The use of U-Net and Radon transforms for multiple attenuation

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Abstract

Radon transform (RT) allows the mapping of multiple and primary reflection events separately in the transformed domain. Hyperbolic Radon transform (HRT) is an example of RT that maps nearly hyperbolic events in the data space to points in the HR space. A methodology of multiple prediction is proposed based on U-Net, a convolutional neural network (CNN) architecture. This network is often applied to image segmentation for classification problems, but the proposed workflow uses the U-Net to predict multiples using HR panels. In this report, we performed predictions using one or two input channels, sparse and nonsparse HR panels, with nonsparse HR panels of multiples as the label. These numerical experiments show that a U-Net can be used to separate the primaries and multiples in the Radon space and therefore predict multiples. This result was achieved using simple geologic models, but further work is required with more complex geologic models. A challenging aspect of this problem is that the transform generates artifacts that are very dependent on the geometry of the input (truncation and sampling artifacts). Because these are very difficult to predict at inference time, they cause a decrease in generalization power.

Theory

- **Hyperbolic Radon transform** (HRT) maps nearly hyperbolic events in the CMP domain to ideally points in the HR domain.

$$m(v,\tau) = \sum_{x_{min}}^{x_{max}} d(x, t = \sqrt{\tau^2 + \frac{x^2}{v^2}})$$

m

d

$$\tilde{d}(x,t) = \sum_{v} m(v, \tau = \sqrt{t^2 - \frac{x^2}{v^2}})^{*}$$

- The most suitable solution can be found by minimizing the cost function using iterative re-weighted least squares (Thorson and Claerbout, 1985).
- These are truncated within maximum and minimum offset and possibly missing traces, thus affecting the resolution of the RT. The concept of sparse RT (Sacchi and Ulrych (1995), Trad et. al. (2003)) helps to address the resolution.
- **U-Net** (Ronneberger et. Al., 2015) is a convolutional neural network architecture usually applied in classification problems. However, we used this network to perform regression to predict the multiples in the RT domain.

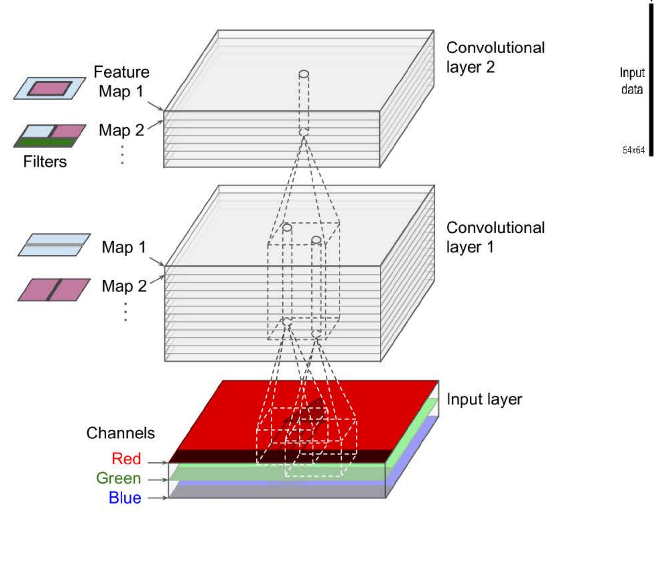

Figure 1: Schematic representation of an RGB image with its three channels (or layers), convolutional layers and feature maps (Géron, 2019).

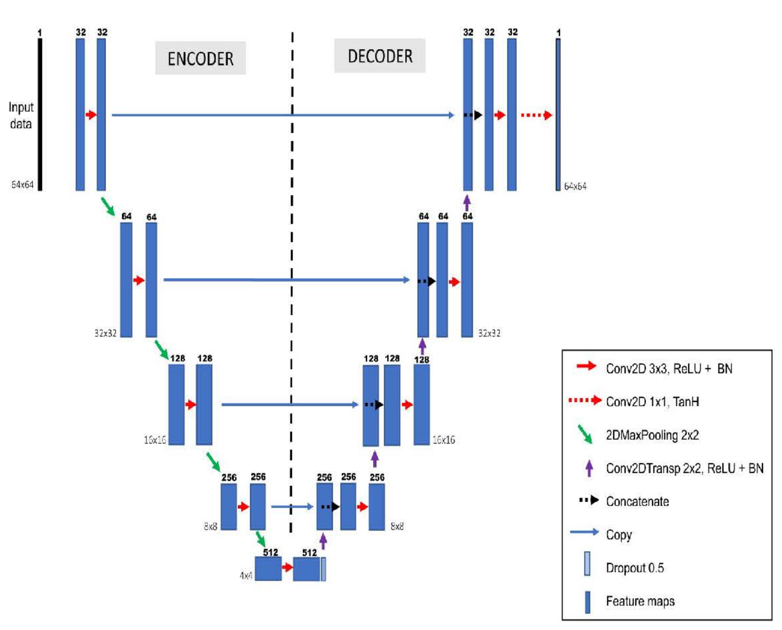

Figure 2: Schematic representation of the U-Net architecture used in the numeric examples.

