

Retinal Vessel Segmentation Using Minimum Spanning Superpixel Tree Detector

Ping Li

Abstract—Abstract goes here.

Index Terms—Keyword 1, keyword 2, keyword 3.

I. INTRODUCTION

INTRODUCTION goes here. 1. The research topics are very popular, very useful, and have great impact and research value

2. The existing methods all have problems, the problems that you are going to solve in the paper

3. Our methods have the theory, therefore our approach can solve the problems in theory as we have the designed

4. Describe the advantages, features, logic, methods, processes, etc. of our methods

5. List explicitly 3 to 4 our contributions/advantages like: Our work makes the following three main contributions:

- **Efficient Structure Restoration** The mixed use of different sizes of patches capture the structural information efficiently, avoiding the absorption of irrelevant information which causes abnormal structures;
- **Balanced Computational Workload** Multiscale solution with dynamic patches adjusts the computational workload in the operation. It significantly reduces the computation in low pyramid level without sacrificing the visual effects, and accelerates the completing process at the same time;
- **Parallel Search & Competitive Mechanism** Parallel search for different size patches is conducted with GPU acceleration. A competitive mechanism is included to select the patch with minimum unit energy.

II. RELATED WORK

Related Work One XXXXXXXXXXXX

XXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

Related Work Two XXXXXXXXXXXX

XXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

Related Work Three XXXXXXXXXX

XXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

III. APPROACH OVERVIEW

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

Fig. 1 shows XXXXX

Fig. 2 shows XXXXX

Cite paper like this [1] or like this [1], [2].

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

IV. METHOD PART I (AT LEAST 7 FORMULAS)

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

Calculate $a + b = c$ is OK.

$$I(p) = \sum_{q \in \Omega} S(p, q) I(q) = \sum_{q \in \Omega} \exp\left(-\frac{D(p, q)}{\sigma}\right) I(q) \quad (1)$$

Algorithm 1 Dynamic Patch-based Image Completion

Input: Image I , cavity C , source $S = I - C$, Number of different size patches v , Pyramid level L

Output: Final Image F

- 1: Initialize F through filling patches randomly
 - 2: Compute image pyramid $I_{l_i}, C_{l_i}, K(l_i)$, $l_i = L, L - 1, \dots, 0$
 - 3: **for** each pyramid level l_i **do**
 - 4: Define the patch sizes with Eq. 1
 - 5: **repeat**
 - 6: **for** All $q \in C$ **do**
 - 7: Parallel Search for v different size patches
 - 8: Retrieve the patch P that satisfies Eq. 1
 - 9: **end for**
 - 10: Calculate the minimum cost boundary
 - 11: Combine all the patches
 - 12: **until** convergence
 - 13: Propagate solution to the next level
 - 14: **end for**
-

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

A. Test Apple One

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

B. Test Apple Two

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

C. Test Apple Three

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

V. METHOD PART II (AT LEAST 7 FORMULAS)

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

XXXXXXXXXXXXXXXXXXXXXXXXXXXX

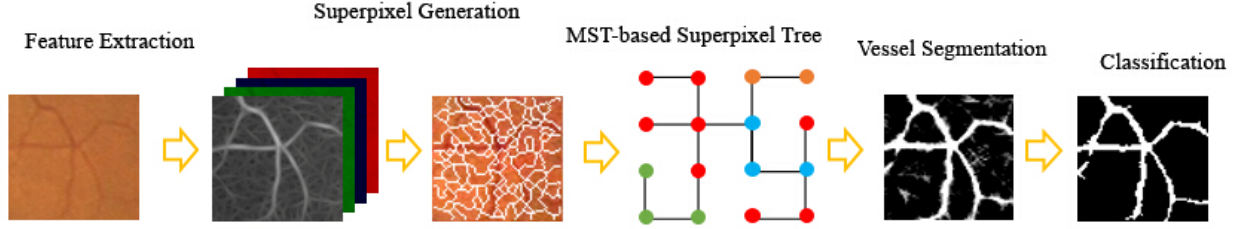


Fig. 1: Overview of the proposed minimum spanning superpixel-based tree detector for retinal vessels.

