Domesticating SAM for Breast Ultrasound Image Segmentation via Spatial-frequency Fusion and Uncertainty Correction

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1 Detailed Process of the DFC Module

We further provide the corresponding algorithm to show the rectifition process of the dual false corrector(DFC) more concretely, as shown in Algorithm 1.

Algorithm 1 The overall workflow of our proposed dual false corrector (DFC).

Given an input image I.
Generate a point prompt p^0 and initial mask Y^0.
Random perturbations of p^0 to generate $p = \{p^1, p^2, \cdots, p^N\}$.
Generate segmentation masks $Y = \{Y^1, Y^2, \cdots, Y^N\}$ based on p.
Calculate $\hat{Y}_{j,k} = \frac{1}{N+1}\sum_{i=0}^{N} Y^i_{j,k}$, to get the average segmentation result $\hat{Y}$.
Calculate $U_{j,k} = -0.5 \cdot [\hat{Y}_{j,k} \cdot \log(\hat{Y}_{j,k} + \epsilon) + (1 - \hat{Y}_{j,k}) \cdot \log(1 - \hat{Y}_{j,k} + \epsilon)]$, to get the uncertainty mask U.
Generate the high uncertainty mask U_h based on the threshold $T_u = \min(U) + 0.5 \times [\max(U) - \min(U)]$.
Calculate average intensity of I within target region I_t and background region I_b
Determine the pixels' intensity range (I_{tl}, I_{th}) and (I_{bl}, I_{bh}) belonging to target and background respectively.
Initialize potential FN mask and FP mask using $(1-\hat{Y}) \cdot U_h$ and $\hat{Y} \cdot U_h$ respectively.
for $(i, j))$ where $U_h(i, j) = 1$ **do**
    if $\hat{Y}(i, j) = 0$ *and* $I_{tl} < I(i, j) < I_{th}$ **then**
        $\hat{Y}(i, j) = 1$
    end if
    if $\hat{Y}(i, j) = 1$ *and* $I_{bl} < I(i, j) < I_{bh}$ **then**
        $\hat{Y}(i, j) = 0$
    end if
end for
return Final rectified segmentation result $\hat{Y}$.

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2 More Experimental Results

2.1 More visualized results

We provide more visual comparison with three task-specific methods and five SAM-based methods, including TransUNet [2], HiFormer [5], H2Former [4], SAM [6], MSA [8], SAMed [9], SAM-Med2D [3] and SAMUS [7] on BUSI [1] dataset, as shown in Fig. 1. Besides, more visualized ablation comparisons on the BUSI test set for the spatial-frequency feature fusion (SFF) module and the dual false corrector (DFC) are shown in Fig. 2 and Fig. 3.

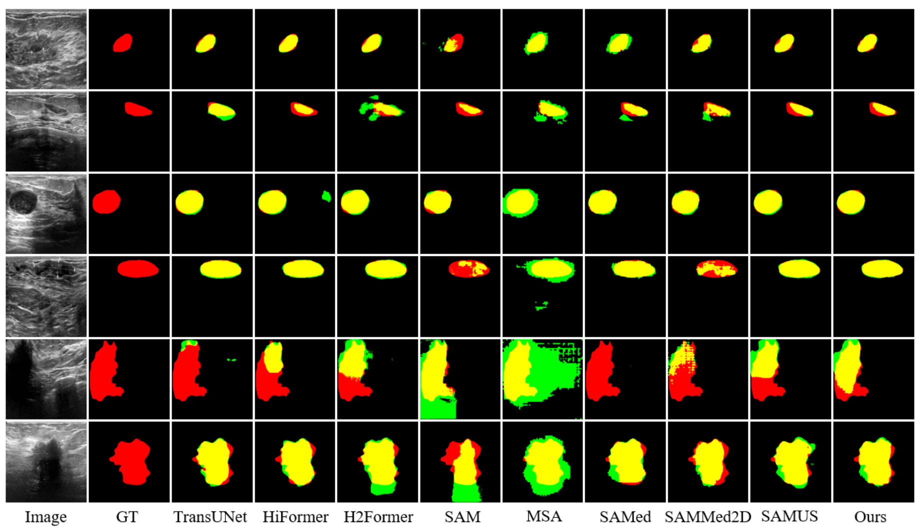

Fig. 1: More visual comparisons with different methods on the BUSI test set. Red, green and yellow represent ground truth, prediction and their overlapping regions, respectively.

