Synthesis and Inpainting-Based MR-CT Registration for Image-Guided Thermal Ablation of Liver Tumors

基于图像生成和补全的MR-CT配准用以肝肿瘤热消融手术的影像学导航

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BackGround and Contribution

◘热消融：

- 升高了肿瘤局部区域的温度(55◦-65◦摄氏度)，导致不可逆的细胞损伤，最终导致肿瘤细胞凋亡和凝固性坏死
- 因此，准确定位肿瘤区域至关重要的
- 在热消融过程中，CT成像通常用于指导介入过程，其中术前CT (pCT)用于规划，术中捕获术中CT (iCT)

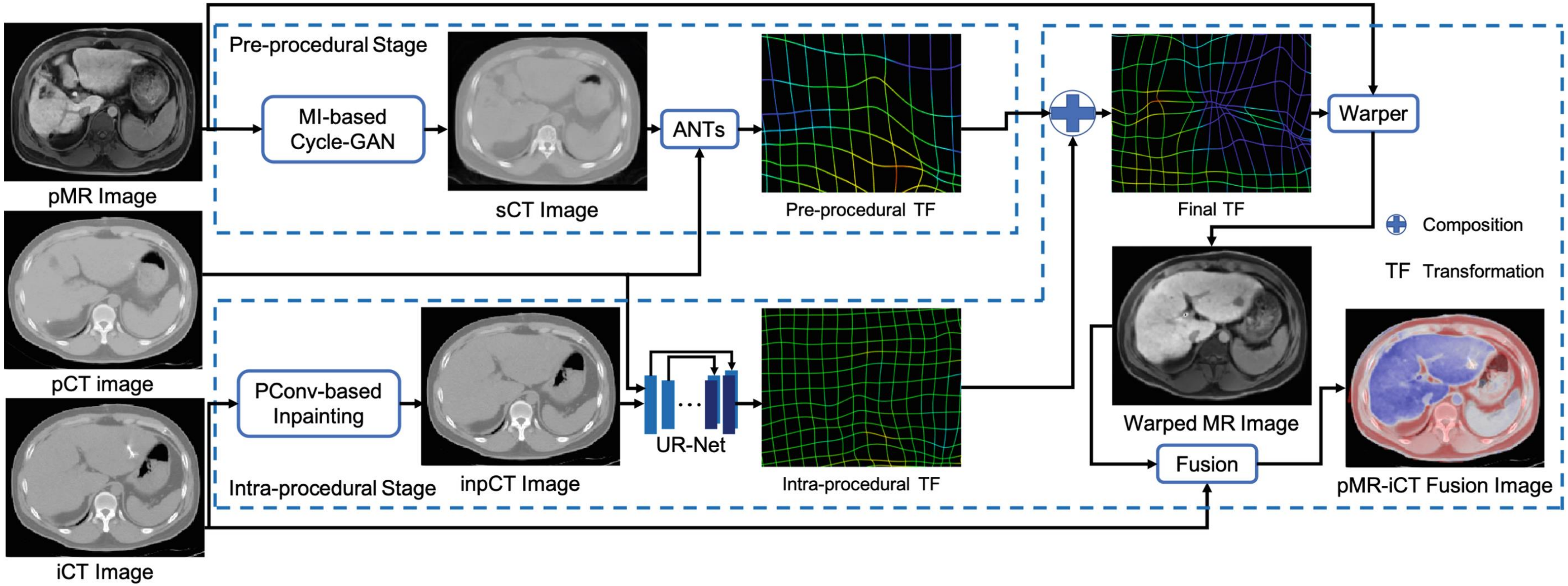
◘存在的问题：

- CT在组织对比度(如动脉)方面相对较差，而且容易受到手术过程中探头引入的伪影的影响。
- 高分辨率pCT和程序前MR (pMR)图像通常在规划期间进行对齐，然后在iCT图像上进行配准，可以更精确地指导探测器定位到所需的ROI
- 这种定位的准确性和速度都很重要，因为它可以弥补因患者定位和呼吸运动而造成的不延迟的变形

