RESEARCH

49(228), November 1, 2015

ISSN 2278–5469 EISSN 2278–5450

Discovery

Reservoir characterization using model based inversion and probabilistic neural network

Maurya SP[1], Singh KH[2]

1.Research Scholar, Indian Institute of Technology Bombay, Mumbai, Maharashtra, India; Email: spm.iitb@gmail.com
2.Associate Professor, Indian Institute of Technology Bombay, Mumbai, Maharashtra, India

Article History
Received: 05 September 2015
Accepted: 20 October 2015
Published: 1 November 2015

Citation
Maurya SP, Singh KH. Reservoir Characterization using Model Based Inversion and Probabilistic Neural Network. *Discovery*, 2015, 49(228), 122-127

ABSTRACT

Seismic Reservoir Characterization (Reservoir Geophysics) is one of the most significant components of the seismic data interpretation. This paper describes a successful application of model based seismic inversion technique and Probabilistic Neural Network to post-stack seismic data for detection of hydrocarbon reservoir zones. The paper is divided into two parts. First, the acoustic impedance (AI) values are derived from seismic datasets by applying the model based inversion algorithm in the time domain. Log data from thirteen wells are analysed with seismic gathers. The correlation coefficient between synthetic and seismic data is 0.98 which shows the efficacy of model based inversion. Second, a Probabilistic Neural Network (PNN) is trained, validated and tested using estimated effective porosity data at the well locations which are used as internal attribute and the results from the model based inversion as external attributes. The trained Probabilistic Neural Network is applied to the seismic volume to obtain an effective porosity variation in 3-D. A high effective porosity value of 16% located between 1060-1065 ms is interpreted to be a reservoir zone. The results suggest that the combination of model based inversion and PNN can be applied effectively to estimate reservoir properties where the relationship between porosity and acoustic impedance is non-linear.

Keywords: 3C-3D Seismic data acquisition, Impedance, Inversion, Neural Network etc.

1. INTRODUCTION

The application of seismic inversion techniques for hydrocarbon detection has been growing steadily in the last two decades. Seismic inversion along with log data helps extract petrophysical properties of the subsurface (porosity, volume of shale, acoustic impedance, elastic impedance and density). The seismic inversion transforms the seismic data into a velocity layer model which are used to produce petrophysical boundaries in the subsurface and make meaningful geological interpretations [11]. The P-impedance, S-impedance, density and porosity parameters are derived from these inversion techniques. These geophysical parameters provide information about the properties of rock constituting the subsurface [4]. In the present study, first, the model based inversion is performed to invert one trace and is compared with the original impedance and correlation coefficient is estimated. If a correlation is more than 0.7, the correlation is assumed to be good and the seismic volume is inverted to compute the elastic parameters. In the second part porosity is predicted from PNN techniques. The results are discussed in the concluding section.

The Study Area

The study area is Blackfoot field located south-east of Strathmore, Alberta, Canada. The seismic (3C-3D) gathers and well log data were recorded in the month of October 1996 by CREWES group and later the data were made available for public access to carry out further academic research work. The seismic data was collected in two areas: the first was designed to detect the thickness of the clastic Glauconitic channel, and the second one was to study the reef-prone Beaverhill lake carbonate [6]. In this paper, the data for studying Glauconitic channel is taken for analysis.

Data Information

No. of Inlines	1199
No. of Cross lines	81
No. of Traces	9639
Well log data	13

2. METHODOLOGY

Model Based Inversion

The Model Based Inversion (MBI) is a type of post stack inversion to compute acoustic impedance from the seismic datasets. The model based inversion technique is also known as blocky inversion. This method is based on the convolutional theory which states that the seismic trace can be generated from the convolution of wavelet with the reflectivity function. The seismic trace is however noisy due to many factors that influences the data from instrument, multiples to cultural noise.

$$\textit{Seismic trace} = \textit{Wavelet} * \textit{Reflectivity} + \textit{Noise}$$

If the noise in the data is uncorrelated with the seismic signal, the trace can be solved for Earth Reflectivity function. This is a non-linear equation which can be solved iteratively [2] as follows:

$$Z=V*\rho,$$

$$r_i = (Z_{i+1}-Z_i) / (Z_{i+1}+Z_i),$$

And

$$AI_N=AI_1 \exp (2\sum^{N}_{i=2} ri)$$

These equations are used in practice for recursive inversion with the aim of transforming reflectivity function into acoustic impedance [1]. AI_1 is the acoustic impedance of the first (top) layer and AI_N is the N^{th} layer acoustic impedance. r_i is the reflection coefficient of the i^{th} layer.

