A deep learning formulation of elastic FWI with numerical and parameterization analysis

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INTRODUCTION

In this study, we combine the recurrent neural network with the knowledge about elastic wave propagation and inversion theory, which forms the theory based machine learning method for full waveform inversion. Based on the Automatic Differential method, the exact gradient based on computational graph would be calculated to update the elastic model. In order to tackle with the cross talk problem in multiparameter full waveform inversion, by modifying the theory based RNN cell, we use different parameterization to mitigate the trade off issue. From the numerical inversion tests, we can see the different effects on the inversion results with different parameterization. It could be the pioneer for us to introduce more complicated machine learning methods into Geophysics inversion problems.

ELASTIC WAVE EQUATION RNN CELL

Figure 1 shows the basic structure of the elastic RNN cell. This elastic RNN cell is designed according to the isotropic elastic wave equation, equation (1) . The light blue ovals are the stress fields the purple ovals are the velocity fields. The green circles represents the mathematical operations. The yellow boxes are the trainable parameters.

$$\begin{cases} \dfrac{\partial \mathbf{v}_x}{\partial t} = \dfrac{1}{\rho}\left(\dfrac{\partial \boldsymbol{\sigma}_{xx}}{\partial x} + \dfrac{\partial \boldsymbol{\sigma}_{xz}}{\partial z}\right) \\ \dfrac{\partial \mathbf{v}_z}{\partial t} = \dfrac{1}{\rho}\left(\dfrac{\partial \boldsymbol{\sigma}_{xz}}{\partial x} + \dfrac{\partial \boldsymbol{\sigma}_{zz}}{\partial z}\right) \\ \dfrac{\partial \boldsymbol{\sigma}_{xx}}{\partial t} = (\lambda + 2\mu)\dfrac{\partial \mathbf{v}_x}{\partial x} + \lambda \dfrac{\partial \mathbf{v}_z}{\partial z} \\ \dfrac{\partial \boldsymbol{\sigma}_{zz}}{\partial t} = (\lambda + 2\mu)\dfrac{\partial \mathbf{v}_z}{\partial z} + \lambda \dfrac{\partial \mathbf{v}_x}{\partial x} \\ \dfrac{\partial \boldsymbol{\sigma}_{xz}}{\partial t} = \mu\left(\dfrac{\partial \mathbf{v}_x}{\partial z} + \dfrac{\partial \mathbf{v}_z}{\partial x}\right) \end{cases} \tag{1}$$

