Applications of machine learning techniques on angle stacks to enhance carbonate reservoir characterization

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Summary

Carbonate reservoirs provide numerous complications for accurate reservoir characterization and management. A seismic survey acquired in the Fall of 2019 over a Silurian (Niagaran) pinnacle reef gas storage reservoir to investigate the applicability of unsupervised machine learning techniques on attributes generated on angle stacks to enhance facies identification in seismic data. Internal heterogeneities are identified within the reef core reservoir facies on the near angle self-organizing map not seen in a SOM calculated on the PSTM volume. Underlying low porosity bioherm facies are accurately revealed on the far angle stack SOM. The spatial distribution of facies is mapped, and will be utilized to constrain future geostatistical models.

Introduction

The Michigan Basin was a prolific hydrocarbon producer throughout the mid to late 20th century. Niagaran (mid-Silurian) pinnacle reefs were widely produced throughout the basin. Following production, many of these reefs were converted to storage reservoirs for natural gas and carbon sequestration. Despite the widespread production, few stratigraphic models of the internal structure and facies distribution of the reefs has been done. Rine et al. (2017) provides a core and log-constrained facies model for Niagaran reefs along the southern trend in the Michigan Basin and illustrates that the reefs are composed of distinct, predictable facies.

Carbonate reservoirs, especially those that have undergone dolomitization, are characterized by a high degree of vertical and lateral heterogeneity (Pranter et al., 2005). Well data provides excellent vertical constraint on the distribution of reservoir properties, however provide little spatial constraint. To better understand the spatial distribution of quality reservoir facies, a recently acquired three-dimensional (3-D) seismic survey over Ray Reef, a reef in the southern reef trend, is integrated with tightly-spaced well log and core data. A suite of attributes was generated on the following volumes: Full-stack PSTM, near angle stack, and the far angle stack. Self-organizing maps (SOM) were then run on each volume to reveal internal heterogeneities not visualized in the original amplitude and individual attribute volumes.

Both core and log data from intersecting wells were then incorporated to map out facies within favorable reservoir zones to target for storage within the pinnacle reef complex. Following the analysis of the SOMs, the resulting facies classification volumes will be used as constraints for

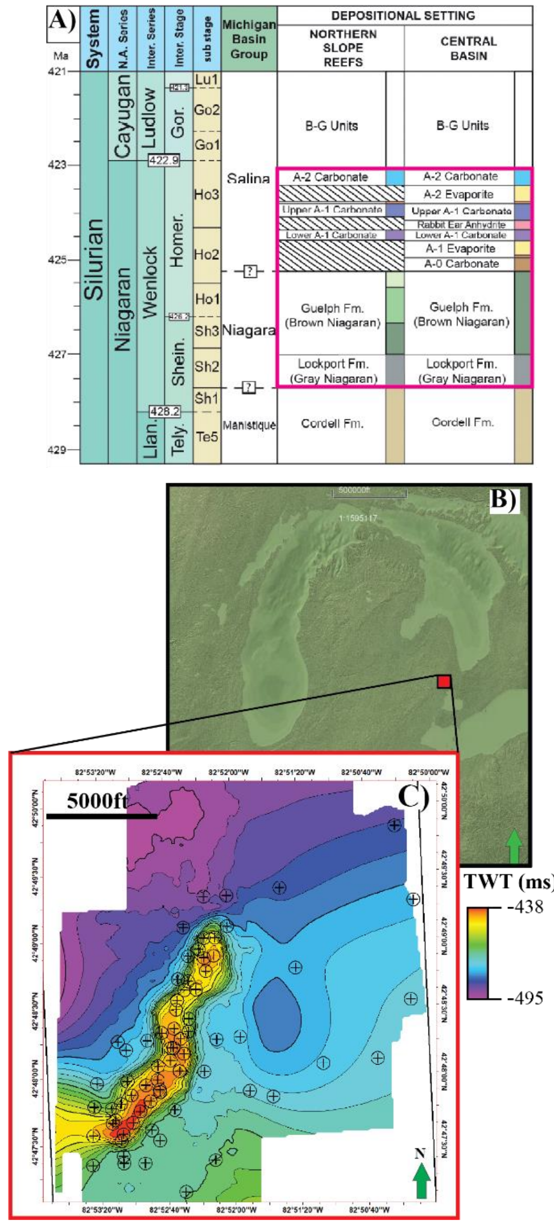

Figure 1: A- Chronostratigraphic chart for the Michigan Basin (After Rine et al., 2017). B- Overview map of the study area. C- TWT structure map of the A1 Carbonate displaying the structure and well locations of the Ray Reef study area.

geostatistical reservoir models to enhance reservoir management.