Methodology

- Synthetics shots of primaries and multiples only are created using a simple velocity model and applying a convolutional model. Then, they get summed, generating the input for the network.

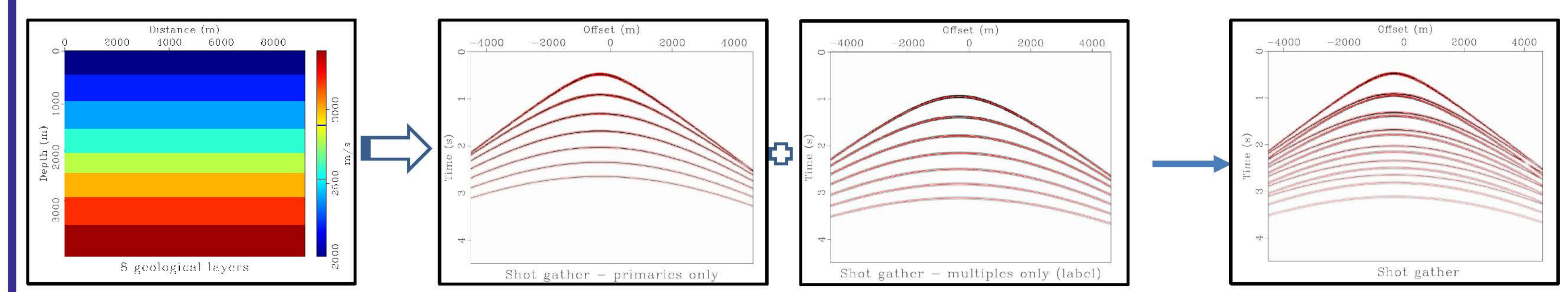

Figure 3: Workflow to generate synthetic seismic shot gathers (eight geological layers case).

- These data sets are sorted by CMP and then applied the transformation to get the HR panels. They will serve as channels and labels for the train. We proposed 2 workflows:

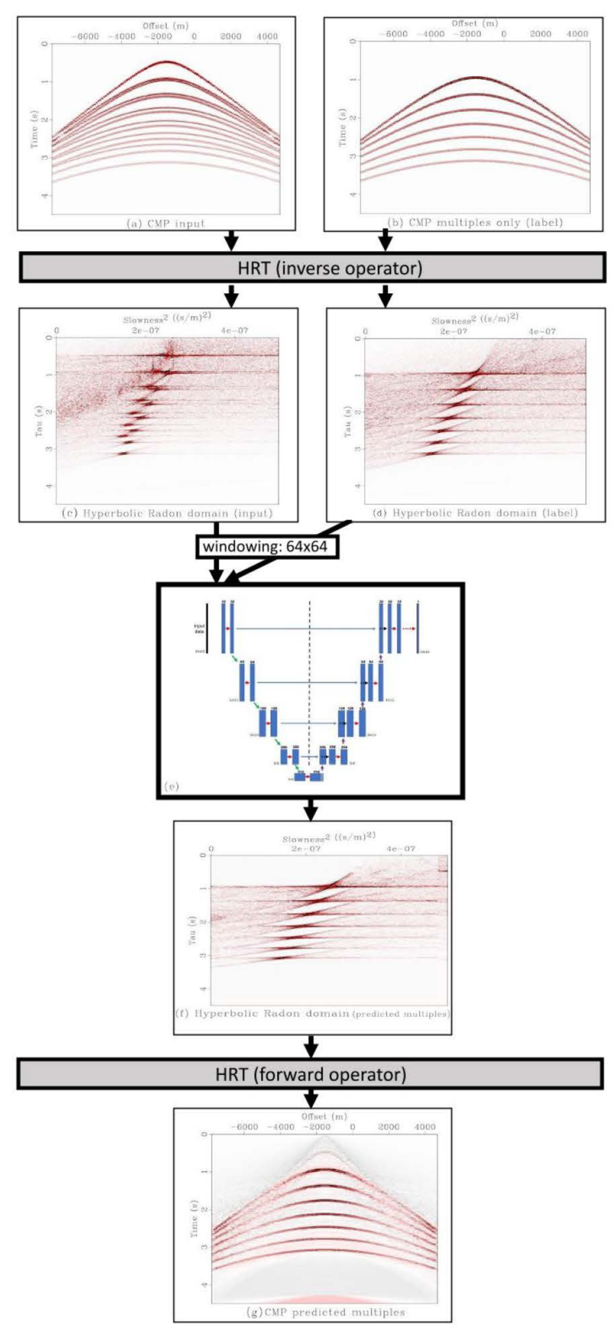

Figure 4: Workflow of the eight geological layers case using one input channel.