An initial low-frequency model for AI is required to perform the inversion which is estimated from well log data. This model provides the low- and high-frequency components missing from the seismic datasets, and also helps reduce the non-uniqueness of the solution. The processing steps of the model based inversion used in this paper are as follows:

1. Calculate the acoustic impedance at well locations using the well log data.
2. Pick horizons in the seismic section to control the interpolation and to provide structural information for model between the wells in the area.
3. Use interpolation along the picked seismic horizons and between the well locations to obtain the initial acoustic impedance model.
4. Block the initial impedance using some selected block size.
5. Extract statistical wavelet from seismic section.
6. Convolve the wavelet with the Earth Reflectivity to obtain synthetic seismic trace. This synthetic trace is different from the observed seismic trace.
7. Next, the Least Squares optimization is performed for minimizing the difference between the real and modeled reflectivity section. This is achieved by analyzing the misfit between the synthetic trace and the real trace and modifying the block size and the amplitude to reduce the error.
8. Repeat step 7 until the lowest misfit between real seismic and synthetic trace is achieved.

Porosity Prediction Using Probabilistic Neural Networks

Probabilistic Neural Network (PNN) analysis is performed to estimate the porosity variation in seismic section. The Emerge module in HRS9.2 software is used for this purpose. The well log and seismic data can be merged on Emerge module. A well log property can also be computed using attributes of the seismic data on Emerge. That property may be any measured log type such as velocity or porosity, or it may even be a derived lithologic attribute, such as volume of shale [8]. The seismic attributes can be calculated internally, or can be used as external attributes. The steps for PNN are as follows:

1. Examine the log and seismic data at well locations to determine which set of attributes is appropriate.
2. Derive a relationship using Neural Networks.
3. Apply the derived relationship to 3-D seismic volume to create a volume of the desired log property.

A neural network is a program that roughly mimics the way the human brain works, with its nonlinear, parallel processing approach. These networks must be "trained" with data and a learning algorithm to work. These networks are sometimes referred to as "artificial neural networks", or ANN [4]. The advantage of such a network is that it can:

1. Predict other logs besides impedance.
2. It can use other attributes besides amplitude and time.
3. It does not need a forward model. No need of an initial guess.
4. It does not require a determined seismic wavelet.
5. It can use cross-validation.

The two main types of problems that a neural network can solve are the classification problem and the prediction problem. In the classification problem, the input dataset is divided into a series of classes, such as sand, shale and carbonate, or gas, wet and oil, etc. In the prediction problem, a parameter of interest is predicted from a number of input values [8]. As an input for designing a PNN model, a sample set obtained from the well logs is split into training, validation and test subsets. The training process is carried out until at least one of the following conditions is met: (i) a minimization of a MSE goal is achieved; (ii) occurrence of three consecutive non-improvements in the MSE for the validation subset (early-stopping); or (iii) a maximum number of iterations are completed [4]. The test subset is used only to estimate the prediction power of the PNN by performing a blind test and it is not used for building the NN model.

3. RESULTS AND DISCUSSIONS

Model based inversion results

Model based inversion is performed in Hampson Russell (version 9.2) software. The first step is well to seismic tie and wavelet extraction from seismic section which is a crucial step in seismic inversion technique. Before applying seismic inversion to the datasets, a time to depth conversion is performed in order to make vertical scale of the well log acoustic impedance data match the vertical scale of seismic section so as to follow the spatial correlation. This time to depth or vice versa conversion is performed by using the sonic well log data and initial two-way travel time derived from the well log data which provides the highest correlation between synthetic and seismic data [10]. Several assumptions are made to derive the seismic signal or wavelet:

1. Time bulk-shift of synthetic trace is correctly determined.
2. The seismic amplitude spectrum is equal to the reflectivity series spectrum.

The synthetic trace is computed from the calibrated sonic, density logs with the statistical wavelet. The sonic log is converted to a velocity log and this velocity is multiplied with density log to find out the impedance. This impedance is then used to compute the Earth reflectivity function which is convolved with the extracted seismic wavelet to yield the synthetic trace. The frequency of the sonic and density signal is much higher (~ 4 times) than the seismic signal.

