Ridge-Based Vessel Segmentation in Color Images of the Retina

Joes Staal*, *Associate Member, IEEE*, Michael D. Abràmoff, *Member, IEEE*, Meindert Niemeijer, Max A. Viergever, *Member, IEEE*, and Bram van Ginneken, *Associate Member, IEEE*

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introduccion

- Metodo
  - Extraccion de la centerline (ridges)
  - Descompone la imagen en patches de acuerdo a los trozos de linea encontrados
  - Aplica un clasificador para decidir si un pixel está en una linea (continuacion de lineas)
- Evaluacion:
  - Area bajo la curva ROC
  - Accuracy

Representacion vasos Ridge detection

- Ridge: puntos de la imagen donde la primera derivada de la intensidad en la direccion de la mayor curvatura cambia el signo.
- La dirección de la mayor curvatura es el primer autovector de la matriz Hessiana (segundas derivadas)

- Calculo de las derivas usando la derivada de la gausiana

image $L(\mathbf{x})$ $\mathbf{x} = (x_1, x_2)^T$

$$L_{x_j} = \frac{\partial L(\mathbf{x}, \sigma)}{\partial x_j}$$

$$= \frac{1}{2\pi\sigma^2} \int_{\mathbf{x}' \in \mathbb{R}^2} \frac{\partial e^{-\|\mathbf{x}-\mathbf{x}'\|^2/2\sigma^2}}{\partial x_j} L(\mathbf{x}')d\mathbf{x}' \qquad (1)$$

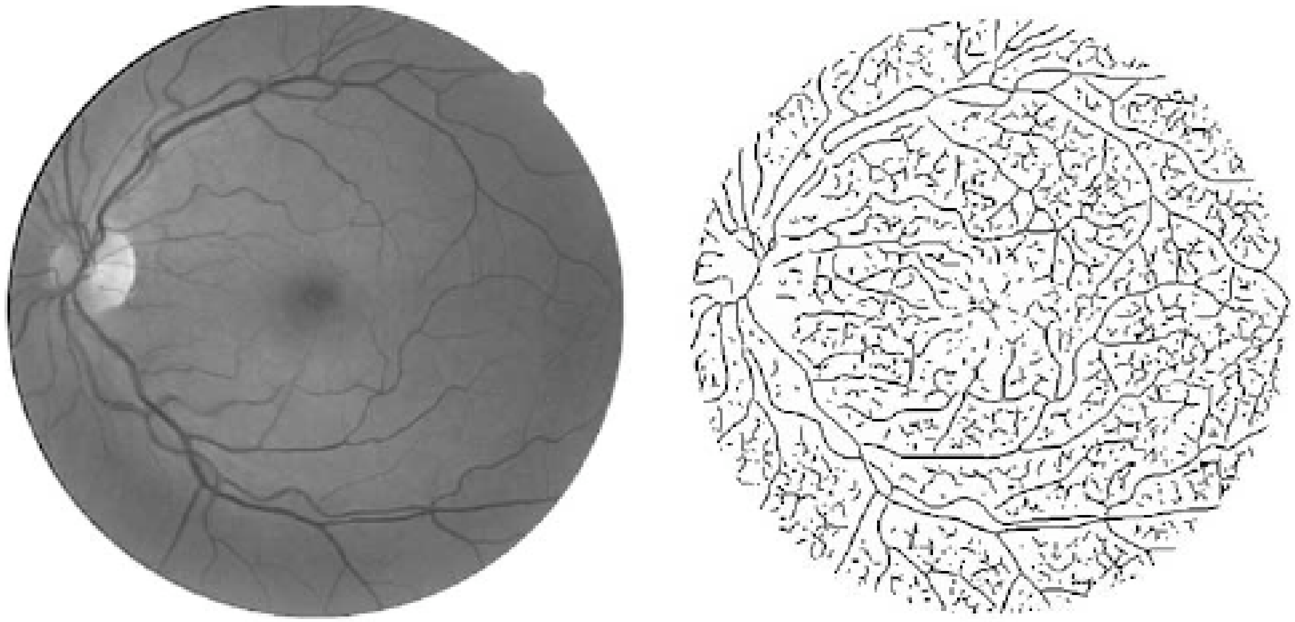
- Define un campo escalar que toma valor -1 en las crestas minimos locales, 1 para las crestas de maximos locales y 0 elsewhere

