Clutter Removal in Ground-Penetrating Radar Images Using Deep Neural Networks

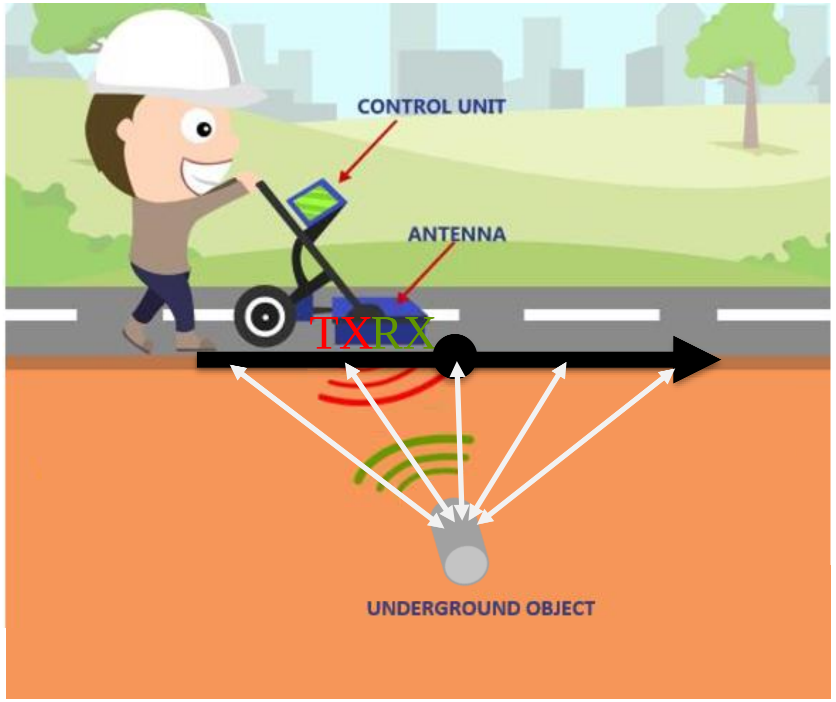
Hai-Han Sun, Weixia Cheng, and Zheng Fan

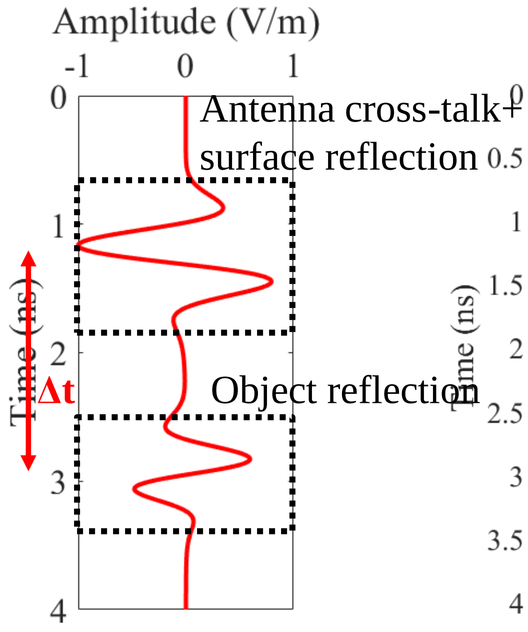
Nanyang Technological University, Singapore

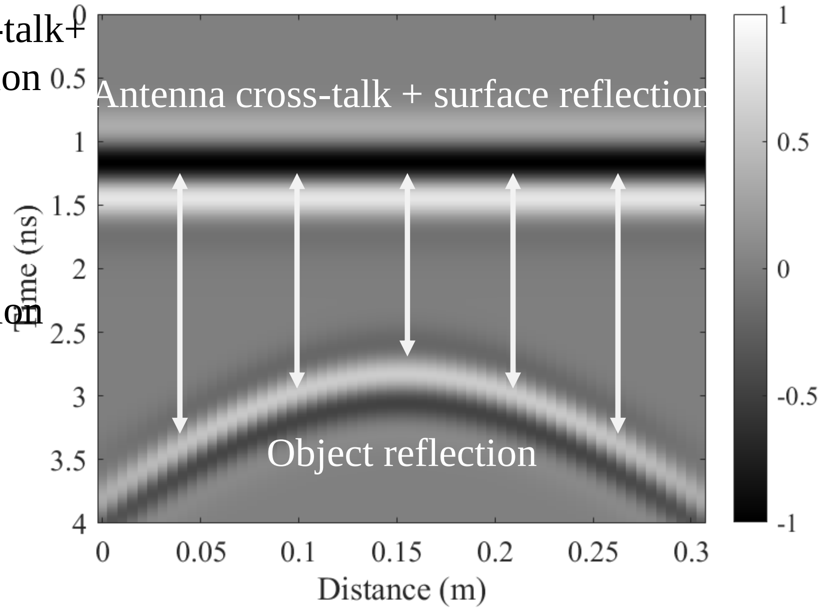
The 2022 International Symposium on Antennas and Propagation
31 October 2022 • Sydney, Australia

Ground Penetrating Radar

- Ground penetrating radar (GPR) is a non-destructive tool that uses electromagnetic waves to inspect subsurface environments.



