Russian Geology and Geophysics © 2019, V.S. Sobolev IGM, Siberian Branch of the RAS
Vol. 60, No. 11, pp. 1319–1325, 2019 DOI:10.15372/RGG2019134 *Geologiya i Geofizika*

Automatic Detection of Geoelectric Boundaries According to Lateral Logging Sounding Data by Applying a Deep Convolutional Neural Network[1]

G.N. Loginov✉, A.M. Petrov

A.A. Trofimuk Institute of Petroleum Geology and Geophysics, Siberian Branch of the Russian Academy of Sciences, pr. Akademika Koptyuga 3, Novosibirsk, 630090, Russia

Received 8 November 2018; received in revised form 2 March 2019; accepted 22 May 2019

Abstract—Lateral logging sounding (LLS) is currently the only widely used Russian method of resistivity measurements, sensitive to vertical electrical resistivity in vertical wells. However, interpreting data measured by this method in thin-layered sections is difficult and requires the utilization of resource-intensive numerical simulation algorithms. Today, the development of computational methods and an increase in computer performance allow us to invert LLS data in the class of two-dimensional axisymmetric models. However, in virtue of the large number of difficulties associated with the nonlocal responses of the probes and their asymmetry, this process requires the active participation of a log analyst. One of the first issues is the creation of an initial approximation of the geoelectric model. It consists in splitting the target interval into layers within which the properties of the medium can be considered constant in the vertical direction, since LLS signals have a very complex shape in the intervals of alternation of beds with different resistivities. We propose applying a fully connected convolutional artificial neural network to automatically create sectional layering suitable for constructing the initial approximation of the geoelectric model for two-dimensional LLS data inversion, including vertical resistivity estimation. The neural network was trained and tested on the synthetic and field data measured in West Siberia. Based on the results of the testing, we established the workability of the proposed approach.

Keywords: lateral logging sounding, boundary detection, two-dimensional inversion, machine learning, artificial neural networks, convolutional neural networks

INTRODUCTION

Currently, due to the complexity of interpretation in a thin-layered section, the lateral logging sounding method (LLS) is progressively less used to evaluate electrical resistivities of the reservoirs. However, an increase in computing resources of today's computers and the development of efficient algorithms for numerical simulation of logging signals make it possible to perform LLS data inversion in the class of two-dimensional axisymmetric models. Such an approach naturally takes into account the influence of the boundaries on the signal shapes and allows the parameters of low-thickness formations to be estimated, which is almost impossible when using interpretation charts. Moreover, two-dimensional LLS data inversion enables determining vertical resistivity. It is because the signals substantially depend on the resistivity anisotropy of a reservoir near its boundaries or even below its bottom (Sukhorukova et al., 2017). LLS is the only method of resistivity measurements widely used in Russia, which is sensitive to vertical resistivity and may now be a reasonably good alternative to significantly more complex three-component induction logging tools. As early as since the 1950s, this method has been included into the obligatory Russian logging complex for oil and gas wells. Therefore, at present, large datasets of the archive materials are available for processing and reinterpretation. Thus, the results of LLS data interpretation are a source of independent reliable information on the resistivity anisotropy of rocks when constructing detailed geoelectric models.

Despite the success in the express-simulation of the signals, the process of two-dimensional LLS data inversion at the moment requires the active participation of a log analyst. The inversion automation is associated with a considerable number of methodic and algorithmic problems, the first of which is the creation of an initial approximation of the geoelectric model. The numerical simulation algorithms mainly employ piecewise-constant partitioning of the medium. Consequently, to create the approximation, it is necessary to divide the target interval into the layers within which resistivity can be considered constant in the vertical direction.

The selection of horizontal boundaries in a geological section with the aim of identifying homogeneous in properties intervals is a classical subtask of well logging data interpretation. Today, there is a wide range of algorithms for automatic bed-boundary resolution, using data from various

[1]This paper was translated by the authors.

