearance Model, Live Wire and Graph Cut (ALG) ideas to exploit their complementary strengths. It consists of three main parts: model building, initialization, and delineation. For the initialization (recognition) part, a pseudo strategy is employed and the organs are segmented slice by slice via the OAAM (Oriented Active Appearance method). The purpose of initialization is to provide rough object localization and shape constraints for a latter GC method, which will produce refined delineation. It is better to have a fast and robust method than a slow and more accurate technique for initialization.

A graph cut approach to image segmentation was also developed in tensor space which enabled segmentation of tensor valued images by natural Riemannian structure of the tensor. The approach captures true variation of object and background. However the method may fail when two textures differ only in scale and it does not give satisfactory performance as like the Gradient vector flow active contour technique. Interactive image segmentation via adaptive weighted distances was used which used soft image segmentation approach. Here, Automatic weighting of different channels was adaptable to wide range of images. The approach produced greater time linearity and better Image labelling but it had greater computational complexity and there is no proper definition of appropriate weights which does not fit image modality. The existing approach also used Curvature Regularity method for boundary smoothening. It does not use edge component to localize edges and it consumes more time. Christo Ananth et al. [6] presented an automatic segmentation method which effectively combines Active Contour Model, Live Wire method and Graph Cut approach (CLG). The aim of Live wire method is to provide control to the user on segmentation process during execution. Active Contour Model provides a statistical model of object shape and appearance to a new image which are built during a training phase. In the graph cut technique, each pixel is represented as a node and the distance between those nodes is represented as edges. In graph theory, a cut is a partition of the nodes that divides the graph into two disjoint subsets. For initialization, a pseudo strategy is employed and the organs are segmented slice by slice through the OACAM (Oriented Active Contour Appearance Model). Initialization provides rough object localization and shape constraints which produce refined delineation. This method is tested with different set of images including CT and MR images especially 3D images and produced perfect segmentation results. Christo Ananth et al. [7] discussed about a model, a new model is designed for boundary detection and applied it to object segmentation problem in medical images. Our edge following technique incorporates a vector image model and the edge map information. The proposed technique was applied to detect the object boundaries in several types of noisy images where the ill-defined edges were encountered. The proposed techniques performances on object segmentation and computation time were evaluated by comparing with the popular methods, i.e., the

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ACM, GVF snake models. Several synthetic noisy images were created and tested. The method is successfully tested in different types of medical images including aortas in cardiovascular MR images, and heart in CT images.

In this new study, the same graph cut segmentation method is applied for liver. The initialization method is further developed making it suitable for the graph cut algorithm. The aims of this comparative evaluation were: 1) verify the feasibility of two different segmentation approaches – graph cut method and geodesic graph cut method and their automation starting from the same adaptive initialization method; 2) apply graph cut segmentation approach to the liver and geodesic graph cut method to hepatic tumors employing the same initialization method for liver and then for tumor initialization;

In this study, datasets of different patients were processed using the above automatic mentioned methods and the results were compared. The paper is organized as follows: Proposed Methodology for liver and tumor segmentation were discussed in Section II. Section III discusses the simulation results of Graph cut and Geodesic Graph cut Segmentation approaches. Section IV concludes this paper with some ideas for improvements.

II. METHODOLOGY

Various algorithms have been developed using pixel-based or/and contour-based methods. Currently, two approaches are under investigation. The first one is Geodesic Graph cut approach and the second method is Graph cuts method that is one of the current cutting edge techniques in image segmentation.

A. *Automatic Liver Initialization Method*

Figure 1 shows the flowchart of an automatic initialization method applied to both Geodesic Graph cut and Graph cut techniques. This method is based on a statistical model distribution of liver average intensity and its standard deviation. First of all, a pre-processing 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. Each slice of the filtered volume was divided into 64 squared sub regions. For each abdominal sub region, the mean image intensity and its standard deviation were calculated to identify most homogeneous regions in terms of pixel intensity (i.e., regions with standard deviation lower than 1% of the peak value of corresponding histogram). By adaptive threshold, images were partitioned and then liver regions were identified.

