BLOOD VESSEL SEGMENTATION IN RETINAL IMAGES: A SUPERVISED METHOD

Based on:

D. Marìn, A. Aquino, M.E. Gegùndez-Arias, J.M. Bravo

"A New Supervised Method for Blood Vessel Segmentation in Retinal Images by Using Gray-Level and Moment Invariants-Based Features" IEEE Trans. Med. Imag., vol. 30, n. 1, 01/ 2011.

Migliorati Andrea 85417
Communication Technologies and Multimedia - Digital Image Processing

http://www.allaboutvision.com/conditions/spotsfloats.htm

Introduction (0)

- **Diabetic Retinopathy** (DR) is the leading pathological blindness cause among working-age people in developed countries (not curable)
- Early stage: capillary dilations (*microaneurysms*)
- Laser photocoagulation can prevent major vision loss if given in time: patients take annual eye-fundus examination
  - (http://www.allaboutvision.com/conditions/diabetic.htm)

Introduction (1)

- Preventive action is a great management and economic challenge due to the huge (growing) number of patients

- Digital images for diagnosis could be exploited:
  - preliminarily finding not-affected patients would reduce workload: improved effectiveness of protocols, economic benefits

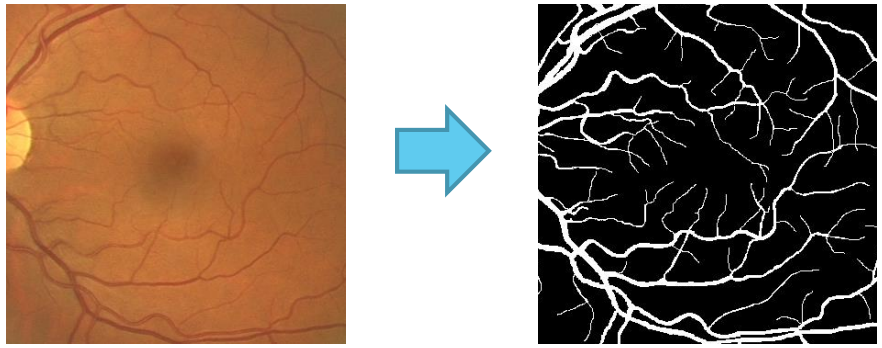
Proposed Method (overview):

- 7-D feature vector out of preprocessed eye-fundus images
- Features as input to a neural network
- Classification results thresholding (vessel/non-vessel)
- Post-processing (pixel gaps filling and false positive removal)

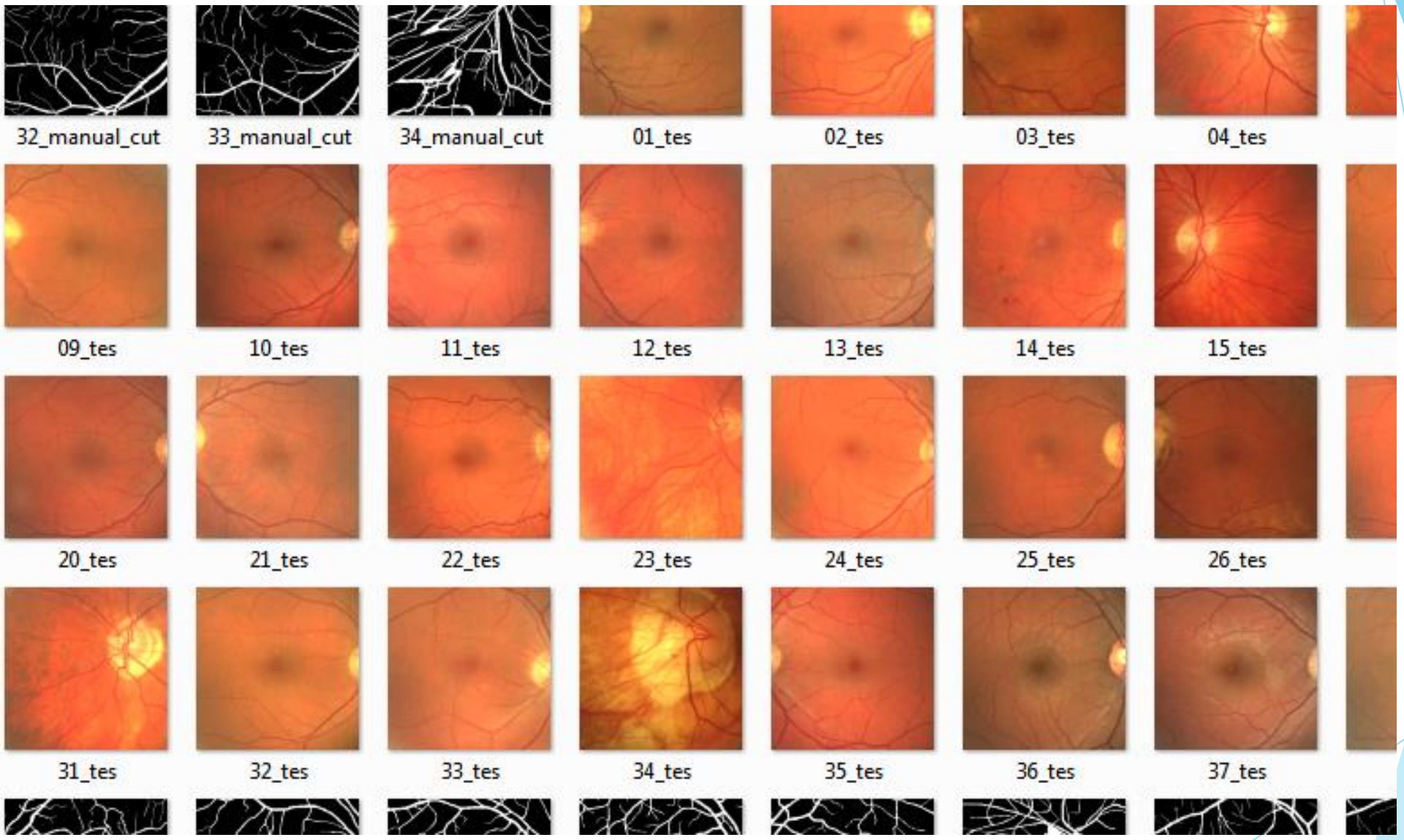
DRIVE database

http://www.isi.uu.nl/Research/Databases/DRIVE/

- 40 eye-fundus image +
- 40 (actually more) manually labeled image for mask reference



- Green channel offers best vessel-background contrast


32_manual_cut
33_manual_cut
34_manual_cut
01_tes
02_tes
03_tes
04_tes
09_tes
10_tes
11_tes
12_tes
13_tes
14_tes
15_tes
20_tes
21_tes
22_tes
23_tes
24_tes
25_tes
26_tes
31_tes
32_tes
33_tes
34_tes
35_tes
36_tes
37_tes

1) Preprocessing:

Input: Green Channel I_G

1. I_{gamma}: vessel central light reflex removal

   - 3x3 morphological opening with a 3 pixels diameter disc → Igamma

2. I_B: background homogenization

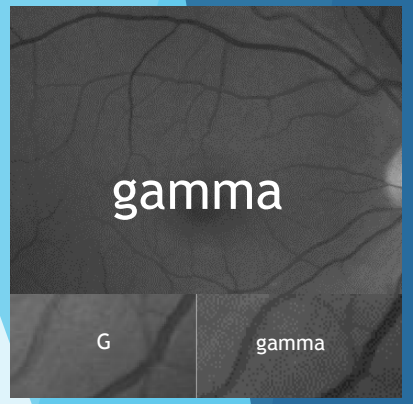
   - 69x69 medianBlur applied to $I_G \rightarrow I_B$
   - $I_{SC} = I_{gamma} - I_B$ (then rescaled to [0,255])
   - I_H obtained from I_{SC} displacing the histogram towards middle gray-scale

