A Review of Coronary Vessel Segmentation Algorithms

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ABSTRACT

Coronary heart disease has been one of the main threats to human health. Coronary angiography is taken as the gold standard; for the assessment of coronary artery disease. However, sometimes, the images are difficult to visually interpret because of the crossing and overlapping of vessels in the angiogram. Vessel extraction from X-ray angiograms has been a challenging problem for several years. There are several problems in the extraction of vessels, including: weak contrast between the coronary arteries and the background, unknown and easily deformable shape of the vessel tree, and strong overlapping shadows of the bones. In this article we investigate the coronary vessel extraction and enhancement techniques, and present capabilities of the most important algorithms concerning coronary vessel segmentation.

Key words: *Coronary vessel, vessel segmentation, X-ray angiography*

INTRODUCTION

Correct assessment, especially accurate visualization and quantification of blood vessels reflected in X-ray angiograms or angiography images, plays a significant role in a number of clinical procedures. For various medical diagnostic tasks, it is necessary to measure the vessel width, reflectivity, tortuosity, and abnormal branching. For example, detecting the occurrence of vessels of a certain width may reveal the signs of stenosis. Grading of stenosis is of importance to diagnose the severity of vascular disease and to determine the treatment therapy.[1,2] Moreover, planning and performing neurosurgical procedures require an exact insight into blood vessels and their branches, which exhibit great variability. In planning, they provide information on where the blood is drawn and drained, to differentiate between the feeding and transgressing vessel. Even as transgressing vessels need to be preserved, the feeding ones are selectively closed through the artery in interventional neuroradiology, such as the brain arteriovenous malformation treatment. During surgery the vessels serve to provide landmarks and guidelines to the lesion. In short, accuracy in the navigation and localization of clinical procedures is determined by how minute and subtle the vascular information is. Although it is possible for medical experts to delineate vessels, manual delineation of the vasculature becomes tedious or even impossible when the number of vessels in an image is large or when a large number of images is acquired.[3] Therefore, the development of automatic and accurate vessel-tree reconstruction from angiograms is highly desirable. However, it has proven to be a challenging task. The key fact is that vessels cannot be characterized uniformly. Thick vessels have more contrast to noise ratios, as compared to small narrow ones, due to the strong presence of blood and contrast agents in the vessels [Figure 1a]. Non-uniform illumination, as shown in Figure 1b, is one of the major sources of angiography image degradation,[3] and is also a hindrance for accurate reconstruction, because it is likely to make an individual vessel break into several segments. We have divided the image processing methods used in coronary angiography into two main categories: (1) vessel enhancement (2) vessel segmentation. These categories are further divided into subcategories. According to,[4,5] the current automatic computer-assisted procedures are still far from providing a precise spatial representation of the vessel tree.

VESSEL ENHANCEMENT

The literature on enhancing X-ray coronary angiographic images for visualization purposes is very limited. Although a

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number of algorithms have been proposed for angiographic image enhancement, the purpose of most algorithms is to improve the subsequent segmentation rather than visualization. These algorithms can hardly be adopted in clinical practice for improving the quality of visualization.

Algorithms based on specific noise models, for example, the quantum noise model,[6] might also fail to work in practice, as image noise, that is, the undesirable appearance of mottled or grainy spots, which do not reflect the true tissue property, is a combination of various sources of noise, with different characteristics.

Attempting to increase the contrast of vascular structures by suppressing or removing the background structures, for example, the piecewise normalization[7] and the rolling algorithm,[8] is also of limited effect, as part of image noise, with the intensity value within the range of foreground structures, for example, vessels, will be enhanced as well. The step of removing the background might at the same time remove some detailed information in low-contrast angiographic images, which is very undesirable. To the best of the authors' knowledge, all angiographic acquisition systems available in the market use a certain technique to enhance the acquired images in real time, that is, during the actual acquisition procedure. Most of these enhancement techniques are based on the so-called unsharp masking technique and allow the operators to customize the degree of enhancement by using multiple gain levels (typically five). The unprocessed image is first blurred and subtracted from the original image, creating an edge image that only contains higher spatial frequency components of the original image. This edge image is further multiplied by a certain gain level and added to the original image, resulting in an edge enhanced image.[9] Although the image edges are visually enhanced, the result is less optimal, as the image noise with a high spatial frequency will also be enhanced, which may introduce an undesirable appearance or influence the perception of the image details.

