Latin America URTeC: 3968978

Exploration and Development based on RTH Technology and AI

Gennady Erokhin[1*]; Maria Erokhina[1]; Kirill Safran[1]; Alexandre Iakovlev[1],1.Geomex Technologies

This paper was prepared for presentation at the Latin America Unconventional Resources Technology Conference held in Buenos Aires, Argentina, 4-6 December 2023.

Abstract

The paper discusses exploration and development issues using artificial intelligence methods based on new seismic attributes of the RTH (Reverse Time Holography) method and well drilling data. RTH attributes are based on two-stage seismic data processing: on decomposition the initial common shot gathers in common image gathers, using the time-reversal algorithms and on synthesis a seismic attributes. It is shown that a detailed analysis of the joint behavior of two vectors: the velocity vector in forward wave and the velocity vector in time-reversed backward scattering wave provides detailed information about the medium. The main differences between RTH attributes and traditional ones obtained during migration are their voxel nature and hyperattributivity. It turned out that this is a key advantage of the new approach to solving problems of geological prediction using artificial intelligence methods. The paper presents the results of using the new method for processing and interpreting 3D seismic data, as well as geological prediction based on RTH attributes for a number of oil and gas fields.

Introduction

The problems of predicting petrophysical parameters, as well as flow rates and other production characteristics are of significant interest, both in theoretical and practical aspects in the oil and gas industry. The inputs to the prediction are seismic attributes and well-log data. Presently seismic attributes are typically calclated in the time domain, while well-log data are depth-specific. This, along with the different detail of the information obtained in seismic and in the well, is the main difficulty in integrating seismic data and well-log data for the purpose of geological prediction of the properties of the medium throughout the entire space. Therefore, in most previous studies, well-log data are recalculated into the time domain, where their integration is carried out. The fundamental feature of the approach described in this paper, from all previous ones, is the use of new generation depth-based seismic attributes obtained using the seismic processing method that implements principles of seismic holography and wave front reversal in time - the RTH (Reverse Time Holography) method (Erokhin, 2019) . The method is vector extensions of the well-known method of depth migration based on wave reversal in time - RTM (Reverse Time Migration) (Baysal et.al., 1983; Whitmore, 1983, McMechan, 1983). The RTH method includes, as a special case, method based on a common image point - Angle Domain RTM (Yoon and Marfurd, 2006; Alkhalifah, 2015), diffraction analysis method ES360 (Koren and Ravve, 2011), CSP (Kremlev et .al., 2011), method of angular anisotropy of reflection - Amplitude versus Offset (AVO) (Chopra and Castagna, 2014), acoustic inversion method (Tarantola, 1984), velocity tomography method based on full-wave inversion (Virieux and Operto, 2009) or based on beam tomography (Popovici et.al., 2016). RTH is a voxel-based method, that is, the assessment of seismic attributes is carried out in each cell (voxel) of geological space independently of each other. Voxels are of arbitrary size, and their coordinates are fixed in the space they fill. The set of seismic RTH attributes includes, in addition to all known attributes, a number of previously unknown ones. The total number of seismic attributes obtained based on the parameters estimation of multidimensional (10-dimensional) statistical distribution in the RTH method reaches several hundred (Erokhin, 2022).

Theory and Methods

Figure 1 shows a comparison of processing workflow in the RTM method (left) and in the RTH (right). The raw seismic data in both cases is the same - common shot gathers. Processing workflow can be divided into two stages: decomposition stage, when the data is recalculated for each point in space (voxel) from the common shot gathers into the common image gathers and an attribute synthesis stage. For the RTM method decomposition uses the second-order acoustic wave equation for pressure, while for RTH it uses first-order acoustic equations for pressure and vector particle velocity. These equations are used for two waves: both forward and time-reversed backward. Obviously, for RTM the power of the data recalculated in this way, which makes up the Common Image Gathers (CIG) data set, will be significantly less than for RTH decomposition, where the Vector Domain Common Image Gathers (VDCIG) data set is formed. In RTM case it is a data space of two parameters, whereas in RTH it is a data space of eight parameters. Next, at the second stage of the processing workflow - the stage of attribute synthesis, the resulting sets CIG and VDCIG are collapsed into attributes. For RTM this occurs on the basis of integration over time and over sources (Imaging Condition), and for RTH based on estimates of the statistical distribution. As a result, for RTM one migration image is obtained - "RTM Imaging", and for RTH a countable number (100 or more) of formally constructed RTH attributes, including "RTM Imaging". It turns out that the set of RTH attributes constructed in this way includes all currently known attributes, including velocity.

