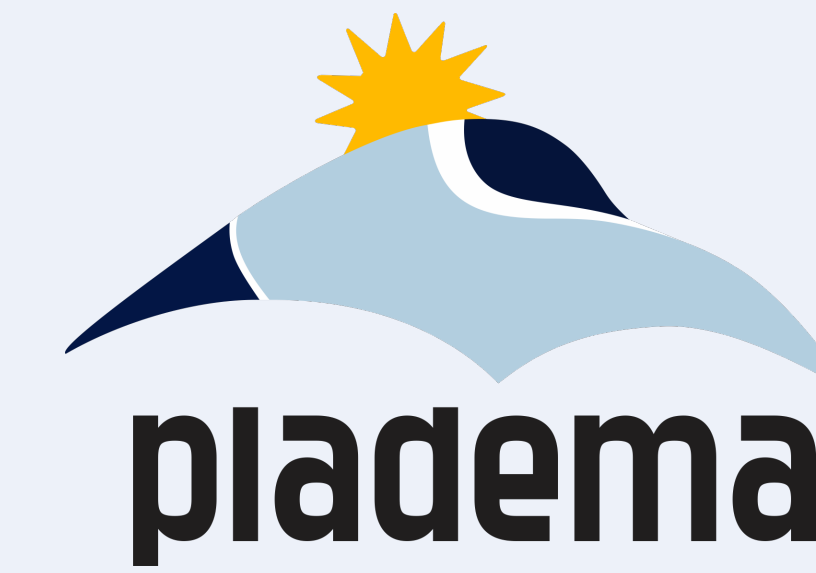


Learning Fully-Connected CRFs for Blood Vessel Segmentation in Retinal Images



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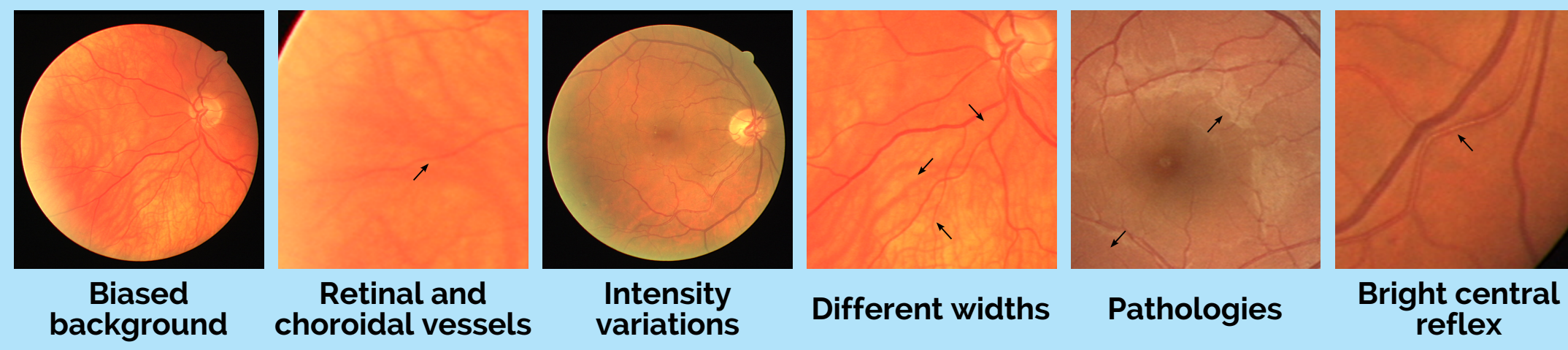
1

INTRODUCTION

motivation

Retinal image analysis is greatly aided by **blood vessel segmentation** as the **vessel structure** may be considered both a **key source of signal**, e.g. in the **diagnosis of diabetic retinopathy**, or a **nuisance**, e.g. in the **analysis of pigment epithelium** or **choroid related abnormalities**.

