Introduction

Nowadays, Machine Learning (ML) is actively used in geophysics including seismic exploration. This study focuses on the applicability and feasibility of Deep Learning for the inverse problem for seismic exploration, which is the estimation of the rock-physics parameters for a fractured reservoir from seismic data.

The main goal of this paper is to prove the efficiency of a neural network in estimating fractured medium parameters, represented as anisotropy parameters of HTI model. As such parameters, we consider the normal and tangential weaknesses of fractures $\Delta N$ and $\Delta T$ (e.g. Bakulin et al., 2000), the Thomsen anisotropy parameters $\varepsilon, \delta, \gamma$ (Thomsen, 1986), as well as the crack density and the aspect ratio (crack opening). Of particular interest is the consistency validation of the parameters predicted by our neural network in comparison with those estimated by analytical formulae (Bakulin et al., 2000). In doing so we use different mathematical formulae, which relate the considered parameters estimation to different effective-medium anisotropy models of a fractured medium, such as Schoenberg's Linear Slip model (Schoenberg, 1980), Hudson's model for penny-shaped cracks (Hudson, 1981) and Thomsen's model for aligned cracks in porous rock (Thomsen, 1995).

Fractured-reservoir characterization is very important in seismic exploration, since the presence of a network of fractures contributes to oil recovery. In the study we deal with mesofractures (e.g. MacBeth, 1995). Mesofractures play a large role in the production of hydrocarbons in tight low-porous rocks with poor permeability. In conducting this study, we relied on its possible practical application in the oil and gas industry. Therefore, such parameters as the depth of the fractured formation, aspect ratio of the fractures, their crack density and others (Table 1) were chosen as plausibly as possible (e.g., Leviant at al., 2019, and Bakulin et al., 2000).

In our study, seismograms of both the vertical $U_Z$-component and the horizontal $U_X$ are the inputs for the developed neural network. At the output, the network predicts fracture parameters and anisotropy parameters. The neural network is trained on synthetic seismograms of reflected waves, which were generated using 2D-elastic numerical finite-difference modelling by Tesseral Pro.

Seismic Modelling

The model consists of two horizontal layers. The isotropic layer lies above the anisotropic. The lower (anisotropic) layer is transversely isotropic (HTI) with a horizontal axis of symmetry due to the presence of aligned vertical fractures. The interface between the two layers lies at a depth of 2400 m. The thickness of the second layer is 600 meters. Input parameters in the upper layer: compressional wave velocity $V_{P1} = 4500 \text{ m/s}$, shear wave velocity $V_{S1} = 2500 \text{ m/s}$, and rock density $\rho_1 = 2500 \text{ kg/m}^3$; in the lower layer: $V_{P2} = 5000 \text{ m/s}$, $V_{S2} = 2750 \text{ m/s}$, $\rho_2 = 2550 \text{ kg/m}^3$. The entire model (its computational domain) has dimensions $4000m \times 3000m$. A source of “expansion type” emits P-wave signal in the form of a Ricker wavelet of a frequency of 25 Hz; the source is located on the earth's surface with coordinates $x = 0$ and $z = 0$.

In the interval (0m, 4000 m) there are 80 geophones set by 50 m step; the first receiver and the source are located at the same point. This model is used as a basic model for generating synthetic seismograms implemented for ML training. For each individual task (Table 1), 1100 models were created, including 800 of them involved in the ML-training set, and 300 models in the ML-testing set. In each model, the fracture parameters (given in Table 1) are varied randomly. Each seismogram generated separately for each model has 80 seismic traces, which correspond to 80 receivers (as shown in Figure 1). Each trace consists of 750 time samples, time step is 4 ms, and the time interval is (0; 3000 ms).

To train the neural network (see Figures 2 and 3), we take the records of the reflected PP- and PS-waves, that is, the events from the time interval from 1000 ms to 2000 ms (Figure 1). Each common-shot-point gather is converted using the ObsPy Python library to an 80x250 matrix (80 traces and 250
time samples in 4 ms steps). Then the centering and normalization processing of the matrix rows is carried out. Each model is assigned two matrices: one of the vertical $U_Z$-component and the other of the $U_X$ (horizontal component). For the neural network, this will correspond to two channels.

**Figure 1** Typical example of synthetic common-shot-point gather generated for the ML training. (a): Model with cracks (the HTI layer) with the fracture weaknesses $\Delta_N = 0.502$, $\Delta_T = 0.177$, and the dip angle $\beta = 5^\circ$. (b): Model without cracks, $\Delta_N = 0$ and $\Delta_T = 0$. The event with the direct P-wave was intentionally removed, since it has too large amplitudes and prevents the analysis of the target reflected waves from the top of the fractured layer (the PP-wave and the converted PS-wave). Therefore, only a truncated time interval is shown (from 1000 ms to 2000 ms).

