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ОЦЕНКА РАССТОЯНИЯ ДО ГРАНИЦЫ ПЛАСТА ПО ДАННЫМ ИНДУКЦИОННОГО КАРОТАЖА НА ОСНОВЕ НЕЙРОННЫХ СЕТЕЙ

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Оценка расстояния до ближайшей границы пласта во время бурения упрощает проводку наклонно-направленных скважин. Для оценки этого расстояния предлагается подход поточечной инверсии данных индукционного каротажа на основе двухслойной геоэлектрической модели пласта с использованием нейронных сетей. Параметры модели определяются с помощью каскада нейронных сетей по набору измерений прибора. Первая сеть вычисляет удельное сопротивление слоя, содержащего точку записи прибора. Последующие сети принимают в качестве входных данных набор измерений прибора и параметры модели, определенные с помощью предыдущих сетей. Все сети обучаются на одной и той же синтетической базе данных. База данных состоит из множества пар, содержащих вектор параметров модели и вектор соответствующих зашумленных измерений прибора. Результаты предлагаемого подхода близки к результатам общего алгоритма инверсии, основанного на методе наиболее вероятной комбинации параметров. В то же время предлагаемый подход работает на несколько порядков быстрее.

Ключевые слова: нейронные сети, нелинейная аппроксимация, инверсия данных индукционного каротажа, двухслойная геоэлектрическая модель пласта, расстояние до границы пласта

NEURAL NETWORK INVERSION OF RESISTIVITY DATA FOR DETERMINATION OF DISTANCE TO A BED BOUNDARY

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Accurate real-time estimation of a distance to the nearest bed boundary simplifies the steering of directional wells. For estimation of that distance, we propose an approach of pointwise inversion of resistivity data using neural networks based on two-layer resistivity formation model. The model parameters are determined from the tool responses using a cascade of neural networks. The first network calculates the resistivity of the layer containing the tool measure point. The subsequent networks take as input the tool responses and the model parameters determined with the previous networks. All networks are trained on the same synthetic database. The samples of that database consist of the pairs of model parameters and corresponding noisy tool responses. The results of the proposed approach are close to the results of the general inversion algorithm based on the method of the most-probable parameter combination. At the same time, the performance of the proposed inversion is several orders faster.

Keywords: neural networks, nonlinear approximation, inversion of resistivity data, two-layer resistivity model, distance to bed boundary

Introduction. Detecting and imaging of bed boundaries is one of the main challenges of reservoir navigation. Propagation resistivity tools provide early detection capabilities and sufficient depth of investigation for proactive geosteering decisions. Fast and accurate calculation of distances to bed boundaries in real time helps quickly estimate the position of the tool relative to the target zone and make wellpath adjustments.

Azimuthal propagation resistivity tool, in addition to coaxial coils, has a transmitter-receiver pair where the transmitter is aligned with the axis of the drill collar and the receiver is perpendicular to it. This arrangement has sensitivity both to resistivity contrast and direction of a bed boundary. Distance to the nearest bed boundary can be directly estimated using three to four tool responses including the azimuthal measurement in the way that is described in the paper [1]. Traditional processing based on multi-parametric user-guided inversion with gradient convergence algorithm [2] performs rigorous scanning of the parameter space to match the modeled and the measured data but takes more time.

Recently, artificial neural networks (ANN) and machine learning have been increasingly used to solve various computational geophysics problems. In particular, approximation of resistivity tool responses by neural networks for 1D multi-layer and 2D models are described in the works [3-5]. In several publications, ANNs are applied directly for inversion of resistivity measurements [6]. However, the authors note that the inverted models are often inaccurate compared to the reference model.

We propose an ANN-based approach to estimate the parameters of two-layer resistivity model of the environment from the resistivity tool responses. The set of neural networks trained to estimate the parameters uses the responses of the tool as input.

Neural networks are applied sequentially taking into account the previous estimated parameters of the model and forming a cascade ANN block. Such a scheme makes it possible to increase the accuracy of inversion and reduce the equivalence of the model parameters.

Tool Description. To test the proposed approach, we perform an inversion of deep azimuthal propagation (DAR) tool responses [7]. The tool has six coaxial coils T1 – T4, R1 and R2 and two coils R3 and R4 transverse to the tool's axis. Here T1 – T4 are transmitters and R1 – R4 are receivers. We have selected a typical six-measurements subset used in practice for inversion. The subset includes four bulk and two azimuthal measurements. The bulk measurements are attenuation (al400, al2m) and phase difference (pl400, pl2m) measured at 400 kHz and 2 MHz. The azimuthal measurements (imvc400, imvc2m) are compensated imaginary parts of induced voltage measured at 400 kHz and 2 MHz.