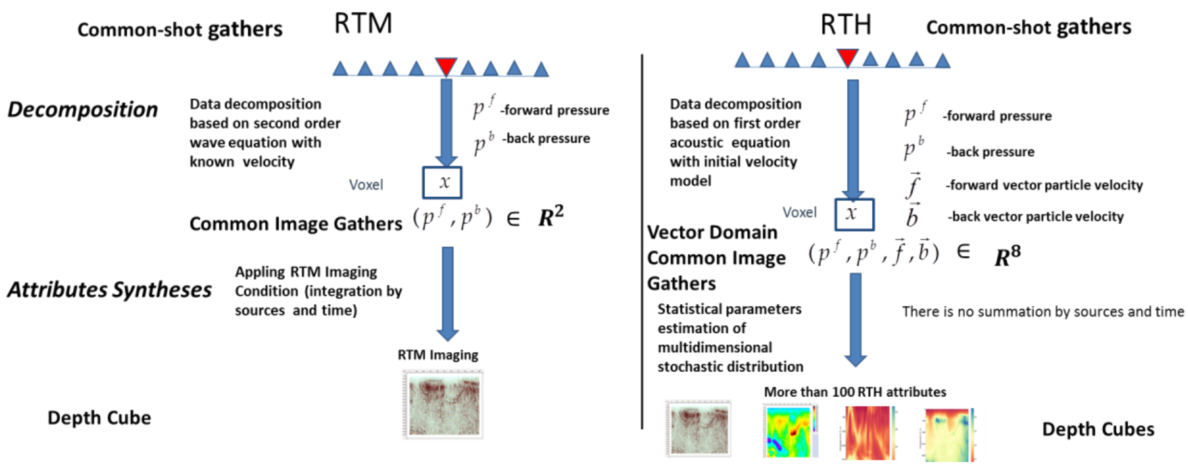
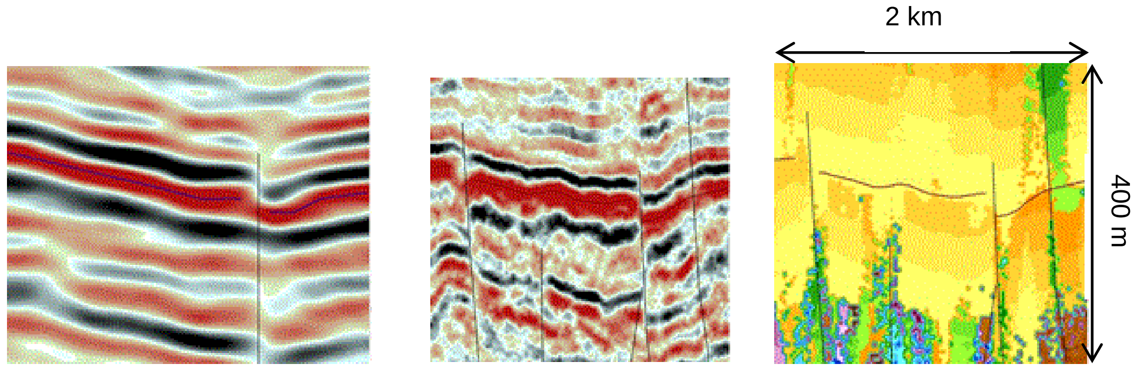