$$\rho(\mathbf{x},\sigma) = -\frac{1}{2}\text{sign}(\lambda)\left|\text{sign}(\nabla L(\mathbf{x}+\epsilon\hat{\mathbf{v}},\sigma)\cdot\hat{\mathbf{v}}) - \text{sign}(\nabla L(\mathbf{x}-\epsilon\hat{\mathbf{v}},\sigma)\cdot\hat{\mathbf{v}})\right| \quad (2)$$

gradient operator ∇ is defined as $(\partial/\partial x_1, \partial/\partial x_2)^T$

$\lambda(\mathbf{x},\sigma)$ is the largest eigenvalue by absolute value of $\mathbf{H} = \nabla\nabla^T L(\mathbf{x},\sigma)$

ϵ is the spatial accuracy



(a) (b)

Fig. 1. (a) Green channel of a fundus image obtained from a digital fundus camera. The diameter of the FOV is 540 pixels. (b) The local minima ridges of (a), $\sigma = 2.0$ pixel. A subset of the ridges coincide with the vessels.

Affine convex sets: agrupando ridge pixels

- Algoritmo de crecimiento de regiones
- Un pixel se añade si forma parte de la misma cresta
  - La direccion dada por el autovector del hessiano tiene que ser similar (producto escalar cerca de 1)
  - Pertenecer al mismo ridge (prod. Escalar entre el autovector y el vector diferencia entre las posiciones cerca de 1)

$$||\mathbf{x}_{\mathrm{g}} - \mathbf{x}_{\mathrm{u}}|| \leq \epsilon_{\mathrm{c}} \tag{3}$$

$$|\hat{\mathbf{v}}(\mathbf{x}_{\mathrm{g}}, \sigma) \cdot \hat{\mathbf{v}}(\mathbf{x}_{\mathrm{u}}, \sigma)| \geq \epsilon_{\mathrm{o}} \tag{4}$$

$$||\hat{\mathbf{v}}(\mathbf{x}_{\mathrm{g}}, \sigma) \wedge \hat{\mathbf{r}}|| \geq \epsilon_{\mathrm{p}} \tag{5}$$

"g" stands for grouped, "u" for ungrouped,
"o" for orientation and "p" for parallelism.

$0 \leq \epsilon_{\mathrm{c}} < \infty$ and $0 \leq \epsilon_{\mathrm{o}}, \epsilon_{\mathrm{p}} \leq 1$.

We refer to these sets of (x_1, x_2) coordinates as affine convex sets: convex because they approximate straight line elements and affine because of the geodesic convexity instead of straight line (Euclidean) convexity.

close to one is recommended. In this paper, $\epsilon_c = 3.0$ pixels, $\epsilon_o = 0.95$, and $\epsilon_p = 0.95$ is used. Fig. 2 illustrates the con-

