Spectral Extrapolation and Random Forest for high resolution prediction of subsurface properties

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Summary

Seismic reservoir characterization workflows such as rock properties prediction are highly dependent on and limited by the quality and resolution of the input data. In this study, a multi-attribute Random Forest machine learning analysis applied to spectrally extrapolated seismic data is implemented to increase both vertical and lateral seismic resolution. This workflow leads to improved detection of thin layers, definition of stratigraphic and structural connectivity, and prediction of rock properties. We compare the results of identical Random Forest processes applied to both the original and spectrally extrapolated seismic data. A suite of seismic attributes is generated and a subset of these attributes is selected using step-wise regression for prediction of 3D acoustic impedance. This approach is illustrated using seismic and well data from the Maui oil and gas field located in offshore New Zealand.

Random Forest Theory

Machine learning methods have become commonplace for seismic data applications. Random Forest is an ensemble machine learning technique that uses bagged decision trees with sample replacement in order to predict target variables from observations (attributes). The target variables can be acoustic, elastic or petrophysical properties. The average set of values from the suite of decision trees is taken as the solution, which decreases the variance of the model without increasing the bias, thereby boosting the immunity of the algorithm to over-training. Figure 1 illustrates the basic architecture of the Random Forest method (Chakure, 2019).

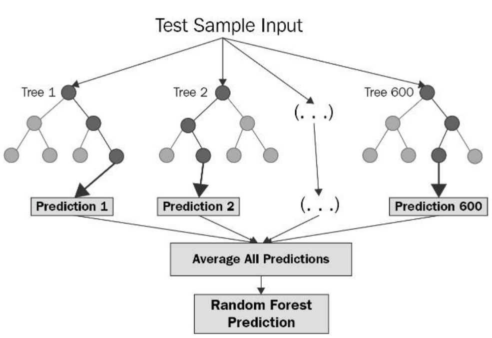

Figure 1: Random Forest scheme using a set of decision trees (Chakure, 2019).

The Random Forest algorithm (and other Machine learning techniques) naturally boosts the frequency content at the location of the training well(s), an effect of the non-linear mapping of the seismic attributes into the log domain containing higher frequencies. However, since the seismic data themselves are narrower band, the accuracy of the predicted high frequency content decays as rock properties (and therefore the information content of the attributes) vary laterally with distance from the well(s). In order to mitigate this effect, we use Spectral Extrapolation as input to Random Forest and compare with the conventional implementation using seismic data as input.

Spectral Extrapolation

When exploring for or producing from thin reservoirs, resolution is critical for accurate detection and characterization. Spectral Extrapolation is a process based on Spectral Inversion (Puryear and Castagna, 2008) for extending the bandwidth of stacked seismic data. It is known that simply boosting the frequencies at the edges of the wavelet band or outside the wavelet band deleteriously increases the noise component in the data. Spectral Extrapolation instead uses higher signal/noise information within the wavelet band to extrapolate to low and/or high frequencies. In this work, we limit the extrapolation to the high end of the spectrum.

Case Study Example

We apply our workflow to the New Zealand Maui field seismic data set. The Taranaki basin is a large Upper Cretaceous-Cenozoic sedimentary basin in the New Zealand area. It is part of a series of interconnected basins, which lie both onshore and offshore along the west coasts. They extend seaward beyond the edge of the continental shelf, and landward to the Permo-Jurassic greywackes and claystones forming the anticlinal axial ranges of New Zealand (Katz, 1974). Located in the central portion of the Taranaki basin and bounded to the east by the Cape Egmont fault zone with 2134 meters of throw (McBeath, 1977), the Maui field is the largest oil and gas field in New Zealand. Production is from Eocene sandstone reservoirs within the coal-bearing Kapuni Formation, deposited in a coastal plain fluvio-marine environment. The reservoir at the validation well is approximately 2780 meters below sea level and 15 meters thick, with significant thinning away from the well.

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Spectral Extrapolation and Random Forest

A) Workflow

Our post-stack workflow comprises well ties followed by Spectral Extrapolation, attribute generation and Random Forest prediction of acoustic impedance (Figure 2).

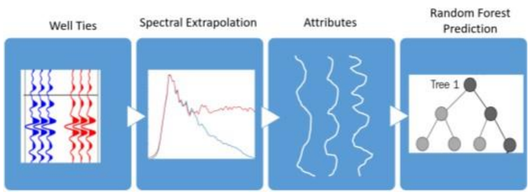

Figure 2: Post-stack Workflow with Spectral Extrapolation and Random Forest.

