Extended Abstract: Artery-Vein Segmentation in Fundus Images using a Fully Convolutional Network

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Abstract

Today, the analysis of retina images is a complex, manual task requiring a highly-skilled clinician. In light of the recent successes of Fully Convolutional Networks (FCNs) applied to biomedical image segmentation, we want to assess its potential in the context of retinal artery-vein (A/V) discrimination. With the aim of improving the automation of vessel analysis, a novel application of the U-Net semantic segmentation architecture (based on FCNs) on the discrimination of arteries and veins in fundus images is presented. By utilizing deep learning, results are obtained that exceed accuracies reported in the literature. Our model was tested on the public DRIVE dataset, measuring performance on vessels wider than two pixels, achieving accuracies of 94.42% and 94.11% on arteries and veins, respectively. This represents a decrease in error of 25% over the previous state of the art reported by [6]. Fully Convolutional Networks combined with careful data augmentation do foster potential in A/V discrimination on a small data set, outperforming previous work. Evaluation masks and predicted A/V annotations on the public DRIVE data set are available at `http://iflexis.com/DRIVEmasks`.

1 Introduction

Several biomarkers have been introduced and examined in order to improve diagnosis of retinal aberrations. One of the most commonly employed is the arteriovenous ratio (AVR). In general, the AVR is a ratio of the average width of the arterioles with respect to the venules, consisting of the central retinal artery equivalent (CRAE) and the central retinal vein equivalent (CRVE). Most authors measure AVR in a standardized region between two concentric circles (0.5 and 1 optic disc diameter) around the optic disc, also known as Zone B [1]. In order to obtain the CRAE, CRVE and derivative AVR, the discrimination of retinal vessels into arterioles and venules is required.

Ample approaches based on classic computer vision have been employed to discriminate between retinal arteries and veins in fundus images. In summary, these works can be grouped into two global approaches for A/V discrimination: (i) graph theory and (ii) intensity based feature extraction from color images. Very recently, a deep learning classification network, as a separate step to segmentation, was applied to this subproblem [5], indicating the potential use of these novel architectures. We develop this approach further based on U-Net [3], performing segmentation between vessels and background, while simultaneously discriminating between arteries and veins in a unified framework, reporting significantly improved results over the previous state of the art.

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2 Data

The DRIVE dataset [4] is publicly available, and has become a frequently used benchmark for research on retinal vessel segmentation. The set consists of both 20 training and 20 test fundus images, all having the same resolution of 584×565. [2] published a manually-labeled AV classified benchmark for DRIVE in 2013.

3 Methodology

The images of the DRIVE data set show significant variability in lighting within the image due to the curvature of the retina. To counter this unfavorable characteristic, a local contrast enhancement is implemented. A Gaussian filter with kernel of 65×65 pixels, zero mean and standard deviation σ of size 10 is applied to the fundus image, after which the output from the convolution is subtracted from the original image.

Due to data scarcity, powerful data augmentation techniques need to be applied. One of the most important data augmentation techniques used in training the model was random cropping. We artificially grow our data set with a factor 8 through rotation at 90, 180 and 270 degrees and horizontal flips. Finally, we have implemented elastic deformation by sampling control points on a regularly spaced 100×100 grid. Each control point has isotropic Gaussian noise added with $\sigma = 20$. This greatly increases the number of synthetic training images.

The main novelty in our work is the combination of vessel extraction and artery-vein discrimination, two processes that have always been dealt with separately in literature. We adapt the original U-Net paper to allow for three class segmentation in the context of A/V discrimination. Our best model comprises a little over 5 million trainable weights, which is significantly smaller than the original U-net. Given that there are few (original) training data, we expect an increased risk of overfitting when moving to a larger network.

A custom weight map is introduced that emphasizes vessel centerline pixels. The motivation behind this weightmap is threefold. Within a fundus image of the DRIVE data set, close to 90% of all pixels are non-vessel, resulting in a huge class imbalance. A custom weightmap does not only counter class imbalance; it leads to equal importance among vessels. Previous work reported high accuracies on primary vessels (e.g. vessel width at least three pixels), whereas the secondary vessels were often omitted in the evaluation. Finally, the use of a weight map also allowed us to ignore the pixels for which the labeling is unknown in the ground truth described by [2].

4 Results

The segmentation output of our model on the 20 DRIVE test images achieved accuracies of 94.42% and 94.11% on retinal arteries and veins, respectively. Qualitative results of our work are displayed in Figure 1. Table 1 provides a detailed benchmark with related work that also reported A/V discrimination performance on the DRIVE data set.

5 Conclusion

To fully extract the cardiovascular information hidden within the retinal blood vessels, arterial and venous parameters should be measured separately, allowing to obtain parameters like CRAE, CRVE and AVR. Manual segmentation is time-consuming and currently limits the applications for retinal fundus photography to be implemented in general cardiovascular screening programs. Automated A/V discrimination algorithms, as the one presented in this paper, could pave the way for automated AVR determination and fractal dimension analysis of retinal arteries and veins.

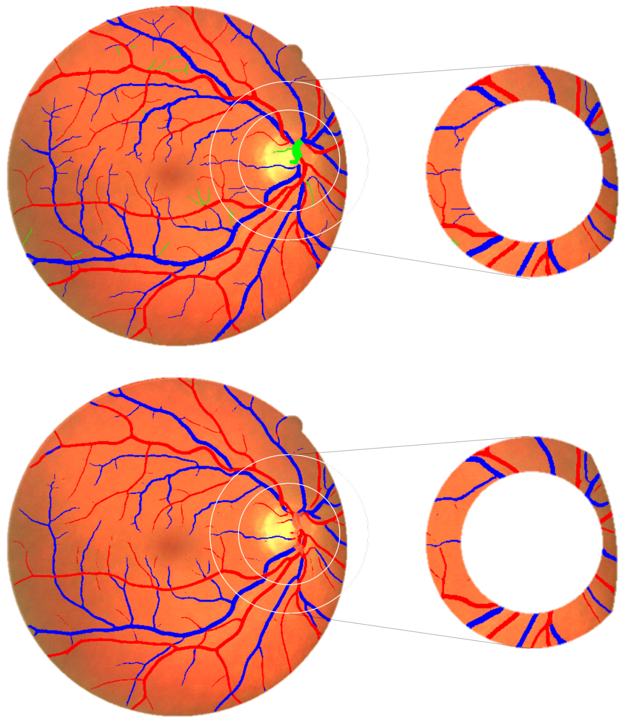

Figure 1: Ground truth (top) and prediction of best model (bottom) of test image 2, along with extracted Zone B.

Table 1: Benchmark with related work (research that reported results on DRIVE data set).

Authors	**Method**	**Dataset split**	**Performance (accuracy)**	**Description of evaluation**
Muramatsu et al. (2011)	LDA classifier	Standard	93%	Limited to centerline pixels of 'major' vessels in Zone B
Mirsharif et al. (2012)	LDA classifier	Standard	84.05% (FOV) 90.16% (Zone B)	Vessel centerline, limited to vessels wider than three pixels
Dashtbozorg et al. (2013)	Graph-based	Standard	87.40%	Vessel centerline, limited to vessels wider than three pixels
Estrada et al. (2015)	Graph-based	Standard	91.70%	Vessel centerline, limited to vessels wider than two pixels
Xu et al. (2017)	LDA classifier	Standard	92.30%	Around 73,000 vessel centerline pixels segmented
Welikala et al. (2017)	CNN	Custom	91.97%	No information on amount of pixels
Our method	**FCN**	**Standard**	**94.25%**	**Vessel centerline, limited to vessels wider than two pixels**

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