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Lumen and media-adventitia border detection in IVUS images using texture enhanced deformable model

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A B S T R A C T

Lumen and media–adventitia (MA) borders in intravascular ultrasound (IVUS) images are critical for assessing the dimensions of vascular structures and providing plaque information in the diagnosis and navigation of vascular interventions. However, manual delineation of the lumen and MA borders is an intricate and time-consuming process. In this paper, a texture-enhanced deformable model (TEDM) is proposed to accurately detect these borders by incorporating texture information with the morphological factors of deformable model. An ensemble support vector machine classifier is used to classify IVUS pixels presented by texture features into different tissue types. The image regionalization maps of different tissue types are further used for texture enhancement modules in the TEDM. The proposed TEDM method has been tested on 1500 images from 15 clinical IVUS datasets by comparing with the manual delineations. Evaluation results demonstrate that our method can accurately detect lumen and MA surfaces with small surface distance errors of 0.17 and 0.19 mm, respectively. Accurate segmentation results provide 2D measurements of MA/lumen areas and 3D vessel visualizations for vascular interventions.

1. Introduction

Intravascular ultrasound (IVUS) is a catheter-based intravascular imaging technique for vascular diseases such as coronary stenosis, atherosclerosis, and calcification (Vykoukal et al., 2014). Delineation of lumen and media–adventitia (MA) borders in IVUS images is a crucial step for the quantitative analysis of vessel characteristics. 3D vessel visualization through border delineation provides intuitive guidance for vascular intervention. A typical IVUS sequence usually contains large amounts of 2D images for segmentation, making manual delineation time-consuming and labor intensive. In addition, manual delineation often involves large inter-operator variability (up to 20%) (Meier et al., 1997). Therefore, it is clinically desirable to develop a computer-assisted algorithm to automatically and accurately delineate MA and lumen borders. However, border detection is challenging for two reasons: (1) There are complex artifacts in IVUS images (Taki et al., 2013), in particular, the shadow artifacts derived from the catheter and guide wire. (2) The double segmentation results of MA and lumen borders are difficult to achieve simultaneously (Athanasiou et al., 2014). Several border detection techniques have been developed for IVUS images, including graph-based methods, deformable models, and feature-based methods. Graph-based methods need complex image preprocessing and efficient user-guided refinement because these methods depend on accurate seed-point initialization and are influenced by low-contrast edges (Sun et al., 2013; Xu et al., 2007; Downe et al., 2008). Instead, deformable models (Han et al., 2003; Chan and Vese, 2001) are effectively used for IVUS image segmentation because the desired vessel border has a characteristic rounded shape and the morphological factors of the deformable model can ensure smooth rounded shapes (Zhu et al., 2011). However, abundant texture features are not used in deformable models during IVUS image segmentation, resulting in certain limitations.

Firstly, the initial contour must be placed close to the desired border during deformable-model-based IVUS segmentation. A semiautomatic deformable model was presented by Hossain et al. for carotid ultrasound images, but initial boundary points were needed on every image (Hossain et al., 2013). Luo et al. proposed an initial searching range based on the continuity of the IVUS images (Luo et al., 2003). These methods were only able to analyze IVUS images frame-by-frame and were difficult to accelerate by parallel computing. The threshold method was used to detect initial contours, but it adopted single intensity information (Taki et al., 2008). Secondly, the smoothness of the borders is influenced by the shadow artifacts caused by the catheter and guide wire in high-frequency IVUS images (Mendizabal-Ruiz et al.,

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2008; Katouzian et al., 2012). Hernandez et al. used an anisotropic operator to enhance image edges, but only the detection of the MA border was finished (Hernandez et al., 2004). A geometric flow measuring the shape irregularities was used in a deformable model to ensure the smoothness of the IVUS surface (Gil et al., 2002). These methods used only gray distribution instead of abundant texture features and could not effectively represent the characteristics of IVUS pixels. Thirdly, the controlling parameters in a deformable model vary from case to case and require substantial manual intervention. However, there are recently few researches which study automatic parameter setting for IVUS image segmentation.

Feature-based pixel classification is generally used for image segmentation by extracting pixel features and modeling feature distribution. Gao et al. proposed a segmentation framework by using region-growing and gray-feature-based unsupervised clustering (Gao et al., 2015). A Bayesian classifier was used to extract the calcified plaque in IVUS images (Han et al., 2003). In addition, vessel contours were extracted and reconstructed with an adaptive k-means clustering method (Shivakumar, 2011). Essa et al. combined Gaussian features and shape priors to detect the MA border, but this method used only information related to intensity differences (Essa et al., 2012). In summary, feature-based statistical segmentation implements information of feature distribution and various classifiers but lacks spatial information. In addition, for IVUS image segmentation, feature-based classification neglects the morphological factors of borders such as continuity, curvature, and elasticity. These factors control the detected borders and retain their rounded shape like the morphological features of real vessels.