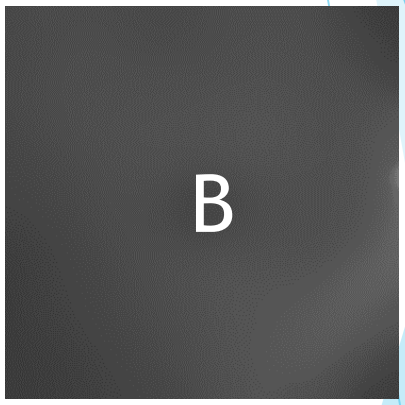
$$I_H(x,y) = \begin{cases} 0 & if\ g < 0 \\ 255 & if\ g > 255 \\ g & otherwise \end{cases}, \qquad g = I_{SC}(x,y) + 128 - \{\text{most present gray level in } I_{SC}\}$$

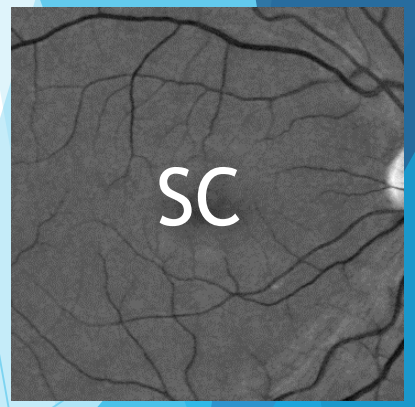
3. I_{VE}: vessel enhancement $I_{VE} = I_H^C - \gamma(I_H^C)$

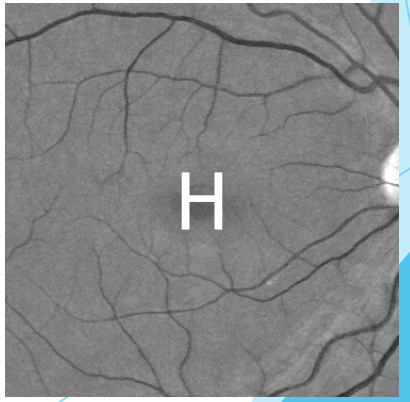
   - γ: morphological opening using a disc of 8 pixels in radius
   - C : complementary image (negative)

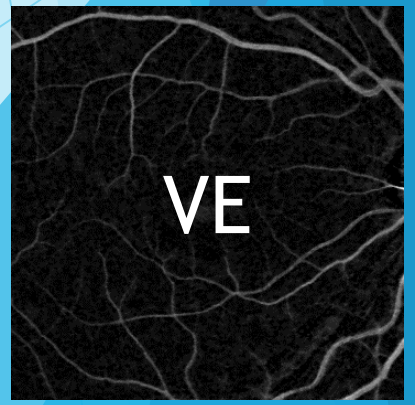
→ **features extraction: 5 from I_H + 2 from I_{VE}**