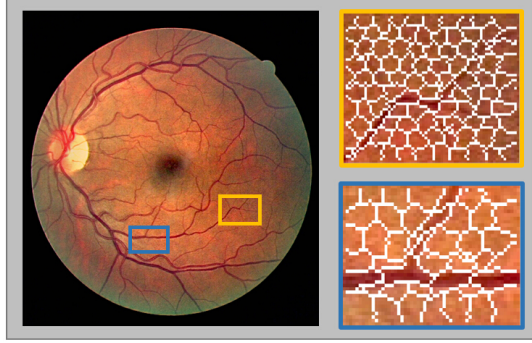


Fig. 2: Patches showing the superpixel region after clustering.

TABLE I: Performance Comparison of Vessel Segmentation

Methods	Connectivity	Area	Length	$C*A*L$
2nd Observer	1	0.9398	0.9347	0.8784
Marin [3]	0.9990	0.8327	0.8314	0.6916
Soares [4]	0.9952	0.8920	0.8889	0.7891
Nguyen [5]	0.9895	0.8727	0.8687	0.7502
Zhang [6]	0.9988	0.8097	0.8108	0.6557
Our method	0.9996	0.9002	0.8982	0.8082

REFERENCES

- [1] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, "Detection of blood vessels in retinal images using two-dimensional matched filters," *IEEE Transactions on Medical Imaging*, vol. 8, no. 3, pp. 263–269, 1989.
- [2] Y. Li and M. S. Brown, "Single image layer separation using relative smoothness," in *IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 2752–2759.
- [3] D. Marin, A. Aquino, M. E. Gegundez-Arias, and J. M. Bravo, "A new supervised method for blood vessel segmentation in retinal images by using gray-level and moment invariants-based features," *IEEE Transactions on Medical Imaging*, vol. 30, no. 1, pp. 146–158, 2011.
- [4] J. V. Soares, J. J. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree, "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," *IEEE Transactions on Medical Imaging*, vol. 25, no. 9, pp. 1214–1222, 2006.
- [5] U. T. Nguyen, A. Bhuiyan, L. A. Park, and K. Ramamohanarao, "An effective retinal blood vessel segmentation method using multi-scale line detection," *Pattern Recognition*, vol. 46, no. 3, pp. 703–715, 2013.
- [6] B. Zhang, L. Zhang, L. Zhang, and F. Karray, "Retinal vessel extraction by matched filter with first-order derivative of Gaussian," *Computers in Biology and Medicine*, vol. 40, no. 4, pp. 438–445, 2010.

A. Test Banana One

XXXXXXXXXXXXXXXXXXXXXXXXXXXX
XXXXXXXXXXXXXXXXXXXXXXXXXXXX

B. Test Banana Two

XXXXXXXXXXXXXXXXXXXXXXXXXXXX
XXXXXXXXXXXXXXXXXXXXXXXXXXXX

C. Test Banana Three

XXXXXXXXXXXXXXXXXXXXXXXXXXXX
XXXXXXXXXXXXXXXXXXXXXXXXXXXX

VI. EXPERIMENTAL RESULTS

XXXXXXXXXXXXXXXXXXXXXXXXXXXX
XXXXXXXXXXXXXXXXXXXXXXXXXXXX

VII. CONCLUSION AND FUTURE WORK

Conclusion goes here.

TABLE II: Computation time statistics of the evaluations of large CSGs (seconds)

No.	Model	Face Num.	Mesh Num.	CGAL	Cork	Carve	QuickCSG	Our Approach [†]				
								Total	Step 1	Step 2	Step 3	Step 4
1	Organic	219k	6	-	14.3	63.1	0.580	2.75	0.892	1.32	0.397	0.118
2	T1	80k	50	1.00k	18.5	10.4	0.388	14.4	0.691	2.71	8.11	2.87
3	T2	7k	50	2.81k	-	16.0	0.804	5.52	0.162	1.11	3.29	0.746
4	Sprocket	11k	52	211	-	4.26	(0.132)*	0.386	0.093	0.105	0.149	0.034
5	Ring & Ball	146k	801	-	-	187	(1.10)	20.0	1.04	3.55	8.61	6.68