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## Super resolution accelerated MRI reconstruction using Deep learning

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# Introduction

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→ MRI as a medical imaging tool

- (+) Non-invasiveness and excellent soft-tissue contrast
- (-) Slow speed image acquisition: A bottleneck to real-time imaging
- (-) Spatiotemporal tradeoff
  - A compromise between spatial and temporal resolution

# Problem

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High fidelity MR images --> Low temporal resolution

- Large hardware setup
- Lengthy data acquisition--> subject motion

Low resolution images --> High temporal resolution

- hard to diagnose finer details
- Less number of pixels to characterize edges or boundaries
- Aliasing and noise

# Proposed directions

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✓ Using MoDL for unfolding aliasing pattern and super-resolution

- *MoDL (Aggarwal et al., 2018)*

✓ Implementing UF loss with MoDL for improving the super-resolution

- *Unsupervised Feature Loss (UFLoss) for High Fidelity Deep learning (DL)-based reconstruction (Wang et al., 2021)*

# Using UF Loss

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→ Inspired from perceptual loss from trained VGG

- *Ledig et al., 2017*

→ Perceptual loss from a training feature mapping network

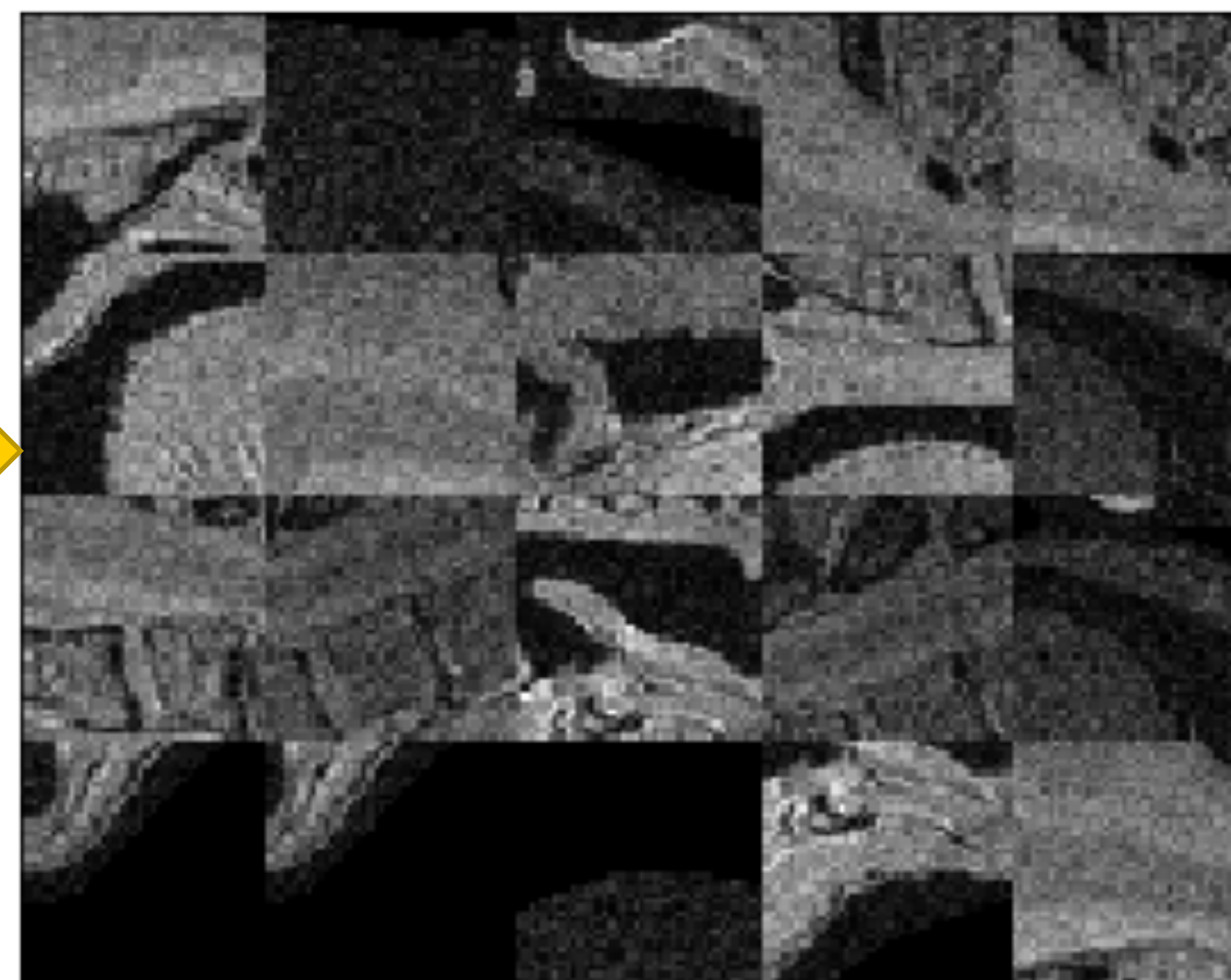
- Encoder is trained with patches from the training sample

