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The use of U-Net and hyperbolic Radon transform for multiple attenuation

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Summary

Radon transform (RT) allows the mapping of multiple and primary reflection events separately in the transformed domain. Hyperbolic Radon (HR) transform 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 abstract, we present the predictions using two input channels, sparse and nonsparse HR panels and using either sparse or nonsparse HR as the label. These numerical experiments show that a U-Net can be used to separate 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.

Introduction

Multiples are periodic in the slowness (reciprocal of velocity) domain but not in the time domain. Therefore, they have a larger moveout than primaries, which makes it possible to separate them in this new domain. Usually, the separation of primaries and multiples in the RT panels is either done automatically, but with simple boundaries, or manually with picking from the user. In this last case, results depend on the processor's expertise and can be time-consuming. A machine learning approach can provide a data-driven methodology that can help to speed the process. In classical processing, the physics of the events is somewhat taken into account through the choice of different basis functions. In machine learning approaches, an algorithm, for example, a network, tries to find patterns and predict them based on the data used for training. Because of its flexibility and black-box nature, this approach should be used with caution. In this abstract, we perform tests to understand how a machine learning approach can be helpful to the seismic processing workflow.

Theory

Radon transform (RT) is a mathematical tool that maps data into a transformed domain, commonly known in geophysics as $\tau - p$ (τ being the transformed time and p the slowness, reciprocal of velocity) or Radon domain. The advantage of this new domain in seismic data processing is that the primaries and multiples can be distinguished due to the difference in velocity and moveout. Consequently, the Radon domain can be conveniently manipulated to filter out multiples and keep in primaries.

The hyperbolic Radon transform (HRT), also known as velocity stack (Thorson and Claerbout, 1985) is the most suitable to map seismic gathers because on CMP gathers the reflection events are described by hyperbolas. From a geometrical point of view, the HRT maps nearly hyperbolic events in the CMP gathers (data space) to points in the hyperbolic Radon space by using the hyperbolic moveout equation (Yilmaz, 2001):

$$t = \sqrt{\tau^2 + \frac{x^2}{v^2}}, \quad (1)$$

where v is the stacking velocity, having the slowness p $(1/v)$ as its reciprocal. Thus, the HRT can be calculated by summing the amplitudes over the hyperbolas.

Within machine learning, the convolutional neural network (CNN) is a type of neural network model that started its development from studies of the visual cortex and motivated the neocognitron (Fukushima, 1980). CNNs have been used in semantic segmentation problems to classify each pixel according to the class of the object it belongs to (Geron, 2019). It is a supervised learning method usually applied to image segmentation and uses labelled data to train the model while running convolutional windows to extract and classify features from the image. One of the most applied CNNs architectures is the U-Net (Ronneberger et. Al., 2015), mainly used for image segmentation problems. The U-Net structure can be described as an assembly of convolutional and pooling layers within an encoder-decoder process. In the encoder part, the network uses a certain number of steps (also known as layers) to down-sample the input data into a smaller size while going deeper, increasing the number of feature maps (having the possibility to use more than one channel). During the decoder part, the network up-samples its size while using the same number of steps to down-sample the data by decreasing the number of filters. It also updates the weights by concatenating them with its corresponding encoder outputs, forming an interconnected U-shaped structure.

The labels are an important parameter in this method since is the information that the network will use to learn how to identify a specific feature in the image. The purpose of training a neural network is to learn the weights and biases and use the backpropagation until the result is satisfactory for your needs, in our case, multiple prediction. As previously mentioned, the U-Net is usually applied in classification problems. However, in the present work, we modified that and used this network to perform regression to predict the multiples in the Radon domain. The hyperparameters, such as the number of filters, weights, widths, strides and padding type were kept the same throughout all the example tests.

Workflow

The tests presented in this abstract were performed with synthetic data obtained with a convolutional model from simple earth velocity models. This provides some control over the types of multiples present in the data. We generated: 1) a data set with primaries and multiples together, and 2) another data set with multiples only. Then, these data sets are transformed into RT panels. Data set 1 serves as inputs, and the multiple-only panels (from data set 2) serve as labels. These inputs and labels can be used to train the network to predict the boundary between primaries and multiples. Figure 1 summarizes the workflow used in the following numerical examples.

