Interpolation Through Machine Learning

– Preliminary Results

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December 11, 2019

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Outline

Background Introduction

Method

- ❑ Residual dense network (RdNet)
- ❑ Model setup

Synthetic Experiment

- ❑ Data set
- ❑ Results
- ❑ Comparison with existing algorithms

Summary

Acknowledgements

Seismic Interpolation Methods

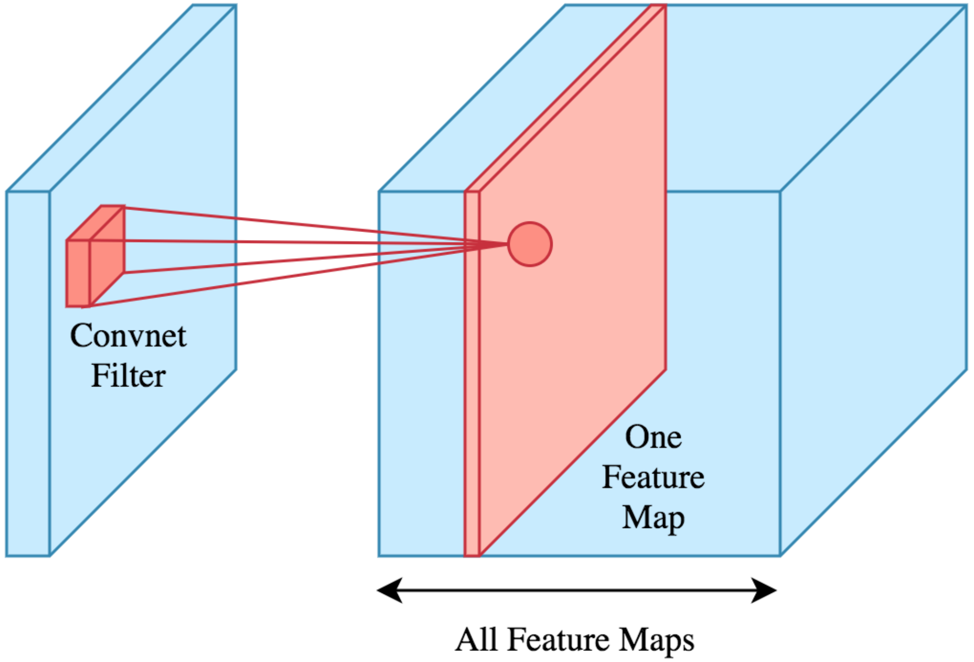
Wave-Equation-Based	**Prediction-Filter-Based**	Mathematical-Transform-Based	**Rank-Reduction-Based**
Wave equation interpolation (Ronen, 1987) Inversion to common offset (Chemingui and Biondi, 2002) FD offset-continuation filter (Fomel, 2003) ⋮	*f-x* interpolation (Spitz, 1991) Half-step prediction filter (Porsani, 1999) *f-x* adaptive interpolation (Naghizadeh and Sacchi, 2009) ⋮	Time-variant Radon Transform (Trad et al., 2002) Fast generalized Fourier Transform (Naghizadeh and Innanen, 2011) Min weighted norm interp (Liu and Sacchi, 2004) ⋮	Rank reduction interpolation (Trickett et al., 2010) Fast reduced-rank interp (Gao et al., 2013) Damped rank reduction (Chen et al., 2016)

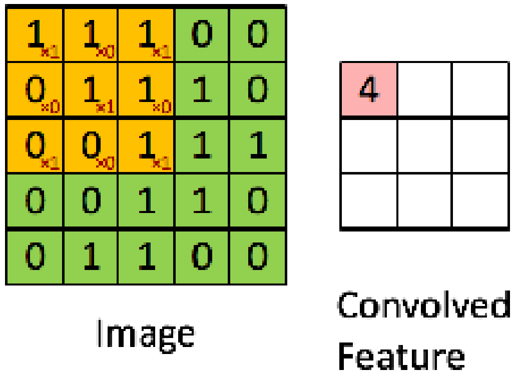
- Normally under certain assumptions
- Optimal parameter varies with dataset

Background

Application of Deep Learning

- Learning capability
- Optimization algorithms integrated in the ML tools

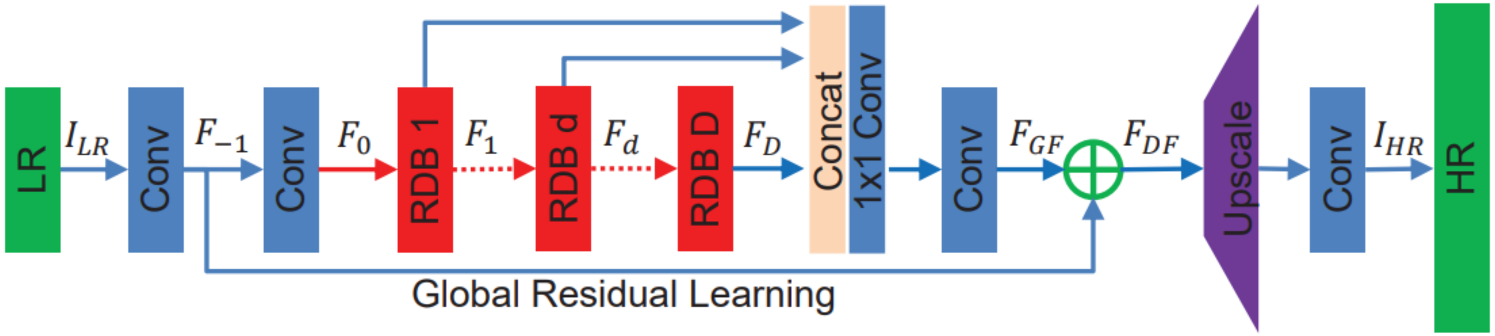




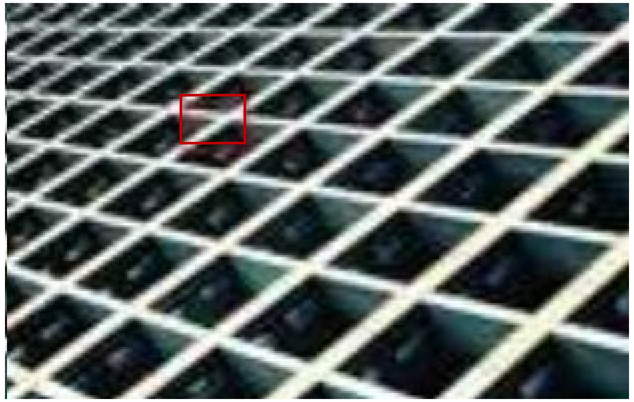
Convolutional Neural Network (CNN)

Sources: https://brilliant.org/wiki/convolutional-neural-network/
https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148

Residual Dense Network (RDNet) for Image Super-resolution



LR Image

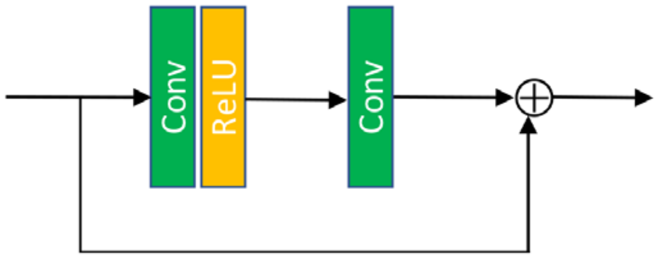


HR Image

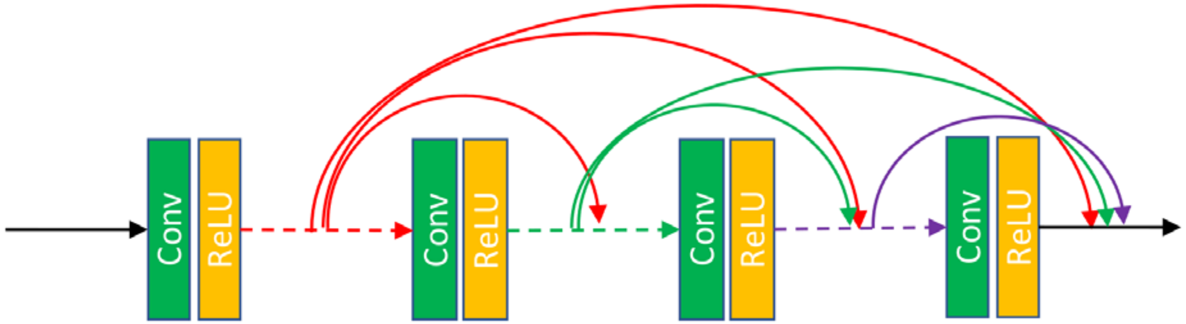
Image Superresolution (Zhang et al., 2018)

Method

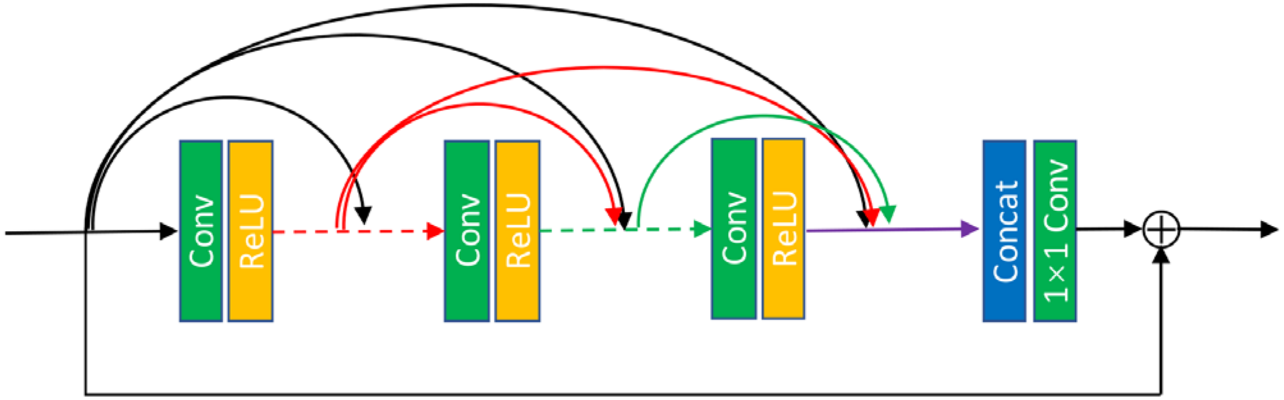
Residual Block



Dense Block



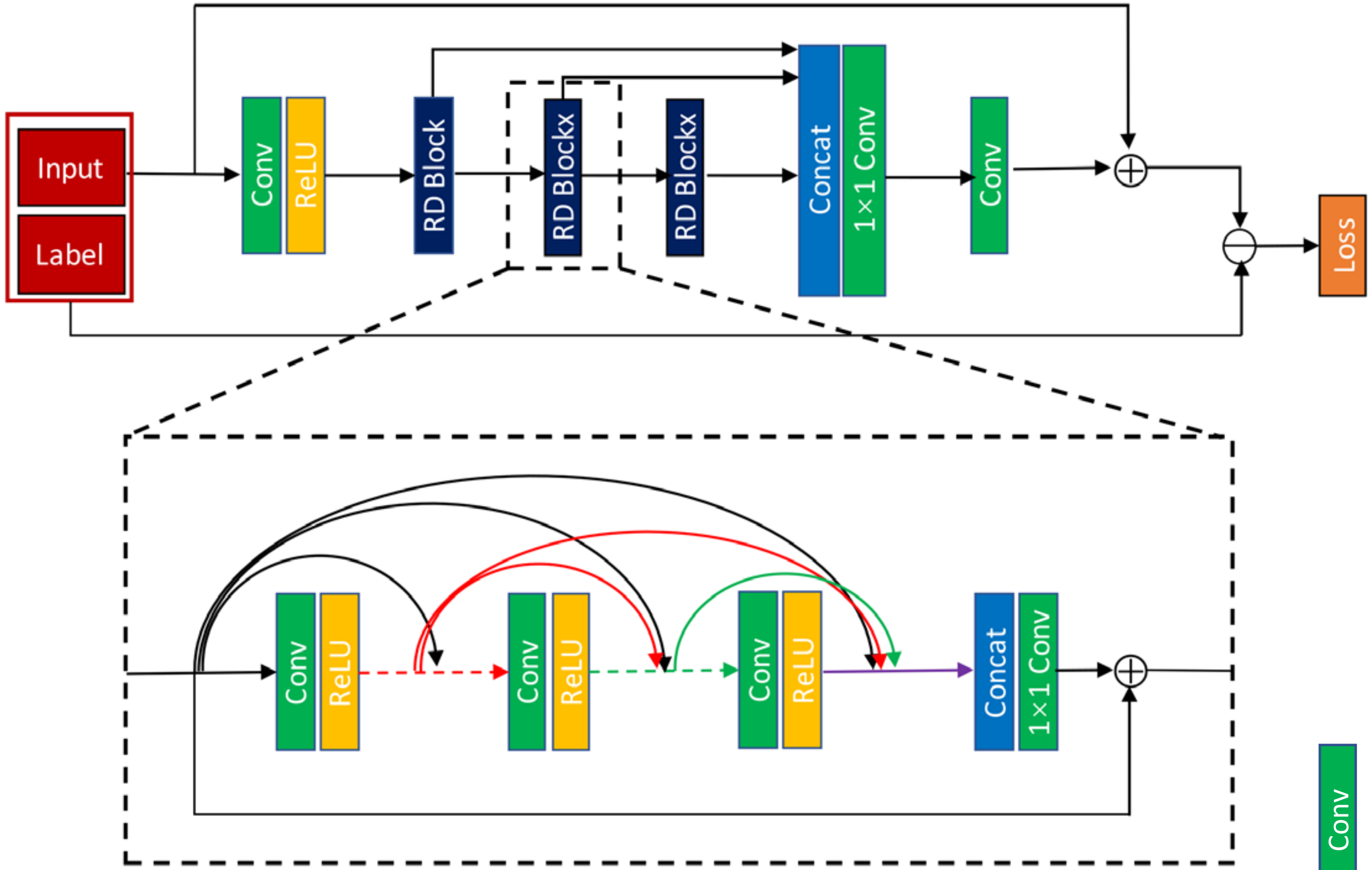
Residual Dense (RD) Block



Figures modified from Zhang et al., 2018

Method

RDNet Used for Interpolation

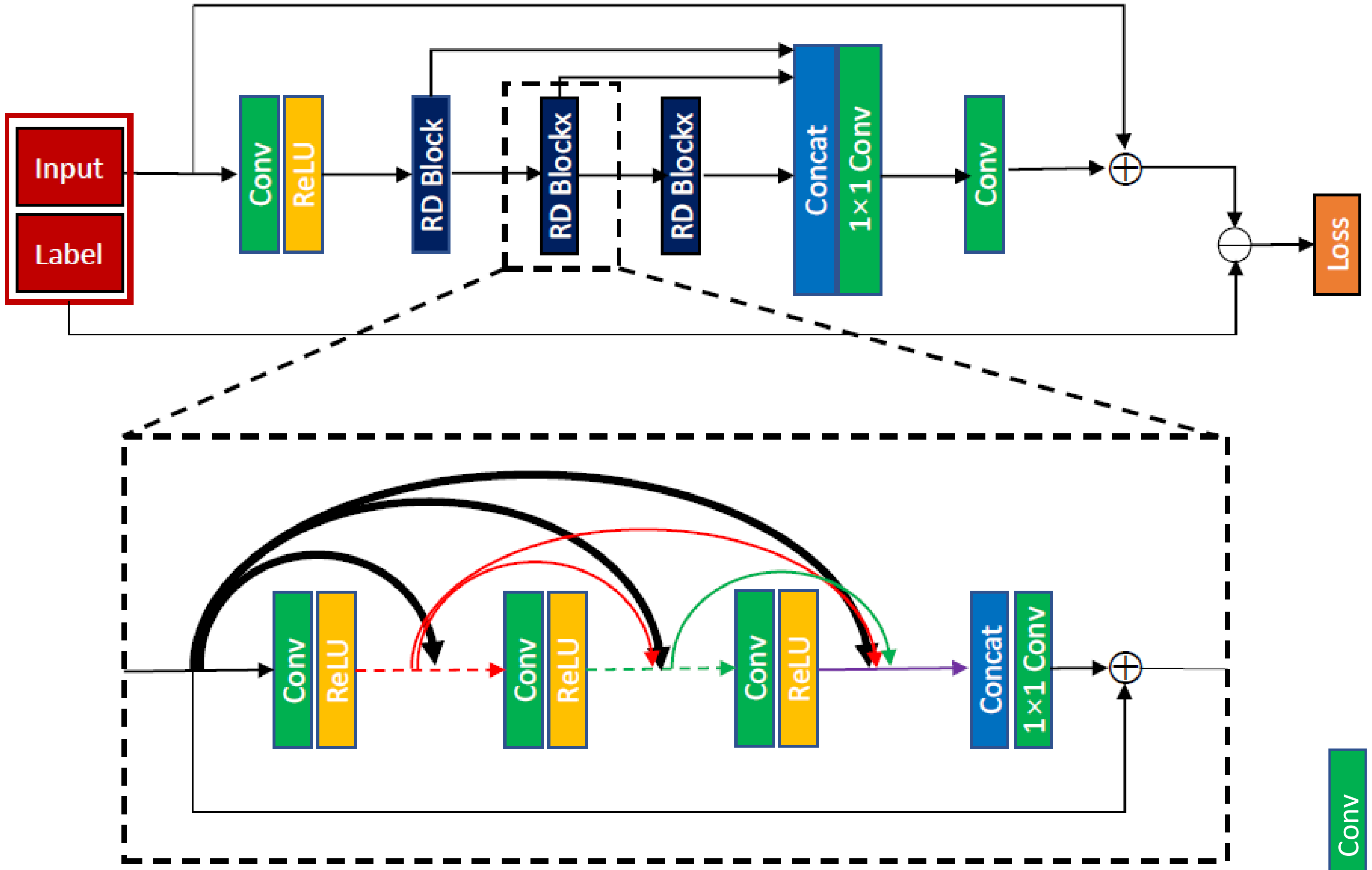


- Contiguous memory mechanism
- Residual learning in local and global levels
- Feature fusion in local and global levels

Conv 64 3 x 3 filter

Method

RDNet Used for Interpolation

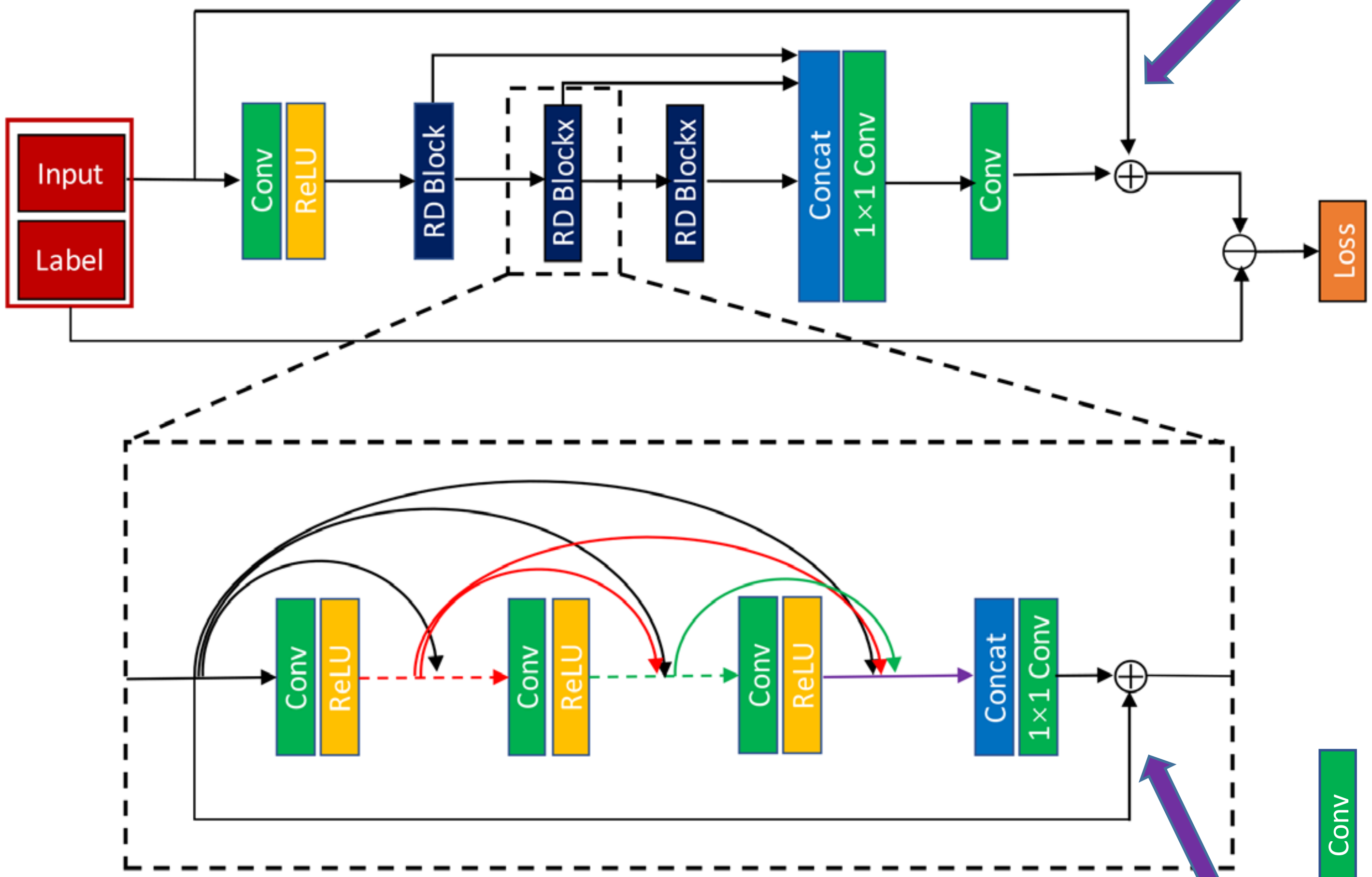


- **Contiguous memory mechanism**
- Residual learning in local and global levels
- Feature fusion in local and global levels

