海洋电磁探测技术与装备实验室

Deep Learning Anisotropic CSEM Resistivity Inversion with Federated Networks

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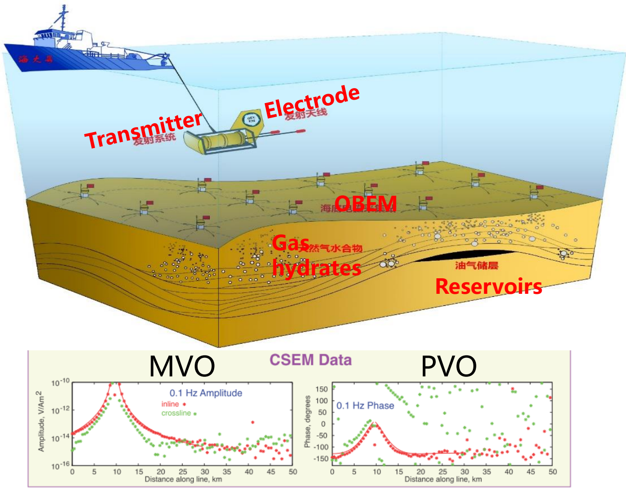
Content

- Motivation
- Methodology
- Numerical results
- Conclusions

Marine CSEM method

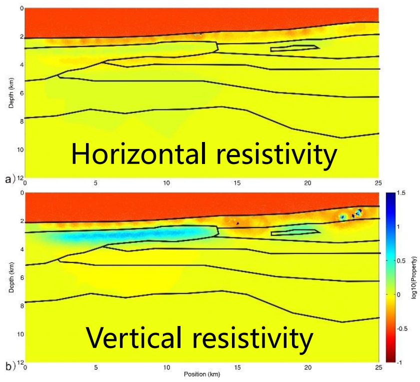
- Horizontal electric dipole source
- Electric (and magnetic) receivers

Resistivity distribution of the seafloor



Inversion

VTI Inversion result



Motivation

- The geophysical inversion methods currently in use can be divided into two broad categories: deterministic and probabilistic methods.
- The application of Deep learning (DL) has already inspired various methods, especially for solving inverse problems.
- Adequate interpretation of MCSEM data requires taking into account the electrical anisotropy of sea-bottom formations.
- Earlier studies have shown that the CSEM inversions usually fail to recover the horizontal resistivities for an VTI resistor.

We try to use DL to invert the anisotropic resistivity distribution of VTI medium and analyze the resolution of horizontal resistivity.

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OUCEM

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Inversion method

OUCEM

Traditional inversion method (model driven)

$$\Phi(\boldsymbol{m}) = \min\{\|\boldsymbol{d} - \boldsymbol{F}(\boldsymbol{m})\|_2^2\}$$

Deterministic method: Depend on initial model ; calculate gradient information.
Probabilistic method: High computational cost, Solving 1D problem.

Deep Learning inversion method (data driven)

$$\boldsymbol{m} = \boldsymbol{Net}(\boldsymbol{d})$$

Inversion model   neural network (NN)   Observe data

Training stage: Built mapping from data space to model space.
Prediction stage: Input EM data → obtain inversion models rapidly.

CNN and RNN

The CNN is a variant of DL with an architecture designed to recognize features with complex topology.

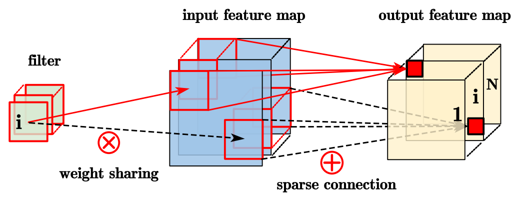
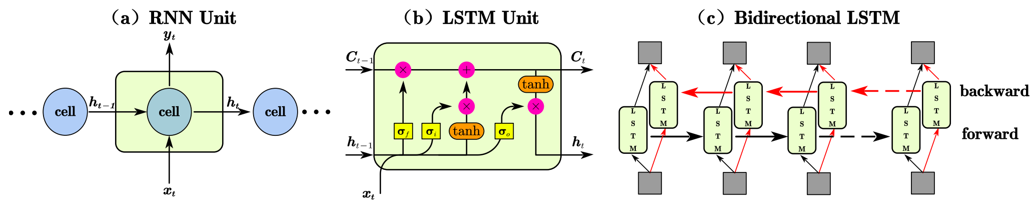


