

Boosted learned kernels for data-driven vesselness measure

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ABSTRACT

Common vessel centerline extraction methods rely on the computation of a measure providing the likeness of the local appearance of the data to a curvilinear tube-like structure. The most popular techniques rely on empirically designed (hand crafted) measurements as the widely used Hessian vesselness, the recent oriented flux tubeness or filters (e.g. the Gaussian matched filter) that are developed to respond to local features, without exploiting any context information nor the rich structural information embedded in the data.

At variance with the previously proposed methods, we propose a completely data-driven approach for learning a vesselness measure from expert-annotated dataset. For each data point (voxel or pixel), we extract the intensity values in a neighborhood region, and estimate the discriminative convolutional kernel yielding a positive response for vessel data and negative response for non-vessel data. The process is iterated within a boosting framework, providing a set of linear filters, whose combined response is the learned vesselness measure.

We show the results of the general-use proposed method on the DRIVE retinal images dataset, comparing its performance against the hessian-based vesselness, oriented flux antisymmetry tubeness, and vesselness learned with a probabilistic boosting tree or with a regression tree. We demonstrate the superiority of our approach that yields a vessel detection accuracy of 0.95, with respect to 0.92 (hessian), 0.90 (oriented flux) and 0.85 (boosting tree).

Keywords: vesselness, retina, oriented flux, filter learning, vessel detection, vessel segmentation

1. INTRODUCTION

The enhancement and detection of curvilinear tube-like structures, ranging from blood vessels to nerves and dendrites, is becoming a crucial step for the evaluation and diagnosis of different pathologies, under different imaging modalities (CT, MRI, optical microscopy, angiography). The inherent variability of the curvilinear structures, either due to pathophysiological variability, or to imaging artifacts, or to contrast and intensity variations, make the problem extremely difficult. Most segmentation methods use an empirical (although principled) formulation of a vesselness measure, i.e. a measure of how well the local appearance of the data match the appearance of an ideal tube-like structure imaged under similar conditions: we will refer to them as hand-crafted. The most widespread measure of *vesselness* assume that blood vessels can be considered as elongated or line structures, of different diameters and orientations, either dark on a brighter background (as in the retinal images), or bright on a darker background (as in CT angiography). Moreover, vessels are assumed to be characterized by a local principal direction and a cross-sectional plane (in 3D) or line (in 2D) with Gaussian intensity profile. Under these assumptions, the most common tool to characterize vessel patterns is through the Hessian matrix.¹⁻³ In order to mitigate some of the limitations of the Hessian-based measures, a family of vesselness measures based on the oriented flux, have been recently proposed.^{4,5} These methods provide successful *tubularity* measures, for their supposed ability in detecting curvilinear structures, resilience to adjacent confounders and robustness to noise. However, no context information is accounted for in these measures, nor they are built to exploit all information embedded in the available data. In order to capture these additional characteristics, machine learning approaches have been proposed to provide a detection score that can be treated as a vesselness measurement.^{6,7} However, they are based on the extraction of user-defined features that are only supposed to capture the discriminant characteristics of vessels and non-vessels.

Building on the idea that the score provided by a supervised classifier may be used as a vesselness measure, and at variance with the hybrid approach proposed in⁸ we propose a fully data-driven approach, in which the features

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to be used with an AdaBoost classifier are learned as optimal linear filters from the training set. By this means, there is no need of any preliminary feature extraction and the testing stage requires only the computation of convolutions of the learned filters with the data and the linear combinations of their responses.

2. BOOSTED VESSELNESS KERNEL (BVK)

Following the approach proposed in⁹ we estimate a set of discriminative convolution kernels (or linear weak learners) allowing a linear classification of each pixel into the two classes of interest through AdaBoost, making the most use of the local appearance information, and then, as in,⁷ we use the classifier output as vesselness measure. Since we are dealing with a problem in which the geometric information is weak, even referencing the position of each pixel with respect to the optic disk, we choose to evaluate image features alone.