Conv 64 3 x 3 filter

RDNet Used for Interpolation

Global Residual Learning

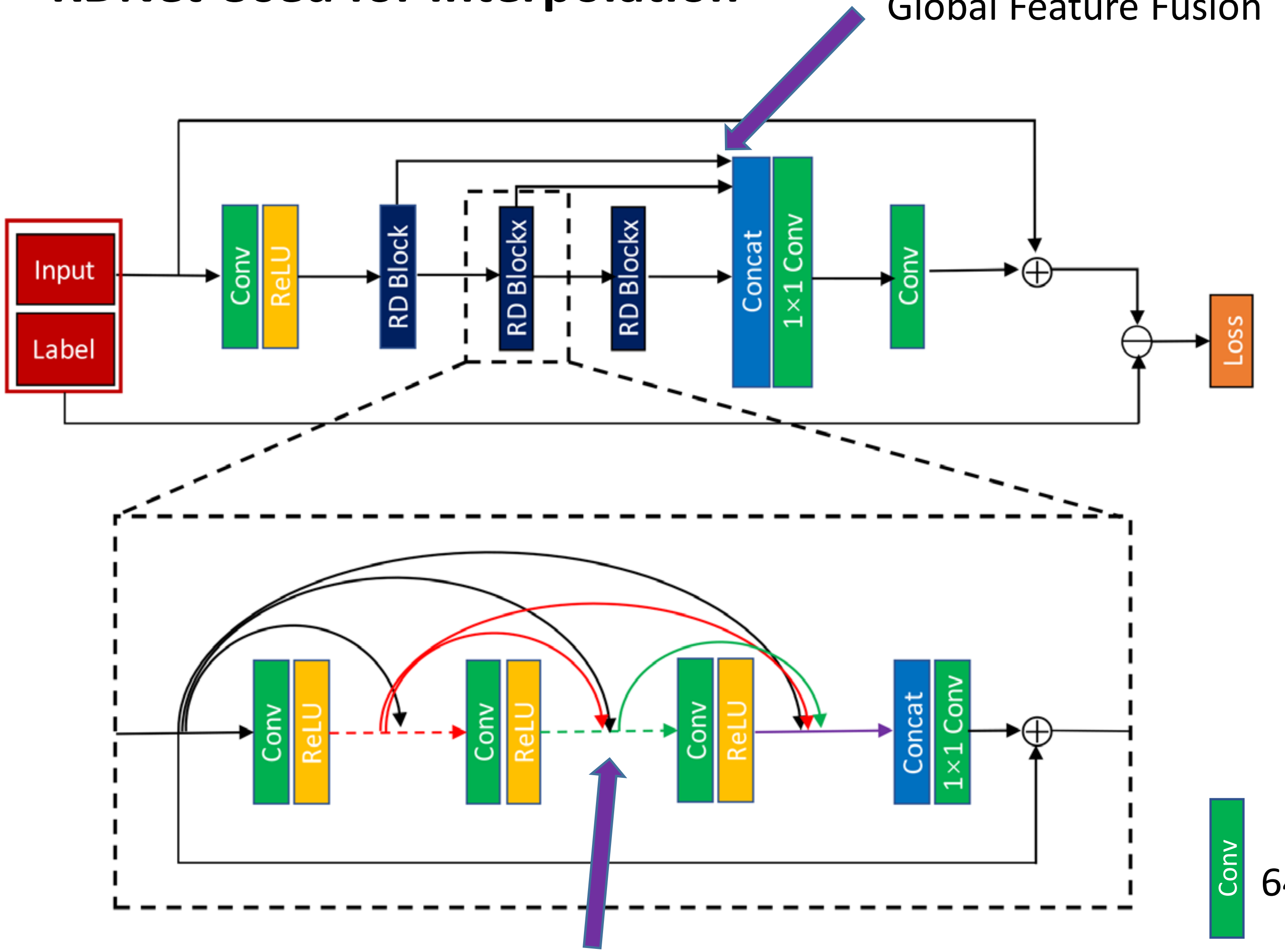


- Contiguous memory mechanism
- **Residual learning in local and global levels**
- Feature fusion in local and global levels

Conv 64 3 x 3 filter

Local Residual Learning

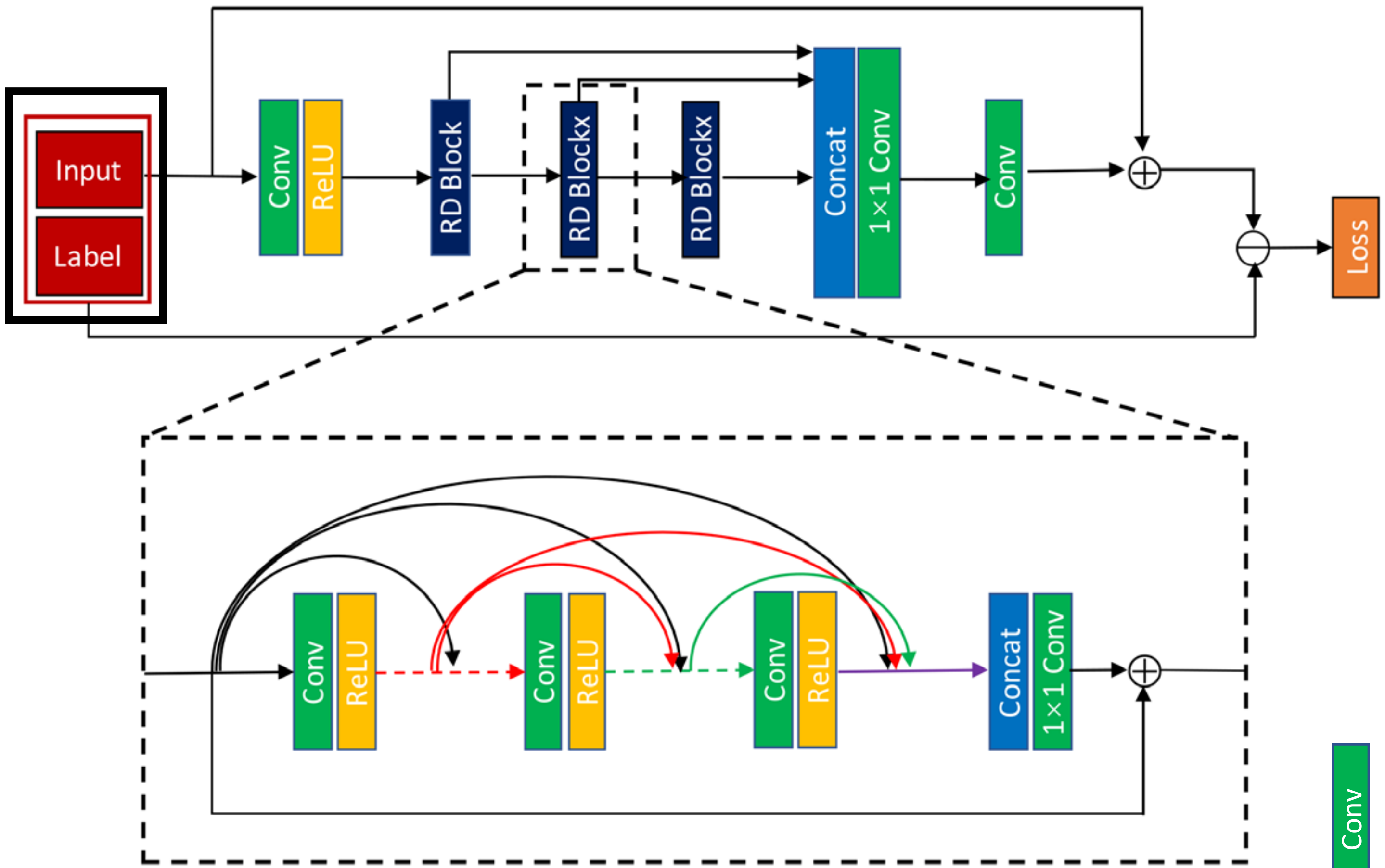
RDNet Used for Interpolation



- Contiguous memory mechanism
- Residual learning in local and global levels
- **Feature fusion in local and global levels**

64 3 x 3 filter

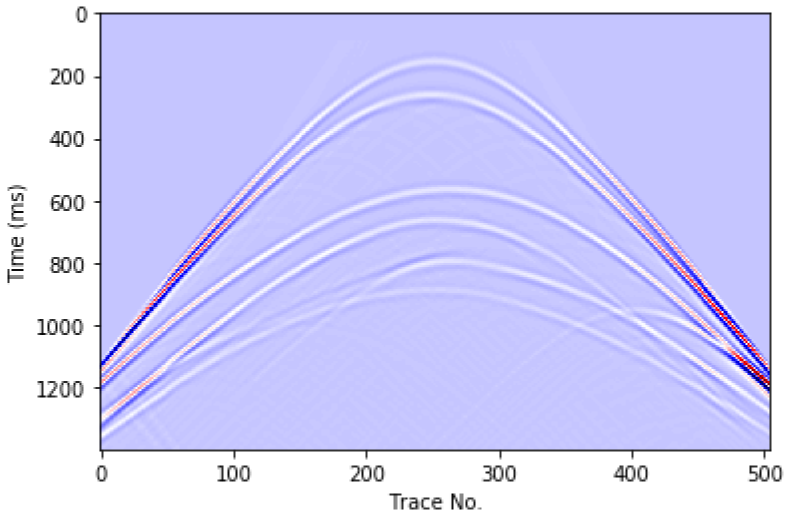
RDNet Used for Interpolation

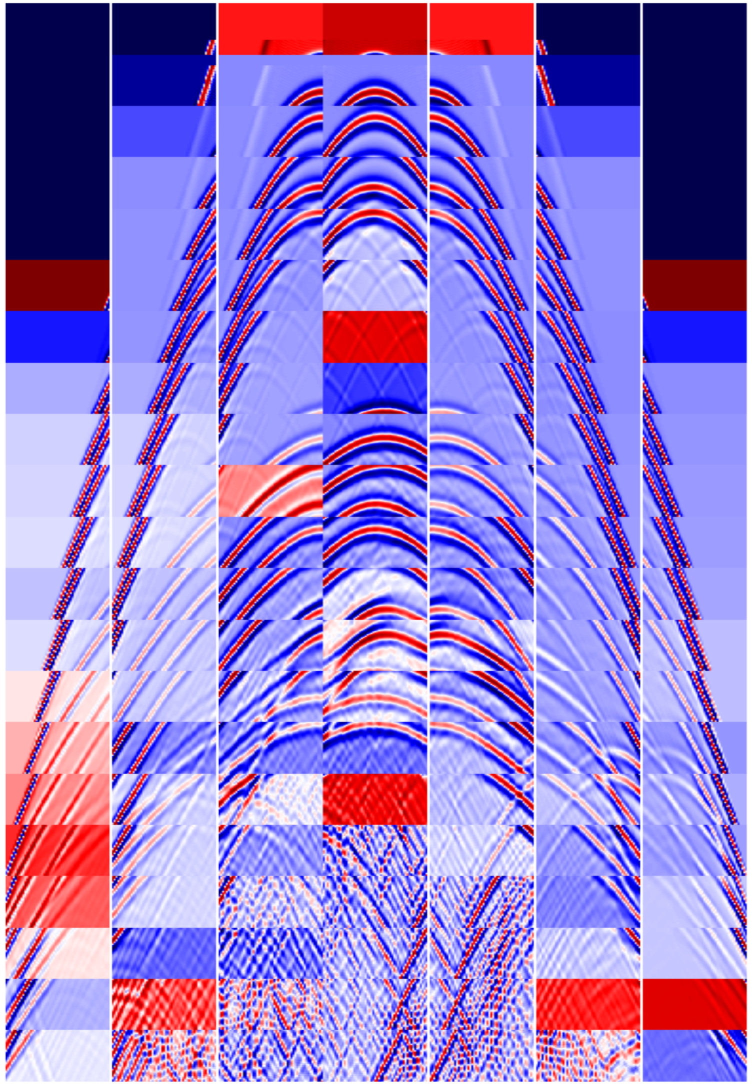


- Training implemented on regular gird and 2D synthetic data
- Input: decimated seismic data (fill missing traces with zeros)
- Label: complete data

Conv 64 3 x 3 filter

Model Setup – Divide each shot into small patches





- With 50% overlap in both temporal and spatial directions
- Patch size: 127 x 127 for regularly missing traces
- Patch size: 128 x 128 for randomly missing traces

Model Setup – Loss Function & Evaluation Metric

- Loss Function – Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{k=0}^{n}(d_{int}^{k} - d_{label}^{k})^2$$

d_{int} : Interpolated data
d_{label} : Label

- Evaluation Metric – Recovered S/N (in dB)

$$R = 20\ log_{10}\frac{\|d_{label}\|_2}{\|d_{label} - d_{int}\|_2}$$

Model Setup – Optimization algorithm

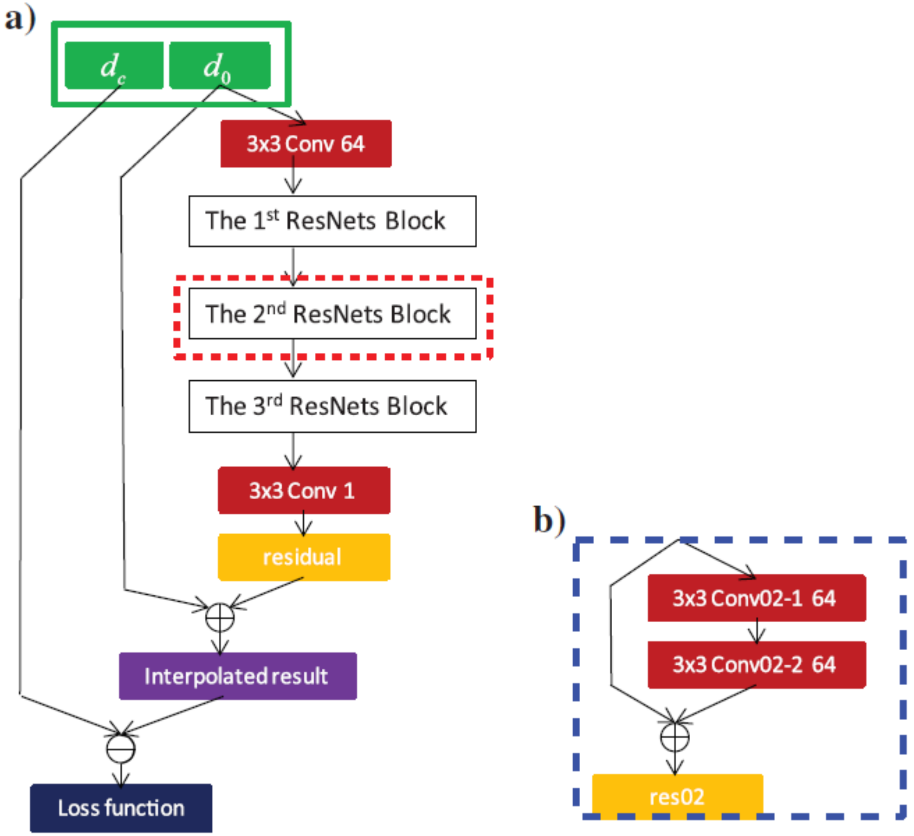
Adam (Kingma and Bai, 2014)

Require: α: Learning rate
Require: $\beta_1, \beta_2 \in [0,1)$: Exponential decay rate
Require: $f(\theta)$: Stochastic objective function
Require: θ_0: Initial parameter vector
$m_0 \leftarrow 0$: Initialize 1st moment vector
$v_0 \leftarrow 0$: Initialize 2nd moment vector
$t \leftarrow 0$: Initialize timestep
while θ_t not converged **do**
$t \leftarrow t + 1$
$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradient)
$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot g_t$ (Update biased 1st moment estimate)
$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot g_t^2$ (Update biased 2nd moment estimate)
$\widehat{m}_t \leftarrow m_t/(1-\beta_1^t)$ (Compute bias-corrected 1st moment estimate)
$\hat{v}_t \leftarrow v_t/(1-\beta_2^t)$ (Compute bias-corrected 2nd moment estimate)
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t/(\sqrt{\hat{v}_t} + \epsilon)$
end while
return θ_t

Learning-rate adaptive adjustment

Methods for Comparison

Residual Network (ResNet)



Wang et al., 2019

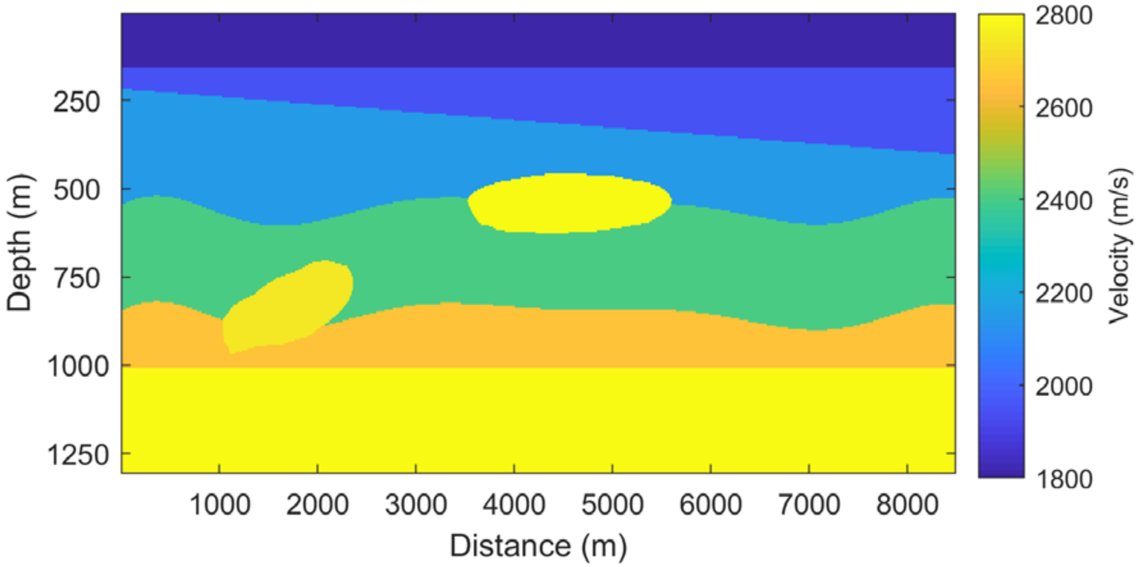
Minimum Weighted Norm Interpolation (MWNI)

$$\mathbf{y} = \mathbf{T}\,\mathbf{x}$$

y: Observation
X: Complete data
T: Sampling Matrix

Minimize $\boxed{\|\mathbf{x}\|_w^2}$
Subject to $\mathbf{T}\,\mathbf{x} = \mathbf{y}$

2D SYNTHETIC DATA

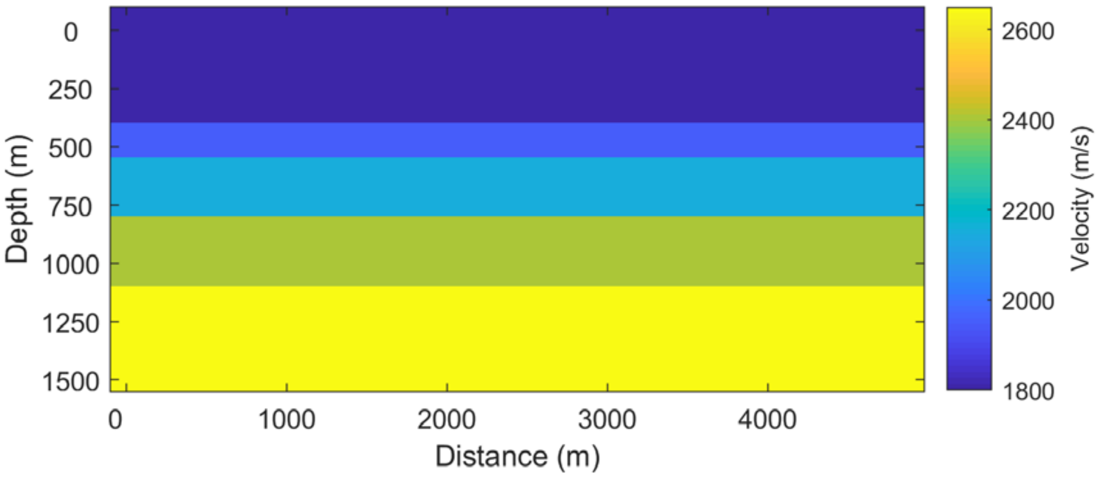


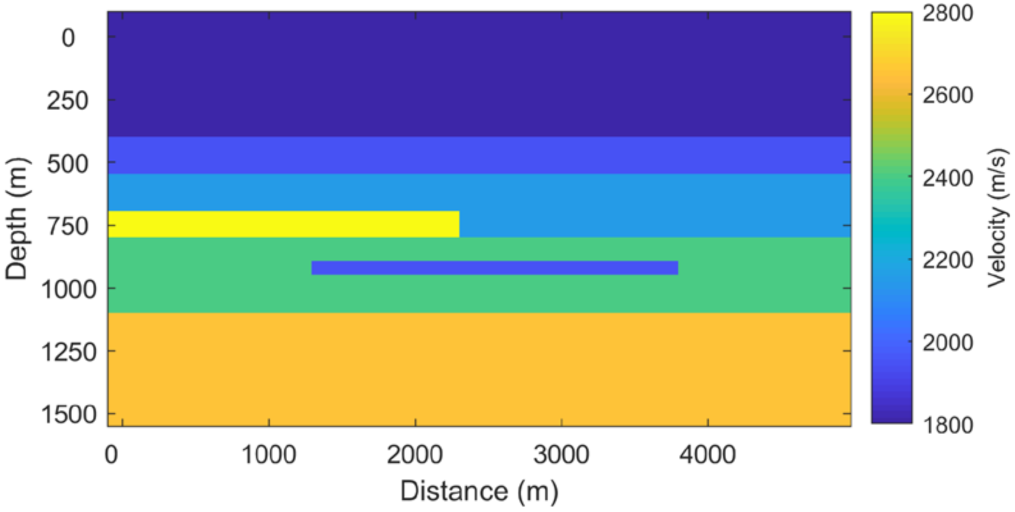
- Receiver spacing: 10 m
- Source spacing: 30m
- Time sampling interval: 1 ms
- No. of shots: 146
- No. of receivers: 513
- Dominant Freq: 20 Hz

