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## Can Data Analytics Help Reduce Seismic Processing Turnaround

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### Summary

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Seismic data volumes are increasing and pressure is growing to accelerate the turnaround time of seismic processing projects. Testing, validation and production administration are time consuming components of a project. Testing is performed to optimize the parameters for each step in the processing sequence. It can be both computer and human resource intensive, as many testing phases require numerous repeat runs and significant interaction with the data. A Proof-of-Concept (POC) example illustrates that parameter testing can be helped by mining for parameters from a database.

## Introduction

Seismic data volumes are increasing and pressure is growing to accelerate the turnaround time of seismic processing projects. Testing, validation and production administration are time consuming components of a project. Testing is performed to optimize the parameters for each step in the processing sequence. It can be both computer and human resource intensive, as many testing phases require numerous repeat runs and significant interaction with the data. A Proof-of-Concept (POC) example illustrates that parameter testing can be helped by mining for parameters from a database.

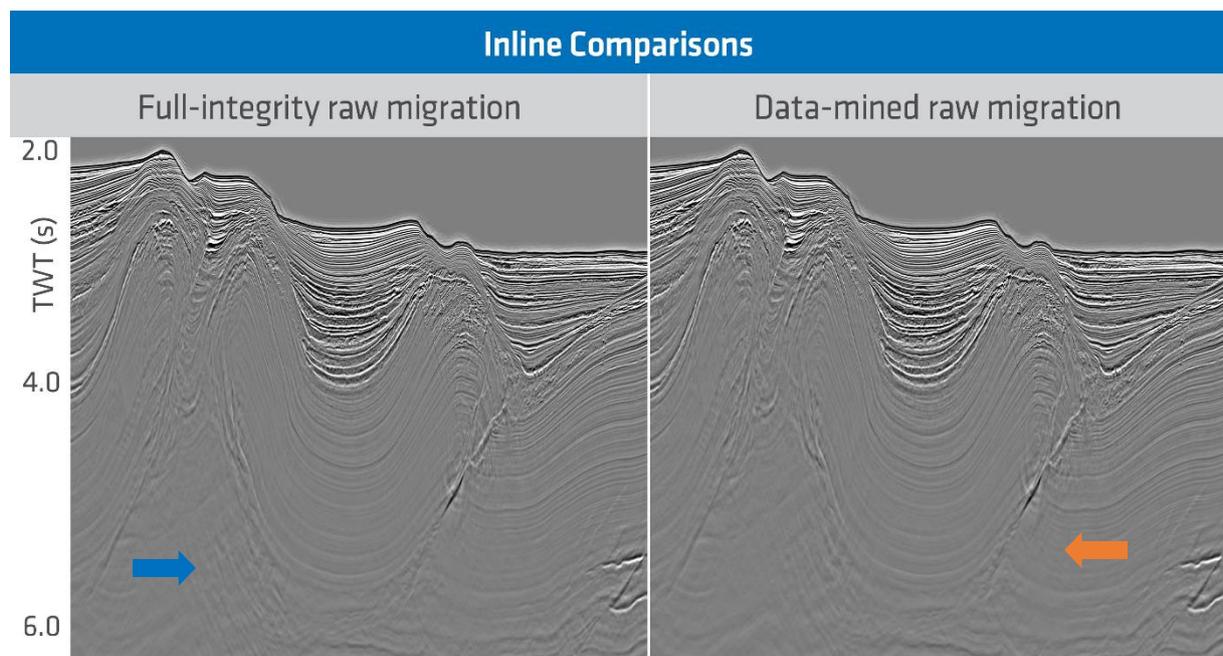
## Method

A substantial amount of seismic data is processed annually, especially considering the uniqueness of data and complexity of processing sequences. Historical activity can be used to construct a database of processing parameters that may be mined to extract the most appropriate parameters for data processing based on similarity criteria and considering: Geological settings, processing challenges and objectives, acquisition geometries, environmental conditions and the processing sequence. The collective expertise and experience stored in a database is an undeniably powerful tool for accelerating turnaround. The data could be mined to either focus testing parameterization, or bypass it altogether.

In this POC work, a database of processing parameters was used for the major steps of a seismic processing project. Key parameters based on ranked similarity to the test data set were extracted, workflows created and run non-stop. No testing of parameters was performed. The goal was to establish if this automated approach could produce meaningful results. Metrics compared the data quality of the database-mined work with a full-integrity project. Statistics were extracted to understand turnaround benefits, and conclusions drawn on the process validity and use case scenarios.

