

Automatic Segmentation of Coronary Artery and Abnormality Detection in Angiographic Images

ANU PRABHA. R¹, S.S. THAMILSELVI²PG Scholar, K. S. Rangasamy College of Technology, Tiruchengode, Namakkal-637 215, India ¹Assistant Professor, K. S. Rangasamy College of Technology, Tiruchengode, Namakkal-637 215, India ²

Abstract --- Coronary Artery Disease (CAD) is the disease commonly leads to Heart Attack. Heart Attacks are due to the formation of plaque along the inner wall of the coronary artery, which narrows the arteries and reduces the blood flow to the heart. In this paper the coronary artery is segmented using Graph cut algorithm, which includes vesselness measure, geodesic measure and edge detection by canny edge detector. The images which contains blockages leads to reduced blood flow in the artery is classified as abnormal images otherwise normal by using Support Vector Machine (SVM) classifier.

Index Terms --- Segmentation, Coronary artery disease, Angiographic image, SVM classifier.

1. INTRODUCTION

Coronary Artery Disease (CAD) is a complex disease that causes reduced or absence of blood flow in one or more of the arteries that encircle and supply the heart. The disease may be focal or diffuse. Apart from rare congenital anomalies (birth defects), CAD is usually a degenerative disease, uncommon as a clinical problem before the age of 30 years and common by the age of 60 years.

In recent years, Coronary artery disease has become one of the most frequently occurring diseases in the world and has increasing trend in its incidence in future. It is the cause of 20–30% of deaths in most industrialised countries. On concerning to World Health Organisation (WHO) report, it is estimated that in India heart problems are increasing in younger generation. According to recent research at least 20 million people suffer from heart attacks. In India it is also reported that CAD tends to occur earlier in life in Indians than other ethnic groups.

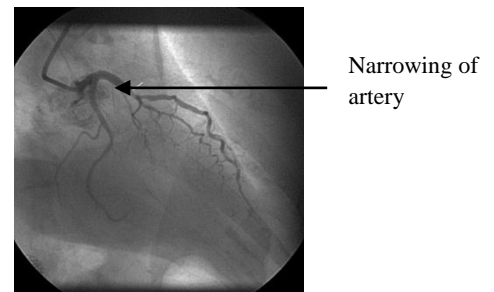


Fig. 1 Blockage in Coronary artery

Coronary Artery Disease is the disease occurred due to the formation of plaques in the coronary arteries. These arteries supply the myocardium (the muscle of heart) with oxygen-rich blood. The plaque is made up of cholesterol, fatty substances, calcium and other deposits. This condition is called Atherosclerosis. When the plaque is growing it narrows the blood flow in the coronary artery. Consequently the blood flow to the heart muscle decreases. This causes a discomfort or a pain. The pain may be felt in body parts such as chest, arms, neck, etc., also called Angina. During Angina the amount of the oxygenated blood flow decreases. But as the disease progresses the lumen of coronary arteries goes on narrowing due to the increased size of plaque. Hence the amount of blood supplied to this tissue becomes inadequate to supply the needs of the tissue. This condition is called myocardial ischemia and the tissues do not work at its fullest capacity. When the lumen of coronary artery has near-complete blockage, severely restricting the flow of oxygenated blood, the tissue in the areas of myocardium dies leading to myocardial infarction (particularly known as heart attack) which also accounts for sudden death.

Although CAD has now become much familiar disease, but death rate is high due to the lack of awareness among the common people. Generally the patients neglect the initial symptoms and they only consult medical experts when those symptoms become severe or critical. But at that time the treatment

becomes complicated and sometimes due to the acuteness and severity of the disease, the patients die before getting proper medication. In order to circumvent such a burning problem one of the common solutions is to make awareness to the people about the CAD diseases and its risk factors. Also the people should aware to proceed the preventive measures at earlier stage. According to the medical experts an early detection at the stage of angina may prevent the death due to CAD if proper medication is given thereafter. Here lies the importance of developing a CAD screening system.

This work deals with the concept of examining the patients angiographic image as a normal or abnormal for screening CAD. Initially this paper starts with vessel segmentation by graph cut algorithm and proceeds with the classification technique using SVM classifier.

II RELATED WORK

Graph-cuts (GC) theory [1], [2], [3], [4] to model vessel structures and obtain a globally optimal segmentation of the coronary tree in angiography images, achieving accurate detection of both the centerline and the vessel borders. One of the critical issues for GC is the design of proper energy terms to assure optimal analysis of local image structures and global segmentation solution. In particular, the original GC definition suffers from the shrinking bias drawback [5] since it tends to produce small contours corresponding to the minimal cut. Hence, with the original GC energy formulation, it is not well suited to segment tubular structures and thin objects like blood vessels.

