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Dual Contrastive Learning with Adversarial Framework for Magnetic Particle Imaging Deblurring

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Abstract

Magnetic particle imaging (MPI) is an emerging medical imaging technique that has high sensitivity, contrast and excellent depth penetration. In x-space MPI reconstruction, the reconstructed native image can be modeled as a convolution of the magnetic particle concentration with a point-spread function (PSF). The deconvolution is practical and valuable as a post-processing way to deblur the native image. However, to accurately measure or model the PSF used for deconvolution is challenging due to the imperfection of hardware and magnetic particle relaxation. The inaccurate PSF may lead to the loss of the content structure of the MPI image. In this study, we developed a dual adversarial framework with contrastive constraint (DC_GAN) to deblur the MPI image. We evaluate the performance of the proposed DC_GAN model on simulated and real data. Experimental results confirm that our model performs favorably against the deconvolution method that are mainly used for deblurring the MPI image.

I. Introduction

Magnetic particle imaging (MPI) is a tracer based on molecular imaging technique that can directly detect and quantify the magnetization of SPIO[1]. MPI has no signal from the background tissue, which provides it unparalleled contrast and sensitivity[2]. Combined with the low-frequency magnetic fields and clinically safe magnetic tracers, MPI can present clinical-grade images with zero tissue signal attenuation and high image sensitivity. Therefore, MPI has a great potential to be applied in clinical applications.

In x-space MPI, the reconstructed image can be modeled as a convolution of the native image with point-spread function (PSF), leading to image blurring[3]. Hence, the deconvolution or other post-processing techniques can be applied to deblur the image and improve its resolution and contrast. The commonly used method is to reconstruct the PSF of the entire sample supplied to the device and then remove the ambiguity through deconvolution[4]. However, a major problem of this method is that we cannot accurately model or measure the PSF due to the hardware imperfections and environmental noise. In this case, with the increasing of the

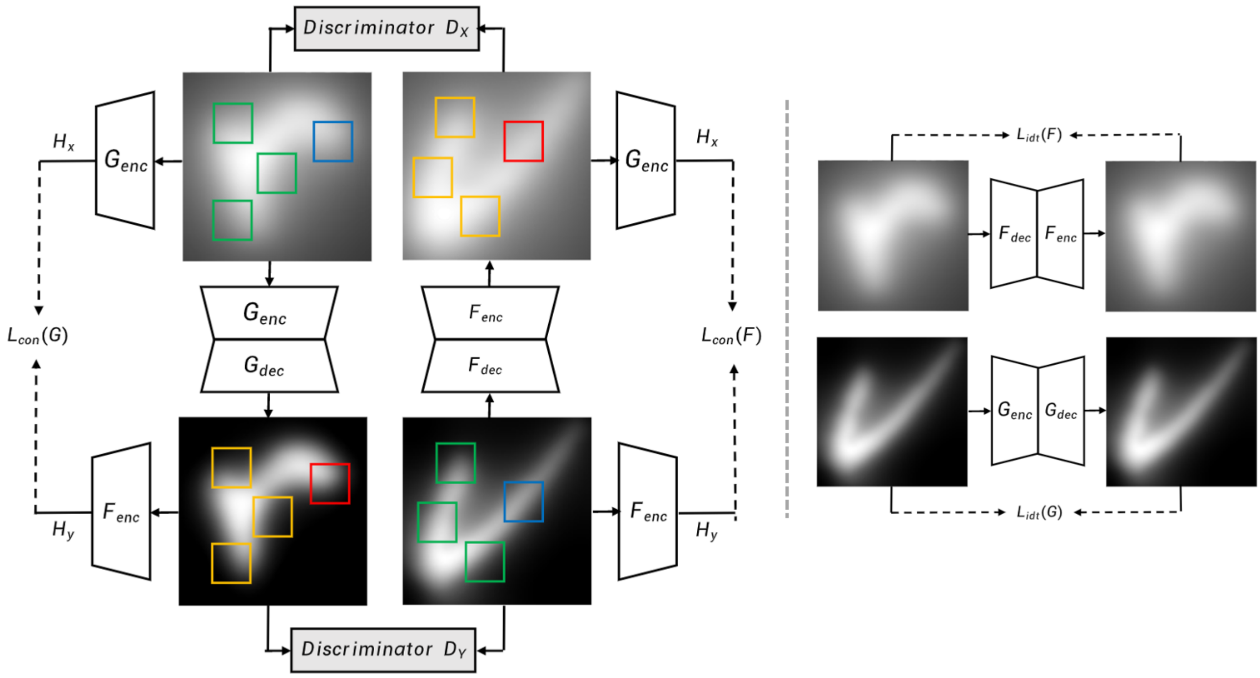

Figure 1: The overall architecture and losses of DC_GAN.

iterations, the structure content of the image will be distorted and the ambiguity cannot be well removed. This shortcoming is more obvious with low gradient strength. Hence, it is important to address this challenge in x-space MPI scanning.