Field Description

Geologic Setting

The Michigan Basin is an intracratonic basin that exhibits unusual circular symmetry and is bounded by a continuous structurally stable area, and covers an area of 316,000 km^2. The Silurian reefs occur in the upper Niagaran Guelph Formation, also known as the Brown Niagaran, which rims the circular Michigan Basin. The reefs are presently buried at depths of 900 to 2000 m. Individual reefs have average widths of approximately 1000 m and average heights of 100 m. Reef development was concentrated in two parallel lineaments on the northern and southern margins of the basin, basinward of wide spread shelf-edge reef complex.

The lithostratigraphy of the reefs is well established (Figure 1a). Silurian reefs overly the Lockport Formation (informally called the "Gray Niagaran"), which is described as a micritic carbonate mudstone. Reefs are laterally encased unconformably by the thin limestones and evaporites of the Silurian Salina Group. Reefs along the southern reef trend have undergone extensive dolomotization. Haynie (2009) provides a well-based geostatistical model of petrofacies in Ray Reef, and defined favorable petrofacies as those with greater than 5 % porosity and permeability greater than 1mD. Overlying facies within the Upper A1 Carbonate and the upper portion of the reef core were proposed as the highest quality reservoir, and the stromatolitic cap facies (underlying the Upper A1 carbonate) and bioherm facies were identified as poor reservoir facies. This model can be greatly improved by incorporating new stratigraphic models and observations made in 3-D seismic.

Data Description

In this study, a 3-D survey with an area of approximately 10 mi^2 acquired in 2019 was used to analyze the internal structure of a Niagaran reef along the southern reef trend. The survey has a 1 millisecond sample rate and two second record length, and a line spacing of 55 ft for both inlines and crosslines. Three volumes were available: a PSTM full stack volume, a near angle stack of 0-10 degrees, and a far angle stack of 20-30 degrees. Angles in excess of 30 degrees were not available due to the relatively small survey geometries and shallow depth of the reef. Resolution within the reef interval is approximately 50 ft. at the time of acquisition, Ray Reef was at near full storage capacity, as it had 64.5 bcfg out of a total storage capacity of 65.4 bcfg.

A total of 81 wells are present within the study area. Of these, 15 are cored and have whole-core derived gamma ray, permeability, porosity, water and oil saturation logs. 7 wells

