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3D System Matrix Calibration by Using Coil Information and Transformer

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Abstract

System Matrix-based image reconstruction approach requires a time-consuming calibration measurement. Existing methods such as compressed sensing and deep learning-based methods treat each row of the system matrix as independent data sample and lack the ability to model the relationships between system matrix rows. We firstly propose to model system matrix row relationships by the coil channel and frequency index, which can be regarded as additional and multimodal information. We propose a transformer-based neural network for 3D fast system matrix calibration, which encodes the information of coil channel and frequency index into system matrix with self-attention mechanism in the transformer.

I. Introduction

System Matrix-based (SM) MPI image reconstruction method [1] offer better image quality compared with X-space-based approach, while it also brings much time cost to measure the SM. Many methods based on compressed sensing (CS) [2, 3] and deep learning [4, 5] have been recently proposed to shorten the SM calibration procedure.

However, despite the success of the previous works, current fast SM calibration methods usually treat each row of the system matrix as an independent data sample. This modelling approach neglects the relationships between SM rows, while SM rows are not completely independent. For example, each SM row possesses two extra information–frequency index and coil channel (i.e., which receive coil in XYZ directions does the SM row comes from). We show a visualization result in openMPI data (calibration #7) to illustrate it. The dimension of each SM row are reduced by using t-SNE and we visu-

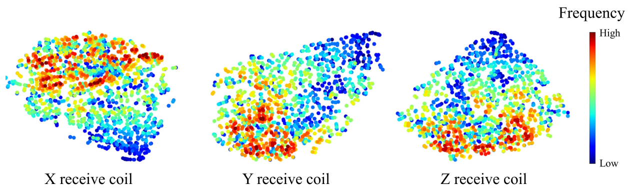

Figure 1: The t-SNE visualization of SM rows. Each point represents one SM row, and the color indicates its frequency index.

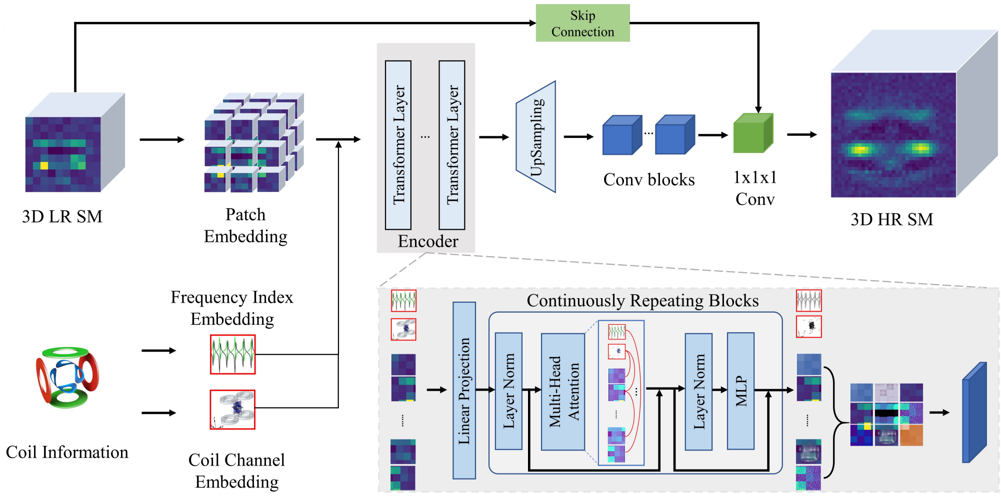

Figure 2: The overall framework of the proposed method.

alize them separately in three receive coils (see Figure 1). The SM rows of similar frequency index are clustered closer together, and this pattern is consistent in the three spatial receive coils. This visualization result shows that such information may help us to calibrate the SM.

In this paper, we propose a novel transformer-based neural networks that can handle the multimodal information for fast 3D SM calibration. The frequency index and coil channel are embedded into space vectors and involved in the self-attention calculation in the transformer.

II. Materials and Method

II.I. Dataset

The SM and phantom ("Resolution") data come from the Open MPI[1] dataset [6] following the previous work [4]. The SM calibration experiment #7 with Synomag-D is used for training set, and we evaluate the model performance in calibration experiment #6 with Perimag. We preserve only the SM rows with signal-to-noise ratio (SNR) > 3 in both training and test datasets.

