ELM for Retinal Vessel Classification

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Abstract. Robust image segmentation can be achieved by pixel classification based on features extracted from the image. Retinal vessel quantification is an important component of retinal disease screening protocols. Some vessel parameters are potential biomarkers for the diagnosis of several diseases. Specifically, the arterio-venular ratio (AVR) has been proposed as a biomarker for Diabetic retinopathy and other diseases. Classification of retinal vessel pixels into arteries or veins is required for computing AVR. This paper compares Extreme Learning Machines (ELM) with other state-of-the-art classifier building approaches for this tasks, finding that ELM approaches improve over most of them in classification accuracy and computational time load. Experiments are performed on a well known benchmark dataset of retinal images.

Keywords: Retinal Vessels, arterio-venular ratio, biomarkers, ELM

1 Introduction

Recent studies [10] point to the importance of the fundus imaging as a substantial part of a large number of diagnostic procedures for a wide variety of pathologies. This technique allows to obtain high resolution images of the internal structures of the retina, such as the micro-vascular tree or the optic disc, as shown in Figure 1. Currently, there is an increasing scientific evidence regarding the role played by micro-vascular diseases in relation to the pathologies associated with macro-vascular structures. Studies such as [10] have shown how a condition in coronary micro-vascular structure, may cause serious heart failure with risk of heart attack and death, without any pathological evidence in coronary macrovascular structures, so that periodic checks of such structures may not reveal the existence of pathology. Moreover, some dysfunctions in skin microvascularity which is estimated to be representative of the entire micro-human circulatory system, have been associated with increased risk of heart attack. However, studies over microvascularization are small relative to the affected population because they need laborious and very invasive techniques. For this reason, researchers are looking for non invasive alternatives and mechanisms allowing accurate analysis of microvascular structures. Retinal imaging allows studying different aspects

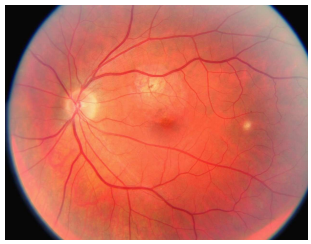

Fig. 1. Image of the retina obtained by fundus imaging.

of the microcirculation in-vivo, whose role in vascular or metabolic diseases is less clear than that of macrocirculation [11]. Image analysis with vascular morphometry techniques carried out over large populations point out correlations between retinal microvascular patterns and different cerebrovascular and cardiovascular diseases and metabolic disorders [13]. We focus on one retinal image biomarker with great diagnostic value, which is the arterio-venular ratio (AVR), computed as the quotient between the averages of the widths of several arterioles and venules. Alternatively, the AVR is also computed as the quotient of the central retinal artery equivalent (CRAE) and the central retinal vein equivalent (CRVE) [9].

The quantification of retinal bio-markers such the AVR, CRAE or CRVE over large populations requires automated tools for vessel segmentation and analysis. We are interested in low complexity and fast approaches that could allow the clinicians to be able to carry out large screening programs. There are two steps in this process:

(a) Image segmentation to obtain the location of the vessel pixels in the image

(b) Vessel pixel discrimination into arteries and veins, needed to compute the AVR.

Current methods for retinal vessel segmentation mechanisms [4] can be roughly categorized as those based on supervised learning [15] and unsupervised [1] techniques. Supervised learning techniques rely on hand labeled images for the offline classifier training process. Segmentation process becomes a pixel classification into two different classes: vessel versus background. On the other hand, unsupervised approaches rely on image processing and analysis techniques specialized for vascular structures. In these approaches, hand labeled images are used only for validation, not for the construction or tuning of the segmentation algorithm. Overall, algorithms based on supervised classification report better segmentation results with a computational overhead due to training process. They are also dependent on the sample used for training and may suffer great errors on outlier retinal images. On the other hand, unsupervised techniques are less computationally demanding but difficult to tune, and sensitive to unexpected variations in the images. The vascular segmentation algorithm used in

this paper follows the approach proposed in [1], which uses an unsupervised and fast segmentation mechanism. The vessel pixel discrimination must be performed following a supervised learning approach, where specific features are proposed to exploit subtle image differences of the artery and vein vessels [14]. In this paper we concentrate on the comparison of Extreme Learning Machine (ELM) [7] approaches against other state-of-the-art classifier building approaches for this task.

