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ИНВЕРСИЯ ДАННЫХ ИНДУКЦИОННОГО КАРОТАЖА НА ПРИМЕРЕ СТРУКТУРЫ С УГЛОВЫМ НЕСОГЛАСИЕМ

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Неструктурные ловушки и края резервуара характеризуются угловыми несоответствиями. Угловое несогласие между наклонно залегающим пластом и субгоризонтальным водонефтяным контактом распространено на месторождениях Северного моря. В настоящей работе представлен подход к инверсии данных индукционного каротажа в режиме реального времени для сценария с угловым несоответствием. Подход использует искусственные нейронные сети для расчета сигналов в параметрических задаваемых поверхностями 2D геоэлектрических моделях. Рассматривается параметрическая модель с двумя непараллельными границами, подходящая для сценариев с угловым несоответствием и выклиниваем. Обучение нейронных сетей для этой параметрической модели выполняется на основе базы данных, содержащей экземпляры с параметрами модели и соответствующими им сигналами. Нейронные сети являются ядром 2D инверсии, основанной на оптимизационном методе Левенберга-Марквардта. Чтобы продемонстрировать применимость подхода и сравнить с результатами 1D инверсии, в синтетической 2D модели анализируются сигналы приборов дальнего и ближнего действия. Показано, что 1D инверсия определяет либо позицию водонефтяного контакта, либо структуру наклонных слоев. В тоже время 2D инверсия дает возможность корректно восстановить расположение непараллельных границ. Производительность 2D инверсии, основанной на нейронных сетях, позволяет применять ее в режиме реального времени.

Ключевые слова: индукционный электромагнитный каротаж, нейронные сети, 2D геоэлектрические модели, угловое несогласие, нейронные сети, интерпретация данных

LWD DATA INVERSION FOR STRUCTURE WITH ANGULAR UNCONFORMITY

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Non-structural traps and reservoir flanks are characterized by angular unconformities. Angular unconformity between dipping formation and sub-horizontal oil-water contact is common in the North Sea fields. This paper presents an approach to real-time inversion of LWD resistivity data for the scenario with angular unconformity. The approach utilizes artificial neural networks (ANNs) for calculating the tool responses in parametric surface-based 2D resistivity models. We propose a parametric model with two non-parallel boundaries suitable for scenarios with angular unconformity and pinch-out. Training of ANNs for this parametric model is performed using a database containing samples with the model parameters and corresponding tool responses. ANNs are the kernel of 2D inversion based on the Levenberg-Marquardt optimization method. To demonstrate applicability of our approach and compare with the results of 1D inversion, we analyze Extra Deep Azimuthal Resistivity tool responses in a 2D synthetic model. It is shown that 1D inversion determines either the position of the oil-water contact or dipping layers structure. At the same time, 2D inversion makes it possible to correctly reconstruct the positions of non-parallel boundaries. Performance of 2D inversion based on ANNs is suitable for real-time applications.

Keywords: resistivity logging, neural networks, 2D resistivity model, angular unconformity, pinch-out, data interpretation

Introduction

The number of wells planned in the reservoir flanks, in the water-oil zone, is increasing. In these cases, there may be an angular unconformity between reservoir top and bottom or the reservoir top and fluid contact. Such geological features cause high uncertainty in geological modeling, depending on the available geological data and the depth of their analysis. Inversion of electromagnetic logging data helps to reduce geological uncertainties and make the optimal decision on well placement while drilling.

Usually, the scenarios typical for a particular field are known from the structural maps and offset wells. In addition to the above-mentioned cases of angular unconformity and pinch-out, sub-vertical faults and formation faults may occur. Each of these special cases can be described by a specific subclass of parametric 2D models. The use of 2D models for describing the resistivity distribution in the medium is more appropriate. At the same time, the calculation of the tool responses in such model is timeconsuming. All known methods for solving Maxwell's equations (integral equations [1, 2], finite difference method [3], volume integral equations [4], etc.) have close performance. Calculation of all tool responses for a 10 m trajectory interval by any of these methods takes a few minutes on a desktop computer. For comparison, in the case of a 1D layered model, this takes about 1 ms.