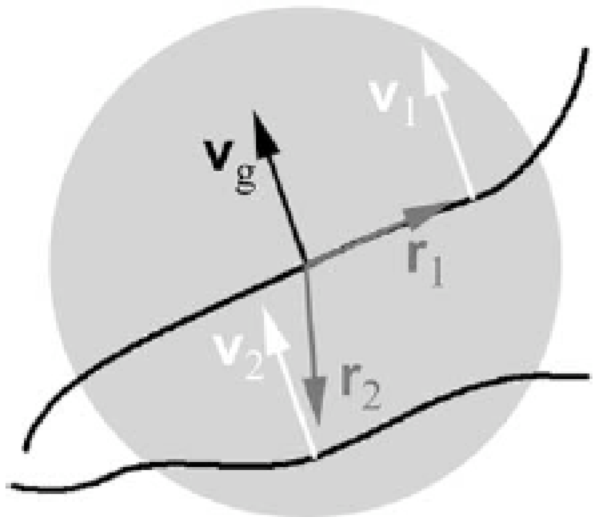
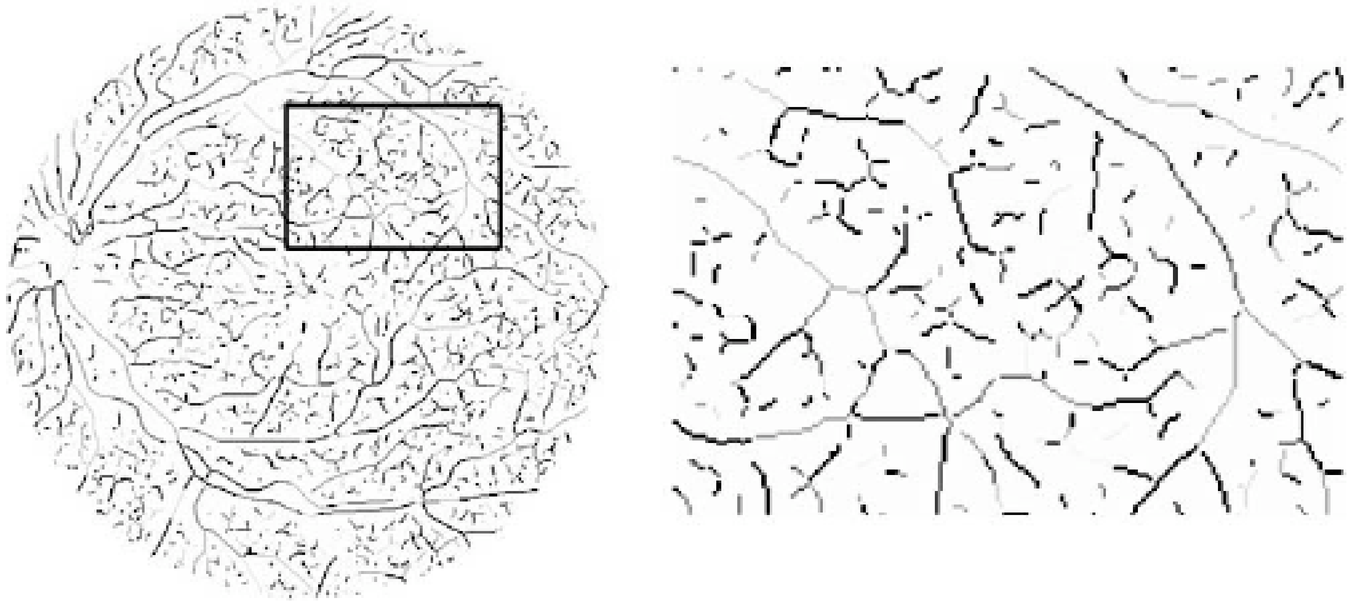


Fig. 2. The dark curved lines are two ridges. The diameter of the disk is ϵ_c. $\mathbf{v}_g$ is the eigenvector belonging to a grouped pixel, $\mathbf{v}_1$ and $\mathbf{v}_2$ are the eigenvectors of still ungrouped pixels. The vectors $\mathbf{r}_1$ and $\mathbf{r}_2$ are unit vectors pointing from the grouped pixels to the ungrouped pixels. The pixel that belongs to the same ridge will be added to the group, because it satisfies the conditions in (3)–(5). The pixel on the parallel ridge does not satisfy condition (5) and will not be grouped.



(a) (b)

Fig. 3. (a) The convex sets of the ridges of Fig. 1(b). Every grouped set has its own color. (b) Blow up of (a). Note that the number of ridge pixels is equal to the number of ridge pixels in Fig. 1.

