From Well Logs to 3D Models: A Case Study of Automated Stratigraphic Correlation in the Midland Basin

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SUMMARY

Advanced 3D geological modeling and automated stratigraphic correlation improve our understanding of the geology at a basin scale. The process of correlating geophysical well logs is sped up using the Dynamic Time Warping (DTW) algorithm. The workflow enables the efficient analysis of extensive datasets that contain thousands of well-logs, reducing the challenges of manual interpretation. Accurate 3D stratigraphic and log property models can be created at a basin scale using various technologies. In this article, we illustrate the concepts with an application to the Midland Basin.

INTRODUCTION

Correlating geophysical well logs is necessary for building basin-scale stratigraphic models, a crucial yet labor-intensive task. In addition, using the manual correlation makes it difficult to take advantage of all the stratigraphic information from dense well-log datasets. There is a clear need for automation to improve efficiency and reproducibility. Various approaches have been introduced to automate geological boundary detection from well-log data. Dynamic time warping (DTW) and artificial intelligence (AI) have been utilized for correlating signal sequences and extended to the domain of geology for well-to-well correlation (Zoraster et al., 2004; Lineman et al., 1987; Smith and Waterman, 1980; Le Nir et al., 1998; Baldwin et al., 1989; Luthi and Bryant, 1997; Po-Yen Wu et al., 2018; Brazell et al., 2019; Tokpanov et al., 2020). Despite advances in automation, the reliance on conventional manual interpretation persists in most log correlation projects, particularly in datasets consisting of tens of thousands of logs. These present significant challenges to reproducible and efficient manual workflows. These workflows often require interpreters to focus on fine-scale details in a limited number of logs, making it challenging and time-consuming to assess the large-scale structure of the subsurface. Furthermore, generating accurate 3D property and stratigraphic volumes from well-log data, especially in horizontal sections of producing formations, faces obstacles such as data quality variability, lateral reservoir variability, and the complexity of accurately modeling these variations.

The focus area of our study is the Midland Basin, whose size, complex geology, stacked pay zones, and variable lithologies make extensive manual interpretation prohibitively expensive. Our study extends the ChronoLog (Sylvester, 2023) automated stratigraphic correlation workflow to address these issues. ChronoLog provides automated tools for constructing high-resolution, three-dimensional stratigraphic models. This framework enables the processing of basin-scale data and allows geo-scientists to visualize and interpret the spatial distribution of rock types, porosities, permeabilities, and hydrocarbon saturation levels in 3D.

STUDY AREA

The study area of interest (AOI) is the Midland Basin, spanning Glasscock, Howard, Martin, and Midland counties. We use an extensive dataset of approximately 30,000 vertical and 6,550 producing horizontal wells (Figure 1). The ChronoLog methodology requires an initial input set of interpreted formation tops to constrain the well-log correlation. We select interpreted formations tops that provide the largest span of our 3D property generation spatially and in-depth; these include the Rustler, Bone Spring/Upper Spraberry, Wolfcamp, Strawn, Devonian Carbonate, and Ellenburger.

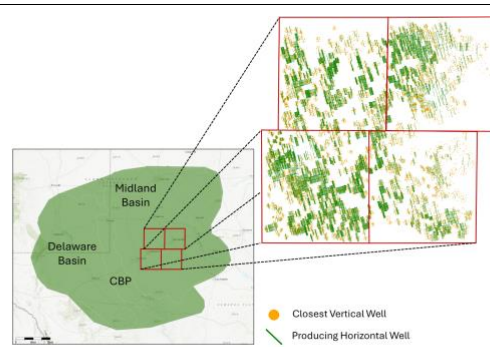

Figure 1: Map of well locations in the Midland Basin, covering Glasscock, Howard, Martin, and Midland counties, indicating vertical and horizontal wells.