BackGround and Contribution

- 大多数配准方法:
  - 没有实时性，只能在准备阶段
  - 没有对手术中，手术器材伪影进行修复
- 本文方案（两阶段）：
  - 1. 手术前: MI+CycleGan从pMR图像生成sCT，将交叉模态配准转化为单模态配准问题，将pMR和pCT配准。
  - 2. 手术中: 使用无监督配准网络(URNet)，将inpainted iCT (inpCT)图像与pCT图像快速进行可变形配准。

Method



ANTs(Advanced Normalized Tools) 是一种传统的精确配准方案

三部分网络：

MI-based Cycle-GAN for Synthesis

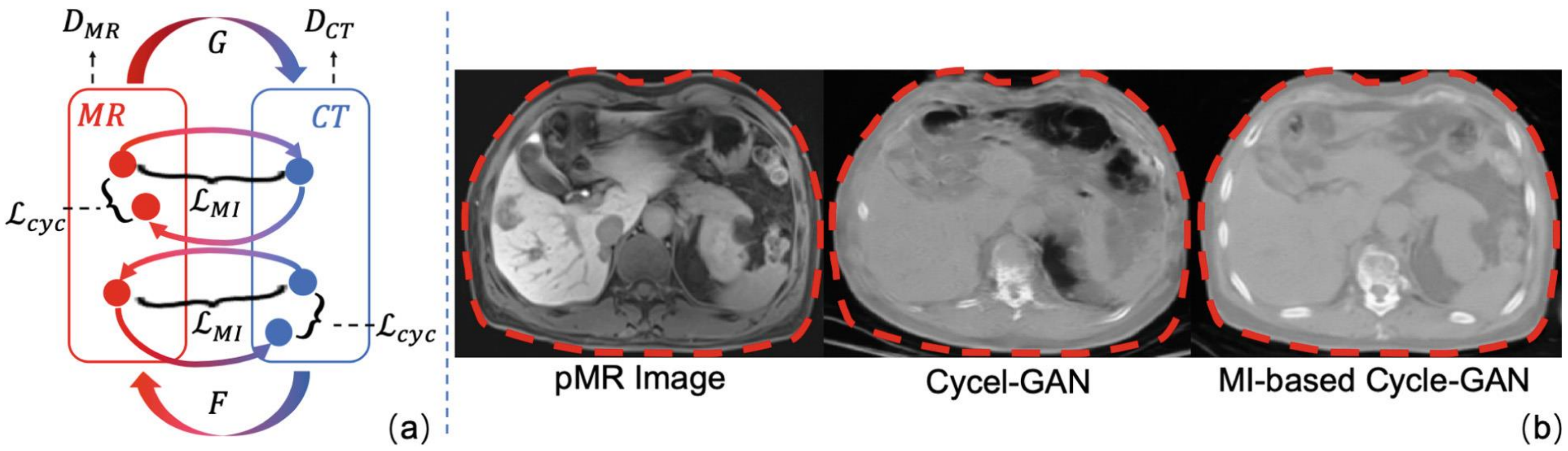
Partial convolution （Pconv-based） inpainting

