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Identification and Quantification of Parasequences Using Expectation Maximization Filter: Defining Well Log Attributes for Reservoir Characterization

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Abstract

Identification and quantification of parasequences remains a key aspect in unconventional reservoir development [1] demonstrated the importance of gamma ray parasequences (GRP) in unconventional play development. Currently, most of the drilling plans in unconventional plays are executed using a ‘factory made’ drilling and completion program. Due to thousands of wells in an unconventional play, it is a very difficult task for operators to incorporate the fine scale reservoir characterization in time for drilling plan.

Currently the upward dirtying and upward cleaning parasequences in shale plays are interpreted qualitatively and manually by a human interpreter on individual well logs. We believe these parasequences hold key information about the underlying geology and their quantification can provide key insights into the depositional environment and hence reservoir quality. Incorporating this information in due time for drilling and completion can aid the decision making process on well placement and hydraulic fracturing design.

In this work, we handle the reservoir characterization challenge on two fronts: we first provide a statistical filtering approach to interpret the parasequences in a well log and then use machine assisted application on other wells in the area of interest. We then use Least-squares fit to obtain slopes of these parasequences. Furthermore, we map these slopes and compare them to the conventional parasequence thickness map to provide quantitative well log attributes to help aid the geologic interpretation.

Introduction

Unconventional play development has key differences to that of a conventional play development. In a conventional porosity, permeability etc. are the key drivers for production. Well spacing and landing the best zone and hydraulic fracturing guide the production performance in horizontal wells. As the well is completed with hydraulic fracturing operation, the geomechanical properties of the layer become of utmost importance ([2]- 6]). [1] proposed that the layered properties of the shale reservoir are highly complex and is composed of alternating brittle and ductile geological sequences also known as brittle-ductile couplets [7]. The optimal landing zone depends on a tradeoff between the brittleness and rock properties such as total organic carbon(TOC). The good rock from the reservoir perspective which is high in TOC is generally more ductile and not a suitable candidate for hydraulic fracturing operation and vice versa.

[1] also correlated the gamma ray parasequences (GRP's) with depositional environment and the mineralogy and hence we believe the parasequences contain important information about both the reservoir properties as well as geomechanical properties. Currently, these parasequences are picked manually and then have to be interpreted separately ([8]- [11]). With growing number of wells in unconventional plays and more and more legacy well data is digitized every day, it is not possible to analyze them in time for key decision making processes.

In this work we present a methodology to:

- a) Easily pick the parasequences to make fine scale stratigraphic static models
- b) Quantify the information in the parasequences to generate maps that can be a visual aid for interpreting the reservoir and geomechanical properties

We show our methodology applied to 90 wells in Barnett Shale.