2.2 Generalization results

We provide visual comparison for gneralization ability evaluation experiment, as shown in the Fig. 4. We applied the model parameters trained on the BUSI dataset to the UDIAT dataset for testing, to evaluate the generalization effect of the model on the unseen breast ultrasound dataset. It can be seen from the visualization results that the breast mass predicted by our proposed model is closer to the ground truth than other models, especially the boundaries of breast masses are more refined. This shows that our model can be well applied to other breast ultrasound data sets under the same challenge with a small amount of training.

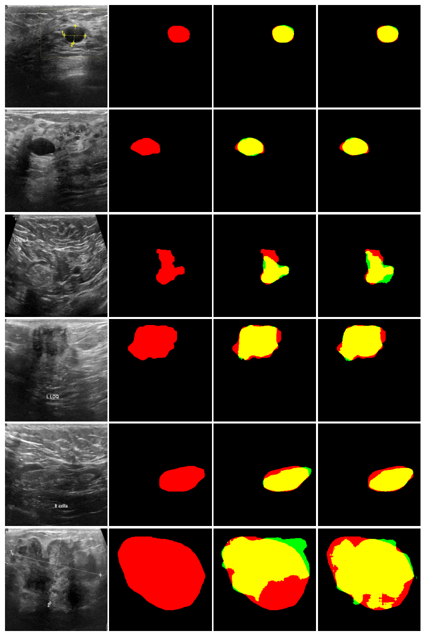

Fig. 2: Visual comparisons of ablation study on the SFF. (a) Input image. (b) GT. (c) W/o SFF (d) SFF.

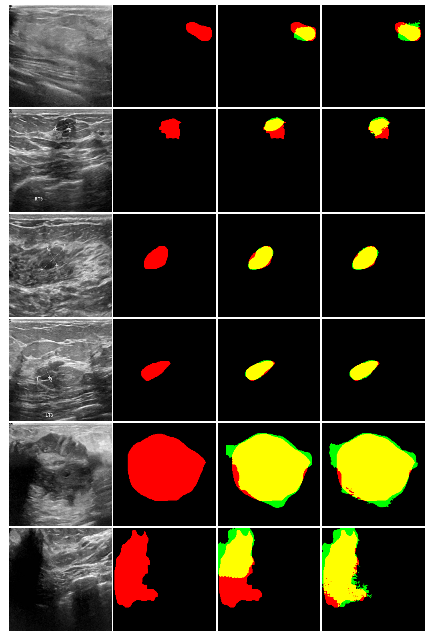

Fig. 3: Visual comparisons of ablation study on the DFC. (a) Input image. (b) GT. (c) W/o DFC (d) DFC.

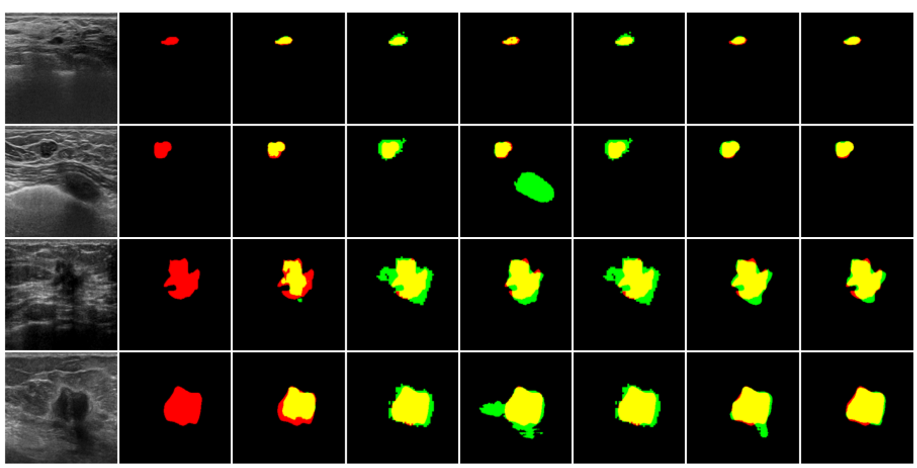

Fig. 4: Visual comparison with SAM-based methods on the UDIAT test set. Red, green and yellow represent ground truth, prediction and their overlapping regions, respectively.

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