

“RAPID” Regions-of-Interest Detection in Big Histopathological Images

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Introduction

Background & Goal

- The sheer volume and size of histopathological images is growing explosively (e.g., 10^6 MPixel).
- Regions-of-interest (ROI) detection in big image is just a preprocessing step, this underscores the need for faster speed.

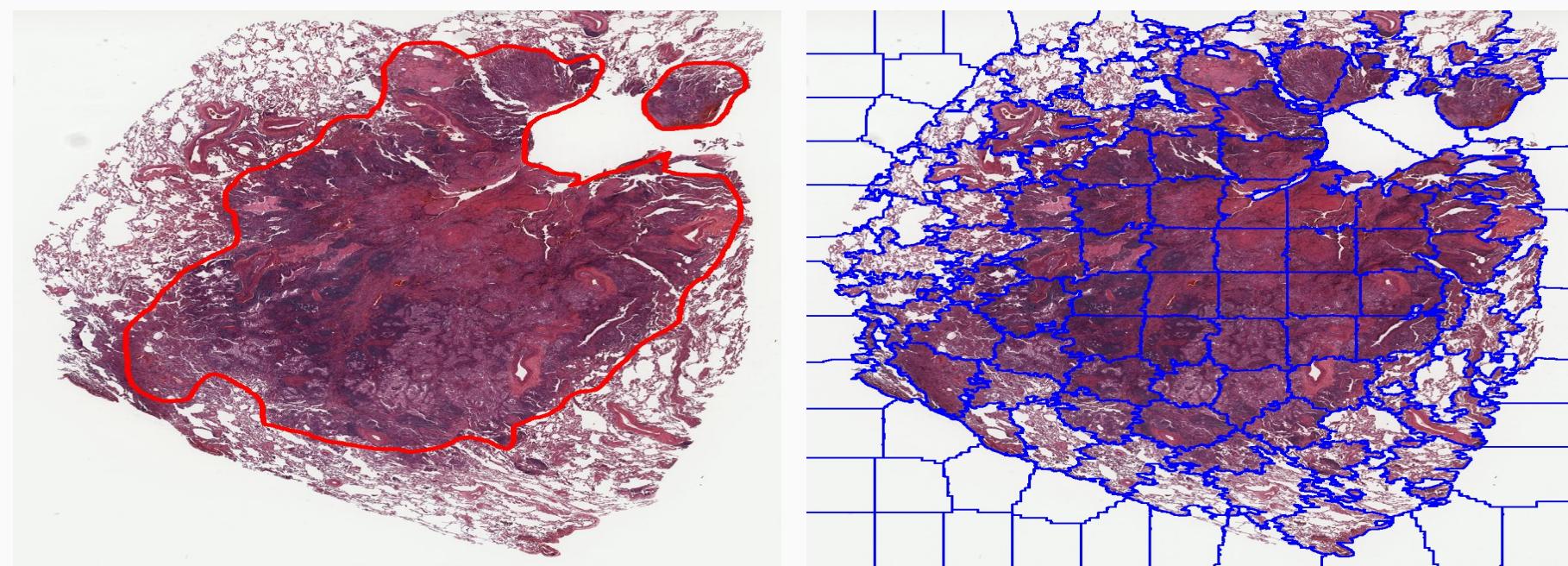


Figure 1: Ground truth (left); Result from [1]

Discoveries

- A coarse-to-fine algorithm [1] gained real-time complexity and is the fastest compared with the state-of-the-art algorithms.
- Only the precision of the boundary between ROI and non-ROI area decides the final accuracy.

Baseline Method

Regular and Adaptive Prediction-Induced Detection (RAPID) is based on a multi-layer coarse-to-fine segmentation algorithm [1, 2].

