Multi-Phase Liver-Specific DCE-MRI Translation via a Registration-Guided GAN

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Abstract

Problem: Gd-EOB-DTPA enhances MRI at the hepatobiliary phase with higher sensitivity and accuracy in detecting small hepatocellular carcinoma (HCC) [2]. However, acquiring GED-HBP is more costly than a conventional dynamic contrast-enhanced MRI (DCE-MRI). Therefore, developing substitutes using virtual images of GED-HBP (v-HBP) using advanced image translation technology can be practically valuable in clinics.

Our Approach:

- Propose a new dataset and a novel application by translating multi-phase DCE-MRIs to generate v-HBP as practical substitutes for GED-HBP.
- Develop a multi-phase and registration-guided GAN, referred to as MrGAN, which addresses both intra-sequence and inter-sequence misalignments.
- Validate the proposed MrGAN using our clinical data with promising results.

Introduction

Gd-EOB-DTPA enhances Liver MRI. Gd-EOB-DTPA is a liver-specific contrast enhancement agent presently used for the diagnosis of liver lesions in MRI. However, acquiring GED-HBP is costly, attributed to the long acquisition time and expensive contrast agents. [1]

Medical Image-to-image translation: Image-to-image translation aims to translate images from one domain to another. Current methods can be categorized into supervised and unsupervised methods. The former construct paired training images to register these multi-modality MRIs but exist small misalignments. The latter tends to generate numerous rich but unrealistic details and artifacts. Beyond the above difficulties, the long scanning time of GED-HBP results in minimal liver morphology changes but significant differences in the intestinal region, which might cause more artifacts.

To address the aforementioned issue, we train the generator with an auxiliary registration network that adapts to the intra-sequence and inter-sequence misalignments, thereby seeking the optimal solution for both translation and registration tasks. Since the paired DCE-MRIs and GED-HBP may exhibit minimal changes in liver morphology but significant differences in the intestinal region, our method applies shape consistency through a pre-trained segmentation network, enabling a more prominent local generation in the liver region.

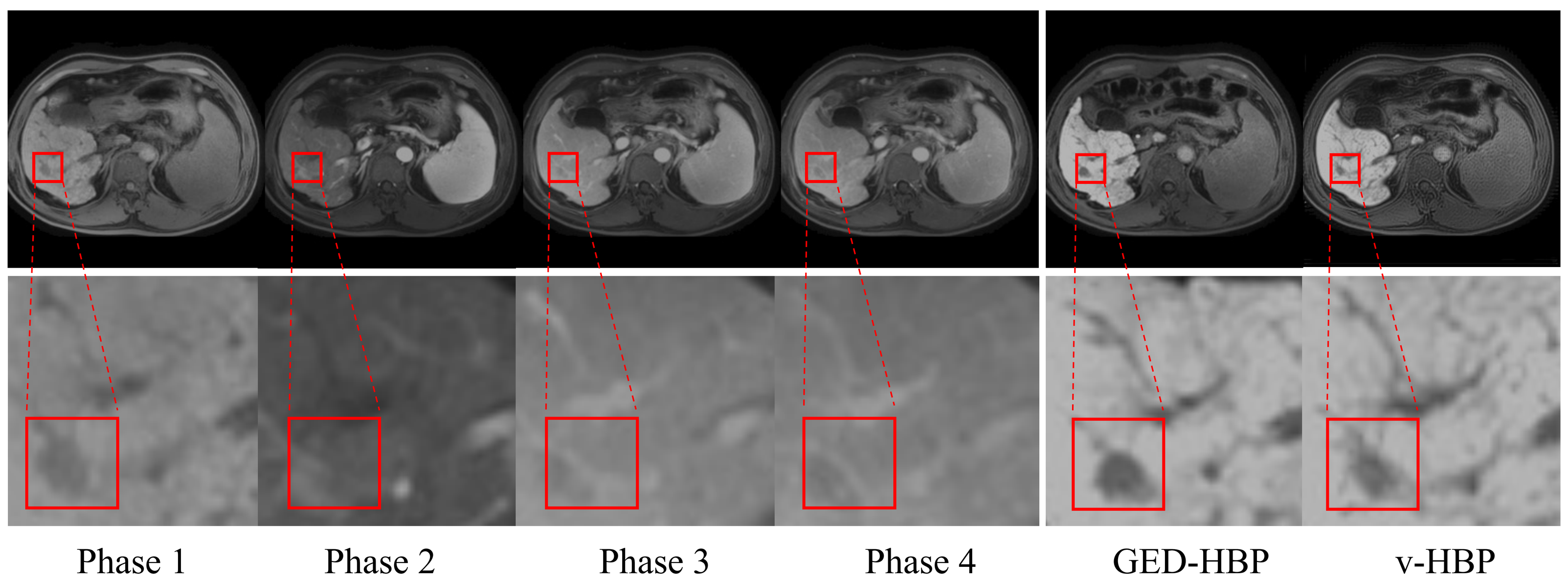

Figure 1. A case from our dataset in which the HCC regions are marked with red boxes by radiologists.

