CARDIAC VESSEL EXTRACTION-A REVIEW

[1] Sukanya A, [2] Rajeswari R
[1]Ph.D Research Scholar, [2] Assistant Professor,
Department of Computer Applications,
Bharathiar University, Coimbatore, India

Abstract: Cardiovascular disease (CVD), a significant and ever-growing problem is now the world's foremost reason of death leading to serious morbidity and mortality, demanding 17.3 million lives every year [1]. Coronary artery disease (CAD) is the most common type of CVD causing death all over the world. Coronary Computed Tomography Angiography (CCTA) is a non-invasive cardiac imaging modality which is used for the cardiac disease diagnosis. Cardiac vessel extraction is necessary in clinical scenario for cardiac image analysis of CCTA datasets. Hence this paper gives a detailed survey of various cardiac vessel extraction techniques available in the literature used for the diagnosis of CAD. The paper also presents the performance results of Frangi's vesselness measure of various 3D cardiac images.

***Index Terms* - Cardiovascular disease, Coronary artery disease, Coronary Computed Tomography Angiography, vesselness measure**
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I. INTRODUCTION

Cardiovascular diseases (CVD) are the major source of mortality globally, as well as in India and coronary artery disease (CAD) is the most popular among them. It is one of the most widespread pathologies in the mechanized world and it is estimated that by 2030 around 23.6 million people will die due to CVD (WHO 2012). Although CAD is one of the most challenging emergencies; if treated promptly and appropriately, significant death and disability can be reduced. Diagnosis of CAD is based on accurate extraction of blood vessels from cardiac images. Many of the vessel extraction methods depend on a measurement called vesselness measure which indicates the probability of a pixel belonging to a cardiac vessel.

A definitive and robust explication of vessel extraction for complete arterial tree structure in coronary angiograms is an essential step towards 3D reconstruction of coronary tree and the extraction of the same is a necessary prerequisite process for the computerized assessment of heart related diseases. Various CTA visualization techniques such as Volume Rendering (VR), Maximum Intensity Projections (MIP), Multiplanar Reformation (MPR) and Curved Planar Reformation (CPR) are employed to assist in CAD diagnosis applications such as lumen segmentation, stenosis grading and classification. As a result, coronary artery vessel extraction from CTA is a prerequisite step for these visualization techniques.

Coronary artery vesselness measure is an obscure process due to (1) image quality is affected by many factors such as spatial and temporal resolution, artifacts due to cardiac motion, (2) high variability of size and curvature, the appearance of image is perturbed by calcifications, stenosis and stents and (3) close to adjacent organs, complicated structure of the blood vessels, reconstruction artifacts and blood vessel overlaps [3, 23]. The Gaussian filter, mean filter, or median filter are the most commonly used standard filters for vesselness measures. Hence, selection of appropriate vesselness measure is crucial for accurately extracting the blood vessels from cardiac images.

The rest of the paper is organized as follows. Section II explains the classification of various extraction methods. Section III gives a review of recent work carried out to extract cardiac vessels. Section IV presents the results of vesselness measure of cardiac images. Section V gives the conclusion.

II. CARDIAC VESSEL EXTRACTION TECHNIQUES

Cardiac vessel extraction techniques vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors. A single vessel extraction method cannot be applied for every medical image to extract the vasculature. While some methods utilize pure intensity-based pattern recognition techniques such as thresholding followed by connected component analysis (CCA) [1], some other methods apply explicit vessel models to extract the vessel contours [2].

Depending on the image quality and the general image artifacts such as noise, some vessel extraction methods may require image preprocessing prior to the vessel extraction. Some other methods apply post-processing to overcome the problems arising from over extraction. We divide vessel extraction algorithms and techniques into six main categories. They are depicted in the following Table 1.

Pattern recognition techniques are further divided into seven categories and they are depicted in Table 2 and the Model-based approaches are classified into a variety of categories as depicted in Table 3. We survey current cardiac extraction methods, covering both early and recent literature related to vessel extraction algorithms and techniques.

