



3D quantitative AVA: a model-based approach for a joint inversion of angle data

T. Tonellot, D. Macé, and V. Richard, Institut Français du Pétrole

Summary

In order to provide a user guided and quantitative approach to AVA integrated processing, we propose a model-based approach to jointly invert angle-limited stacks. In a first step, we use a multiwell calibration analysis to extract a single wavelet for each angle stack volume. Then, we use an elastic inversion approach based on a 3D formalism in which a priori information is provided for each parameter (P- and S-impedance). For both calibration and inversion purposes, the Knott-Zoeppritz equation is used to compute the predicted synthetic data associated to a specific incidence angle. The inversion involves the computation of a global objective function which is minimized in order to compute an optimal model for each elastic parameter. This model best explains the AVA information of the angle stacks and the stratigraphic/petrophysics knowledge introduced through the a priori information. The method is illustrated on a real 3D marine case study.

Introduction

In contrast to conventional AVO analysis, two approaches have appeared in recent works to estimate the elastic properties of the subsurface from PP prestack seismic data. The first one, introduced by Connolly (1999) and based on the linearization of the Knott-Zoeppritz equation, consists in sequentially inverting angle-limited stacks to obtain "elastic impedances", and then in extracting the P- and S-impedances from a linear fit to the logarithm of the "elastic impedance". The second approach consists in simultaneously inverting all the angle-stacks, in order to globally estimate the P- and S-impedances. This kind of method is less sensitive to local noise in the angle-stacks, and should provide more robust estimates of the elastic parameters.

Nevertheless, all these methods are limited by the fact that S-impedance is badly determined from PP data. In our model-based AVA elastic inversion, angle stacks for a range of angles of incidence are simultaneously inverted for P- and S-impedances (and optionally for density). In addition, we introduce a priori information in the inversion process in order to improve the determination of the elastic model parameters.

In the following, we first describe our methodology and then present a first 3D application on real marine data.

Model-based AVA elastic inversion

Angle stacks multiwell calibration

The first part of the quantitative processing consists in a detailed well-to-seismic calibration. Because NMO stretch and tuning are among the most serious factors hampering confident AVA analysis, we have decided to extract one single wavelet for each angle stack. Thus, each wavelet will be able to compensate for some of the preprocessing issues (corrections for wavelet variations) through the elastic inversion.

We apply sequentially to each angle stack, the calibration methodology described by Lucet et al. (2000), in order to extract an optimal wavelet for each angle. Note that the synthetic trace at a well for a given angle, is obtained here by convolving the Knott-Zoeppritz reflection series (computed from density, and P- and S-impedance logs at well) with a wavelet. The methodology provides also an optimal location for each well mainly in terms of correlation coefficient between synthetic and real traces. As the angle stacks are processed sequentially, a given well may have a different optimal location according to the angle. Consequently the final optimal location for each well is chosen as the one which gives the higher correlation coefficient for all the angles.

Joint stratigraphic inversion

The second part of the quantitative processing consists in a joint stratigraphic inversion of all the angle-limited stacks.

We adopt a Bayesian inverse calculation to estimate elastic parameters from seismic data as thoroughly developed by A. Tarantola (1987). We assume that the seismic noise is described by a Gaussian probability with zero mathematical expectation and covariance operator C_d , and that the uncertainties on the a priori model are described by a Gaussian probability with zero mathematical expectation and covariance operator C_m . The maximum likelihood model minimizes the sum of two objective functions :

$$J = J_s + J_g$$

where J_s and J_g are respectively the seismic and "geological/petrophysical" objective functions.

We assume that the seismic noise is uncorrelated from one trace to another within each angle-stack volume and from one angle volume to another : the data covariance C_d is diagonal, with a seismic variance σ_s function of the noise level in the data. Thus J_s measures the mean square error between model-predicted and actual angle stack data :

$$J_s(m) = \sum_{\theta} \left\| R_{\theta}(m) * W_{\theta} - d_{\theta}^{obs} \right\|_{C_d^{-1}}^2$$

where $R_{\theta}(m)$ is the Knott-Zoeppritz reflection coefficient series corresponding to the current elastic model m and

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to the angle θ , W_θ is the wavelet, and d_θ^{obs} is the observed seismic trace at the angle θ .

J_g measures the error between a priori and predicted model parameters according to the norm associated to C_m^{-1} , where C_m is the multiparameter covariance matrix in model space. The choice of C_m which has a patent-pending status is described by Tonellot et al. (1999), and permits the introduction of a 3D a priori geometry derived from interpreted horizons and stratigraphic knowledge. This covariance operator acts as a geologically oriented multichannel filter in the model space and allows to include local petrophysical information.

Using this geometrical framework and the available well logs, an a priori model for each elastic parameter is built by filling the inter-well volume using a standard interpolation technique. The confidence on this a priori model is incorporated within the inversion by means of a priori user defined parameters : a variance for each elastic parameter uncertainty, a correlation coefficient of the inter-parameter uncertainties, and a correlation length which tunes the confidence in the a priori expected variations of the elastic parameters along the geometrical framework.

Once the a priori information is specified, the objective function is minimized using a standard conjugate gradient technique.

Illustration

We apply the proposed methodology on a 3D marine data set. Five angle-limited stacks are provided after a preserved amplitude processing and NMO corrections. They correspond respectively to the stack of angles 0-6, 6-12, 12-18, 18-24, and 24-30 degrees. Each angle cube contains 141 lines with 251 traces by line. Log data (P- and S-impedances and density) were available at 3 wells. An interpretation of the main near offset reflections is also available (time picking).

Firstly, the seismic data were calibrated to well logs and five wavelets were extracted using the multiwell angle-stack calibration. The a priori models in P and S-impedance were computed by using two horizons which delineate the reservoir zone, and by interpolating the well log information along correlation lines defined by stratigraphic knowledge. A priori parameters were set within each of the three defined geological units, according to some information about the lateral heterogeneity of the elastic parameters in the target interval.

Secondly, according to our model-based elastic inversion, the five angle cubes are inverted simultaneously using a 3D stratigraphic/petrophysical constraint in the model space. This method gives an optimal model in P- and S-impedance. The residuals corresponding to this optimal model, mainly contain incoherent noise as is illustrated on line 10 (Figures 1 and 2). Thus, the inverted impedances correctly explain the amplitude variation of the seismic with angle, and the P and S reflectivities (Fig. 3) show a great improvement of the resolution. Note that the

resolution of the S-reflection series is mainly controlled by the far-angle signal bandwidth (20-77Hz), whereas the resolution of the P-reflection series is controlled by the short-angle bandwidth (27-90Hz).

As the inverted data sets are amplitude calibrated at well location through the wavelets, the inversion results can be used for quantitative interpretation with increased accuracy and resolution. For example, from the inverted P- and S-impedance volumes (in a similar bandwidth), we can compute rock properties such as Poisson's ratio and Lamé's parameters (Fig. 4 and 5) as it is suggested by Goodway et al. (1997). For this case study, these rock properties would allow to characterize the complex channelised reservoir in a turbidite environment.

Conclusion

We introduce a new methodology for AVA analysis based, on one hand on the joint stratigraphic inversion of angle-limited stacks using an appropriate forward modeling to compute the synthetic gathers, and on the other hand on the use of a full 3D formalism which permits the introduction of a priori information (geological and petrophysical knowledge) in the inversion process. This joint elastic inversion scheme constrained by a priori impedance information improves stability and uniqueness. The approach is very flexible, thus allowing additional developments, for example on the forward modeling side and on application to new data types (converted waves,...).

Acknowledgments

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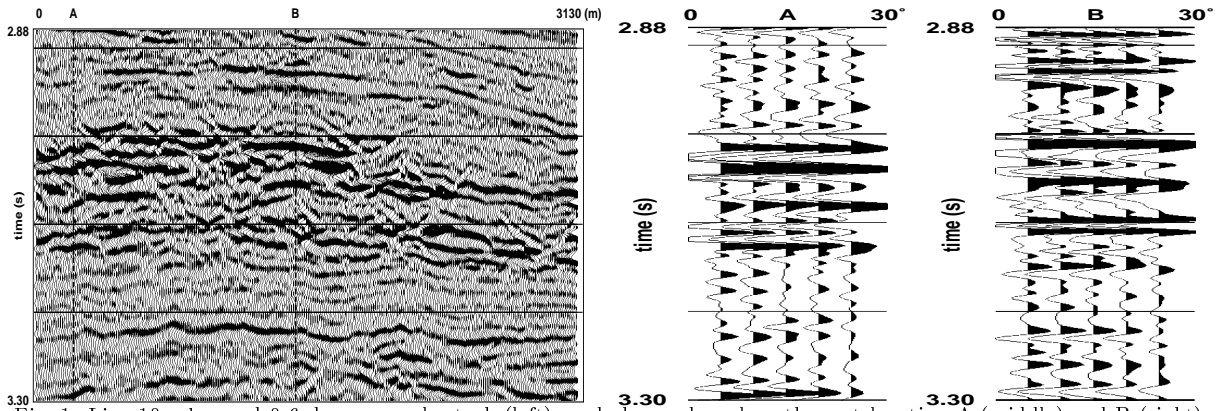


Fig. 1: Line 10: observed 0-6 degrees angle stack (left), and observed angle gathers at location A (middle) and B (right).

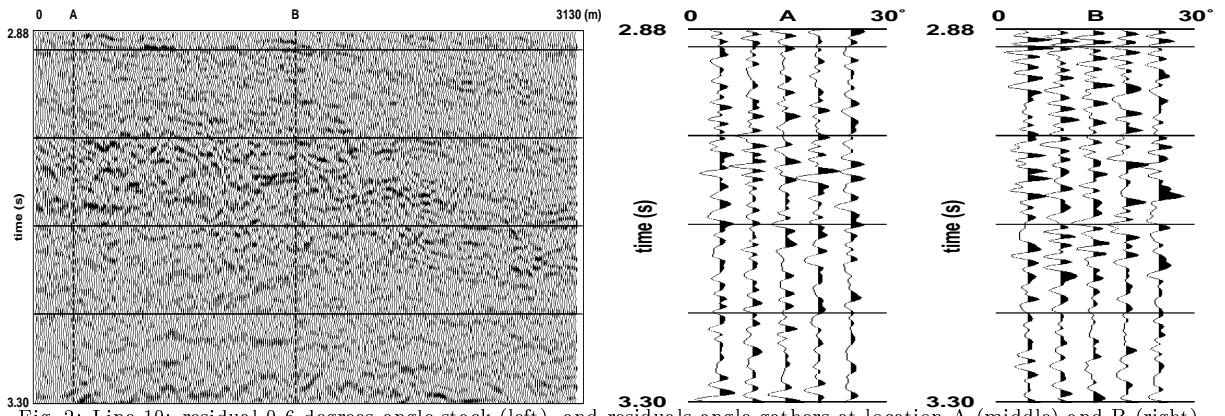


Fig. 2: Line 10: residual 0-6 degrees angle stack (left), and residuals angle gathers at location A (middle) and B (right).

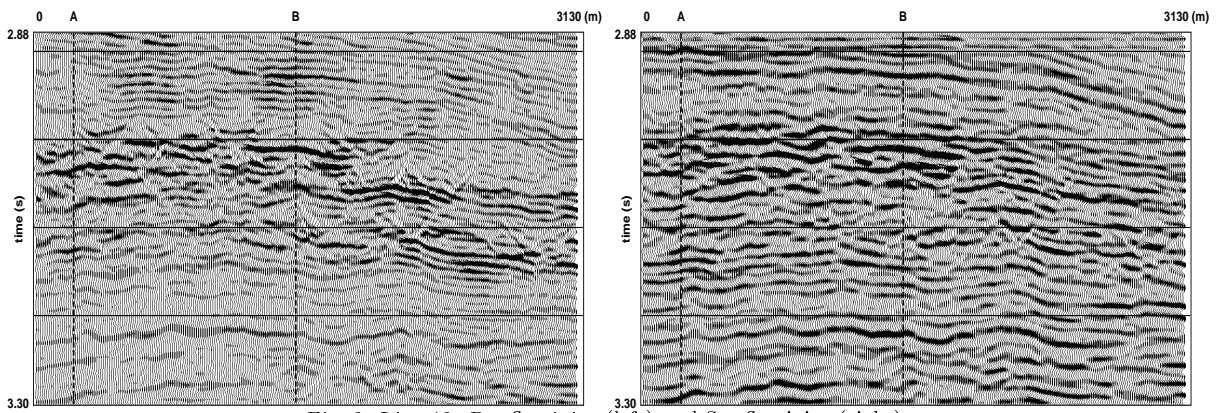


Fig. 3: Line 10: P-reflectivity (left) and S-reflectivity (right).

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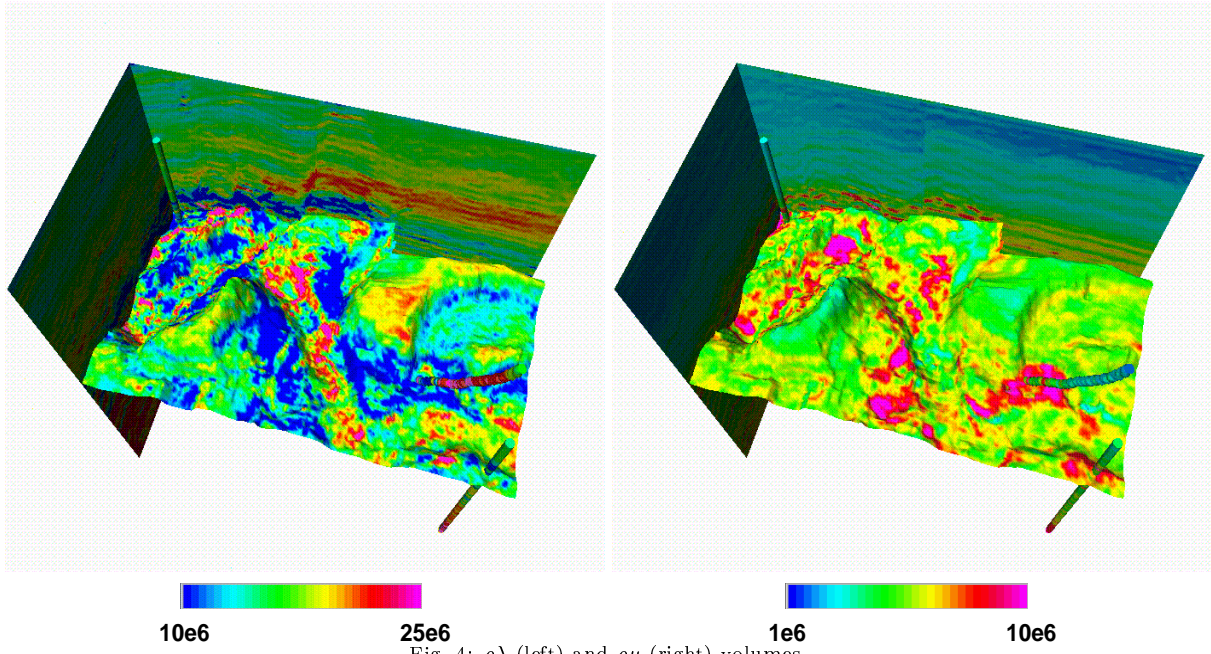


Fig. 4: $\rho\lambda$ (left) and $\rho\mu$ (right) volumes.

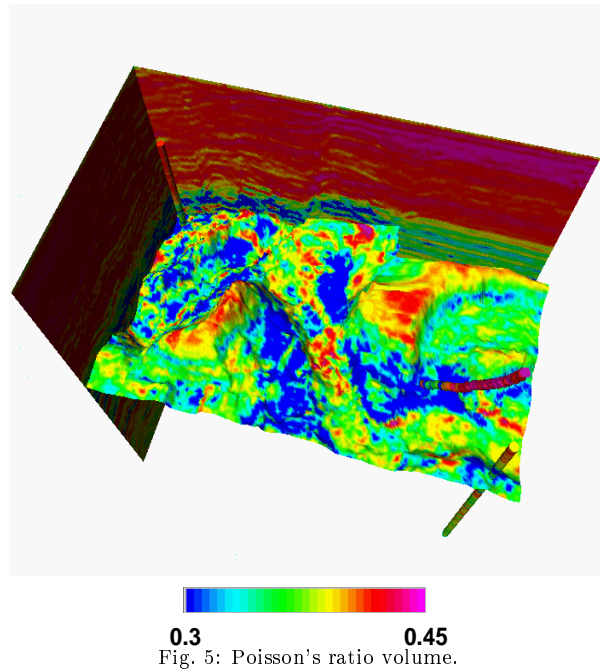


Fig. 5: Poisson's ratio volume.



3D Seismic Inversion Orocuál Field - Las Piedras, Monagas-Venezuela

Nohemí Del V. García Piñero, PDVSA-Venezuela, Garcianu@pdvsa.com

Muriel Amy, Beicip-Franlab-Francia, Amy@beicip.fr

Raimundo E. Ronny Franco, PDVSA-Venezuela, Ronnyrm@pdvsa.com

Introduction

Seismic inversion techniques, integrating 3D poststack seismic data, impedance logs and geological knowledge, are widely used as a first step of lithoseismic reservoir characterisation procedures. They produce acoustic impedance images which are much more convenient for inferring reservoir properties (Net to gross, Shaliness, Porosity, etc.) than the conventional seismic.

These techniques were applied to the Las Piedras formation in the Orocuál field, Venezuela, using IFP's InterWell software.

The main objective of the study was to provide an acoustic impedance distribution of the Intra Las Piedras Fm. in order to detect and delineate lateral variations or heterogeneities of shallow Miocene to Pliocene sands.

The Interwell Inversion

The procedure followed to achieve this 3D seismic inversion project was :

- Evaluation of the amplitude spectrum of the 3D seismic data set, and estimation of the level of random noise.
- Generation of synthetic traces and calibration to seismic data (well by well and using the multi-well module) to extract an optimal seismic wavelet from the 3D seismic data.
- Construction of an initial impedance model based on the seismic interpretation and impedance values observed in the wells.
- Inversion processing of the seismic data by iterative modification of the impedance model.
- Analysis of the results.

The Inversion Results

The seismic inversion performed on the Las Piedras formation of the Orocuál field allowed to highlight lateral impedance variations in the Las Piedras interval.

Before the realisation of a petrophysical study (crossplots between impedances and petrophysical properties (porosity, shaliness, etc.), a quick analyse of the impedance results was realised on a section

where is displayed a well, with its GR (left) and Resistivity (right) curves (Figure 1), that can be considered as referential.

- Firstly, from the observation of the well information only, in the lower part of the stratigraphical column, the comparison of the GR, ILD and impedance curves seems to indicate that the levels of low impedance could correspond to reservoir levels (high resistivity and low GR).
- Secondly, the observation of the impedance section crossing this well (Figure 1) shows at the basal part of Las Piedras formation three levels of low values (green and blue colours). So, correlated with the well information, these low impedance levels can be assimilated to three sand levels.

In the higher part of the column, some levels of low impedances can also be observed but it is more difficult to make difference between sands and shales without a detailed study.

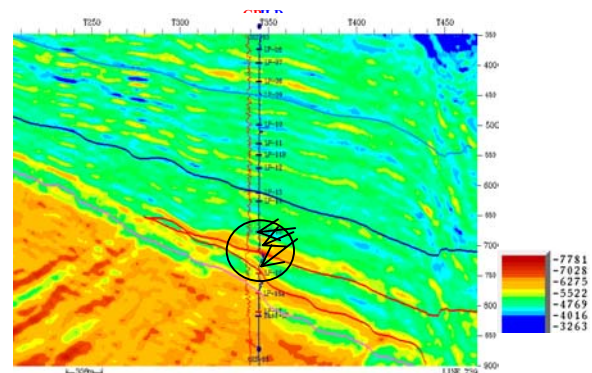


Figure 1 - Impedance section – Sands levels localisation on the basal part of Las Piedras formation.

Conclusions

This 3D seismic inversion allowed to produce a 3D optimal impedance model that matches seismic data, geological knowledge and well log data. The final impedance cube shows an improved resolution of the seismic information. In comparison to the a-priori model (which determines the low frequency component of the impedance), the seismic inversion has brought additional information (in the range of the seismic resolution). Lateral variations of the impedance can be observed and could be linked to lateral changes of facies, fluid content or petrophysical properties.

To better characterise the inversion results in terms of reservoir properties, these variations need to be calibrated on well information (lithological

3D Seismic Inversion Orocual Field – Las Piedras

interpretations, petrophysical properties, etc.). After the realisation of a detailed petrophysical study, it is recommended to convert the impedance cube in a cube of petrophysical.

The results of the 3D seismic inversion would also be used to constrain the geostatistical study.



Análise dos parâmetros da equação do tempo de percurso de reflexão em meios com anisotropia do tipo VTI para inversão de dados sísmicos.

Soraya I. L. Tuma, Liliana A. Diogo & Carlos A. Mendonça,

Instituto de Astronomia, Geofísica e Ciências Atmosféricas/USP, soraya@iag.usp.br

Abstract

In order to characterize a VTI anisotropic medium, a CRS (controlled random search) inversion algorithm was implemented to invert the nonhyperbolic moveout of the traveltimes reflection time. The conducted numerical study evaluates the influence of the data acquisition array upon the uncertainties for the model parameter estimates. As a result, optimal data acquisition parameters are determined such as the corresponding estimates for the NMO velocity and the anisotropic parameter are estimated with a minimum uncertainty.

Introduction

O comportamento anisotrópico, com respeito à propagação das ondas sísmicas, do tipo VTI (meio transversalmente isotrópico com eixo de simetria vertical) é comumente encontrado em folhelhos e em meios compostos por uma sucessão de camadas horizontais, homogêneas e isotrópicas, cujas espessuras são muito menores do que o comprimento da onda sísmica.

O desenvolvimento teórico para a propagação de ondas sísmicas em meios com anisotropia VTI encontra-se bem estabelecido e várias são as publicações que reportam sobre os danos, qualitativos e quantitativos, na imagem sísmica obtida através do processamento sísmico convencional empregando-se a aproximação hiperbólica para os tempos de percurso de reflexão.

Alkhalifah (1997) propôs a utilização da informação do *moveout* não hiperbólico para a análise de velocidades e para a determinação do parâmetro de anisotropia (ϵ), introduzido por Alkhalifah & Tsvankin (1995). A qualidade da estimativa desses valores depende principalmente de quanto a curva de tempo de percurso difere do caráter hiperbólico e da sensibilidade da variação dos tempos de percurso com respeito aos parâmetros a serem estimados.

A componente não hiperbólica da curva de tempo para um meio com anisotropia VTI depende diretamente do valor do parâmetro de anisotropia (ϵ), sendo o desvio do *moveout* hiperbólico maior para os afastamentos maiores. Desta forma, espera-se uma maior estabilidade na estimativa do parâmetro de anisotropia com o aumento do afastamento fonte-receptor.

Neste trabalho foi implementado um algoritmo de inversão dos tempos de percurso para a estimativa da velocidade e do parâmetro ϵ . Considerando-se que o afastamento máximo fonte-receptor depende da geometria de aquisição (afastamento mínimo, intervalo e número de receptores), propôs-se utilizar a análise das variâncias da estimativa dos parâmetros do modelo para avaliar o efeito dos parâmetros da geometria de aquisição na amostragem da curva de tempo de percurso e consequentemente na estimativa dos parâmetros do modelo.

Préface

A equação que descreve os tempos de reflexão ($t(x)$) em um meio anisotrópico difere da aproximação hiperbólica, convencionalmente empregada no processamento sísmico de reflexão. Hake et al. (1984) derivaram uma equação para $t(x)$ com base na expansão de Taylor até quarta ordem. Tal aproximação, da mesma forma que a aproximação hiperbólica para meios isotrópicos, é limitada apenas a pequenos afastamentos fonte-receptor (menores que a profundidade da interface). Tsvankin & Thomsen (1995) deduziram um fator de correção para o termo de quarta potência (responsável pela descrição do caráter não hiperbólico de $t(x)$), compensando a ausência dos termos de ordem superior e tornando a expressão mais precisa e válida para afastamentos grandes, maiores que a profundidade do refletor. Posteriormente Alkhalifah and Tsvankin (1995) simplificaram a formulação introduzindo o coeficiente de anisotropia (ϵ), apresentando a seguinte expressão para ondas qP:

$$t^2(x) = t_0^2 + \frac{x^2}{V_{\text{nmo}}^2} + \frac{2x^4}{V_{\text{nmo}}^2 [t_0^2 V_{\text{nmo}}^2 + (1+2\epsilon)x^2]} \quad (1)$$

Onde, x é a distância fonte-receptor, t_0 é o tempo de reflexão normal à interface e V_{nmo} é a velocidade que corrige o NMO (*normal moveout*), ou seja, a diferença em tempo devido ao afastamento fonte-receptor

A dependência do tempo com respeito ao parâmetro de anisotropia (ϵ) aparece no terceiro termo da expressão (1), o qual é responsável pelo caráter não hiperbólico de $t(x)$. Portanto, o desvio do *moveout* hiperbólico é diretamente dependente do valor de ϵ e quanto maior for afastamento (x) mais evidente será essa diferença.

Dados sísmicos

Os dados sintéticos para o exemplo apresentado foram gerados pelo programa ANRAY95 (Gajewski & Psencik, 1995). Adotou-se um modelo correspondente a um folhelho anisotrópico cujos valores do coeficiente de anisotropia e velocidade, $\epsilon=0.153$ e $V_{nmo}=3853\text{m/s}$, respectivamente, foram calculados a partir dos coeficientes de Thomsen publicados em Thomsen (1986). Definiu-se uma camada cuja espessura proporcionaria um tempo normal $t_0=1\text{s}$. A geometria de aquisição adotada correspondeu a um sismograma CMP com 96 traços, com afastamento mínimo igual a 50m e espaçamento entre receptores de 50m.

Problema Inverso

O problema inverso considerado consiste em recuperar, a partir dos dados observados, os parâmetros que caracterizam o meio segundo os aspectos cinemáticos de propagação das ondas sísmicas. Apenas as ondas qP foram consideradas. Portanto, os elementos do vetor dos parâmetros do modelo (\mathbf{r}) correspondem ao coeficiente de anisotropia (ϵ) e a velocidade (V_{nmo}) , e os dados observados aos tempos de percurso das ondas P refletidas.