The kth element in convex set number i, consisting of K_i points, will be denoted by $\mathbf{c}_i(k), k = 1, \ldots, K_i$. The vector

For every point in a convex set i there is a corresponding direction $\hat{\mathbf{v}}_i(k)$, the direction in which the ridge is detected.

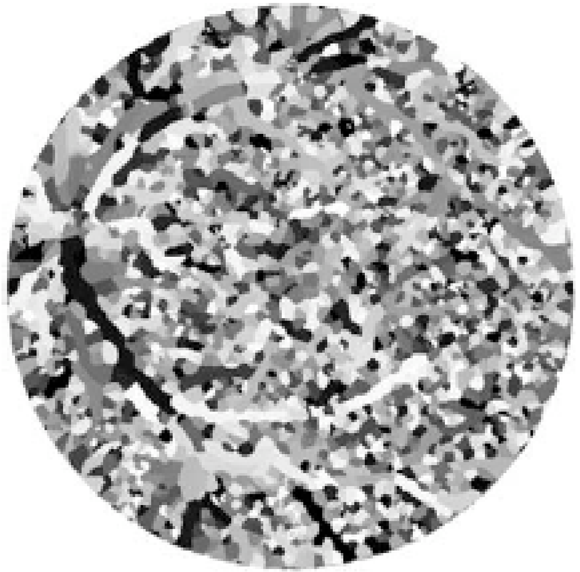


Fig. 4. Convex set regions of the convex sets of Fig. 3(a).

Clasificadores y caracteristicas

- Objetivo: clasificar cada pixel de la iamgen como vaso o no vaso sanguineo
- Training…..
- Usan kNN por experiencias previas
- A posteriori prob. vessel

$$p(\text{vessel}) = \frac{n}{k},$$

The performance of the system is measured with receiver operating characteristic (ROC) curves [27]. An ROC curve plots the fraction of pixels that is falsely classified as vessel against the fraction that is correctly classified as vessel. The fractions are determined by setting a threshold on the posterior probability. The closer a curve approaches the top left corner, the

area under the curve, A_z, which is 1 for a perfect system.

- Feature selection:
  - Sequential forward selection
  - Se escogen en orden la mejora, es un algorimo "greedy"

Convex set features

- De los puntos en el convex set se obtienen los perfiles de intensidad en la direccion $\hat{\mathbf{v}}(k)$ con $\mathbf{c}(k)$ como punto medio
- El promedio de estos perfiles es la caracterizacion del convex set

$$\psi(n), \text{ with } n = -N, \ldots, N,$$

Caracteristicas del perfil

1) The height of the profile: $h = \psi(0)$.
2) The width of the profile defined as the distance between the strongest right and left edge of the profile: $w = n_{\mathrm{re}} - n_{\mathrm{le}}(n_{\mathrm{re}} = \arg\max_{n>0} \psi'(n)$, with ψ' the first derivative of the profile. n_{le} is defined similar for $n < 0$).
3) The height divided by the width: h/w.
4) The edge strength, defined as: $s_{\mathrm{e}} = \psi'(n_{\mathrm{le}}) + \psi'(n_{\mathrm{re}})$.
5) The edge strength divided by the width: s_{e}/w.
6) The edge height: $h_{\mathrm{e}} = 1/2(\psi(n_{\mathrm{le}}) + \psi(n_{\mathrm{re}}))$.
7) The height minus the edge height: $h - h_{\mathrm{e}}$.
8) The height divided by the edge height: h/h_{e}.

Otras

9) The distance between the first and last point of a convex set: $d = ||\mathbf{c}(1) - \mathbf{c}(K)||$.
10) The length of a convex set: $l = \sum_{k=2}^{K} ||\mathbf{c}(k) - \mathbf{c}(k-1)||$.
11) The curvature of a convex set, approximated by: $\kappa = \sum_{k=2}^{K} \hat{\mathbf{v}}(k) \cdot \hat{\mathbf{v}}(k-1)$.
12) A rectangular image patch of size $1.5 \times w$ by K is sampled in the green plane around a convex set. The mean μ_{g} for this patch is computed.
13) The standard deviation σ_{g} for the green patch.
14) The mean value of the green plane at the locations of the convex set divided by the the mean value of the red plane.
15) At different scales σ the mean value of $\lambda(\sigma)$ at the locations of the convex set: $\bar{\lambda}(\sigma) = 1/K \sum_{k=1}^{K} \lambda(\mathbf{c}(k), \sigma)$, this is a measure of ridge strength (see Section II-A).

