Breast Anatomy Enriched Tumor Saliency Estimation

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Outline

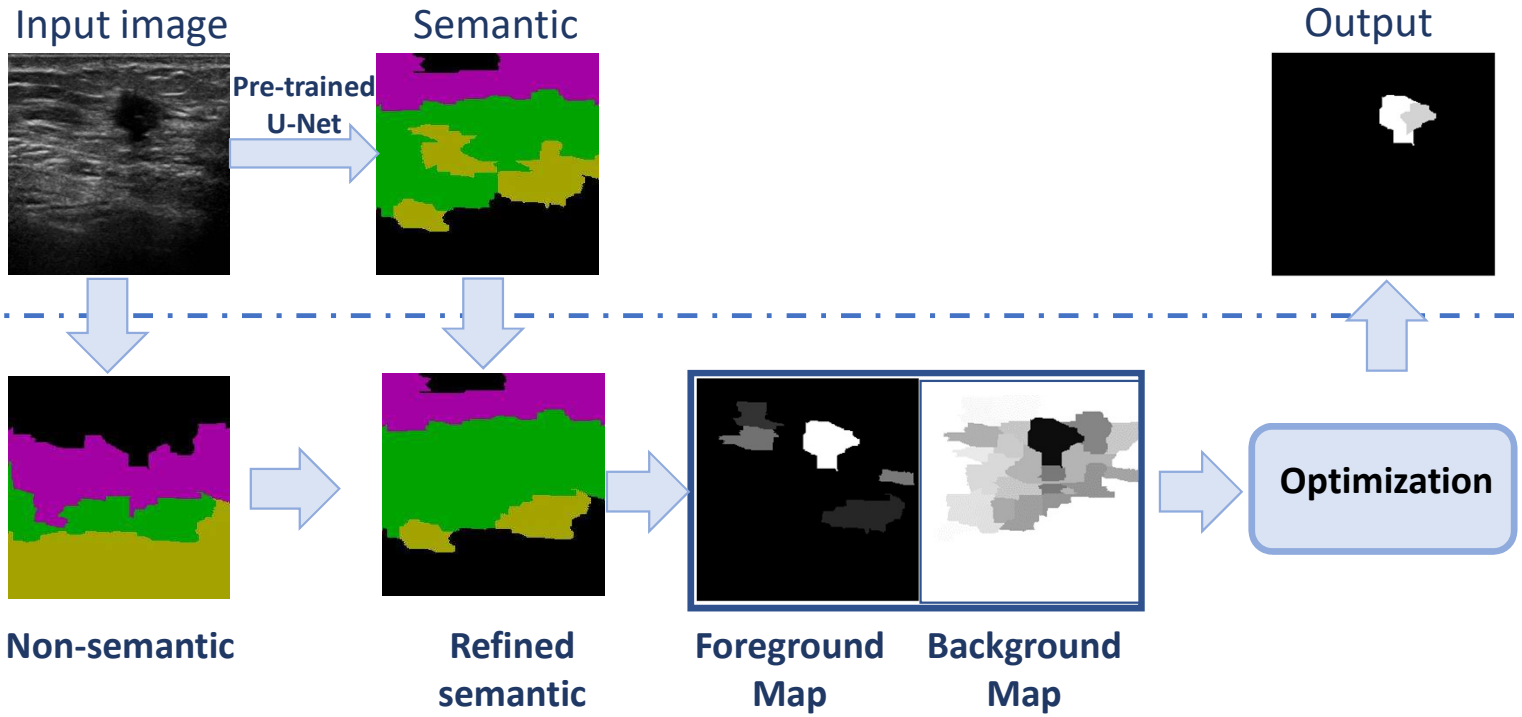
- Challenges
- The proposed Approach
- Experimental Results
- Contributions

Challenges

- Sensitivity of current methods to varied qualities of the images, such as low contrast, more artifacts, etc.;
- Challenging to extract domain knowledge because of the various tumor shapes, contours, sizes, etc.;
- Lack of large open-access datasets with annotated images for training.