challenges



our contribution

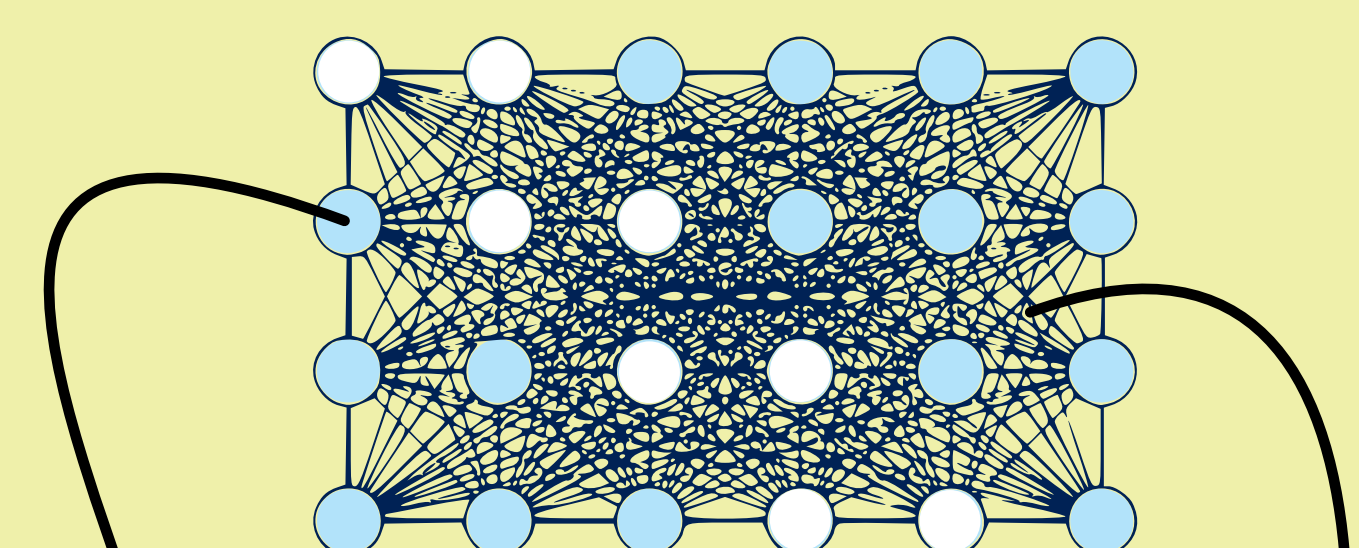
We present a **novel method** for **blood vessel segmentation** in **fundus images** based on a **discriminatively trained, fully connected conditional random field (CRF)** [1].

2

energy definition

The **segmentation task** is posed as an **energy minimization problem** in a **fully connected CRF**:

$$E(\mathbf{y}) = \sum_i \psi_u(y_i, \mathbf{x}_i) + \sum_{i < j} \psi_p(y_i, y_j, \mathbf{f}_i, \mathbf{f}_j)$$



unary potentials
Log-likelihood over the label assignment:

$$\psi_u(y_i, \mathbf{x}_i) = -\langle \mathbf{w}_{uy_i}, \mathbf{x}_i \rangle - \beta_{y_i}$$

pairwise potentials
Similar distribution but considering only the interactions between pixels features and their labels

$$\psi_p(y_i, y_j, \mathbf{f}_i, \mathbf{f}_j) = \mu(y_i, y_j) \sum_{m=1}^M w_p^{(m)} k^{(m)}(\mathbf{f}_i^{(m)}, \mathbf{f}_j^{(m)})$$

potts model

$$\mu(y_i, y_j) = [y_i \neq y_j]$$

$$k^{(m)}(\mathbf{f}_i^{(m)}, \mathbf{f}_j^{(m)}) = \exp \left(-\frac{|\mathbf{p}_i - \mathbf{p}_j|^2}{2\theta_p^2} - \frac{|\mathbf{f}_i^{(m)} - \mathbf{f}_j^{(m)}|^2}{2\theta_f^2(m)} \right)$$

pixel distance feature similarity

estimation of scale values

Scale values of the **pairwise kernels** are estimated following [2], by taking the **median of the distance over random sampled pairs of pixels**.