B. *Automatic Tumor Initialization Method*

This step was applied only to liver volume. It was used as a mask in order to prevent processing overloads and avoids errors related to the presence of surrounding tissues presenting similar gray scale distributions. Voxels belonging to 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.

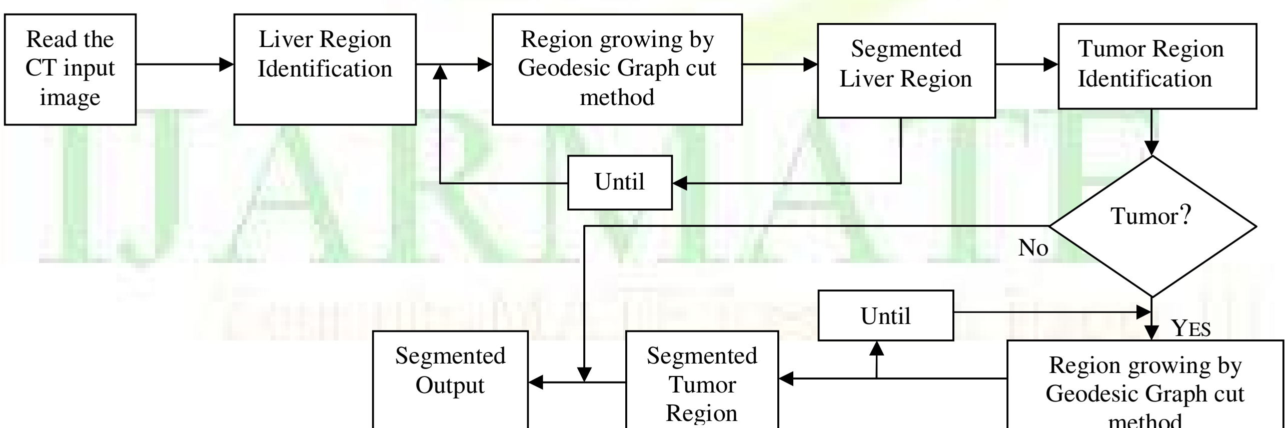

Fig. 1 Flow chart of Initialization method

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C. Geodesic Segmentation of Liver and Tumors

Geodesic segmentation can be improved by inclusion of explicit edge information to encourage placement of selection boundaries on edges in the image and allow user more freedom in placing strokes. The region term alone can often carry the segmentation in such cases, but global color models without spatial locality information can often select disjoint regions. The use of geodesic distance can avoid selection of disjoint regions. This section presents how geodesic distances and edge information can be combined in a graph cut optimization framework, and then presents a way to use the predicted classification accuracy from the inferred color models to automatically tune the trade off between the strengths and weaknesses of the two.

The unary region term can be computed as follows:

$$R_l(x_i) = s_l(x_i) + M_l(x_i) + G_l(x_i) \qquad (2.1)$$

where $M_l(x_i)$ is based on global color model as it is used for graph-cut segmentation, $G_l(x_i)$ is based on geodesic distance, and

$$s_l(x_i) = \begin{cases} \infty, & \text{if } x_i \in \Omega_{\bar{l}} \\ 0, & \text{otherwise} \end{cases} \qquad (2.2)$$

indicates the presence of a user stroke where $\bar{l}$ is the label opposite l (i.e. if l = F, then $\bar{l}$ = B). Fast Gauss Transform is used to compute foreground/background color models. $P_l(c)$ is used for both global similarity and geodesic distances. $M_l(xi)$ is computed by

$$M_l(x_i) = P_{\bar{l}}(C(x_l))) \qquad (2.3)$$

$G_l(xi)$ is computed by normalizing the relative foreground/background geodesic distances

$$G_l(x_i) = \frac{D_l(x_i)}{D_F(x_i) + D_B(x_i)} \qquad (2.4)$$

For boundary term we use:

$$B(x_i, x_j) = \frac{1}{1 + \| C(x_i) - C(x_j) \|^2} \qquad (2.5)$$

where C(x) € [0,255].

