EAGE ANNUAL 2019
81ST CONFERENCE + EXHIBITION
LONDON | THE UNITED KINGDOM

Tu_R16_05

Near Surface Characterization in Southern Oman: Multi-Wave Inversion Guided by Machine Learning

S. Masclet[1]*, T. Bardainne[1], V. Massart[1], H. Prigent[1]

[1] CGG

Summary

Shallow stratigraphy in Southern Oman is characterized by the presence of an anhydrite layer causing a strong velocity inversion which makes seismic imaging particularly difficult. This known shallow sharp velocity inversion cannot be easily captured with reflected wave-based techniques or even acoustic full waveform inversion. We propose to recover it by applying multi-wave inversion, an approach combining information from P wave first breaks and ground-roll dispersion curves. In addition, an unsupervised machine learning technique is used to improve the quality of surface wave dispersion curve picks, crucial for the reliability of the multi-wave inversion results. With this innovative approach, the joint inversion of first breaks and surface waves leads to a better high resolution P-wave velocity model of the near surface which enables improved deep imaging.

Introduction

The near-surface in Southern Oman commonly features a shallow anhydrite layer and carbonate sequences with high velocities overlying lower velocity clastic series. This geological sequence yields a shallow sharp velocity inversion (see check-shot curve on Figure 6b) causing seismic imaging to be particularly challenging. Capturing this shallow velocity inversion accurately during model building is necessary to image deeper targets without any distortions or migration artefacts. Despite some major recent advances in land depth imaging technology (Sedova et al., 2017), this known shallow sharp velocity inversion remains nearly impossible to capture with conventional reflection-based model building techniques due to insufficient near angles and a poor signal-to-noise ratio (SNR) in the very shallow seismic data. Moreover, diving-wave full waveform inversion (FWI) is impeded by illumination gaps in the lower velocity layers. More recently, Multi-Wave Inversion (MWI) using first breaks (FB) and dispersion curves (DC) of surface waves (SW) (Bardainne, 2018) was developed to provide near-surface high resolution velocity models in the shallow range depths (0-200m), potentially capable of resolving the sharp velocity inversion in this region. As in every inversion process, the result is not always guaranteed as its reliability depends on the quality of the FB and DC picks. A time-consuming preconditioning sequence, including data regularization and denoising, is usually the only option to improve the accuracy of the picks. With the emergence of machine learning (ML) applications in the oil and gas industry, we propose here an automated ML dispersion curve-picking flow tailored to improve picking reliability on both low and high frequencies of the phase velocity spectra and demonstrate its impact on the MWI results. We illustrate our method on a wide azimuth (WAZ) broadband dense dataset.

Multi-Wave Inversion: The challenge of picking dispersion curves

The success of MWI strongly depends on the reliability of the surface wave velocity picking, which could be much more challenging compared to conventional first break picking. However, the fundamental mode of the surface wave is generally most energetic and thus easier to isolate and to pick. To improve the SNR compared to the field data, the surface waves are modelled by interferometry (Chiffot et al., 2017). This allows the extension of DC profiles to the lowest frequencies and thus increasing the maximum depth of velocity update by MWI. Phase velocity/frequency spectra are then computed and the maximum energy is automatically picked inside a pre-defined velocity corridor to extract the phase velocity without picking unwanted modes or noise. But examples of DC from our survey (Figure 1) exhibit large variability and the difficulty to define an *a priori* velocity corridor. The velocity corridor would need to be wide enough to capture significant velocity variations, especially at low frequencies where the dispersion is larger, but sufficiently constrained to exclude higher order modes. Heavy preconditioning is often the solution to increase DC quality and obtain a narrower velocity corridor. To improve reliability, we propose an unsupervised ML technology to guide the DC picking.

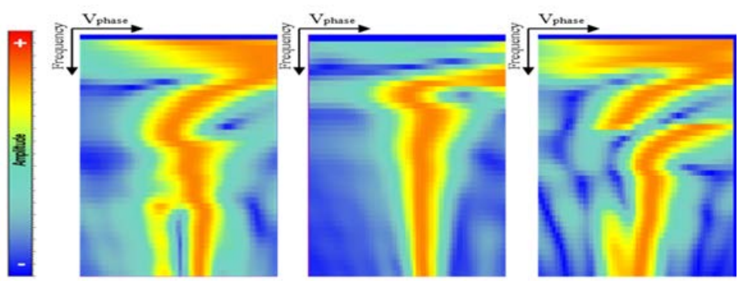

Figure 1 *Examples of three phase velocity/frequency spectra illustrating the large variability in surface wave dispersion curves across the survey area*

