

Computer Aided Detection and Measurement of Peripheral Artery Disease

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Abstract. Computer-Aided Tomography Angiography (CTA) images are the standard for assessing Peripheral artery disease (PAD). This paper presents a Computer Aided Detection (CAD) and Computer Aided Measurement (CAM) system for PAD. The CAD stage detects the arterial network using a 3D region growing method and a fast 3D morphology operation. The CAM stage aims to accurately measure the artery diameters from the detected vessel centerline, compensating for the partial volume effect using Expectation Maximization (EM) and a Markov Random field (MRF). The system has been evaluated on phantom data and also applied to fifteen (15) CTA datasets, where the detection accuracy of stenosis was 88% and the measurement accuracy was with an 8% error.

Keywords. Computer aided detection, peripheral arterial disease, stenosis quantification, vessel detection.

Introduction

Peripheral artery disease (PAD), or peripheral vascular disease, is a severe ailment, with high mortality rates being experienced in recent times.

As a medical imaging investigation modality, Computed Tomography Angiography (CTA) is a reliable tool for the identification of arterial abnormalities. The 3D image analysis of CTA data is the basis for the diagnosis, quantification and surgical planning of vascular diseases [1].

The main arterial abnormalities in the peripheral artery are: stenosis (narrowing of the blood vessels), occlusion (total obstruction of a vessel) and calcification (accumulation of calcified atherosclerotic plaque). CTA images of the peripheral arteries also present a series of challenges associated with the partial volume effect (i.e. the mixture proportion of intensities of peripheral vessel boundary voxels and surrounding tissue), inhomogeneous bone tissue, image noise and the large number of image slices (up to 1000 per scan). Due to these factors a system that can automatically detect and quantify (CAD-CAM) PAD is highly desirable but has yet to be successfully developed.

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A wide range of segmentation techniques have been applied for PAD CAD. Felkel et al. [2] overviewed existing segmentation methods for peripheral vessels in CTA datasets, identifying issues such as the non-homogenous distribution of the contrast agent and the partial volume effect. However, most of these approaches require manual intervention. A system for vessel visualisation and analysis has been applied to MRI images [3] and the detection analysis was limited and not targeted at PAD or its particular challenges (e.g. the proximity of bone). The main achievement of the system was the automatic quantification of stenosis.

The CAM task has been explored in the literature but applied to the more general application of vascular measurement and was only assessed on a 3D synthetic phantom representing vessels with different structures [4].

This paper proposes an integrated CAD-CAM system for detecting PAD. The CAD system automatically detects the peripheral arteries using a sequence of image segmentation operations: optimal thresholding, 3D region growing and bone removal, a fast morphology operation, artery centerline detection and distortion correction. Accurate measurement of the artery diameters is performed orthogonal to the centreline and is combined with a method to compensate for the partial volume effect based on Expectation Maximization (EM) and Markov Random fields (MRF).

1. Methods

The following major algorithmic steps are used to extract and measure the dimensions of the peripheral vascular network.

Optimal thresholding – the high-contrast vessels in CTA images can be detected using intensity thresholding. The threshold value is estimated using an optimal selection algorithm.

3D region growing – a 3D region-growing algorithm is seeded at a location determined by automatically identifying the bifurcation of the aorta at the junction with the common iliac artery. The bifurcation of the aorta is identified using thresholding (a), labeling and removing other objects such as spinal cord by taking into account the anatomical information of abdominal region based on length, angle and location features.

Bone removal – bone detection is problematic in the upper (pelvic) and lower (popliteal) regions of the image data. A connected component analysis algorithm is used to label the image in 2D and 3D regions. For each of the problematic sub-volumes, the algorithm utilises anatomical and spatial information. For example, the hip bones are large in comparison with the iliac arteries, so this characteristic is used for identifying and removing the bone tissue in this region. A fast morphology operator is used to repair holes and lost connectivity in the vessel construction. The method uses efficient shift operations applied to packed bit arrays using the BigInteger data structure of the C# programming language. With this novel implementation, the maximum number of arithmetic operations is at most 27 for the entire image, independent the size of the morphological mask used.

Centerline detection - a thinning algorithm, proposed by Lee [6], was implemented and tested. The algorithm uses a fast, iterative, symmetrical erosion technique using topological information of the image. The algorithm is based on a decision tree method and finds all the deletable surface points. In order to create a smooth

centreline and correct distortions, an interpolation method based on Catmull Rom splines [5] was employed. This method is based on the general approach of spline curves where an interpolating curve is constructed from a given sequence of points and is constrained to pass through each point.

Orthogonal plane construction – image cross-sections normal to the peripheral vessel centreline are obtained from a sliced-based rendering technique (SBVR) [7] which uses texture for visualization of 3D data sets. The image data is represented as a 3D texture and a view-aligned bounding box is generated around the volume. The intersection between a plane and the bounding box is performed. The intersection slices are a series of polygons characterized by the intersection vertices between the plan and the bounding box, which can be at most 6 vertices. The polygons are then decomposed into a series of non overlapping triangles derived from the polygon centroid. These triangles are textured through linear interpolation using the intersection points and the volume data. Since the original data set is a lattice with values specified at certain points, an interpolation scheme is used to sample the values.

