Hybrid pattern matching algorithms for automated stratigraphic well correlation and log pattern recognition in Malaysian Basin

Introduction

Well-log stratigraphic correlation is one of the most important process in subsurface reservoir characterization workflows. However, this process typically completed by human interpreters manually, which can be time consuming and highly dependent on geologist experience and knowledge of geological deposition of the area. Artificial intelligence can successfully reduce the time spend to correlate and reduce the bottleneck to many subsurface characterizations. This paper leverages a pattern matching strategy for stratigraphic correlation and deep learning to recognize stratigraphic log patterns.

Proposed approach

We develop a novel automated correlation strategy utilizing Dynamic Time Warping (DTW), Directed Acyclic Graph (DAG), and Dijkstra’s algorithm. The new hybrid methodology enables consistent and robust well correlation.

Our method formulates around the Dynamic Time Warping (DTW), an algorithm for aligning and measuring similarity between two signals. In geosciences community, DTW was first implemented by Smith and Waterman (1980) to align well logs and perform lithostratigraphic correlation. Lallier et al. (2009, 2016) later improvised and proposed the use of a stochastic variation of the DTW algorithm. DTW has flourished particularly in stratigraphic correlation as it allows a non-linear mapping of one sequence of well logs to another by minimizing the distance between the two.

In Figure 1 (left picture), consider two stratigraphic zones X and Y in two separate wells W₁ and W₂. Correlation between these two zones $DTW(X,Y)$ measures the similarity of two sets of zones by calculating the correlation value between two zones and representing the result as a path in a cost table of size length of $X \times$ length of $Y$ (right picture of Figure 1). The series of points in this cost table corresponds to the well log samples in the zone intervals.

![Figure 1: Stratigraphic correlations between two zones X and Y in two wells W₁ and W₂. In the right picture, an example of a cost correlation path candidate in a DTW cost table.](image)

The minimum cost path through the table corresponds to the optimal correlation between zone X and zone Y is obtained by computing iteratively the cost path $P$ from the top right to bottom left cell:

$$DTW(X,Y) = \min_P \{d_n(X,Y)\}, \quad P = (p_1, p_2, \ldots, p_N)$$

$$d_n(X,Y) = \left( \sum_{i=1}^{n_X} \sum_{j=1}^{n_Y} |x_i - y_{i+j}|^2 \right)^{1/2}$$

Our method utilizes DTW by finding the minimum cost correlation path of normalized values of selected log types $k$ (e.g. shale volume, gamma ray, neutron, density, resistivity, etc.):
\[
Correlation(X, Y) = \frac{1}{K} \left[ \sum_{k=1}^{K} DTW_k(X, Y) \right]
\]

The disadvantage of DTW on its own is that it may lead to inconsistent pairwise correlation, which we overcome by adopting the combination of directed acyclic graph (DAG) and Dijkstra’s shortest path algorithm. We implement index topological arrangement using DAG (Thulasiraman and Swamy, 1992) to ensure the consistency of each possible correlation with geological pattern. DAG utilizes depth weightages as constraint to select candidate zone pairs prior to DTW correlation calculation. The depth weightages consist of Paleo-dip angle difference \(\Delta DIP\) and True Stratigraphic Thickness difference \(\Delta TST\). DAG is also used for combinatorial analysis of local zones to allow possible combinatorial configurations of zones within the same well location as correlation candidates.

![Figure 2](image)

**Figure 2** An example of topological ordering of a direct acyclic graph (DAG) between two wells \(W_1\) and \(W_2\) containing three zones respectively \((X_1, X_2, X_3, Y_1, Y_2, Y_3)\). In this study, zones are considered as nodes and edges are the lines that connect two zones/nodes. Every edge goes from the earlier in the ordering (in this case, source node \(X_1\) marked in red) to later in the ordering. Blue edges indicate possible combinatorial configurations within same well location. Black edges indicate possible correlation zone pair inter-wells that meet the requirements of the depth weightages specified, while red edges indicate the edges that do not meet those requirements hence eliminated.

Finally, we employed Dijkstra’s algorithm (Dijkstra, 1959) to find the shortest path from a single source node, by connecting a set of nodes that have minimum distance (DTW cost) from the source. Given there is no source node (or seed well zone), the method reiterates Dijkstra’s algorithm for all local zones, find and rank the source nodes with shortest path tree. This hence avoids bias in the final path selection.

![Figure 3](image)

**Figure 3** Building of a first draft correlation set through the 3-step iterative stratigraphic correlation algorithm consists of petrophysical-based local zonation, Directed Acyclic Graph and Dijkstra’s algorithm through the Dynamic Time Warping as preferred correlation calculation method.