Função Objetiva

A função objetivo $(f(\mathbf{r}))$ foi definida pela norma euclidiana (L2) da diferença entre os tempos observados e calculados. Assumindo, portanto, a seguinte forma:

$$f(\mathbf{r}) = \left[\sum_{i=1}^n (f(\mathbf{r}) - \text{obs}_i)^2 \right]^{1/2} \quad (2)$$

Onde \mathbf{r} é o vetor de parâmetros do modelo, $f(\mathbf{r})$ é a equação (1) do modelo direto para o cálculo do tempo de percurso, e obs_i é o vetor dos dados observados.

O valor do tempo normal (t_0) em (1) foi assumido como já obtido através da análise do comportamento hiperbólico de $t(x)$ para afastamentos curtos.

Algoritmo de minimização

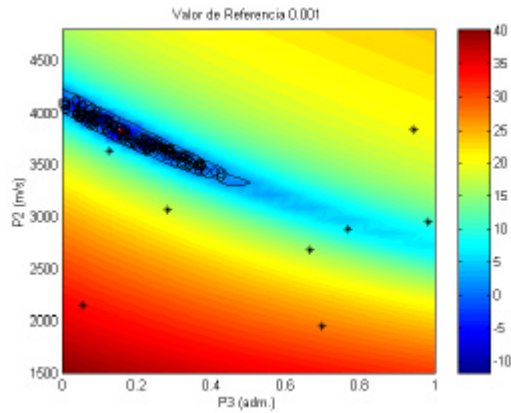
Para a minimização da função objetivo optou-se pela utilização do procedimento de busca aleatória controlada - CRS (*controlled random search procedure*) (Price, 1977), por ser um método de busca global, de fácil implementação computacional e adequado à solução de problemas inversos não lineares. O CRS não é um método amplamente difundido no meio geofísico como os métodos globais conhecidos por *simulated*

annealing e algoritmos genéticos, embora algumas aplicações tenham mostrado sua eficiência na inversão de dados magnéticos (Silva & Hohmann, 1983) e de refração sísmica (Smith & Ferguson, 2000).

Neste algoritmo, a busca do mínimo global inicia com N modelos (ou pontos no espaço de parâmetros) gerados aleatoriamente, onde N deve ser maior do que o número de parâmetros do modelo mais um ($m+1$). A cada iteração do procedimento CRS, são selecionados aleatoriamente ($m+1$) pontos da população de modelos corrente, os quais formarão um simplex. Um novo modelo (p) é gerado a partir deste simplex, através do rebatimento de um dos seus vértices, \mathbf{r} , escolhido aleatoriamente entre as ($m+1$) soluções em relação ao centróide, \mathbf{c} , definido pelos outros m pontos do simplex. Cada ponto do espaço dos modelos pode ser representado por um vetor e a fórmula $(\mathbf{r} - 2\mathbf{c} + \mathbf{r})$ resume o processo de rebatimento. Se o valor da função objetivo para o novo modelo for menor do que o maior valor da função para os modelos anteriores, então o ponto em que função é maior é descartado e o novo modelo passa a ser incorporado à população de modelos correntes. Desta forma, os pontos em que a função objetivo tem valor grande vão sendo descartados gradativamente e os modelos restantes aninham-se nas proximidades dos pontos de mínimo existentes.

Nas aplicações efetuadas foram gerados 8 pontos para iniciar a busca pelo método CRS. O processo de inversão foi implementado para executar o CRS diversas vezes, fornecendo ao final uma nuvem de soluções alternativas. Adotou-se como uma estimativa final a solução obtida através da mediana do conjunto de soluções fornecidas pelo CRS.

Os limites dos parâmetros do modelo foram definidos entre 0 e 1 para a anisotropia (ϵ) e entre 1500 e 4500m/s para a velocidade (V_{nmo}) . Na Figura 1 são apresentadas as curvas de nível da função objetivo, sobre as quais foram representados os 8 pontos iniciais para a busca, o conjunto das soluções obtidas pelo método CRS, a solução final (valor da mediana) e o ponto correspondente à solução desejada. Também está representado o contorno que corresponde ao valor projetado para a incerteza na estimativa dos parâmetros do modelo.



Fra 1 Mapa da função objetivo.

An se a v a r n a s a r e r s

A incerteza da estimativa dos parâmetros do modelo pode ser avaliada considerando-se a estimativa por mínimos quadrados para um problema linearizado nas vizinhanças do ponto correspondente à solução do problema inverso.

A estimativa dos parâmetros requer a solução do sistema: $\mathbf{G} \cdot \mathbf{p} = \mathbf{d}$. Onde \mathbf{p} é o vetor dos dados observados, \mathbf{d} é o vetor dos parâmetros do modelo e \mathbf{G} é a matriz do sistema linearizado, denominada matriz de sensibilidade, composta pelas derivadas dos tempos teóricos (t) com respeito a cada um dos parâmetros do modelo (α e V_{nmo}) em cada posição dos receptores. Desse modo, o número de colunas da matriz \mathbf{G} depende do número de parâmetros do modelo e o número de linhas da quantidade de receptores utilizados.

$$\mathbf{G} = \begin{bmatrix} \frac{\partial t}{\partial \alpha}(x_1) & \frac{\partial t}{\partial V_{nmo}}(x_1) \\ \vdots & \vdots \\ \frac{\partial t}{\partial \alpha}(x_n) & \frac{\partial t}{\partial V_{nmo}}(x_n) \end{bmatrix} \quad (3)$$

A estimativa por mínimos quadrados é obtida fazendo:

$$\mathbf{m} = (\mathbf{G}^T \mathbf{G})^{-1} \mathbf{G}^T \mathbf{d} \quad (4)$$

E tem incerteza associada definida pela matriz de covariância:

$$[\text{cov}(\mathbf{m})] = \sigma^2 (\mathbf{G}^T \mathbf{G})^{-1} \quad (5)$$

sendo σ é o desvio padrão dos dados assumido igual para todos os afastamentos. Na obtenção da equação (5) assume-se também que os erros são aditivos, não correlacionáveis e que possuem média nula. A equação (5) permite que a variância dos parâmetros do modelo seja avaliada em termos de uma aproximação linear desenvolvida na vizinhança da solução obtida quando se resolve

o problema inverso. O cálculo da matriz das covariâncias para diferentes arranjos de aquisição de dados permite determinar o arranjo particular no qual as incertezas associadas são mínimas. Para determinar tais arranjos foram efetuadas duas análises: I) variando-se o afastamento mínimo fonte-receptor e o intervalo entre receptores, ambos de 50 em 50m até um máximo de 500m, como um valor numérico de teste e II) variando-se o intervalo entre receptores, mesmos valores da análise anterior, e o número de receptores com um mínimo de 25, máximo de 200 e incremento de 25. O desvio padrão considerado para os dados foi de 0,001s.

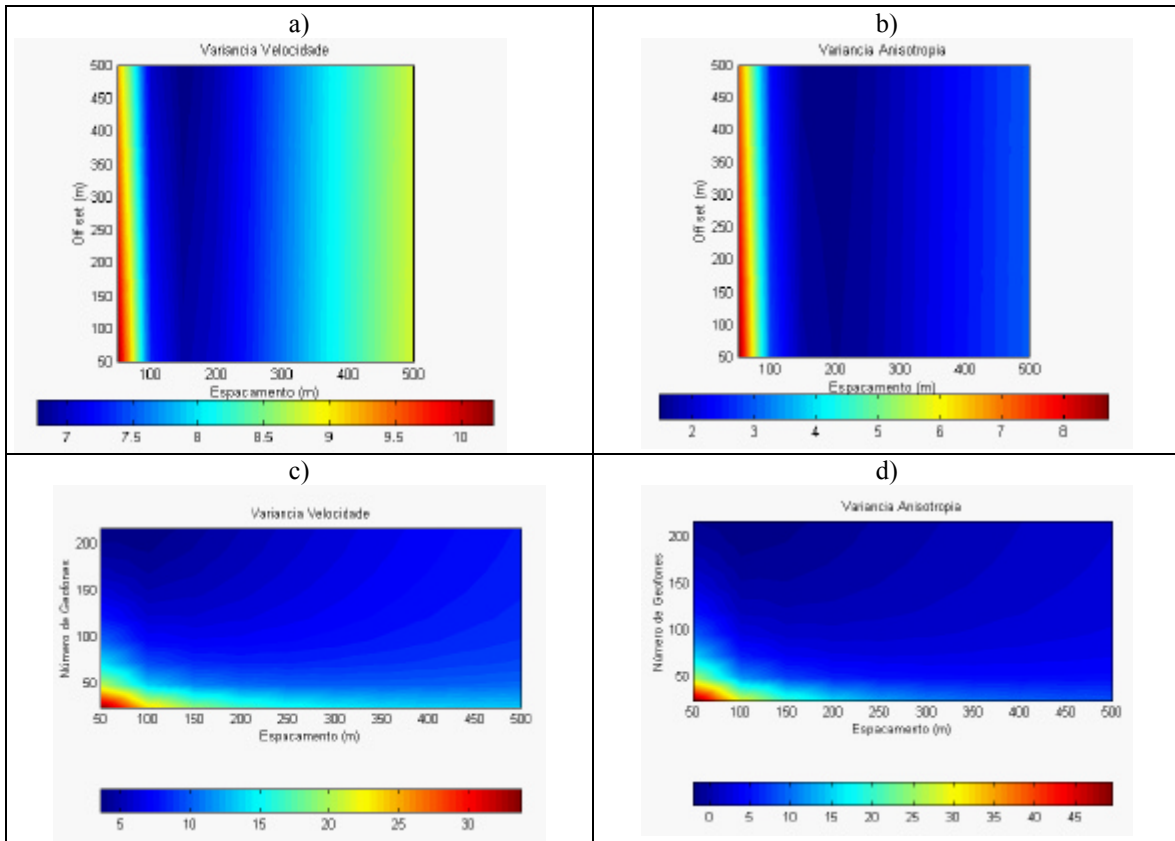
Res a s s

Dos resultados apresentados nas Figuras 2a e 2b, conclui-se que: i) o afastamento mínimo não tem grande influência no valor dos desvios padrão dos parâmetros do modelo e ii) que a partir de 200m aumentar o intervalo entre receptores, apesar de aumentar o afastamento máximo, não promove um decréscimo no desvio padrão.

De acordo com as Figuras 2c e 2d, se observa que quanto maior é o espaçamento entre receptores e maior o número de receptores no arranjo, menor é o desvio padrão na determinação dos parâmetros, o qual é coerente com o comportamento da curva do tempo de percurso referente aos afastamentos fonte-receptor grandes. Portanto, não basta aumentar x_{\max} através do espaçamento entre receptores, é necessário aumentar a densidade de receptores.

C n s e s

O algoritmo do CRS foi eficiente na busca do mínimo global dos parâmetros do modelo. Da análise da variância dos parâmetros, pôde-se estabelecer que o afastamento fonte-receptor mínimo não tem grande influência no comportamento da função objetivo e que além do afastamento máximo, também a densidade de receptores deve ser considerada para uma amostragem adequada da curva de tempo de percurso visando a caracterização de um meio com anisotropia do tipo VTI.



F ra2 Análise das variâncias dos parâmetros do modelo.

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Construção de Seções de Impedância de Reflexão Através da MZO

José Acúrcio Canário de Moraes, PETROBRAS S/A, Brasil

Abstract

This work is concerned with the theoretical meaning of acoustic and elastic impedance, as well as its practical determination from seismic data. It describes and comments the various impedance definitions that exist in the literature, introducing the term Reflection Impedance as a unifying concept. The construction of a reflection impedance section that corresponds to a given multicoverage seismic data set strongly depends on the ability of accurately extracting angle-dependent reflection coefficients from primary reflections within the data. It is shown that the method of Kirchhoff true-amplitude migration to zero offset, performed twice using different weight functions, can provide good estimates of the required reflection coefficients and reflection angles. An algorithm to further construct the reflection impedance section after determination of the reflection angles is also described. Applications of the obtained algorithm to synthetic data examples are provided to test and validate the approach.

Introdução

A inversão sísmica para geração de seções de impedância é um dos processos utilizados para a caracterização de parâmetros petrofísicos, como porosidade, permeabilidade, tipos de fluídos, saturação, litologia e a arquitetura interna dos reservatórios dentre outros.

Até recentemente a inversão sísmica mais utilizada foi a de impedância acústica. Para os cálculos consideram-se apenas a velocidade das ondas compressoriais, e a densidade das rochas envolvidas nas trajetórias dos raios, utilizando-se ângulos de incidência nulos ou próximos disso. Para ângulos de incidência não nulos, o comportamento elástico se manifesta através da dependência das velocidades, não só compressoriais, mas também cisalhantes. Nesses casos deve se utilizar o conceito de impedância elástica de reflexão, que é função das velocidades das ondas compressoriais e cisalhantes, densidades das rochas e ângulo de incidência. A correlação da impedância de reflexão com os dados sísmicos fica melhor caracterizada através do empilhamento de seções de ângulo do que de afastamento comum.

A construção de seções de impedância de reflexão tem como pilar, a utilização de amplitudes verdadeiras que é o suporte dos atributos sísmicos. O processamento consagrado para preservação de amplitudes sísmicas é o de migração pré-empilhamento à

verdadeira amplitude. Contudo por trabalhar com um volume de dados muito elevado, aliado a processamento prévio para a determinação de um modelo de velocidades, a migração em profundidade tem um custo computacional bastante alto, tornando-se uma limitação importante para sua aplicação. A migração para afastamento nulo (MZO), é uma rotina de processamento no tempo, na qual seções sísmicas de afastamento comum são transformadas em seções simuladas de afastamento nulo à verdadeira amplitude. Neste caso, as reflexões primárias, após a transformação MZO, têm espalhamento geométrico igual ao que seria observado na situação de afastamento nulo. Os coeficientes de reflexão, no entanto, se mantêm preservados, o que possibilita a sua utilização em diversas operações à verdadeira amplitude.

Para o presente trabalho utilizou-se modelo sintético com geologia simplificada porém compatível com modelos reais. Os modelos de velocidades utilizados, visaram simular anomalias de amplitudes, possíveis indicadoras de hidrocarbonetos.

Impedância de Reflexão

O conceito de impedância de reflexão está ligado à propagação de ondas compressoriais e cisalhantes em meio elástico, com ângulos de reflexão variados.

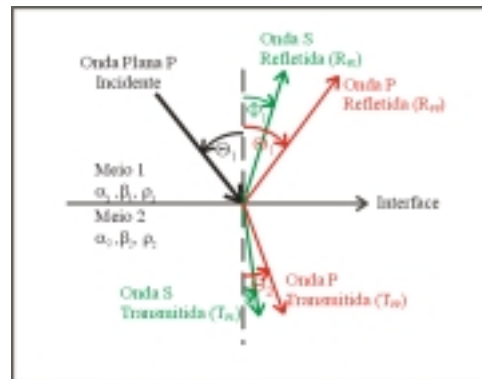


Figura 1- Ondas geradas por reflexão e transmissão na interface entre dois meios elásticos a partir de uma onda plana P incidente.

Quando uma frente de onda chega sobre uma interface que separa dois meios elásticos, semi-infinitos, homogêneos e isotrópicos, ela é particionada, sendo parcialmente refletida e parcialmente transmitida. A Figura 1 procura representar de forma simplificada esse esquema, onde a frente de onda é representada por um raio, respeitando as condições

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limites dos meios elásticos, em relação a continuidade dos componentes normais e tangenciais do deslocamento e as dificuldades para passagem da interface, conhecida como impedância.

Os seis parâmetros elásticos independentes, α_1 , α_2 , β_1 , β_2 , ρ_1 e ρ_2 , mais os valores θ_1 e θ_2 , que são respectivamente os ângulos das ondas P incidente ou P refletida e P transmitida, e, Φ_1 e Φ_2 são os ângulos das ondas S refletida e transmitida, constituem-se nos parâmetros básicos para os cálculos dos coeficientes de reflexão e transmissão bem como para os cálculos das impedâncias acústicas e elásticas.

A generalização do Princípio de Fermat, conhecida como Lei de Snell, define a relação entre todos os tipos de ondas e suas relações, onde p é conhecido como parâmetro do raio.

$$\frac{\sin\theta_1}{\alpha_1} = \frac{\sin\theta_2}{\alpha_2} = \frac{\sin\Phi_1}{\beta_1} = \frac{\sin\Phi_2}{\beta_2} = p \quad (1)$$

As equações que definem os limites entre dois meios elásticos em termos de amplitudes foram recriadas por Telford et al. (1976) a partir das equações definidas por Zoeppritz e que traduzem a continuidade dos deslocamentos e dos impedimentos na passagem da interface, entre os meios 1 e 2 (Figura 1).

$$\begin{bmatrix} \cos\theta_1 & -\sin\phi_1 & \cos\theta_2 & \sin\phi_2 \\ \sin\theta_1 & \cos\phi_1 & -\sin\theta_2 & \cos\phi_2 \\ Z_1 \cos 2\phi_1 & -W_1 \sin 2\phi_1 & -Z_2 \cos 2\phi_2 & -W_2 \sin 2\phi_2 \\ \gamma_1 W_1 \sin 2\theta_1 & W_1 \cos 2\phi_1 & \gamma_2 \sin 2\theta_2 & -W_2 \cos 2\phi_2 \end{bmatrix} \begin{bmatrix} R_{rr} \\ R_{rs} \\ T_{rs} \\ T_{rr} \end{bmatrix} = \begin{bmatrix} \cos\theta_1 \\ -\sin\theta_1 \\ -Z_1 \cos 2\phi_1 \\ -\gamma_1 W_1 \sin 2\theta_1 \end{bmatrix} \quad (2)$$

Para uma onda P com incidência normal, as equações de Zoeppritz se simplificam consideravelmente: as componentes tangenciais do movimento e do cisalhamento são nulas, R_{PS} , T_{PS} e θ_1 valem zero, conduzindo a um sistema de duas equações e duas incógnitas:

$$R_{pp} + T_{pp} = 1 \quad \text{e} \quad Z_1 R_{pp} - Z_2 T_{pp} = -Z_1 \quad (3)$$

A solução do sistema é uma expressão bem conhecida para o coeficiente de reflexão R que é dependente da impedância acústica Z_j ,

$$R = R_{pp} = \frac{Z_2 - Z_1}{Z_2 + Z_1} \quad (4)$$

Já para um meio acústico, cuja incidência não seja normal, a equação (4) não pode ser aplicada no cálculo do coeficiente de reflexão. Neste caso a solução do sistema (2) é dada por:

$$R = \frac{\rho_2 \alpha_2 \cos\theta_1 - \rho_1 \alpha_1 \cos\theta_2}{\rho_2 \alpha_2 \cos\theta_1 + \rho_1 \alpha_1 \cos\theta_2} = \frac{\rho_2 \alpha_2 \sec\theta_2 - \rho_1 \alpha_1 \sec\theta_1}{\rho_2 \alpha_2 \sec\theta_2 + \rho_1 \alpha_1 \sec\theta_1} \quad (5)$$

onde o coeficiente de reflexão pode ser expresso como

$$R = \frac{E_2 - E_1}{E_2 + E_1}, \quad (6)$$

onde

$$E_j = \frac{\rho_j \alpha_j}{\sqrt{1 - \alpha_j^2 p^2}} = \rho_j \alpha_j \sec\theta_j, \quad (7)$$

que pode ser chamada de impedância acústica de reflexão, em analogia com a impedância acústica usual, em que Z_j é E_j para $\theta_j = 0$.

Manipulando-se algebricamente a Equação (6), chega-se a uma fórmula recursiva a partir da série de coeficientes de reflexão R_j

$$E_{j+1} = E_j \frac{1 + R_j}{1 - R_j}, \quad (8)$$

com $j = 1, 2, 3 \dots$. Assume-se que a impedância da primeira camada ($j = 1$) é conhecida.

A impedância elástica de reflexão I seria uma função com propriedades análogas à impedância acústica de reflexão, ou seja, o coeficiente de reflexão relacionado com as impedâncias dos meios elásticos, que seria função dos valores de parâmetros α , β , ρ e do ângulo de incidência θ , que por sua vez dependem do tempo de trânsito t :

$$R = \frac{I_2 - I_1}{I_2 + I_1}. \quad (9)$$

Os coeficientes de reflexão e as impedâncias elásticas de reflexão serão calculadas em função do tempo e no domínio contínuo. Como não se tem solução explícita para $R(t, \Delta)$ em função de $I(t)$, observando-se que $R(t, 0) = 0$, define-se a refletividade $\tilde{R}(t)$ como o seguinte limite,

$$\tilde{R}(t) \equiv \lim_{\Delta \rightarrow 0} \frac{R(t, \Delta) - R(t, 0)}{\Delta} = \partial_{\Delta} R(t, 0). \quad (10)$$

Tomando-se a Equação (10) como uma aproximação de primeira ordem e aplicando-se o limite na Equação (9) a função refletividade pode ser tomada como

$$\tilde{R}(t) = \frac{I'(t)}{2I(t)} \quad (11)$$

Trabalhando-se algebricamente as equações de Zoeppritz (2), e aplicando-se o limite na Equação (9), para o caso elástico chega-se a função refletividade

$$\tilde{R}(t) = \frac{1}{2} (1 - 4\beta^2 p^2) \frac{\rho'}{\rho} + \frac{1}{2} \sec^2 \theta \frac{\alpha'}{\alpha} - 4\beta^2 p^2 \frac{\beta'}{\beta}, \quad (12)$$

onde ρ' , α' e β' são as derivadas temporais em relação a ρ , α e β , respectivamente.

Assim, multiplicando-se a Equação (12) por Δ e aproximando as derivadas

$$\alpha' \approx \frac{\Delta\alpha}{\Delta}, \quad \beta' \approx \frac{\Delta\beta}{\Delta} \quad \text{e} \quad \rho' \approx \frac{\Delta\rho}{\Delta}$$

obtem-se a expressão que é a aproximação de primeira ordem de Aki e Richards (1980), que é uma das

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formas de linearização das equações de Zoeppritz mais consagrada na literatura geofísica

$$R(t) \approx \frac{1}{2} (1 - 4\beta^2 p^2) \frac{\Delta\rho}{\rho} + \frac{\sec^2 \theta}{2} \frac{\Delta\alpha}{\alpha} - 4\beta^2 p^2 \frac{\Delta\beta}{\beta} \quad (13)$$

onde θ representa o ângulo de incidência e p o parâmetro do raio dado pela Lei de Snell, Equação (1).

Para o caso em que o parâmetro de raio é nulo, tem-se que

$$\tilde{R}(t) = \frac{1}{2} \frac{\rho'}{\rho} + \frac{1}{2} \frac{\alpha'}{\alpha} = \frac{I'}{2I} \quad (14)$$

Resolvendo-se a equação diferencial acima, nota-se que a solução é dada por $I = K\rho\alpha$, onde K é uma constante. Considerando-se $K = 1$, obtém-se a solução da impedância acústica tradicional de incidência normal,

$$I = Z = \rho\alpha \quad (15)$$

Tomando agora o valor da velocidade da onda S nula, $\beta = 0$, e resolvendo a equação diferencial, a solução é para impedância acústica de reflexão,

$$I = E = \rho\alpha \sec \theta \quad (16)$$

onde novamente se toma a constante K da equação, como unitária.

Quando $\beta \neq 0$ e $p \neq 0$, ou seja, $\beta p \neq 0$, observa-se que não é possível encontrar uma solução geral. Pode-se então supor alguma condição sobre α , β e ρ de maneira a encontrar uma solução.

Assumindo que $\frac{\beta'}{\beta} = v \frac{\rho'}{\rho}$, ou equivalentemente

$\beta' = a\rho^v$, com $a > 0$, onde v é uma constante de proporcionalidade, chega-se a

$$\tilde{R}(t) = \frac{1}{2} (1 - 4\beta^2 (1+v)p^2) \frac{\rho'}{\rho} + \frac{\sec^2 \theta}{2} \frac{\alpha'}{\alpha} = \frac{I'}{2I} \quad (17)$$

cujas soluções são dadas por

$$I = \begin{cases} \exp\left(-2\left(1 + \frac{1}{v}\right)\beta^2 p^2\right) & v \neq 0 \\ \left(\frac{\rho}{\rho_0}\right)^{-4\beta^2 p^2} & v = 0 \end{cases} \quad (18)$$

que é uma generalização da impedância acústica de reflexão para o caso elástico.

Migração para Afastamento Nulo (MZO)

A migração para afastamento nulo (MZO), pode ser vista como uma transformação de configuração, executada em duplo passo, onde os dados originais em afastamento comum, são migrados e posteriormente demigrados para afastamento nulo à verdadeira amplitude, em operação única através de uma transformada de empilhamento de Kirchhoff, dada por

$$\hat{U}_0(\xi_0, t_0) = \frac{1}{\sqrt{2\pi}} \int_{A'} d\xi K_{MZO}(\xi, \xi_0, t_0) D^{1/2} U(\xi, t) \Big|_{t=\tau_{MZO}(\xi, \xi_0, t_0)} \quad (19)$$

Quando se observa a expressão da integral de empilhamento do tipo Kirchhoff, definida na Equação (19), vê-se que para cada ponto situado na seção de afastamento nulo a ser simulada, será colocado um valor de amplitude, determinado pelo empilhamento ponderado. Uma nova função peso, diferente da primeira, é definida como

$$\tilde{K}_{MZO}(\xi, \xi_0, t_0) = \cos \theta K_{MZO}(\xi, \xi_0, t_0) \quad (20)$$

sendo $K_{MZO}(\xi, \xi_0, t_0)$ a função peso original para o algoritmo da MZO. A razão entre as duas respostas de saída, obtidas com os pesos diferentes, é a estimativa do cosseno do ângulo de reflexão.

A grande vantagem do método é que sem nenhum conhecimento prévio da posição do refletor e do ponto de reflexão, executando-se a MZO com pesos distintos, para todos os afastamentos dos dados sísmicos pode-se calcular o coeficiente e o ângulo de reflexão, esta ferramenta básica para geração de seções em ângulo de reflexão comum, e também elementos para estudos de AVO e AVA.

Seções de Impedância de Reflexão

Para construção das seções de impedância de reflexão, inicialmente gerou-se modelo elástico sintético que simulou um domo com capa de gás com inversão de velocidades (Figura 2).