Data Split: 80% for training, 20% for validation

Synthetic Experiment

2D SYNTHETIC DATA

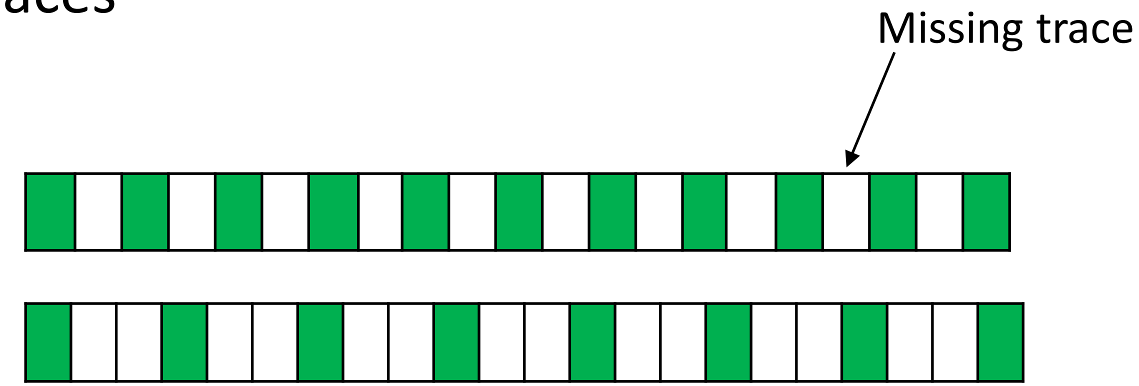




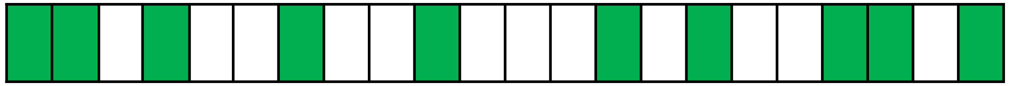
Velocities to generate two test shots

Synthetic Experiment

- Regularly missing traces
  - Halved trace interval
  - 1/3 of trace interval

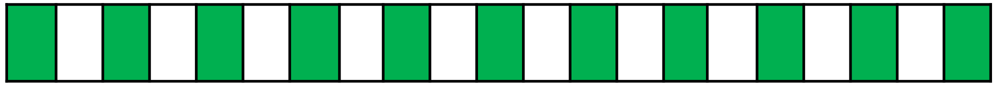


- Randomly missing traces
  - 10% missing traces
  - 30% missing traces
  - 50% missing traces



Synthetic Experiment

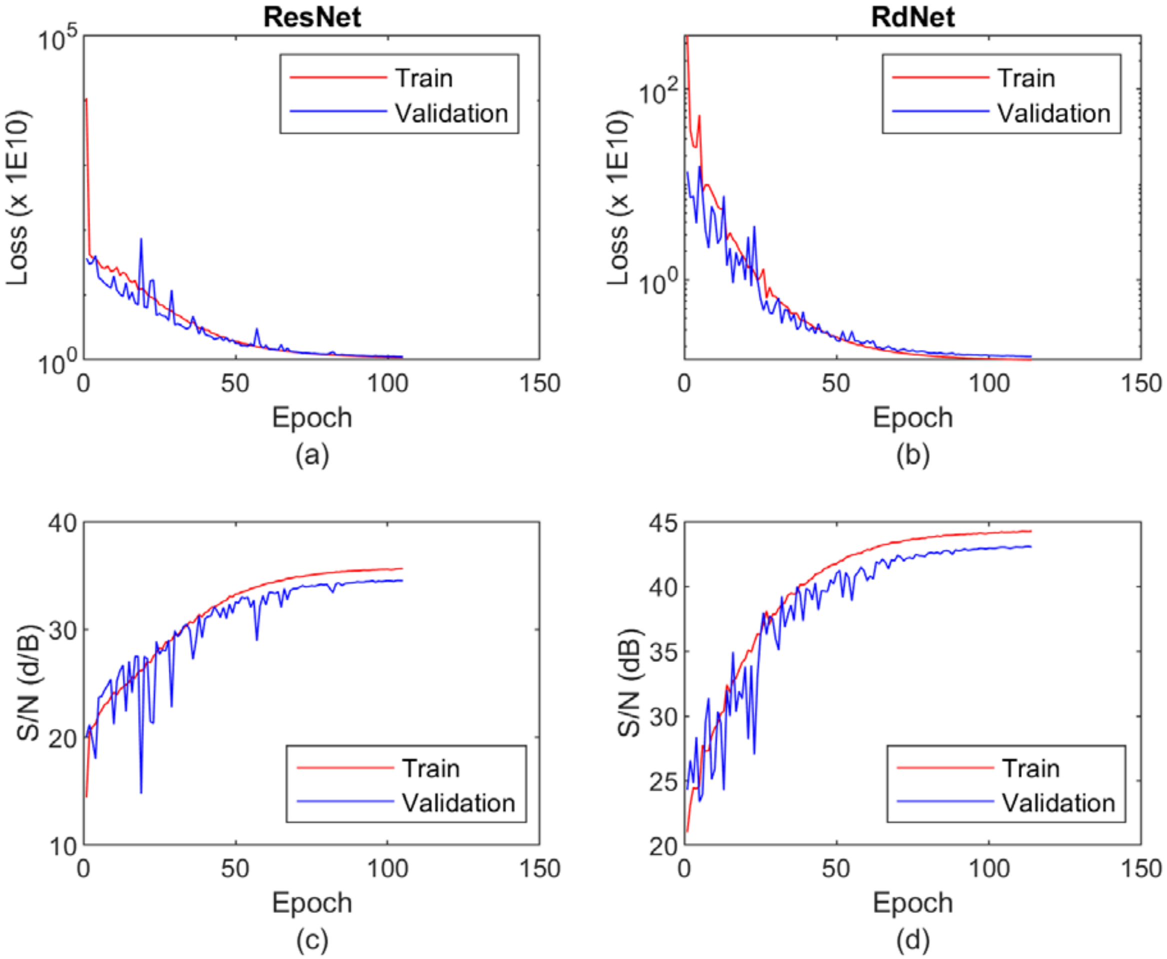
Training Result – Regularly missing traces

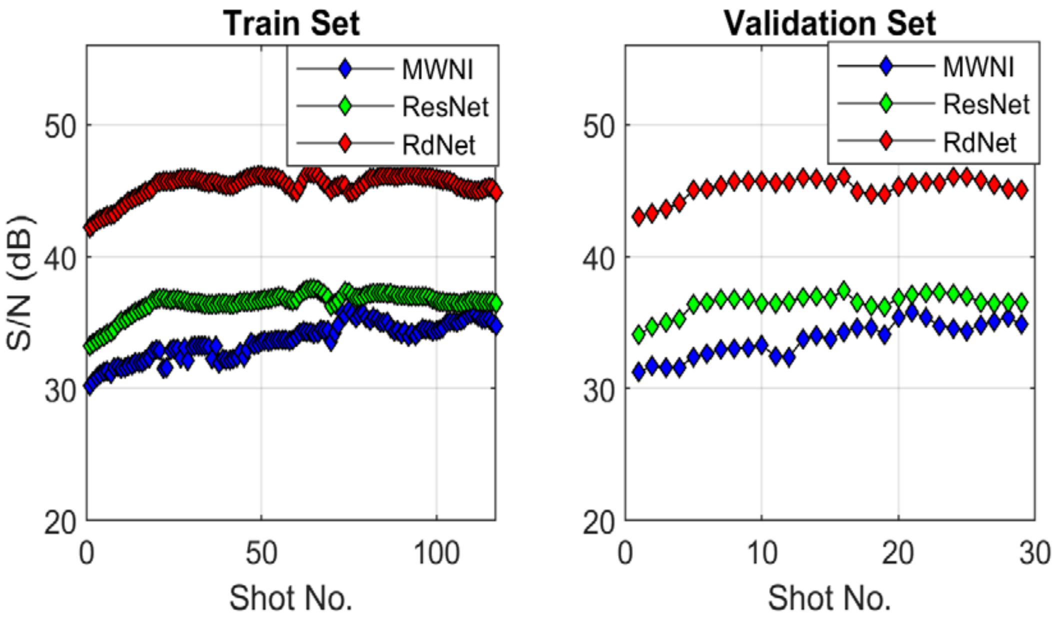


- Interpolation with halved trace interval

Loss

Recovered S/N

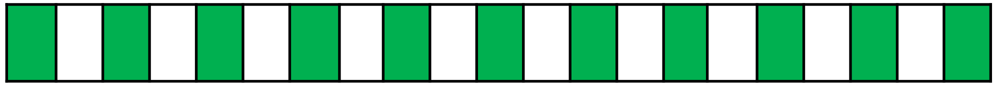




S/Ns for individual shots

Synthetic Experiment

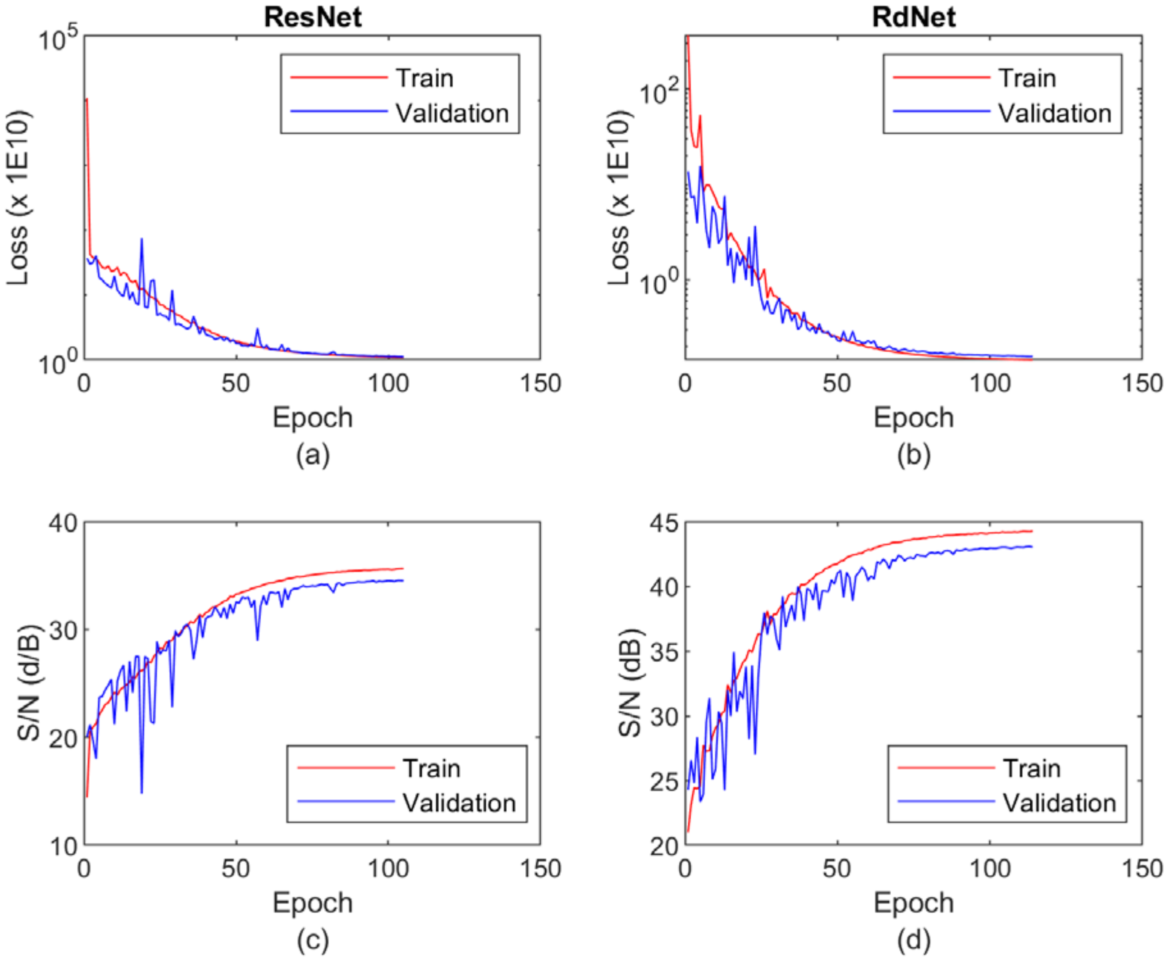
Training Result – Regularly missing traces