It is important to note that some primaries and multiples are almost overlapping in the shot domain and therefore they will be closer in the HR domain, which is something to keep close attention to if the network will understand and map this difference.

Examples and Discussion

To better understand how the U-Net works in multiple prediction, some tests were carried out feeding the network with different HR panels. The sparse HRT uses more external iterations in the RT (Sacchi and Ulrych (1995), Trad et al. (2003)) given a higher-resolution HR panel. The network was fed with two channels, sparse and nonsparse HR panels, as an effort to constrain the training further (by using more information) and understand how the input labels influence the training:

- Train with 3, 5, and 8 geological layers and predict for 8 geological layers using sparse and nonsparse HR as input and nonsparse HR as the label,
- Train with 3, 5, and 8 geological layers and predict for 8 geological layers using sparse and nonsparse HR as input and sparse HR as the label.

Something worth mentioning is that when using the RT is important to consider that the data suffer from aliasing artifacts when not regularly sampled in offset (Moore and Kostov, 2002). Therefore, it will not have a good Radon panel causing an increase in the amplitude of aliased events that fall outside the p analysis window (Marfurt et al., 1996). In this regard, the sparse RT (Thorson and Claerbout (1985), Sacchi and Ulrych (1995), and Trad et al. (2003)) tries to address that, having the chance to improve the multiple prediction. And so, some tests were done to see if the network would understand that and take the higher-resolution information towards increasing the prediction quality by using the sparse Radon as the label.

The examples presented in Figures 2 and 3 use the approach of using two channels as the input, sparse and nonsparse, instead of just using one. We expect the network will have more information while using less background noise and differentiating the near-overlapping events, consequently making a better prediction of multiples.

Figure 2(c) shows the result in the shot domain of the prediction while HR nonsparse as the label. Figure 3(c) shows the result using HR sparse as the label. Qualitatively comparing the results in the HR panels (Figures 2(f) and 3(f)) we can see that the labels have a large influence on the predictions. Using HRT sparse as the label does the job of predicting the multiples but not as well as the one using a nonsparse label. Furthermore, as shown in Figure 3(c) the long offsets of the sparse label prediction were attenuated in the right side of the shot domain. Therefore, the prediction using the nonsparse HRT shows a better multiple prediction.

It is important to emphasize that since the network does not understand the experiment's Physics. However, only the match between prediction and label patches of images, the result is not usually increased by inputting a higher quality Radon, for example. That is why the key is to perform tests to understand what a better input information for the network can be.