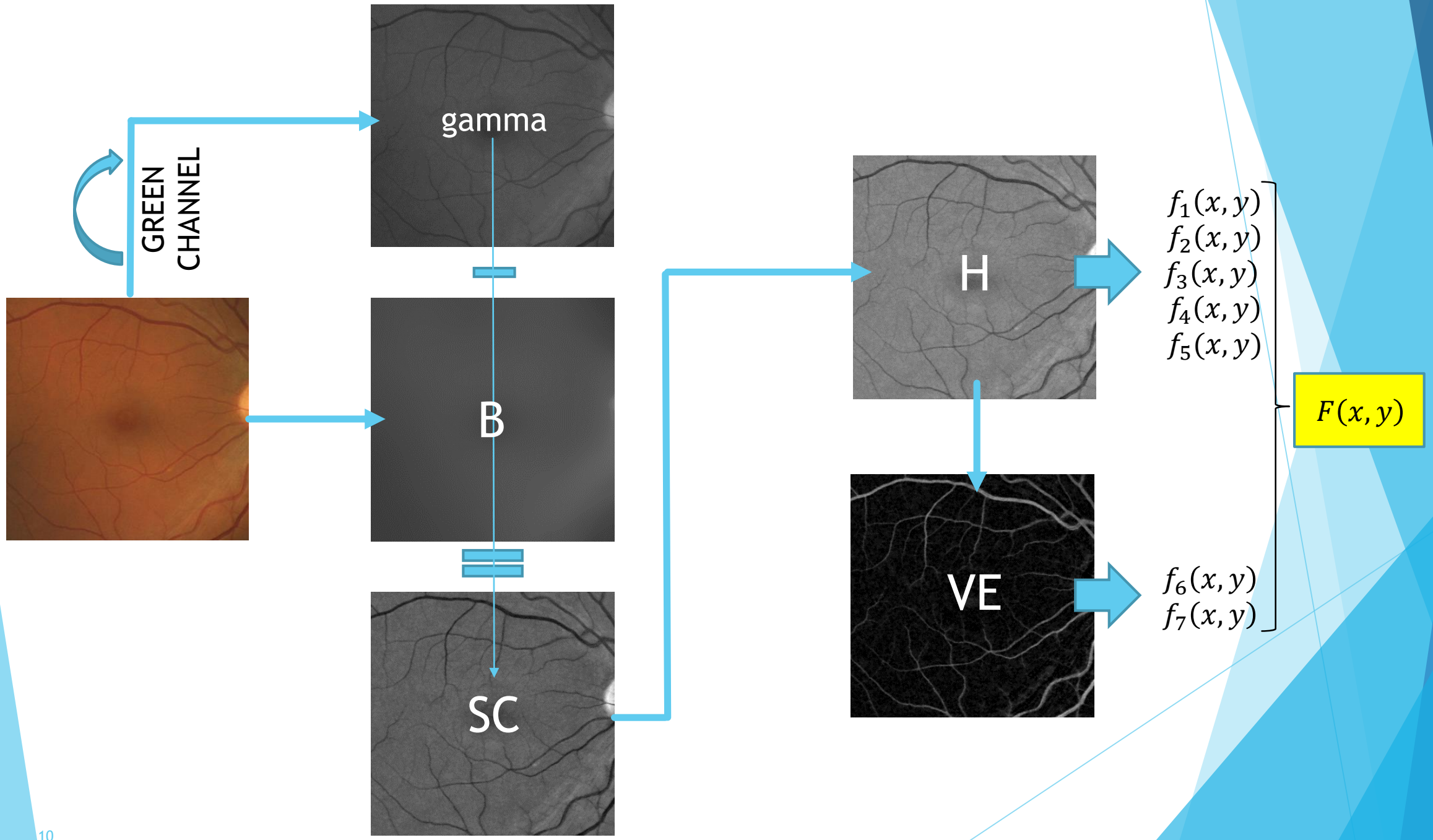


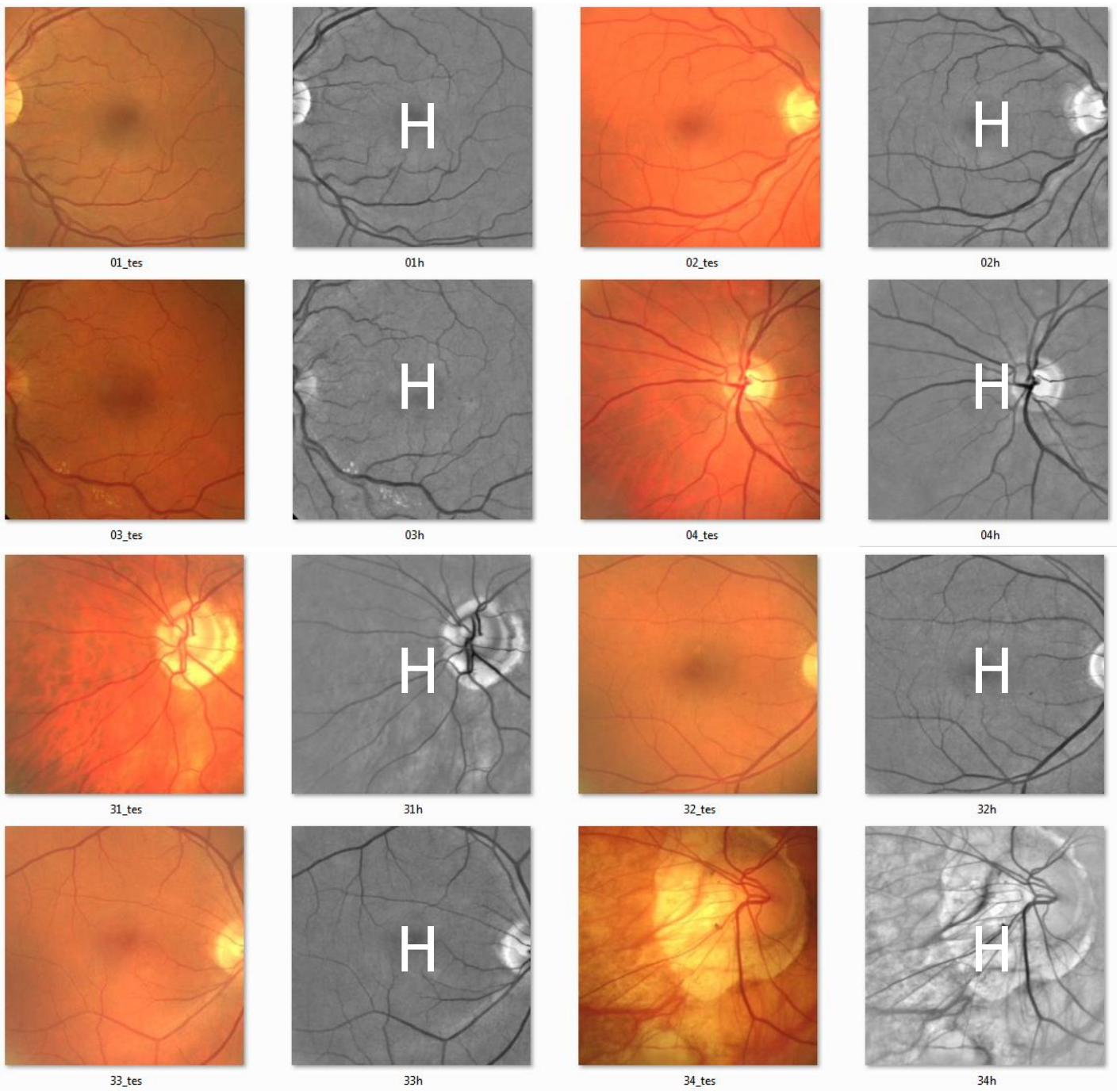









GREEN CHANNEL
gamma
B
SC
H
VE
$f_1(x,y)$
$f_2(x,y)$
$f_3(x,y)$
$f_4(x,y)$
$f_5(x,y)$
$f_6(x,y)$
$f_7(x,y)$
$F(x,y)$



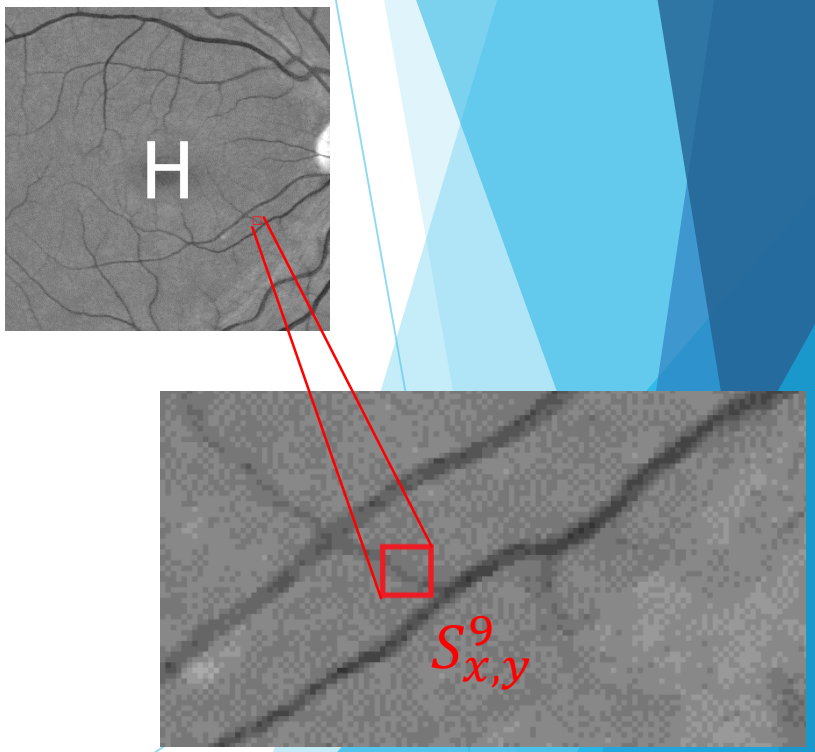
Background homogenization problem

2.1) Features extraction: H

- Blood vessels are darker then their surroundings: a good choice is to observe local gray-level variations
  - $S^9_{x,y}$ **<u>: 9x9 squared window centered on pixel (x,y)</u>**

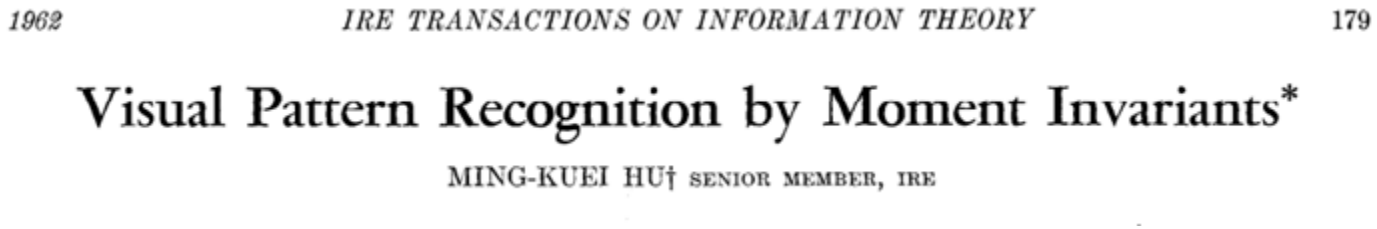
- 5 features out of image H (for each pixel of it):

$$\left[\begin{aligned}
f_1(x,y) &= I_H(x,y) - \min_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} \\
f_2(x,y) &= \max_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} - I_H(x,y) \\
f_3(x,y) &= I_H(x,y) - \operatorname{mean}_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} \\
f_4(x,y) &= \operatorname{std}_{(s,t)\in S^9_{x,y}} \{I_H(s,t)\} \\
f_5(x,y) &= I_H(x,y)\,.
\end{aligned}\right]$$