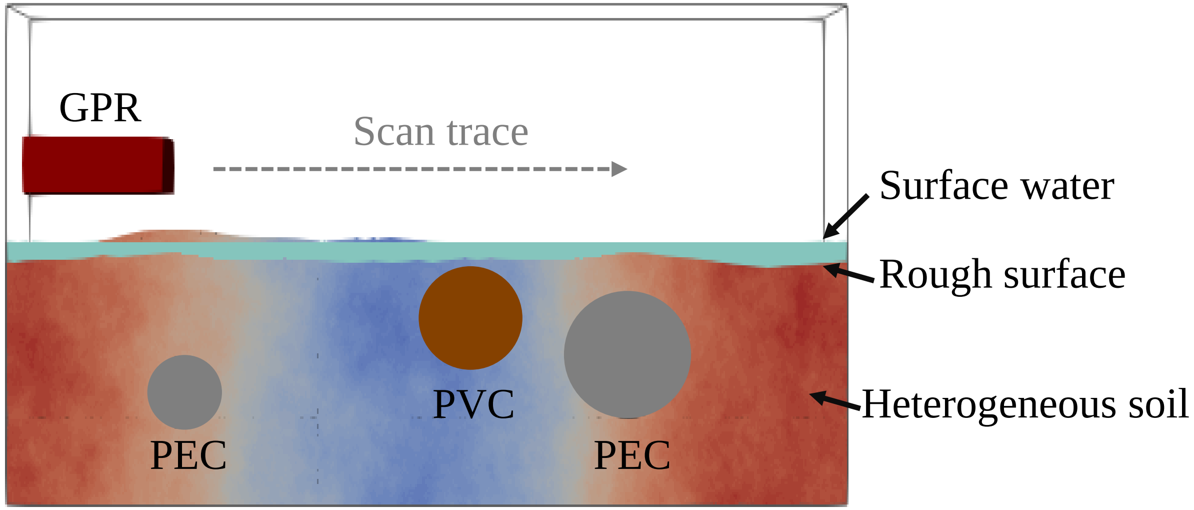


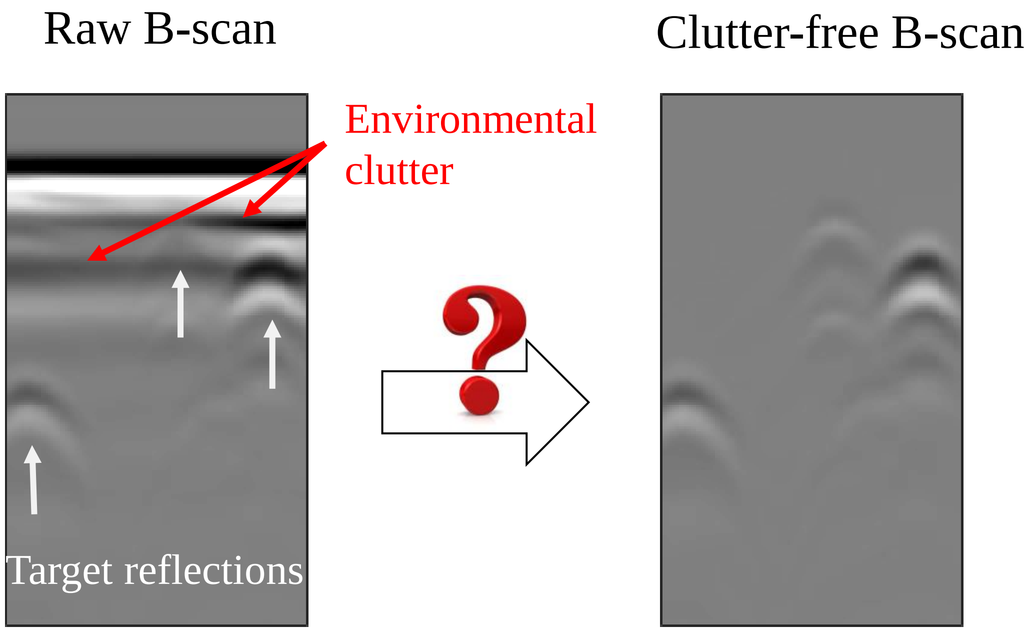


- A-scan
- B-scan

$$depth = \frac{v \times \Delta t}{2} \qquad v = \frac{c}{\sqrt{\varepsilon_r}}$$

Research Question



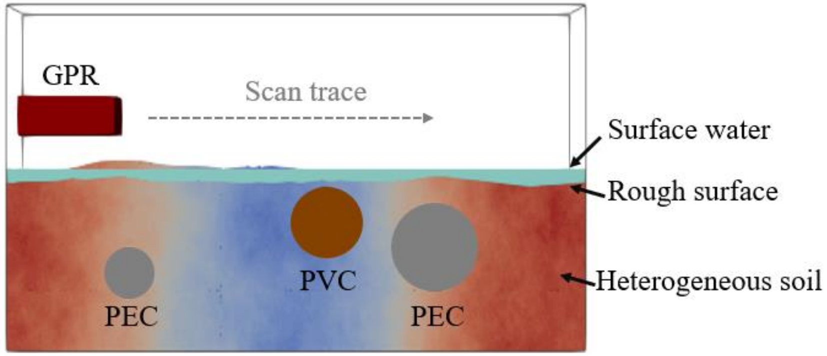


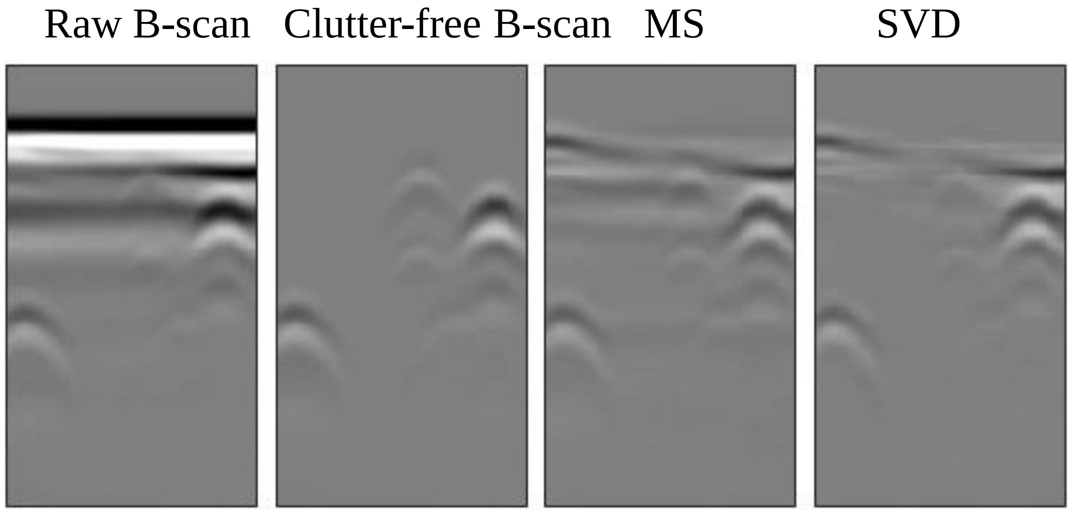
Research Question

Most popular clutter removal methods

- Mean subtraction (MS) [1]
- Subspace-based methods [2]
  - singular value decomposition (SVD)
  - principle component analysis (PCA)

Can we leverage advantages of deep neural networks to remove clutter in radargrams?