Research on IVUS texture analysis for segmentation has been very limited, and this paper contributes to this field by combining texture classification into deformable models for vessel border detection. Compared with existing IVUS segmentation methods, the novelties of the proposed texture-enhanced deformable model (TEDM) include: (1) An ensemble support vector machine (SVM) classifier is used for texture-based IVUS pixel classification for the first time. (2) Information related to significant IVUS texture is combined with the morphological factor from a deformable model for accurate border detection. The extensive experiments on 1500 IVUS patient datasets demonstrate the effectiveness of the proposed method.

2. Materials and methods

Our TEDM method is used to detect the MA and lumen borders on each image being segmented in one IVUS patient sequence. With all the detected borders in a sequence, the MA and lumen surfaces of a 3D vessel are acquired for diagnosis and guidance in vascular interventions. The block diagram of the TEDM is illustrated in Fig. 1. For the processing of each IVUS image, the TEDM consists of two major stages: IVUS pixel classification with texture features (Section 2.2) and texture enhancement modules (Section 2.3). In the first stage, abundant texture features of IVUS pixels are extracted for each image. These IVUS pixels represented by the texture features are classified into different tissue types and acquire regionalization maps through an ensemble support vector machine (SVM) classifier. A deformable model has three limitations on IVUS image segmentation: improper initial contours, an edge indicator influenced by shadow artifacts, and inefficient manual parameter tuning. Therefore, in the second stage of the TEDM, regionalization maps from the first stage are used for three texture enhancements, i.e., (1) texture-controlled initialization, (2) texture-enhanced edge indicator, and (3) adaptive parameterization, to solve the above problems. Finally, these three texture enhancements are integrated into the deformable model, and this texture-enhanced model evolves iteratively to detect the MA and lumen borders accurately.

2.1. TEDM method

A traditional deformable model approximates the evolution of borders by tracking the zero level set of a higher-dimensional function φ (Li et al., 2005). φ evolves under the internal penalty momentum $\varsigma(\varphi)$, image gradient information $\zeta(\varphi)$ and external information $\xi(\varphi)$ (Eq. (1)).

$$\frac{\partial\varphi}{\partial t} = \mu\varsigma(\varphi) + \lambda\zeta(\varphi) + \upsilon\xi(\varphi) = \mu\left[\Delta\,\varphi - \mathrm{div}\left\{\frac{\nabla\varphi}{|\nabla\varphi|}\right\}\right] + \lambda\left[\delta(\varphi)\mathrm{div}\left\{g\frac{\nabla\varphi}{|\nabla\varphi|}\right\}\right] + \upsilon g\delta(\varphi)$$
$$\varphi(x,y,\,t=0) = \varphi^{0}(x,\,y) \tag{1}$$

In internal penalty momentum $\varsigma(\varphi) = \Delta\,\varphi - \mathrm{div}\left\{\frac{\nabla\varphi}{|\nabla\varphi|}\right\}$, Δ is the Laplacian operator and $\mathrm{div}\left\{\frac{\nabla\varphi}{|\nabla\varphi|}\right\}$ approximates the mean curvature. The image gradient force $\zeta(\varphi) = \delta(\varphi)\mathrm{div}\left\{g\frac{\nabla\varphi}{|\nabla\varphi|}\right\}$, $\delta(.)$ denotes the Dirac function, g is the edge indicator, defined as

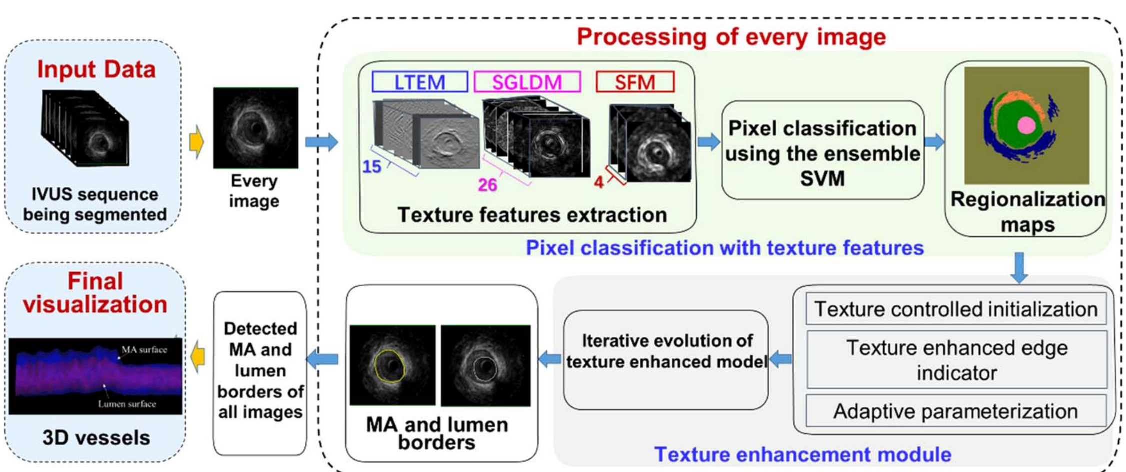

Fig. 1. Block diagram of the texture enhanced deformable model (TEDM).