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Abbreviations

LMR - Lambda Mu Rho
S/N - Signal to Noise
AI- Acoustic Impedance
MBI- Model Based Inversion
CI- Colored Inversion
MLSSI- Maximum Likelihood Sparse Spike Inversion
BLI - Band Limited Inversion
EI - Elastic Impedance
AVO - Amplitude Vs Offset
PNN - Probabilistic Neural Network
MLFN - Multilayer Feed Forward Neural Network
RBFNN - Radial Basis Function Neural Network
NMO- Normal Move Out
HRS - Hampson Russell Software
FFT- Fast Fourier Transform
CC - Correlation Coefficients
RMS - Root Mean Square
QC - Quality Check
LPSSI - Linear Programming Sparse Spike Inversion
LFM - Low Frequency Model
MLD - Maximum Likelihood Deconvolution
VSP - Vertical Seismic Profile
CDP - Common Depth-Point

FWI - Full Waveform Inversion

Symbols Used

Z_P - P- impedance

Z_S - S- impedance

μ - Shear modulus

k - Bulk modulus

ρ - Density

V_P - P-wave velocity

V_S - S-wave velocity

$S(t)$ - Seismic trace

$R(t)$ - Reflectivity

$*$ - Convolutional operator

$N(t)$ - Noise component of data

Z_i - Impedance of i^{th} layer

ρ_i - Density of i^{th} layer

V_i - Velocity of i^{th} layer

R_i - Reflectiob coefficient of i^{th} layer

AI_N - Acoustic impedance of N^{th} layer

$E(R)$ - Objective function

α - Sparsity

σ - Poisson's ratio

Z - Impedance

O - Operator

$f^{-\theta}$ - Frequency spectrum of AI

r - Square root of reflectivity variance

-
- m - Number of reflections
 t - Total number of samples
 n - Square root of noise variance
 ψ - The likelihood that a given sample has a reflection
 $e(i)$ - Errors in input trend
 r_j - Seismic reflectivity
 S_k - Scaled reflectivity
 $\lambda\rho$ - Lambda-rho
 $\mu\rho$ - Mu-rho
 PP - Reflection from P-wave to P-wave
 SS - Reflection from S-wave to S-wave
 R_P - P-reflectivity
 R_S - S-reflectivity
 R_D - Density reflectivity
 $R(\theta)$ - Reflection coefficient
 R_{pi} - P-reflectivity at i^{th} interface
 T_i - i^{th} seismic trace sample
 W_j - Extracted seismic wavelet j^{th} term
 W - Matrix of wavelet
 D - Derivative matrix
 $T(\theta)$ - Angle trace
 $W(\theta)$ - Wavelet at angle θ
 D - Operator of differentiation derivative
 J - Object function
 τ - Weight factor
 λ, μ - Lamé parameters
 t_i - Time at i^{th} sample
 E - Calculated prediction error
 κ - Normalized correction coefficient
 $L(t)$ - Target log
 w_0, w_1, w_2, w_3 - Weights

E^2 - Mean square prediction error

A_{ij} - i^{th} example of j^{th} attribute

L - $N \times 1$ matrix of logs values

A - $N \times 1$ matrix of attributes values

W - 4×1 matrix of weights

w_i - Specified length operators

$\hat{L}(x)$ - Measured log value

$D(x, x_i)$ - Distance between the point of entry and each point of training

σ_j - Smoothing parameter

E_V - Prediction error

I - Mapping function

V - A set

v_i - Threshold coefficient of neuron

w_{ij} - Weight coefficient (association between the i^{th} and j^{th} neurons)

ψ_i - Potential of the neuron

$f(\psi_i)$ - Transfer function

x_p, \hat{x}_p , - Vectors containing the calculated and required activity of the output neurons

Abstract

To characterize the reservoir, seismic inversion methods have been frequently used for estimating attributes like Elastic Impedance, P-impedance, S-impedance, Density, V_P/V_S ratio and gamma ray logs from seismic and well log data. These attributes allow us to understand subsurface lithology for geo-seismic analysis, its extent and shape etc. The purpose of this research is to compare various seismic post- and pre-stack inversion methods from the seismic and well log data tie-ups. Furthermore, state-of-art geostatistical techniques have also been used intensively for further testifying the results obtained from post-stack inversion methods.