UR-Net

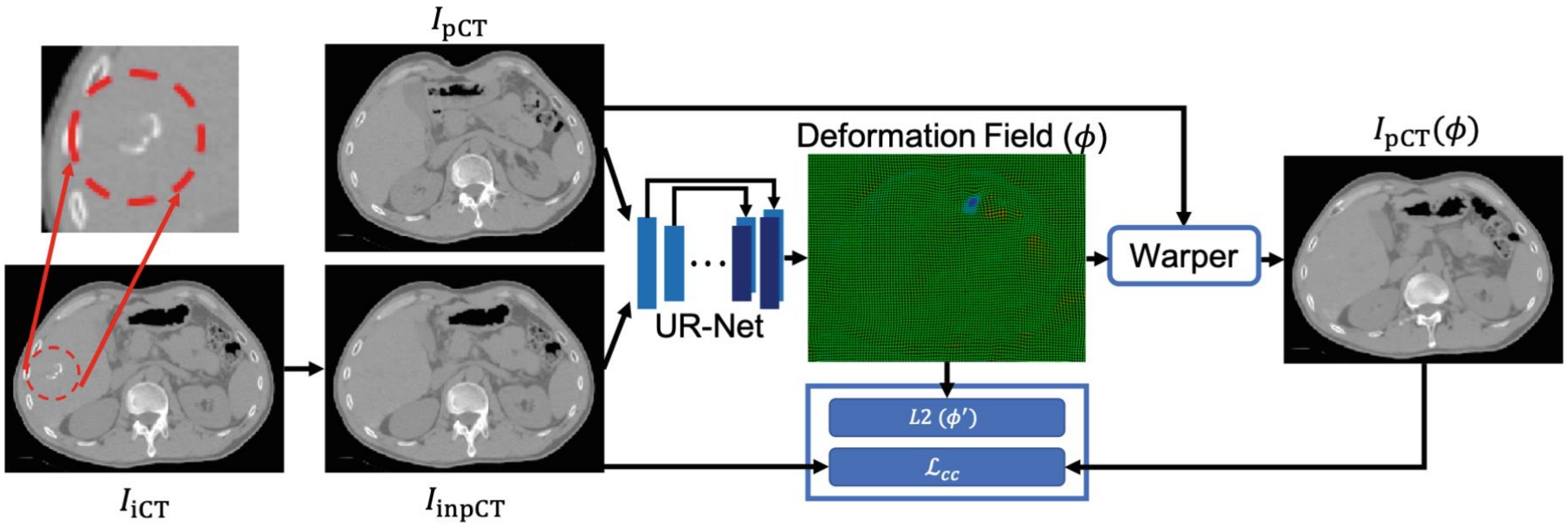
Cycle-GAN with mutual information constraint

- 跨模态配准：模态间存在很多差异，一个主流方案是转化为单模态问题
- 直接采用CycleGAN会引入边缘的漂移，因此引入互信息约束

$$\mathcal{L}_{\mathrm{MI}} = \sum\sum p(x,y)\log\frac{p(x,y)}{p(x)p(y)};$$



Intra-procedural Registration



- 实际上就是VoxelMorph的结构

$$\mathcal{L} = -\mathrm{S}(I_{\mathrm{inpCT}}, I_{\mathrm{pCT}}(\phi)) + \mathrm{Reg}(\phi),$$

- 部分卷积网络：
  - 给定一个覆盖探测器及其工件的粗糙掩模(例如，一个边界框或一个多边形)，inpainting网络可以重建底层组织并逐层更新掩模，直到掩模缩小
  - 将3D unet中的卷积模块改成Partial Conv

Partial Convolutional

卷积模块加入一个Mask，标记有效区域

$$x' = \begin{cases} \mathbf{W}^T(\mathbf{X} \odot \mathbf{M}) \frac{\mathrm{sum}(\mathbf{1})}{\mathrm{sum}(\mathbf{M})} + b, & \text{if } \mathrm{sum}(\mathbf{M}) > 0 \\ 0, & \text{otherwise} \end{cases}$$

每一次卷积之后，更新mask。只有这个位置在卷积时存在1个有效区域的输出，这个位置的mask就更新为1

$$m' = \begin{cases} 1, & \text{if } \mathrm{sum}(\mathbf{M}) > 0 \\ 0, & \text{otherwise} \end{cases}$$

损失函数两个区域分别计算

$$\mathcal{L}_{hole} = \frac{1}{N_{\mathbf{I}_{gt}}} \|(1-M) \odot (\mathbf{I}_{out} - \mathbf{I}_{gt})\|_1, \mathcal{L}_{valid} = \frac{1}{N_{\mathbf{I}_{gt}}} \|M \odot (\mathbf{I}_{out} - \mathbf{I}_{gt})\|_1$$

“感知损失”， $\Psi_p^{\mathbf{I}_*}$ is the activation map of the p-th selected layer given original input

$$\mathcal{L}_{perceptual} = \sum_{p=0}^{P-1} \frac{\|\Psi_p^{\mathbf{I}_{out}} - \Psi_p^{\mathbf{I}_{gt}}\|_1}{N_{\Psi_p^{\mathbf{I}_{gt}}}} + \sum_{p=0}^{P-1} \frac{\|\Psi_p^{\mathbf{I}_{comp}} - \Psi_p^{\mathbf{I}_{gt}}\|_1}{N_{\Psi_p^{\mathbf{I}_{gt}}}}$$