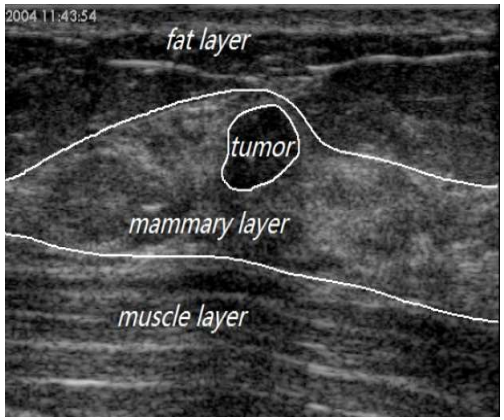
The proposed Approach - Flowchart

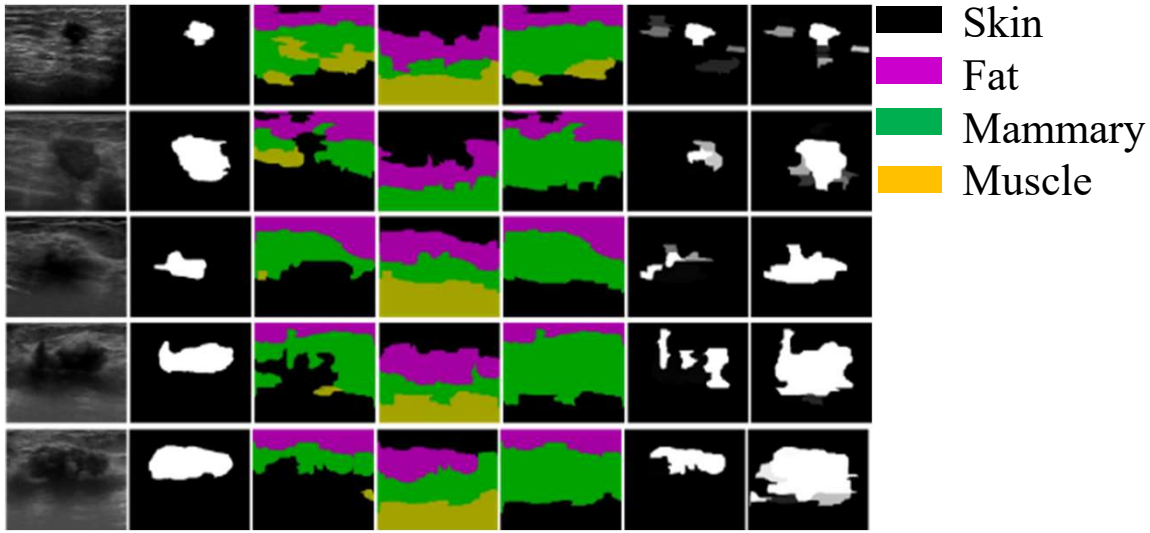
Tumor saliency estimation is to discover the tumor regions that draw radiologists' attention by modeling the human visual mechanism.



Semantic Breast Anatomy

- Anatomy knowledge: breast structure, candidate tumor location, and tumor appearance characteristic





(a) (b) (c) (d) (e) (f) (g)

The visual effects of refining SBA maps. (a) original images; (b) ground truths; (c) *SBA* maps generated by U-Net[1]; (d) the non-semantic layers [2]; (e) the refined SBA maps; (f) the FGs based on (c); and (g) the FGs based on (e). The different colors identified different layers in SBA maps (c) and (e), respectively.

Optimization

- Model the adaptive-center bias (*C*), foreground (*F*) and background (*T*) cues and correlation (quadratic term) hypothesis of human visual mechanism.

