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Robust semi-automated path extraction for visualising stenosis of the coronary arteries

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Abstract

Computed tomography angiography (CTA) is useful for diagnosing and planning treatment of heart disease. However, contrast agent in surrounding structures (such as the aorta and left ventricle) makes 3D visualisation of the coronary arteries difficult. This paper presents a composite method employing segmentation and volume rendering to overcome this issue. A key contribution is a novel Fast Marching minimal path cost function for vessel centreline extraction. The resultant centreline is used to compute a measure of vessel lumen, which indicates the degree of stenosis (narrowing of a vessel). Two volume visualisation techniques are presented which utilise the segmented arteries and lumen measure. The system is evaluated and demonstrated using synthetic and clinically obtained datasets.
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1. Introduction

Coronary heart disease is a major health concern. This disease stems from the underlying problem of *atherosclerosis*, which is a build up of plaque (consisting of substances including cholesterol, calcium, and others) on the interior surface of arteries supplying the heart. Coronary heart disease typically manifests in two forms: heart attack, and angina. A heart attack occurs when blood flow is completely blocked, typically from a dislodged portion of plaque. Angina – typically brought on by physical activity – is a chest pain or discomfort caused by an inadequate blood flow due to a narrowed artery.

Computed tomography angiography (CTA) provides high-resolution, high-contrast images of the thoracic cavity and as such is emerging as a useful imaging modality for diagnosis and treatment planning for coronary heart disease [1]. An intravenous contrast agent (such as an iodine-based compound) is injected into the patient causing the blood – and hence vessels – to exhibit high intensities in the resultant images [31]. In practice, motion artefacts due to the beating heart must be reduced using electrocardiographic (ECG) retrospective reconstruction (called ECG gating) [26].

From the acquired images, radiologists and cardiac surgeons require tools to easily identify *stenotic* (narrowed or constricted) arteries. A number of post-processing techniques are currently employed including: thin-slab maximum intensity projection (MIP) [12], curved planar reformatting (CPR) [17], and direct volume rendering (DVR) [35]. Each of these techniques exhibit varying strengths and weaknesses, depending on the task: MIP is useful for visualising calcified plaques, however 3D information is discarded; CPR lays flat vessels of interest, but surrounding contextual structures appear deformed; DVR can depict the 3D relationship between vascular and contextual structures, however specifying display parameters to clearly visualise the arteries is difficult and sometimes not possible. Hybrid rendering approaches [38] (which display both direct volume rendered and segmented polygonal structures) or tagged volume rendering [25] (which uses a number of *a priori* binary volumes to separate structures of interest) are other suitable techniques.

This paper proposes the use of segmentation methods to aid visualisation of stenotic vessels. The proposed technique is relevant for a range of vascular images and applications, however the focus is on the coronary arteries in CTA. The method consists of

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four stages: vessel enhancement, centreline extraction, stenosis measure computation, and volume visualisation. The centreline extraction stage extends an existing technique [29] by deriving a novel cost function using morphological top-hat by opening to enhance the vessels. The resultant continuous centreline is then used to compute a quantitative measure of stenosis based on the vessel radius. Two volume visualisation techniques using the resultant segmentation and measure – one based on MIP, one based on DVR – are discussed and demonstrated using clinically obtained datasets. The segmentation method is evaluated using various synthetic and clinical datasets using three criteria: efficiency, accuracy, and reproducibility.

2. Related work

Vessel enhancement and segmentation is a broad area of research; a partial review of the field can be found in [19]. The existing work can be loosely organised into five categories: differential geometry, active contours, skeletonization, tracking, and minimal path extraction methods.

Differential geometry approaches utilise the differentiability of Euclidean space to derive measures which indicate the 'vesselness' of each pixel in an image. Sato et al. [28] and Frangi et al. [13] both proposed multi-scale line filters based on Gaussian differentials. Manniesing et al. [23] extended this to control anisotropic diffusion filtering, which smooths inside the vessels while maintaining sharp boundaries. Another approach presented in [20] computes the degree of belonging to the medial axis (centreline). This 'medialness function' is realised by convolving the whole image with a kernel; the kernel is typically a multi-scale construct utilising second-order derivatives (computed using the Hessian matrix). These methods tend to be computationally expensive because they process the whole dataset.