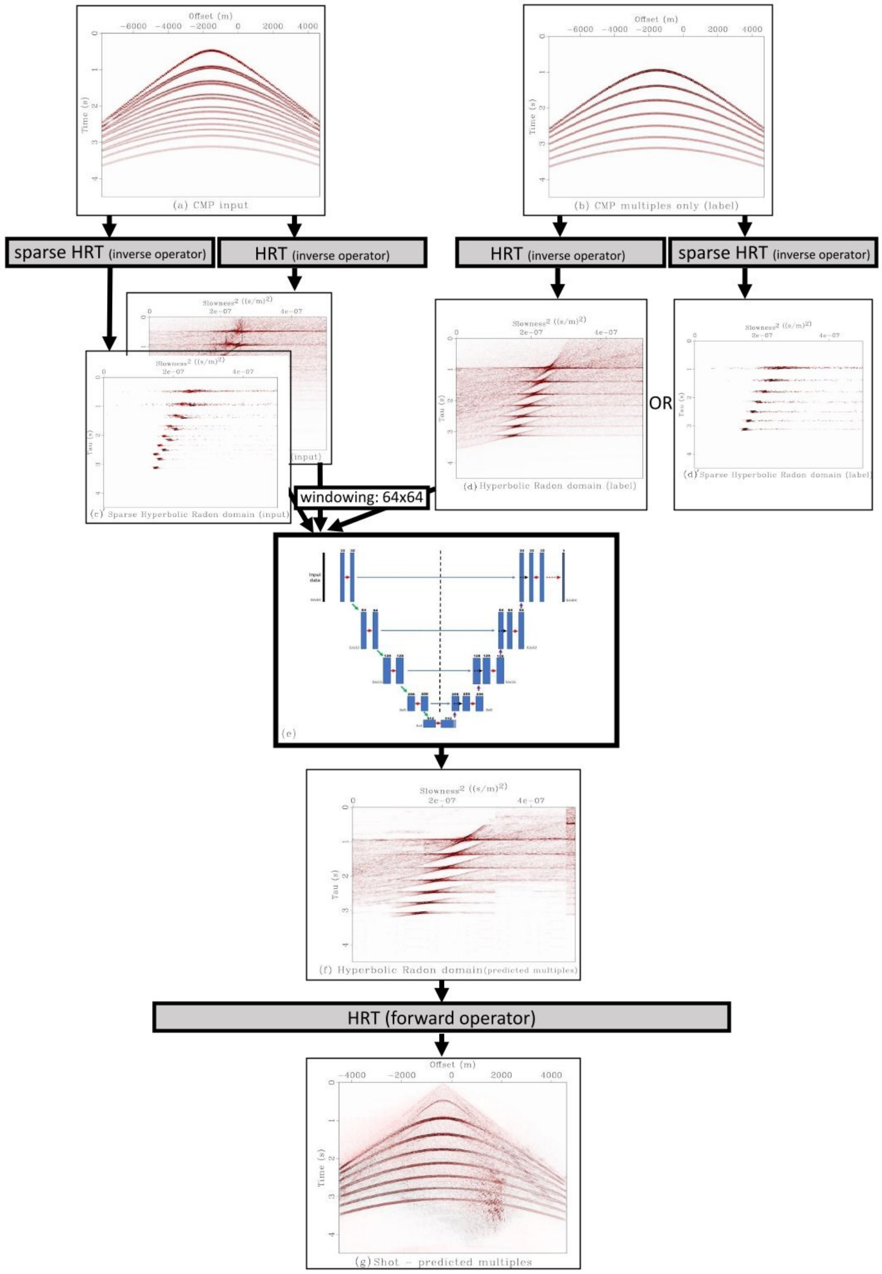

Figure 1. Workflow of the 8 geological layers case using 2 channels. Synthetic shot gathers are sorted by CMP resulting in the input data, with multiples and primaries (a) and, the input label, with multiples only (b). Then the HRT (inverse operator) is applied to generate the hyperbolic Radon panels of the input (c) and labels (d). Also, the sparse HRT is applied to generate the sparse HR panels of the sparse input (c)' and sparse labels (d)'. The input data and one of the labels will be fed into the U-Net (e). The network then predicts, after training, the hyperbolic Radon panels of multiples only (f). The inverse HRT (forward operator) using least squares is then applied to return the data to the CMP domain (g).