Figure 1. RTM &RTH processing workflow comparison

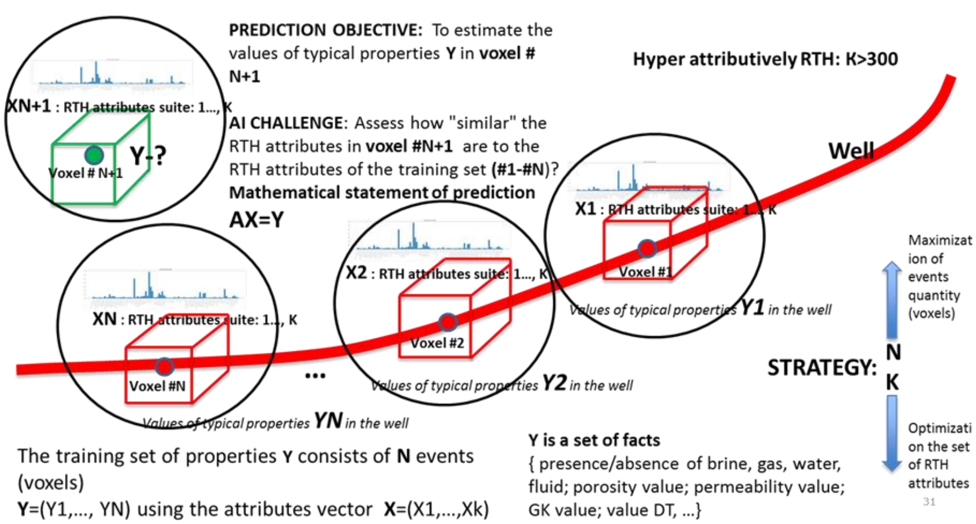
The main difference between RTH attributes and traditional ones is their voxel nature and hyper-attributability. Figure 2 shows examples of depth sections of 3 cubes of seismic attributes. Figure 1a shows a depth-section of a traditional PSDM depth migration cube. The vertical line indicates the author's identification of the fault using this attribute. The horizontal curved thin line corresponds to the roof of the foundation. Figure 1b shows one of the "phase" attributes of the RTH, which is similar to PSDM and Figure 1c is a depth-section of the RTH velocity cube. Here the thin wavy line corresponds to the velocity inversion - the boundary of high (top) and low values of the medium velocity (bottom). The inversion boundary coincides with the roof of the foundation. The joint interpretation of the RTH attributes of Fig 1b, 1c allows us to clearly detail the faults and a sharp decrease in velocity (green-burgundy colors in Fig 1c) that is associated with fracturing. The size of spatial cells (voxels) in which the values of RTH attributes are estimated in Fig. 1b, 1c are taken to be 12.5 meters by 12.5 meters laterally and 2.5 meters in depth. This example shows only two RTH attributes out of more than 300 obtained simultaneously during processing.



a b c

Figure 2. Comparison of PSDM depth section (a) and RTH Phase attributes (b) and RTH velocity attributes (c) for fractured foundation. Voxel size is 12.5x12.5x2.5 meters.

It turned out that such hyper-attributability and high spatial resolution of the method are the key advantages of RTH as a method of processing seismic data over traditional migration methods such as RTM in solving prediction problems using artificial intelligence (AI) methods. Based on the calculated voxel-based attributes and well data, an information pairs are quite naturally formed in voxels encountered along the well trajectory: a set of RTH attributes - a set of well-log data that are used for machine learning (ML) (Fig. 3).



Figue 3. Prediction technique based on RTH attributes and well-log data using AI approach

This technologically advanced formation of a training sample allows spatially precise (within voxel size) prediction of various lithofacies, petrophysical and other properties, as well as any parameters of a hydrocarbon field, using artificial intelligence methods.

The RTH prediction roadmap consists of three stages. The first stage of RTH involves seismic data processing and interpretation. As a result, RTH attribute cubes, stratigraphic boundaries, fracture zones, fault zones, angular scattering anisotropy, etc. are obtained. Figure 4 shows one example of the result at this stage. The Figure shows a Frequency Map in the productive gas horizon, built using only the RTH attribute. At the second stage of prediction, a data set of pairs "RTH attributes" - "well data" is prepared for training by a neural network. And at the third stage, the neural network itself is trained and the target geological attributes are predicted. Training is carried out based on either MLP (Multylayer Perceptron) or RF (Random Forest) algorithms.