✉Corresponding author.
E-mail adress: LoginovGN@ipgg.sbras.ru (G.N. Loginov)

methods or sets of methods (e.g., (Maiti and Tiwari, 2005; Berdov et al., 2012)). Most of them are based on gradient or dispersive approaches. However, they are not applicable to LLS, as far as all the probes are asymmetric. LLS logs are characterized by a complex asymmetric shape, which depends on the formation thickness, resistivity contrast between the formation and the host rocks, and on the borehole parameters. The transition of the gradient sondes through the formation boundaries is marked by extremal values on the apparent resistivity logs. This fact greatly simplifies their selection. Apart from that, in sections with the alternation of rocks differentiated by resistivity, a large number of extremums not connected with boundary crossing appear on the logs. It does not allow them to be used directly as indicators of the boundaries. The discreteness of the depth readings and measurements shifts the positions of the extremums and decreases their values. The effect of vertical resistivity also changes the shape of the logs when approaching anisotropic formations. Thus, on the one hand, for the LLS method it is difficult to formulate a reliable formal criterion for selecting the boundary. On the other hand, omitting a thin but electrically contrasting layer, which is a characteristic error of the gradient and dispersion methods, can critically affect the inversion results.

Currently, artificial neural networks and machine learning are widely used in geophysical data processing and interpretation. For example, for the joint correlation of logging and seismic data (Haris et al., 2018), selection of geological objects in seismic images (Zhang et al., 2018) and acceleration of the direct and inverse LLS problems (Agbash and Sobolev, 2016).

In this investigation, for detecting boundaries from LLS data we apply a fully connected convolutional neural network.

ARTIFICIAL NEURAL NETWORK ARCHITECTURE

The choice of a neural network architecture is determined by the following key factors: the type of the problem to be solved (regression, classification, forecasting); type and size of input data (digital signals, images, etc.); functional limitations (accuracy, operating speed). The problem of detecting boundaries is reduced to a binary classification of each LLS measurement by depth into two classes: boundary and nonboundary (True/False). It should be noted that in the general case positions of the boundaries do not coincide with these of the measurement points. That is, when using this approach, positions of the boundaries are determined with an accuracy of half of the discretization step only. Nevertheless, this accuracy is sufficient to create a starting model for the two-dimensional inversion, since present-day algorithms specify the positions of the boundaries in the signal fitting process.

The type of problem to be solved mainly affects the form of an optimized objective function. The input data are readings of the several probes (usually no more than 6). In this work, only signals of the gradient sondes are used, since the design of a potential sonde leads to a different form of signals when crossing the boundaries, and to low resolution. This may adversely affect the operation of the algorithm. During the inversion process, measuring intervals of different lengths along the borehole can be analyzed. Therefore, from the point of view of functional limitations, we should point out the need to organize the network architecture without reference to a specific record length. Thus, taking into account the data type, the most reasonable way is to use convolution as the kernel of training operators.

The basic elements of an artificial neural network architecture are layers and neurons. The number of layers and neurons in most cases is responsible for the regularization of the problem solution and is established experimentally. A separate network layer consists of neurons, each of which is responsible for the selection of a certain “abstract” characteristic (Goodfellow et al., 2016). By convolutional neural network training is meant the learning or optimization of filters for input data, which best distinguish the features required to solve the classification problem. The learning process is the minimization of the cost functional L between the initial data markup y and the neural network results p:

$$L = -y\,log\left(p\right) + \left(1-y\right)log\left(1-p\right), \qquad (1)$$

where $p \in \left[0,1\right]$ is the probability of belonging to the class True (boundary presence), and y = 0 or 1.

Currently, a lot of research has been done on the use of various neural network architectures in computer vision tasks. We applied a fully connected convolutional neural network (FCCNN) of various configurations. The results of their application are compared using the ROC (Receiver Operating Characteristic) curve and the pivot table of accuracy. The FCCNN architecture implies that each neuron of each layer is connected to all neurons on the next and previous layers.