In this paper, as in earlier works [5, 6], we approach the problem of acceleration of the 2D solver based on data science methods. The approach consists of choosing a parameterization of the geologic formation, preparing a database consisting of pairs of model parameters and tool responses, training ANNs and using these ANNs for fast calculation of tool responses for a particular model. Database is generated using rigorous solver [1, 2]. Acceleration of database generation and training of neural networks is done on CPU and GPU clusters. High performance of ANN solver is achieved by parallelizing computations based on OpenMP and MKL libraries.

In the first work in described direction [5], a method for accelerating the 2D solver using neural network approximation was presented. A fault model with nine parameters was taken with the strike axis perpendicular to the curtain section with some additional restrictions. The volume of the database providing sufficient accuracy was about 10^4 samples. The speed of the obtained neural network solver is of 1 μs order that exceeds the speed of the solver for the 1D layered model. In [6], the same approach was applied to a three-layer model with a wall, where the orientation of the strike axis is arbitrary. The volume of the database had increased to 10^6 samples.

In this paper, we continue to develop our approach for another subclass of 2D models that describes angular unconformity. Here, as in [6], the strike axis can be oriented arbitrarily with respect to the well trajectory. The angular unconformity model has less parameters than the model in [6], but their ranges are wider; therefore, the sizes of databases are approximately the same (about 10^6 samples).

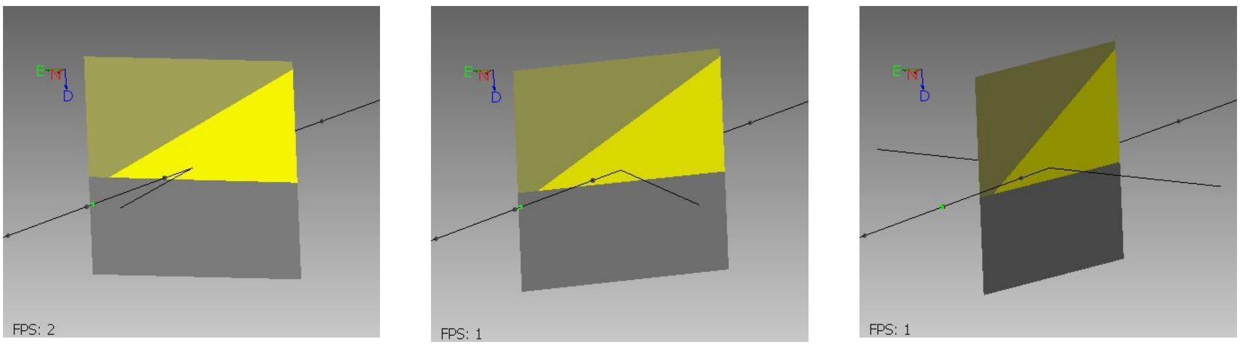


Fig. 1. The 2D model with three layers and two nonparallel boundaries used for inversion. Three different orientations of the strike axis are shown

Table 1

Parameters of the 2D model and their ranges

Parameter	**Ranges**	**Units**
Boundary dips θ_1, θ_2	$0:360$	degree
Distances d_1,d_2	$-45:45$	meter
Resistivities ρ_1, ρ_2, ρ_3	$0.6:2000$	$\mathrm{Ohm}\cdot\mathrm{m}$
Roll ψ, azimuth φ	$0:360$	degree

Resistivity model

We consider the 2D parametric model with two non-parallel boundaries suitable for scenarios with angular unconformity and pinch-out (Fig. 1). The model is defined in the model plane and has the strike axis. The position of boundaries are determined by the (signed) distance to the origin and the dip angle. For database generation used for ANN training, the tool is located at the origin and may rotate around its axis by the *roll* angle ψ and by the *azimuthal* angle φ. The seven parameters of the 2D model plus two angles responsible for orientation of the tool constitute the nine parameters of the problem (see Table 1). The parameter units given in Table 1 are used throughout the paper.

Tools. We perform simulation for tools providing multiple and azimuthal propagation resistivity (MPR & APR) and extra deep bulk and azimuthal resistivity (EDAR) measurements [7, 8]. The tools are schematically presented in Fig. 2.