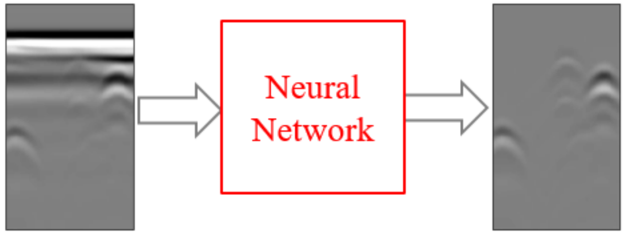




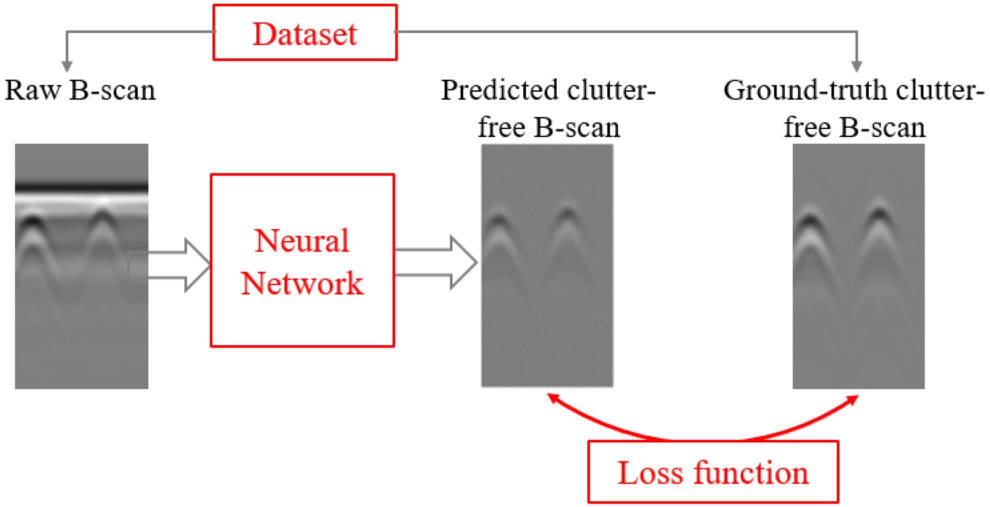
[1] H. Brunzell, “Detection of shallowly buried objects using impulse radar,” *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 2, pp. 875–886, Mar. 1999.
[2] R. Solimene, A. Cuccaro, A. Aversano, I. Catapano, and F. Soldovieri “Ground clutter removal in GPR surveys,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 7, no. 3, pp. 792–798, Mar. 2014.

Methodology

How to use deep neural networks to remove clutter in radargrams?



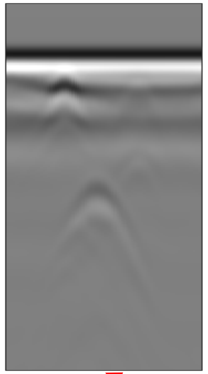
- **Dataset preparation**: build a large-scale dataset that contain diverse clutter for network training
- **Neural network design**: build suitable neural network architecture that can be trained to effectively remove clutter and restore target responses
- **Selection of loss function**: find suitable loss function to drive the network optimization for the clutter removal task



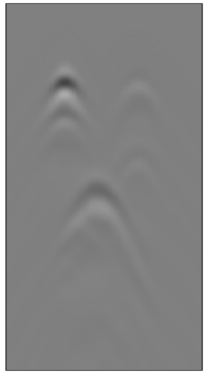
Dataset Preparation

Sub-dataset	GPR system	Subsurface environment	Number of data
Synthetic sub-dataset	1.5-GHz GSSI system in gprMax	Six different soil conditions with four types of soil surfaces	1,920
Sand sub-dataset	Multi-polarimetric GPR system	Sandy soil with uneven surface and random distributed moisture content	6,000
Concrete sub-dataset	Single-polarimetric GPR system with mono-static and bi-static antenna configurations	Concrete	4,000

Raw radargram



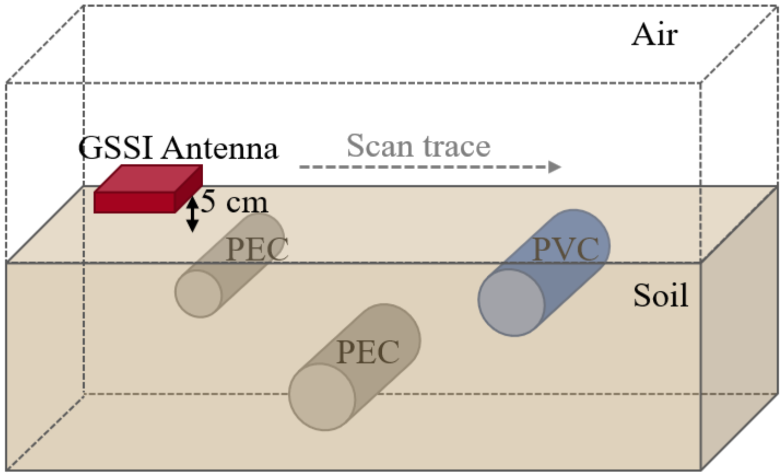
Clutter-free radargram



Data pair

The different GPR systems and subsurface environments in the dataset preparation provide diverse distributions of real-world clutter. This allows the neural network to learn complex clutter distributions, thus improves the effectiveness of network in removing clutter in real scenarios.

Dataset Preparation：Simulated Dataset



Soil types

Dry sand ($\varepsilon_r = 3.0,\ \sigma = 0.001$ S/m)

Damp sand ($\varepsilon_r = 8.0,\ \sigma = 0.01$ S/m)

Dry clay soil ($\varepsilon_r = 10.0,\ \sigma = 0.01$ S/m)

Wet clay soil ($\varepsilon_r = 12.0,\ \sigma = 0.01$ S/m)

Dry loam soil ($\varepsilon_r = 10.0,\ \sigma = 0.001$ S/m)

Heterogeneous soil ($\varepsilon_r = 3.5 - 12.5,\ \sigma = 0.01 - 0.07$ S/m)

