Two inversion case studies from the SCOOP and STACK area of Oklahoma

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Objectives

We showcase here the seismic characterization of the Meramec and the Devonian Woodford in the SCOOP/STACK trend in Oklahoma formations, using multicomponent seismic data in the STACK area and the conventional vertical component seismic data in the SCOOP area, using deterministic prestack impedance inversion. The objective is to demonstrate how the joint impedance inversion carried out over seismic data from the STACK area was used to derive rock-physics parameters (Young's modulus and Poisson's ratio), and how the derived sweet spots compared with those obtained with just the conventional seismic data. Finally, we compare the unsupervised machine learning (ML) facies classification results with those obtained from the impedance inversions mentioned above.

Methods

The stacked dataset volumes were correlated with the available well control in terms of synthetic seismograms for both PP and PS for the dataset from the STACK area and with PP data only for the other volume. A zero-phase wavelet was estimated from the seismic data using a statistical process in both cases.

For the low-frequency trend generation, a relatively new approach was used, that makes use of both well log data as well as seismic data to establish a relationship between seismic attributes and the available well log curves. A multi-regression approach is used, wherein a target log is modeled as a linear combination of several input attributes at each sample point which in this case happen to be the relative acoustic impedance, some instantaneous attributes and different versions of the filtered seismic data. The low-frequency impedance models for simultaneous and joint inversions are generated using the above approach.

Once the well-to-seismic correlation for both PP and PS data is done satisfactorily, the depth-time curves for both get determined. The V_P/V_S ratio determined this way is valid at the location of the well only. The horizons picked on PP and PS data will match at the location of the wells, but laterally will exhibit travel-time differences, which are used to compute the V_P/V_S ratios for specific intervals.

ML methods such as k-means clustering, principal component analysis, self-organizing mapping and generative topographic mapping were used to generate unsupervised facies classification by making use of some of the attributes generated through impedance inversion and others generated separately. Interesting comparisons of facies with the inversion outputs were noticed.

Conclusions

Besides the fact that density attribute could be derived from the joint inversion and not from simultaneous inversion (due to offset limitation), the sweets spots derived from the former were found to be distinct in their definition spatially, rather than bleeding off at the edges. The equivalent attributes (besides density) derived for the SCOOP area also showed promise. Much of the facies information compared favourably with the inversion results, and a positive correlation was seen with facies classification obtained from the available wells on the 3D seismic volumes.

We demonstrate for the first time how the derived sweet spots derived from the 3C3D data compared with those obtained with just the conventional seismic data, and the comparison of the unsupervised ML facies classification results with those obtained from the impedance inversions.