Model description. A two-layer model of the medium is described by the layer resistivities ρ_1, ρ_2, the coordinate Z of the bed between the layers relative to the tool measure point (MP) and the tool dip angle θ (see Figure 1). The ranges of the specified parameters are 0.1-1000 Ohm·m for ρ_1 and ρ_2, 0.2-5 m for Z, and 60-120 deg for θ. The tool MP can be located in any of two layers. The pointwise inversion allows determining all of the listed parameters with the exception of the dip angle.

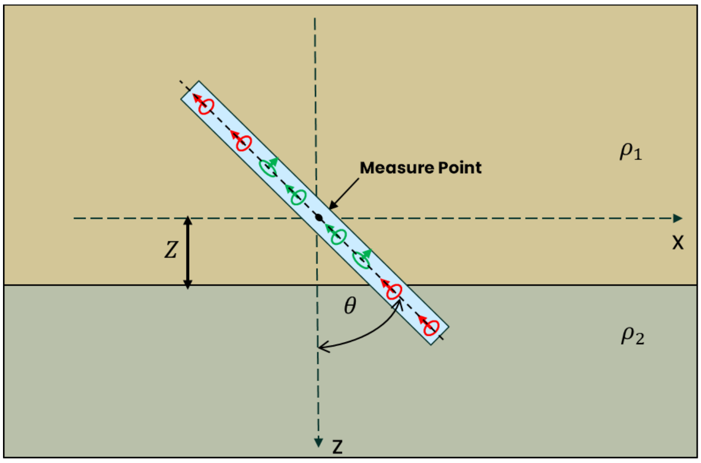

Fig. 1. Two-layer model of the medium with the tool.

Neural networks training. The synthetic database for ANNs training contains several hundred thousand samples. Each sample includes a randomly generated vector of model parameters and the corresponding vector of tool responses. To ensure successful ANN training and make the approach applicable to the real field data, the database has to be preprocessed. We add noise to the vectors of tool responses and also mark model vectors that appear to represent homogeneous models that are particular case of two-layer model. The database formed in this way is used to train a set of feedforward ANN-based classifiers and approximators applied in inversion. The methodology of training feedforward artificial neural networks is described in [8-9].

Cascade ANN inversion block. The proposed approach is based on the cascade ANN inversion block described below. In the environment model used by this block, the tool MP can only be in the upper layer. The block contains three pre-trained neural networks used as approximators. The first network converts the tool responses into the conductivity of the first layer. Further, the obtained conductivity σ_1 is added to the first ANN input and the resulting extended vector of parameters is converted by the second network into the distance to bed Z. In the same way, the output of the second network is added to its input and the resulting vector of parameters is converted by the third network into the conductivity of the second layer σ_2 (see Figure 2). If the tool responses are measured in a layered medium with more than two layers, the block outputs the parameters of an equivalent two-layer model. In the case when the responses are received in a homogeneous medium, the conductivity of the medium σ_1 defined using the first ANN of the cascade inversion block. At the end, the obtained conductivities are recalculated into the resistivity of the layers and together with the distance to the boundary Z go to the block output.

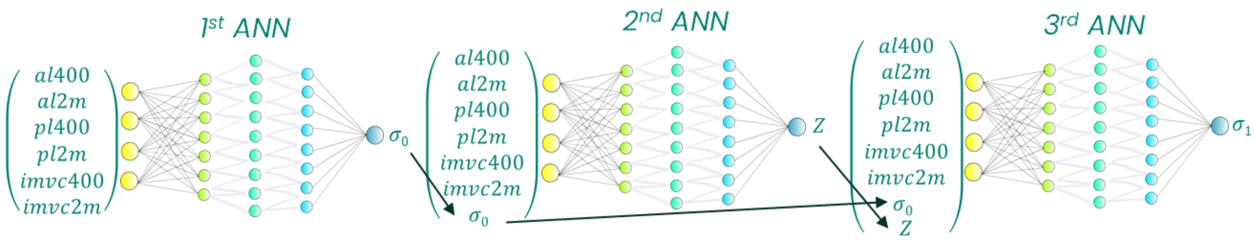

Fig. 2. Flowchart of the cascade ANN inversion block.