Vessel diameter measurement – the diameter of the peripheral vessel is measured directly from the orthogonal image cross-section extracted in (e) and computed as the diameter of the equivalent circle. To minimize the measurement error, especially for narrow vessels, an algorithm based on a maximum a posterior (MAP) expectation maximization (EM) algorithm is used to compensate for partial volume errors. For this, the mixture percentage (percentage of the mixture of peripheral vessel and surrounding tissue) for each voxel is determined, making use of the image as input and of the voxel’s neighbours. The algorithm is iterative and the estimation of tissue mixtures is determined at each iteration by maximizing the conditional expectation.

Stenosis identification – finally, a stenosis is identified as a distinctive narrowing of the vessel diameter over a short length of vessel.

2. Results

The proposed CAD-CAM system has been validated using a vascular phantom and real patient data. For the CAD system validation, the real data was supported by ground-truth assessed by two experienced radiologists.

Vascular Phantom: The vascular phantom used for the CAD-CAM system assessment simulates the vessel’s anatomy and can be used in conjunction with other imaging acquisition systems. The MAP-MRF method was evaluated on phantom data and compared with the threshold method for performance assessment. A threshold of 200 (HU) was used, corresponding to the simulated artery in the phantom. The results in table 1 show that the MAP-MRF method is superior to the threshold algorithm, resulting in significantly smaller errors for the estimation of the vessel diameters.

Table 1. The average diameter measurements obtained by applying threshold and MAP-MRF methods on 32 phantom samples of 18 slices each

Diameter true value (mm)	1	2	4	6
Threshold mean value (mm)	1.326	2.532	4.637	6.682
Threshold Percentage error	32%	26.6%	15.9%	11.3%
MAP-MRF mean value (mm)	1.108	2.136	4.284	6.341

MAP-MRF Percentage error	11%	6%	7%	6%
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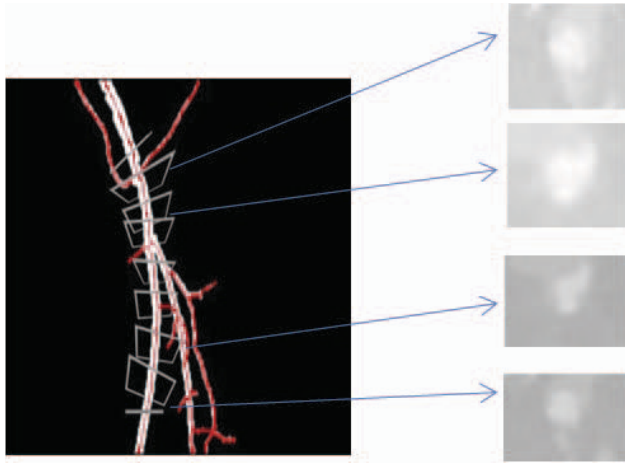


Figure 1. a. (left) Vessel centerline (in red) overlaid onto the extracted artery; b. (right) vessel intensity cross-section orthogonal to the artery centreline;

Real patient data: The CAD-CAM methodology was applied to fifteen (15) CTA scans of patients with PAD supplied by CHUV, Lausanne. The images were acquired with GE Multi-slice helical CT having the following parameters: 120kV, 749 mA, slice thickness 0.6 mm. Fig. 1a shows the extracted vascular network (in white), the centerline (in red) and a series of plane sections that orthogonally intersect the profile. Figure 1b shows examples of the image intensity cross-section through the planes. Fig. 2a shows the result of the optimal thresholding in a region near the head of the femur, which detects both vessel and adjacent bone tissue. Figure 2b shows the result after successful removal of the bone tissue. Figure 3 shows a profile of the vessel diameter in the slice and the corresponding slice number. The dashed lines indicate the stenotic region, characterized by a significant reduction in vessel diameter measured over two consecutive slices. From the 15 patient scans a total of 149 stenotic segments were identified by the radiologist's assessment, for which the CAD stenosis detection resulted in a sensitivity was 0.88 (131 correctly detected) while the specificity was 0.96 (i.e. 3 false positives).



Figure. 2 a) Maximum intensity representation of vessel contiguous to femur bone; b) after bone removal

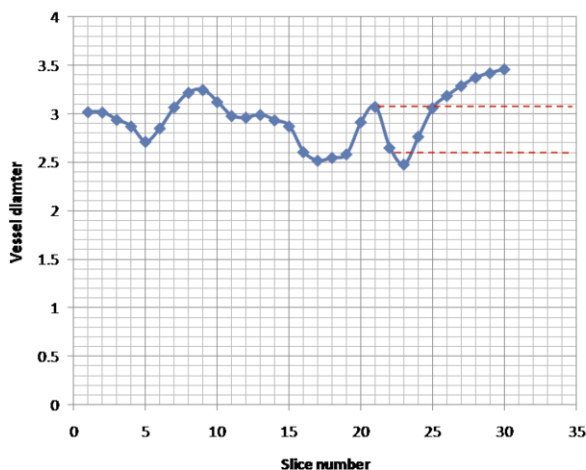


Figure 3. Vessel profile for a short section of a CTA sample data.

3. Discussion

Quantitative results from a phantom target have been used to validate the accuracy of the vessel detection and diameter measurement. When applied to CTA patient scan data the system was able to detect 131 locations of stenosis compared to the 149 reported by the radiologist (i.e. sensitivity of 0.88), with a false positive rate of only 4%. These results are particularly promising as, according to the radiologists' assessment, 132 of the stenoses can be attributed to soft plaque deposits, which can be more challenging to detect than the hard plaque variety. The results demonstrate the potential application of CAD-CAM for PAD, which we believe can be further improved using more sophisticated algorithms for determining the degree of vessel narrowing in stenosis.

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