# Results from UF loss

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Training image sample



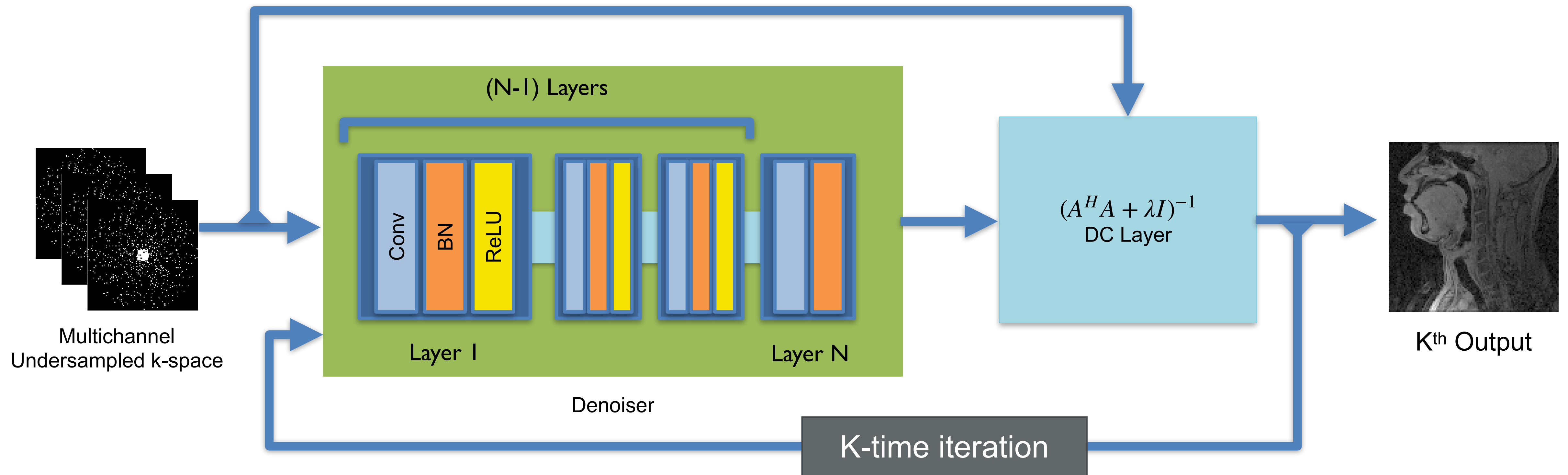
Training patches

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# Super resolution

MoDL

# MoDL Network



H. K. Aggarwal et al., 2019



# Dataset

## Step 1: Data collection

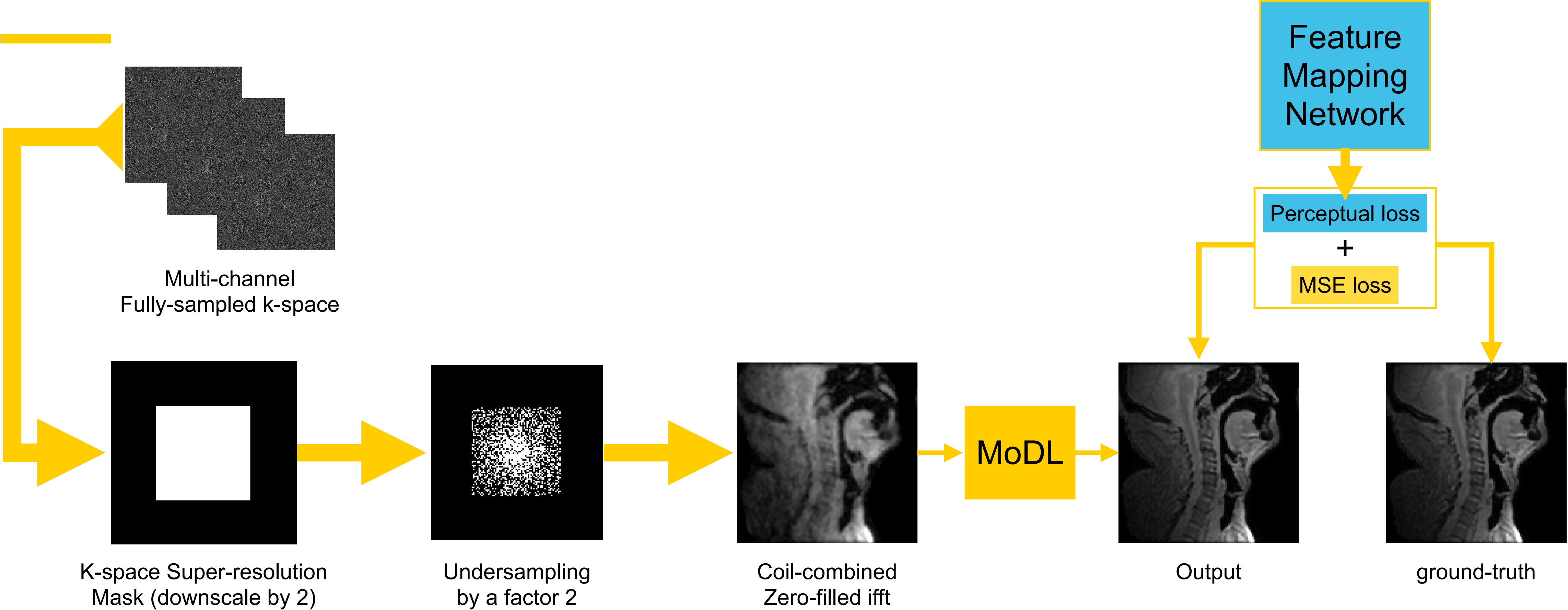
- 5 subjects at 3T GE Premier scanner
  - [FOV:  $24 \times 24 \times 24 \text{ cm}^3$ ;  $(k_x, k_y, k_z) = 128 \times 128 \times 32$ ; Flip angle:  $5^\circ$ ; Scan time: 20 *secs*]
- Each subject was scanned with 3 different receive coils
- 15 Fully-sampled volumetric upper airway datasets
  - For training: (4x3=) 12 datasets (4 subjects)
  - For testing: (1x3=) 3 datasets (1 subjects)
- ESPIRiT coil maps from 5% of the center k-space

# Phase 1: Data-preprocessing (in image domain)

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- Step 1: High-res ground truth (128x128) to Low res (64x64)
  - Maxpooling
- Step 2: Undersampling by a factor of 4 in k-space
- Step 3: train MoDL to learn the aliasing and noise pattern