“风格损失”, Kp is the normalization fact $1/C_p H_p W_p$

$$\mathcal{L}_{style_{out}} = \sum_{p=0}^{P-1} \frac{1}{C_p C_p} \left\| K_p \left(\left(\Psi_p^{\mathbf{I}_{out}}\right)^{\intercal} \left(\Psi_p^{\mathbf{I}_{out}}\right) - \left(\Psi_p^{\mathbf{I}_{gt}}\right)^{\intercal} \left(\Psi_p^{\mathbf{I}_{gt}}\right) \right) \right\|_1$$

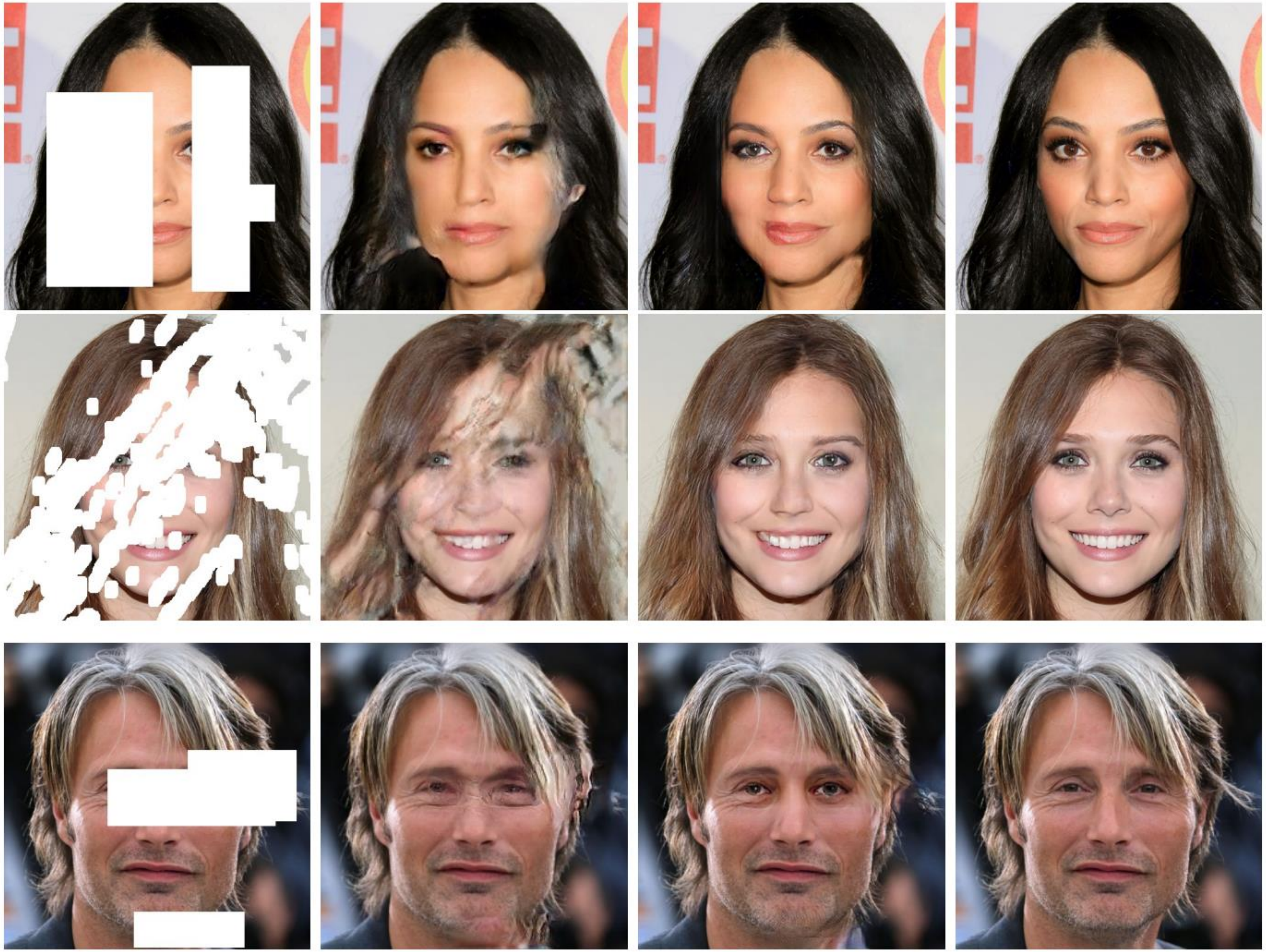
$$\mathcal{L}_{style_{comp}} = \sum_{p=0}^{P-1} \frac{1}{C_p C_p} \left\| K_p \left(\left(\Psi_p^{\mathbf{I}_{comp}}\right)^{\intercal} \left(\Psi_p^{\mathbf{I}_{comp}}\right) - \left(\Psi_p^{\mathbf{I}_{gt}}\right)^{\intercal} \left(\Psi_p^{\mathbf{I}_{gt}}\right) \right) \right\|_1$$