Surface types

Flat surface

Grass surface

Rough surface

Rough surface + water puddle

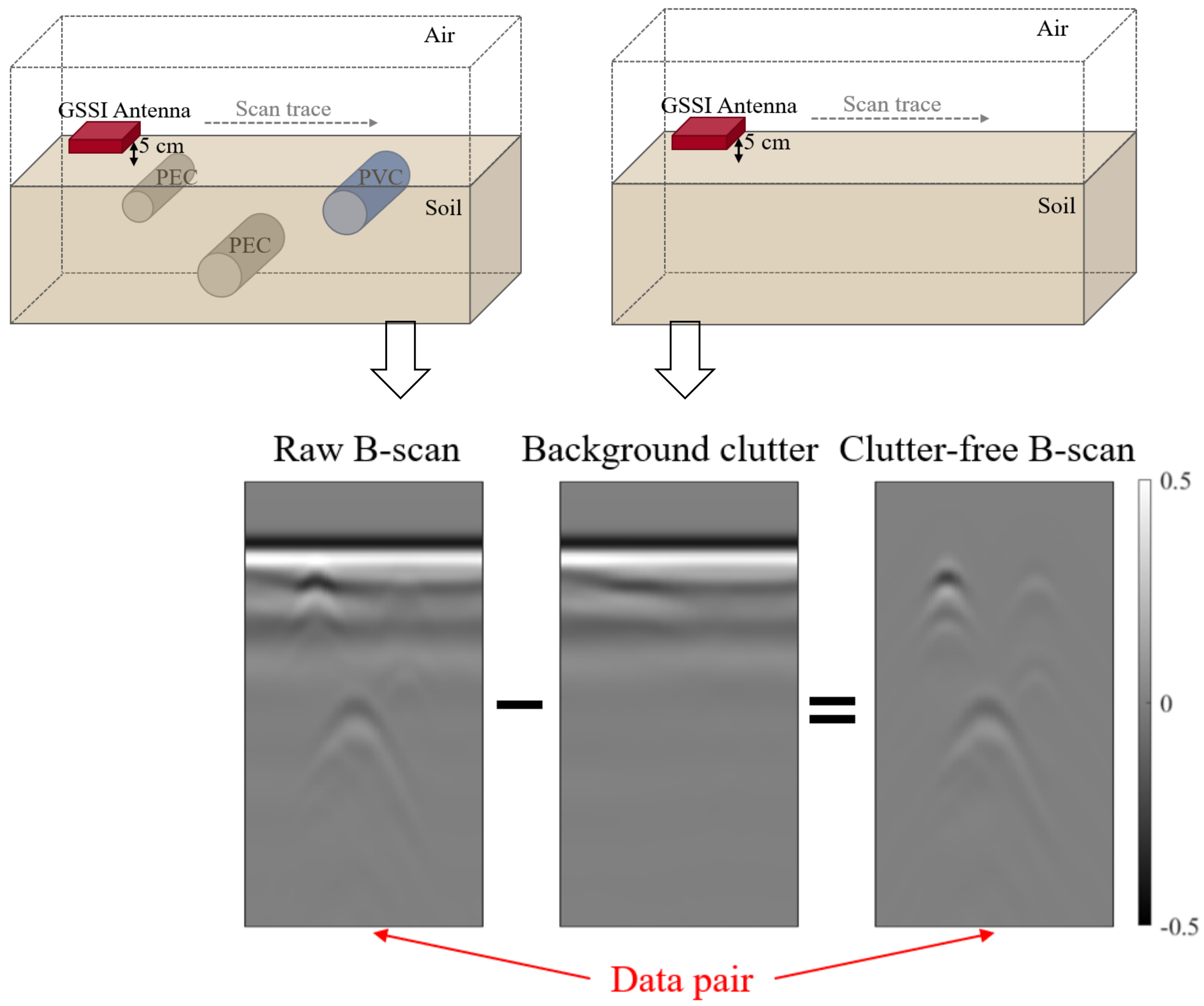
Object types

PEC pipe

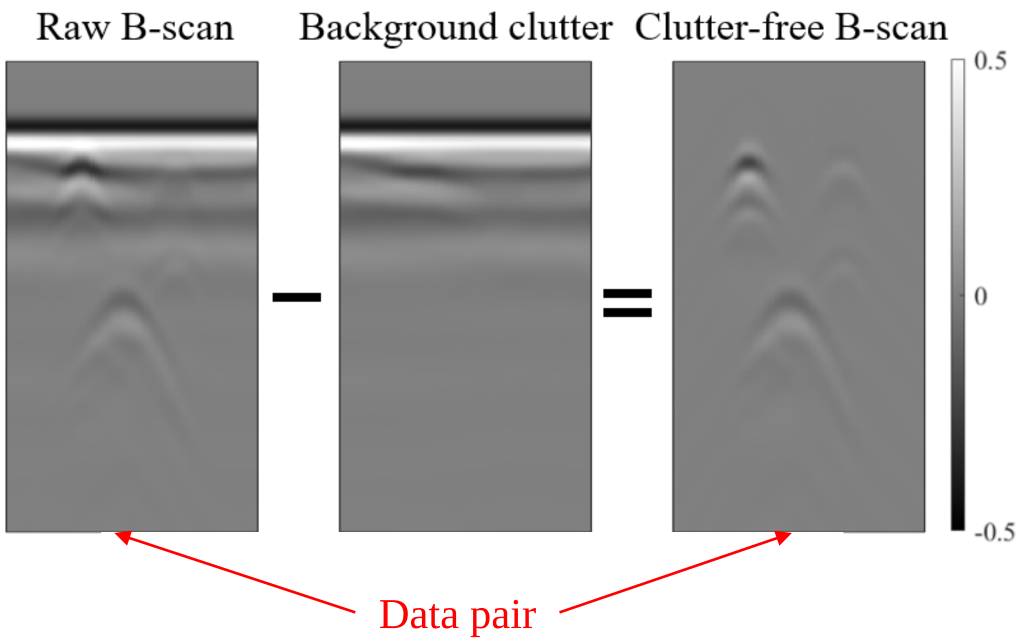
PVC pipe ($\varepsilon_r = 3.5,\ \sigma = 0$ S/m）

(different depths and radii)