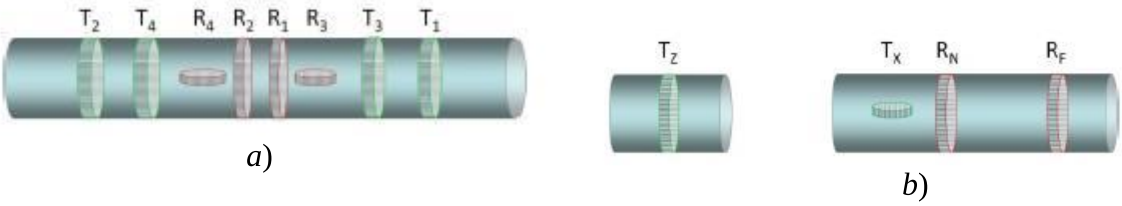


Fig. 2. Layout of tools: *a*) MPR & APR, *b*) EDAR

ANN solver. The approximation of the tool responses is built using feedforward networks with several hidden layers. Each hidden layer contains several tens of neurons. We use a separate ANN to approximate the individual tool response. The input network layer is formed by nine model parameters. All parameters, except the resistivities, go to the input unchanged. The latter, in turn, are preliminarily converted into real parts of the wavenumber corresponding to the operation frequency of the response. The output of ANN is the final tool response.

The databases required for training are generated with distributed computations using the in-house solver described in [1, 2]. Separate databases with several hundred thousands of samples are built for the azimuthal and co-axial tool responses at each frequency. By a sample we mean a vector of the model parameters and the corresponding vector of co-axial or azimuthal tool responses. The vectors of the parameters of the model are generated randomly according to predetermined distributions that take into account the peculiarities of the problem. Network training was conducted by using the Levenberg-Marquardt optimization algorithm implemented in in-house Python-based library.

Inversion Algorithm. In 2D inversion, we search for the model parameters that minimize the difference between the synthetic and measured signals. Generally speaking, we search for the minimum of the objective function

$$f(p) = \sum_{m=1}^{M}\sum_{i=1}^{I}\frac{|s_{mi}^{sim} - s_{mi}^{meas}|^2}{\sigma_{mi}^2} + \alpha\sum_{j=1}^{N}|p_j - p_j^{exp}|^2$$

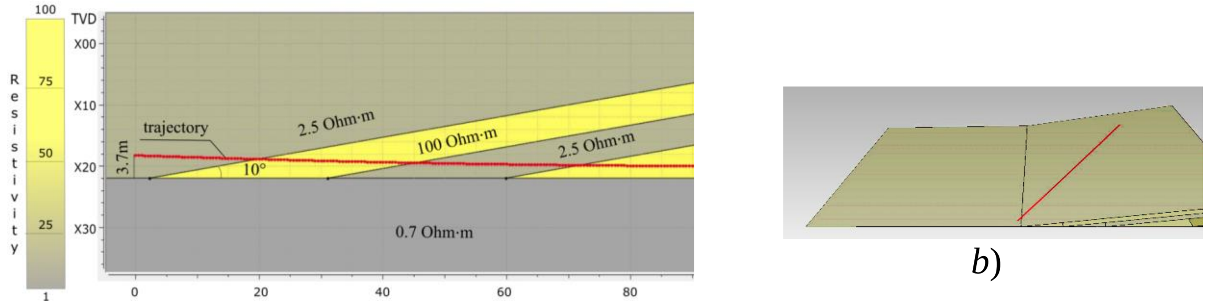
In the expression above $p = (p_1, \dots, p_N)$ are the model parameters, s_{mi}^{sim} and s_{mi}^{meas} are the i^{th} synthetic and measured signals at the m^{th} measure point, σ_{mi} is the measurement error of the i^{th} signal at the m^{th} point composed of the absolute and relative errors, p^{exp} are the parameters of the expected model, and α is the stabilization parameter responsible for the proximity of the sought model to the expected model.

We optimize the model parameters using the Levenberg-Marquardt optimization algorithm, using it interval-by-interval. Each parameter may be fixed or searched for within predefined limits. To reach global minimum, we usually make about a thousand of optimization iterations each starting from a random initial guess. Typical computation time for 1000 optimizations is about 4 minutes in non-parallelized version. So actually instead of hours we need minutes or less for real-time 2D inversion.

First, we try to match the data with 1D layered model. Then we switch to 2D model if any of following “non-1D” indicators are observed: a) the data match is poor; b) the resulting models on the neighboring intervals are inconsistent; c) the azimuthal measurements deviate from “up” or “down” and point to different directions. The resulting 1D layered models and 2D models can be combined all together into the curtain section if necessary.

