Research on prediction method of S-wave velocity based on deep learning

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Abstract. Aiming at the s-wave velocity prediction problem, based on the analysis of the advantages and disadvantages of the empirical formula method and the rock physics modeling method, combined with the s-wave velocity prediction principle, the deep learning method is introduced, and a deep learning-based logging s-wave velocity prediction method is proposed. This method uses a deep neural network algorithm to establish a nonlinear mapping relationship between reservoir parameters (acoustic time difference, density, neutron porosity, shale content, porosity) and s-wave velocity, and then applies it to the s-wave velocity prediction at the well point. Starting from the relationship between p-wave and s-wave velocity, the study explained the feasibility of applying deep learning technology to s-wave prediction and the principle of sample selection, and finally established a reliable s-wave prediction model. The model was applied to s-wave velocity prediction in different research areas, and the results show that the s-wave velocity prediction technology based on deep learning can effectively improve the accuracy and efficiency of s-wave velocity prediction, and has the characteristics of a wide range of applications. It can provide reliable s-wave data for pre-stack AVO analysis and pre-stack inversion, so it has high practical application value and certain promotion significance.

1. Introduction
S-wave velocity logging data is a basic prerequisite for reservoir and reservoir fluid prediction using prestack AVO analysis technology and prestack inversion technology [1, 2]. However, in the actual exploration and development process of the oilfield, due to the cost and other factors, few shear wave logging data are collected. This leads to great difficulties in the application of geophysical technology based on prestack seismic data due to the constraints of shear wave logging data. In this case, the estimation of shear wave velocity using conventional logging data has become a hot issue, and a large number of scholars have carried out the research on the estimation method of shear wave velocity [3, 4, 5]. At present, there are two main methods for S-wave velocity estimation: empirical formula method and petrophysical modeling method. The empirical formula method is simple and easy to use, but the estimation accuracy is not high, and is limited by the region; Although the estimation accuracy of rock physical modeling method is high, the process is complex, the parameters are various, the operation is difficult, and the practical application efficiency is not high. Based on the existing methods and principles of shear wave velocity prediction, this paper discusses the principle of shear wave velocity...
prediction by analyzing the advantages and disadvantages of empirical formula and rock physics modeling. On this basis, the deep learning technology in the field of artificial intelligence is introduced, and a shear wave velocity prediction method based on deep learning is proposed. Through the case study, it is considered that this method has the advantages of both the above two methods, can improve the accuracy and efficiency of S-wave velocity estimation, and can replace the empirical formula method and rock physics modeling method to a certain extent in practical application, which has high application value.

2. Methods, principles, advantages and disadvantages of traditional S-wave estimation

2.1. Empirical formula method
The empirical formula method is a fitting relationship between P-wave velocity and S-wave velocity of rocks, which is established by scholars in the process of studying the variation law of P-wave velocity and S-wave velocity of rocks through laboratory data, such as the P-wave velocity $V_p$ of water saturated sandstone and shale measured by Castagna et al. And Thomsen et al. $P$ and shear wave depth $V_s$. The linear equations [6, 7, 8] were fitted; According to the ultrasonic data in the laboratory, Han fitted the velocity $V_p$ and S-wave velocity $V_s$ relation [9]. The mudstone baseline formula proposed by Castagna et al. In 1985 is as follows:

$$V_p = 1.16V_s + 1.36 \text{km/s}$$

(1)

The empirical formula proposed by Han is [9]:

$$V_s = 0.79V_p - 0.79 \text{km/s}$$

(2)

By using these formulas, we can quickly calculate the S-wave velocity of a well without S-wave data in a work area, because almost all wells will measure the P-wave velocity curve. However, it should be noted that these empirical formulas are established on the basis of statistical analysis of laboratory measurement data in a specific area. Simple and direct reference may cause large errors [10].