LEARNING FULLY CONNECTED CRF'S PARAMETERS USING SOSVM

structured output svm We optimize this expression using [3].

$$\min_{\mathbf{w}, \xi \geq 0} \frac{1}{2} \|\mathbf{w}\|^2 + C\xi$$

$$\text{s.t. } \forall (\bar{y}^{(1)}, \dots, \bar{y}^{(n)}) : \sum_{i=1}^n \langle \mathbf{w}, \varphi(s^{(i)}, y^{(i)}) - \varphi(s^{(i)}, \bar{y}^{(i)}) \rangle \geq \sum_{i=1}^n \Delta(y^{(i)}, \bar{y}^{(i)}) - \xi$$

training set

Weights are learned from the **training set**: $S = \{(s^{(1)}, y^{(1)}), \dots, (s^{(n)}, y^{(n)})\}$

unary feature vector, bias constant and pairwise feature vector $s^{(i)} = \{x^{(i)}, B, f^{(i)}\}$ $y^{(i)} \in \mathcal{L} = \{-1, +1\}$ **manual annotation**

feature map

$$\varphi(s, y) = \left(\sum_k \varphi_u(\mathbf{x}_k, y_k), \sum_k \varphi_\beta(B, y_k), \sum_k \sum_{j < k} \varphi_p(y_k, y_j, \mathbf{f}_k, \mathbf{f}_j) \right)$$

unary term bias term pairwise term

$\varphi_u(\mathbf{x}_k, y_k) = \mathbf{x}_k \otimes \varphi_{y_k}(y_k)$ $\varphi_\beta(B, y_k) = B \varphi_y(y_k)$ $\forall m : [\varphi_p(y_k, y_j, \mathbf{f}_k, \mathbf{f}_j)]_m = \mu(y_k, y_j) k^{(m)}(\mathbf{f}_k^{(m)}, \mathbf{f}_j^{(m)})$

loss function

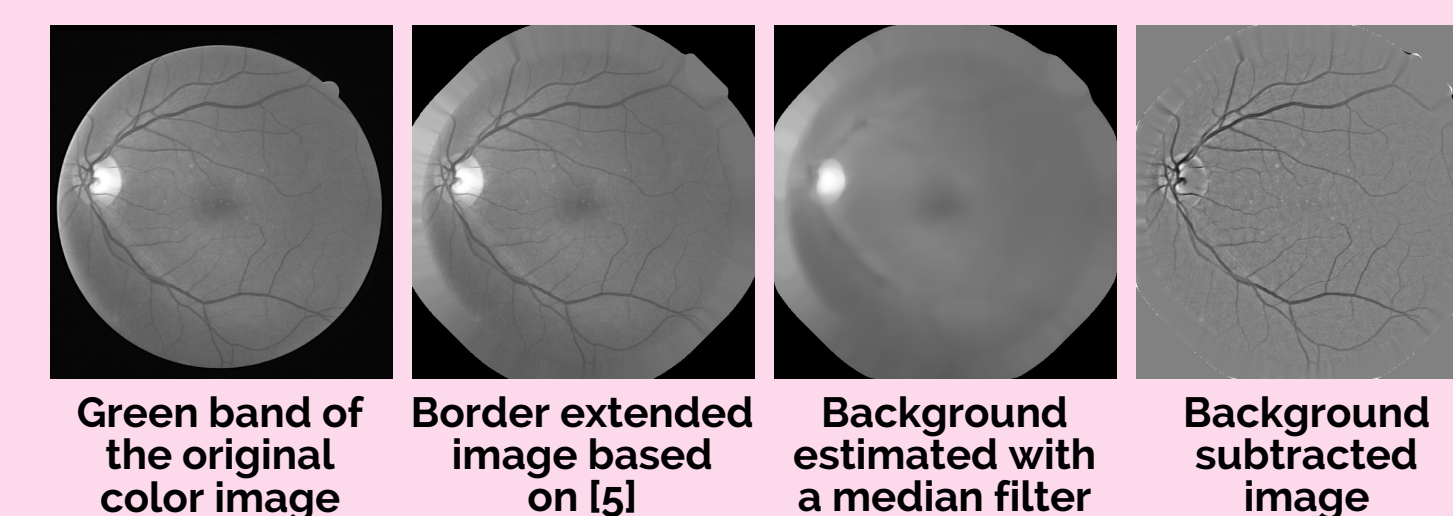
Hamming loss
 $\Delta(y, \bar{y}) = \sum_i [y_i \neq \bar{y}_i]$

weight vector $\mathbf{w} = (\mathbf{w}_u, \mathbf{w}_\beta, \mathbf{w}_p)$ **weights for unary, bias and pairwise terms, respectively**