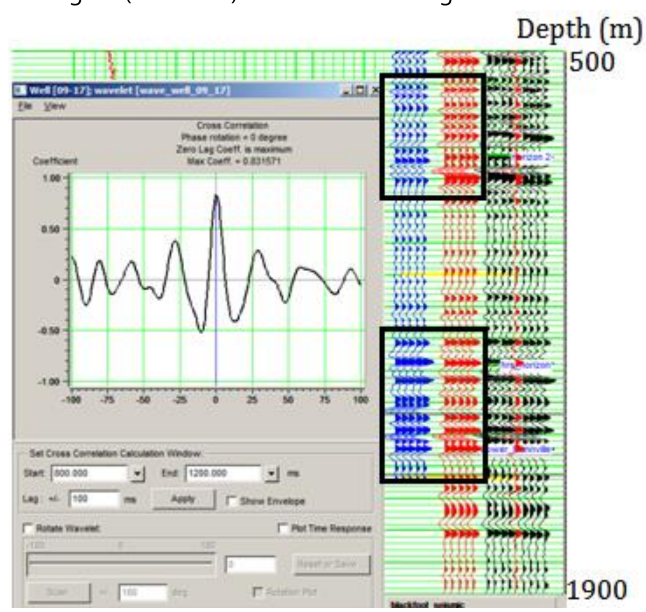

Figure 1 Correlation of seismic with synthetic trace shown for well BH-01-08

In Figure 1 seismic to well tie task is shown. The synthetic trace is shown in blue color, the composite seismic trace in red and the seismic section in black. The blue traces (synthetic) and red traces (seismic) agree well as highlighted in rectangles. The parameters used in inversion analysis are as follows:

- Inversion time interval: 300-1300 ms
- Impedance change constraint: ±25%
- High cut frequency: 10Hz

- Separate scales
- Number of iterations: 10

The iterations are used to reduce the differences between real and synthetic seismic traces. The impedance change constraints are used to restrict the deviations of inversion impedance relative to the average impedance of the model, which is represented by filtered well impedances. The inversion results at the well location are compared to those estimated from the log data at wells BH-01-08 as shown in Fig 1. For a better comparison between the original and the inverted seismic section a high cut filter is applied to the well log data because of the presence of high frequencies in the data. The red curve shows the original impedance calculated from well log data, the blue curve is the inverted impedance estimated from seismic data and the black curve the initial guess model calculate for well BH-01-17 (Figure 2). Both the original impedance and the inverted impedance agree well indicating that the inversion results are reliable.

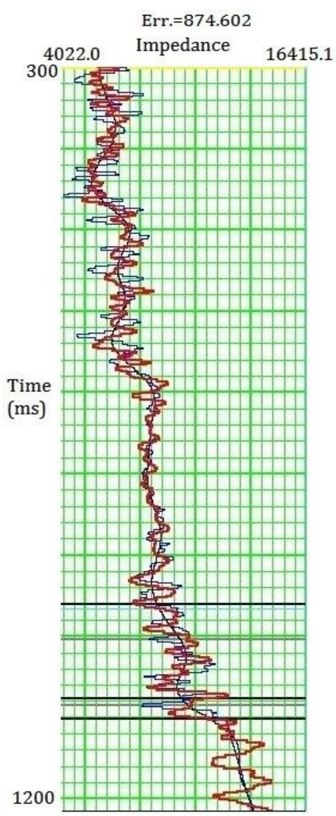

Figure 2 Model based inversion results for BH-01-17

The inverted AI typically, is comparable to the filtered well-log impedance [6], [7]. Here, synthetic traces generated from the resulting AI are correlated with the seismic traces for all wells and the differences between the original filtered log and inverted result are measured. The agreement between the synthetic traces and the data show good correlations for most wells. The plot in Figure 3 shows the variation of correlation coefficient (CC) for various boreholes. The correlation coefficient varies from 0.96 to 0.99. A high CC suggests all the wells tie extremely well with the seismic data with an average CC of about 0.98. The Figure 4 shows an RMS Error along with borehole. This is the RMS or average difference between the real log impedances and impedances estimated from inversions. The RMS Error in AI varies from 620 to 980.