Application of Machine Learning to guide Dispersion Curve picking

In order to filter out the outliers as well as defining geologically dependent corridors, we use K-means clustering, an unsupervised ML method (MacQueen, 1967). After defining the distance between two DC images, a K-means clustering based on this measure is applied to all the DC images parameterized with 10 classes and a sufficient number of iterations. During this process, a centroid image is created for each class corresponding to the most representative DC image of the class. The number of classes is gradually lowered by checking their spatial distribution and the centroid velocity profiles until a minimum number of classes representing our entire survey is obtained (6 in our case). We observed that the distance measured between DC images and their centroid provides valuable information on the quality of the DC itself. Low quality DC's were discarded based on their distance from the centroid prior to DC picking (Figure 2). An example of 2 classes with their respective DC profiles is displayed by Figure 3c and 3d. The clustering map reveals a correlation with geological features such as a major fault and near surface elevations (Figure 3a, 3b, black line and arrow point out similar features).

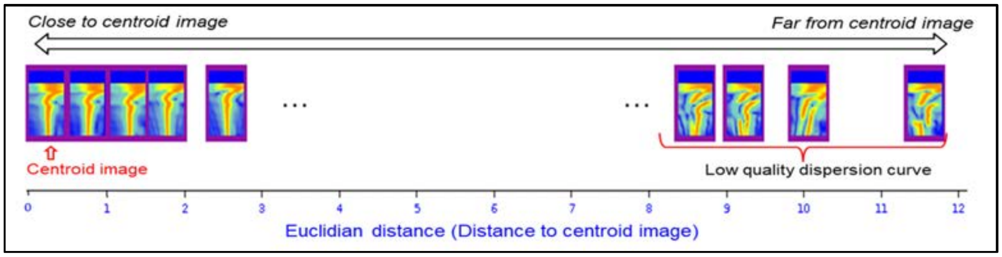

Figure 2 *Euclidian distance plot for Class 2. DC images at the farthest distance from the centroid image show low quality and are by consequence discarded.*

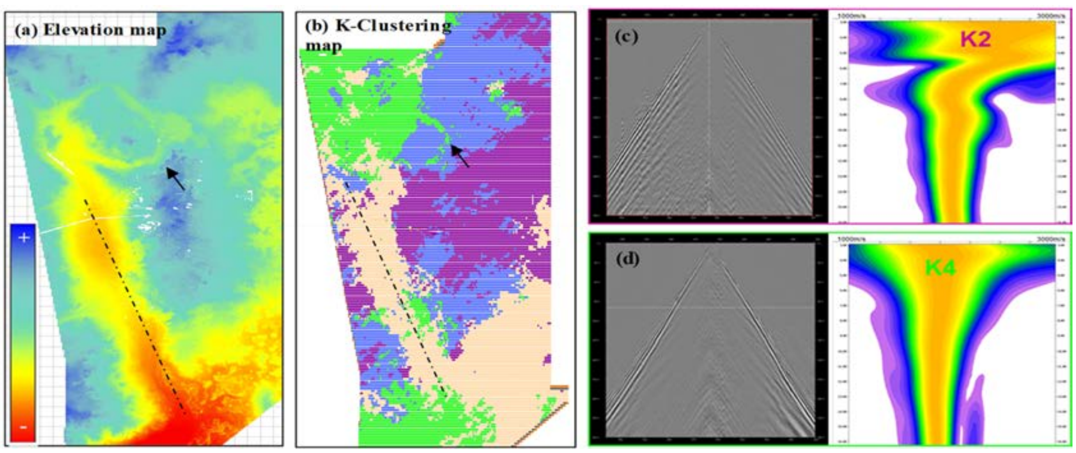

Figure 3 *(a) Elevation map; (b) K-means clustering map: 4 main classes (green, purple, blue and beige) + 2 outlier classes (orange and grey) close to survey edges; Examples of Class 2 (c) and Class 4 (d) shot gathers and theirs corresponding dispersion curves.*

