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Interpolation Through Machine Learning

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Abstract

Inspired by image superresolution reconstruction, a CNN-based residual dense network (RdNet) is adopted for seismic trace interpolation. Synthetic examples demonstrate its effecitveness to reconstruct the regularly missing traces and accommodate spatial aliasing. Further studies are needed to improve its performance on randomly missing cases.

Introduction

Previous research has attempted to apply machine learning techniques to the interpolation of missing seismic traces, and obtained some promising results, e.g., **Jia et al. (2018)** used a support vector regression (SVR) approach integrated with Monte Carlo analysis for seismic data interpolation, in which only the effective part of patches are selected for training, and the missing traces are generated from the learned regression model; **Wang et al. (2019)** adopted an eight-layer residual learning network, Residual Network (ResNet), to reconstruct the regularly missing traces with high accuracy. This algorithm could avoid some certain assumptions (e.g., linear events, sparsity and low-rank) that most conventional interpolation algorithms typically use.

In this study, the RdNet is used to interpolate both regularly and randomly missing traces based on 2D sythetic data. Comparisons are made with the interpolation results using ResNet and MWNI.

Method

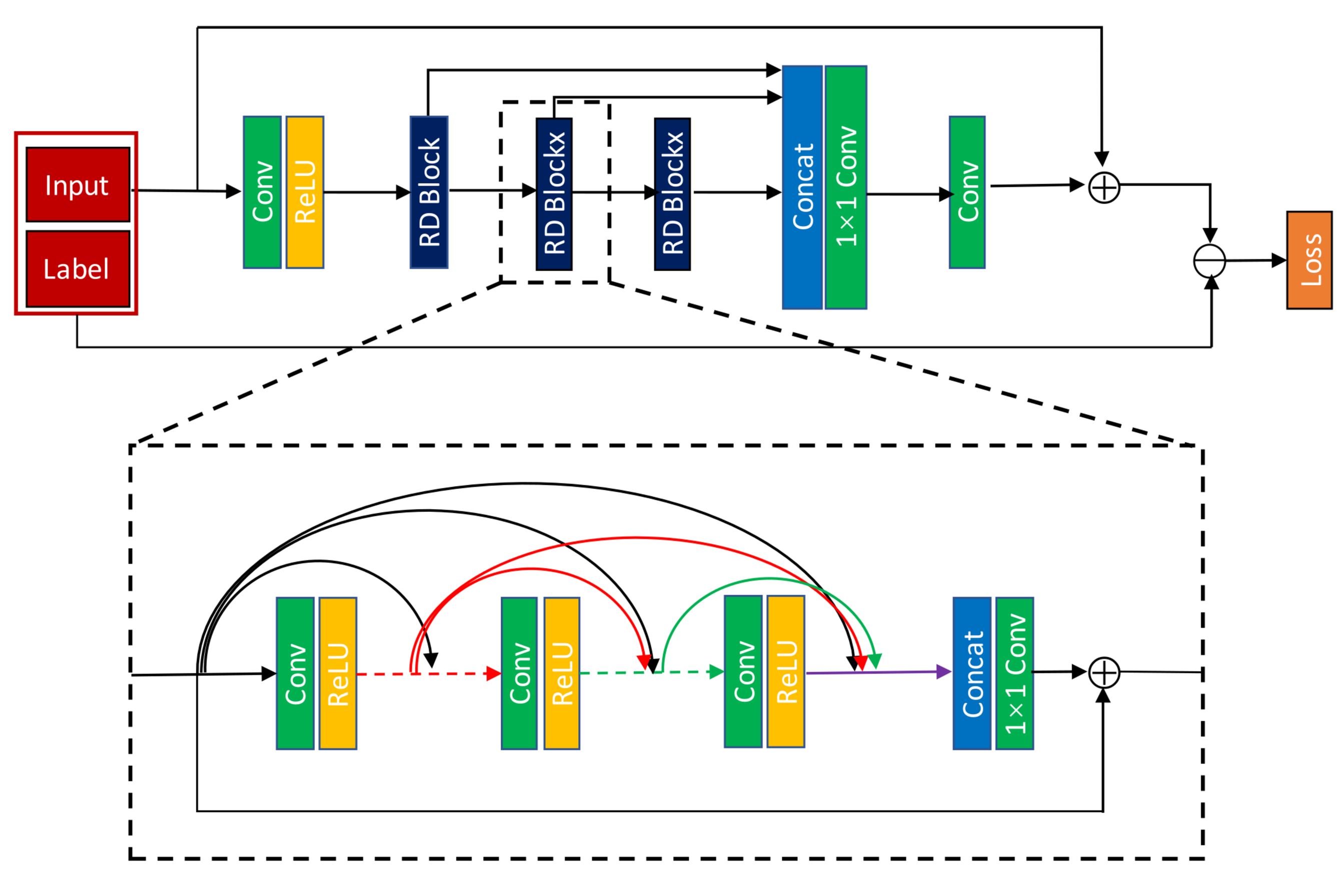

Figure 1: The architecture of the RdNet (modified from **Zhang et al., 2018**).