Theory and Methods

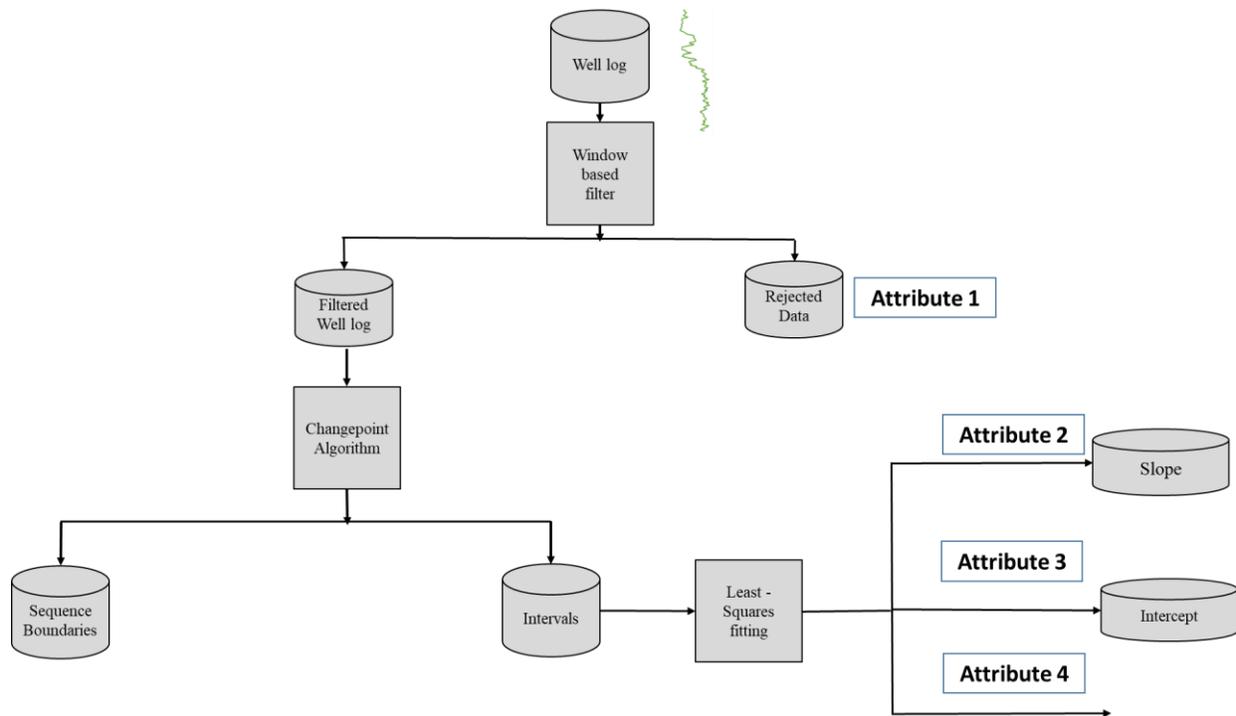


Figure 1. Workflow followed in our study. We feed the well log into a preprocessing window based filter. The filtered log is then used for changepoint analysis. The sequences are defined by the changepoints. We then obtain a least-squares fit in the intervals and define the primary well log attributes.

Fig. 1 shows our workflow for this study. The workflow consists of a pre-processing step to remove the noise from the well logs. The processed well logs are then fed into a changepoint algorithm. We then use the intervals determined by changepoint analysis for deriving our well log attributes using a least-squares fit.

Step 1: Pre-Processing of the data

We first use the well log trace for a pre-processing. This step is required to remove noise from the data. For this purpose, we use a sliding window based filter ([7], [12], [13]- [15]). The traditional despiking methods do not work in our case as the well logs we used have both the spikes as well as maximum

flooding surfaces (MFS's). MFS appears as a spike on the well log trace and geologists use these surfaces to guide their interpretation.

However, for a high frequency signal like well logs, these surfaces have a finite thickness and hence cannot be removed by traditional de spiking algorithms which are very effective in removing random spikes otherwise. These spikes pose a challenge in the following steps where we use a least square fitting in the intervals.

Step 2: Identification of parasequences

For identification of parasequences, we use offline changepoint analysis ([13], [16]) provided a detailed account of this method. Changepoint analysis is broadly classified into online and offline analysis. Offline analysis is performed once the data is already acquired and online changepoint analysis is useful for real time data acquisition such as measurement while drilling (MWD) data. The algorithm looks for distributional changes in the data and when a change is being found, it sets a boundary also called changepoint at that interval. Traditionally, changepoint analysis is used for a time series data so we use the similar notations as defined by [16].

A discrete time signal is defined as:

$$\text{the discrete signal, where } (0 \leq t \leq T) \quad (1)$$

A small sub signal for analysis between the limits a to b, can then be defined as:

$$\text{is a sub signal where } (0 \leq a \leq t \leq b \leq T), \text{ and} \quad (2)$$

$V(\tau)$ is some operation applied to a subset of the data, where a specific sub signal has the indices

$$\tau = \{t_1, t_2, \dots\} \subset \{1, \dots, T\} \quad (3)$$

Now, changepoint detection becomes a model selection problem in which the best segmentation minimizes the selection criterion $V(\tau, y)$. A linear penalty function, $p(\tau)$ is then used to regularize the solution.

The generalized version of the problem with an unknown number of changepoints is then formulated as:

$$\min_{\tau} V(\tau) + p(\tau) \quad (4)$$

The three main components of changepoint analysis are: cost function, search method and constraints [17]. Cost function is generally selected on the heterogeneity of the signal. A more continuous signal with minimal abrupt changes is considered homogeneous. In our case, it is the upward dirtying and upward cleaning sequences in a gamma ray log. In this study we use a parametric cost function based on maximum likelihood method. Two variants of the method are generally used: change in median and change in mean.