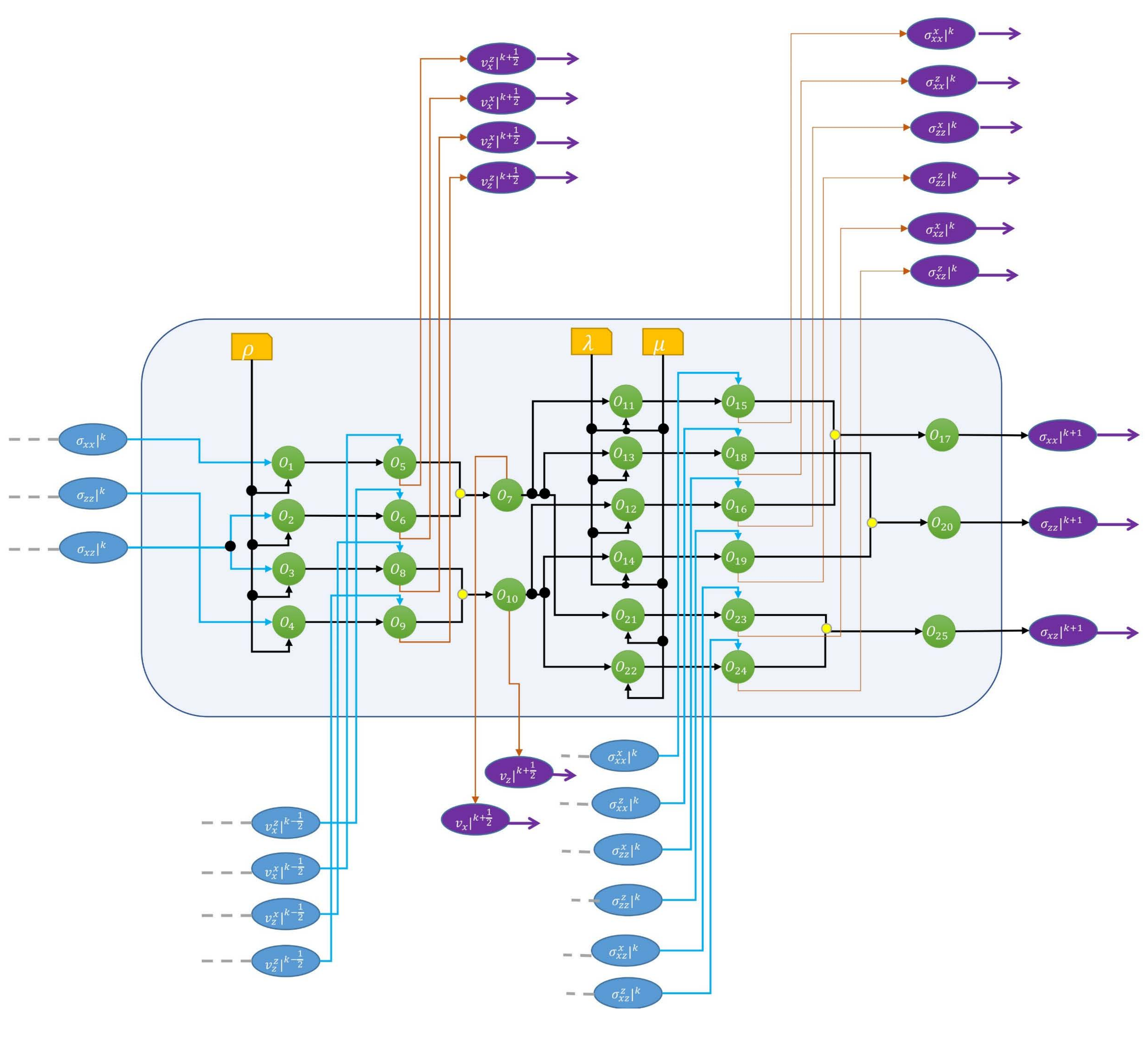

Fig 1. Elastic RNN cell

NUMERICAL TESTS

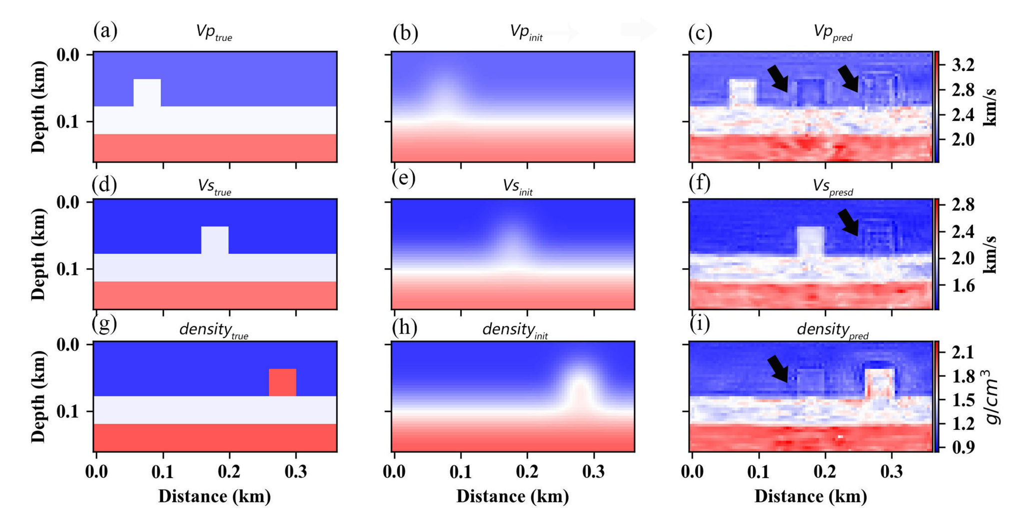

Fig.2. Velocity parameterization

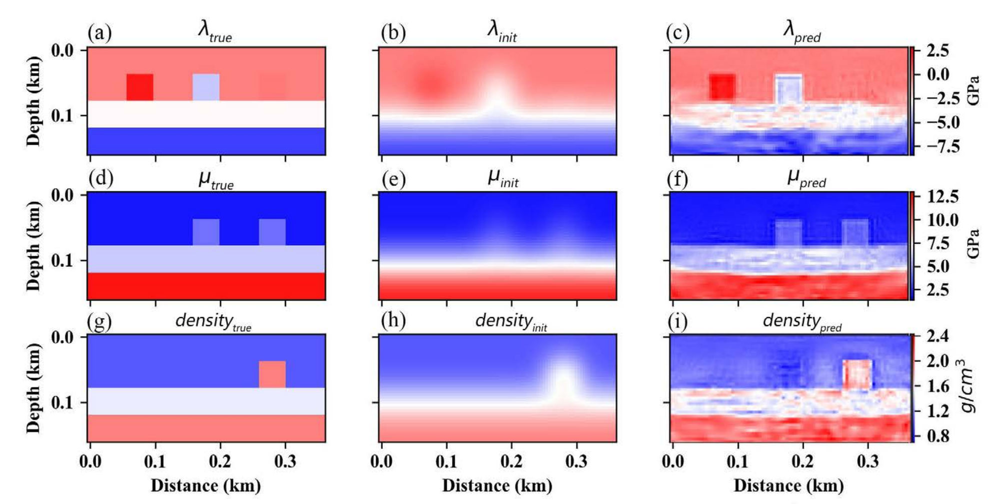

Fig.3. Modulus parameterization

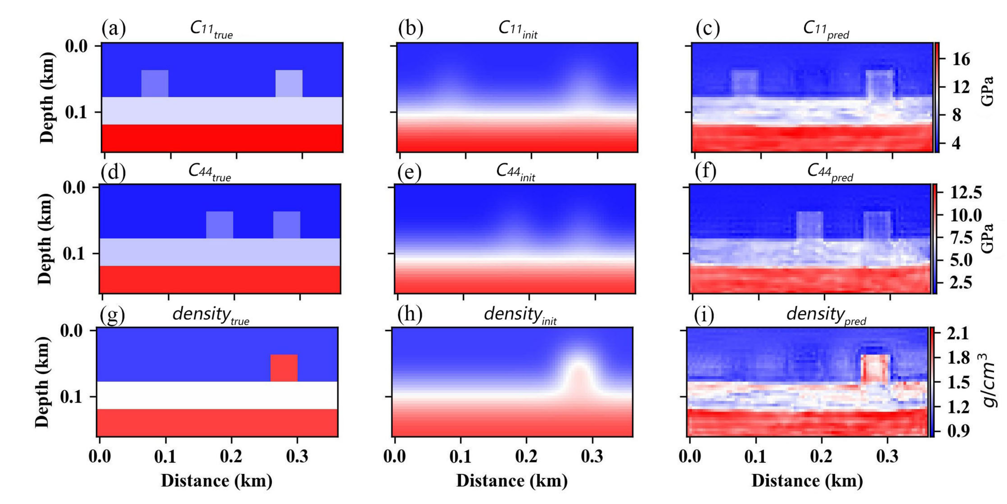

Fig.4. Stiffness matrix parameterization

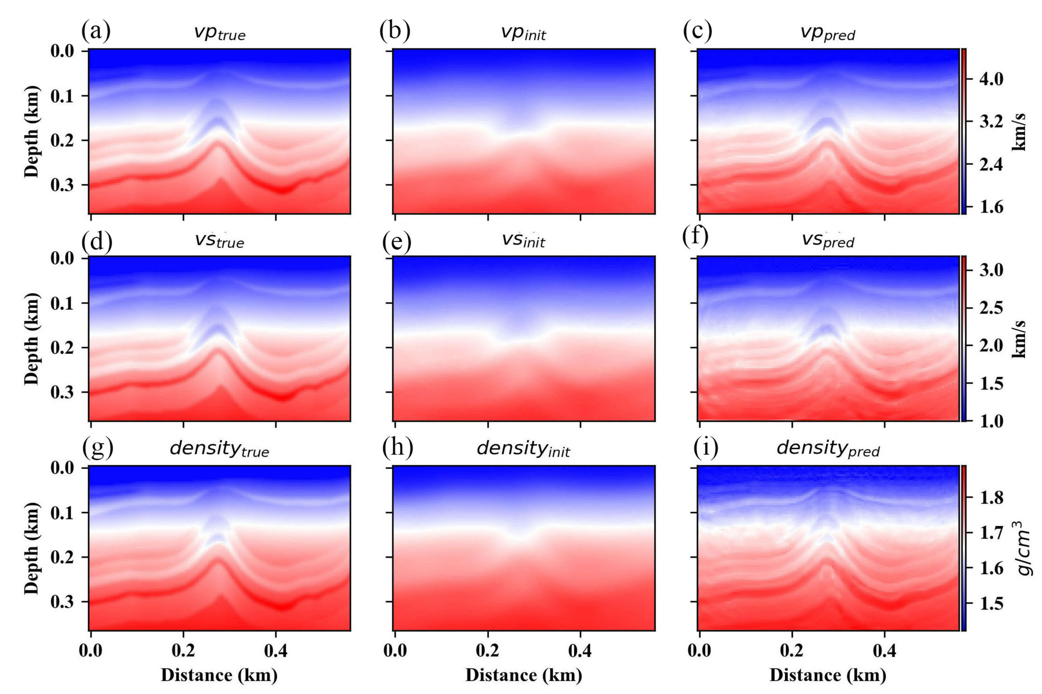