A novel GC energy functional tailored to the vessel segmentation problem. The energy formulation takes into account 1) the local vessel appearance, using a vesselness measure; 2) the local connectivity to other vessel regions, using geodesic paths; and 3) a measure of edgeness based on a new multiscale version of the adaptive Canny detector [6], which allows an accurate vessel boundary detection. Several methods that exploit photometric and structural properties of tubular structures have been proposed [7]–[11]. An excellent review of basic geometrical features for tubular like structures can be found in [12]. Nonetheless, in the case of vessel segmentation in angiography sequences, the problem is still challenging; highly reliable, fully automatic methods are not established yet [13]. An extensive overview of different methods for vessel extraction can be found in [14]. Recently, an

interesting approach to vessel segmentation has been proposed in [15], which fuses local features with local directional information; unfortunately, the authors do not provide a quantitative evaluation of their method. Nonetheless, most works are based on local image analysis to extract vessels or employ an a priori model to help vessel extraction. In contrast, the GC technique is an optimal segmentation tool that combines local and contextual image information analysis by modeling relations between neighboring pixels [2], [3], [16]. The goodness of the GC solution depends on the suitability of the energy terms and their reliable computation. It is worth to mention that GC suffers from the “shrinking bias” problem; since the energy function definition makes it proportional to the length of the boundary of the result, GC is biased to segment small, isotropic regions. This problem can be overcome in different ways [5] and [17] have addressed this problem by incorporating flux information in the GC framework. In [18], a geodesic distance term to the GC energy function, computed from some strokes manually defined by the user as an initialization step of the segmentation. Differently than previous methods, the paper [19] tailor the GC energy function in such a way that long and thin structures can be easily and automatically segmented and none of the previous methods incorporates local appearance, geodesic paths, and an edgeness measure in a compact, unified framework.

SVM classifier is based on the fact that with an appropriate function to a sufficiently high dimension, data from two categories can always be separated by a hyperplane [20]. The support vector machine (SVM) proposed by Vapnik et al [21], which maps training vectors into a higher dimensional space and finds a separating hyper-plane with the maximal margin. SVMs have been used in many areas including ECG beat classification, EEG analysis and text classification with good results.

III METHODOLOGY

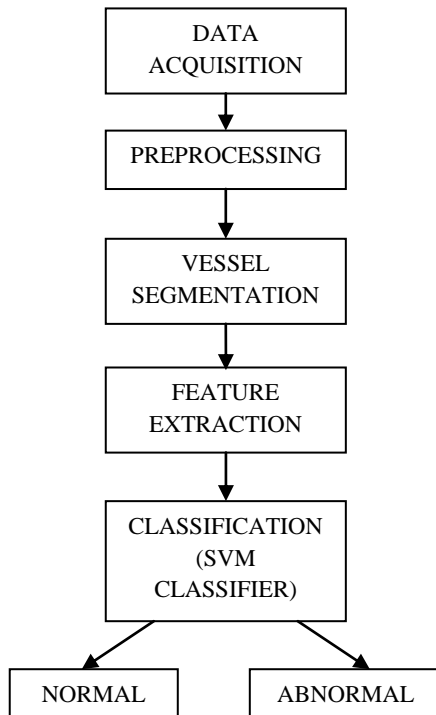


Fig. 2 Proposed methodology Flow diagram

A. GRAPH CUT ALGORITHM

In Graph-Cuts, let $X = (X_1, \dots, X_i, \dots, X_{|P|})$ the set of pixels for a given grayscale image I ; $P = (1, \dots, i, \dots, |P|)$ the set of indexes of I ; N the set of unordered pairs $\{i, j\}$ of neighboring pixels of P under a 4-8 neighborhood system, and $L = (L_1, \dots, L_i, \dots, L_{|P|})$ a binary vector whose components L_i specify assignments to pixels $i \in P$. Each L_i can be either "fore" or "back" indicating if it belongs to the foreground or background, respectively. GC formulation defines the cost function $E(L)$, which describes soft constraints imposed on boundary and region properties of L as