Numerical Test with 2D Synthetic Model. To test our approach we consider scenario with oil-water contact in dipping formation. The model is presented in 2D curtain section below (Fig. 3). Trajectory, which is represented by red line in Fig. 3a, is 200 m long. It is located 2 m above oil-water contact (OWC). The true dip of layers above OWC is equal to 10 degrees. The water zone has resistivity of 0.7 Ohm·m, dipping layers have alternating resistivity of 100 Ohm·m and 2.5 Ohm·m. The angle between horizontal projection of the trajectory and the strike axis is equal to 30 degrees. A similar case with dipping formation was considered in [9].

To simulate synthetic tool measurements for that model the method described in [1] is employed. Normally distributed random noise with dispersion equal to one standard measurement error is added to each measurement to more realistically represent field data.



a)

Fig. 3. 2D Synthetic Model – *a*) 2D curtain section view, *b*) 3D view

EDAR and APR measurements on a 200 m interval along the trajectory are shown in Fig. 4. Let us look at the EDAR measurements. The dots show the direction to an excess of conductivity usually referred to as 'target direction'. Similarly to borehole images, the top and bottom of the track correspond to borehole top, while the middle of the track corresponds to borehole bottom. There are sections where measurements deviate from strictly "up" or "down" directions. One can note that different measurements point to different directions. Such behavior is an indicator of "non-1D" environment.

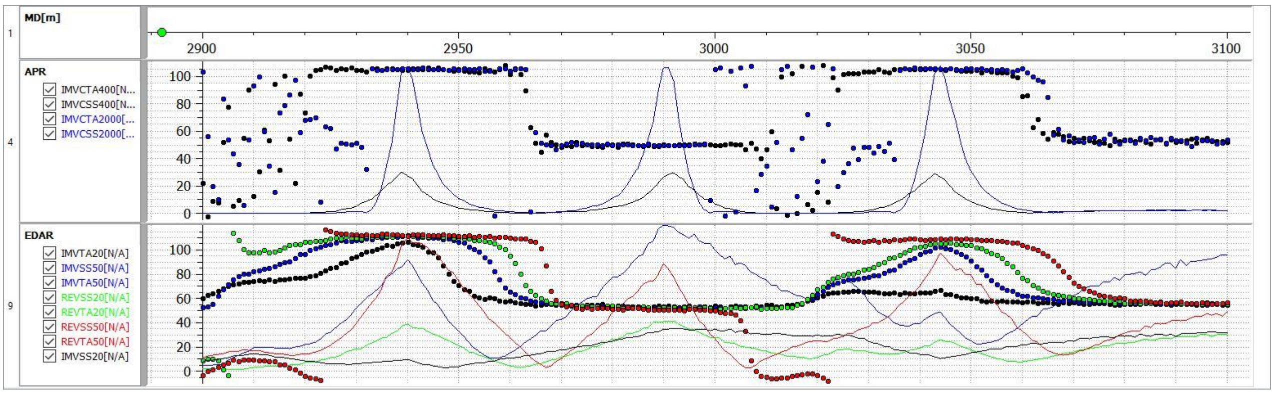


Fig. 4. EDAR and APR measurements. The solid lines are the signal strength in relative scale from 0 to 100, the dots show the target angle direction.

The results of the 1D inversion on this interval using algorithm described in [10-12] are displayed in Fig. 5. In synthetic case we have a priori information that the layer-cake model will have contradiction in boundary orientation due to fact that the OWC and layer boundaries have different dip. This fact explains why 1D layered model cannot accurately model this case.

Although the model has only three layers, it is sufficient to produce a consistent model with good data match. The biggest discrepancy is observed along the 3025-3050 m interval, where an additional layer is needed. The reconstructed OWC surface is continuous and has nearly zero dip. From Fig. 6 it becomes clear how the formation structure is arranged, what angles it has, in which direction relative to the structure the well trajectory goes, and how it intersects each layer.

