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Interpolating High-Resolution Well Log Volume Using Seismic Dip Vectors and Control Grids

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Summary

Seismic-guided volumetric well log interpolation is a unified solution for inversion, interpolation, and integration problems. For inversion, it uses both the direct measurement from the borehole and the indirect measurement from seismic data to derive the parameters of geological formations; for interpolation, it employs the sparsely distributed well logs to interpolate a full 3D volume of well logs; for integration, it uses a combination of the information from boreholes, structural models (horizons, grids, faults, etc.), and/or seismic surveys.

There are multiple documented approaches to generate a volume of pseudo well logs including geo-statistical, image-guided, and neural-network-based. In this paper, we present a unique way of interpolating high-resolution well log volumes which combines the model-driven and data-driven approaches. The model-driven approach is interactive and allows input from human interpreters. The data-driven approach enables interpolation following the local geological structural patterns from the seismic dip vectors. In the experiments, we demonstrated that the approach can be successfully applied to both synthetic and real-world datasets with models of control grids, and/or seismic dips.

1. Introduction

Volumetric well log interpolation is a unified solution for inversion, interpolation, and integration problems. For inversion, it uses both the direct measurement from the borehole and the indirect measurement from seismic data to derive the parameters of geological formations; for interpolation, it employs the sparsely distributed well logs to interpolate a full 3D volume of well logs; for integration, it uses a combination of the information from boreholes, structural models (horizons, grids, faults, etc.), and seismic surveys.

There are multiple documented approaches to generating a volume of pseudo well logs such as seismic image-guided (Hale 2009, 2010; Karimi and Fomel, 2015) and neural-network-based (Yenugu et. al., 2010; Aguilar and Verma 2014). The image-guided approach is a purely data-driven approach, which utilizes the tensor field from a seismic dataset, but it lacks the interactive guidance of a human interpreter. The neural-network-based approach predicts the well log according to the correlation between a seismic wavelet and logs in the training dataset. Log curves are usually averaged within a depth zone, which results in the loss of vertical resolution. The neural-network-based approach also lacks the interpreter's control.

To preserve the benefits of the data-driven approach, we combine both control grids and seismic data in our interpolation algorithm while still allowing human input from high-level. We first extract the dip vectors from the seismic volume with an array of log-Gabor filters, and combine them with the human operator's high-level

interpretation, such as grids and formation tops, to generate a high-resolution seismic attribute-like volume, R-cube. The volumetric well log interpolation step is then guided by the calculated R-cube.

The next section introduces the method for the volumetric well log interpolation, and section 3 demonstrates the application of the proposed algorithm with both a synthetic and a real-world dataset.

2. Method

Our method to interpolate seismic-guided well log volume includes the following steps as shown in Figure 1.

1. Calculate the volumetric dips from seismic data using an array of log-Gabor filters.
2. Assign arbitrary and unique integer values (R-values) to the control grids (geology model). The R-values are the indices of the stratigraphic layers, which is correlated to the stratigraphic depth when linearly aligned.
3. Within each zone, use the volumetric dip and control grids to interpolate a volume of R-values, i.e., R-cube.
4. Apply well log interpolation using log points with the same R-values in their corresponding zone, and interpolate based on the distance to the borehole.
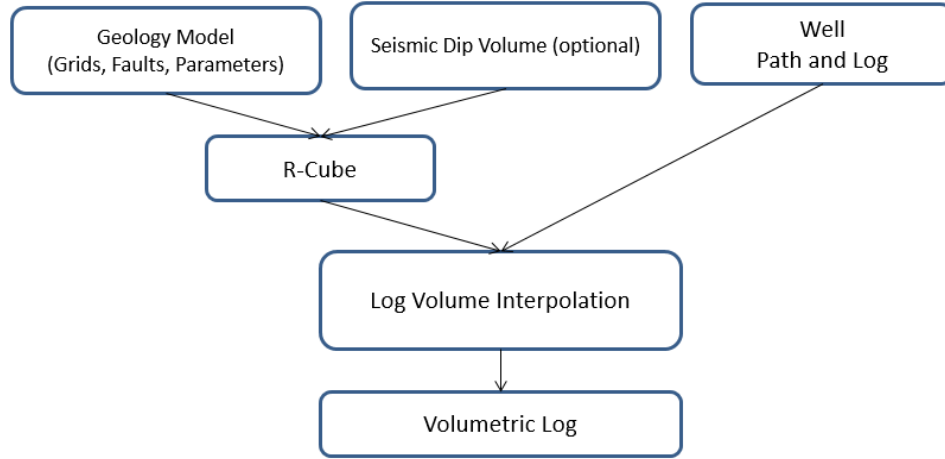

Figure 1: The workflow of volumetric log interpolation

Section 2.1 summarizes the method to generate the seismic dip volume, and section 2.2 introduces the generation of R-cube from control grids and dip volume. The interpolation step is introduced in section 2.3.