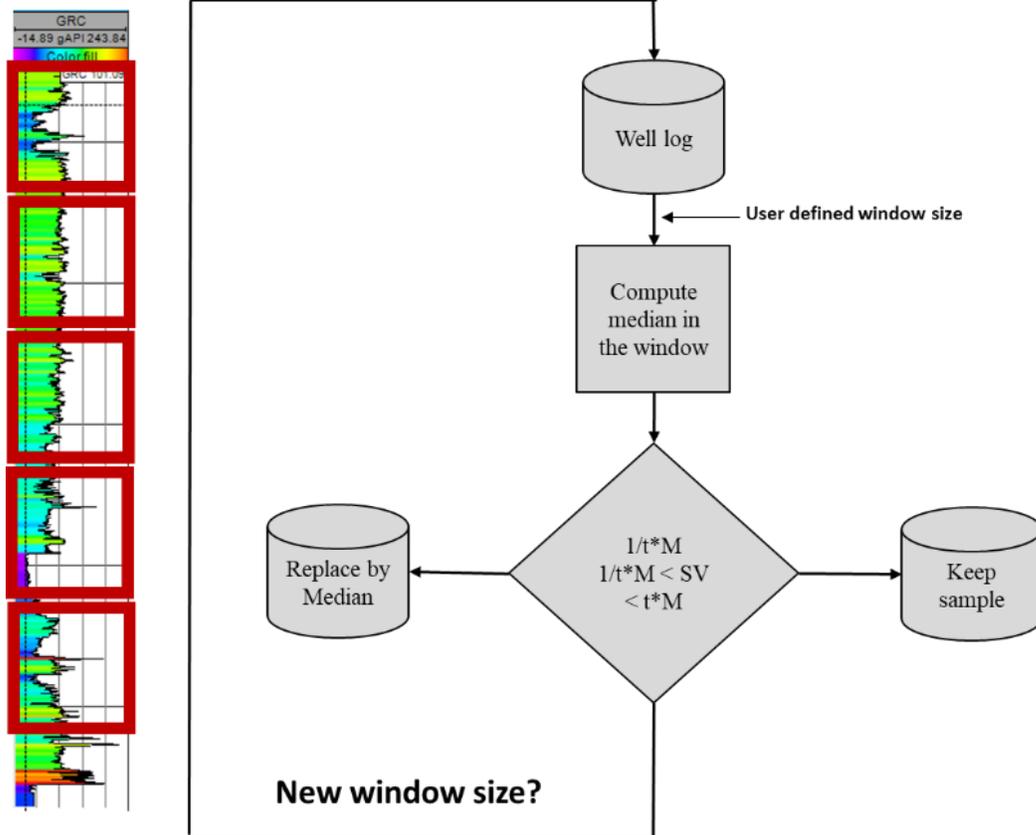


Figure 2. Our proposed window based filter. We define a fixed size window and then slide it across the full well trace. We compute the median inside each window and decide a threshold (t) above the median to classify the samples as noise. The filter is symmetric as we use a $1/t$ threshold as lower limit. The samples classified as noise are then replaced by median in that window for changepoint analysis. The replaced samples are stored separately to further analysis as they may contain important information about MFS.

The change in mean can be modeled as:

$$c_{\text{median}}(y_t) = \sum_{t \in I} \|y_t - \text{median}(y)\| \quad (5)$$

and change in median can be modeled as:

$$c_{\text{mean}}(y_t) = \sum_{t \in I} [y_t - \text{mean}(y)]^2 \quad (6)$$

In our study both methods yield similar results.

For search method we use Pruned Exact Linear Time (PELT) algorithm because it provides an exact solution as well as is computationally efficient ([17]). For constraint, we use a linear penalty.

Step 3: Definition of well log attributes

To derive the quantitative well log attributes we first use the identified changepoints as our sequence boundaries. Once the boundaries are identified, we compute a least-squares fit between the changepoints.