Key features of RdNet:

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

Loss Function - Mean Squared Error (MSE):

$$L = \frac{1}{n}\sum_{i=1}^{n}[D_{label} - D_{int}]^2, \tag{1}$$

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

$$M = 20\log_{10}\frac{||D_{label}||_2}{||D_{label} - D_{int}||_2}, \tag{2}$$

Data Set

Synthetic seismic data are generated based on a 2D velocity model (Figure 2). The training is implemented in a patch-wise fashion. In total, $\sim$20,000 patches are generated, 20% of which are used for training and 80% for validation.

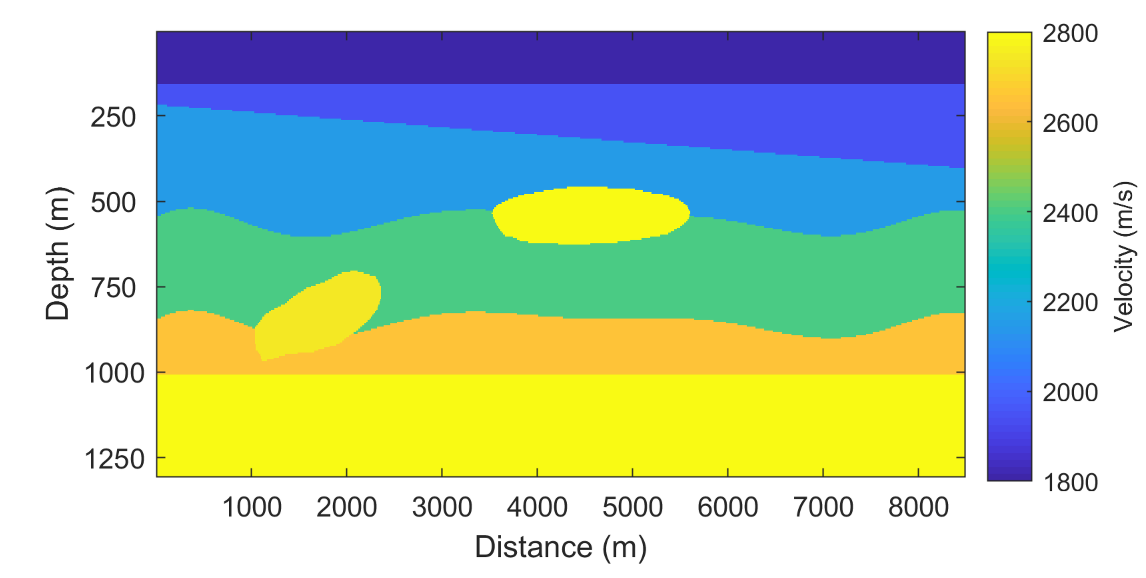

Figure 2: Velocity model used to generate synthetic data.

Parameters for forward modeling:

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

Results

- **Regularly missing cases:** Reconstruct seismic traces with 1/2 and 1/3 of the original trace spacing, respectively.
- **Randomly missing cases:** Reconstruct 10%, 30% and 50% randomly missing traces, respectively.