2.1 Seismic Dip Volume

First we convert the post-stack seismic volume is from the time domain into the depth domain. We then calculate the dip vectors. Yu et. al (2013) introduced a method to generate the apparent dips of 3D seismic data with an array of log-Gabor filters. The algorithm to generate the apparent dip vectors from seismic images are summarized as follows.

The 2D log-Gabor filter is defined in frequency domain (Field, 1987):

$$H(f,\alpha) = H_f \times H_\alpha,$$

where H_f is a radial component, and $H\alpha$ is an angular component. The radial component is 2D Gaussian in logarithmic scale, and the angular component is Gaussian along orientations. More specifically,

$$H(f,\alpha) = exp\left(-\frac{ln^2(f/f_0)}{2ln^2(\sigma_f/f_0)}\right) \times exp\left(-\frac{(\alpha-\theta)^2}{2\sigma_\alpha^2}\right),$$

where f_0 is central frequency, and θ is the filter direction.

The 2D seismic image in the spatial domain $I(x,y)$ is converted into frequency domain $\hat{I}(u,v)$ by 2D Fourier transform, and then followed with the application of log-Gabor filter,

$$\hat{Y}^{<w,\theta>}(u,v) = H^{<w,\theta>}(u,v)\hat{I}(u,v),$$

where H is the log-Gabor filter with orientation θ and central frequency w. Since it is an array of log-Gabor filters, their central orientations θ can be in a series of orientations, such as $\{-\frac{\pi}{2}, -\frac{5\pi}{8}, -\frac{\pi}{4}, ..., +\frac{\pi}{4}, \frac{5\pi}{8}\}$, and w can be in single or multiple scales.

By inverse Fourier transform, we convert $\hat{Y}^{<w,\theta>}(u,v)$ into a complex image in the spatial domain. The resulting convolved image has a real part, $Y_r^{<w,\theta>}(u,v)$, and an imaginary part, $Y_{im}^{<w,\theta>}(u,v)$. The norm of the complex image is called orientation energy, $Y^{<w,\theta>}(u,v)$, in the specific orientation q and scale w. The apparent dip γ at pixel (x,y) is derived as:

$$\gamma(x,y) = \arg\max_{\theta} \sum_{w} Y^{<w,\theta>}(x,y).$$

Figure 2 shows an example of the OVF generated for a 2D seismic slice near a salt dome.
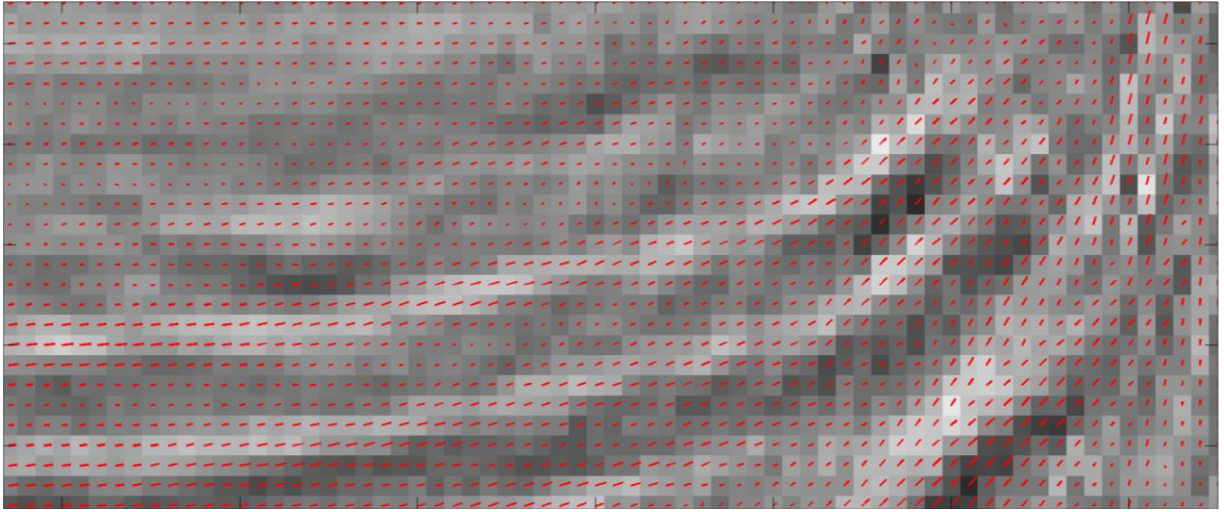

Figure 2: Dip Vectors from Seismic Amplitude Data. (Data Courtesy of Fairfield Nodal)

The generated dip vectors and control grids (if there are any) are then used together to generate the R-values.

