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Convolutional neural network-based reverse time migration with multiple energy

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Summary

Reverse time migration (RTM) has the advantage that it can handle steeply dipping structures and offer high-resolution images of the complex subsurface. However, there are some limitations on the aperture illumination and computation efficiency. RTM with multiple (RTMM) can help to improve the illumination but will generate crosstalk because of the interference between different orders of multiples. One solution is to apply least-squares reverse time migration, which updates the reflectivity and suppresses artifacts through iterations. However, the accuracy depends heavily on the input and accuracy of the background velocity model. We proposed a method based on a convolutional neural network (CNN) in the RTMM that behaves like a filter applying the inverse of the Hessian in the LSRTM but with less computational cost. This approach can learn patterns that represent the relation between the reflectivity obtained through RTMM and the true reflectivity obtained from velocity models through a modified residual U-Net. Once trained this neural network (RTMM-CNN) can be used to improve the quality of migrated images. The baseline model (RTM-CNN) is using the same neural network architecture but without multiple energy added. Numerical experiments show that RTMM-CNN can recover major structures and thin layers with higher resolution and improved accuracy compared with the RTM-CNN method.

Theory / Method / Workflow

In this section, a modified U-Net-based reverse time migration with multiple energy (RTMM CNN) will be delineated in detail. The workflow is shown in Figure 1. For a simple introduction, the input includes RTMM initial image and background velocity. The input for the baseline model RTM-CNN contains RTM images and the same background velocity. After training through the modified U-Net, we can obtain a predicted reflectivity model as the outcome.

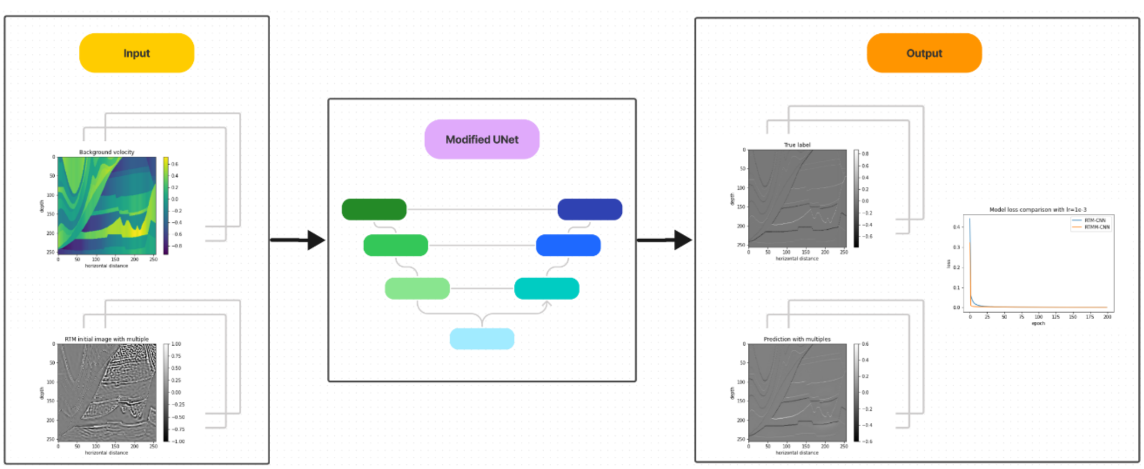


Figure 1. Workflow for a modified U-Net based RTM with multiple reflections.

U-Net (Ronneberger et al., 2015) has efficient segmentation performance replying to data augmentation with annotated samples. In this proposed method, we developed a modified U-Net with more multilayer convolutional blocks and skip connections to learn from residuals and patterns for the regression task. For the encoder part, the network down-sampling our sample data into small sizes for learning key features of different reflectors from RTMM images, background velocities and true reflectivity labels. Then, the subsurface structure key features are up-sampled to the original dimensions by transpose convolutions. Additional skip connections help to strengthen the training result with weak constraints.

The network operator acts similar as the least-squares reverse time migration (Dong et al., 2012). For LSRTM, the solution is derived from the minimum difference between true and migrated images,

$$\mathbf{m}^* = \arg\min_{\mathrm{m}}\{\tfrac{1}{2}\left\|\mathbf{\Gamma m} - \mathbf{m}_{mig}\right\|_2^2\}, \tag{1}$$

A formal solution to equation 1 is

$$\mathbf{m}^* = \mathbf{\Gamma}^{-1}\mathbf{m}_{mig} = \mathbf{\Gamma}^{-1}(\mathbf{L}^T\mathbf{d}), \tag{2}$$

where $\mathbf{\Gamma}^{-1}$ is the inverse Hessian, $\mathbf{L}^T$ is the adjoint operator and $\mathbf{d}$ represents the observed seismic data.