The slope (s_k) and intercept (ζ_k) for the signal gamma ray (g) and depth (z) can be computed as:

$$s_k = \frac{(N_{2k} - N_{1k} + 1) \sum_{n=N_{1k}}^{N_{2k}} g_n z_n - \sum_{n=N_{1k}}^{N_{2k}} z_n \sum_{n=N_{1k}}^{N_{2k}} g_n}{(N_{2k} - N_{1k} + 1) \sum_{n=N_{1k}}^{N_{2k}} z_n^2 - \left(\sum_{n=N_{1k}}^{N_{2k}} z_n \right)^2} \quad (7)$$

$$\zeta_k = \frac{\sum_{n=N_{1k}}^{N_{2k}} g_n - s_k \sum_{n=N_{1k}}^{N_{2k}} z_n}{(N_{2k} - N_{1k} + 1)} \quad (8)$$

where in the fitting interval k is defined as,

$$g_n \approx s_k z_n + \zeta_k \quad (9)$$

Our first well log attribute comes from the window based filter. As the filter is removing both the spikes and finite difference MFS, the residual contains the information on MFS. The second attribute is the slope of the least square fit in the interval (S_k), the third attribute is intercept (ζ_k), and fourth attribute is the filtered well log itself (g_n). Figure 4 A) show the changepoint analysis done on an individual well. Figure 4 B show the true ability of the algorithm. Notice that the algorithm can identify the individual parasequences efficiently even with a noisy signal. Figure 6 shows some of these attributes. The slope is discreet in nature i.e. one slope for each fit for each parasequence interval.

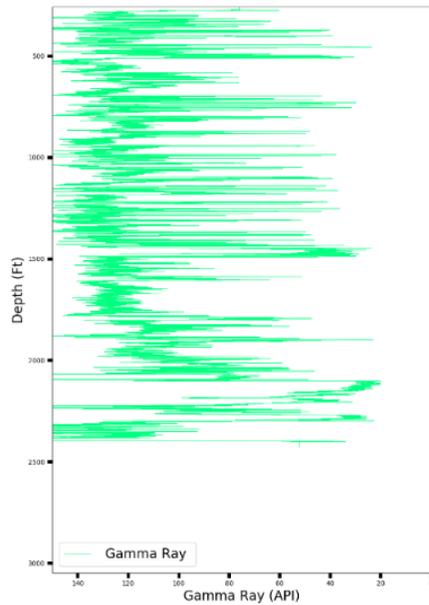
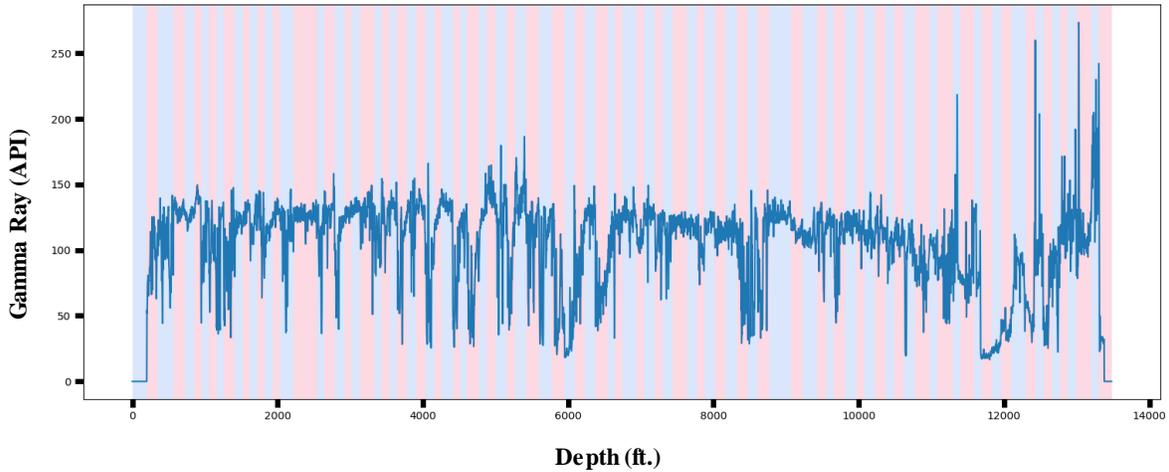


Figure 3. A representative gamma ray curve through the Barnett Shale utilized in this study.

Results

Figure 1 shows the representative gamma ray log used to train the penalty function, size of the window and minimum number of samples in this study. Figure 4 shows the changepoints obtained in the study. Each interval Figure 4 is separated by pink and blue color. We use these intervals for least square fitting. Figure 5 shows the fits on these intervals and the filtered well log.