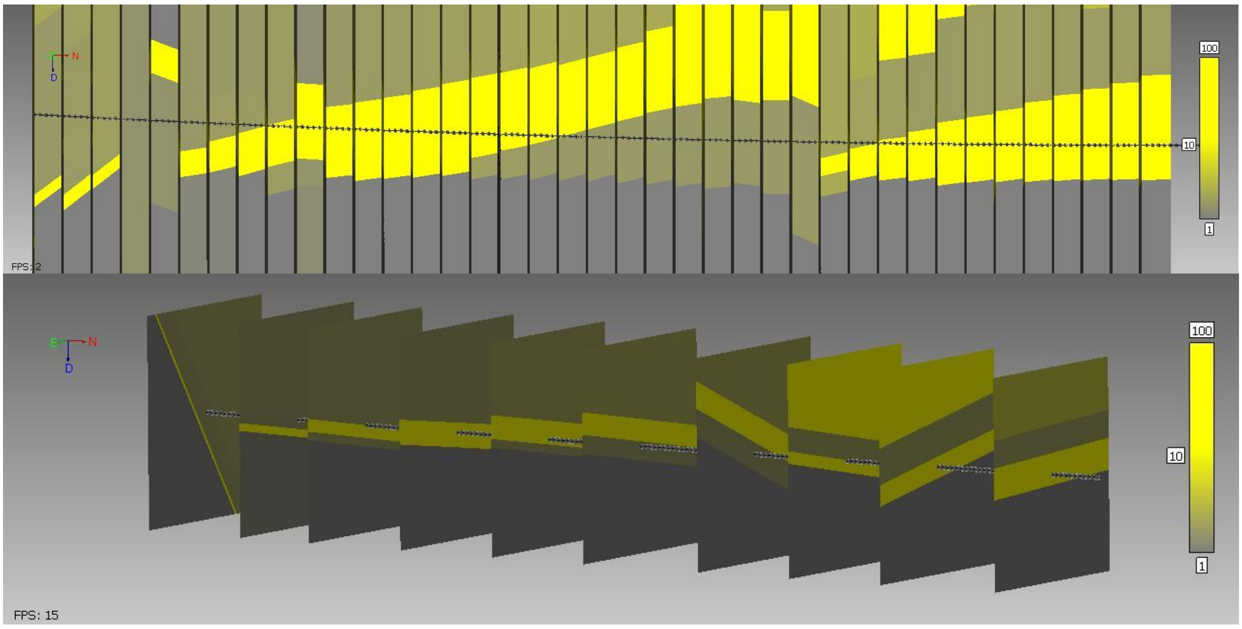


Fig. 5. The 1D inversion results with transverse views every 20 m

Fig. 6 and Fig. 7 show results of the 2D inversion and data match. APR and EDAR measurements are shown in relative scale from 0 to 100.

