Effective features for artery-vein classification in digital fundus images

Andrea Zamperini, Andrea Giachetti
Dipartimento di Informatica,
Università di Verona
andrea.giachetti@univr.it

Emanuele Trucco, Khai Sing Chin
VAMPIRE, School of Computing,
University of Dundee
e.trucco@dundee.ac.uk

Abstract

In this paper we present an analysis of image features used to discriminate arteries and veins in digital fundus images. Methods proposed in the literature to analyze the vasculature of the retina and compute diagnostic indicators like the Arteriolar to Venular ratio (AVR), use, in fact, different approaches for this classification task, extracting different color features and exploiting different additional information. We concentrate our analysis on finding optimal features for the vessel classification, considering not only simple color features, but also spatial location and vessel size and testing different supervised labeling approaches. The results obtained show that best results are obtained mixing features related with color values and contrast inside and outside the vessels and positional information. Furthermore, the discriminative power of the features changes with the image resolution and best results are not obtained at the finest one. Our experiments demonstrate that using a good set of descriptors it is possible to achieve very good classification performances even without using vascular connectivity information.

1. Introduction

Artery/vein classification is a relevant task in retinal image analysis, due to the possibility of extracting, from classified vascular trees, diagnostic indicators as the Arteriolar to Venular ratio (AVR), that has been linked to pathologies as hypertension or atherosclerosis. For this reason several authors proposed methods to discriminate veins and arteries on retinal images [3, 9, 7] and/or complete frameworks for the automatic computation of AVR [1, 4, 6].

If the overall approach of these techniques seems, in general, similar (detection of a region of interest near the optic disc, vessel segmentation, classification of centerline pixels as vein or artery using features evaluated in a neighborhood and use of the vascular tree context to improve the classification results, AVR estimation), single steps of the procedures are often different and it is not so clear which are the algorithmic options producing the best results. Specific analyses are needed to better understand the critical aspects of each different task.

In this paper we try to analyze in detail the problem of finding optimal features and classification approaches in order to assign to single pixels belonging to the vascular centerline the correct label. The work is focused on providing accurate AVR and/or other biomarkers estimation for the VAMPIRE (Vasculature Assessment and Measurement Platform for Images of the REtina) tool [8], a software for the analysis of retinal images developed in a collaborative framework involving 11 international centres from the UK, Italy, Singapore and the US.

The paper is organized as follows: Section 2 discusses the vessel classification approaches found in literature, Section 3 presents the contribution of our work, Section 4 the results of our experiments and Section 5 a short discussion.

2. Relevant features for A/V discrimination

It is generally assumed that veins and arteries present different color and size features: arteries are usually thinner and brighter and present more frequently a central reflex with a high red component. Context based cues can be used to distinguish vessel types: the ”alternation rule” assumes that moving on a circle surrounding and close to the OD, arteries and veins are often alternate and it is clear that connected point in the vascular tree should have the same label.

However, it is not easy to have a perfect vessel classification on the basis of this kind of features for several reasons. The absolute color of the blood varies between images and across subjects [6], image resolution and quality is not constant, size and color of similar vessel change with position. Context based features may fail as well due to vessel crossings. Several different solutions have been therefore proposed to discriminate veins from arteries, usually starting from a previous segmentation providing local vascular

978-1-4673-2051-1/12/$31.00 ©2012 IEEE

centerline and estimated width and direction.

Chrastek et al [1] used the information on the red channel at crossing location to classify vessel segments. Grisan et al. [3] used two color features (mean of hue and standard deviation of red) in different sectors and a clustering approach to separate the vessel classes. However, authors of the same research group did not find the method working on different images in a later application [4], so they moved to a different classification approach based on the estimation of the central reflex. Kondermann et al. [7] used ROI based and profile based feature vectors obtained with a principal component analysis applied to the local pattern. Muramatsu et. al [5] used six simple features, e.g. color components in central pixels and their contrast with outside the vessel. Niemeijer et al. [6] used 27 color features (color components, averages and maxima), measured at centerline points and in local profiles perpendicular to the vessel direction.

