Reconstruction and coil combination of undersampled concentric-ring MRSI data using a Graph U-Net

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Introduction

MR spectroscopy imaging (MRSI) is an imaging modality that has many applications in medicine, as it allows the identification of various biochemical substances in vivo [1]. In recent years, fueled by advances in deep learning (DL), new imaging techniques have been developed in medicine and also MRI has gained from this development [2]. However, in MRSI irregular sampling schemes can be beneficial, and for those, DL based reconstruction is lacking. Here, we investigate geometrical deep learning for k-space reconstruction of undersampled concentric-ring sampled MRSI data.

Data and Method

Non-water suppressed MRSI data was collected from seven volunteers in ten random positions. In each scan concentric ring trajectories where used. Graphs were defined by connecting point pairs with a distance less than 1.5 times Nyqusit criterion. These rings were undersampled, by fully sampling the inner 6 and then skipping every second of the outer rings (figure 2, right).

We evaluated two models. The first network (referred to as GNN) consists of four gaussian mixture model (GMM) convolutional layers [3], each followed by a tanh activation function. The second model (U-Net) is a U-net [4]. Here five GMM convolutional layers are used, each followed by max-pooling or up-sampling with a window size of 4x2 and tanh or ReLU activation.

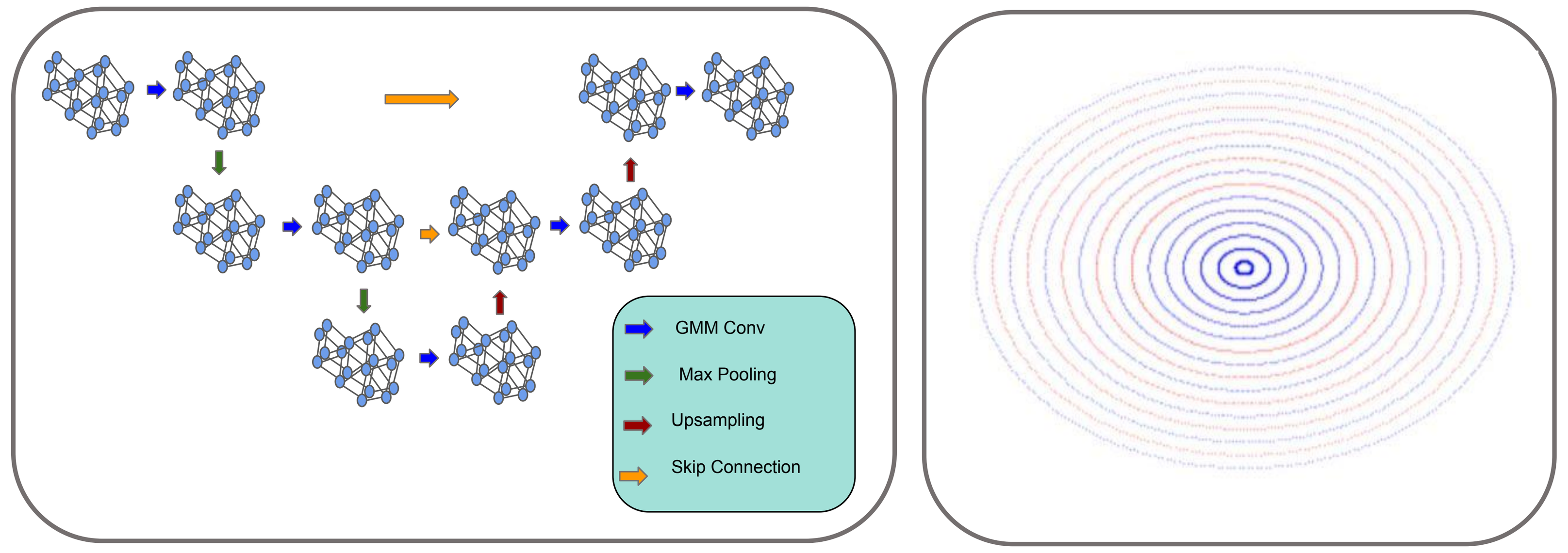

Figure 2: Visualization of U-net structure on the left. Concentric ring sampling on the right. The undersampled rings are colored in red.

Evaluation & Results

First the four layer GNN was trained on fully sampled and undersampled data, as well as with and without self-connecting edges. The training and validation loss, computed by the mean squared difference, is shown in figure 3 on the left. Self-connecting edges improve the validation loss during training of the network in both cases.

In figure 3 on the right, the training- and validation loss of the graph U-net with undersampled data with and without self-connections is plotted. In this case, the omitted self-connecting edge leads to a reduced and more stable loss.

	GNN	U-net
Position 1	137.0	67.9
Position 2	55.7	53.0
Position 3	42.5	27.8
Position 4	126.9	39.1

Figure 1: Mean squared error of GRAPPA, GNN and U-net

On the test set we reconstructed images from understampled data by the GNN with self-connecting edges and the graph U-net without self-connecting edges and used Fourier transform in all spacial dimensions to reconstruct the image. The mean squared error of each scanned position is presented in figure 1 and shows that the U-net performs best. In figure 4 qualitative results of each approach are compared.