FEATURES

preprocessing

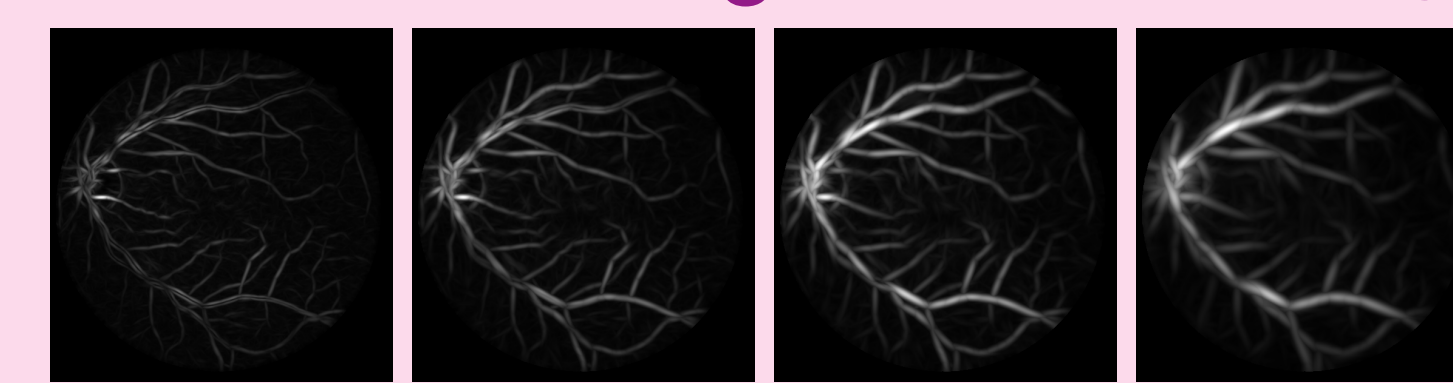
Images are **preprocessed** to **avoid false detections in the border of the FOV** and to **reduce the effect of biased illumination**.



unary features

line detectors [4]

2d multiscale gabor wavelets [5]



vesselness enhancement inspired on [6]



pairwise feature

vessel enhancement inspired on [7]