The neural network training was carried out utilizing the Adam (Adaptive Moment Estimation) method (Kingma and Ba, 2014), which practically does not require complicated adjustment and is widely employed in training neural networks.

TRAINING SAMPLE AND TRAINING PROCESS

To solve the problem of automating the selection of the boundaries by the means of a convolutional neural network, models are needed that contain horizontal boundaries between layers with all types of radial structure. In earlier studies, the signal equivalence from various models was evaluated. It was found that the approximation of a radial resistivity change by a piecewise-constant profile has almost

Table 1. Parameters of synthetic models of Western Siberia terrigenous deposits

No.	Lithotype	Invasion zone		Resistivity annulus		Bed
		Resistivity, Ohm·m	h, m	Resistivity, Ohm·m	h, m	Resistivity, Ohm·m
1	Oil-saturated sandstone	15–30	0.2–0.7	–	–	16–30
2	Oil-water-saturated sandstone	15–30	0.2–0.6	3–6	0.1–0.25	7–20
3	Water-saturated sandstone	12–20	0.2–0.7	–	–	3–8
4	Carbonatized sandstone	–	–	–	–	$\rho_h = 20–500/\lambda = 1–1.2$
5	Argillaceous deposits	–	–	–	–	$\rho_h = 3–8/\lambda = 1–3.5$
6	Anisotropic sandy-argillaceous reservoir	*	*	*	*	*

*Parameters of anisotropic sandy-argillaceous reservoirs were determined by the formulas for the alternation of sandy (No. 1–3) and argillaceous (No. 5) deposits (Hagiwara, 2013).

no effect on the shape of the signals when crossing the boundaries, even with a rough partition of the reservoir zones into the invasion zone, resistivity annulus and undisturbed formation (Petrov et al., 2017). Another important parameter is the thickness of the layers: gradient sondes are unfocused, and the enclosing rocks strongly influence readings of the long probes. That is, the smaller the characteristic thickness of the layers, the more difficult the task of identifying horizontal boundaries, so when simulating the signals for the training sample, we used small thicknesses. The situation is further complicated by the well-known influence of resistivity anisotropy on the shape of LLS signals when crossing the boundaries (Fitch, 1982).

The artificial neural network training was conducted on synthetic LLS signals of the SKL-76 complex (Kayurov et al., 2015) and field signals of the SKL-76 and K1A-723 (Scientific and Production Commercial Firm “Geofizika”, Ufa) complexes. All the data were presented with a measurement sampling step of 0.2 m by depth. The training was conducted in two stages. At the first stage, we utilized synthetic LLS signals of the SKL-76 complex, calculated using a finite element algorithm of the AlondraWL software package (Sukhorukova et al., 2017), taking into account the borehole effect and displacement of the conductive mud by the tool. Five randomly generated models of the medium each contained 500 layers (total thickness from 400 to 650 m) corresponding to resistivities of Western Siberia terrigenous deposits (Table 1). The parameters of the layers within lithotypes are uniformly distributed. The thicknesses of the layers are distributed lognormally with a 0.15 m shift. The detection of interlayers with a thickness less than the discretization step does not seem possible, but they may be

