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Automated Geosteering While Drilling Using Machine Learning. Case Studies

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Abstract

Today's oil & gas industry faces a number of different challenges. Drilling activities are ramping up due to an increase in hydrocarbon demand combined with a reduction of easy-to-recover reserves. Horizontal drilling is growing and has become an integral part of field development. The geology is becoming more and more complex requiring drilling through dense layers targeting thin-layered reservoirs with lateral changes and anisotropy. In recent years, companies have been looking at the ways of optimizing drilling costs by increasing efficiency and process automation. This has been a driver for many companies to stay profitable and efficient in the market.

One of the areas of interest for process automation has been a geosteering. Geosteering is the real-time adjustment well trajectory while drilling to maximize effective footage in the target zone. In this paper, innovative new approaches to automation of the geosteering process will be discussed. This approach has been successfully tested and deployed in several leading O&G companies.

The main objective of automated geosteering is to optimize horizontal well placement while freeing up time operational geologists had spent doing routine work in order to focus on complex and more intense tasks as well as the reduction of operational errors related to human factors. This paper will provide details on several automated geosteering algorithms. They have been tested successfully on large numbers of wells. The results of automated geosteering were as close as 90% to the manual interpretations done by geologists. When the results diverged, the geologists often "agreed" with the interpretation proposed by the algorithm.

Introduction

Geosteering of horizontal wells is an integral part of the well construction process. Geosteering models are updated on the fly based on new data acquired while drilling. The wellbore's stratigraphic position and formation dip are then determined and further instructions are put in place to modify the trajectory in order to stay in the target interval.

Typically, geosteering models are built and updated using log correlation from lateral well (MWD&LWD data) and an offset well(s). Commonly, a nearby vertical offset well is used.

There are two approaches to geosteering:

Match the dynamic log (offset well log projected along the horizontal well) with the lateral well log.

This approach is called Model-based geosteering.

The lateral well log is projected into the vertical domain and correlated against offset well log. This approach is called Strat-based geosteering. The approach allows the correlation the lateral log data on itself when the wellbore is going stratigraphically up or down and crossing the same beds.

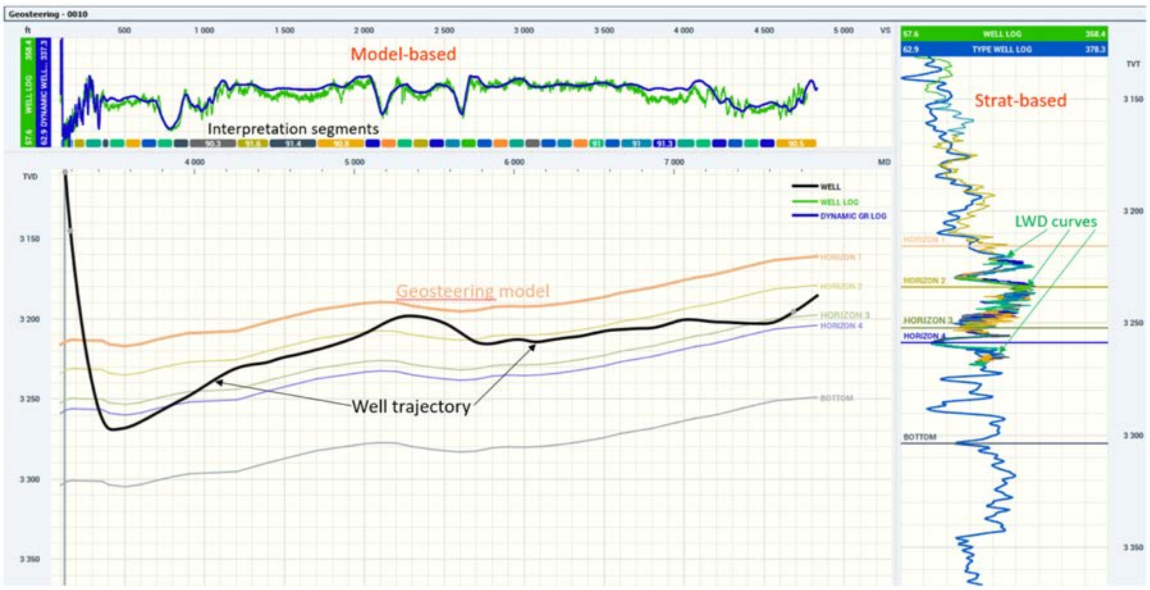

Figure 1—Geosteering model example. Horizontal track represents model-based geosteering approach. Vertical track represents strat-based geosteering technique. Segments with various bed dips are displayed as colored logs on the vertical track.

The geosteering process is very intense. It requires geologists to manually update the geosteering model by changing both the bed dip and length of the segments of the model to obtain the best match between lateral and offset well logs. If a mistake is made at the beginning of the interpretation, the geologist needs to go back and re-steer the well. The automation of this process has become highly sought after. Various approaches to automation have been proposed (Rajaieyamchee, 2010; Omeragic, 2013).

At first, these methods suggested using the same approach of correlating the logs and finding the best match (eg. Pearson correlation, Euclidean distance etc.). The result was unstable. The constructed geosteering model would have significantly differed from a manual one interpreted by a geologist. New algorithms were developed, but the results were inconsistent in different wellbore sections (ex. Curve, landing, lateral). After an integrated complex method was developed which incorporated the benefits of the other ones, a stable and advanced correlation algorithm resulted.

Methodology

Geosteering can be done using an automated approach or a semi-automated process with Spectrum.

It can be also combined with manual interpretation in some complex parts of the well. As new data comes in while drilling, autocorrelation of logs and spectrum calculation is done on the fly. A system of alerts and a calculated algorithm confidence level informs the geologist if his/her input is required.

Automated Geosteering Algorithms

When the horizontal well is drilled, it consists of vertical, curve, and lateral sections. Each section has its own characteristics therefore it requiring unique methodologies. Drilling the vertical or curve section, formation dip variations have minimum impact. On the other hand, bed dip changes in the lateral section have a huge impact on how segment size and dip are determined.

When started, the algorithm determines the interpretation start depth and required methodology based on the trajectory data (inclination). If the well is approaching its landing point and about to start lateral section, the algorithm automatically switches to the appropriate methodology when steering in lateral.