The other method used for the enhancement of angiography images is registration of algorithms. Image registration is a useful approach to correct artifacts. In this technique, the correspondence between pixels in mask and live images are calculated. Then a certain warping method is applied to the mask image. After subtracting the two images, the artifacts can be greatly eliminated.[10] First,[11] the mask image is decomposed into many sub-image blocks. With a template matching method, based on typical similarity measures, the rigid matching between the mask sub-image blocks and the live image can be achieved. Second, the control point pairs are selected with Harris corner detection, and are extracted in the original and transformed mask images. By using the multilevel B-spline as the mapping function, a global elastic registration is accomplished. Figure 2 gives the registration results.[11]

VESSEL SEGMENTATION

Many segmentation methods have been used to visualize blood vessel structures in the human body. These blood vessel segmentation methods may be classified as follows: Pattern recognition, model-based tracking and propagation, neural network, fuzzy, and artificial intelligence-based methods.[12-20] Artificial Intelligence-based approaches utilize knowledge to guide the segmentation process and delineate vessel structures. Different types of knowledge are employed in different systems from various sources. One knowledge source is the technique of acquisition of the properties of the image, such as cine-angiography, digital signature algorithm (DSA), computed tomography (CT), magnetic resonance imaging (MRI), and magnetic resonance angiography (MRA). Some applications utilize a general blood vessel model as a knowledge source. A statistical method is also presented for vessel segmentation.[21]

Poli and Valli[22] proposed a computationally efficient algorithm based on a set of linear filters, obtained as linear combinations of properly shifted Gaussian kernels, sensitive to vessels of different orientation and radius. Another type of linear filter, the morphologically connected set filter, was utilized by Wilkinson and Westenberg,[23] to capture filamentous structures. Together with a shape criterion that could distinguish filamentous structures from others, connected set filters could help to extract filamentous details without distortion. Similarly, Eiho
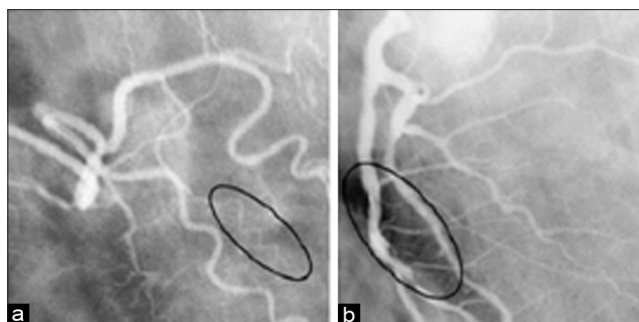
Figure 1: Angiography images with typical hindrances for accurate vessel-tree reconstruction such as (a) low-contrast vessels and (b) non-uniform illumination[5]
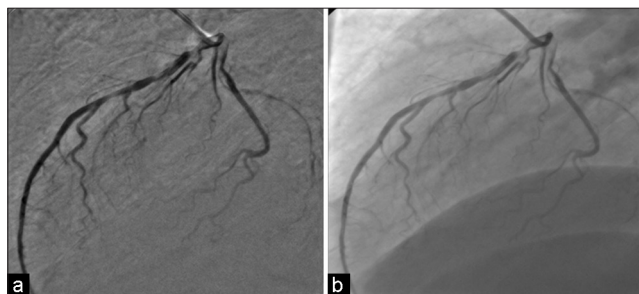
Figure 2: (a) The subtraction image after registration; (b) Original live image[11]

and Qian[24] and Zana and Klein[25] used morphological operators such as erosion, dilation, and top-hat to enhance the shape of the artery and remove other points. These methods were unable to suppress sudden noise and edge noise and were less efficient in capillaries. Non-linear anisotropic filtering was also applied for vessel enhancement.[26-29] This method searched for the local orientation of a vessel to perform anisotropic smoothing without blurring its edge. While Krissian *et al*.[26] performed a particular version of anisotropic diffusion, Orkisz *et al*.[29] used a kind of filter bank called 'sticks', which could be seen as a set of directional structuring elements. Similar approaches were also proposed by Czerwinski *et al*.,[30,31] Kutka and Stier,[32] Chen and Hale,[33] and Du *et al*.[34,35] The last two references combined the outputs of directional operators, without an explicit extraction of the vessel local orientation.