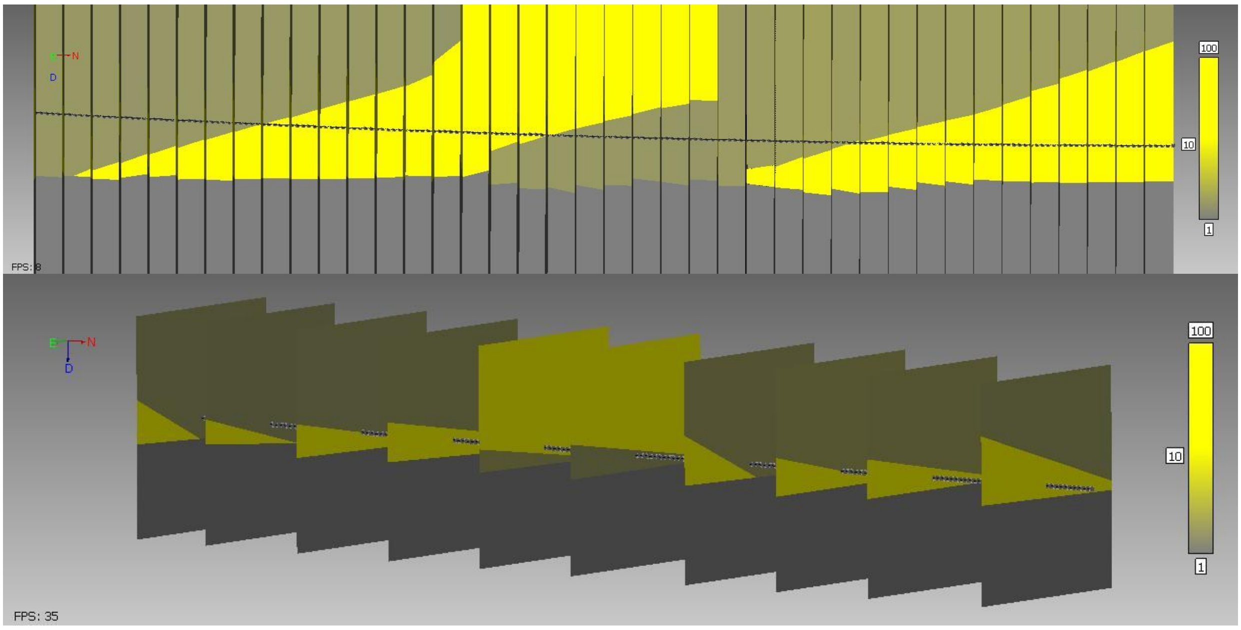


Fig. 6. The 2D inversion results with transverse views every 20 m

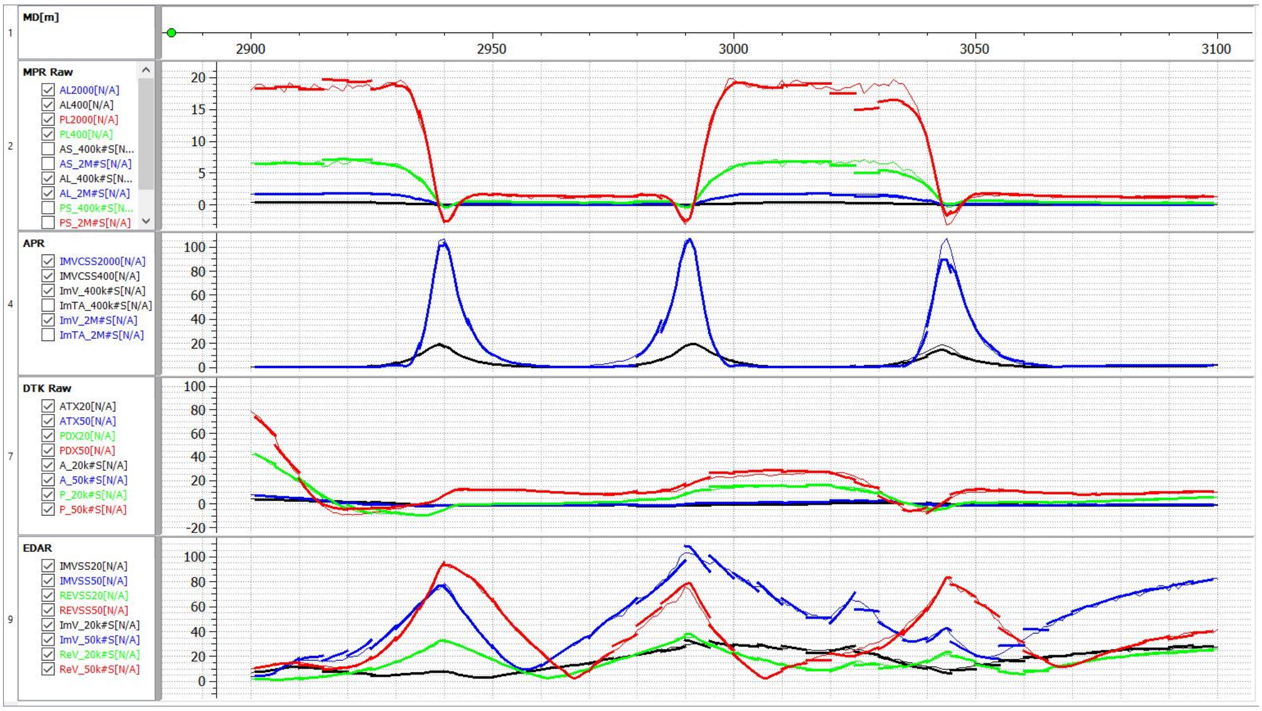


Fig. 7. The measured and synthetic data match for 2D inversion.
The thin lines are measured data, and the bold lines are synthetic tool responses

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Summary. We compare the interval-by-interval 1D multi-layer inversion and interval-by-interval 2D inversion for the parametric model with two non-parallel boundaries on the synthetic dataset generated for the angular unconformity scenario. In this scenario in view of 1D layered model limitations, 1D inversion cannot reconstruct OWC and layers as seen in the transverse planes. 2D inversion on most intervals provides match of all data including azimuthal measurements and makes it possible to obtain laterally consistent results both in the curtain section and in the transverse planes. The results of 2D inversion can be used for estimation of the OWC position and the true dip and dip azimuth of the layers. The developed 2D inversion algorithm based on ANN forward modeling demonstrates performance and accuracy that are sufficient for real-time applications.

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