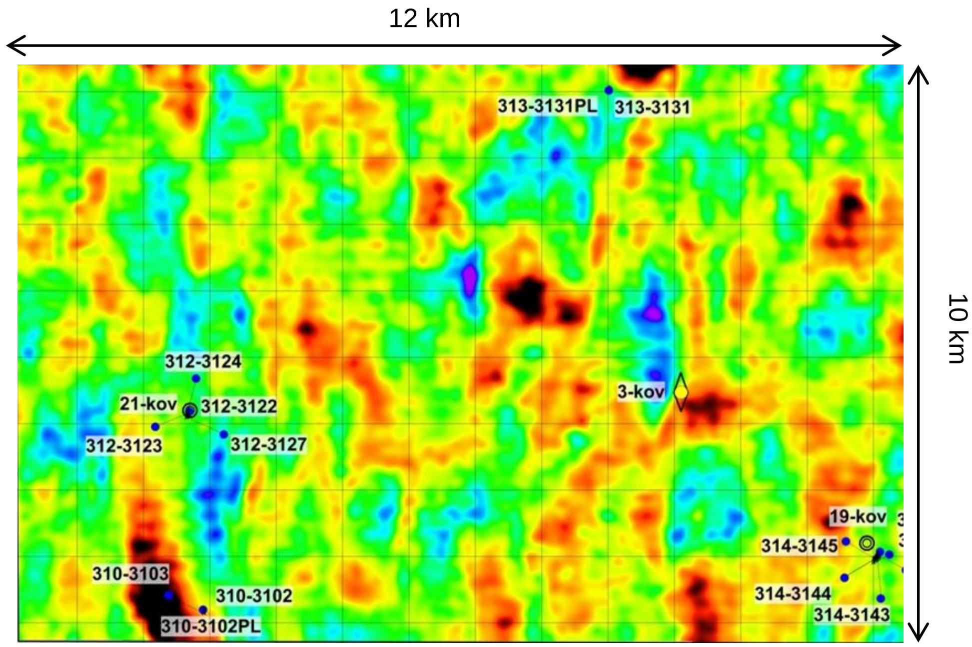


Figure 4. RTH Frequency Map in the productive gas horizon: from -50 Hz (red color, vector particle velocity rotates counterclockwise) up to +20 Hz (blue color, vector particle velocity rotates clockwise)

Results

The roadmap presented in the article for predicting geological parameters based on RTH attribute data and drilling data, consisting of 3 stages, is characterized by its simplicity and clarity. The RTH prediction process is technologically advanced and very effective for horizontal wells. This is explained that for conventional attributes, obtained on the basis of migration images (of the type shown in Fig. 2a) observed horizontal variability of attributes is significantly inferior to the depth variability. At the same time, well-log data in horizontal wells have significant variability at small distances. In RTH attributes, horizontal variability is much higher than in RTM, and it is comparable to vertical variability.

Figure 5 shows the results of the prediction porosity in some productive gas horizon. The thickness of the horizon is about 50 meters, the area is 120 sq. km. The prediction used porosity data from 9 wells. The prediction accuracy is high, as evidenced by the results of blind testing. Figure 6 shows oil production prediction based on available data at 4 wells and RTH attributes. In both predictions, the entire volume was divided into voxels with dimensions of 25 per 25 meters in lateral direction and 5 meters in depth.