METHODOLOGY

Data Selection and Pre-processing:

Our well data preprocessing pipeline starts with automated data cleaning. It comprises curve categorization, verification of information, splicing, merging, depth shifting, normalizing, and quality editing. The gamma-ray curves are also standardized to an interval from 0 to 1, an important step when evaluating numerical well-to-well correlation and for the following well-curve imputation step. To maximize the collection of available well data, we impute missing log curves on the clean well data using an ARLAS (Gonzalez et al., 2023) model trained specifically for the Permian Basin. Using ARLAS, a consistent collection of five logs is available in every interpreted well: the bulk density, gamma-ray, neutron porosity, deep resistivity, and compressional sonic curves.

To apply the stratigraphic correlation workflow effectively, we seek to maximize the largest collection of wells where we have manual interpretation defining a formation's top and base depth. The availability of manually interpreted tops varies across formations, and the subset of wells containing all required tops is limited. However, our iterative modeling approach does not require tops at every well location. It is sufficient to have a coverage of interpretation across the AOI, but not every well in the dataset must have an interpretation for every formation. This significantly expands the pool of wells incorporated into the workflow.

Dynamic time warping-based well-to-well correlation

Chronolog uses a DTW algorithm to align well logs based on manually interpreted formation tops and normalized gamma-ray curves pairwise. This method aligns geological features across pairs of well logs, accounting for discrepancies in deposition times or layer thickness resulting from geological processes.

A well connectivity graph is first created to reduce the computational overhead of the dynamic time warping, which is significant at the basin scale. ChronoLog only evaluates pairwise correlations for connected nodes in this graph. The edges of this graph represent proximity or relational ties to neighboring wells. In parts of the AOI that are well covered spatially by interpretation, the graph is cut between wells more than 3 km apart. We still attempt to include data in parts of the AOI with sparse well coverage; here, a Delaunay triangulation creates edges between wells, which are not subject to the 3 km maximum proximity. The objective is to ensure a comprehensive network that facilitates as much accurate stratigraphic analysis as possible.

DTW will always yield a result, even for unrelated sequences. For this reason, we filter the set of well pairs based on the normalized DTW cost (Rath et al., 2003) for the pair.

For two sequences s_1 and s_2 with length N_1 and N_2 , this cost is:

$$C_{norm} = Cost(s_1, s_2)/(N_1 * N_2) .$$

After computing this cost across our dataset of wells, we identify pairs where the cost is greater than the 99th percentile. The network connectivity graph is cut for these pairs, and if a well is left unconnected from the graph, it is removed from the analysis. Using least-squares optimization, ChronoLog creates a consistent set of pair-wise depth correlations (Wheeler and Hale, 2014). The result is a chronostratigraphic diagram that aligns the well curves in relative geologic time (RGT) (Figure 2).

ChronoLog then applies a Continuous Wavelet Transform (CWT) and systematically identifies stratigraphic boundaries by detecting zero-crossings in the wavelet transform, indicating geological feature changes (Cooper et al., 2009). This segmentation is later used to create aggregated 3D properties across the basin. The scale parameter in this method can be thought of as the bandwidth of a Ricker wavelet. Less fine detail is retained as the scale increases. This study uses a setting of 4 samples to produce a rich set of stratigraphic layers without additional manual interpretation.

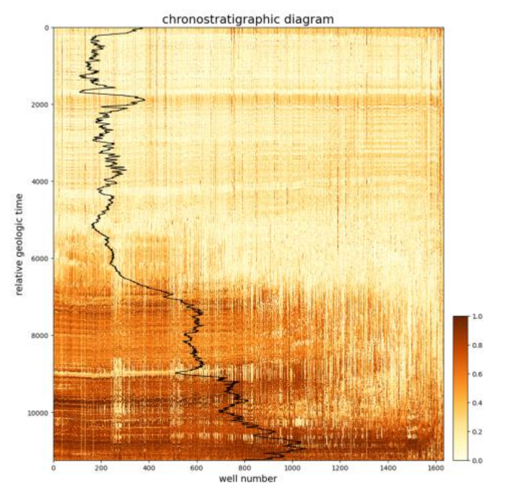

Figure 2: Chronostratigraphic diagram illustrating the alignment of well logs in RGT, utilizing normalized gamma-ray curves for Rustler formation.

