Anatomical Prior-Inspired Label Refinement for Weakly Supervised Liver Tumor Segmentation with Volume-Level Labels

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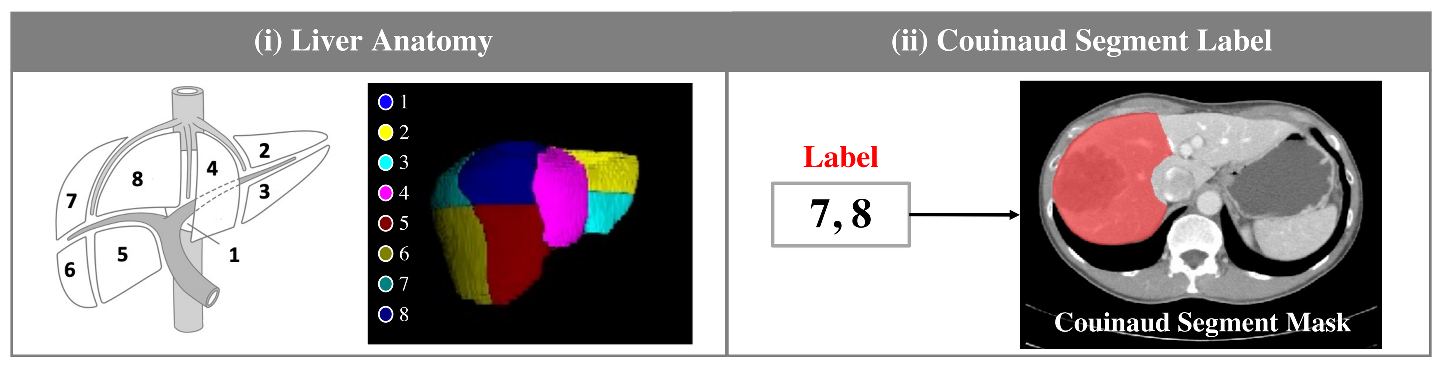
Introduction

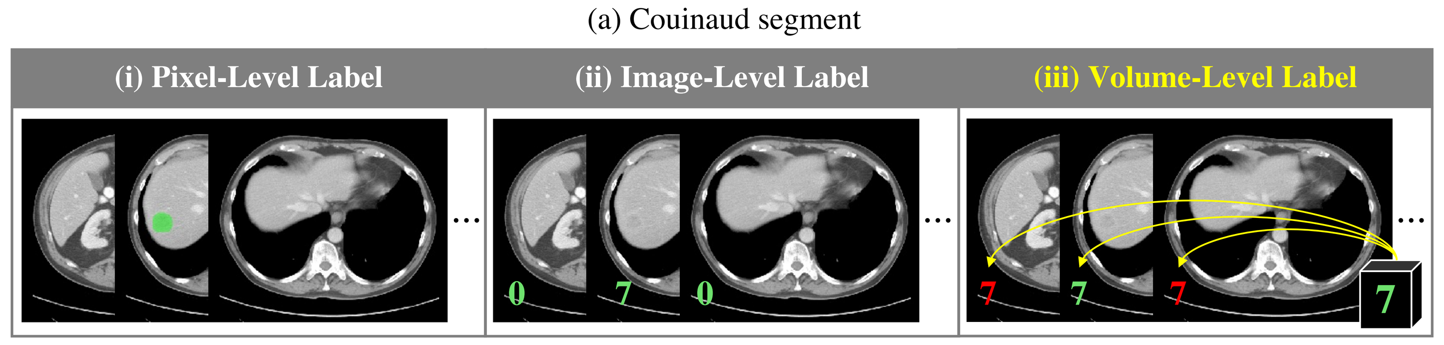
❖ Background

- Liver cancer is one of the leading cause of death globally, and automatic liver tumor segmentation is important for assisting doctors in clinical practice.
- Existing models for liver tumor segmentation usually require accurate pixel-level labels, while acquiring such dense labels is laborious and costly.