Partial Convolutional

平滑损失，R where R is the region of 1-pixel dilation of the hole

$$\mathcal{L}_{tv} = \sum_{(i,j)\in R,(i,j+1)\in R} \frac{\|\mathbf{I}_{comp}^{i,j+1} - \mathbf{I}_{comp}^{i,j}\|_1}{N_{\mathbf{I}_{comp}}} + \sum_{(i,j)\in R,(i+1,j)\in R} \frac{\|\mathbf{I}_{comp}^{i+1,j} - \mathbf{I}_{comp}^{i,j}\|_1}{N_{\mathbf{I}_{comp}}}$$

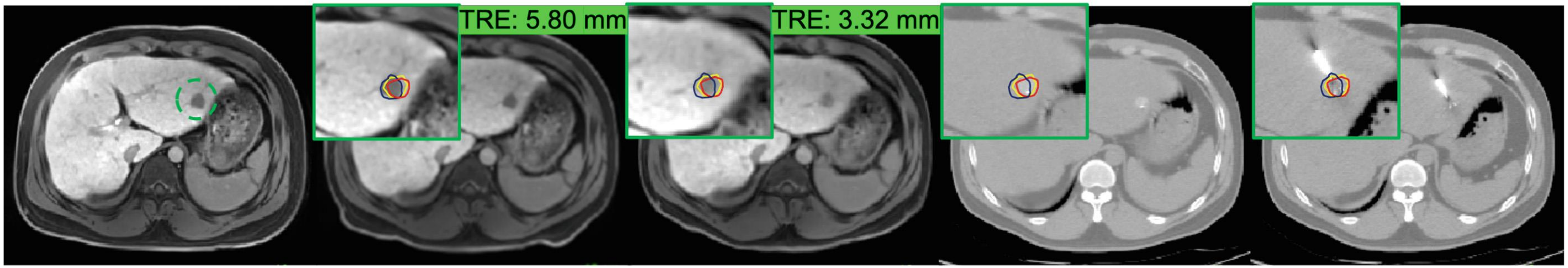
$$\mathcal{L}_{total} = \mathcal{L}_{valid} + 6\mathcal{L}_{hole} + 0.05\mathcal{L}_{perceptual} + 120(\mathcal{L}_{style_{out}} + \mathcal{L}_{style_{comp}}) + 0.1\mathcal{L}_{tv}$$