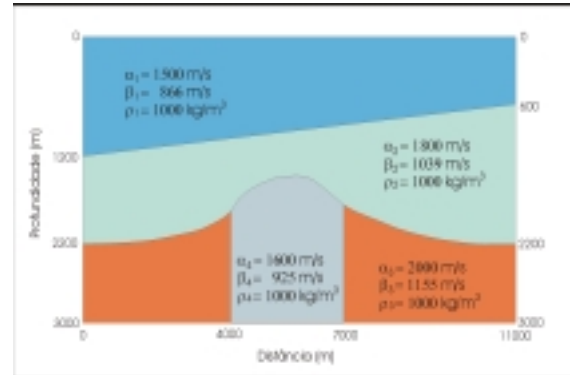


Figura 2 – Modelo de Domo com Capa de Gás.

O volume sísmico adquirido passou por processamento convencional para se obter a matriz de velocidades, insumo para a aplicação da MZO dupla visando a obtenção dos ângulos de incidência.

Após a aplicação da MZO dupla foi construída seção de ângulo comum sintetizada na Figura 3. De posse da matriz de ângulos do evento e do valor do ângulo que se deseja construir a seção, busca-se o traço cujo o ângulo mais se aproxime do ângulo desejado, identificando a qual afastamento pertence. De

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posse dessa informação, vai-se até a seção de MZO com o valor de afastamento encontrado e retira-se o todo o traço correspondente, colocando-o na seção em construção. A operação é repetida até que a seção seja toda completada.

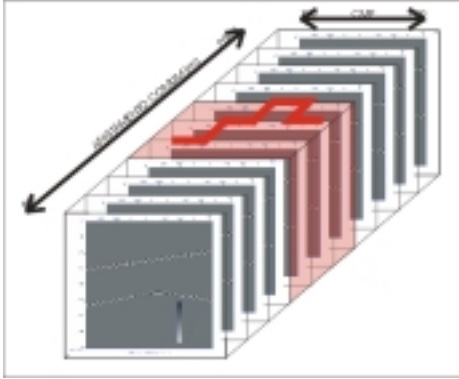


Figura 3– Esquema de construção de seção de ângulo comum.

A seção de ângulo comum construída (Figura 4), passa por processo de eliminação dos ruídos causados pelo operador de MZO e também se aplica a correção de espalhamento geométrico, utilizando-se velocidade rms , velocidade v_0 da primeira camada e o tempo de trânsito t_0 , já que a MZO levou todos os eventos para afastamento nulo.

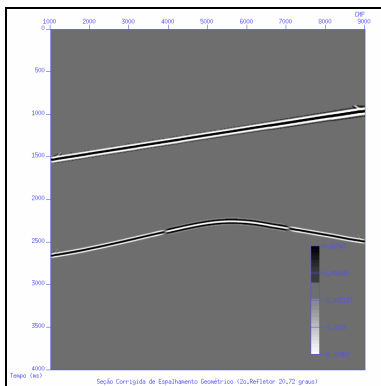


Figura 4– Seção de ângulo comum de 21°.

Na construção de seções de impedância de reflexão, produto final deste trabalho, utilizou-se da seção corrigida de espalhamento geométrico e aplicou-se a fórmula recursiva discreta, Equação (8). Para o segundo refletor, construiu-se uma seção de reflexão de 18°, visto que, foi o ângulo em que a seção mostrou comportamento mais homogêneo para as três porções do refletor, embora a porção direita esteja contaminada por valores de impedância herdados do refletor superior (Figura 5).

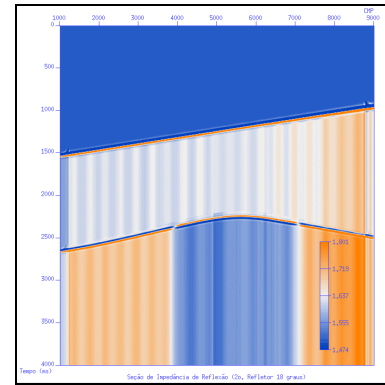


Figura 5– Seção de Impedância de Reflexão do segundo refletor (ângulo de reflexão = 18°).

Conclusões

A construção das seções de ângulo comum e de impedância de reflexão se mostrou relativamente eficiente na recuperação dos parâmetros elásticos e também no processamento sísmico, já que o uso da MZO simplifica e agiliza os cálculos envolvidos.

Para que o uso do método da geração de seções de impedância de reflexão se torne de uso prático, se faz necessário a aplicação de testes em dados reais. Alguns testes poderão ser feitos tanto no campo exploratório quanto no explotatório, visando discriminar verdadeiras anomalias de amplitudes causadas por presença de gás e falsas anomalias causadas por rochas de baixas velocidades. Mesmo sem a correlação, as seções de impedância de reflexão são bons instrumentos qualitativos para o gerenciamento de reservatórios petrolíferos.

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Examples of artificial neural networks applied to seismic amplitude data

Paulo Marcos de Carvalho, PETROBRAS

Abstract

Artificial neural networks are data processing tools with applications in many scientific and technological fields. This paper gives a brief description of two types of networks that are among the most used in geophysical problems: the multi-layer perceptron and the self-organizing map. The former belongs to the group of networks that learn by supervised training. An example of its application to the problem of classification of seismic amplitude anomalies based on sparse well data shows its ability to interpolate information with few control points. The latter network belongs to the unsupervised training group. Application to the same amplitude anomaly problem with no prior information shows its ability to discriminate the information based solely on the characteristics of the seismic data.

Introduction

Recently, there has been a large increase in the use of artificial neural network (ANN) in the processing and interpretation of seismic data. The work of van der Baan and Jutten (2000) gives an overview of the use of ANN in geophysics and lists many references about its theory and applications.

Under the name of ANN there are many kinds of algorithms that try to simulate the processing of information by the nets of physical neurons inside the brain. These algorithms can perform many different data processing tasks, such as, interpolation, classification, pattern recognition, inversion and others. The literature about ANN is vast. The books of Freeman and Skapura (1991) and of Wasserman (1989) give introductory level description about many types of networks.

In this paper I will briefly describe two types of ANNs that are among the most employed in geophysical problems: the multi-layer perceptron (MLP) and the competitive layer (CL) nets. I will also exemplify their work with simple numerical examples and apply them to the problem of classification of seismic amplitude anomalies.

Artificial neural networks

I will not get into the details of the functioning of ANNs, but will give only a general description of how the nets of interest work. ANNs are non-linear systems that process input data according to their

internal configurations and generate the results as their outputs. Besides having a structure and a flow of information that resembles those of the brain, the ANNs have the capabilities of 'learning from training' and of 'generalization' that are related to processes performed by the brain.

Training is the process of setting up the internal configuration of the network in order to make it give the correct answer when data from a training data set are presented to it. The learning stage is completed when the network consistently gives the correct answers for the entire training set. Generalization can be understood as the capability of the system to behave smoothly when processing data not belonging to the training set. In the case of an ANN designed for classification purposes this means that, when presented to inputs similar, but not equal, to the training examples of a particular class, the network will be able to classify them correctly.

ANNs can be subdivided in two major groups according to the kind of algorithm used for training. The algorithms are of supervised or unsupervised training. In a classification problem, supervised training means assigning a priori the class of each training data vector. In unsupervised training, only the desired number of classes is specified – training data are identified as clusters according to their distribution and the logic of the network.

Multi-layer perceptron network

The MLP network is an array of layers with interconnected processing units (the artificial neurons). MLP learns by supervised training and it is also known by the name of the method used to train it: the error *backpropagation* algorithm (Rumelhart et. al. 1986). An input vector representing an object to be classified is given to the net and distributed through the connections to the processing units of the first layer. Each unit multiplies the vector components by weights, sum the products and submit it to an activation function that generates an output. The output vector of one layer is passed to the next layer till processing reaches the last layer where the output is interpreted in terms of classes. In the training phase, the error between the actual and the desired output is backpropagated through the network to adjust the weights of the units. After the network is adjusted for all training vectors it's used only in the forward direction to classify the complete input data set.

Examples of Artificial Neural Networks

To illustrate the use of the network with a simple numerical example, the MLP is used to identify the four quadrants of a plane. Each point of the plane is formed by the pair of integer numbers (n,m), both varying from -10 to +10 ($\{n,m \in \mathbb{Z} \mid -10 \leq n,m \leq 10\}$). These points are the two component input vectors. In the training phase, a class from 1 to 4 is assigned to each quadrant according to the usual mathematical definition. Sixteen points, four from each quadrant, are used as the training set. Table 1 shows the results. For reference, the points along the horizontal and vertical axis are shown in bold face. The 'x' represents a training point and the numbers are the result of the classification. When no class is identified a zero is assigned. Notice that they are mostly aligned along the Cartesian axes.

Competitive layer network

The CL network presented in this paper learns by unsupervised training. Its structure is simpler than the MLP structure, although the overall concept of competitive networks can be related to a very ambitious goal: to imitate the physical distribution on the cerebral cortex of brain activities, such as, speech, hearing, motor functions and others (Kohonen, 1984). The CL network consists of a single layer of units that learns by a self-organizing process. Each unit corresponds to a class to be identified and can be interpreted as a vector in the data space. During the training stage the class vectors move inside the space according to the clustering of the training data. At each training step, the class vectors compete: the vector that is closest to the current training vector wins and is moved towards it. As training goes on the movements of the class vectors are progressively restrained and, after a proper number of iterations, a stable state is reached. At this point, each class vector is positioned at a central location with respect to the class it represents.

Table 2 is an example of the use of a one-dimensional Self-Organizing Map (SOM) (Kohonen, 1984) to the same problem of table 1. SOM is a special type of unsupervised AAN that uses a competitive layer. With the SOM, the organization of the data in the input space is somehow reflected in the output (the classification). In this example the network was set to identify four classes. Points of the plane (not shown) were randomly selected for training. The classification shows that each of the four quadrants was identified as a class with reasonably accuracy and in an ordered way. In this case the axis (bold face numbers) were included in the classes. It must be remembered

that with the SOM network there is no control on the choice of the classes.

To better show the mapping property of the SOM, it was set to divide the same portion of the Cartesian plane in 50 classes. Instead of showing the classification of the data, figure 1 shows the end points of each of the 50 class vectors. Although the input data are pairs of integer numbers, the components of the class vectors are real numbers. A line was drawn connecting the points in the ascending order of the classes, from 1 to 50, showing that the space was divide in an organized way.

Application to amplitude anomalies

To exemplify the use of ANNs to a real problem, the MLP and the SOM were applied to a set of attribute maps derived from seismic data. Figure 2.a shows the map of the amplitudes picked at the reflector at the top of low impedance reservoir sands. The area is already under production, so most of the strongest negative amplitudes (blue areas) are known to be due to hydrocarbon accumulations. Some anomalies, such as the one inside the black rectangle are pitfalls caused by the interference of the side lobes of upper positive anomalies shown in the map of figure 2.b as red areas. These maps, together with the map of the time thickness of the sands (figure 2.c), were used to test the ANNs. The aim is to detect the hydrocarbon accumulations avoiding the pitfalls.

The MLP was trained with the eight points plotted in the map of figure 2.a. Black points are for hydrocarbon accumulations and red points are for no accumulation. The result of the classification by the MLP network for the entire data set is presented in figure 3. In this map the areas classified as hydrocarbons accumulation are shown in red, other areas in yellow. It can be seen that the thickest parts of the accumulations were detected and pitfalls were avoided.

The SOM network was trained with points randomly selected (not shown in the figures). It was set to separate the data in four classes. Figure 5 shows the result of the classification. It is interesting to note that one class corresponds to the thick parts of the accumulations (red) and other to the thinnest parts (yellow). Also the non-hydrocarbon areas were divided in two groups: one for the low amplitude/thin thickness areas (green) and other comprised mostly by the pitfall anomalies (blue).

Examples of Artificial Neural Networks

Conclusions

The description of two types of ANNs and examples of their functioning with a simple numerical problem were presented. The results with seismic amplitude anomalies show that both types can be useful tools for reservoir characterization and seismic interpretation. The MLP network showed its ability to interpolate sparse information (for example, fluid content derived from wells) consistently to a vast area with the assistance of seismic attributes. The SOM showed its ability to discriminate different data characteristics without any prior information. This property is specially interesting for use in seismic facies identification.

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Table1: Classifications of points on a portion of the Cartesian plane according to quadrants using MLP network. (See text for explanation.)

Acknowledgments

I would like to thank PETROBRAS for permission to publish this work. I am also grateful to Ricardo Freitas Alves for implementing the ANN programs in the Petrobras proprietary software package for geology and geophysics.

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2	2	2	2	2	2	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3

Table 2: Classification of points of the same portion of the Cartesian plane as in table 1 using SOM network. (See text for explanation.)

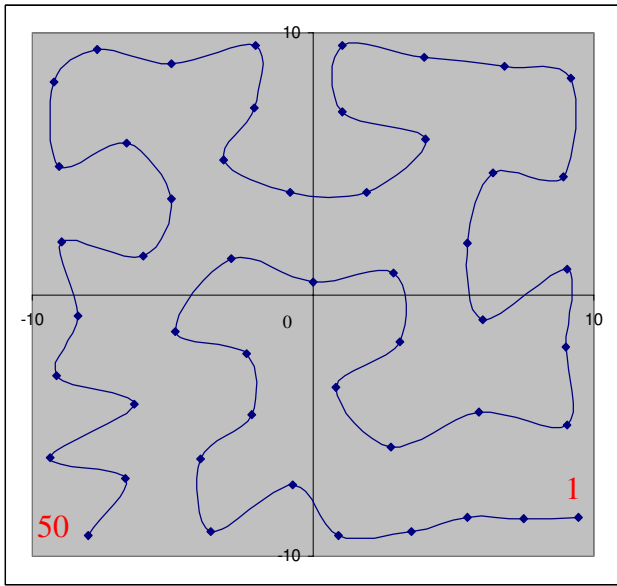


Figure 1: End points of class vectors of a SOM network trained to identify 50 classes on a portion of the Cartesian plane. Line links the end points of class vectors in ascending order from 1 to 50.

Examples of Artificial Neural Networks

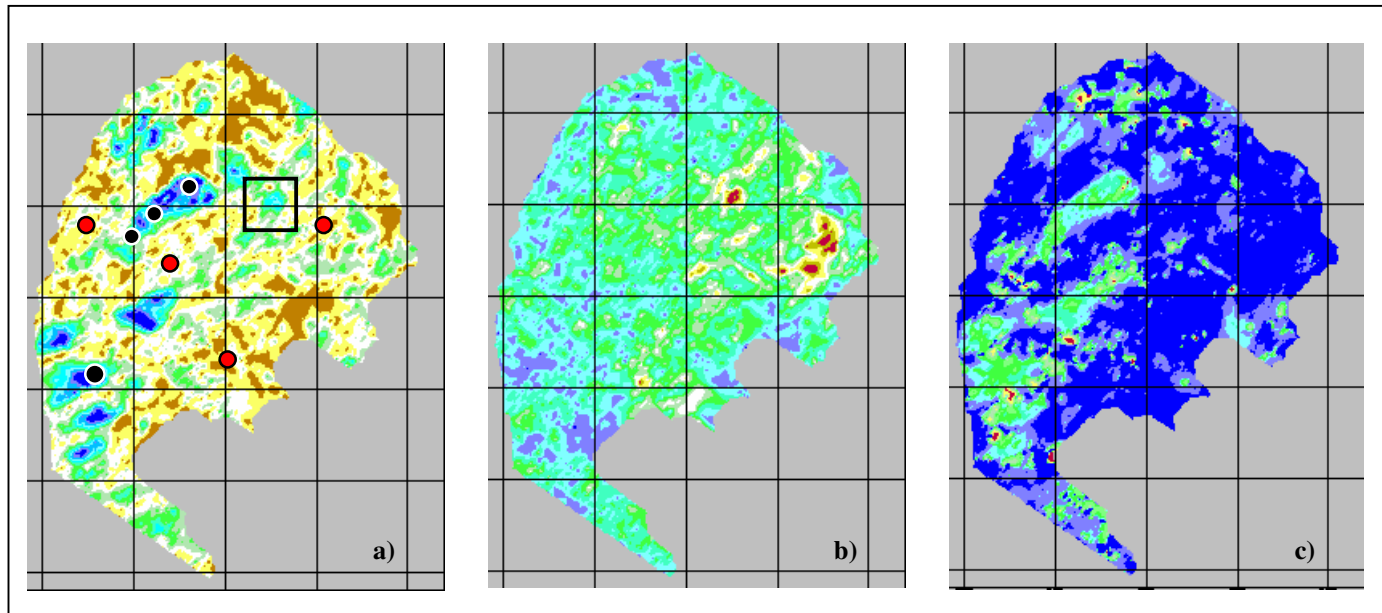


Figure 3: Set of maps for ANN classification: a) Negative amplitudes of reflector at top of reservoir sands: most negative amplitudes are in blue; training points for MLP: black for hydrocarbon accumulations, red for no accumulation; black square marks a pitfall anomaly. b) Positive amplitudes of reflector above the top of reservoir sands: most positive amplitudes are in red. c) Time thickness of reservoirs: thickest portions are in light blue and green.

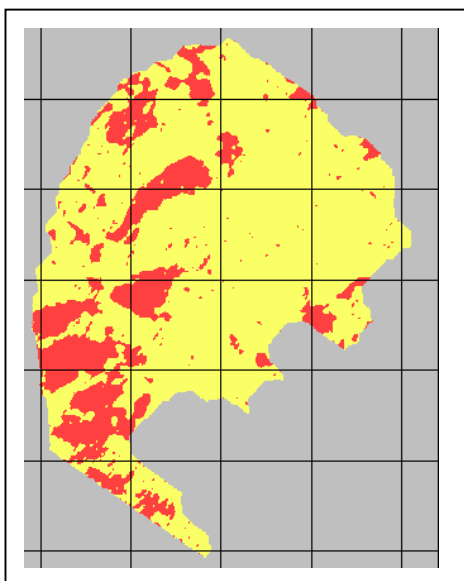


Figure 4: MLP network classification of maps in figure 3: hydrocarbon accumulation areas are in red, non-hydrocarbon areas in yellow.

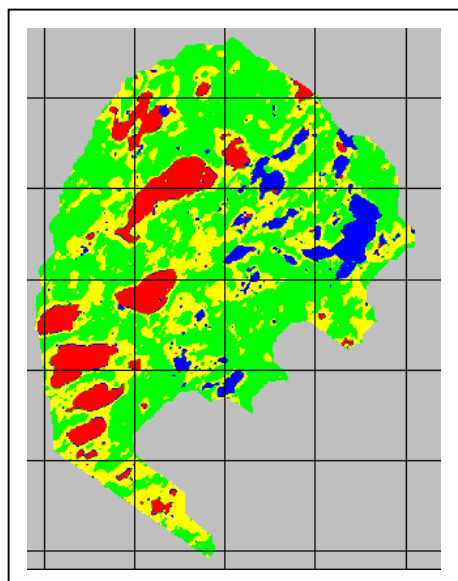


Figure 5: SOM network classification of maps in figure 3: class 1 in red; class 2 in yellow; class 3 in green; class 4 in blue.



Inversão Híbrida de Dados Sísmicos

Vânia Lúcia A. Machado, PETROBRAS - E&P/GEREX/SAG

Amin Bassrei, IF/UFBA & CPGG/UFBA

Jurandyr Schmidt, PETROBRAS - E&P/GEREX/GEPROG/GEF

Resumo

Usualmente métodos de otimização baseados em algoritmos determinísticos (busca local) ou estocásticos (busca global) são utilizados na solução de problemas inversos. Alternativamente podemos utilizar um sistema híbrido de otimização, combinando-se o algoritmo de pesquisa global com o de pesquisa local. O objetivo dessa combinação é compartilhar o trabalho entre os dois métodos, para cada um agir na sua faixa de melhor desempenho. O global atua procurando a região de interesse e a pesquisa local age definindo o mínimo global dessa região. Investigamos a aplicabilidade do algoritmo estocástico *Simulated Annealing* em conjunto com a inversão linearizada utilizando decomposição de valores singulares. Os algoritmos determinísticos e estocásticos foram utilizados separadamente e na forma híbrida em dados sintéticos 1D (inversão do coeficiente de reflexão global) e 2D (tomografia de tempo de trânsito).

Introdução

Neste trabalho investigamos a aplicabilidade da técnica global conhecida por *simulated annealing* (SA) em conjunto com a inversão linearizada, utilizando decomposição de valores singulares.

O problema tratado no caso 1D, modelo estratificado com camadas plano-paralelas, foi a inversão do coeficiente de reflexão global no domínio (ω, p) , para a obtenção dos parâmetros de subsuperfície, no caso: velocidades e densidades (Fokkema e Ziolkowski, 1987 e Ziolkowski et al., 1989). No caso 2D, com geologia mais complexa, podendo conter, por exemplo, falhas, dobramentos, camadas inclinadas, domos, etc, utilizamos a tomografia sísmica de tempo de trânsito para a obtenção das velocidades sísmicas das rochas (Schots, 1990).

Para a inversão local, ou linearizada, utilizamos o método dos mínimos quadrados amortecidos (Menke, 1984) para reduzir as possibilidades de singularidades com a matriz, evitando-se oscilações bruscas na solução:

$$\mathbf{m}^{est} = (G^T G + \lambda I)^{-1} G^T \mathbf{d}^{obs}, \quad (1)$$

onde \mathbf{m}^{est} é o modelo estimado, G é a matriz das derivadas parciais, λ é o fator de amortecimento, I é a matriz identidade e \mathbf{d}^{obs} é o dado observado. Para a inversão da matriz utilizamos a decomposição de valores singulares (Lanczos, 1961).

Para a inversão global utilizamos o VFSA, *very fast simulated annealing*. É uma técnica de modelagem iterativa na qual os atributos são modificados cada vez mais lentamente, até a conclusão do processo. A otimização do processo envolve a simulação da evolução de um sistema físico em banho térmico até o resfriamento ideal num estado de energia mínima (Sen e Stoffa, 1995). A cada temperatura, o material tangencia o equilíbrio térmico onde a probabilidade de se estabelecer no estado i com energia E^i é dado pela distribuição de Gibbs/Boltzmann:

$$P(E^i) = \frac{1}{Z(T)} e^{(-E^i/kT)}, \quad (2)$$

onde

$$Z(T) = \sum_{j \in S} e^{(-E^j/kT)}, \quad (3)$$

S consiste de todas as configurações possíveis, k é a constante de Boltzmann, T é a temperatura e $Z(T)$ é a função de distribuição.

Para o método híbrido utilizamos a combinação dos dois métodos acima, seguindo as sugestões de Chunduru et al. (1997). Parte-se do método de pesquisa global através do VFSA e a decisão para a aplicação da inversão linearizada é baseada nas mudanças de percentagem do erro *rms* entre dados observados e dados calculado (e_d). Assim a decisão para aplicar o método de pesquisa local segue as seguintes condições:

$$E_i \leq (\% E_{inicial}),$$

$$E_i \leq E_{min},$$

$$\Delta E_i / E_i < A,$$

onde E_i é o erro da i -ésima iteração entre o dado observado e o recuperado, $\% E_{inicial}$ é uma percentagem escolhida do e_d inicial, E_{min} é um valor fornecido ao programa, ΔE_i é $|E_i - E_{i-1}|$, onde E_i significa o erro e_d na iteração i e E_{i-1} significa o

erro e_d da iteração anterior. A é um parâmetro livre.

Desta forma, a primeira e segunda condições significam que VFSA domina até que e_d seja reduzido a uma certa percentagem do erro inicial e a um valor mínimo estabelecido. E a terceira condição, significa que a pesquisa local será aplicada quando a curva de erro do VFSA começar a se estabilizar, ou seja, a razão entre a diferença no erro da atual iteração com o erro da iteração anterior pelo erro da iteração deve estar dentro de um padrão estabelecido. No caso estudado estabelecemos que a inversão linearizada não seria aplicada antes que o e_d corrente diminuisse em 50% do e_d inicial, ou seja, a $\%E_{inicial}$ foi de 50%, que esse e_d tinha que ser inferior a 0.1%, ou seja, E_{min} de 0.1%. E, para garantir que o sistema estivesse estabilizado, A foi de 0.00005. Pudemos verificar que o VFSA segue rápido, inicialmente, até um patamar de erro e além desse segue muito lentamente para um mínimo global. É justamente nesse ponto que entra o algoritmo de procura local, pois supomos que já encontramos a região desejada.

Aplicação a dados sintéticos 1D

A análise do emprego dos algoritmos foi feita de maneira segmentada, a fim de permitir uma melhor identificação dos aspectos relevantes a cada situação. Em uma primeira etapa estudamos cada algoritmo, individualmente, aplicado a dados sintéticos para a escolha daqueles que melhor atuassem em seus domínios. Em uma segunda etapa combinamos estes para compor o método híbrido. Esta última combinação foi aplicada aos mesmos dados sintéticos a fim de compararmos suas atuações. A CPU utilizada foi uma IBM Risc system 6000 com 58H power station. O modelo escolhido foi constituído por camadas plano paralelas, meio acústico 1D e sem a presença de múltiplas, espessuras variáveis e diminuição de velocidade na terceira camada, conforme pode ser visualizado na Figura 1. Com esse modelo geramos o sismograma no domínio $\tau - p$ composto por 25 traços. Cada traço possui um parâmetro de raio p constante, 100 amostras no tempo, sendo o intervalo de amostragem de 4ms. O primeiro traço tem p de 0.02 s/km e foi utilizado como o dado observado nas inversões. O número de parâmetros de dados foi de 100 e o número de parâmetros de modelo foi de 10. Portanto a matriz $G_{M \times N}$ foi formada de 100x10 elementos. Para a inversão linearizada fixamos o valor do amortecimento em 10^{-6} e utilizamos co-

$\rho=1.20 \text{ g/cm}^3$	$v=1500 \text{ m/s}$	$z=50 \text{ m}$
$\rho=2.50 \text{ g/cm}^3$	$v=2500 \text{ m/s}$	$z=100 \text{ m}$
$\rho=2.00 \text{ g/cm}^3$	$v=2000 \text{ m/s}$	$z=150 \text{ m}$
$\rho=2.75 \text{ g/cm}^3$	$v=2700 \text{ m/s}$	$z=100 \text{ m}$
$\rho=3.20 \text{ g/cm}^3$	$v=3100 \text{ m/s}$	$z=120 \text{ m}$

Figura 1: Modelo sísmico utilizado para geração dos dados sintéticos 1D. Observar a variação nas espessuras e a diminuição de velocidade na terceira camada.

mo critério de parada erro inferior a 10^{-7} .