The main disadvantage of the methods in this category is that they can hardly detect vessels in a wide range due to the fixed scale analysis. Although these algorithms can be extended to multiple scales by using sticks of variable length, the computation time would increase greatly. Hessian-based multiscale filtering has been proposed in a number of vessel enhancement approaches.[36-41] One advantage of this approach, in this category, is that vessels in a wide range of diameters can be captured due to the multiscale analysis. In this method, an input image is first convolved with the derivatives of a Gaussian at multiple scales and then the Hessian matrix is analyzed at each pixel in the resulting image, to determine the local shape of the structures at that pixel. The ratio between the minimum and the maximum Hessian eigenvalues is small for line-like structures, but it must be high for blob-like ones. Krissian *et al*.[42] has specifically introduced several models of vessels and has used Hessian eigenvalues to define a set of candidate pixels, which can be the centerlines of the vessels. For each of these candidates, pre-defined, multiscale response functions have been computed, to determine the likelihood of the pixels corresponding to vessels of different scales (radii). The drawbacks of the Hessian-based approaches are that they are highly sensitive to noise, due to the second-order derivatives, and they tend to suppress junctions, as junctions are characterized similar to the blob-like structures. Junction suppression leads to the discontinuity of the vessel network, which is of course undesirable. To deal with this problem, Agam *et al*.[43] proposed a filter model that is based on the correlation matrix of the regularized gradient vectors (first-order derivatives), to avoid the need for second-order derivatives. This model generated a good performance when dealing with thoracic CT images. However, when dealing with angiography images, which are noisier and suffer from non-uniform illumination, it shares the same limitations of Hessian-based filters in finding small and low-contrast vessels. The reason is that it is still using the Hessian eigenvalues to pre-select the vessel-candidate pixels at which the filter is applied. In[5] a new framework proposed for the vessel enhancement filter, Utilizing the directional information present in an image. The proposed approach alleviates the calculation of the Hessian eigenvalues in a noisy environment. Specifically, the input image is first decomposed by a decimation-free directional filter bank (DDFB) into a set of directional images, each of which contains line-like features in a narrow directional range. The directional decomposition has two advantages. One is, the noise in each directional image will be significantly reduced compared to that in the original one due to its omni-directional nature. The other is, because a one-directional image contains only vessels with similar directions, this decomposition-filtering-recombination scheme also helps to preserve junctions.

The directional images are recombined to generate the output image with enhanced vessels, and the suppressed directional images are recombined to generate the output image with enhanced vessels, and the suppressed applied to enhance vessels in the respective directional images. Finally, the enhanced experimental results show that this approach is less noise-sensitive, can reveal the small vessel network, and avoid junction suppression.

Figure 3 gives the segmentation results[5] and comparison with the Frangi and Shikata models. An edge detection method was also employed to extract edges that may be parallel to the opposing edges of the vessel segment. These methods use an adaptive threshold scheme to extract the vascular segments from medical images. Computation of this threshold value may not be satisfactory for all the qualities of the images.

On the other hand, ridge tracing tubular objects and several other approaches were used to track the vascularity in a medical image. An adaptive tracking method was also presented to extract the extended tracts of vascularity in the X-ray angiograms.[15,22] Model-based approaches for
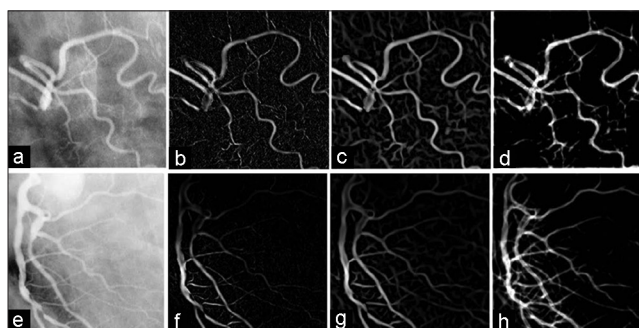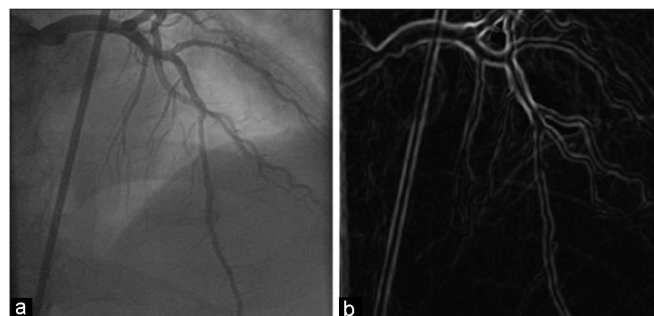

Figure 3: Qualitative results for two cardiac angiography images. (a and e) Original images, (b and f) enhanced images by Frangi method, 43.22 s each, (c and g) by Shikata method, 43.11 s, and (d and h) by the DFB-based approach, 49.08 s. The Frangi and Shikata models fail to enhance small vessels accurately, but the DFB-based approach succeeds[5]

explicit vessel structures were also applied to extract the vascularity in a medical image. One of these approaches used a deformable spline or the snake model to extract the vessel structures,[12,23] by deforming the spline or the snake to minimize some energy functions. Most of the present snake models could not provide a better capture range or evolution stop mechanism.