Dataset Preparation： Simulated Dataset

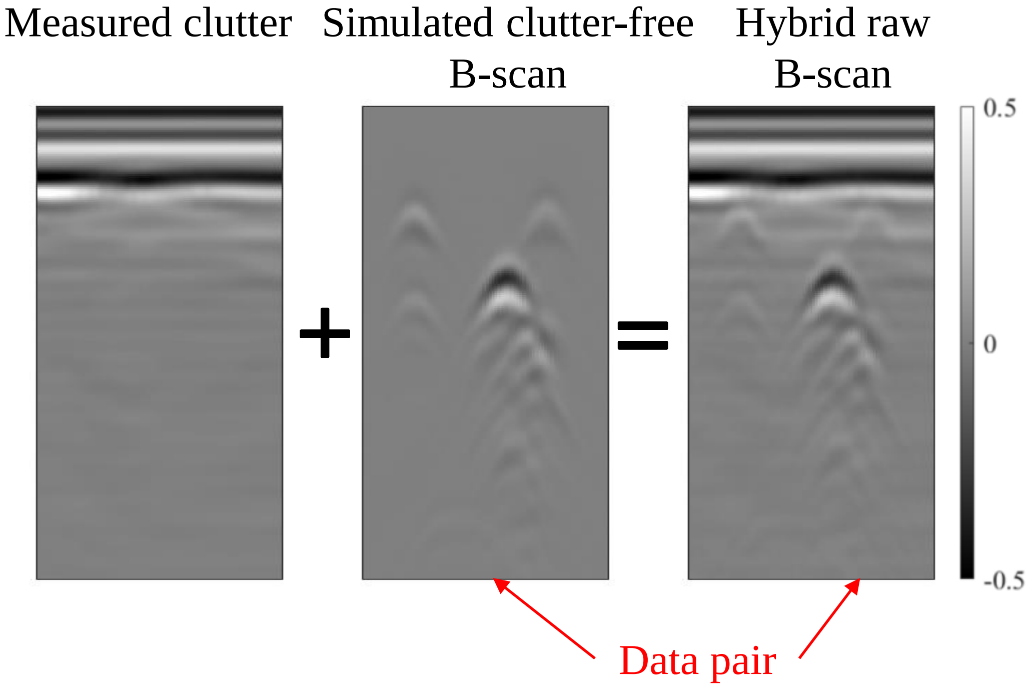


Simulated Dataset

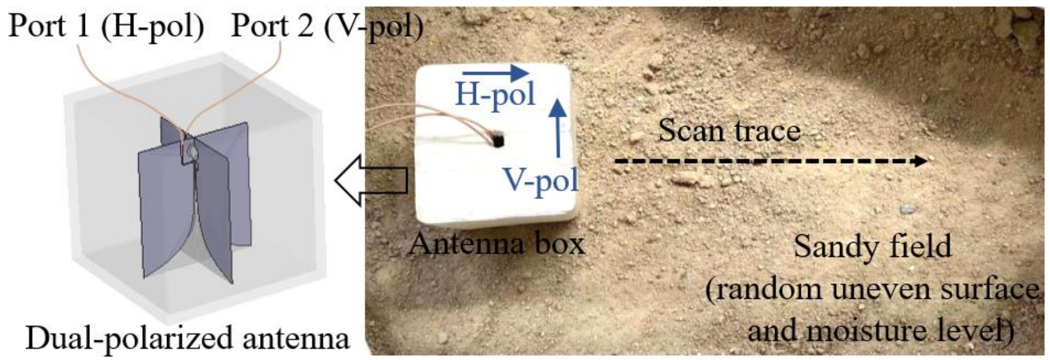


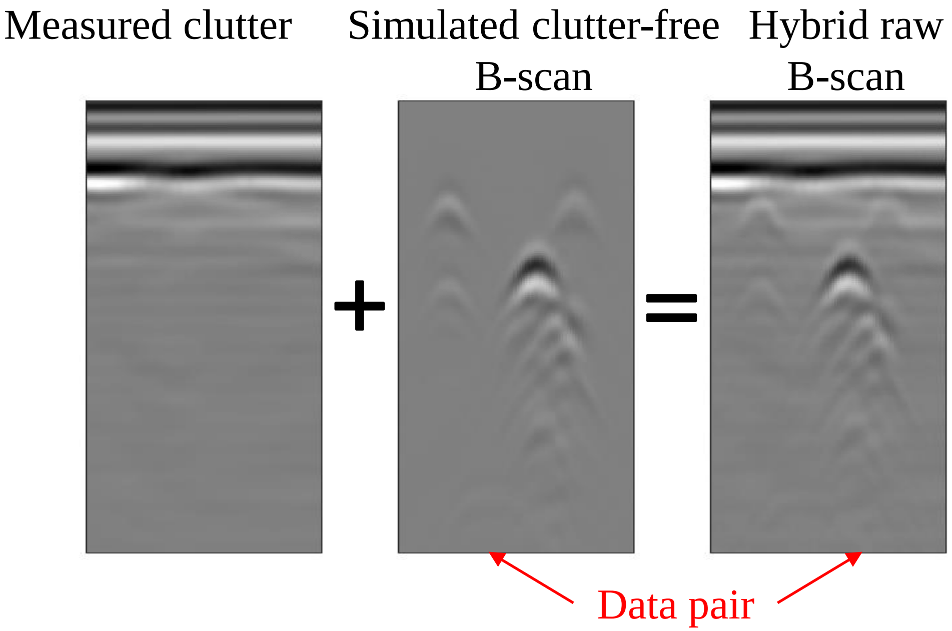
Measured Dataset： Sand Dataset

Concrete Dataset