Similarly, this modified U-Net can be used as an alternative way of inverse Hessian to determine the imaging result. The benefit is that there is no need to compute the expensive inverse Hessian operator or process the shot records. The forward modeling or feedforward procedure in our proposed method for a multilayer CNN is $\mathbf{\Gamma}_{unet}$, and the solution can be determined as:

$$\mathbf{m}_{pred} = \mathbf{\Gamma}_{unet}(\mathbf{m}_{rtmm}, \mathbf{m}_{vel}), \tag{3}$$

where $\mathbf{m}_{rtmm}$ is the RTMM initial image, $\mathbf{m}_{vel}$ denotes the background velocity model and $\mathbf{m}_{pred}$ represents the output reflectivity coefficient prediction.

The mean squared error (MSE) loss is applied to evaluate the model performance and penalize the large prediction errors:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{m}_{pred}^{i} - \mathbf{m}_{true}^{i})^2, \tag{4}$$

where $\mathbf{m}_{pred}$ is derived from equation 3 which inputs RTMM initial images and velocity in the U-Net, and $\mathbf{m}_{true}$ denotes the true reflectivity models.

Results and Observations

To avoid the overfitting and fixed learning pattern issue, we decided to test our proposed model on a different model, the Foothill model, which has never participated in neither training nor testing process. The true velocity model is shown in Figure 2, and 300 windows are chosen to test our model performance. The total model size is 1600x1000, with 10 meters spatial interval. We have used 99 shots and 798 receivers which locating at the near surface. The total recorded time is 7.2 seconds.

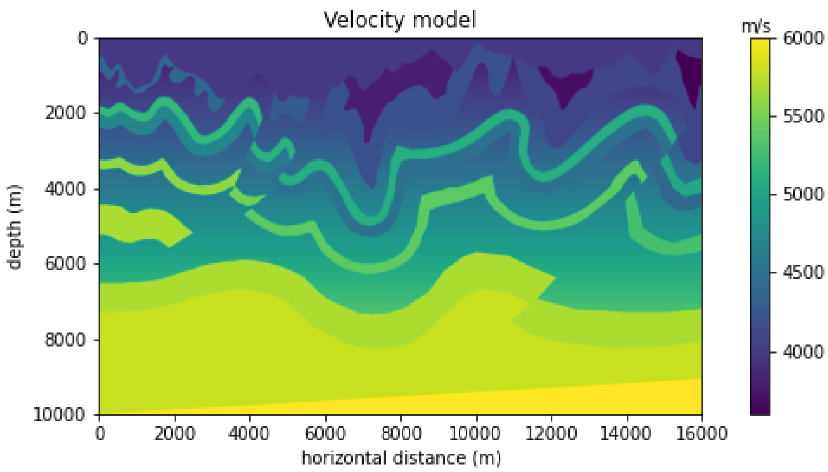
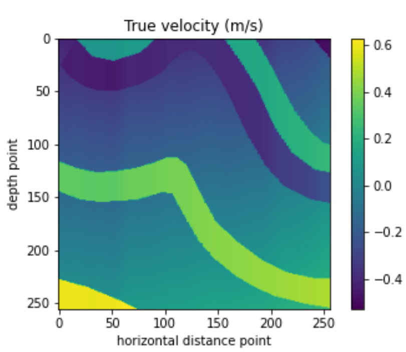


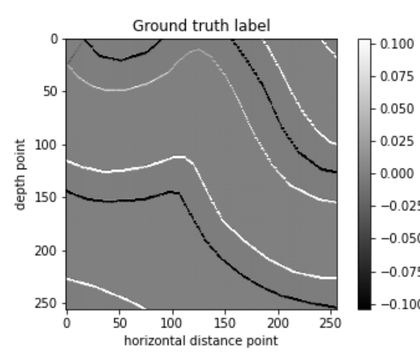
Figure 2. Foothill velocity model which is used for testing

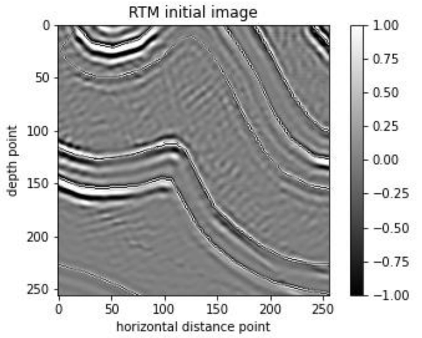
For this numerical example, one windowed result is shown in Figure 3. RTMM initial image (Figure 3d) has higher amplitudes of curvature boundaries than the RTM image (Figure 3c). Correspondingly, the RTMM-CNN result (Figure 3f) provides improved resolution with fewer artifacts compared with the RTM-CNN outcome (Figure 3e). For instance, Figure 4 shows the detailed comparison extracted from the left and upper-right parts of Figure 3. RTMM-CNN outputs (Figure 4c and f) can predict either dipping events or curvature boundaries with sharpening resolution. Both Figure 3 and 4 can prove that RTMM-CNN results have a better fit and are closer to the true reflectivity labels compared with the RTM-CNN when given an unseen velocity input.