Caracteristicas sobre los pixels

- Define para cada CSR un sistema de coordenadas local
  - Origen: el centroide del CSR
  - Primer eje: la linea que une los dos extresmos

1) The value of the red plane of the image at the pixel location: $r(\mathbf{x})$.
2) The value of the green plane of the image at the pixel location: $g(\mathbf{x})$.
3) The ratio of the green values and red values of the pixel: $g(\mathbf{x})/r(\mathbf{x})$.
4) The chance that the corresponding convex set belongs to a vessel: $p(\mathbf{c} = \text{vessel})$.
5) The distance between the pixel and the closest point on the convex set: $d_{\text{closest}} = ||\mathbf{x} - \mathbf{c}_{\text{closest}}||$.
6) The difference in the red values of the pixel and the closest point on the convex set: $r(\mathbf{x}) - r(\mathbf{c}_{\text{closest}})$.

7) The ratio of the red values of the pixel and the closest point on the convex set: $r(\mathbf{x})/r(\mathbf{c}_{\text{closest}})$.
8) The difference in the green values of the pixel and the closest point on the convex set: $g(\mathbf{x}) - g(\mathbf{c}_{\text{closest}})$.
9) The ratio of the green values of the pixel and the closest point on the convex set: $g(\mathbf{x})/g(\mathbf{c}_{\text{closest}})$.
10) The coordinate of the pixel with respect to the first axis: x'_1.
11) The coordinate of the pixel with respect to the second axis: x'_2.
12) $L_{x'_1}$, $L_{x'_2}$, $L_{x'_1 x'_1}$, and $L_{x'_2 x'_2}$ at different scales σ. (Note that these are the number of scales $\times$ 4 features).

materiales

- 40 imagenes, 20 para train, 20 para test
- Etiquetados manuales para entrenamiento y validacion

resultados

The ridges in the images are extracted from the green channel at scale $\sigma = 1.5$ pixel. To obtain approximately straight lines, the maximum size of the convex sets is set to 25 pixels.

$$N = 15,$$

Training sets for the convex sets are constructed by counting how many of their pixels intersect with the vessel pixels in the manually labeled ground truth images. If more than 50% of the pixels in a convex set intersect they are labeled as vessel, else as nonvessel.

To compensate for the lighting variations and to enhance local contrast, the pixels of every color channel C_i of the images are locally normalized to zero mean and unit variance

$$N_i(\mathbf{x}, \sigma) = \frac{C_i(\mathbf{x}) - \mathcal{E}_\sigma\{C_i\}(\mathbf{x})}{\sqrt{\mathcal{E}_\sigma\{C_i^2\}(\mathbf{x}) - \mathcal{E}_\sigma^2\{C_i\}(\mathbf{x})}} \qquad (7)$$

with

$$\mathcal{E}_\sigma\{C\}(\mathbf{x}) = \frac{1}{2\pi\sigma^2} \int_{\mathbf{x}' \in \mathbb{R}^2} C(\mathbf{x}') \mathrm{e}^{-\|\mathbf{x}-\mathbf{x}'\|^2/2\sigma^2} \mathrm{d}\mathbf{x}' \qquad (8)$$

acting as a local averaging operator. A value of $\sigma = 8.0$ pixels

A. Settings

The ridge measures are extracted from the green channel and scales $\sigma = 0.5, 1.0, 2.0$, and 4.0 pixels are used.

With these settings a total 18 features per convex set is extracted. For the training of the classifier, only every fourth convex set is taken. This reduces computation time and memory resources.

