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Implicit neural representation FWI

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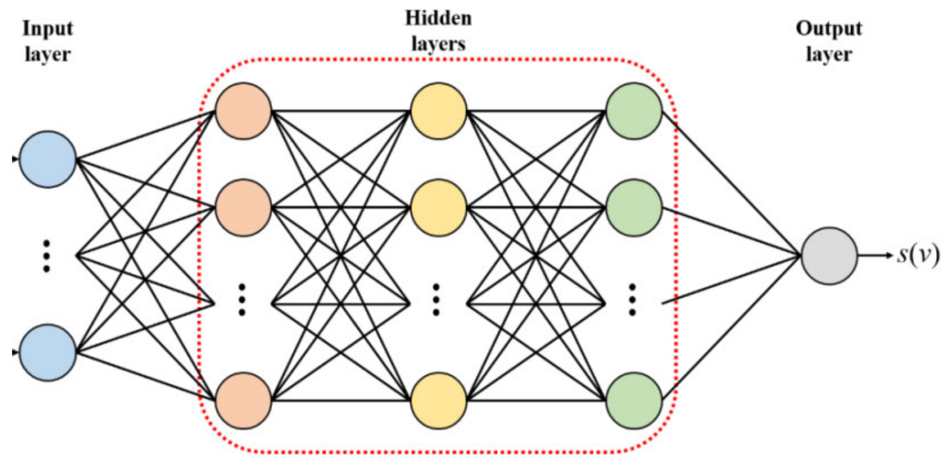
Outline

- Coordinate-based multilayer perceptron (MLP)
- Implicit neural representation FWI (No initial models)
- Numerical tests
- Conclusions and future study

Part one: Coordinate-based Multilayer perceptron (MLP)

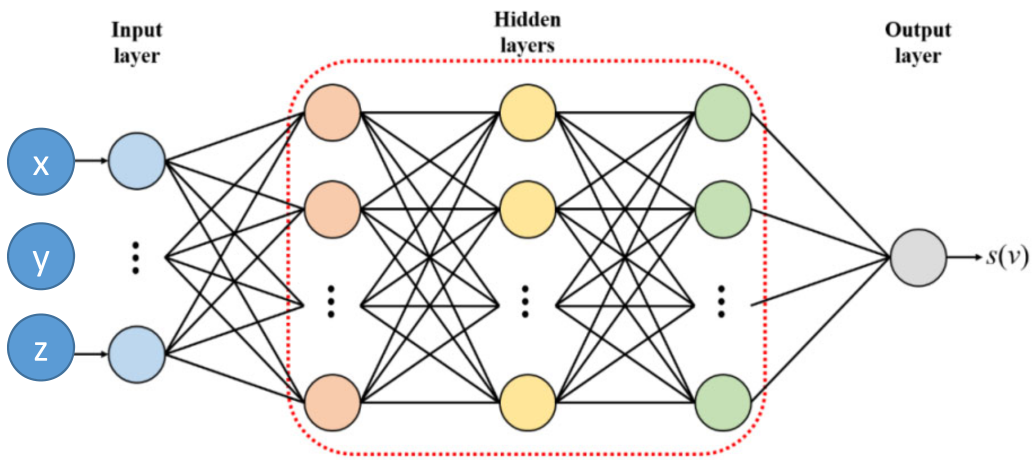
Part one: Coordinate-based MLP

Multilayer perceptron (MLP)



Inputs for the network are imagines, and signals.

Coordinate-based MLP



Inputs are coordinates Information.

Part one: Coordinate-based MLP

Why MLP $\longrightarrow$ Good ability of recovering low frequency information

Tanick et al. 2020:

