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Segmentation of coronary artery using graph cut technique

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ABSTRACT

Accurate segmentation of coronary artery is very essential in order to find the depth of arterial disease. In this paper we propose an accurate automatic algorithm based on graph cut technique for the segmentation of coronary artery. To achieve the optimal segmentation vesselness measure, geodesic path and edge extraction technique are combined with graph cut technique.we evaluate the proposed method on the public images from coronary artery stenoses detection. The experimental results prove that segmentation results of the proposed method perform well with respect to centerline extraction and vessel border detection.
Keywords: segmentation, coronary artery, centerline, coronary angiography

I. INTRODUCTION

Automatic enhancement and perfect segmentation of coronary artery helps the doctors for more accurate and fast patient data analysis. Segmentation of coronary artery is one of the difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedure. For this reason considerable care should be taken to improve the probability of rugged segmentation. However accurate vessel segmentation is still challenging; highly reliable, fully automatic methods are not established till now.

In this paper we use graph cut technique to model vessel structure. To extract the centerline and vessel borders and to obtain minimum average segmentation error optimal thresholding technique is used. However the existing graph cut technique cannot be directly used for the segmentation of coronary arteries because it suffers from the following drawbacks:1)unable to segment tubular structure like blood vessels 2)cannot be applied directly on X-ray images because the X-ray images are characterized by low signal to noise ratio, poor vessel appearance, vessel bifurcation and variable image contrast.3)design of energy terms are not proper to assure optimal image analysis 4)original graph cut technique produces small contour corresponding to minimal cut.

We propose a novel graph cut technique to the vessel segmentation problem. The novel graph cut technique incorporates the following1) the local vessel appearance using vesselness measure 2) connectivity to other vessel structure using geodesic path and 3) edge extraction using canny edge detector for the accurate vessel boundary detection. Finally the proposed method is applied on the public images to evaluate the effectiveness of the algorithm.

II. BACKGROUND

In this section, we present the graph cut technique and the vesselness measure, which are used in our method.

A.Graph-Cuts:

Consider an arbitrary set of data elements (pixels) *P* and some neighborhood system represented by a set N of all (unordered) pairs $\{p, q\}$ of neighboring elements in P. For example, P can contain pixels in a 2D (or 3D) grid and N can contain all unordered pairs of neighboring pixels under a standard 8 neighborhood system. Let $\boldsymbol{L} = (L1, \ldots, Lp, \ldots, L|P|)$ be a binary vector whose components Lp specify *assignments* to pixels p in P.Each Lp can be either "object" or "background". Vector $\boldsymbol{L}$ defines segmentation. Then, the soft constraints that we impose on boundary and region properties of $\boldsymbol{L}$ are described by the cost function

$C(\boldsymbol{L}) = \lambda \cdot R(\boldsymbol{L}) + B(\boldsymbol{L})$ Where

R($\mathbf{L}$)=Σ *Rp(Lp) (regional term)* *B*($\boldsymbol{L}$)=Σ*B(p,q)*

δ(Lp, Lq) (boundary term) *δ(Lp, Lq)={ 1 if Lp = Lq*

0 otherwise

The coefficient $\lambda \geq 0$ in specifies a relative importance of the region properties term $R(A)$ versus the boundary properties term $B(\boldsymbol{L})$. The regional term $R(\boldsymbol{L})$ assumes that the individual penalties for assigning pixel p to "object" and "background", correspondingly Rp("obj") and Rp("bkg"), are given. For example, $Rp(\cdot)$ may reflect on how the intensity of pixel p fits into given intensity models (e.g. histograms) of the object and background.

B.Optimal solution using graph cut:

To segment a given image we create a graph $G = \langle V, E \rangle$with nodes corresponding to pixels $p \in P$ of the image. There are two additional nodes: an "object" terminal (a source S) and a "background" terminal (a sink T). Therefore,

V=P U {S,T} The set of edges E consists of two types of undirected edges: *n-links* (neighborhood links) and *t-links* (terminal links). Each pixel p has two t-links $\{p, S\}$and $\{p, T\}$ connecting it to each terminal. Each pair of neighboring pixels $\{p, q\}$ in N is connected by an n-link. Without any ambiguity, an n-link connecting a pair of neighbors p and q is also denoted by $\{p, q\}$.Therefore,

E =N U {{P,S},{P.T}}

The following tables gives weights of edges in E.