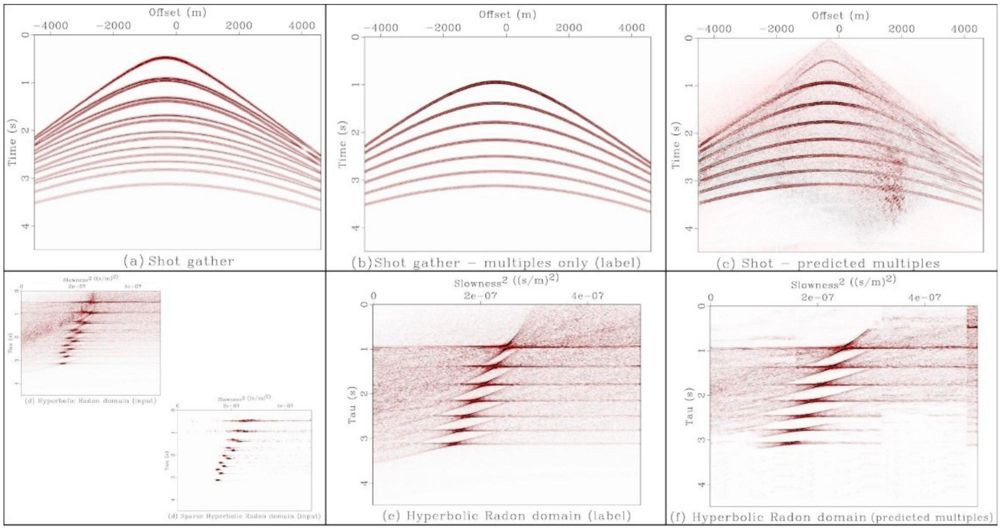

Figure 2. Eight geological layers case using 2 channels and nonsparse HR as the label. Shot 98 with primaries and multiples (a), its sparse and nonsparse HR panel (2 channels) used as inputs (d). Shot 98 just with multiples (b) and its nonsparse HR panel used as the label (e). Shot 98 after the U-Net prediction for the 8 geological layers case using the 3, 5, and 8 geological layers training (2 channels) and HRT (forward operator) (c) and its HR panel result from the prediction (f).

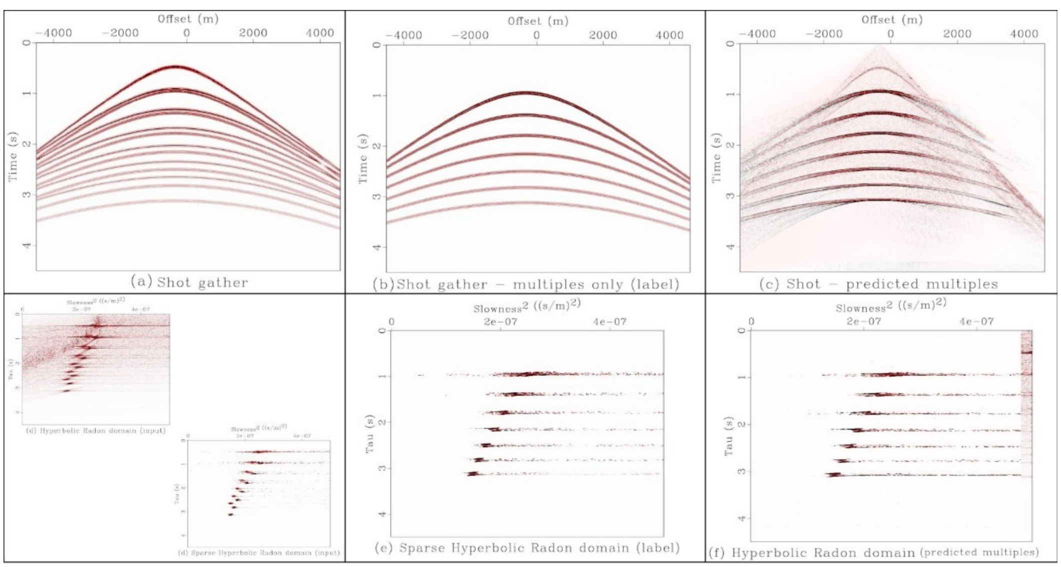

Figure 3. Eight geological layers case using 2 channels and sparse HR as the label. Shot 98 with primaries and multiples (a), its sparse and nonsparse HR panel (2 channels) used as inputs (d). Shot 98 just with multiples (b) and its sparse HR panel used as the label (e). Shot 98 after the U-Net prediction for the 8 geological layers case using the 3, 5, and 8 geological layers training (2 channels) and HRT (forward operator) (c) and its HR panel result from the prediction (f).

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. Train with two channels, sparse and nonsparse HRT, and using nonsparse HRT panels of the multiples as label resulted in better multiple predictions than the one using sparse HRT. For future work, we will train the network with multiple channels using different features, such as the parabolic Radon transform, to further constrain the multiples prediction. As well as using various geologic models in the training.

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