Super resolution accelerated MRI reconstruction using Deep learning

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Introduction

→ MRI as an intervention 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

Relevance of the problem

→ High fidelity MR images are expensive

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

→ Low resolution images are achievable

- Parallel-imaging and state-of-the-art reconstruction techniques

Relevance of the problem (cont'd)

- To catch the RT temporal resolution, Highly accelerated under-sampling required
  - Induces aliasing and incoherent noise-pattern

- Low resolution images are hard to diagnose finer details
  - Less number of pixels to characterize edges or boundaries

Solution

- ✓Unfold aliasing and noise pattern using model-based DL framework
  - ➢MoDL (Aggarwal et al., 2018)
- ✓Improve spatial resolution (upscaling) with super resolution
  - SRResNet (Ledig et al., 2017)

Benefits

✓Unfold aliasing and noise pattern using model-based DL framework

✓Improve spatial resolution (upscaling) with super resolution

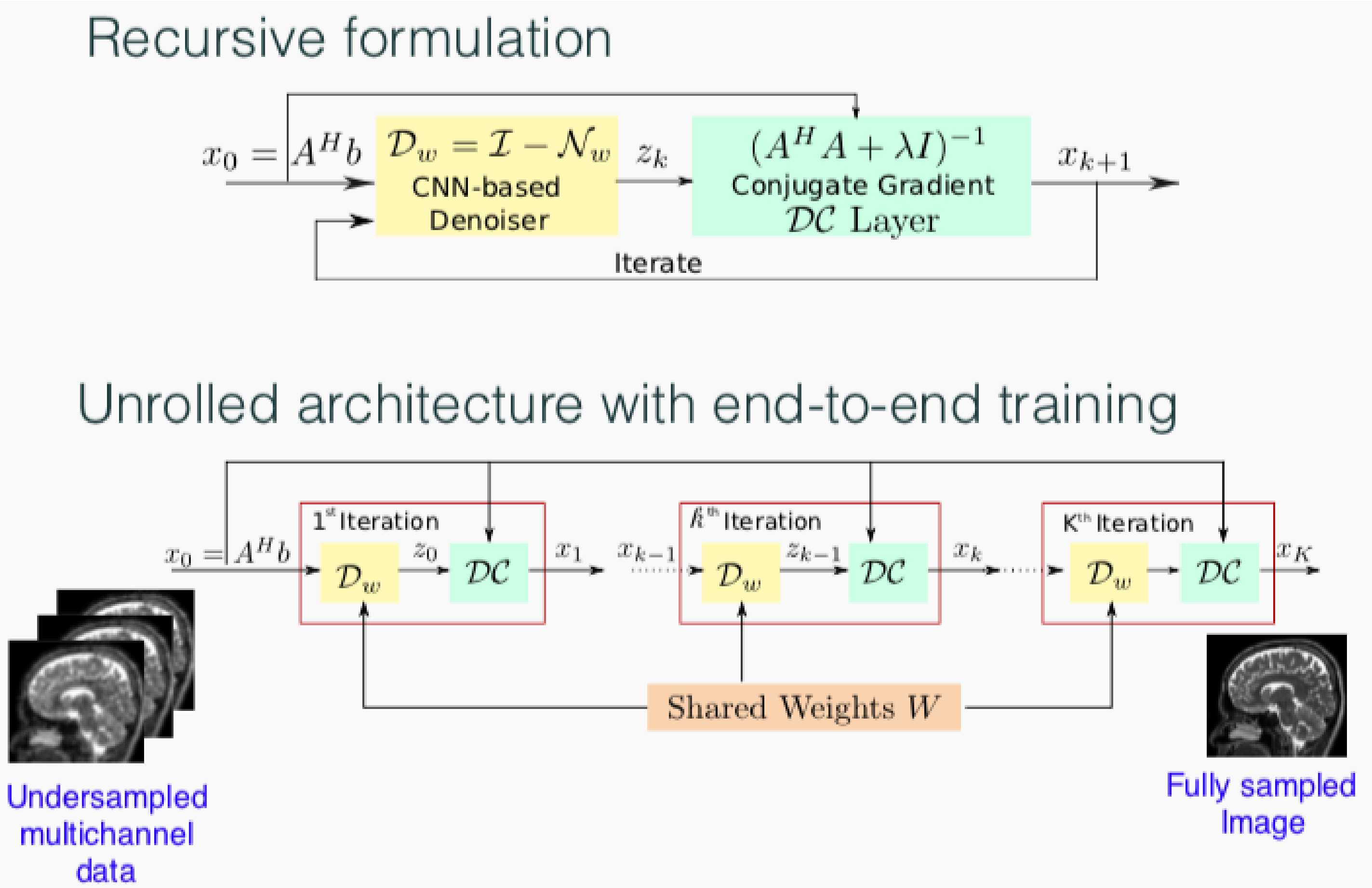
- A transformation between low-res to high-res

