A Deep Neural Network as Surrogate Model for Forward Simulation of Borehole Resistivity Measurements

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Abstract

Inverse problems appear in multiple industrial applications. Solving such inverse problems require the repeated solution of the forward problem. This is the most time-consuming stage when employing inversion techniques, and it constitutes a severe limitation when the inversion needs to be performed in real-time. In here, we focus on the real-time inversion of resistivity measurements for geosteering. We investigate the use of a deep neural network (DNN) to approximate the forward function arising from Maxwell's equations, which govern the electromagnetic wave propagation through a media. By doing so, the evaluation of the forward problems is performed *offline*, allowing for the *online* real-time evaluation (inversion) of the DNN.

Keywords: Deep Learning, geosteering, forward problem, inverse problem, resistivity measurement

1. Introduction

Oil companies have been vastly using geosteering technology to: (a) explore specific oil reservoirs, and (b) maximize the production from the existing reservoirs [1, 6, 9]. In geosteering, it is common to use a so-called logging-while-drilling (LWD) instrument for drilling through the Earth's subsurface. LWD instruments contain multiple transmitters and receivers that record some measurements while drilling. Using the aforementioned recorded measurements, it is necessary to solve an inverse problem in real-time to produce a map of the

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Earth's subsurface, which allows to adjust the well trajectory and reach a specific subsurface location. This act of adjusting the well trajectory during drilling to achieve specific targets is called geosteering.

Due to the real-time decision-making required during geosteering, rapid solvers are needed to interpret the measurements recorded in the field. Mathematically speaking, in geosteering we consider two different problems: (a) a forward problem $\mathcal{F}(\mathbf{T}, \mathbf{P}) = \mathbf{M}$, in which for a given subsurface properties $\mathbf{P}$ and trajectory $\mathbf{T}$, we compute the measurements $\mathbf{M}$ by solving a partial differential equation (PDE) [2, 7], and (b) an inverse problem $\mathcal{I}(\mathbf{T}, \mathbf{M}) = \mathbf{P}$, in which the measurements $\mathbf{M}$ and the trajectory $\mathbf{T}$ are known, and we predict the subsurface properties $\mathbf{P}$ [3, 6, 9]. The inverse problem typically consists of minimizing a given loss function.

There exists multiple approaches to solve an inverse problem. One of them is a gradient-based technique. However, it may lead to a local minimum of the loss function. The second family of methods is statistic-based ones. They require multiple solutions of the forward problem [10]. In all the aforementioned traditional methods, the forward solver needs to be solved multiple times. This is the most time-consuming task, which often limits real-time decision-making.

In the recent decade, the use of DNNs has been increased for a variety of applications in industry such as computer vision [11], speech recognition [12], and biometrics [13], to mention a few, due to their high performance when facing complicated engineering problems. This new popularity of DNNs has also inspired researchers in the fields of computational geophysics and computational mechanics to apply these techniques for their applications [3, 5, 14–16]. In [3], we propose a novel technique to approximate the inverse operator $\mathcal{I}$ using a deep neural network (DNN) [5]. However, since the inverse operator is not well-defined, i.e., for one input it may have multiple outputs, results exhibit some deficiencies. It is possible to improve such an approximation using the following loss function:

$$\mathcal{I}_{\theta^*} := \arg\min_{\theta \in \Theta} \|\mathcal{F} \circ \mathcal{I}_\theta(\mathbf{M}) - \mathbf{M}\|, \tag{1}$$

where θ is the set of weights corresponding to the DNN. Using this DNN approach and Equation (1) as its loss function, we need to solve the forward problem during training until we arrive at the minimizer of the loss function, which imposes a tremendous computational time to this stage. Moreover, calling a function $\mathcal{F}$ to solve the forward problem during training enforces implementation complexities.

In this work, to overcome the above limitations, we propose the use of a DNN to approximate the forward function $\mathcal{F}$. Then, the problem of solving the forward function reduces to the evaluation of a trained DNN, which is considerably faster than any of the existing numeric or semi-analytic methods. Moreover, it becomes more convenient to impose Equation (1) for the deep learning (DL) approach. Then, we use this approximation of the forward function in the inversion of the resistivity measurement in geosteering to achieve a faster inversion method compare to the traditional ones.

The rest of this work is organized as follows: Section 2 introduces the forward problem. Section 3 provides the details of the dataset we use to train our DNN. Section 4 shows some numerical results to illustrate the performance of our DNN. Section 5 is dedicated to conclusions and future work.