B) Well Ties

Maui wells 1 and 2 were tied using reflectivity computed from sonic and density log data. The logs, wavelet and synthetics for the training and validation wells are shown in Figures 3 and 4. Statistical wavelets were used and the seismic data were rotated to zero phase based on the synthetic correlation. The seismic well ties had high (> .8) correlations for both the training (Maui-1) and validation (Maui-2) wells.

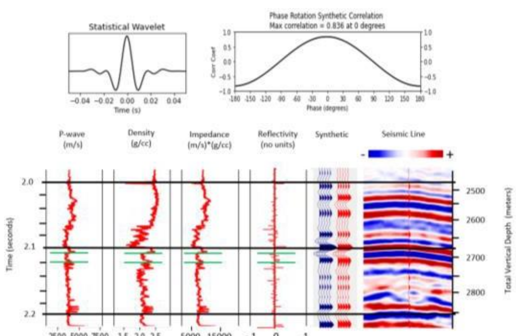

Figure 3: Well tie on seismic data at Training well. Green lines indicate top and base of the reservoir.

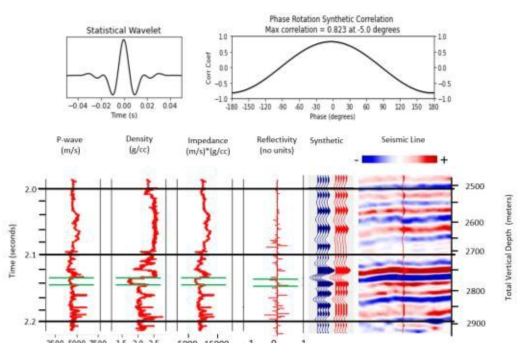

Figure 4: Well tie on seismic data at Validation well. Green lines indicate top and base of the reservoir.

The phase-calibrated seismic data are input to the Spectral Extrapolation, and the well ties are used as calibration for the Random Forest machine learning prediction.

C) Spectral Extrapolation

Figure 5 shows the spectra of the original seismic data and Spectral Extrapolation. An arbitrary line through the original seismic data and spectrally extrapolated seismic data with overlain gamma ray logs is shown in Figure 6.

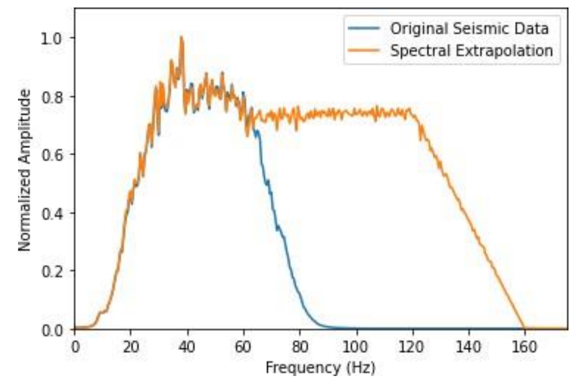

Figure 5: Amplitude spectra of the original seismic data and Spectral Extrapolation

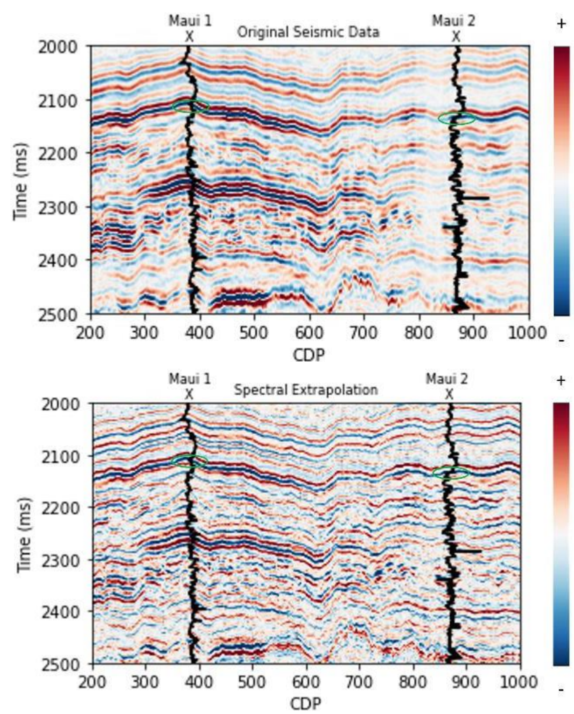

Figure 6: Arbitrary line through original seismic data (top plot) and Spectral Extrapolation (bottom plot). Gamma ray logs are shown by black curves. Green circles show reservoir.