Active contour methods segment vascular structures by propagating a surface or front. The surface is typically embedded in a higher dimensional function such as the zero level-set. Lorigo et al. [21] was one of the first to extend the classical geodesic active contour model to 3D images for use segmenting vascular structures. In this method a one-dimensional curve (corresponding to the tubular centreline) was evolved in 3D space. Holtzman-Gazit et al. [15] formulated a level-set cost function based on three terms: the zero crossings of the second-order derivative, a minimal variance term to penalise lack of homogeneity inside and outside the evolving surface, and a geodesic active surface term to regularise the functional. They showed this approach was suitable for detecting thin vascular structures with low contrast compared to their background. Yan and Kassim [42] also presented a level-set based approach suitable for segmenting thin vessels. Their method was founded on the principle of capillary action—the attraction of fluid to the walls of a bounding tube. This phenomena was used to derive an adhesion energy term for propagating an active contour. In [9], three separate approaches were brought together: firstly a multi-scale Hessian-based line filter was used for enhancement, then a level-set based approach (which implicitly handled change in topology) was used to provide an initial segmentation, and finally a geometric deformable model (triangulated mesh) driven by a gradient energy cost function was evolved to provide the final result.

Skeletonization converts a binary volume to a discrete centreline – or skeleton – using a method such as distance-ordered homotopic thinning [27]. Pruning and graph analysis techniques must then be applied to transform the unordered discrete set of points into an acyclic graph [14,10]. The challenge for skeletonization is to obtain a good initial segmentation. In [14] a region-growing technique was used to produce the initial binary volume. Such intensity-based techniques are susceptible to noise and varying intensity within the vessel, so therefore in [8] an additional gradient magnitude criteria was added to the traditional lower and upper thresholding strategy. Because these methods only consider pixels comprising the vessel, they are relatively fast; however, they operate in discrete pixel space which can cause the centreline to exhibit stair-case artefacts. In [22] a level-set based method was applied to produce the initial segmentation, followed by a graph analysis method to order and smooth the skeleton.

Similar to skeletonization, *tracking* methods only consider the pixels in close proximity to the vessel centreline, and therefore tend to be relatively fast. Such methods are typically iterative in nature; at each step an operator is applied to compute a continuous point on the centreline and a direction to step. Wink et al. [39] proposed a 'centrelikelihood' operator based on the termination of a number of radially projected lines. Aylward and Bullitt [5] used a Hessian-based metric to compute both the centre point and step vector, as well as estimate the radius. Tracking methods tend to be highly susceptible to noise: once the computed centre point deviates from the actual, it is difficult for the algorithm to recover.

Minimal path techniques frame the centreline extraction problem in terms of cost function minimisation. In [37] a hybrid tracking-path technique was presented. An initial estimate of the centreline was found by tracking in a helical or 'corkscrew' motion. A cost function – based on a centrelikelihood measure similar to that discussed above in [39]– was then iteratively minimised. Unfortunately, the authors indicate this method was not robust in the presence of noise. Wink et al. [40] explored two best-first minimal path search algorithms: Dijkstra's algorithm and A*. Dijkstra's algorithm operates on a cost function and fans out from the start position, accumulating the cost of each possible discrete path until the end point is reached. The A* algorithm is a generalization which uses a heuristic function $h(\vec{x})$ to better steer the search process (a simple – but common – heuristic function is the Euclidean distance between the current node and the goal). If $h(\vec{x}) = 0$ then A* reduces to Dijkstra's method. The authors compared both unidirectional (expanding from start to end) and bidirectional (expanding from both start and end) searches. As discussed by Sethian [29], Dijkstra's method (and by generalization A*) is inconsistent with the underlying continuous problem: the resultant minimal path is bound to the discrete grid. In contrast, Fast Marching approximates the continuous solution to the underlying partial differential equation (see Fig. 1). For this reason, our proposed method builds upon the Fast Marching minimal path extraction framework set out

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