2. Forward Problem

In this work, we consider borehole resistivity measurements. Therefore, the forward function $\mathcal{F}$ corresponds to Maxwell's equations, which govern the electromagnetic wave propagation through a media [7]. The subsurface properties represent the electrical properties of the formation. In this application, it is a common practice to approximate the media using a sequence of 1D layered formations since it is sufficient to recover the material properties of the aforementioned 1D layered formation at each logging position [6–8] (see Figure 1). Therefore, we consider $\mathbf{P} = (\rho_u, \rho_l, \rho_h, a, d_u, d_l)$ to represent the subsurface properties, where: (a) ρ_u and ρ_l are the resistivity values of the upper and lower isotropic layer with respect to the current LWD tool position, respectively, (b) ρ_h and $a = \frac{\rho_h}{\rho_v}$ are horizontal resistivity and anisotropy factor of the host layer, respectively, and (c) d_u and d_l are the distance from the center of the instrument to the upper and lower bed boundary positions, respectively.

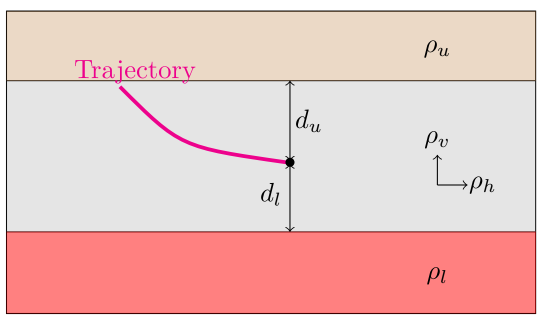

Figure 1: 1D media and a trajectory at its last position.

In this work, we consider almost horizontal trajectories, which correspond to the most challenging and commonly used situations in this problem. To parameterize the trajectory, we consider the step size between each two sequential logging positions to be one foot, and each trajectory consists of 65 logging positions. Therefore, each trajectory section is almost $20m$ long, which corresponds to the depth of investigation of the logging instrument. Moreover, we consider $\mathbf{T} = (t_f, t_v)$, where t_f is the trajectory dip angle of the final logging position and t_v is the variation of the trajectory dip angle at each step. Hence, we have $83^\circ \leq t_f \leq 97^\circ$. Furthermore, the logging instrument is capable of rotating and changing its dip angle for at most 3° in a $20m$ long trajectory. Therefore, at each logging position, we have $-0.046^\circ \leq t_v \leq 0.046^\circ$.

The recorded measurements are post-processed values of the magnetic field acquired at the receivers. As the first logging instrument, we consider a coaxial symmetric tool that incorporates two receivers and two transmitters and operates at the frequency of $500kHz$. The distance between the two receivers is $40cm$ and between the two transmitters is $180cm$. The transmitters and receivers are symmetrically distributed along the tool with respect to its center [3]. For this instrument, we record the attenuation and phase difference at each logging position. Let H^1_{zz} and H^2_{zz} to be the zz coupling of the magnetic field at the first and the second receivers, respectively, where the first and the second subscripts show the orientation of the transmitter and the receiver, respectively. Then, we compute our measurements as follows:

$$\ln \frac{H^1_{zz}}{H^2_{zz}} = \underbrace{\ln \frac{\mid H^1_{zz} \mid}{\mid H^2_{zz} \mid}}_{\times 20 \log(e) = \text{attenuation } (dB)} + i \underbrace{\big(ph(H^1_{zz}) - ph(H^2_{zz})\big)}_{\times \frac{180}{\pi} = \text{phase difference (degree)}}, \quad (2)$$

where ph evaluates the phase of a complex number.

As the second instrument, we consider a short-spacing azimuthal tool which contains one receiver and one transmitter whose operating frequency is $10kHz$. The distance between the transmitter and the receiver is $12m$. Analogous to the recorded measurements of the previous tool, we evaluate the attenuation and the phase difference at the receiver using Equation (2), where $H^2_{zz} = 1$.

There exist semi-analytic methods [2] and numerical methods [7, 8] to solve the aforementioned forward problem. In this work, we use a DNN to approximate the forward operator and obtain the magnetic field at the receivers. The time-consuming stage of this approach is the training that we perform *offline*. Then, the *online* problem of solving the forward problem reduces to the evaluation of a trained DNN. Using this DNN approach, we obtain a faster and consequently more convenient technique for real-time decision making for solving the forward problem. Considering all the assumptions above, in our forward problem $\mathcal{F}(\mathbf{T}, \mathbf{P}) = \mathbf{M}$, the input is a vector of dimension 8, and the output is a matrix of dimension 65×4.

3. Ground Truth

To produce our training dataset, we consider all the subsurface properties $\mathbf{P}$ in the logarithmic scale. Then, we consider some physical features of the geological targets to produce physically meaningful data and to avoid generating large useless datasets. Specifically, we consider $0 \leq \log(\rho_u), \log(\rho_l), \log(\rho_h) \leq 3$, $0 \leq \log(a) \leq 1$, and $-2 \leq \log(d_u), \log(d_l) \leq 1$.