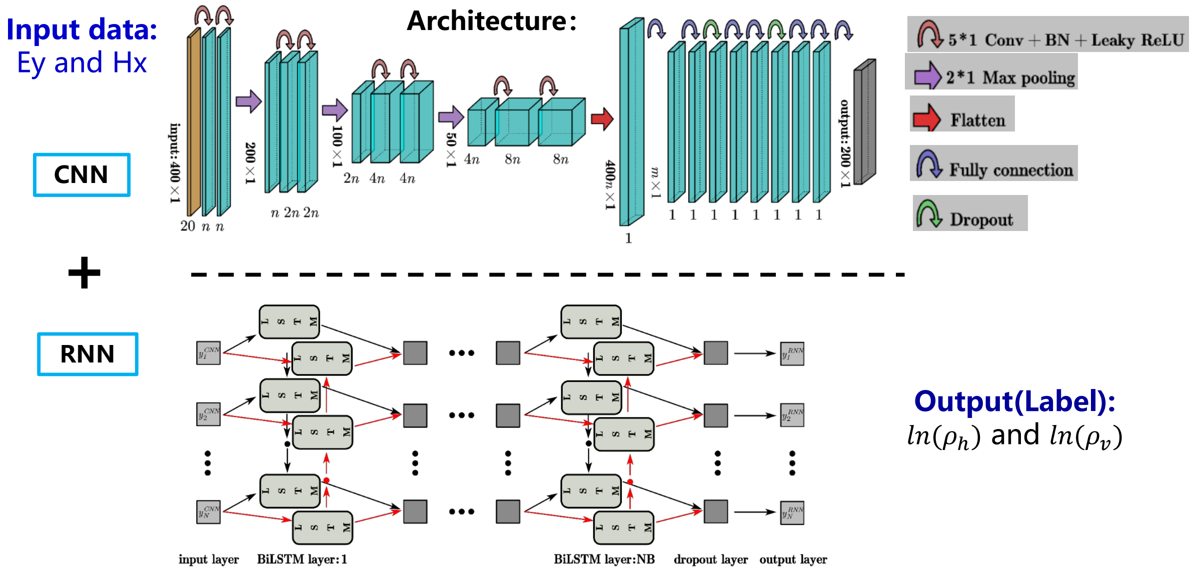
Illustration of the convolutional operation in CNN

RNN has shown strong capability for learning meaningful information from an ordered sequence.

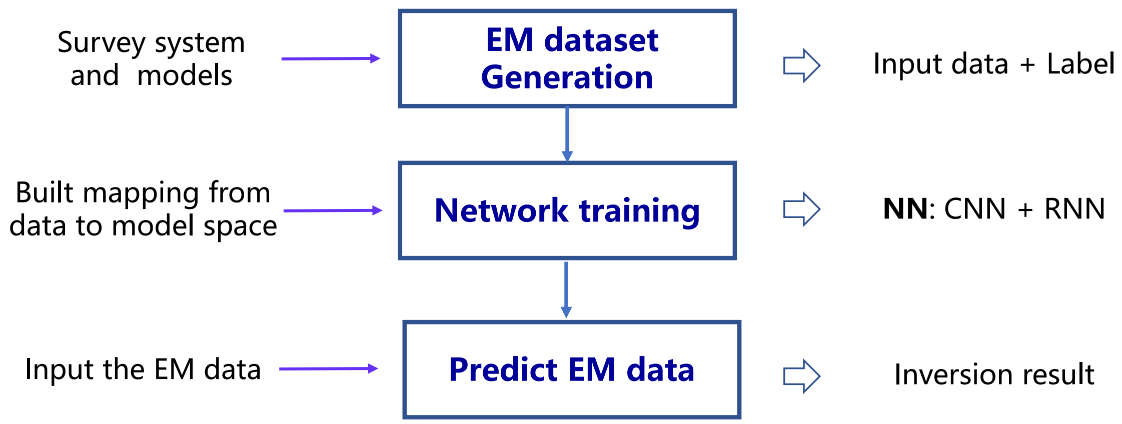


Structure of the recurrent neural networks (RNN)