If we are given a set of N observations $\mathbf{f}_1, \dots, \mathbf{f}_N \in \mathbb{R}^d$ and labels $l_1, \dots, l_N \in \{-1, +1\}$, we want to design a function $H : \mathcal{F} \mapsto \{-1, +1\}$, a *classifier*, that predicts the label l of a generic observation \mathbf{f} . As the observations $\mathbf{f}_i \in \mathbb{R}^d$ we are dealing with are image regions, d is the number of pixels in a $\sqrt{d} \times \sqrt{d}$ region. We denote the unknown joint probability distribution density of (\mathbf{f}, l) as $p(\mathbf{f}, l)$ and the *expectation* of a random variable w with respect to p as $E_p[w]$. The unknown probability density $p(\mathbf{f}, l)$ can be written as a Parzen window estimate with a Gaussian kernel $G_\sigma(\cdot)$ with zero-mean and standard deviation σ , resulting in the smoothed expected risk

$$\text{Err}_{\hat{p}_g}(H) = -\frac{1}{N} \sum_{i=1}^N \int G_\sigma(\mathbf{f} - \mathbf{f}_i) l_i H(\mathbf{f}) d\mathbf{f}. \quad (1)$$

A classifier H is designed by additively and linearly combining several weak classifiers $h_m(\mathbf{f})$, each of them doing at least better than the chance.¹⁰ If we consider M weak classifiers $h_m : \mathbb{R}^2 \mapsto \{-1, 1\}$, and a set of M scalar parameters $\alpha_1, \dots, \alpha_M \in \mathbb{R}$, we can build a strong vesselness estimator as:

$$V_M(\mathbf{f}) = \sum_{m=1}^M \alpha_m G_\sigma * h_m(\mathbf{f}). \quad (2)$$

Restricting h_m to be computed as the sign of a scalar product $h_m(\mathbf{f}) = \text{sign}(\gamma_0 + \gamma_1 \cdot \mathbf{f})$, with $\gamma_0 \in \mathbb{R}$ and $\gamma_1 \in \mathbb{R}^d$, the parameters γ_0 and γ_1 can be estimated by minimizing via gradient descent the empirical error:

$$\text{Err}_{\hat{p}_g}(h_m) = \frac{1}{2} - \frac{1}{2N} \sum_{i=1}^N w_{i,m} l_i \text{erf} \left(\frac{\gamma_{0,m} + \gamma_{1,m} \cdot \mathbf{f}}{\sqrt{\gamma_{1,m}^T \Sigma \gamma_{1,m}}} \right) \quad (3)$$

with w_i the weight of the training sample (\mathbf{f}_i, l_i) , and $\text{erf}(\cdot)$ is the error function. In practice, each estimated $\gamma_{1,m}$ can be rearranged as an image and interpreted as a vesselness filter kernel, providing as output a weak-vesselness measure, that is combined with other kernels to provide the *strong* vesselness measure V_M . In our approach, the single weak-vesselness kernel is sequentially estimated within an AdaBoost framework. By this means, the boosting is performed by initializing the weight $w_{i,1} = 1/N$ in Eq. 3. Then, the algorithm to boost learned filter is described below.:

Algorithm 1 Boosting learned kernels

- 1: **for** $m = 1$ to M **do**
 - 2: Estimate $\gamma_{1,m}$ and $\gamma_{0,m}$ minimizing Eq. 3
 - 3: Estimate the empirical error $\epsilon_m = P_{w_m}[h_m(\mathbf{f}_i) \neq l_i]$
 - 4: Estimate the weak-vesselness weight $\alpha_m = \frac{1}{2} \log \frac{1 - \epsilon_m}{\epsilon_m}$
 - 5: Update the sample weights $w_{i,m+1} = w_{i,m} \frac{\exp(-\alpha_m l_i h_m(\mathbf{f}_i))}{z_m}$
 - 6: **end for**
 - 7: Evaluate the strong vesselness measure $V_{BLK}(\mathbf{f}) = \sum_{m=1}^M \alpha_m g_\Sigma * h_m(\mathbf{f})$
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3. RELATED METHODS

3.1 Hand crafted vesselness measures

3.1.1 Hessian-based vesselness (HES)

Starting from a scale-space representation of an image $I(x, y)$, $L(x, y; t) = G_\sigma(x, y) * I(x, y)$, where $G_\sigma(\cdot)$ is a Gaussian function with variance σ , the larger eigenvalue λ_1 and the smaller eigenvalue λ_2 of the Hessian matrix can be computed. In² the ridgeness score $R(x, y) = \lambda_2/\lambda_1$ and the Frobenius norm of the Hessian $S(x, y)$ are combined to provide a vesselness measure at the position (x, y) for scale t :

$$v_{hess}(x, y; t) = \begin{cases} 0 & \lambda_1 > 0 \\ \exp\left(-\frac{R^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right) & \text{otherwise.} \end{cases} \quad (4)$$

The final vesselness measure $V(x, y)$ across the different scales is computed as the maximum response $V_{hess}(x, y) = \max_t v_{hess}(x, y; t)$.