$$E(L) = U(L) + \lambda B(L) \quad (1)$$

the unary term is denoted as

$$U(L) = \sum_{i \in P} U_i(L_i) \quad (2)$$

and the boundary term as

$$B(L) = \sum_{\{i,j\} \in N} B\{i,j\} \Omega(L_i, L_j) \quad (3)$$

where the characteristic function $\Omega(L_i, L_j)$ is 0, if $L_i = L_j$ and 1, otherwise. The unary term $U(L)$ is defined assuming that individual penalties for assigning pixel i to "fore" and "back" [i.e., $U_i(\text{fore})$ and $U_i(\text{back})$] are given by foreground and background models. In this case, the foreground is the vessel denoted by "vess." The term $B(L)$ comprises the boundary properties of segmentation L . Any $B\{i,j\} \geq 0$ should be interpreted as a penalty for a discontinuity between i and j . Finally, the coefficient $\lambda \in R^+$ specifies the relative importance of the boundary term against the unary term. The GC algorithm imposes hard constraints on the segmentation result by means of the definition of seed points where labels are predefined and cannot be modified. The notations $V \subset P$, $B \subset P$, $V \cap B = \Phi$ refer to the subsets of vessel (foreground object of interest) and background seeds, respectively. Boykov and Funka-Lea [3] show how to efficiently compute the global minimum of $E(L)$ among all segmentations L satisfying the hard constraints $\forall i \in V, L_i = \text{"vess"}, \forall i \in B, L_i = \text{"back"}$, using a minimum cut algorithm on a graph defined by nodes and edges, which are image pixels and pixel relations, respectively. Let us describe the details of the graph created to segment an image. A graph $G = (Y, E)$ is created with nodes Y corresponding to pixels $i \in P$ of the image. There are two additional nodes: the foreground terminal (source S) and the background terminal (sink T); therefore, $Y = P \cup \{S, T\}$. The set of edges E consists of two types of undirected edges: n -links (neighborhood links) and t -links (terminal links). Each pixel i has two t -links $\{i, S\}$ and $\{i, T\}$ connecting it to each terminal. Each pair of neighboring pixels $\{i, j\}$ in N is connected by an n -link. Without introducing any ambiguity, an n -link connecting a pair of neighbors i and j will be denoted by $\{i, j\}$, giving

$$E = N \cup \{\{i, S\}, \{i, T\}\}_{i \in P} \quad (4)$$

The vesselness V at every pixel i as $V(i) = \max_{s \in \{s(1), \dots, s(Q)\}} V(i, s)$. The vessel and background models combining the vesselness map $V(i)$ and the geodesic distance map D_i . The unary potentials at each pixel i as

$$U_i(\text{"vess"}) = -\ln(p(L_i = \text{"vess"})) \quad (5)$$

$$U_i(\text{"back"}) = -\ln(p(L_i = \text{"back"})) \quad (6)$$

The probability of a pixel to be marked as "vess" is computed using the vesselness-geodesic measure VG, $p(L_i = \text{"vess"}) = VG(x_i)$ and the opposite probability as $p(L_i = \text{"back"}) = 1 - p(L_i = \text{"vess"})$.

An image-dependent multiscale edgeness measure is used for the boundary term. First, run the Canny edge detector algorithm on the image at different threshold levels. Then, compute the edge probability at each pixel by averaging the edge thresholds for different scales. The final boundary potential over the multiscale edgeness map is computed as $B\{i,j\} = J_i$.

B. SVM CLASSIFIER

Support Vector Machines also called as Support Vector Network in machine learning approach is a supervised learning models combined with other learning algorithms used for data analysing and pattern recognition. Its application area includes classification and analysis of regression. Let us consider a set of training examples, each example is denoted as concerning to one of two categories either positive or negative, then the SVM training algorithm develops a model which assigns a new examples into one category or the other, making it a binary linear classifier which is non-probabilistic.

SVM purpose is to classify the input samples where the input samples for classification are linearly separable. In an n-dimensional space, SVM separates input samples into the two classes using hyperplanes. The optimal separating hyperplane maximizes the margin between the samples which are closest to each other in the two different classes.

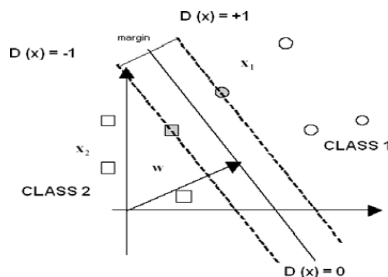


Fig. 3 SVM structure

Given a set of n points(vectors): x_1, x_2, \dots, x_n such that x_i is a vector of length m, and each belong to one of two classes label them by "+1" and "-1". To

find a separating hyperplane that separates these points into the two classes. "The positives" (class "+1") and "The negatives" (class "-1") assuming that they are linearly separable.