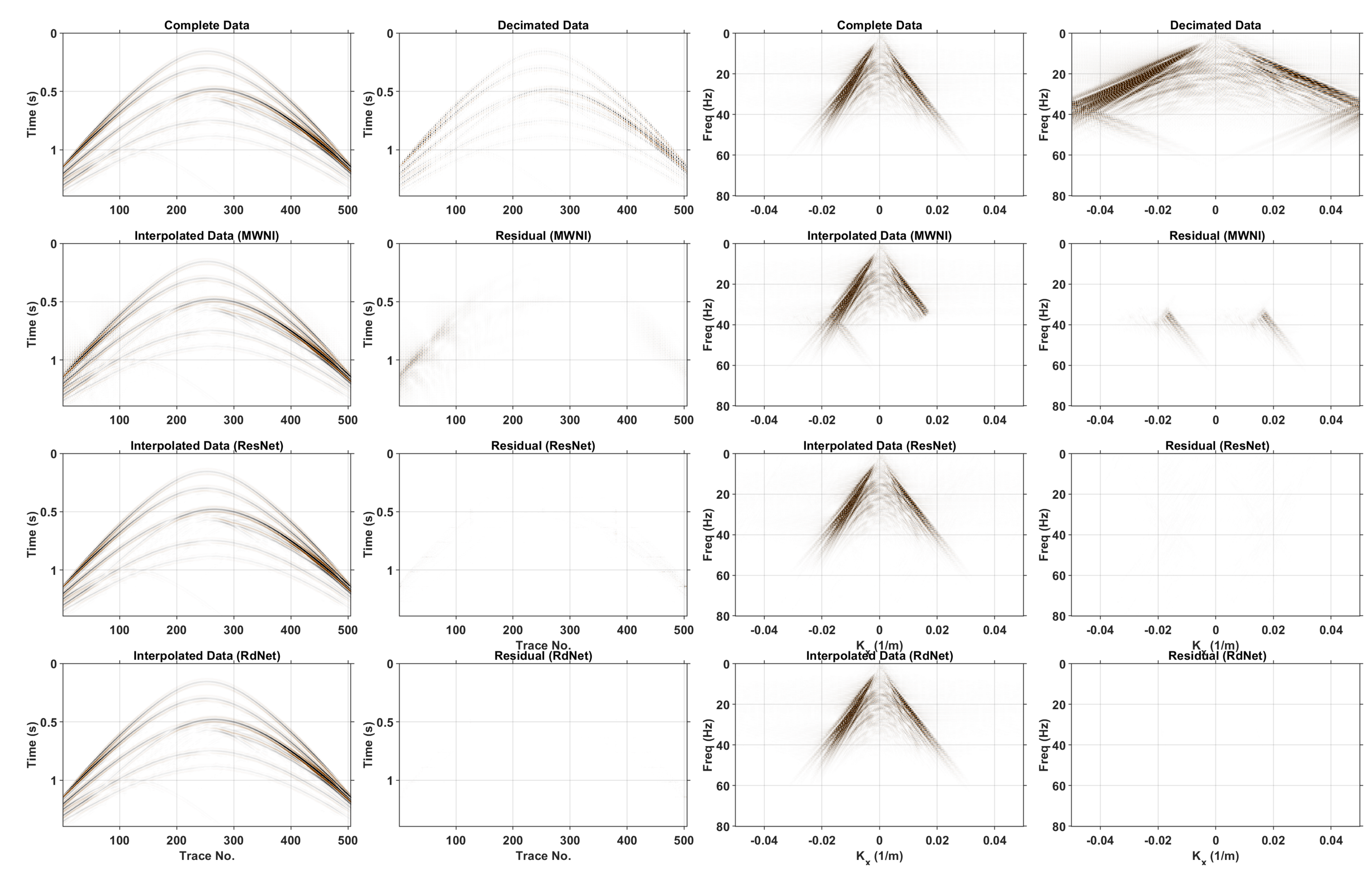

Figure 3: Interpolation results (for validation shot #12) with 1/3 of original trace interval. S/Ns for the reconstructed shot gathers are 14.7, 27.7 and 37.5 dB, respectively.

