



29. Schmucker-Weidelt Kolloquium für Elektromagnetische Tiefenforschung

One-dimensional Deep Learning Inversion of Marine Controlled Source Electromagnetic Data

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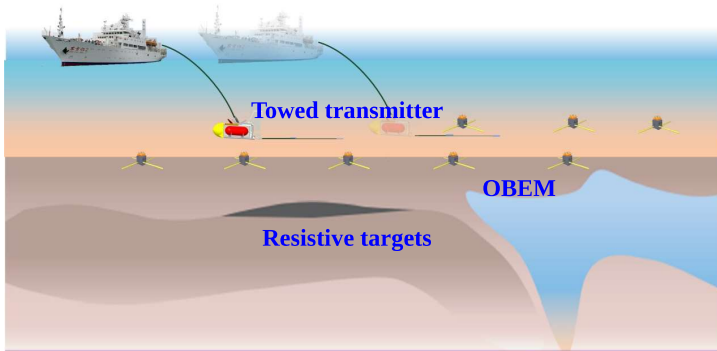
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1. The CSEM and Deep Learning

The CSEM method

The marine controlled-source electromagnetic (CSEM) method uses low-frequency electromagnetic energy generated by a deep towed electric dipole to remotely map the resistivity distribution of the seabed.



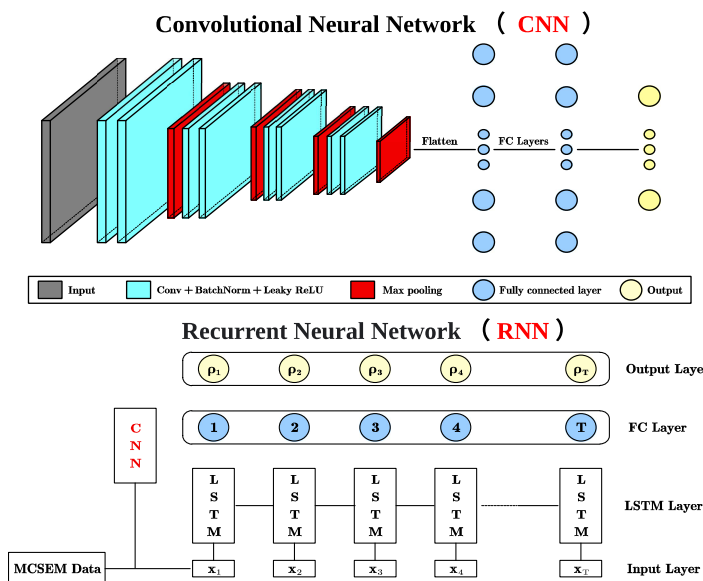
Traditional inversion method :

- (1)Local:
 - Gauss - Newton;
 - Occam;
 - Conjugate Gradient ...
- (2)Global :
 - Monte Carlo;
 - Simulated Annealing;
 - Genetic algorithm ...



The Deep Learning(DL) – CNN & RNN

DL is a class of machine learning algorithm that uses a pure data-driven procedure to construct the prediction function, and has ability to retrieve the target instantaneously with an only step.

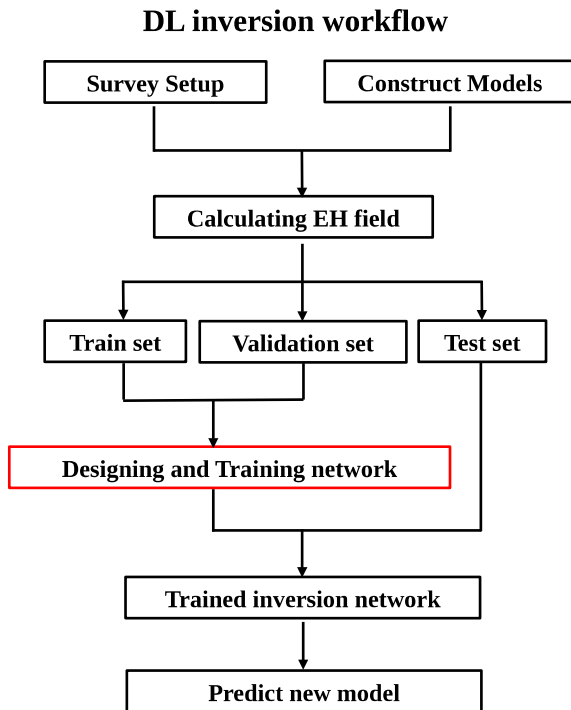


DL inversion has been applied for EM data :