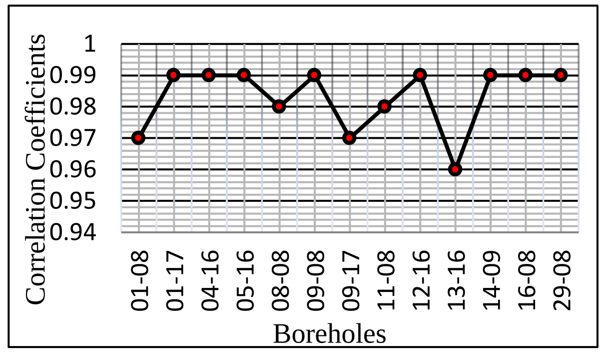

Figure 3 Correlation Coefficient for all 13 wells

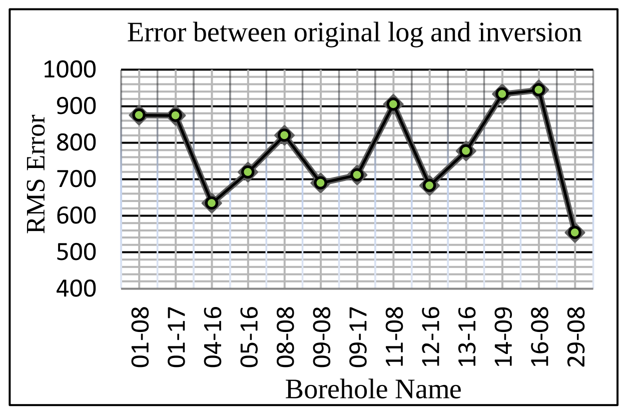

Figure 4 RMS error of all 13 boreholes

A cross section of the inversion result is shown in Figure 5 for boreholes 01-17 and 09-17. The low impedances near 1060-1065 ms interval are clearly visible (shown by circle) in this figure. The RMS average impedance at 1065 ms, measured within a 10 ms time window, also show low impedances near most wells. Y axis shows time in millisecond and the in lines are plotted on x-axis. The 3-D seismic volume is also inverted into acoustic impedance not discussed in this paper, also shows low impedance at around 1060 ms time section.

Predicting Porosity from PNN

The results from model based inversion are used as external attributes for predicting porosity. The porosity prediction is performed by Emerge module of HRS software. Emerge divides the entire dataset into two groups (Figure 6): a training dataset (original wells, in black) and a validation dataset (predicted data, in red).

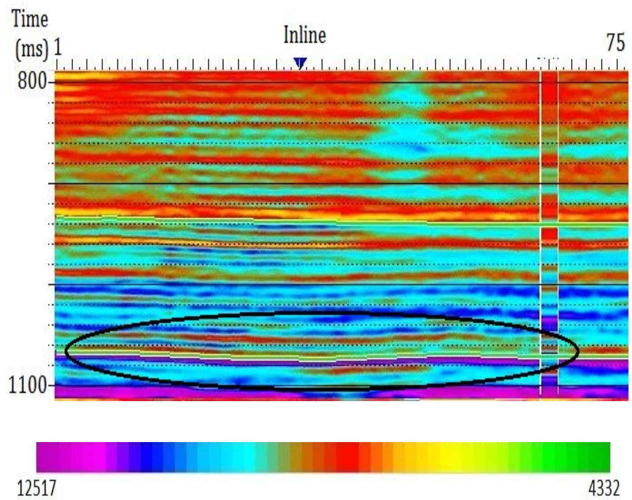

Figure 5 Inverted seismic cross section for borehole 01-17 and 09-17

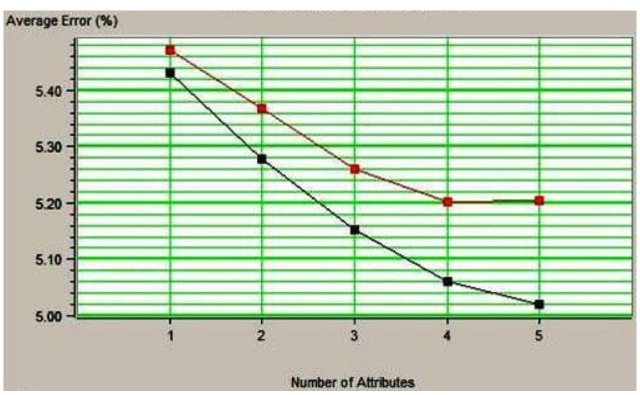

Figure 6 Average root-mean-square error (vertical axis) of five attributes (horizontal axis)

