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Seismic multiple removal based on nonlinear predictive filtering

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Abstract Summary

In seismic data, the acoustic reflections on geologic layers are analyzed, which occur due to the difference of the acoustic impedance between adjacent layers. These reflections can be divided on two categories: primary reflections, which reflect on a single subsurface; and multiple reflections, which are reflected multiple times before returning to the sensor. The later is a noise that can be attenuated using predictive deconvolution, which makes use of the periodicity of the multiples to predict and subtract these reflections. On this work, we analyzed the performance of this technique in a maritime seismic dataset with low depth, measured on the southwest coast of Taiwan. To improve the performance of the filtering, nonlinear filters based on neural networks were used. The objective of this work is to compare the performance of these filters with the linear filter, together with comparing the performance of single-gap and double-gap filters. The results show that the combined use of nonlinear filtering and double-gap prediction achieves the best performance on the analyzed scenario.

Introduction

Reflection seismology measures the reflection of mechanical waves at layers beneath the surface. A source, located at the surface, generates a pulse that is reflected by lower layers, and captured by sensors. By analyzing the propagation time of the received waves, it is possible to estimate the depth of the subsurface layers (Yilmaz, 2001).

The first reflection on an interface between layers is known as a primary reflection. These are used to map the depth of the layers on the subsurface. However, it's possible that a wave is reflected multiple times before returning to the surface, which is known as multiple reflections (Verschuur, 2006). The multiple reflections can hinder image analysis and its attenuation is an important problem in seismic imaging (Verschuur, 2006; Yilmaz, 2001).

Predictive deconvolution using linear filters is one of the best-known techniques for attenuating multiples (Robinson, 1954). Recently, predictive deconvolution of multiples using non-linear filters based on artificial neural networks has been proposed and tests on synthetic data have shown that non-linear filtering produces significantly better results than linear filtering in the attenuation of multiples (Carvalho et al., 2018).

In this article, our objective is to assess the nonlinear predictive framework proposed in (Carvalho et al., 2018) on real seismic data. The other objective is to assess if the use of double-gap predictive filtering improves the performance of the single-gap structure used in Carvalho et al. (2018). The tests are performed on seismic data from the southwest coast of Taiwan, which was previously studied in (Christian Berndt, 1999) and (Forel et al., 2005).

Method and Theory

To process the data, we first use a band-pass filter, to remove measurement noise from the image. Next, we mute traces with noise, including noise that occurs before the first water bottom layer reflection.

Next, we transform the data to the $\tau - p$ domain since, on this domain, hyperbole are mapped to ellipses, which makes the multiple reflections become periodic events (Verschuur, 2006). The periodicity of the multiples is essential to use the predictive deconvolution method. After filtering, the data is transformed back to the original domain, and stacking is done to the CMPs.

The filtering is applied on each trace individually in the $\tau - p$ domain. The primary reflections $p(k)$ are estimated using the prediction error, which is given by (Robinson, 1954; Verschuur, 2006)

$$p(k) = t(k) - f\left(\mathbf{t}(k-L)\right), \tag{1}$$

where $t(k)$ is the original trace in the $\tau - p$ domain, $f(\cdot)$ is the predictor input-output mapping and $\mathbf{t}(k-L) = [t(k-L), t(k-L-1), \ldots, t(k-L-K+1)]^T$ is a vector containing K past samples of $t(k)$. Note that $f\left(\mathbf{t}(k-L)\right)$ is the predicted multiples.

Only one delayed window is used in (1), which is why this filtering is called single-gap (Verschuur, 2006). The prediction delay L is chosen to match the periodicity of the multiples and is selected according to the water layer propagation time in maritime data (Yilmaz, 2001).

Alternatively, the double-gap employs two delayed windows, one is $\mathbf{t}(k-L)$, and the second one is $\mathbf{t}(k-2L) = [t(k-2L), t(k-2L-1), \ldots, t(k-2L-K+1)]^T$. The second window allows the double-gap filter to better model the second-order multiple reflections (Verschuur, 2006). In this case, the estimated primary reflections are given by

$$p(k) = t(k) - f\left(\mathbf{t}(k-L), \mathbf{t}(k-2L)\right). \tag{2}$$

We have analyzed three filters as predictors: a linear Finite Impulse Response (FIR) filter, and two neural networks: Extreme Learning Machine (ELM) (Guang-Bin Huang, 2006) and Echo State Network (ESN) (Jaeger, 2001). The first is the most used on the literature (Verschuur, 2006). The two later were tested on synthetic data in (Carvalho et al., 2018).

