Unsupervised Liver Tumor Segmentation with Pseudo Anomaly Synthesis

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Motivation

Q1: Should pseudo-anomalies approximate the queries in test phase?

- There is no clear definition of what constitutes an anomaly, there shouldn't be any bound or limit on pseudo anomaly.
- We advocate generating a diversity of anomalies to facilitate a model to learn the comprehensive normal spectrum, instead of matching known abnormal patterns.

Q2: How should the segmentation model be trained on the synthesis data?

- A covariate shift is likely to exist between the synthesized and real anomalies, according to Fig 1(C). Good-fit models on the pseudo-anomalies may fail to detect real anomalies.
- The model optimization on anomaly synthesis for pseudo-supervised segmentation should stop early to preserve the model's generalizability on queries.

Method

We adopted the DREAM[1] architecture and incorporated three key elements: random-shape anomaly generation, two-phase learning mechanism, and UNet reconstruction network.

Random-shape Anomaly Generation

Algorithm 1 Random-shape Pseudo Anomaly Generation

Input: *Image, Threshold*

Output: *AnomalyMask, Label*

```
NoiseImage ← gaussianNoise(Image_height, Image_width)
BlurImage ← gaussianBlur(NoiseImage, kernal_size)
StretchImage ← rescaleIntesity(BlurImage, (0, 255))
AnomalyMask ← binarize(StretchImage, Threshold)
AnomalyMask ← Morph_open_close(AnomalyMask, kernel_ellipse)
if sum(AnomalyMask) > 0 then
    Label ← 1
else
    Label ← 0
end if
```

The pseudo anomaly synthesis is shown in Fig. 1(B) and formulated as:

$$I_s = (1 - M_s) \odot (I + C) + M_s \odot I, \qquad |C| \in (minRange, maxRange)$$

where I_s represents synthesized anomalies, $\odot$ is the element-wise multiplication, and C is randomly drawn from a Gaussian distribution within a defined range

Two-stage Training Strategy

Due to the covariate shift of the synthesized anomalies, we observed high perturbations in evaluation performance, therefore, we propose to train the networks in two steps: As Depicted in Fig. 2(A), the reconstruction network is trained to restore anomalous regions, while the segmentation network estimates an accurate segmentation map for the anomaly.

- The reconstruction model is first trained with L_1 loss:

$$L_{rec}(I_s - \tilde{I}_s) = |I_s - \tilde{I}_s|$$

- After freezing the well-trained generative module, Focal Loss [2] is adopted to slightly train the segmentation model to avoid bias introduced by the covariance shift, :

$$L_{seg}(M_s - \tilde{M}_s) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C}\alpha_j(1-\tilde{m}_{s,ij})^{\gamma}\log(\tilde{m}_{s,ij})$$

where $\tilde{I}_s$ is the reconstruction image, $\tilde{M}_s$ is the estimated anomaly mask, $\tilde{m}_{s,ij}$ denotes the predicted probability of class j at pixel i, and $\alpha_j$is the weight for class j.