Methods-Overview

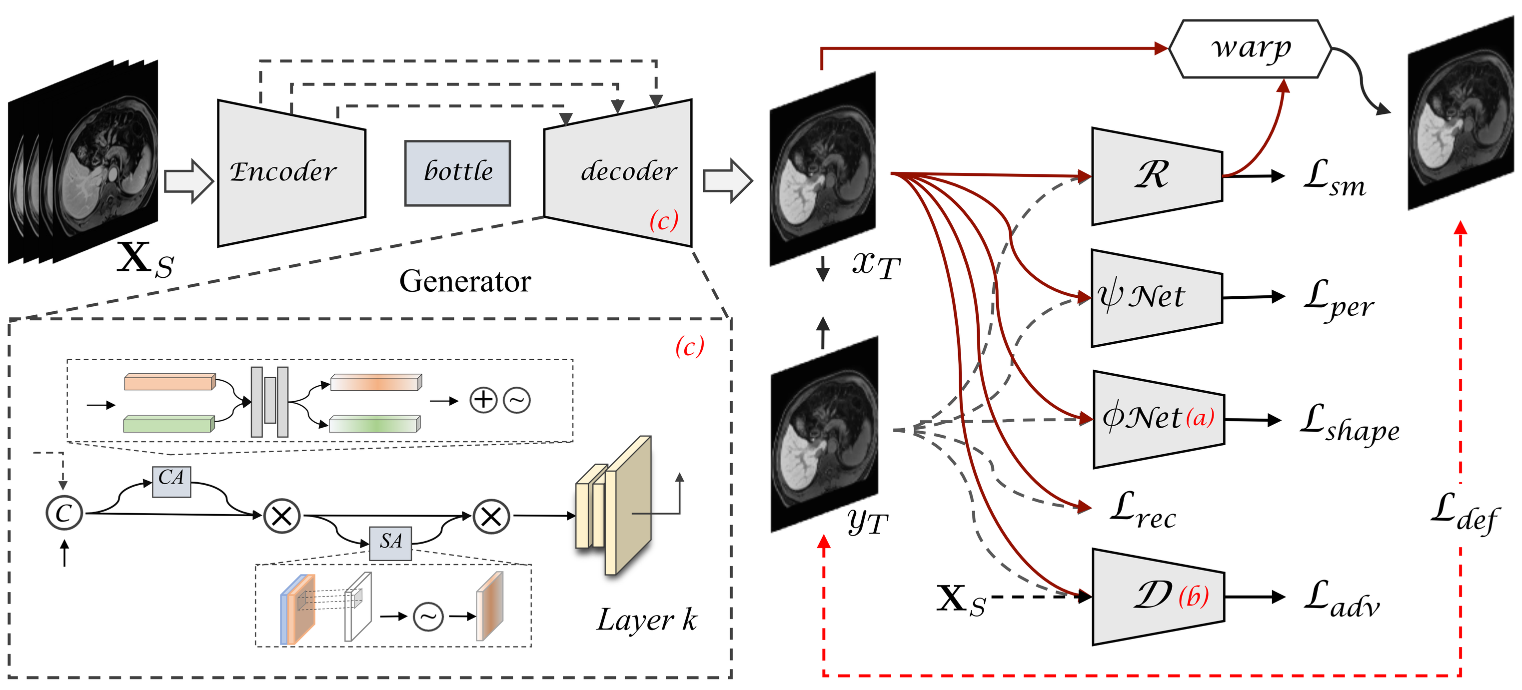

Figure 2. The framework of our MrGAN method.

1. Pre-trained liver anatomy segmentation network ϕ as shape priors.
2. Generator $\mathcal{G}$ translates multi-phase images input into v-HBP.
3. Discriminator $\mathcal{D}$ ensures good image fidelity and contains the right target characteristics.
4. Auxiliary registration network $\mathcal{R}$ guides the generator to address misalignment problem.