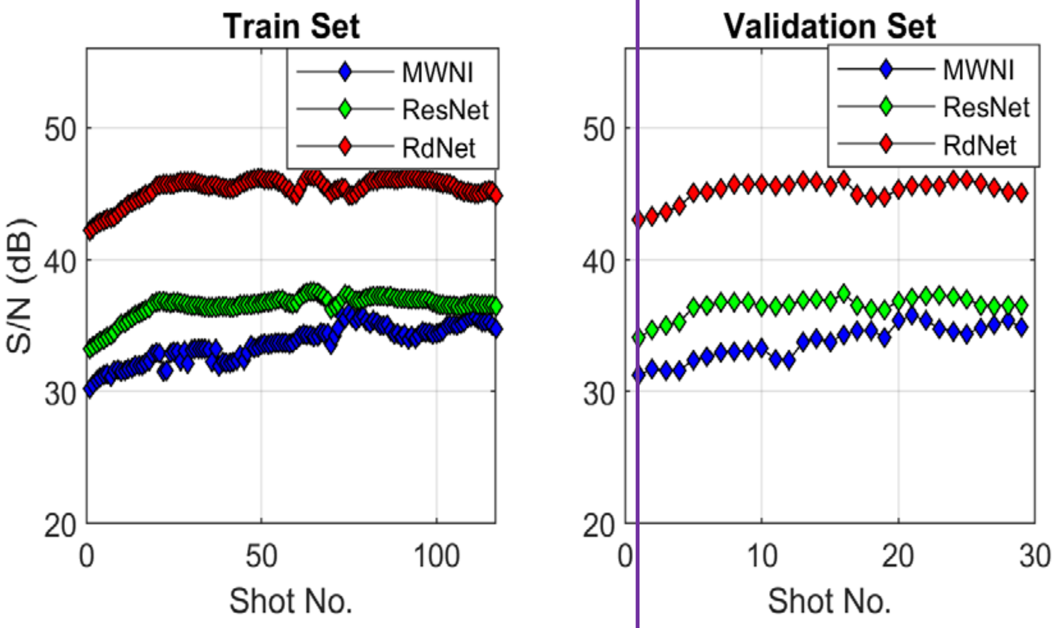


- Interpolation with halved trace interval

Loss

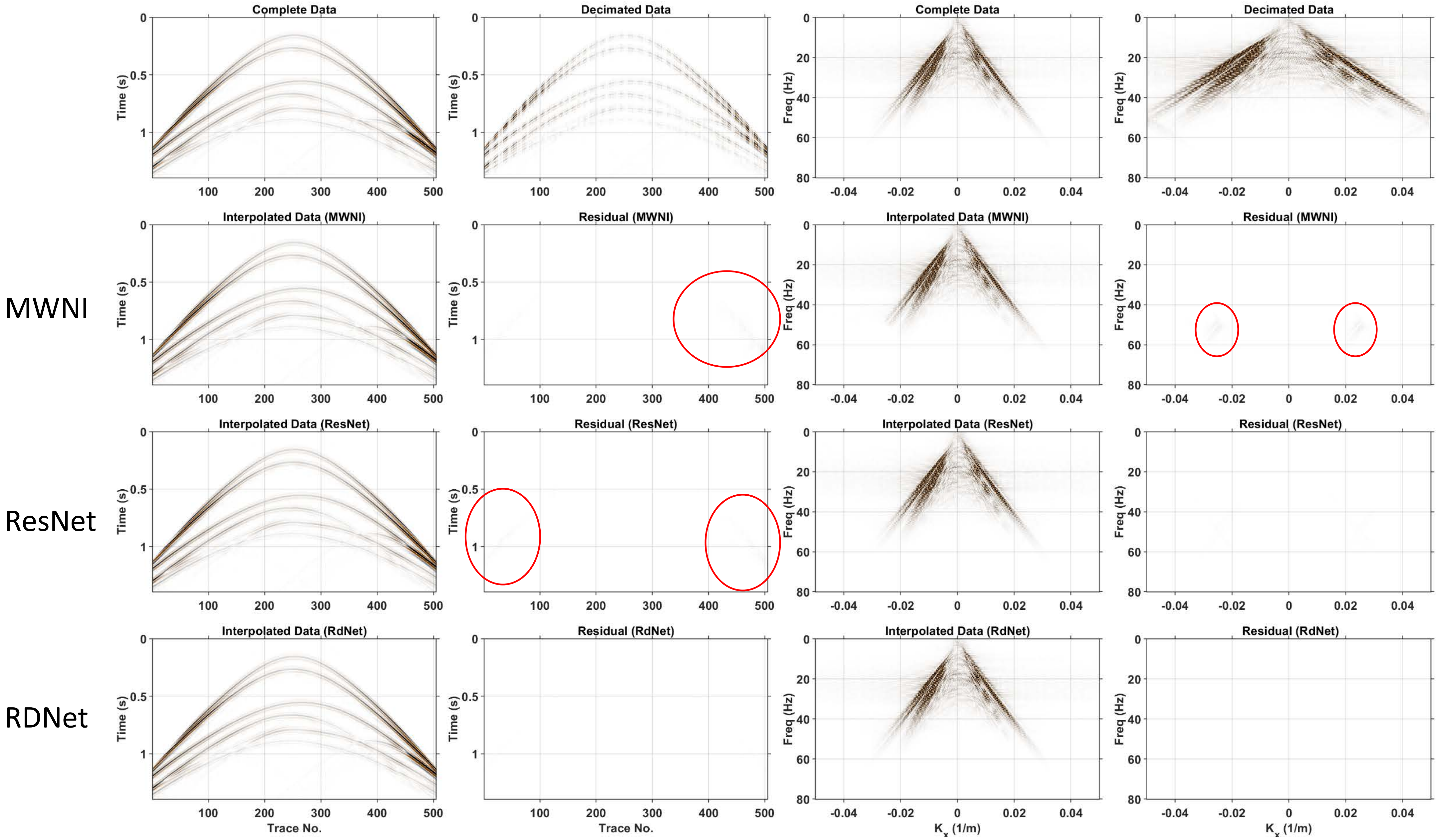
Recovered S/N





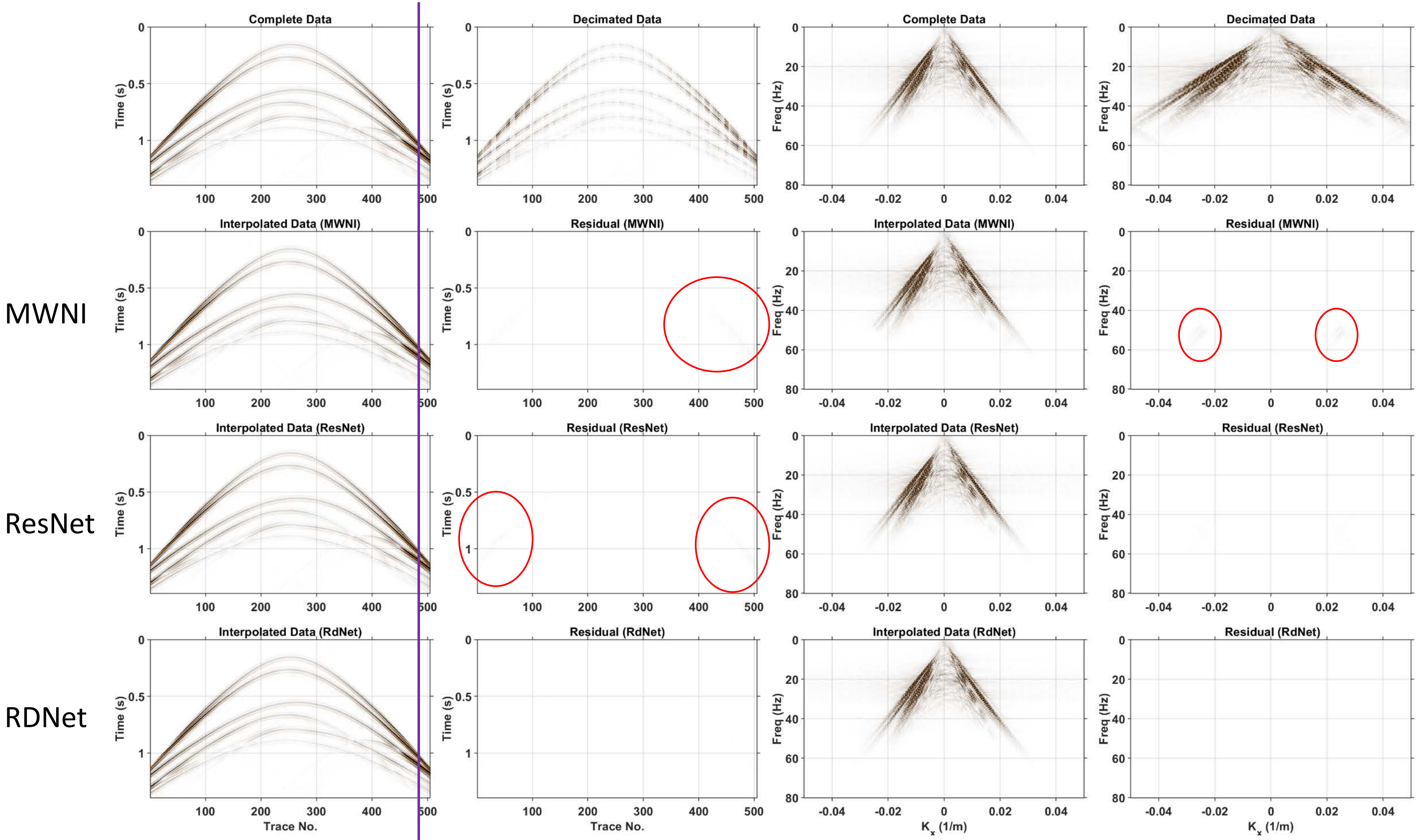
S/Ns for individual shots

Synthetic Experiment



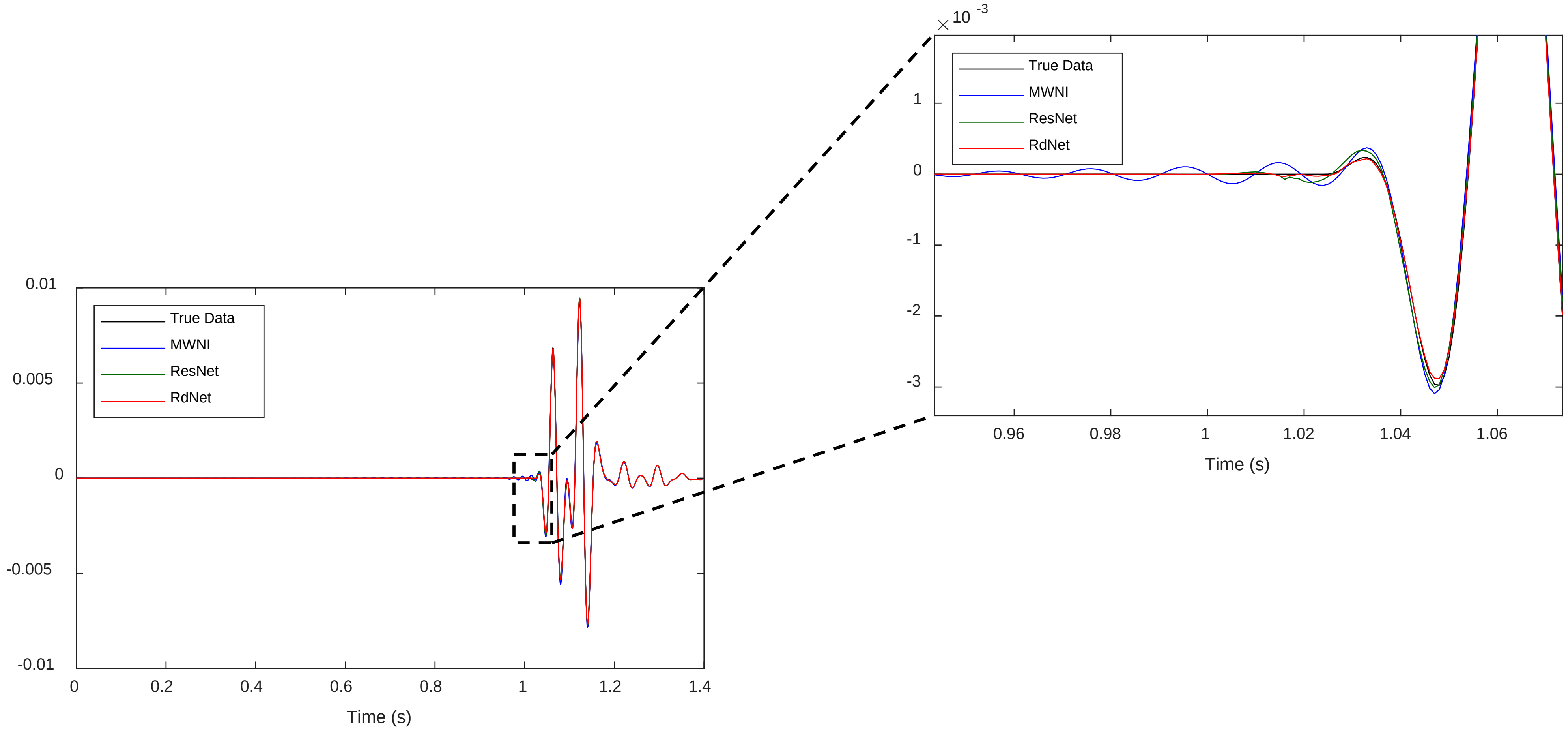
SNR:
31.3, 34.1, 43.0

Synthetic Experiment



SNR:
31.3, 34.1, 43.0

Training Result – Interpolation with halved trace interval



Synthetic Experiment

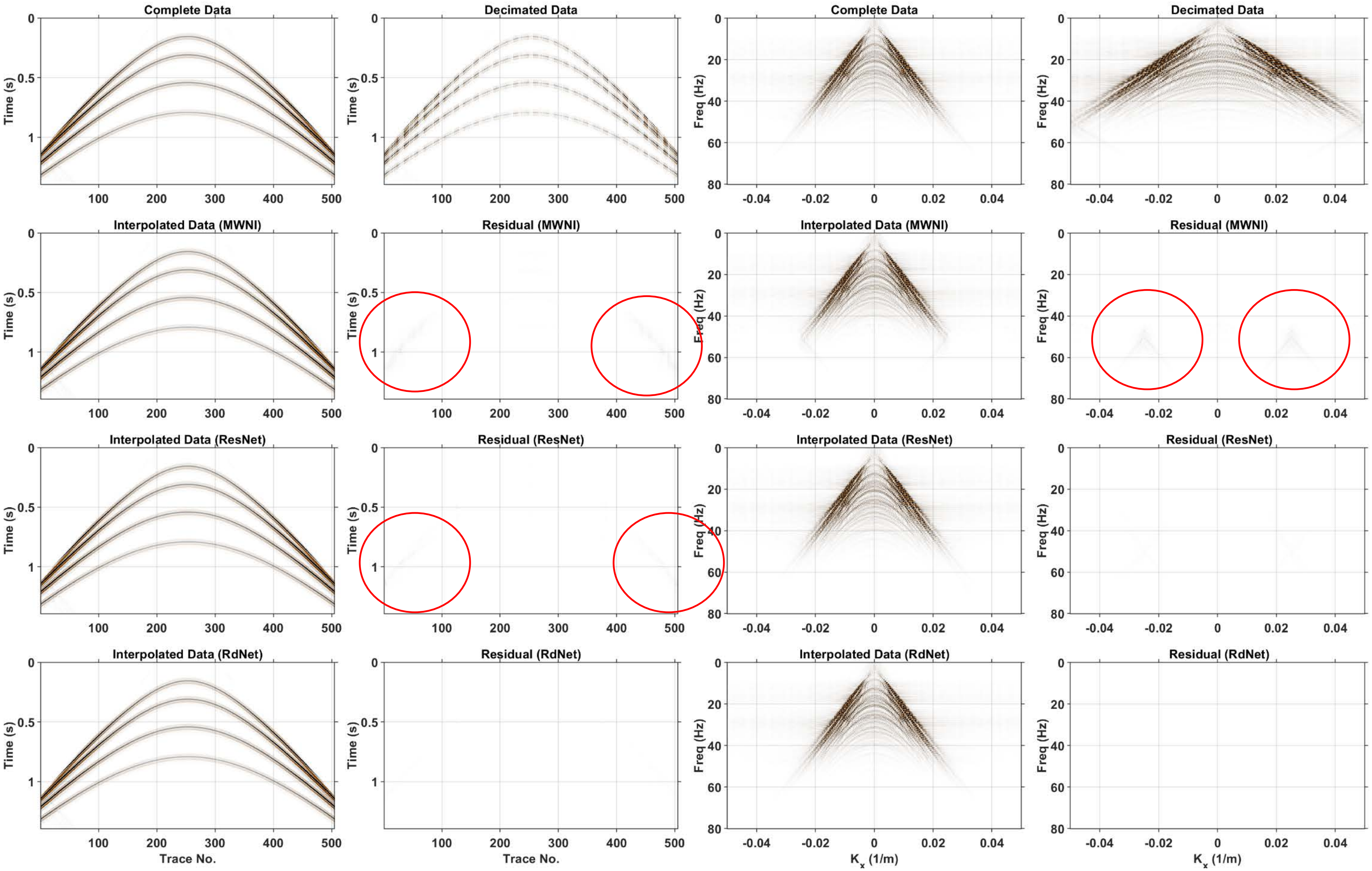
Test Shot #1

MWNI

ResNet

RDNet

SNR:
29.7, 34.4, 42.5



Synthetic Experiment

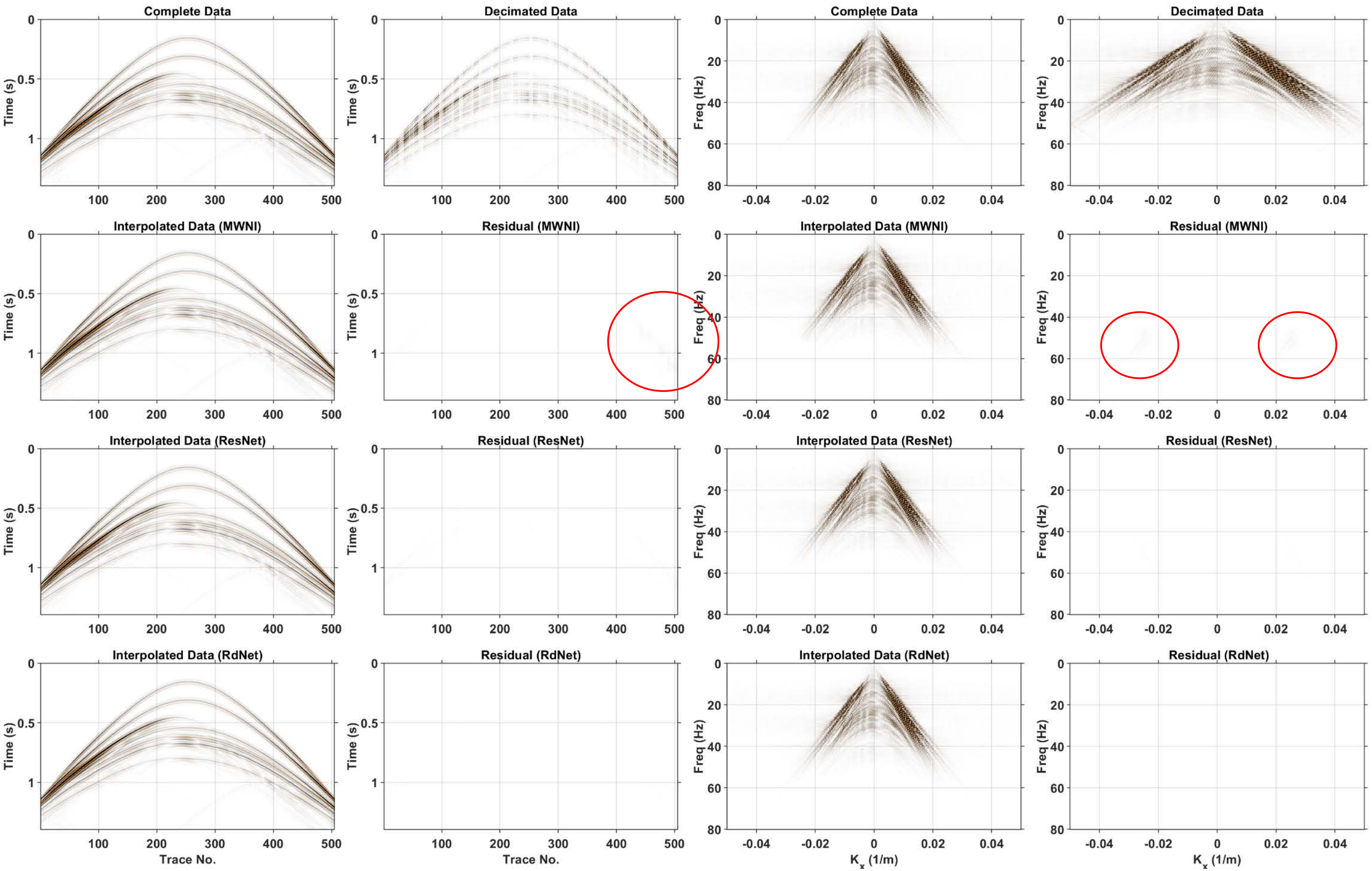
Test Shot #2

MWNI

ResNet

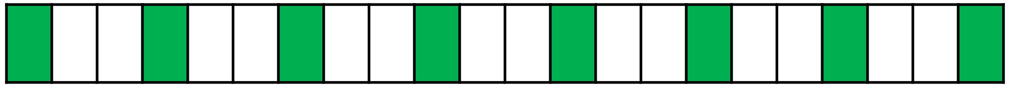
RDNet

SNR:
34.4, 35.9, 43.4

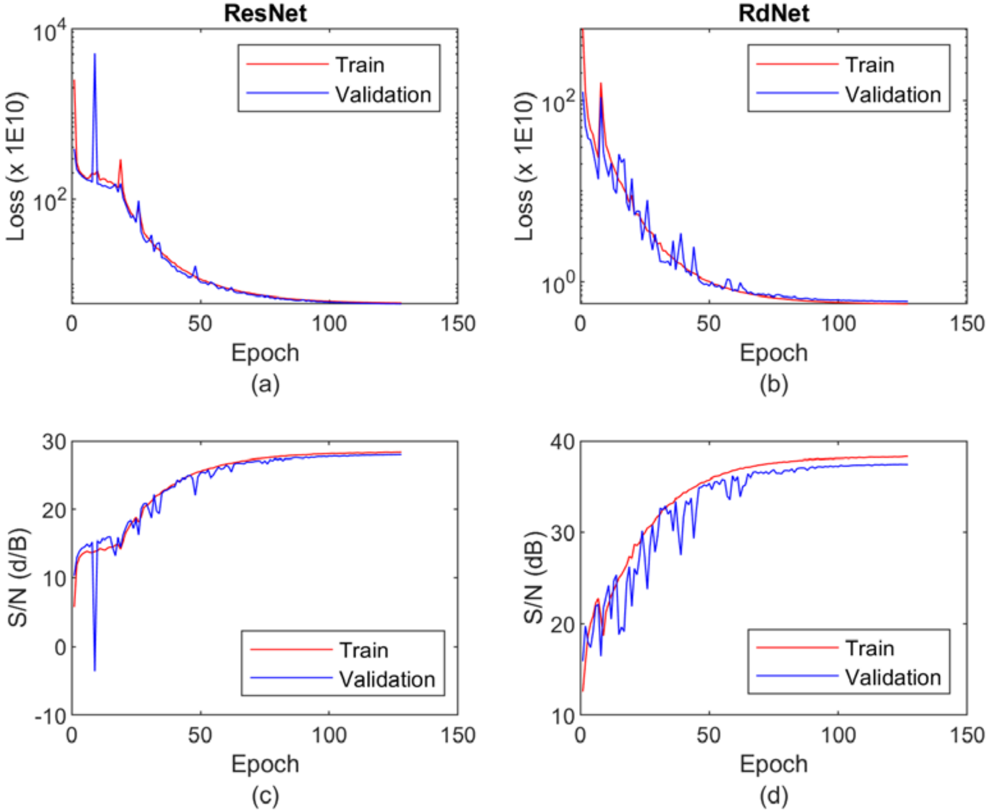


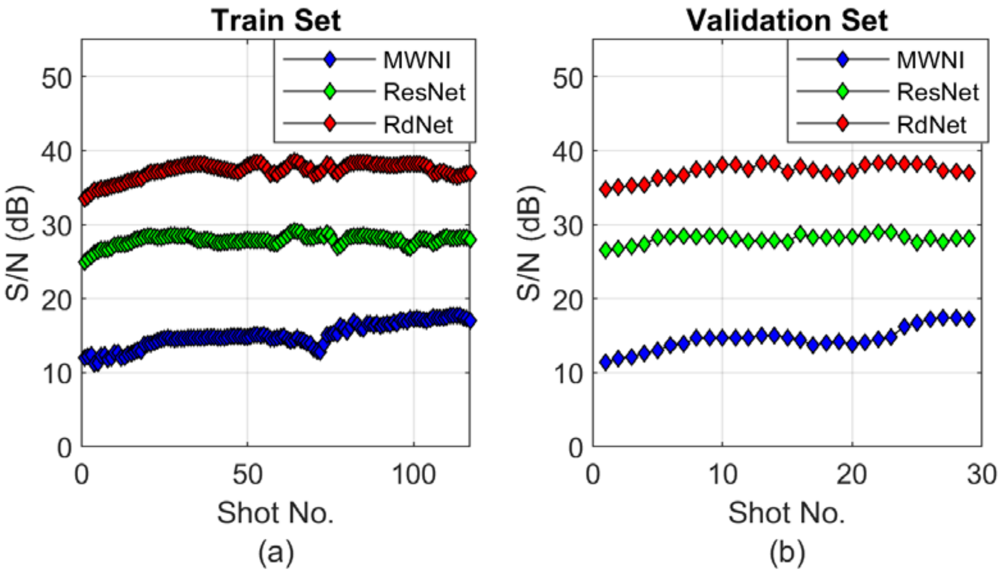
Synthetic Experiment

Training Result – Regularly missing traces



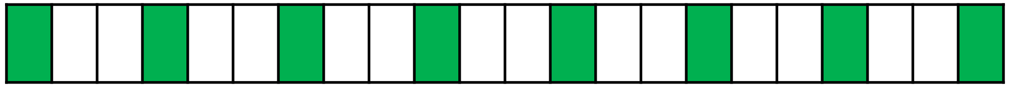
- Interpolation with 1/3 trace interval