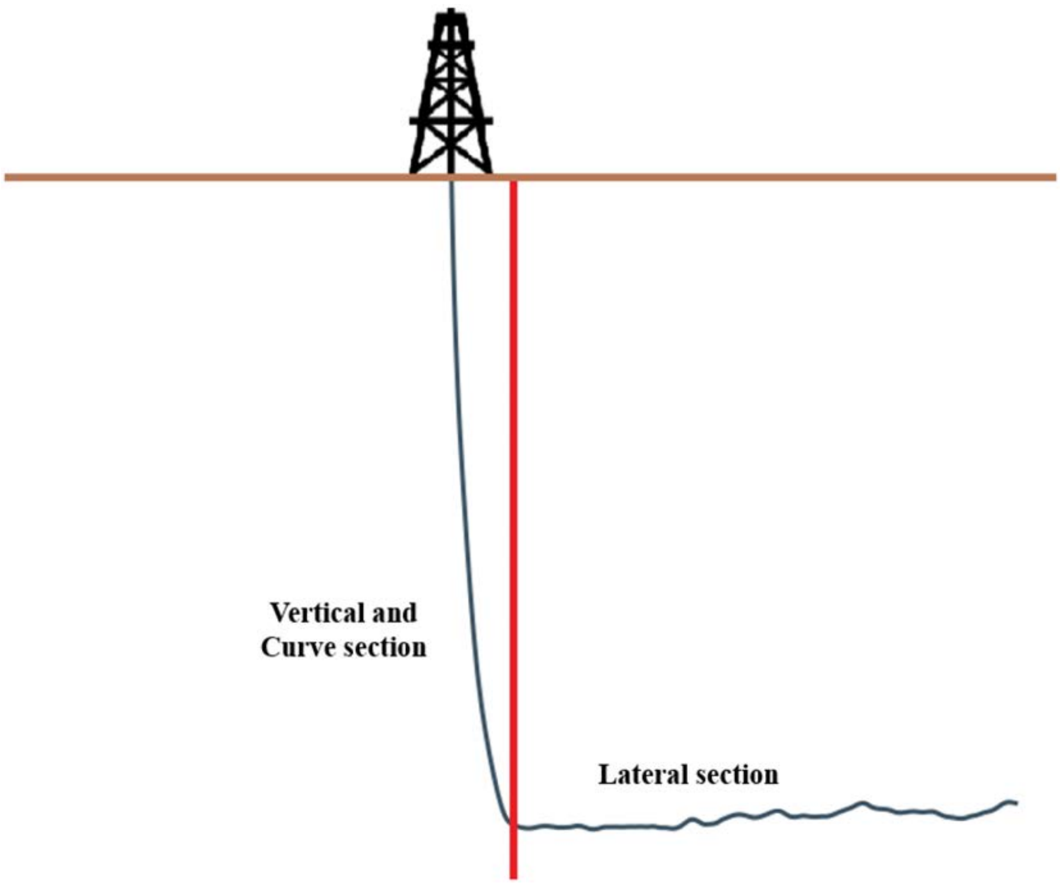

Figure 2—Vertical/Curve and Lateral section of the wellbore

Automated Geosteering in Vertical/Curve Section

The most important things to account for when it comes to drilling the curve/landing section of a well are formation thickness changes and possible faults while constraining formation dip. Therefore, the geosteering model consists of the lateral log segments correlated and shifted in the vertical track. This model reflects changes in geology in the vertical part of the well relative to the offset well. The wellbore position is determined for every segment and the geosteering model is adjusted accordingly.

Machine learning is used to correlate the lateral and offset well logs. A neural network was developed and trained to find and correlate the logs in a way similar to how a geologist would do it. To simulate signals from a horizontal well, various signal distortions were used such as adding noise, smoothing, extension, compression, and a small change in amplitude.

Data preparation and processing. Data preparation is very important to train neural network and get the best results. The selected model is trained using the gradient descent method. Training is done faster and more accurately if the components (characteristic partial derivatives) have a similar scale. For this, it is necessary that the characteristic values themselves have approximately the same scale. The following data preparation steps were used:

- MinMax: linear transformation of the interval of method values (minimum, maximum) to the interval (0, 1).
- Quantile transformation. A non-linear transformation that changes the probability distribution of each method from the original to the uniform.
- Smoothing. The smoothed curve of the geophysical method is obtained from the original by averaging over a certain depth interval with some weighting factors (cosine window, Gaussian window, etc.). Smoothing helps to partially get rid of noise.

Architecture. To implement this task, such architectures as an encoder-decoder, Siamese networks, and triplet network were considered. Models were built on the basis of fully connected layers.

- Encoder – neural network "compressing" the input signal with the input being the signal and the output being a compressed vector representation of this sequence.
- Decoder – a neural network that restores data from a compressed vector representation obtained at the output of an encode.

When training the model, logging curves related to different intervals of the wellbore are output and the input is slightly distorted, but related to the same intervals. Thus, the model learns to convert distorted signals related to a certain interval to the form of the original signal. The encoder is trained to form a similar vector representation for the plot of the log curves measured on the same section of the cross-section. After the training, only an encoder is used through which signals from a horizontal and offset well are passed and vector signal representations already obtained at the output are compared with each other using the Euclidean distance.

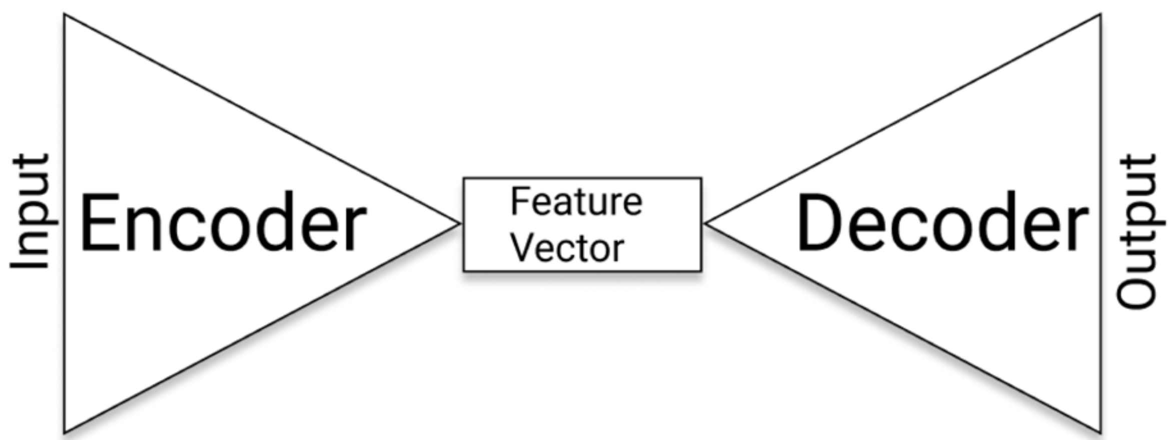

Figure 3—Encoder-decoder architecture diagram

Siamese network

The basis of the Siamese network is still the same encoder with the distance between the obtained vectors being measured. When two similar intervals arrive at the input, the distance will be close to zero; when different intervals arrive, the distance will be closer to 1 (Koch, Gregory, 2015).