$$\partial_t e_i = -e_i \lambda_i;$$

e_i $\longrightarrow$ i^{th} components of training loss

λ_i $\longrightarrow$ i^{th} eigenvalue NTK

Determined by the activation function

$$e_i = e^{-\lambda_i t} + C$$

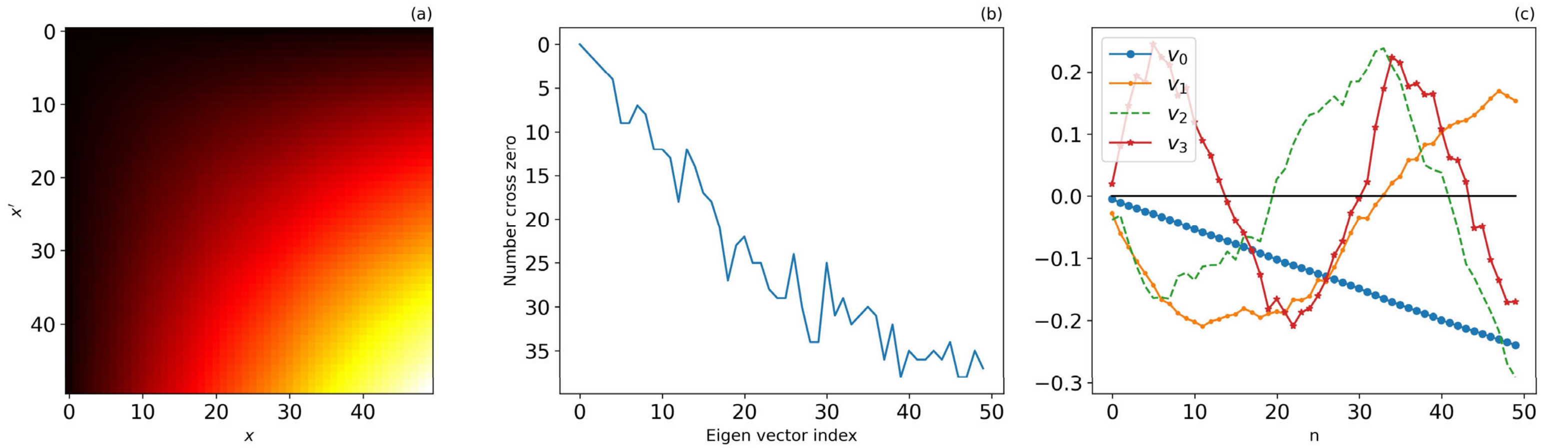
the i^{th} components of the training loss will decay exponentially with the rate of λ_i.

λ_i large $\Rightarrow$ Eigenvector for low frequencies

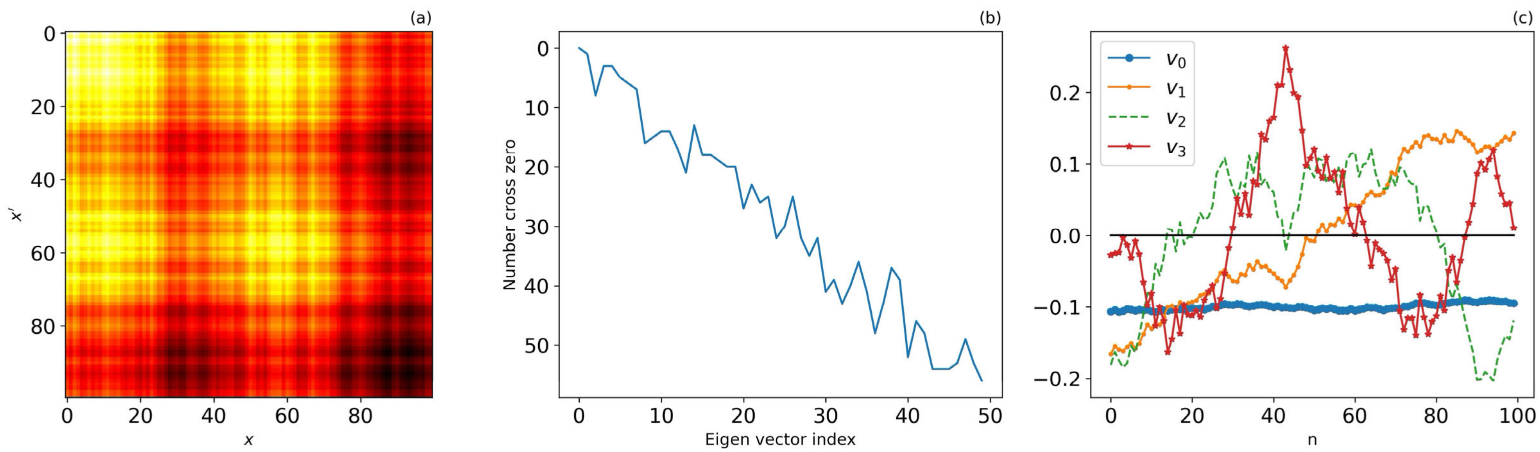
Low frequency components in MLP loss function are first learned.

Part one: Coordinate-based MLP

Large eigenvalue components correspond to eigenvectors representing low frequency information



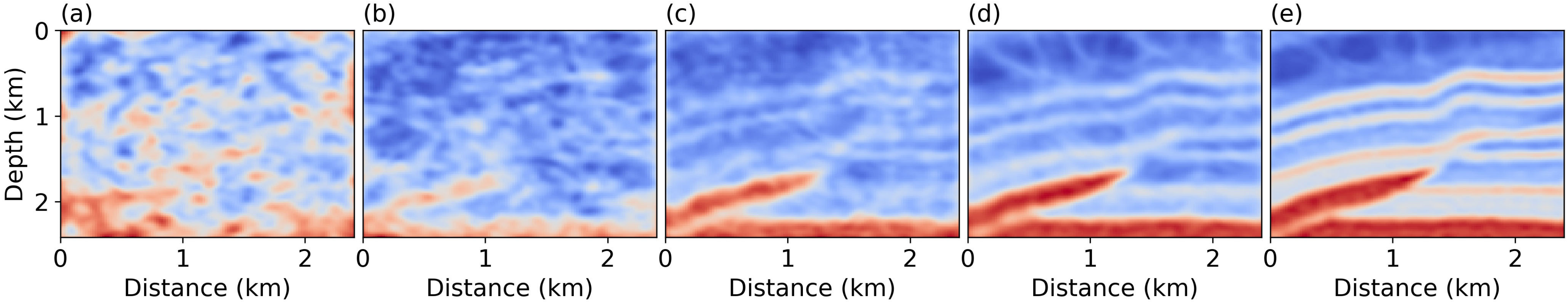
NTK analysis of the Relu activation function