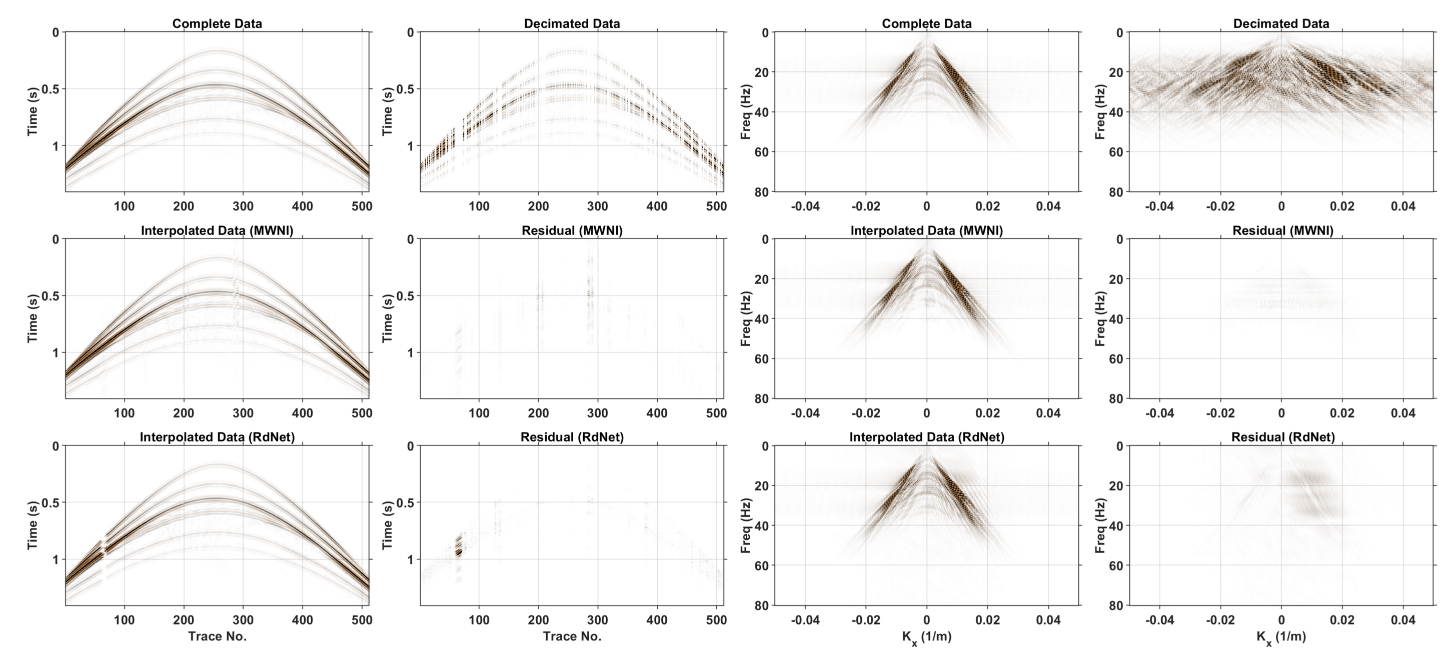

Figure 4: Interpolation results of validation shot #22 for the case of 50% missing traces. S/Ns for the reconstructed shot gather are 24.3 and 13.9, respectively.

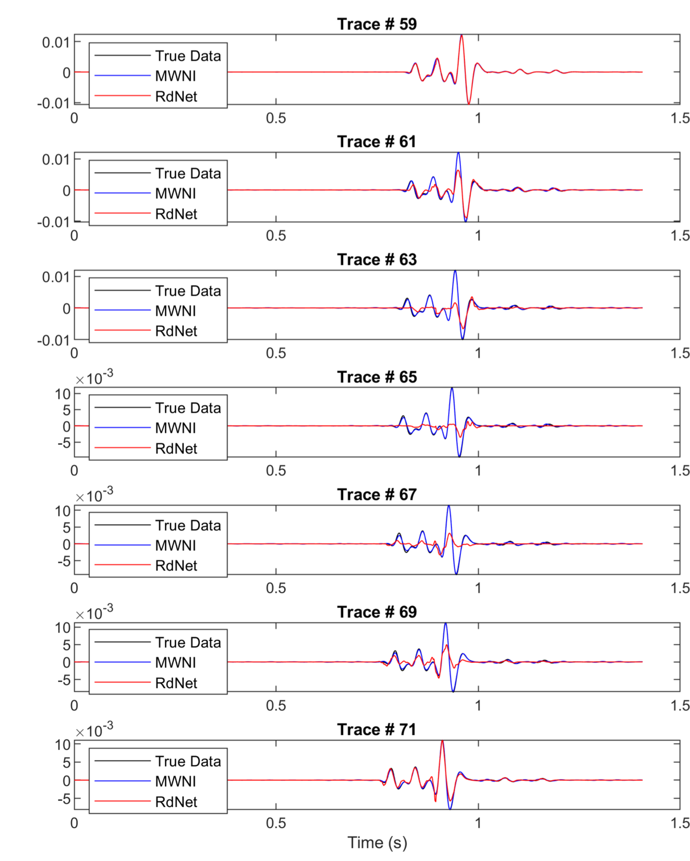

Figure 5: Interpolation results of five traces using RdNet for the shot gather in Figure 4.

Table 1: Average recovered S/N (in dB) using three interpolation methods.

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	33.7	15.0	47.2	33.9	25.0
	Validation	33.8	14.6	47.3	33.7	25.2
	Test	32.0	13.2	42.7	34.4	21.7
ResNet	Train	36.5	27.9	N/A	N/A	N/A
	Validation	36.5	28.1	N/A	N/A	N/A
	Test	35.1	25.8	N/A	N/A	N/A
RdNet	Train	45.4	37.3	41.5	31.9	22.5
	Validation	45.2	37.2	40.9	30.2	21.7
	Test	42.5	31.4	41.1	31.7	22.7

Conclusions

- RdNet outperforms ResNet and MWNI in regularly missing cases, and could accommodate spatial aliasing.
- RdNet can generate comparable though degraged results than MWNI for the randomly missing cases.
- With the increase of percentage of missing traces, interpolation errors are likely to focus in the area with large trace-gap, which is expected to be solved by including more train data.
- Neural network training is implemented on a simple dataset (2D synthetic data) and regular grid. Future research will consider more complex scenarios.

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