In this research, four types of post-stack inversion methods, namely, bandlimited inversion (BLI), colored inversion (CI), maximum likelihood sparse spike inversion (MLSSI) and model based inversion (MBI) methods have been performed to the post-stack seismic data from the F3 block, the Netherlands. For the pre-stack inversion, namely, simultaneous inversion (SI), lambda-mu-rho (LMR) transform and elastic impedance inversion (EI) have been applied on the seismic data of the Penobscot region, Canada. Using post-stack inversion, the data was inverted into P-impedance. The final inverted P-impedance section derived from post-stack inversion methods displayed high-resolution images within the two-way travel time range of 1300 to 1800ms time intervals. This has revealed mutually reliable low impedances results (at 1700ms time interval).

The use of SI was done for the computation of compressional and shear-wave impedances (Z_P and Z_S), V_P/V_S ratio and Lambda-Mu- Rho (LMR) attributes and their extraction. The results have suggested absence of any major reservoirs present in the Penobscot region. Data conditioning was performed to evaluate its impact on SI and LMR

transform derived results.

The elastic impedance inversion was also employed to estimate subsurface elastic properties in the inter well region. These elastic properties assist in identifying gas-bearing formation from gas free formation, as well as overpressure zones. Seismic reflection data from the Penobscot region, were used for the analysis, which was performed in two steps. Initially, the method was tested with zero Gaussian noise level on synthetic data and subsequently with incremental levels of 10% 20% and 30% Gaussian noise levels. The analysis shows that efficacy of elastic impedance inversion decreases only by 3.5% with addition of Gaussian noise levels even up to 30% in the data compared to zero Gaussian noise level. Hence, it may be assumed that Gaussian noise does not make highly significant changes in the EI values.

In the second step, EI was applied to the real time data and variation of was estimated for near and far-angle stack gathers. The analysis demonstrates that the inverted results follow the well log results satisfactorily. The results also revealed higher resolution images for the far-angle stack data compared to the near-angle stack data. Therefore, it may be assumed to be fairly established that the pre-stack data of Penobscot region does not contain any major gas or overpressure zones.

Four types of geostatistical techniques: single attribute analysis, multi attribute analysis, probabilistic neural network, and multilayer feed forward network methods have been also used to predict volumes of various petrophysical parameters (porosity, density, P-wave, and gamma ray) within the F3 block post-stack data. In these techniques, seismic and well log data derived attributes have been used as an internal attribute while model based inversion derived impedance has been used as an external attribute. Firstly, single attribute analysis has been performed which could not provide consistent result. Thereafter, multi attribute analysis was performed.

Subsequently, from the estimates, the predicted logs derived from multi attribute analysis technique show correlation values of 0.95, 0.94, 0.93 and 0.79 for porosity, density, P-wave and gamma ray, respectively. Probabilistic neural network and multilayer feed forward network analysis have been performed using model based inversion results as as an external attributes. The correlation coefficient derived from probabilistic neural network is 0.97, 0.96, 0.95, and 0.82 for porosity, density, P-wave and gamma ray,

respectively. The correlation coefficient derived from multilayer feed forward network is 0.96, 0.95, 0.94, and 0.86 for porosity, density, P-wave and gamma ray, respectively. From these four geostatistical techniques, probabilistic neural network method seems to slightly better correlation coefficient than multi attribute analysis. However, PNN and MLFN could be considered as yielding almost identical results.

In summary, the aforesaid post-stack inversion methods have yielded fairly accurate and reliable results and unequivocally confirm the presence of reservoir (at 1700ms time interval).

Pre-stack method suffers from the limited band-width of the seismic data as well as from paucity of well-log data. No reservoir was detected within the pre-stack data after applying all the pre-stack inversion methods.

The reservoir properties have been better estimated with probabilistic neural network in comparison to multi attribute analysis and multilayer feed forward neural network. The results are illustrated in form of tables, graphs and images etc. and have been discussed separately to draw the conclusions.