2.2) Features extraction: Hu moments

- Original paper: http://www.sci.utah.edu/~gerig/CS7960-S2010/handouts/Hu.pdf

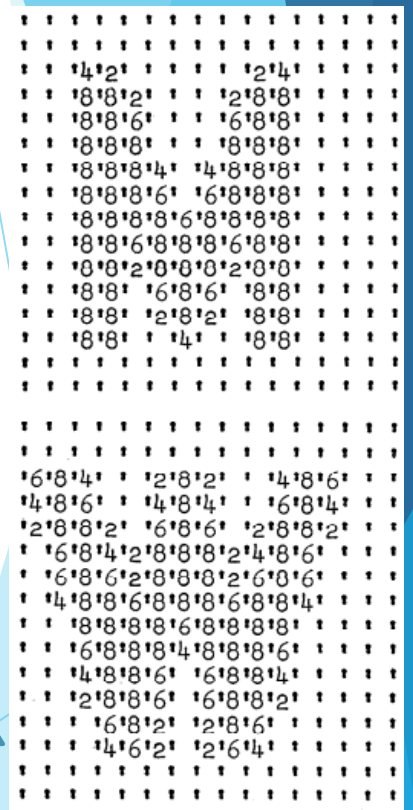


1962 IRE TRANSACTIONS ON INFORMATION THEORY 179

Visual Pattern Recognition by Moment Invariants*

MING-KUEI HU† SENIOR MEMBER, IRE

- Group of 7 nonlinear centralized moment expressions, derived from algebraic invariants applied to the moment generating function under a rotation transformation. **The result is a set of absolute orthogonal moment invariants, used for scale, position, and rotation invariant pattern identification**
- Moments were used in a simple pattern recognition experiment to successfully identify various typed characters
- **<u>They simply (appear to) have no physical meaning</u>**



Two samples of the digitalized inputs for the letters M and W.

2.2) Features extraction: VE (1)

- Moment invariants (***Hu***) are included in the feature vector:
  - $\boldsymbol{f_6(x,y), f_7(x,y)}$ extracted from this new sub-image:

$$\boldsymbol{I_{VE}^{S_{x,y}^{17}}(x,y)\ x\ G_{0,1.7^2}^{17}(x,y)}$$

    - $I_{VE}^{S_{x,y}^{17}}(x,y)$: 17 squared neighbourhood around pixel (x,y), each pixel of I_{VE}
    - $G_{0,1.7^2}^{17}(x,y)$: 0 mean-1.7 std gaussian-values 17 squared neighbourhood around pixel (x,y):
      - the product 'moves' about 97% of energy in a 9x9 neighbourhood. This leads Hu invariants to take reasonably distant values for vessels and non-vessels allowing proper classification (greater values for vessels, lower for non-vessels)

2.2) Features extraction: VE (2)

- These are the 2 features included in the vector (choosen 2 out of 7 proposed **(*)**):

$$\left[\begin{array}{l} f_6(x,y) = |\log(\phi_1)| \\ f_7(x,y) = |\log(\phi_2)| \end{array}\right]$$

- In greater detail:

$$\phi_1 = \eta_{20} + \eta_{02}$$
$$\phi_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2$$

$$\left\{\begin{array}{ll} \eta_{pq} = \dfrac{\mu_{pq}}{(\mu_{00})^{\gamma}} & p,\ q = 0,1,2,\ldots \\ \gamma = \dfrac{p+q}{2} + 1; & (p+q) = 2,3,\ldots. \end{array}\right.$$

$$\mu_{pq} = \sum_i \sum_j (i-\bar{i})^p (j-\bar{j})^q I_{\mathrm{VE}}^{S_{x,y}^{17}}(i,j)$$

$$\left\{\begin{array}{ll} m_{pq} = \sum_i \sum_j i^p j^q I_{\mathrm{VE}}^{S_{x,y}^{17}}(i,j) & p,\ q = 0,1,2,\ldots \\ \bar{i} = \dfrac{m_{10}}{m_{00}}, \quad \bar{j} = \dfrac{m_{01}}{m_{00}} & \end{array}\right.$$

HuMoments

Calculates seven Hu invariants.

C++: void `HuMoments`(const Moments& **m**, OutputArray **hu**)

C++: void `HuMoments`(const Moments& **moments**, double **hu**[7])

Python: `cv2.HuMoments`(m[, hu]) → hu

C: void `cvGetHuMoments`(CvMoments* **moments**, CvHuMoments* **hu_moments**)

Python: `cv.GetHuMoments`(moments) → hu

Parameters:
- **moments** – Input moments computed with `moments()` .
- **hu** – Output Hu invariants.

The function calculates seven Hu invariants (introduced in [Hu62]; see also http://en.wikipedia.org/wiki/Image_moment) defined as:

$$\begin{array}{l} hu[0] = \eta_{20} + \eta_{02} \\ hu[1] = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\ hu[2] = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\ hu[3] = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\ hu[4] = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ hu[5] = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\ hu[6] = (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{array}$$

where η_{ji} stands for `Moments::nu`$_{ji}$.

These values are proved to be invariants to the image scale, rotation, and reflection except the seventh one, whose sign is changed by reflection. This invariance is proved with the assumption of infinite image resolution. In case of raster images, the computed Hu invariants for the original and transformed images are a bit different.

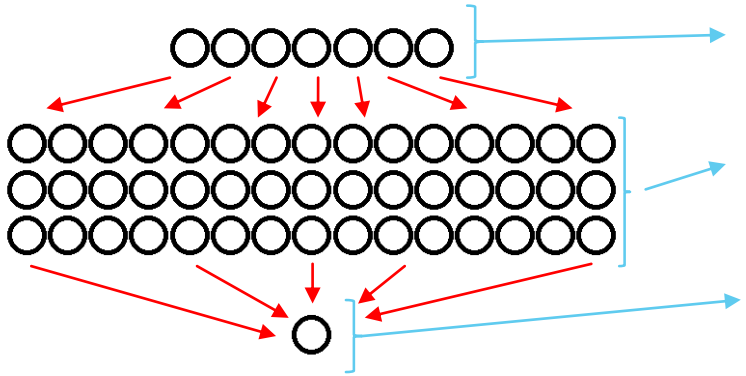
(*)

3) Classification (1)

- Each pixel is characterized by a 7D vector in feature space:

$$F(x,y) = (f_1(x,y), \ldots, f_7(x,y))$$

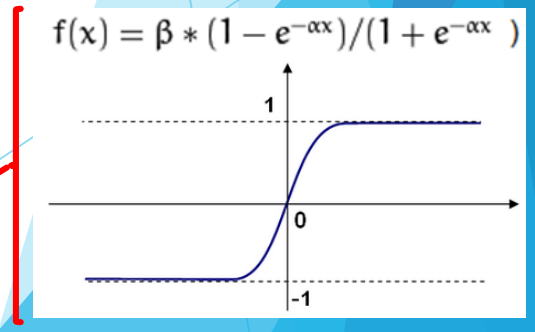
- Data linear separability grade is not high enough for a proper classification accuracy level:
  - solution: multilayer feedforward Neural Network with 3 hidden layers



Input layer: 7 neurons (# equal to the total n. of features)

Hidden layers: 15 neurons each (optimal configuration)

Output layer: 1 neuron attached to a NL logistic sigmoid activation function → NN output is thought as a-posteriori probability value



3) Classification (2)

