Real-Time Retinal Vessel Segmentation on High-Resolution Fundus Images Using Laplacian Pyramids

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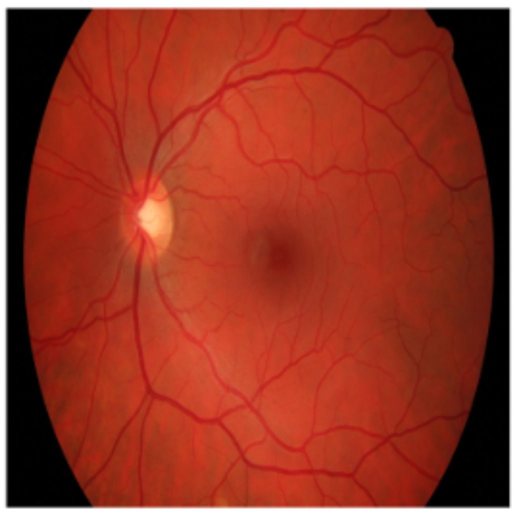
Blood Vessel Segmentation

Input:
- High resolution RGB fundus image I
- Large image pixel domain Ω

Further challenges:
- Important structures have low contrast
- Various background structures B

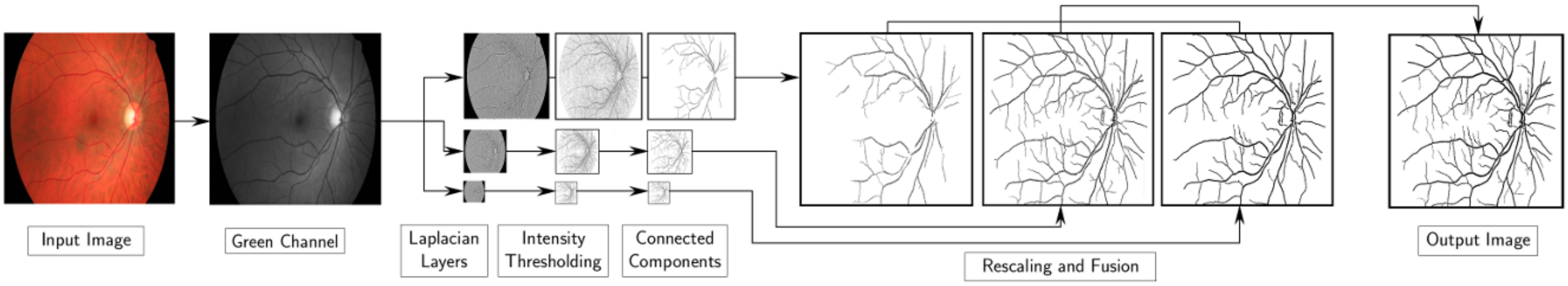


Goal: Extract blood vessels using binary mask

$$S(i,j) = \begin{cases} 1, & \text{if } (i,j) \in \Omega \cap B \\ 0, & \text{if } (i,j) \in B \end{cases}$$

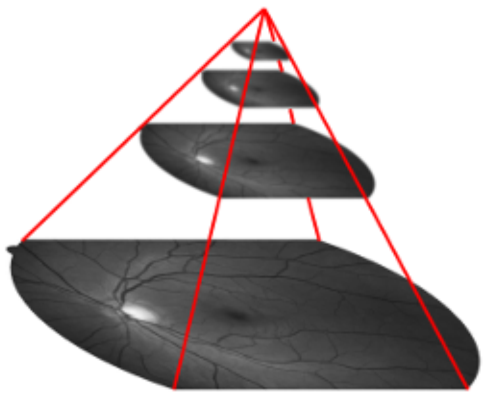
Our contribution:
- Robust, simple and fast approach
- State of the art results
- No parameter adjustment