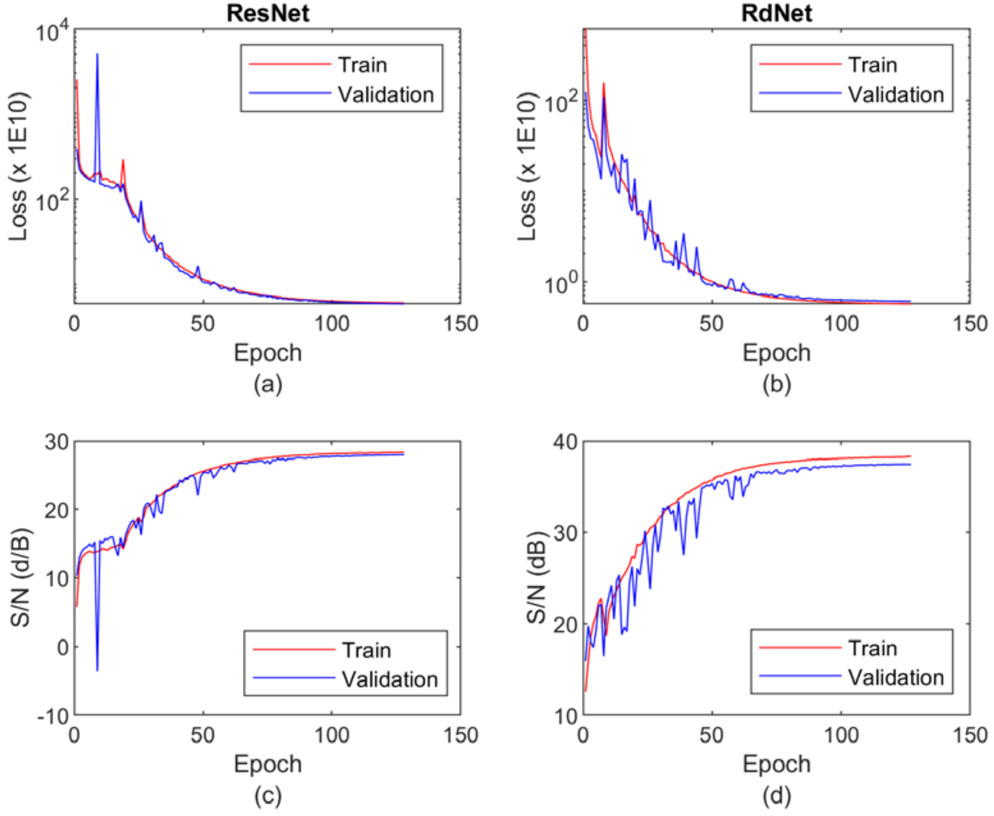


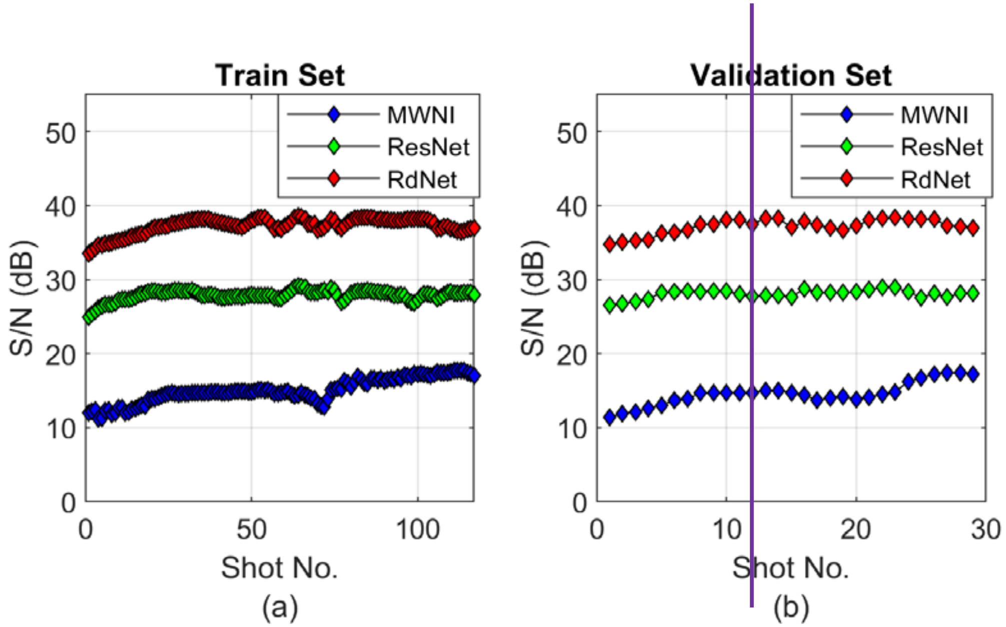
Synthetic Experiment

Training Result – Regularly missing traces

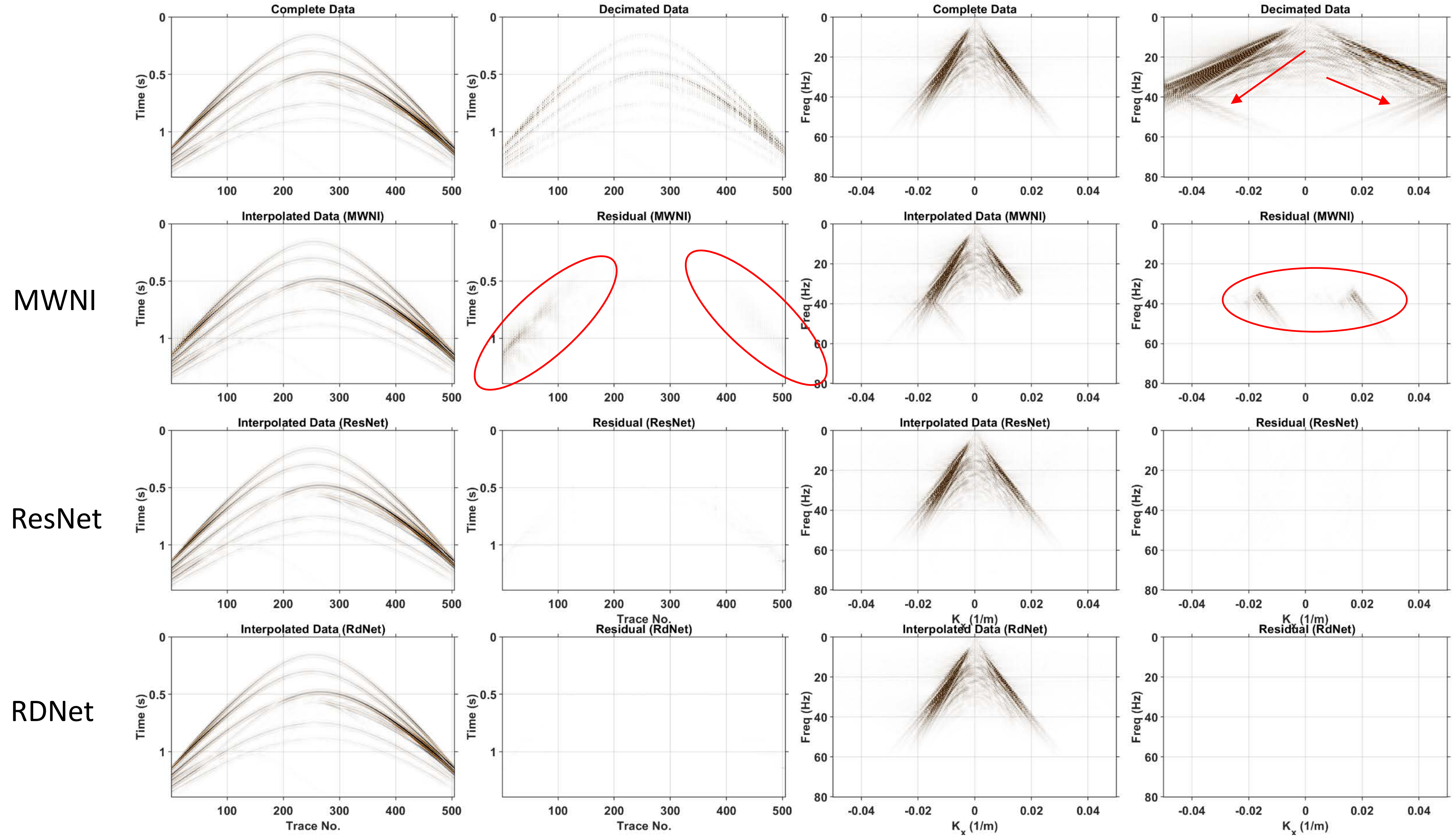


- Interpolation with 1/3 trace interval





Synthetic Experiment



SNR:
14.7, 27.7, 37.5

Synthetic Experiment

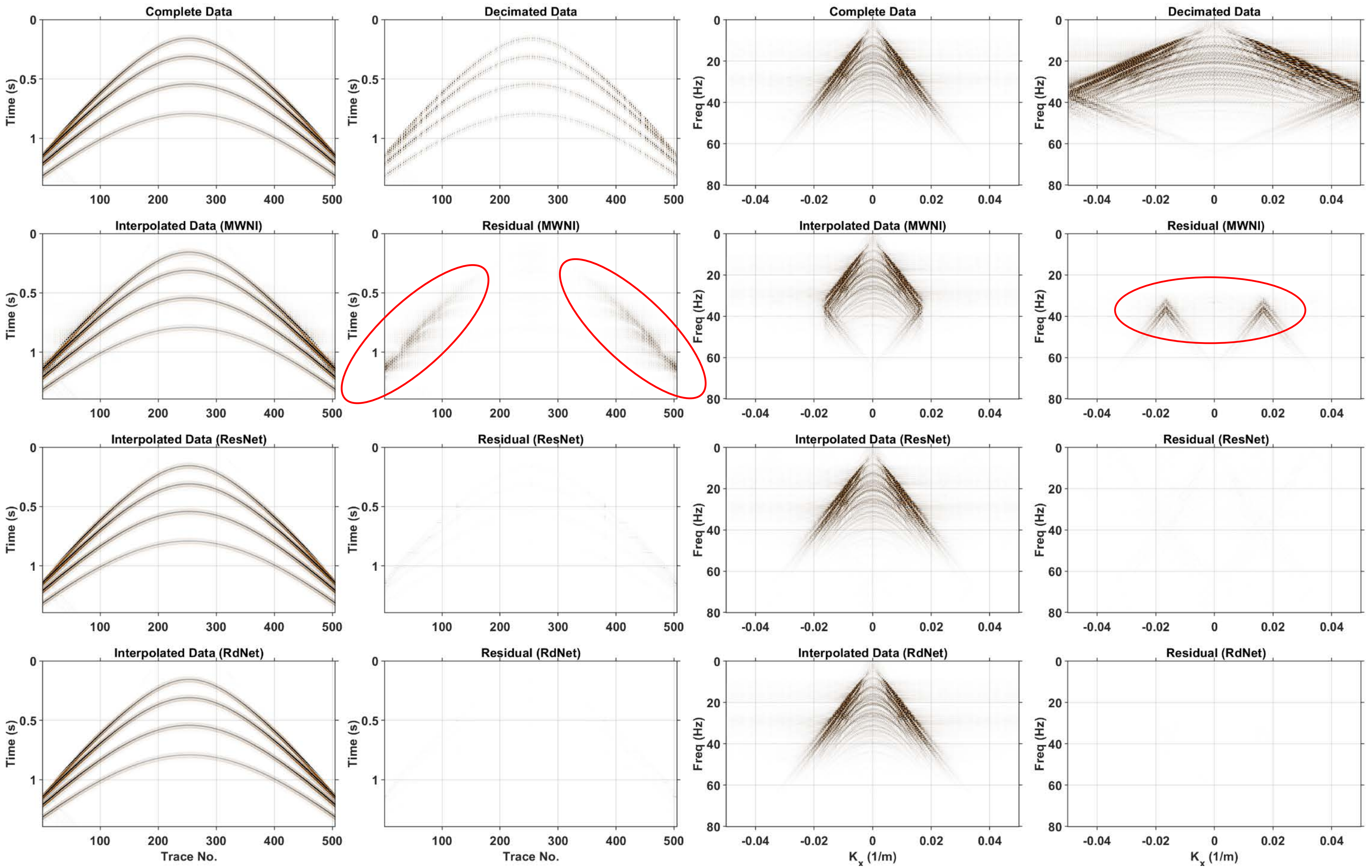
Test Shot #1

MWNI

ResNet

RDNet

SNR:
10.9, 27.7, 35.2



Synthetic Experiment

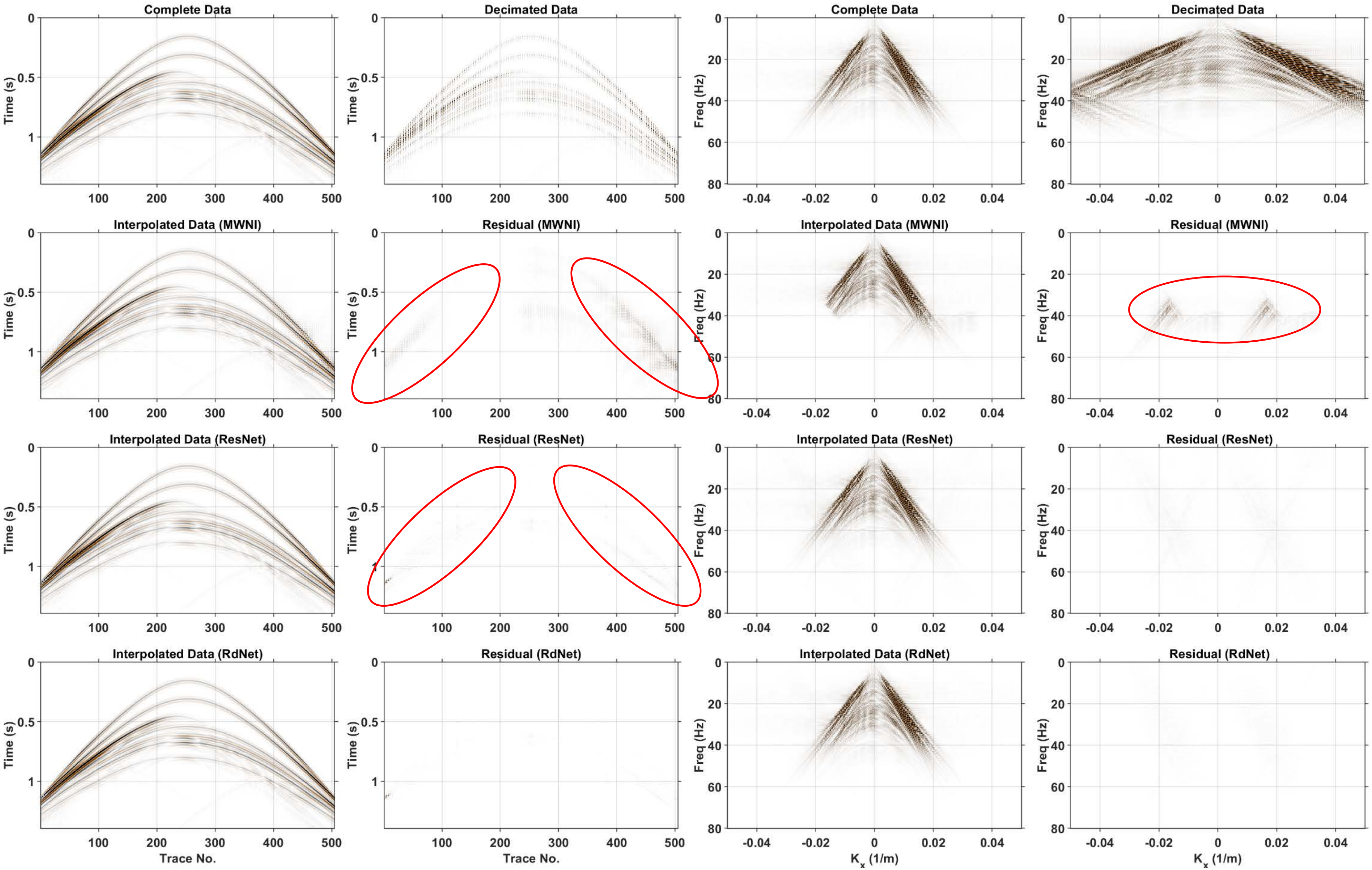
Test Shot #2

MWNI

ResNet

RDNet

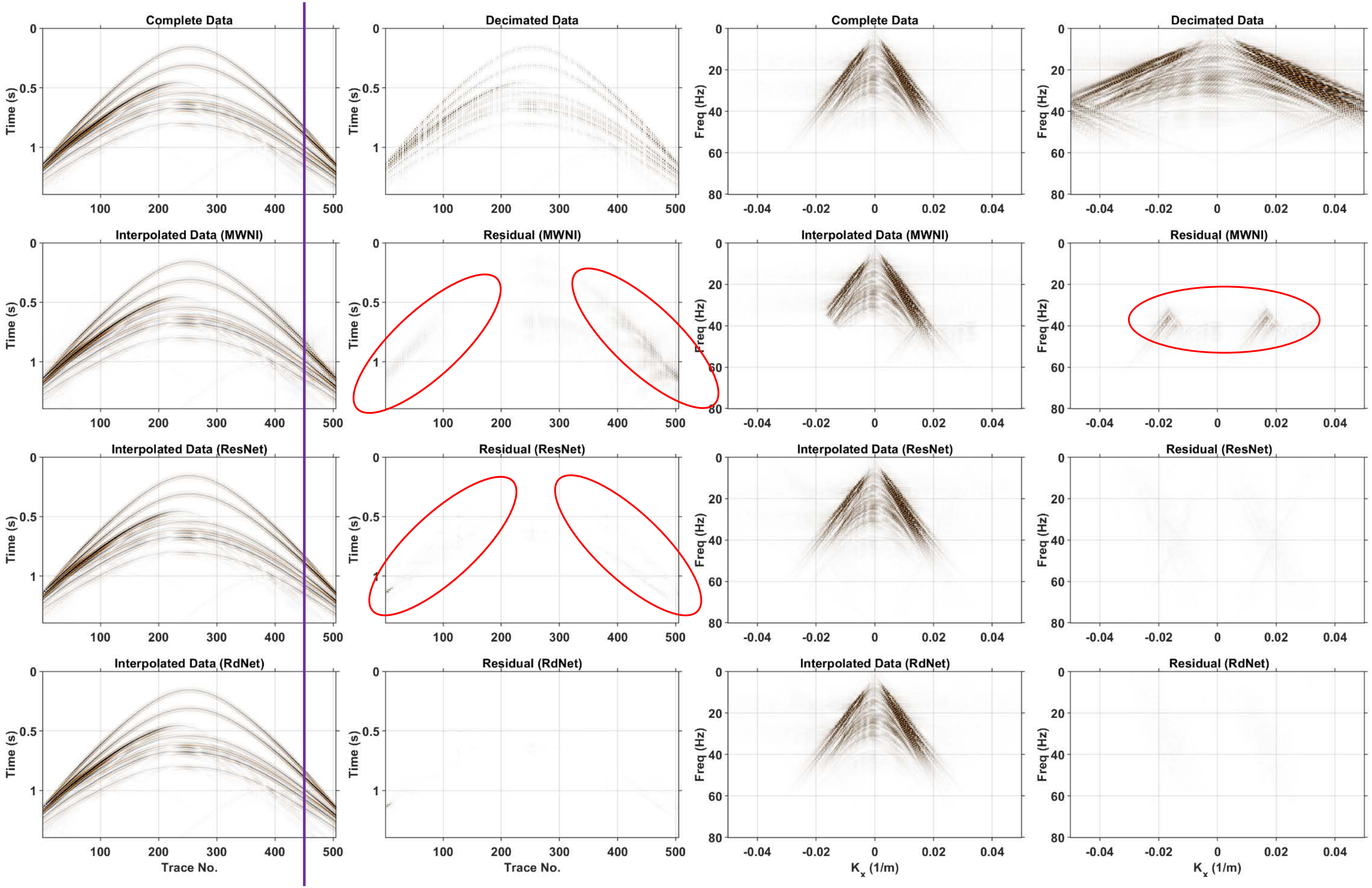
SNR:
15.5, 23.8, 27.7



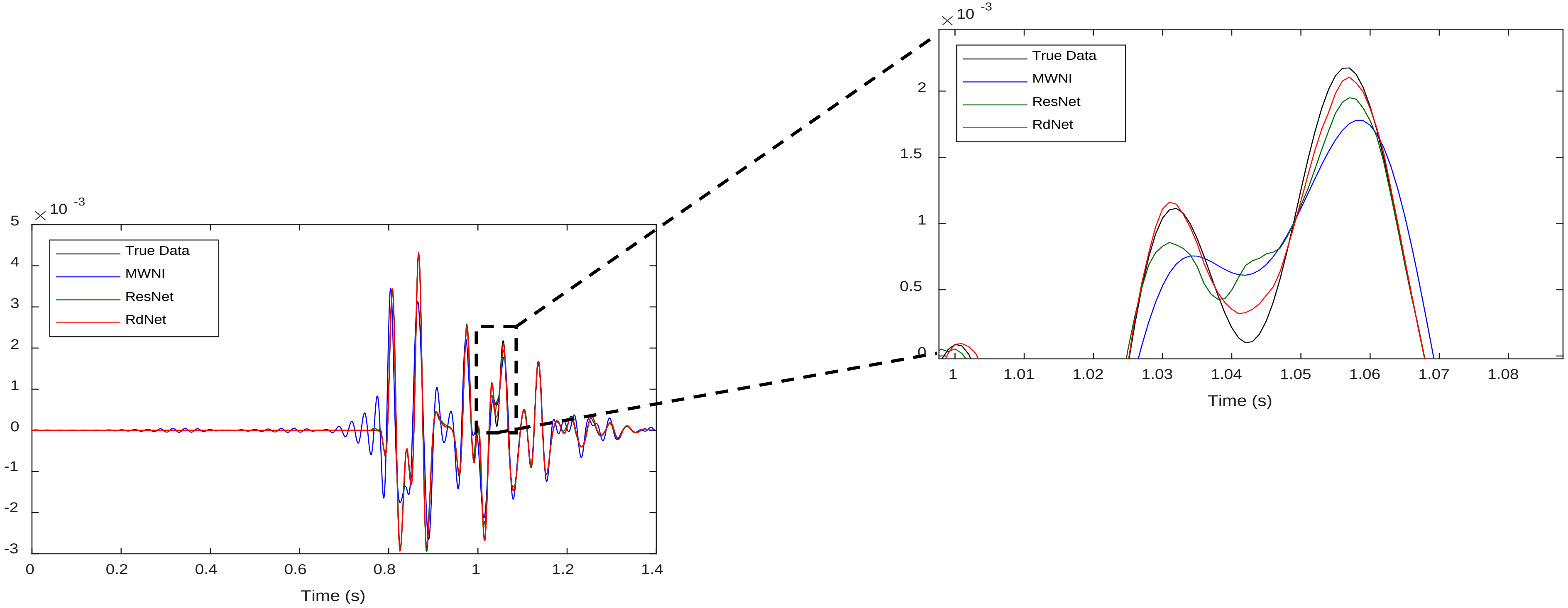
Synthetic Experiment

Test Shot #2

SNR:
15.5, 23.8, 27.7

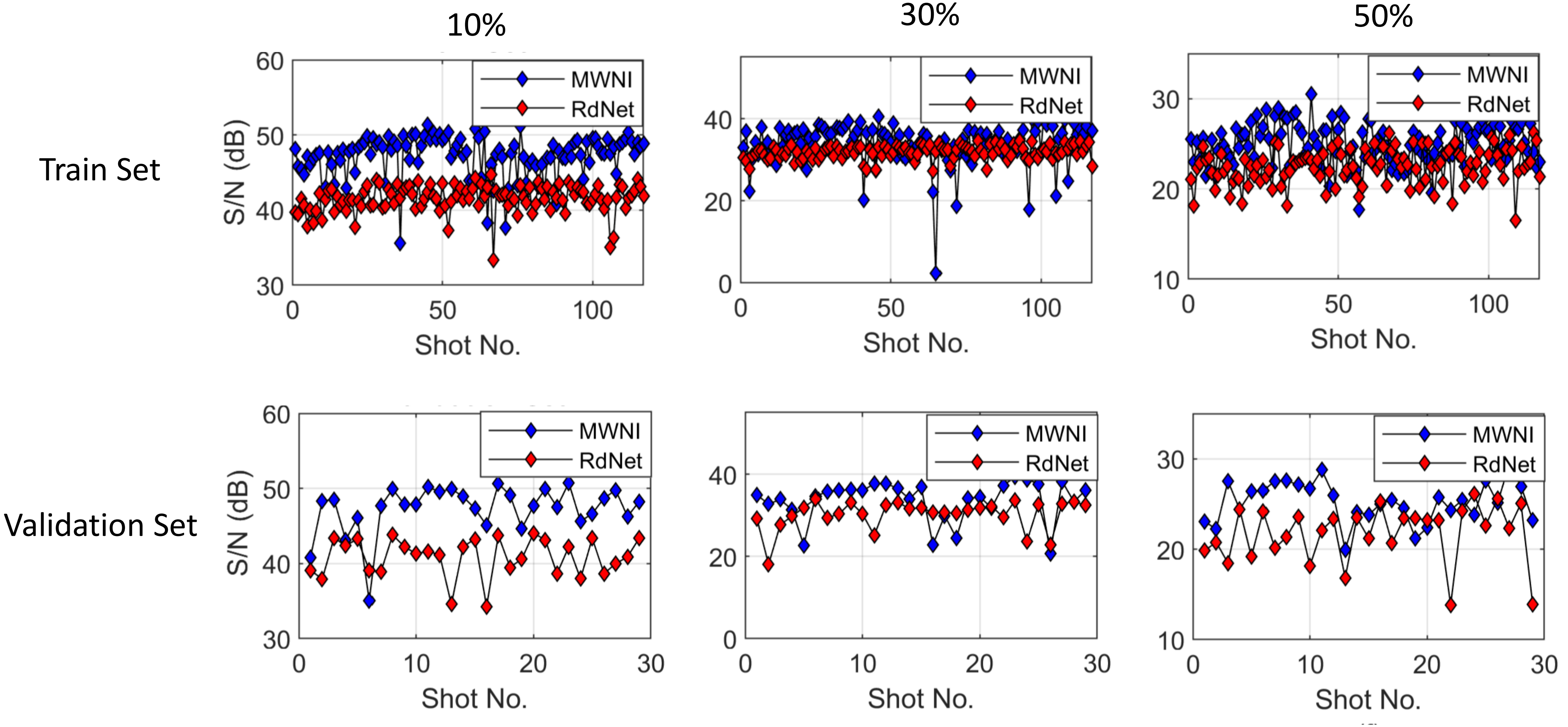


Training Result – Interpolation with 1/3 trace interval



Synthetic Experiment

Training Result – Randomly missing traces

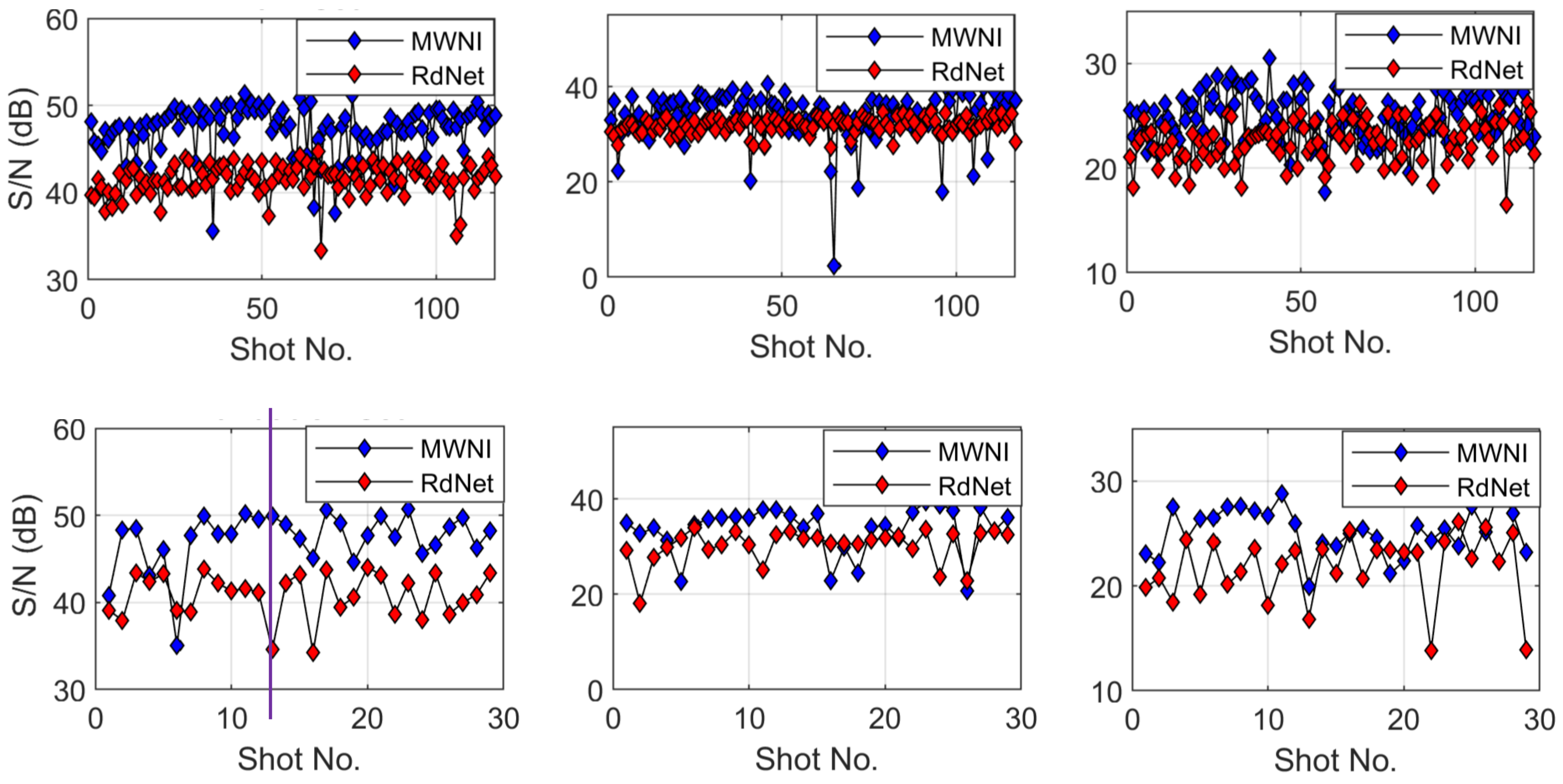


Training Result – Randomly missing traces

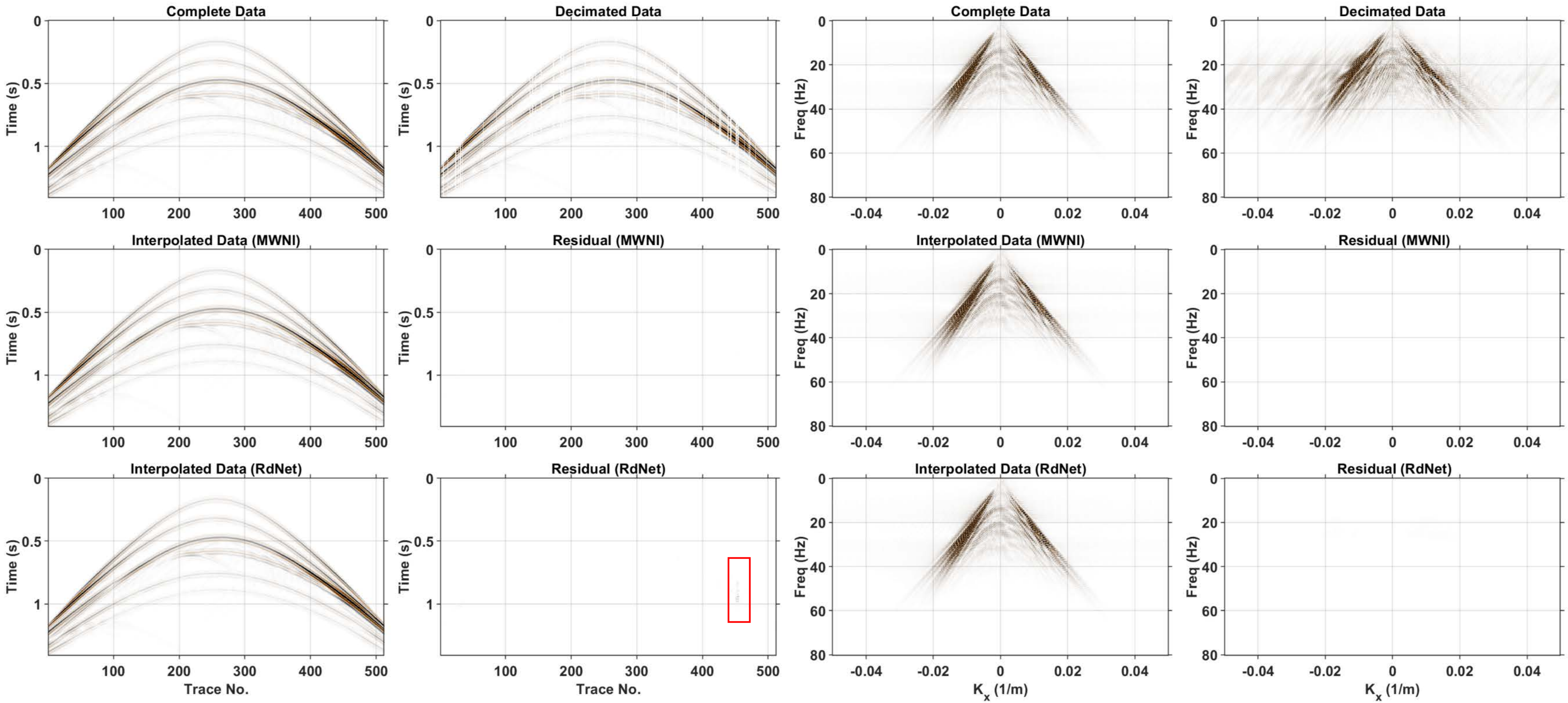