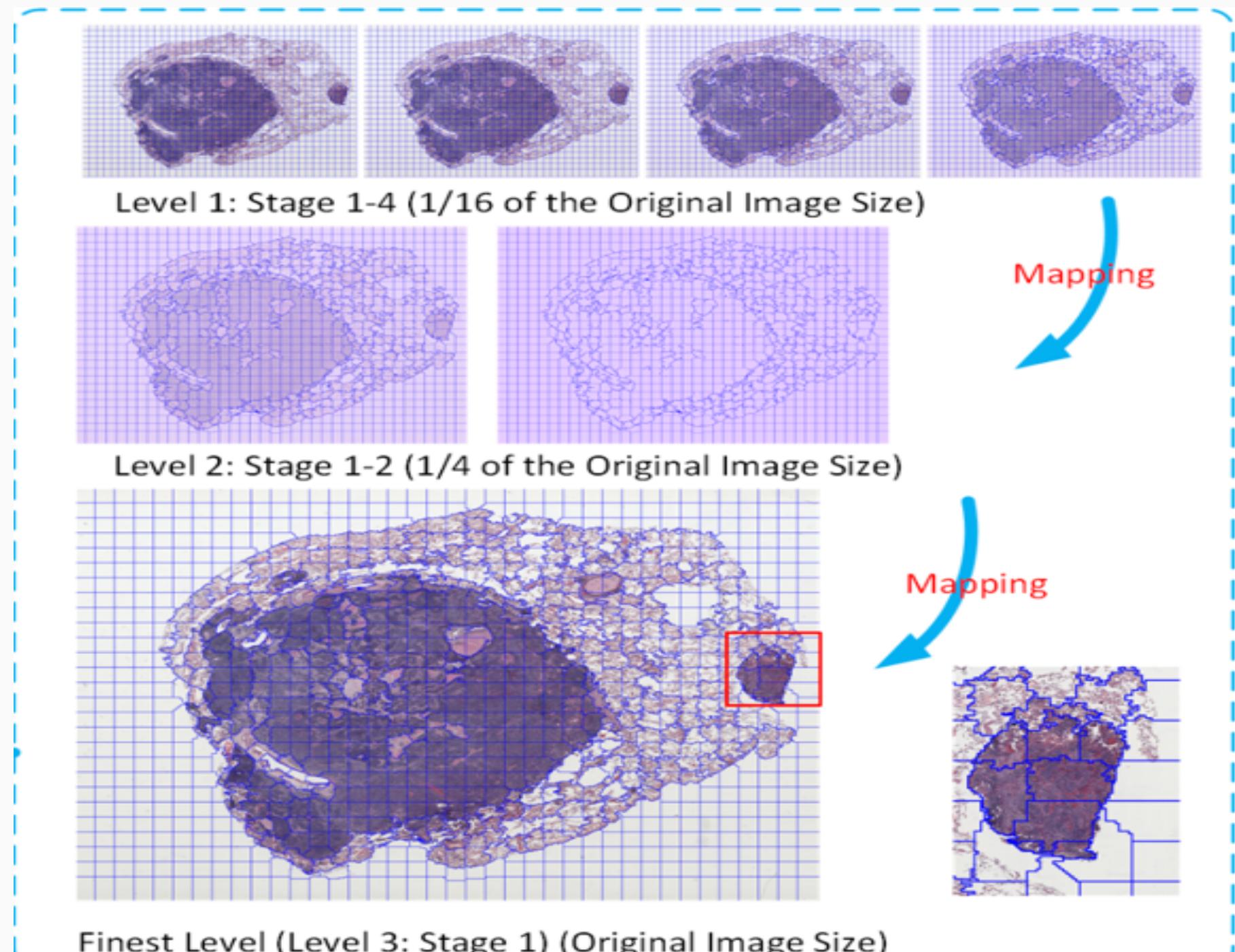


Figure 2: Multi-layer segmentation framework [2]

Energy Function

$$E(\mathbf{s}, \mu, \mathbf{c}) = \sum_p E_{col}(s_p, c_{sp}) + \lambda_{pos} \sum_p E_{pos}(s_p, \mu_{sp}) + E_{topo}(s) + \lambda_b \sum_p \sum_{q \in N_4} E_b(s_p, s_q) + \lambda_s E_{size}(s) \quad (1)$$

Boundary blocks: block which has at least one neighbor that has a different superpixel label.

$$E_b(s_p, s_q) = \begin{cases} 1, & s_p \neq s_q, \\ 0, & otherwise. \end{cases} \quad (2)$$

References

- Jian Yao, Marko Boben, Sanja Fidler, and Raquel Urtasun. Real-time coarse-to-fine topologically preserving segmentation. 2015.
- Ruoyu Li and Junzhou Huang. Fast regions-of-interest detection in whole slide histopathology images. 2015.