Development of 3D Geological Models

Our workflow does not require every well to contain interpreted tops for every formation. Instead, a basin-wide chronostratigraphic diagram is created in a layercake fashion, stacking diagrams and segmented sequences assembled for the Rustler, Bone Spring/Upper Spraberry, Wolfcamp, Strawn, Devonian Carbonate, and Ellenburger formations. For this reason, many of the wells in the dataset may lack certain stratigraphic layers identified by ChronoLog.

A problem with naively imputing the missing sequences by a simple interpolated grid is that the result may not preserve the correct sequence. This is particularly relevant when geology is structurally complex. Instead, we use an iterative method based on interpolating segment thickness relative to a common reference point, as shown schematically in Figure 3. The algorithm starts with an established reference point across the dataset, and then an interpolated map of segment thickness across the basin is computed. This thickness map is then used to forecast the interval of this segment in wells where it is missing. The top of the segment becomes the common reference point, and the algorithm iterates until consistent segmentation exists in all wells.

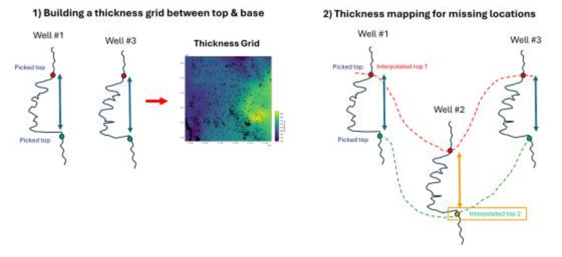

Figure 3: A schematic depicting the iterative process for interpolating missing formation tops, involving two main steps: 1) constructing a thickness grid between identified tops and bases, and 2) applying thickness mapping to estimate missing formation tops.

With every stratigraphic top identified at each well location and characterized by a high spatial density, we can now interpolate depth values and log properties beyond the immediate areas surrounding the wells to generate maps with regular grids. This involves gridding both the identified stratigraphic tops and the average property values found between these tops, which serves as a foundation for building 3D geological models.

Extended Stratigraphic and Property Model

Expanding on the initial model, we now include all vertical wells in the dataset, regardless of whether their formation tops have been manually identified. By plotting the locations of these wells on the stratigraphic grids, we can identify previously missing formation tops while using all existing log curve data from those wells. We address gaps in the log curve data using the k-nearest neighbors' algorithm, creating a comprehensive dataset and a complete property model with both formation tops and comprehensive well-log data.

This expanded effort allows us to develop 3D stratigraphic and log property models, capturing each vertical well's known formation top and the log curve data. Following the methodology of the initial model, we use spline interpolation to fine-tune the log curve attribute grids. This technique ensures that geological features are depicted accurately, avoiding overlaps and ensuring continuity in our models.

CASE STUDY

In this section, we describe chronostratigraphic diagrams and log correlations generated with the automated stratigraphic correlation workflow and highlight their value in interpreting geological features. The workflow starts by selecting formations with well-supported tops, such as the Rustler, Bone Spring/Upper Spraberry, Wolfcamp, Strawn, Devonian Carbonate, and Ellenburger. We limited the distance between well pairs to 3,000 meters for correlating wells. With a segmentation scale set at 4, we identified 1,570 stratigraphic units for 1,939 wells, which helped us create a detailed gridded model. This setup enabled precise spatial analysis.

Development of Stratigraphic and Property Models

We developed a 3D geological model using well-log data, featuring one stratigraphic volume and six property volumes, including normalized gamma-ray, sonic, neutron porosity, density, and resistivity. Each property volume offers insights into different aspects of the geology. The model is structured as a volumetric array, resembling a stack of layers, each representing a geological layer or formation (Figure 4b). This setup, visualized in Figure 4a, assigns a specific X-Y-Z coordinate to every point in the grid. We chose a 50-meter spatial resolution for the X and Y axes to balance detail with computational efficiency. To validate the accuracy of our 3D models, we generated synthetic logs for vertical wells within the AOI. We calculated the normalized Root Mean Square Error (RMSE) against the existing ARLAS logs. An example log track of a selected well in Figure 5 displays a comparison for the neutron log, with ARLAS logs in blue and synthetic logs in red. Validation focused on depth intervals with overlapping signals, showcasing the synthetic logs' capability to reconstruct a continuous signal throughout the wellbore. The findings show a normalized RMSE between 10-15% across all compared well logs, indicating a relatively close match.