For the computation of the features for the CSR the following settings are used. In the training phase, the *a posteriori* probabilities for the convex sets are computed using (6) in a leave-one-out fashion, i.e., the convex sets of one image are classified with a classifier trained on the convex sets of the other images in the training set.

The derivatives with respect to the local coordinate systems

The derivatives with respect to the local coordinate systems are taken at scales $\sigma = 0.5, 1.0, 2.0$, and 4.0, resulting in 27 features. For the training, only every fourth pixel in the x_1 and x_2-directions is used.

The feature selection is also done on a leave-one-out basis. This is done for every image and the A_z value of all images is averaged to obtain a criterion upon which it is decided to include a feature or not.

The kNN-classifiers for the classification of the convex sets and the CSR use $k = 101$.

Because kNN-classifiers are sensitive to scaling between different features, in all experiments each feature is normalized independently to zero mean and unit variance.

Feature selection

TABLE I
SELECTED FEATURES FOR THE CONVEX SETS. FOR EVERY ADDED FEATURE THE OBTAINED AREA UNDER THE ROC CURVE IS GIVEN

Utrecht database		Hoover database	
	A_z		A_z
λ, σ = 2.0	0.843	λ, σ = 2.0	0.934
h	0.864	d	0.945
κ	0.870	μ_{g}	0.948
σ_{g}	0.871	λ, σ = 4.0	0.947
λ, σ = 1.0	0.872	λ, σ = 1.0	0.948
μ_{g}	0.873	h_{e}	0.950
λ, σ = 4.0	0.874	all features	0.940
all features	0.864		

TABLE II

SELECTED FEATURES FOR THE CONVEX SET REGIONS. FOR EVERY ADDED FEATURE THE OBTAINED AREA UNDER THE ROC CURVE IS GIVEN

Utrecht database		Hoover database	
	A_z		A_z
$p(\mathbf{c} = \text{vessel})$	0.8755	$p(\mathbf{c} = \text{vessel})$	0.8955
$g(\mathbf{x}) - g(\mathbf{c}_{\text{closest}})$	0.9314	$g(\mathbf{x})/g(\mathbf{c}_{\text{closest}})$	0.9653
d_{closest}	0.9372	d_{closest}	0.9677
$L_{x'_1}$, $\sigma = 1.0$	0.9437	$L_{x'_1 x'_1}$, $\sigma = 2.0$	0.9683
$L_{x'_2}$, $\sigma = 2.0$	0.9463	$L_{x'_2 x'_2}$, $\sigma = 2.0$	0.9680
$L_{x'_2 x'_2}$, $\sigma = 1.0$	0.9472	$r(\mathbf{x})/r(\mathbf{c}_{\text{closest}})$	0.9682
$L_{x'_1 x'_1}$, $\sigma = 2.0$	0.9485	$L_{x'_1}$, $\sigma = 1.0$	0.9684
$r(\mathbf{x})/g(\mathbf{x})$	0.9490	all features	0.9589
$L_{x'_2 x'_2}$, $\sigma = 2.0$	0.9497		
$L_{x'_2}$, $\sigma = 1.0$	0.9498		
$g(\mathbf{x})$	0.9500		
all features	0.9493		

