Neurocomputing 149 (2015) 708–717

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Hierarchical retinal blood vessel segmentation based on feature and ensemble learning

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ARTICLE INFO

Article history:
Received 5 April 2014
Received in revised form
25 June 2014
Accepted 28 July 2014
Communicated by: Shiguang Shan
Available online 12 August 2014

Keywords:
Convolutional neural network
Ensemble learning
Feature learning
Random forest
Retinal blood vessel segmentation

ABSTRACT

Segmentation of retinal blood vessels is of substantial clinical importance for diagnoses of many diseases, such as diabetic retinopathy, hypertension and cardiovascular diseases. In this paper, the supervised method is presented to tackle the problem of retinal blood vessel segmentation, which combines two superior classifiers: Convolutional Neural Network (CNN) and Random Forest (RF). In this method, CNN performs as a trainable hierarchical feature extractor and ensemble RFs work as a trainable classifier. By integrating the merits of feature learning and traditional classifier, the proposed method is able to automatically learn features from the raw images and predict the patterns. Extensive experiments have been conducted on two public retinal images databases (DRIVE and STARE), and comparisons with other major studies on the same database demonstrate the promising performance and effectiveness of the proposed method.

1. Introduction

Retinal blood vessel segmentation has been widely used in various scenarios. For example, change of the retinal blood vessel appearance is an important indicator for various ophthalmologic and cardiovascular diseases, such as diabetes, hypertension, and arteriosclerosis [1], therefore, automatic segmentation and analysis of the retinal vasculature play an extremely vital role in the implementation of screening programs for diabetic retinopathy, the evaluation of retinopathy of prematurity, foveal avascular region detection, arteriolar narrowing detection, the diagnosis of cardiovascular diseases and hypertension, and computer-assisted laser surgery [2]. Moreover, the generation of retinal maps and detection of branch points have been utilized for temporal or multimodal image registration, retinal image mosaic synthesis, optic disc identification, fovea localization and biometric identification [2].

Both manual delineation and automatic algorithms have been used in retinal vessel segmentation. However, they have not gained wide acceptance due to several challenges. Manual delineation is skill demanding, tedious, time-consuming, and infeasible if given a large volume of fundus image databases. Accuracy of the automatic segmentation algorithms (to be reviewed in Section 2) is limited due to low blood vessel contrast, irregular shaped bright and dark lesions (in the form of hemorrhages, exudates, drusen and the optic disc boundary), intricate vessel topology (including vessel crossing and branching, as well as variation of vessel diameter and vessel grey levels) and nonuniform illumination of images as well as image deformation of scaling, skewing and other distortions.

In this paper, we present the hybrid method based upon convolutional neural network (CNN) [3] and ensemble random forests (RFs) [4] for automatic retinal blood vessel segmentation. We first employed a set of preprocessing steps to correct the nonuniform illumination of retinal images and to improve vessel contrast. We then used CNN to extract a set of hierarchical features which are not only invariant to image translation, scaling, skewing and other distortions, but also contain image based multi-scale information of the geometric structure of retina. We finally trained ensemble RFs to obtain a vessel classifier. The whole pipeline of the proposed method is trainable and automatic. Moreover, our method can effectively deal with the challenges of retinal vessel segmentation, as shown by our evaluations conducted using two publicly available databases (the DRIVE [5] and STARE [1]) and comparisons with state-of-the-art. Experimental results show that our approach is competitive with state-of-the-art by achieving sensitivity/specificity/accuracy/AUC values of 0.8173/0.9733/0.9767/0.9475 for the DRIVE database and of 0.8104/0.9791/0.9813/0.9751 for the STARE

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http://dx.doi.org/10.1016/j.neucom.2014.07.059
0925-2312/

database. In contrast, previous methods of Fraz [6] produced values of 0.7406/0.9807/0.9480/0.9747 for the DRIVE database and of 0.7548/0.9763/0.9534/0.9768 for the STARE database.

The rest of this paper is organized as follows. Section 2 gives a review of related work reported in the latest literature. Section 3 provides the description of CNN and RF. Section 4 gives a detailed description of the proposed method. Section 5 evaluates the proposed method. Further, the concluding remarks are included in Section 6.

2. Related work

There are a number of methods available in the literature for retinal blood vessel segmentation, as reviewed by Fraz et al. [2]. These methods can be broadly divided into two categories: unsupervised and supervised [2,3].

