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Automatic segmentation of cross-sectional coronary arterial images

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ABSTRACT

We present a novel approach to segment coronary cross-sectional images acquired using catheterization imaging techniques, i.e. intra-vascular ultrasound (IVUS) and optical coherence tomography (OCT). The proposed approach combines cross-sectional segmentation with longitudinal tracking in order to tackle various forms of imaging artifacts and to achieve consistent segmentation. A node-weighted directed graph is constructed on two consecutive cross-sectional frames with embedded shape constraints within individual cross-sections or frames and between consecutive frames. The intra-frame constraints are derived from a set of training samples and are embedded in both graph construction and its cost function. The inter-frame constraints are imposed by tracking the borders of interest across multiple frames. The coronary images are transformed from Cartesian coordinates to polar coordinates. Graph partition can then be formulated as searching an optimal interface in the node-weighted directed graph without user initialization. It also allows efficient parametrization of the border using radial basis function (RBF) and thus reduces the tracking of a large number of border points to a very few RBF centers. Moreover, we carry out supervised column-wise tissue classification in order to automatically optimize the feature selection. Instead of empirically assigning weights to different feature detectors, we dynamically and automatically adapt those weighting depending on the tissue compositions in each individual column of pixels. The proposed approach is applied to IVUS and OCT images. Both qualitative and quantitative results show superior performance of the proposed method compared to a number of alternative segmentation techniques.

1. Introduction

Coronary atherosclerosis is an inflammatory disorder that involves deposition of cholesterol and other fatty substances within the arterial wall. It can lead to progressive narrowing of coronary arteries, which can cause angina, or sudden blockage of the coronary arteries leading to acute myocardial infarction. Intra-vascular Ultrasound (IVUS) and optical coherence tomography (OCT) are catheter-based technologies, which capture 2D cross-sectional images of the coronary arteries. Both modalities measure the back-scattered signal from the surrounding vessel structure after sending sound wave in IVUS or light in OCT. These provides a much detailed visualization of lumen, stent strut location, and plaque morphology. A coronary cross-section is generally seen as a lumen and a coronary vessel wall, the latter consisting of three layers: intima, media and adventitia. There are two types of borders of clinical interest: the lumen-intima border that corresponds to the inner coronary arterial wall and the media-adventitia border that represents the outer coronary arterial wall located between the media and adventitia (see Fig. 1). This work is concerned with segmenting the media-adventitia boder in IVUS and lumen boder in OCT. The segmentation of the lumen border in OCT allows, for instance, quantitative analysis of vessel narrowing and its impact on blood supply to myocardium, and the localization of the media-advetitia border in IVUS provides both the exterior geometry of the coronary vessel and the region of interest for virtual histology.

Various techniques have been developed to segment IVUS images, e.g. Klingensmith et al. (2000), Cardinal et al. (2006), Papadogiorgaki et al. (2008), Sonka et al. (1995), Takagi et al. (2000), Essa et al. (2011), Destrempes et al. (2014), Gao et al. (2015), Su et al. (2017) and Zakeri et al. (2017). Methods that fit contours to local image gradients, e.g. Klingensmith et al. (2000), are susceptible to common artifacts, such as speckle noise and acoustic shadow. Moreover, user initialization is often necessary in order to converge to meaningful local minima. There are also methods that use global regional information, instead of intensity discontinuities. For instance in Cardinal et al. (2006), Cardinal et al. assumed that each region consists of uniform scattering in tissue and has its own statistically distinctive Rayleigh distribution. However, it is expected that arteries captured in

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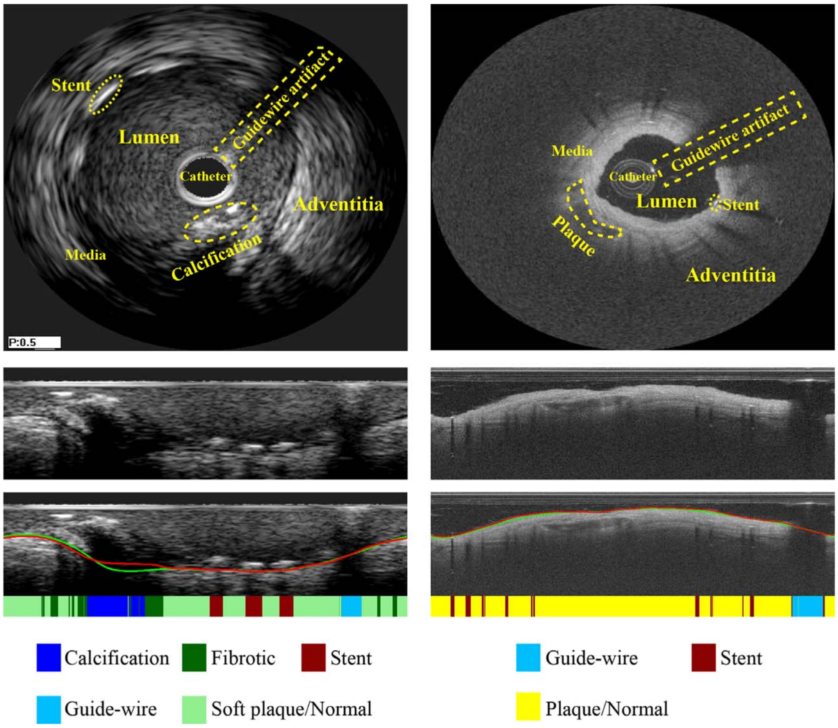