Methods - Standard Generative Adversarial Network

Generative adversarial network. Minimize conditional and patch adversarial loss as

$$\min_{\mathcal{G}}\max_{\mathcal{D}} \mathcal{L}_{adv}(\mathcal{G},\mathcal{D}) = \mathbb{E}_{\mathbf{X}_S,y_T}[\log \mathcal{D}(\mathbf{X}_S,y_T)] + \mathbb{E}_{\mathbf{X}_S,y_T}[\log(1-\mathcal{D}(\mathbf{X}_S,\mathcal{G}(\mathbf{X}_S)))]. \tag{1}$$

Reconstruction loss. As the generator is tasked to not only fool the discriminator but also approximate the ground truth output in an L_1 sense by,

$$\min_{\mathcal{G}}\mathcal{L}_{L_1}(\mathcal{G}) = \mathbb{E}_{\mathbf{X}_S,y_T}[\|y_T-\mathcal{G}(\mathbf{X}_S)\|_1], \min_{\mathcal{G}}\mathcal{L}_{L_1^*}(\mathcal{G}) = \mathbb{E}_{\mathbf{X}_S,y_T}[\|y_T^*-\mathcal{G}(\mathbf{X}_S)^*\|_1], \tag{2}$$

Contact Information

- Project page: https://github.com/Jy-stdio/MrGAN/
- Web: https://zmiclab.github.io/
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Methods-Registration-guided Generative Adversarial Network

Beyond the standard GANs, our MrGAN introduces a deformable loss for alleviating the misalignment problem, a smoothness loss for minimizing the gradient of the deformation field, a shape consistency loss, and a perceptual loss enabling more realistic global details and prominent local liver regions.

Deformable registration network.

$$\min_{\mathcal{G},\mathcal{R}} \mathcal{L}_{def}(\mathcal{G},\mathcal{R}) = \mathbb{E}_{\mathbf{X}_S,y_T}[\|y_T - \mathcal{G}(\mathbf{X}_S)\circ \mathcal{R}(\mathcal{G}(\mathbf{X}_S),y_T)\|_1], \tag{3}$$

$$\min_{\mathcal{R}} \mathcal{L}_{sm}(\mathcal{R}) = \mathbb{E}_{\mathbf{X}_S,y_T}[\|\nabla \mathcal{R}(\mathcal{G}(\mathbf{X}_S),y_T)\|_2^2]. \tag{4}$$

Shape consistency.

$$\min_{\mathcal{G}} \mathcal{L}_{sp}(\mathcal{G}) = \mathbb{E}_{\mathbf{X}_S,y_T}[\|\phi(\mathcal{G}(\mathbf{X}_S)) - \phi(y_T)\|_2], \tag{5}$$

Perceptual similarity.

$$\min_{\mathcal{G}} \mathcal{L}_{per}(\mathcal{G}) = \mathbb{E}_{\mathbf{X}_S,y_T}\sum_l \frac{1}{H_lW_lC_l}\|\psi_l(\mathcal{G}(\mathbf{X}_S)) - \psi_l(y_T)\|_2, \tag{6}$$

Finally, we combine all the loss functions above as follows,

$$\min_{\mathcal{G},\mathcal{R}}\max_{\mathcal{D}} \mathcal{L}_{total}(\mathcal{G},\mathcal{R},\mathcal{D}) = \mathcal{L}_{adv} + \lambda_1\mathcal{L}_{rec} + \lambda_2(\mathcal{L}_{def}+\mathcal{L}_{sm}) + \lambda_3\mathcal{L}_{sp} + \lambda_4\mathcal{L}_{per}. \tag{7}$$

Results

Table 1. Ablation study: quantitative results under different settings.

Methods	Quantitative Metrics			
	MAE ↓	PSNR↑	SSIM↑	LPIPS↓
baseline	0.104±0.037	18.100± 2.187	0.632± 0.055	0.220± 0.042
MrGAN w/o att	0.102± 0.040	18.812± 2.31	0.671± 0.064	0.198± 0.046
MrGAN w/o seg	0.103± 0.037	18.760± 2.152	0.679± 0.057	0.199± 0.044
MrGAN w/o reg	0.104± 0.045	18.581± 2.086	0.651± 0.054	0.208 ± 0.042
MrGAN	**0.096±0.035**	**19.108±2.134**	**0.685±0.065**	**0.186±0.045**

Table 2. Quantitative results of different models on the task of image translation.

Metrics / Methods	MAE↓	PSNR↑	SSIM↑	LPIPS↓
cycleGAN	0.221±0.039	11.588±0.847	0.182±0.056	0.605±0.027
pix2pix	0.124±0.035	18.080±2.053	0.621±0.054	0.240±0.044
pix2pixHD	0.119±0.034	18.353±1.990	0.625± 0.058	0.216±0.034
Our MrGAN	**0.096±0.035**	**19.108±2.134**	**0.685±0.065**	**0.186±0.045**