10% 30% 50%

Train Set

Validation Set



Synthetic Experiment

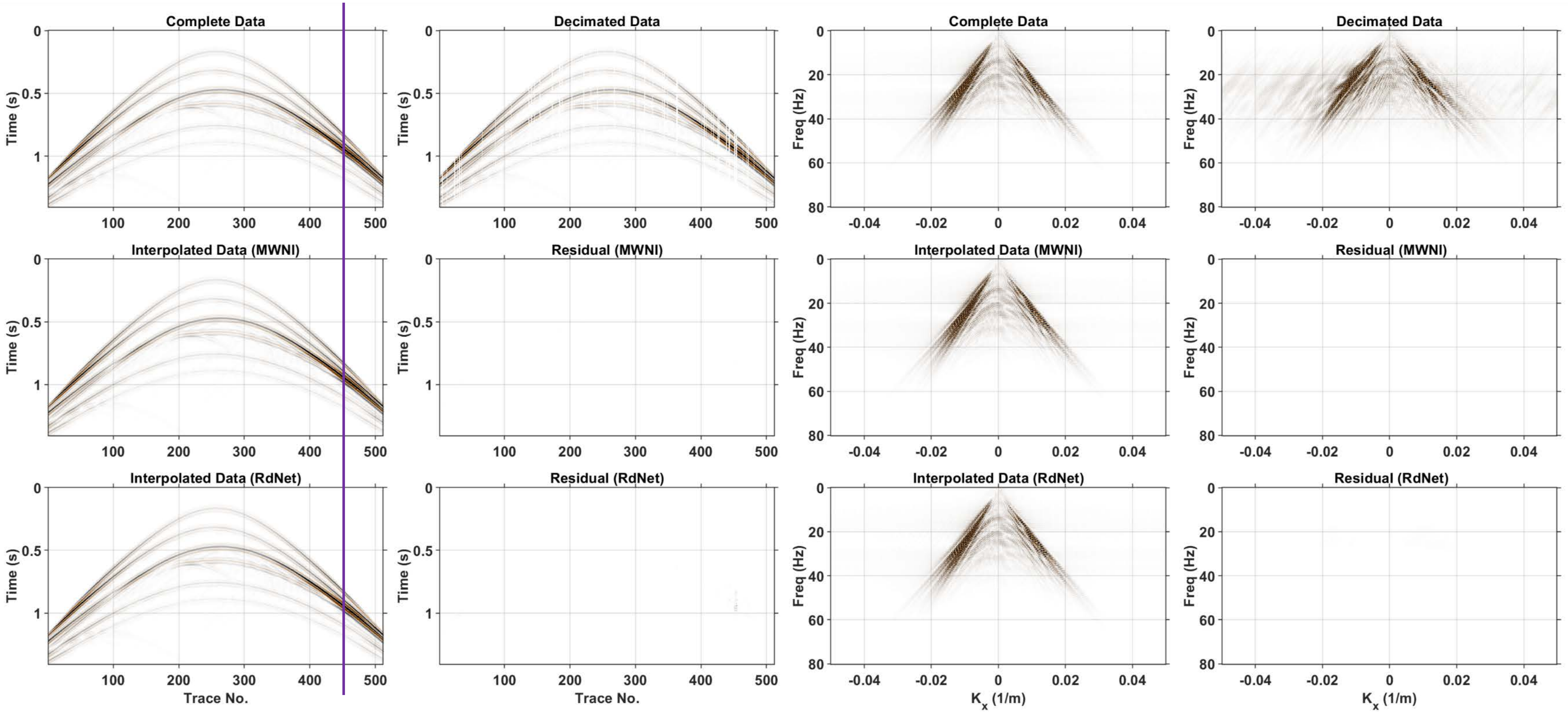


MWNI

RDNet

SNR: 49.9, 34.6

Synthetic Experiment



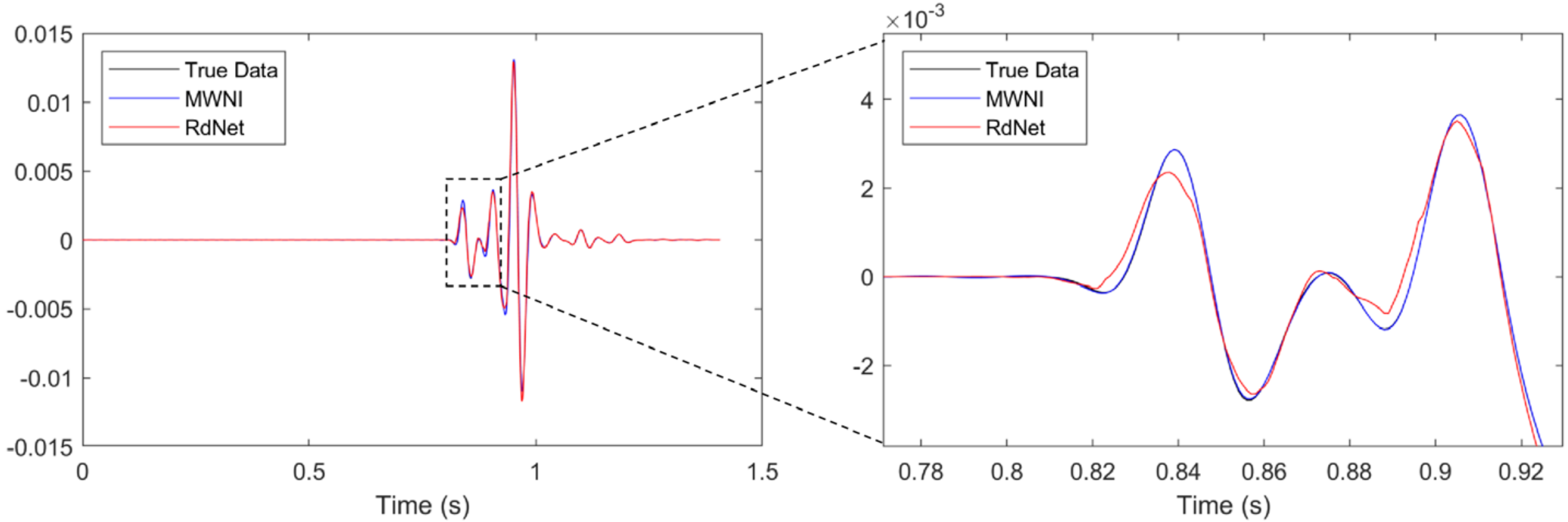
MWNI

RDNet

SNR: 49.9, 34.6

Synthetic Experiment

10% missing traces

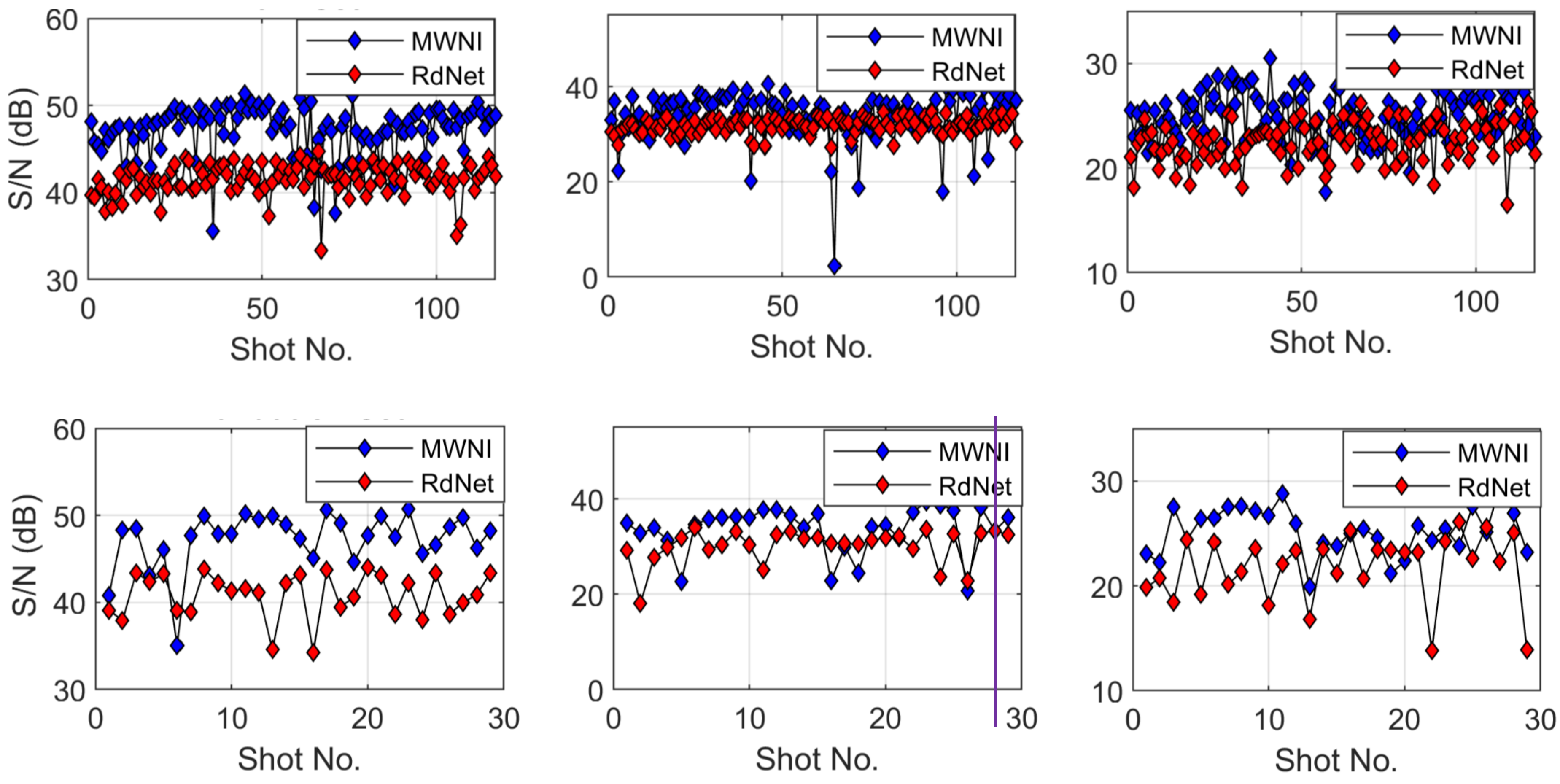


Training Result – Randomly missing traces

10% 30% 50%

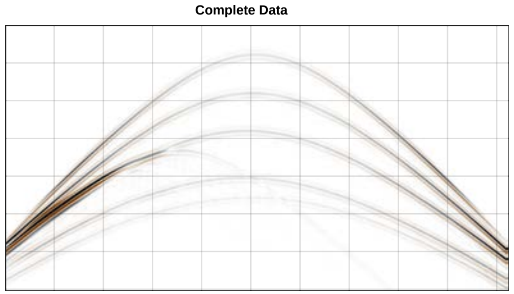
Train Set

Validation Set



Synthetic Experiment

30% missing traces



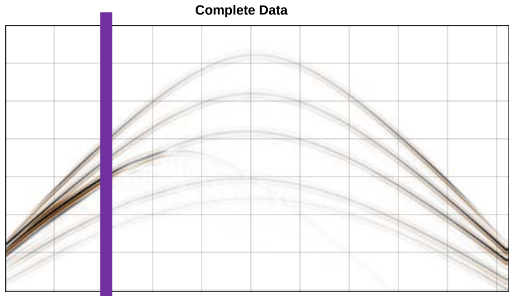
MWNI

RDNet

SNR: 36.1, 32.6

Synthetic Experiment

30% missing traces

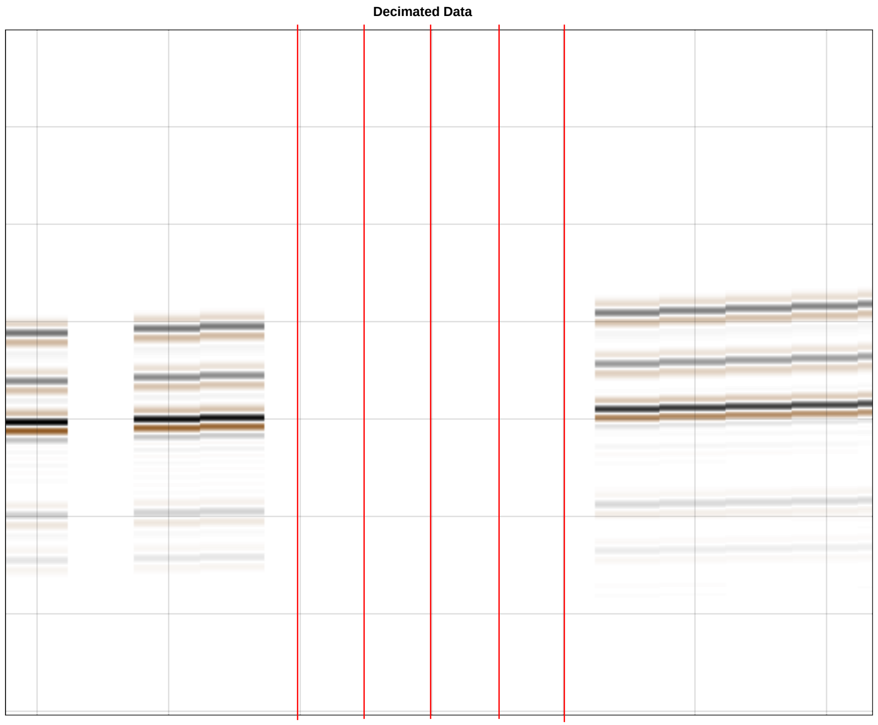


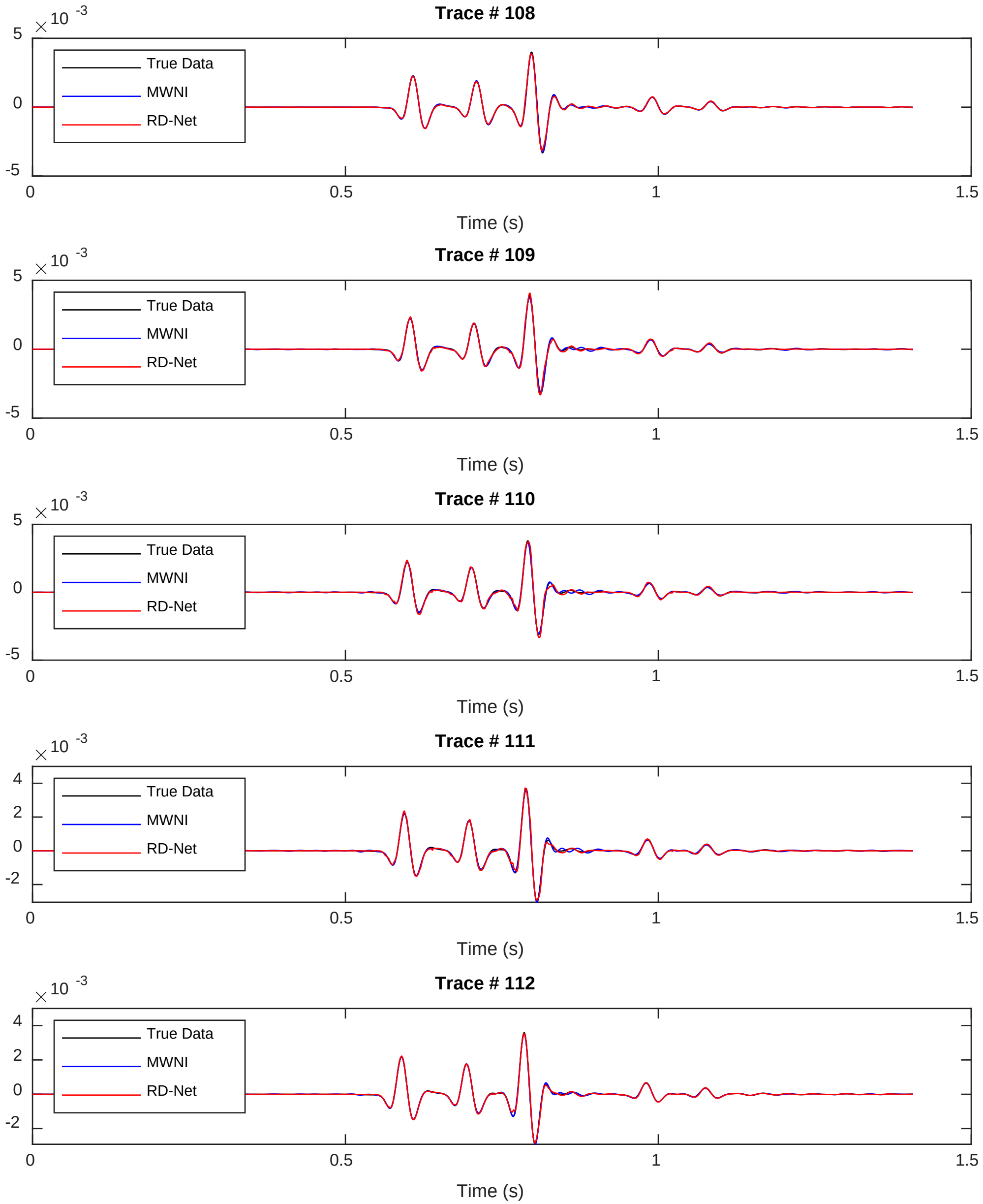
MWNI

RDNet

SNR: 36.1, 32.6

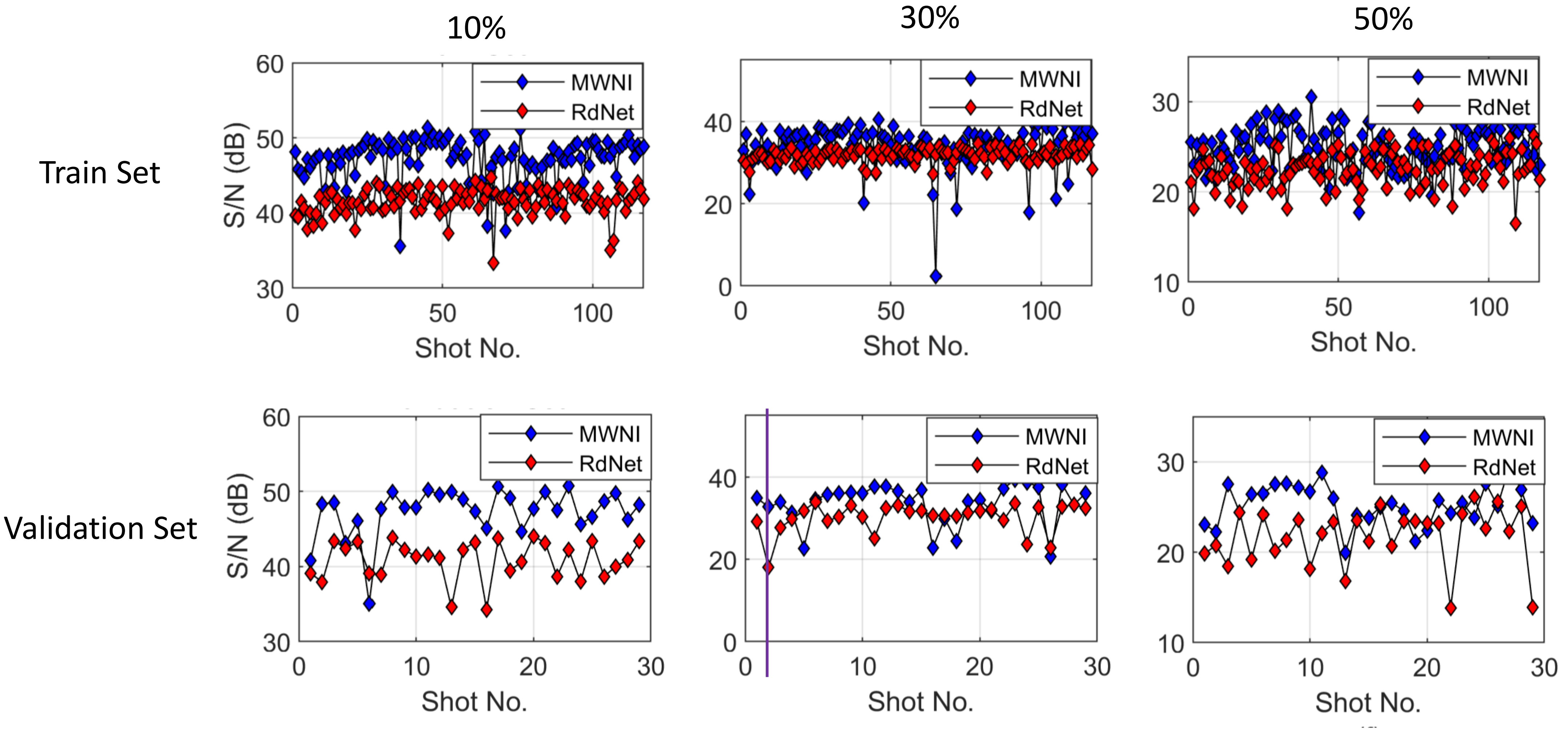
Synthetic Experiment





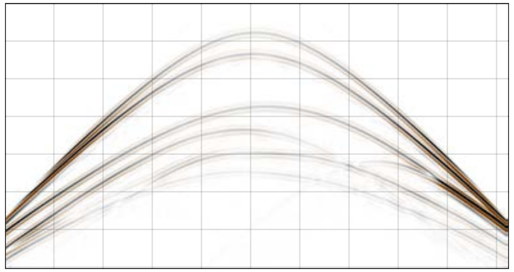
Synthetic Experiment

Training Result – Randomly missing traces



Synthetic Experiment

30% missing traces