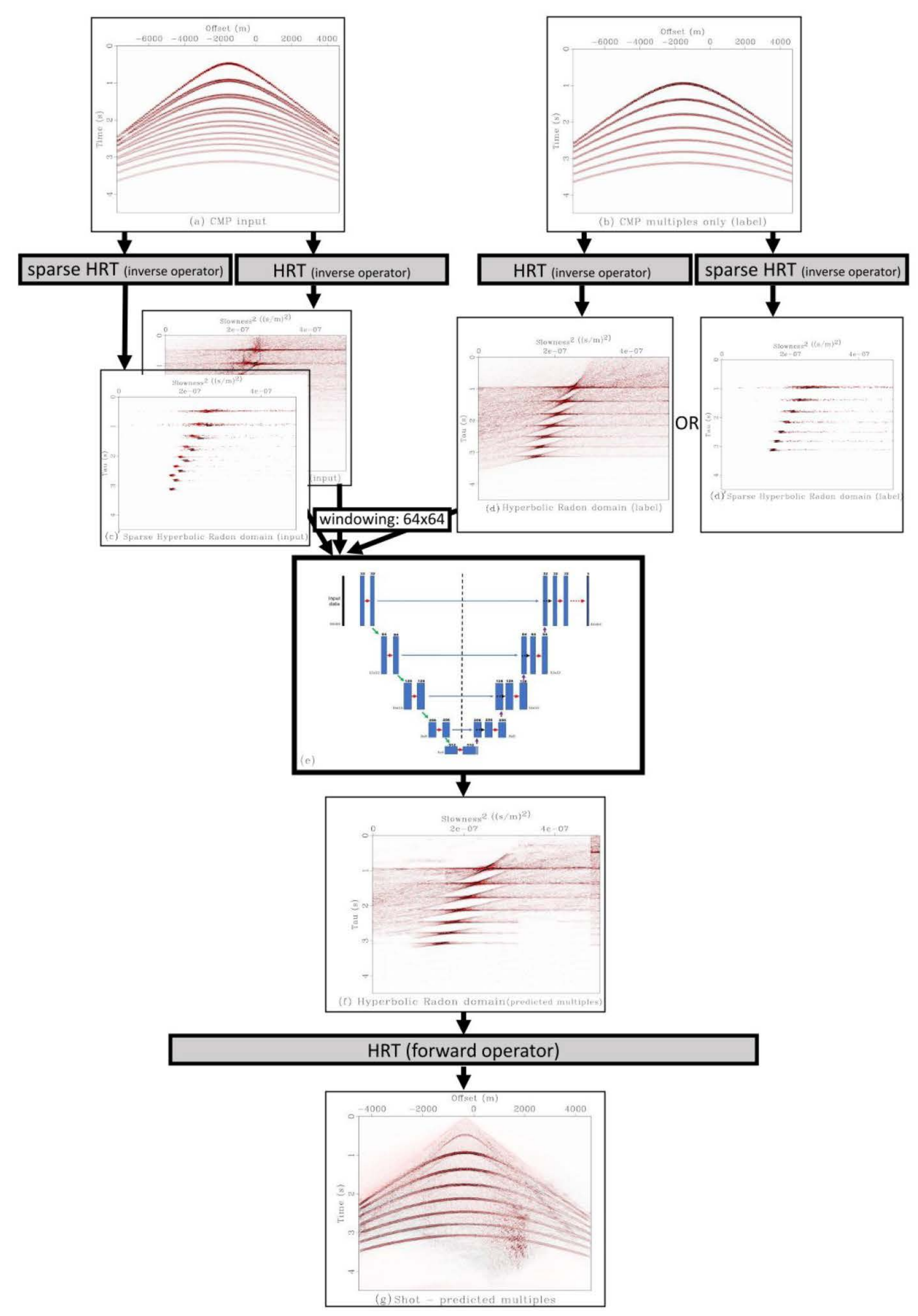

Figure 5: Workflow of the eight geological layers case using two input channels.