In recent years, numerous data-driven methods have been developed to deblur the image[5][6]. Although they have achieved remarkable performance, these fully supervised methods require paired data. We have known that the ideal deblurred MPI images which retain a relatively complete and clear content structure are not fully available due to the incorrect PSF used for deconvolution. Therefore, those supervised methods are not applicable to solving this problem. Moreover, they would limit the generalizations in practice due to the domain gap between the synthetic and real data.

In this study, we proposed an unsupervised method that effectively minimize total MPI image blur. We developed a Dual Contrastive Deblurring method with adversarial framework to model the latent-space representation by exploring the relationship between the native image and high resolution deblurring data. Our method achieves better performances than other deblurring methods.

II. Methods

The architecture of our method and the final objective are as follow.

II.I. Overview of the proposed method

Fig. 1 presents the overall architecture of our proposed DC_GAN. Let X ={x ∈ X} and Y ={y ∈ Y} be the source and target domains, domain X contains a series of native MPI images with low gradient scanning, and domain Y contains MPI images after deconvolution. Our method has two generators: G : XßY and F : Y → X, which translate images to domain X and Y, respectively. Moreover, there are two discriminators, D_X and D_Y which are used to judge whether the image belongs to the corresponding domain. The general objective is described blow.

II.II. General Objective

The overall loss function is given as:

$$L = \lambda_{con} L_{con} + \lambda_{GAN} L_{GAN} + \lambda_{idt} L_{idt} \tag{1}$$

Where L_{GAN}, L_{idt} and L_{con} are the GAN loss, identity loss and contrastive loss, respectively, and λ_{con},λ_{GAN} and λ_{idt} are all scale values that denote their associated weighting parameters.

The L_{con} is established as the self-supervised contrastive loss to maximize the mutual information between corresponding patches of the input and the output.

As for the GAN loss L_{GAN}, it is expected to encourage the output to be visually similar to the images from corresponding domain.

The identity loss is used to guarantees the features from $G(y)$ similar with features from y, thus preventing

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generators from unnecessary changes, avoid mode collapse.

III. Experiments and results

The performance of our proposed method is evaluated using simulated and real MPI images, and the datasets and experimental results are discussed.

III.I. Datasets

We used simulated and real MPI data for evaluation.

III.I.1. Simulated data

In this study, we selected 1600 images from the MNIST dataset and resized them to 101x101 as simulated phantoms for MPI. Combined with Langevin function, we use MATLAB to program the x-space reconstruction method as described in [7] to generate simulated MPI images for training.

We test our proposed method on different data, showing that it increases the MPI image quality compared with the deconvolution. We design two-tube phantoms with different distances to evaluate the spatial resolution of the MPI image.

III.I.2. Real data

In order to verify the effectiveness in real data, we choose two tube phantoms as testing data. The phantom was filled with SPIONs (Micromod Partikeltechnologie GmbH,

Rostock, Germany). And the distance between the tubes was set to 5mm.

III.II. Experiments results

We applied DC_GAN to simulated and real data to evaluate its performance.

III.II.1. Simulating experiments

We compared our proposed DC_GAN with the deconvolution image on simulated images to analyze its performance. We design two-tube phantoms with different distances to evaluate the spatial resolution of the MPI. The field of view is 20mmx20mm. Each tube has a diameter of 1.2mm, and the gap between the two tubes is 1.4mm, 1.8mm, 2.2mm, 2.6mm and 3.0mm. The native MPI and the reconstructed images using different methods are displayed in Fig. 2. The third and the fourth rows show that the results generated by our method greatly improved the spatial resolution compared with the deconvolution. The normalized signal intensity profiles are plotted from the red lines and showed in the last row.