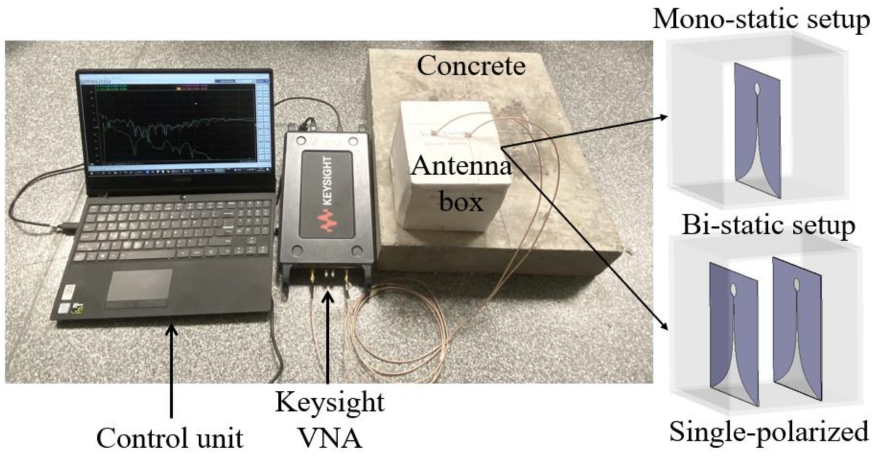


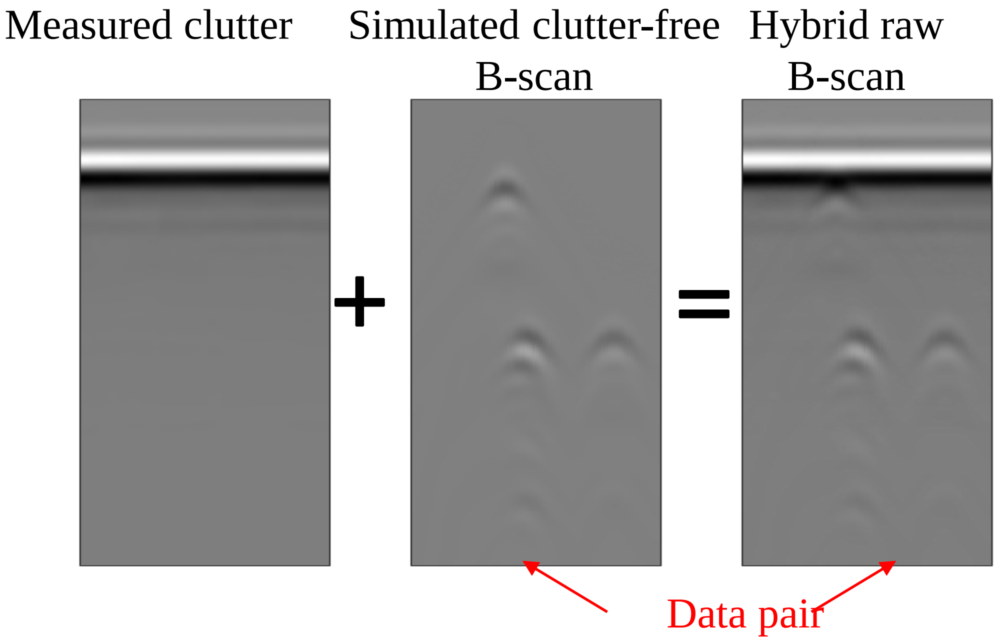
Sand Dataset



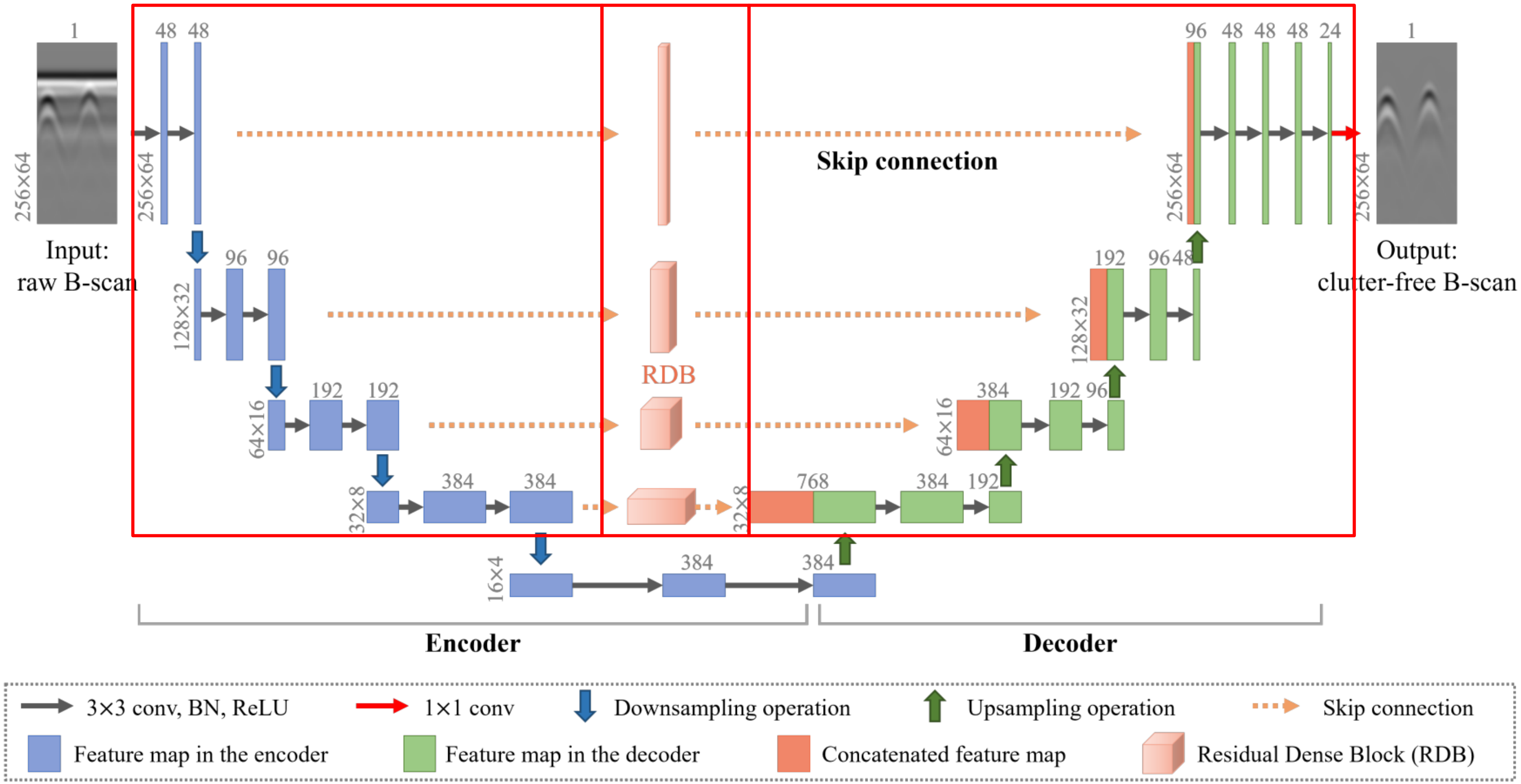


Concrete Dataset

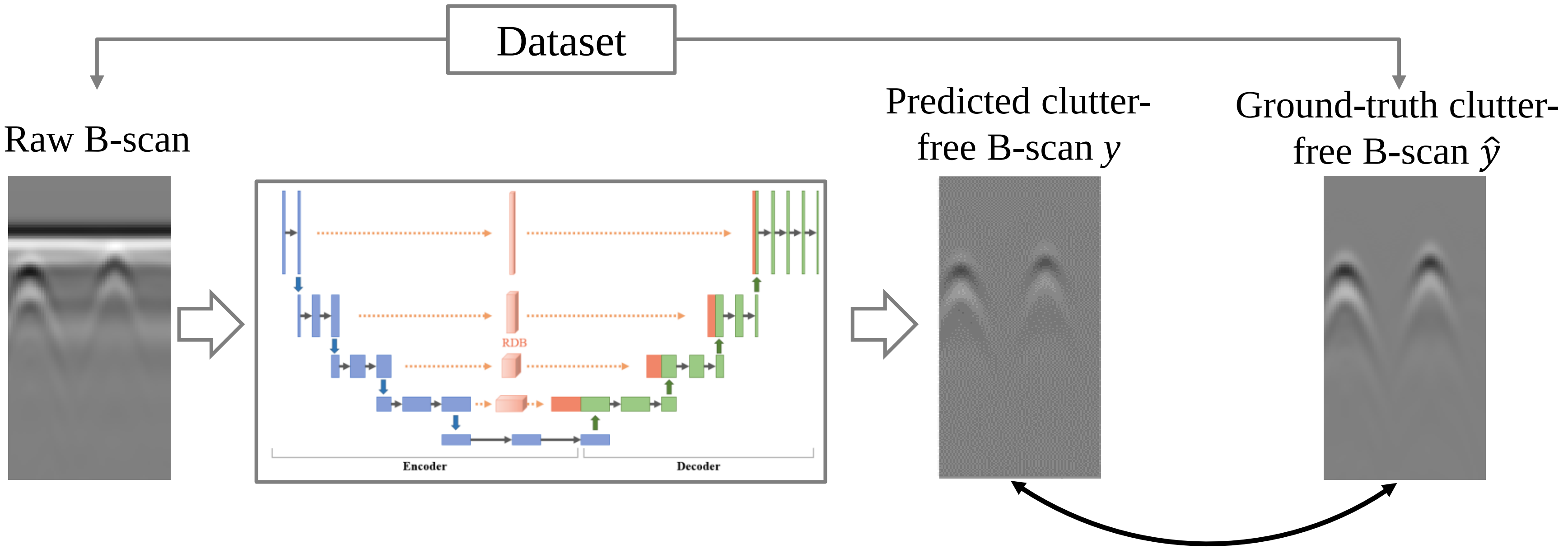




Clutter-Removal Neural Network (CR-Net)