To allow for global weighting of relative importance of the region and boundary components,

$$E(L) = \lambda_R \Sigma R_{L_i}(x_i) + \lambda_B \Sigma B(x_{i,} x_j) | L_i - L_j | \qquad (2.6)$$

The boundary weight serves the role of the traditional fixed region/boundary weighting in graph cut methods, and adjusted to individual images by considering only the size of the image (due to the disproportionate scaling of an objects area (unary term) and perimeter (boundary term)). The region weight λ_R is the relative weighting of the geodesic distance and other region components. Posterior probability of a pixel with color c belonging to foreground (F) or background (B) respectively is considered, assuming equal priority. This functions as a simple Bayesian classifier in which error can be estimated by

$$\varepsilon = (1/2) [(\{ \Sigma_{x \in F} P_B(C(x)) \} / \{|\Omega_F|\}) + (\{ \Sigma_{x \in B} P_F(C(x)) \} / \{|\Omega_B|\})] \qquad (2.7)$$

When there is no error ($\varepsilon = 0$), Color-based terms (M and G) are given full weight, and when the color models become indistinct ($\varepsilon \geq 0.5$), they are given no weight:

$$\lambda_R = \begin{cases} 1 - 2\varepsilon, & \text{if } \varepsilon < 0.5 \\ 0, & \text{otherwise} \end{cases} \qquad (2.8)$$

The geodesic and boundary terms are further weighted based on the local confidence u(x) of the geodesic components:

$$u(x_i) = (| D_F(x_i) - D_B(x_i) | / | D_F(x_i) + D_B(x_i) |)^\gamma \qquad (2.9)$$

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where empirically γ= 2 to 2.5 works well.
To weight the geodesic component by u(xi), the region terms are redefined as follows:

$$R_l(x_i) = s_l(x_i) + M_l(x_i) + u(x_I)\,G_l(x_i) \tag{2.10}$$

This maintains the weight of geodesic distance term

Weighting of boundary costs are spatially adapted based on u(x) as follows:

$$B(xi,xj) = \frac{1 + (u(x_i) + u(x_j))/2}{1 + \| C(x_i) - C(x_j) \|^2} \tag{2.11}$$

When this geodesic confidence is low, this suggests that geodesic segmentation alone would consider this to be near a boundary, and the effect of the geodesic component is reduced, shifting control to the more accurate edge-finding term. The net effect of this spatially adaptive weighting is to both increase the relative weighting of the unary geodesic distance term and increase the cost of a boundary cut in what are clearly interior/exterior regions.

D. Graph cut Segmentation of Liver and Tumors

The Graph-Cut Technique solutions allow avoiding local minima, providing numerical robustness and do not use any shape-prior characteristics that would constrain too strongly recoverable shapes. The Graph-Cut Algorithm produces also better segmentation results than other fully automatic methods found in literature in both terms of accuracy and time processing. To discriminate liver from background, we set a range threshold equal to 2σ. The initialization rules are as follows:

- v (voxel) Є liver, if I(v) (image intensity of voxel) Є L2 (liver domain) and v Є BIG.
- v Є Background if I(v) Є B2 (Background domain) or if I(v) Є L2 and v does not belong to BIG (biggest 18 connected component after thresholding).
- v Є 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. Graph-cut method is not iterative and is based on global minimization of defined energy function classes on a discrete graph.

III.SIMULATION RESULTS

Automatic liver segmentation by the Geodesic graph-cut algorithm succeeds to include the tumors inside liver segmentation. The reason is that the Geodesic graph-cuts include neighboring contextual information enabling to overstep edges between tumors or vessel and liver parenchyma.