Conclusions

- The HRT is an important tool for separating multiple and primary reflection events;
- The U-Net was able to partially predict multiples using inference, but ideally, various geologic models should be used during training to produce a better prediction;
- Train with two channels, sparse and nonsparse HRT, and using nonsparse HRT labels resulted in better multiple predictions than the one using sparse HRT as the label;
- Future work: train the network with multiple channels using different features, such as the parabolic Radon transform, to further constrain the multiples prediction;
- RT generates artifacts that are difficult to predict, decreasing the generalization.

References

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Results

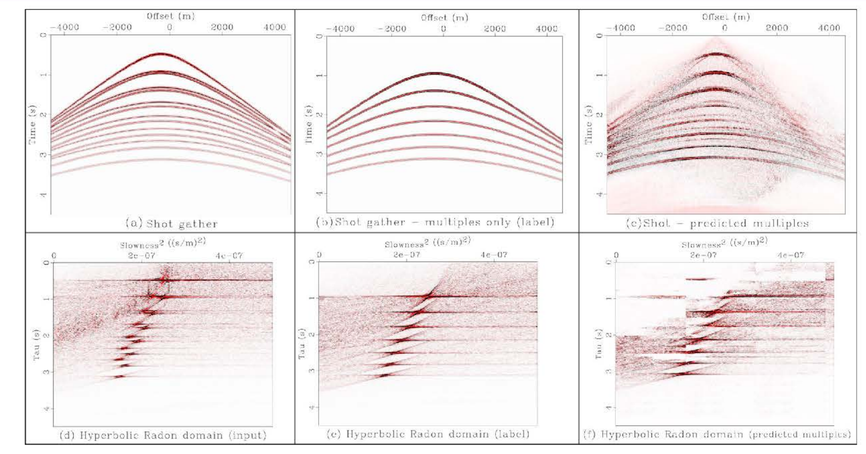

Figure 6: Train with 3 geological layers, prediction for 8 geological layers case using one input channel.

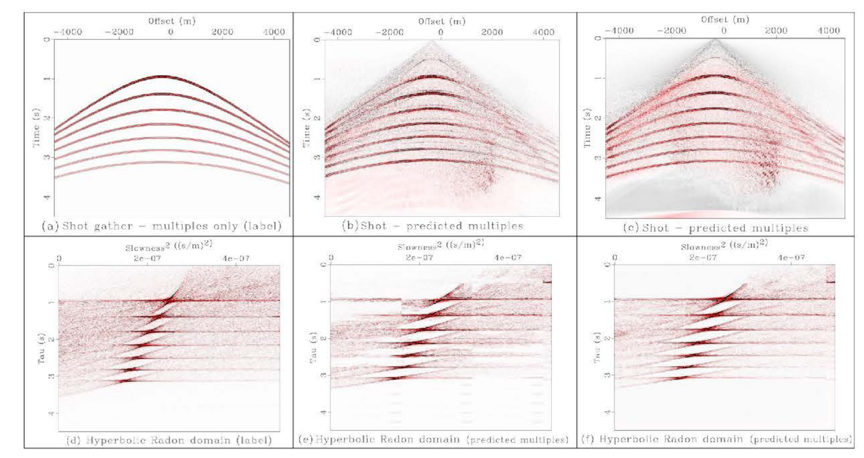

Figure 7: Train with 3, 5, and 8 geological layers, prediction for 8 geological layers case using one input channel.

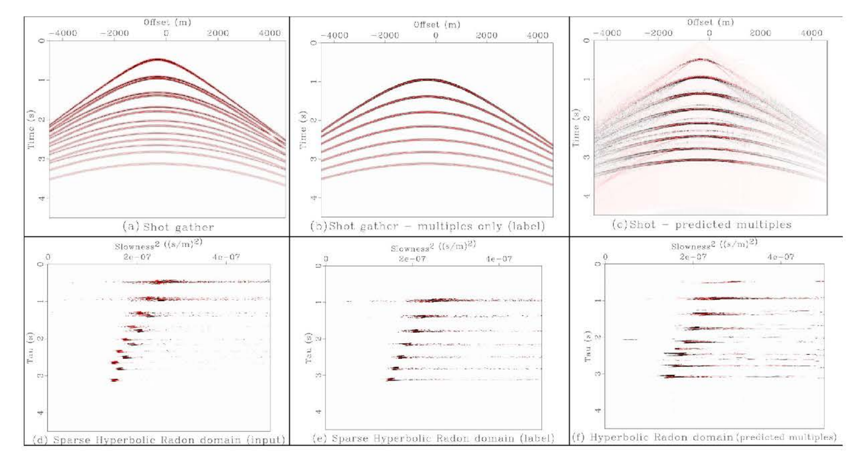

Figure 8: Train with 3 and 5 geological layers, prediction for 8 geological layers case using one input channel.