Loss function



$$\text{Loss} = \text{MAE}(y, \hat{y}) + \text{L}_{\text{MS-SSIM}}(y, \hat{y})$$

- Mean absolute error loss

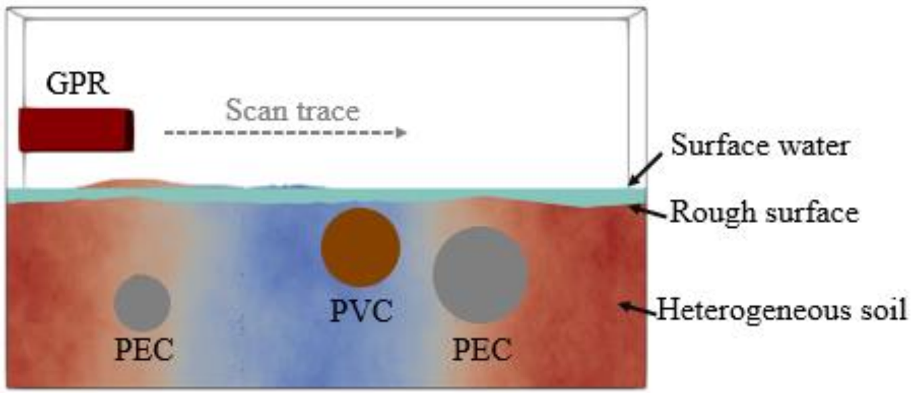
$$\text{MAE}(y, \hat{y}) = \frac{1}{H \times W} \sum_{i,j} |y_{i,j} - \hat{y}_{i,j}|$$

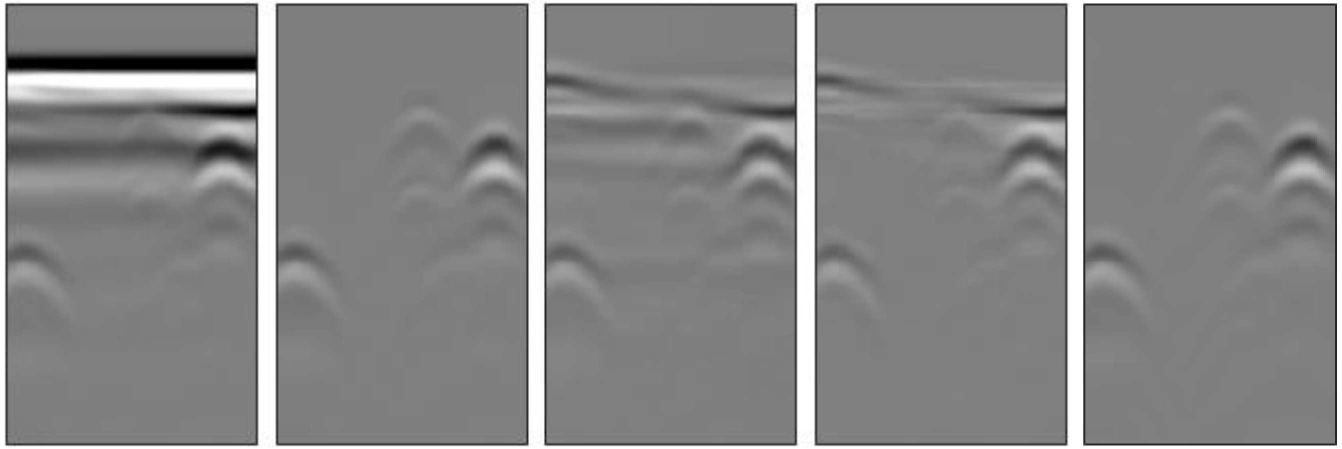
- Multi-scale structural similarity loss

$$\text{MS-SSIM}(y, \hat{y}) = [l_M(y, \hat{y})]^{\alpha_M} \cdot \prod_{k=1}^{M} [c_k(y, \hat{y})]^{\beta_k} [s_k(y, \hat{y})]^{\gamma_k}$$