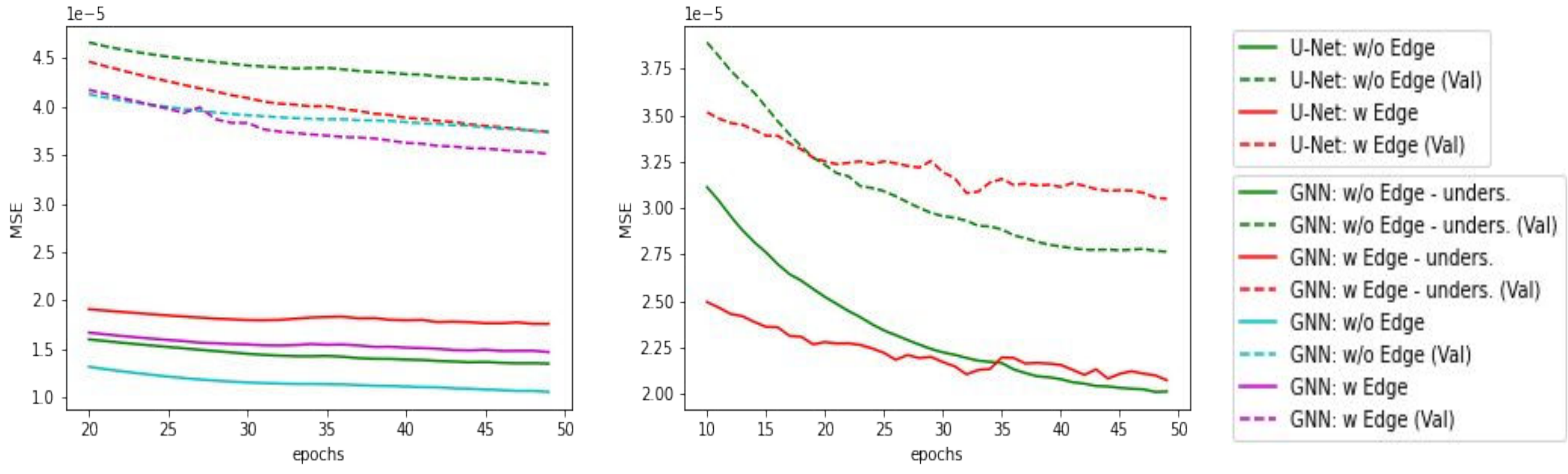

Figure 3: Training/Validation Loss of GNN and U-net

Discussion

Compared to GNN, the graph U-net leads to an improvement of the reconstruction of undersampled concentric-ring MRSI, due to its ability to identify high-level features.

The omission of self-connecting edges leads to a decreased and more stable loss with the U-net. This may be the case, because the network is forced to search for informative features in the neighborhood of each node, instead of simply passing on information.

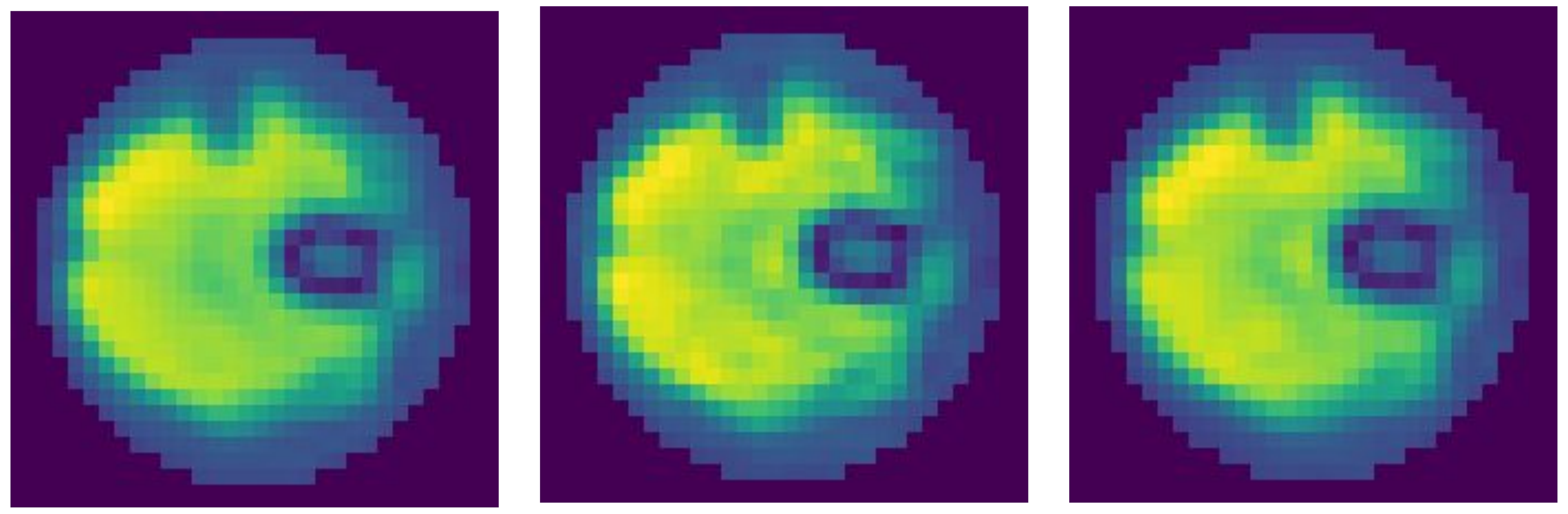

Figure 4: From left to right: Ground Truth, naive GRAPPA, GNN, graph U-net

References

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