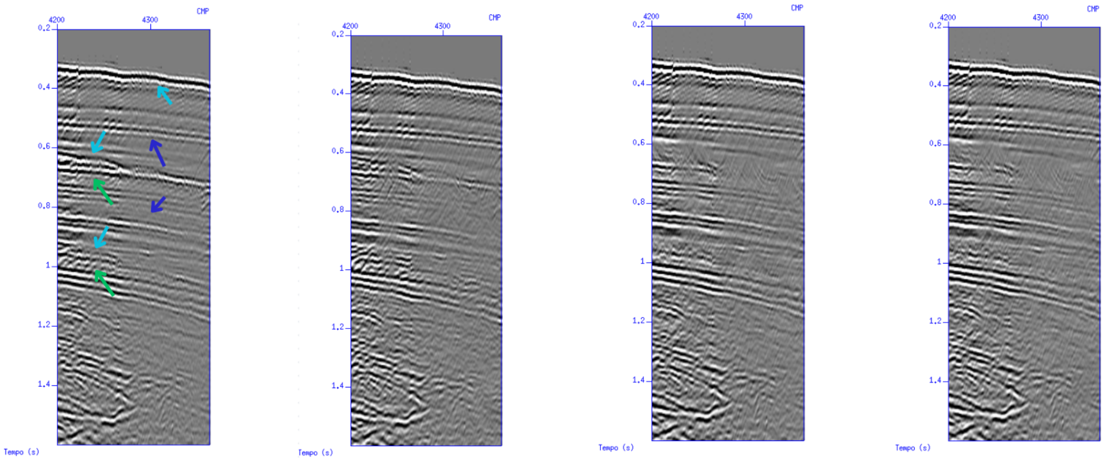
The ELM is a feedforward neural network, which has a single middle layer with N neurons. The values of synaptic weights of the input layer are randomly chosen and the activation function of the neurons is the hyperbolic tangent (Guang-Bin Huang, 2006). The outputs of the neurons are linearly combined and the result is the prediction output. To optimize this network, we adjust only the linear output layer, which is a linear optimization problem. Because of the nonlinear activation function, this network is nonlinear, which means it can model the nonlinear behavior of the system.

The ESN has a similar structure to the ELM, with the addition of feedback to the hidden layer neurons, which makes it a recurrent neural network. The middle layer weights are also randomly assigned, but with appropriate constrains (Jaeger, 2001). The feedback makes this network more flexible to model the system than the ELM.

Since the three filter structures are optimized by adjusting a linear filter on their output, we optimized all of them using the least squares technique.

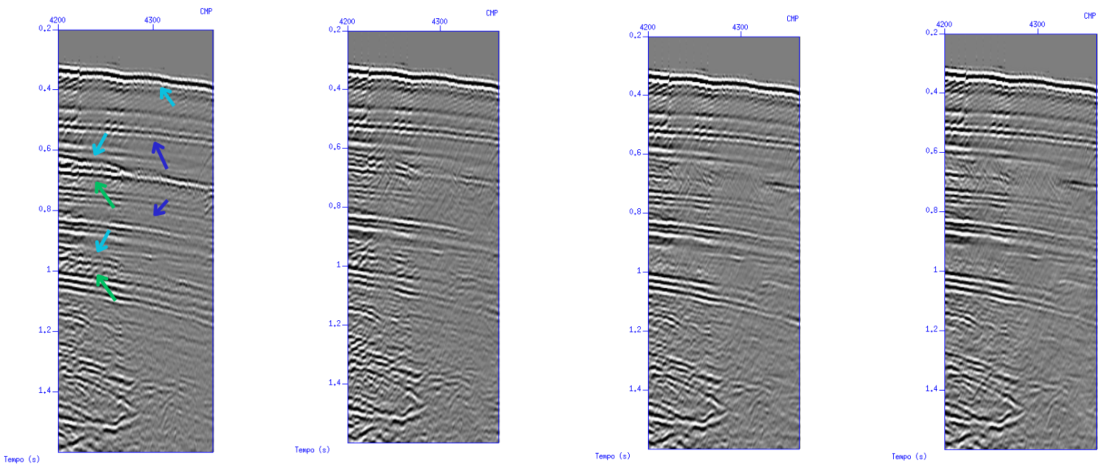
To project the filter, we need to choose the number of input samples K, and the prediction step L. The first one should be adjusted to have the lowest possible value, since, if it has too many samples, the filter may model parts of the system which are not multiple reflections, distorting primary reflections. The prediction step L is selected according to the water layer propagation time, since the multiple reflections have this periodicity in the $\tau - p$ domain. For the neural networks, we also need to optimize the number of neurons N on the hidden layer.