2.2. Petrophysical modeling method
The physical properties of rock, such as the P-wave velocity and the shear wave velocity, are determined by the composition of rock, the structure between the components, namely the internal structure of the rock, and the temperature and pressure environment in which the rock is located. For the actual underground rock, its components include minerals, porosity and cementation are very complex. The internal structure of rock, including the size, shape and arrangement of mineral particles, is very complex, and it is difficult to accurately solve its physical properties. For the convenience of research, the physical modeling technology of rock can equivalent the actual underground rock to ideal medium by certain assumptions, and then calculate its physical properties by using the physics principle. In the process of rock physics research, many rock physical models were proposed, including Voigt Reuss Hill model, Hashin Shtrikman model, DEM model, Wyllie equation, Gassmann equation, Xu white model, etc.

3. Background of shear wave estimation method based on deep learning
As mentioned earlier, when predecessors used the laboratory measurement data to study the variation law of P-wave velocity and S-wave velocity of rocks, they found that there is a good correlation between them. Simple linear formula such as one-dimensional linear equation can often better fit the relationship between them, and sometimes this relationship can even be applied to different basins. For example, the empirical formula (formula 2) proposed by Han Dehua can better fit the consolidated muddy sandstone in the Gulf of Mexico [10] studied by Han Dehua, the poorly consolidated North Sea sample [11] studied by blangy, and the unconsolidated pure sandstone in Ottawa [12] studied by Yin. Although the clay content of these different samples varies greatly (0% - 55%) and the porosity also varies greatly (0.04-0.39), the P-and S-wave velocity relationship can still be reflected by formula (2).
In practice, the prediction of the shear wave velocity by this method is often in error with the measured one. Scholars also gradually realized that simple linear quasi combination between P-wave velocity and S-wave velocity can not establish the relationship between them accurately, and constantly seek to improve the accuracy of the relationship description by appropriate methods. In 1992, Li Qingzhong established the parabola formula between the P-wave velocity and the shear wave velocity; In 2014, Li proposed to use multiple fitting method to further improve the correlation between the longitudinal and horizontal wave velocity by adding gamma and density curves, thus improving the prediction accuracy of the shear wave [24]. Although the rock physical modeling method considers the composition and structure of rock from a more micro point of view and establishes an equivalent model, then the frontal longitudinal and shear wave velocity of rock are derived by the physical method. But for the rock components (mineral type and content) and structure (mainly pore aspect ratio), although the relatively accurate results can be obtained through core analysis and test, the data of the whole well section still need to be obtained by interpretation of logging curve, such as GR, SP, CNL, den and other curves to explain the mud content curve, and AC, CNL The porosity curve is explained by den isocurve, and the porosity aspect ratio of the whole well section is determined by using porosity curve. Therefore, the rock physical modeling method can use logging curve to estimate the shear wave velocity indirectly.

4. Principle of deep learning shear wave estimation method

4.1. Principle of DFNN

Take a three-layer deep neural network with two hidden layers and one output layer as an example (Fig. 1). The input layer is the characteristic space of training sample, that is, the reservoir parameters used to predict the shear wave velocity. If two reservoir parameters are selected, a 2-dimensional column vector \([x_1, x_2]^T\) can be used. In practice, the more reservoir parameters of input layer, the higher the dimension.

When DFNN is used for model training, the xavier[30] initialization method is used to generate the corresponding weight coefficient W and offset term B randomly according to the input data and the output results after the neurons are processed. The sigmoid function is selected for each neuron activation function, and its expression is:

\[
f(x) = \frac{1}{1 + e^{-(x)}}
\]

In the process of forward propagation, all the input layer data are input to each neuron in the first hidden layer in the form of weighted average, then the input data of three neurons neu1, neu2 and neu3 in the first hidden layer are expressed as:

\[
z_1 = w(x_1, 1) \cdot x_1 + w(x_2, 1) \cdot x_2 + b_1
\]

\[
z_2 = w(x_1, 2) \cdot x_1 + w(x_2, 2) \cdot x_2 + b_2
\]
\[ z_3 = w(x_1, 3) \cdot x_1 + w(x_2, 3) \cdot x_2 + b_3 \]  \hspace{1cm} (6)