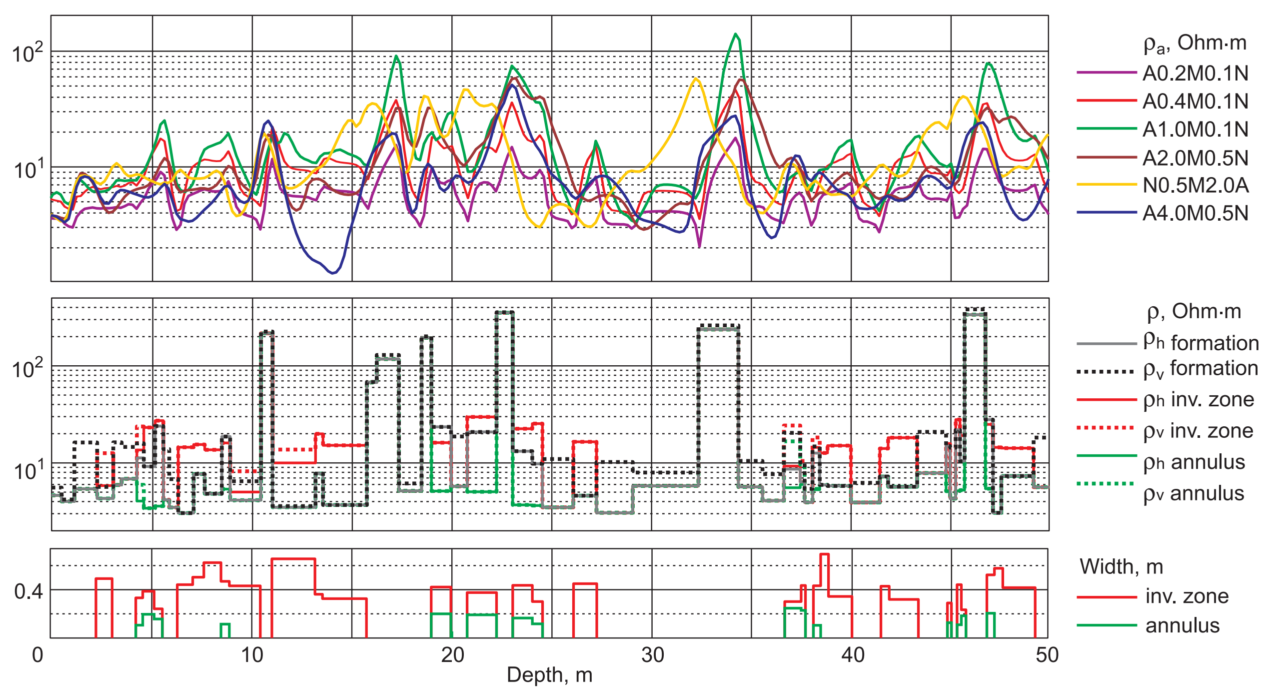

Fig. 1. Fragment of the model of terrigenous deposits and the corresponding LLS signals.

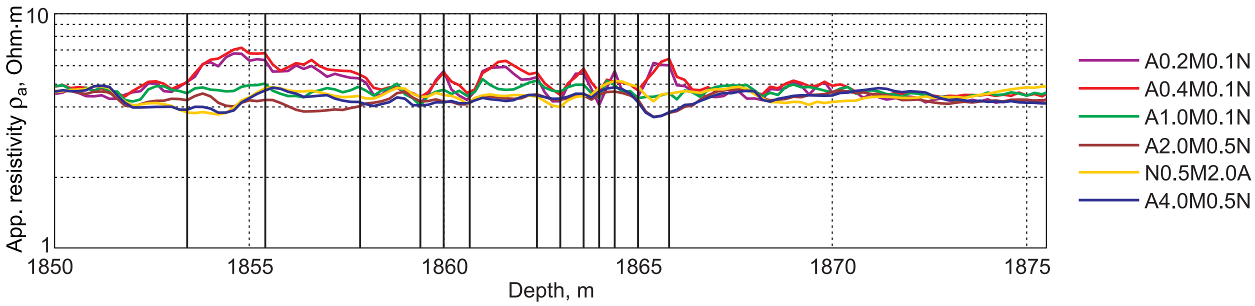

Fig. 2. Example of a segment of the field LLS logs measured at the Fedorov field and used for the network training.

present in the section during the field measurements. Therefore, in order to make the sample closer to the data recorded in practice, interlayers with a thickness less than the discretization step were added to the synthetic models. Adding such thin layers can be considered as additional noise in data.