The paper is structured as follows: Section 1 gives a brief overview of approaches dealing with retinal microvasculature analysis in fundus images. Section 2 presents the image processing pipeline for retinal vessels and the feature extraction approach for artery/vein discrimination, as well as a brief description of implementation details. Section 3 gives a brief review of ELM as supervised classification technique applied to the problem of artery/vein classification. Section 4 reports obtained classification results obtained with different supervised classification approaches. Finally, 5 gives a discussion about the implemented and tested approach, and addresses next lines of research and development.

2 Feature Extraction

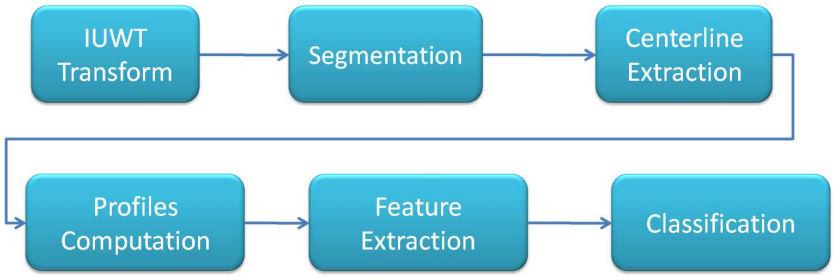

Fig. 2. Retinal Image Analysis Pipeline.

Figure 2 depicts the image processing pipeline implementing our approach. First we perform the vessel segmentation. After image acquisition, we first perform a field of view (FOV) detection, selecting the region-of-interest for the following processes. Next, we apply an isotropic undecimated wavelet transform (IUWT) [1] at several wavelet scales. This transformation achieves contrast enhancement, increasing the difference between structures of different luminance value. We apply a thresholding operation on the IUWT contrast enhanced images, followed by a connected component analysis removing spurious small connected components, falling below the minimum length of a vessel candidate to be measured. Segmentation threshold is set to 15%-20% of the lowest luminance value inside the region of interest (FOV). This value over-segments the images, ensuring that most of the vessel tree is retained. The center line is obtained by

reducing vessel regions to one-pixel-wide skeletons using a thinning algorithm. Afterward, a branch detector is applied in order to identify and separate vessel bifurcations and vessels segment, and obtained vessel segments are approximated with B-spline curves for regularization, and curvature and section computation. Finally, we use a Full Width at Half Maximum (FWHW) algorithm to estimate vessel caliber along such sections. Figure 3 shows a sequence of partial results of the vessel segmentation. On the localized vessels, sections that are perpendicular to the local orientation of the B-spline representing the vessel are draw at regular intervals of the vessel centerline as shown in Figure 4. These sections are then used for image feature extraction for vessel type discrimination by classification, prior to AVR calculation.

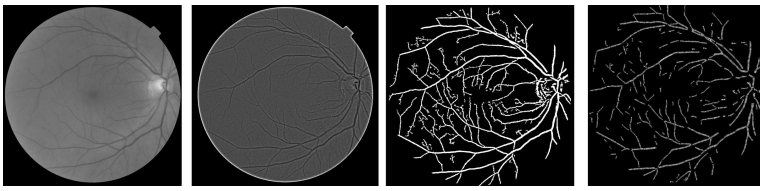

Fig. 3. Sequence of partial results of vessel segmentation. Left to right: original image, FOV detection, IUWT contrast enhancement, vessel detection.

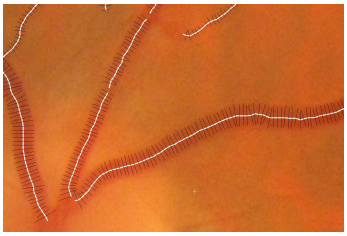

Fig. 4. Extracted vessel profiles overlaid on the input image.

Several studies [19, 16] show that only photometric features are useful for artery/vein classification. Morphometric features such as width or tortuosity are pathological biomarkers, thus may change severally depending if the patient has a potential disease or not. Therefore, in our study we define only photometric features based on pixel luminance and chrominance information. More precisely, we extract the following features:

– Mean and standard deviation of green and red value in RGB color space along the vessel segment. We excluded blue channel because its signal-to-noise-ratio is very low compared with the other two, thus does not add discriminant capabilities for the classification.

– Along the perpendicular sections we distinguish two parts, illustrated in Figure 5: outer pixels lying at a distance from the centerline above 40% of the estimated vessels width, depicted by black segments in Figure 5, inner pixels lying at a distance below this threshold, depicted by white segments in Figure 5. We compute the difference of the means of of green and red channels of the outer and inner pixels. These features model the contrast between foreground, i.e. vessels, and background.
– Mean and standard deviation of Hue channel in HSV color space along the vessel segment.
– Mean luminance inside the vessel, and the difference in luminance between outside and inside the vessel.