- Puzyrev, 2019;
- Oh et al. 2019 ;
- Bin liu et al. 2020 ;
- Daniele Colombo et al. 2020 ;
- Davood Moghadas, 2020 ;
- Puzyrev, 2021;
- Zhengguang Liu et al. 2021 ;



2. The DL inversion workflow and architecture



CNN and RNN Architecture

Number	Layer type	Filters/ Neuron	Size/Stride
CNN			
1	Input		
2	Convolutional	16	3x3/1
1	Max pooling		2x2/1
2	Convolutional	32	3x3/1
1	Max pooling		2x2/1
2	Convolutional	64	3x3/1
1	Max pooling		2x2/1
2	Convolutional	128	3x3/1
1	Max pooling		2x2/1
1	Dropout		
6	FullyConnected	512	
1	FullyConnected	200	
1	Output	200	
RNN			
1	Input		
1	LSTM	200	
1	FullyConnected	500	
1	Dropout		
1	FullyConnected	200	
1	Output	200	

$$F(X)=RNN(CNN(X))$$



3. DL Inversion of Synthetic Dataset

Dataset

Survey setup:

Transmitter position:

$$x=0,y=0,z=950 \text{ m};$$

Frequencies used:

$$0.01/0.025/0.1/0.25/1/2.5/10\text{Hz};$$

Receivers: 50:50:20000m;

Model parameters:

Max depth: 4 km , 200 layers;

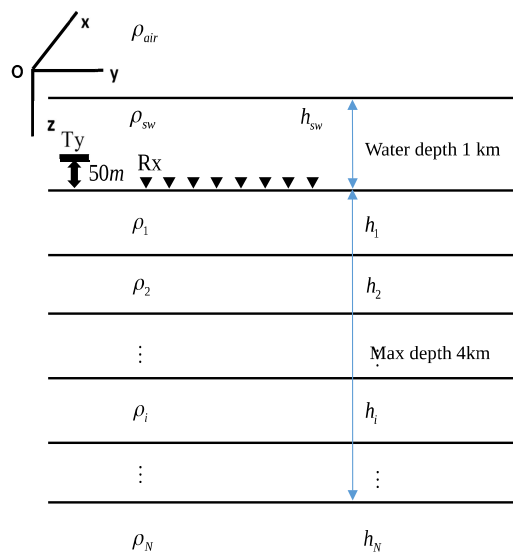
Background: 1 ohm-m;

Targets: 0/1/2; 100-400 m ;

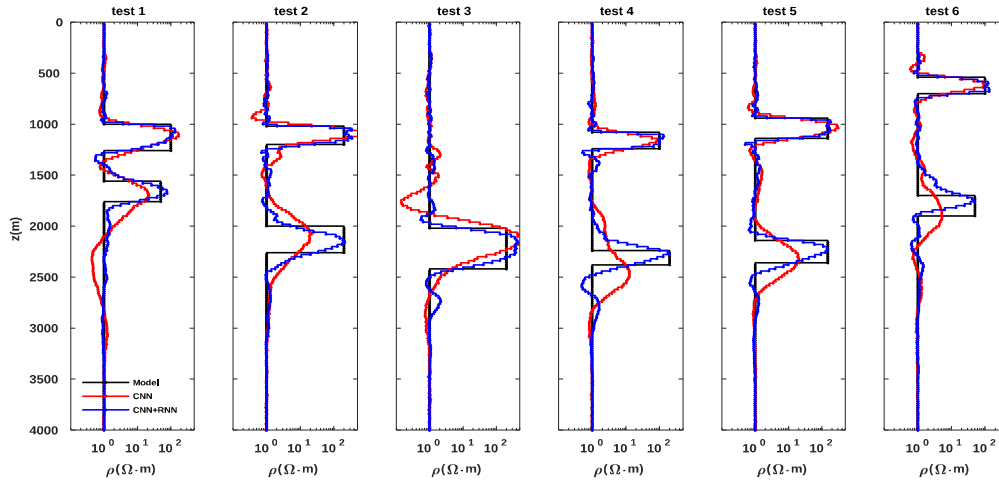
$$50/100/150/200 \text{ ohm-m};$$

Dataset: 20,000 Models;

Train :validation :test=8:1:1;



DL inversion of noise free data



- Both amplitudes and phases of E_y and H_x at 7 frequencies were used in inversion.
- Reservoirs were located at different depths with variable resistivity and thickness.