After nonlinear transformation of logic function, the output of three neurons in the first hidden layer is \( f_1(z_1), f_2(z_2), f_3(z_3) \) their weighted average results are used as the input of neurons in the next hidden layer. Therefore, the input data of the two neurons in the second hidden layer are as follows:

\[ z_4 = w(1,4) \cdot f_1(z_1) + w(2,4) \cdot f_2(z_2) + w(3,4) \cdot f_3(z_3) + b_4 \]  \hspace{1cm} (7)

\[ z_5 = w(1,5) \cdot f_1(z_1) + w(2,5) \cdot f_2(z_2) + w(3,5) \cdot f_3(z_3) + b_5 \]  \hspace{1cm} (8)

Similarly, the output of the two neurons in the second hidden layer is: \( F_4(z_4), f_5(z_5) \) The sum of their weighted average is used as the input of the output layer neurons:

\[ z_6 = w(4,6) \cdot f_4(z_4) + w(5,6) \cdot f_5(z_5) + b_6 \]  \hspace{1cm} (9)

After the output layer, the final prediction result \( f \) can be obtained_6 (z_6).

4.2. Construction of objective function

In order to achieve the least square error between the final output and the measured data, it is necessary to construct a function with \( w \) and \( b \) as independent variables:

\[ \text{Minimize } g(b, w) = \sum_{i=p}^{p}(f(b + x_i^T w) - y)^2 \]  \hspace{1cm} (10)

4.3. Regularization of objective function

In order to satisfy the first-order optimal condition of gradient 0, the objective function should be convex, that is, its Hessian matrix is positive definite matrix or semi positive definite matrix. But in fact, the objective function is a non-linear function of \( w \) and \( b \), which is a non convex function. Therefore, we can ease the problem by adding regular terms to the objective function. The common regular terms are L1 norm or L2 norm. Because they are convex functions, we can adjust the weight coefficient of norm to control the adjustment intensity, which is generally relatively small.

5. Analysis of practical application effect

The data of the measured shear wave logging in several oilfields in Jiyang depression of Bohai Bay Basin are collected, including the conventional logging curves (GR, SP, AC, CNL, etc.) and the interpreted reservoir parameter curves (porosity and mud content). The main purpose of this study is clastic rock formation. The depth of clastic rock formation in these 10 wells is different from 500m-1000m. In the study, the data of 5000m of measured shear wave logging are selected as sample data (40000 measured sample points in total).

5.1. Key parameter setting

The first key to the establishment of S-wave velocity prediction model is the setting of input layer, that is, which logging curves to use to establish the relationship with S-wave velocity, which is related to the rationality and reliability of samples. Castagna et al. Proposed that under the condition of known lithology, for sandstone with high clay content and relatively pure sandstone, the empirical relationship can be fine tuned to better fit these two types of sandstone [6]. When Han statistically analyzed the ultrasonic laboratory data of 70 water saturated argillaceous sandstones, it was found that when these data were classified according to clay content (greater than 25% and less than 25%) and porosity (greater than 15% and less than 15%), the fitted empirical formulas of P-and S-wave velocity were different [9].

It shows that the relationship between P-wave velocity and S-wave velocity changes with clay content and porosity. Therefore, when establishing the relationship between logging curve and measured S-wave velocity, in addition to choosing P-wave velocity, considering clay content and porosity will make the
prediction of S-wave velocity more accurate. Although GR and SP curves can reflect the clay content of rocks, they are not suitable for constructing samples due to the influence of radioactive minerals and mud. The density curve and neutron porosity curve are also the curves reflecting the porosity and clay content of rock, and are not affected by radioactive minerals and mud environment, so they can be used. Finally, the depth neural network training model of shear wave velocity was established by using five curves of P-wave velocity (VP), density (DEN), neutron porosity (CNL), logging interpretation shale content (SH) and logging interpretation porosity (port).