The horizontal axis shows the number of attributes used in the prediction and the vertical axis is the root-mean-square prediction error for that number of attributes. Five attributes and an operator length of 7 samples are chosen for analysis. From the figure, the two curves deviate more beyond chosen attributes (4), hence only 4 attributes are used for prediction of porosity. To determine the seismic attribute that is most significant in predicting the porosity, a cross-plot of porosity estimated from that particular attribute with the porosity calculated from log (actual porosity) is done (Figure 7) and a normalized correlation value is estimated. A 3-D cross section of the predicted porosity is shown in Figure 8. A high porosity between 1060-1065 ms level are clearly visible (shown in purple color) in this figure. The porosity at the time 1065 ms is measured to be nearly 16%. The y-axis plots Xlines, the x-axis, the inlines and the z-axis shows the time in millisecond.

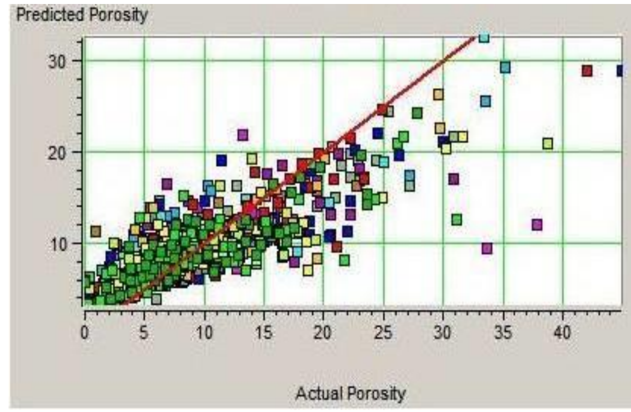

Figure 7 Crossplot of predicted porosity and actual porosity

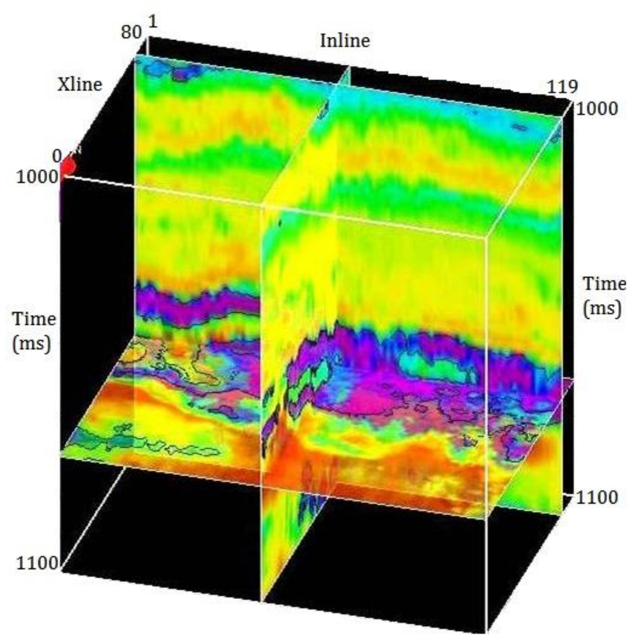

Figure 8 Cross-section of 3-D predicted porosity at 1065-ms

4. CONCLUSIONS

3-D Seismic volume has been successfully inverted into acoustic impedance. In figure 6 at right side along a column the original impedance (calculated from well log) is shown which agrees extremely well with the inverted seismic section. The inversion results indicate that the model based inversion technique can resolve the low impedance regions between time sections of 1060ms to 1065ms. The predicted porosity is high 16% between 1060-1065 ms. The impedance and porosity values suggest that it could be due to sand channel. The low impedances shown in yellow-green region (Fig 6) are proposed to be sand channel regions. This channel is more clearly visible (high resolution) in figure 9 which is indicated from the predicted porosity. The correlation coefficient is calculated and an average value of 0.98 shows a very high correlation between synthetic and seismic dataset. The synthetic relative RMS error of 778 suggests the efficiency and reliability of model based inversions. Based on the present study it is concluded that a sand channel (Reservoir) is present at between 1060 ms-1065 ms time in seismic section confirming results from previous studies.

ACKNOWLEDGMENT

We thank CGG Veritas for providing the HRS software and the Blackfoot seismic data for processing and analyzing and their incessant support for research and development work.

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