Table 1: Categories of cardiac extraction techniques

S.NO.	VESSEL EXTRACTION ALGORITHMS
1	Pattern recognition techniques
2	Model-based approaches
3	Tracking-based approaches
4	Artificial intelligence-based
5	Neural network-based approaches
6	Tube-like object detection approaches

Table 2: Categories of pattern recognition techniques

S. No.	Pattern recognition techniques
1	Multi-scale approaches
2	Skeleton-based approaches
3	Region growing approaches
4	Ridge-based approaches
5	Differential geometry-based approaches
6	Matching filters approaches
7	Matching filters approaches
8	Mathematical morphology schemes

Table 3: Categories of Model-based approaches

S. No.	Model-based approaches
1	Deformable models
	A. Parametric deformable models
	B. Geometric deformable models and front propagation methods
2	Parametric models
3	Template matching approaches
4	Generalized cylinders approaches

Here we provide a table that compares the papers against such criteria as dimensionality, imaging modality, pre-processing, and user interaction.

III. Literature review of cardiac vesselness measures for the diagnosis of CVD

Chuan et al proposed a method using a multiscale enhancement and dynamic balloon tracking (MSCAR-DBT) method [3]. The multiscale coronary response (MSCAR) method along with 3D multiscale filtering, analysis of the eigen values of Hessian matrices and EM estimation segmentation were used to intensify and segment the vasculature within the cardiac region. A 3D dynamic balloon tracking (DBT) method is used to track coronary arteries after the segmentation process.

Farsad et al evaluated a method on coronary artery centerline extraction using second order local features [4]. They have presented an improved center-line tracing algorithm for automatic extraction of coronary arterial tree based on robust local features. The algorithm uses an improved scanning scheme based on eigenvalues of Hessian matrix for consistent identification of true vessel points and adaptive look-ahead distance schema for calculating the magnitude of scanning profile. The experimental results outperforms well under difficult situations such as poor image quality and complicated vessel geometry.

Asma et al proposed a coronary artery segmentation method based on multiscale analysis and region growing [5]. Here a multiscale region growing (MSRG) method for coronary artery segmentation is proposed. The algorithm is developed for 2D X-ray angiogram images. Initially, a region growing rule incorporating both vesselness and direction information in a unique way is introduced. Performing the process in a multiscale fashion helps to extract thin and peripheral vessels often missed by other segmentation methods. The MSRG segmentation method was also implemented with different enhancement filters and it has been shown that the Frangi filter gives better results.

Daniel et al proposed a method for vesselness-based 2D–3D registration of the coronary arteries [6]. The method is based on the iterative stochastic optimization of their similarity measure, which relies on the 3D coronary vessel model, obtained from a cardiac CTA dataset, and a 2D X-ray image of the coronary arteries. The similarity measure is obtained by applying a vesselness filter to the

2D image, and then weighting it with a function based on the squared distance transform of the projected 3D vasculature. Their test results show that it performs very well for the task of 2D–3D registering of the coronary vessel tree .

Rashindra et al presented a Vessel Enhancing Diffusion A Scale Space Representation of Vessel Structures [7]. The method enhances vascular structures within the framework of scale space theory and combines a smooth vessel filter which is based on a geometrical analysis of the Hessian’s eigen system, with a nonlinear anisotropic diffusion scheme. Vessel enhancing diffusion (VED) is applied to patient and phantom data and compared to linear, regularized Perona-Malik, edge and coherence enhancing diffusion. The method performs better than most of the existing techniques in visualizing vessels with varying radii and in enhancing vessel appearance.

Niessen et al proposed a model-based segmentation of cardiac and vascular images [8]. For vessel segmentation, prior shape information is introduced based on the notion that vessels are elongated structures. For cardiac segmentation, shape information derived from a training set of segmented images is incorporated in an automatically constructed point distribution model of the heart.

Szeling et al proposed an Orthogonal planar search (OPS) for coronary artery centerline extraction [9]. The orthogonal planar search (OPS) for coronary artery centerline extraction is used in coronary artery diseases diagnosis. The search mechanism exploits a data-driven algorithm to extract the centerline. Firstly, the best representation of vessel cross section on orthogonal planar is determined. The orthogonal planars (axial, coronal and sagittal) are sufficient for finding the best representation of cross section along the tubular structure. Then, the center of gravity from the crosssection is computed as centerline point iteratively. Branching detection and termination are invoked in this proposed method.

Marcin et al presented a vessel detection method based on eigenvalues of the Hessian matrix and is related to airway tree segmentation [10]. It is based on the analysis of Hessian matrix eigenvalues combined with a multiscale image analysis approach. Results show that the method in general can be used to airway detection in 3D medical images, however it requires improvements to this specific purpose.