3.1.2 Optimally Oriented Flux tubeness (OOF)

The Optimally Oriented Flux (OOF) filter is computed by convolving the second derivatives of the image with the indicator function of the sphere.⁴ Given a position (x, y) in the image I , a radius r , and an orientation p , the OOF filter response $f(x, y; r, p)$ is obtained by integrating the projected image gradients in the p direction over a sphere ∂S_r of radius r centered at (x, y) :

$$f(x, y; r, p) = \frac{1}{4\pi r^2} \int_{\partial S_r} (\nabla(G_\sigma * I(x + rn_x, y + rn_y)) \cdot p) p \cdot n \, dS, \quad (5)$$

where $n = (n_x, n_y)$ is the outward versor normal to ∂S_r , G_σ is a smoothing Gaussian function with standard deviation equal to σ , and dS is the infinitesimal area element of the sphere ∂S_r . The idea of enhancing vessel structures through $f(x, y; r, p)$, is that the smaller its value, the more likely is that the position (x, y) is the center of a vessel with scale r and orientation p . Hence, the OOF tubeness measure can be computed as:⁴

$$f_{OOF}(x, y; r) = \max_{p_1, p_2 | p_1 \perp p_2} -f(x, y; p_1, r) - f(x, y; p_2, r). \quad (6)$$

In order to prevent a strong response of $f_{OOF}(x, y; r)$ to the edges, the optimally oriented flux has been extended⁵ with an antisymmetry function correction term, to obtain an oriented flux antisymmetry (OFA) tubeness $v_{OFA}(x, y; r)$, that yields high responses along centerlines of curvilinear structures at their associated scales (as the f_{OOF} measure), at the same time annihilating the OOF response away from the structure centerlines:

$$V_{OFA}(x, y) = \max_r v_{OFA}(x, y; r). \quad (7)$$

3.2 Learned probabilistic boosted tree (PBT)

In⁷ a learning-based vesselness measurement has been proposed for 3D CT coronary data, based on a classifier that assigns a high score to voxels inside the vessels and a low score to those outside, making use of both position features (in this case with respect to the heart reference), and image features. Given a point at coordinates (x, y) with intensity $I(x, y)$ and gradient $G(x, y) = (G_x, G_y) = (\nabla_x I, \nabla_y I)$, and the angle between the gradient G and the y axis as $\alpha = \arccos(G_y)$, 24 local features based on the image intensity and gradient are extracted. The features to be used are I , \sqrt{I} , $\sqrt[3]{I}$, I^2 , I^3 , $\log I$, $\|G\|$, $\sqrt{\|G\|}$, $\sqrt[3]{\|G\|}$, $\|G\|^2$, $\|G\|^3$, $\log \|G\|$, α , $\sqrt{\alpha}$, $\sqrt[3]{\alpha}$, α^2 , α^3 , $\log \alpha$, G_x , G_y . In total, there are 20 local features for each sampling point, based on intensity, gradient and gradient orientation, that are sampled in the 5x5 neighborhood of the position under analysis, resulting in a total of 25x24 image features. These features are then fed to a trained probabilistic boosting tree (PBT)¹¹ to classify a pixel as inside a retinal vessel or belonging to the retinal background, providing as output the vesselness measure V_{PBT} .

