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Research Paper

Segmentation of vessels in angiograms using convolutional neural networks

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ABSTRACT

Coronary artery disease (CAD) is the most common type of heart disease and it is the leading cause of death in most parts of the world. About fifty percent of all middle-aged men and thirty percent of all middle-aged women in North America develop some type of CAD. The main tool for diagnosis of CAD is the X-ray angiography. Usually these images lack high quality and they contain noise. Accurate segmentation of vessels in these images could help physicians in accurate CAD diagnosis. Many image processing techniques have been used by researchers for vessel segmentation but achieving high accuracy is still a challenge in this regard. In this paper a method for detecting vessel regions in angiography images is proposed which is based on deep learning approach using convolutional neural networks (CNN). The intended angiogram is first processed to enhance the image quality. Then a patch around each pixel is fed into a trained CNN to determine whether the pixel is of vessel or background regions. Different elements of the proposed method, including the image enhancement method, the architecture of the CNN, and the training procedure of the CNN, all lead to a highly accurate mechanism. Experiments performed on angiograms of a dataset show that the proposed algorithm has a Dice score of 81.51 and an accuracy of 97.93. Results of the proposed algorithm show its superiority in extraction of vessel regions in comparison to state of the art methods.

1. Introduction

Coronary artery disease (CAD) is currently the number one cause of death in many parts of the world, causing one in every four deaths in the US and affecting more than 13 million people there. Healthy arteries are smooth and elastic. CAD occurs when arteries get narrowed or blocked because of fat, cholesterol or other substances, called plaque, circulating in the blood. Plaques that accumulate on the inner walls of arteries create stenosis. Stenosis in arteries causes restriction of the flow of blood to the heart and leads to critical situations such as heart attacks [1].

Among various methods that exist for diagnosing CAD disease, X-ray angiography is known to be the main standard procedure. In this method, the arteries are filled with a contrast agent in order to show the arteries in the X-ray images. For this purpose, a long and thin hallow tube, called catheter, is inserted into an artery in the patient's arm or groin. The tube is then guided through the major coronary arteries that are intended to be examined. When the catheter arrives at the target arteries, the contrast agent is injected and a number of X-ray images are recorded. The taken sets of images, called angiograms, would visualize the coronary vasculature.

However, the captured angiograms usually have a low quality due to the existing limitations on X-ray radiation. The emission of X-ray in angiography is restricted due to its side effects on human body. As a result, usually there is a low contrast between the vessel region and its background. Various computer based methods are introduced in order to aid the usability of these images. Meanwhile, a critical step towards the detection of stenosis is the accurate segmentation of vessel regions from its background. The captured images may suffer from uneven brightness, presence of tissues other than arteries, noise and blurriness caused by heart motions and movements of the camera [2]. These problems make the segmentation of vessels in X-ray angiograms a challenging task.

Existing vessel segmentations can be categorized in three main groups of model-based, tracking-based, and pattern recognition-

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based methods [3]. Active contours are a group of segmentation methods that belong to the model-based methods. Active contour methods include two main approaches [4] of edge-based and region-based. In edge-based models local edge information is used as a criterion to stop the curve from evolving. The region-based models perform by using statistical information from the inside and outside of the curve and are less affected by the presence of noise. The Work of [4] is an example of active contour models for vessel extraction. A local feature fitting function is proposed to detect the vessel in different sizes. Also, it is supposed to be resistant against the presence of noise, inhomogeneity and complexity of the background in the image. Nonetheless, active contours approaches usually fail in the handling of non-uniform illumination. Also, active contours are highly dependent on the initial selection of contour and they usually have high computational complexity.

The tracking-based segmentation methods use local information to detect the vessels. Tracking-based methods start from an automatically or manually selected initial point and follow the path that better matches the vessel profile to track the vessel edges or the vessel centerlines. By completely scanning the image, a connected region that locates vessel regions would be obtained. In Ref. [5] an iterative probabilistic tracking method is proposed for the segmentation of retinal vessels. Authors of Ref. [5] manually select a starting point to track the vessel using continuity in vessel gray levels. The tracking-based models could deal with vessel crossings and bifurcations and they provide geometrical features of the extracted vessel. The method proposed by Zhou Sh. et al. [6] is another example of tracking-based method that uses fuzzy inferring and tracking. Authors of Ref. [6] firstly enhance the images by applying Gabor and Hessian filter. The artery vessels are chosen from a group of candidates derived by a probabilistic tracking operator (PTO). A sun-operator, as vessel structure pattern detector (SPD), assigns the extracted parts of the vessel to bifurcation or crossing groups [6]. The tracking-based models might be misled when the resolution is low or complex image background exists.