Para o VFSA utilizamos o número máximo de temperaturas de 1000, temperatura inicial para todos os parâmetros de 10000, número de movimentos igual a 1 e decaimento de 0.5. O resultado deste foi o modelo inicial que o método híbrido utilizou como entrada para a busca local. A Figura 2 apresenta as velocidades e densidades recuperadas pelo método híbrido. O tempo gasto de CPU foi de 8min46s, ao passo que o VFSA para a obtenção de resultado semelhante levou 23min21s com e_d de 0.000365% e e_m de 3.897%, e para o híbrido o e_d foi de 0.020% e o e_m de 4.07%. Com a finalidade de testarmos os modelos na presença de ruído, acrescentamos 1.5% de ruído aleatório aos dados. Com isso obtivemos as velocidades e densidades recuperadas da Figura 3. O tempo gasto de CPU foi de 15min42s, e_d de 0.00547 e e_m de 3.32%. O resultado comparado com o obtido através do VFSA isoladamente, nos mostra aproximações semelhantes (e_d de 0.00054% e e_m de 3.23%), porém com um gasto de tempo inferior (cerca de 3 vezes).

Aplicação a dados sintéticos 2D

Para a inversão sísmica de dados tomográficos 2D escolhemos trabalhar com a geometria poço-a-poço, onde colocamos as fontes no poço da esquerda e os receptores no poço da direita. O número de raios, ou número de equações, é determinado pelo número de fontes multiplicado pelo número de receptores. Lembramos, também, que o meio 2D será descrito como um meio 1D uma vez que o vetor modelo, no caso a vagariedade, contém o meio 2D rastreado horizontalmente. O modelo escolhido para os testes

Inversão Híbrida de Dados Sísmicos

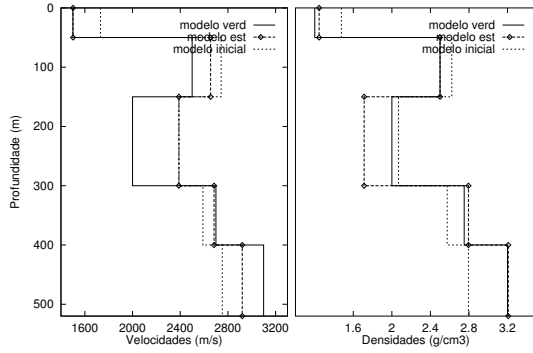


Figura 2: Recuperação das velocidades e densidades para o modelo 1D pelo algoritmo híbrido. A linha contínua representa o modelo verdadeiro, a tracejada o modelo inicial e a tracejada e pontilhada o recuperado. O Tempo de CPU foi de 8min46s e e_m 4.07%. Dados livres de ruído.

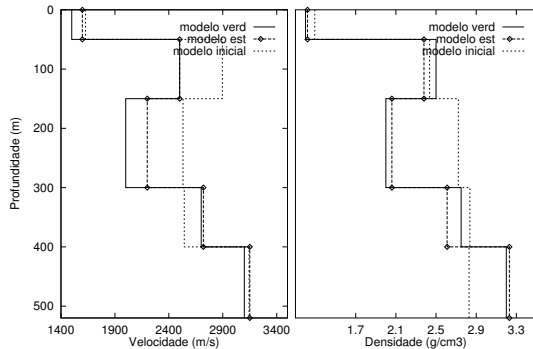


Figura 3: Recuperação das velocidades e densidades para o modelo 1D pelo algoritmo híbrido. A linha contínua representa o modelo verdadeiro, a tracejada o modelo inicial e a tracejada e pontilhada o recuperado. Tempo de CPU: 15min42s. Dados contaminados com ruído.

de inversão foi constituído de 100 blocos, cada qual com $10m \times 10m$ e a distribuição de velocidade pode ser visualizada na Figura 4A, simulando um trecho de uma bacia sedimentar que sofreu falhamento com posterior erosão e subsequente deposição de camadas plano paralelas. Para os testes com as inversões local, global e híbrida fizemos simulações com o dado adquirido para sistemas determinado (100×100), sobredeterminado (196×100) e subdeterminado (49×100). E, em cada simulação, utilizamos três tratamentos diferentes para a matriz tomográfica e para o dado observado. Primeiro, que chamamos de reto-retro, utilizamos raios retos para a matriz tomográfica e tempos de trânsito

retos. O segundo, que chamamos de curvo-curvo, utilizamos raios curvos e tempos de trânsito curvos. E, o terceiro, que chamamos de reto-curvo, constou da utilização da matriz com raios retos e os tempos de trânsito curvo. Nos casos determinado e sobredeterminado, para dados livres de ruído os 3 métodos apresentaram o mesmo padrão de recuperação do modelo, porém quando acrescentamos ruído pudemos perceber a superioridade para a recuperação do modelo com o método híbrido. Já no caso subdeterminado, tanto dados livres de ruído quanto dados contaminados com ruído o método híbrido foi superior ao de inversão linearizada e muito próximo ao VFSA. Podemos verificar na Figura 4B, 4C e 4D a recuperação dos modelos para o VFSA, SVD e o híbrido, para esse último caso com os dados contaminados por ruído.

Conclusões

Métodos de otimização local e global têm sido comumente utilizados para a estimativa de parâmetros de dados geofísicos. Esses métodos têm suas vantagens e desvantagens. Métodos locais requerem uma boa solução inicial ao passo que métodos globais são eficientes com pouca informação inicial, mas o gasto com o tempo computacional é bem maior. As vantagens de ambos podem ser combinados. Nesse estudo combinamos com sucesso VFSA com inversão linearizada com SVD para desenvolvermos um método de inversão híbrido associando as vantagens do método local e global. Dentre as várias possibilidades de combinação escolhemos a proposta defendida por Chundururu et al. (1997) que consiste na intervenção através dos padrões da diferença entre dado observado e dado calculado. Os resultados com os dados sintéticos 1D com e sem ruído provaram que o método híbrido é mais eficiente em termos de tempo computacional quando comparado com o VFSA isoladamente. Pudemos observar que para dados sintético tomográficos 2D, nos casos determinado e sobredeterminado, para dados livres de ruído os 3 métodos testados apresentaram o mesmo padrão de recuperação do modelo, porém quando acrescentamos ruído percebemos a superioridade para a recuperação do modelo com o método híbrido. Já no caso subdeterminado, tanto dados livres de ruído quanto dados contaminados com ruído o método híbrido foi superior ao de inversão linearizada e muito próximo ao VFSA. O método híbrido não pode ser avaliado com o dado real, uma vez que o resultado com o VFSA não foi satisfatório ou suficiente para ini-

cializar a inversão linearizada, isto foi atribuído ao tratamento preliminar do dado. Esse resultado deve ser amenizado entretanto, pelo fato de que nenhum único método de otimização deve ser tomado como o melhor para todos os problemas de inversão sísmica. Cada caso deve ser estudado isoladamente para que analisando os dados que estão à disposição, possamos tomar a decisão mais correta em termos objetivos quanto ao gasto computacional em relação aos resultados a serem alcançados.

Agradecimentos

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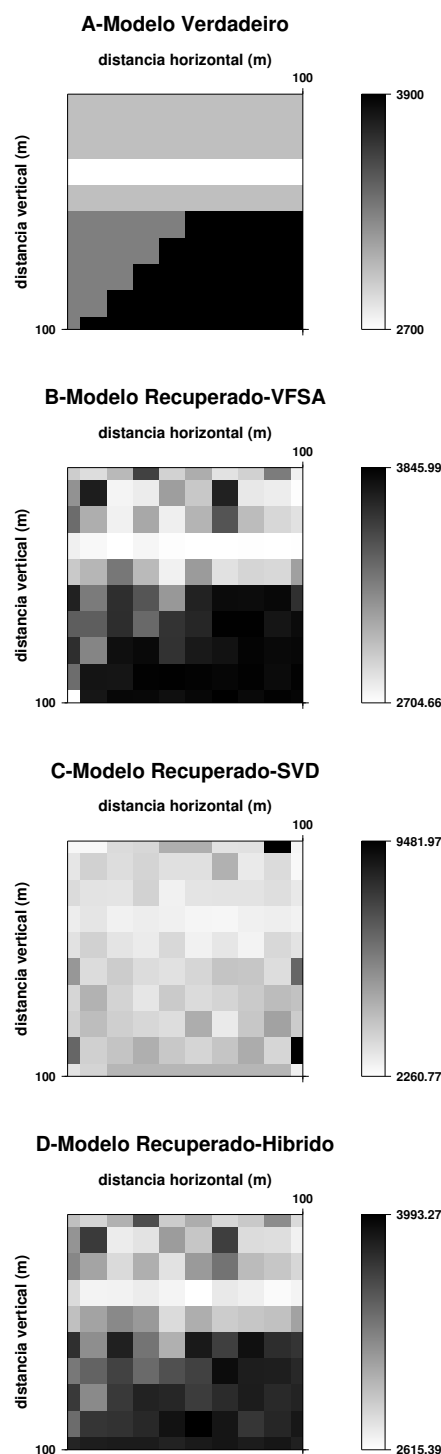


Figura 4: A-Modelo sintético 2D, B-Modelo recuperado pelo VFSA, C-Modelo recuperado pela inversão linearizada e D-Modelo recuperado pelo híbrido. Dados contaminados por ruído.



Lithology and Fluid Type Determination in Tertiary Clastic Reservoirs Through Elastic Rock Properties Estimation.

Alvaro Chaveste and Bruce Hill, Scott Pickford*, Houston

Abstract

Amplitude versus Offset (AVO) techniques seek to detect the interfaces bounding anomalous low Poisson's ratios associated, generally, to the presence of gas. In the area under study the brine-bearing sands' Poisson's ratio is considerably lower than the encasing shales and the additional decrease in the ratio due to gas, as modeled using Gassmann's (1951) equation, is only about 10 percent. The differentiation between gas and wet sands is not easy with most AVO techniques. To reduce the uncertainty in determination of the rocks' lithology and saturating fluid, rock properties are estimated from seismic data and calibrated to properties computed from well logs. The Lambda-Mu-Rho (LMR) method (Goodway et al, 1997) used in this study computes, from seismic data's amplitude variation with offset and post-stack inversion, attributes dependent upon the rocks' incompressibility (Lamba or λ), shear modulus (Mu or μ) and bulk density (Rho or ρ).

The rock properties obtained from the seismic data are cross-plotted in the same manner as those computed from the well logs. The areas of the cross-plot identified as gas-bearing sands in the well data matched the producing interval in the attributes' sections computed from the seismic. The study shows that, for the area under study, the LMR seismic attributes, when calibrated to well log data, help locate sand bodies and reduce the uncertainty in the determination of the type of saturating fluid.

Introduction

The study's geological setting is that of Tertiary gas traps of deltaic origin with the reservoir sands' distribution strongly influenced by the sea level at the time of deposition. The traps consist of sand channels encased in shale and are difficult to be delimited by structural interpretation. Furthermore, the detection of a sand body does not guarantee that this will be a gas producer.

Modeling of different attributes from well log data shows that LMR attributes discriminate between wet and gas sands when these are evaluated in cross-plots. For seismic data, the LMR attributes are computed through analysis of both pre-stack and post-stack data. The zero offset P- and S-wave reflectivities are first estimated in P-wave reflection time from the

data's reflection amplitude variation with offset. Smith & Gidlow (1985) first proposed a technique to estimate these reflectivities by weighted averaging the normal moved out (NMO) corrected pre-stack data. In this study the reflectivities are obtained by inverting the data to fit the two term Fatti's (1994) modification to Smith and Gidlow's approximation to the Zoeppritz equations:

$$R(\theta) \approx (Rp)(1 + \tan^2 \theta) - 8 \left(\frac{W}{V} \right)^2 (Rs) \sin^2 \theta \quad (1).$$

Where θ is the angle of incidence computed from offset and velocity information, $R(\theta)$ is the reflectivity as a function of angle of incidence, Rp and Rs are P- and S-wave reflectivities and V and W are the P- and S-wave velocities respectively.

Impedance reflectivities (Rp and Rs), estimated using Fatti's equation, have smaller uncertainties than velocity reflectivities obtained with Smith and Gidlow's approximation, which assumes that Gardner's velocity-density relationship holds. The P- and S-wave acoustic impedances, obtained from inverting the respective (Rp and Rs) reflectivities are then combined through equations 2 and 3 to obtain $\text{Lambda} * \text{Rho}$ ($\lambda\rho$) and $\text{Mu} * \text{Rho}$ ($\mu\rho$).

$$\mu\rho = Is^2 \quad (2)$$

$$\lambda\rho = Ip^2 - 2\mu\rho = Ip^2 - 2Is^2 \quad (3)$$

where Ip and Is are the P and S wave acoustic impedances ($Vp * \rho$ and $Vs * \rho$ respectively).

Results

The method's sensitivity to pore fluid type is first evaluated from log data by analytically replacing gas by water using Gassmann's and density-average equations. The rocks' mineral, fluid and pore space incompressibilities, required by Gassmann's equation, are estimated by minimizing the difference between the real and modeled velocity logs. Modeled log reconstruction is done by re-assembling the rock's incompressibility from those of the minerals, fluids and pore space through the use of volume fractions of the constituent phases. The rocks' shear moduli, required to reconstruct the P and S wave velocity logs are computed directly from the measured density and shear velocity logs.

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We evaluated the rocks' acoustic impedance, Poisson's ratio and LMR sensitivity to lithology and fluid type. The changes in acoustic impedance due to fluid replacement are small as seen in figure 1 (difference between green and blue lines) and difficult to detect without previous knowledge of the intervals where the fluid has been replaced.

Although Poisson's ratio shows higher separation from a gas to wet sand the amount of change does not stand out by itself (figure 2). Additionally, AVO techniques that seek to detect the interfaces where large Poisson's ratio changes occur would show strong anomalies at both the top and base of the sand's body independently of the type of saturating fluid. AVO attributes such as Poisson's reflectivity

and Shuey's (1985) gradient would adequately locate the sand body, but would not help in the prediction of pore fluid type.

When $\lambda\rho$ and $\mu\rho$ are cross-plotted (figures 3 and 4), the formations' wet sands, gas sands and shales fall in different locations of the cross-plot; thus allowing pore fluid type and lithology estimation. Analysis of the figures show that sands are more rigid than shales and that pore fluid type modifies mainly the sands' incompressibility, which appears lower when the fluid type is gas. The combined LMR attributes λ/μ (ratio) and $[\rho*(\lambda-\mu)]$ (difference) both have low values when the lithology is sand (not shown). The effect of gas is to further reduce both, the ratio and the difference.

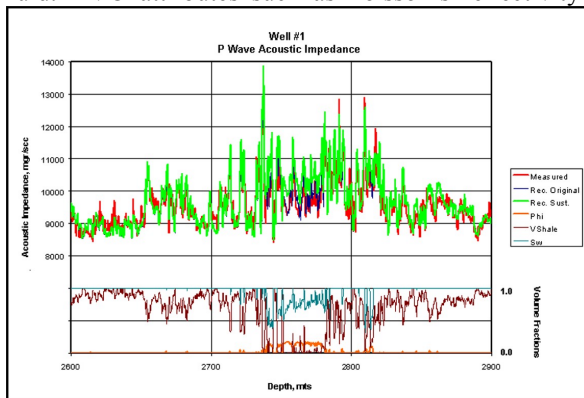


Figure 1

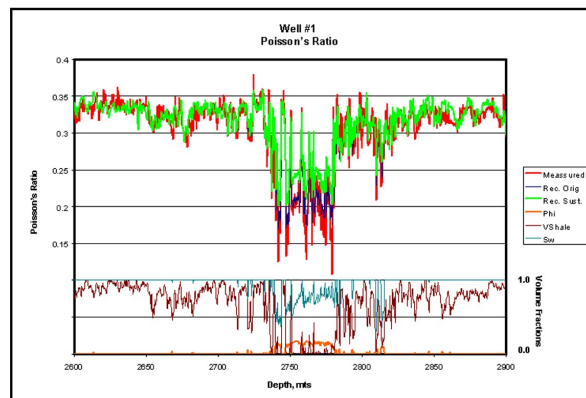


Figure 2

Figures 1 and 2 show, respectively, the P-wave acoustic impedance and Poisson's ratio for the reservoir interval. The red line is the physical property (either acoustic impedance or Poisson's ratio) computed from measured data, the blue line is the property computed from reconstructed logs (P- and S- wave velocities and density), and the green line is the reconstructed property after the pore fluid type has been analytically modified to 100% water. The three curves at the bottom represent, in a scale from 0.0 to 1.0, the rocks' computed volume fraction of porosity (phi), shale volume (Vshale) and water saturation (Sw)

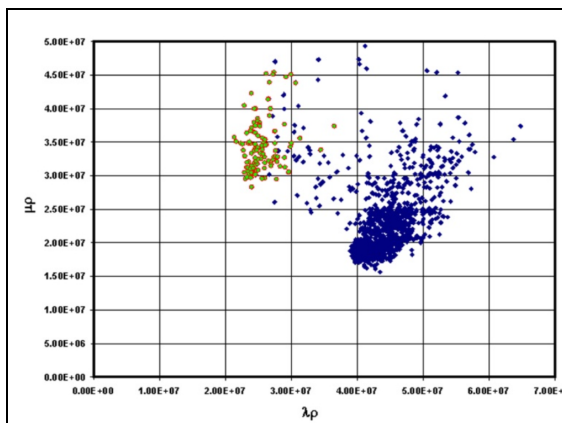


Figure 3

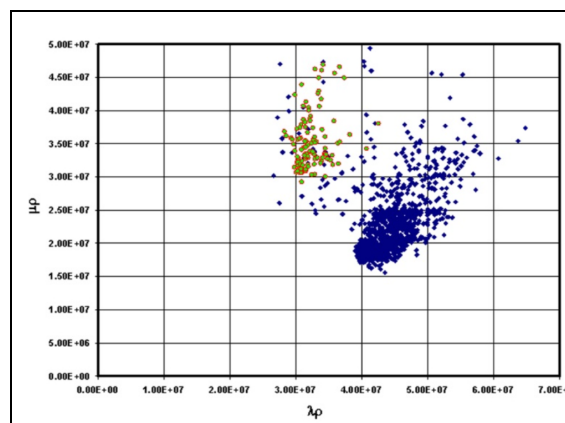


Figure 4

Figures 3 and 4, where two different saturating fluid conditions are analyzed, show $\lambda\rho$ vs $\mu\rho$ cross-plots for the depth interval of figures 1 and 2. The green and red points in figure 3 represent the samples that meet the conditions of: porosity larger than 10%, water saturation less than 80% and shale volume less than 18%. In figure 4, gas was replaced by water. The green and red points show where $\lambda\rho$ and $\mu\rho$ would appear in the cross-plot if water saturation had been 100% ($Sw=1$).

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The depth interval under analysis corresponds to a reflection time of approximately 1.7 seconds. Figure 5 shows the pre-stack synthetic tie to the pre-stack time migrated, true amplitude processed common depth point gather at the well location.

Lambda*Rho ($\lambda\rho$) and Mu*Rho ($\mu\rho$) attributes, obtained from the seismic acoustic impedances, are cross-plotted in figure 6 in a similar fashion to that of the well logs in figures 3 and 4. The area of the seismic cross-plot corresponding to gas sands, as determined from the well log sensitivity analysis (yellow polygon), map back to the gas-bearing interval identified in the seismic-to-synthetic tie of figure 5.

Conclusions

The sensitivity analysis done from well data shows that the reservoir's Lamé's parameter lambda is, approximately, 40% higher when the saturating gas is replaced by brine. On the other hand, the rocks' shear moduli, which are, for the study area, lower for shales than for sands, are less dependent upon the type of

pore fluid. Given these observations, the LMR attributes $\lambda\rho$, $\mu\rho$ and the combined attributes λ/μ and $\rho*(\lambda-\mu)$ can be used to help locate sand bodies and reduce the uncertainty in the determination of the type of saturating fluid. The LMR method provides, for the area under study and when calibrated with well data, a method to reduce the risk in the location of sand bodies and in the determination of saturating fluid type.

The LMR seismic attributes, which are dependent upon the rock's elastic properties, have characteristics that make them easier to interpret than other AVO or trace attributes techniques; namely: the rock properties are evaluated in intervals and not in interfaces; $\lambda\rho$ and $\mu\rho$ can be computed from well data, thus allowing a means of controlled testing and modeling of different physical conditions of the formations under study. Additionally, the seismic inversion to acoustic impedance is done after removing the seismic wavelet by sparse spike inversion, thus providing increased vertical and horizontal resolution and better interpretability.

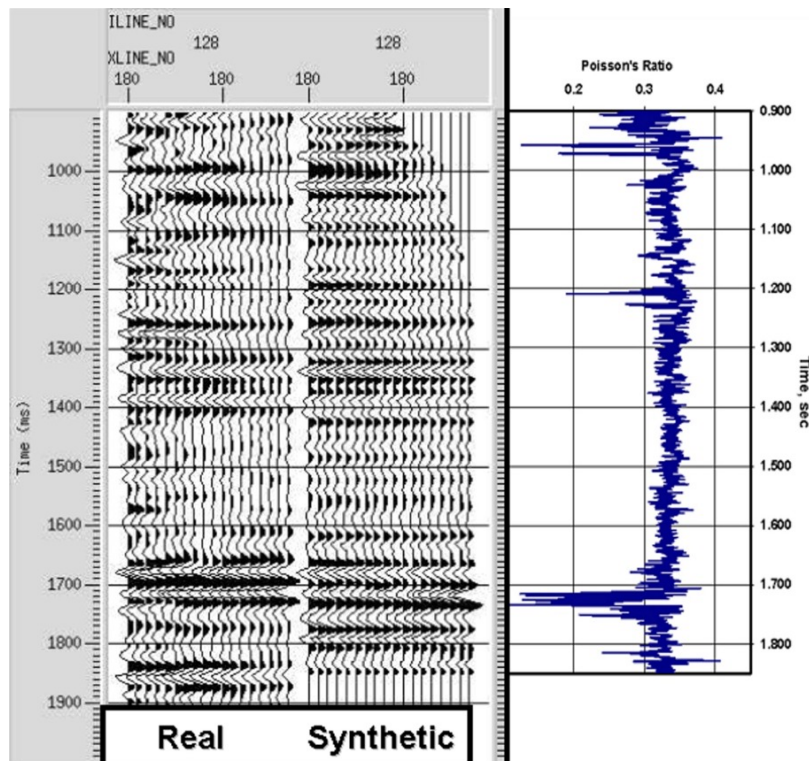


Figure 5

Pre-stack seismic-to-synthetic tie. Curve at right represents Poisson's ratio computed from well log data. The interval under evaluation (2600-2900 meters in figures 1 and 2) corresponds to an approximate time of 1.6 to 1.8 seconds.

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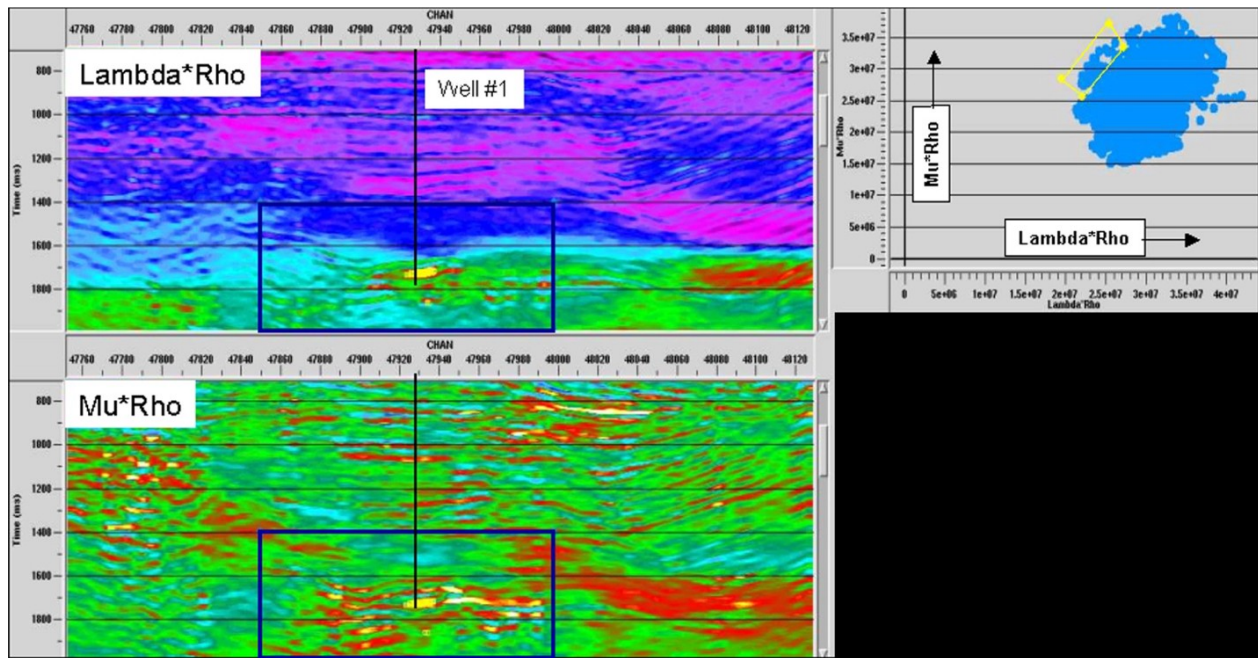


Figure 6

The $\lambda\rho$ and $\mu\rho$ values computed from seismic data are cross-plotted in a similar fashion as those computed from well logs (figures 3 and 4). The seismic attributes inside the blue polygon are cross-plotted in the figure's upper right corner as the blue scatter. A region similar to that determined from the well modeling is selected from the cross-plot (yellow polygon) and mapped back to the seismic attributes (yellow points). These points correspond to the known gas-bearing interval.