4 a)



4 b)

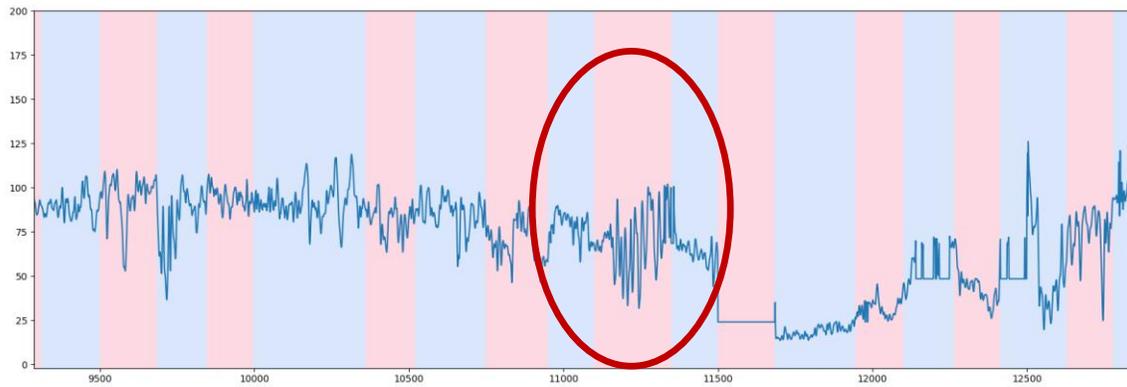


Figure 4. A) Sequence boundaries (separating pink and blue zones) and identification the parasequences as changepoints on full log trace. B) Zoomed in section to focus on the detailed identification of parasequences. Notice the sequence highlighted in maroon circle. The zone is noisy but clearly a different sequence than neighboring sequences that algorithm can accurately distinguish.

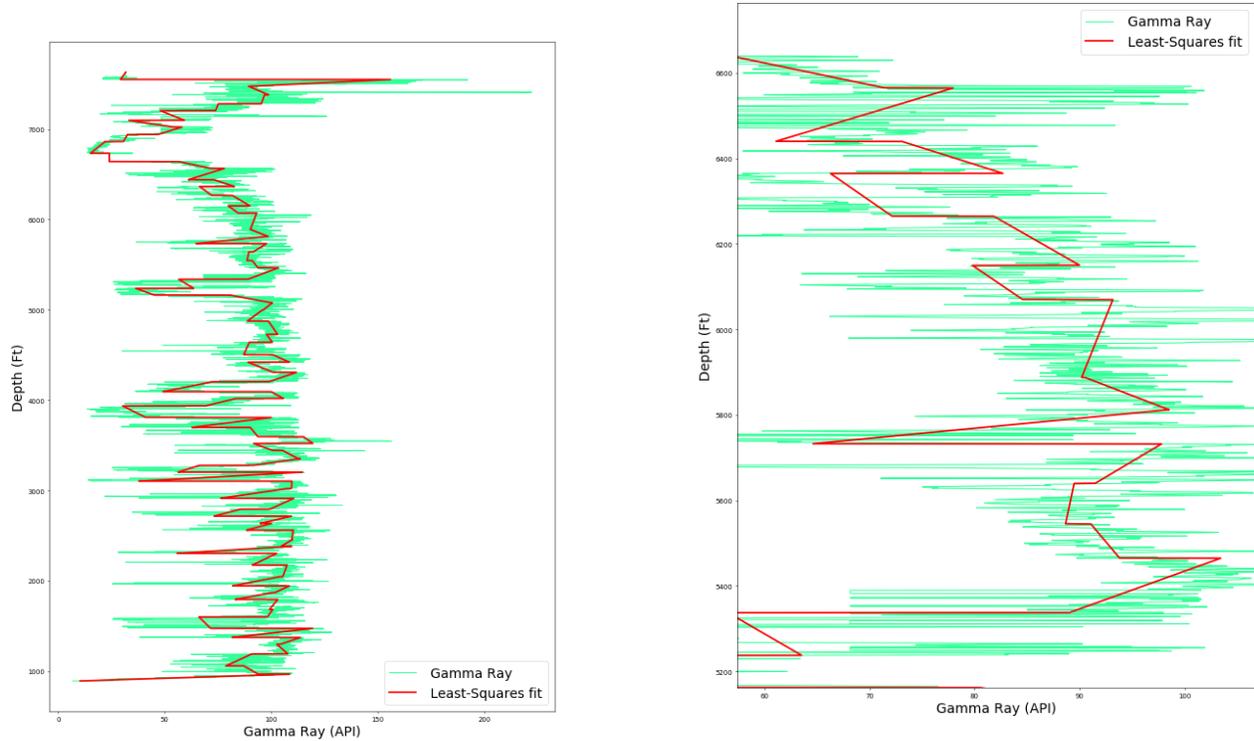


Figure 5. On the left is the least-squares fit on the intervals defined by the changepoint algorithm. On the right side is the zoomed section of the well log showing the fits. This interpretation is currently done manually by a human interpreter.