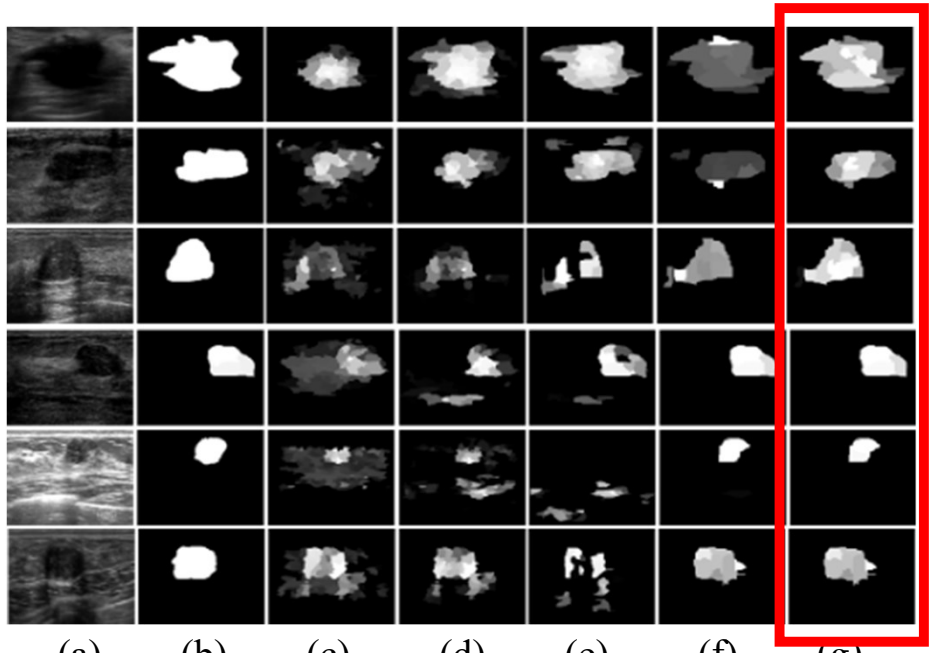
$$\begin{aligned} &minimize\ E(S) = S^T\big(-(\alpha \ln(C) + \beta \ln(F))\big) + \\ &\gamma(1-S)^T(-\ln(T)) + \sum_{i=1}^{N}\sum_{j=1}^{N}\big(s_i - s_j\big)^2 r_{ij}\, D_{ij} \\ &\text{subject to}\ \ 0 \le\ s_i\ \le 1, i = 1, 2, \cdots, N; \\ &B^T S = 0, B = (b_1, b_2, \cdots b_N)^T,\ b_i = \{0,1\} \end{aligned} \tag{1}$$

$$r_{ij} = exp(-\left|I'_i - I'_j\right|/\sigma_1^2) \tag{2}$$

$$D_{ij} = exp(-\left\|rc_i - rc_j\right\|_2/\sigma_2^2) \tag{3}$$

where the terms r_{ij} and D_{ij} define the similarity and the spatial distance between the *i*th and *j*th regions, respectively

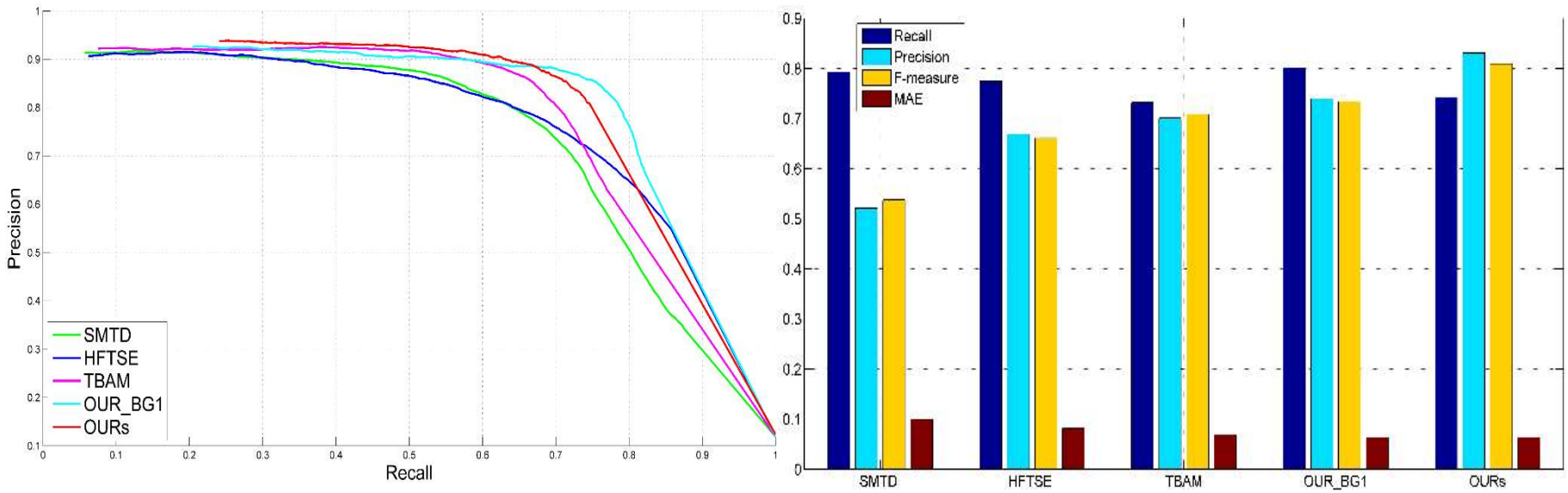
Experimental Results (1)