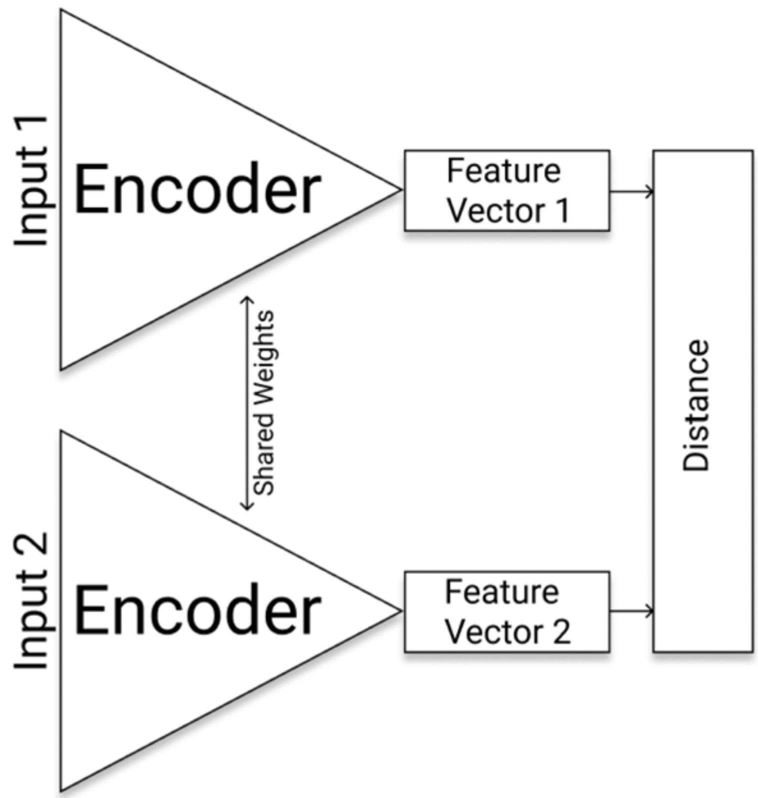

Figure 4—Siamese network. Architecture diagram

Triplet Network

This architecture differs from the Siamese network in that, in addition to the similar initial interval, we send different intervals. Thus, the model learns to position the vectors of similar signals close to each other in the vector space of a given dimension while the others are distant (Schroff, Kalenichenko, Philbin, 2015).

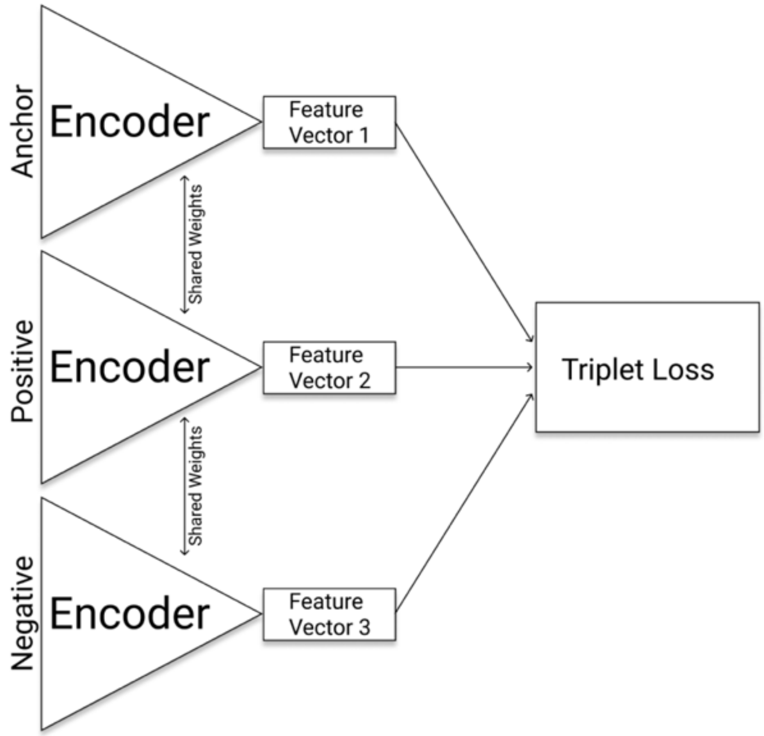

Figure 5—TripletNet Architecture diagram

Based on the number of experiments run, Triplet Network have demonstrated the best results.

Training

Training a neural network over the entire training sample is typically impossible due to limited resources (large number of samples do not fit into RAM). Therefore, at each step of the gradient descent, the gradient of the loss function is calculated only on a part of the training sample. For each part, the data is normalized to obtain zero expectation and unit variance. This is called Batch Normalization. (Ioffe, Szegedy, 2015)

To prevent retraining of the neural network at each era of training, part of the neurons are excluded from the network without contributing to the result. This method is used by adding Dropout. It is only used in training (Hinton, Srivastava, Krizhevsky, Sutskever, Salakhutdinov, 2012).

During the training, cyclic cosine annealing is used to prevent model jamming at local minima. Initially, training begins with a high learning rate, then rapidly decreases. When the minimum value is reached, the cycle repeats again (Loshchilov, Hutter, 2017).

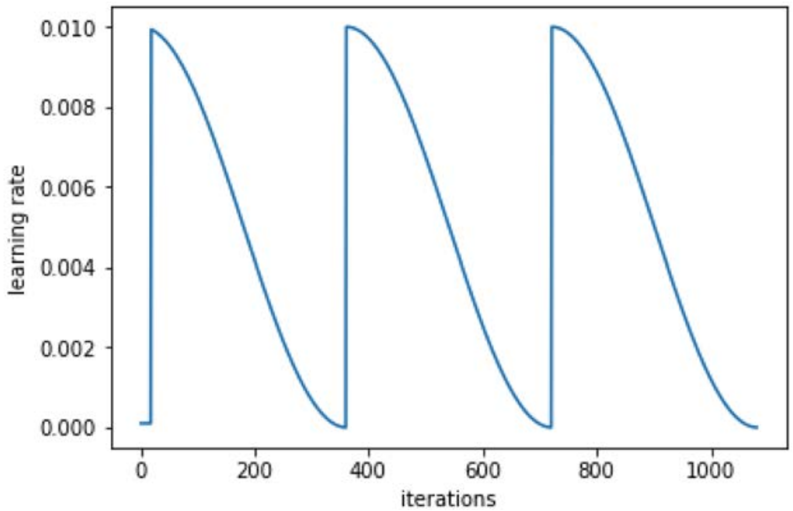

Figure 6—Changes in training pace in cosine annealing.

A sharp increase in speed at the beginning of a new training cycle contributes to breaking the local minimum.

The model is trained using a loss function called Triplet Loss, which has the form:

$$\mathcal{L}(A, P, N) = \max(\lVert f(A) - f(P) \rVert^2 - \lVert f(A) - f(N) \rVert^2 + \alpha, 0)$$

where A — original interval (anchor), P — similar interval (positive), N — different interval (negative), α — difference in distance between positive and negative

This function reduces the distance between original interval (anchor) and similar interval (positive), which refer to the same layer (layers), and maximizes the distance between different intervals (negative).

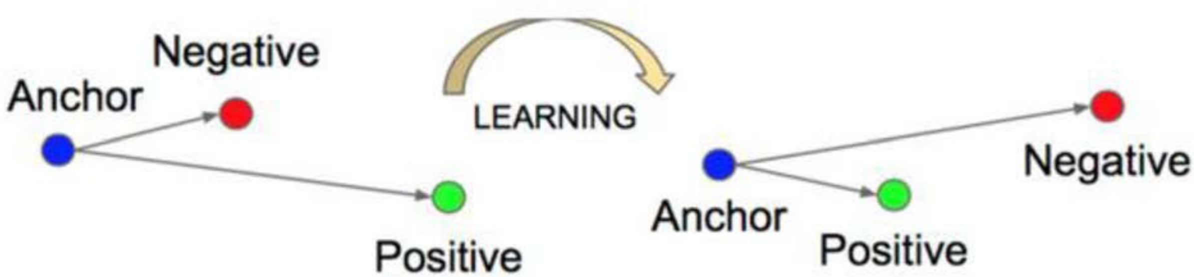

Figure 7—Triplet Net Training Process

During the training, random intervals of wells are selected as anchors. Positive samples are generated by distorting original intervals. As a negative interval example, a random segment in the well above or below the original signal (anchor).