MoDL

- A model-based recovery framework with DL priors

$$x_{rec} = \arg\min_{x} ||Ax - b||_2^2 + ||x - D_w(x)||_2^2$$

MoDL (cont'd)



Source: Aggarwal et al., 2018

Dataset Preparation

→ Total of 16 3D volumetric scan from 4 subjects

- Each scan has 32 slices; total 512 slices

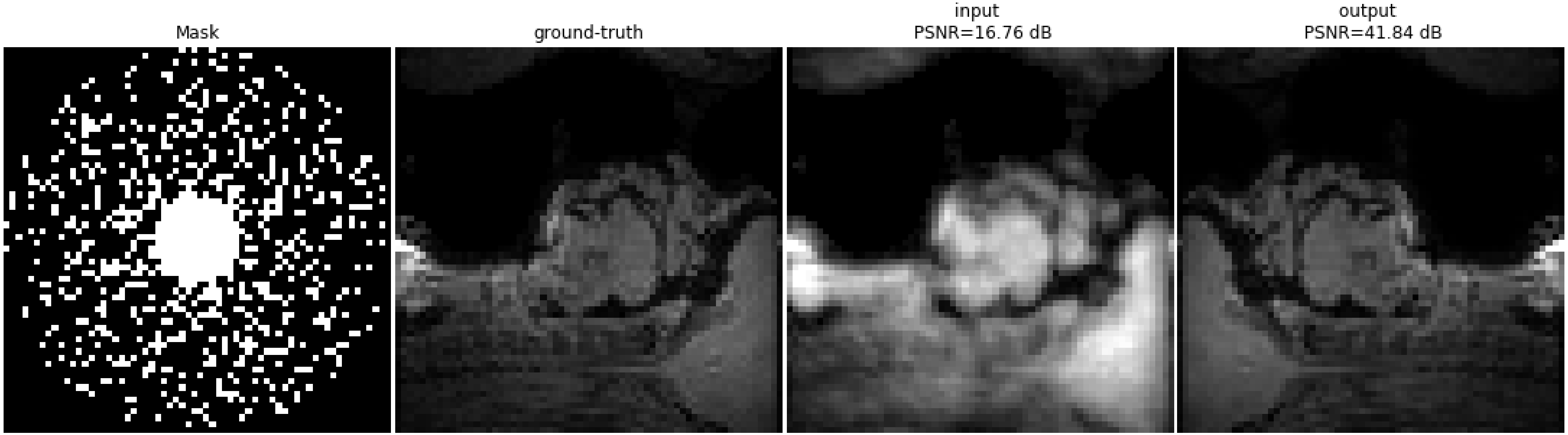
→ Prepared two dataset with 256 slices for each

- 1st dataset
  - training for MoDL and testing for SRResNet
- 2nd dataset:
  - Testing for MoDL and training for SRResNet