2.2 Control Grids and R-Cube

We first define a 3D volume as a placeholder for the target well log volume, with an arbitrary resolution, say m by n by p. We then interpolate the log values on each voxel. As an analogy to a seismic volume, the targeting log volume will have m samples in each trace, n lines, and p traces in each line. The log volume can have a much higher vertical resolution than the seismic volume, such as half a foot. To derive the log values, a synergy of seismic dip information and high-level geological model is defined as the R-cube, which is a seismic attribute-like volume, and is used to guide the well volume interpolation. The R-cube has the same dimension and size as the target well log volume.

To generate the *R*-cube, we need a geology model defined by a few control grids. For *k* control grids, {G_1, G_2, … G_k}, they divides the volume into k-1 zones, {Z_1, Z_2, … Z_{k-1}}. We then assign each control grid with a unique *R* value, {R_1, R_2, … R_k}. In the *R*-cube, each sample's *R*-value on a single trace within each zone is unique. The R-value within a zone can be either linear-distributed (model-driven), seismic-dip-guided (data-driven), or hybrid. The following introduces these three approaches.

  a.   *Linear R-Value within Zone – Model-Driven Approach*

If we assume the R-values are linearly distributed in each zone in each trace, the *R*-value at location (*x, y, z*), i.e., *R(x,y,z)*, can be computed by the linear interpolation using its top (G_i) and bottom (G_{i+1}) control grids' depth locations (d_i and d_{i+1}) at bin location (*x, y*), and their R values (R_i and R_{i+1}). We have the linear relationship between the *R*-values and the vertical depth *z* in a trace with control grids as:

$$\frac{R(x,y,z) - R_i}{R_{i+1} - R_i} = \frac{z - d_i}{d_{i+1} - d_i}$$

Then the R(x,y,z) can be calculated throughout every sample in every trace in the volume. In the experiment section, the first experiment demonstrates using the model-driven approach to derive *R*-values.

  b.   *Dip-guided R-Value within Zone – Data-Driven Approach*

In case we want to use the seismic dip vector to guide the *R*-values interpolation instead of linear, we first compute a trace at the corner of the volume with the linear method as shown above, and then derive its neighboring traces *R*-values with the following steps.

Given a trace, each sample has an *R*-value R_k, and depth at z_k. We can then derive R-values of its neighboring traces:

$$R_{k+1} = \text{Interp1D}(Z_k\text{-}d^*\tan(\gamma_k), R_k, Z_{k+1}),$$

where Z_k, R_k, and γ_k are vectors of depth, *R*-values, and dips for samples on trace *k*. R_{k+1} and Z_{k+1} are the R-values and depth vector on trace with index of k+1. Interp1D is a 1-D linear interpolator, in the form of:

$$y'=\text{Interp1D}(x,y,x'),$$

where x and y are training dataset, which are vectors used to approximate a linear function f: y=f(x). When a new set of x-values are applied, x', with the same approximate function, the y' is then calculated with y'=f(x').

Figure 3 shows an illustration of how the *R*-value on trace *k* projects to its neighboring trace *k*+1 (in either in-line or cross-line axis) along the apparent dip γ. For sample P on trace k, its *R*-value is r_i, while the depth is z_i. Following P's dip vector γ, the projected point Q on trace *k*+1 has the same *R*-value r_i, but a different depth at z_i-*d**tan(γ_i), where *d* is the distance between two traces *k* and *k*+1.

  c.   *Hybrid Approach*

The dip-guided *R*-value can be constrained with any control grids as in the model-driven approach. In such a case, the control grids' *R*-value will be used in the training dataset of the Interp1D function. Given an initial trace, we can compute the *R*-value for each sample on its trace with the model-driven approach as introduced above in section 2.2a. For the neighboring trace, the *R*-value for each sample can be derived by the following:

  1.   Let vector X = {Z_i}, where Z_i is the depth of *i*-th control grid's depth value.
  2.   Let vector Y = {R_i}, where R_i is the R-value of the *i*-th control grid.

3. Append element $\{Z_j\text{-}d^*\tan(\gamma_j)\}$ in vector X, where j is the sample index along the trace, and all other variables are defined as the data-driven approach as shown in section 2.2b.
4. Append element $\{R_j\}$ in vector Y.
5. Sort vector X and Y
6. The *R*-value on the trace can be then derived as Interp1D(X, Y, X'), where X'=$\{Zj\}$, the vector of sample depth on the neighboring trace.