Federated Neural Network Design



DL Inversion Workflow



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  - Isotropic example
  - Anisotropic example
  - inversion of noisy data
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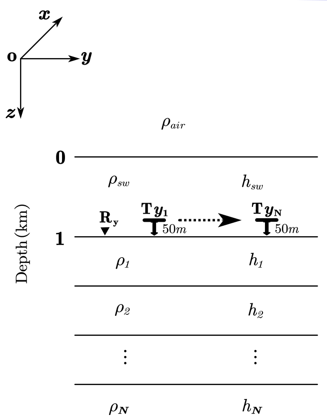
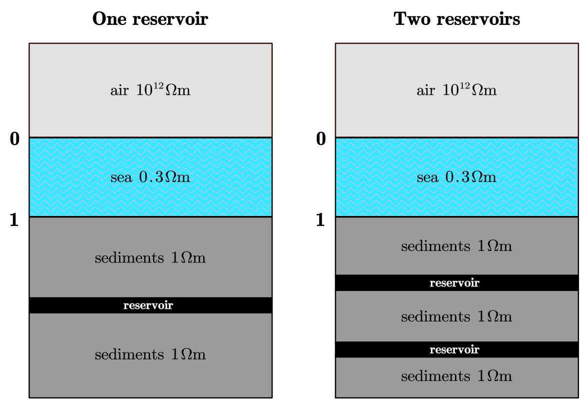
Data set preparation





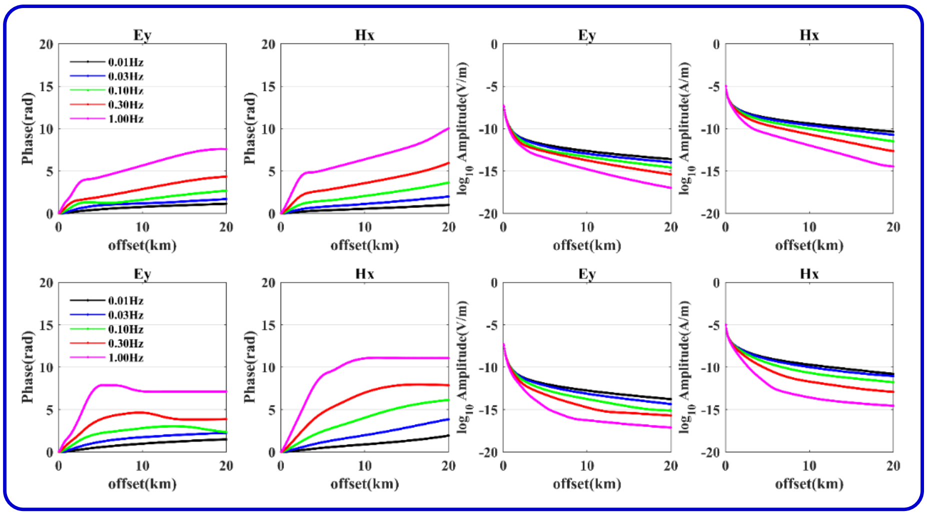
Transmitter: y-HED
Receivers: 400; **Range**: 50 m to 20 km
Component: Ey Hx, phase and amplitude
Frequency : 0.01, 0.025, 0.1, 0.25, 1 Hz

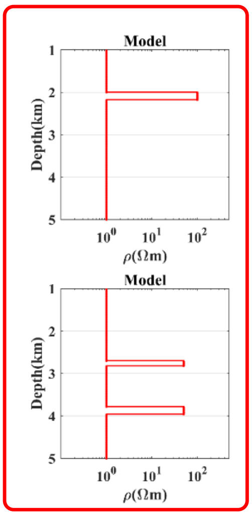
Model configuration

Baseline model: 200 equal thickness of 20 m layers, seafloor to 4 km

Reservoirs: Depths: 500-3000 m
Thicknesses: 100 m to 400 m
Strengths: 50 to 200 Ωm