The models differ in the distribution of layer thicknesses, ratio of the number of layers from different lithotypes and drilling mud resistivity. The division into lithotypes is conditional: the differentiation of sediments according to LLS data is possible only by the resistivity value and type of its radial change. For that reason, the models used should be regarded as geoelectric: they describe well the most probable signal shapes near the boundaries between different terrigenous rocks but are not a lithological description of the section. A fragment of the model and an example of synthetic LLS signals is shown in Fig. 1.

To create the training sample, segments of LLS logs and the corresponding positions of the boundaries were formed randomly from the synthetic and field data. The boundary resolution for the field LLS measurements was carried out according to data from a set of borehole electromagnetics. The total number of the field data used was 1 km (5000 depth readings). The segments formed from one model could partially overlap. The training sample comprised 4000 examples of the registered LLS signals and corresponding boundaries, 64 readings each. An example of such a segment is shown in Fig. 2. The number of readings in the training samples was chosen experimentally. At the input of the neural network, the data were entered on a logarithmic scale; no additional processing or scaling was performed. As a result of applying the neural network to the input data, the probability of boundary presence was assigned to each depth sample. Since we use the convolutional model of a neural network, this allows the trained model to be applied to the data of arbitrary length.

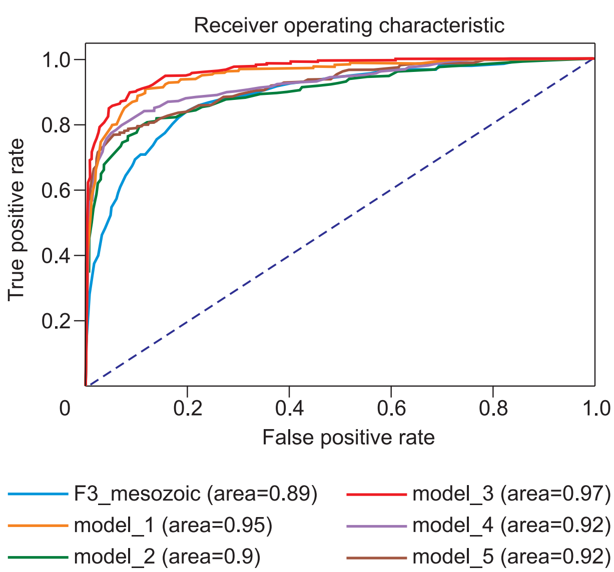

Fig. 3. ROC curves of applying the convolutional fully connected neural network for different synthetic models of the borehole environment (model_1–model_5) and the field data. The legend shows the area under the ROC curve.

To select the optimal parameters of the neural network, a series of experiments was carried out. The experiments consisted in the selection of the optimal number of layers, length and number of filters. Table 2 presents a comparative analysis of the operating quality of the trained neural networks on the full available set of the model and field data, consisting of 17,000 measurement points by depth. For most machine learning methods and neural networks in particular, the choice of performance metrics is not obvious, so the table shows 3 metrics by which one can evaluate the effectiveness of the proposed approach: the residual, the area under the ROC curve and the minimum accuracy for all the considered test models. The accuracy is the percentage of correct answers in relation to the total number of examples. This approach to the analysis of the results in Table 2 was chosen in order to determine the minimum threshold of the working efficiency for different sections.

Based on the results of the experiments, we chose a neural network of four layers with 16 filters, each 32 readings long. It should be noted that in the case of the simulated data, the accuracy averaged above 90%, whereas on the field data it could be about 60%. This result, among other things, is associated with a high degree of ambiguity in the detection of the boundaries from the field data. In such a way, the accuracy metric can be significantly reduced if the neural network detects the boundary in the adjacent reading from the one specified by the log analyst. Obviously, in practical use of the algorithm, this effect will not matter.