NTK analysis of the sin activation function

Part one: Coordinate-based (MLP)

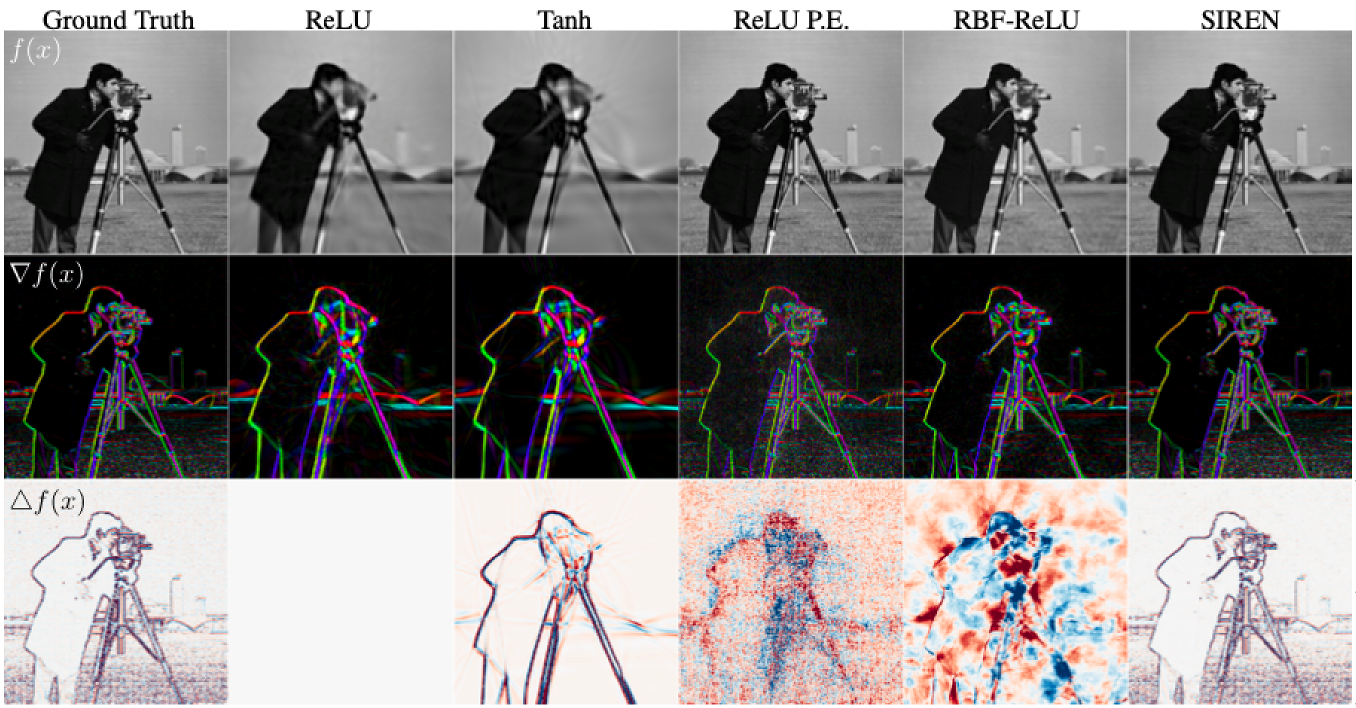
Low frequency components in MLP loss function are first learned.



Training a MLP with sin activation layer to represent a single image.
From left to right are the training prediction.
(a) 10 epoch, (b)40 epoch,(c) 80 epoch, (d) 120 epoch, (e) 200 epoch.

Part one: Coordinate-based MLP

The activation functions in MLP.



Sitzmann V, et al Implicit neural representations with periodic activation functions[J]. Advances in Neural Information Processing Systems, 2020, 33.

Comparison of different activation functions in neural network architectures fitting the representation of an image

Part Two: Implicit neural Representation FWI: a FWI without the using of initial model