❖ Weak labels



(a) Couinaud segment



(b) Comparing strong and weak labels for liver tumor segmentation

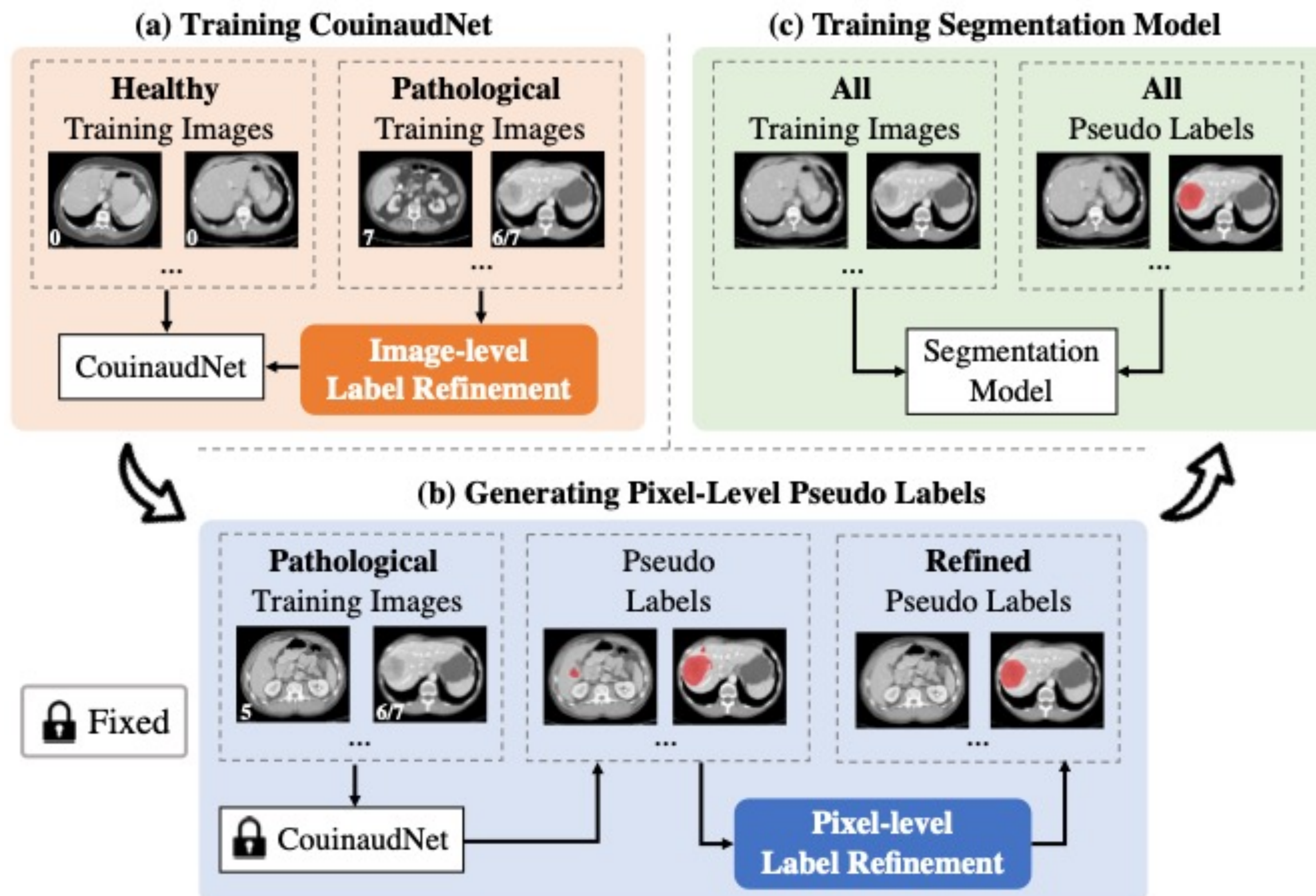
- Couinaud segment is often used by radiologists to describe the localization of liver tumors and can be used as image-level labels for training liver tumor segmentation models. In our method, we study a more challenging setting with volume-level labels, which can be treated as noisy image-level labels.

❖ Contribution

- We propose to train deep neural networks for liver tumor segmentation using **volume-level labels**, which greatly reduces human annotation effort.
- We treat the volume-level labels as noisy image-level labels and propose two **label refinement** strategies based on anatomical priors to reduce the training noise and improve the performance.
- The experimental results quantitatively demonstrate the effectiveness of our proposed method.