Fig.5. Velocity parameterization

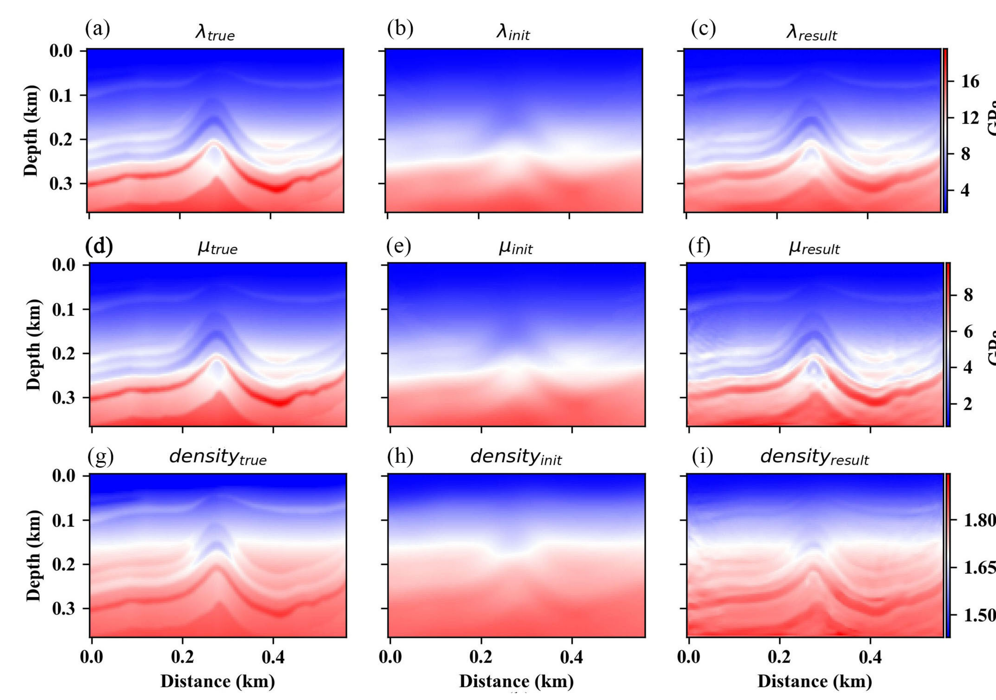

Fig.6. Modulus parameterization

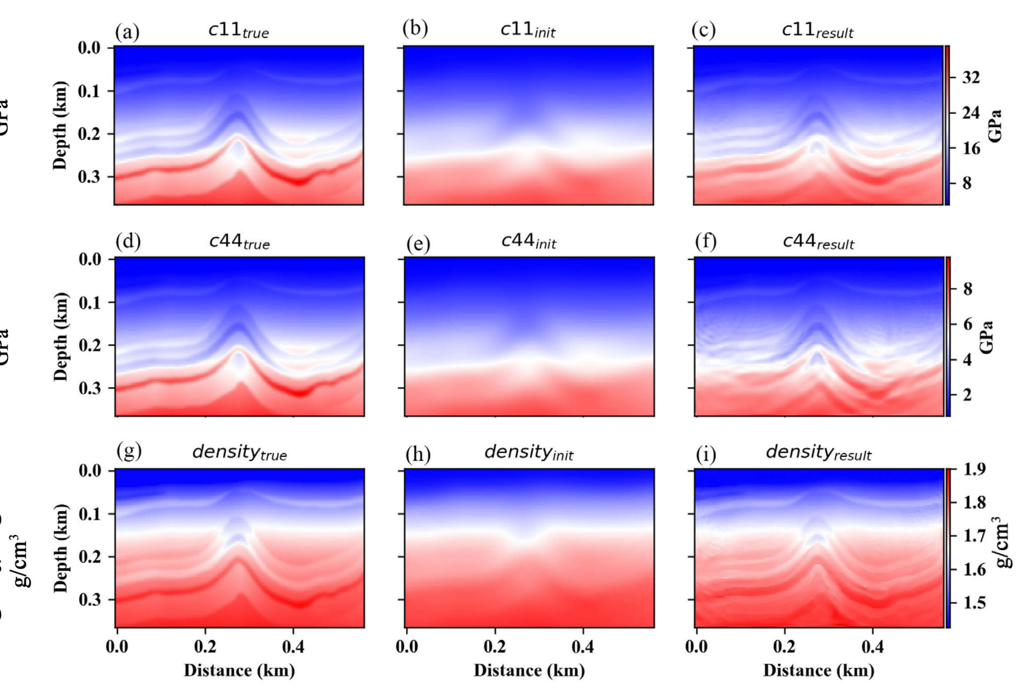

Fig.7. Stiffness matrix parameterization

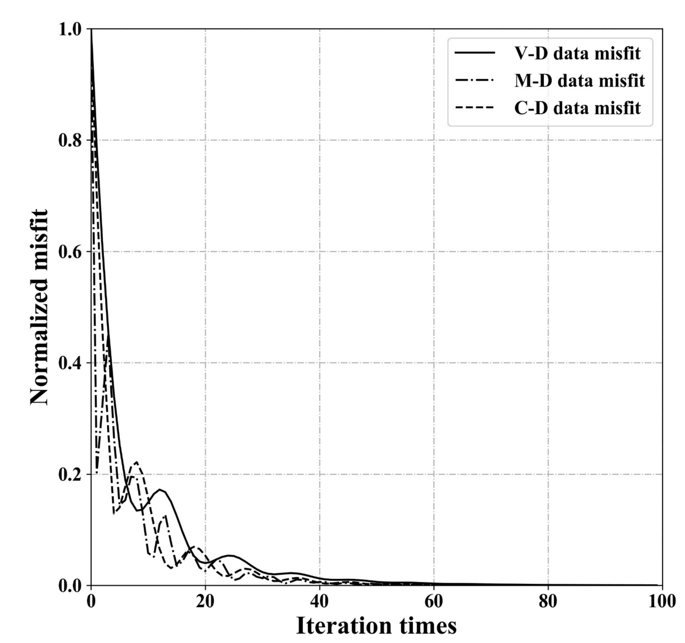

Fig.8. Data misfit

Figure 2-4 are the inversion results by using the RNN based full waveform inversion with different parameterization. Three box anomalies are located at different positions of the model and we can see the different effect of different parameterization on the inversion results. The cross-talk problem has been mitigated by using a different parameterization. Figure 5-7 are the results of another model. We can see also see the effect of the different parameterization on density.

Figure 8 is the data misfits. We can see that the inversion for the velocity parameterization is more stable than other parameterization. Figure 9 shows the inversion with different levels of noise we can see that this inversion method is sensitive to noise. The inversion results are influenced by a small amount of noise. Also the inversion for Vs is more sensitive than the inversion for Vp and density.