Table 2. Results of experiments on the choice of the neural network parameters

Number of filters/filter length	3 layers	4 layers	5 layers	6 layers
16/16	89.4/66.4	87.9/60.9	87.9/67.9	89.4/66.1
16/32	88.9/60.9	91.9/64.2	85.4/60.2	90.0/65.3
32/16	87.0/60.4	83.1/59.2	77.3/51.2	75.7/51.4
32/32	87.2/61.4	80.8/58.9	77.9/53.8	75.1/56.5

Note. The cells indicate the area under the ROC curve and the accuracy.

The trained neural network was applied to each borehole model separately. The main criterion for the success of the trained neural network was the area under the ROC curve for various borehole environment models (Fig. 3). The ROC curve demonstrates the sensitivity of the true positive (True, boundary presence) algorithm responses to its false positive responses. The true positive response is the case when the algorithm correctly indicates the boundary position. The false positive response is when the algorithm indicates the presence of a boundary where there is none. The vertical axis shows the percentage of the true correct answers, while on the horizontal one is the percentage of the false correct answers. The speed of the true positive responses is the ratio of the true positive responses to the total number of the positive values (True, boundary presence). Similarly, the speed of the false positive responses is the ratio of the false positive responses to the total number of the negative values (False, boundary absence).

For the synthetic data (model_1–model_5), the area under the curve is at least 90%, which corresponds to the high