The fits obtained by least-squares shown in Figure 5 is currently interpreted manually by a human interpreter. We selected a representative well in the area for tuning the algorithm via selecting optimal window size for preprocessing, penalty function to highlight the sequences of interest. This process is far less complicated than the neural net based approach ([18]- [21]).

Figure 7 shows the same intervals on a typical desktop computer with a commercial software using the standard well log trace visualization. We pick three horizons as: Horizon 1, Horizon2 and horizon 3. The sequence of interest lies between horizon one and two. Horizon 3 is the top of Forsberg limestone and is used as a datum.

Notice the sequences are now better identified in the filtered well logs clearly demarcating the trend boundaries. The quantitative measure of the sequences i.e. slope of these parasequences is also shown on track 3 with a dual polarity color scheme. The sequence type; aggregational, progradational or retrogradational can also be now inferred easily with the sign of the slope. A positive slope indicates cleaning upwards and a negative slope indicates dirtying upwards sequence. Near zero slope indicates an aggregational trend similar to one defined by [22].

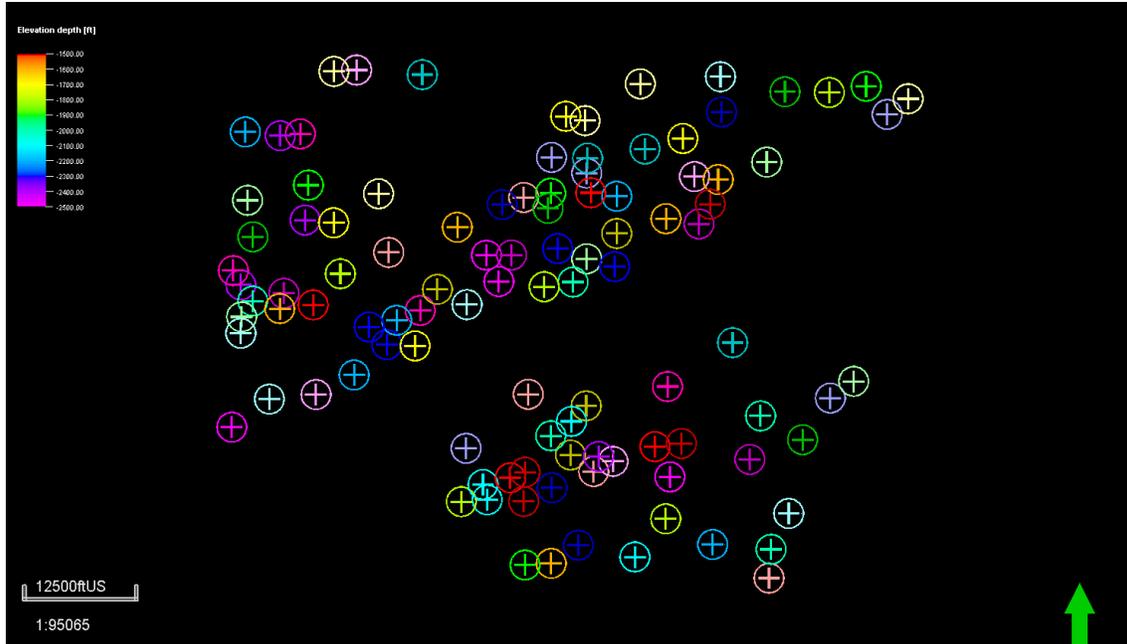


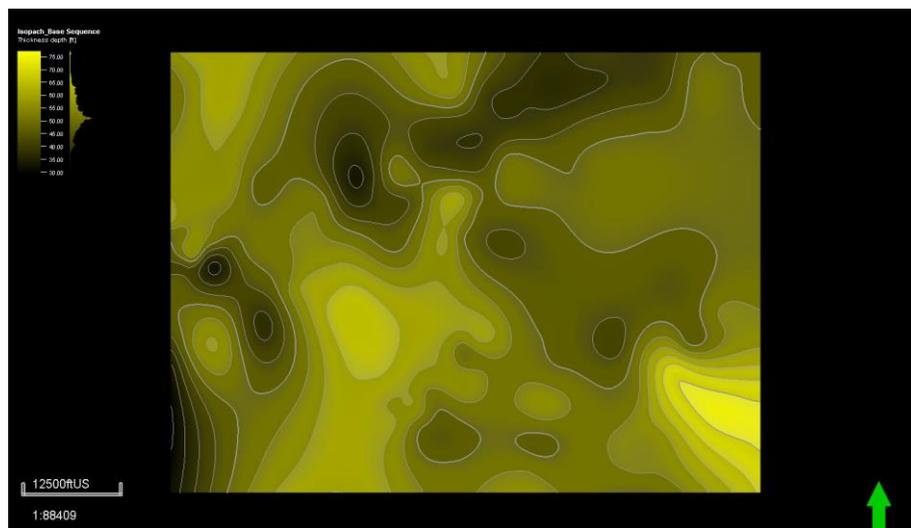
Figure 6. Location of the wells used in the study. The wells are clustered into two different clusters due to a possible fault present in the region.

Figure 8 a shows the conventional parasequence map generated using this workflow. The warmer color shows the thicker intervals. This map can then be utilized in interpretation of the depositional environment and inference of proximal and distal setting, depositional rate, accommodation space and changes in sea level.

