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End-to-end MPI image reconstruction with dual-task generative adversarial network

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Abstract

Traditional reconstruction methods, such as system matrix and x-space, are either extremely time-consuming or result in very blurry images. Here, we propose a novel dual-task generative method to realize high-quality MPI image reconstruction. In this method, the generative model simultaneously undertakes two MPI image processing tasks: reconstruction and segmentation. The main task of image reconstruction generates MPI images, while the auxiliary task of image segmentation guides the main task to focus on key areas of objects in MPI images during the generation process. Our dataset includes simulation dataset and OpenMPI phantom data. Our experimental results showed that the proposed dual-task model, with its superior generalization ability, outperforms both traditional MPI reconstruction methods and single-task generative methods. Our results also suggested that the tasks of image generation and image segmentation significantly promote each other during the MPI image reconstruction.

I. Introduction

Multi-task learning is a joint machine learning strategy that leverages the intrinsic correlations among multiple related tasks to achieve mutual benefits in terms of performance enhancement [1]. It inspires us that, if we can make use of the multi-task learning to optimize the MPI reconstruction model in conjunction with other MPI image processing tasks, the MPI reconstruction quality is expected to be improved significantly. In the current study, we propose a novel dual-task deep-learning method to realize high-quality MPI image reconstruction. The core of the method is a Transformer-based generative model, which we term TransGAN.

II. Methods

II.I. Dual-task learning

A schematic illustration of the proposed MPI reconstruction framework and the core generative model TransGAN is depicted in Fig. 1. TransGAN includes two components: a generator and a discriminator. The generator of TransGAN is a dual-task architecture featuring a shared portion in the early stage, along with two branches for image reconstruction and segmentation, respectively. The input to the generator is a 1D voltage signal, and the outputs are the reconstructed and segmented images, respectively. The discriminator of TransGAN is a classification network, which automatically calculates the

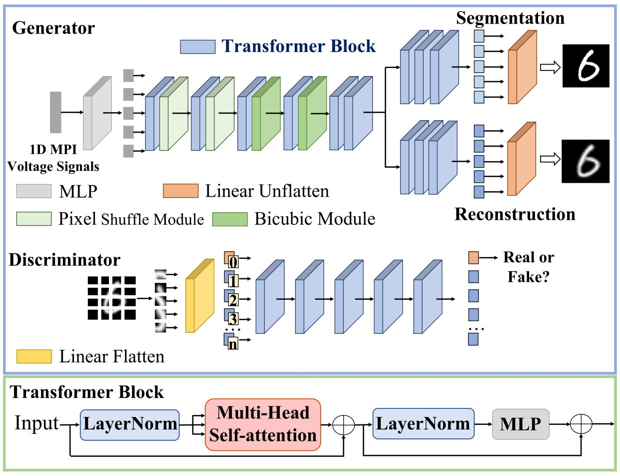

Figure 1: The detailed architecture of the generator and discriminator in proposed dual-task TransGAN.

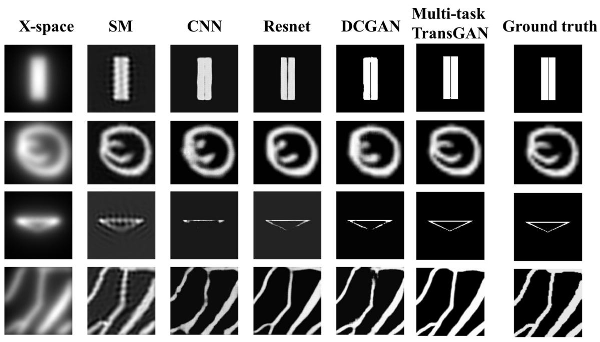

Figure 2: Representative reconstructed MPI images by using x-space, system matrix, CNN, Resnet, DCGAN, and our proposed TransGAN.

difference between the generated images and the true distribution of MNPs (considered as the ground truth).

The generator takes the signal vector as its input, and passes it through a multiple-layer perceptron (MLP) to a vector of length H×W×C and the H and W is 8 and C is 128. The vector is reshaped into an 8×8 resolution feature map, each point a C-dimensional embedding. This feature map is next treated as a length-64 sequence of C-dimensional tokens, combined with the learnable positional encoding. Then, we used four up-sampling modules to gradually increase the number of channels from 128 to 1, and the resolution of the feature map also gradually increased to 128 × 128.