Classifier-based inversion. As mentioned above, the cascade inversion block works correctly in a layered medium represented by an equivalent two-layer model with the tool MP located in the first layer. To be applied in real-world conditions, the cascade block should be built into an extended inversion algorithm, which involves the passage of the tool through a homogeneous medium and both layers of a two-layer medium. Below is a description of such extended inversion algorithm in which, in addition to the cascade block, we use two classifier networks. The first classifier indicates whether the tool responses are obtained in a homogeneous medium or in a layered one. The second indicates the index of the layer in which the tool is located in the equivalent two-layer model. We call this approach as classifier-based and the detailed flowchart is shown in Figure 3.

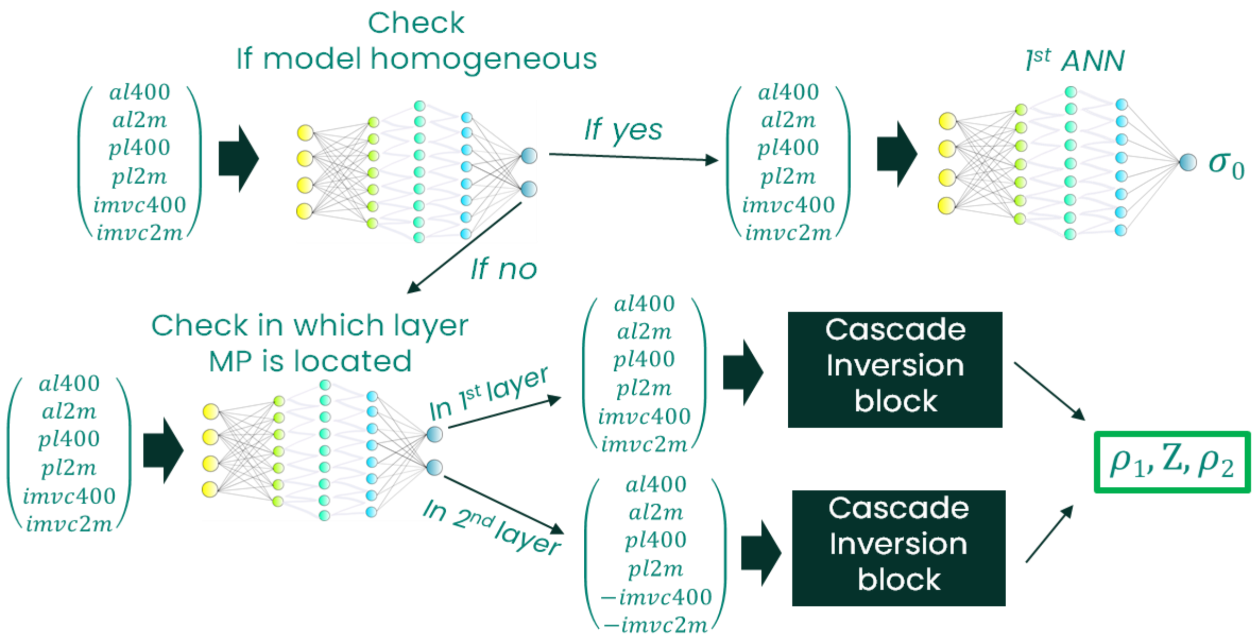

Fig. 3. Flowchart of the classifier-based inversion.

The inversion of the tool responses at each particular point of the log is carried out in several steps:

1. The tool responses go to the input of the classifier, which determines whether the tool is in a homogeneous or layered medium.
2. If the tool is in a homogeneous medium, its conductivity is calculated using the first network from the cascade inversion block and the inversion ends there.
3. If the tool is in a layered medium, the responses go to the input of the second classifier, which determines in which layer of the equivalent two-layer model the tool is located.
4. If the tool is in the second layer, then the responses are pre-converted to the equivalent position of the tool in the first layer using the symmetry of the model.

Then the responses pass to the input of the cascade inversion block and are converted into environmental parameters.

Results. To compare the results of the described ANN inversion with general inversion [Sviridov et al., 2014], a realistic synthetic model was built. Figure 4 shows the case containing the reservoir with a layered structure in which layers of low resistivity alternate with layers of high resistivity, wellpath and corresponding noisy DAR responses.