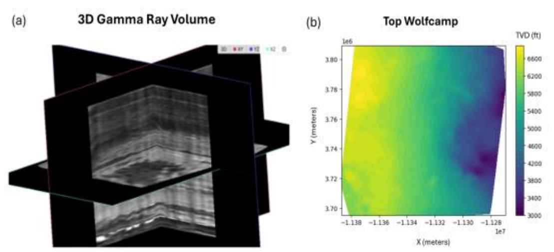

Figure 4: (a) 3D gamma ray model; (b) Map view showing the Wolfcamp formation top, represented as a stacked 2D layer within the stratigraphic volume.

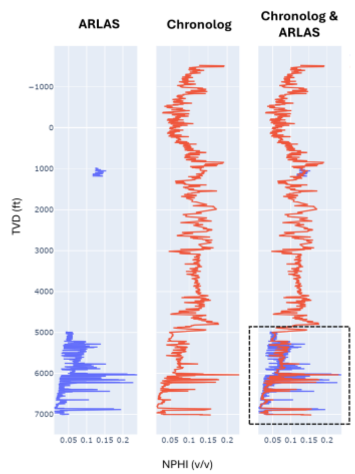

Figure 5: Log track comparison between synthetic logs (red) and ARLAS logs (blue) for a selected well.

Deriving Log Data for Horizontal Wells in Reservoir Analysis

Extracting log data from horizontal sections of wells is a critical step in understanding and evaluating reservoirs. This process provides key insights that help make informed decisions, optimize production, manage reservoirs effectively, and improve profitability. To do this, we rely on two main data sources: directional surveys (DS), which give us the X-Y coordinates for the paths of horizontal wells, and a set of 3D models of the stratigraphy and property data from well logs (Figure 6. a - 6. c). Using the X-Y coordinates obtained from DS, we map and collect the log curve data and the stratigraphic tops for horizontal wells from the 3D models. We compute a comprehensive statistical analysis on these sections to determine critical metrics such as the 2nd and 98th percentiles, median, minimum, maximum, and average log responses (Figure 6b). This approach allows the statistical analysis of any curve attributes, including petrophysical properties, at any X-Y-Z coordinate.

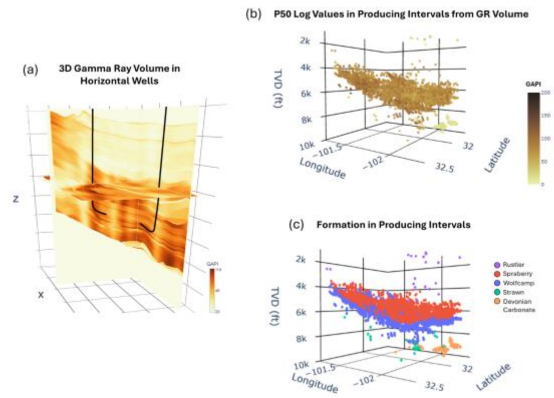

Figure 6: Diagrams showcasing well log data extraction from horizontal wells for reservoir analysis. (a) 3D gamma-ray volume analysis, (b) median gamma-ray values in producing wells, and respective (c) formation names.

CONCLUSIONS

Advanced 3D geological modeling and ChronLog automated stratigraphic correlation pipeline have enhanced the understanding of the Midland Basin's subsurface geology. These technologies have increased the accuracy and efficiency of constructing 3D stratigraphic and property models, aiding in exploring and developing unconventional hydrocarbon resources.

ACKNOWLEDGMENTS

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