How we trained MoDL

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

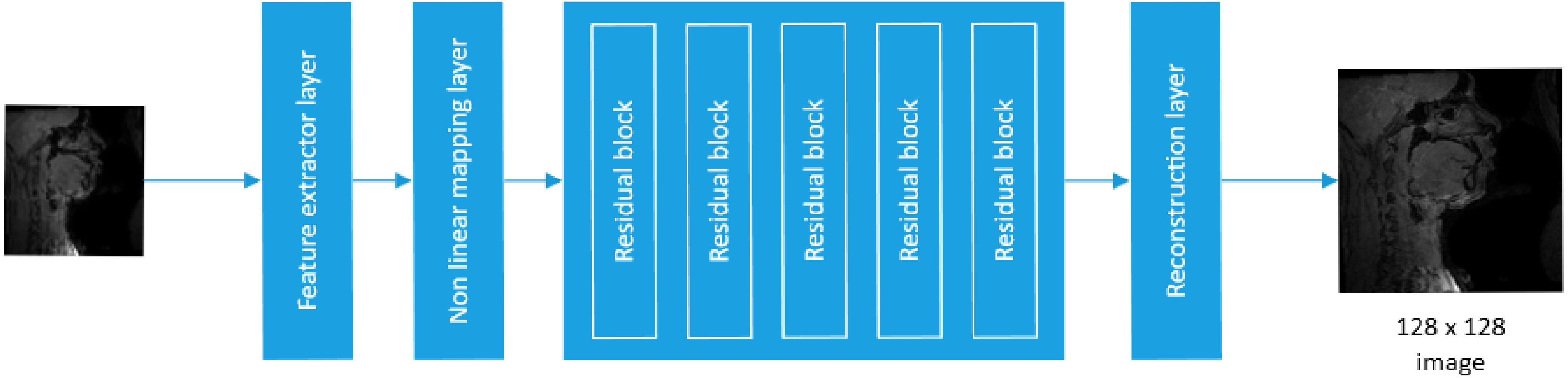
MoDL test results:



Super resolution

SR Resnet

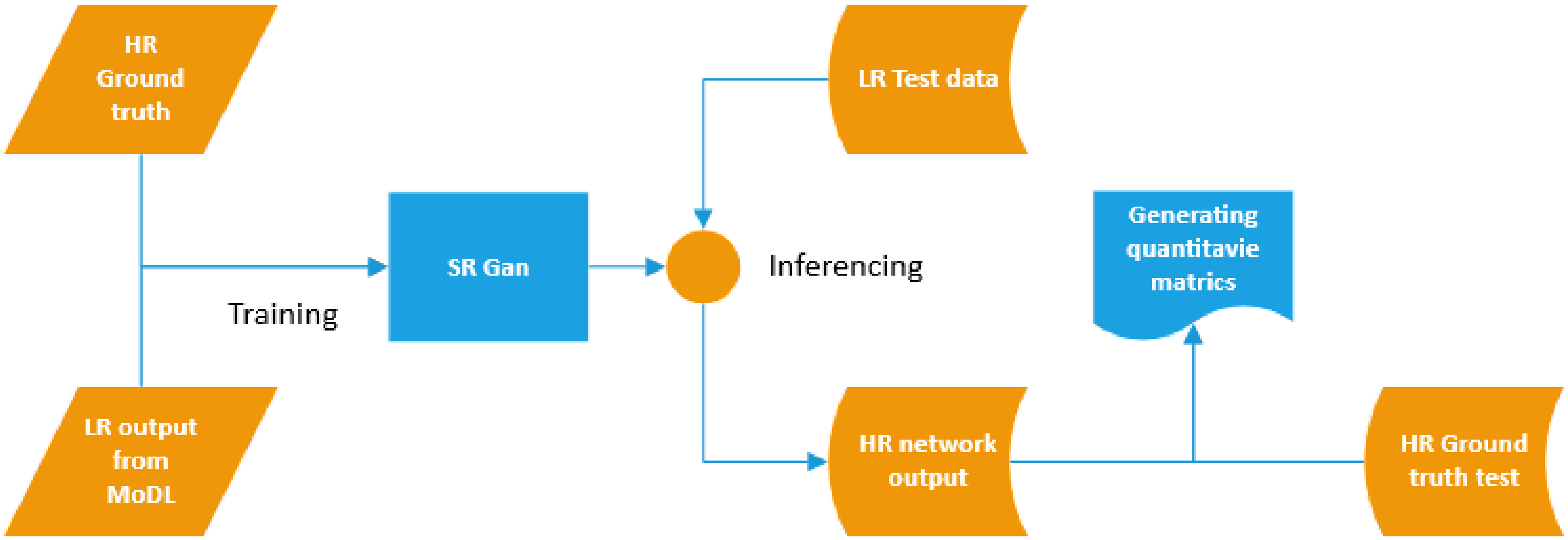
Network architecture



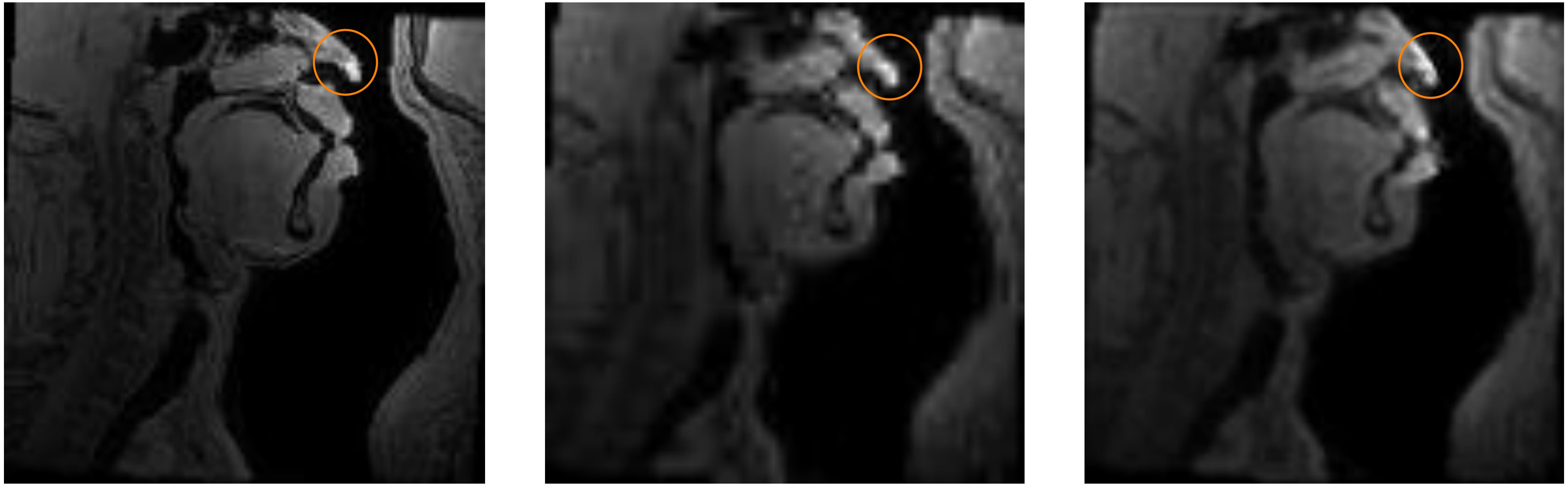
Loss : MSE, L1
Optimizer : Adam (0.9, 0.99)
Learning rate = 1e-4