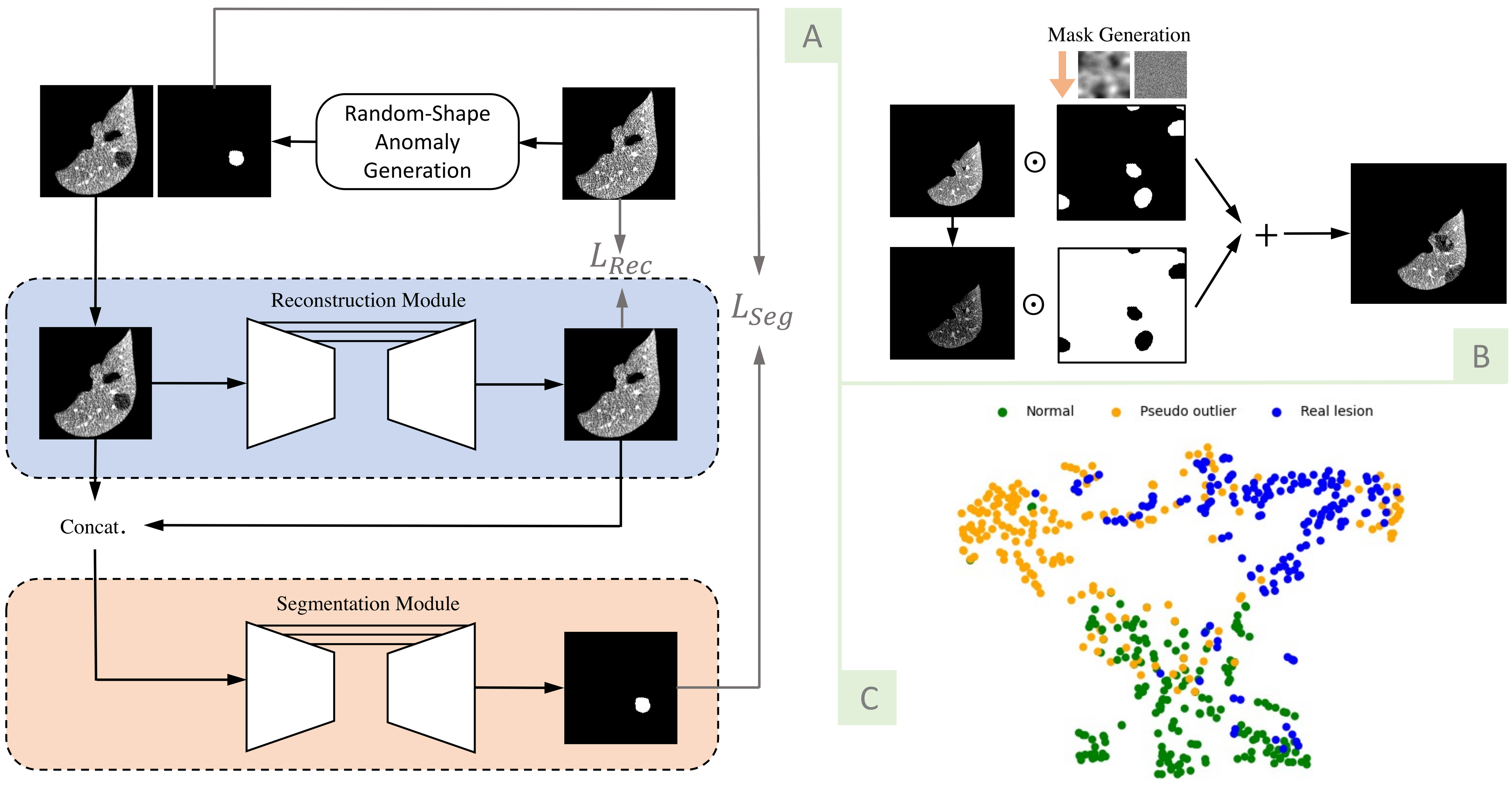

Fig. 1. (A) Systematic diagram of the proposed unsupervised liver tumor segmentation scheme. During training, synthetic abnormalities are fed to a restoration net followed by a segmentation net. The two models are trained in two phases to avoid model overfitting on synthesis. (B) Proposed synthesis pipeline based on Gaussian noise stretching. (C) Liver image embedding by 2-D TSNE.