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Posibilidad de nuevos yacimientos gasíferos en campo Santa Rosa: Interpretación de volumen 3D "petrofísico" usando Inversión Sísmica y Redes Neuronales

Nicolás Martín/PDVSA E&P y Federico Riart*/PDVSA UE Anaco Gas

RESUMEN

Los resultados de aplicar inversión sísmica y redes neuronales sobre el volumen sísmico Santa Rosa ha permitido caracterizar a la Fm. Merecure como una secuencia de arenas productoras de gas a diferentes niveles. Aunque la discriminación litológica entre arenas y lutitas usando impedancia onda-P no es concluyente (rango similar de impedancias), la correlación entre impedancia y $(\frac{D}{N})$ es significativa y muestra que las arenas limpias ($V_{SH} < 0.16$) se caracterizan por valores positivos y relativamente altos de $(\frac{D}{N})$. Además, el parámetro $(\frac{D}{N})$, que representa la diferencia entre porosidades estimadas por registros de densidad y neutrón, suele ser un indicador de presencia de gas en formaciones limpias, por lo cual es posible diferenciar arenas gasíferas en el campo Santa Rosa mediante el análisis del comportamiento del parámetro $(\frac{D}{N})$.

Mediante la técnica de redes neuronales fue posible transformar el volumen 3D de impedancia en un volumen 3D "petrofísico" con amplitudes representando valores del parámetro $(\frac{D}{N})$. El análisis cualitativo de los mapas pseudo- $(\frac{D}{N})$, obtenidos para cada unidad estratigráfica de la Fm. Merecure, muestra zonas con mayor probabilidad de arenas limpias gasíferas que se corresponden con la presencia de estructuras y trampas en el área de estudio.

INTRODUCCION

El presente estudio muestra la aplicación de las técnicas de inversión sísmica post-apilamiento y redes neuronales sobre el volumen sísmico Santa Rosa, como parte del soporte geofísico para identificar arenas gasíferas en dicho campo. El objetivo de la inversión sísmica fue caracterizar a la Fm. Merecure (Oligoceno) mediante tendencias de impedancia asociadas con lutitas, cuerpos arenosos y fluidos asociados (petróleo y/o gas) usando el programa STRATA (Hampson-Russell).

Adicionalmente, se utilizó el programa EMERGE (Hampson-Russell) para detectar posibles zonas de arenas gasíferas dentro del volumen sísmico. Este programa usa registros de pozo, petrofísica y sísmica (atributos e impedancia) para extrapolar las características petrofísicas en cada pozo mediante la técnica de redes neuronales. El resultado final es un volumen que representa la distribución tridimensional estimada del parámetro petrofísico seleccionado.

UBICACIÓN Y GEOLOGIA

El Campo Santa Rosa se ubica en el Área Mayor de Anaco en el estado Anzoátegui, sub-cuenca de Maturín en la cuenca Oriental de Venezuela. Se localiza a 10 Km. al noreste de la ciudad de Anaco y al suroeste de la población de Santa Rosa, abarcando un área total de 300 Km².

Estructuralmente el Campo Santa Rosa está conformado por un anticlinal truncado (Fig. 1) contra el corrimiento de Anaco (pliegue de doble inmersión). El anticlinal es asimétrico con rumbo SO-NE sugiriendo que el mecanismo de entrapamiento es de tipo estructural/ estratigráfico, constituido básicamente por fallas normales e inversas, sellos laterales estratigráficos de adelgazamiento de arena y sellos lutíticos verticales.

METODOLOGIA

Procesamiento sísmico: Los datos sísmicos 3D consisten de 300.000 trazas (500 "inlines" x 600 "crossline") con separación entre líneas de 25 m y muestreo de 4 ms, cubriendo un área de 220 Km². El procesamiento involucro deconvolucion consistente con superficie, análisis de velocidades, estáticas residuales consistente con superficie, DMO y migración diferencias finitas en tiempo. Ningún post-proceso fue aplicado al volumen migrado para asegurar que las amplitudes representen adecuadamente la serie de reflectividad del subsuelo.

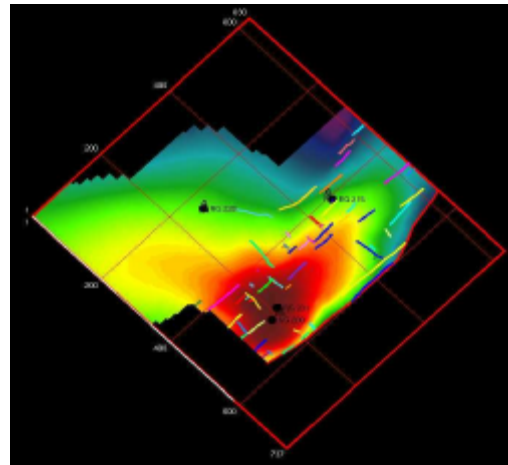


Fig. 1 Mapa estructural del tope de la Fm. Merecure de edad Oligoceno y pozos con información sísmica y densidad.

Información de pozos: Consistió de 7 pozos con registros de densidad y sónico (onda P) usados como modelos iniciales durante la inversión sísmica. Para la etapa de correlación entre los atributos sísmicos (convencionales e impedancia) y las propiedades petrofísicas se usaron perfiles de porosidad, saturación, arena neta, permeabilidad, etc. La Fig. 2 muestra el registro de densidad y sónico (onda P) corregido por "check-shot" para el pozo RG-200 ubicado en el alto estructural (Fig. 1). Las unidades estratigráficas de la Fm. Merecure son ME-A, ME-I, ME-K, ME-PU, ME-RU, ME-S6 y Fm. Vidoño (Creatácico).

Posibilidades de nuevos yacimientos gasíferos en Santa Rosa mediante Inversión Sísmica y Redes Neuronales

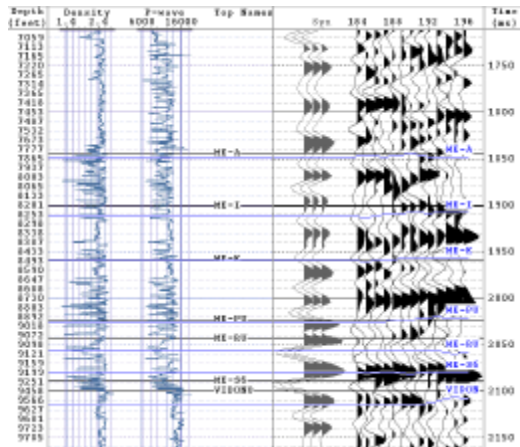


Fig. 2 Registros sísmico y densidad del pozo RG-200 y correlación sísmica-pozo.

Estimación de ondícula: Para efectuar la inversión sísmica post-apilamiento del volumen migrado Santa Rosa se usó una ondícula promedio en toda el área. La estimación de la ondícula consistió de las siguientes etapas: i) estimación del espectro sísmico, ii) calibración pozo-sísmica y iii) estimación de la fase mediante criterio de máximo valor de variograma sintético-sísmica. La ondícula estimada tiene una frecuencia central de 22 Hz y fase -10 grados. La Fig. 2 muestra la correlación pozo-sísmica final para el pozo RG-200 usando STRATA (Hampson-Russell). En general, la correlación fue aceptable cerca de la localización de los pozos, degradándose lateralmente debido a la baja calidad de los datos sísmicos (Fig. 2).

Generación modelo inicial de impedancia: Este modelo representa los valores de impedancia inicial y condiciones de borde que el algoritmo de inversión debe respetar para asegurar la unicidad de la inversión final. La generación del modelo de impedancia inicial implica:

- Control vertical. La calibración pozo-sísmica permitió asignar a cada muestra en tiempo (traza sísmica), en la ubicación del pozo, un valor de impedancia inicial usando los registros de densidad y sísmico (onda P).
- Control horizontal. La interpretación 3D representó un control lateral del modelo inicial de impedancia, donde los horizontes interpretados representan bordes que controlan la interpolación 3D de los valores verticales de impedancia para cada pozo.

Inversión sísmica 3D: Se usó el método de inversión 3D post-apilamiento basado en un modelo inicial de impedancia ("model-based inversion"). Este método tiene la ventaja de proporcionar un criterio de convergencia durante la inversión. En efecto, una traza "error" (diferencia entre las trazas real e invertida) es calculada para cada perturbación de la impedancia inicial. La impedancia invertida óptima corresponde a aquella

perturbación que minimiza la traza "error" según el criterio de mínimos cuadrados.

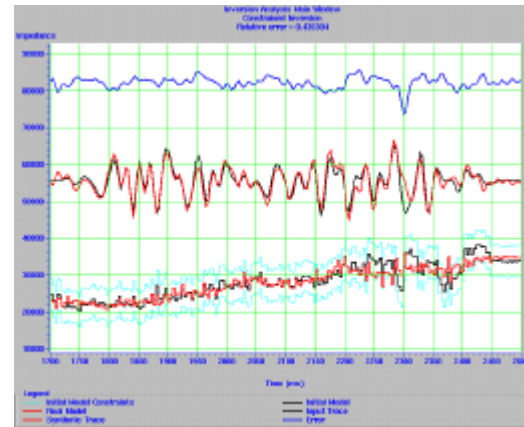


Fig. 3 Análisis de sensibilidad de la inversión sísmica para el pozo RG-200. Los perfiles de impedancia observada (negro) e invertida (rojo) se muestran en la parte inferior. La traza "error" es indicada en la parte superior

El error promedio fue 5-12% para una variación máxima de la impedancia inicial (pozo) de 15%. La Fig. 3 muestra la traza "error" para el pozo RG-200 usando inversión basada en un modelo. En color negro se muestra el perfil de impedancia inicial y en color rojo la impedancia invertida (abajo). Se puede observar la excelente correlación de la impedancia invertida con la observada en el pozo RG-200 hasta la base de la última unidad hidráulica ME-S6, así como, la correspondencia entre las trazas sísmica y sintética. En el centro se muestran las trazas real y sintética usando la impedancia invertida. La traza "error" se indica en la parte superior (Fig. 3).

ANÁLISIS DE RESULTADOS

Discriminación litológica usando la impedancia: La fig. 4 muestra el comportamiento de la impedancia en función del contenido de arcilla (V_{SH}) del pozo RG-200. Las arenas poseen valores V_{SH} entre 0.10-0.4. Se observa un fuerte solapamiento entre los valores de impedancia asociados a lutitas (20.000-40.000) y arenas (28.000-40.000). Por lo tanto, la impedancia onda-P no permitió discriminar adecuadamente entre lutitas y arenas en el campo Santa Rosa.

Posibilidades de nuevos yacimientos gasíferos en Santa Rosa mediante Inversión Sísmica y Redes Neuronales

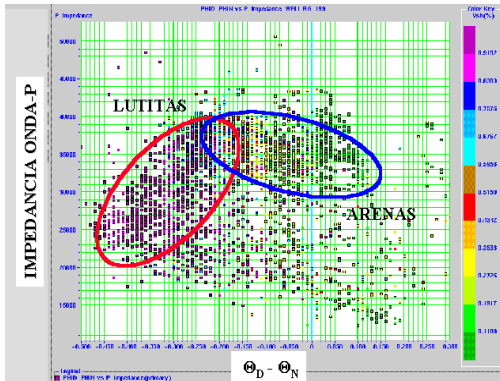


Fig. 4 Gráfico cruzado de impedancia (onda P) vs $(D - N)$ típico en el área de estudio. No existe una buena diferenciación de arenas y lutitas en base a sus valores de impedancia. La escala de colores indica valores de contenido de arcilla (V_{SH})

Discriminación litológica usando $(f_D - f_N)$: Para caracterizar a los cuerpos arenosos de la Fm. Merecure se generaron diversos gráficos cruzados entre impedancia y propiedades petrofísicas para cada pozo. La finalidad es encontrar algún parámetro petrofísico que sea sensible a la presencia de arenas (así como, tipo de fluido) y que pueda ser correlacionado con la impedancia. La Fig. 5 muestra que el parámetro $(D - N)$, representando la diferencia entre porosidades estimadas por registros de densidad y neutrón, es un buen indicador de presencia de arenas limpias con gas.

En efecto, se observa una buena separación entre arenas limpias y sucias (arcillosas) usando el gráfico impedancia vs $(D - N)$, donde las arenas limpias poseen valores positivos relativamente altos de $(D - N)$. En contraste, las lutitas y arenas arcillosas se caracterizan por valores negativos a ligeramente positivos de la variable $(D - N)$ (Figs. 4 y 5). La escala de colores representa valores de V_{SH} .

Adicionalmente, el análisis de tendencias muestra que las arenas sucias y limpias se pueden representar por las siguientes ecuaciones empíricas, mediante el ajuste por mínimo cuadrados (Fig. 5):

$$Y_{SUCIA} = -49223X + 38762 \quad (\text{Arenas sucias})$$

$$Y_{LIMPIA} = -30462X + 33214 \quad (\text{Arenas limpias})$$

donde X y Y son la impedancia y $(D - N)$, respectivamente.

Simulación de perfiles $(f_D - f_N)$ mediante algoritmos neuronales: Mediante la técnica de redes neuronales es posible invertir impedancia acústica a valores de $(D - N)$. Por lo tanto, las amplitudes positivas y anómalas del volumen "petrofísico" $(D - N)$ pueden ser interpretadas como zonas asociadas a cuerpos arenosos limpios con una probabilidad significativamente alta de contener gas.

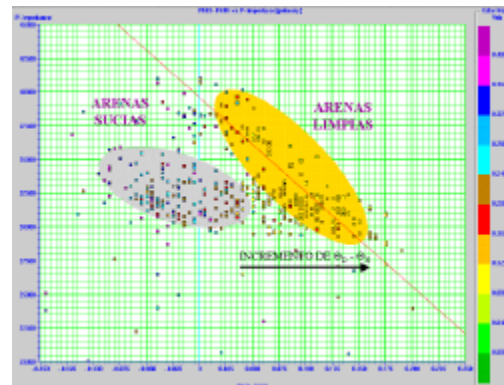


Fig. 5 Tendencias generalizadas de impedancia onda P en función de $(D - N)$ para arenas limpias y arcillosas. Los valores positivos y relativamente altos se asocian a arenas limpias con gas

La técnica de redes neuronales del programa EMERGE (Hampson-Russell) usa atributos sísmicos convencionales (amplitud, fase instantánea, etc.), impedancia acústica invertida, registros de pozo y propiedades petrofísicas (porosidad, contenido de arcilla, $(D - N)$, etc.), que se combinan para diseñar un operador de clasificación neuronal que reproduce el comportamiento del parámetro petrofísico de interés $(D - N)$ observado en cada pozo (dato duro). Este operador aplicado a cada traza del volumen sísmico y/o impedancia (dato débil) genera un volumen pseudo- $(D - N)$.

La Fig. 6 muestra la aplicación de la técnica neuronal a los pozos usados en el presente estudio. En color negro se representa el registro $(D - N)$ real y en color rojo el registro $(D - N)$ estimado usando la técnica neuronal. Se observa un grado de ajuste de 0.94 lo que indica la efectividad del método de redes neuronales en predecir el comportamiento del parámetro petrofísico $(D - N)$.

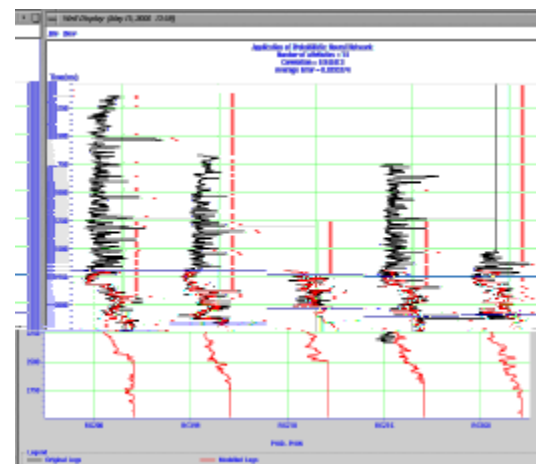


Fig. 6 Reproducción de registros $(D - N)$ para los pozos del campo Santa Rosa usando la técnica de Redes Neuronales

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Neuronales. Los registros pseudo- $(\phi_D - \phi_N)$ se indican en color rojo.

El valor de validación (reproducción de un perfil de pozo $(\phi_D - \phi_N)$ a partir del resto de los pozos) oscila alrededor de 0.82.

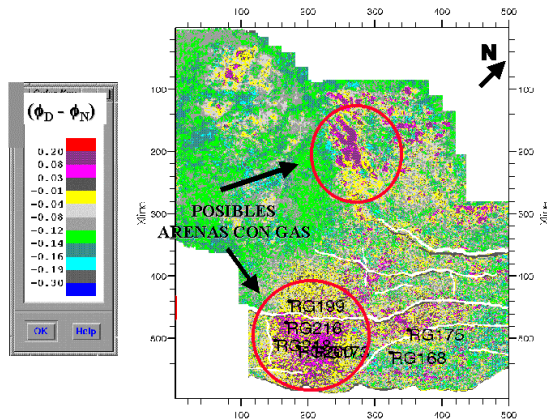


Fig. 7 Mapa volumétrico pseudo- $(\phi_D - \phi_N)$ asociado al intervalo ME-I y ME-K (Fm. Merecure) indicando valores RMS de $(\phi_D - \phi_N)$. Valores positivos altos de $(\phi_D - \phi_N)$ son interpretados como arenas limpias gasíferas en campo Santa Rosa.

Mapas volumétricos pseudo- $(\phi_D - \phi_N)$: Para cada unidad estratigráfica se generó un mapa pseudo- $(\phi_D - \phi_N)$ indicando la distribución areal de dicho parámetro. Los mapas muestran valores RMS de $(\phi_D - \phi_N)$ entre tope y base de cada unidad, siguiendo la interpretación estructural. La Fig. 7 muestra el mapa pseudo- $(\phi_D - \phi_N)$ asociado al intervalo ME-A y ME-I. En general, las mayores acumulaciones de arenas con gas (rojo-fúcia) se concentran en altos estructurales contra las fallas hacia el sur. Además, la alineación de las anomalías pseudo- $(\phi_D - \phi_N)$ se corresponde con la alineación del anticlinal que corre paralelo al corrimiento de Anaco, que representa la zona más somera de la estructura, y donde debería existir las mayores acumulaciones de gas en el área. Hacia el noreste, se observan altos valores de $(\phi_D - \phi_N)$ no alineados con el corrimiento, y que estructuralmente se corresponde con un anticlinal formado detrás de uno de los planos axiales de deformación cuya proyección hacia el este constituye una falla. Este anticlinal representa una trampa no evidenciada en la Fm. Merecure (Oligoceno) hasta el momento en el campo, pero que a niveles superiores de edad Mioceno probó alto contenido de gas.

CONCLUSIONES

- 1) El uso de redes neuronales permitió ubicar zonas con mayor probabilidad de ocurrencia de cuerpos arenosos con gas en el campo Santa Rosa.
- 2) Ha sido posible convertir el volumen de impedancia Santa Rosa a calidad de arena (sucias y limpias) y/o tipo de

fluido, mediante el uso de redes neuronales que permiten relacionar atributos sísmicos e impedancia con calidad de arena. La correlación impedancia- $(\phi_D - \phi_N)$ resultó significativa, indicando que las arenas limpias gasíferas presentan valores positivos altos del parámetro $(\phi_D - \phi_N)$.

3) La revisión estructural de las áreas prospectivas del análisis del volumen "petrofísico" Santa Rosa, generado por redes neuronales, ha mostrado ser crucial para el desarrollo de nuevas áreas prospectivas dentro de un yacimiento en fase de explotación.

4) La inversión sísmica es una fase fundamental para el desarrollo de un campo en proceso de exploración y/o explotación.

AGRADECIMIENTOS

Los autores desean expresar su agradecimiento a PDVSA E&P y UE Anaco Gas (Pto. La Cruz) por permitir la publicación de este trabajo. También deseamos extender nuestro reconocimiento a Alberto Rusic petrofísico de UE Anaco Gas por su valiosa colaboración en la interpretación de los registros de pozo y datos petrofísicos. Un agradecimiento especial a Lizbeth Meza y Juan Carlos Monro ambos de UE Anaco Gas por el suministro de información de topes interpretados, datos de pozo e información petrofísica.



Prestack Inversion with Adaptive Regularization

Indrajit G. Roy and Mrinal K. Sen, Institute for Geophysics, University of Texas at Austin, TX 78759.*

Summary

Pre-stack seismic waveform inversion is a highly challenging task. The non-linearity and non-uniqueness together with compute intensive forward modeling, make the problem intractable. Here we report on a new approach to addressing these issues that make use of innovative gradient calculation, adaptive regularization, and an efficient conjugate gradient scheme. The results from our approach are highly encouraging in that we are able to invert large dataset with nearly 600 model parameters fairly rapidly. Not only that, because of the use of adaptive regularization, we are able track smooth as well as sharp variations in the impedance, V_p and V_s profiles when realistic starting solutions are used. Thus we hope that the algorithm can be applied to routine analysis of large volume of seismic data. The results from the pre-stack inversion will be used in seismic reservoir characterization.

Introduction

Pre-stack waveform inversion of seismic data to delineate elastic properties of the earth is computationally demanding and complex task. Computational complexity arises due to the presence of (1) strong nonlinearity *visa-vis* multi-modality, (2) large dimensioned system, (3) strong level of illposed-ness and (4) presence of both coherent and noncoherent noises. Attempts on pre-stack inversion via least squares formalism were made (McAulay, 1985; Kormendi and Dietrich, 1991) earlier. It is widely acknowledged that gradient based minimization schemes for a nonlinear least squares problem although provide a flexible framework, suffer substantially in robustness due to the presence of strong non-linearity and multi-modality of the objective or data misfit error functional. It thus requires a good starting model to converge to a global minimum. Recently, Xia et al. (1998) used very fast simulated annealing for full waveform inversion (sen and Stoffa 1995). For practical applications, Xia et al. (1998) proposed a hybrid scheme in which arc-tangent parameterization was used in background velocity estimation which was then used as starting

solution. However, in the final step an ad-hoc regularization was employed. Robust solutions were obtained because much care was taken to define the starting model and the search space based on travel time and AVO inversion.

Salient features of our algorithm are as follows: (1) an efficient and accurate method of forward problem and Jacobian matrix computation, (2) a robust gradient descent method in the framework of generalized least squares approach and (3) use of an adaptive regularization weights during iterative minimization of error functional. We demonstrate these with two realistic synthetic examples here.

Forward Problem

We transform our data to plane wave domain and generate plane wave synthetics using reflectivity method. We modified the reflectivity calculations such that partial responses are saved and a gradient matrix can be computed as a by-product of the forward modeling. Our new gradient calculation scheme requires only one extra forward modeling evaluation. We also have an option to pre-compute the reflectivity response of the overburden layers and only invert for the properties of the target zone.

Inversion with adaptive regularization

Prestack inversion involves minimization of data misfit error between observed and computed data. If \mathbf{d} is a vector observed data, $\mathbf{g}(\mathbf{m})$ is the vector of computed data for some model \mathbf{m} then we may define the data misfit error E_d or error functional as

$$E_d = (\mathbf{d} - \mathbf{g}(\mathbf{m}))^T \mathbf{C}_d^{-1} (\mathbf{d} - \mathbf{g}(\mathbf{m})). \quad (1)$$

The suffix T denotes the transpose of the vector or matrix. \mathbf{C}_d^{-1} is the data covariance matrix, which is usually responsible for weighting data suitably if there is any possible noise contamination in the data. Minimization of error functional E_d is a non-trivial problem. This is due to the fact that E_d possesses strong nonlinearity *visa-vis* multimodality in general. An ordinary gradient descent type algorithm to minimize such functional often renders sub-

Prestack Inversion with Adaptive Regularization

optimality due to the presence of local minima. However situation improves considerably if we are able to design an algorithm where instead of minimizing the error functional defined in (1), we minimize a smooth variant of it whose smoothness is controlled adaptively. We thus define a smooth functional as

$$S(\mathbf{m}; \alpha) = E_d + \alpha (\mathbf{m} - \mathbf{m}_{pri})^T \mathbf{C}_m^{-1} (\mathbf{m} - \mathbf{m}_{pri}) \quad , \quad (2)$$

where \mathbf{m}_{pri} is the a priori model, \mathbf{C}_m^{-1} is the model covariance matrix and α is the regularizing weight which plays a central role in the algorithm. Note that as α approaches zero, the smooth functional $S(\mathbf{m}, \alpha)$ approaches the error functional E_d . The model covariance matrix works as a smoothness operator. Here we make the following strategy; we minimize $S(\mathbf{m}, \alpha)$ via nonlinear conjugate gradient technique to get model update vector $\Delta \mathbf{m}^\alpha$ corresponding to each α value where the regularization weight is obtained via modified discrepancy principle of Engl (1987). The formula that we use in determining α is given by

$$\|G^T G \Delta \mathbf{m}^\alpha - G^T \mathbf{u}\|_2^2 = \delta^a \alpha^{-b} \quad , \quad (3)$$

where, G is the Jacobian matrix, \mathbf{u} is the vector of data residual between observed and computed data, δ is a small value denoting noise level in data, a and b are two arbitrary constants whose values are chosen suitably with a constraint

$$\frac{3}{2}a - 2 = b > 1 \quad . \quad (4)$$

Numerical Results

We have tested our inversion algorithm on two synthetic models. Our first example is on a staircase type four-layer model (Figure 1). In this model the first layer is 200 ms thick water layer, the second layer comprises low gradient for V_p , V_s and density, the third layer is characterized by a steep gradient for V_p , V_s and density and the fourth layer is a half space. For such a model, we generated synthetic τ - p gather (Figure 2) with horizontal slowness ranging from 0-0.3 s/km. We used a zero phase Ricker wavelet with a peak frequency of 30 Hz for the

source function. Since in most practical problems it is difficult to identify the layer interfaces from seismograms, we assume that the model consists of 229 layers with two way time of 4 ms each, in our inversion. We use a realistic smooth velocity model as a starting model (Figure 1). The inverted model is superimposed on the starting and true models and displayed in Figure 1. The reconstructed profiles for all three parameters V_p , V_s and density are in good agreement with the actual profiles. Note that the reconstructed profile for V_p is much better resolved than those of V_s and density. The scheme is able to reconstruct the impedances reasonably well. We notice that P-wave impedance is better resolved than that of S-wave. The best-fit τ - p gather is also plotted on the adjacent panel of the Figure 2. The data generated by the reconstructed model are in excellent agreement with those of the actual model.