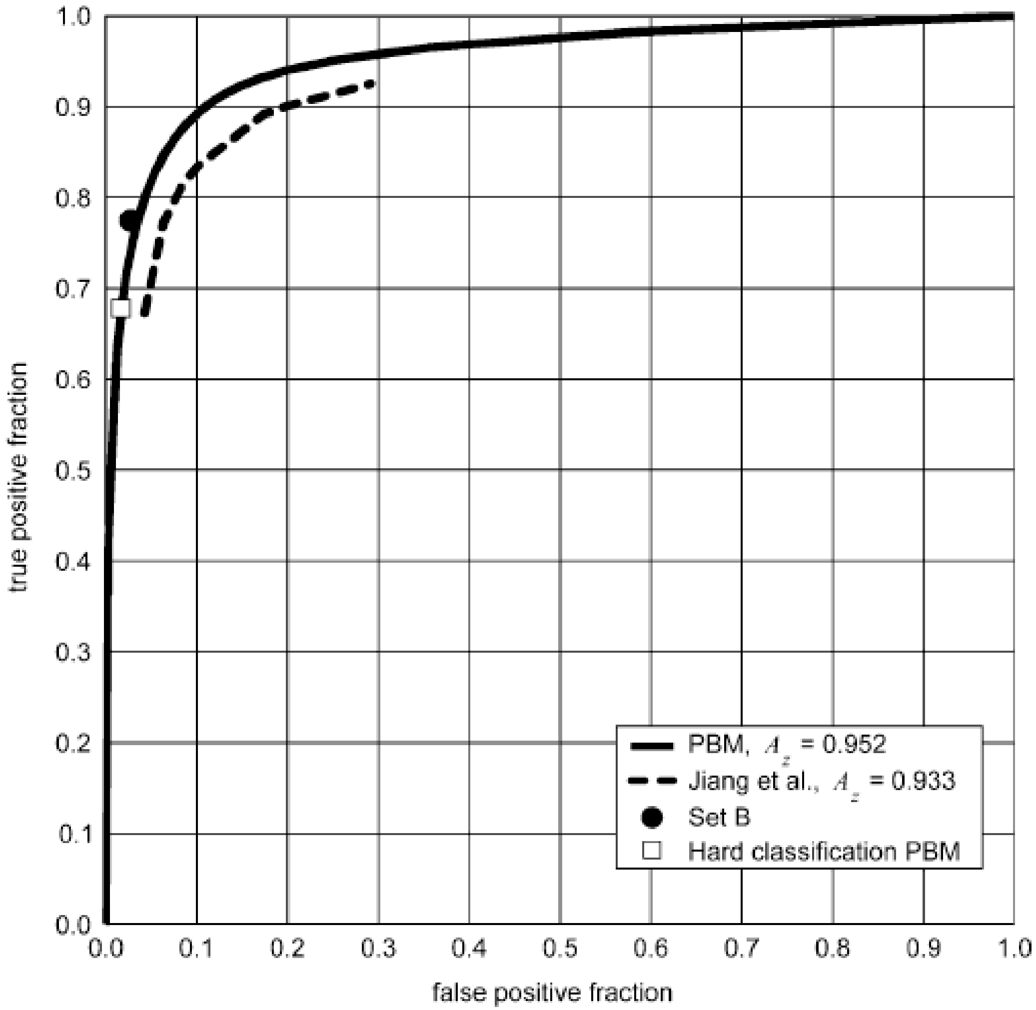


Fig. 5. Results for the Utrecht database. The PBM gives $A_z = 0.952$ and the method of Jiang *et al.* [2] $A_z = 0.933$. Comparing set B to set A, false and true positive fractions of (0.0275, 0.775) are found. Performing a hard classification on the results of the PBM gives (0.017, 0.678) for the false and true positive fractions.