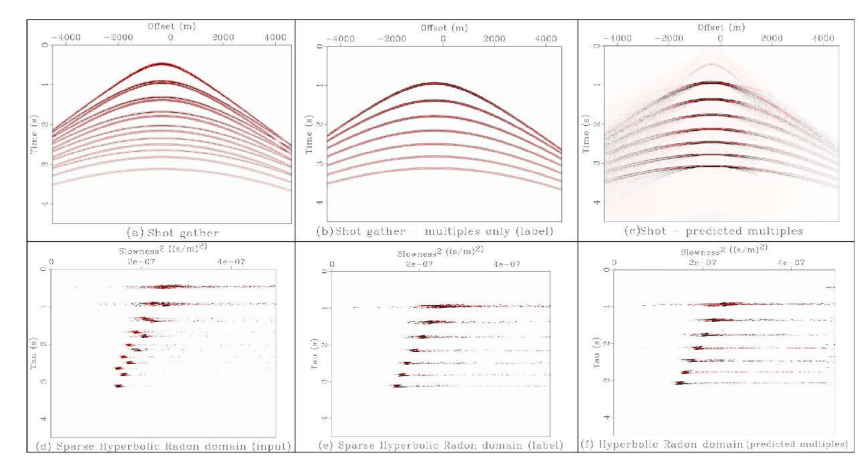

Figure 9: Train with 3, 5, and 8 geological layers, prediction for 8 geological layers case using one input channel.

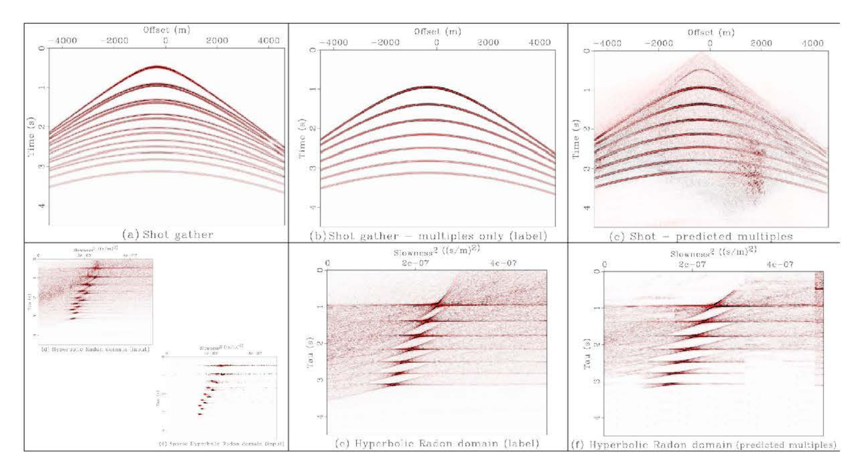

Figure 10: Train with 3, 5, and 8 geological layers, prediction for 8 geological layers case using two input channels and nonsparse label.

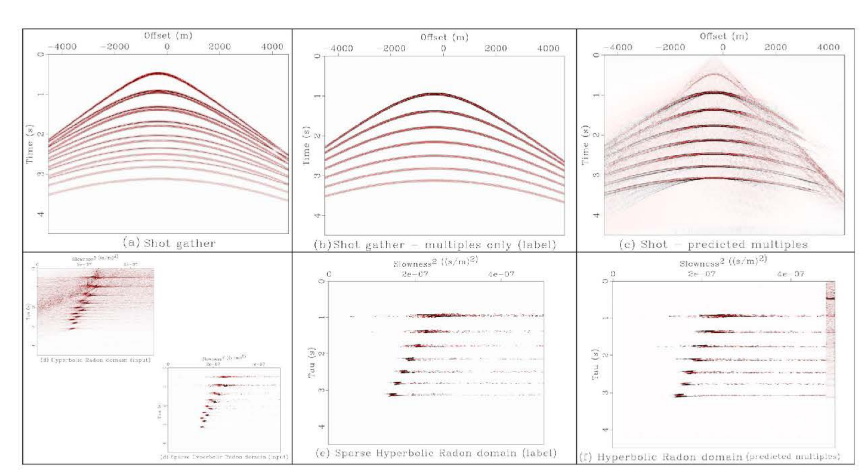

Figure 11: Train with 3, 5, and 8 geological layers, prediction for 8 geological layers case using two input channels and sparse label.

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