Our Multi-Scale Approach



Background

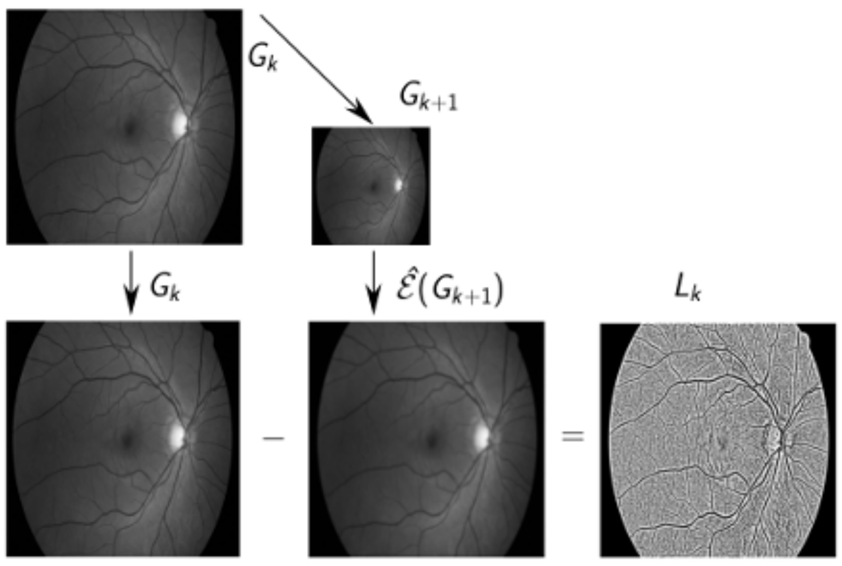
Reduction and Expansion of Images: Gaussian Pyramid



- From K_k to K_{k+1} use downsampling and smoothing
$$\hat{\mathcal{R}}(K_k)(i,j) = \sum_{u,v=-2}^{2} h_\alpha(u+3, v+3)\, K_k(2i+u, 2j+v)$$
- From K_{k+1} to K_k use upsampling with interpolation
$$\hat{\mathcal{E}}(K_{k+1})(i,j) = 4 \sum_{u,v=-2}^{2} h_\alpha(u+3, v+3)\, K_{k+1}\left(\tfrac{i+u}{2}, \tfrac{j+v}{2}\right)$$
- Output is multi-scale Gaussian pyramid

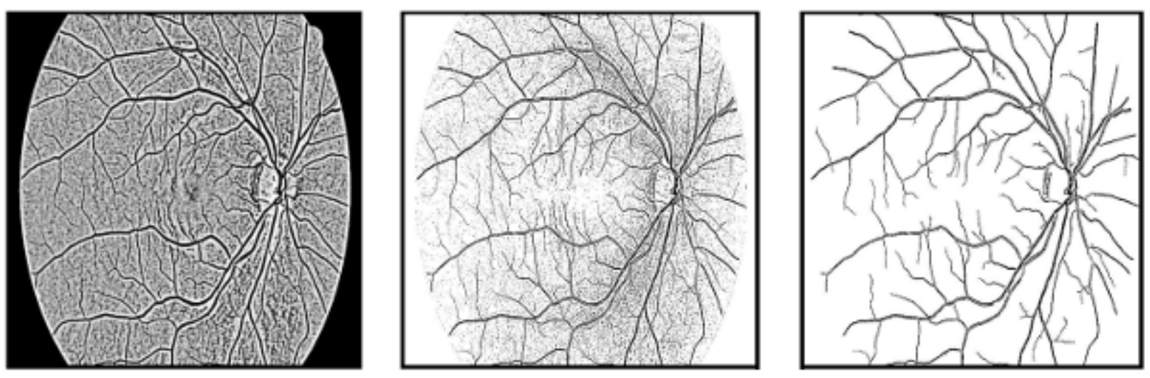
Construction of Laplacian Pyramid

- Gaussian Pyramid
$$G_1 = \hat{\mathcal{R}}(I)$$
$$G_2 = \hat{\mathcal{R}}(G_1)$$
$$G_3 = \hat{\mathcal{R}}(G_2)$$
$$G_4 = \hat{\mathcal{R}}(G_3)$$
- Laplacian Pyramid
$$L_1 = G_1 - \hat{\mathcal{E}}(G_2)$$
$$L_2 = G_2 - \hat{\mathcal{E}}(G_3)$$
$$L_3 = G_3 - \hat{\mathcal{E}}(G_4)$$