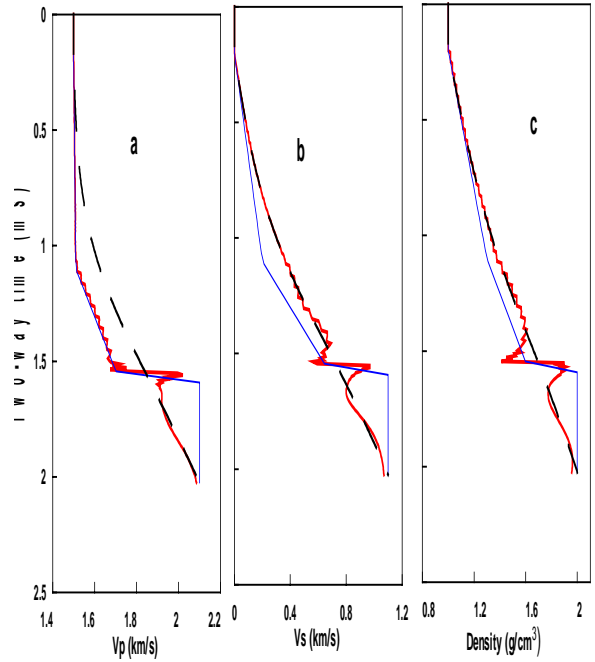


Figure 1 : (a), (b) and (c) are profiles for V_p , V_s , density vs two-way time. Fine solid line is the true model, heavy broken line is the starting model and heavy solid line is reconstructed profiles.

Prestack Inversion with Adaptive Regularization

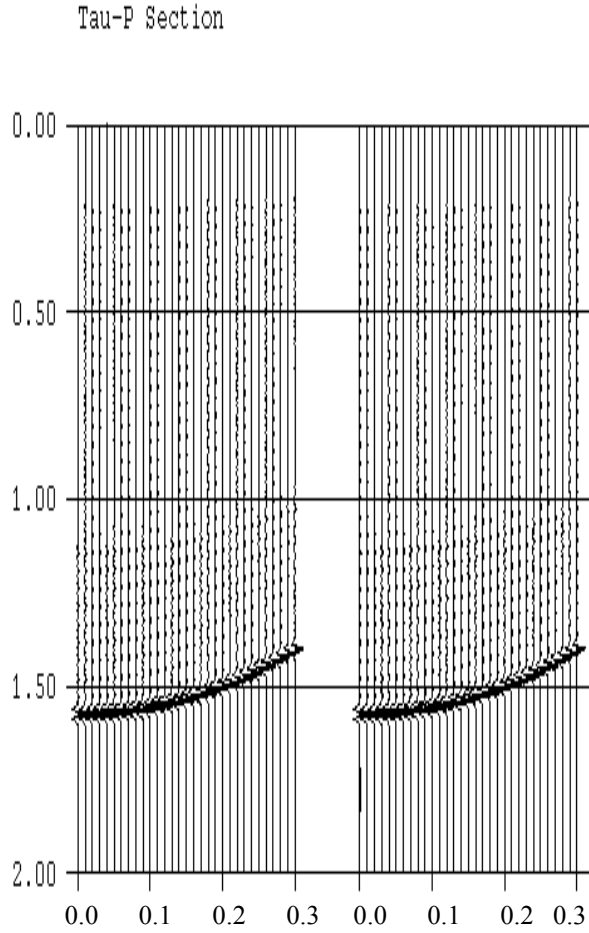


Figure 2: τ -p gathers for (a) actual model, (b) inverted model shown in figure (1).

Our next example uses a model derived from a well log. The profiles of P- and S-velocity and density are presented in Figure 3. We generated synthetic τ -p gathers with a sampling interval 4 ms in the horizontal slowness ranging from 0-0.3 s/km using this model (Figure 4). Once again we discretize the model with fine layers of two way time of 4 ms each. Thus our model consists of 154 layers having 462 model parameters. Inversion algorithm starts off from a smooth model (Figure 3). The reconstructed profiles after inversion (Figure 3) are in excellent agreement with the actual profiles. The best-fit τ -p gather is also plotted in the adjacent panel of Figure 5. We observe that in both the examples although there are overall good agreement between actual and

the reconstructed profiles, the V_p and impedance are better resolved than the V_s profiles. The fact is well understood as our data of τ -p gather contain a very little information on the low-frequency component of the shear wave profile. Our conjecture remains that the inversion of τ -p gathers of converted wave will improve the resolution the S-velocity profiles.

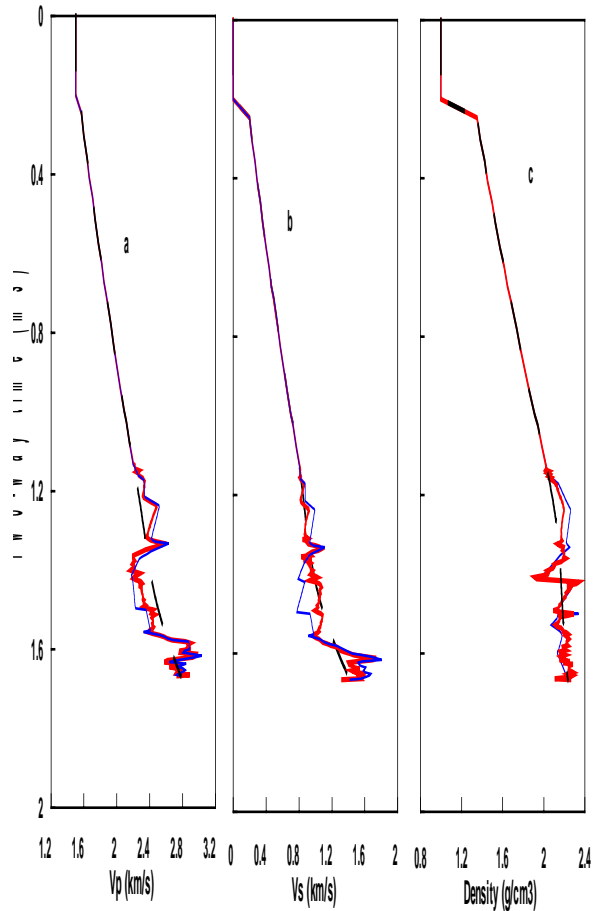


Figure 3: (a), (b), (c) and (d) are profiles for V_p , V_s , density vs two-way time. Fine solid line is actual, heavy broken line is a rough estimate and heavy solid line is reconstructed profile.

Prestack Inversion with Adaptive Regularization

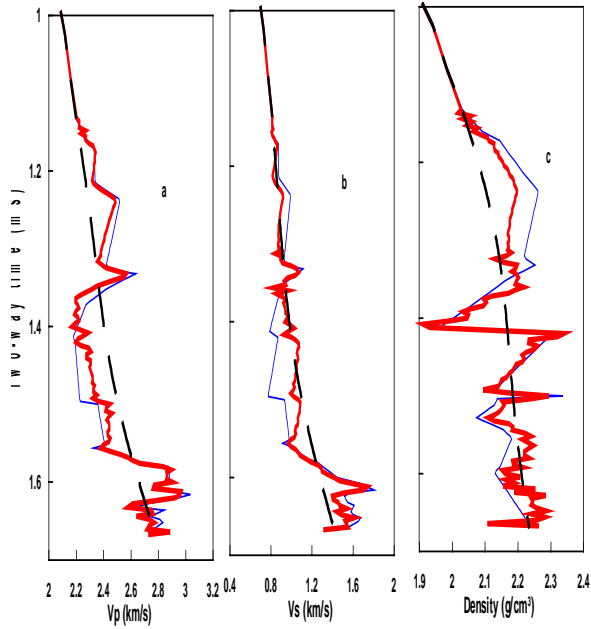


Figure 4: (a), (b), (c) are the zoomed version of the Figure (3)

Conclusions

We have developed a pre-stack seismic data inversion in τ - p domain based on gradient type optimization scheme where smooth functional is minimized with nonlinear conjugate gradient technique to determine model update corresponding to each adaptively determined regularization weight. The algorithm is able to reconstruct the model parameters both for discrete and continuum models reasonably well. The algorithm is found to be efficient. We hope to implement the algorithm in routine analysis for large volume of seismic data

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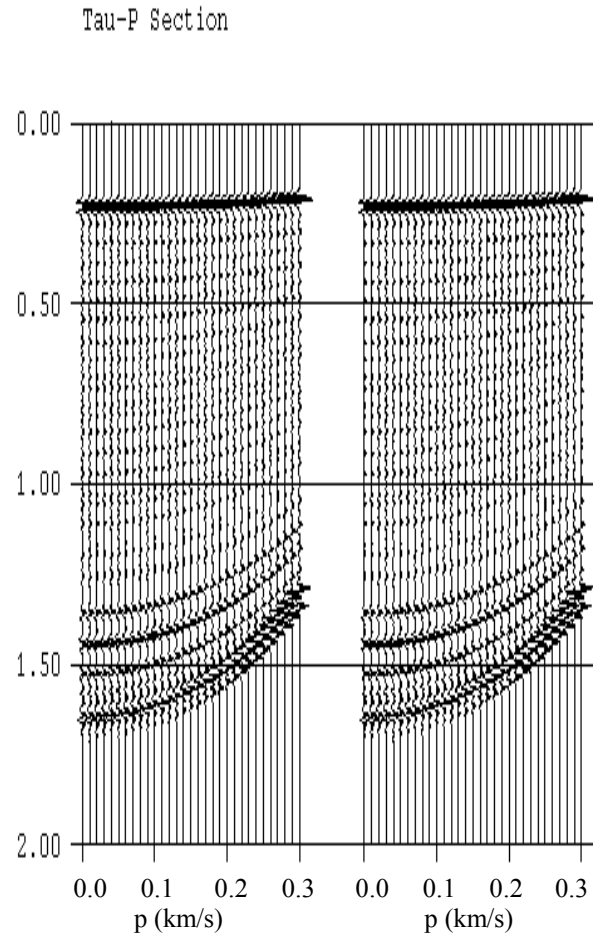


Figure 5: τ - p gathers for (a) actual model, (b) inverted model shown in Fig 3.



Pre-stack Waveform Inversion: Current Status and Future Directions

Mrinal K. Sen, Institute for Geophysics, The University of Texas at Austin, USA

Abstract

Pre-stack seismic waveform inversion is a highly challenging task. The non-linearity and non-uniqueness together with compute intensive forward modeling often make the problem intractable. Much progress has been made in the last decade in the application of global and local optimization methods in model parameter estimation, data fitting and uncertainty estimation. In isotropic media, we found that a hybrid multi-stage waveform inversion approach based on prior travel time and AVO analysis in the plane wave (delay time – slowness or τ - p) domain is fairly robust and computationally efficient. Much of current research is focused on including the effects of transverse isotropy on AVO and pre-stack analysis. Unlike isotropic media, P wave normal moveout analysis in the delay time-ray parameters (τ - p) domain reveals that only two anisotropy parameters, namely, elliptic velocity (α_{el}) and k can be derived successfully in a weak transversely isotropic medium. Based on travel time analysis, an efficient strategy can be made to apply full waveform inversion for parameter estimation and uncertainty analysis. We use the α_{el} and k derived from travel time analysis to constrain the travel time fit; the three free parameters β_0 , δ and density ρ are allowed to vary within a pre-defined search window that is chosen based on a priori knowledge. As in isotropic media, We use synthetic seismograms generated by a reflectivity algorithm and a global optimization method called very fast simulated annealing (VFSA) in search for optimal earth models. An extensive uncertainty analysis is carried out using all the models sampled by multiple VFSA runs. The results are presented as approximate marginal posterior density functions of different model parameters and correlation matrices. The correlation matrices clearly demonstrate the trade-off between different anisotropy parameters. The results reveal that the acoustic impedance is the best-resolved parameter. Uncertainties in many of the parameters can be greatly reduced by joint inversion of PP and PS data as recorded by the modern Ocean bottom cables (OBC). Application of (τ - p) based waveform inversion for such multi-component data including the effects of anisotropy is fairly straightforward in that the forward modeling method remains unchanged. However, issues such as regularization, penalty functions, data and model weights and objective functions need to be reevaluated for computational efficiency and robustness of the algorithm.

Introduction

Estimation of rock properties from reflection seismic data is an area of active research. Subsurface rock properties are manifested in seismic data as variations in travel times, amplitudes, and waveforms. It is well recognized that the travel times are sensitive to smooth changes (or low frequency variations) in velocity field while the amplitudes are affected by fractional or high frequency variations in elastic parameters. Low frequency velocity fields are useful for time to depth conversion, i.e., they can be used for estimating depths. However more detailed estimates of velocity field are necessary for lithology discrimination and direct detection of hydrocarbons ; this is achieved by amplitude versus offset or AVO analysis. An AVO analysis is based on a 'primaries only' model of P wave reflection coefficient; mode-converted waves and internal multiples are not included. Several of the limitations of AVO analysis can be overcome by using a more rigorous pre-stack seismic waveform inversion. In this approach synthetic seismograms are computed for an assumed earth model and compared against the data. If the fit is not acceptable, the model is perturbed, the synthetic data are regenerated and the procedure is repeated. Unlike the AVO analysis, which is a one-step procedure, the prestack waveform inversion is an iterative procedure. Formally this is done by casting the model-fitting problem as an optimization procedure in which we seek an optimum earth model that explains the observations. In other words, we search for the minimum of a suitably defined error function that measures the misfit between observed and synthetic seismograms. It is well recognized that the waveform inversion problem is highly non-linear and the error function has multiple troughs. Thus one has to make careful choice of optimization methods and data domain. The parameter estimation problem depends largely on the following: the forward modeling method, the optimization method, and uncertainty analysis. In my talk, I will describe these, for completeness, and show several examples including new results from waveform inversion in VTI media.

Multi-stage waveform inversion in isotropic media

For practical application and routine use of pre-stack inversion, our goal has been to devise algorithms that are sufficiently fast and accurate. A multi-stage waveform inversion appears to be well suited for the purpose. The motivation for employing

Prestack inversion

a multi-stage inversion stems from the fact that there are two kinds of attributes that the seismic data provide: travel time and amplitude. The travel time is affected by the long period (smooth) variation of the velocity; the relationship between the two is nonlinear. However, the amplitude is quasi-linearly related to the short period (rapid) impedance changes. The distinct nature of the two kinds of information available from seismic data favors an approach that treats the travel time and amplitude separately. The basic philosophy of the multi-stage inversion is described in the schematic diagram displayed in Figure (4). The nonlinear relationship between the travel time and smooth velocity field suggests a nonlinear inversion approach for this part of the problem. For the AVO inversion, a linearized inversion method (Smith and Gidlow, 1987) can be used to obtain a solution in a least squares sense. The combination of the background and the perturbation may not always explain all the features in the data such as the post-critical reflections and the converted waves. However, the combination provides us with a reasonable starting model for a full elastic waveform inversion. The fine-tuning of the model can be achieved by VFSA again. The algorithm has been applied successfully in the inversion of seismic profiles from marine seismic data (Xia et al., 1998; 2000).

Transverse Isotropy

Our basic approach in VTI media is very similar to that used in the inversion in isotropic media. The forward modeling, optimization method and the uncertainty estimation procedures are the same. We, however, have different model parameters that need to be carefully taken into account. In our VFSA inversion, we require realistic search windows for the VTI parameters. The parameters used in the VFSA waveform inversion are: α_{el} , κ , δ , β_0 , ρ and later thickness or two-way-time. The algorithms searches for optimal values of these parameters; these are converted to α_0 , ϵ , δ , β_0 , and ρ for the generation of synthetic seismograms. This is because Sen and Mukherjee (2000) showed that only two parameters α_{el} , κ can be determined by interactive travel time analysis. Detailed discussions of $\tau(p)$ moveout analysis can be found in Sen and Mukherjee (2001). Sen and Mukherjee (2001) derived the following equation for $\tau(p)$ in weak VTI media for quasi-P waves

$$\tau(p) = \tau_0 \left(1 - p^2 \alpha_{el}^2\right)^{1/2} \left[1 - \frac{2p^4 \alpha_{el}^4 \kappa}{\left(1 - p^2 \alpha_{el}^2\right)} \right]^{1/2},$$

where

$$\alpha_{el} = \alpha_0 \sqrt{1 + 2\delta}$$

$$\kappa = \frac{\epsilon - \delta}{(1 + 2\delta)^2},$$

α_{el} is called the elliptic velocity and κ is a new anisotropy parameter that is a function of ϵ and δ . The non-elliptic $\tau(p)$ moveout is caused by a fourth order term in ray-parameter and by the anisotropy parameter κ . Note that κ is zero for elliptically anisotropic and isotropic media in which case the $\tau(p)$ trajectories are elliptical. Iterative fitting of reflections using the above equation result in estimates of elliptic velocity and κ . The trade-off between these two parameters is also discussed in Sen and Mukherjee (2001).

We use narrow search windows on α_{el} and κ , based on our $(\tau-p)$ moveout analysis; those for δ , β_0 and ρ are generally chosen based on our prior knowledge of these parameters. Example of inversion in VTI media is shown in Figure 1.

DISCUSSIONS

We have seen rapid advancement in technology in the use of amplitude and waveform data for estimating rock properties from seismic data; they include AVO and pre-stack inversion. The challenges to seismic waveform inversion are as follows:

- The forward modeling is computationally very intensive,
- The relationship between data and model is highly nonlinear,
- The objective function is multi-modal,
- There exist significant trade-off between different model parameters, and
- Both the data and model sizes are very large.

Most research in waveform inversion has focused on these issues. The $(\tau-p)$ domain appears to be the most appropriate in that forward modeling is very fast and that it generalizes easily to anisotropy and multi-

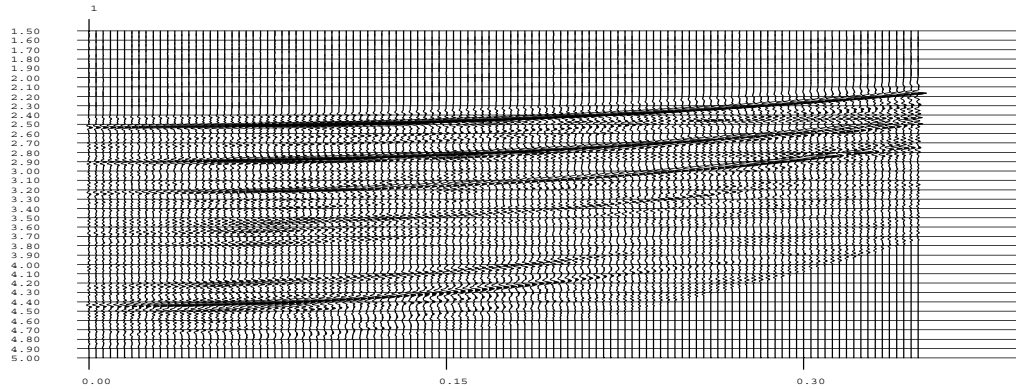
component data analysis. Uncertainty analysis is a very important step of inversion; the results from uncertainty analysis are very useful in the interpretation of inversion results.

In the next decade we will see more widespread use of multi-component data. Once the vector fields are recorded with high degree of fidelity by the OBCs, they will be extremely useful in waveform inversion. For example, joint inversion of PP and PS data will help reduce uncertainty in density and shear wave velocity. They will also be extremely useful in determining anisotropy parameters from seismic reflection data. 1D waveform inversion even including anisotropy and multi-component field data is feasible and will soon become practical since the forward modeling algorithm lends itself to

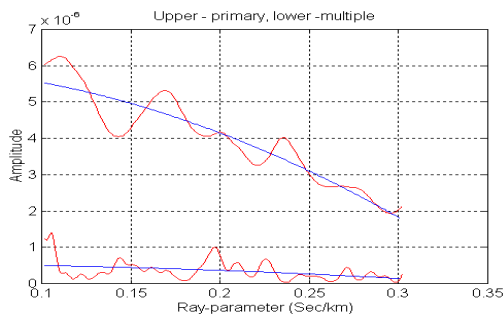
parallelization. Thus cheap cluster of PCs can be dedicated to pre-stack inversion.

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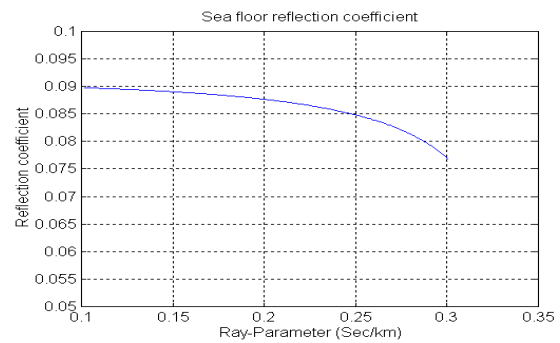
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(a)



(b)



(c)

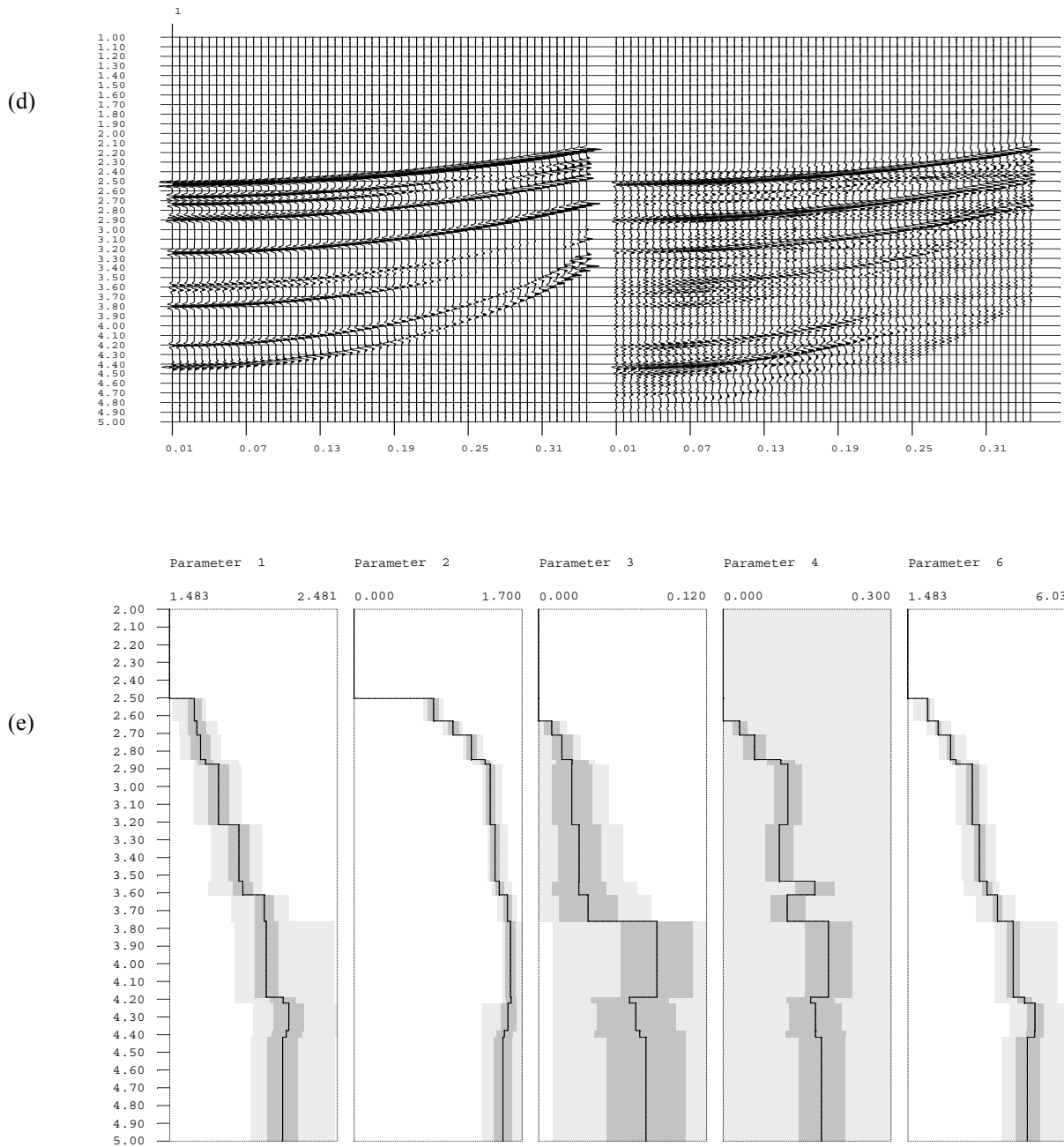


Figure 1. Gulf of Mexico data example of pre-stack inversion in VTI media: (a) a τ -p gather from one of the cmp locations, (b) primary and multiple seafloor amplitude, (c) sea-floor reflection coefficient, (d) Data fitting, (e) Model estimation, the light shade corresponds to the prior and dark shade corresponds to uncertainties (posterior). The mean model is shown with a dark line.



Prediction of sonic and porosity well logs by using neural networks in Eastern Venezuela

Marisela Sánchez Arandía, Universidad Simón Bolívar, Omar Uzcategui* and Mojtaba Taheri, Pdvsa Intevep

Summary

Neural networks have been used successfully in many geophysical applications for pattern recognition and property estimation. In this study, we take advantage of the strength of neural networks to predict well logs using seismic attributes at an Eastern Venezuelan field. Due to the depth of the target (more than 16000 ft.), the frequency content of the seismic data is so low that conventional impedance estimations are not enough to describe reservoir properties.

A neural network is trained at several well locations with porosity logs, sonic velocities, and seismic attributes to build a nonlinear mathematical model. This model is applied to the whole 3D seismic data to generate pseudo sonic velocity and pseudo porosity cubes. The results shown that, the neural network estimations improved the resolution in the pseudo logs compared to those obtained directly from seismic inversion.

Introduction

Extracting rock and reservoir parameters from seismic data has been always a challenge. The main problems to do this lie on a nonlinear relationship between rock properties (as porosity and sonic velocity) and their seismic response. Also, there is a difference of scale between well and seismic data which depends on the frequency content of the seismic and varies with depth and spatial location.

Traditionally, a theoretical relationship between physical rock properties and seismic data has been looked for (Angelier et al., 1982). However, seismic amplitudes depend on so many petrophysical parameters, that a good theoretical relation is difficult to obtain (or to invert for these parameters) over conventional P-wave data. Additionally, seismic data may have different problems (such as noise, bad source or geophone coupling, etc.) that one to one relationship between seismic amplitude and physical properties is difficult to believe. A different approach is to derive statistical and nonlinear relationships (Todorov et al., 1998).

Neural networks can be used as nonlinear estimators. They can approximate any nonlinear function with an arbitrary precision. However, even when they have been used widely in geophysical applications (Van der Bann and Jutten, 2000), further studies are still needed to determine the precision of their estimates as a function of the input data parameters.