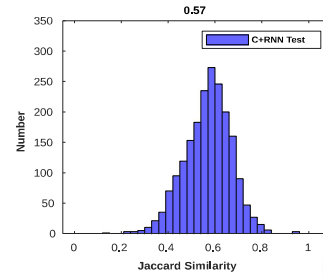
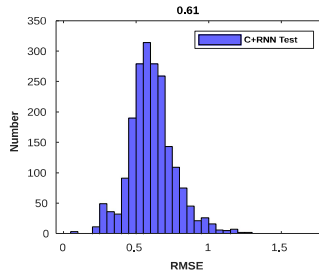
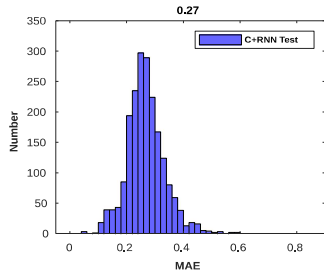
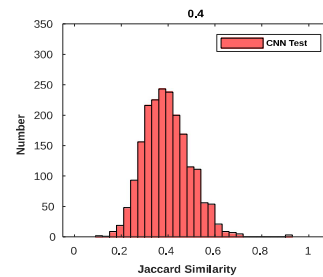
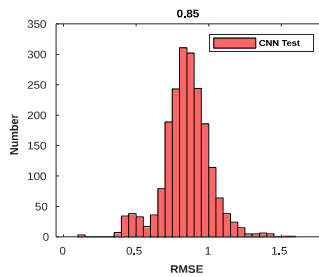
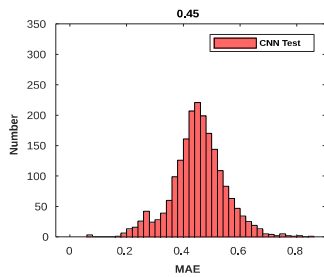
DL inversion of noise free data

Evaluation of inversion results: MAE / RMSE / Jaccard Similarity

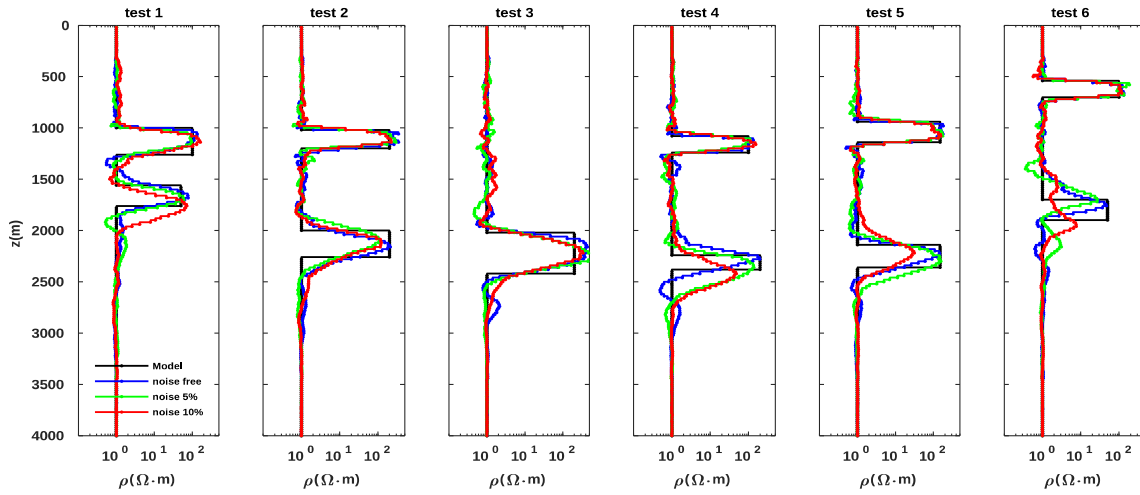
$$MAE = \frac{1}{N} \sum_{n=1}^N |y_n^{pre} - y_n^{tru}|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N |y_n^{pre} - y_n^{tru}|^2}$$