Using the above considerations, we solve the forward problem using a rapid semi-analytic solver [2] for 50,000 randomly selected synthetic model problems, and we use this dataset for the training, validation, and testing of our DNN. We use 80% of the data for training, 10% for validation, and 10% for testing the trained DNN. For more details regarding the dataset, see [3].

4. Numerical Results

We designed a DNN containing multiple convolution residual blocks to train [4]. Figure 2 shows the results of our trained DNN for our test dataset. Each Figure shows the ground truth vs. the predicted values for one type of measurement. The blue line in the figures represents the equality between the ground truth and the predicted value, which corresponds to a perfect approximation. As evident in the figures, the cloud of points is concentrated around the blue line. These results indicate a good approximation of the forward function using our DNN approach. Moreover, the value of r^2 parameter shows a well-trained DNN.

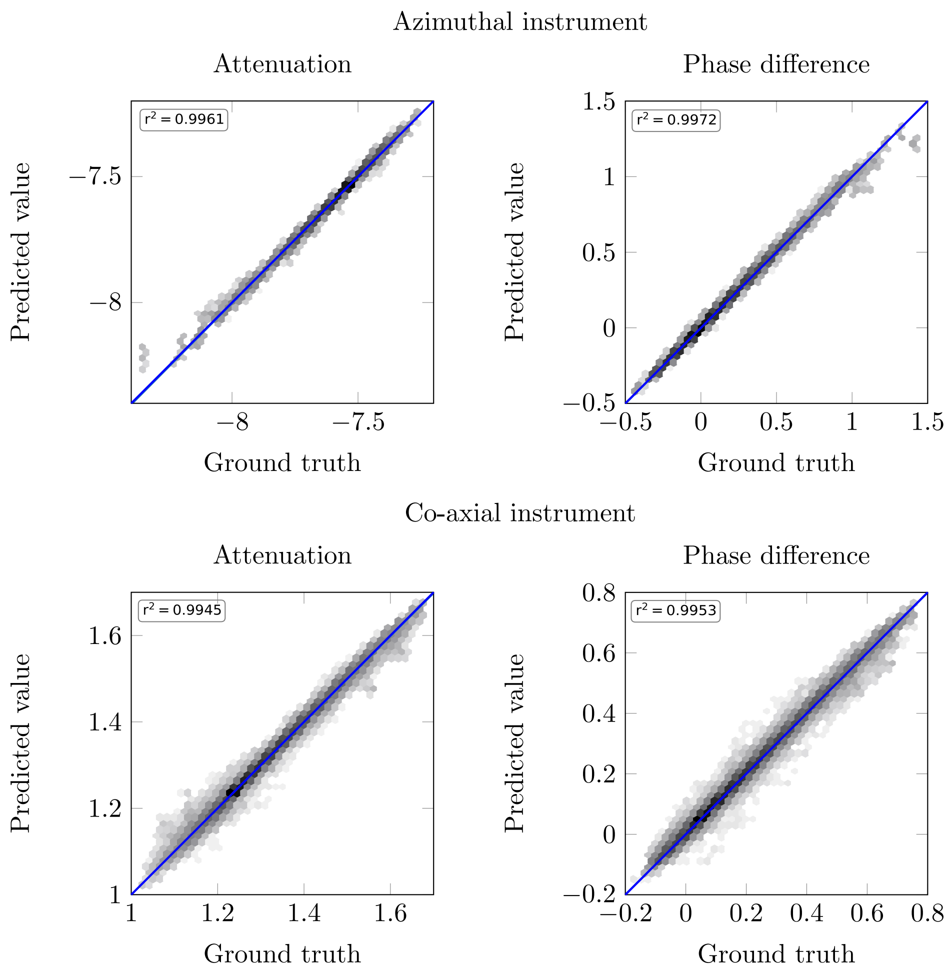

Figure 2: Comparison between ground truth and predicted values using a trained DNN. Blue line indicates the equality of the predicted values and the ground truth.

5. Conclusion

The results presented in this work show that it is possible to use a DNN as a surrogate model to approximate a forward function arising from a PDE. Using this approach, the time-consuming stage of performing the inversion, which consists of solving the forward problem for a large number of times reduces to training a DNN *offline* and evaluating it *online* while performing the inversion in real-time in the field. Hence, it seems a good alternative for solving inverse problems in real-time as it occurs, for example, during geosteering operations.

Although this method can be an adequate alternative for some applications, it requires a large enough dataset to produce a reasonably accurate forward function. Thus, it may be challenging to use in some applications.

As future work, we shall use this DNN approximation of the forward function to invert resistivity measurements using existing traditional inversion methods. Moreover, we shall employ this approximation to propose a fully implemented DL approach to approximate the inverse operator for resistivity measurements. Using the aforementioned approach, we expect to achieve a faster and consequently more suitable technique than with traditional inversion methods for real-time inversion. As the final stage, to use this approach to the oil industry, we shall investigate the effect of noisy data, which is the case in the real-life application.

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