In this work, we use a neural network approach to obtain sonic velocities and porosity values from well log information and seismic attributes. A backpropagation method is used to train the network with sonic velocity and porosity information from several wells drilled in an Eastern Venezuelan field with a depth target of more than 16.000 ft. At this depth, seismic frequency content is very low, so a neural network approach is needed to improve the frequency content in the estimations. An example using seismic modeling also shows how the resolution obtained by the neural network changes as a function of the frequency content in the seismic.

Methodology

In general, there is a complex relationship between a physical rock property measured by a well log and the seismic attributes calculated at that well location. In our case, it is assumed that this relationship holds between sonic velocities, porosity values and seismic attributes. Because seismic information is measured in time and well logs are obtained in depth, we convert first the well log information from depth to time using check-shot information. Then, the seismic traces closest to these well locations are extracted from the 3D cube and are used (together with the sonic velocity and porosity profile) to train a neural network.

Neural networks provide a convenient way to relate in a nonlinear fashion several seismic attributes with a single (or multiple) log property. However, designing and training a network may become a difficult problem due to the need to solve complex processes to determine the optimal network configuration and weight distribution. Also, there may not be guarantee of a good overall performance due to overtraining of the network (Van der Bann and Jutten, 2000). Even when many different types of neural networks with varying architectures and applications are available, here, a backpropagation network was used due to its relative simplicity and good record doing well log prediction (Todorov et al., 1998).

Additionally, the best set of seismic attributes to do the estimation needs to be determined. We follow the step-wise regression (Hampson et al., 2000; Draper and Smith, 1966) that assumes the best combination of M+1 attributes includes the previous best M attributes as members. Finally six (6) seismic attributes were used in the training and estimation process. These attributes were (in order of importance) acoustic impedance, seismic time, trace integral, envelope amplitude, instantaneous phase and frequency.

Resolution analysis in well log estimation by neural networks

The low seismic frequency content in the area (less than 20 Hz for the target depth) required a resolution study to see the performance of the neural network at these low frequencies. The analysis consist in filtering the sonic logs converted to time and using these filtered profiles as the input seismic data, instead of the real traces, to do the training and estimation network process. The estimation results (under these ideal conditions) are then evaluated as a function of the filtered frequencies, in order to obtain a good idea about the performance of the network.

Eastern Venezuelan field example

In Figure 1 we show a map with the well locations in the study area. Eighteen wells with sonic, porosity and check-shot information are used in the training process. Also, a 3D seismic survey of about 100 km² covers the area and is used for the estimation. The target zone in this area is more than 16.000 ft deep with a seismic response between 3.0 and 4.0 seconds. The frequency content at this depths is less than 20 Hz with a very low seismic resolution.

In order to test the resolution of the neural network estimations, the logs are filtered with several low pass filters and then these filtered profiles are taken as seismic traces to train the network. Final sonic velocity estimations at a given well location are made as a function of the filtered frequencies. Figure 2 shows the result of this test. The first trace on Figure 2 shows the original sonic profile, the second trace is the estimate obtained from the original sonic profiles, without any filtering. The idea here is to evaluate how good was the training of the network. As we see, both traces (1 and 2) are very similar so we are sure that the network is well trained and can do a good estimation under this ideal condition. The third trace is the result obtained by the network with a sonic profile filtered up to a frequency of 60 Hz. As we see, the result is still good even when we begin to loss resolution due to the missing high frequencies. The fourth trace was obtained from a maximum input frequency of only 20 Hz. The last trace in Figure 2 was obtained directly form the 3D seismic. Comparing the results obtained from the 20 Hz and the real seismic trace, we may conclude that the seismic frequency content in the area is about 20 Hz and our estimates will be around the resolution obtained for this frequency. However, we must pointed out that what we are showing in Figure 2 are estimations for filtered logs profiles up to 20 Hz. The frequency content of the neural network estimation (as we may check out in this figure) is more than 20 Hz.

After the training is finished, the estimation process for the whole 3D seismic cube is done. Figure 3 shows measured sonic logs and the predicted one from neural network corresponding to a well located on the central trace of the

seismic inline shown on Figures 4 and 5. A very good match between both profiles can be seen from Figure 3 and only small differences can be seen in the high frequency components of the sonic log not obtained by the neural network. Figures 4 and 5 show the results over the same inline of the 3D seismic cube and for the impedance and the neural network estimation, respectively. Comparing Figures 4 and 5, we see an increase in resolution which is due to the neural network. Figure 5 also shows in its central trace the true sonic log corresponding to a well located on this inline. Similar results (not shown here) are also obtained for the porosity estimations.

Conclusions

The previous results show that a neural network approach provides good estimations of sonic log values from seismic attributes. As shown by the resolution tests, the resulting estimates are limited by the frequency content of the seismic data, nevertheless an increase in the resolution was obtained compared to that shown by the original seismic.

Although this neural network approach provides a good alternative for seismic-guided well log estimations, further studies are still needed to determine the accuracy as a function of main input parameters, such as seismic frequency, new seismic attributes, location and distribution of wells.

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Resolution analysis in well log estimation by neural networks

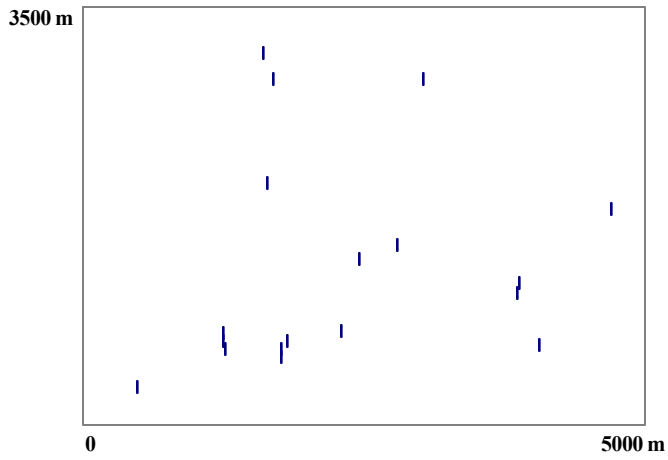


Figure 1: Map showing well locations and seismic data.

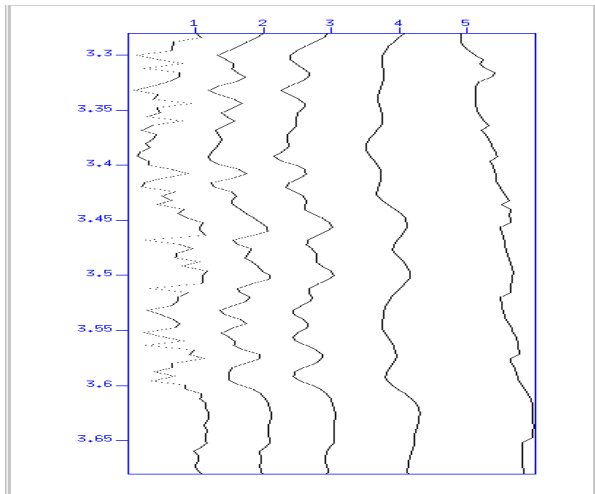


Figure 2: Seismic resolution analysis for a sonic well log estimation

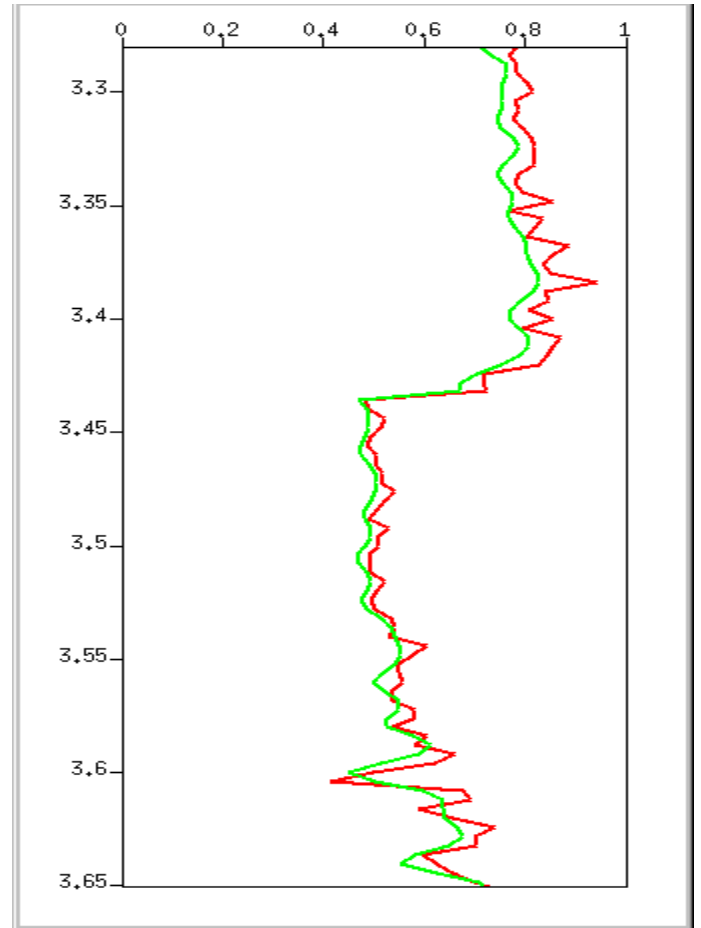


Figure 3: Measured sonic logs, in red, and the predicted one in green, corresponding to the central trace in Figures 4 and 5

Resolution analysis in well log estimation by neural networks

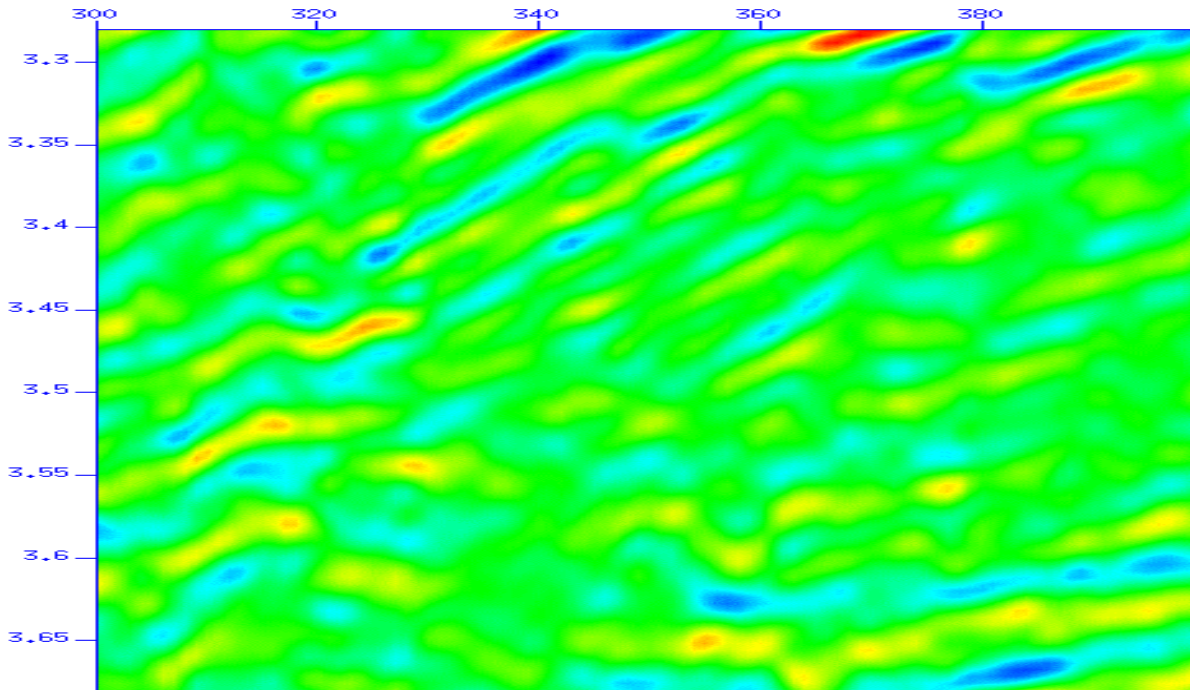


Figure 4. Seismic impedance estimation for the same line shown in Figure 2.

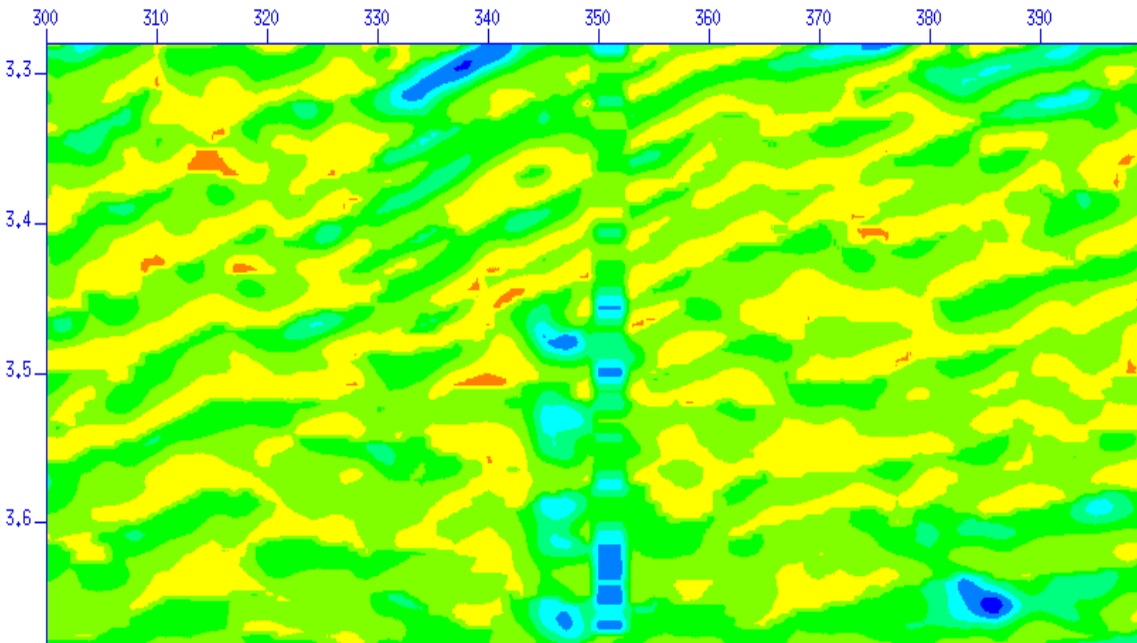


Figure 5. Sonic velocity estimation obtained by the neural network. Central trace shows the true sonic log velocity.

Surface Wave Dispersion Inversion Using Improved Genetic Algorithm

Meijian An and Marcelo S. Assumpção, Instituto Astronômico e Geofísico, Universidade de São Paulo

Abstract

The tasks of surface wave dispersion inversion are to optimize the model of lithospheric structure and to maintain the model diversity. Genetic algorithm, a random global optimization algorithm, is capable of realizing these tasks and has been used in the dispersion inversion for several years. But for the inversion of complex structure model, simple genetic algorithm will become inefficient. In order to improve its efficiency, we suggest a jumping hybridization procedure. New hybridized genetic algorithm is more efficient than its predecessor. We also invert P wave velocities of crustal layers by adding the constraint of the time difference Ps-P besides inverting for the layer thickness and S velocity.

Introduction

The surface wave dispersion inversion is a complex non-linear geophysical problem. An efficient inversion algorithm of surface wave dispersion should carry out three tasks. The first is to find the global solution region. The second is to maintain solution diversity in the whole acceptable model space (however, if all observational errors are enough random, the global optimum should be close to the real solution). Additionally, a good algorithm should be flexible to be modified and then still robust after

changing some conditions. Genetic algorithm (GA) is a global optimization algorithm and satisfies the above three tasks. Moreover, GA can be extended to provide quality solutions more efficiently through parallelization, time utilization, relaxed function evaluation, and hybridization (Goldberg, 1999). Using simple GA (SGA) to invert surface wave dispersion, Shi and Jin (1996) found the optimal solution and Loman and Snieder (1994, 1995) searched all acceptable solutions.

We show that it is difficult for simple GA to find complex crustal structure in the surface wave dispersion inversion. For example, SGA is efficient on the S velocity inversion, but it is more difficult on the simultaneous inversion of several different parameters such as thickness, S velocity and so on. Part of difficulties is because the addition of other parameters will enlarge the model space, which requires more search work. Another difficulty comes from the tradeoffs of different parameters, for example the tradeoff between thickness and S velocity inside a layer (figure 1).

GA has been developed from a simple global optimal skill, more than 10 years ago, to a comprehensive technical method today. So it should be possible to improve the genetic algorithm for the inversion of surface wave dispersion. In this paper, we propose a jumping hybridization method on GA.

Crustal P wave velocities have little effect on the surface wave dispersion. For the inversion of only S wave velocities and thickness, adding the Ps-P time difference (Ps is the P to S conversion at the Moho) in the inversion does not help constrain the solutions because of the uncertainty of P velocities and the tradeoff between S velocity and layer thickness. But, when we also include P velocities (or the ratio of P to S velocity, V_p/V_s) of crustal layers to be inverted, Ps-P can help to optimize P velocities. In this way, the P velocities (or V_p/V_s) of the crust can be estimated in surface wave dispersion inversion.

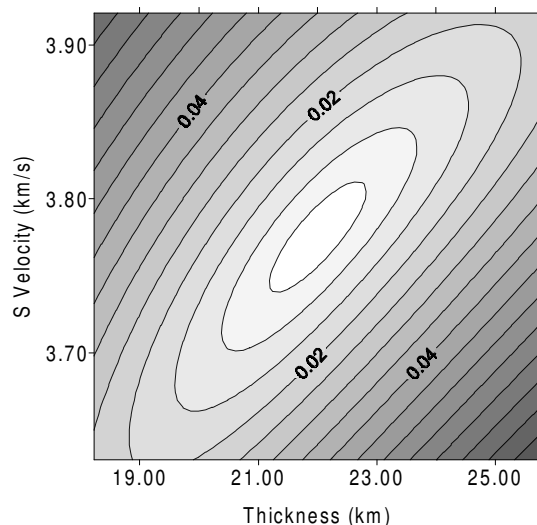


Figure 1 - Misfit of surface wave velocities as function of thickness and S velocity of a layer in one theoretical model, showing tradeoff between thickness and S velocity.

Hybridized GA

The main idea of hybridization is that some good models are improved by changing the parameters in random steps in the GA generation. This hybridization procedure is like a trial-and-error jumping in random direction. The iteration step (the distance from the starting model) increases exponentially until the model stops improving.

Using a theoretical model, we examined the efficiency of the new hybridized GA (HGA) by comparing with SGA (see Table I and Table II). The

Dispersion Inversion Using Improved GA

Table I - Optimal results of simple and hybridized GA with string lengths of 5. Each parameter setting was run 5 times with respective initial models.

	Population size	Number of generations	Initial jump step	Average number of evaluated models	Best model's misfit	Average misfit of best models in 5 runs
SGA	40	500	0	20000	0.0086	0.0234
HGA	25	250	5	18399	0.0049	0.0081
			8	17645	0.0076	0.0095

Table II - Optimal results of hybridized GA with population size of 15. Each parameter setting was run 5 times with respective initial models.

Number of generations	String length	Initial jump step	Average number of evaluated models	Best model's misfit	Average misfit of best models in 5 runs
250	5	5	9550	0.0081	0.0100
		8	9410	0.0080	0.0104
		10	9250	0.0085	0.0099
	8	5	12420	0.0052	0.0065
		8	11301	0.0052	0.0069
		10	10710	0.0038	0.0068
	12	5	16505	0.0053	0.0096
		8	15803	0.0065	0.0079
		10	15701	0.0024	0.0070

hybridized GA is much more efficient. Moreover, it is less sensitive to the initial models, population size and the precision of searched model. These results are ideal for its application, because the results of normal GA are strongly dependent on the initial parameter settings and this dependence could make GA stick around local optima and prevent reaching the global optimum in one run. On the other hand, the hybridized GA can be used in more accurate model searching because it is insensitive to the precision of the searched model.

Application to Paraná Basin

The lithospheric structure of the Paraná basin was investigated in recent years by Snoke and James (1997), Assumpção et al (2001). Several techniques have been used with teleseismic events to estimate deep structure beneath the network, such as: body-wave tomography, surface wave dispersion, SKS splitting, and receiver function. We did the lithosphere inversion of Paraná basin by hybridized GA of surface wave dispersion using the observed dispersion data of Snoke and James (1997) and Assumpção et al (2001). A constraint of average Ps-P for the Paraná basin of 4.98s (Assumpção, 2001) was used. The inversion misfit function is the rms of

dispersion velocities weighted with the observational errors. Inverted parameters of each layer are layer thickness, S wave velocity and Vp/Vs ratio. The inversion model includes five layers: sediments, upper and lower crust, lithospheric lid and anthenosphere. The search ranges of thickness, S velocity and Vp/Vs in 5 layers are respectively (1.5-

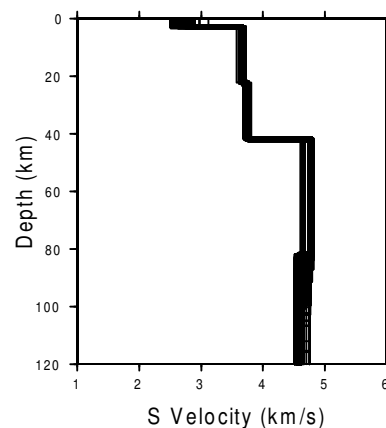


Figure 2 - Inverted models with misfit less than 0.025km/s and Ps-P residual less than 0.1s.

Dispersion Inversion Using Improved GA

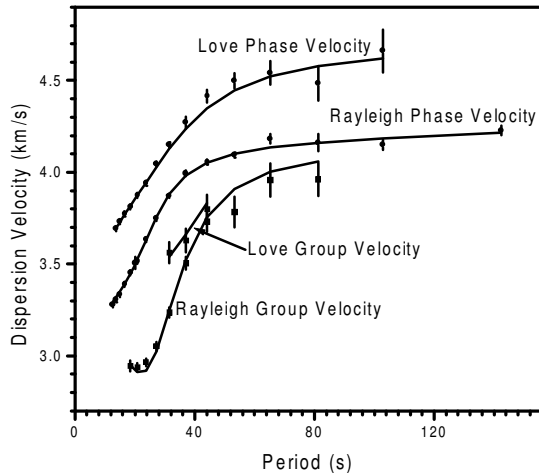


Figure 3 - Dispersion fitting. Symbols are the observational data, lines are inverted dispersion of one acceptable model with misfit of 0.02km/s.

3.5, 2.5-3.5, 1.7-1.9), (15-20, 3.0-4.0, 1.7-1.9), (15-20, 3.0-4.5, 1.7-1.9), (40-200, 3.5-6.0, 1.7-2.0), (half-space, 3.5-6.0, 1.7-2.0). String length of each parameter is 12. The best model's misfit is less than 0.02km/s, while the average observational error of velocities is 0.032km/s. All best models, with misfit less than 0.025km/s and Ps-P error less than 0.1s, are shown in figure 2 and one of the best models is visualized in figure 3. By comparing the inversion results with those inverted by linearized least-square method (Snoke and James 1997) and the neighborhood algorithm (Snoke and Sambridge, 2000), we conclude the inverted model (thickness and S velocities) for the Paraná basin is similar to the results computed by the other algorithms. The S velocity in the sedimentary layer is not well constrained because there are not dispersion data of period less than 13s. The average crustal thickness is about 41-42km. There is some indication of decreasing S velocity below about 100km, but probably not significant. The V_p/V_s ratios are not well constrained. In the upper crust V_p/V_s tends to be less than 1.75, and in the lower crust it tends to be higher than 1.75, which could indicate a more mafic lower crust. However, we still need to analyze the significance of these results. In the upper mantle, V_p/V_s is not constrained at all.

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Emails:

Meijian An, meijian@iag.usp.br

Marcelo S. Assumpção, marcelo@iag.usp.br



The elastic impedance log estimation puzzle

Lúcia Duarte Dillon, Guenther Schwedersky and Guilherme F. Vasquez, PETROBRAS/CENPES, Brazil

Abstract

There is always some confusion when a clear physical meaning must be established for the Elastic Impedance (EI) as a real rock point property since it is, in fact, only an approximation of reality. This is specially striking for EI logs generation and very different approaches can be found in the literature for this purpose. In fact, the accuracy of the EI log generation may be critical for a well based far–offset inversion process since it must be applied for: a) feasibility analysis, b) wavelet extraction c) low frequency constraint.

In this context, the main goal of this work has been to carefully analyze some fundamental aspects related to the EI log generation process, focusing the main three applications described above. The discussion involves both theoretical arguments, as practical examples obtained from synthetic data, and real well log data sets.

Introduction

Rock physics has been used as an important tool in improving the interpretation of "compressional-wave impedance" or "acoustic impedance" (AI) inversion for desired reservoir properties such as porosity, lithotype, fluid content and saturation. As widely shown in the last couple of years, in many situations the shear-wave information can drastically improve this kind of interpretation. A robust way of introducing shear-wave information into consideration is the far–offset seismic amplitude inversion. The term "elastic impedance" (EI), as proposed by Connolly (1999), has been used to describe the result of this inversion. Following the same direction, rock physics can also be used as a powerful tool to improve the far offset inversion interpretation. The EI inversion process assumes that, considering some approximations, the EI can be translated into an impedance as a real rock point property that makes all processes very similar to the well known zero–offset acoustic impedance (AI) inversion. That is why it opens avenues for using accumulated rock physics knowledge, both experimental (data from cores and/or logs) and theoretical, in order to improve the far–offset inversion interpretation process. However, there is always some confusion when we try to establish a clear physical meaning for EI as a real rock point property since it is, in fact, only an approximation of reality. This is specially striking for EI logs generation and very different approaches can be found in the literature for this purpose.

EI logs generation

In fact, the accuracy of the EI log generation may be critical for a well based far–offset inversion process since it must be applied for: a) feasibility analysis, b) wavelet extraction, c) low frequency constraint.

Several options for the EI estimation can be considered. Similarly to the AI case, the main assumption is that EI satisfies a relation of the type:

$$Ri(\theta) = \frac{EI_{i+1} - EI_i}{EI_{i+1} + EI_i} \quad (1)$$

Then,

$$EI_n \cong EI_1 e^{2S} \quad (2), \text{ and } S \cong \int Rpp_n(\theta) \quad (3)$$

where $R_i(\theta)$ is the $Rpp(\theta)$ (P-wave reflection coefficients) between layers i and $i+1$. However, differently from AI, for the far offset case, depending on the elastic contrasts along the geologic interval observed, this assumption may be very far from reality.