Method

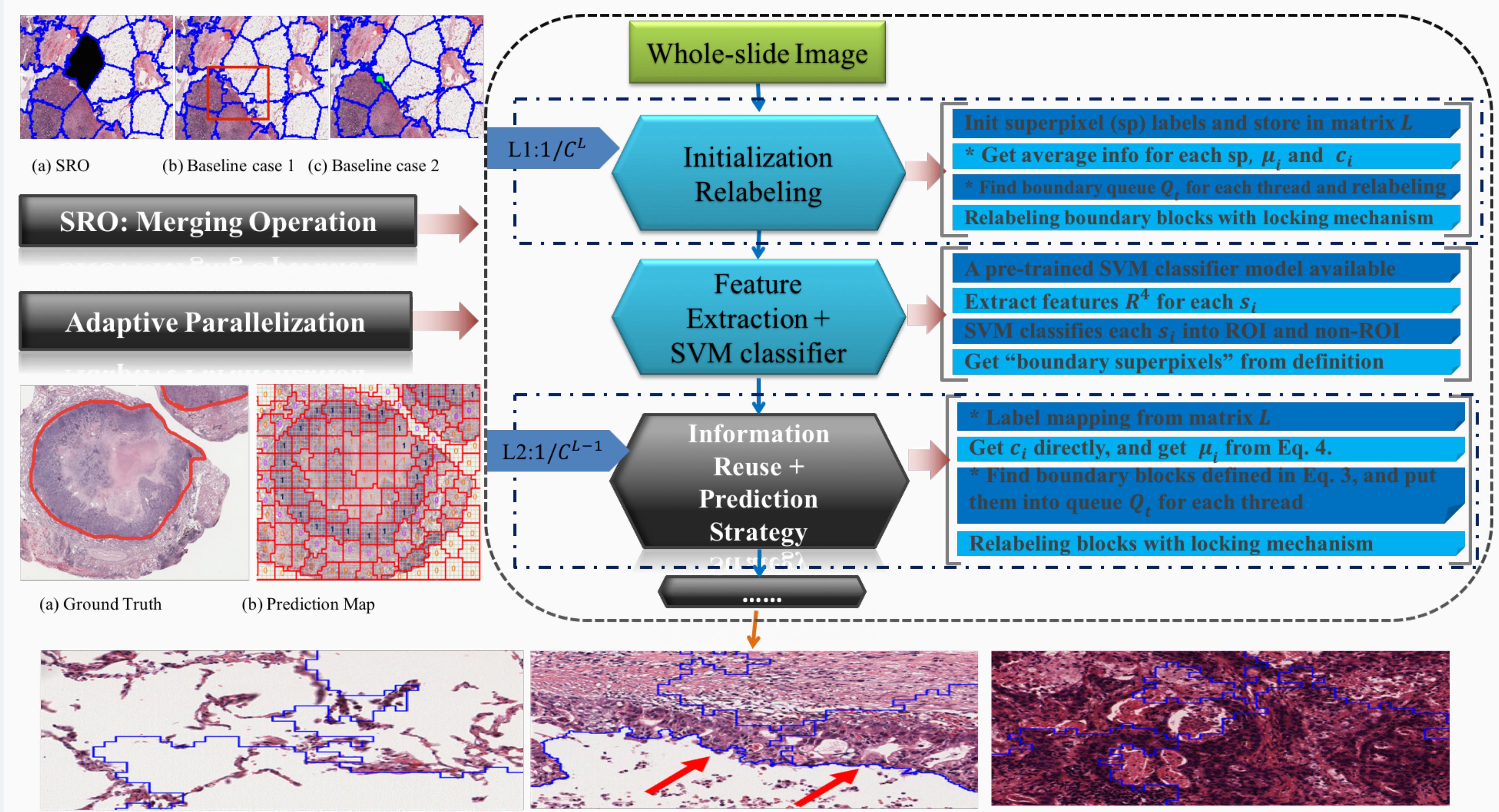


Figure 3: Parallel “RAPID” arithmetic flow, the steps marked with * is trivially parallelization; For the bottom figure, coarse segment in non-ROI and ROI (left and right); fine segment at the boundary (middle).