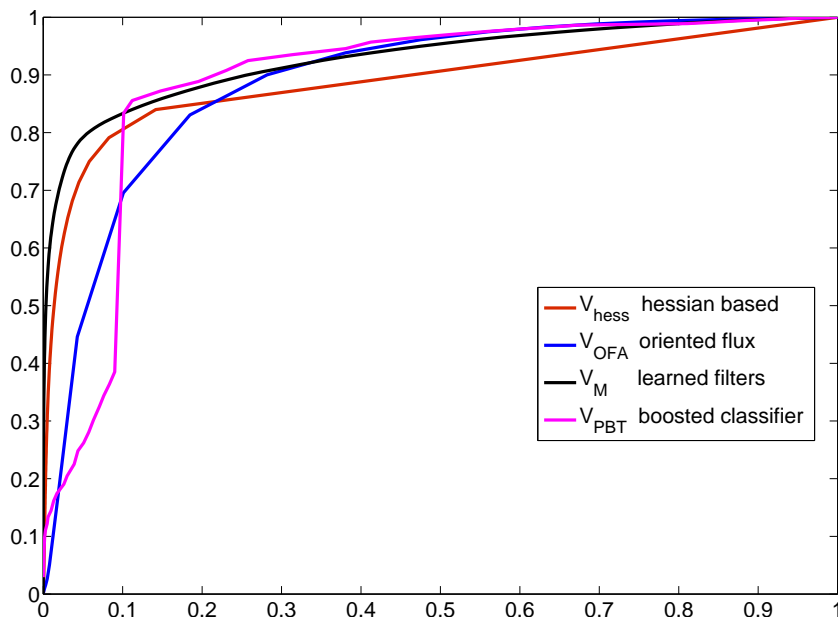


Figure 1. ROC curves obtained by thresholding the different vesselness measures. On the x-axis the fraction of false positive pixels (1-specificity) and on the y-axis the fraction of true positive pixels (sensitivity).

4. EXPERIMENTS AND RESULTS

We applied the proposed procedure to the DRIVE¹² data set, learning the kernels on the training set composed by 20 retinal fundus images, with corresponding manual annotation of retinal vessels. The additional 20 images in the DRIVE dataset for testing were used for evaluating the vesselness measures. For training the proposed boosted kernels, a random subset of pixels from the green plane of the training images (1.3% of the total) was extracted after normalizing the image¹³ to obtain a uniform appearance and reduce inter-image variability. For each selected pixel (x_i, y_i) , we defined f_i as the square window neighborhood of 15x15 pixels centered on the selected pixel, with a 3-scale pyramidal representation, so that f_i is a real valued vector with 225x1 elements. In order to reduce the intra-class variability of f_i , each 15x15 window was preventively rotated so as to have the vessel horizontally oriented.

The method proposed in⁷ were trained using a probabilistic boosted tree (PBT) with depth set to 3 and with 20 weak-learners for each node, on the same features described in the original paper, with the exception of those providing the localization of the pixel with respect to the heart (that would be translated to reference retinal structures).

Testing was performed convolving the test image with R different rotated versions of each estimated h_m (at the orientations $r\pi/R$ radians, with $r = 0, \dots, R - 1$), obtaining then R different $V_M(x_i; r)$. The estimated vesselness for each pixel (x, y) is then simply $V_M(x, y) = \max_r V_M(x, y; r)$. The same training and testing procedure has been performed for the machine-learning vesselness of,⁷ whereas for the hessian-based and OFA vesselness measure, their value has been computed for each pixel of each image. Representative results of the vesselness output for the different methods are reported in Fig. 2. When the four methods are operated with the best respective threshold estimated through a ROC analysis, they provide a mean vessel detection accuracy of 0.90 for OFA, 0.92 for HES, 0.85 for PBT, and 0.95 for BLK.

Representative results of the vesselness output for the different methods are reported in Fig. 2, whereas the ROC curves of the four methods for vessel detection on the retinal 20 retinal images used is shown in Fig. 1. The curve of the proposed method is mostly above all others, demonstrating its better ability in discriminating

(even with a small number of weak-learners) vessel pixels from non-vessel pixels. When the four methods are operated with the best respective threshold, they provide a mean vessel detection accuracy of 0.90 for V_{OOF} , 0.92 for V_{HES} , 0.90 for V_{PBT} , 0.94 for V_{LRT} , and 0.95 for V_{BK} .

5. CONCLUSIONS

We present a very general method for estimating data-driven boosted filters that proved to be able to effectively learn the discriminative characteristics of vessels and non-vessels data. In the case study of retinal vessels enhancement and detection, the proposed method outperformed both the hessian-based vesselness enhancement, the asymmetry oriented flux and the feature based PBT. The proposed method has the advantage of being modular, since weak classifiers can be added in a greedy fashion thanks to the underlying AdaBoost, with low computational complexity at training time and requiring only a set of convolution at testing time. Since it learns discriminative linear kernels from the raw data (or from some preprocessing of them), it can be extended straightforwardly to higher dimensional data with no increase in complexity.

