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Three-Dimensional Magnetic Particle Imaging Resolution Enhancement Method Based on Structured Distillation Contrast Learning

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Abstract

Magnetic Particle Imaging (MPI) is a novel imaging technique for visualizing the spatial distribution of magnetic nanoparticles. Due to variations in gradient field strength and scanning trajectories, MPI resolution shows anisotropy. This paper presents CSDNet, a model based on structured distillation contrast learning. It extracts low-resolution directional features from a two-dimensional isotropic teacher network to guide the training of the student network and improve the resolution in three dimensions through deblurring. The introduced contrast loss significantly improves the ability to extract image details. Experimental results confirm CSDNet's superior performance in detail recovery and accuracy.

I. Introduction

MPI suffers from anisotropic resolution due to variations in gradient field strength and scanning trajectories [1]. The 2D deep learning-based resolution enhancement methods fail to fully leverage the spatial information. 3D deep learning-based resolution enhancement methods, on the other hand, lack automatic adjustment for different dimensions, resulting in suboptimal improvement for resolution anisotropy.

To address the anisotropic resolution problem in 3D MPI, we introduce the Contrastive Structural Distillation Network (CSDNet). CSDNet utilizes a 2D isotropic teacher network to learn image features in the low-resolution direction, enhancing the resolution of tomographic images. Then using generated high-resolution images as prior information to enhance the training of the 3D student network for improved performance.

II. Methods

The three-dimensional vascular dataset from MedMNIST [2] is used as the original MNPs concentration distribution. Field-Free Point (FFP) scanning imaging is simulated by performing layered scanning and varying the driving field frequency along a Cartesian trajectory. A 2D image (in the x-y plane) is first reconstructed in the 2D x-space under a gradient field strength ($3\,\mathrm{T\,m^{-1}}$), and then stacked to form 3D images. Since the z-axis is obtained through mechanical displacement, we refer to the z-axis as the low-resolution direction. We slice the three-dimensional data along the x-z plane to obtain the input data for training the two-dimensional teacher network. The acquired 3D MPI images are used as the source domain, while the original 3D phantom images, consisting of 1,100 images (32x32x32), serve as the target domain for training the student network.

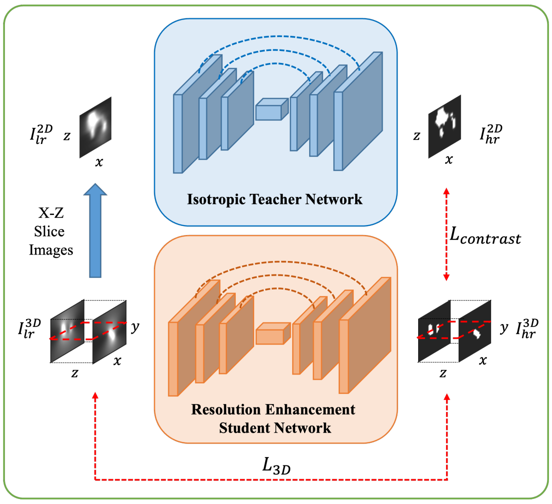

Figure 1: CSDNet Architecture Overview.

II.I. Architect

The architecture of the 2D isotropic teacher network F_t is similar to U-Net, which is designed to learn 2D image deblurring $I_{lr}^{2D} \mapsto I_{hr}^{2D}$. We train the teacher network using the SmoothL1 loss function [3], saving the trained weights. The architecture of the 3D student network F_s is similar to F_t, but all convolutional and pooling layers are replaced with their 3D counterparts to handle volumetric data in 3D space. The key difference is that the student network introduces the InfoNCE contrastive loss [4] as an additional loss, which measures the similarity between the student network and the teacher network. The input data are passed through both the pre-trained teacher and student networks for forward propagation, obtaining their respective prediction results. The 2D output serves as the query sample, and the corresponding 3D output slice at the same position is treated as the positive sample, with the remaining slices as negative samples. The cosine similarity between the query sample, positive sample, and negative samples is computed, with the cosine similarity of the positive sample considered to be the correct class, and the cosine similarity of the negative samples considered to be the negative class. The contrastive loss is then computed using cross-entropy. The total loss is the weighted sum of the original SmoothL1 loss and the contrastive loss:

$$\mathrm{L} = \mathrm{L}_{3\mathrm{D}} + \alpha \mathrm{L}_{\mathrm{contrast}} \tag{1}$$

where α is the weight of the contrastive loss, set to 0.1.

III. Results

We compare CSDNet with several other resolution enhancement networks, RRDB [5], RCAN [6], and EDSR [7].

Table 1 lists the metrics for various 3D resolution enhancement models. CSDNet improved PSNR and SSIM by 1.447 dB and 0.258, respectively, compared to the best-performing EDSR model, while reducing RMSE by 1.173. These experimental results validate the effectiveness and superiority of CSDNet in detail recovery and accuracy. In summary, the CSDNet model demonstrates superior performance in enhancing the resolution of 3D MPI, particularly excelling in detail recovery and accuracy.

Table 1: Metrics calculation on simulation dataset.

	PSNR	SSIM	RMSE
Original Input	13.146	0.133	56.763
RRDB	30.044	0.702	8.247
RCAN	20.859	0.252	23.607
EDSR	30.747	0.636	7.626
CSDNet	**32.194**	**0.921**	**6.453**

IV. Conclusion

CSDNet processes 3D MPI image through deblurring, successfully improving image quality by introducting a 2D isotropic teacher network along the low-resolution direction, which guides the 3D resolution enhancement network in modeling low-resolution direction information. Compared to other models, CSDNet demonstrates outstanding performance in improving 3D MPI resolution.

Author's statement

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