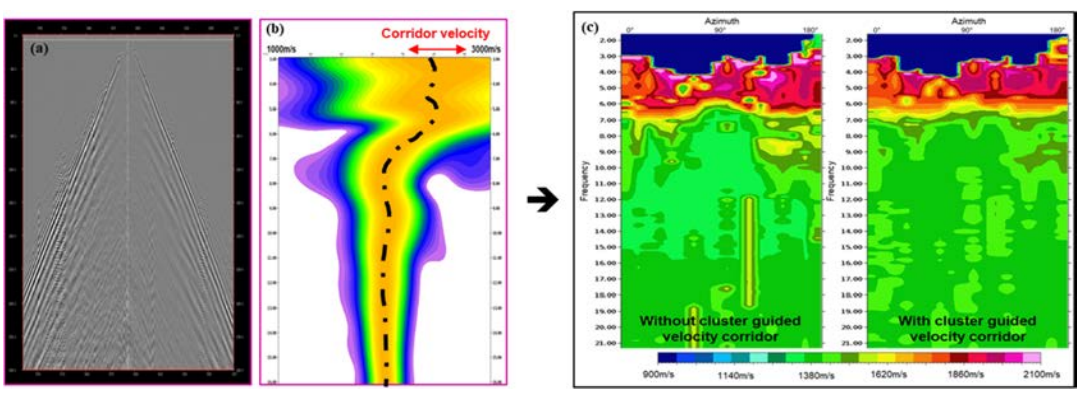

Figure 4 *(a) Example of a cross-spread gather viewed in shot direction belonging to Class 2; (b) with its corresponding mono-azimuth dispersion curve overlaid with the cluster-guided corridor; (c) with its picked phase velocities for all azimuth from 0-180^o without ML guide (left) and with ML guide (right).*

After removing some outlier phase-velocity spectra due to poor SNR, we then use the clustering to define an optimized corridor for each class featuring a distinct velocity trend. The velocity corridor is estimated on the representative DC of the class (Figure 4a, 4b). Using these cluster-guided corridors, a new set of phase velocities are picked on the entire survey in 18 different azimuth directions. The picked phase velocities now appear more stable (Figure 4c).

Multi-Wave Inversion results

The MWI workflow, fed with the optimized phase velocity picks for all the 18 azimuth sectors, was run in two steps. The first step was designed to model from the DC picks a single 3D volume of Rayleigh wave velocity on the sub-surface grid. It was performed by applying a tomographic process that converts the spatially irregular frequency-dependent picks to regularized (x, y, period) Rayleigh wave velocity (Figure 5). The tomographic result with ML-guided DC picking shows sharper fault discontinuities, less noise and less artefacts at the survey edges.

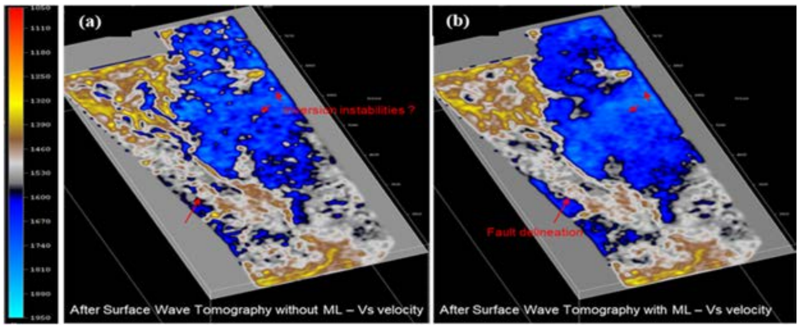

***Figure 5** Surface wave tomography results at period of 160ms: (a) without ML guided DC picking; (b) with ML guided DC picking.*

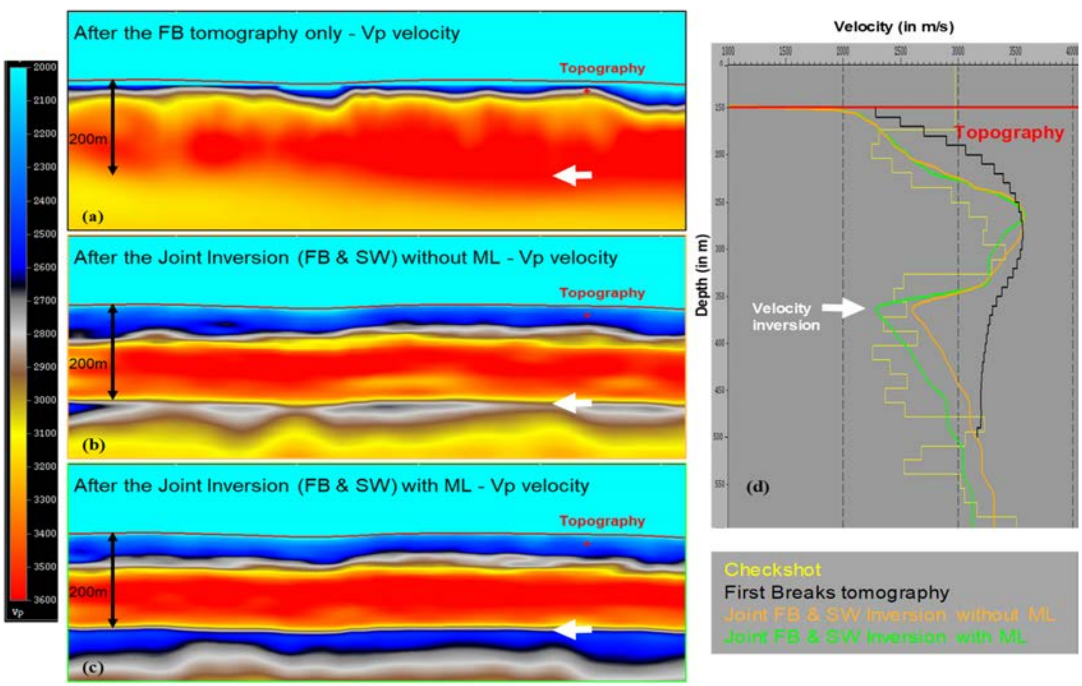

***Figure 6** P-velocity model: (a) after FB tomography; (b) after MWI without ML guided DC picking; (c) after MWI with ML guided DC picking; (d) Velocity profiles at well location.*