Christian et al proposed the tube detection approach based on the gradient vector flow and an analysis of the resulting vector field [11]. This approach is able to identify tubular objects surrounded by different tissues such as blood vessels in proximity of calcifications. After identification of the tubular structures their centerlines are extracted and grouped into complete tree structures. Based on gray value information, the centerline length tubular structures not belonging to the coronary arteries are removed.

Krissian et al developed minimally interactive knowledge-based coronary tracking in CTA using a minimal cost path and algorithm for minimally interactive coronary artery tracking [12]. Tracking ability and accuracy results are demonstrated on 16 CTA images. First, a region of interest is automatically selected and a denoising filter is applied. Then, for each voxel the probability of belonging to a coronary vessel is estimated from a feature space and a vesselness measure is used to obtain a cost function. The vessel starting point is obtained automatically, while the end point is provided by the user. Finally, the centerline is obtained as the minimal cost path between both points.

Pascal et al developed robust coronary artery tracking from fluoroscopic image sequences [13]. They have presented a new method to track the coronary arteries in an X-ray fluoroscopy setting. First, the principal coronary artery centerlines are extracted at a first time instant. Secondly, in order to estimate the centerline coordinates in subsequent time frames, a pyramidal Lucas-Kanade optical flow approach is used. Finally, an active contour model coupled with a gradient vector flow (GVF) formulation is used to deform the estimated centerline coordinates towards the actual medial axis positions. The results show that the centerlines were correctly tracked in 92% of the image frames.

Yefeng et al proposed the robust and accurate coronary artery centerline extraction in CTA by combining model-driven and data-driven approaches [14]. They have automatically segmented chambers to 1) predict the initial position of the major coronary centerlines and 2) define a vessel-specific region-of-interest (ROI) to constrain the following centerline refinement. The proposed prior constraints have been integrated into a model-driven algorithm for the extraction of three major coronary centerlines. After extracting the major coronary arteries, the side branches are traced using a data-driven approach to handle large anatomical variations in side branches. Experiments on the public Rotterdam coronary CTA database demonstrate the robustness and accuracy of the proposed method.

Guanyu et al developed automatic centerline extraction of coronary arteries in coronary computed tomographic angiography [15]. They have presented and validated a fully automatic centerline extraction algorithm for coronary arteries in CCTA images. The algorithm is based on an improved version of Frangi’s vesselness filter which removes unwanted step-edge responses at the boundaries of the cardiac chambers. Building upon this new vesselness filter, the coronary artery extraction pipeline extracts the centerlines of main branches as well as side branches automatically. This algorithm was first evaluated with a standardized evaluation framework named Rotterdam Coronary Artery Algorithm Evaluation Framework used in the MICCAI Coronary Artery Tracking challenge 2008 (CAT08).

Mohammad et al presented a performance comparison of vesselness measures for segmentation of coronary arteries in 2D CTA image [16]. Performance measures including noise suppression, edge smoothness, branch disconnection and centerline smoothness are used for comparing the performance of vesselness functions. The study reveals that Frangi’s vesselness performs well in suppressing the background noise, whereas, the other vesselness measures perform better at enhancing vessels throughout crossings and bifurcations.

Greenspan et al presented a simulation tool (SVG) for generating synthetic vessel angiographic images under predetermined geometrical parameters [17]. A method for calculating global performance measures based on the comparison of the reference centerline and an estimated centerline was implemented.

Aytekin et al descibed a 3D tubular structure detection method [18]. The proposed method works based on the eigenvalues of the Hessian matrix, yet it employs a direct 3D vector field singularity characterization. The Gradient Vector Flow vector field is used and the eigenvalues of its Jacobian are exploited in computing a parameter free vesselness map. Results on phantom and real patient data exhibit robustness to scale, high response at vessel bifurcations, and good noise/non-vessel structure suppression.

Metz et al developed a semiautomatic method based on a minimum cost path approach and evaluated for two different cost functions [19]. The method is based on a frequently used vesselness measure and intensity information, and a recently based on region statistics. User interaction is minimized to one or two mouse clicks distally in the coronary artery. The starting point for the minimum cost path search is automatically determined using a newly developed method that finds a point in the center of the aorta in one of the axial slices. Table 4 depicts the literature survey of cardiac image diagnosis methods.