Of course, the vascular structure can be used to constrain the local feature based classification, even if also the vascular graph analysis is not simple in general. A typical approach (e.g. [5]) consists of detecting crossings and use a majority voting to label coherently central vessel pixels inside segments. Rothaus et al. [9] proposed recently a rule-based method to propagate the vessel labels through the vascular graph.

In this paper we, however, focus on vessel pixel classification in order to define clearly which are the features and the labeling approaches that provide the better results in the specific task. This means that the results obtained on classification tests do not involve vascular graph reasoning and can therefore furtherly improved.

3 Our approach

We tried to better understand which are the most relevant features related to the vascular classes and how they can be used to discriminate veins and arteries on heterogeneous images. For this reason we considered a large number of features, including not only color and size descriptor, but adding also explicitly context related values such as spatial position with respect to the optic disc.

In order to have a complete analysis we tried to separate features that can be different in veins and arteries for different reasons, trying to analyze their real contribution to the classification.

3.1 Central color and within-vessel variations

The principal features used for vessel classification are related to color. Color space components in a neighborhood of the central pixels or along a profile perpendicular to the vessel are usually considered, usually after a color component normalization to zero mean and unitary standard deviation. We similarly tested a large set of color features, but decided to analyze separately color features related to the internal part of the vessel and color features including the contrast with the background. We did not find necessary to consider profiles perpendicular to the vessel direction, due to the fact that we analyzed variations within circular regions around the central pixel. This makes the technique also more robust, not depending on the local estimation of the vessel direction. So, to characterize the color inside the vessel and the central reflex, we used the central pixel color components(R,G,B,H,S,V) and component derivatives, and also mean, minimum, maximum and variance of that values in a disc of diameter equal to the locally estimated vessel diameter (small region in Fig. 1).

3.2 Contrast with surrounding pixels

It is then interesting to check if the contrast with the background provide relevant information for vessel classification (and to see which are the most discriminative parameters). For this purpose we computed as further features averages and standard deviations of color components and color derivatives in a disc with diameter equal to twice the locally estimated vessel diameter (large region in Fig. 1). In this case the computed features are largely dependent on the contrast between vessel color and background color.

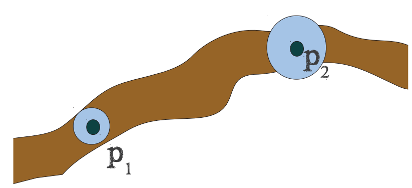

Figure 1. Small (only internal, radius equal to half vessel width) and large (radius equal to vessel width) region used to compute color features potentially characterizing the vessel type.

3.3 Position and size

Vessel size is considered in some work a potentially discriminative feature, but often not considered due to the fact that it changes with the distance from the optical disc [7]. But this is not a reason to avoid its use, but rather a reason to use it in combination with spatial information. Actually, if we consider the results in [3], where it is reported that color features are more discriminative if used independently in different sectors around the OD, it is reasonable to think that color features should be also combined with spatial information in order to obtain a better classification. We decided to test the discriminative power of spatial features like angular and radial distance from the OD center and distance from the image optic center. The analysis of the discriminative power of these features alone and combined with size and color based one is surely relevant to determine how to improve the performance of classification tools. To compute angular distances from the estimated OD center we used the OD locator developed for the VAMPIRE tool [8, 2], based on multiscale ellipse fitting. The angular position α is computed differently in case of left or right image in the first case we consider a clockwise orientation, and in the second case counterclockwise as shown in (Fig. 2) so that the possible effects of the variable on the image color should be the same.

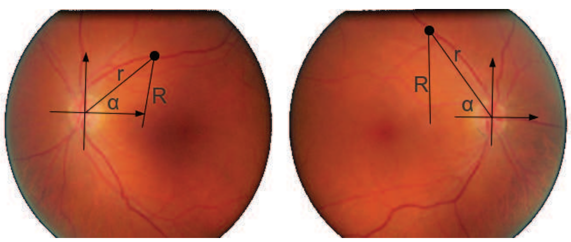

Figure 2. Measurements related to image position: linear distances from the estimated OD center and image center and angular position with respect to the OD center differentiated for left and right images.