In addition, in the construction of DFNN neural network, a large number of tests were carried out on the main parameters such as the number of hidden layers, the number of neurons and the number of iterations. By comparing the calculation efficiency and the accuracy of prediction results, the DFNN neural network parameters with 3 hidden layers, 6 neurons and 200 iterations were selected.

5.2. Prediction accuracy analysis and comparison with traditional methods

Different model training methods are used in the research process, including training and prediction with all 10 wells, training with most wells and verification with a few wells. Taking the method of selecting 9 wells for training and 1 well (E2) for verification as an example, this paper expounds the accuracy of S-wave velocity prediction by depth learning, and compares the S-wave velocity prediction effect of depth learning method with empirical formula method, petrophysical modeling method and multiple regression method.

Figure 2. (Left). Prediction of shear wave velocity in well E1 (black is the measured curve, and color is the prediction curve, in which green is the empirical formula method, pink is the petrophysical modeling method, blue is the multiple regression method, and red is the deep learning method)

Figure 3. (Right). Prediction of shear wave velocity in well E2 (black is the measured curve, color is the prediction curve, in which green is the empirical formula method, pink is the petrophysical modeling method, blue is the multiple regression method, and red is the deep learning method)
Figure 4. (Left). Prediction of shear wave velocity in well E3 (black is the measured curve, and color is the prediction curve, in which green is the empirical formula method, pink is the petrophysical modeling method, blue is the multiple regression method, and red is the deep learning method)

Figure 5. (Right). Prediction of shear wave velocity in well E4 (black is the measured curve, and color is the prediction curve, in which green is the empirical formula method, pink is the petrophysical modeling method, blue is the multiple regression method, and red is the deep learning method)

It can be seen from the above results (Fig. 2-Fig. 5) that the empirical formula method is the most unstable. The predicted S-waves on wells E2 and E4 are in good agreement with the measured S-waves, while the predicted S-waves on wells E1 and E3 are in poor agreement with the measured S-waves. This is because the empirical formula method depends on the coefficients of the empirical formula, and the coefficients are different in different regions; The results obtained by petrophysical modeling method are slightly better, but the method usually refers to a certain target interval, and the part beyond the target interval will lead to large errors in S-wave velocity predicted by the method due to different petrophysical parameters (such as the upper half of well E2); The S-wave velocity predicted by the multiple regression method and the deep learning method are in good agreement with the measured S-wave velocity. Through the quantitative analysis of the prediction results of different methods (Table 1), it can be seen that the prediction accuracy of S-wave velocity by deep learning method is the highest, and the average error is about 5.1%.

Table 1. Relative error of shear wave velocity predicted by different methods

| Method                      | Well No. |
|-----------------------------|----------|
|                            | E1       | E2       | E3       | E4       |
| Empirical formula %         | 12.75    | 4.58     | 15.97    | 5.68     |
| Petrophysical modeling %    | 7.48     | 8.98     | 10.11    | 7.10     |
| Multiple regression %       | 5.81     | 5.34     | 8.59     | 4.11     |
| Deep learning %             | 4.44     | 3.17     | 8.39     | 4.43     |
6. Conclusion
In this paper, a prediction method of S-wave velocity based on depth learning is proposed. By establishing the depth learning model of P-wave velocity, density, porosity, shale content, neutron porosity and S-wave velocity, the S-wave velocity is predicted and compared with the traditional method. The results show that the prediction method based on depth learning has the highest accuracy, the error with the measured S-wave velocity is the smallest. The results show that the proposed method has strong generalization ability and stability, and can provide guidance and reference for the estimation of shear wave velocity.

It should be pointed out that it is still necessary to continuously add new measured S-wave velocity to the model for training, so as to further improve the prediction ability and applicability of the model.

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