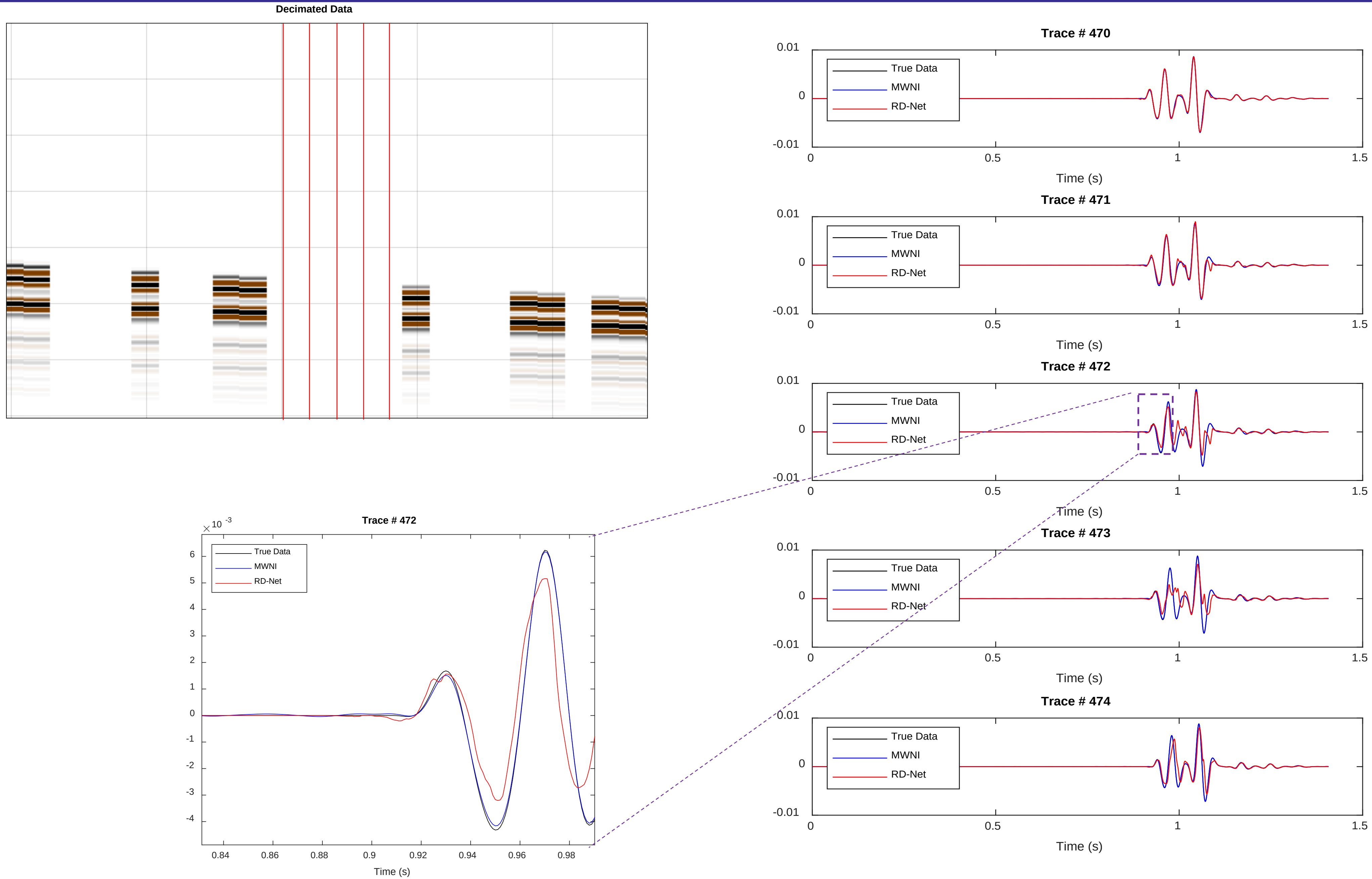


MWNI

RDNet

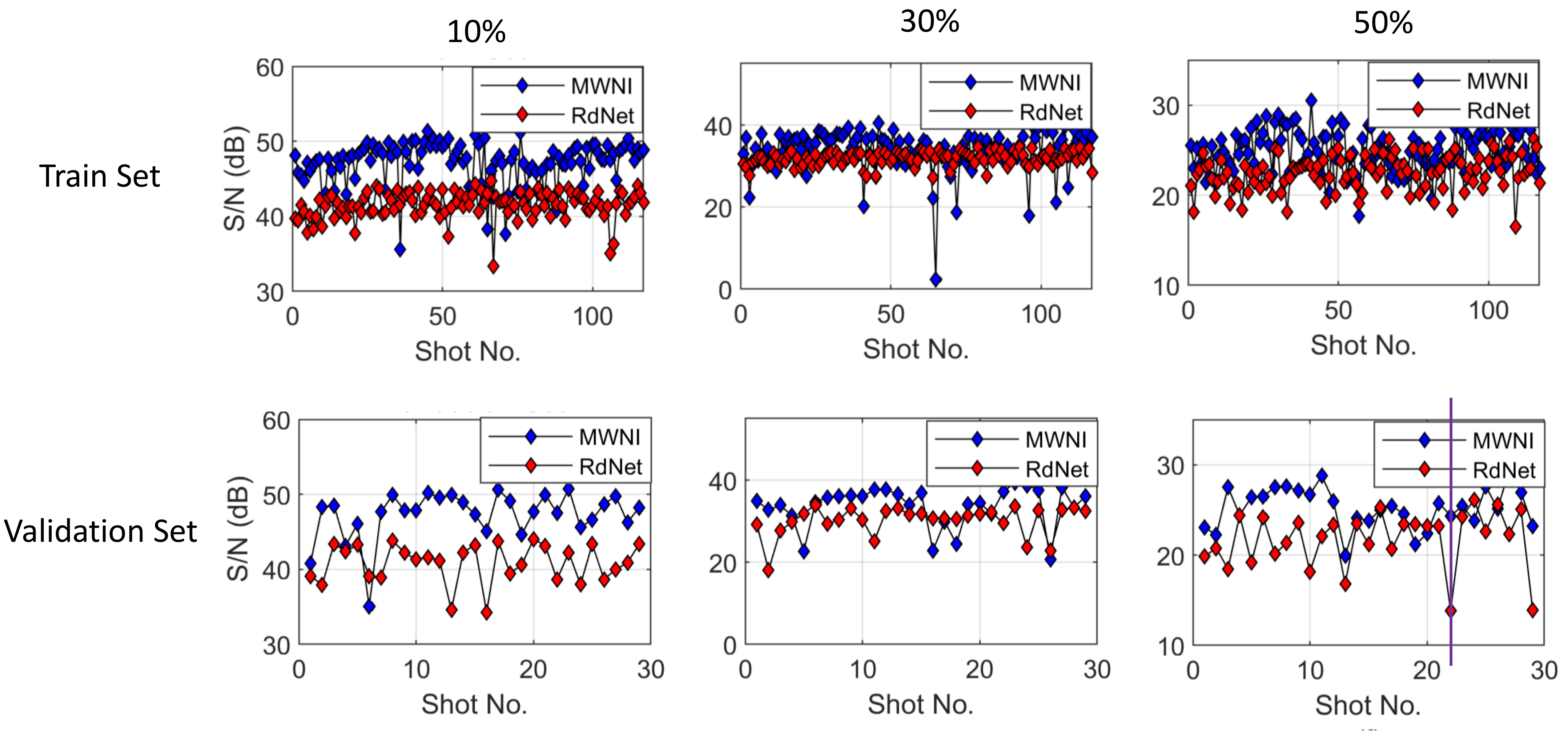
SNR: 32.7, 18.1

Synthetic Experiment



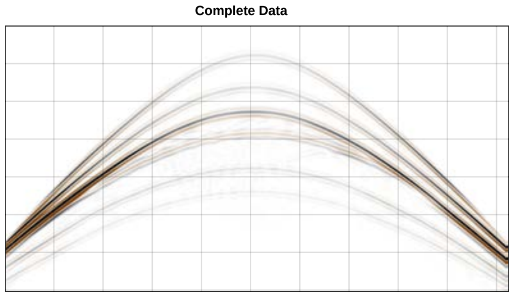
Synthetic Experiment

Training Result – Randomly missing traces



Synthetic Experiment

50% missing traces

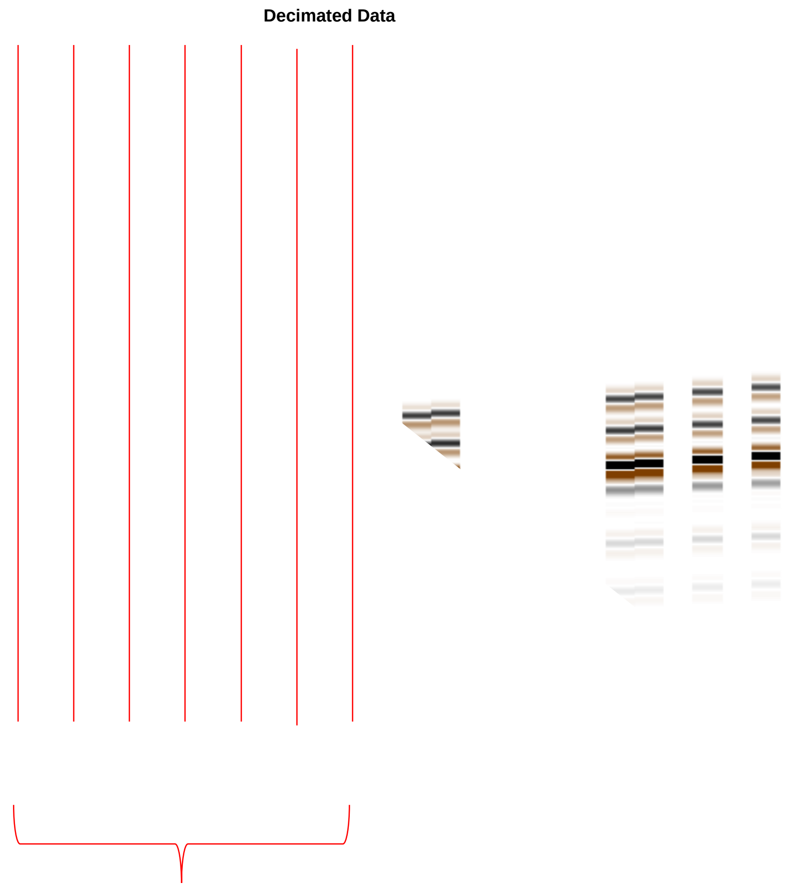


MWNI

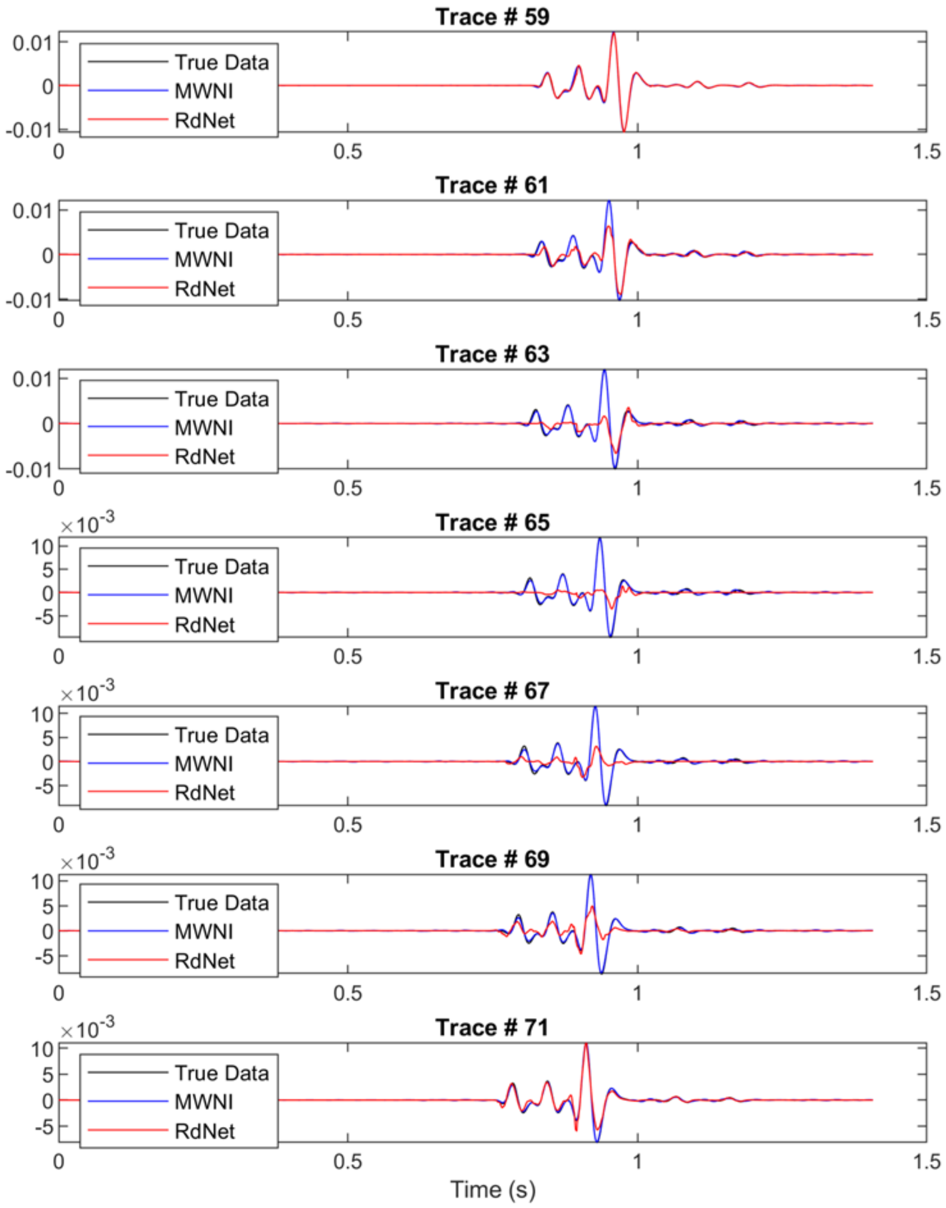
RDNet

SNR: 24.3, 13.9

Synthetic Experiment



14 consecutive missing traces



Summary

Residual Dense Network:

- Outperforms ResNet and MWNI in the case of regularly missing cases
- Accommodate spatial aliasing
- Produce comparable though slightly degraded results than MWNI for randomly missing cases
- Errors accrue in regions with big data gaps as missing percentage increases
- Simple application on 2D noise-free synthetic data, regular grid …

Acknowledgements

- All CREWES sponsors
- NSERC (CRDPJ 461179-13)
- Canada First Research Excellence Fund (CFREF)

Thank you!