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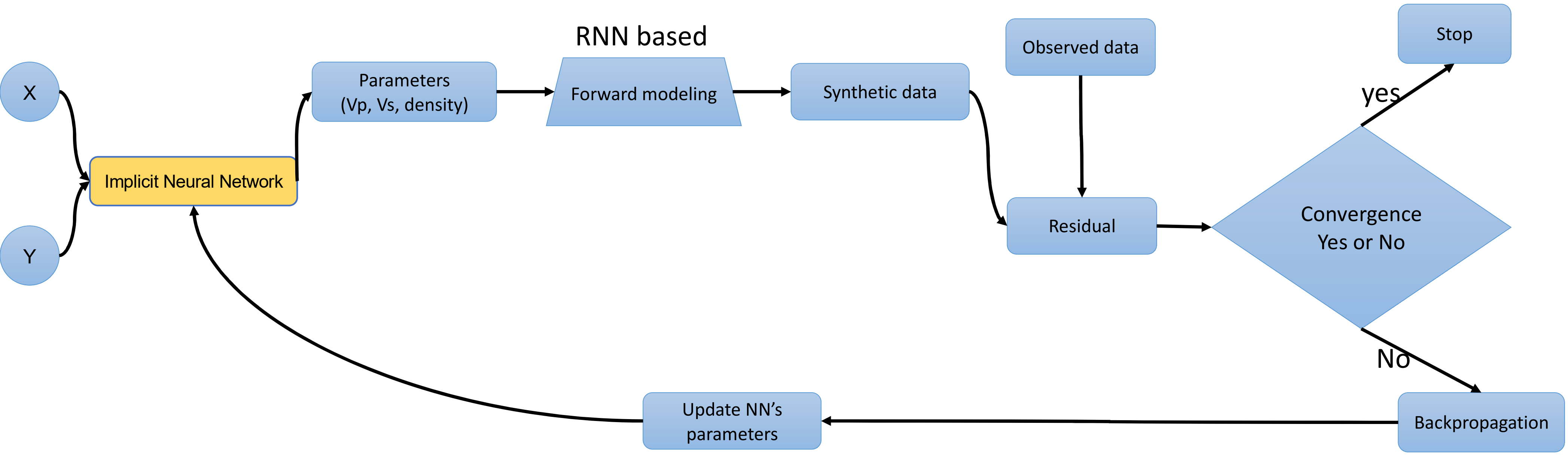
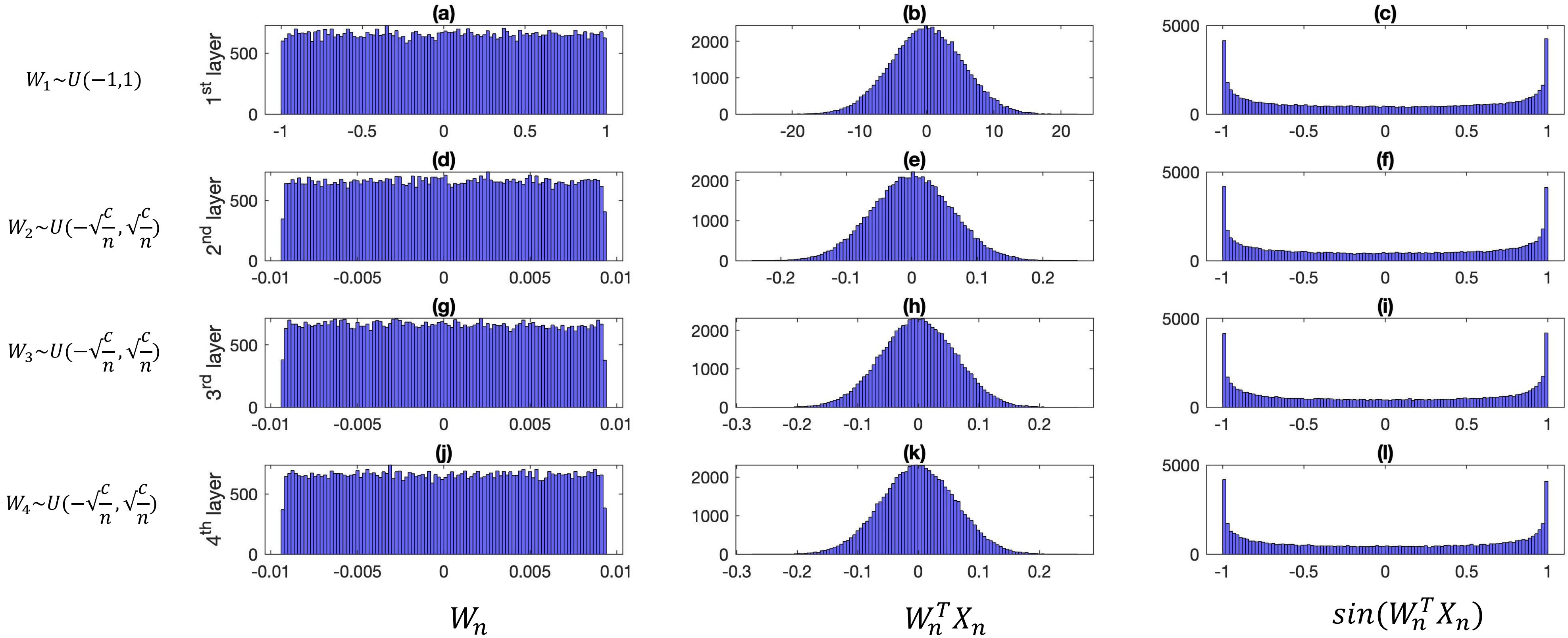
The basic structure of IFWI.