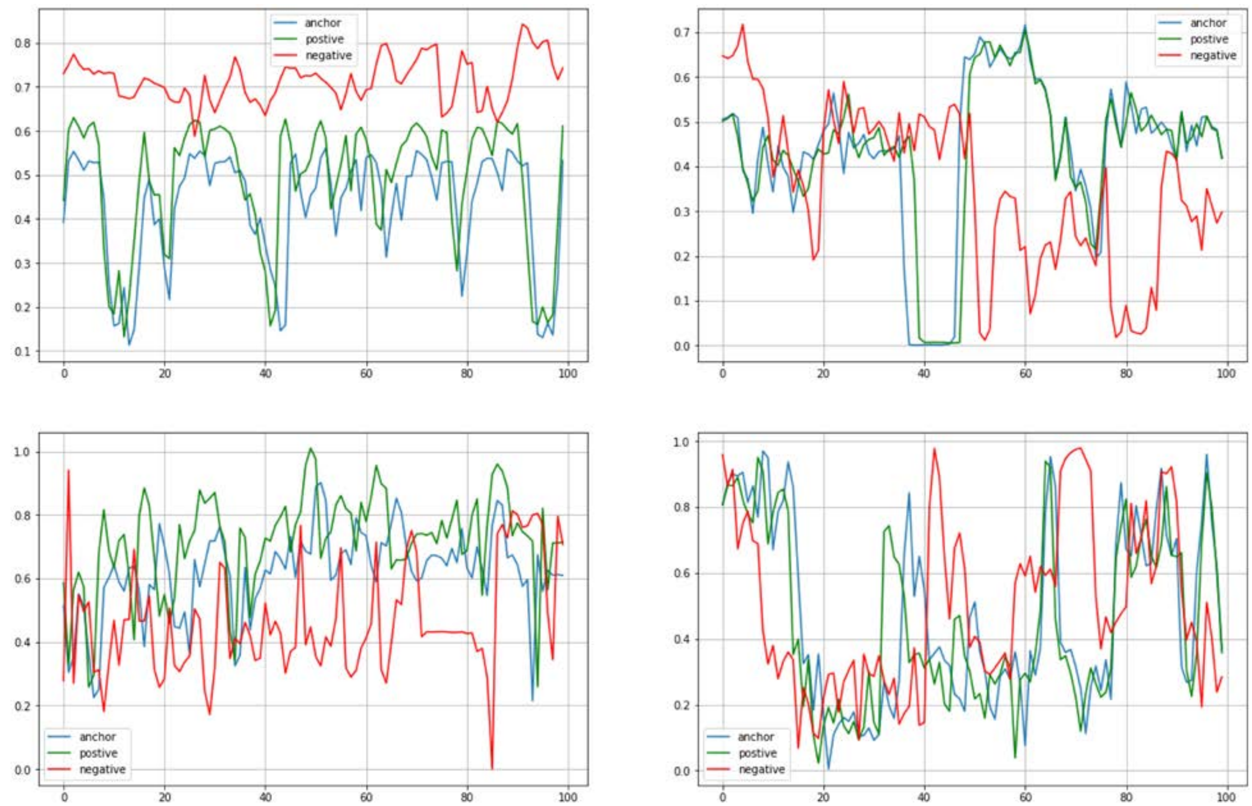

Figure 8—Training signals examples

The Trained neural network model converts the logs (input data) into its vector representation and Euclidean Distance is calculated between the Encoder vectors. This method proved to be more reliable compared to Pearson's correlation, Spearman's correlation, MSE mean squared error (MSE), and mean absolute error (MAE). These metrics are more sensitive to the shifts of individual sections within the interval.

Metric value - Euclidean distance between the Encoder vectors.

For each lateral depth value, it calculates TVT depth on typewell by finding segments with minimal metric value. Metric is calculated for different segment sizes to find the best result. The algorithm starts with bigger segments to calculate the metrics followed by reduction of segment size to get the best accuracy.

The shift is then calculated as the difference between the depth for lateral and typewell. It takes 100m above and below from the initial shift to determine the actual shift. If the determined shift is higher than 100 m from the initial shift, then the algorithm will show wrong results. In this case it is required to manually edit the initial shift and rerun the algorithm.

When the actual shift is found, the segment size and search area are reduced. The process is repeated, with the shift being fine-tuned until the minimum segment size is reached (this value can be set). The heatmap on Fig. 9 shows the metric value calculated by the algorithm. Red colors represent the best match while blue colors represent the worst match.

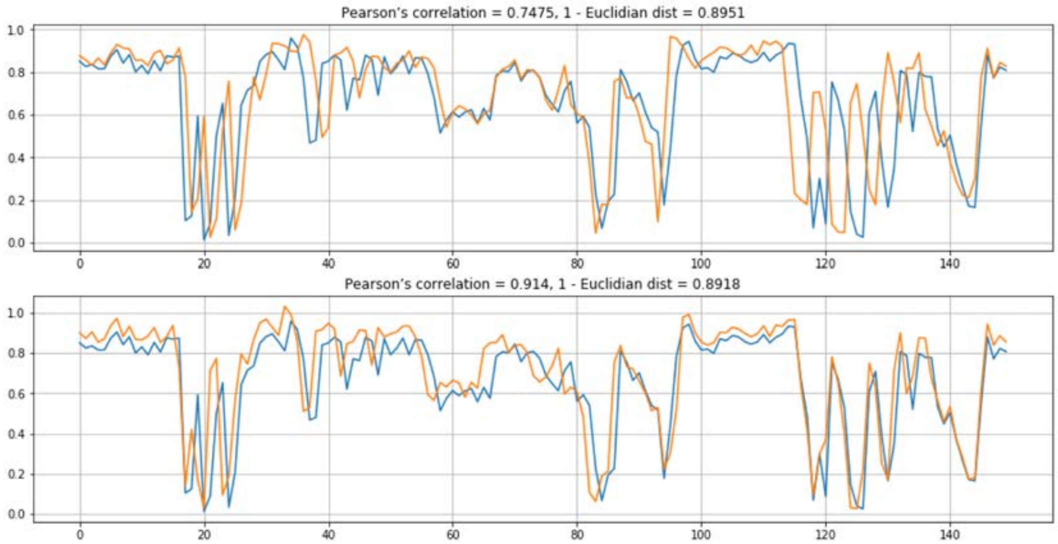

Figure 9—Signals difference using the neural network model and the Pearson correlation coefficient

The algorithm selects the points with minimal metric. The postprocessing analysis is then made relative to these points. On Fig. 10 the results of the processing are shown.