feature selection

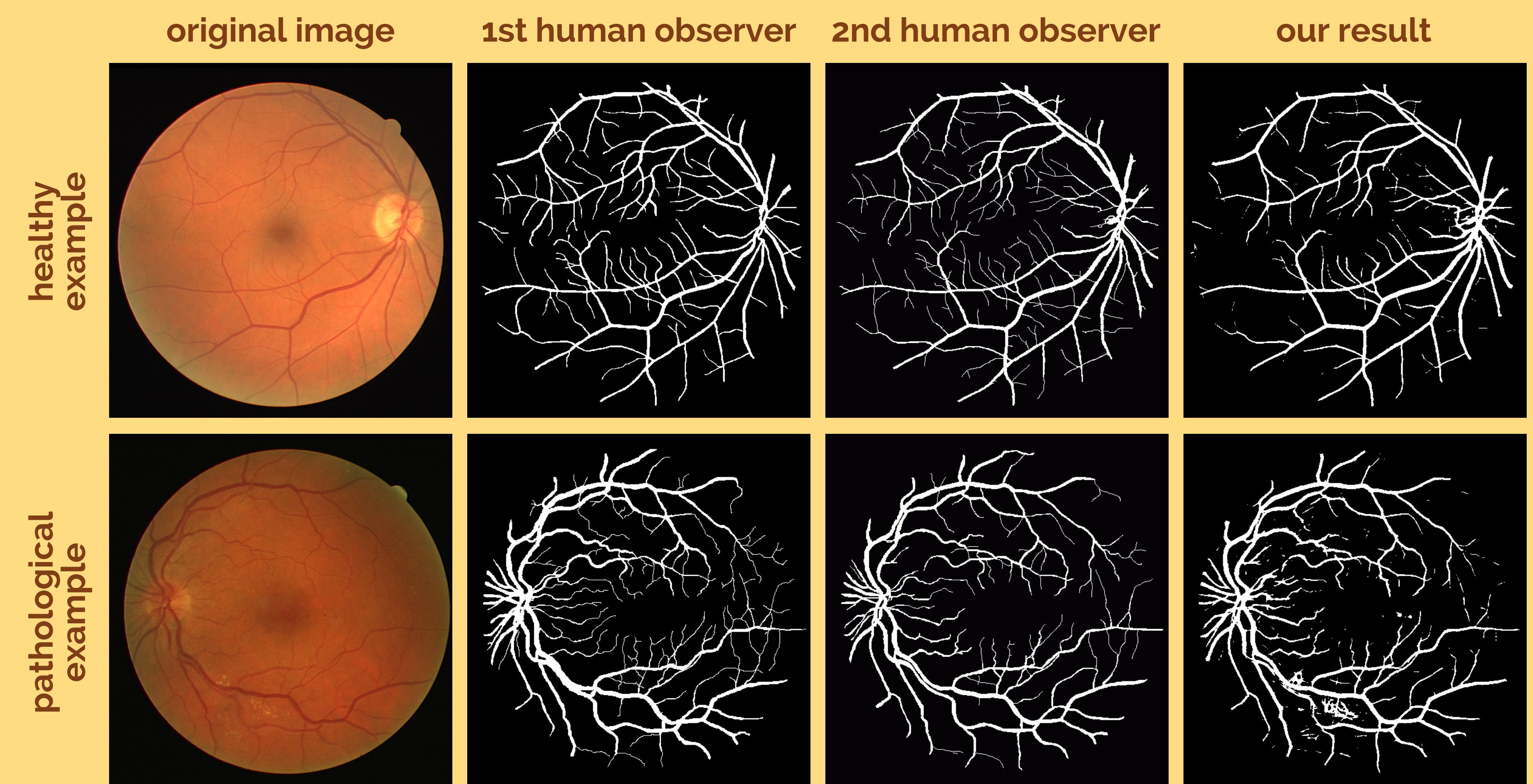
Best configuration of features is found by minimizing the distance to a second human observer performance, using a validation set.