3.4 Testing discrimination at different resolutions

All the descriptors summarized above create a complete set of 86 elements, that have been grouped in different categories (color inside, color inside and around, size, position) to allow us to analyze their individual or category-related ability to discriminate veins and arteries.
This ability, however, may depend also on the image acquisition device characteristics, for example its resolution. High resolution sensors can capture finer details (e.g. central reflexes), but may be more noisy. To verify the effect of a simple resolution change not influenced by other changes in the imaging device we performed, for this reason, the same classification tests not only on an original annotated high resolution image set, but also on corresponding low resolution ones. These datasets have been obtained rescaling the original (high resolution) one by different factors simulating resolution of other devices. On all the obtained datasets we computed the color features in a similar way and checked how the resolution influences the feature behavior and the overall classification results.

4 Experimental results

We performed our tests on a database of 42 images acquired within the Tayside diabetic screening programme at Ninewells Hospital, Dundee, in accordance to the current regulations (ethics, Caldicott, anonymization). Images have high resolution (2336x3504), and type-2 field, i.e., centered on the macula.

On the selected images, vessel central points have been annotated manually by experts using a user friendly tool based on the VAMPIRE software package [8]. A total of 656 points have been selected (326 labelled as arteries and 330 as veins) with a protocol targeted to the AVR calculation. Example vein/artery points selected in one of the images are shown in Fig. 3.

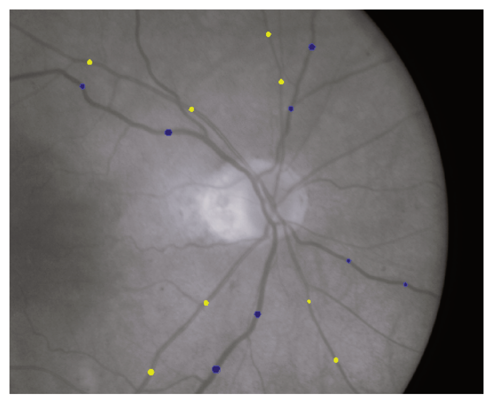

Figure 3. Example annotation of manually selected central vessel points belonging to veins(yellow) and arteries(blue). The circles sizes are proportional to the assigned vascular diameter.

On these images we performed supervised classification and feature selection tests based on the computation of the parameters described in the previous section, using the PRTools Matlab toolkit [10]. In order to exploit maximally the available data, without creating biased results we performed classification procedures with a leave-image-out protocol, e.g. averaging results obtained by taking test points on one image and training points on all the other in the dataset.
Images have been also subsampled by different factors (0.625, 0.5, 0.25, 0.125, 0.0625) in order to simulate acqui-

sition with sensor with different resolutions and tests have been repeated at each obtained resolution.

A first comparison was done using the complete feature set and performing the Leave Image Out procedure with different linear and nonlinear classifiers (Linear and Quadratic Normal Bayes, Parzen Classifier, Linear and radial basis Support Vector Machine. In this case best results were provided by the linear Bayes normal classifier (see Fig. 4. This may be considered surprising, but it confirms what reported in literature [6]: the reason is probably due to overfitting affecting non linear and data adapted discriminative. These methods are more sensitive to inter-subject variations of vessel size and color.
The best classification accuracy is rather good (average error 0.06875), especially considering that we do not use vascular network information.

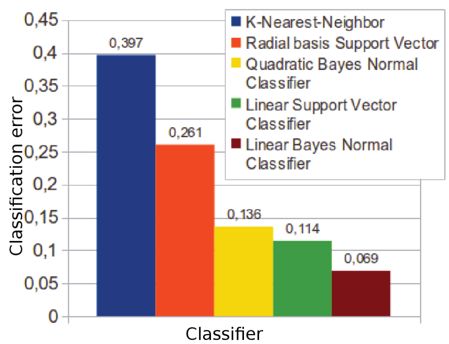

Figure 4. The normal linear Bayes classifier provided the best results if compared with other widely applied classifiers. Nonlinear methods produced sensitively higher error rates.