* **Superpixel Regularity Optimization (SRO):** defines a merging operation. When the superpixel size after moving a block p_i from s_{pi} is smaller than a lower threshold, SRO searches another neighbor superpixel s_{pm} with conditions: 1) minimum gross energy; 2) $Size(s_{pm}) < \mu_{InitSize}$, μ is the upper bound.

* **Information Reuse:** The average brightness information for each superpixel is directly passed to the next level. The position information is converted with Eq. 3.

$$\mu_{i+1} = C \times \mu_i - \frac{C-1}{2} \quad (3)$$

C : compression ratio, i : image level

* **Prediction Strategy:** “Boundary super-

pixel” (shown in left bottom Fig 3, purple 0 and the blue 1) is a superpixel that is classified as ROI or non-ROI, and has at least a neighbor which is classified otherwise.

$$E_b(s_p, s_q) = \begin{cases} 1, & s_p \neq s_q, y_{sp} \neq y_{sq}, \\ 0, & otherwise. \end{cases} \quad (4)$$

Newly defined boundary blocks decreases the size of the boundary queue.

* **Parallelization Scheme:** evenly splits the rows in image. Use locking mechanism on the superpixel average info vector when relabeling.

$$startR = totalR * i / totalThreads \quad (5)$$

$$endR = totalR * (i + 1) / totalThreads$$

Results

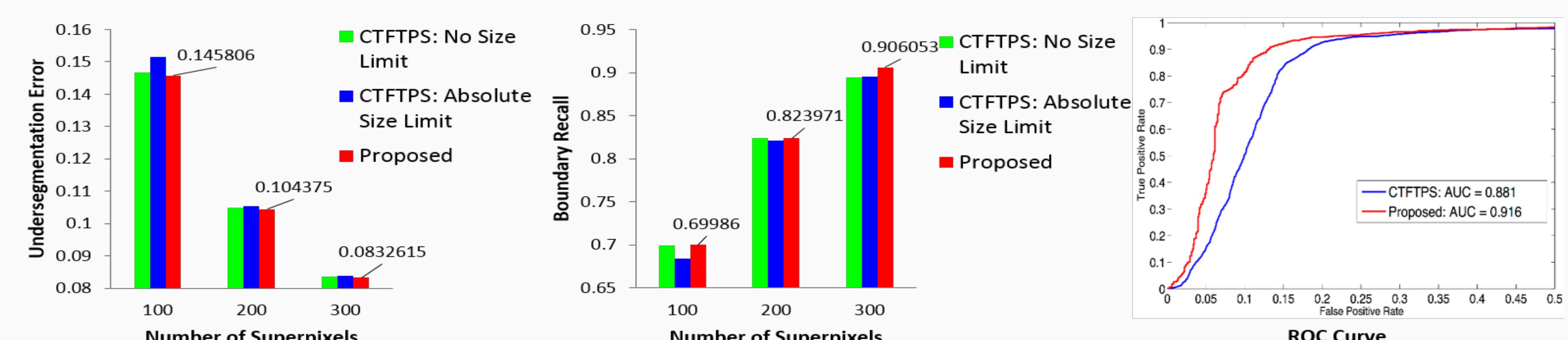


Figure 4: Comparison between CTFTPS with and without superpixel regularity optimization.

Table 1: Comparison of the average time cost.

Average Image Size	Grain	SLIC	CTFTPS	Multi-CTFTPS	RAPID
4712 × 5867	1 × 1	12.90s	3.29s	3.54s	1.56s
23561 × 29335	4 × 4	N/A	27.26s	28.98s	6.96s
	1 × 1	809s	79.46s	66.46s	17.54s

Table 2: Average time cost of Parallel RAPID with different number of threads.

Average Image Size	Grain	2T	4T	8T	14T	24T
4712 × 5867	1 × 1	1.09s	0.63s	0.49s	0.42s	0.34s
23561 × 29335	4 × 4	4.39s	3.79s	1.95s	1.69s	1.54s
	1 × 1	12.13s	7.83s	6.29s	5.83s	5.20s

Parallel RAPID gained 13 times speedup compared with [1], and around 160 times with SLIC.