IV RESULTS

A. INPUT IMAGE

The angiographic image(normal [a] and abnormal [b]) is taken as input for vessel segmentation and abnormality detection in coronary artery disease.

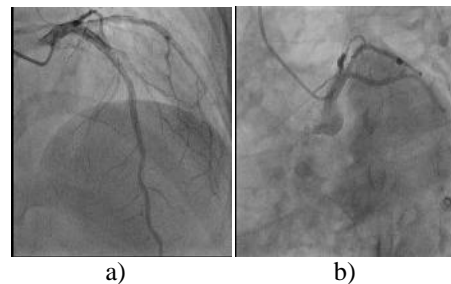


Fig. 4 Input image

B. PREPROCESSING

Input image is smoothed by Gaussian filter.

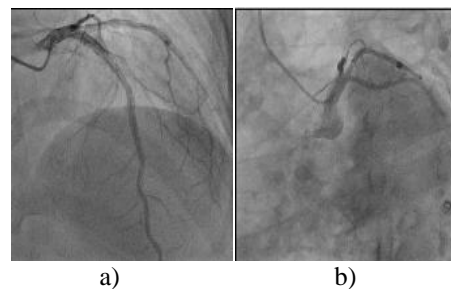


Fig. 5 Preprocessed image

C. VESSEL SEGMENTATION

By graph cut algorithm, the image is decomposed into N cuts. Each N cuts are taken as vertices and their edges have minimum edge weight. The segmentation includes vesselness measure, geodesic measure and edgeness measure.

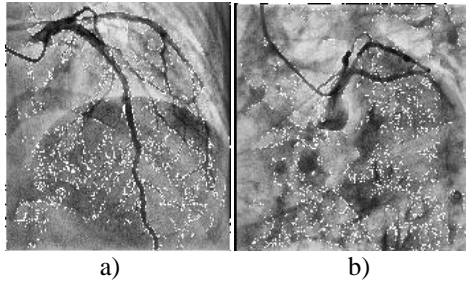


Fig. 6 Vessel segmentation

D. FEATURE EXTRACTION

The extracted features for image classification as normal or abnormal are tabulated in Table 1.

Feature	Normal	Abnormal
Mean	60.316	81.464
Variance	5279.702	5592.820
Energy	0.28129	0.17081
Skewness	0.92228	0.35160
Kurtosis	2.68385	1.91457

Table. 1 Feature Values for normal and abnormal images

E. CLASSIFICATION

The extracted features are given as input to SVM classifier and it classifies the image as normal or abnormal.

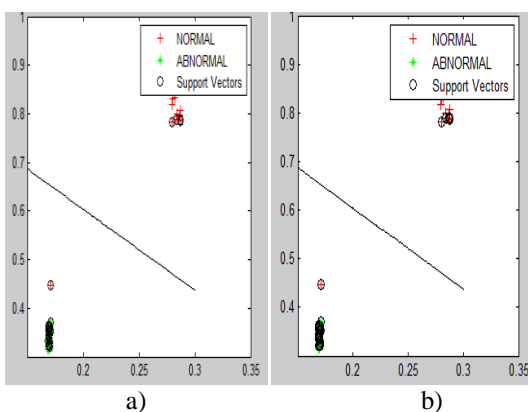


Fig. 7 SVM classification

V CONCLUSION

Segmentation of coronary arteries in angiographic images is a fundamental tool to evaluate arterial diseases and choose proper coronary treatment. An accurate segmentation of coronary artery allows the physician to access different medical imaging information. Segmentation of vessels in angiographic images is done by Graph cut algorithm on analysis of vessel appearance, local connectivity to other vessels (Geodesic distance) and edginess detection by canny edge detection algorithm. The abnormality detection is efficiently done by SVM classifiers using the image characteristics.