(a)

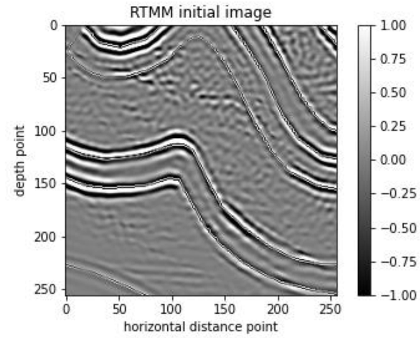


(b)

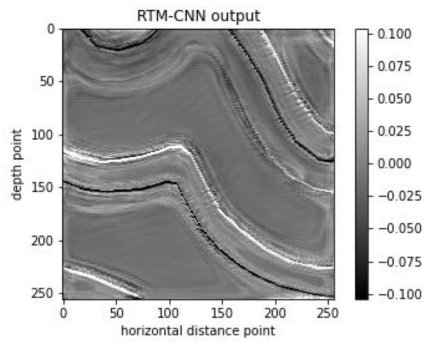




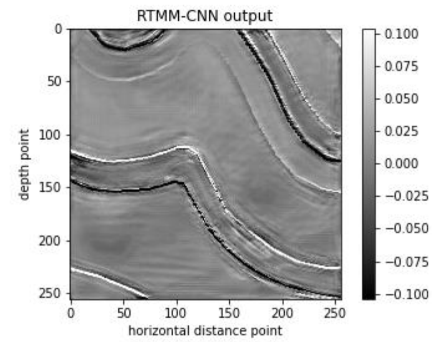
(c)



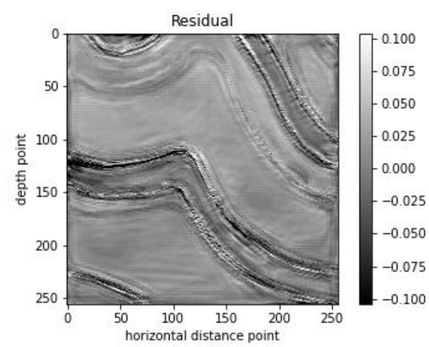
(d)



(e)

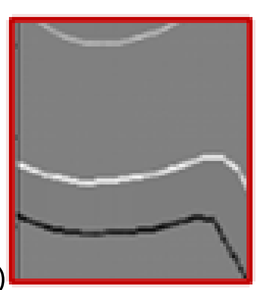
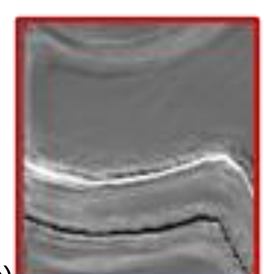
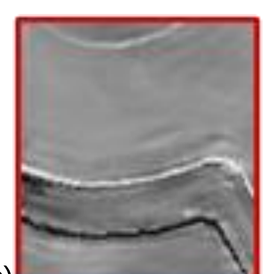


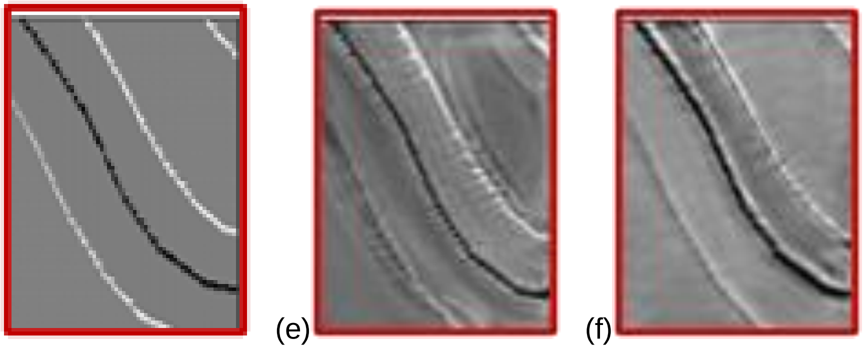
(f)



(g)

Figure 3. (a)True velocity model, (b) ground truth reflectivity coefficient label, (c) RTM images, (d) RTMM images, (e) RTM-CNN prediction, (f) RTMM-CNN prediction and (g) the residual between (f) and (e).

(a)  (b)  (c) 



(d) (e) (f)

Figure 4. Enlarged regions from the Foothill model given the accurate velocity model as the input. (a) and (d) give the true label; RTM-CNN outputs are shown in (b) and (e), and corresponded RTMM-CNN predictions are in (c) and (f).

Conclusions

The proposed method RTMM-CNN can provide improved reflectivity coefficient prediction compared with the RTM-CNN output. It takes the benefit of multiple reflections that can widen the subsurface structure illumination. The neural network operator acts as the least-squares reverse time migration, which can suppress image artifacts and improve the reflector resolution. The next step is to let the model learn how to predict a steady reflectivity when given a more smoothed input and field data.

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