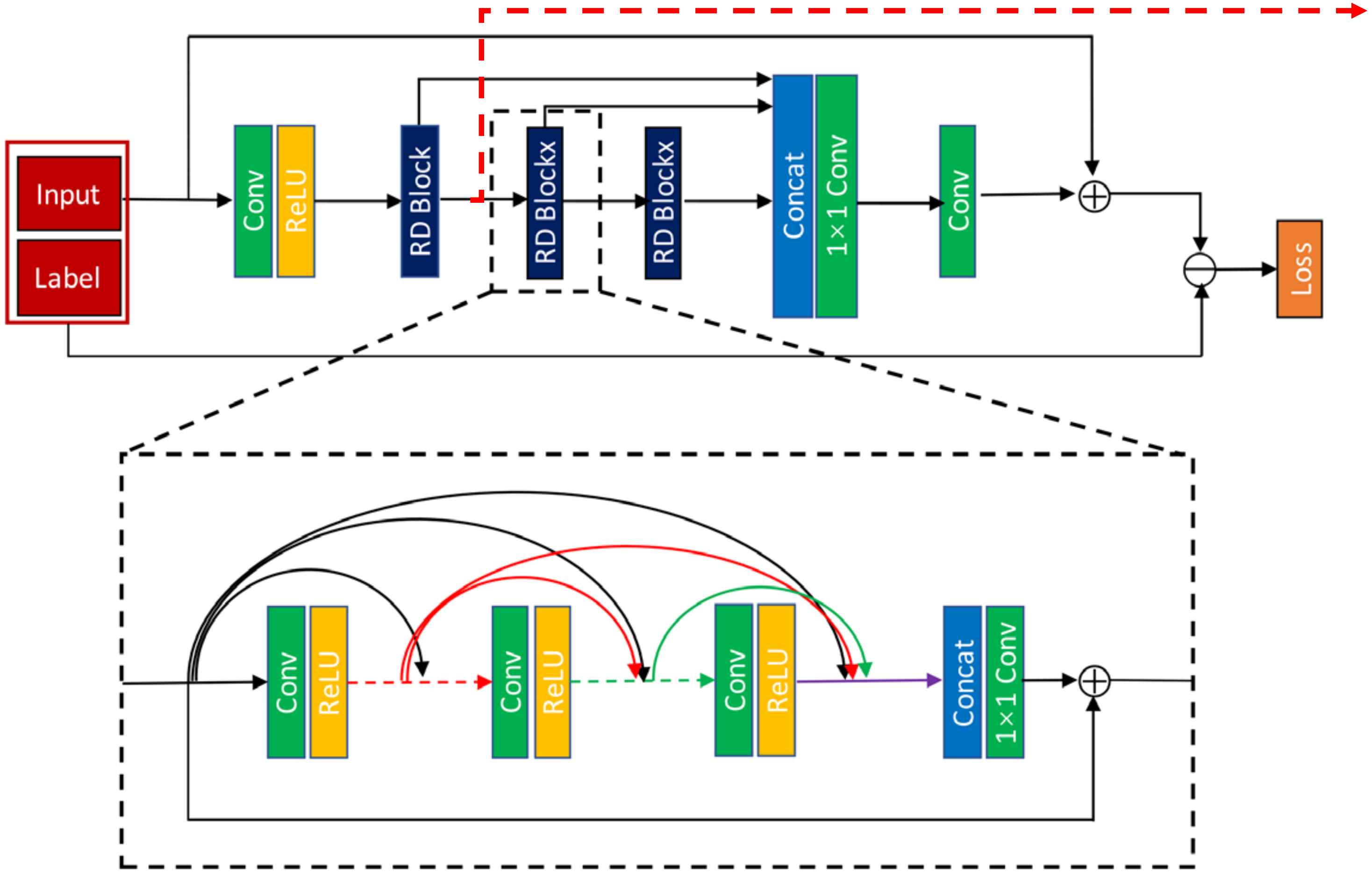
Result Summary

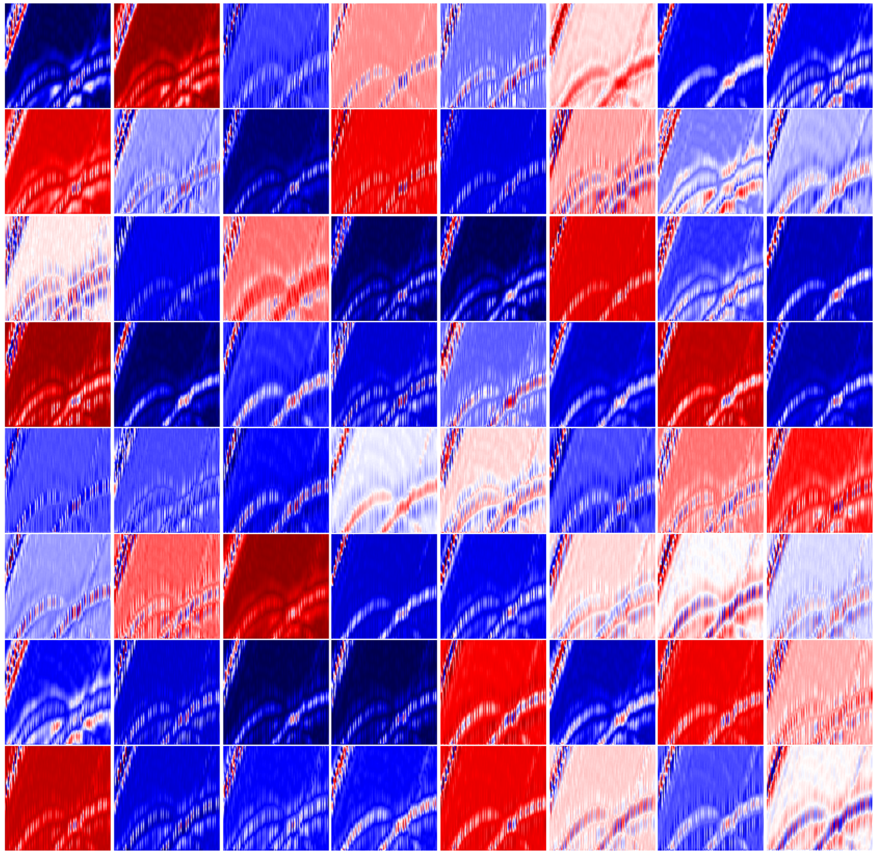
Interpolation Methods		Regularly Missing Cases		Randomly Missing Cases		
		1/2 of the original trace spacing	1/3 of the original trace spacing	10% missing traces	30% missing traces	50% missing traces
MWNI	Train Set	33.7	15.0	47.2	33.9	25.0
	Validation Set	33.8	14.6	47.3	33.7	25.2
	Test Set	32.0	13.2	42.7	34.4	21.7
ResNet	Train Set	36.5	27.9	N/A	N/A	N/A
	Validation Set	36.5	28.1	N/A	N/A	N/A
	Test Set	35.1	25.8	N/A	N/A	N/A
RdNet	Train Set	45.4	37.3	41.5	31.9	22.5
	Validation Set	45.2	37.2	40.9	30.2	21.7
	Test Set	42.5	31.4	41.1	31.7	22.7

No. of Parameters	727, 041
Size of Train Set	16,029
Size of Validation Set	3,973
Batch Size	16
GPU	GTX 1660 Ti, 6GB

Synthetic Experiment

Training Result – Regularly missing traces

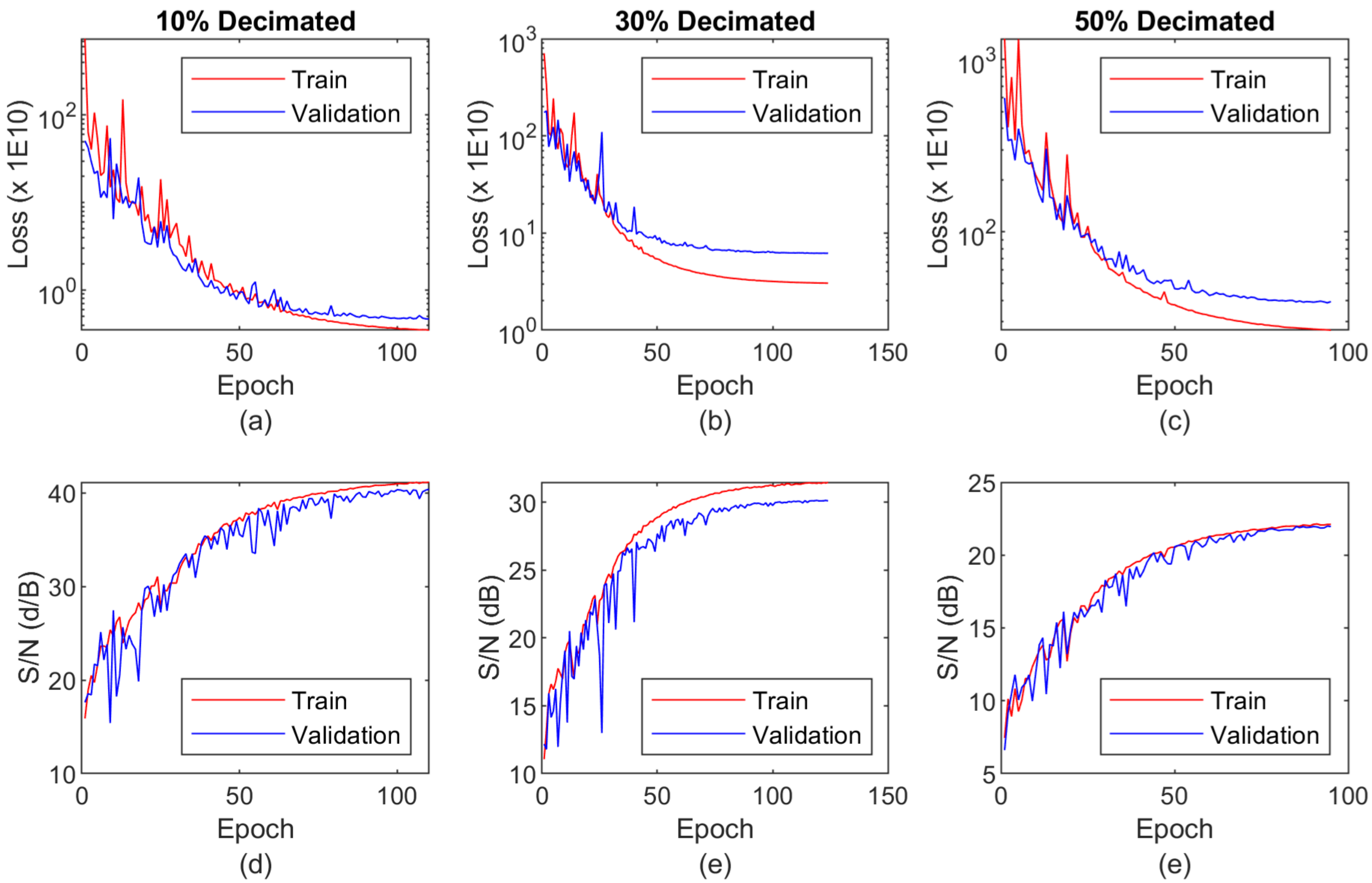




Training Result – Randomly missing traces

Loss

Recovered S/N

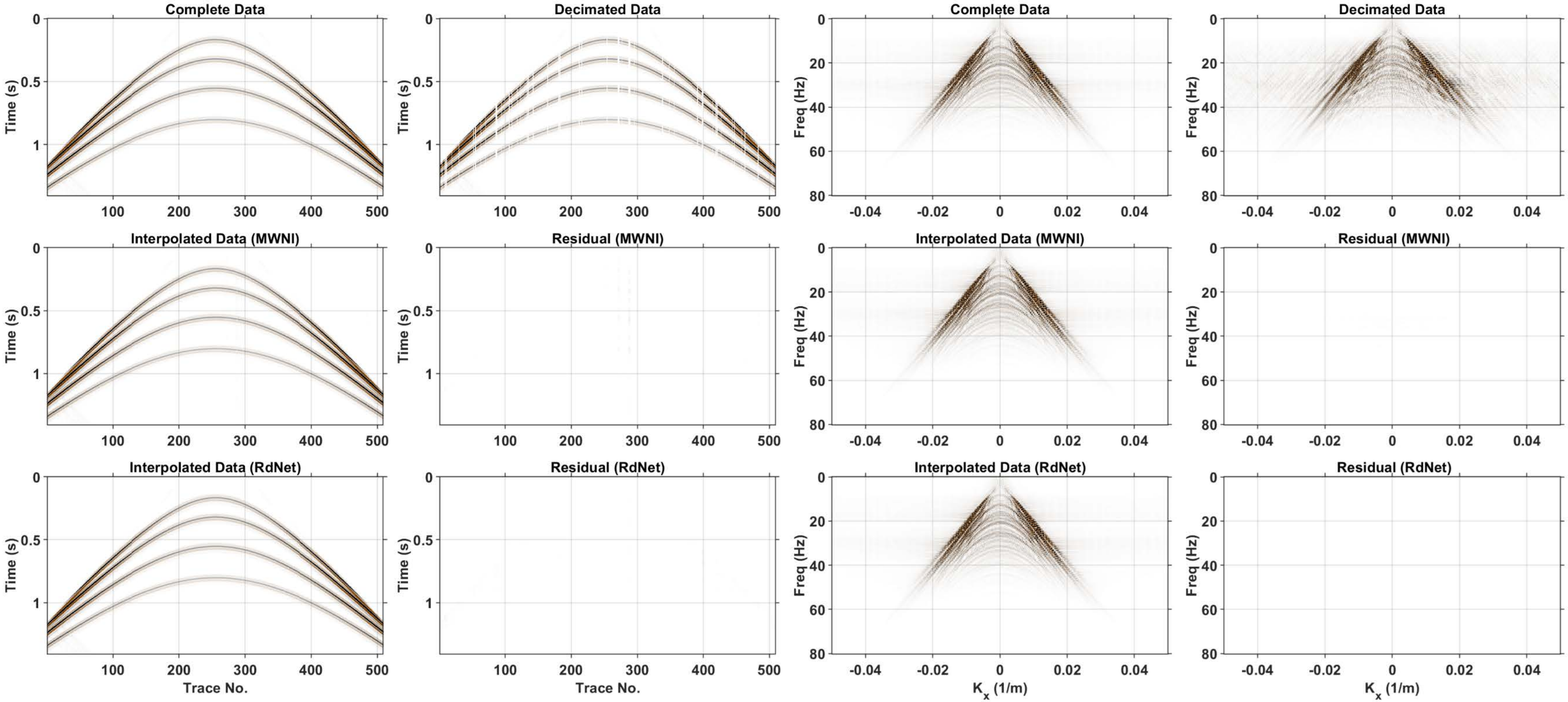


Synthetic Experiment

10% missing traces – Test Shot #1

MWNI

RDNet



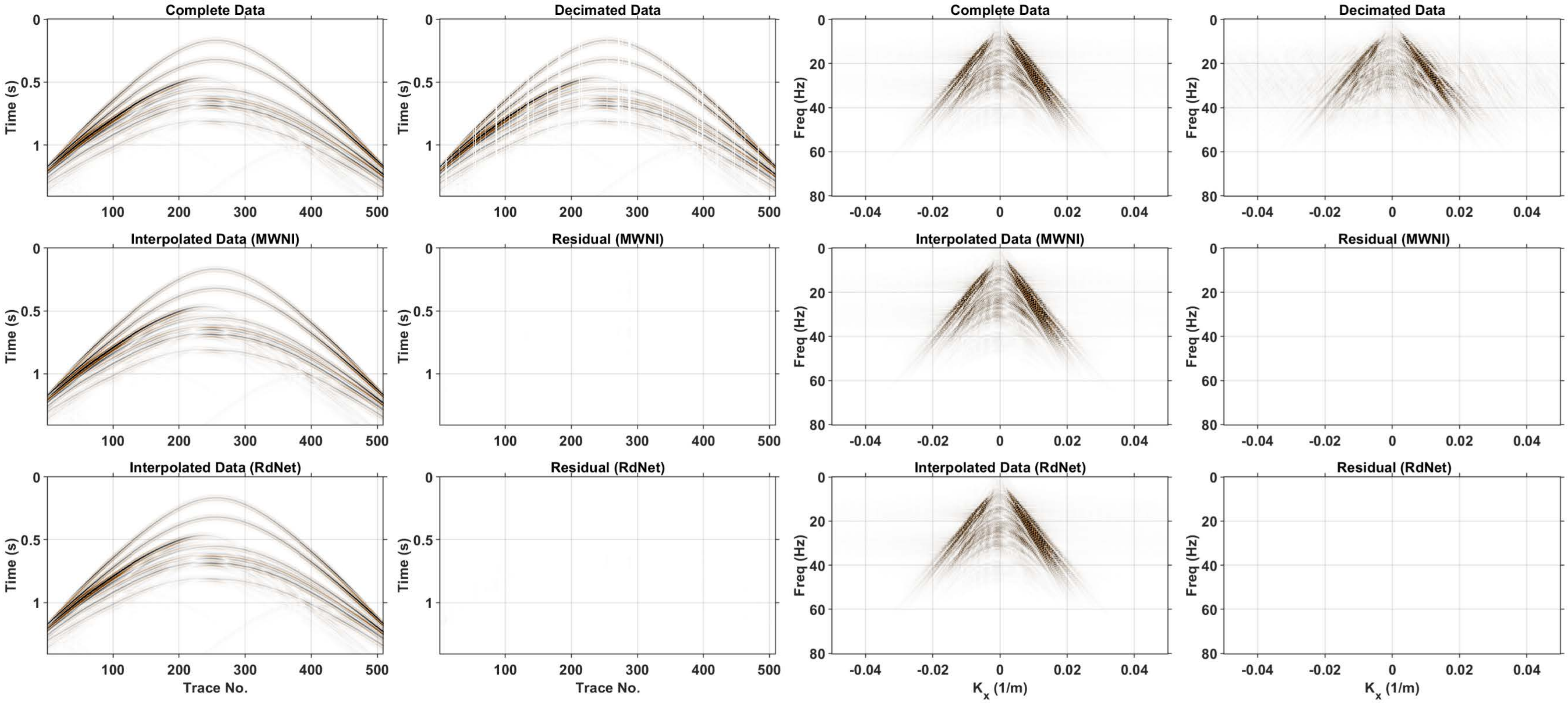
SNR: 39.7, 41.0

Synthetic Experiment

10% missing traces – Test Shot #2

MWNI

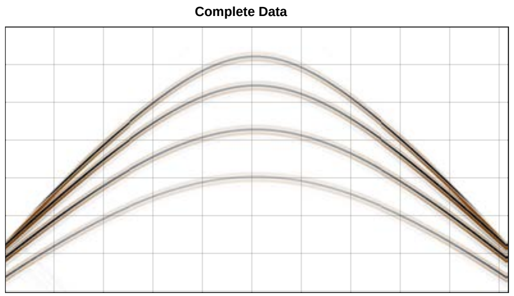
RDNet



SNR: 45.6, 41.2

Synthetic Experiment

30% missing traces – Test Shot #1



MWNI

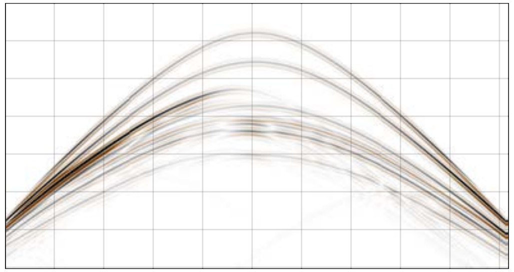
RDNet

SNR: 32.1, 31.3

Synthetic Experiment

30% missing traces – Test Shot #2

Complete Data



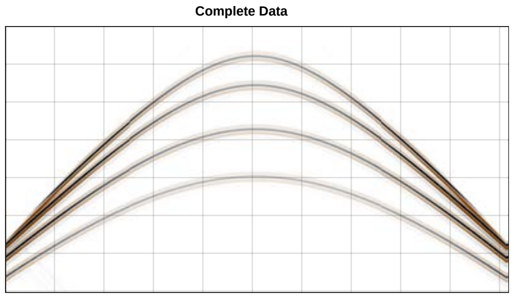
MWNI

RDNet

SNR: 36.7, 32.1

Synthetic Experiment

50% missing traces – Test Shot #1



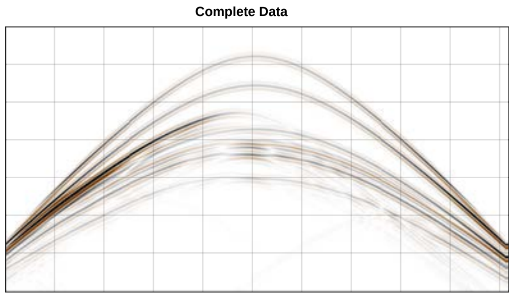
MWNI

RDNet

SNR: 19.1, 23.6

Synthetic Experiment

50% missing traces – Test Shot #2



MWNI

RDNet

SNR: 24.2, 21.7