REFERENCES

1. Y. Y. Boykov and M.-P. Jolly, "Interactive graph cuts for optimal boundary & region segmentation of objects in N-D images," in Proc. Int. Conf. Comput. Vis., 2001, vol. 1, pp. 105–112.
2. Y. Boykov and V. Kolmogorov, "An experimental comparison of mincut/ max-flow algorithms for energy minimization in vision," in Proc. Int. Conf. Pattern Anal. Mach. Intell., 2004, vol. 26, pp. 359–374.
3. Y. Boykov and G. Funka-Lea, "Graph cuts and efficient N-D image segmentation," Int. J. Comput. Vis., vol. 70, no. 2, pp. 109–131, 2006.
4. C. Rother, V. Kolmogorov, and A. Blake, "Grabcut: Interactive foreground extraction using iterated graph cuts," J. ACM Trans. Graph., vol. 23, no. 3, pp. 309–314, 2004.
5. V. Kolmogorov and Y. Boykov, "What metrics can be approximated by geo-cuts, or global optimization of length/area and flux," in Proc. Int. Conf. Comput. Vis., 2005, vol. 1, pp. 564–571.
6. S. Candemir and Y. Akgul, "Adaptive regularization parameter for graph cut segmentation," in Image Analysis and Recognition. New York: Springer, 2010, pp. 117–126.
7. M. Schaap et al., "Standardized evaluation methodology and reference database for evaluating coronary artery centerline extraction algorithms," Med. Image Anal., vol. 13, no. 5, pp. 701–14, 2009.
8. F. Benmansour and L. Cohen, "Tubular structure segmentation based on minimal path method and anisotropic enhancement," Int. J. Comput. Vis., vol. 92, pp. 192–210, 2011.
9. D. Lesage, E. D. Angelini, I. Bloch, and G. Funka-Lea, "A review of 3D vessel lumen segmentation techniques: Models, features and extraction schemes," Med. Image Anal., vol. 13, no. 6, pp. 819–845, 2009.
10. N. Sang, H. Li, W. Peng, and T. Zhang, "Knowledge-based adaptive thresholding segmentation of digital subtraction angiography images," Image Vis. Comput., vol. 25, no. 8, pp. 1263–1270, Aug. 2007.
11. D. Franchi, P. Gallo, L. Marsili, and G. Placidi, "A shape-based segmentation algorithm for x-ray digital subtraction angiography images," Comput. Methods Prog. Biomed., vol. 94, no. 3, pp. 267–278, Jun. 2009.
12. K. Krissian, G. Malandain, N. Ayache, R. Vaillant, and Y. Troussset, "Model-based detection of tubular structures in 3D

International Journal of Innovative Research in Science, Engineering and Technology

An ISO 3297: 2007 Certified Organization,

Volume 3, Special Issue 1, February 2014

International Conference on Engineering Technology and Science-(ICETS'14)

On 10th & 11th February Organized by

Department of CIVIL, CSE, ECE, EEE, MECHANICAL Engg. and S&H of Muthayammal College of Engineering, Rasipuram, Tamilnadu, India

- images," *Comput. Vis. Image Understand.*, vol. 80, no. 2, pp. 130–171, 2000.
13. P. Fallavollita and F. Cheriet, "Towards an automatic coronary artery segmentation algorithm," in *Proc. Eng. Med. Biol. Soc.*, 2006, pp. 3037–3040.
 14. M. Schneider and H. Sundar, "Automatic global vessel segmentation and catheter removal using local geometry information and vector field integration," in *Proc. IEEE Int. Symp. Biomed. Imag. Piscataway, NJ: IEEE Press*, 2010, pp. 45–48.
 15. V. Kolmogorov and R. Zabih, "What energy functions can be minimized via graph cuts," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 2, pp. 147–159, 2004.
 16. A. Vasilevskiy and K. Siddiqi, "Flux maximizing geometric flows," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 12, pp. 1565–1578, Dec. 2002.
 17. B. L. Price, B. Morse, and S. Cohen, "Geodesic graph cut for interactive image segmentation," in *Proc. IEEE Trans. Comput. Vis. Pattern Recog.*, 2010, pp. 3161–3168.
 18. R. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," in *Medical Image Computing and Computer-Assisted Intervention*, (Lecture Notes Computer Science, Vol. 1496). New York: Springer-Verlag, 1998, pp. 130–137.
 19. Antonio Hernandez-Vela, Carlo Gatta, Sergio Escalera, Laura Igual, Victoria Martín-Yuste, Manel Sabaté, and Petia Radeva "Accurate coronary centreline extraction, calibre estimation and catheter detection in angiographies" *IEEE transaction on information technology in Biomedicine*, November, 2012.
 20. G.Subha Vennila, L.Padma Suresh, K.L.Shunmuganathan "Dermoscopic image segmentation and classification using machine learning algorithms" *International Conference on Computing, Electronics and Electrical Technologies*, 2012.
 21. "Coronary heart disease diagnosis by artificial neural networks including genetic polymorphisms and clinical parameters" *Journal of Cardiology*, 2012.