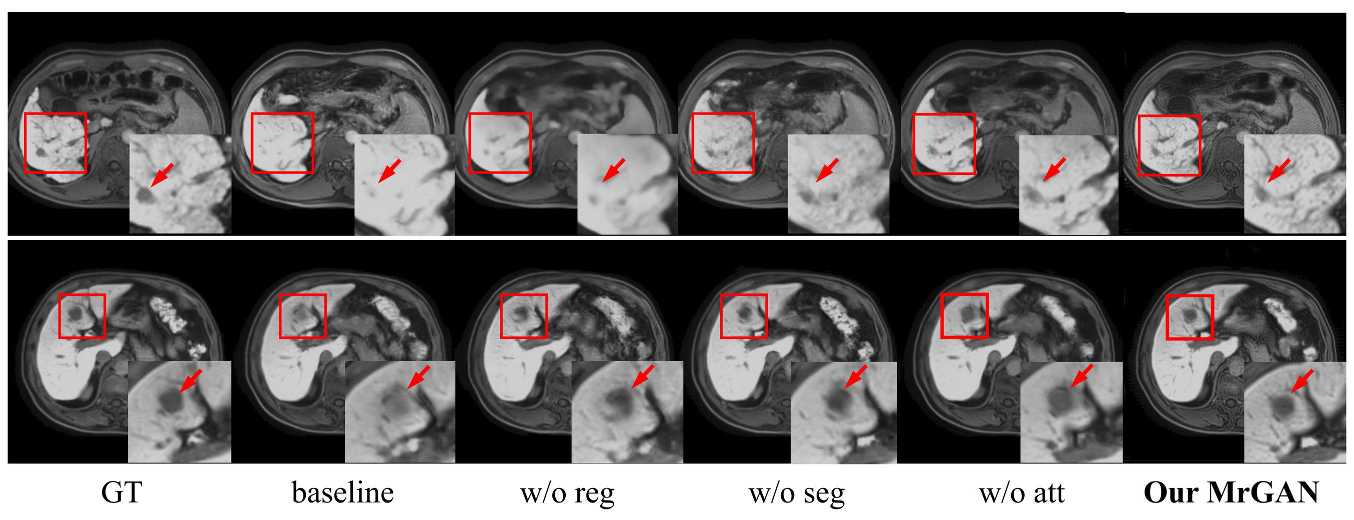

Figure 3. Ablation study: qualitative results with ground truth (GT) in different settings

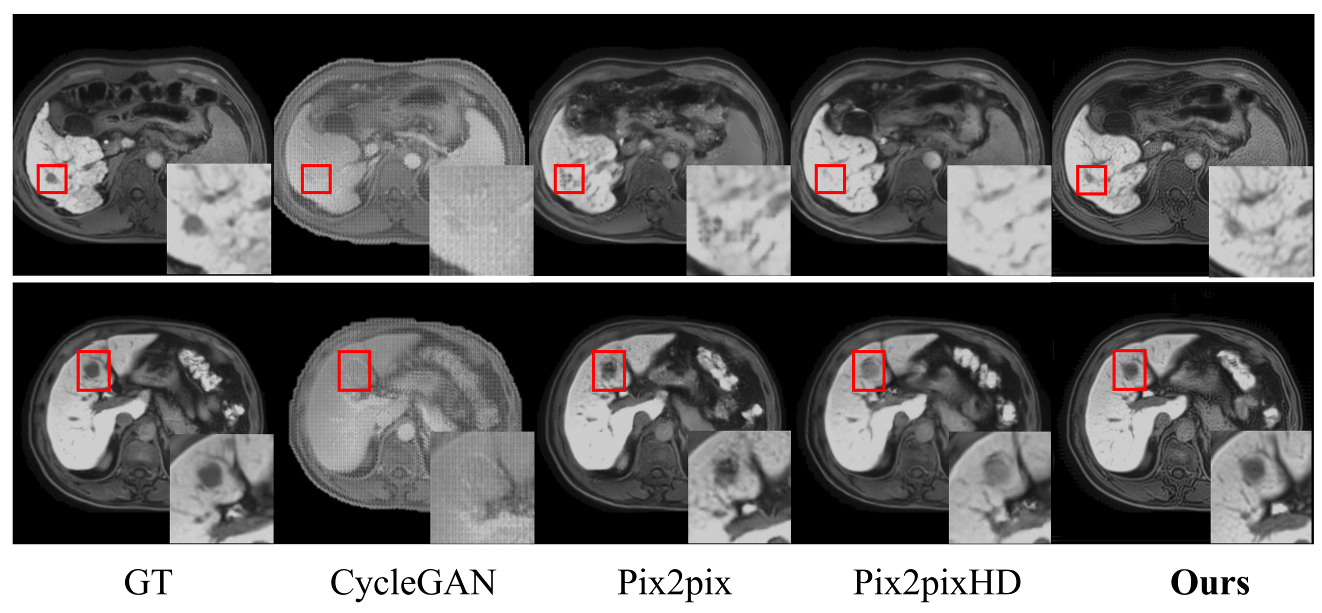

Figure 4. Visualized results of different methods on the task of image translation.

References

[1] Andrei S Purysko, Erick M Remer, and Joseph C Veniero. Focal liver lesion detection and characterization with gd-eob-dtpa. *Clinical radiology*, 66(7):673–684, 2011.

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