Input data and label

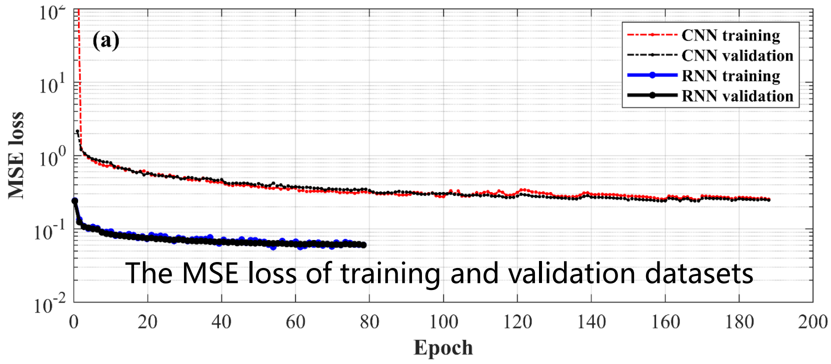




Input data: Ey and Hx amplitudes and phases

Label: true resistivity distributions

NN training



Learning rate: 0.001
Optimization: Adam

DataSet split ratio: 8/1/1

The MSE errors of CNN are converged to a minimum value of ~0.1. Then the error was further brought down by the RNN training phase more than one order of magnitude over the CNN training error.

NN training

Correlation matric (**R**) is used to evaluate the performance of DL models

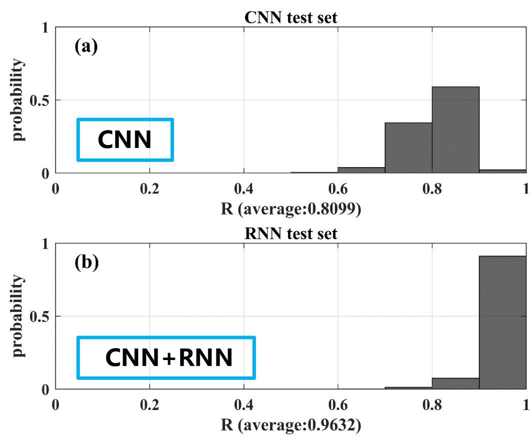
$$\boxed{R = \frac{\mathrm{Cov}(\boldsymbol{y}^{pre}, \boldsymbol{y}^{tru})}{\sqrt{D(\boldsymbol{y}^{pre}) \cdot D(\boldsymbol{y}^{tru})}}}$$

Compares the similarity of different models

R=~1: estimated model close to true model

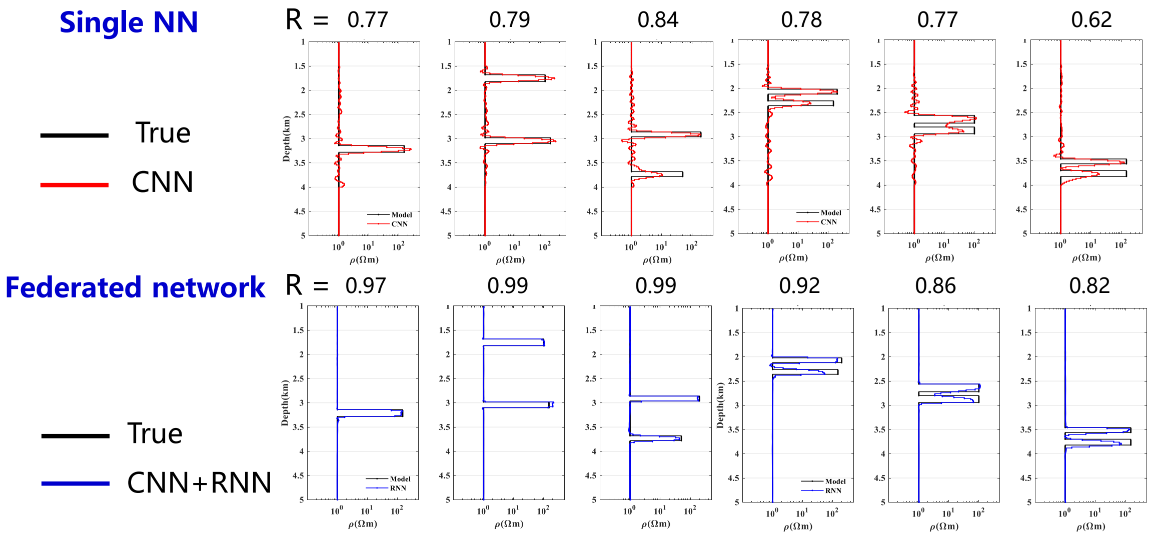
R=0.5 – 0.6: considered as acceptable accurate

