Breast Anatomy Enriched Tumor Saliency Estimation

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Objectives:

Most tumor segmentation approaches achieve good performance on breast ultrasound (BUS) images collected in controlled settings; however, the performance degrades greatly with BUS images from different sources. Tumor saliency estimation (TSE) has attracted increasing attention to solve the problem by modeling radiologists' attention mechanism.

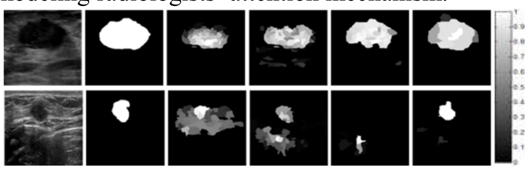

Fig. 1. Tumor saliency detection examples. (a) original images; (b)the ground truths; (c)-(f) the saliency maps generated by [1], [2], [3] and the proposed method, respectively. The region with higher intensity indicates the region has higher probability belonging to a tumor.

Highlights:

- Producing the semantic breast anatomy by utilizing CNN and refining it with breast ultrasound image topology property;
- Proposing a novel strategy to generate a more accurate background map with the assist of semantic breast anatomy and the spatial constraint;
- Achieving the best performance among the latest TSE models and increasing 10% of $F_{measure}$ on the public BUS dataset.

Breast Anatomy Enriched Top-down Model :

- **Semantic Breast Anatomy (SBA) / Foreground map (FG) generation:** first, we utilize U-Net [4] to generate the initial four semantic breast anatomy layers (see Fig.2.). Then we refine the wrong breast anatomy layers by combining the non-semantic decomposing layers which is generated by [3].

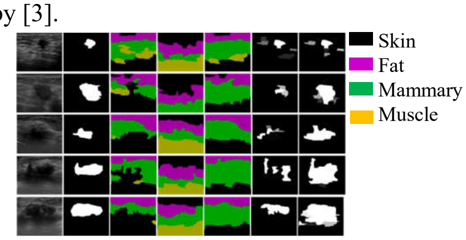

Fig. 2 The visual effects of refining SBA maps. (a) original images; (b) ground truths; (c) *SBA* maps generated by U-Net; (d) the non-semantic layers [3]; (e) the refined SBA maps; (f) the FGs based on (c); and (g) the FGs based on (e). The different colors identified different layers in SBA maps (c) and (e), respectively.

- **Background map (BG) generation**: generate more accurate background maps with the assist of semantic breast anatomy.
- **Optimization**: The final saliency maps are generated by the optimization framework integrating foreground cue (F), background cue(T), adaptive-center bias(C), and region-based correlation.

$$minimize\ E(S) = S^T\big(-(\alpha \ln(C) + \beta \ln(F))\big) + \gamma(1-S)^T(-\ln(T)) + \textstyle\sum_{i=1}^{N}\sum_{j=1}^{N}\big(s_i - s_j\big)^2 r_{ij}\, D_{ij} \quad (1)$$

$$subject\ to\quad 0 \le s_i \le 1, i = 1,2,\cdots,N;$$

$$B^T S = 0, B = (b_1, b_2, \cdots b_N)^T, b_i = \{0,1\}$$

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

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

where the defines r_{ij} as the similarity, and D_{ij} as the spatial distance. b_i is 1 if the ith region is adjacent to the image border, and 0 otherwise .

The optimization will make 1) the region have high saliency value if the region is near the adaptive center, and the probability of the region belonging a tumor is high and the probabilities of the region being the background is low;2)the closer similar regions to have similar saliency value.

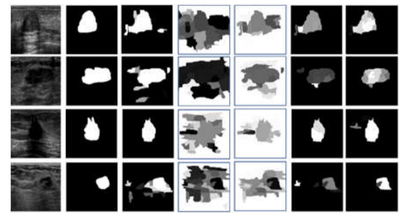

Fig 3 The effects of different components in the objective function. (a) original images; (b) ground truths ; (c) the FGs; (d) the BG maps in [3]; (e) the proposed BGs; (f) the saliency maps based on (d); and (g) the saliency maps using new BG.

Results:

- **Overall TSE performance on dataset (610 images)**

Metrics: Precision-Recall curve, average precision, recall ,F-measure and mean absolutely error (MAE).

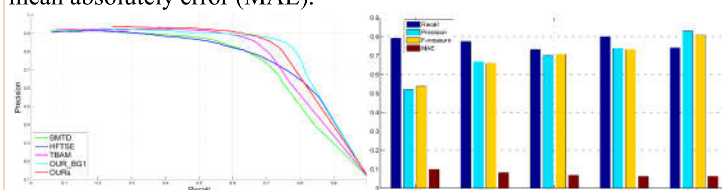

Fig. 4. The P-R curves, MAE and $F_{measure}$ values of the five models.

- **Segmentation comparison with the other CNN models**

Model	Training Setting	DSC	JI (IOU)	TPR	FPR	ACC	AUC- ROC
U-Net[4]	LR=1·10^{-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[3]	LR = 1·10^{-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 = 1·10^{-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)

Conclusion:

We propose a novel TSE model by utilizing the semantic breast anatomy knowledge. The refining SBA strategy is effective even when the semantic information could not be generated accurately due to the limited number of images. Incorporating better saliency maps into other CNN models will enhance the segmentation performance.

References:

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