# Phase 2: Data-preprocessing in k-space



# imaging metric

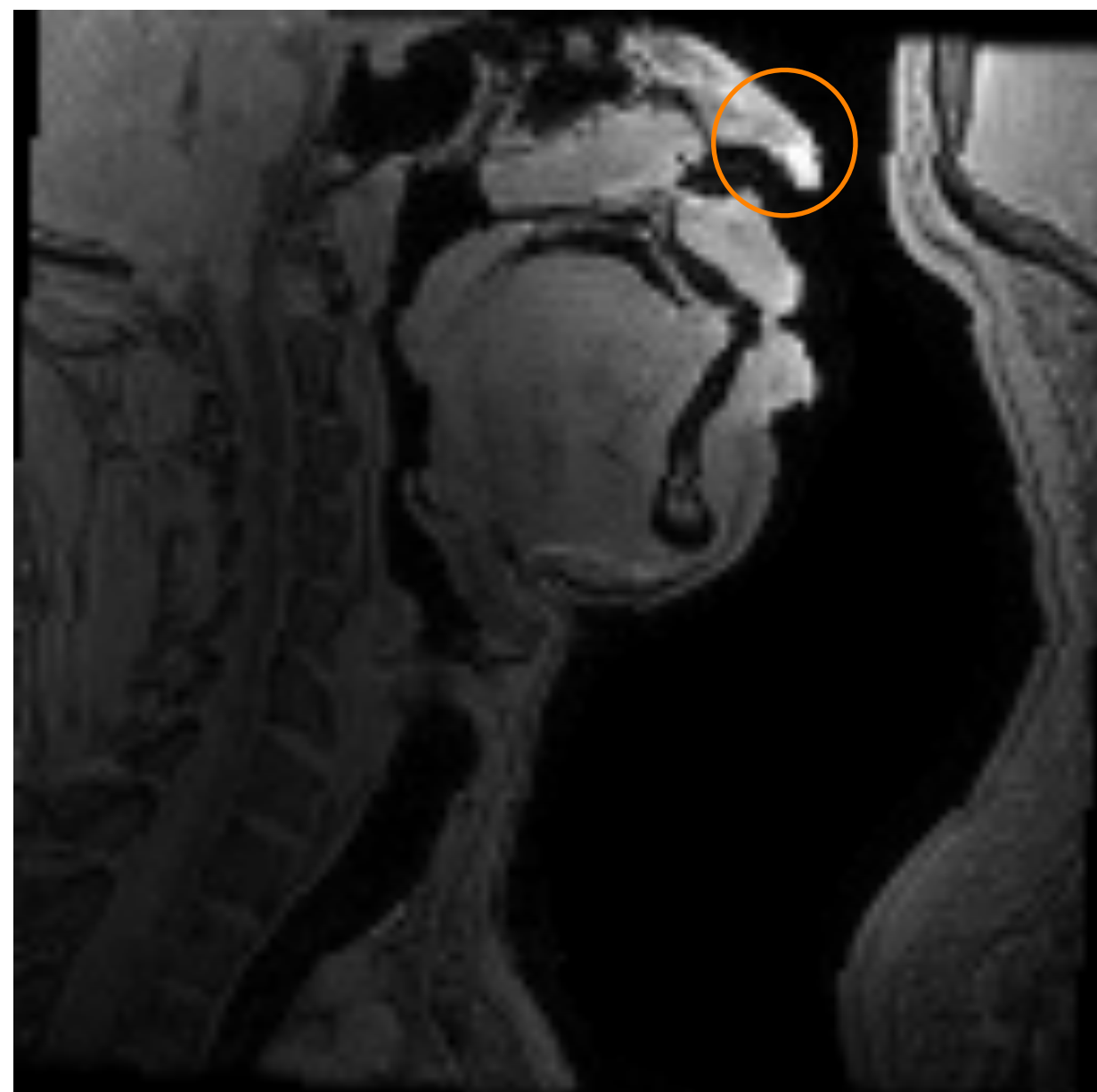
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$$\text{PSNR} (X, X_r) = 10 \log_{10} \frac{\max |X_r|^2}{MSE}$$