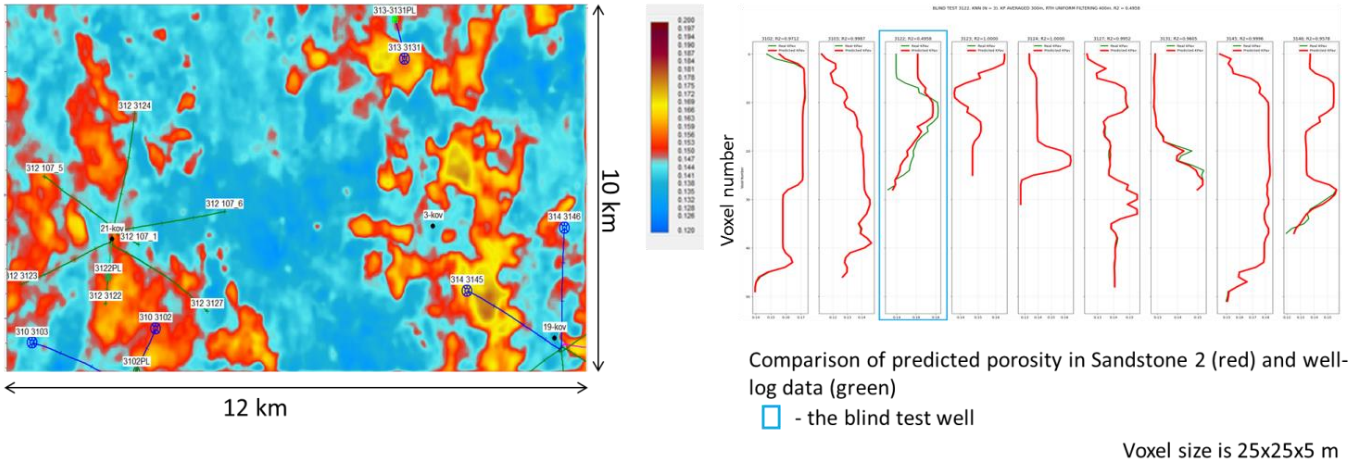


Figure 5. Porosity prediction in Sandstone based on RTH attributes and well-log data