$$JS = \frac{|A \cap B|}{|A \cup B|}$$



DL inversion of noise data

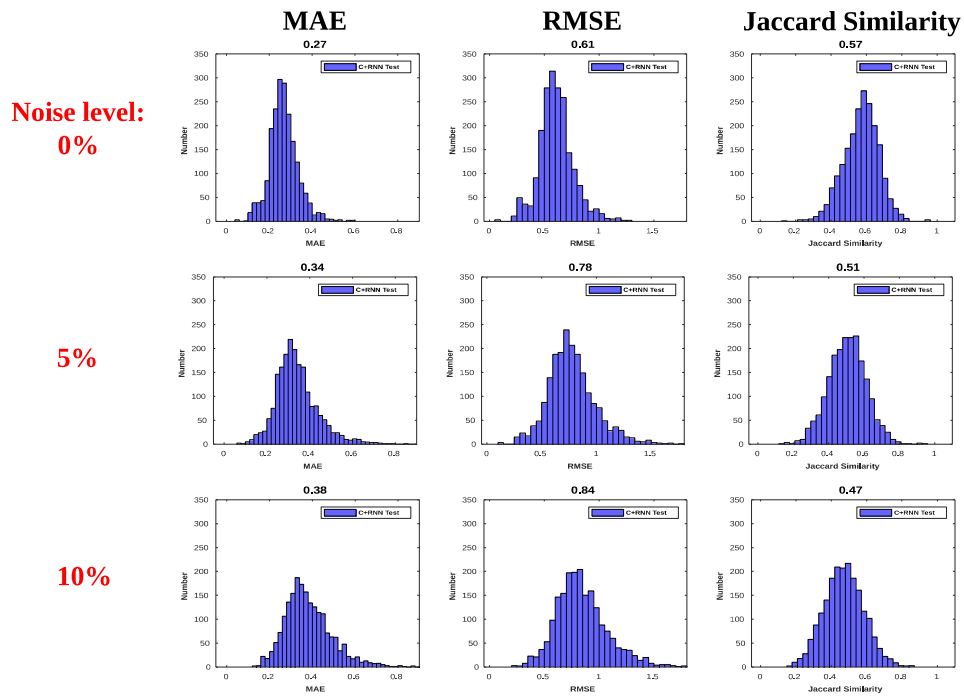


Blue: noise free; green: 5%; red: 10%

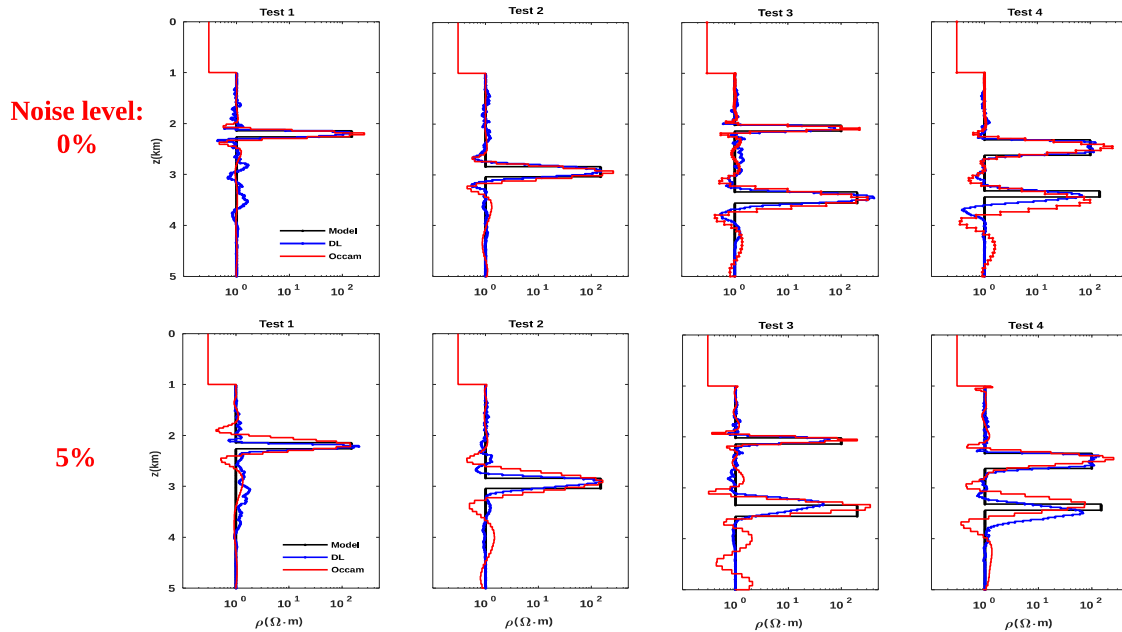
- Both amplitudes and phases of E_y and H_x from 7 frequencies were used in inversion.
- Reservoirs were located at different depths with variable resistivity and thickness.