This procedure can be recursively applied to obtain the *R*-values for every trace in a volume. In the third section, the second experiment demonstrates the well log volumetric interpolation with this hybrid approach.
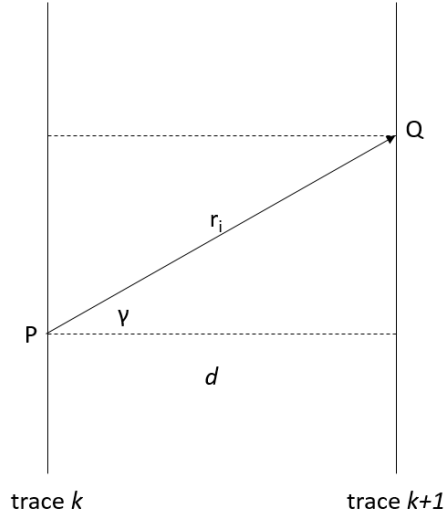

Figure 3: An illustration of r value interpolation over neighboring trace from seismic dip vector. From trace *k* to its neighboring trace *k*+1, the bin spacing is d, and point P and point Q have the same *R*-value r_i, and Q is the projection of P along P's apparent dip vector γ. If p's depth is at z_i, the q's depth is at $z_i\text{-}d^*\tan(\gamma)$.

2.3 Volumetric Log Interpolation

Once we have the *R*-cube calculated (section 2.2), we can use the *R*-value to guide the interpolation of the well log volume with the inverse distance method. The idea of using the *R*-value is to apply log interpolation, using log sample points with the same *R*-values in their corresponding zone, and interpolate based on the distance to the borehole. The algorithm is summarized as follows:

- Treat all log samples in wells as a point set of position and log value.
- To interpolate well log at a target location (x_s, y_s, z_s) in the log volume, first identify the r_s value at that location from the pre-calculated *R*-value slice/volume.
  - For each well *i*, identify the log sample :
    - With the same r_s if one exists
    - Record its location on the well path: (x_w, y_w, z_w), calculate the distance to the target location (x_s, y_s, z_s), and save it as d_i
    - Record its log value: v_i

The interpolated value *v* at target location (x_s, y_s, z_s) is defined as:

$$v(x_s, y_s, z_s) = \frac{\sum_{i=0}^{n}\left[f\left(\frac{1}{d_i}\right)*v_i\right]}{\sum_{i=0}^{n} f\left(\frac{1}{d_i}\right)} \cdot$$

The benefits of volumetric well log interpolation using *R*-cube are the following:

- **Independent to the geo-models**. The *R*-cube is as an intermediate dataset between the geological model and the interpolation. The step to build the R volume is based on the geological model, but it is a separate step that precedes the interpolation.
- **Improved accuracy**. Using an accurate layer as indicated by *R*-value, the *R*-value volume can be in high-resolution, which results in a high-resolution log volume.
- **Simple and fast** with the inverse distance calculation.
- **Handles horizontal wells and multiple wells**. The well samples used in the interpolation are treated as a point set in 3D space, so it can handle wells regardless their path pattern.

3. Experiments and Results

In this section, we apply the algorithm to interpolate a well log with the model-guided approach (section 2.2a) in the first experiment. In the second experiment, we build *R*-values with a hybrid approach as introduced in section 2.2c.

Experiment 1. Teapot Dome – Model-Driven Approach

In this experiment, we apply the well log interpolation to a 3D dataset, *Teapot Dome*, using control grids from formation tops (Sussex, Shannon, F2WallCreek), and 363 selected wells which are used to generate a high-resolution 3D gamma ray volume, achieving a high sample rate of 0.5 ft/sample. *R*-values are calculated with the model-driven approach using control grids and formation tops as input. The seismic dips are not used to generate *R*-values since the dips are near parallel to the control grids within the interpolation zone, and the model-driven approach is sufficient to create a high-quality well log volume.

Figure 4 is a 3D view of the Teapot Dome datasets including three control grids and wells. Three grids are generated from the formation tops of Sussex, Shannon, and F2WallCreek. Figure 5 shows the 3D volume of *R*-cube calculated from the control grids, while the interpolated GR volume is demonstrated in figure 6, and a vertical slice is presented in figure 7. Note that in figure 7, each interpolated trace has 8000 samples, and the interpolated GR achieves a high resolution at 0.5 ft/sample.

To validate our interpolated log volume, we extract the logs from the interpolated 3D GR volume along the paths of validation wells not used in the training dataset, and then compare these to the original GR logs in these validation wells. As shown in figure 8, the predicted GR values correlate highly with the original ones.

Experiment 2. Salt Dome – Hybrid Approach

In the second experiment, we utilize a hybrid approach to interpolate the well logs, which uses a combination of control grids (model-driven), and seismic dips (data-driven). Figure 9 shows a vertical slice from a seismic survey which contains a salt dome. Three control grids (green, blue, and yellow) are used in the *R*-value calculation together with the dip vectors from this vertical slice. The seismic dip vectors used in the interpolation are partially demonstrated in figure 2. Figure 10 shows the corresponding *R*-value in figure 9, except in the area of the salt dome. Note that the interpolated *R*-value is constrained by the three control grids. The control grids force the *R*-value to be the same regardless the seismic patterns.