**Figure 2** Neural network’s blocks.

**Figure 3** Neural network structure. $N$ is the dimension of the output space $\mathbb{R}^N$. 
Neural network structure

The neural network consists of two types of blocks, which for convenience we will call Conv and FC. The Conv block consists of a convolutional (two-dimensional) layer, followed by the activation function ReLU and batch normalization. The FC block consists of a fully connected layer and Tanh activation function (hyperbolic tangent), as shown in Figure 2.

Figure 3 shows the structure of the neural network containing the convolutional layer parameters as well as the data dimensions. The loss function optimized by the training algorithm is the mean square error (MSE Loss). The optimization method is Adam (Adaptive Moment Estimation) with the following parameters: learning rate = $3.0 \times 10^{-4}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$. The training took place in 200 epochs and with a batch size of 100.

Results

Table 1 shows the list of tasks including the fracture parameters estimated in each task.

<table>
<thead>
<tr>
<th>Task</th>
<th>Description</th>
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<tr>
<td><strong>Task A</strong></td>
<td>Normal and tangential weaknesses of fractures $\Delta_N$ and $\Delta_T$ that characterize one system of vertical fractures.</td>
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<tr>
<td><strong>Task B</strong></td>
<td>Two systems of fractures — two pairs of weaknesses: $(\Delta_{N1}$ and $\Delta_{T1})$ and $(\Delta_{N2}$ and $\Delta_{T2})$. (Orthorhombic model.)</td>
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<td><strong>Task C</strong></td>
<td>Extended set of input parameters: $\Delta_{N1}$, $\Delta_{T1}$, $\Delta_{N2}$, $\Delta_{T2}$ and $\beta_1$, $\beta_2$, where $\beta_1$, $\beta_2$ are dip angles for each fracture system (vary in the range from -90° to 90°, where the positive direction corresponds to the clockwise).</td>
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<tr>
<td><strong>Task D</strong></td>
<td>Thomsen parameters for a Saturated (oil and/or water) model ($\delta(V)$, $\gamma(V)$, $\varepsilon(V) = 0$), as well as crack density $e$.</td>
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<tr>
<td><strong>Task E</strong></td>
<td>The same ($\delta(V)$, $\gamma(V)$, $\varepsilon(V)$) but for a Dry model (e.g., cracks filled by gas).</td>
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<tr>
<td><strong>Task F</strong></td>
<td>Thomsen’s model with aligned cracks in porous rock (Thomsen, 1995). Estimation of $\Delta_N$, $\Delta_T$, as well as the crack density and the crack aspect ratio $\alpha$ (the crack opening).</td>
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</table>

For Tasks A, and D-F, we use the neural network shown in Figure 3. For better results in tasks B and C (two fracture systems), the structure of the neural network was slightly changed to increase its capacity: one Conv and one FC blocks were added, and the number of channels was increased (4-6-2 vs. 6-8-6-4). Our neural network provides quite accurate results. Relative error in estimating each parameter for the tasks listed in Table 1 (including one or two fracture systems) doesn’t exceed 1-2% and 2-4%, respectively. The neural network also well restores the relationships between the parameters, e.g. the fracture weakness $\Delta_N$, $\Delta_T$ and the crack density $e$, given by the simple analytical equations (Bakulin et al., 2000): $\Delta_T = 16e[3(3-2g)]$, and $\Delta_N = 4e[3g(1-g)]$ (that is the case of dry cracks in the Linear Slip model). In that case, the relative error doesn’t exceed 1-2%. In addition, dip angles are also estimated with an accuracy of 3-4°. In Task F, for Thomsen’s (1995) rock-physics model (Table 1), our neural network predicts the aspect ratio ($\alpha$) with an error of 14.2%.

Conclusions

In this work, we demonstrate that neural networks are an effective tool for estimating the anisotropic parameters of a fractured medium from seismic data with sufficiently high prediction accuracy. Of course, we considered a simple rock-physics model. Nevertheless, neural networks have the property of scalability, that is, for more complex tasks it is not difficult to create a new network or supplement an existing neural network, as can be seen, for example, in our research when moving from the task
with single fracture system to two fracture systems. Recall that for the problem with two systems of fractures, we only added two additional blocks in the neural network and increased the number of channels.

In addition, for further research we can include, for example, the task of estimating the type of fluid saturation in cracks (gas, oil and/or water) by ML. We also are capable to estimate the anisotropy parameters for the orthorhombic model, as well as the stiffness tensor $\{C_{ij}\}$, the depth of the fractured reservoir, etc.

It is also of interest the complication of the subsurface-earth model by the addition of more layers with various fracture parameters as well as the consideration of azimuthal anisotropy by 3D viscoelastic modelling. We consider modern methods for 2.5D elastic (Tulchinsky et al., 2012) or 3D viscoelastic modelling (Levin et al., 2016; Charara et al., 2011; Myasnikov et al., 2016), which opens up new possibilities in our future research on ML application for fractured reservoir characterization.

References