3

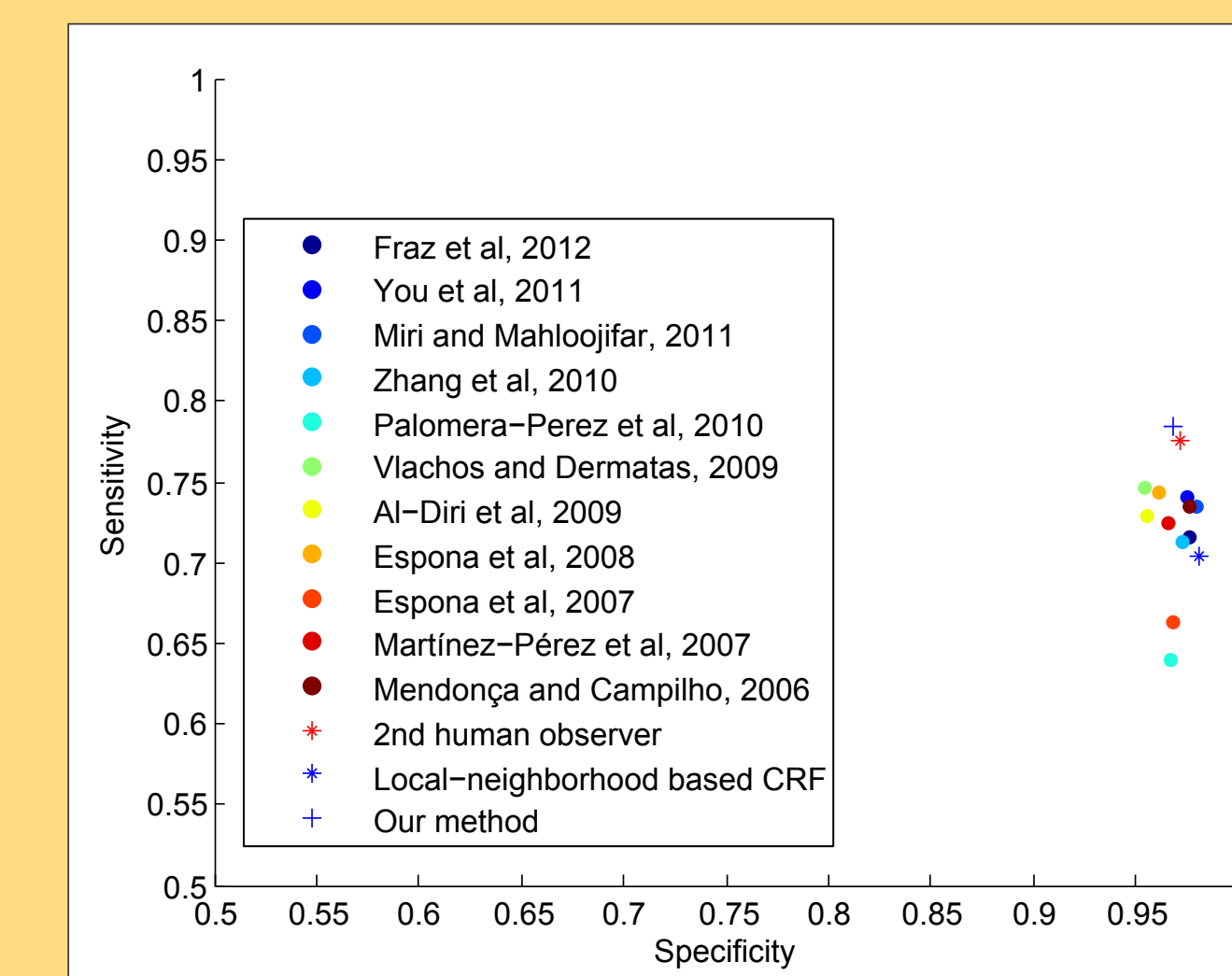
VALIDATION AND RESULTS

qualitative evaluation

Experiments and evaluation are performed on **DRIVE dataset**



quantitative evaluation



evaluation metrics

Our results are compared with the **state-of-the-art** in terms of **sensitivity and specificity**

$$Se = \frac{TP}{TP + FN}$$

$$Sp = \frac{TN}{TN + FP}$$

Our method is **statistically tied** with the **performance of a second expert annotator**, and achieves a **much higher sensitivity** than all other current segmentation systems.

- [1] Krähenbühl, P., Koltun, V.: Efficient inference in fully connected CRFs with Gaussian edge potentials. In: *NIPS*. (2012)
- [2] Schölkopf, B.: Support Vector Learning. PhD thesis, Oldenbourg Verlag, Munich (1997)
- [3] Joachims, T., Finley, T., Yu, C.N.J.: Cutting-plane training of structural SVMs. *Machine Learning* 77(1) (2009) 27–59
- [4] Ricci, E., Perfetti, R.: Retinal blood vessel segmentation using line operators and support vector classification. *IEEE T-MI* 26(10) (2007) 1357–1365
- [5] Soares, J.V., et al.: Retinal vessel segmentation using the 2-d Gabor wavelet and supervised classification. *IEEE T-MI* 25(9) (2006)
- [6] Sinthanayothin, C., et al.: Automated localisation of the optic disc, fovea, and retinal blood vessels from digital colour fundus images. *British Journal of Ophthalmology* 83(8) (1999) 902–910
- [7] Saleh, M.D., Eswaran, C.: An efficient algorithm for retinal blood vessel segmentation using h-maxima transform and multilevel thresholding. *Computer Methods in Biomechanics and Biomedical Engineering* 15(5) (2012) 517–525

REFERENCES

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For any further information and implementation details:
Project webpage: <http://pages.saclay.inria.fr/matthew.blaschko/projects/retina/>
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