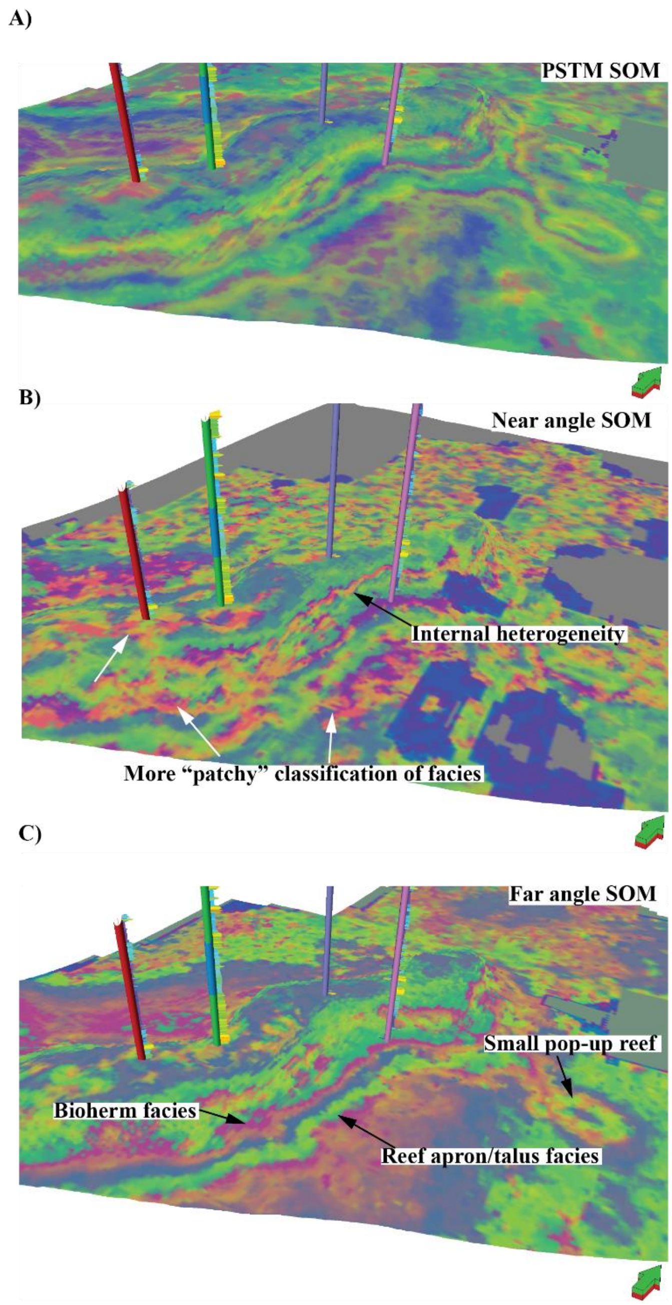

Figure 2 SOM results 5 ms below the A-1 Carbonate surface. Well log shown is porosity. A- PSTM. B- Near stack SOM. C- Far stack SOM. Note the near stack highlights internal heterogeneity within the reef, while the PSTM and Far angle stacks display more laterally continuous classes.

have sonic logs and 6 have density logs. The remaining wells provide GR and neutron logs.

Methods

Well Data
Formation tops and interpreted seismic surfaces were provided by Consumers Energy. Wells containing sonic logs were utilized to calculate time-to-depth relationships. These time-depth relationships were then applied to nearby wells to tie well data to the seismic data. Neutron logs were converted to neutron porosity logs constrained by porosity values derived from whole-core measurements following the method described by Shier (1991) and Haynie (2009).

Attributes
A suite of seismic attributes which have been proven in previous work to highlight facies changes in carbonate reservoirs was generated on each volume. This included: Instantaneous frequency, instantaneous phase, GLCM entropy and GLCM variance. Instantaneous phase is defined as the arc tangent of the ratio of the imaginary and real parts of the seismic trace. It is independent of amplitude and is related to the propagation of the seismic wave front, and can be applied to analyze bed continuity and configurations. Instantaneous frequency is the time derivative of instantaneous phase. Low instantaneous frequency values have been shown to correlate to high porosity zones within Niagaran reefs along the northern reef trend. (Toole, 2012). GLCM attributes are not sensitive to amplitudes but rather measures the texture of the seismic data. In this study, the entropy and variance attributes were utilized. GLCM entropy measures the roughness of the amplitude within a search window and GLCM variance represents the variance within the GLCM matrix. GLCM attributes on their own are difficult to interpret, but are useful in machine learning applications (Gao, 2004; Gao, 2007). Energy ratio similarity (ERS), a coherency attribute was calculated on the PSTM volume to use as a visual aid in timeslice (Figure 3 b,c).

Self-Organizing Maps (SOM)
Self-organizing maps are a type of artificial neural network that utilizes competitive learning to create clusters of similar data points in multi-dimensional space and then project them onto a 2-D map. SOMs attempt to capture the variations of all the input attributes, and thus make them a powerful tool for multi-attribute analysis. Applying SOMs to angle stacks will reveal subtle features not easily identified in the PSTM volume, as each angle range contains different information. Near angles generally contain more high-frequencies in addition to lithological information, while far angles generally provide more information regarding fluid type. By isolating clusters and correlating them to well locations with core descriptions, quick classification of the clusters is possible. It is important to note that for each SOM, each