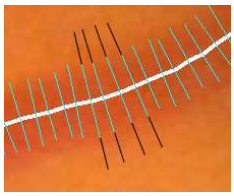

Fig. 5. Localization of outer and inner pixels along the sections drawn perpendicular to the vessel centerline.

3 Extreme Learning Machines

3.1 Basic ELM

The Extreme Learning Machine (ELM) [8] is a very fast training algorithm for single-layer feedforward neural networks (SLFN). The key idea of ELM is the random initialization of the SLFN hidden layer node weights. Consider a set of M data samples $(\mathbf{x}_i, y_i)$ with $\mathbf{x}_i \in \mathbb{R}^d$ and $y_i \in \Omega$. Then, a SLFN with N hidden neurons is modeled as the following expression:

$$\mathbf{y} = \Phi(\mathbf{x}) = \sum_{i=1}^{N} \beta_i f(\mathbf{w}_i \cdot \mathbf{x} + b_i), j \in [1, M], \tag{1}$$

where $f(x)$ is the activation function, $\mathbf{w}_i$ the input weights to the i-th neuron in the hidden layer, b_i the hidden layer unit bias and β_i are the output weights. The application of this equation to all available data samples can be written in matrix form as

$$\mathbf{H}\beta = \mathbf{Y},$$

where $\mathbf{H}$ is the hidden layer output matrix defined as the output of the hidden layer for each input sample vector, $\beta = (\beta_1 \dots \beta_N)^T$ and $\mathbf{Y} = (\mathbf{y}_1, \dots, \mathbf{y}_M)^T$.

The way to calculate the output weights β from the hidden-layer to the target values is computing the Moore–Penrose generalized inverse of the matrix $\mathbf{H}$, denoted as $\mathbf{H}^{\dagger}$. The mean least squares solution is $\beta = \mathbf{H}^{\dagger}\mathbf{Y}$.

The orthogonal projection method can be used to calculate the pseudo-inverse. In the case of $\mathbf{H}\mathbf{H}^T$ being non-singular, $\mathbf{H}^{\dagger}$would be obtained by $\mathbf{H}^{\dagger} = \mathbf{H}^T(\mathbf{H}^T\mathbf{H})^{-1}$. Thus, the output weightsβ are calculated

$$\beta = \mathbf{H}^T \left(\mathbf{H}^T\mathbf{H}\right)^{-1}\mathbf{Y}.$$

According to ridge regression theory [5], it was suggested [18] that Thikonov regularization [17] can be used to have better generalization performance. This regularization is achieved by adding a positive value $1/\lambda$ to the diagonal of $\mathbf{H}\mathbf{H}^T$. The calculation of the output weights is

$$\beta = \mathbf{H}^T \left(\frac{\mathbf{I}}{\lambda} + \mathbf{H}^T\mathbf{H}\right)^{-1}\mathbf{Y}.$$

In our experiments, the basic ELM is denoted as "ELM", and the regularized ELM is denoted as "ELM(w/regul)". The implementation of both ELMs is available at [6].

3.2 OP-ELM

The Optimally Pruned Extreme Learning Machine (OP-ELM) was proposed in [12] with the goal of solving the problem that ELM faces with highly correlated variables. The basic ELM does not cope well with variables irrelevant to the problem at hand. The OP-ELM proposes a three-steps methodology, to address this problem:

1. Construct an SLFN using ELM.
2. Rank the best neurons using LARS algorithm. This process is akin to a "regularization" of the ELM. It uses Allen's PRESS [2] formula to L_1 regularize the ELM.
3. Select the optimal number of neurons using Leave-One-Out (LOO) criterion.

The LOO method is usually costly, since it requires to train the model on the whole data set except one sample for all the samples of the data. However, in the OP-ELM the situation is linear between the hidden layer and the output one. The LOO error has a closed matrix form, given by the PRESS method [2]. This closed form allows a fast computation of the MSE, and therefore the computation of the output weights is still computationally fast, and theoretically more robust than the original ELM to correlated variables. The code of OP-ELM is made available by Miche et al. at [3].