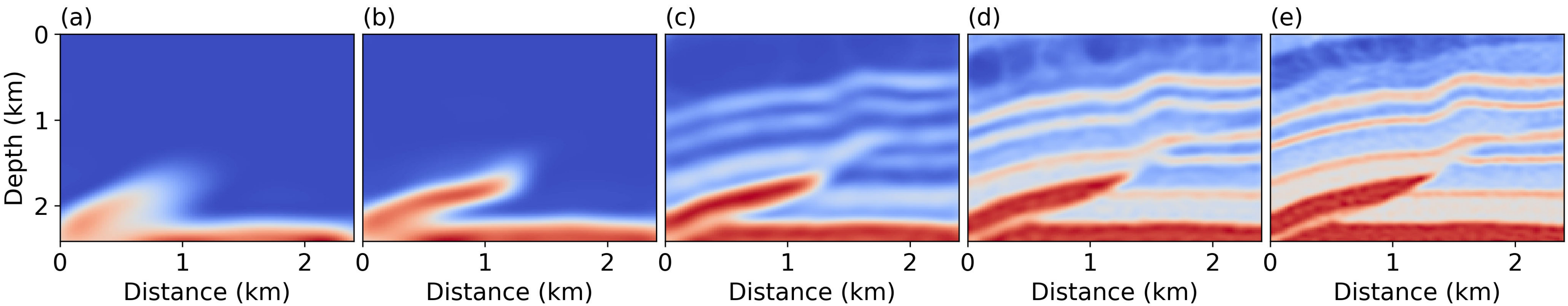
Part TWO: Implicit neural Representation FWI

Initialization the weights in network



Part TWO: Implicit neural Representation FWI

Proof of how initialization weights influence the prediction results



The prediction result training a network to generate a velocity model with different c value with a four layer coordinate based MLP. (a) c=1, (b) c=3, (c) c=9, (d) c=15, (e) c=20. With a broader range of weights are generated, more detail of the image can be resolved.

Part Three: Numerical tests

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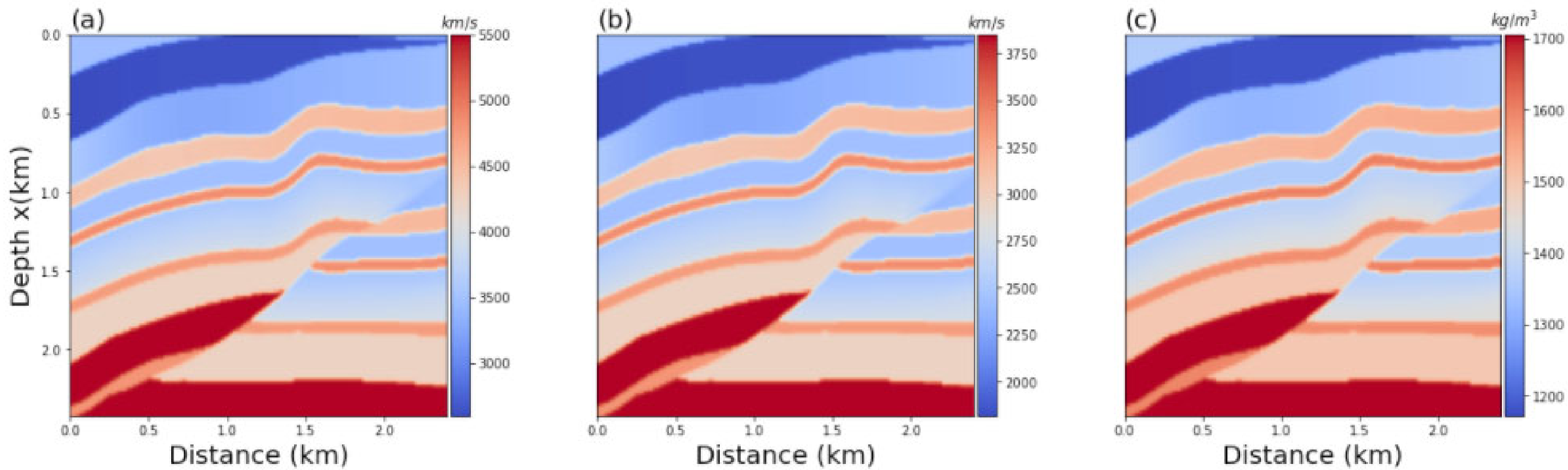
Model size: nz=nx=125   Grid length: dz=dx=20m

Maximum receiving time: 2.6s   Dt=0.002s

Wavelet: Ricker's wavelet (10 Hz main frequency)