- **<u>Training step:</u>** training set $S_T = \left\{\left(F^{(n)}, C_k^{(n)}\right) | n = 1, \dots, N; k \in \{1,2\}\right\}$
  - built up with features out of the first 20 DRIVE images: H + VE + manually labelled vessels. Then the other 20s are predicted
  - <u>features fi normalized *0μ-1σ*</u>: $\overline{f_i} = \frac{f_i - \mu_i}{\sigma_i}$
  - back-propagation training algorithm
- → **<u>NN application to 'unseen' eye-fundus image:</u>**
  - NN output is a number $p(C_1|F(x,y)) = 1 - p(C_2|F(x,y))$ Є [0,1] (for each pixel)
- **Final step → predicted image ICO obtained applying a thresholding scheme:**

$$\boldsymbol{I_{CO}(x,y) = \begin{cases} 255\ (\equiv C_1), & if\ p(C_1|F(x,y) \geq Th \\ 0\ (\equiv C_2), & otherwise \end{cases}}$$

4) Post-processing

- 2 steps:
  I. filling vessels gaps:
     - pixels with at least 6/8 neighbors classified as vessel points must also be ‘vessel’

  II. removing falsely detected isolated vessel pixels
     - pixels surrounded by 24 (5x5) classified as non-vessel points must also be ‘non-vessel’

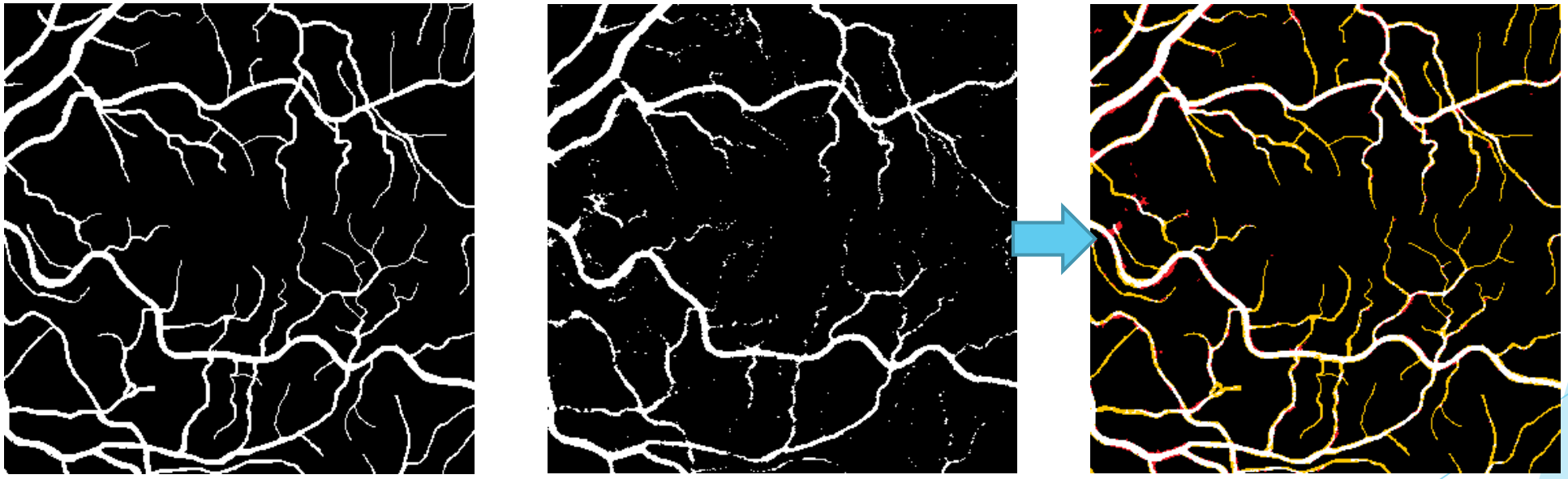
RESULTS:

Results(1):

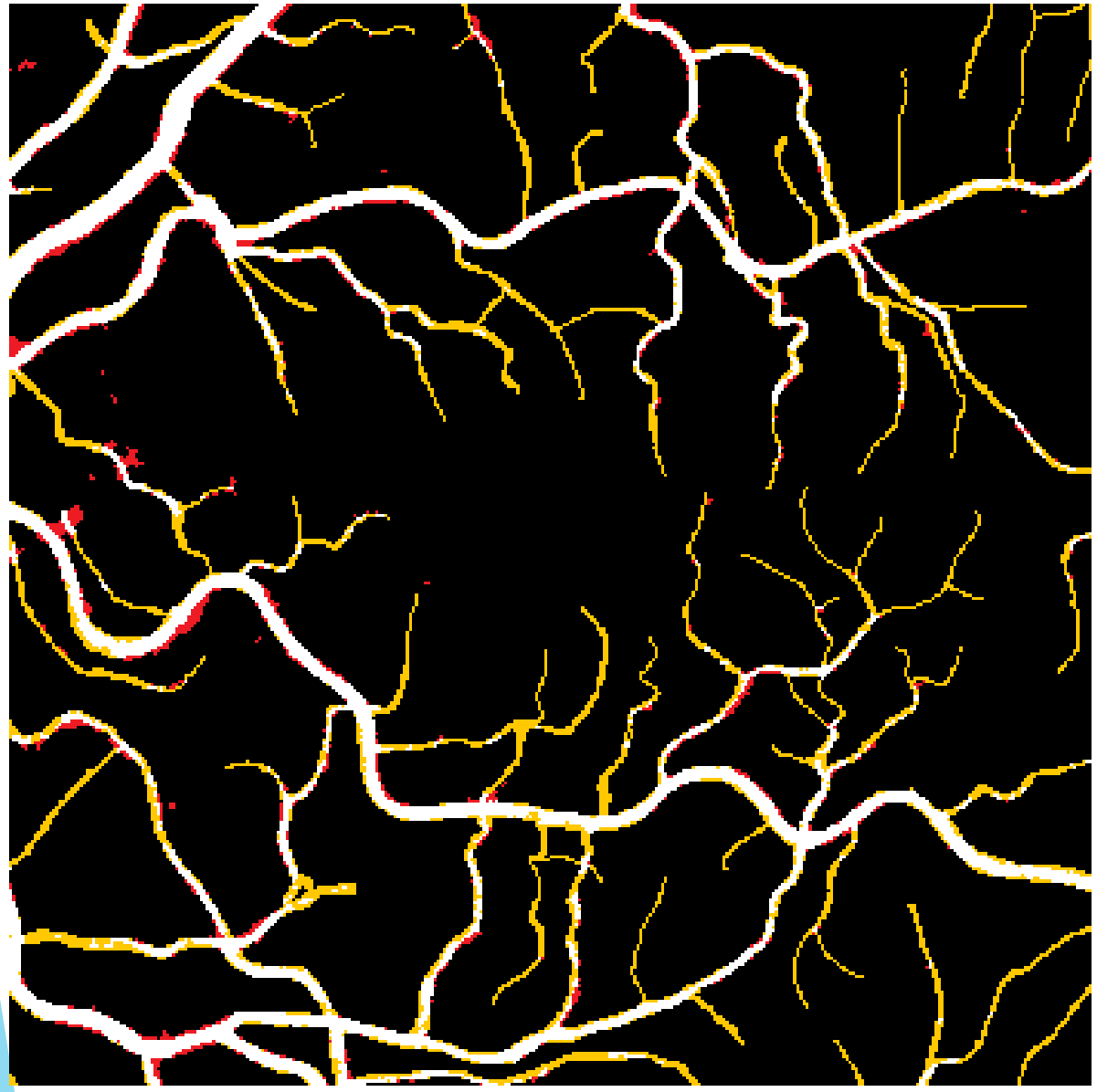
100% accuracy reference

Predicted (I_{CO})