R=0.6 – 0.8 or above: a good match

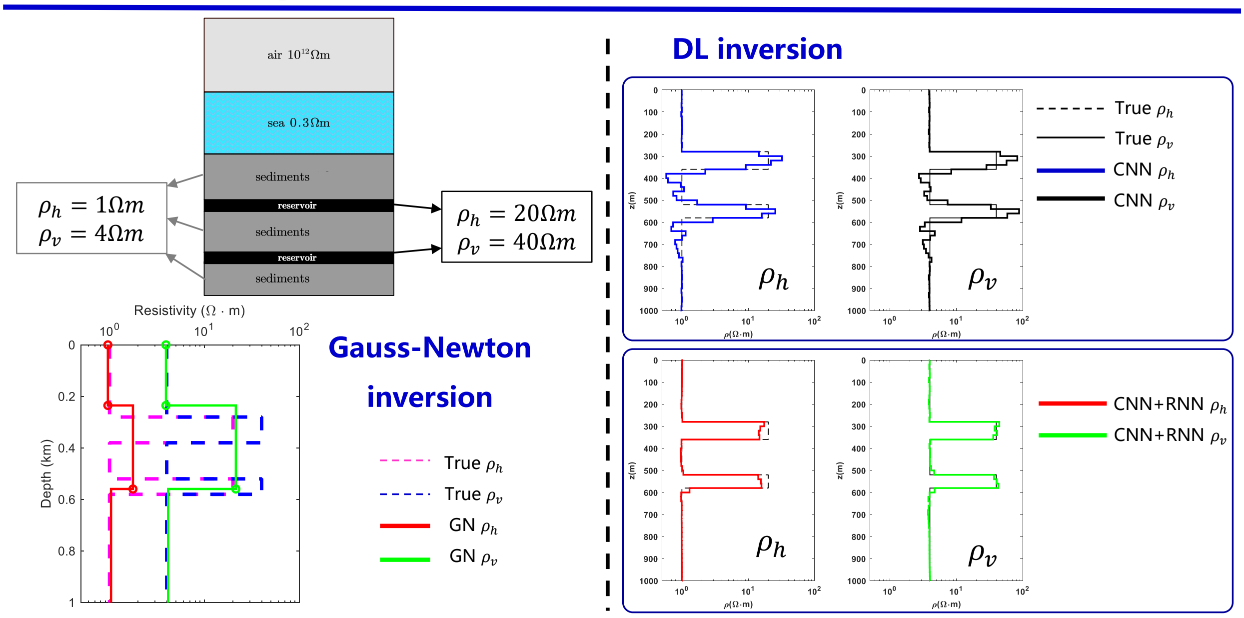


Isotropic inversion results

Isotropic inversion results of **the noise-free dataset** with **noise free network**.



Anisotropic inversion results



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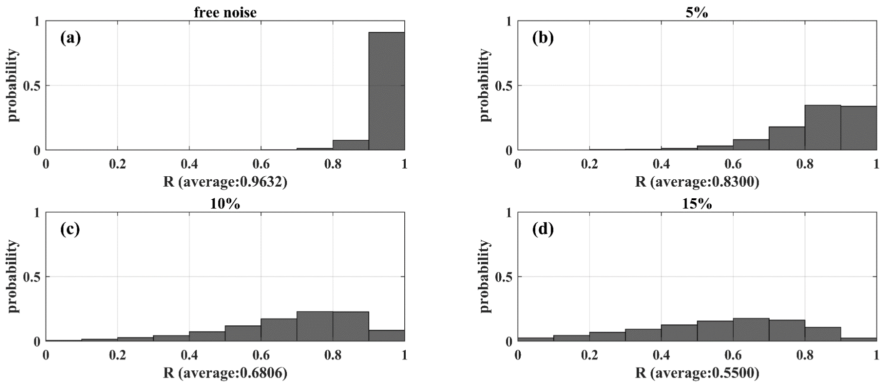
DL inversion of noisy data