10.1190/segam2021-3594792.1

Spectral Extrapolation and Random Forest

The accuracy of Spectral Extrapolation is limited by the signal-to-noise ratio and the accuracy/stability of the extracted wavelet. Thus, the process is performed in the stack domain, in which these data characteristics are naturally enhanced. The Spectral Extrapolation results are high cut at frequencies where noise begins to significantly degrade the result. This cutoff is estimated by the quality of the high frequency well tie. Thus, a balance between resolution and noise must be struck. Typically, the method produces at least a doubling of the original bandwidth with useful signal. Figures 7 and 8 show the high frequency well ties at the training and validation wells.

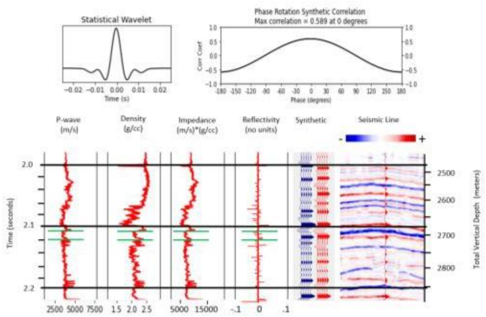

Figure 7: Well tie on Spectral Extrapolation at Training well. Green lines indicate top and base of the reservoir.

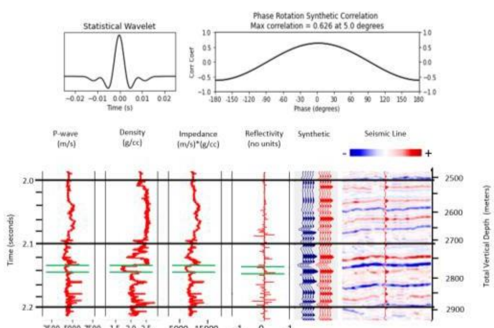

Figure 8: Well tie on Spectral Extrapolation at Validation well. Green lines indicate top and base of the reservoir.

D) Random Forest prediction of acoustic impedance

We predict the acoustic impedance in the 3D volume using a subset of attributes determined by training and validation. Our candidate trace attributes include the following:

1: Mandal-Ghosh trend attribute
2: input seismic
3: first derivative
4: second derivative
5: instantaneous phase
6: cosine instantaneous phase
7: instantaneous frequency
8: average frequency
9: average phase
10: quadrature
11: integrated quadrature
12: envelope
13: derivative envelope
14: integrated amplitude
15: integrated absolute amplitude
16: dominant frequency

The stepwise regression method, which incrementally determines a subset of uncorrelated attributes that best predict the target log, was applied to the original seismic data at the training and validation wells (Figure 9). For consistency, the same subset is then computed for the spectrally extrapolated data. Each of these attribute datasets is then used as input to Random Forest.

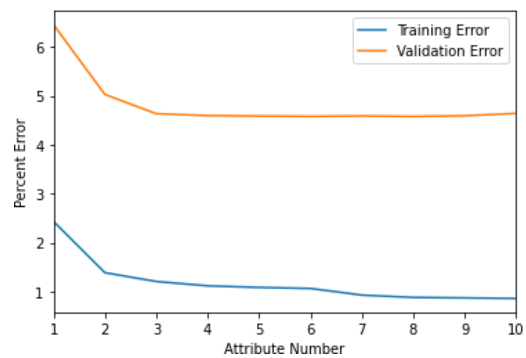

Figure 9: Step-wise regression for training and validation wells.

The selected attributes are as follows:

1: Mandal-Ghosh trend attribute
2: quadrature
3: input seismic
4: cosine instantaneous phase

The Mandal-Ghosh trend attribute is chosen to approximate the low frequency trend (Mandal and Ghosh, 2019) of the acoustic impedance using the seismic data, making it a useful input to the model. The results of the Random Forest prediction of acoustic impedance using both the original seismic data and the spectrally extrapolated data are show around the Maui-2 validation well in Figure 10. Note the improved differentiation of thin layers using the Spectral Extrapolation.