Figure 8 b shows the slope of these intervals mapped in the area of interest. As slopes of aggregational sequences are near zero, the aggregational sequences are subdued and retrogradational / progradational sequences are highlighted yielding a sharper image. This image can now be used for conventional interpretation not just qualitatively but also quantitatively. Our current research involves using these attributes along with 3D seismic to map these parasequences across the field and as an aid to conventional modeling.

Figure 7 shows a discrete log indicating qualitative estimate of brittle- ductile couplets. Generally cleaning upward sequences are identified as brittle zones due to high detrital mineral content and higher shale volumes are identified as ductile zones. Setting up simplistic cutoffs on slope values can give us an estimate of brittle ductile couplets in the zone of interest. Our workflow can be easily extended to other logs such as mineralogy or core derived properties on a one dimensional well log trace. We use gamma ray log in this study as gamma ray logs are almost always available on any well log suite. This analysis can now be directly integrated with engineering datasets to optimize the horizontal well landing zones for hydraulic fracturing and identification of sweet spots and also for reservoir simulation at different scales ([23]- [33]).

8 A)



8 B)

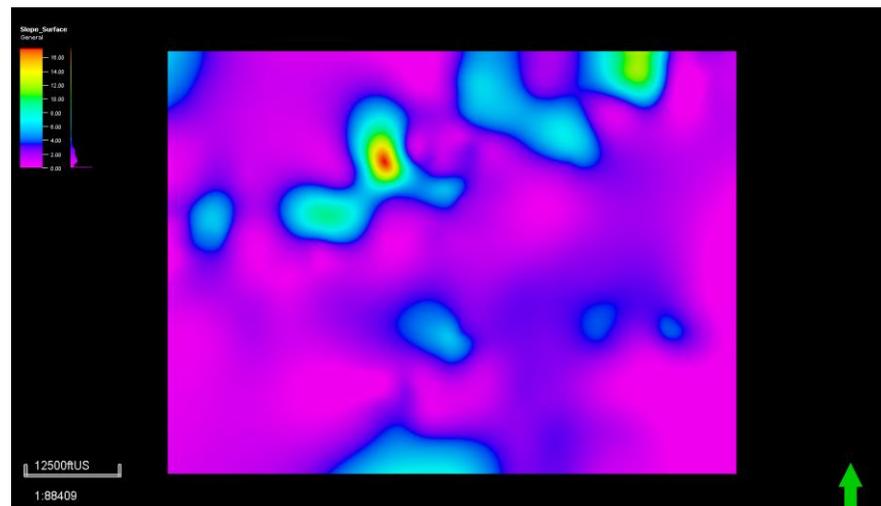


Figure 8. A) Conventional parasequence thickness map B) Slope of the parasequences mapped in the same area. Notice some of the areas are better highlighted than the parasequence map alone. Sequences with higher slopes are more likely to be progradational or retrogradational than aggregational. Also notice that the thinner sequences have higher slope (rapidly changing sea level and/or limited accommodation space).

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