Results



(a) No filtering (b) Linear Filter (c) ELM (d) ESN

Figure 1: Results after stacking for each type of single-gap filter.



(a) No filtering (b) Linear Filter (c) ELM (d) ESN

Figure 2: Results after stacking for each type of double-gap filter.

To asses the performance of the filters, tests were performed on seismic data from the southwest coast of Taiwan (Christian Berndt, 1999; Forel et al., 2005). The stacked section without multiple suppression is shown in Figure 1a. Arrows with the same color indicate primaries and multiples of the same event (multiples are on higher propagation time). In order to adjust the hyper-parameters of the filters, we analyzed the results on these events.

The first event we analyze is the first water bottom multiple, which occurs at 0.66 s on CMP 4200. This is the multiple with the higher amplitude, and it should be noted it overlaps with the green arrow event after CMP 4280. This overlap is an additional challenge to the filtering, as, when the multiple overlaps with the event, the filter should not erase the event. Another event we analyze is the second order multiple of the water bottom, and the first multiple of the green arrow event, that occur around 0.9 s on CMP 4200.

Figure 1 shows the results obtained for the single-gap filters. The two models based on neural networks were able to attenuate the first water bottom layer multiple. However, these filters also attenuated the signal where there is overlap with the green arrow primary, which is undesirable. The linear filter had worst performance at attenuating the water bottom multiple.

The results for double-gap filter at Figure 2, show that the non-linear models were able to attenuate the first water bottom multiple, but did not attenuate as much as the single-gap filters did the overlapped event. The linear filter had similar performance to the single-gap linear filter, also not being able to attenuate the multiples.

The second order multiple of the water bottom and the first multiple of the green arrow were not well attenuated by the single-gap filters. However, the non-linear double-gap filters were able to attenuate these, as expected by the addition of the second input samples window used on the double-gap model. Both ELM and ESN displayed similar results.

Conclusions

On this article, we assessed the performance of nonlinear filters based on ELM and ESN neural networks at attenuating multiple reflections. The results showed that, using these nonlinear filters, it's possible to improve the performance of the predictive deconvolution, compared to using the linear filter. It was also showed that the use of double-gap filter improves the performance of these models, specifically at attenuating second order multiples. As a next step, we are going to use the same technique on more datasets to analyze the performance of these filters for other types of maritime data.

References

Carvalho, H. S., F. Shams, R. Ferrari, and L. Boccato, 2018, Application of extreme learning machines and echo state networks to seismic multiple removal: International Joint Conference on Neural Networks.

Christian Berndt, G. F., 1999, Seismic de-multiple strategy in the submarine slope of taiwan accretionary wedge.: The Leading Edge, 74–80.

Forel, D., T. Benz, and W. D. Pennington, 2005, Seismic data processing with seismic un*x: Society of Exploration Geophysicists.

Guang-Bin Huang, Qin-Yu Zhu, C.-K. S., 2006, Extreme learning machine: Theory and applications: Neurocomputing.

Jaeger, H., 2001, The "echo state": Approach to analysing and training recurrent neural networks: GMD - Forschungszentrum Informationstechnik. GMD-Report.

Robinson, E., 1954, Predictive decomposition of time series with application to seismic exploration.

Verschuur, D. J., 2006, Seismic multiple removal techniques, past, present and future: European Association of Geoscientists and Engineers.

Yilmaz, O., 2001, Seismic data analysis, processing, inversion, and interpretation of seismic data: Society of Exploration Geophysicists.