2.1. Unsupervised methods

The unsupervised methods can be further classified into five main subcategories: matched filtering, morphological processing, vessel tracking, multiscale analysis, and model-based algorithms. The matched filter based methodology convolves a kernel based on the Gaussian or its derivatives with the retinal image to enhance the vessel features [1,7]. In order to design the matched filter kernel, this methodology exploits the piece-wise linear approximation, the decrease in vessel diameter along vascular length, and the Gaussian-like intensity profile of retinal blood vessels. Mathematical morphology coupling curvature evaluation [8] and matched filtering for centerline detection [9,10] is also deployed for retinal vessel segmentation. Vessel tracking based methodology [11] segments a vessel using local information and works at the level of a single vessel rather than the entire vasculature. The multiscale approaches are based upon scale-space analysis. The multiscale second-order local structure of an image (Hessian) is examined, and a vesselness measure is obtained on the basis of eigenvalue analysis of the Hessian [12]. The model based approaches include the vessel profile models [13–16], active contour models [17], and level sets based geometric models [18].

2.2. Supervised methods

Supervised methods utilizing ground truth data usually consist of two stages: (1) feature extraction, (2) classification. During feature extraction stage, the features can be obtained by means of two ways: hand-crafted features and learning based features.

The first approach is based on hand-designed feature extraction, where each pixel is projected into a set of features predefined with prior knowledge before classification. Neimeijer et al. [19] applied the Gaussian and its derivatives at multiple scales to form a feature vector for each pixel, augmented with the green channel of the RGB image. Stall et al. [5] used ridge profiles to compute a feature vector for each pixel, then performed feature selection. In [20], a feature vector is composed of the pixel intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales. Ricci and Perfetti [21] deployed line operators to form a feature vector. Lupascu et al. [22] used a feature vector at different spatial scales for each pixel. In [23], a feature vector is obtained by combination of moment-invariant and gray-level features. In [6], the method utilized a feature vector based on the orientation analysis of gradient vector field, morphological transformation, line strength measures, and Gabor filter responses.

The second approach deploys Artificial neural network (ANN) or its variants to segment retinal blood vessels, where feature extraction and classification are integrated into one pipeline: feature extraction itself is directly learned from raw image and not enforced by designers, then followed in the ANN process is a generation of predictions. Nekovei and Sun [24] presented a method using a back-propagation network for the detection of blood vessels. In this method, neural network is directly applied to the image pixels without any prior feature extraction. For each pixel being classified, raw pixel values in a square window centered on it are fed to the network as input.

Although these supervised methods have achieved satisfactory segmentation results in some scenarios, there are still some issues. In hand-designed feature extraction approaches, the features must be very carefully predefined before classification, making feature detection very time-consuming and tedious. Most importantly, hand-designed features have to be redesigned for datasets with different characteristics. In contrast, the approaches based upon feature learning can extract features automatically from the raw images. Moreover, CNN is supervised feature learner able to learn complex invariances such as scale and rotational invariance. However, the classification mechanism in ANN or its variants is fairly simple: usually nonlinear activation functions are employed in the last output layer to predict patterns, which results in the low performance of ANN. Considering all of above, we propose to combine two well-known classifiers: Convolutional Neural Network (CNN) and Random Forest (RF). In this paper, CNN works as a trainable hierarchical feature extractor, and then ensemble RFs perform as the trainable classifier supplied with hierarchical features learned from CNN.

3. Methodology

The proposed method leverages trainable hierarchical features extracted using the CNN algorithm [3] and performs classification

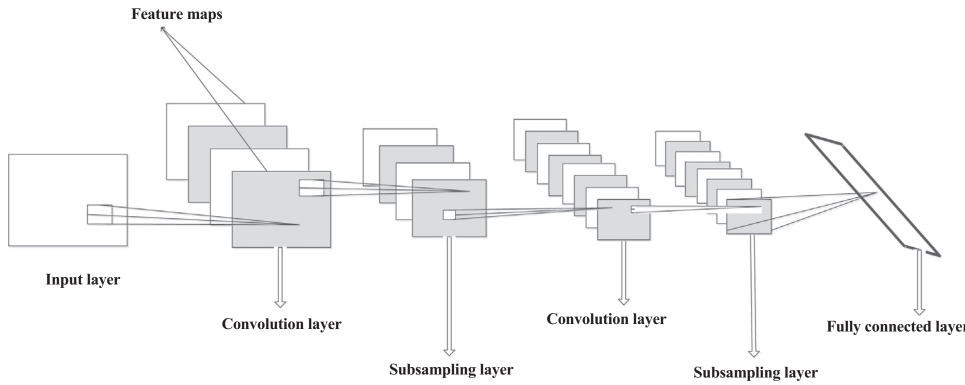

Fig. 1. Schematic diagram of convolutional neural network.