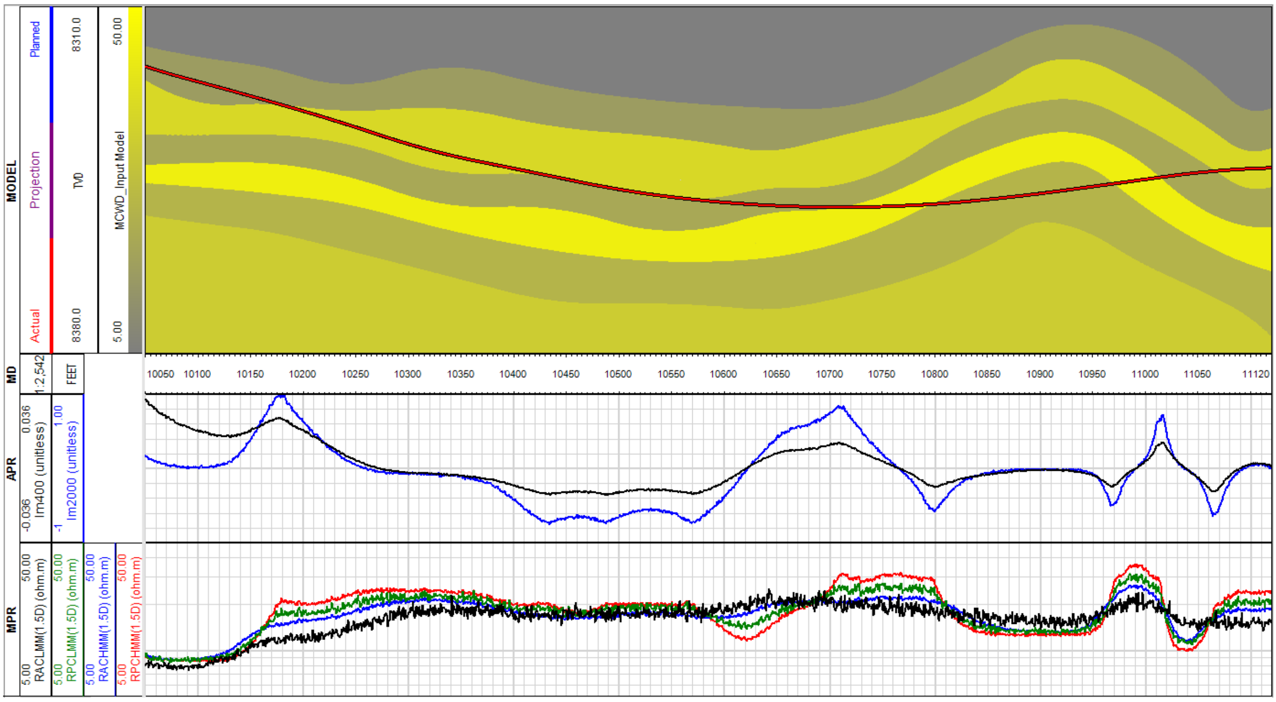

Fig. 4. Synthetic model consisting of seven layers with thicknesses smoothly varying along the well path (red line) at the first track from the top, measured depth in feet on the second track, dimensionless azimuthal measurements of DAR on the third track, and apparent resistivity based on axial measurements of DAR on the fourth track.

We apply three approaches of point-by-point inversion using a two-layer resistivity formation model. The first is the proposed ANN inversion, the second is the general inversion, and the third is the combination of the first and second. In the last case of the combined inversion ANN inversion result is passed as an expected model and initial guess of the general inversion, and the final model at each point is improved with the single gradient descent. Figure 5 shows the results of three approaches with misfit indicators. Misfit is defined as the root mean square difference between the reference responses and the responses in the inverted model.