Number of epochs : 500, 1000
Number of residual units : 5

Processing pipeline



Qualitative Results



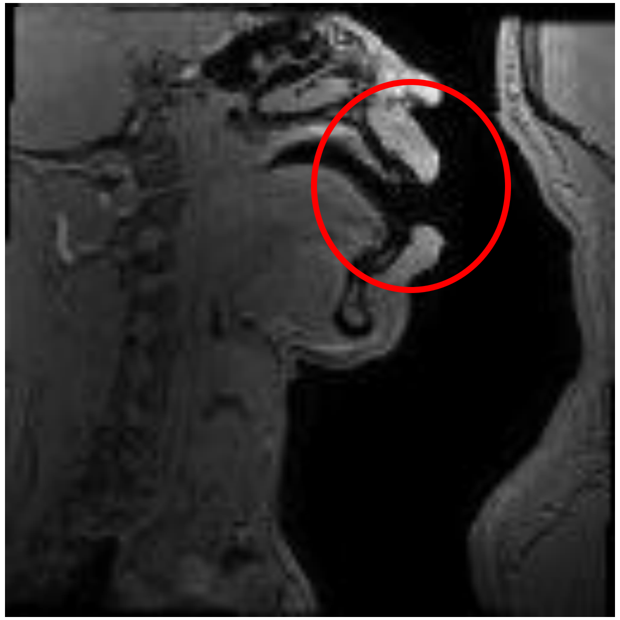
High resolution GT

Low resolution input

High resolution output

IOWA

Qualitative Results



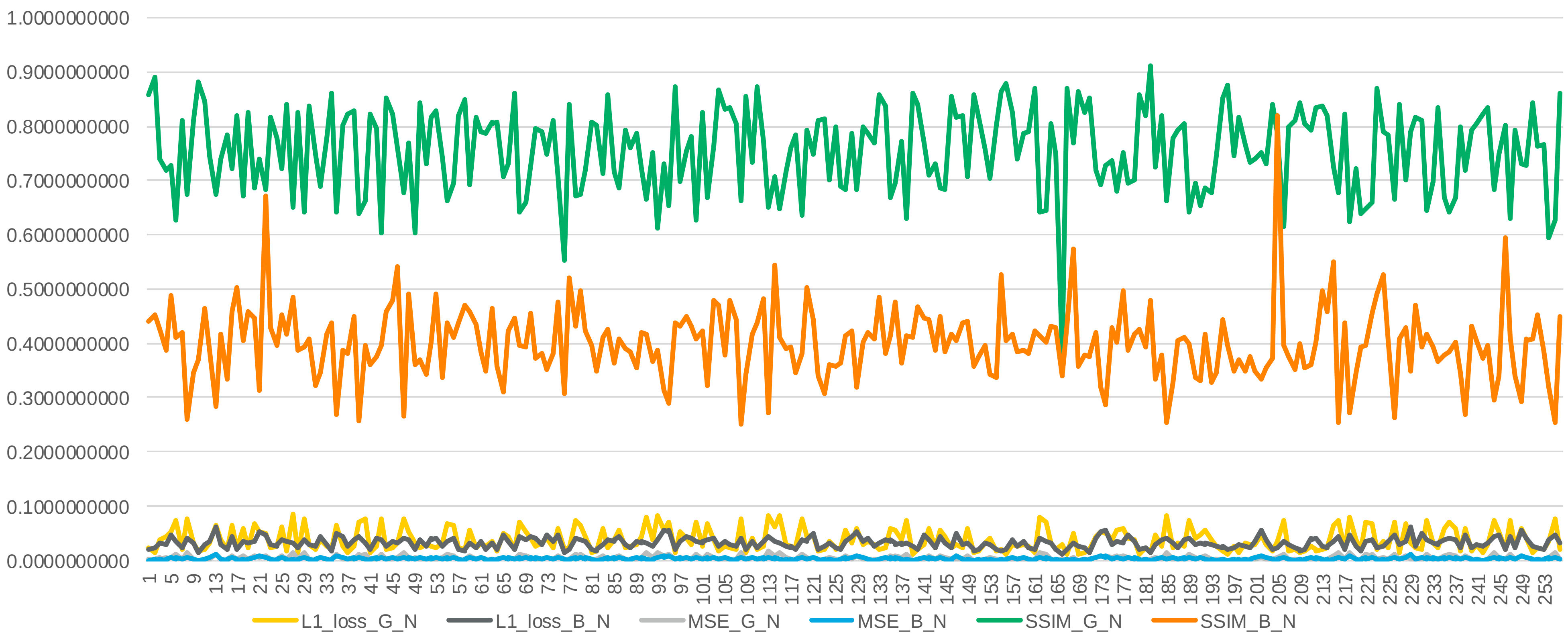