4 Results

This section shows the comparative results obtained during the retinal vessels classification experiment. For this study we used the feature vectors of 5730 vessel sections, extracted from several images which have been labeled as arteries

or veins by two human experts. For this evaluation we used several supervised classification approaches implemented in the public available Weka software `http://www.cs.waikato.ac.nz/ml/weka/`, version 3.7.9. We set each classifier learning algorithm parameters to their default values. In this evaluation we tested single classifier approaches, thus we did not include ensemble approaches such as Random Forest.

The results of 10-fold cross-validation experiment for each algorithm are summarized in Table 1. Worst results were obtained by SVM with linear kernel, hence indicating that the best decision boundary between artery and vein classes is not linear. OP-ELM obtains the best classification accuracy, followed by MLP and SVM with non-linear RBF kernel. Table 2 shows training and testing times

Classifier	Accuracy
Naive Bayes	82.7
MLP	91.1
SVM(Lineal)	73.3
SVM(RBF)	92.5
ELM	89.4
ELM(w/regul)	90.5
OP-ELM	**93.6**

Table 1. Classification mean accuracy results from 10-fold cross-validation.

of tested classifiers. As expected a simple Naive Bayes classifier is the fastest approach, while OP-ELM is the slowest approach. However, regarding testing times OP-ELM is one of fastest approaches. In our case, testing times are more important than training times, because our retinal quantification application is oriented to carrying out large population screening programs, where small differences in testing times will be amplified by the population size.

Classifier	Training Time	Testing Time
Naive Bayes	0.05	0.01
MLP	4.64	0.01
SVM(Lineal)	15.49	0.07
SVM(RBF)	1.94	0.09
ELM	3.91*	0.03
ELM(w/regul)	1.11	0.04
OP-ELM	55	0.02

Table 2. Training and Testing Times.
*: Note that the greater training time of ELM compared to ELM(w/regul) is due to the use of SVD on the calculation of the pseudo-inverse in the case of ELM.

Figure 6 shows the results of an experiment using ELM, ELM with regularization and OP-ELM by evaluating classifier accuracy against the number of hidden nodes. As can be seen, OP-ELM outperforms basic ELM with and without regularization. Moreover, OP-ELM requires many fewer hidden nodes before convergence, compared with basic ELM.

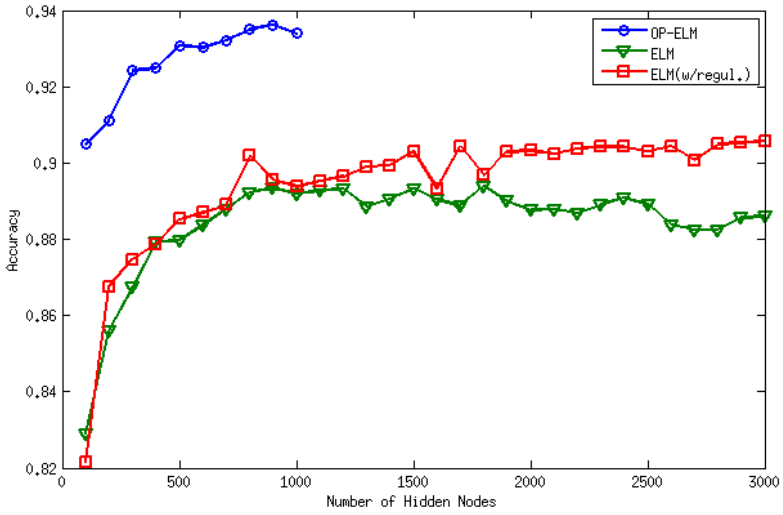

Fig. 6. Accuracy results for increasing hidden layer sizes.

5 Conclusion and Feature Work

In this paper we have introduced a system for retinal image vessel segmentation and classification. Classifying retinal vessels into arteries or veins is a crucial step for retinal image quantification based on the extraction of biomarkers such as vessels tortuosity or arterio-venular ratio (AVR). Therefore, the final supervised classifier is a key element of this system. We have performed a comparative experiment between state-of-the-art classifiers and Extreme Learning Machines(ELM). Our results shows that the approach based on Op-ELM outperforms other supervised classification approaches such as SMV or MLP, in terms of accuracy and testing times.

In the future, we plan to implement an hybrid approach for retinal vessels classification, by fusing a supervised Classification using OP-ELM with unsupervised classification by using Fuzzy K-means. This approach would try to overcome the problems arising from the presence of inter-image contrast and

luminosity variability, that are difficult to cope with a single Supervised Classification approach.

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