The well logs in the three virtual wells (blue, green, and light blue) are randomly generated. The interpolated well log image is shown in figure 11. The blue curves (thin-line) are the contour of the *R*-values in figure 10, while the thick blue lines are the boundary of interpolation around the salt dome.
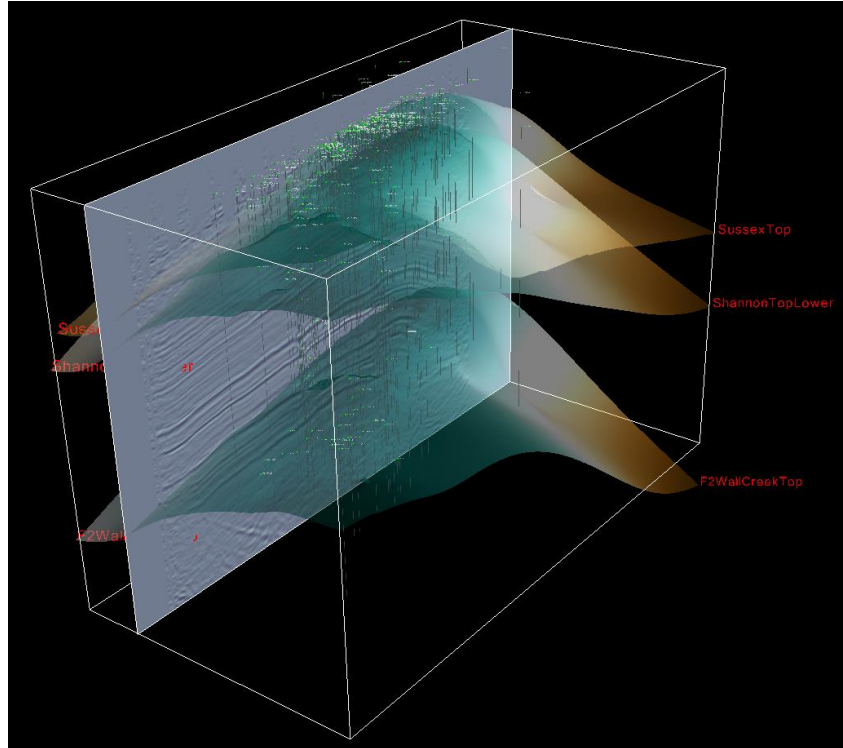
Figure 4: Teapot Dome and Well log Settings. (Data courtesy of US Department of Energy)
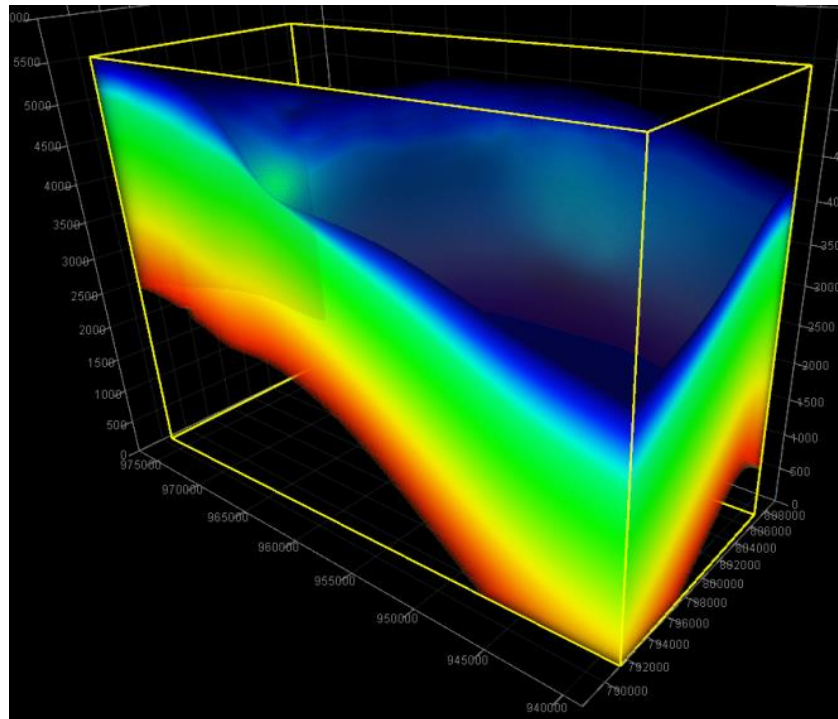