(a) (b) (c) (d) (e) (f) (g)

The visual effects of detecting the saliency maps by the five models. (a) original images (b)ground truths (c)-(g) the saliency maps generated by [3], [4], [2], OUR_BG1 and OURs, respectively.

Experimental Results (2)



Overall performance: The P-R curves, MAE and $F_{measure}$ values of the five models.

Experimental Results (3)

Model	Training Setting	DSC	JI (IOU)	TPR	FPR	ACC	AUC- ROC
U-Net[1]	LR = $1 \cdot 10^{-4}$	0.891 (±0.005)	0.817 (±0.008)	0.900 (±0.009)	0.120 (±0.027)	0.977 (±0.002)	0.950 (±0.006)
[5] +saliency maps[2]	LR = $1 \cdot 10^{-4}$	0.890 (±0.013)	0.832 (±0.014)	0.904 (±0.016)	0.092 (±0.008)	0.979 (±0.001)	0.955 (±0.002)
[5] +saliency maps by this proposed method	LR = $1 \cdot 10^{-4}$	**0.908** (±0.011)	**0.846** (±0.012)	**0.909** (±0.016)	**0.089** (±0.019)	**0.983** (±0.004)	**0.961** (±0.008)

Segmentation comparison with the other CNN models

Contributions

- The refining SBA strategy is effective even when the semantic information could not be generated accurately due to the limited number of training images.
- Achieve the best performance among the latest TSE models and increasing 10% of $F_{measure}$ on the public Breast Ultrasound images dataset.
- Incorporating better saliency maps into other CNN models will enhance the segmentation performance.

References

[1] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” International Conference on Medical image computing and computer-assisted intervention, 2015, pp. 224–241.

[2] F. Xu, Y. Zhang, H. D. Cheng, B.Zhang, J. Ding, C. Ning, and Y.Wang, “Tumor Saliency Estimation for Breast Ultrasound Images via Breast Anatomy Modeling,” arXiv preprint arXiv:1906.07760, 2019. Unpublished.

[3]H. Shao, Y. Zhang, M. Xian, H. D. Cheng, F. Xu, and J. Ding, “A saliency model for automated tumor detection in breast ultrasound images,” IEEE International Conference on Image Processing, 2015, vol. 2015-December, pp. 1424–1428

[4] F. Xu, Y. Zhang, M. Xian, H. D. Cheng, B.Zhang, J. Ding, C. Ning, and Y.Wang. "A Hybrid Framework for Tumor Saliency Estimation.,” International Conference on Pattern Recognition, 2018, vol. 2018-August, pp. 3935–3940.

[5] A. Vakanski, M. Xian, P. Freer. "Attention Enriched Deep Learning Model for Breast Tumor Segmentation in Ultrasound Images.,” Ultrasound in Medicine & Biology, 2020. In press.

Thanks.