Application of Machine Learning Algorithms Using Seismic Data and Well Logs to Predict Reservoir Properties

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Ivan I Priezzhev
IPLAB LLC

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Application of Machine Learning Algorithms Using Seismic Data and Well Logs to Predict Reservoir Properties

I. Priezzhev* (Gubkin University), E. Stanislav (MIMGO)

Summary

This paper provides for a comparison of the classic seismic inversion technique with several multivariate predictive techniques based on machine learning algorithms (linear regression, ACE regression, Random Forest, Neural Network) using seismic data and well logs to estimate rock physical properties. Currently, the estimation of reservoir properties is commonly based on comparative analysis of the distribution of the properties in wells and the elastic properties according to the results of the seismic inversion. Most of the commercial seismic inversion technologies are based on the classical one-dimensional models of seismic exploration involving plane-parallel medium that is described by the linear convolution equation. However, presumably, in some complex cases the linear operators of convolution type cannot properly describe the seismic field distribution. It is assumed that there is a nonlinear absorption of energy of seismic waves in some geological environments, such as in fractured, fluid - rich layers. Such nonlinearity can be shown by vertical and horizontal changes in the seismic wavelet. This paper aims to demonstrate that in certain nonlinear cases using a nonlinear predictive operator based on machine learning algorithms allows to estimate rock physical properties more accurately.

Introduction

Estimation of rock physical properties based on seismic data in combination with well logs data is an important task in hydrocarbon exploration. Currently, the majority of commercial inversion technologies assessing rock elasticity are usually based on the application of linear equations of the convolution type for estimating the functions of the reflectivity along the seismic track and follow-up evaluation of acoustic and elastic parameters of the geological formation (Hampson and Russel, 2005). Estimation of reservoir physical rock properties according to the obtained elastic data technology is commonly based on the comparative analysis of the distribution of reservoir properties in wells and the elastic properties according to the results of seismic inversion. The workflow includes multiple steps requiring to define a lot of parameters for every step, which can produce very subjective results.

Direct well log prediction technique of application of a set of seismic attributes based on neural networks with back allocation training approach was introduced by Hampson et al (2001). In 2008 we proposed the well log prediction technology that uses only raw seismic data (one cube only) with moving multi traces window and is based on neural network with genetic training algorithm (Priezzhev et al, 2008). The proposed technology called “Genetic Inversion” was successfully applied to Shtokman field (offshore northern Russia) (Veeken et al, 2009). There are several successful case studies based on this technology (Gorain and Thakur, 2015, Gorain, 2017, Klokov et al, 2017, Leginowicz and Pirowska, 2013, Naviset et al, 2017, Watanabe et al, 2017). At present time, we continue to develop this approach. (Kobrunov and Priezzhev, 2016).

In this paper, for the purposes of evaluating reservoir properties, it is proposed that the raw seismic data is used directly through the application of nonlinear predictive operators constructed by applying a combination of machine learning algorithms. Such operators can be constructed as a result of joint use of several seismic cubes and well logs data. This assumes the application of spatial distribution patterns of seismic field around the point forecast in the borehole.

Method

The input of the prediction requires simultaneous use of all available seismic cubes - full, angular, and azimuthal stacks. In order to accelerate the computation we propose to define the region of interest by two surfaces, i.e. the top and bottom of the target layer. Predictive workflow is performed in two main stages: the training stage and the computation stage. At the first learning stage a predictive operator is built based on the joint use of seismic and well log data. It assumes the use of spatial distribution of seismic field around every point forecast in the borehole using moving window approach (figure 1).

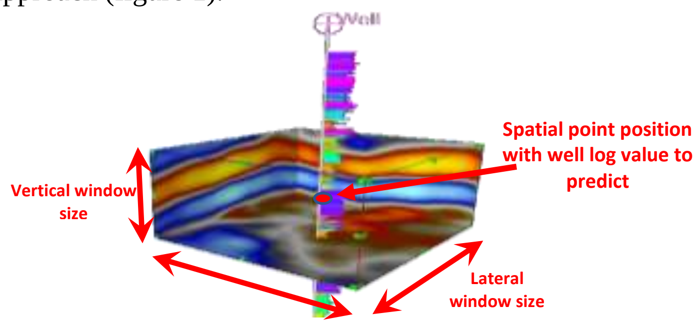

Figure 1. *Scheme of obtaining a pair for training – seismic array data from the moving window and the value of the predictive parameter at the well in the center of the window.*

The second stage (computation) involves the application of predictive operator for all the points in the seismic cube. The result of the predictive construction is presented in the form of a seismic cube with predictive values type according to the applied well log type for this prediction. To estimate the accuracy of the prediction we applied a well-known cross validation method according to which we selected the wells used for the training, whereas the other wells were used for the quality control.