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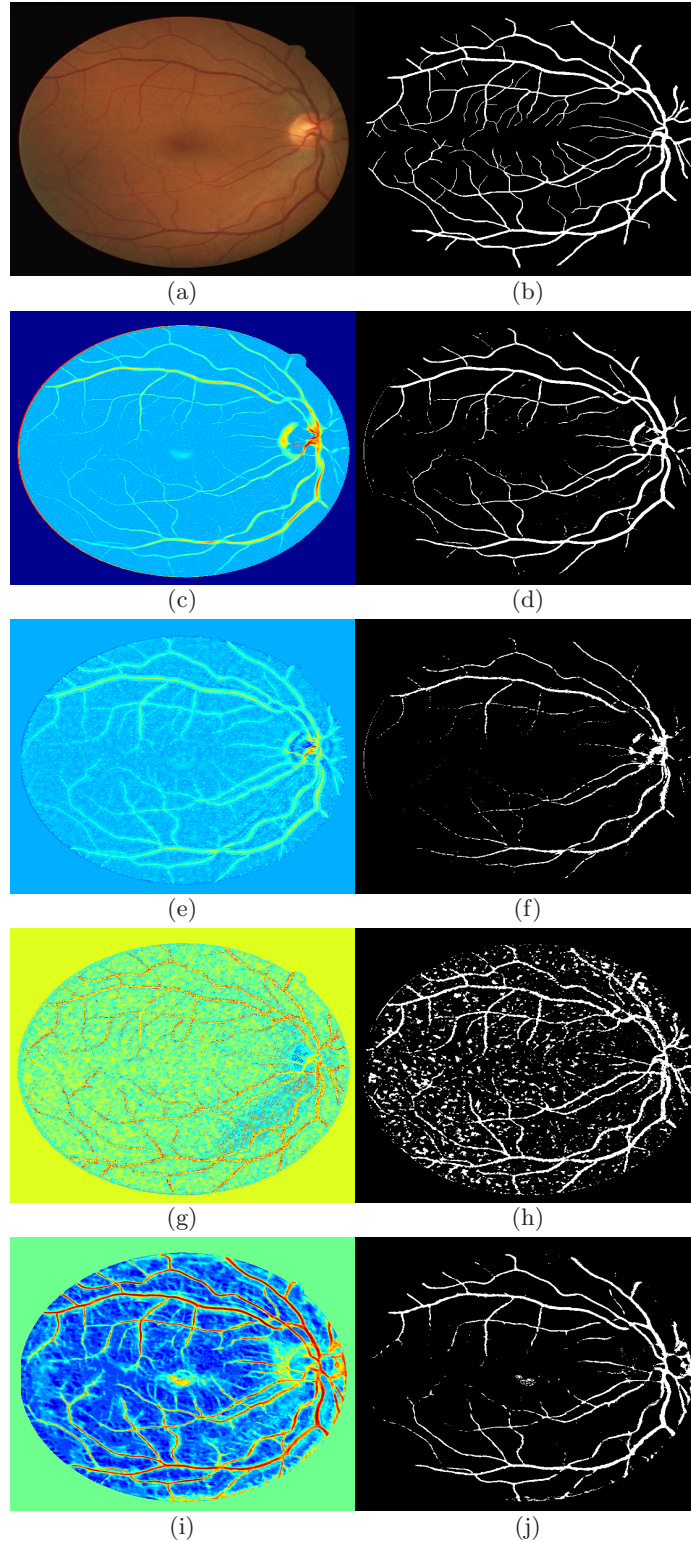


Figure 2. Vesselness measure on a random image of the DRIVE retinal dataset. Top row, the original image and the vesselness maps obtained with the the hessian-based method V_{hess} ,² the oriented flux V_{OFA} ,⁵ the learned vesselness on image and gradient features V_{PBT} ⁷ and the proposed boosted learned vesselness. Bottom row, the corresponding vessel segmentation obtained by thresholding the vesselness map.