Post-processed



Results(2):



→ FN (false negative)
(non detected vessels)

→ FP (false positive)
(wrongly detected vessels)

Performance measures (1)

- The algorithm is evaluated in terms of:

  (TP = true positive, TN = true negative)

  - **Sensitivity**

    (ratio of well classified vessel pixels)

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

  - **Specificity**

    (ratio of well classified non-vessel pixels)

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

  - **Positive predictive value**

    (vessels that are correctly classified)

    $$Ppv = \frac{TP}{TP + FP}$$

  - **Negative predictive value**

    (non-vessels that are correctly classified)

    $$Npv = \frac{TN}{TN + FN}$$

  - **Accuracy**

    $$\mathrm{Acc} = \frac{TP + TN}{TP + FN + TN + FP}$$

Performance measures (2)

	se	sp	ppv	npv	acc
21	0,699789	0,995164	0,961528	0,950479	0,951663
22	0,656272	0,994603	0,968773	0,918975	0,925832
23	0,65199	0,976426	0,853288	0,930276	0,920054
24	0,642053	0,995211	0,976097	0,901264	0,912757
25	0,560459	0,998802	0,993154	0,87996	0,895076
26	0,664265	0,982562	0,866116	0,945154	0,936354
27	0,638075	0,995231	0,973028	0,910699	0,919379
28	0,682131	0,991627	0,941765	0,940175	0,940366
29	0,698811	0,986435	0,911698	0,942336	0,938415
30	0,658418	0,98671	0,892569	0,945131	0,939562
31	0,59833	0,998242	0,986239	0,921872	0,928666
32	0,686065	0,99293	0,945613	0,946388	0,946302
33	0,640801	0,99593	0,967862	0,935463	0,938908
34	0,613515	0,97688	0,912631	0,865247	0,874245
35	0,691653	0,989002	0,927065	0,940719	0,939006
36	0,610911	0,99334	0,960673	0,905535	0,91291
37	0,667405	0,991514	0,942312	0,934867	0,935774
38	0,672509	0,991227	0,946475	0,929186	0,931489
39	0,708613	0,986889	0,913497	0,945457	0,941404
40	0,742758	0,983654	0,864366	0,964621	0,954025
	0,66154	**0,990006**	**0,933748**	**0,928943**	**0,930033**

post-processing

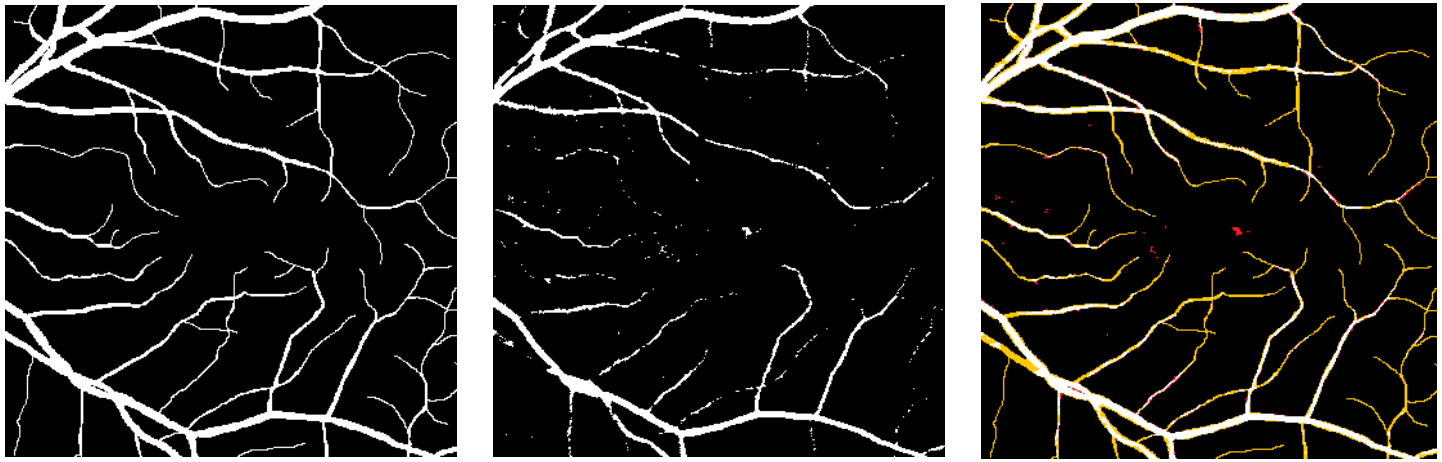
		se	sp	ppv	npv	acc
21	post	0,697427	0,995359	0,963109	0,949842	0,951264
22	post	0,655761	0,994569	0,96863	0,918682	0,925568
23	post	0,652482	0,976874	0,856152	0,930194	0,920364
24	post	0,641255	0,995246	0,976164	0,901359	0,912804
25	post	0,559577	0,998931	0,99386	0,880034	0,89517
26	post	0,660045	0,98433	0,87727	0,944636	0,937282
27	post	0,636727	0,995334	0,973669	0,910007	0,918883
28	post	0,679648	0,992258	0,945744	0,939756	0,940469
29	post	0,697316	0,987216	0,915974	0,942263	0,93893
30	post	0,657013	0,988724	0,907402	0,944875	0,940969
31	post	0,598635	0,998221	0,986139	0,92164	0,928475
32	post	0,684719	0,993327	0,948344	0,946261	0,94649
33	post	0,639087	0,996245	0,970209	0,935165	0,938873
34	post	0,613783	0,976735	0,912679	0,864563	0,873745
35	post	0,689286	0,989237	0,928142	0,940425	0,938894
36	post	0,608848	0,993388	0,960809	0,905114	0,912535
37	post	0,665716	0,991881	0,944586	0,934526	0,935746
38	post	0,670294	0,991413	0,947523	0,928573	0,931091
39	post	0,706851	0,987406	0,916632	0,945036	0,941448
40	post	0,739355	0,984793	0,871417	0,964421	0,954768
		0,65991	**0,990474**	**0,936791**	**0,928626**	**0,930124**

Best case

Worst case

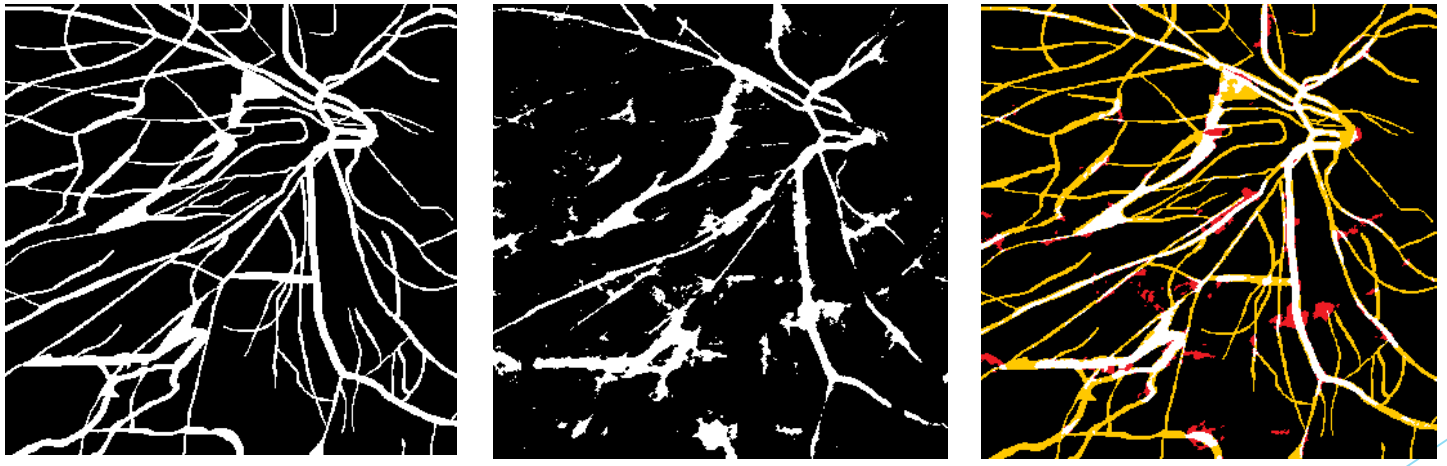
Best case / worst case:

BC

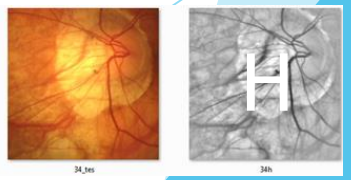


Acc ≈ 95%
Se ≈ 70%

WC



Acc ≈ 87%
Se ≈ 61%



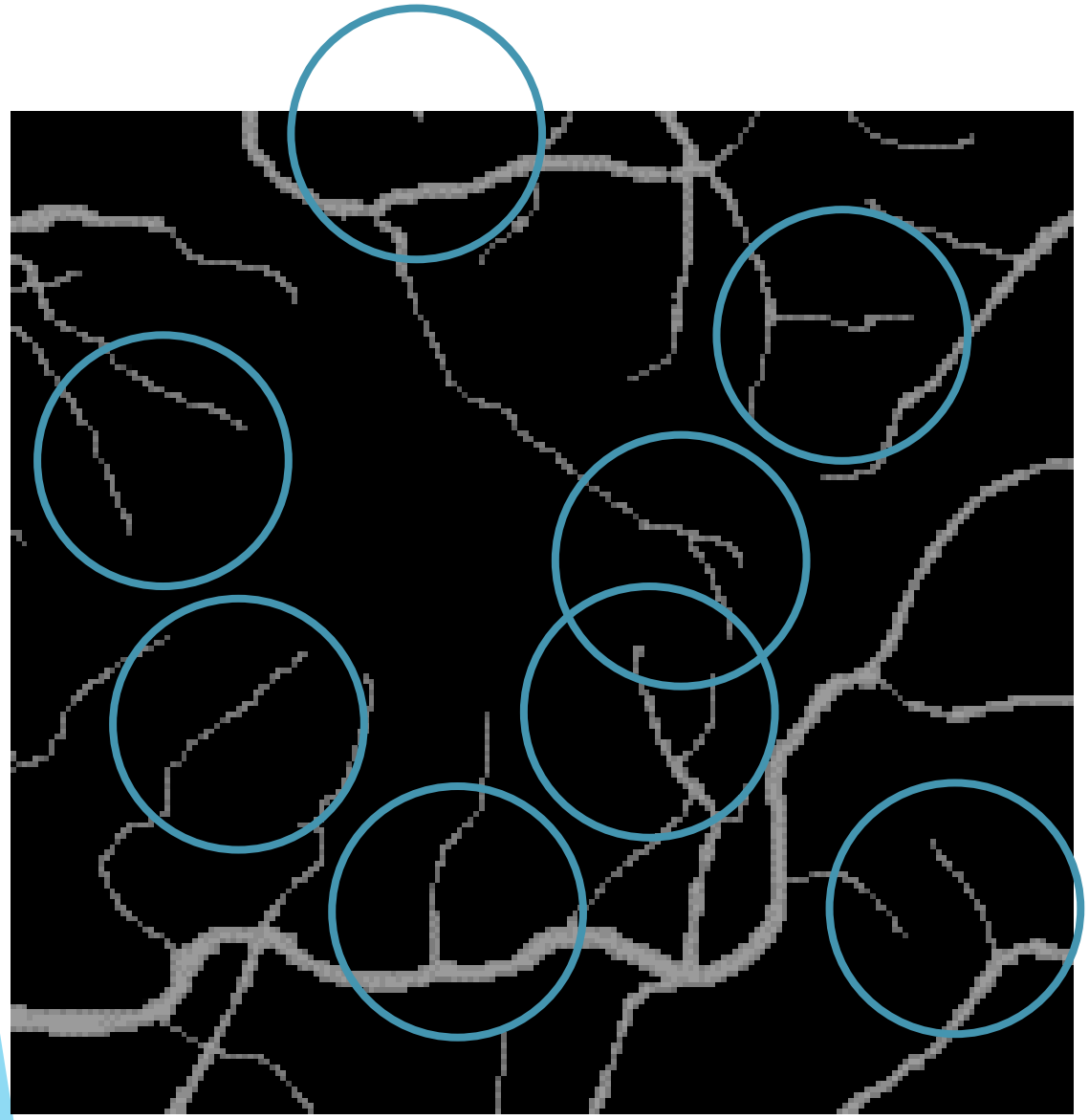
Performance measures: *Th*

- ***Th* = 0.45** is set to provide maximum average accuracy (different values tested)
  - ..yet *Se*/*Acc* slowly vary with *Th*: not a critical parameter

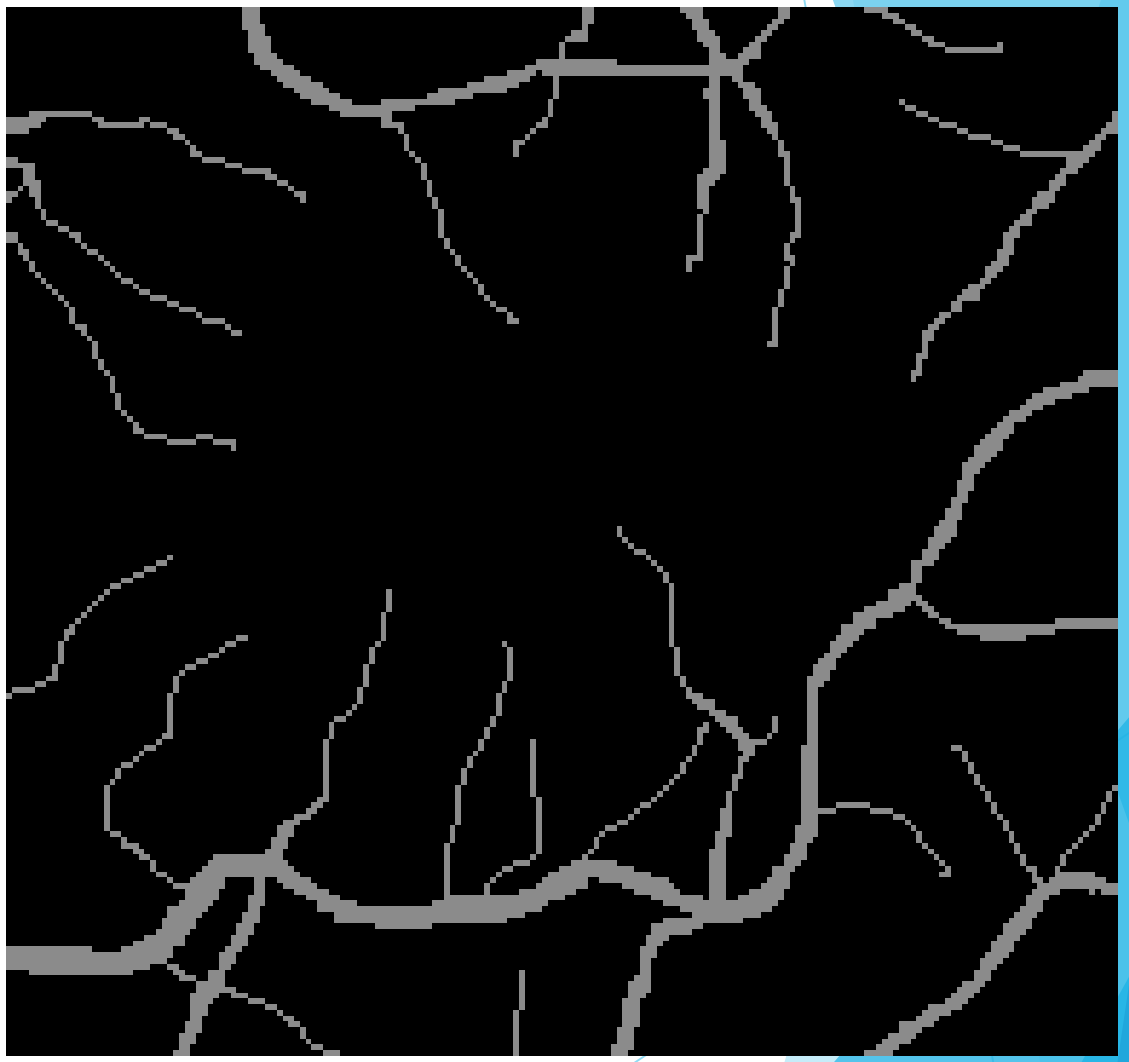
Conclusions:

Problems: Sensitivity

- Results show that Sensitivity is the lowest computed evaluation parameter: $Se = \frac{TP}{TP+FN}$
  - FN is too high because thin vessels disappears in predicting (below Th)…
  - **…+ 2 different hand-labelled vessel/non-vessel eye fundus image are given in DRIVE database. Look at finest vessels details: what is a *real* vessel?**



01_manual1.tif



01_manual2.tif

Problems (2):

- **Pupil reflex removal** (RED pixels)
- **Cross-validation of data** (YELLOW pixels (?))
- Post-processing may be applied or not:
  - since the classification is pixel-by-pixel, results often show many small disconnected segments. Post-processing methods designed to reduce noise by removing small connected components will also remove these disconnected segments

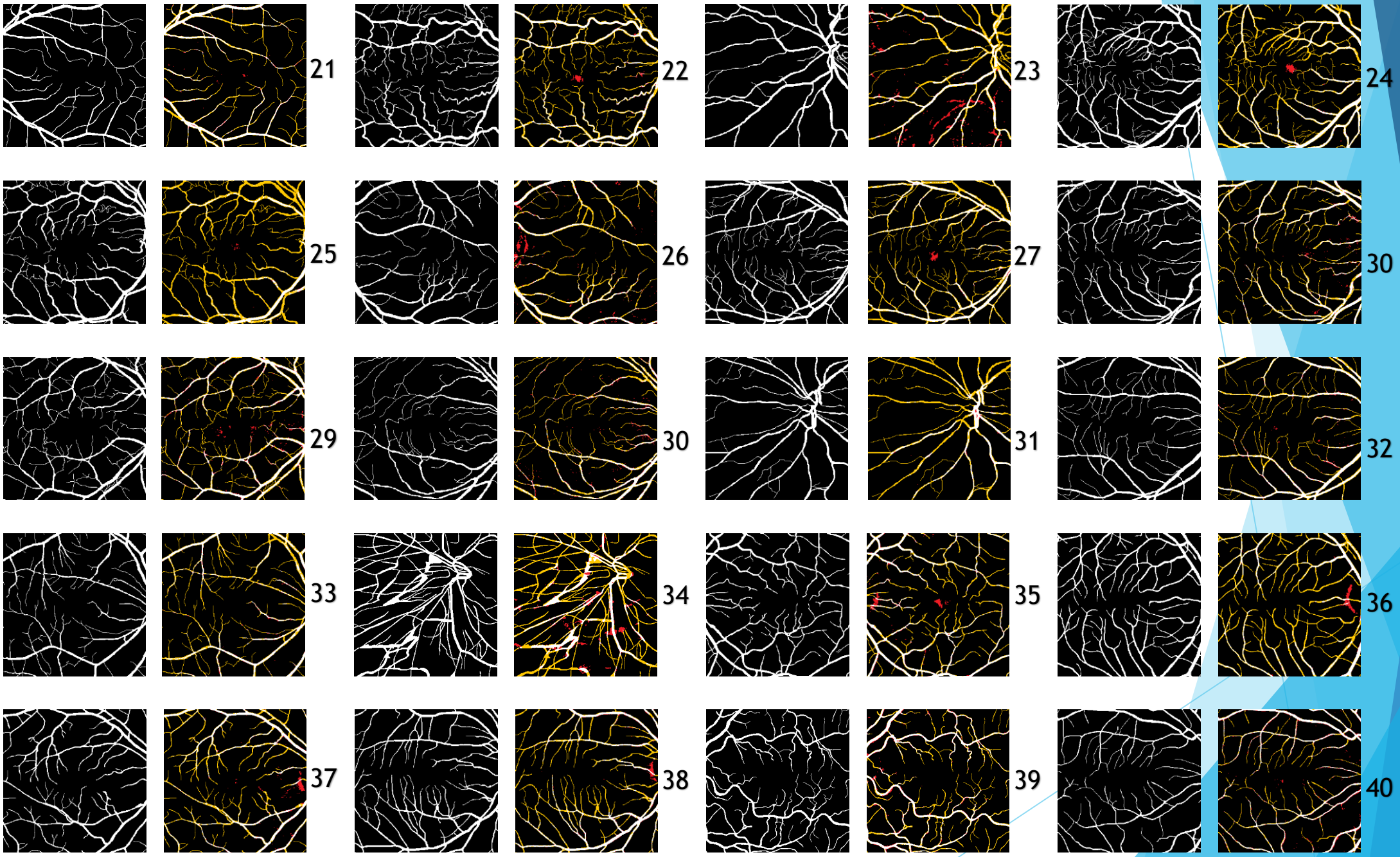

21
22
23
24
25
26
27
30
29
30
31
32
33
34
35
36
37
38
39
40

Table 3 – Performance measures for supervised methods.

Methodology	Sensitivity	Specificity	Accuracy
Human observer	0.7763	0.9723	0.9470
	0. 8951	0.9384	0.9348
Sinthanayothin et al. [30]	0.833	0.91	–
Abramoff et al. [31]	0.7145	–	0.9416
Staal et al. [32]	–	–	0.9442
	–	–	0.9516
Soares et al. [33]	–	–	0.9466
	–	–	0.9480
Ricci and Perfetti [34]	–	–	0.9563
	–	–	0.9584
Osareh and Shadgar [35]	–	–	–
Lupascu et al. [37]	0.72	–	0.9597
Xu and Luo [36]	0.7760	–	0.9328
You et al. [38]	0.7410	0.9751	0.9434
	0.7260	0.9756	0.9497
Marin et al. [39]	0.7067	0.9801	0.9452
	0.6944	0.9819	0.9526

Blood vessel segmentation methodologies in retinal images – A survey (2012)

M.M. Fraza, P. Remagninoa, A. Hoppea, B. Uyyanonvarab, A.R. Rudnickac, C.G. Owenc, S.A. Barmana

(*) each metodology, where 2 rows are present 1° row refers to DRIVE database, 2° to STARE database. Otherwise evaluation refers to DRIVE database

Thanks for the attention