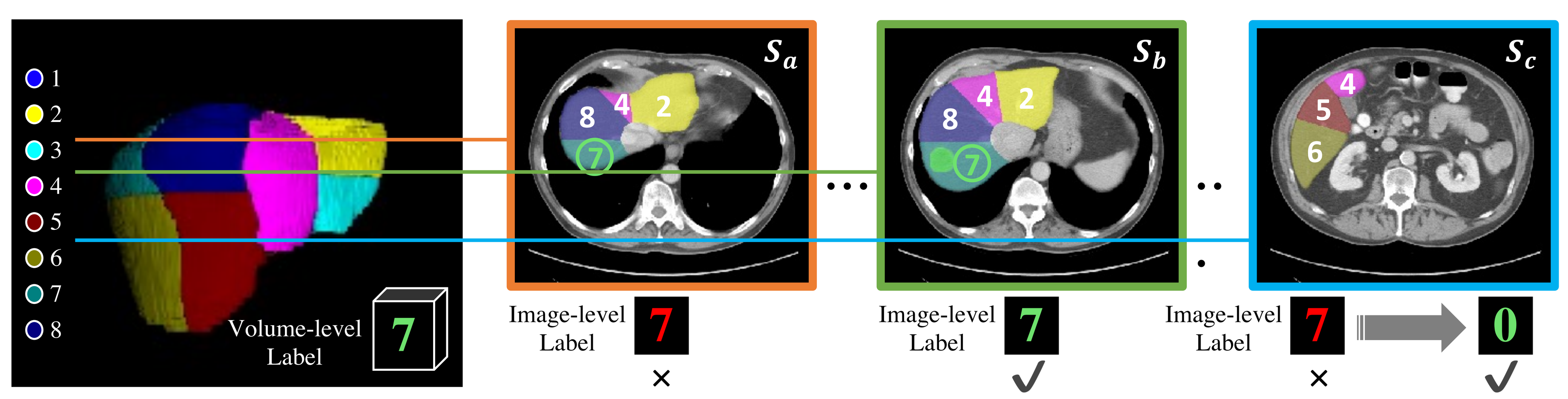
Method

❖ Overview of the proposed method



❖ Image-level label refinement

All eight Couinaud segments of the liver can not exist on the same CT slice simultaneously.



❖ Pixel-level label refinement

Tumors should be continuous across adjacent slices.
Continuity index is proposed to re-weight the pixel-level prediction probability:

$$m_k = \mathbb{I}\,(f^c(x_k) \geq \tau)$$

$$CI_k = c \cdot \max\{\mathrm{DICE}(m_k\ , m_{k-1}\ ), \mathrm{DICE}(m_k\ , m_{k+1})\}$$

$$\widehat{m_k} = \mathbb{I}\,(f^c(x_k) * CI_k \geq \tau)$$

Experiments

❖ Comparison with State-of-the-Arts

Supervision	Methods	Dice per case(%)	Dice global(%)
Pixel-level	nnU-Net [3]	49.8	48.9
Image-level	CouinaudNet [10]	34.3	33.3
Volume-level	CouinaudNet [10]	5.9	8.1
	Ours	35.6	32.2

Comparison of liver tumor segmentation results on 3DIRCADb test set.

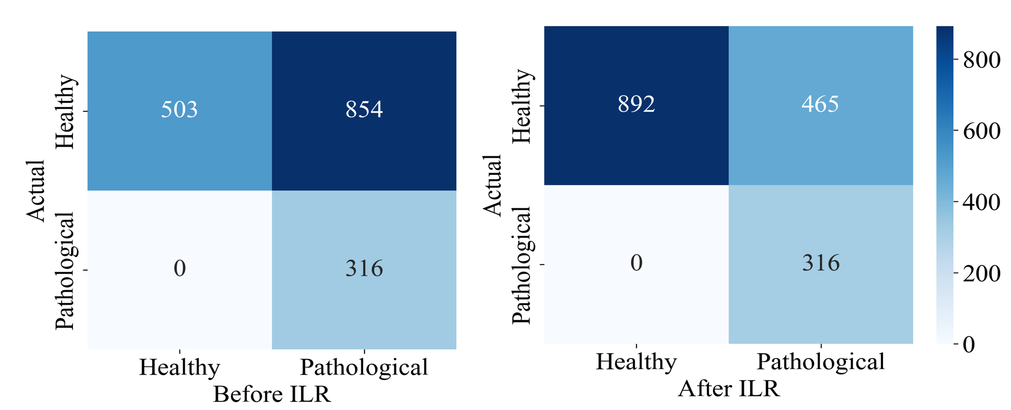
Supervision	Methods	Dice per case(%)	Dice global(%)
Pixel-level	nnU-Net [3]	70.5	86.7
Image-level	CouinaudNet [10]	62.2	74.0
Volume-level	CouinaudNet [10]	23.1	28.5
	Ours	58.9	72.3

Comparison of liver tumor segmentation results on MSD08 test set.