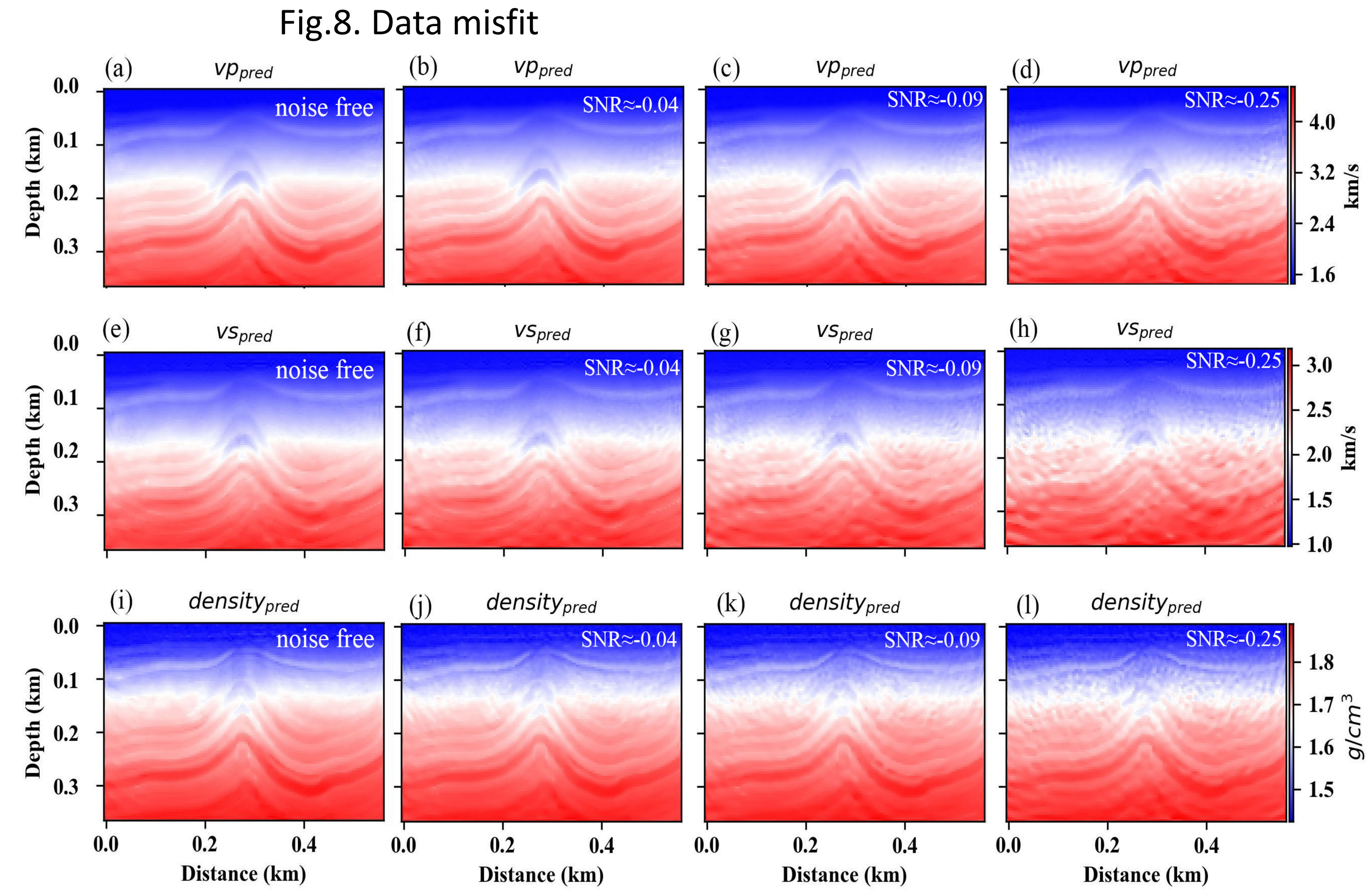

Fig 9. Noise stress test

CONCLUSIONS

In this study, we perform full wave form inversion by using the recurrent neural network. The RNN cells are designed according to the elastic RNN cell. Based on the Automatic Differential engine built inside the machine learning library, the exact gradients based on the compactional graph would be calculated. Numerical test shows that RNN based FWI can give us the right inversion results. Stress tests shows that this method is still sensitive to noise. To tackle with the cross talk problem we use different parameterizations to release this issue, we can see that different parameterization can help to improve the inversion results. Noise test shows that the inversion is still sensitive to noise.

Acknowledgement

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