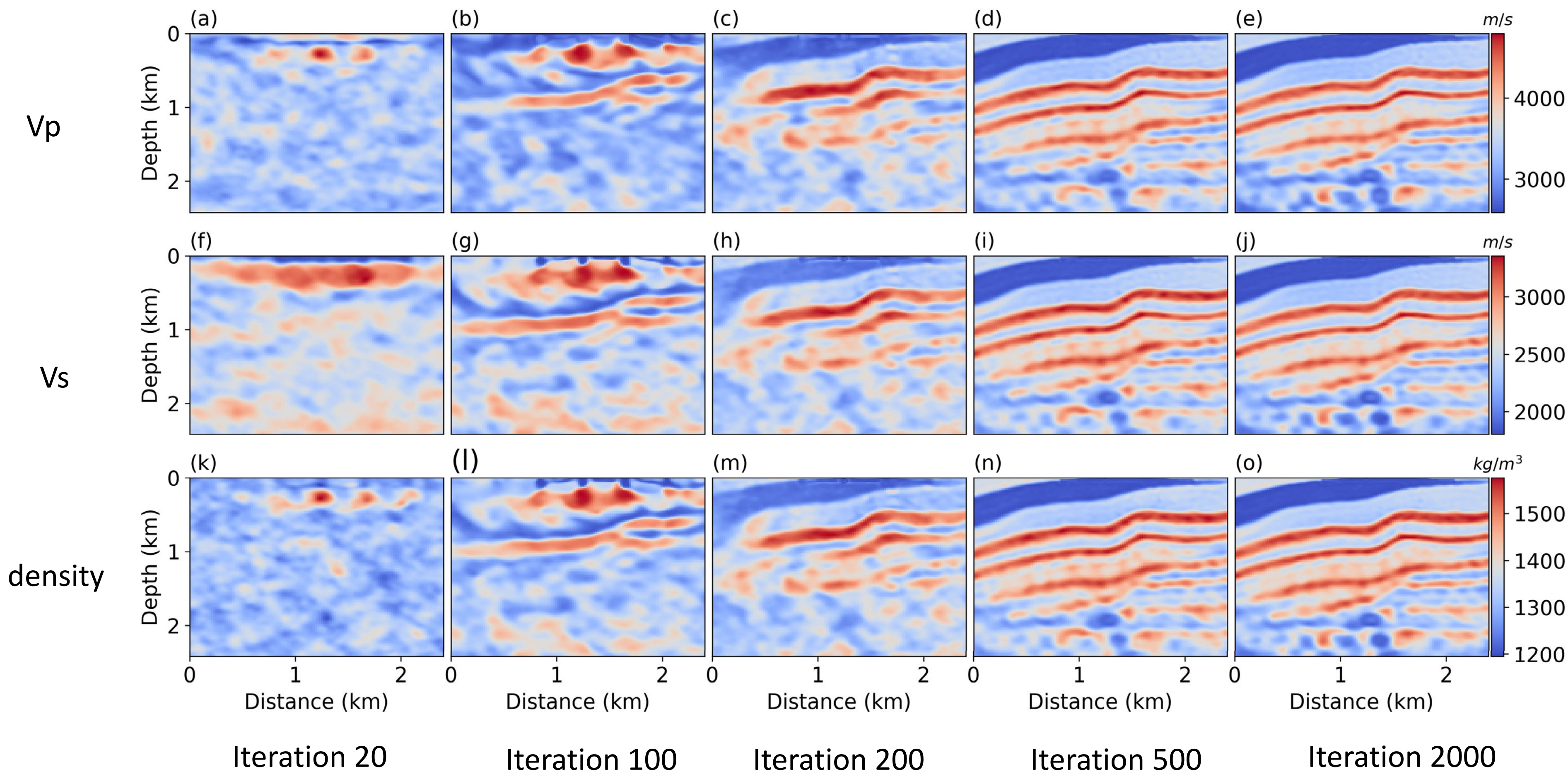
Maximum iteration time: 2000

GPU Device: Nvida V100



True Vp   True Vs   True Density

Part Three: Numerical tests



