Computers & Geosciences 37 (2011) 1174–1180

Contents lists available at ScienceDirect

Computers & Geosciences

journal homepage: www.elsevier.com/locate/cageo

# 3D porosity prediction from seismic inversion and neural networks

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ARTICLE INFO

*Article history:*
Received 10 March 2010
Received in revised form
19 August 2010
Accepted 31 August 2010
Available online 20 November 2010

*Keywords:*
Reservoir characterization
Seismic inversion
Feed-forward neural network
Matlab

ABSTRACT

In this work, we address the problem of transforming seismic reflection data into an intrinsic rock property model. Specifically, we present an application of a methodology that allows interpreters to obtain effective porosity 3D maps from post-stack 3D seismic amplitude data, using measured density and sonic well log data as constraints. In this methodology, a 3D acoustic impedance model is calculated from seismic reflection amplitudes by applying an $L_1$-norm sparse-spike inversion algorithm in the time domain, followed by a recursive inversion performed in the frequency domain. A 3D low-frequency impedance model is estimated by kriging interpolation of impedance values calculated from well log data. This low-frequency model is added to the inversion result which otherwise provides only a relative numerical scale. To convert acoustic impedance into a single reservoir property, a feed-forward Neural Network (NN) is trained, validated and tested using gamma-ray and acoustic impedance values observed at the well log positions as input and effective porosity values as target. The trained NN is then applied for the whole reservoir volume in order to obtain a 3D effective porosity model. While the particular conclusions drawn from the results obtained in this work cannot be generalized, such results suggest that this workflow can be applied successfully as an aid in reservoir characterization, especially when there is a strong non-linear relationship between effective porosity and acoustic impedance.


## 1. Introduction

During the last decades, several methods for mapping acoustic impedance from post-stack seismic amplitude data were developed and tested with the aim of providing additional information for detailed reservoir characterization. Nowadays, most of the research efforts in this field are focused in the inversion and interpretation of variations of seismic reflection amplitude with change in distance between source and receiver (amplitude vs. offset) from pre-stack data. However, post-stack data obtained from recorded P-waves are still widely used because of their ready availability and low time-consuming processing. Because wells in a reservoir field are often spaced at hundreds or even thousands of meters, the ultimate goal of a seismic inversion procedure in the context of reservoir characterization is to provide models not only of acoustic impedance but also of other relevant physical properties, such as effective porosity and water saturation, for the inter-well regions. Such quantitative interpretations may sometimes require the use of other seismic attributes additionally to the traditional seismic reflection amplitudes (Rijks and Jauffred, 1991; Lefeuvre et al., 1995; Russell, 2004; Sancevero et al., 2005; Soubotcheva, 2006).

The seismic inversion method that is presented in this work is classified as a deterministic inversion method (Russell, 1988). Although many recent papers have demonstrated some advantages of geostatistical methods over deterministic methods (Francis, 2005; Robinson, 2001), the latter can still provide geologically plausible acoustic impedance models at a much lower computational cost. The first deterministic inversion methods for acoustic impedance mapping were developed in the late 70 s and became to known generally as recursive inversion (Lavergne and Willm, 1977; Lindseth, 1979). The basic premise of those and of all methods that were subsequently developed in the 1980s is the local validity of the 1-D convolutional model. During the 1980s, sparse-spike inversion methods were developed consisting of some techniques that make use of an additional premise that the reflections occur as sparsely distributed spikes within a layered Earth (Oldenburg et al., 1983; Russell, 1988). In this case the reflectivity function is mathematically represented as the product of the reflection coefficients and a Dirac delta function shifted by the two-way travel time to each layer. Two well known methods that fall in this category are the $L_1$-norm sparse-spike inversion (Sacchi and Ulrych, 1996), which is applied in the methodology described in this work, and the maximum likelihood inversion (Hampson and Russell, 1985).

Prediction of reservoir properties from acoustic impedance can also be thought as a kind of inversion and traditionally have been addressed through the application of multivariate statistics and,

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doi:10.1016/j.cageo.2010.08.001

more recently, Neural Network (NN) methods. The main advantages of NN methods over most traditional statistical methods can be summarized as follows: (i) the ability to extract nonlinear relationships between the input data and the target values; (ii) less sensitivity to the presence of noise in the data; and (iii) there is no need to known the underlying statistical distribution of the input data. NN methods have been successfully applied in a wide variety of applications in reservoir characterization such as porosity and permeability prediction from seismic and well-log data or seismic facies/attributes classification (Leiphart and Hart, 2001; Hampson et al., 2001; Walls et al., 2002; Pramanik et al., 2004; Calderon, 2007). In general, these papers compare performances of NN models with traditional regression methods, demonstrating that the former can provide higher correlation coefficient between actual and predicted reservoir property values and minimize the problem of sparse well coverage.