(a) Input (b) GntIpt (c) PConv(Ours) (d) Ground Truth

Dataset and Pre-processing

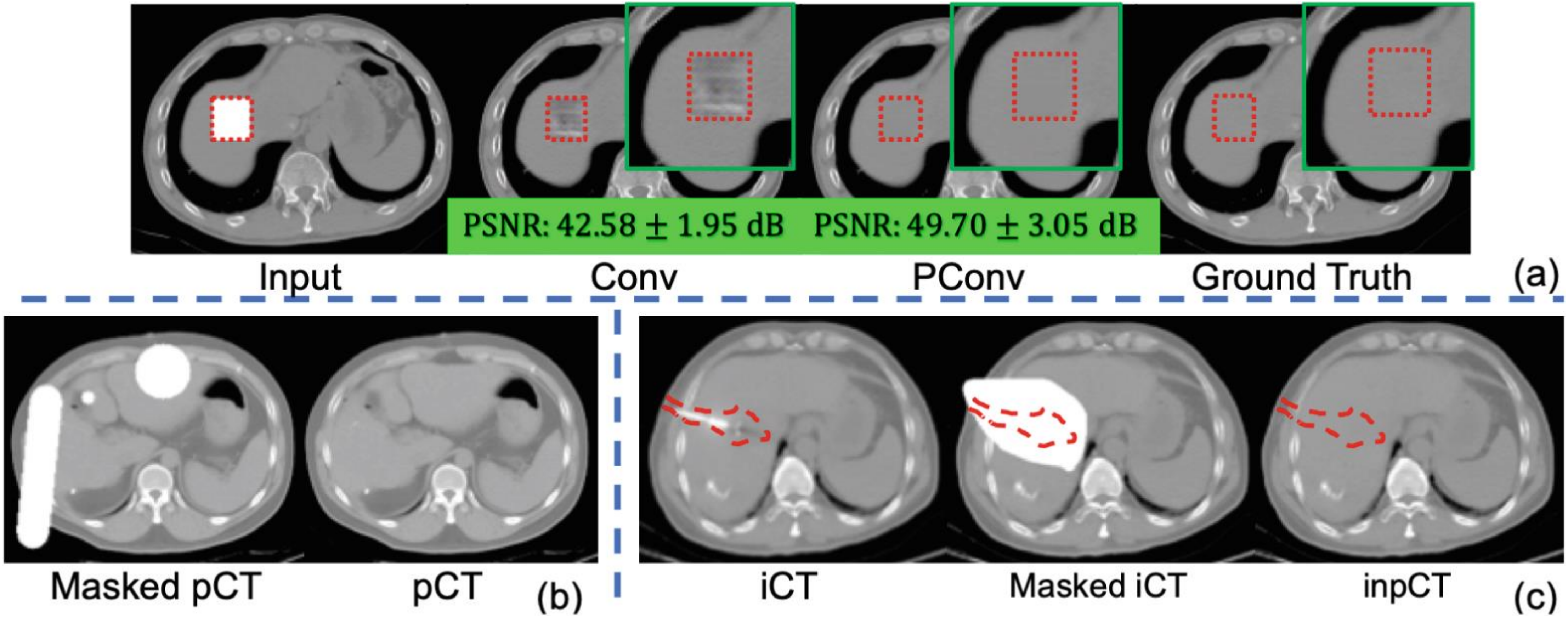
- 39例数据 undergoing liver tumor ablation were included in our experiment
- 全部具有pMR, pCT and iCT
- 11例测试，28例训练
- 256 × 256 × 128 with isotropic voxel distances



pMR Image ANTs Proposed pCT Image iCT Image

Table 2. Results of pMR-iCT (rigid and deformable), pMR-pCT (rigid and deformable), and pCT-iCT (deformable only) registration.

		Rigid		Deformable	
		FLIRT	ANTs	ANTs	Proposed
pMR-iCT					
Liver	Dice (%)	48.44 ± 40.40	85.52 ± 2.92	86.59 ± 3.30	$\mathbf{86.96 \pm 3.00}$
	TRE (mm)	-	52.56 ± 9.85	5.18 ± 2.43	$\mathbf{4.93 \pm 2.72}$
pMR-pCT					
Liver	Dice (%)	48.07 ± 40.40	87.03 ± 2.60	89.55 ± 2.04	$\mathbf{90.59 \pm 1.73}$
	TRE (mm)	-	6.63 ± 2.73	5.59 ± 2.01	$\mathbf{4.67 \pm 2.00}$
Tumor	Dice (%)	12.88 ± 25.76	51.10 ± 17.13	55.34 ± 5.70	$\mathbf{62.45 \pm 4.66}$
	TRE (mm)	-	6.71 ± 2.27	6.08 ± 1.40	$\mathbf{3.89 \pm 0.99}$
pCT-iCT					
Liver	Dice (%)	-	-	87.90 ± 5.25	$\mathbf{88.63 \pm 5.53}$
	TRE (mm)	-	-	5.06 ± 3.29	$\mathbf{4.37 \pm 3.30}$



PSNR: 42.58 ± 1.95 dB
PSNR: 49.70 ± 3.05 dB
Input
Conv
PConv
Ground Truth
(a)
Masked pCT
pCT
(b)
iCT
Masked iCT
inpCT
(c)