$$\text{L}_{\text{MS-SSIM}}(y, \hat{y}) = 1 - \text{MS-SSIM}(y, \hat{y})$$

Experimental Results



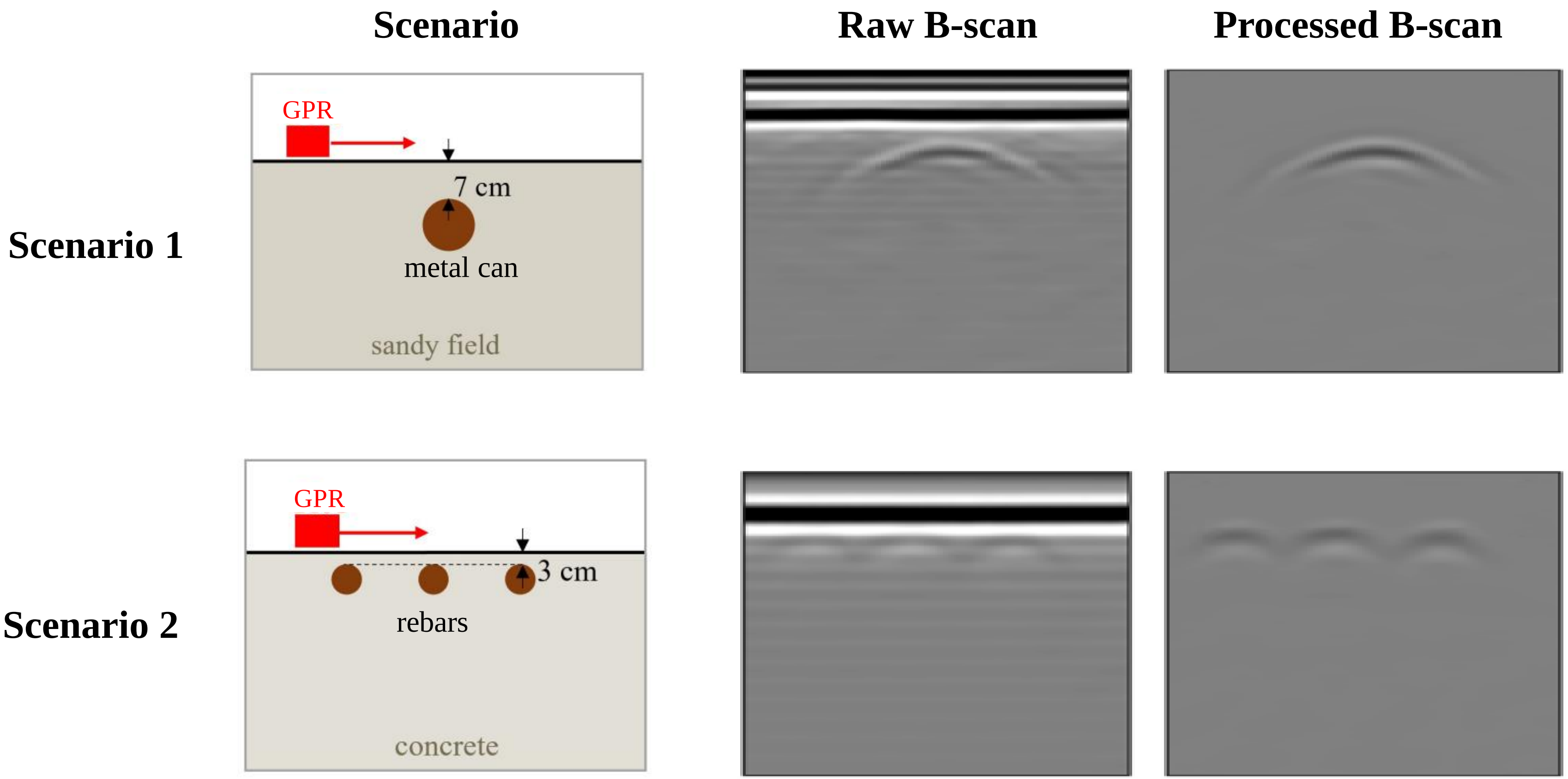


$$\mathrm{MAE}\left(y,\hat{y}\right)=\frac{1}{H\times W}\sum_{i,j}\left|y_{i,j}-\hat{y}_{i,j}\right|$$

Methods	MS	SVD	CR-Net (ours)
MAE $\times$ 10^{-4}	59.62	47.82	7.59

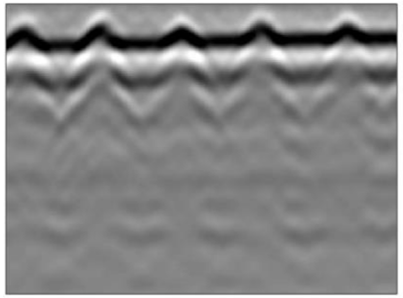
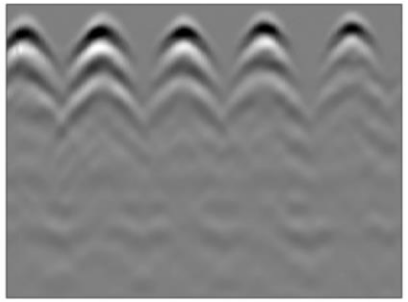
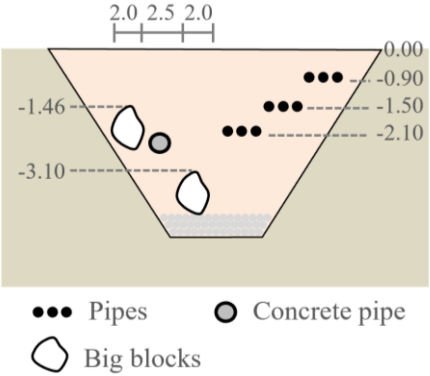
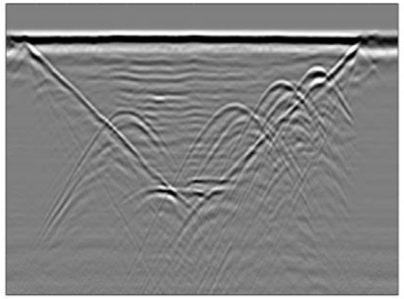
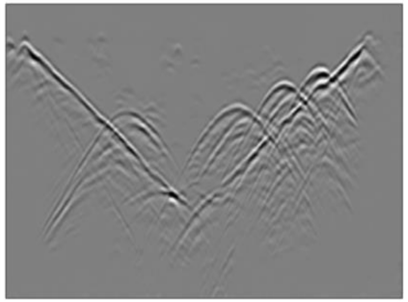
The network outperforms the existing methods by a large margin in removing clutter and recovering target responses in the simulated data.

Experimental Results



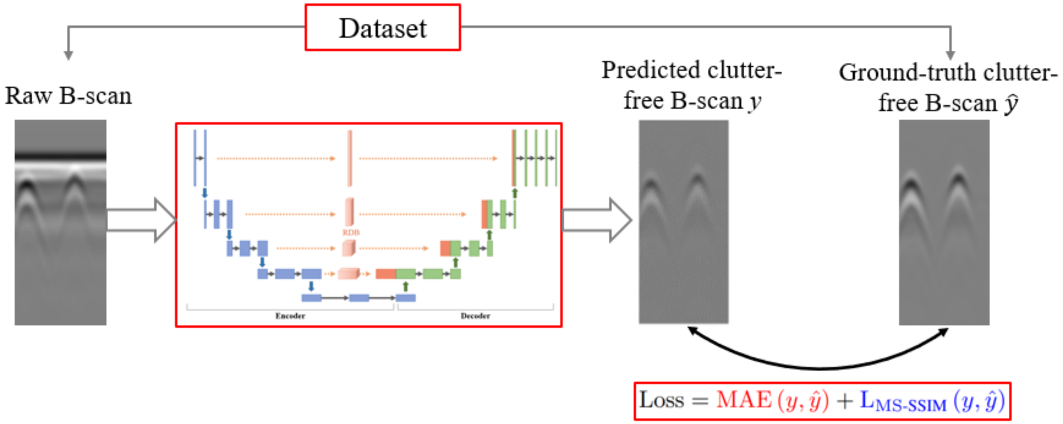
The network is highly effective in removing clutter and restoring object reflections in field measured radargrams.

Experimental Results

	Scenario	Raw B-scan	Processed B-scan
Scenario 3 [3]	GPR data were collected on a concrete building; the detail was not given.		
Scenario 4 [4]			

The network enjoys good generalization capability in eliminating clutter in various real-world scenarios.

Conclusion



A deep learning-based method is presented for clutter removal in GPR radargrams.

- A large-scale dataset that contain diverse and complex real-world clutter for network training
- Neural network architecture to effectively remove clutter and restore target responses
- Suitable loss function to drive the network optimization for the clutter removal task

The well-trained neural network enjoys great generalizability in removing clutter and restoring target responses in real-world radargrams.

Dataset + Code: *https://haihan-sun.github.io/GPR.html*

Thank you!

Q&A