## 2. Methodology

### 2.1. Seismic inversion

The basic premises behind all seismic inversion methods in the context of this work are as follows: (i) the Earth can be represented locally by a stack of plane and parallel layers with constant physical properties; (ii) the seismic trace $s(t)$ can be represented by the convolution of the reflectivity coefficient series $r(t)$ with a band-limited wavelet $w(t)$ and the addition of a random noise $n(t)$:

$$s(t) = r(t)w(t) + n(t). \tag{1}$$

For zero incident angles, $r(t)$ is directly related to the contrast in the acoustic impedance ($AI$) of superposed layers through the expression

$$r_j = \frac{IA_{j+1} - IA_j}{IA_{j+1} + IA_j}, \tag{2}$$

where $r_j$ is the reflection coefficient at the $j$th interface of a set of $N$ superposed layers, and $IA = \rho v$ where $\rho$ e $v$ are the density and P-wave velocity, respectively. Under these conditions and assuming that multiple reflections were eliminated from the seismic data, the $AI$ value of each layer can be calculated from the knowledge of the $AI$ value of the layer above, through a recursive equation

$$IA_{j+1} = IA_j \left( \frac{1 + r_j}{1 - r_j} \right), \tag{3}$$

which in turn can be generalized to provide the $AI$ value of an arbitrary $M$ layer by

$$IA_M = IA_1 \prod_{j=2}^{M} \left( \frac{1 + r_j}{1 - r_j} \right). \tag{4}$$

The natural logarithm is applied to both sides of Eq. (4) in order to obtain a linear approximation:

$$\ln(IA_M) = \ln(IA_1) + \sum_{i=2}^{M} 2 \left[ r_i + \frac{r_i^3}{3} + \frac{r_i^5}{5} + \cdots \right], \tag{5}$$

from which we can discard the high-order terms leading to the expression

$$AI_M = AI_1 \exp(2 \sum_{j=2}^{M} r_j). \tag{6}$$

Eq. (6) is a practical formula used in recursive inversion for transformation of reflectivity into impedance. $AI_1$ is the known acoustic impedance in the top layer and $AI_M$ is that of the $M$th layer. $r_j$ is the reflection coefficient of the $j$th layer. This approximation is valid for most of the practical cases where $r_j \le |0.3|$ (Oldenburg et al., 1983; Berteussen and Ursin, 1983).

In practice, the $AI$ values at the positions of each seismic sample can be extracted from a 3D model covering the entire seismic volume, calculated through ordinary kriging of the kwon $AI$ values at the well log positions. For a properly usage of the recursive inversion, the seismic traces should be deconvolved into reflectivity series as suggested by Eq. (6). To accomplish this, we apply a constrained sparse-spike optimization procedure that minimizes the objective function

$$J(\mathbf{r}) = \alpha \sum_{j=1}^{M} |r_j| + \frac{1}{2} \left\| \frac{1}{\sigma} (\mathbf{s} - \mathbf{W}\mathbf{r}) \right\|^2 \tag{7}$$

using the conjugate-gradient algorithm (Shewchuk, 1994). The first term in Eq. (7) is provided in order to allow minimization of the $L_1$-norm of the reflectivities, where $\alpha$ controls the sparsity of the solution. With the second term, the algorithm also minimizes the difference between the synthetic seismic traces (**Wr**) and the observed traces (**s**). **W** is a wavelet coefficient matrix and $\sigma$ is the standard deviation of the seismic data noise. Other optimization algorithms can also be used to minimize Eq. (7), such as Iterative Reweighted Least Squares (Björck, 1996) or soft-tresholding algorithms (Loubes and De Geer, 2002).

It is important to point out that this constrained sparse-spike inversion will provide an impedance model that does not display the actual reflection series but displays only the largest reflectors (Oldenburg et al., 1983). In other words, this means that small wavelength features in the log impedance curve will not be recovered by the inversion and, therefore, the interpreter has to be cautious while analyzing the inversion results.

After estimating **r** from the seismic amplitudes, then it is inverted into $AI$ according to the following sequential steps (Ferguson and Margrave, 1996):

(1) compute the linear trend of a spatial correspondent AI vector and subtract it, obtaining a residual $AI_{res}$ vector;
(2) compute the Fourier spectra of $AI_{res}$;
(3) apply Eq. (6) to the reflectivity series, obtaining a relative $AI_{rel}$ vector;
(4) compute the Fourier spectra of $AI_{rel}$;
(5) determine a scalar $\alpha$ to match the mean power of $AI_{rel}$ and $AI_{res}$;
(6) multiply the spectra of $AI_{rel}$ by $\alpha$;
(7) low-pass filter $AI_{res}$ and add to the result of step (6);
(8) inverse Fourier transform the result of step (7); and
(9) add the low-frequency trend from step (1) to the result of step (8).

It is of course possible to include an extra constraint on impedances directly in Eq. (7). However, by the approach described in this paper it is possible to keep control of the frequency contents involved and the frequency cut-offs to properly add the trend in acoustic impedance.

Due to the sparse distribution of wells, the low-frequency trend of step (1) was extracted from spatial correspondent $AI$ traces estimated by kriging. A low cut-off for coupling the low frequency trend and a high cut-off were defined by finding where the energy content of the original seismic traces approaches to zero in the amplitude spectrum. This characterizes the band-limited nature of the seismic data.

### 2.2. Porosity prediction using Neural Networks

The procedure outlined here can be applied to reservoirs that do not show a linear relationship between $AI$ and the reservoir property that needs to be mapped. For the particular example shown in this