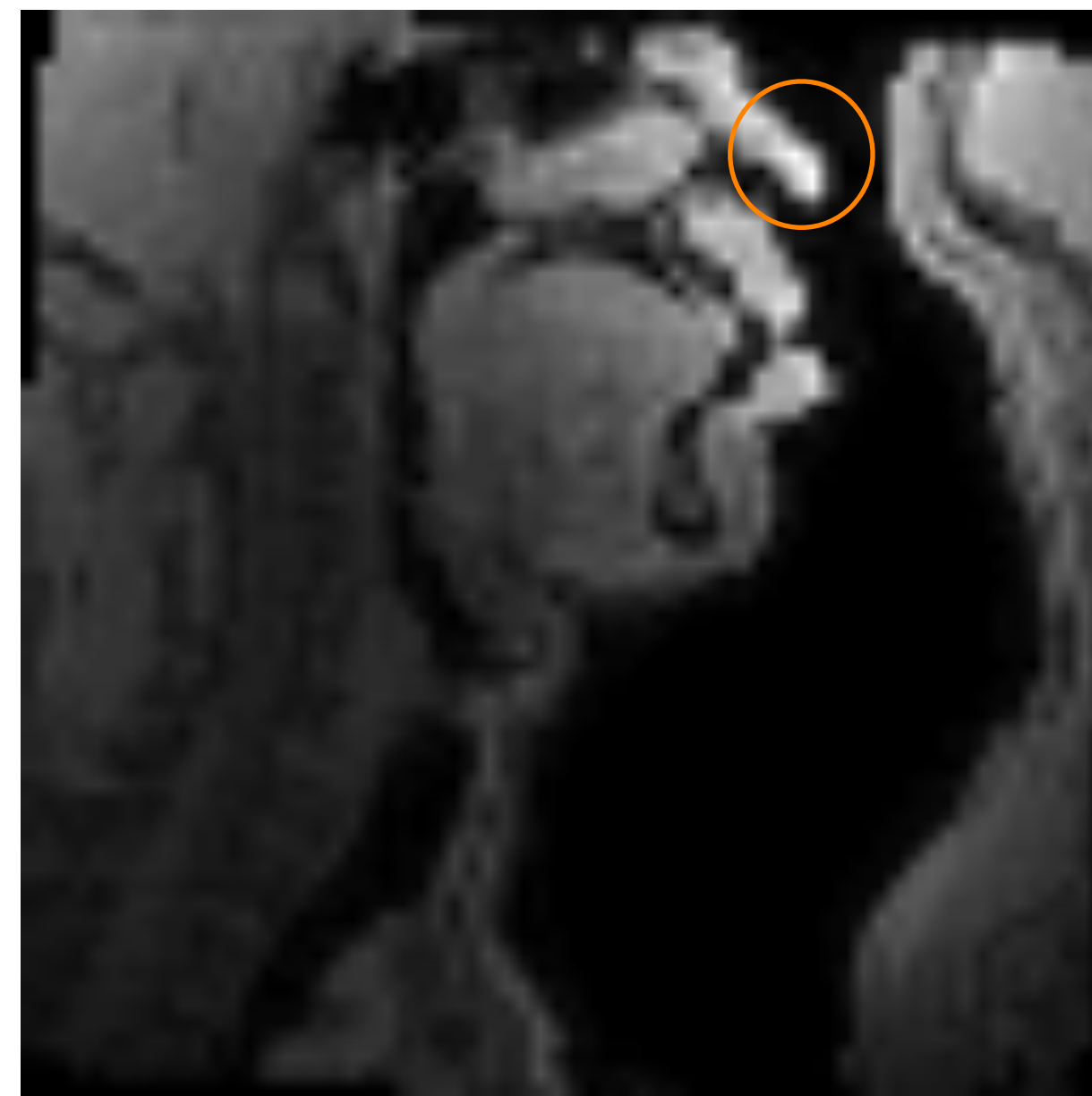
$$\text{MSE} (X, X_r) = \frac{1}{NM} \sum_i^N \sum_j^M |X[i, j] - X_r[i, j]|^2$$