Fig. 1. Example IVUS and OCT images. First row: original images. Second row: polar transformed images. Last row: segmented media-adventitia border in IVUS and lumen border in OCT using the proposed method (red); the groundtruth is shown in green. The bottom of each segmented image visualizes our tissue classification results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

IVUS contains various forms of diseased tissue which greatly compromises their assumption. Textural information has also been used. Papadogiorgaki et al. (2008) proposed to use discrete wavelet frames to construct decomposition trees to identify vessel wall borders. RBF is then used to smooth the initial contour obtained by applying a threshold on those texture features. However, the method suffers from the presence of stent or severe calcium plaque. Recently in Su et al. (2017) and Zakeri et al. (2017), pixel-wise classification was used to obtain initial wall borders. Su et al. (2017) used double neural networks to segment wall borders, while Zakeri et al. (2017) used sparse representation based classification and then refined the result using an active contour model. To deal with heterogeneous texture in high-frequency IVUS images remains a challenge.

Similar approaches have been applied to OCT imaging, e.g. Kauffmann et al. (2010), Gurmeric et al. (2009), Unal et al. (2010), Tung et al. (2011), Ughi et al. (2012), Tsantis et al. (2012) and Cao et al. (2017), which has become increasingly popular due to its high resolution. Parametric active contours can cope with small gaps introduced by stent shadow as long as the landmark points are localized on the lumen border. For example, the methods proposed in Kauffmann et al. (2010), Unal et al. (2010) and Gurmeric et al. (2009) rely on active contour parametric interpolation to cope with the acoustic shadow caused by stent. However, guide-wire and blood residue can cause much larger and more irregular acoustic shadow that interpolation alone may not be sufficient. The work in Kauffmann et al. (2010) requires occasional user inspection and intervention based on assumptions of the regularity of the lumen border. Tung et al. (2011) used a convex hull based approach to identify guide-wire shadow casting on the lumen border after an initial segmentation. It is assumed that most part of the lumen border in OCT is clearly visible and continuous. Thus, a large discrepancy between derived convex hull and initial segmentation indicates optical shadow. However, the lumen border may not always be convex, particularly at bifurcations. Although more sophisticated texture analysis techniques may improve the segmentation performance, e.g. Tsantis et al. (2012), these data driven approaches generally suffer from the imperfection in imaging and natural variations in anatomical structure and tissue composition. Others also resorted to user interaction to eliminate the ambiguity in imaging, e.g. Ughi et al. (2012).

In an attempt to overcome the shortcomings of imaging features, anatomical and imaging priors have been used to constrain the segmentation. Sonka et al. (1995) requires the user to draw an elliptic shape to identify the region-of-interest (ROI) and uses parametrized prior knowledge on arterial wall thickness and double echo pattern in objective function to carry out segmentation. However, these hard constraints may not be valid in some cases, e.g. media thickness. Takagi et al. (2000) extended the work by incorporating spatio-temporal filters to reduce blood speckles in order to enhance contrast. This however does not address the issue of acoustic shadow or scattering due to stent or calcification. More recently in Essa et al. (2011), an auxiliary border is used to tackle the distractions caused by stent and calcification and assumed the real media-adventitia border is beneath the auxiliary border in a simultaneous segmentation. The behavior of the auxiliary border can be hard to predict, particularly when there is no such distractions.

Learning and using appropriate priors are hence important. One approach is to adopt user interaction and directly impose prior knowledge through initialization and/or user adjustment, e.g. Sonka et al. (1995), Klingensmith et al. (2000), Cardinal et al. (2006), Veksler (2008), Jones et al. (2014) and Sun et al. (2013). Sun et al. (2013) proposed a semi-automatic graph-based method, in which a pre-segmentation of the lumen is necessary to construct the graph. A combination of edge and region based costs are assigned to each node. The method requires the user to interactively correct the segmentation result on the longitudinal view. Incremental user input are allowed until satisfactory segmentation is achieved. The maximum inter-frame difference is set as a global constant in order to impose the smooth constraint. An alternative is to generalize priors and impose them as constraints in order to achieve automated segmentation. Unal et al. (2008) used signed distance transform to implicitly represent prior shapes and applied principal component analysis (PCA) to generalize the shape variation. Its automated initialization of the media-adventitia border, however, is based on the maximum gradient information which is susceptible to imaging artifacts. In Wahle et al. (2006), short vertical image segments are collected along media-adventitia borders to score image segments in unseen images