Table 4: Comparison of cardiac image diagnosis methods

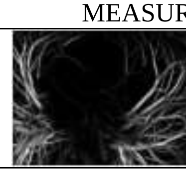
Article	Cardiac Imaging modality /dimension	Techniques	Features
Chuan et al [2012]	3D CTA	Based on multiscale filtering, analysis of the eigen values and EM estimation segmentation. Arteries tracked by a 3D dynamic balloon tracking (DBT) method after the segmentation process	Intensify and segment the vasculature within the cardiac region
Farsad et al[2012]	3D CTA	Based on second order local feature	Results are accurate and more robust under complicated situation.
Asma et al [2016]	2D X-ray angiogram	Based on multiscale region growing (MSRG)	the Frangi filter gives better results
Daniel et al [2009]	3D CTA and 2D X-ray angiography	Vesselness-based similarity measure based on squared distance transform.	Accurate. It performs very well for the task of 2D–3D registering of the coronary vessel tree
Rashindra et al [2007]	3D CTA	Based on geometrical analysis of hessian eigen value with non linear diffusion scheme. Vessel enhancing diffusion (VED) filter applied.	Efficient in extracting the smaller vessels of the vasculature.
Niessen et al [2002]	3D CTA	model-based segmentation of cardiac and vascular image.	Time-consuming and tedious process.
Szeling et al [2016]		orthogonal planar search (OPS) is applied.	Branching detection and termination are invoked
Marcin et al [2009]	3D CTA	Based on hessian matrix eigen value analysis with multiscale image analysis approach.	Used for airway detection in 3D medical image

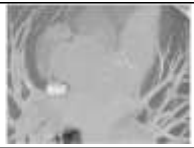
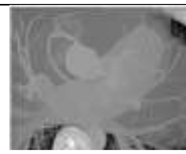
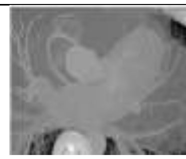
Christian et al [2008]	3D CTA	Based on tube detection approach	Results are accurate
Krissian et al [2008]	3D CTA	Based on minimal cost path	Minimally interactive knowledge based coronary tracking
Pascal et al [2016]	X-ray fluoroscopy image	Based on pyramidal Lucas Kanade optical flow approach. Active contour model with GVF is used.	Centerline tracked with 92 % accuracy
Irina et al [2016]	3D CTA	Based on Frangi, otsu,canny edge detector and morphological skeletonization.	Accurate for images with good spatial resolution
Yefeng et al [2013]		Based on model driven and data driven approach	Accurate and robust technique
Guanyu et al [2012]	3D CTA	Based on improved Frangi's vesselness measure	Extracts arteries with excellent performance
Mohammad et al [2016]	2D CTA	Studies vesselness measure for segmentation	Frangi's vesselness measure performs well in suppressing background noise.
Greenspan et al [2001]	3D CTA	Developed SVG simulation tool	Accurate method
Aytekin et al [2010]	3D CTA	Based on 3D tubular structure detection method	Results are accurate and robust
Metz et al [2009]	3D CTA	Semi-automatic method based on minimum cost path approach	User interaction is minimized

IV. CARDIAC VESSELNESS MEASURE

Various cardiac images used in this study are as given in Table 5.

Table 5: Cardiac images used in this study

S NO	MIP OF CARDIAC IMAGES	FRANGI'S VESSELNESS MEASURE
1		

2		
3		
4		
5		

The performance of cardiac image segmentation can be computed based on the validity of the pixels using the quality measures. Some of the quality measures used in this study for comparison is PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error) [21].

The Peak Signal to Noise Ratio (PSNR) is the performance measure widely used to measure the quality of images [23]. The higher PSNR indicates the higher quality of images. The PSNR depends on Mean Squared Error (MSE). MSE represents the mean squared error between the original image and segmented image. The lower the value of MSE the lower is the error [24].

Table 6 depicts the performance of Frangi's vesselness

Table 6: Performance comparison of the Frangi's vesselness measure

S.NO	FRANGI'S VESSELNESS MEASURE	
	MSE	PSNR
1	0.4691	75.5347
2	0.4638	75.5834
3	0.4665	75.5583
4	0.5741	74.6577
5	0.4645	75.5774

V. CONCLUSION

Cardiac vessel extraction is necessary process for cardiac image analysis of CCTA datasets. Hence this paper provided a detailed survey of various cardiac vessel extraction techniques available in the literature used for the diagnosis of CAD. The paper also presented the performance results of Frangi's vesselness measure.

VI. ACKNOWLEDGMENT

The authors are very grateful to the KG hospital for providing data for the research work and convey their sincere thanks to Bharathiar University for valuable support.

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