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Cover Sheet

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Lateral Heterogeneity Analysis Using Multiwell ZVSP Unsupervised Machine Learning Classification

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Abstract

In 3D and 2D surface seismic interpretation, seismic waveform shapes and attributes can identify facies and reservoir parameters laterally with more details than traditional amplitude mapping. Herein, a method on 1D zero offset VSP (ZVSP) data was adapted, giving a unique perspective of lateral heterogeneity analysis using VSP seismic waveform shapes and attributes. The downgoing wavefield of VSP measures seismic wave variation in the vertical direction. When enough VSPs are covering an area, we can combine them to get an insight into both vertical and lateral variations.

An unsupervised machine learning clustering algorithm based on K-means and self-organizing maps (SOM) was used to group the waveforms based on their shape similarity and attributes (frequency spectrum). The algorithm produced a cluster map, a probability map, and a typical wavelet for each cluster. These were then used to analyze the vertical and lateral heterogeneity from well to well based on VSP waveform attributes. The used example data were an open dataset, the Poseidon 3D data from the NW Shelf, Australia (Browse Basin), provided by GEO Science Australia. Six wells were available with VSP datasets.

This technique can be of use to incorporate additional attributes from VSP into extensive 3D subsurface interpretations. For precautions, the VSP measurement or data preconditioning must be done reliably prior to clustering. Such A method may function well for vertical well ZVSP where variation was noticed because of the vertical seismic ray path.

In this study, the application of VSP data has been extended from the conventional single well-to-well basis. The value of integrating VSP characterization has been investigated from various wells and numerous measurements to discern both vertical and lateral heterogeneity in a studied area.

Keywords: VSP Machine Learning, Waveform Classification

Introduction

Seismic waveform shapes and attributes carry information about facies and reservoir parameters. In 2D and 3D surface seismic data, this attribute mapping analysis provides lateral details about the reservoir to balance traditional structural mapping analysis. The waveform shapes interpretation method is normally integrated into the seismic waveform's classifications. Andersen and Boyd (2004) depicted a two-type classification method: unsupervised and supervised classifications used to describe and display the seismic reflection character. They reported that this method can identify character differences among thousands of data points.

In the present study, the seismic waveforms classification was adapted on 1D ZVSP data, which provide a unique perspective on lateral heterogeneity analysis based on VSP seismic waveform shapes and attributes. Traditionally, VSP is employed to provide seismic traces of the well for correlation with surface seismic. With VSP having vertical wavefield propagation, it carries vertical high-resolution information. In addition, the waveshape would be useful to extract valuable information on the wavefield propagations. These data could be extracted in the form of direct measurement of attenuation (Q), geometric divergence, or amplitude analysis for the correlation of acoustic impedance inversion (Campbell et al., 2005).

When there are enough VSPs covering an area, they can be combined to get an insight into both vertical and lateral variations. In this paper, I used the unsupervised machine-learning classification to describe and show seismic characters found in VSPs waveforms. In particular, the waveform shapes and attributes of the VSPs downgoing waveforms.

Data and Method

The example data used were an open-source dataset, the Poseidon 3D data from the NW Shelf, Australia (Browse Basin), provided by GEOscience Australia. There were six wells available with VSP datasets. The Browse Basin covers an area of approximately 140,000 km^2 and lies entirely offshore, north of Broome. The Browse Basin, which forms part of the Westralian Superbasin, is a northeast-trending depocenter containing up to 15 km of Paleozoic to Cenozoic sediments (Government of Western Australia, 2014). Figure 1 below shows the distribution of the available wells.

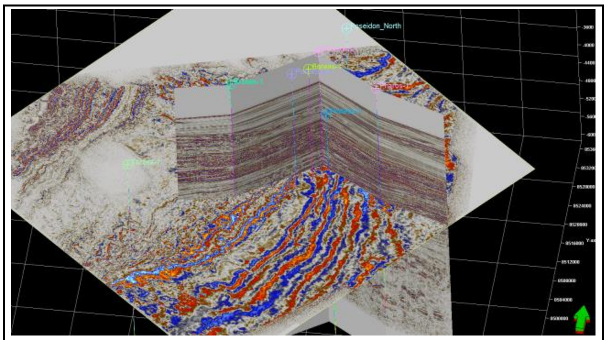

Figure 1: Well locations and example of 3D seismic time slice and random line. Data provided by GEOScience Australia, retrieved from https://terranubis.com/datainfo/NW-Shelf-Australia-Poseidon-3D

Ideally, the waveforms classification only deals with the variation due to geology. However, the challenge of working with multiple VSP datasets from multiple wells is the difference in the acquisition system (different tools, different gun systems, etc.). This is the case that was observed with Browse VSP data. Table 1 summarizes the variation in the acquisition system.

Well Name	Years	Downhole Tools
Kronos-1	2010	VSI
Pharos-1	2014	VSI
Poseidon-1	2009	VSI
Posideon-2	2010	VSI and QAST
Proteus-1ST2	2014	VSI
Torosa-1	2006	VSI

Table 1: List of available wells and the downhole tools. VSI=Schlumberger Versatile Seismic Imager, QAST= Schlumberger Q Analog Seismic Tool.

Data preconditioning was applied only for geometric correction and waveforms normalization. The downgoing wavefield was extracted using a median velocity filter. It was noticed that this preconditioning did not solve the issue with the variation in acquisition. However, the waveforms classification algorithm will be tested if it also picked up any variation due to acquisitions.