Evaluation of inversion results of noise data



DL inversion: Compared with Occam Inversion



- Both amplitudes and phases of E_y and H_x from 7 frequencies were used in inversion.
- Reservoirs were located at different depths with variable resistivity and thickness.



4. Summary and Outlook

(1) The DL algorithm can be used for inversion of the Marine CSEM data. The results of the inversion for a synthetic dataset show that it has ability to accurately recover the subsurface resistivities.

(2) The results of inversion for noisy datasets show the DL inversion is a robust method. With the increased level of noise, it can keep its high-level target recognition ability with the performance of only slightly 'blurring' the shapes of the target.

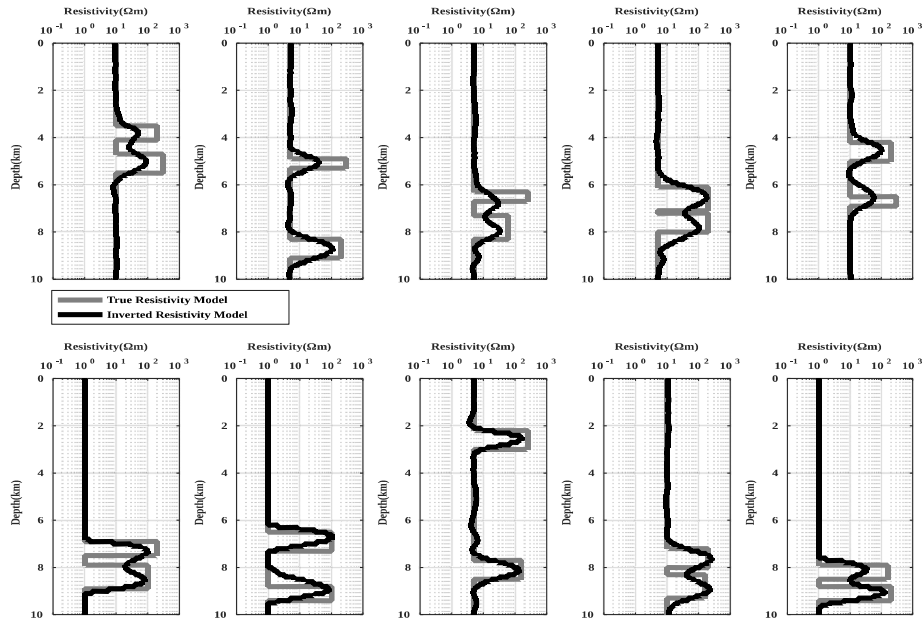
(3) By comparison to the conventional Occam Inversion, the result of DL is better than the Occam (which brings too much smoothing). Furthermore, DL is computationally highly efficient and can complete the inversion instantly once the train process has completed.

We will focus on application of the DL to 2D Marine MT and CSEM data.



Outlook 1: Anisotropy inversion of Multimodal Deep Learning of CSEM & MT & Seismic Data

DL inversion Results from noise free MT data



Outlook 2: The Combination of DL and tradition inversion methods

DL and Occam inversion cooperated

(1) Method Feature :

Occam: the inversion result depend on initial model.

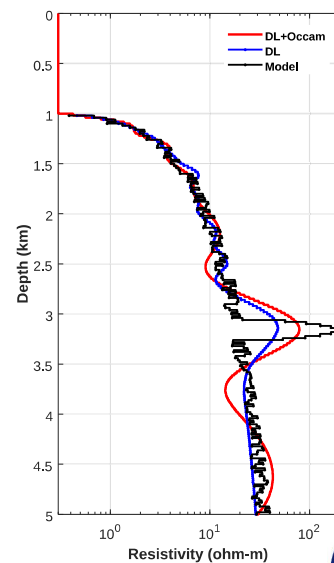
DL: the resistivity background of model would be learned well.

(2) Idea:

Accurate initial model could be provided by DL results for Occam inversion.

Then, the local solution would be found by Occam inversion method.

(3) Result:





Thank You!
Questions!