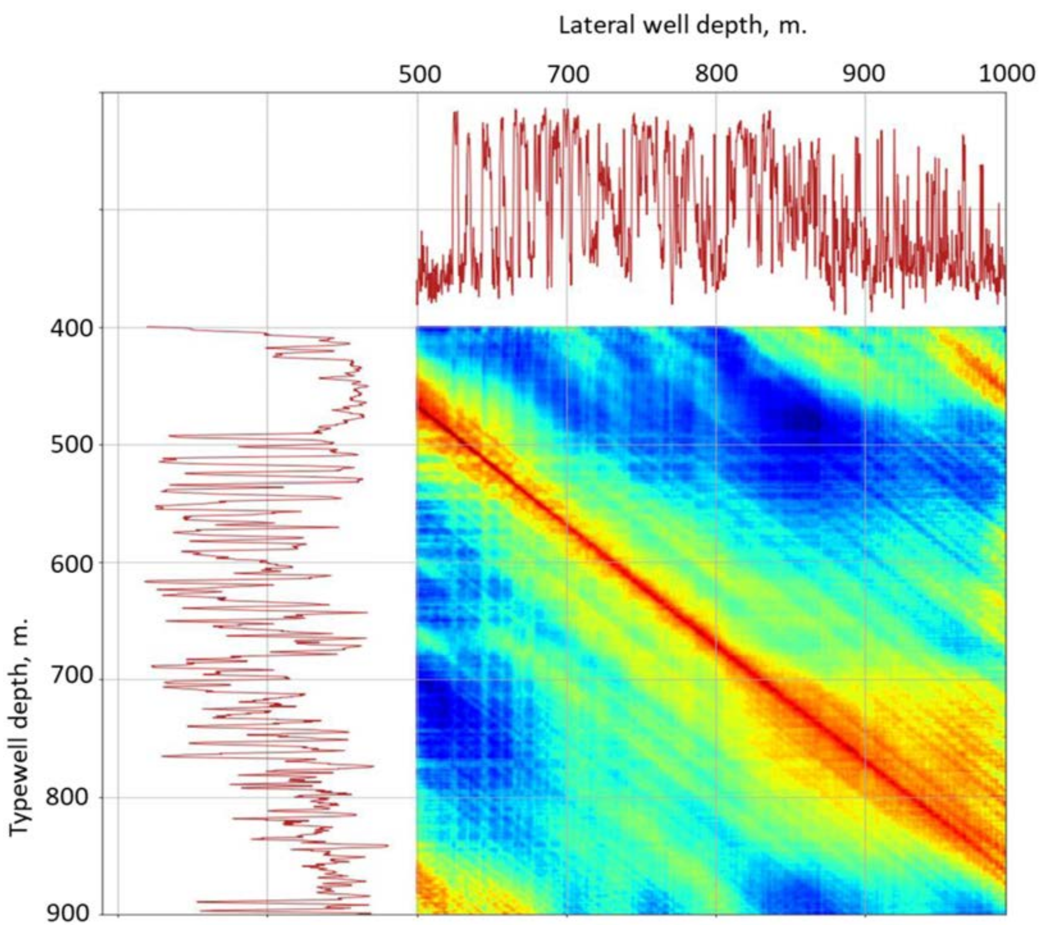

Figure 10—Heat map. Depth comparison of lateral and offset wells.

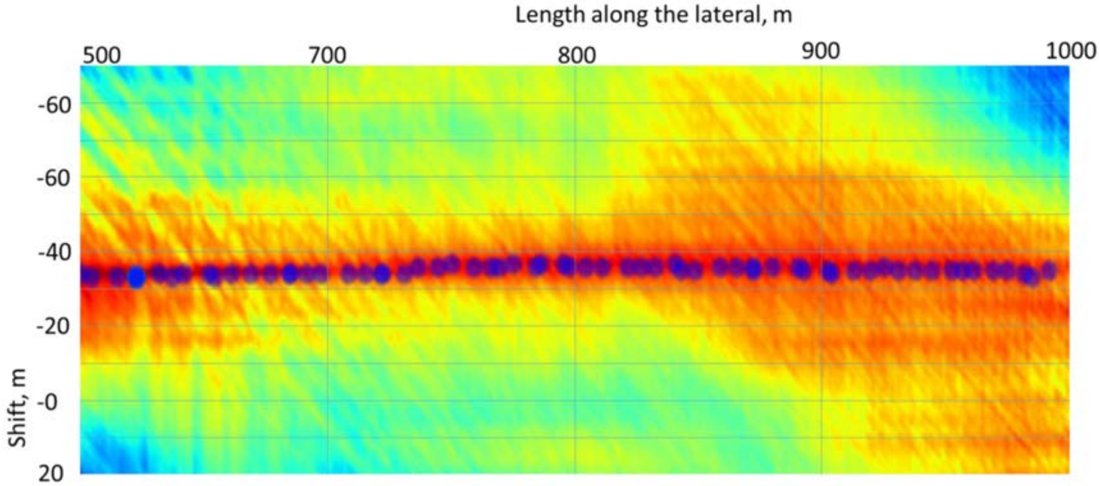

Figure 11—Determination of the shift of lateral well relative to typewell

The algorithm stops working when dip is in the 3-10 degree range. As a result, a geosteering model is constructed for the vertical section.

Automated Geosteering Algorithm in Lateral Section

This algorithm is automatically selected after the vertical/curve section is completed. The interpretation start is picked automatically based on the results of the vertical/curve section. THL (True Horizontal Length) scale is being used for calculations. THL is a plane along the lateral which follows the changes in the well azimuth and is projected into the 2D. The geosteering model along the lateral is split into several segments which are used to define formation dip changes. The model is updated honoring the regional dip and dip range as well as the structural grid slice trend.

Several methods are used in the algorithm:

Basic methods of consistent interpretation. In this method, segment length and dip are sequentially selected and regional dip and dip range are defined. Dip range provides minimum and maximum dip allowed for the autocorrelation. The segments dip values are computed to find the best log match between lateral and offset well following one of the methods below:

- Euclidean distance between curves (minimum)
- Pearson correlation coefficient (maximum)
- Sum of module differences (minimum)
- Euclidean distance between vector representations of curves by a neural network model trained to define similar curves (minimum)-комбинация вышеописанных величин

Several basic methods can be used to interpret and calculate the bed dip. Moreover, the segment length can be also incorporated in these calculations.

Basic "Looking forwar"d Algorithm. On some occasions the algorithm chooses a false dip that corresponds to the best value of convergence. In other cases, the above algorithm may find a wrong dip that corresponds to the local extremum value. At the same time, there may be other dip or multiple dips that matches the true geological dip. It may not correspond with the extremum of the whole range of searched dips. An additional run can be added to compensate for such cases. In the additional run, local extremums of the similarity function can be searched. Whenever a dip matches the local extremum, the next segment can be added for which the best possible dip may be searched. Additionally, an angle difference between the dip identified in the previous iteration (e.g., in case of the first segment, this may be a regional dip) and the chosen dip can be calculated. In the dip range for the first segment an optimal dip is chosen while maximizing the KF value in the following formula:

$$KF = \frac{V1 \times V2}{\Delta a^{pow3}}$$

V1 and V2 are local extremums of similarity function, $\Delta\alpha$ is the difference in dips between the current and previous segments, pow3 is the influence of the difference in dips between the previous and the current segment (penalty) on decision making. In case of a high penalty, a segment dip can be chosen which corresponds with the local extremum of the angle which is as near as possible to the dip of the previous segment.

Wellbore kinks method. If the wellbore is kinking and crossing the same bed several times, the wellbore kink method can be used to determine formation dip with high accuracy.