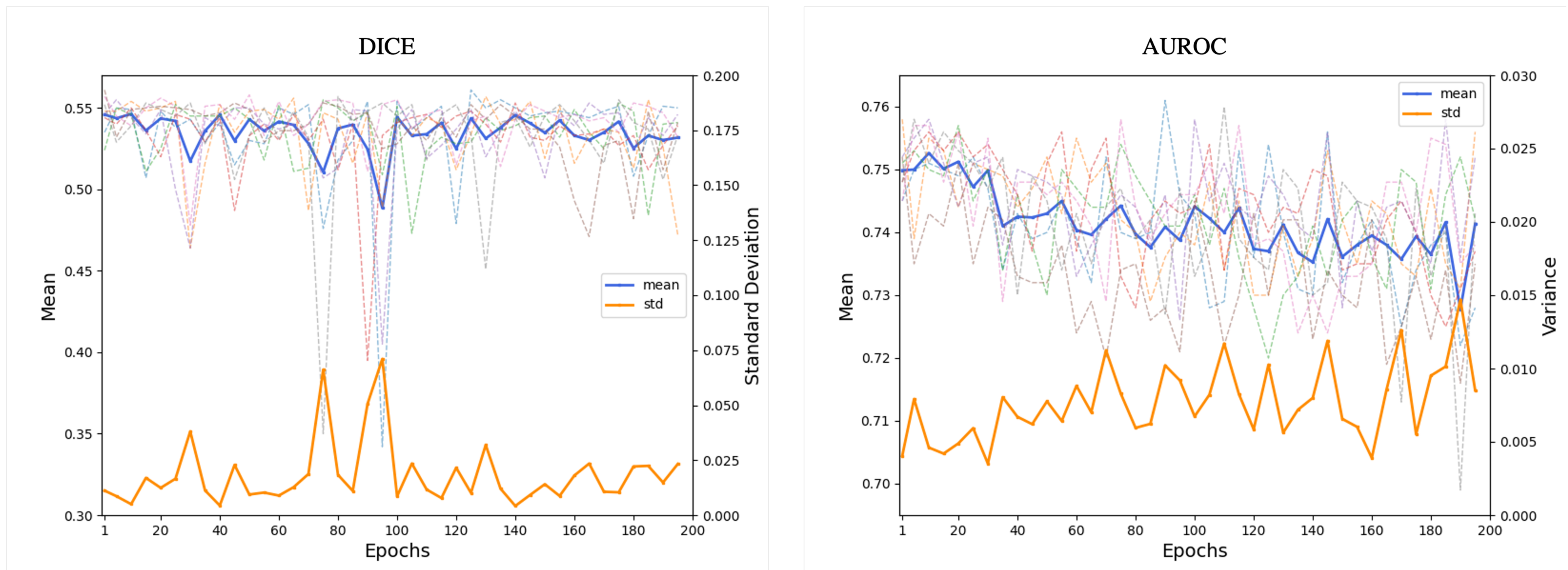

Fig. 2. Evaluation performance of the segmentation network reveals a tendency to overfit shortly after a short period of training.

Results

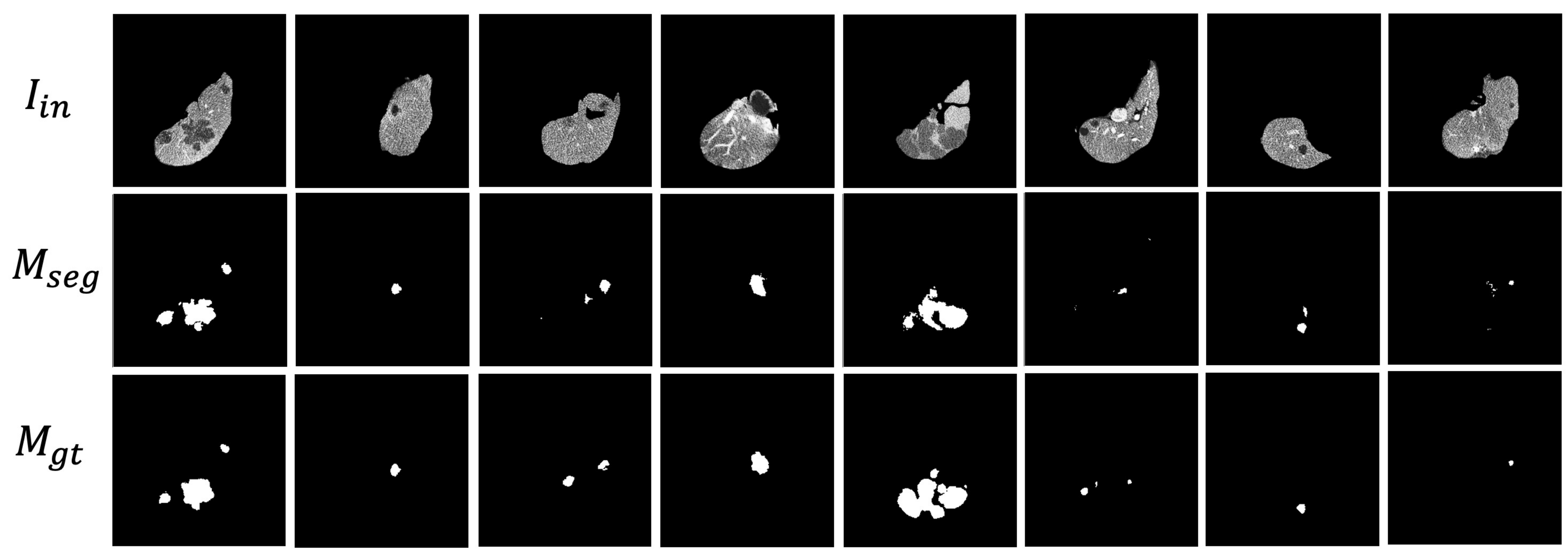

Fig. 3. Qualitative results of tumor segmentation on real liver tumor data. I_{in}: Input, M_{seg}: segmentation mask, and M_{gt}: Ground-Truth.

Table 1. Ablation study of two-phase training (TP), pseudo anomaly (PA), and reconstructive network. The baseline is DRAEM model [1].

	+TP	+PA	+UNet	Dice
				14.75 ± 14.28
Base line	✓			21.31 ± 12.54
	✓	✓		30.17 ± 5.50
		✓	✓	40.06 ± 6.85
	✓	✓	✓	$\mathbf{53.03 \pm 1.78}$

[1] Zavrtanik, Vitjan, Matej Kristan, and Danijel Skočaj. "Draem-a discriminatively trained reconstruction embedding for surface anomaly detection." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2021.
[2] Lin, Tsung-Yi, et al. "Focal loss for dense object detection." Proceedings of the IEEE international conference on computer vision. 2017.