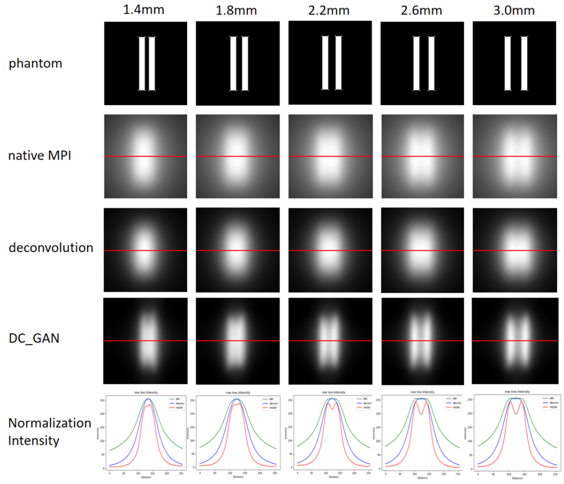

Figure 2: Simulated dual-tube experimental results for resolution enhancement.

Table 1: Evaluation results for the simulated experimental data via different methods

Resolution	Methods			
	Deconvolution		DC_GAN	
	PSNR	SSIM	PSNR	SSIM
1.0mm	12.818	0.069	15.87	0.71
1.4mm	12.204	0.066	14.934	0.691
1.8mm	11.415	0.058	14.322	0.671
2.2mm	10.86	0.055	14.312	0.654
2.6mm	10.428	0.057	14.651	0.64
3.0mm	9.94	0.055	14.85	0.621
3.4mm	9.443	0.049	14.897	0.601

The comparison of the quantitative evaluations is listed in Table 1.

Furthermore, we used the MNIST phantoms which were more complex than the resolution phantoms to prove the effectiveness of our proposed method. The results were shown in Fig. 3, which showed that our method can achieve better performance compared with the deconvolution method in improving the quality of the final image.

In addition, to further verify the robustness to the noise, we added white Gaussian noise to the native MPI images. The visual results were displayed in Fig. 4, which showed that our method gain a better performance compared with the deconvolution method at the expense of the added noise.

III.II.2. Phantom experimental results

Additionally, we scanned two-tube phantoms under isotropic modes with a MPI scanner (MOMENTUM, Magnetic Insight, USA). Fig. 5 shows that the artefacts are effectively removed using our method.

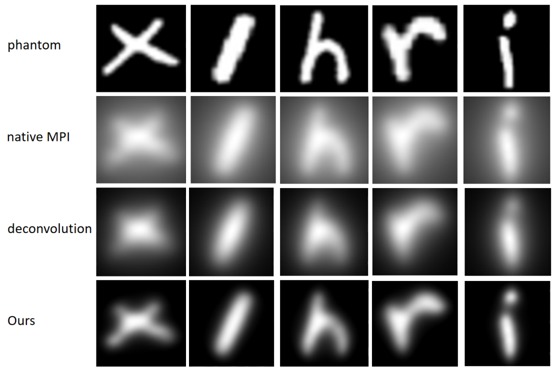

Figure 3: Simulated MNIST experimental results.

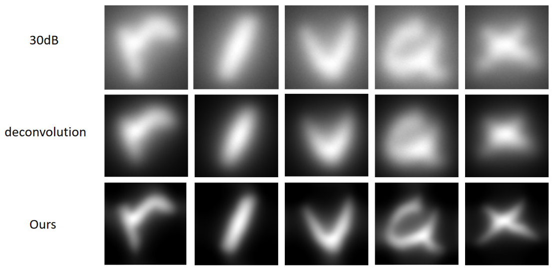

Figure 4: Simulated experimental results with the noise level of 30dB via different methods.

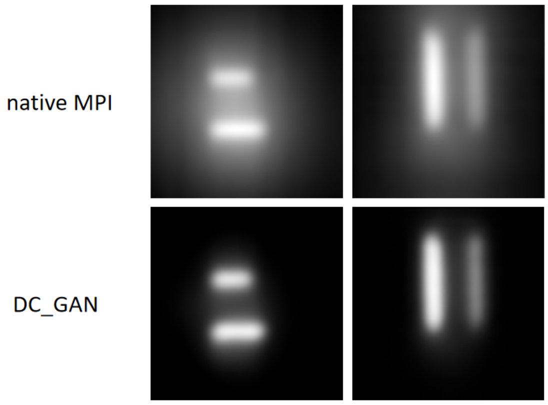

Figure 5: Experimental results on real data.

IV. Conclusions and discussion

We developed an unsupervised dual adversarial framework with contrastive learning to improve the spatial resolution of native images in x-space MPI. The key idea is to find the mapping between different image domains using unpaired data to translate the boundary features. We replace the widely-used cycle-consistency constraint by patch-wise contrastive constraint, which could help the structure of the native MPI be retained. The simulation and phantom experiments demonstrated the DC_GAN achieves better performance compared to the deconvolution.

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Author's statement

Conflict of interest: Authors state no conflict of interest.

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