Filtering methods such as Hessian-based filters, Flux-based filters [7,8] and non-linear diffusion can be categorized as pattern recognition-based approaches. Frangi et al. [9] proposes analysis of eigenvalues in Hessian matrix for detection of the vessel region. Work of Refs. [10] and [2] are other filtering methods that take advantage of decimation-free directional filter bank (DDFB), Hessian filter, and guided filtering, for enhancement of X-ray angiography images. In Ref. [11], Hessian filter is used for detection of coronary arteries region-of-interest (ROI). It then performs the segmentation using both the extracted ROI and measurements of a flux flow filter. Also, in the work of Ref. [12], that is a pattern recognition-based method, an algorithm is proposed for automatic vessel extraction using graph-cuts [13]. Authors of Ref. [12] use graph-cut that is based on geodesic paths and multistage edge maps. However, geodesic methods are usually sensitive to noise and complex vessel structures and background regions.

Recently deep learning methods have shown promising results in various image processing and medical imaging applications [14–19]. Convolutional neural networks (CNN) are among powerful deep learning methods that are suitable for image processing applications. While these networks are introduced more than two decades ago [20], their usage has increased rapidly in recent years. The recent growth of usage is due to the development of techniques that have facilitated the training of these networks [21]. CNNs consist of several convolutional and pooling layers which are usually followed by one or more fully connected layers. CNNs can be used as an effective tool for automatic feature extraction.

Deep convolutional neural network is configured for the detection of retinal vessel in Ref. [14]. In Refs. [15,16] the CNN is used for the classification of lung disease. Works of Refs. [17] and [18] are other researches that have considered CNNs for medical imaging applications for the detection of brain tumors and the diagnosis of skin cancer. Moreover, Ref. [19] proposes a deep learning approach for segmentation of lesions from skin images. In Ref. [22] Nasr et al. present a deep learning method for segmentation of vessels in angiograms. In Ref. [22], a single path CNN is used based on relatively large sized windows, hence it can be considered that global patches are being used. The use of single source of information in Ref. [22] results in a relatively poor performance in accurate detection of the boundaries of vessels in some images. Accurate segmentation of boundaries is essential in diagnosis of stenosis.

In the proposed method in this paper the networks accuracy is improved in comparison with the preliminary version of the work presented in Ref. [22] using the following three novelties:

- Combination of the information that exist in local and global patches.
- Usage of the neighboring pixels' labels that are obtained from an initial segmentation map.
- Taking advantage of edges locations that exist in patches produced by a canny edge detector.

Here, the authors propose a deep learning method for extraction of vessel in X-ray angiograms. The proposed method performs accurate extraction of vessel boundary regions in challenging situations of complex backgrounds and the presence of noise. In this proposed method, initially the input image is preprocessed to enhance the contrast and to reduce the image noise. Two convolutional neural networks are designed. The first CNN uses local and global image patches to establish an initial segmentation probability map. The input of the second CNN includes the output of the first CNN as well as edge information from canny edge detector. The second CNN corrects the outcome of the first, especially in the challenging border regions. A training mechanism is devised to train the networks to correctly distinguish vessel border regions from those of background and inside vessel regions. Experimental results demonstrate that the proposed method outperforms existing angiogram segmentation algorithms in terms of vessel extraction accuracy.

The organization of the rest of this paper is as follows. In Section 2 the proposed method for detection of vessel regions is explained. Experiments done for evaluation of the proposed method are given in Section 3 and Section 4 concludes the paper.

2. Proposed method

The block diagram of the proposed method is shown in Fig. 1. The propose method consist of four steps: a) contrast enhancing, b) first CNN stage, c) second CNN stage, and d) binary vessel map formation. These four stages are shown in Fig. 1. The first step consists of an image enhancing procedure; the result is fed to the first CNN stage. The first CNN stage uses both local and global features to form a vessel probability map. We also feed the enhanced image into an edge detector stage to form an edge map. The second CNN stage, as shown in Fig. 1(c), receives both the edge map and the vessel probability map to find an enhanced vessel probability map. In the fourth stage, shown in Fig. 1(d), a threshold is applied to the enhanced probability map to form a binary map. The largest connected component in the final binary map shows the segmented vessels. In sub-sections 2.1–2.4 different steps of the proposed method are discussed.

2.1. Contrast enhancing

The contrast enhancing procedure is directed towards improving the performance of the first CNN stage. Thus, the proposed