On top of above correlation strategy, we develop a novel geological pattern labelling method, which uses convolutional neural network (CNN) to classify log patterns. This method classifies the correlated well zones based on log pattern and gives another dimension of geological interpretation automatically. Training datasets used in this workflow are simulated mathematically using the reference log shape pattern template from Slatt (2006). These responses often are interpreted in terms of rock types and depositional environments.
Two-dimensional images of log shape patterns that represent stratigraphic features are randomly generated by using a set of assumptions and parameters. By randomly choosing the parameters from some predefined ranges, we automatically produce numerous log patterns based on our stratigraphic understanding. Generated log shape labels are used to train deep learning for pattern classification.

**Figure 4** Schematic of 11-layer deep convolutional neural network for log pattern classification.

The model created for this purpose is an 11-layer deep convolutional neural network (Figure 5). This model uses 5x5 convolutional filters in the network. The input data are pre-processed into a 2D image representation, convolved and down-sampled repeatedly. The final classification is achieved by flattening the convolved image and feeding it to a classic feed-forward densely connected neural network. The K output classes that represent the stratigraphic pattern classes (either vertical transition, log shape, or slope trend patterns) are normalized by a final softmax layer.

3. Field application

The field used for this study is located in one of the basins in Malaysia. The trap is a buried-hill erosional relief beneath a local unconformity that is overlain by a thick transgressive marine shale. The reservoirs were deposited during the Lower Middle Miocene age, with shallow marine shore face depositional environment and general geological dipping of 10-15°. Nine wells, three regional top markers and seismic horizons are identified as anchors from the field were used in the study.

**Figure 5** Well section. Regional top markers and reference horizons are used as constraint anchors within which the automated stratigraphic correlation will be conducted.

Below are the steps for the application:

1. Local zonation using petrophysical cut-offs based on log responses to distinguish volume of shale (VShale), lithology changes and petrophysical properties. The set of well logs used for zonation is gamma-ray (GR), density, neutron and resistivity. The VShale is calculated using Density-Neutron (DN), instead of traditional use of GR log, in order to overcome the standalone misinterpretation of
GR profile due to local presence of radioactive minerals in sand facies such as Glauconite and Pyrite.

2. Declaring the background zones governed by field top markers that are clearly seen on seismic data. Due to the dominant sand intervals, the background zones are determined based on field-wide chrono-stratigraphy top markers. The method correlates zones within these pre-determined anchors.

3. Perform combinatorial analysis and first order correlation using a base zonation cut-off. Base zonation cut-off is equivalent to ~70% VShale, to discrimination cut-off for shale, slightly silty and/or silty shale facies. The first order combinatorial analysis and correlation gives correlatable segmented zones based on log signature and cut-off. In addition, the first run provides first correlation screening that can be used by user to qualify the cut-off used and adapted with their expert knowledge in the area.

Figure 6 Outcome after step 3, the first order correlation results within the pre-defined anchors. This serves as a first impression to qualify the cut-off used and plan for the next order correlation.

4. Perform second order correlation using lower cut-off value to perform sub-zonation within the first order zonation. Cut-off ~30% VShale is used to discriminate the clean sand, silt and silty sand facies from the high silty and shaly ones. The correlation result can be used to indicate wells with anomalous log signature compared to other wells in the area due to local enrichment of accessory minerals and compartmentalization.

Figure 7 Outcome after step 5, flattened on the second reference horizon showing the deposition of sands during Lower Middle Miocene age.

5. Perform top marker selection based on knowledge expert user interpretation (Figure 7). User can fine-tune the correlation provided based on user knowledge on the area. The method can be used to re-correlate and fix the zonation of the anomalous zones based on the accepted correlation from the other wells.

6. Perform constrained stratigraphic pattern recognition (Figure 8).
Using analytically prepared stratigraphic log pattern, convolutional neural network is used to classify similar stratigraphic patterns from real logs.

Output from the method are updated top markers with detailed zonation and correlation that can be used by geo-modeler to update reservoir static model. The method also produces stratigraphic patterns on top of the correlation. This enables geologist to further classify the log shapes into depositional environment (EOD) patterns.

Conclusions

We propose a hybrid pattern matching algorithms utilizing AI-assisted techniques that automate stratigraphic well correlation and a log signature-based stratigraphic pattern recognition using convolutional neural network. We consider limitations such as implementation on complex geology such as fault cut-out, multiple depositional system settings, and application on horizontal well sections. The method proves to be a robust and reliable approach in performing automatic well correlation as demonstrated on the field data.

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References