# Qualitative Results ( phase 1 )

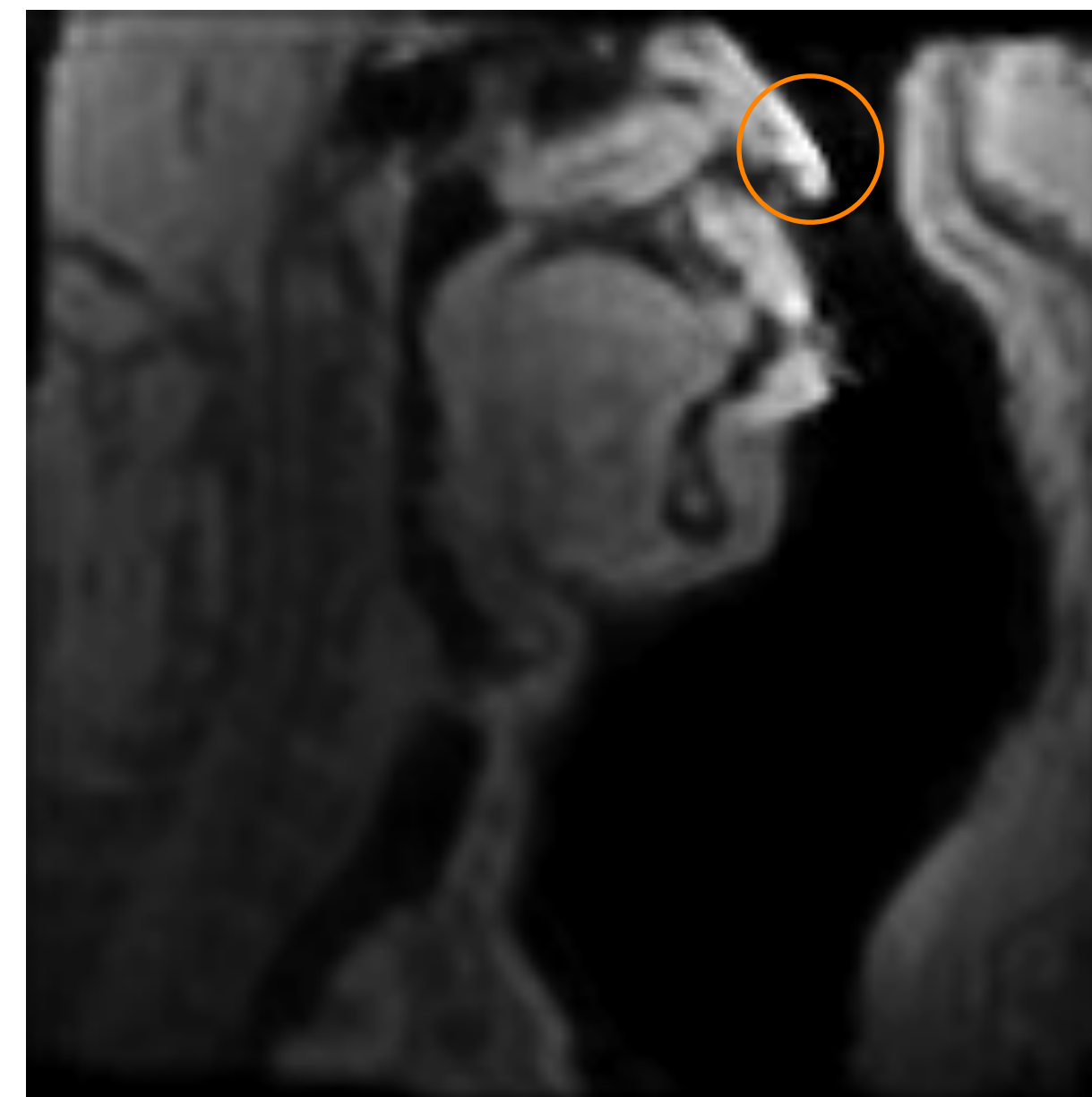
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High resolution GT