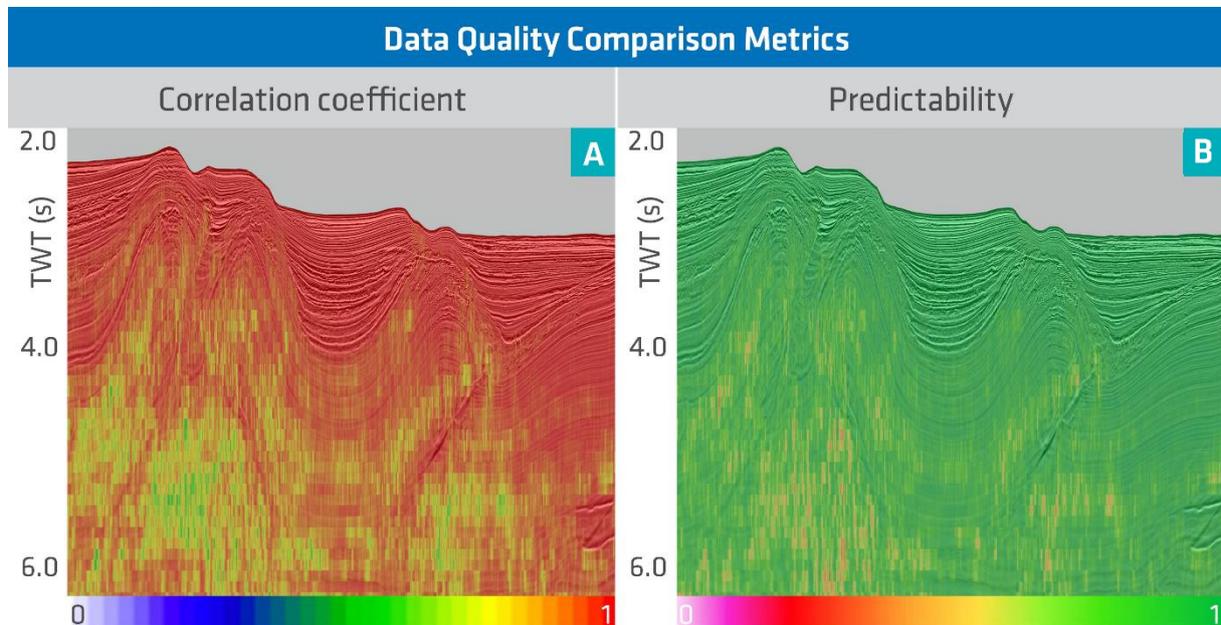
## Proof-of-Concept case study

The Malaysian Sabah 3D data set was acquired in water depths varying from 100 m to 3000 m. The data is dominated by a fold and thrust belt within the Miocene turbidites. Using a 400 km<sup>2</sup> volume, key processing parameters for all steps in the data domain pre-processing and migration were mined from a database. The resulting raw migration was then compared to the full-integrity equivalent whose parameters were excluded from the database, and which was run in advance of the data analytics test. Figure 1 shows a comparison of the two data sets.



**Figure 1.** A raw migration stack response comparison of a full-integrity processing project (left); and an automated approach using data mining of a parameter database (right). Blue arrow (left) highlights more coherent noise, whilst orange arrow (right) indicates more random noise.

The migrated stacks look similar. The orange arrow indicates there is more scattered noise in the data-mined version, however, the blue arrow shows there is more coherent noise in the Full-integrity data. Correlation analysis, predictability, and Signal-to-Noise content were generated at each key processing step, but did not affect the mined parameters. Only the final comparisons are shown. Correlation analysis between the two volumes (Figures 2A and 2B), highlight that the deeper data-mined example is different, indicating the subtle difference in noise content between the two volumes.



**Figure 2.** (A) Correlation coefficient and (B) predictability.

The S2N content in Figure 3B show that the full-integrity data has a better response (notably 30-70 Hz)—albeit marginal. Overall, the data quality from the database-mined approach is equivalent to the full-integrity process, and was achieved in one-third of the time. An equivalent level of success cannot always be expected, but as parameter databases become more sophisticated and better populated, the principle should be broadly applicable.

### Discussion

The same velocity model was used for the migrations, and was taken from the full-integrity project, however, the industry is awash with examples of how to expedite model building. Automated quality control (QC) may enable a quick validation of each processing workflow, and there many examples of how machine learning-infused techniques may help corroborate the parameterization of processes.