As the predictive operators, we applied several linear and non-linear multivariate regression techniques based on various machine-learning algorithms. This choice is motivated, firstly, by a presumably complex non-linear relationship of the seismic field and the forecast well log and, secondly, the presence of strong correlations between the adjacent values of spatial distribution of seismic fields and different types of input seismic cubes. Additionally, no need to know wavelet and low frequency model and, as result, less subjective results. A high degree of freedom of predictive operator based on nonlinear algorithms can provide a more accurate forecast with a higher correlation coefficient for the predicted values and the well log values used for this prediction. Also, nonlinear methods of the forecast are less sensitive to a number of the applied input values for predictive operators. Although, these operators can be non-stable and non-unique and can create different results for different realizations, to stabilize the predictive operators and to obtain more unique results, we apply the Tikhonov regularization approach (Tikhonov and Arsenin, 1977).
As the forecast operators, we applied the following methods:

- Classical linear multivariate regression. Seismic attribute-based analysis of the quantitative prediction of the effective parameters of a formation based on the classical multiple linear regression (Hampson et al, 2001, Leiphartand and Hart, 2001).
- ACE (alternating conditional expectation) regression. The method for constructing nonlinear predictive operator based on alternating conditional expectation ACE, proposed by Breiman and Friedman (1985).
- Random Forest regression. One of the highly effective machine-learning algorithms proposed by Breiman (2001) which consists of using the committee (ensemble) decision trees.
- Neural network. A neural network is a nonlinear operator, which is widely used in the oil industry for the forecast models (Hampson et al., 2001; Veeken et al., 2009; Priezzhev et al., 2014). In order to build a nonlinear predictive operator based on a neural network we apply a hybrid training procedure that makes use of genetic and gradient algorithms in each step of training (Kobrunov and Priezzhev, 2016). The proposed procedure avoids a lot of disadvantages of classical genetic algorithms, especially their low speed of convergence. The proposed procedure also avoids a number of disadvantages of gradient methods, such as the high level of dependence on the initial values and convergence to the nearest local minimum of the object function.

Example

To demonstrate the technology, we use a dataset that includes 3D seismic full stack volume and several wells with density log of an oilfield in Western Siberia. The productivity of the oilfield relates to the set of inclined deltaic layers of Cretaceous period called “clinoform” and to the continental sediments of the Jurassic period. According to the well log interpretation, these layers can be detected by low density or low acoustic impedance distribution. To obtain a 3D volume of density or acoustic impedance distribution we applied classic post-stack seismic inversion (with low frequency model) and machine learning multivariate predictive analysis using a linear regression, ACE regression, neural network and Random Forest regression. Only one trace and 100 milliseconds time window were used like input for predictive operator. The results provided in Figure 2 – 2a is an acoustic impedance as the results of seismic inversion; 2b demonstrates the results of density prediction using linear regression; 2c – ACE regression; 2d - neural network results, and 2e - Random Forest results. It is clear that the results of the classic seismic inversion do not have a good resolution when compared to the other algorithm results. Linear regression has a good resolution in the high frequency region and low resolution in the low frequency region. ACE regression results have a good resolution in the low frequency region but do not have a good resolution in the high frequency region. Neural network results have a better resolution while detecting thin layers when compared to Random Forest results. However, the amplitudes in the Random Forest correspond better to the well logs. All the resulting figures demonstrate very similar pictures of the layer distribution and make it possible to detect some major layers as the potential candidates for new well placement.