Other tests have been then dedicated to the analysis of the contribution of the different feature types. Fig. 5 shows the best classification accuracies obtained with the normal linear Bayes classifier using subsets of features described in Section 3 and considering color variations within the vessel size or also outside. The plots show some interesting facts:

- Color variations are more informative considering both vessel and background than using vessel only. Contrast with external pixels give more information than internal variability (central reflex), even if the addition of features based on the internal variations slightly improve the results.

- Size information alone does not improve the color based classification accuracy, while positional information does relevantly reduce the classification error

- Adding size information to the color and positional information has a negligible effect.

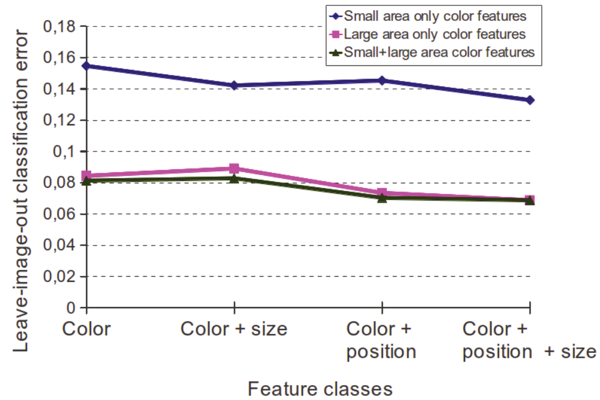

Figure 5. Classification errors obtained with different groups of features.

It is worth noting that the classification results and the role of feature groups does change with the resolution and that the accuracy does not necessarily decrease with it. Figure 6 shows the errors obtained at different subsampling rates, that is maximal at half the original size. This is probably due to the reduction of noise of the high resolution sensor. Only if we consider the internal color variation alone the accuracy increases with higher resolutions, due to the visibility of the central reflex, but the global result remains poor.

Discrimination obtained with individual features and backward/forward feature selection tests provides also relevant information about the information hidden in the different parameters. If we consider the classification errors obtained with single features it results that vessel size is one of the best features and that a lot of color features are relevant for the classification. The most discriminative color features seem the standard deviation of the value measured in the large neighborhood of the vessel center and value and standard deviation of the red channel both inside and around. As expected, position alone does not provide any hint on the vessel class.

However, if we perform a greedy backward feature selection (e.g. removing iteratively from the complete set the less influent features), we interestingly note that the best result can be obtained using a reduced set of about 16 features, and that this set includes both color features computed in the large and in the small regions and positional cues (distances from the OD center and image center). Information on vessel width can be removed without effect. This could suggest the possibility of performing a feature selection step in the future classification applications we are developing,

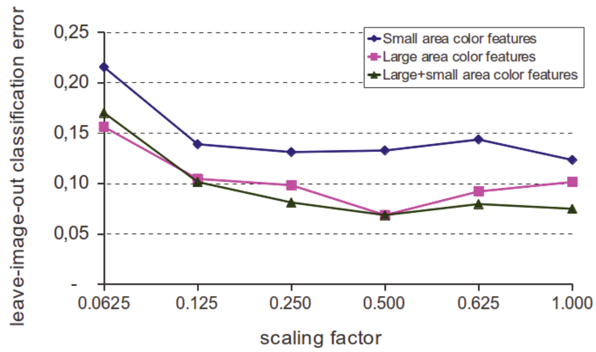

Figure 6. Effect of image subsampling on artery/vein classification. The accuracy is higher at a reduced resolution (1168x1752), probably due to noise in color channels. Higher resolution, as expected, allow a better discrimination using only the internal color features, due to the increased visibility of the central reflex.

however, the feature selection should be trained on a large set of images of different kind in order to provide reliable results. A feature selection would also make probably more accurate the classification results obtained with nonlinear classifiers. We will perform future tests to verify these hypotheses.