The algorithm finds the point where the wellbore is kinked and projects logs from the left and right part of the wellbore (from that point) into vertical TVT domain to determine the dip range of the layers. The dip at which both left and right pieces of the logs are matched will be very close to the actual formation bed dipping. The algorithm finds all the wellbore kinks and determines formation bed dip. Fig 12. Shows an example of the wellbore kink correlation method. Changing the dip by just only 0.2 deg (from 89.8 to 90) will significantly disturb the log correlation.

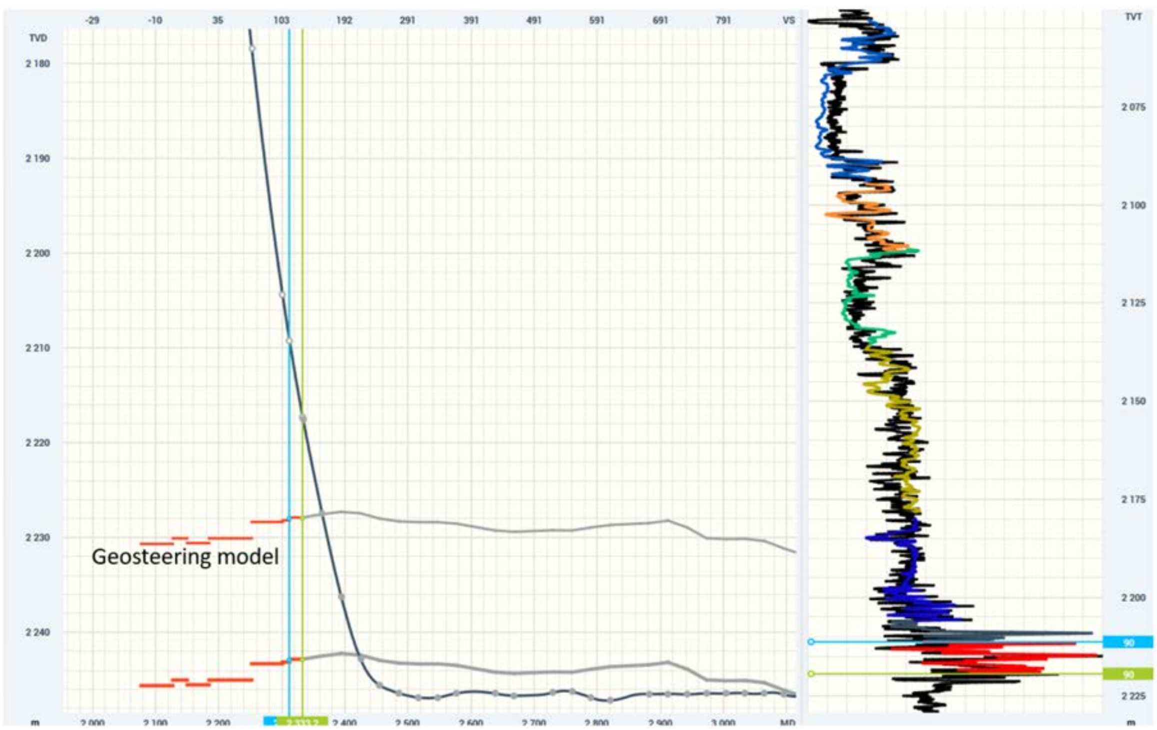

Figure 12—Geosteering model example after automated geosteering is completed in vertical section. On the vertical track, log correlation is displayed using Strat-based method. Log colors correspond to the various segments of the wellbore. Black – typewell LWD.

Figure 13—Wellbore Kinks Method. Above – correct formation bed dip (89.8 deg). Below - wrong formation bed dip (90 deg)

Correlation on itself. Calculating a log's correlation on itself coefficient can be done for the entire geosteering interpretation. The correlation on itself happens when the trajectory crosses the same beds several times. If the interpretation is correct then the lateral logs data will match itself in the vertical TVT domain. By placing the repeated logs on the same axis, it is possible to calculate a correlation coefficient of the interpretation as Euclidean distance between points with same TVT.

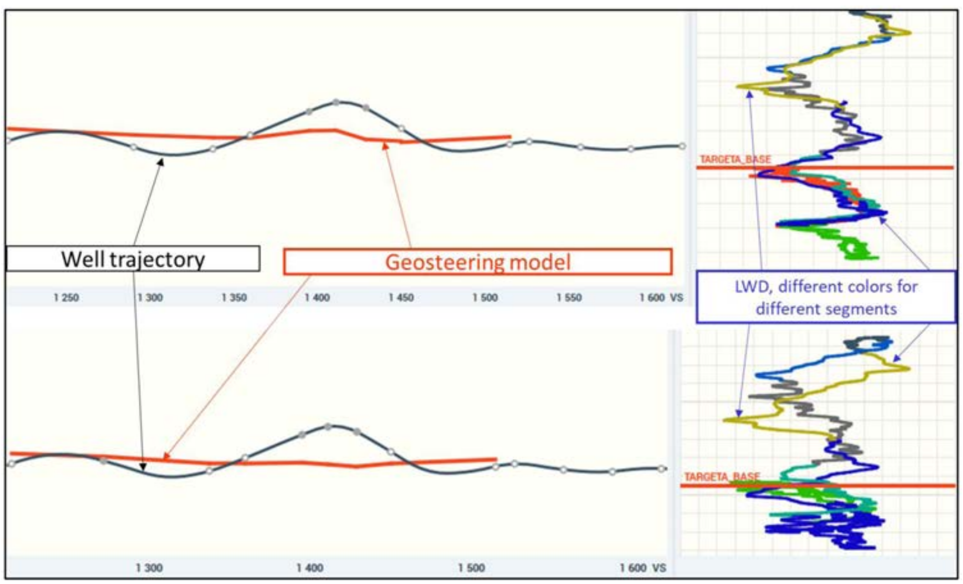

Figure 14—Correlation on itself. Above – correct interpretation. Below – distorted one

Big Segments Method. Regional dip and dip range are defined. It is possible to select a structural grid instead of regional dip if required.

Interpretation is completed using big segments methodology. A longer section of the wellbore is selected (eg. 200-600 m). This section is interpreted based on the number of basic algorithms (refer to previous sections). For every calculated interpretation within this large segment a convergent coefficient K is calculated between lateral log and offset well dynamic log using the formula below:

$$K = \frac{T^{pow1} \times SC^{pow5}}{(SQ^{pow2} \times (\sum \Delta\alpha)^{pow3} \times (\sum \Delta\beta)^{pow3} \times (\sum \Delta\gamma)^{pow4}}$$

where:

T – Pearson correlation coefficient

pow1 – Pearson correlation coefficient weight

SQ – Euclidean distance

pow2 – Euclidean distance weight

∑Δα – the sum of the difference in dips between adjacent segments

∑Δβ – penalty, difference in average slope of segments with regional dip

pow3 – penalty weight. The parameter can be changed interactively. If the parameter has higher values, the algorithm will tend to construct geosteering model following regional dip

∑Δγ – the sum of the differences in the dips of the segments with the dip determined in the vicinity of these segments by kinks

SC – self-correlation value

pow5 – self-correlation value weight

pow1, pow2, pow4, pow5 and pow3 - values that were selected experimentally because of multiple runs of algorithms for a set of wells

The geosteering model with highest convergent coefficient (**K**) is selected. The algorithm with the highest K is applied to the first 0.1-0.6 of the big segment. The rest of the segments are calculated using a similar approach described above. When the distance to the end of the wellbore becomes less than the size of the big segment, the segment size decreases. When the size of the big segment decreases to 10-100 m, then this segment is considered as the last segment and the interpretation applies to the rest of the wellbore. As a result, we have an interpretation which consists of parts interpreted by various methods with the best offset well and lateral log match as well as correlation on itself while honoring regional dip or structural surface grid trend.