Table 1

Graph arc	**Cost**
(p,q)	*B(p,q) for (p,q) Ɛ N*
(s,p)	*λ Rp(background) for p Ɛ I ,P Ɛ (o U B)* *K for p Ɛ o* *0 for p Ɛ B*
(p,t)	*λ Rp (object) for p Ɛ I ,P Ɛ (o U B)* *0 for p Ɛ o* *K for p Ɛ B*

III. PROPOSED METHOD

In this section, we present a fully automatic method for vessel segmentation method for vessel segmentation based on graph theory.

A. Seed selection technique:

In order to extract the foreground object (vessel) from background region we want to accurately choose the threshold value.

1. Sketch the histogram of the given image and choose the threshold value in the deep valley region.
2. Segment the given image using threshold value which is obtained in step1.This will produce two group of pixels with gray level values >T and G2 consisting of pixels with values <T.
3. Compute the average intensity values μ1 and μ2 for the pixels in regions G1 and G2.
4. Compute a new threshold value using the formula T=O.5(μ1+μ2).
5. Repeat steps 2 through steps 4 until the difference in T in successive iterations is smaller than a predefined a predefined parameter T.

B. Geodesic distance map:

In order to find the connectivity between various vessel regions we use the concept of geodesic distance map. Geodesic distance is nothing but the shortest distance between the two pixels. From the set of all possible path between the two pixels, we select one pixel with minimum distance. The path is computed using Dijkstra shortest path algorithm. we compute the geodesic distance map D and assign the cost to each path. Finally we choose the path having the least cost. The path having the least cost is called as object pixel(vessel regions) and the path having the highest cost(non vessel region) is called as background pixel.

C. Boundary detection

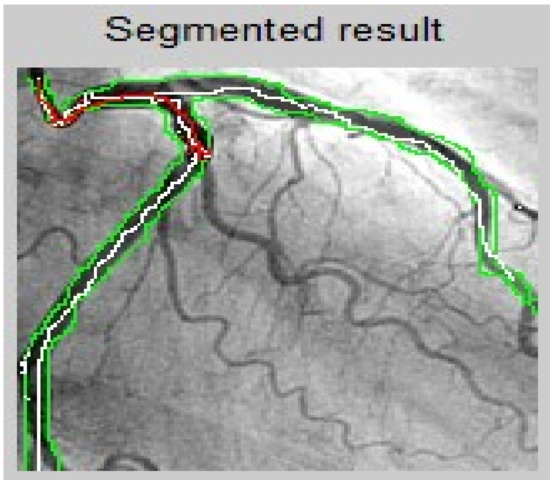
Edge is nothing but the boundary between the two regions of an image with relatively distinct gray level properties. Edge is also defined as set of connected pixels that lies on the boundary between two regions of an image. Edge normally contains more valuable boundary information. In this paper we use canny edge detection algorithm for detecting the edges.

D. Graph cut segmentation:

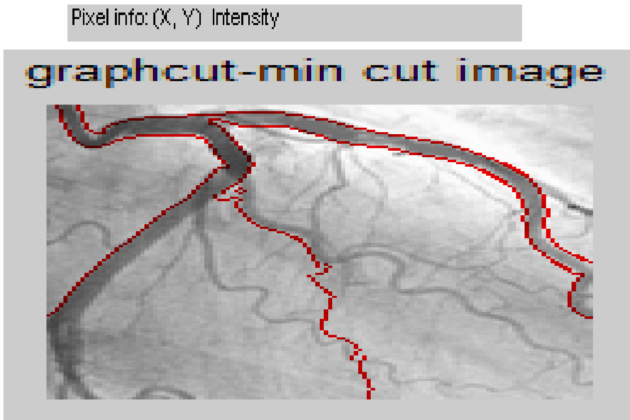
Finally we apply the proposed graph cut algorithm on the boundary detected image .Then, once we obtain the segmentation from graph cut technique, we keep only the biggest connected component in the final segmentation. An example of final segmentation is shown in the figure given below.

IV. EXPERIMENTAL RESULTS

For our experiment we have chosen Matlab. Then we applied our proposed algorithm on the coronar artery image. Following are the series of images from that results from our experiment.



Vessels & background extraction



geodesic distance map

V. CONCLUSION

In this paper we propose a novel approach for coronary artery segmentation using graph cut technique. The proposed approach produces a very effective result of coronary artery segmentation. In our future research we deal with irregularity at bifurcation and crossings and try to use a supervised method to optimize the threshold value and a method to segment overlapped arteries based on contrast liquid opacity.

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