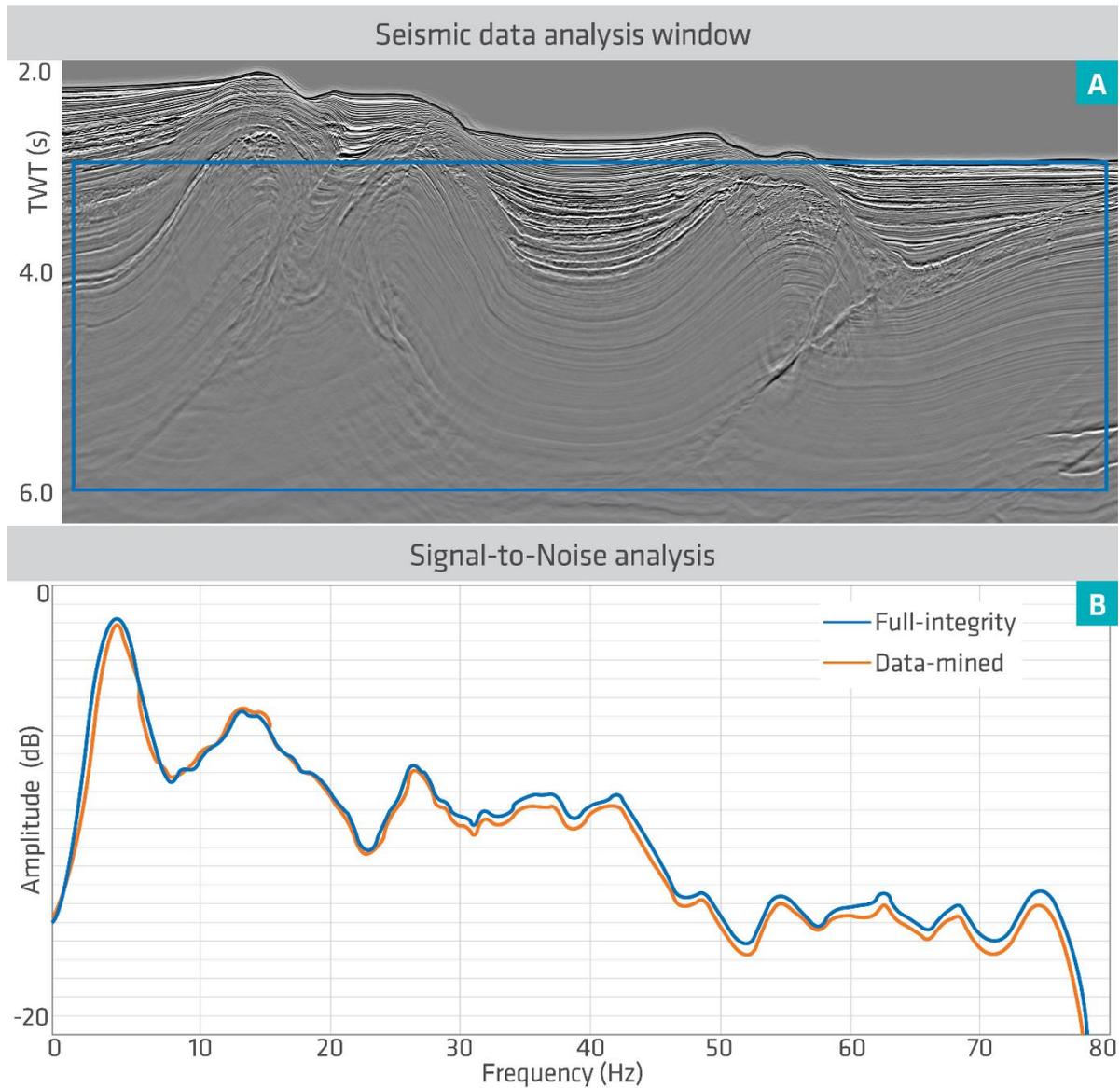
Mined parameterization could be considered for fast-track seismic processing data sets, especially if used with automated QC and model building techniques, or to pre-condition data for model building. Finally, a database would need to evolve; the inclusion of seismic processing algorithms that improve data quality would be absent from the database until appropriate usage enables its addition.

### Conclusions

The POC example demonstrates that a collectivized digital experience database can be mined to parameterize several consecutive processing steps without human intervention. The data quality metrics show that, for this data, the seismic quality is comparable to a full-integrity project. The turnaround benefits were significant; the database-mined sequence completed in significantly less time than the full-integrity work.

### Acknowledgements

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**Figure 3.** (upper) Analysis window used to compute the Signal-to-Noise attribute; and (lower) Signal-to-Noise comparison of the full-integrity and data-mined results.