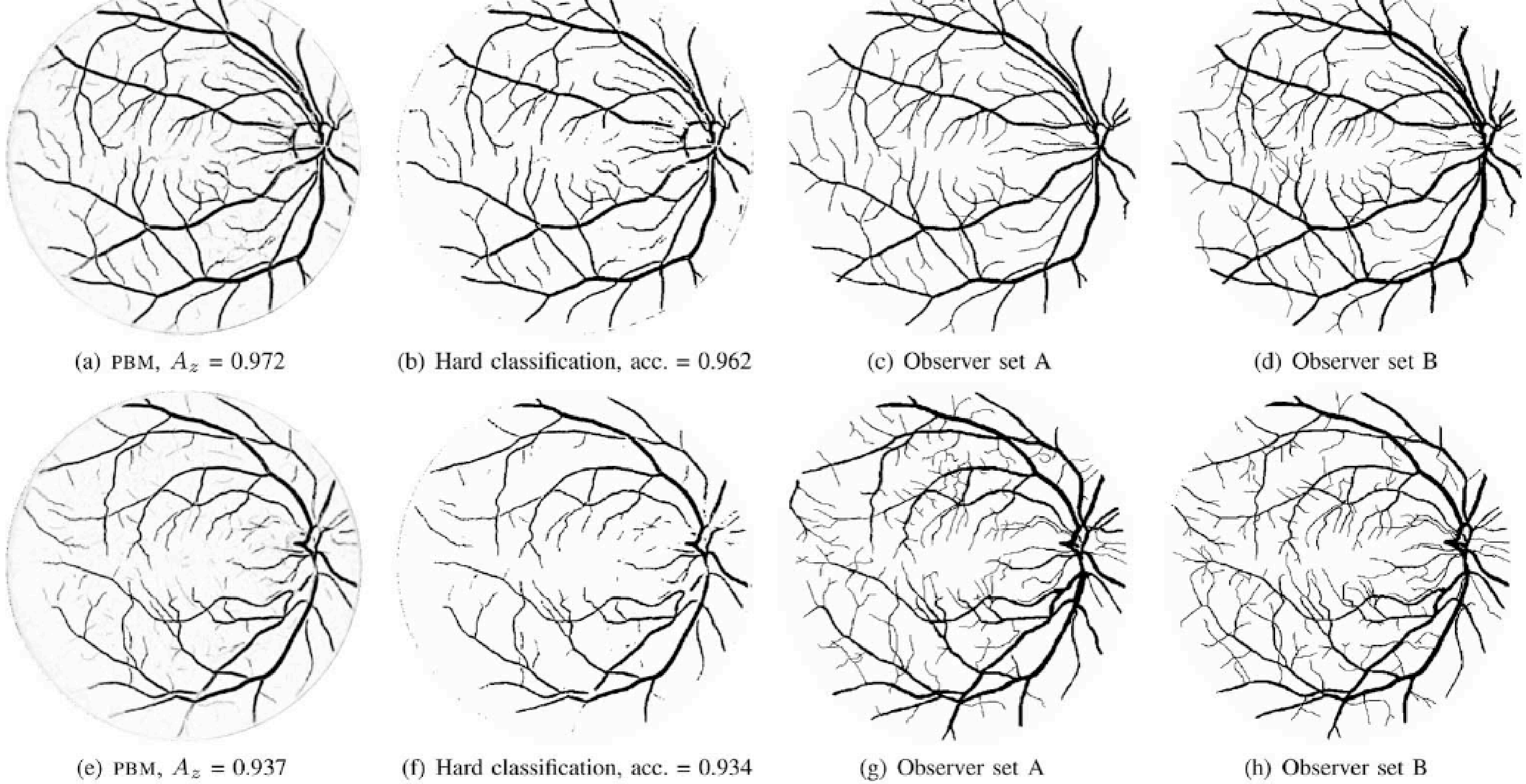


Fig. 6. First column: Best and worst result of the PBM. The grey value denotes the prior probability of the pixel being vessel (bright for the lower values and dark for the higher values). Second column: hard classification. Third column: observer from set A. Fourth column: observer from set B.

TABLE III

RESULTS FOR THE DIFFERENT DATABASES AND METHODS. ROWS 1–3 GIVE THE AREA UNDER THE ROC-CURVES, ROWS 4–8 THE ACCURACY (THE SUM OF THE NUMBER OF CORRECTLY CLASSIFIED FOREGROUND AND BACKGROUND PIXELS, DIVIDED BY THE TOTAL NUMBER OF PIXELS)

Criterion	Method	Database	
		Utrecht	Hoover
A_z	Hoover		0.7590
	Jiang	0.9327	0.9298
	PBM	0.9520	0.9614
Accuracy	2nd obs.	0.9473	0.9351
	Hoover		0.9275
	Jiang	0.8911	0.9009
	PBM	0.9441	0.9516
	Most likely class	0.8727	0.8958