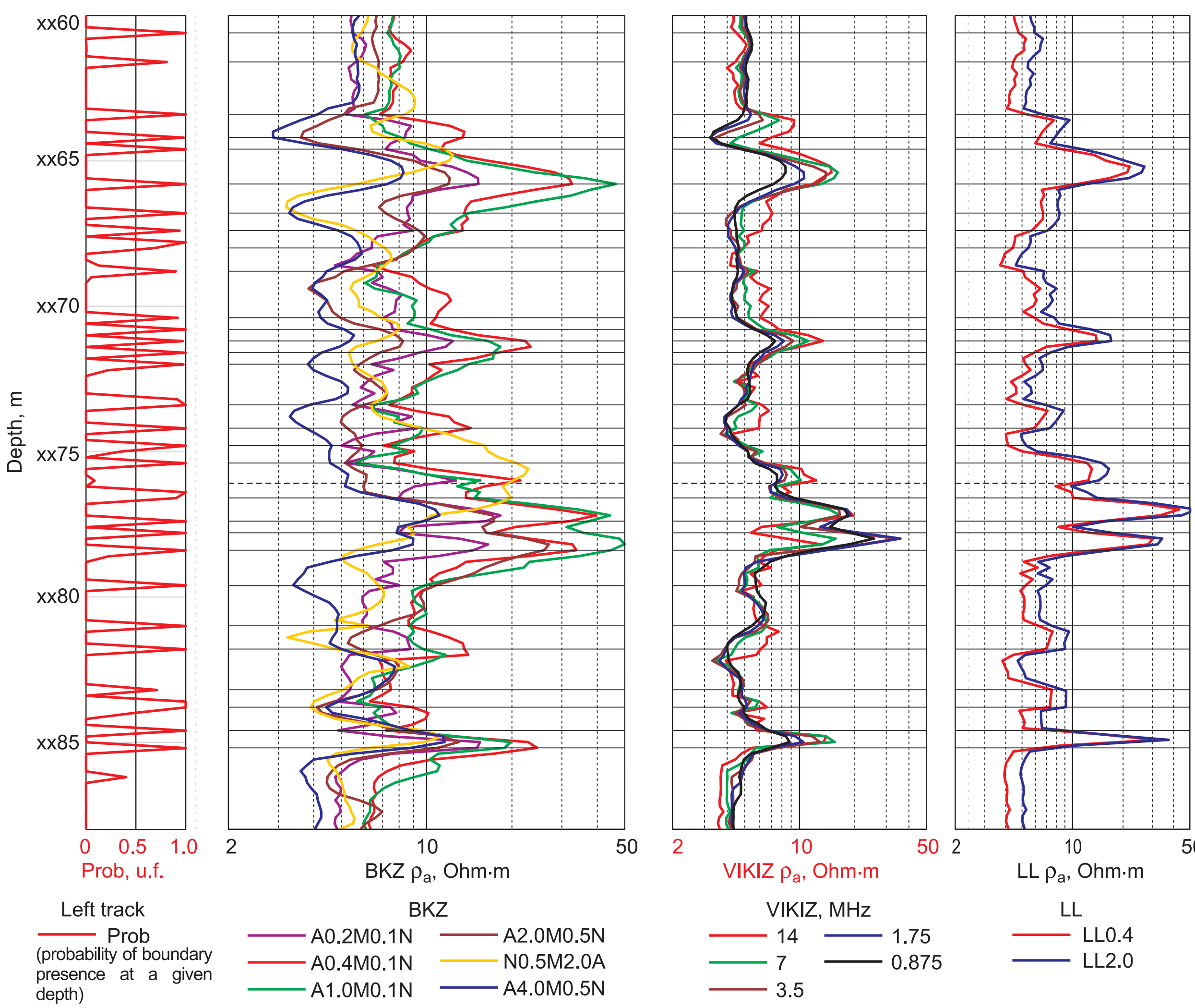

Fig. 4. Result of employing the algorithm to the field data measured at the Russkin field. The solid gray horizontal lines show the geoelectric boundaries detected by the algorithm. The dotted line shows the boundary missed by the algorithm.

accuracy of the algorithm. For the field data from the Fedorov field (F3_mezozoy), the area is 89% of the maximum possible area under the ROC curve, which also demonstrates the high reliability of the proposed approach.

RESULTS AND DISCUSSION

The trained neural network was tested on model and field data. Fig. 4 shows the results of testing the algorithm on the field data measured at the Russkin field. The comparison of the detected boundaries with the data of high-frequency isoparametric induction logging sounding (HIILL) and lateral logging (LL) shows the workability of the proposed approach.

However, in this example we can distinguish the missing boundary (shown by the dotted line) and ambiguous operation on the interval with a smooth change in electrical resistivity with depth (xx70–xx72 m). Under such conditions, the algorithm approximates the smooth change by a fairly frequent piecewise-constant partition. This behavior can be either true, since most of the existing LLS inversion algorithms are based on piecewise-constant parameterization of the medium or lead to the selection of too thin layers where this is not necessary.

In the training sample, an emphasis is placed on the alternating intervals of thin enough interlayers, since it is these sections that are most difficult for manual selection of the boundaries, and two-dimensional inversion is necessary for the correct reconstruction of their parameters. To extend the applicability of the algorithm and improve its accuracy, it is desirable to increase the representativeness of the training sample with examples of the signals measured in different geological conditions. The considered neural network architecture does not require large computational resources for training. This allows one to perform training again or to conduct additional training to adapt to specific geological conditions or an oilfield.

It ought to be remarked that in relation to field data in the sections where the change in electrical resistivity in the vertical direction can differ from piecewise-constant, the very concept of a horizontal boundary is not always fully applicable. The result of the work of the developed algorithm is the probability of finding the boundary at each depth; its conversion into sectional layering is performed using the threshold coefficient. Therefore, the question of the correctness of the boundary selection in one or another case will always depend on the opinion of a particular log analyst. However, even in the most difficult environments with thin lamination or gradient resistivity change by depth, manual work is reduced to correcting a relatively small number of errors made by the algorithm, based on the analysis of probability values. Compared to the manual boundary selection, it significantly speeds up the process and minimizes errors in complex sections.