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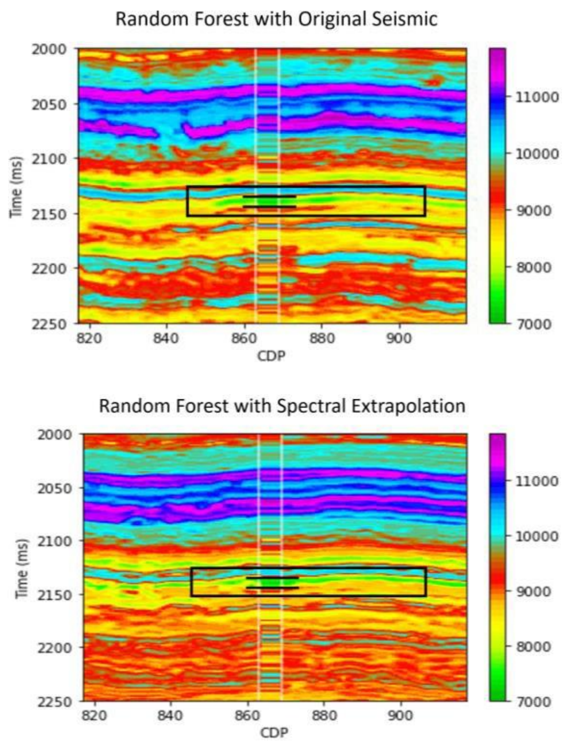

Figure 10: Random Forest applied to the original seismic (top) and Spectral Extrapolation (bottom). The white vertical lines indicate the Maui 2 validation well with the computed acoustic impedance log. Black boxes define the zoomed reservoir section in Figure 11.

The acoustic impedance zoomed to reservoir level together with the original seismic data are shown in Figure 11. The top and base of the reservoir are indicated by black horizontal lines. The black vertical lines show the Maui 2 validation well with the computed acoustic impedance log. As previously noted, Random Forest prediction provides some improvement in resolution proximal to the training well as a consequence of the fitting or training process. However, broader bandwidth data more sensitive to lateral changes in rock properties are desirable to fully take advantage of the method. The Random Forest result with Spectral Extrapolation as input shows significant enhancements in imaging for the thinner portions of the reservoir.

Conclusions

In this work, Random Forest 3D acoustic impedance prediction was performed using conventional and spectrally extrapolated seismic data as input. The results demonstrate the suitability and advantages of using data processed by Spectral Extrapolation as input to machine learning rock properties prediction. Improved reservoir delineation and thickness definition can be observed throughout the section and at the reservoir level. Proposed future work includes more extensive mapping of the reservoir in 3D using the acoustic impedance volumes generated by this workflow.

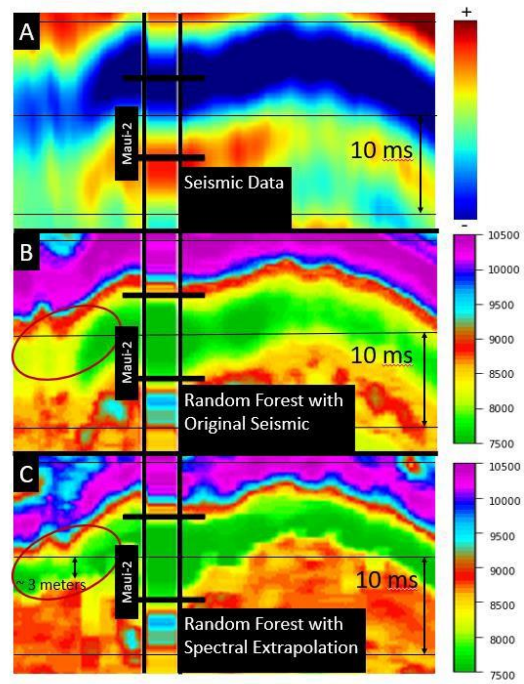

Figure 11: Zoomed reservoir section for A) the original seismic data, B) acoustic impedance from Random Forest applied to original seismic data and C) acoustic impedance from Random Forest applied to Spectral Extrapolation – resolves the reservoir layer down to approximately 3 meters thickness. Timing lines are spaced at 10 ms.

Acknowledgements

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