The second step of the workflow consists of jointly inverting the FB picks and the volume of Rayleigh velocities. Figure 6 highlights the gradual improvement of the P-velocity model from FB tomography alone, MWI without ML picking and MWI with ML picking. The Vp model from the FB tomography (Figure 6a and Figure 6d, black curve) does not properly catch the first velocity increase as it may suffer from poor coverage between 0m and 100m, nor the sharp velocity inversion as expected. The velocity inversion is partially resolved with the MWI without ML-guided picking (Figure 6b and Figure 6d, orange curve). However, the low velocity contrast is affected by the presence of outliers and badly picked DC, as the result the output model is still slightly off from the checkshot. Finally, the velocity inversion is well resolved by the MWI with ML-assisted picking (Figure 6c and Figure 6d, green curve) and the velocity trend follows correctly the checkshot trend down to 500m, confirming the reliability of the DC picks at very low frequency. Migration of the near offset stack using respectively the velocity models from FB tomography, MWI without ML-guided picking and MWI with ML-guided picking illustrates how crucial it is to obtain an accurate velocity model in the near surface (Figure 7). Geological features such as faults appear clearly and seismic layering in the tilted blocks is significantly improved with the MWI ML-guided workflow.

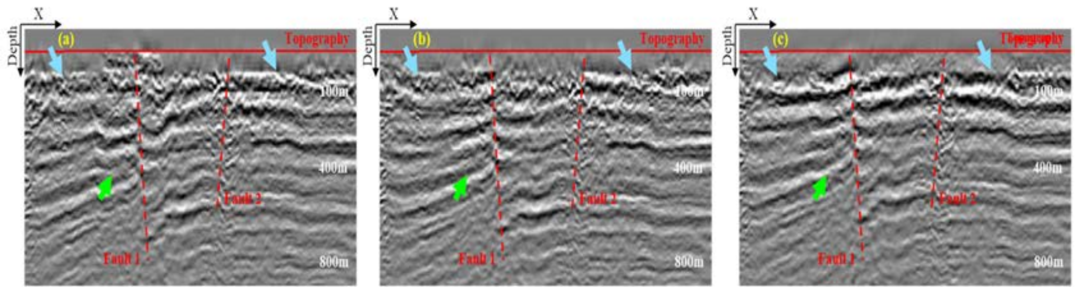

Figure 7 *Depth migrated near common offset vector: (a) with FB tomography model; (b) with MWI without ML picking velocity (c) with MWI with ML picking velocity; Cyan and green arrows point respectively to structural image and seismic continuity improvement*

Conclusions

A ML-guided MWI workflow is proposed to capture a challenging shallow velocity inversion in Southern Oman. First, the unsupervised clustering helps to define more stable picking corridors for different areas, in order to extract better quality surface wave DC's, especially at low frequencies where their quality is lower. The MWI captures the shallow velocity inversion, which is impossible to recover with either FB tomography only or diving wave FWI only. By incorporating this shallow inversion layer into the velocity model, the resulting seismic image is significantly improved and more interpretable. The MWI result revealed shallow horizons in the reflectivity image that could be used as input to additional iterations of the MWI workflow in order to further improve the structural content of the image.

Acknowledgements

We would like to thank Occidental Petroleum and the Ministry of Oil and Gas of the Sultanate of Oman for permission to present the data examples. We also thank David Le Meur and Song Hou for their support and CGG for permission to publish these results.

References

Bardainne T., [2018], Joint inversion of refracted P-waves, surface waves and reflectivity. 80th EAGE Conference & Exhibition.

Chiffot C., Prescott A., Grimshaw M., Oggioni F., Kowalczyk M., Cooper S., Le Meur D., Johnston R., [2017], Data-driven interferometry method to remove spatially aliased and nonlinear surface waves, SEG International Exposition and Annual Meeting, Extended Abstracts.

MacQueen, J., [1967], Some methods for classification and analysis of multivariate observations. Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Statistics, 281--297, University of California Press, Berkeley, Calif.

Sedova A., Royle G., Hermant O., Retailleau M. and Lambare G., [2017], High-resolution land full-waveform inversion: a case study on a data set from the Sultanate of Oman: 79th Conference and Exhibition, EAGE, Expanded Abstracts, We A3 04.