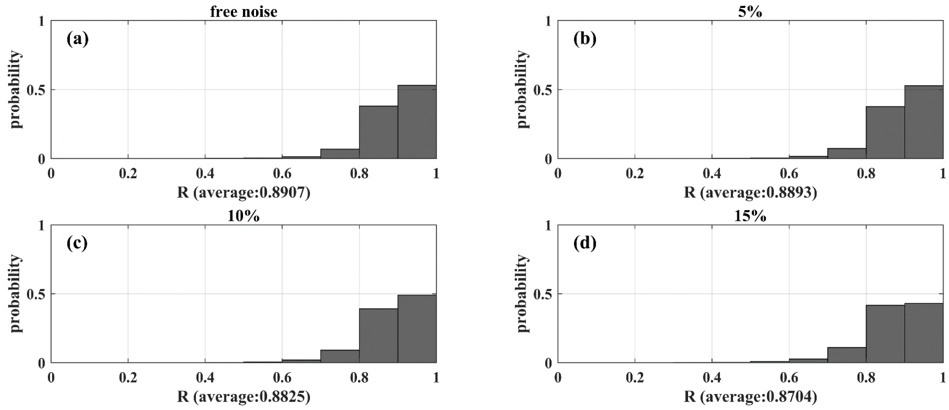
The R of DL inversion of the noisy dataset with **noise free** network.



Due to the increased noise level in the data, the average R drops significantly, and reducing the generalization ability of the network.

DL inversion of noisy data

DL inversion with **15% noise data trained network**.



A significant improvement of R shows that network has learned noise feature. As the level of noise in the dataset increases, the generalization ability of the network decreases correspondently.

DL inversion of noisy data

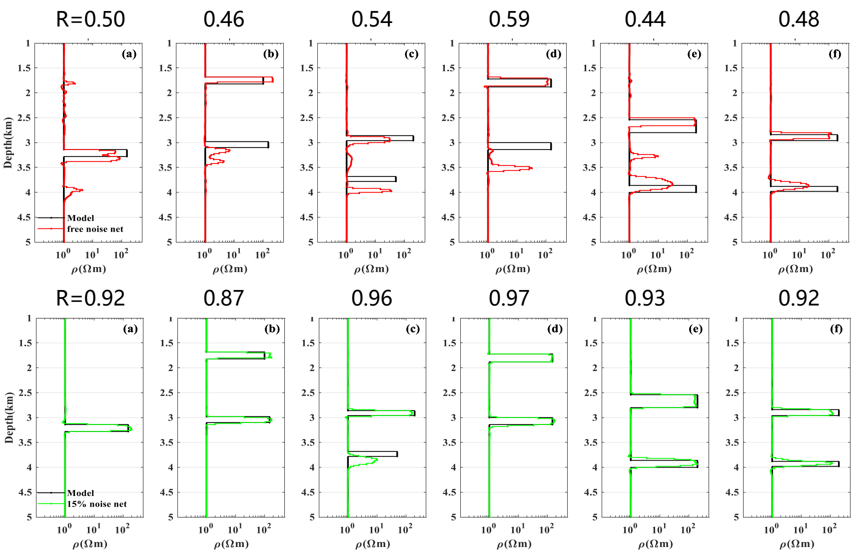
The DL inversion results of data containing 15% noise.

Federated network

True

Noise free NN

15% noise NN



In the presence of high level data noise, the network needs to be retrained so that the network to learn the noise features from the data.

Conclusions

- We propose a novel DL workflow for 1D VTI inversion of marine CSEM data, using federated networks of CNN and RNN.

- In the presence of the low level of noise, the trained noise free network allows for accurate estimation of the subsurface resistivity distributions. However, for higher level of noise, the strategy of re-training the neural network on noisy data may be considered.

- DL inversion would be a strategy that can improve the inversion resolution of reservoir horizontal resistivity than traditional inversion methods.