5 Discussion

We performed several tests aimed to understand which groups of features are useful to discriminate veins and arteries in digital fundus images. Results are quite interesting and could be useful to improve the performances of existent systems for the estimation of related biomarkers such as the AVR.
First of all, color contrast between vessels and background appear the most important cue for discrimination, but there are vessels that are not well recognized so simply and require to add more information. This information can be related to vessel position and to the color variations inside the vessel, while the vessel width does not seem to add useful information.
Finally, image resolution should be taken into account: it seems that high resolution sensors introduce noise and can reduce the color based information: the same features computed on subsampled images gave, in fact, better results even if an excessive subsampling could remove the information about the central reflex in vessels. The dependency of performance on color confirms the importance of normalizing image resolution in studies involving different-resolution fundus cameras. to guarantee consistency.

1	Large area mean Value
2	Large area min Hue
3	Large area max Saturation
4	Large area mean Red
5	Large area std Blue
6	Large area min Blue
7	Small area min Red
8	Small area min Value
9	Distance from OD center
10	Large area min gradient norm
11	Large area std Value
12	Large area max Blue
13	Distance from image center
14	Large area max Value
15	Small area mean gradient norm
16	Central pixel Value

Table 1. Last 16 features removed from the whole set performing a backward feature selection procedure. With these subset of features the classification accuracy is the same obtained with the full set. Note that this discriminative subset includes both large area and small area color variations, positional cues and does not include vessel width.

References

[1] R. Chrbstek, M. Wolf, K. Donath, H. Niemann, and G. Michelsont. Automated calculation of retinal arteriovenous ratio for detection and monitoring of cerebrovascular disease based on assessment of morphological changes of retinal vascular system, 2003.

[2] A. Giachetti, K. S. Chin, E. Trucco, C. Cobb, and P. J. Wilson. Multiresolution localization and segmentation of the optical disc in fundus images using inpainted background and vessel information. In *ICIP*, pages 2145–2148, 2011.

[3] E. Grisan and A. Ruggeri. A divide et impera strategy for automatic classification of retinal vessels into arteries and veins. September 2003.

[4] A. R. L. Tramontan, E. Grisan. An improved system for the automatic estimation of the arteriolarto- venular diameter ratio (avr) in retinal images. 2008.

[5] C. Muramatsu, Y. Hatanaka, T. Iwase, T. Hara, and H. Fujita. Automated selection of major arteries and veins for measurement of arteriolar-to-venular diameter ratio on retinal fundus images. *Comp. Med. Imag. and Graph.*, 35(6):472–480, 2011.

[6] M. Niemeijer, X. Xu, A. V. Dumitrescu, P. Gupta, B. van Ginneken, J. C. Folk, and M. D. Abràmoff. Automated measurement of the arteriolar-to-venular width ratio in digital color fundus photographs. *IEEE Trans. Med. Imaging*, 30(11):1941–1950, 2011.

[7] C. Nieuwenhuis, D. Kondermann, and M. Yan. Blood vessel classification into arteries and veins in retinal images. In *Proc. of the SPIE Medical Imaging*, volume 6512, San Diego, USA, Feb. 2007.

[8] A. Perez-Rovira, T. MacGillivray, E. Trucco, K. Chin, K. Zutis, C. Lupascu, D. Tegolo, A. Giachetti, P. Wilson, A. Doney, and B. Dhillon. Vampire: Vessel assessment and measurement platform for images of the retina. In *33rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3391–3394, 2011.

[9] K. Rothaus, X. Jiang, and P. Rhiem. Separation of the retinal vascular graph in arteries and veins based upon structural knowledge. *Image Vision Comput.*, 27:864–875, June 2009.

[10] F. van der Heijden, R. Duin, D. de Ridder, and D. M. J. Tax. *Classification, Parameter Estimation and State Estimation: An Engineering Approach Using MATLAB*. Wiley, 1 edition, Nov. 2004.