Figure 5: The R-Cube of the Teapot Dome dataset. An R-cube is created using the control grids defined from formation tops (Sussex, Shannon, F2WallCreek).
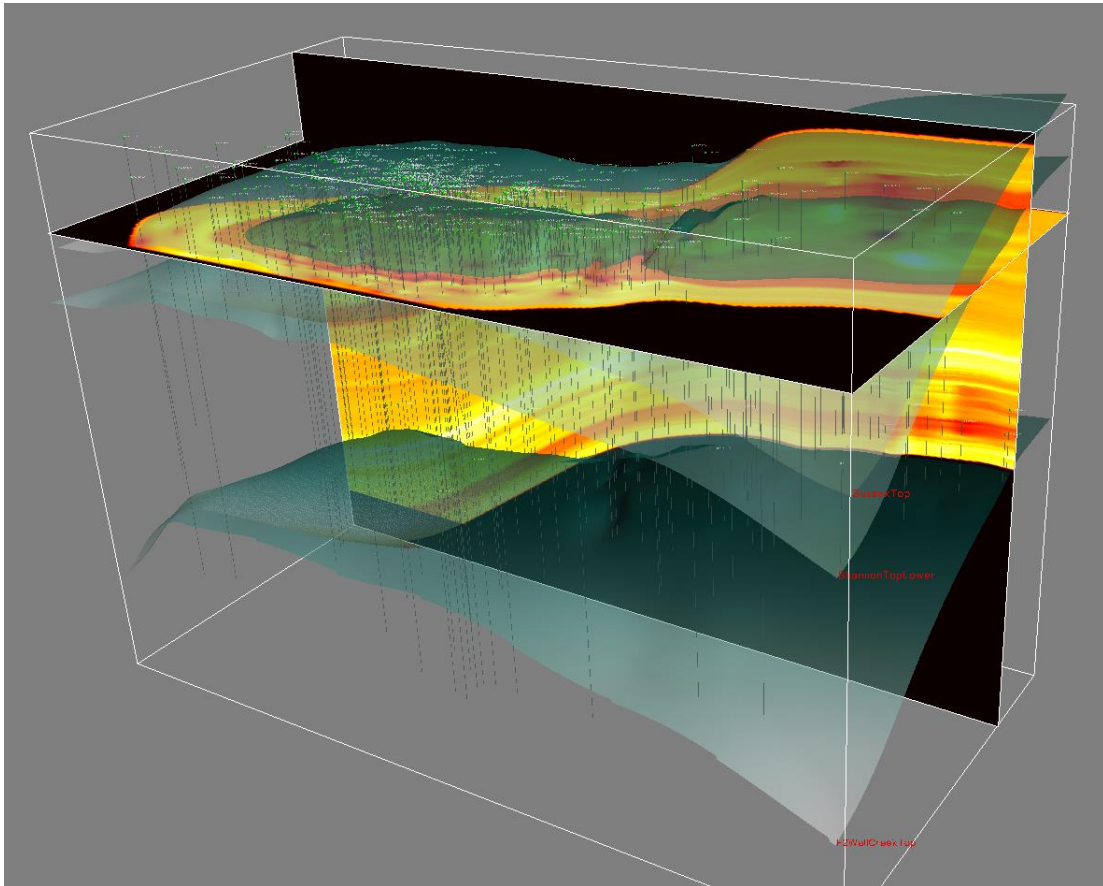
Figure 6: The interpolated high resolution volumetric GR. Each trace has 8000 samples, with 0.5 ft/sample as sample rate.
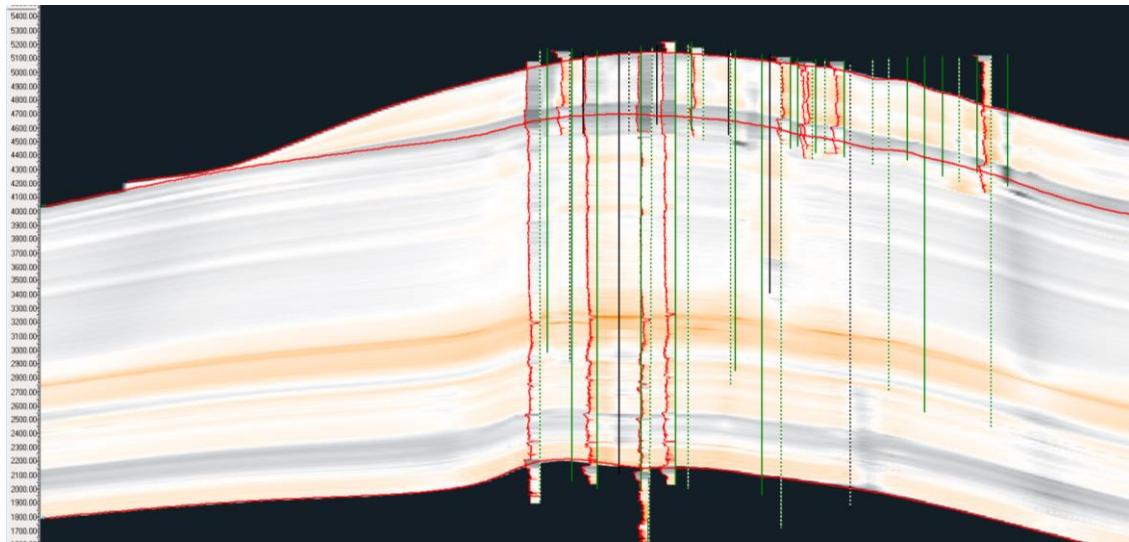