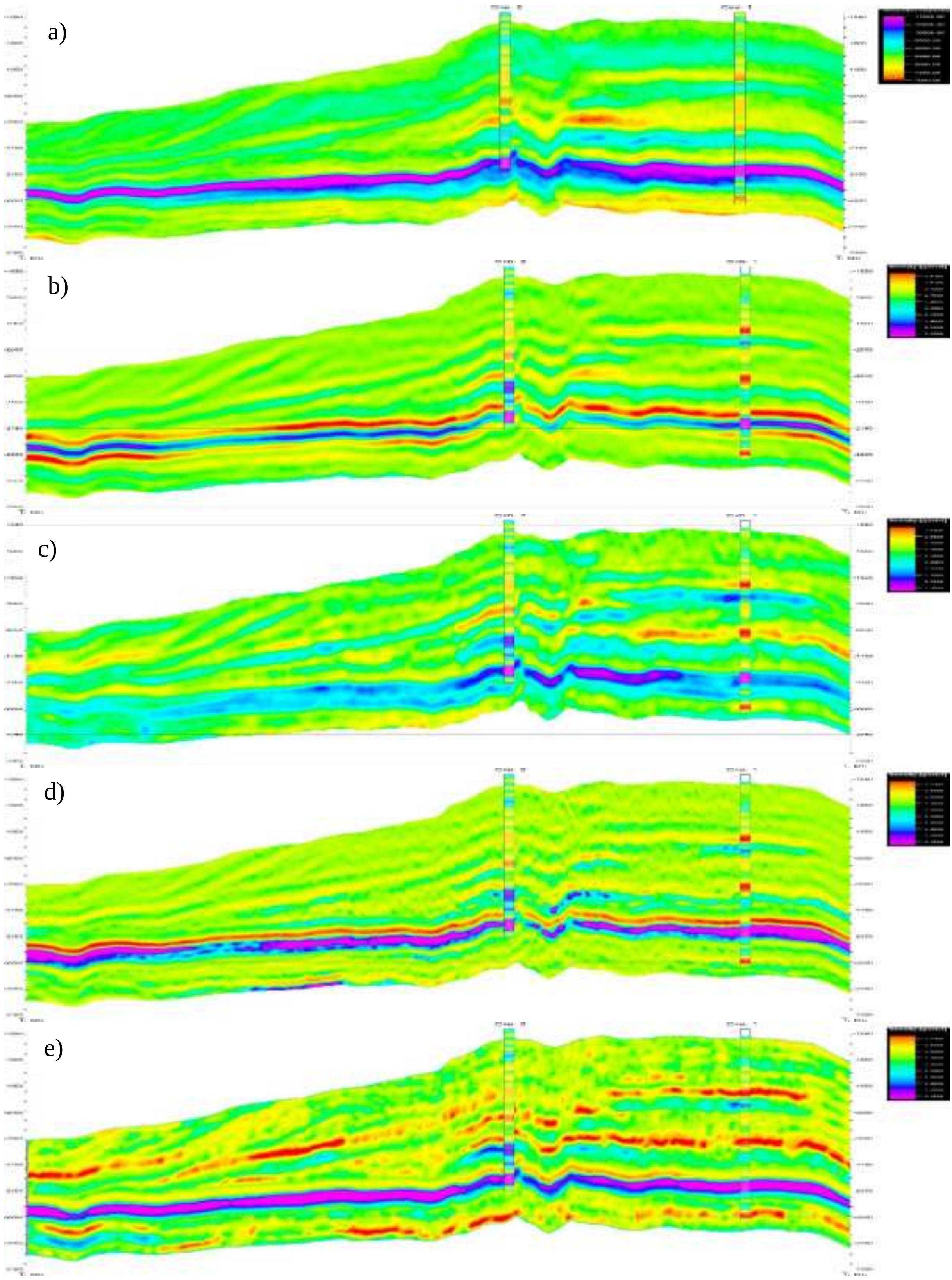

Figure 2. *Cross-section from acoustic impedance (a) and density volumes (b, c, d, e) predicted by different approaches. (a) – results of classic post stack inversion, (b) – results of density prediction using linear regression, (c) – ACE regression prediction result, (d) – neural network prediction result and (e) – Random Forest prediction results. The right well is used for learning (b, c, d, e) and the left well is not used for learning (b, c, d, e).*

Conclusions

Nonlinear predictive techniques based on neural network, ACE regression and Random Forest allow obtaining a better resolution when compared to the linear techniques based on the classic seismic inversion or linear regression.
Combination of linear and nonlinear predictive techniques makes it possible to get a clearer image of the formation with the differentiation of the major and thin elements.
The proposed technique allows to perform simultaneous application of several machine learning algorithms for the purposes of predicting well logs via seismic dataset and can be highly effective to get predictive volume which can be applied for future modeling and new well placement.

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