High resolution GT

Low resolution input

High resolution output

IOWA

Quantitative results



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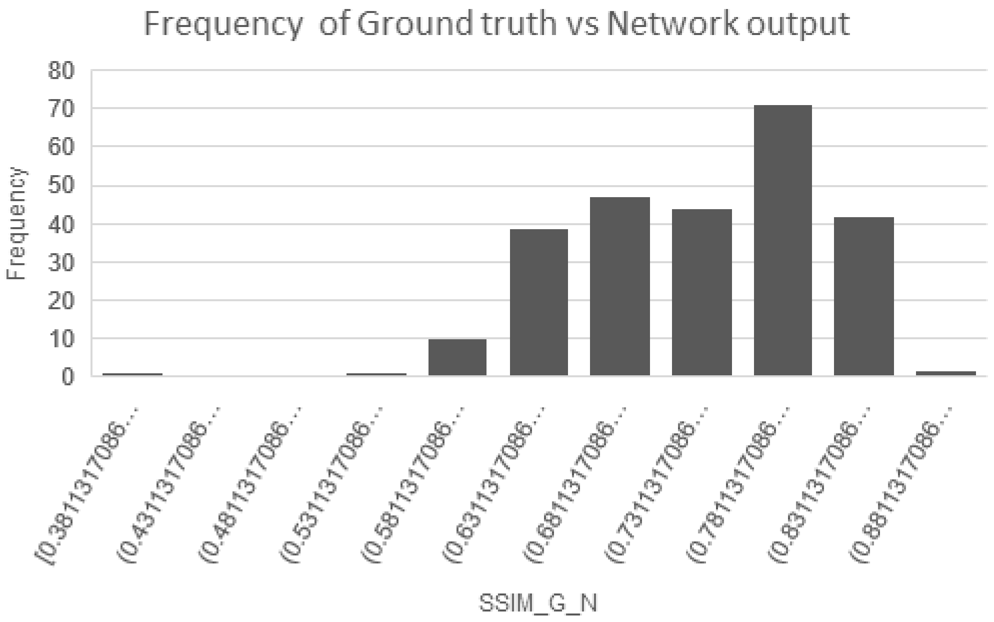
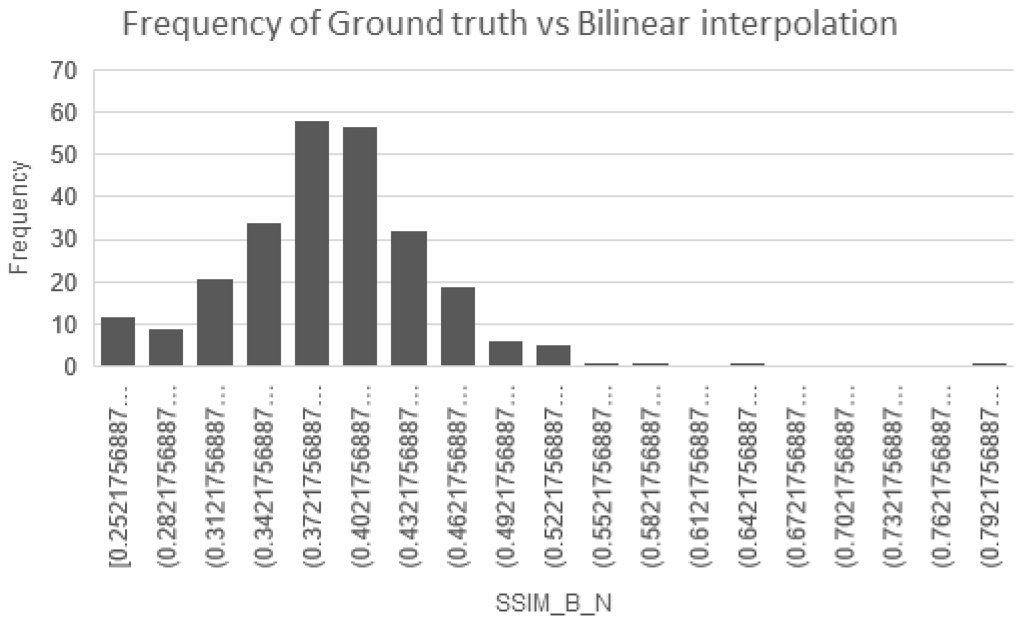
Quantitative results





Thank you