Low resolution input



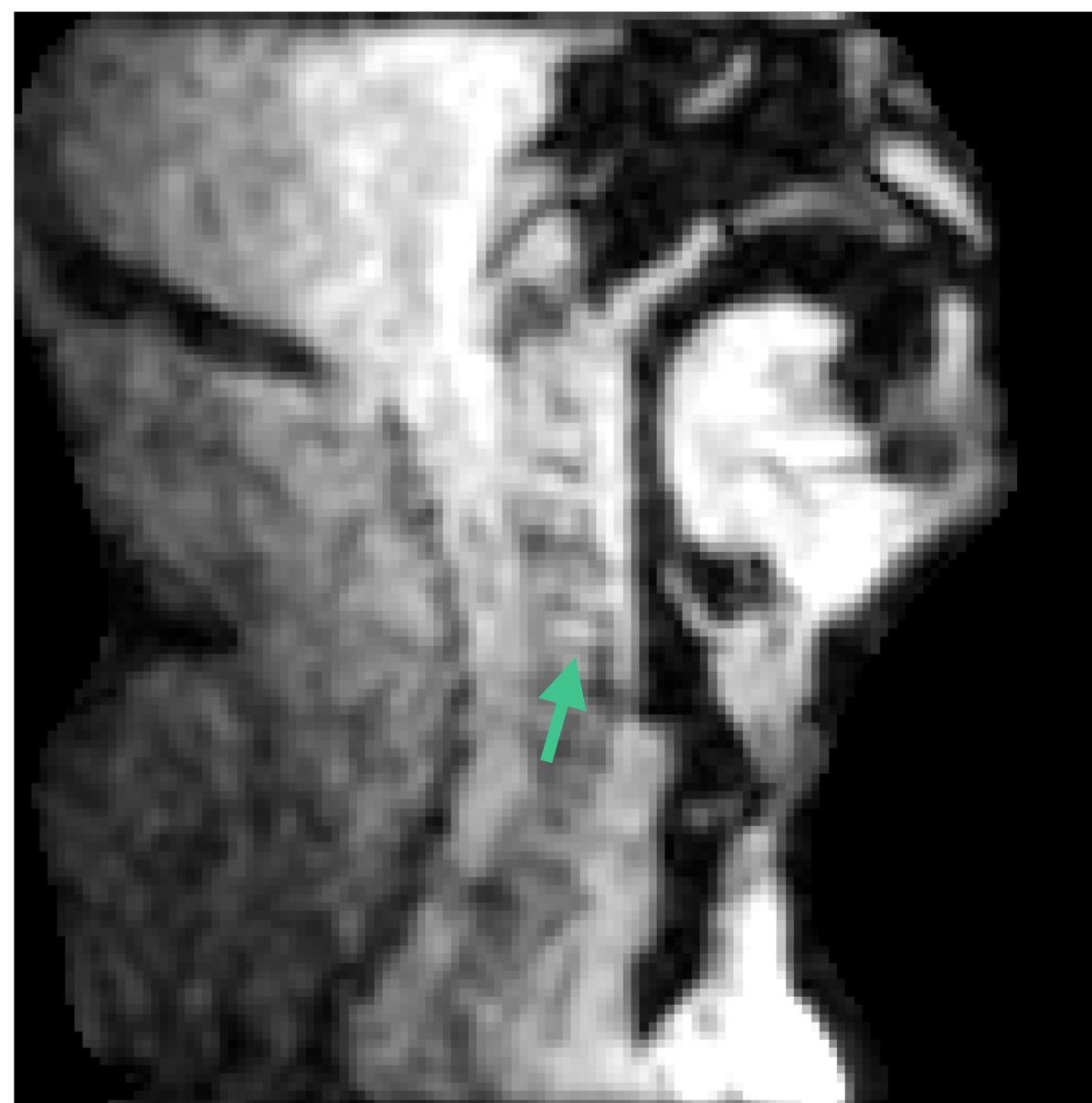
High resolution output

# Qualitative Results ( phase 2 )

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High resolution GT



Low resolution input



High resolution output

# Conclusion

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Our result improved in phase 2 since

- We have modified the network from 2-step training to 1 step
- preprocessing in k-space domain rather than image domain
- More samples for training

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**Thank you**

**IOWA**