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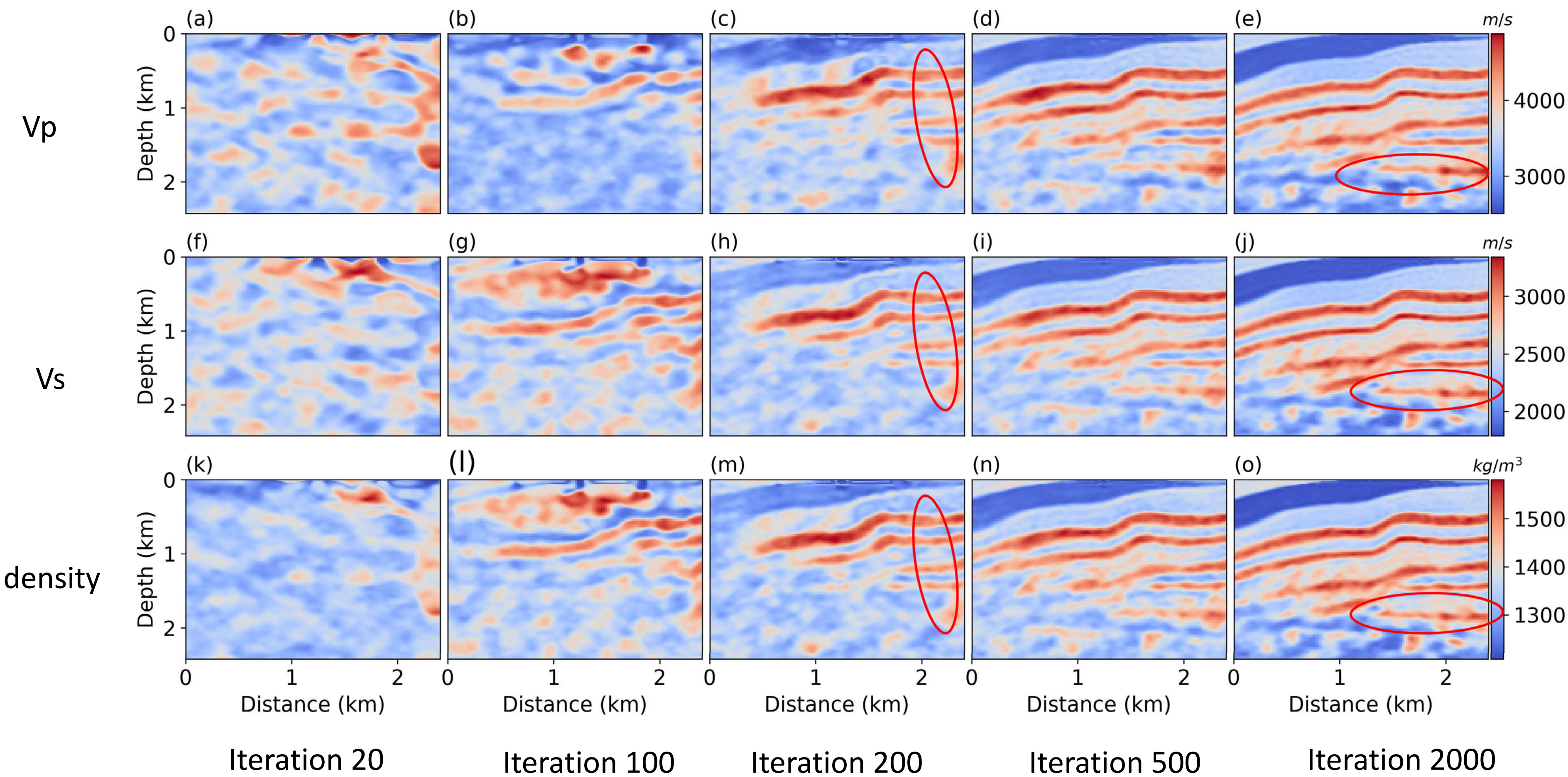

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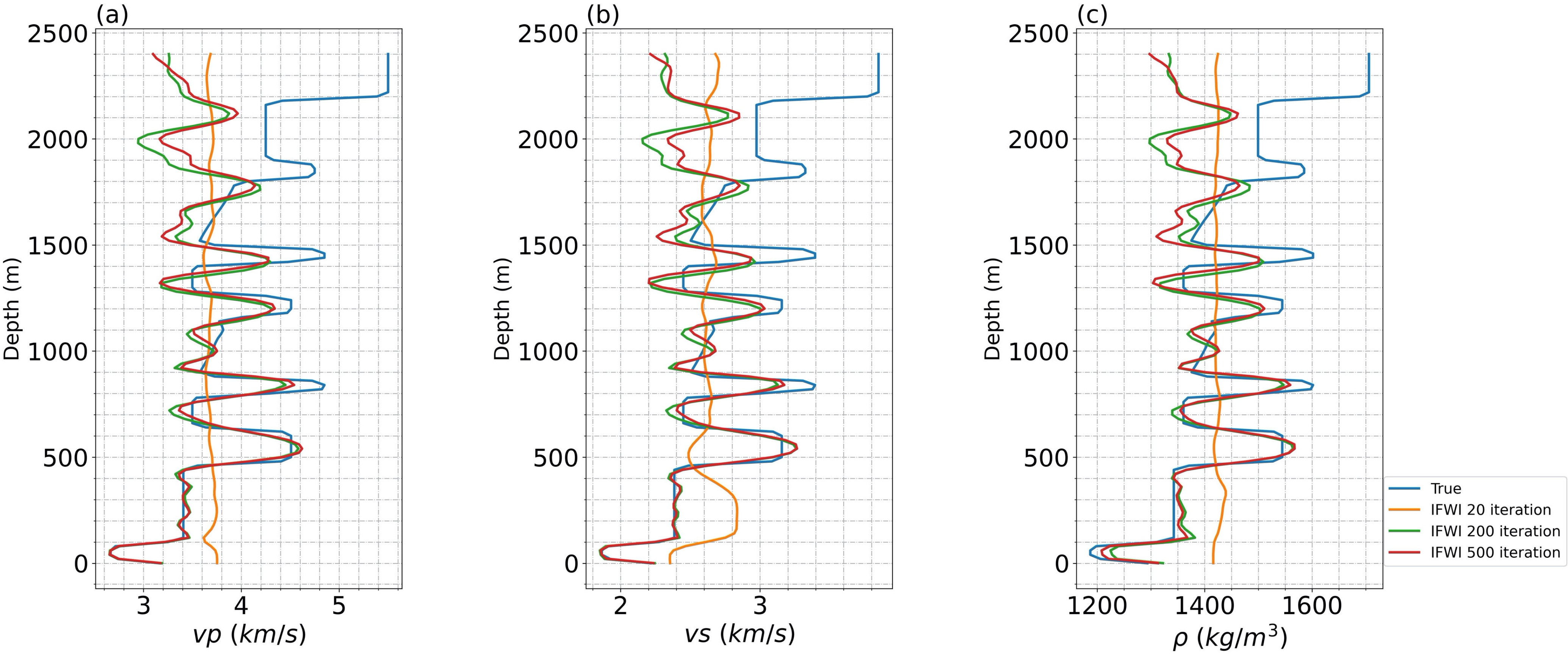