The algorithm stops working when there is no more data in the lateral.

Geosteering Spectrum

To evaluate potential structure changes (ex. presence of faults) in additional to automated geosteering algorithm log-to-log correlation, Geosteering Spectrum was developed. The Spectrum shows a TVD heat map representing the potential location of the selected horizon (for example, Top Target or Bottom Target) in space. Brighter colors represent the higher likelihood of the horizon position.

How it works

The potential position of the selected horizon is shown above and below the wellbore. Interpretation start can be selected. Thus, each point of the spectrum corresponds to certain wellbore MD depth and estimated horizon position.

For each point, a criterion of the probable horizon position is calculated. The value of the criterion is in the range of [0, 1]. To calculate the criterion, two nearby segments are created. For every segment thousands of different geological dips are analyzed. The highest criterion of every combination is selected. Then the algorithm moves on to the next point and the process is repeated. A heatmap is created based on the calculated values of the criterion and visualized along the wellbore.

To calculate the criterion, forward and backward segments are created with the target point lying between these segments. For each of the segments, numerous scenarios with horizons positions are created with various formation dips. For each combination of the horizons, a dynamic log from typewell is calculated along the wellbore and compared with lateral well log and the criterion is calculated using the formula below:

$$criterion = f(\log_{dynamic}, \log_{measured}) = k_{MAE} * (1 - MAE_{norm}) + k_{corr} * corr_{X,Y}$$

Mean absolute error (MAE) and Pearson correlation coefficient (corr) are used for comparison. Their proportion in the total criterion depends on the variance of the log on the segment being analyzed. For each segment the maximum obtained value of the function is taken. The final criterion is calculated using the formula:

$$criterion_{total} = criterion_{segment1} * criterion_{segment2}$$

The higher the criterion value, the higher the probability for the target horizon to pass through this point.

If we immediately assign a color to the calculated criterion value, then the difference between "good" and "bad" points would be difficult to distinguish visually for wells with bad log correlations. To increase the image contrast, the calculated criterion value is divided by the maximum among all points with corresponding MD. Then it is raised to a power greater than one. With this conversion, values close to maximum will be close to 1, and the relative distance between close to maximum and smaller values will increase.

$$criterion_{contrasted} = \left(\frac{criterion}{criterion_{max}}\right)^{power}$$

A point is painted by a color linearly interpolated from blue to red in accordance with the criterion value (0 - blue, 1 - red). The space between all points is filled with gradient fill.

Using Spectrum in Geosteering

Spectrum represents the range of geosteering possibilities and their relative likelihood for a given horizon. It helps to optimize the process of updating a geosteering model in order to determine and model the most likely scenarios. It helps to avoid potential mistakes related to the multivariance of constructing a geosteering model.

Geosteering Spectrum shows a probabilistic ranking of the horizon location (compared to deterministic one done by automated geosteering algorithm). If there is any uncertainty in the horizon position, Spectrum can help to resolve it by providing the most likely scenarios.

On fig. 15, the log correlation was good at the first part of the wellbore. That is why the horizon was determined to be at lower TVD. However, if we look at the fig. 16 the overall logs correlation matches better if we use a Geosteering Spectrum. In this case the horizon position is shallower in TVD space.

Figure 15—Result of AG work.

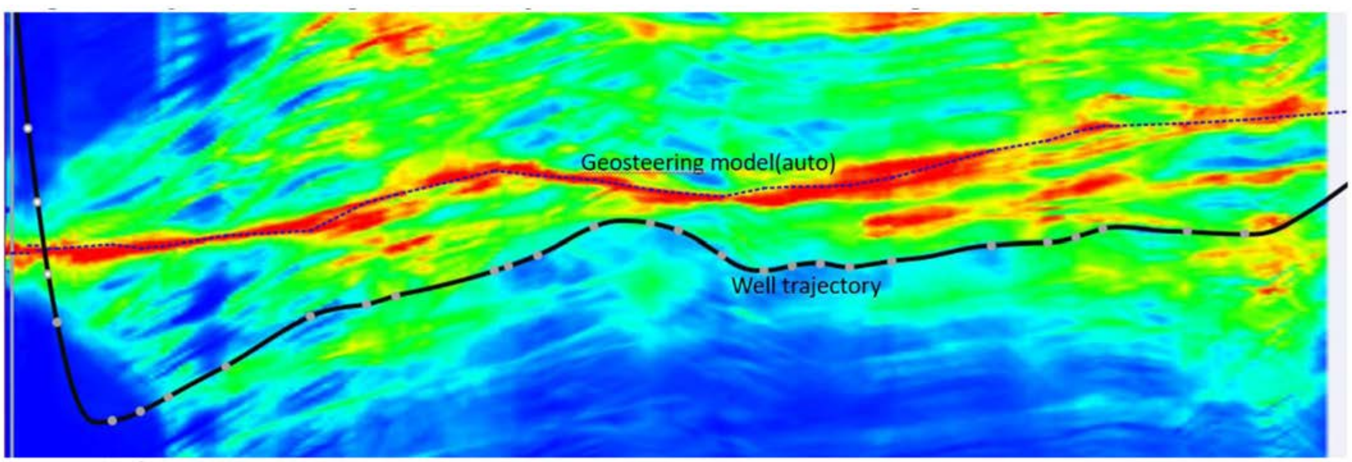

Figure 16—Geosteering spectrum example with geosteering model, calculated automatically.