CONCLUSIONS

We developed an algorithm for automatic detection of geoelectric boundaries according to LLS data, on the basis of a fully connected convolutional neural network. The algorithm was trained on synthetic and field LLS data typical of terrigenous deposits of Western Siberia, including those corresponding to measurements on anisotropic intervals. The algorithm is capable of distinguishing in the section both rather thick layers and thin but electrically contrast interlayers. Accordingly, its usage allows generating the layering of a complex section, which is applicable for the two-dimensional data inversion with minimal participation of a log analyst. It is significant that the calculation of the neural network results does not require considerable computational resources and time. In addition, the neural network employment does not require to carry out preliminary data preparation: the algorithm can work with raw measurements in the .las format.

The algorithmic part of the study was carried out with the financial support of the Russian Foundation for Basic Research in the framework of the research project No. 18-35-00412. The methodic part of the study and the training sample formation were conducted with the support of the Fundamental Scientific Research project No. 0331-2019-0014 'Borehole geophysics in conductive anisotropic dispersing media, based on high-performance solutions of three-dimensional problems, high-precision logging data and laboratory core studies'.

REFERENCES

Agbash, I.A., Sobolev, A.Yu., 2016. Fast analogues of direct and inverse problems of Russian laterlog by neural network technology, in: Proc. XII Int. Sci. Congr. "GEO-Sibir'-2016" (Novosibirsk, 18–22 April 2016) [in Russian]. SGUGiT, Novosibirsk, pp. 196–200.

Berdov, V.A., Vlasov, A.A., Lapkovskii, V.V., 2012. Detection of reservoir boundaries in well profiles according to the well log via Petrel, in: Proc. VIII Int. Sci. Congr. "GEO-Sibir'-2012" (Novosibirsk, 10–12 April 2012) [in Russian]. SGGA, Novosibirsk, pp. 76–80.

Fitch, A.A., 1982. Developments in Geophysical Exploration Methods–3. Applied Science Publishers, Elsevier.

Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning, Vol. 1. MIT Press, Cambridge,

Hagiwara, T., 2013. Macroscopic anisotropy at multiple scales, in: Transactions of the SPWLA 54th Annual Logging Symposium (New Orleans, 22–26 June 2013). Paper CCCC, https://www.onepetro.org/conference-paper/SPWLA-2013-CCCC.

Haris, A., Murdianto, B.S., Sutattyo, R., Riyanto, A., 2018. Transforming seismic data into lateral sonic properties using artificial neural network: a case study of real data set. Int. J. Technol. 9 (3), 472–478.

Kayurov, K.N., Eremin, V.N., Petrov, A.N., Suhorukova, K.V., Nikitenko, M.N., Arzhantsev, V.S., 2015. SKL hardware systems for logging in oil-gas wells and its interpretation base. Neftyanoe Khozyaistvo, No. 9, 38–43.

Kingma, D.P., Ba, J.A., 2014. A method for stochastic optimization. arXiv Preprint 15, 1412.6980. https://arxiv.org/abs/1412.6980.

Maiti, S., Tiwari, R.K., 2005. Automatic detection of lithologic boundaries using the Walsh transform: A case study from the KTB borehole. Comp. Geosci. 31 (8), 949–955.

Petrov, A.M., Sukhorukova, C.V., Nechaev, O.V., 2017. Possibilities and limitations of LLS at determining the parameters of anisotropic axisymmetric models of medium, in: Proc. XIII Int. Sci. Congr. "GEO-Sibir'-2017" (Novosibirsk, 17–21 April 2017) [in Russian]. SGUGiT, Novosibirsk, pp. 181–186.

Sukhorukova, K.V., Petrov, A.M., Nechaev, O.V., 2017. Numerical inversion of electric logs in anisotropic clay sediment intervals. Karotazhnik, No. 4 (274), 34–48.

Zhang, G., Wang, Z., Chen, Y., 2018. Deep learning for seismic lithology prediction. Geophys. J. Int. 215 (2), 1368–1387.

Editorial responsibility: I.N. El'tsov