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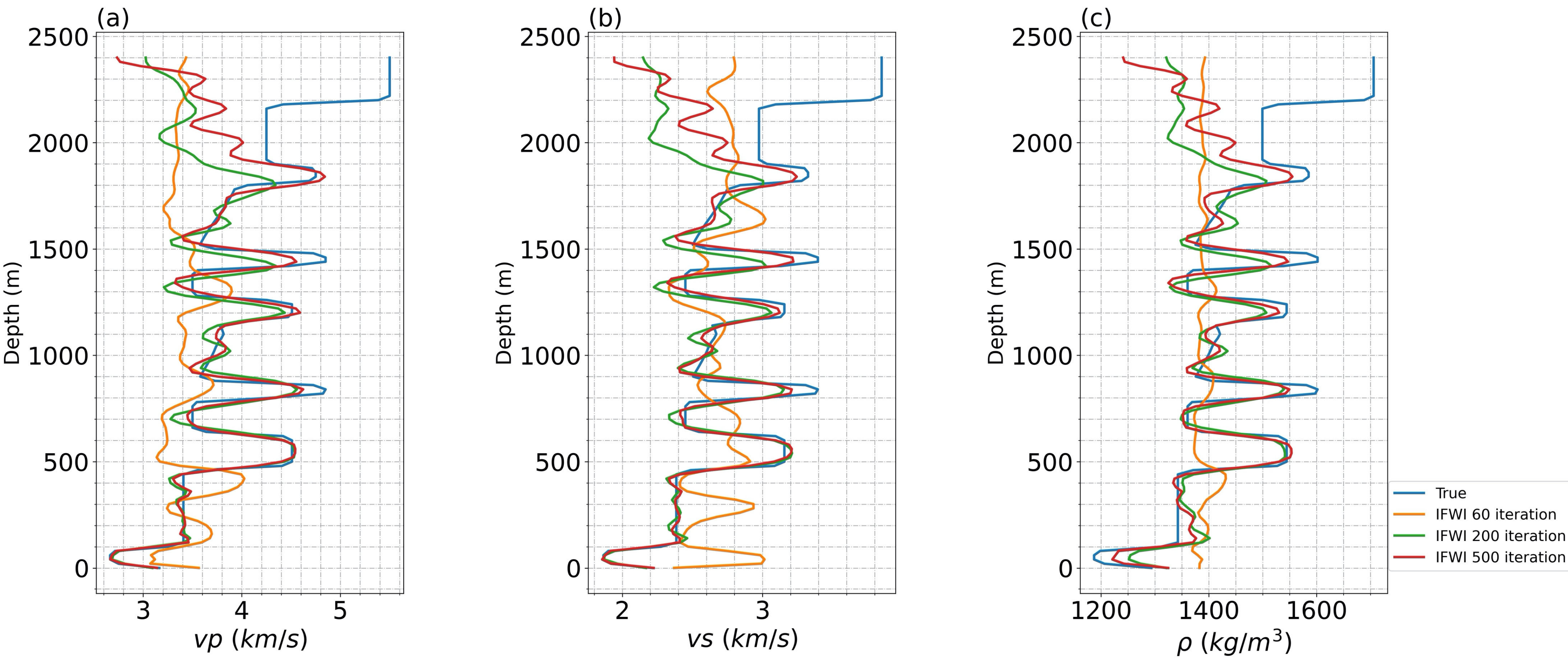

Conclusions

(1) We discussed why MLP has good ability of recovering the low frequency components in objective function.
(2) We use the combination of the coordinates based MLP and RNN FWI to perform elastic FWI without the initial models, and the results predicted with IFWI is promising.

Problems and improvements

(1) Depend heavily on acquisition system to light up the whole simulation area.
(2) Convergence time is longer compared with conventional FWI.

Thanks

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