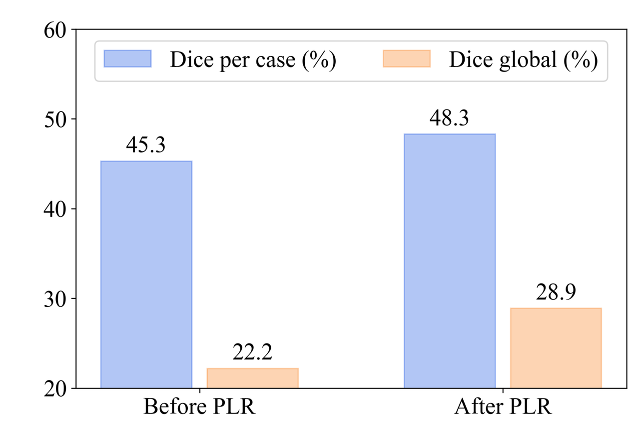
❖ Self evaluation

ILR	PLR	Dice per case(%)	Dice global(%)
		5.9	8.1
✓		21.9	17.9
	✓	12.7	17.2
✓	✓	35.6	32.2

Ablation study

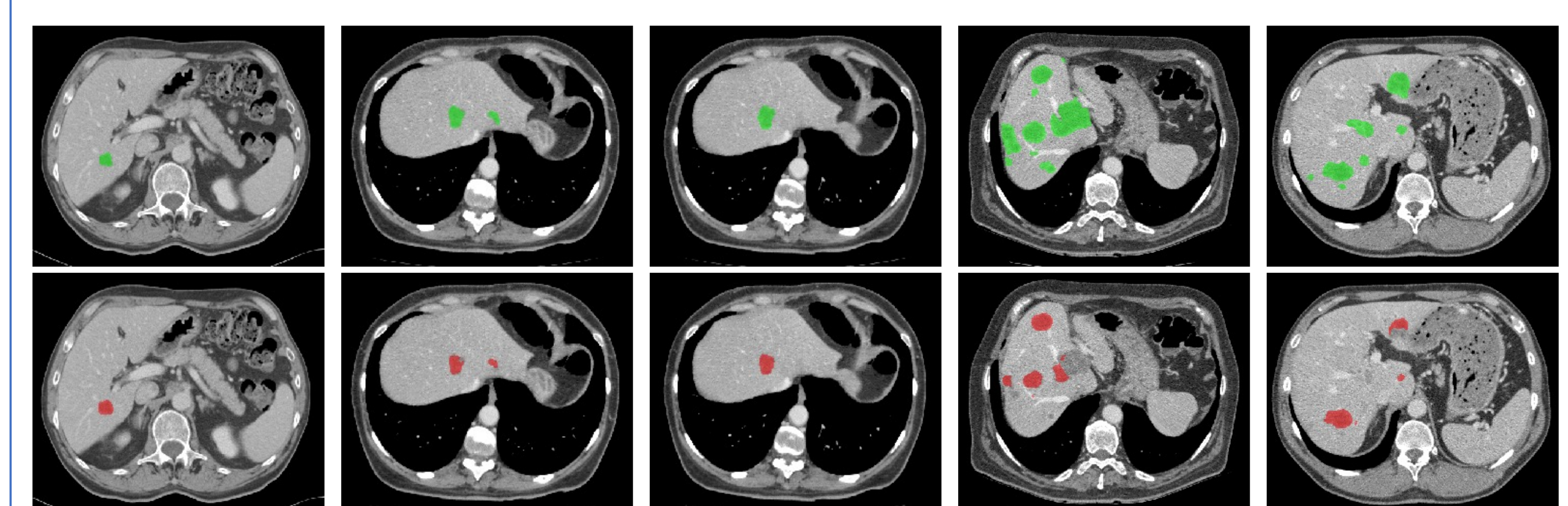


Evaluation of image-level labels



Evaluation of pixel-level pseudo labels

❖ Visualization results



(a) (b) (c) (d) (e)