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Automatic segmentation of vessels from angiogram sequences using adaptive feature transformation

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ABSTRACT

This paper proposes an efficient method for automatically segmenting vessels from angiogram sequences. The method includes two steps: extracting high-contrast angiograms and segmenting vessels. First, we select high-contrast angiograms automatically using vessel intensity distribution. Based on multiscale Hessian-based filtering, we propose an adaptive feature transformation function to improve the vesselness response. This method overcomes numerous problems, which exist in the X-ray angiograms by using the scale factors and transformed intensities. Various scales are established to mitigate variations of the intensity distribution. The transformed intensities are applied to coping with lower contrast and nonuniform intensity distribution. Finally, the connected component labeling method is used to extract the vessels. The proposed method can distinguish between the vessel and the background in a complex background. In our experiments, 20 angiogram sequences are used to evaluate the accuracy of the selected high-contrast angiogram. The accuracy of extracting high-contrast angiograms is 98%. For evaluating the accuracy of the segmentation results, 72 angiograms were selected. The accuracy of the proposed segmentation method is 96.3%. The Kappa value is 81.8%. After inspection by a cardiologist, the experimental results show that the proposed method can automatically and accurately segment vessels.

1. Introduction

Cardiovascular disease is one of the major types of heart disease. For diagnosing and treating cardiovascular disease, coronary angiography is a vital evaluation and operation tool. Clinicians may not easily obtain complete vessel structures from 2D X-ray angiograms because of the complex background and noise. Accurate quantitative coronary angiography (QCA) in clinical examinations can assist clinicians in assessing cardiovascular diseases. Moreover, computer-assisted extraction of the vessel structure is a crucial step in 2D coronary angiography. Recently, various image analysis technologies have been proposed for cardiovascular examinations. Vessel segmentation is essential for motion analysis, stenosis detection, and 3D reconstruction. However, vessel segmentation from X-ray angiograms entails difficulties caused by nonuniform intensity distribution, low-contrast angiograms, and various vessel shapes. Additional factors including noise and overlapped organs also exacerbate the problem. Therefore, this paper proposes a method that can accurately segment vessels under such complex conditions.

Several proposed vessel segmentation methods can be classified as tracking-based [1–5], model-based [6–12], and pattern recognition [13–24]. Tracking-based methods entail using local operators to detect vessels. Traditional tracking-based methods cannot work effectively because of bifurcations or vessel crossings. For achieving high accuracy, Gabor filters and circular templates have been proposed. Zhou et al. [3] utilized vessel features to track vessels and identify vascular structures based on probabilistic tracking and fuzzy inferring. However, this method requires higher computational costs for creating new templates because of the variation of vessel widths. Zamani Boroujeni et al. [4] proposed an improved center-line tracing algorithm based on local features in multiscale enhanced angiograms. This method involves employing a scanning scheme based on Hessian-based filtering to detect vessel points and includes a look-ahead distance method for calculating the magnitude of each vessel point. However, the method cannot extract vessel features because of the low contrast and noise. An adaptive geometrical vessel tracking method [5] was proposed, entailing an algorithm that first detects seed points in an enhanced image and then extracts vessel points from the

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original angiogram based on the geometric features. Vessel points were recursively detected in scanlines, which were adjusted according to the estimated vessel diameters. However, angiograms have shortages such as low contrast, nonuniform intensity distribution, and background noise. Thus, these methods cannot effectively track vessels in complex background conditions.

Model-based methods, such as deformable splines and active contour models, involve using a set of parametric curves to automatically segment vessels. Active contours can be categorized into two categories: edge-based and region-based. Edge-based models use local edge information to stop the evolving curve on the object boundary. Region-based models apply regional statistics information to control curve evolution. Chan and Vese [6] proposed a typical region-based active contour model that involves using a level set method, which requires utilizing image statistics inside and outside the curves to control the evolution. However, region-based active contour methods cannot mitigate nonuniform intensity distribution effectively. Recently, many improved algorithms [7–9] based on region-based active contour model have been proposed for solving this problem. Li et al. [7] defined a local binary fitting (LBF) model, which utilizes local region information as a constraint to contend with nonuniform intensity. Zhang et al. [8] also introduced a local image fitting (LIF) model for segmenting images. However, an LIF model cannot accurately segment vessels, and an LBF model is highly sensitive to the initial location of the active contour. Sun et al. [10] proposed an active contour model, which can segment vessels with nonuniform intensity and solve the initial state of the active contour, using local morphology features. However, model-based methods cannot set parameters appropriately and this may affect computational efficiency.

Pattern recognition methods, such as morphology filters [13–17] and multiscale Hessian-based filtering [18–24], automatically detect objects according to vessel features. The morphology top-hat operator has been used as a preprocessor to improve low contrast [13–14]. However, these methods do not perform well because of complex vessel structures and variations in vessel widths. For obtaining a complete vessel structure, a multiscale morphological operator method was proposed [13]. In previous research, a fuzzy morphological opening was used to segment vessels [15–17], and multiscale morphological operators were used to combine fuzzy morphological filters with a linear structuring element [15].