- Output highlights blood vessels in coarse to fine order

Intensity Thresholding and Connected Components



- Carefully chosen global intensity threshold
- Label connected structures using nearest neighborhood
- Keeping large connected structures (vessels) and remove small connected structures (noise)

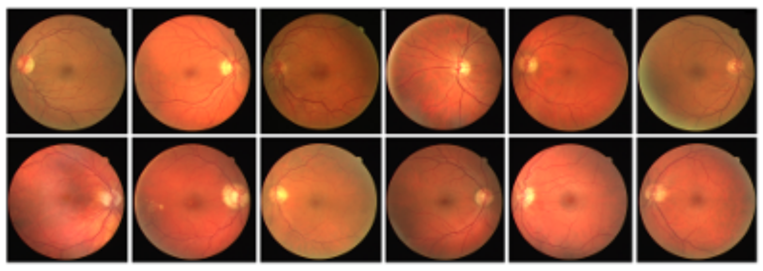
Rescaling and Fusion of Segmented Pyramid Layers

- Expand all layers to original resolution using upsampling operator $\hat{\mathcal{E}}$

Dataset

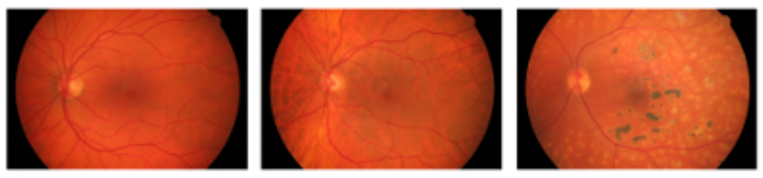
DRIVE Dataset

- 40 images with low resolution
- Classic dataset
- Standard benchmark test



High Resolution Dataset

- 3 categories with 15 images each
- Introduces additional challenges



Results

Performance: Our method is competetive in quality but much faster

Test Datasets	DRIVE (565 × 584)			High Resolution (3504 × 2336)			
Method	**Se**	**Sp**	**Acc**	**Se**	**Sp**	**Acc**	**Runtime**
Our Approach	0.6534	0.9860	0.9572	0.694	0.981	0.955	1.81s
Budai et al.	0.644	0.987	0.9572	0.669	0.985	0.961	26.69s
Fan et al.	0.736	0.981	0.960	-	-	-	-
Frangi et al.	0.660	0.985	0.9570	0.622	0.982	0.954	39.29s
Krause et al.	-	-	0.9468	-	-	-	-
Mendonça et al.	-	-	0.9452	-	-	-	-
Odstrcilik et al.	0.7060	0.9693	0.9340	0.774	0.966	0.949	18min

Robustness: Our method handles additional background structures

Category	Healthy			Glaucomatous			Diabetic		
Method	**Se**	**Sp**	**Acc**	**Se**	**Sp**	**Acc**	**Se**	**Sp**	**Acc**
Our Approach	0.700	0.988	0.956	0.710	0.979	0.956	0.674	0.978	0.952
Budai et al.	0.662	0.992	0.961	0.687	0.986	0.965	0.658	0.977	0.955
Frangi et al.	0.621	0.989	0.955	0.654	0.984	0.961	0.590	0.972	0.946
Odstrcilik et al.	0.786	0.975	0.953	0.791	0.964	0.949	0.746	0.961	0.944

Summary

- In practice parameter-free method
- Competitive to state-of-the-art methods but much faster
- Method scales well for even higher resolution

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