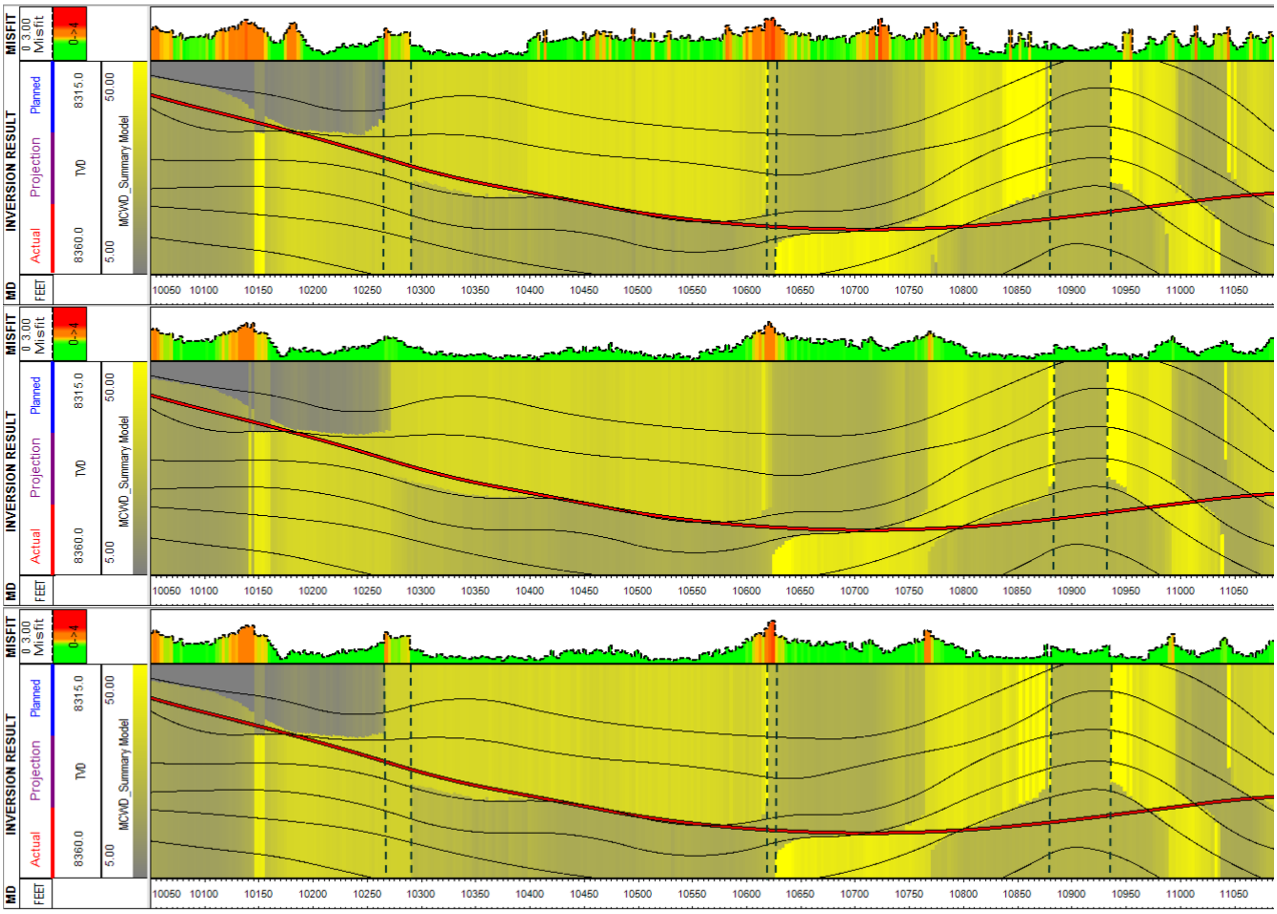

Fig. 5. The results of three approaches separated by blank lines. The ANN inversion results are at the top, the general inversion – at the center, the combined inversion – at the bottom. Each picture is accompanied by the misfit track at the top and the measured depth track at the bottom. Thin solid lines on the inversion results show the boundaries of the reference model, and dashed lines indicate homogenous models.

All three inversion results show similar pictures with the distances to the nearest boundaries that practically coincide with the reference reservoir model (black lines). In practice, the presented results would make it possible to understand the structure of the reservoir near the trajectory and help in geosteering well path adjustments. However, at some intervals with high misfit value an inversion with three layers is preferable (for example, 10000-10160, around 10275, around 10625, around 10770, and around 11000).

The ANN inversion has a slightly larger misfit at most points and identifies the homogeneous environment at a greater number of intervals. The combined inversion improves data match of the ANN inversion to the values compared with that of the general inversion results (see misfit tracks) except for the intervals identified as the homogeneous model. Typical computational times of the presented results are about of 1 millisecond per point for the ANN inversion, 1 second for the general inversion, and 20 milliseconds for the combined inversion.

Conclusions. We proposed a new ANN-based approach for resistivity data inversion. The approach is developed for two-layer resistivity formation model and tested on the synthetic example. The results of ANN inversion are close to the ones given by the general inversion algorithm. At the same time, the ANN-based approach is several orders faster. ANN inversion result can be used as a good initial model for a general gradient-based inversion algorithm for its acceleration. The proposed approach assumes processing of tool responses only, and no user input is required.

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