II.II. Model architecture and implementation details

The overall framework of our proposed method can be seen in Figure 2. The low resolution SM component is encoded by pure transformer, with coil information (i.e., frequency index and coil channel) involved in self-attention calculation. Our proposed model contains four transformer layers and two upsampling block. Each upsamling block contains one upsampling module with trilinear interpolation and four 3D convolution operations.

[1]https://magneticparticleimaging.github.io/OpenMPIData.jl/latest/

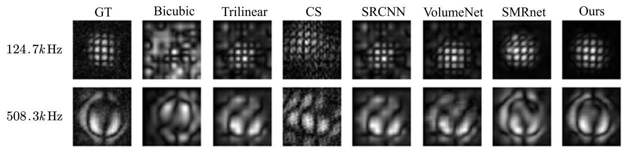

Figure 3: The visualization for two frequency components.

The patch size is set as 1 and the hidden representation dimension F is 1024. The number of heads is 8, and each head dimension d is 128. The channels number c of convolution operation is 64. We first train the model 10 epochs with linear warmup and then 100 epochs with constant learning rate for 64 times downsampling (4x downsampling ratio in three spatial dimension). For image reconstruction, we use the standard kaczmarzReg algorithm with parameter $\lambda = 0.75$ and iter $= 3$. We use the same metrics with [4].

III. Result

III.I. SM calibration and image reconstruction results

We first show the 3D SM calibration results in Table 1 in terms of nRMSE metric. our model show great superiority over other methods in terms of the metric nRMSE (4.33% for 64 times downsampling). We also show the recovered two SM rows (center slice) in Figure 3. Besides, we assess the image reconstruction of "Resolution" phantom in terms of pSNR and SSIM metrics. Our method also achieves the best performance and has a relative improvement of about 6% compared to the second best method for the pSNR metric.

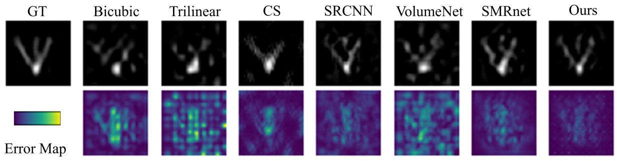

Figure 4: The image reconstruction result for "Resolution" phantom in OpenMPI dataset. The first row shows the center slice of the reconstructed image, and the second row shows the corresponding 3D error map averaged in z-axis.

Table 1: SM calibration and image reconstruction results on OpenMPI dataset for 64 times downsampling. The metric nRMSE is used to assess SM recovery and metric pSNR and SSIM is used to assess image quality reconstructed by the SM.

Method	nRMSE	pSNR	SSIM
bicubic	8.91%	55.34	0.9975
trilinear	6.80%	59.86	0.9993
CS	7.70%	57.39	0.9981
SRCNN [7]	5.18%	62.35	0.9996
VolumeNet [8]	5.90%	60.96	0.9995
3dSMRnet [4]	4.86%	64.85	0.9997
Ours	**4.33%**	**65.55**	**0.9998**

III.II. Visualization

We also visualize the reconstructed image to provide an intuition evaluation. We show the center slice of 3D images and the 3D error map averaged in z-axis in Figure 4. The baseline models generate low-quality image reconstruction result with much noise and artifacts in 64x downsampling, while our proposed method still provides relatively better image quality.

IV. Conclusion and discussion

In this paper, we propose a novel transformer-based model that utilizes the multimodal information (i.e., frequency index and coil channel) for fast 3D SM calibration. Our results on the Open MPI datasets have shown its effectiveness over other methods.

Though we firstly attempt to utilize the coil channel and frequency index for SM calibration, the encoding method for the two multimodal information in this work may not be the optimal. It remains a open problem how to leverage the multimodal information to model the relationships between SM rows and generate better accuracy. For example, SM rows can be modelled as nodes in graph-format data, and the frequency index and coil channel can be used for the edge modelling. Graph Convolution Networks (GCNs) [9, 10] are considered to show superiority in such graph-format data mining.

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Author's statement

Conflict of interest: Authors state no conflict of interest.

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