A. Liver and Tumor Segmentation Results

Liver and Tumor Segmentation results by Geodesic Graph cut method are given below in Figure 2:

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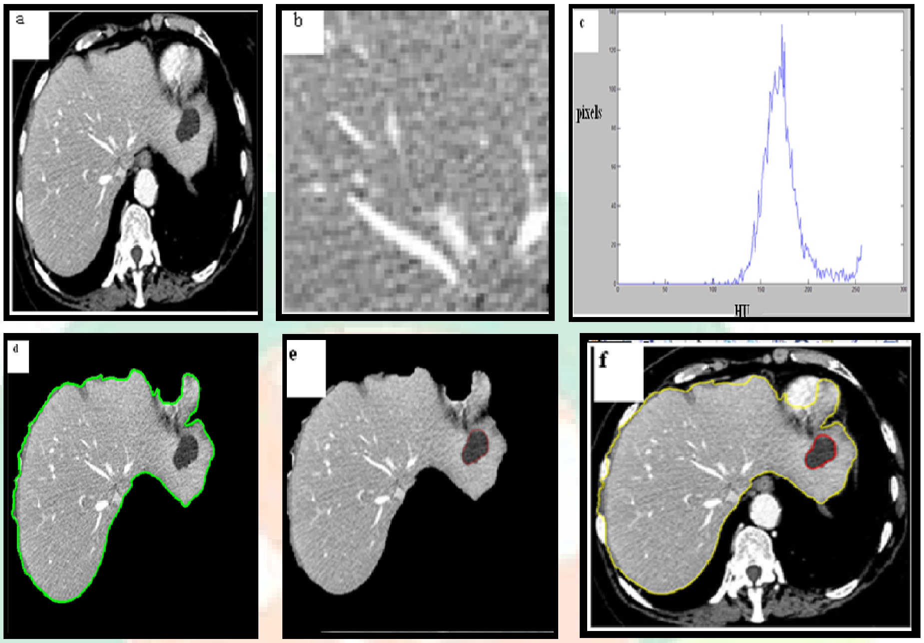

Fig. 2 (a) Input Image. (b) Liver Seed Region. (c) Histogram of the Liver Region (d)Segmented Liver Region. (e)Final Tumor Contour (f) Finally Segmented Liver and Tumor

B. *Segmentation Accuracy of Liver and Tumor*

Geodesic Graph Cut algorithms 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. Geodesic Graph Cut algorithm reached therefore a slightly better average DSC, but on nine cases over 25 (36%) Geodesic Graph Cut algorithm produced a liver surface segmentation with a higher DSC than Graph cuts. Geodesic graph-cut algorithm detected 48 tumors leading to a detection rate of 92.31%, while Graph cut algorithm detected 44 tumors for a detection rate of 84.62%. Regarding the volume overlapping of hepatic tumors, Geodesic graph-cut algorithm provided an average DSC of 88.65% ± 3.01, while Graph cut method reached a lower average DSC equal to 87.10% ± 2.99.These values are shown in Table – I.

TABLE I
COMPARISON OF LIVER AND TUMOR SEGMENTATION

Performance parameters	Liver				Tumor			
	GRAPH CUT		GEODESIC GRAPH-CUT		GRAPH CUT		GEODESIC GRAPH-CUT	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
DSC	96.16%	0.87%	87.1 %	2.99 %	87.1 %	2.99 %	88.65 %	3.01 %
FNR	3.87%	0.98%	8.97 %	2.26 %	8.97 %	2.26 %	9.89 %	2.93 %
FPR	3.35%	1.19%	8.99 %	3.95 %	8.99 %	3.95 %	6.10 %	2.52 %
Processing time	1.505s	0.196s	1.009s	0.096s	1.796s	0.128s	1.945s	0.308s

IV. CONCLUSIONS

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 Graph cut technique and Geodesic graph-cut techniques, demonstrating the feasibility of two different approaches. The comparative assessment showed that the Geodesic graph-cut method provided superior results in terms of accuracy and did

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not present the described main limitations related to the Graph cuts method. The proposed image processing method will improve computerized CT-based visualizations enabling non invasive diagnosis of hepatic tumors.

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