The unsupervised classification was used to provide insights about waveforms variation without prior information. The employed algorithms were K-means and SOM. The process consists of two stages, the learning phase and classification. Within the first stage, the typical waveform for every class was defined. In the second stage, the program calculated the similarity or probability value, which is a measure for the resemblance with the master waveforms for every seismic waveform. The highest probability range is defining the class category for the waveform under examination.

During the classification, two waveform segments will be placed in the same class if their waveforms have a similarity. It can be calculated from the distance between the waveforms; for example, the distance can be taken as the square difference between two waveforms.

The parameter used to compute similarity was mainly based on the downgoing waveform shapes. Sensitivity analysis using various windows and methods was also tested in the exercises to compute similarity. It was concluded to compute the similarity distance using a combination of correlation coefficient and square difference. The waveforms were limited to a 50-ms window in the analysis.

The workflow output classification map, the probability map for each wavelet class, and the typical wavelet for each class were used to analyze the vertical and lateral heterogeneity from well to well based on VSP waveform attributes.

Result and Discussion

Both K-means and SOM algorithms were used for the classifications. The results showed that K-means was more sensitive in classifying the waveforms. It was suggested that SOM was perhaps too sensitive to the noise present in the dataset. These two methods require a number of clusters to be classified (K number in K-means). In this paper, a number of clusters were derived based on the interpretation of lithology distribution observed in the well logs. Parameter testing was conducted to assess the sensitivity of the cluster's distributions; I used five classes for distribution. The results are displayed in Figure 2, left panel. The class distribution map was defined based on the probability of each class. For instance, Class 3 and Class 4 probability maps were displayed in the same figure (middle panel and right panel).

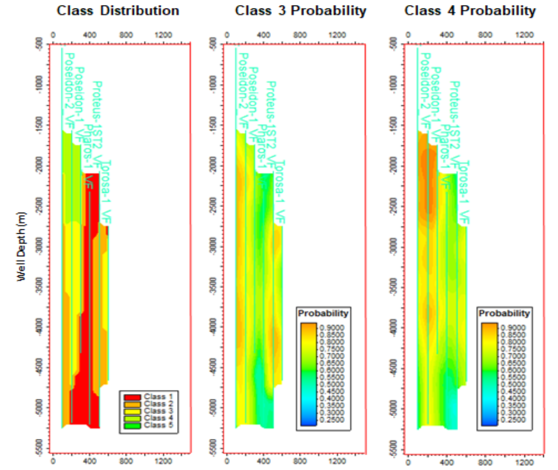

Figure 2: Left panel shows waveforms class distribution (K-means) in all wells. Middle and right panel shows an example of the probability map for waveforms Class 3 and waveforms Class 4.

Because the classification distance is based on waveform shapes and spectrum, it was predictable to see a strong correlation of classes' distribution with depth. The start of certain classes observed to be different from well to well, which may correlate with the geological structure or other subsurface properties.

The classification workflow can be used to identify similar downgoing characters in multiple wells. Hence, it can be used to map out the lateral character heterogeneity seen by downgoing VSP waveforms. For example, Class 3 and Class 4 were showing distinctive changes in waveforms within shallower depths. Such a change in waveforms is identified in the estimated typical waveforms for each cluster displayed in Figure 3. This character was also showing between Poseidon-1 and Poseidon-2, and slightly similar for farther well such as Torosa-1.

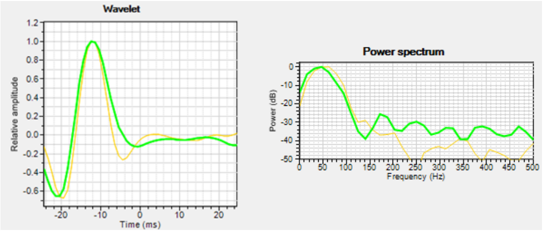

Figure 3: Typical downgoing wavelet for Class 3 (dark yellow) and Class 4 (green).

Another way to analyze the classification results was to compare them with the surface seismic. The classification results can be plotted as a discrete log for each well. The example in Figure 4 shows a cross section through Kronos-1, Poseidon-2, and Proteus-1ST2. Similar classification results were observed at time intervals between 2000 to 3000 ms, between Kronos-1 and Proteus-1ST2, while Poseidon-2 showed some difference. Such outcomes require further analysis by integrating the geological interpretation and VSP waveforms attribute.

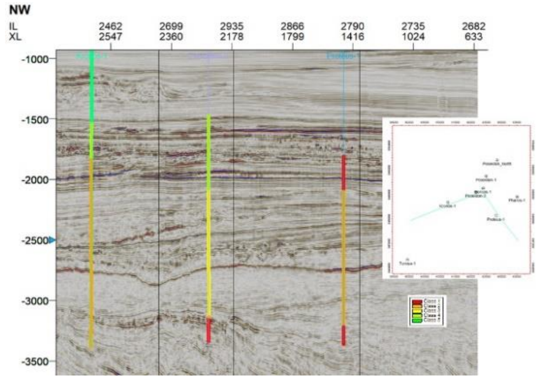

Figure 4: Random line crossing Kronos-1, Poseidon-2, and Proteus-1ST2. Showing comparison of classifications results with seismic.

Conclusions

This study showed the value of integrating VSP characterization from multiple wells using machine learning to discern an area's vertical and lateral heterogeneity. With more data being acquired, the conventional VSP analysis can be expanded from a single well-to-well basis into a more integrated multiwell interpretation for an oil field. While machine learning can be very influential, its use relies upon forming the right questions to ask from the data. Specifically, for subsurface data analysis, information from geology knowledge should consistently be included as a priori information.

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