Multiscale Hessian-based filtering approaches are proposed in the literature. Vessel enhancement is a primary preprocessing procedure based on the Hessian matrix. Frangi et al. presented a multiscale Hessian-based filtering method for describing local vessel structures [18] toward obtaining the second-order local feature of the vessel based on the eigenvalues of the Hessian matrix. In this method, both

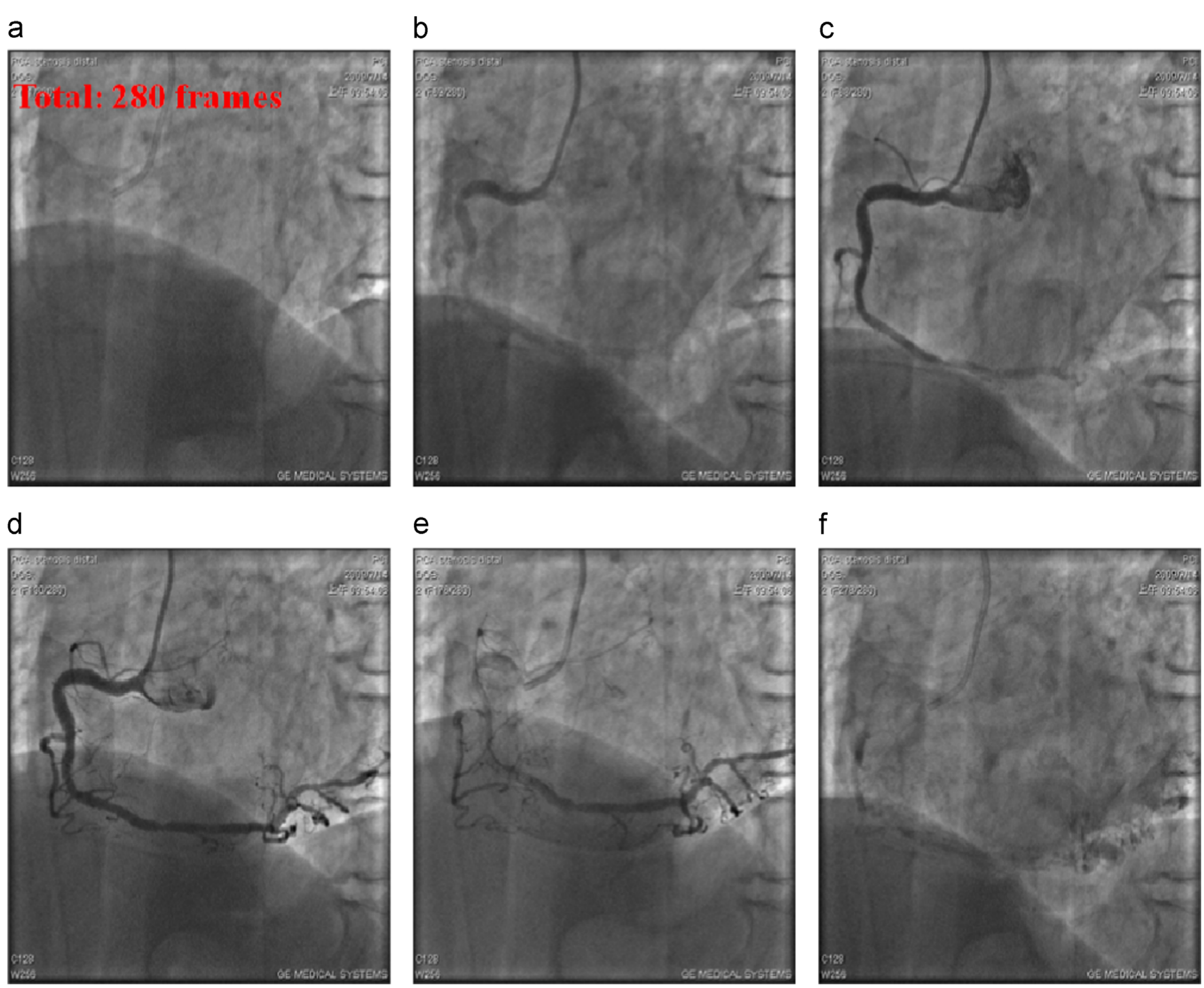

Fig. 1. Responses to the injection of contrast agent: (a) angiograms before injecting contrast agent; (b) and (c) angiograms when the contrast agent is not distributed completely in vessels; (d) angiograms when contrast agent is distributed into vessels completely; (e) angiograms after some contrast agents are attenuated; and (f) all contrast agents attenuated.