We used segmentation and reconstruction loss functions to constrain network training, where the reconstruction loss includes mean absolute error(MAE) loss with a weight set to 20, and the segmentation loss includes BCE loss and Dice loss with weights set to 5.

Table 1: Quantitative reconstruction performance of x-space, system matrix, CNN, Resnet, DCGAN, single-task model and our proposed method with three metrics.

Methods	RMSE	PSNR	SSIM
X-space	0.0918	11.0038	0.6196
SM	0.0166	19.7552	0.9602
CNN	0.0117	21.4450	0.9784
Resnet	0.0094	22.2147	0.9821
DCGAN	0.0069	24.9417	0.9860
Single-task model	0.0036	28.5850	0.9929
Our proposed method	**0.0012**	**39.3996**	**0.9976**

II.II. Dataset

We first built a large grayscale image dataset, including a total of 656,370 images, with a size of 128×128 pixels. 638,137 pairs were used as the training set for optimizing the parameters of our proposed model, and 18,233 pairs were used as the testing set for evaluating the MPI reconstruction performance. The image dataset contains six forms of patterns: bars, rectangles, triangles, ellipses, numbers, and blood vessels. Then, we used our developed MPI simulation software MPIRF [2] to generate the corresponding 1D MPI voltage signals for each image in the simulation image dataset.

To ensure our simulation data is close to the real measured MPI data in the scanner device, the simulation parameters were set according to the system parameters of Bruker Preclinical MPI Scanner of Open MPI Data. We defined the size of field of view (FOV) as 12.8 mm×12.8 mm. The simulation used 2D excitation, and the trajectory of the field-free point was a Lissajous trajectory. MPIRF generated 1D time-domain voltage signals in the x and y directions. We used signals in both directions as the input of our proposed method by concatenating signals from the x and y directions into one 1D signal, so the dimension of the input signal is 1×3264.

We also expanded the dataset to fulfill the requirements of reconstructing real phantom. To avoid an inverse problem for simulation involving image reconstruction, we use the formula $\mathbf{u}_r = \mathbf{Sc} + \mathbf{n}$ to obtain the one-dimensional time-domain signal corresponding to a two-dimensional image, where $\mathbf{n}$ is the randomized Gaussian noise, $\mathbf{S}$ represents z=19 layer system matrix, $\mathbf{c}$ is image vector.

III. Results

We evaluated the MPI reconstruction performance of our proposed framework with two traditional reconstruction methods of system matrix (SM) and x-space and state-of-the-art deep learning methods for image generation, such as CNN [3], Resnet [4] and DCGAN [5]. In SM method, we used the Kaczmarz algorithm as the iter-

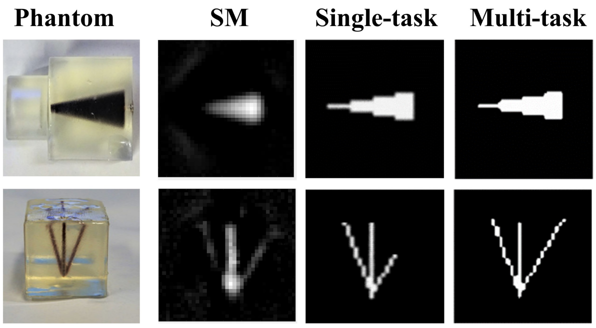

Figure 3: Reconstructed phantoms by using system matrix, single-task model and multi-task model.

ative solver to reconstruct the images. The visualization of reconstructed images of our proposed method and the above-mentioned methods are illustrated in Fig. 2 and the results of quantitative evaluation indicators are illustrated in Table 1.

We also reconstructed two phantoms from the Open-MPI dataset, as shown in Figure 3. It can be seen that the reconstruction performance of our proposed method is better than system matrix method and single-task model.

IV. Discussion

One limitation of our study is that our model is based on data-driven training. In our future study, we aim to integrate the physical constraints of the system matrix within our model framework to address the issue and to substantiate the viability of our method in actual biological environments.

V. Conclusion

In our current study, we propose a deep-learning based multi-task method to realize high-quality MPI image reconstruction. The model incorporates an auxiliary segmentation task into the MPI image generation task to improve the performance and efficiency of MPI reconstruction. Both simulation and real phantoms experiment indicates that the proposed method outperforms traditional reconstruction methods, such as system matrix (SM), x-space, and CNN-based deep learning methods.

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Author's statement

Conflict of interest: Authors state no conflict of interest.

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