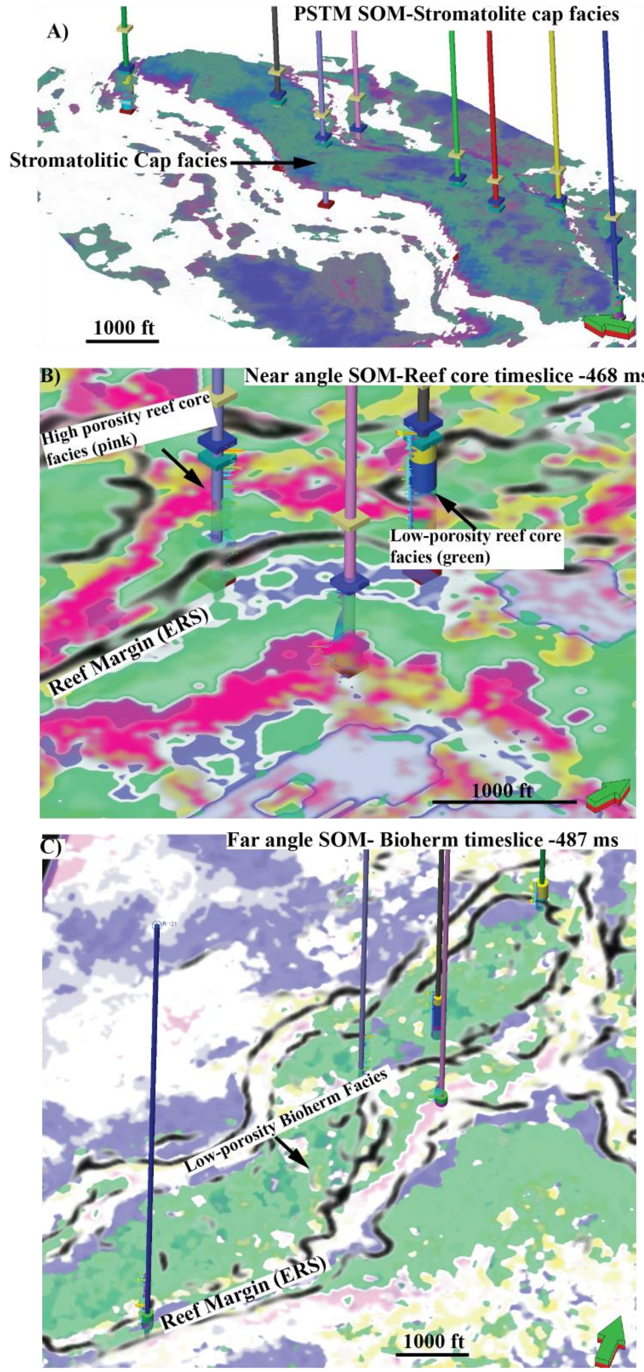

Figure 3: Facies identification using the three SOMs. A- Identification of the continuous stromatolitic facies overlying the reef core. Surface shown is the A-1 Carbonate shifted down 9 ms. B- Near angle SOM reveals internal heterogeneity within the reef core facies. C- Far angle SOM provided the best characterization of the underlying bioherm facies. Note the containment of the bioherm facies within the reef

color will respond to a different classification. So for example, a cluster represented by the color green in the PSTM SOM will not be the same cluster represented by green in the far angle SOM.

Results

Facies Identification

The SOM for the PSTM volume presents a laterally continuous and smooth distribution of classifications (Figure 1a). It excelled at imaging the overlying stromatolitic cap facies, which is characterized by low porosity and permeability (Figure 2a). When compared to the near and far angle stacks, it failed to capture smaller-scale heterogeneity within the reef core itself (Figure 2b). The near angle stack SOM revealed smaller-scale changes within the reef core than the PSTM and far angle stack SOMs (Figure 2b). Heterogeneity is indicated by the more "patchy" distribution of classes indicated in Figure 2b and is likely a better representation of the geology. This is attributed to the limitation of angles to those corresponding to near-vertical reflections, which provide more accurate representation of lithological boundaries. Correlating clusters to well data revealed a discontinuous pink facies which cuts through a continuous green facies within the reef (Figure 3b). At the well location, this corresponds to a high porosity (10 %) within the pink facies and low porosity (3 %) within the green facies. The far angle stack SOM provided a clear image of the underlying bioherm facies in addition to delineating reef talus/slope deposits (Figure 2c, Figure 3c). The far angle SOM also identified a small neighboring reef located to the east of the main reef (Figure 2c). Co-rendering the SOM timeslice with an ERS timeslice illustrates how the cluster interpreted to be the bioherm conforms to the margins of the reef (Figure 3c).

Conclusions

By integrating SOMs on full, near and far angle stacks, facies identification with core and log data throughout the entire Ray Reef complex, accurate facies mapping is now within the entire reef complex. The two angle stacks provide a powerful insight to facies distribution not gained from the PSTM volume. The near angle SOM reveals the spatial extents of internal heterogeneities within the reef-core reservoir facies which are attributed to dolomitization. The far angle stack SOM provides better imaging of the underlying non-reservoir bioherm facies and adjacent slope facies. Facies maps will serve as valuable spatial constraints of facies distributions for future petrophysical modeling of Ray Reef.

Further testing is being done on the reef with structural attribute based SOMs to understand the reef core and identify possible barriers to flow. Additionally, future SOMs will be calculated within a tight window between the A-1 Carbonate and underlying Gray Formation with core-based supervision to further constrain the classifications of the facies. Knowledge gained from the angle stack SOMs will be applied to future cell-based reservoir models to enhance reservoir management. The ultimate goal of this research is to quantitatively characterize reservoir properties (facies, porosity, and permeability) within Ray Reef through geostatistical cell-based models to optimize the reservoir for gas storage. Constructed models will then be tested and calibrated with well production and pressure data to ensure accuracy.

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