A[44] new external force for active contours is presented, which solves both the problems. An extension of the gradient vector flow snake (GVF snake) method is presented. First, adaptive balloon force has been developed to increase both the GVF snake's capture range and convergence speed. Subsequently, a dynamic GVF force is introduced to provide an efficient evolution-stop mechanism [Figure 4].

Artificial intelligence–based approaches use a rule- and knowledge-based expert system, to segment coronary vessels from digital subtracted angiograms.[4,18,45]

Automated systems and high processing throughput are needed in computationally intensive tasks, including visualization of the coronary blood flow and three-dimensional reconstruction of the vascular structure from biplane medical images.[12,14-16,18,20] The previous blood vessel

segmentation algorithms are limited by at least one of the following drawbacks. The drawbacks are, applicability of the method for a limited number of morphologies, the need of user involvement to select the region of interest, and lack of adaptive capabilities, which results in poor quality of the segmentation, requiring a large computational effort for blood vessel segmentation. A[46] model-based segmentation method is introduced for extracting blood vessel structures from poor quality coronary angiograms. This method extracts blood vessels in the angiograms by exploiting the spatial coherence existing in the image. Figure 5 gives the segmentation results.[46]

Table 1 presents the capabilities of some important algorithms mentioned earlier for coronary vessel segmentation. Coronary X-ray angiography is taken as the 'gold standard' for the assessment of coronary artery disease.

Thus, algorithms presented in Table 1 are specifically used for X-ray angiography. In this table, the comparison is based on different aspects. For instance as long as preprocessing is concerned, algorithms presented in the second and the third row need preprocessing. By comparing the results of these algorithms, the Truc[5] can be seen by using multiscale analysis, together with directional filters, and an acceptable

Figure 4: Normal X-ray coronary angiogram. (a) Input image, (b) improved GVF method[44]
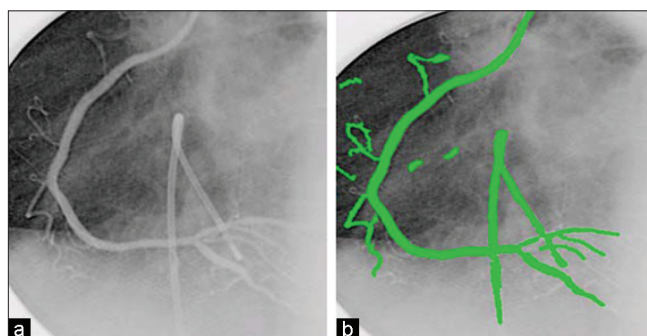
Figure 5: (a) A real image and (b) its segmentation result[46]

Table 1: A brief comparison of the coronary vessel segmentation algorithms in the X-ray angiogram

Algorithm	Year	Classification	Input type	Multi-scale	Pre-processing	A prior knowledge	User interaction	Centerline	Junction	Whole tree
Poli and Valli[22]	1997	PRA	XRA	✓	×	✓	✓	✓	✓	✓
Eiho and Qian[24]	1997	PRA	Coronary XRA	×	✓	✓	✓	✓	✓	✓
Klein *et al*.[12]	1997	MBA	Coronary XRA	×	✓	✓	✓	✓	×	×
Kottke and Sun[14]	1990	AIBA	Coronary XRA	×	×	✓	×	×	✓	✓
Devi[44]	2008	MBA	Coronary XRA	×	×	✓	✓	×	✓	✓
Cemal Köse[46]	2008	MBA	Coronary XRA	×	×	✓	×	×	✓	✓
Truc[5]	2009	PRA	Coronary XRA	×	✓	✓	×	×	✓	✓

XRA: X-Ray Angiography, MBA: Model-based approach, PRA: Pattern Recognition Approaches, AIBA: Artificial Intelligence–Based Approaches

performance is obtained in the segmentation of coronary vessels.

CONCLUSION

In this article we have tried to cover both early and recent literature related to coronary vessel segmentation algorithms and techniques. Our aim was to introduce the current segmentation techniques. We intended to give the practitioner a framework for the existing research.

Accuracy of the segmentation process is crucial according to the nature of the work and leads to more precise and repeatable radiological diagnostic systems. Accuracy can be improved by incorporating *a priori* information on vessel anatomy and making use of a high level knowledge guide for the segmentation algorithm. Even though expert knowledge and guidance is essential in segmentation systems, the sheer volume of the medical image data requires more automatic segmentation systems, to reduce the work load.

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