Figure 7: A vertical display the GR Volume. One cross section (line 206) is adapted from the generated GR volume in figure 9, overlaying with a few wells on this slice. The GR logs in these wells are displayed and color filled.
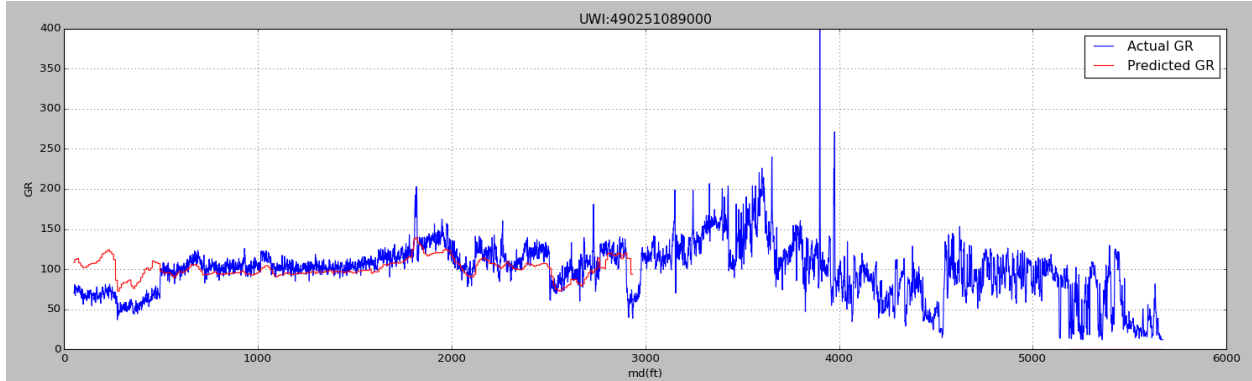
Figure 8: GR Prediction. The GR in this well is not used in the interpolation. The predicted gamma ray (GR) log (red) from the synthetic log volume is well aligned with the original GR log (blue).
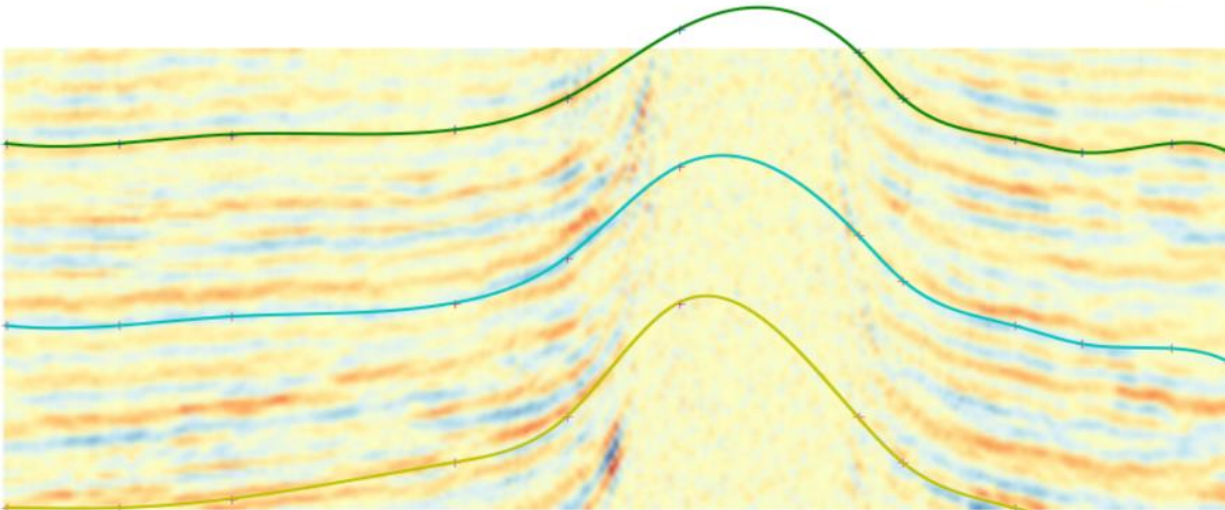

Figure 9: Three control grids overlaid on the seismic survey of a salt dome. (Data courtesy of Fairfield Nodal.)