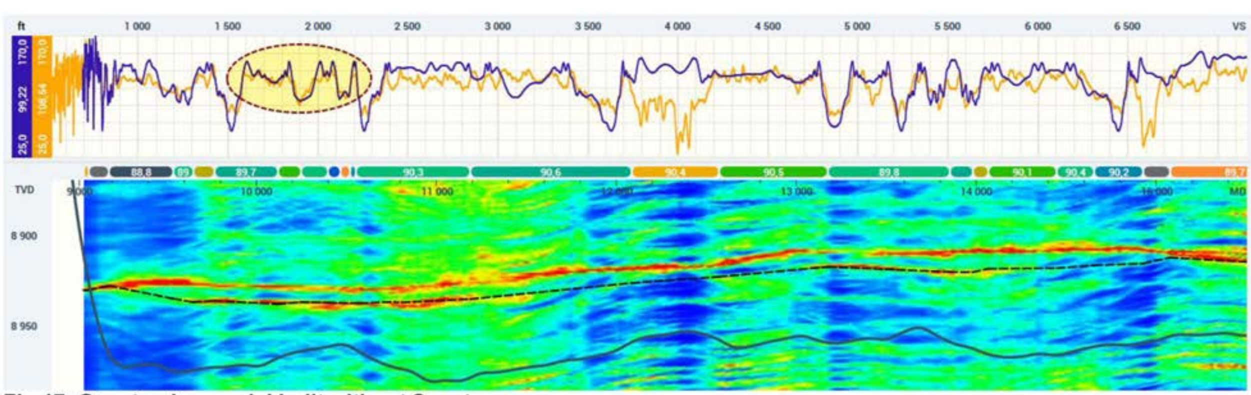

Figure 17—Geosteering model built without Spectrum

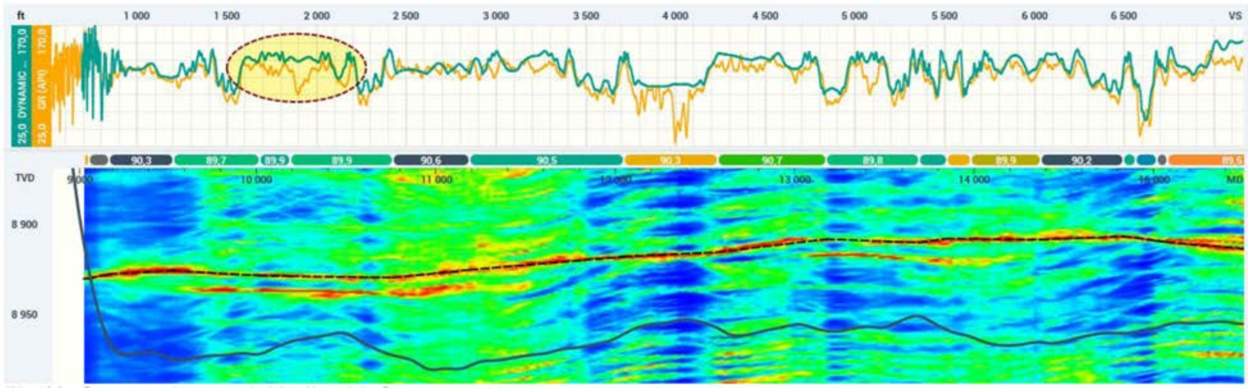

Figure 18—Geosteering model built with Spectrum

Automated Geosteering While Drilling

When the algorithm is running, it waits for the new data to come in. The data can be imported either by WITSML connection or by manually loading .las and trajectory data.

Once new data is loaded, Geosteering Spectrum and Confidence Level curve will be automatically updated while the waiting algorithm evaluates the newly acquired data.

Alerting System

Alerts can be preset and automatically generated to inform stake holders if one of the user designated conditions are met:

Trajectory exited target zone
Automated geosteering algorithm stopped working or WITSML connection dropped out
Confidence level curve shows low values

Confidence Level

Confidence level is calculated and displayed for every geosteering segment. It is calculated using the Pearson correlation coefficient between lateral and offset well logs using the model-based geosteering method. Low Confidence Level can be an indication of complex geology and/or data quality issues (noise, gaps). The geologist will check those intervals with low geosteering confidence level and can manually adjust the model if required.

Automated Geosteering: Limitations

The current version of the algorithm does not work well with sudden, severe dip changes within short distances (eg. > 5 deg within 50 m interval). This kind of geology is not very common. It is recommended to have manual input from the geologist when dealing with such situations.

The current version of the algorithm does not work well with large fault throws in the lateral section. Most of the time it can update the geosteering model correctly by smoothing the segment dips and showing the correct depths however it is recommended to have manual input from a geologist when dealing with such cases.

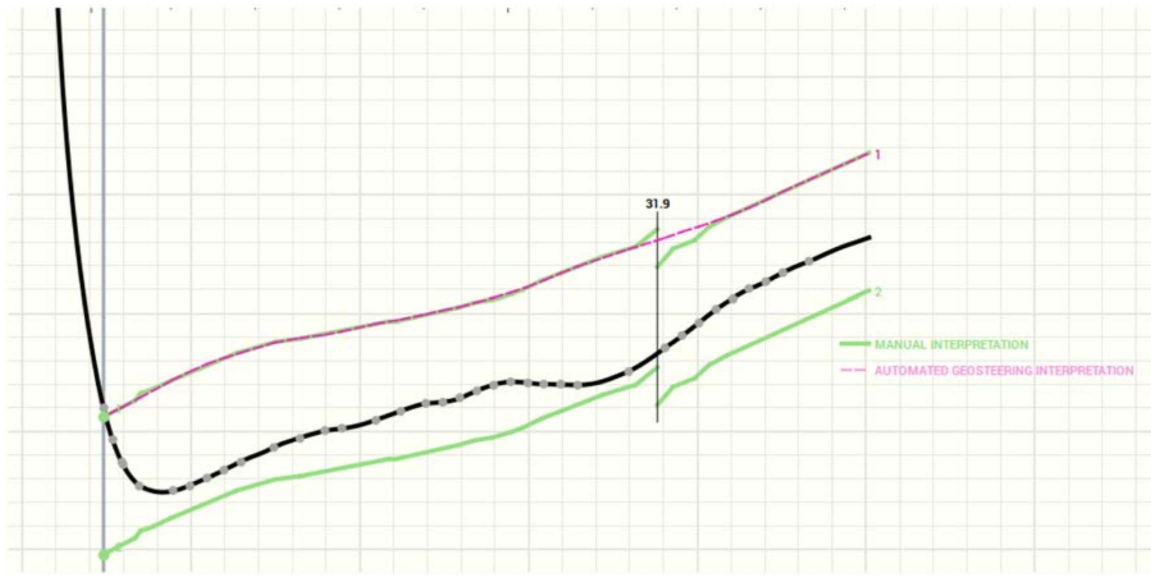

Figure 19—Manual interpretation vs. Automated geosteering interpretation

Geosteering Spectrum. Limitations

When the spectrum is computed, parallel horizons modelling is used. In case the thickness is changing significantly or there are pinch outs, the spectrum might not be an accurate representation of the geology.

The spectrum is used to show a general trend of the formation dip. Local dip changes within a short distance might not be represented correctly. Manual input might be required to address that in some areas.

On wells with poor log correlation, spectrum might be noisy. Work is underway to address this limitation.

Conclusion

Automated geosteering algorithms determine the model which best matches offset well log data and previously drilled lateral section data while honoring geological constrains (regional dip, dip range, grid slice). The algorithm has evolved from a simple one to something much more complex and integrated.

The algorithm has been tested in many different geological environments. If there are minimum lateral changes, the algorithm has demonstrated a success rate of 90% as compared to the manual interpretations done by geologists. When dealing with complex geology with lateral variations algorithm has shown a 50-60% success rate.

When the results diverge from manual interpretations, the geologists often (in 50% of the occasions) "agreed" with the interpretation proposed by the algorithm.

Using advanced methods of automated geosteering can optimize and increase operational efficiency. The geologists will focus more on the complex areas while leaving the simpler geology for the algorithm to do its magic. The geologist can spend more time analyzing geology rather than focusing on trying to adjust the geosteering model to find the best log match. This will result in better well placement within the target window, reduction of human errors, and increase the number of drilling rigs the one Geo can handle at a time.

The described algorithm was the first of its kind and has been tested on hundreds of wells from different geological basics. It is a proven tool for geosteering.

To optimize and improve the algorithm, neutral network training was/is applied to learn from real data samples.

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