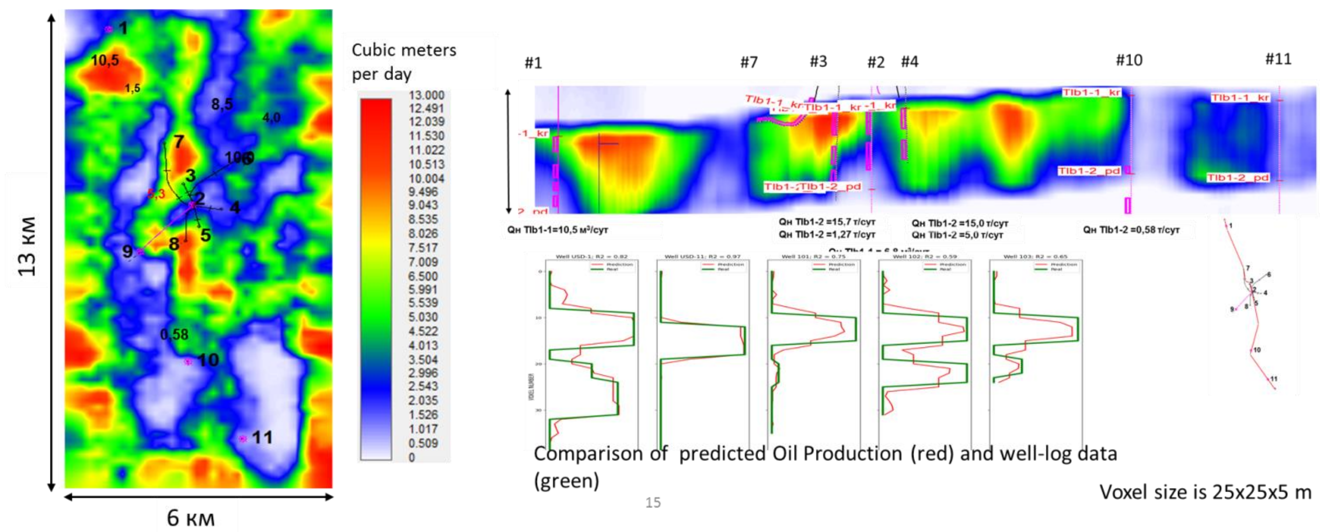


Figure 6. Prediction of Oil Production in Target Horizon

Discussion

Each step of the prediction approach described above, of course, needs to be tested for different geoscience conditions. Next, regarding the computational aspect of the RTH prediction. The choice of voxel size is very important, since the total volume of RTH attributes calculations depends on it. After all, all attributes are calculated for each individual voxel. To do this, a set of tasks is formed that are executed simultaneously on different computing cores of the supercomputer. The higher the detail (the greater the number of voxels), the more computing cores need to be used in calculations. The latter affects the cost of calculations. However, on the other hand, a large number of voxels affects the stability and precision of the prediction (see strategy in Fig. 3). An important step in preparing data for prediction by ML is also the selection of the optimal set of "significant" attributes for a given specific task. This affects the learning speed of the neural network. The fewer attributes, the higher the learning rate. Optimization of all calculations in RTH approach using neural networks on graphics accelerators is the further path of necessary research.

Conclusions

A new technology for processing and interpreting seismic data, called RTH, allows us to assess the geological structure of the Earth at a new qualitative level and so helps to optimize exploration and development costs. RTH technology aggregates many approaches into one, thereby sharply reducing the costs of using set separate specialized programs. In addition RTH approach dramatically increases the spatial resolution of seismic attributes. It turned out that the inherent RTH hyper-attributability and voxel-based orientation is the key advantage of the new approach to solving problems of geological prediction using artificial intelligence methods and well data. The paper present the results of using RTH approach for processing and interpreting 3D seismic data, as well as for geological prediction based on it for a number of oil and gas fields.

References

Alkhalifah, T., 2015, Scattering-angle based filtering of the waveform inversion gradients. *Geophysical Journal International*, 200, 363–373, http://dx.doi.org/10.1093/gji/ggu379.

Baysal, E., D. D. Kosloff, and J. W. C. Sherwood, 1983, Reverse time migration. *Geophysics,* 48, 1514–1524, https://doi.org/10.1190/1.1441434

Chopra and Castagna, AVO, 2014, Publisher*: Society of Exploration Geophysicists* , pp. 304

Erokhin G., Reverse Time Holography Approach based on the Vector Domain Common

Image Gathers, 2019. *SEG Technical Program Expanded Abstracts* 2019: 4107-4111.,

https://doi.org/10.1190/segam2019-3201622.1

Erokhin Gennady, 2022, Time-dependent scattering in reverse time holography method, *83rd EAGE Annual Conference & Exhibition*, Jun 2022, Volume 2022, p.1 – 5 https://doi.org/10.3997/2214-4609.202210094

Koren Z., Ravve I, 2011, Full-azimuth subsurface angle domain wavefield decomposition and imaging Part 1: Directional and reflection image gathers. *Geophysics*, 76, S1-S13.

Kremlev, A.N., G. N., Erokhin, L. E. Starikov, and S.V. Rodin, 2011, Fracture and cavernous reservoirs prospecting by the CSP prestack migration method. *73th Conference & Exhibition*, EAGE, Extended Abstracts, B024

McMechan, G. A., 1983, Migration by extrapolation of time-dependent boundary values: *Geophysical Prospecting*, 31, 413–420, doi: 10.1111/ j.1365-2478.1983.tb01060.x.

Popovici A., Tanushev N.and Hardesty S. 2016, High-resolution, wide-azimuth beam tomography for velocity model building: SEG Technical Program Expanded Abstracts 2016, P.5349 -5353

Tarantola, A., 1984, Inversion of seismic reflection data in the acoustic approximation. *Geophysics,* 49, 1259–1266. http://dx.doi.org/10.1190/1.1441754

Virieux, J., and Operto, S., 2009, An overview of full-waveform inversion in exploration geophysics. *Geophysics*, 74, WCC1–WCC26. http://dx.doi.org/10.1190/1.3238367

Whitmore, N. D., 1983, Iterative depth migration by backward time propagation. *53th Annual International Meeting, SEG,* Extended Abstracts,382–385.

Yoon, K., and K. J. Marfurt, 2006, Reverse-time migration using the Poynting vector. *Exploration Geophysics*, 37, 102–107.