4. Conclusions

In this paper, we presented a method to interpolate well logs with control grids and/or seismic dips with both vertical and horizontal wells. The resulting volume has high resolution (as high as 0.5ft per sample). Our approach was a synergy of data and model. The use of control grids makes the workflow more interactive and human-controllable at high-level, while the seismic dip patterns guide the log interpolation at a detailed level within a depth zone between control grids. As shown in the experiments, the method can successfully interpolate well logs with a satisfactory degree of accuracy using synthetic and real-world datasets. Our future work is to incorporate other seismic attributes, such as coherence, to address faults and other geo-bodies for volumetric well log interpolation.
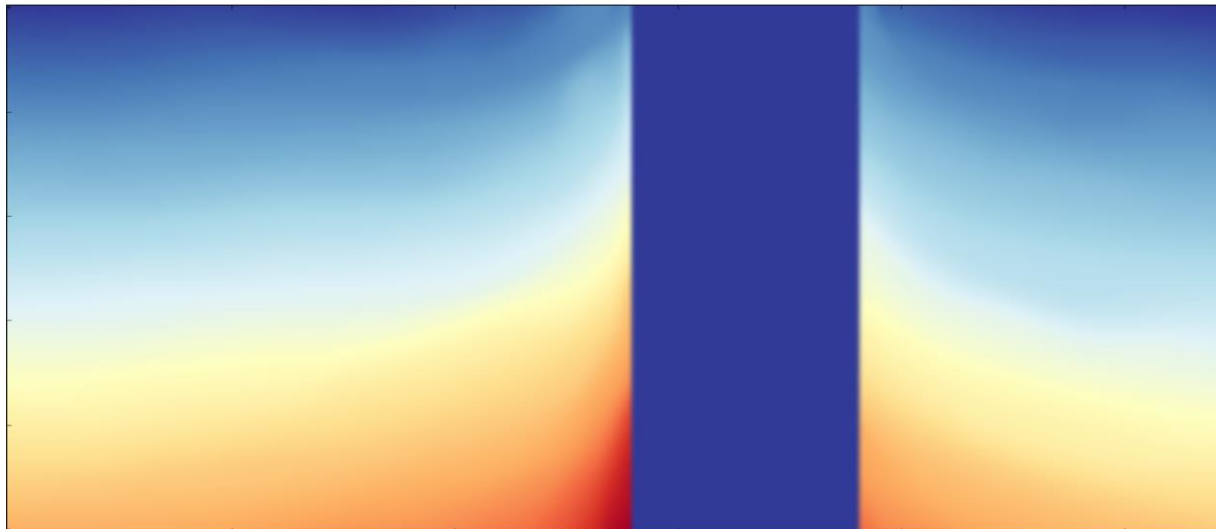
Figure 10: A vertical display of the R values. R values are interpolated based on the grids given as well as the seismic in figure 4 except in the region of salt dome. Note that the R-value interpolated is constrained by the interpreted model, i.e., three control grids. The control grids force the R-value to be the same regardless the seismic patterns.
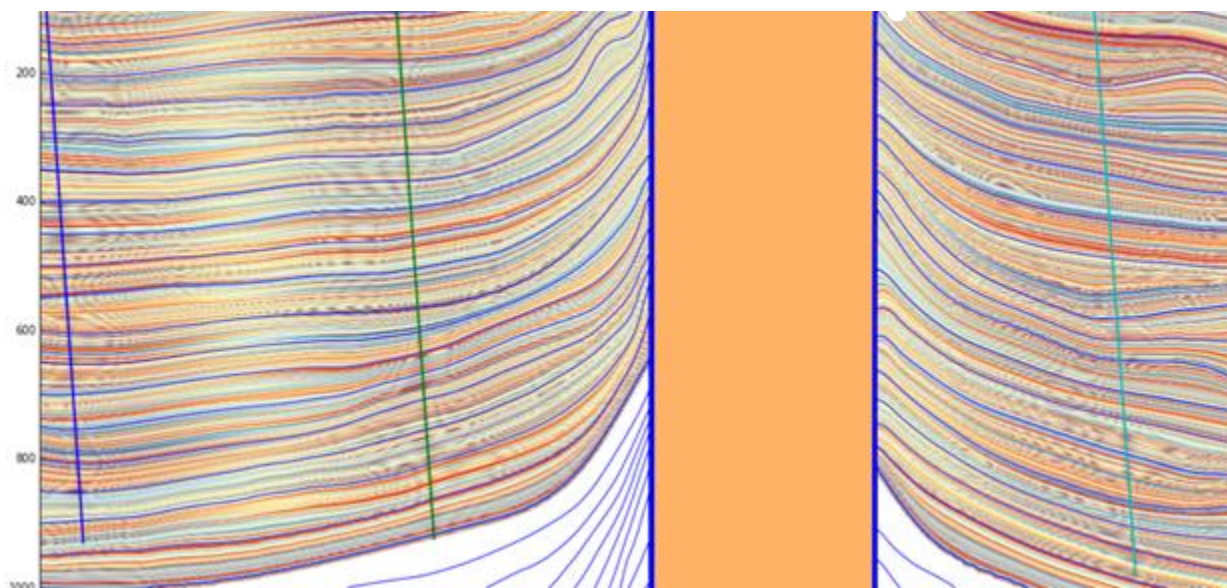

Figure 11: Interpolated GR in High Resolution. Three pseudo wells (blue, green and light blue) with random generated GR logs values are used for the interpolation. The dark-thick blue vertical lines are the interpolation boundaries of the salt dome in the center.

Acknowledgments

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