First, the EI as presented by Connolly (1999), comes from an analytical integration of the P-wave reflection coefficients ($Rpp(\theta)$) as a function of the incident angle θ , obtained by the well known Aki & Richards (1980) linearization (see equation 4) of Zoeppritz (1919) equations:

$$Rpp(\theta) = \frac{1}{2} \left(\frac{\Delta Vp}{Vp} + \frac{\Delta \rho}{\rho} \right) - 2\bar{K} \left(2 \frac{\Delta Vs}{Vs} + \frac{\Delta \rho}{\rho} \right) \sin^2 \theta + \frac{1}{2} \frac{\Delta Vp}{Vp} \tan^2 \theta$$

(4), where:

$$\bar{X} = \frac{1}{2} [(X)_i + (X)_{i+1}] \quad \text{for } X = Vp, Vs \text{ or } \rho$$

This analytical integration is an approximate solution supposing low impedance contrasts and assuming a constant value for the ratio between the shear wave velocity (Vs) and the P-wave velocity (Vp). The expression for EI given by Connolly is:

$$EI = Vp \left(\frac{1 + \tan^2 \theta}{2} \right) \cdot Vs \left(\frac{1 - 8K \sin^2 \theta}{2} \right) \cdot \rho \left(\frac{1 - 4K \sin^2 \theta}{2} \right) \quad (5)$$

where Vp and Vs are the P and S-wave velocities respectively, ρ is the density and $K = (Vs/Vp)^2$. The great advantage of this derivation is to arrive to a point formula, a function of just Vp , Vs and ρ . However, the impact of making the Vs/Vp ratio constant must be evaluated for each case.

The numeric methods to derive EI also assume that equations 1, 2 and 3 hold, but the integration: $S \cong \int Rpp(\theta)$, is calculated numerically. The Rpp

coefficients may be obtained by the full Zoeppritz solution or by the Aki & Richards approximation.

A synthetic example

In order to evaluate the behavior of the EI derived using the three mentioned approaches, a synthetic model consisting of a repetitive sequence of three rock types was built (figure 1). Table 1 specifies the V_p , V_s and ρ values for these rocks. A 30-degree angle of incidence was assumed. The results for three approaches can be seen in figure 2. All the results were normalized in relation to the first sample.

Table 1

	V_p (m/s)	V_s (m/s)	ρ (g/cc)	Litho Color
SHALE	3048	1270	2.44	Blue
SANDSTONE (OIL SAT.)	2540	1325	2.09	Cyan
CALCILUTITE	3958	1847	2.50	Green

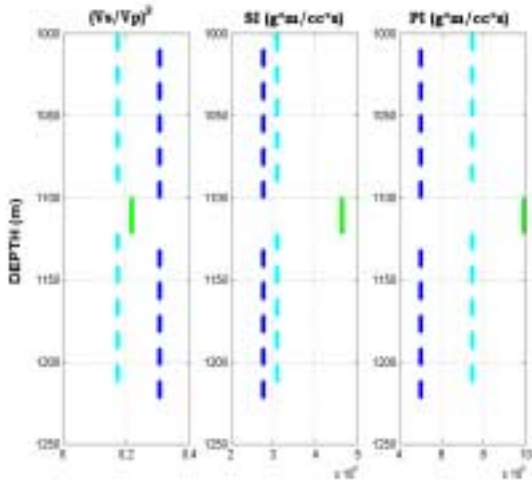


Figure 1

The EI resulting from the integration of $Rpp(\theta)$ Zoeppritz's coefficients is, obviously, very far away from a real rock point property of the layers. Actually, it can be shown that for $Rpp(\theta)$ derived from Zoeppritz's equations, mainly for high angles of incidence (greater than 20 degrees), and in presence of large elastic properties contrasts, the coefficients are not symmetric, i.e.:

$$Rpp_{i \rightarrow i+1} \neq Rpp_{i+1 \rightarrow i}$$

For this reason, the EI calculation by numeric integration (equations 4 e 5), assuming that equation (3) holds, will lead us to an unstable, false, low frequency com-

ponent in the derived EI, even starting from accurate $Rpp(\theta)$ reflection coefficients.

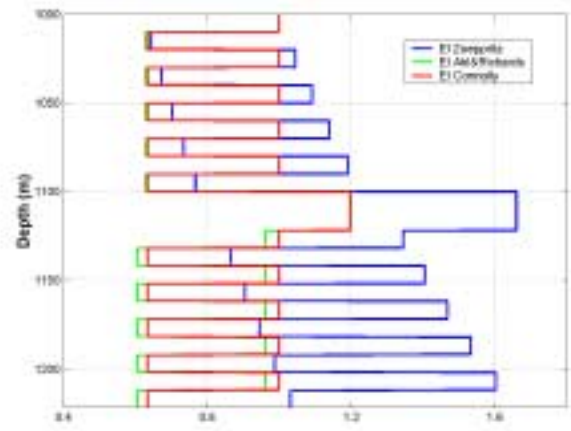


Figure 2

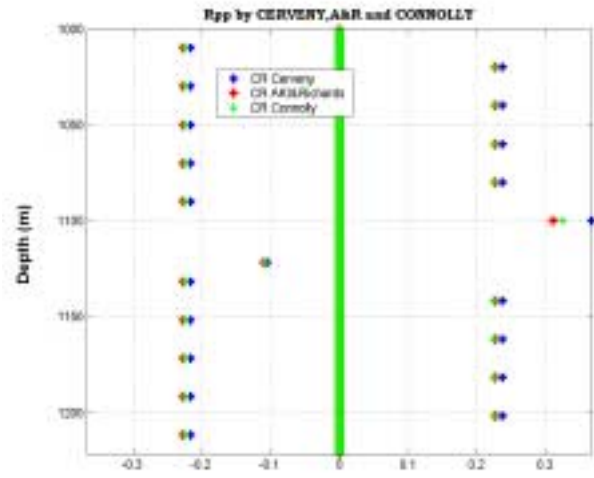


Figure 3

Actually, as can be observed on figure 3, the $Rpp_{i, i+1}$ is always greater than $Rpp_{i+1, i}$ and that is the main reason why the $Rpp(\theta)$ numeric integration process will always generate a large erroneous low frequency drift that will lead to completely wrong absolute values for EI. This example shows that this kind of EI logs derivation should not be used for feasibility analysis or low frequency constraint in the inversion process.

The EI calculated from the numeric integration of the Aki & Richards's $Rpp(\theta)$ coefficients, as seen in figure 2, doesn't behave either as a real rock point property. However, as expected, the errors involved are much smaller than for the Zoeppritz's case since for Aki & Richards's linearization there is no asymmetry ($Rpp_{i, i+1}$

$=Rpp_{i+1,i}$), as exemplified in figure 2. Actually, some authors, as discussed by Castagna and Backus (1993), argue that in real layered media, instead of two infinite half spaces, the Zoeppritz formulation is not valid due to the local superposition of the P wave and converted S wave what would roughly cancel the predicted asymmetry. The conclusion is that Aki & Richards approximation may be, in some cases, more appropriate for both $Rpp(\theta)$ and subsequent EI derivation.

For the EI derived from Connolly's formula, the assumption of a constant $K=(Vs/Vp)^2$ guarantees that $Rpp(\theta)$ can be expressed as a full differential. The result of its integration will then work as a real rock property function of Vs , Vp and ρ . The consequence is that the resulting EI will always be the same for the same lithologies, as also shown in the example of figure 3. However, to make it possible, a background K must be assumed, and what is the penalty for that?

In order to illustrate the above discussion, let's now take a real example for EI log and Rpp coefficients calculations of an oil saturated tertiary turbiditic reservoir.

A real example

Figure 4a shows again the remarkable difference between the results if the three main ways were considered to calculate the EI final log (Zoeppritz, Aki & Richards and Connolly). Plotted on figure 4b are the observed differences between Rpp coefficients derived from Aki & Richards approximation and Connolly formula if related to those of Zoeppritz. Differently from the Aki & Richards case, one can observe a significant scattering between the Rpp derived from Connolly formula and Zoeppritz. Certainly, depending on the case, this difference may be harmful for the wavelet extraction. Thus, Connolly's formula may not be the best choice for this task.

As mentioned before, EI is not a true physical property of rocks and, consequently, there is not also a true and unique way to derive it. The whole thing acts like a puzzle of approximations. The most suitable EI log depends on its application: feasibility analysis, wavelet extraction or low frequency constraint. In fact, usually the best log is not derived directly from one of the proposed approaches but from a combination of different logs.

For instance, for low frequency constraint purposes, Connolly's EI formula is always the best choice. However, for wavelet extraction, the more accurate Zoeppritz's Rpp coefficients are suitable or, as proposed by Backus, Aki & Richards's Rpp calculations should be used for this task.

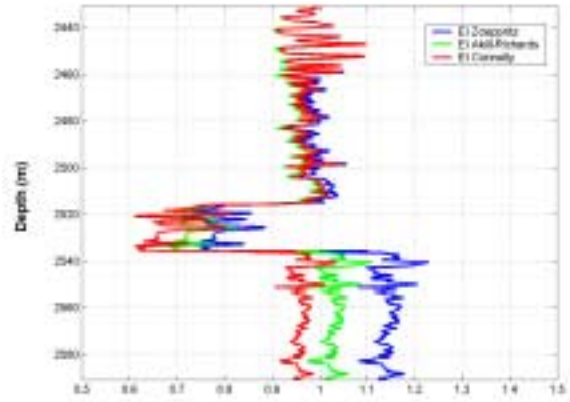


Figure 4a

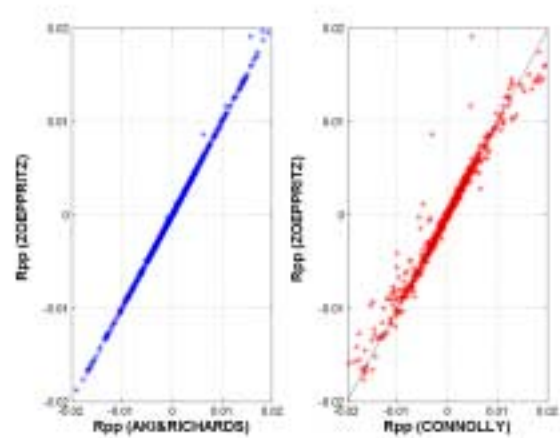


Figure 4b

On the other hand, for feasibility analysis, in order to have a basis to derive an EI log that can be universally calibrated in reference to different lithologies and fluid properties, a composition of the EI derivation proposals should be considered in order to minimize the weakness of each. This idea was proposed by Van Riel (1999) and Dillon et al (1999). The suggestion is to compose an EI log using the low frequency (less than 8 Hz) components from Connolly's formula and the high frequency components from the numeric integration of the Zoeppritz's or Aki&Richards's reflection coefficients.

Also, for feasibility analysis, a "quick look" approach may be considered to overcome a few problems of the EI log estimation. It consists on applying a previous filtering process to the input logs (Vs , Vp and ρ). For most real geologic sequences, where usually elastic property contrasts are not so prominent, this filtering is enough to avoid the problems related to the numeric integration approach, and a reasonable and consistent final EI log can be obtained by both Aki & Richards's

or Zoeppritz's R_{pp} numerical integration. Figures 5a and 5b illustrate this procedure. The same log (figures 4a and 4b) was taken but a previous moving median filter of 31 samples was applied individually to V_p , V_s and ρ logs before any calculation. Now, it can be observed that the EI values obtained by the three methods are much closer, as well as the R_{pp} coefficients from Connolly's formula, when compared to those of Zoeppritz's or Aki & Richards's, have much less scattering. Anyway, for wavelet extraction it's still strongly recommended to reference to Zoeppritz's R_{pp} coefficients or, in some cases, as discussed previously, to the Aki & Richards's reflection coefficients.

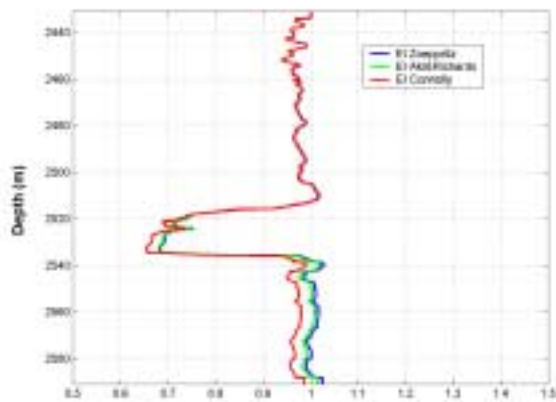


Figure 5a

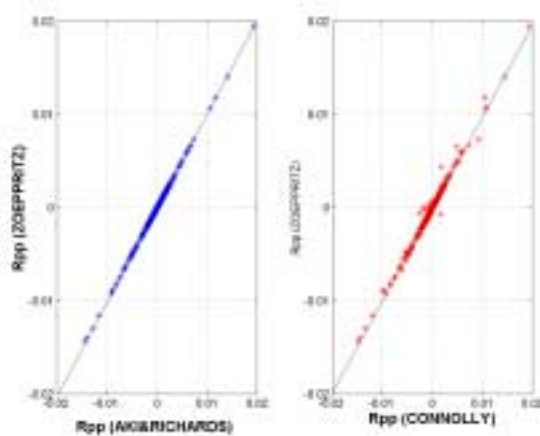


Figure 5b

Conclusions

- The EI log estimation process, focusing three main approaches, has been discussed. This discussion involved both theoretical arguments and practical examples obtained from synthetic and real well log data sets.
- EI is not a true physical property of rocks. Consequently, there is not a true and unique way to derive it. The most suitable EI log depends on its applications:

feasibility analysis, wavelet extraction or low frequency constraint. In fact, usually the best log is not derived directly from a single one, but from a combination of different proposed approaches.

- For wavelet extraction, the direct calculation of the reflection coefficients based on full Zoeppritz's equations or Aki & Richards's approximation is the most appropriate procedure.
- For low frequency constraint, due to the inherent error associated to numerical integration techniques, Connolly's formula is always more indicated.
- Finally, for feasibility analysis, a composition of the EI derivation proposals should be considered in order to minimize the weakness of each. This EI log would be generated using the low frequency (less than 8 Hz) components from Connolly's formula and the high frequency components from the numeric integration of Zoeppritz's or Aki&Richards's reflection coefficients.
- It is important to notice that, using these procedures, this EI log may be considered as a universally calibrated reference to different lithologies and fluid properties. This issue opens avenues for using accumulated rock physics knowledge, both experimental (data from cores and/or logs) and theoretical, in order to improve the far-offset inversion interpretation process.

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Tomografia pela Técnica de Reconstrução Algébrica Aplicada a GPR / Poço

Jadir da Conceição da Silva / UFRJ – jadir@geologia.ufrj.br

Resumo

O imageamento da subsuperfície constitui-se atualmente em um dos principais desafios imposto ao geofísico. Dados de GPR, tais como tempo de trânsito e amplitude da onda eletromagnética, associados com velocidade e atenuação, quando adquiridos entre poços vizinhos, permite reconstruir a geometria de subsuperfície, estimando constante dielétrica e condutividade elétrica. A técnica de tomografia por reconstrução algébrica (ART) é aplicada para imagear uma camada apresentando uma falha normal, encaixada em um meio altamente resistivo. São mostradas as imagens de velocidade e atenuação resultante da tomografia ART, bem como imagens de valores de constante dielétrica e condutividade calculados através de modelos físicos simplificados, relacionando estes parâmetros. Mesmo desconsiderando aspectos importantes como reflexões, refrações e difrações, os resultados permitem distinguir com certa eficácia a camada falhada, o que demonstra a utilidade da técnica ART no imageamento geofísico.

Introdução

Os principais fatores que descrevem a propagação de ondas eletromagnéticas de alta frequência (radar) são velocidade e atenuação. Estes fatores, por sua vez, são funções das propriedades elétricas e dielétricas dos materiais. Sabe-se, de antemão, que os materiais reais apresentam condutividade (σ) e polarizabilidade (ϵ). Partindo das equações de Maxwell, no que concerne as leis de Ampère e Faraday, temos

$$\nabla \times \mathbf{H} = \mathbf{J} - i\omega \mathbf{D}$$

$$\nabla \times \mathbf{E} = i\omega \mathbf{B}$$

que acrescidas das equações constitutivas $\mathbf{J} = \sigma \mathbf{E}$, $\mathbf{B} = \mu \mathbf{H}$ e $\mathbf{D} = \epsilon \mathbf{E}$, onde σ , ϵ e μ são condutividade elétrica, permissividade dielétrica e permeabilidade magnética do meio, respectivamente, resulta na seguinte expressão para a componente campo elétrico

$$\nabla^2 \mathbf{E}(\mathbf{r}, \omega) + (\omega^2 \mu \epsilon + i\omega \sigma \mu) \mathbf{E}(\mathbf{r}, \omega) = 0. \quad (1)$$

A solução simplificada da equação (1), em termos de onda plana (David & Kung, 1996), no domínio do

tempo, adaptado ao caso do raio com direção e/ou comprimento de trajeto genérico η , excluindo reflexões, refrações e difrações, é

$$E(\eta, t) = E_0 \exp[i(K_\eta \eta - \omega t)],$$

onde $K_\eta = (\omega^2 \mu \epsilon + i\omega \sigma \mu)^{1/2} = \alpha + i\beta$ é o número de onda complexo na direção η , sendo α sua parte real e β a parte imaginária. Este número de onda complexo resulta em uma atenuação e deslocamento de fase da onda eletromagnética plana, tal que

$$E(\eta, t) = E_0 \exp(-\beta \eta) \exp[i(\alpha \eta - \omega t)]. \quad (2)$$

Vê-se claramente que a onda atenua de um fator $e^{-\beta \eta}$, enquanto sofre um deslocamento de fase de $\alpha \eta$ radianos. Resolvendo K_η para α e β , temos

$$\alpha = \omega \left[\frac{\mu \epsilon}{2} \left(1 + \frac{\sigma^2}{\epsilon^2 \omega^2} \right)^{1/2} + 1 \right]^{1/2} \quad (3)$$

$$\beta = \omega \left[\frac{\mu \epsilon}{2} \left(1 + \frac{\sigma^2}{\epsilon^2 \omega^2} \right)^{1/2} - 1 \right]^{1/2}. \quad (4)$$

Determinação de Velocidade e Atenuação

Inicialmente, propomos o número de onda como sendo

$$K_\eta = \omega^2 \mu \epsilon_0 \left(\epsilon' + i \frac{\sigma}{\epsilon_0 \omega} \right)$$

onde $\epsilon' = \text{Re}(\kappa)$, a parte real da constante dielétrica, e $i\sigma/\epsilon_0\omega$ representa as perdas. No entanto, de acordo com Davis & Annan (1989), a relaxação da molécula de água exige redefinir a constante dielétrica complexa como

$$\kappa = \epsilon' + i \left(\epsilon'' + \frac{\sigma}{\epsilon_0 \omega} \right)$$

Tomografia GPR / Poço

onde ε'' está relacionada às perdas a altas frequências, normalmente associadas com problemas de relaxação. Podemos agora reescrever a equação (2) da seguinte forma

$$E(\eta, t) = E_0 \exp[iK_\eta (\eta - Vt)],$$

onde V é a velocidade de fase da onda. Davis & Annan (1989) mostram que para $\omega < 1000$ MHz, limite superior de aplicabilidade da técnica GPR, o valor de $\varepsilon'' = 0$. Isto implica em um valor para a velocidade de fase da onda de

$$V = \frac{c}{\left(\varepsilon' + i \frac{\sigma}{\varepsilon_0 \omega} \right)^{1/2}}.$$

onde c é a velocidade da luz no vácuo. Analisando a equação (2), percebemos que a atenuação (att) é a parte imaginária do número de onda. Como ela é exponencial, basta multiplicar pelo fator 8,68 para convertê-la à unidade usual de dB/m, isto é,

$$att = 8.68 \operatorname{Im} \left[\omega (\mu \varepsilon_0 \kappa)^{1/2} \right] \quad (6)$$

Como a aplicabilidade da técnica GPR exige que $\sigma / \varepsilon_0 \varepsilon \omega \ll 1$, as equações (5) e (6) reduzem-se às formas simplificadas

$$V = \frac{c}{\sqrt{\varepsilon'}} \quad (7)$$

$$att = \frac{1,69 \times 10^3 \sigma}{\sqrt{\varepsilon'}}. \quad (8)$$

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As equações (7) e (8) revelam a possibilidade de se determinar conjuntamente a constante dielétrica e a condutividade de um meio qualquer a partir do conhecimento da velocidade (V) e da atenuação (att) da onda eletromagnética neste meio. Visto que a tomografia aqui proposta procura inverter tempo de trânsito e amplitude do campo elétrico, é necessário a elaboração de um modelo direto relacionando os parâmetros requisitados. Para tal, proporemos o modelo geológico da Figura (1).

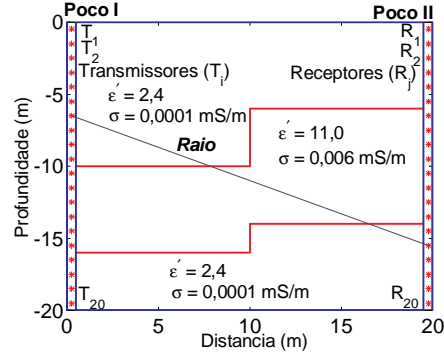


Figura 1: Modelo geológico idealizado para a aplicação da técnica ART de imageamento geofísico.

Pelas equações (2), (3) e (4), nota-se que o tempo de trânsito e a atenuação da onda, incluindo todos os conjuntos de parâmetros do meio (condutividade, polarizabilidade e permeabilidade magnética) e da própria onda ($\omega = 60$ MHz) são dados por $t = \alpha \eta / \omega$ e $\ln(|E_0 / E_\eta|) = 8,68 \beta \eta$, no caso de futuramente especificarmos att em unidades dB / m. As Figuras 2(a) e 2(b) exibem o tempo de trânsito e o campo elétrico gerados através de raios retos como aquele exemplificado na Figura (1). Como o raio cruza regiões com diferentes propriedades físicas, as equações para tempo e atenuação tomam as formas abaixo,

$$t = \frac{1}{\omega} \sum_{n=1}^N \alpha_n \Delta \eta_n \quad (9)$$

$$\ln \left(\left| \frac{E_0}{E_\eta} \right| \right) = 8,68 \sum_{n=1}^N \beta_n \Delta \eta_n, \quad (10)$$

onde $\Delta \eta_n$ é o comprimento do raio na região n e direção η . Já para o modelo inverso, a região mostrada na Figura (1) será subdividida em 20x20 células elementares j e o comprimento do i -ésimo raio em cada uma delas será denotado por s_{ij} . Desta forma, os modelos para tempo de trânsito e atenuação serão:

$$t_i = \sum_{j=1}^M s_{ij} v_j, \quad i = 1, 2, \dots, N. \quad (11)$$

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$$\ln \left(\left| \frac{E_0}{E_\eta} \right| \right)_i = \sum_{j=1}^M s_{ij} (att)_j, \quad i = 1, 2, \dots, N. \quad (12)$$

onde v_j é a vagarosidade relacionada à célula j , M é o número total de células (400) e N o número total de raios. Ambas as equações (11) e (12) podem ser generalizadas pela equação matricial $\mathbf{y} = \mathbf{A}\mathbf{x}$. A técnica ART iterativa original parte de N dados no vetor \mathbf{y} (Gordon et al., 1970, e Mersereau & Oppenheim, 1974), sendo \mathbf{A} uma matriz $N \times M$, onde $M = (k \times k)$ são as dimensões da região a ser imageada. Primeiramente define-se os dados calculados $y_i^q = \sum_j A_{ij} x_j^q$ para cada raio i e cada iteração q . A seguir calcula-se

$$x_j^{q+1} = x_j^q + A_{ij} \frac{(y_i - y_i^q)}{\sum_k A_{ij}^2}. \quad (13)$$

Em outras palavras, raios são traçados através da região a ser imageada e os tempos de trânsito e amplitude da onda eletromagnética calculados. A diferença entre os dados observados e calculados é redistribuída ao longo de cada raio e os novos valores dos parâmetros calculados de acordo com a equação (13). Este procedimento é repetido até que os resultados converjam de acordo com certo critério de parada. Gordon et al. (1970), estabelece que a entropia

$$S^q = - \frac{1}{\ln M} \sum_{j=1}^M \frac{x_j^q}{\bar{x}} \ln \left(\frac{x_j^q}{\bar{x}} \right)$$

nos dá o melhor critério estatístico de parada, onde \bar{x} é a média das componentes do vetor \mathbf{x} . Neste trabalho, o critério de parada proposto é :

$$\left| S^{q+1} - S^q \right| < \frac{1}{500} S^q.$$

As Figuras 2 (c) e 2(d) mostram os resultados da inversão ART. A seguir, utiliza-se as equações (7) e (8) para calcular os valores de constante dielétrica e condutividade (Figuras 3(a) e 3(b)). Comparando estes resultados com os dados do modelo geológico (Figura 1), observa-se que estes parâmetros foram reproduzidos de maneira satisfatória, o que corrobora a eficácia da técnica ART no imageamento geofísico.

Conclusões

Neste trabalho, foi aplicada a técnica ART de tomografia de tempo de trânsito e amplitude da onda eletromagnética, para investigação de GPR tomado poço a poço, com o objetivo de reconstruir um meio geológico heterogêneo. As antenas transmissoras e receptoras foram arranjadas de forma a melhor imagear a camada falhada, distinguindo-a do meio encaixante. A velocidade e a atenuação da onda nestes meios foram reconstruídos com sucesso; e através delas, reproduziu-se com igual sucesso os valores de constante dielétrica e condutividade elétrica. Mesmo para raios retos, desconsiderando, porém, efeitos importantes como reflexões, refrações e difrações, a eficácia da técnica ART fica comprovada, o que leva a concluir ser esta técnica perfeitamente aplicável à geometria mais complexas, principalmente se for adotado um algoritmo mais eficiente de traçados de raios que leve em consideração efeitos de reflexões, refrações e difrações no seu comportamento.

Agradecimentos

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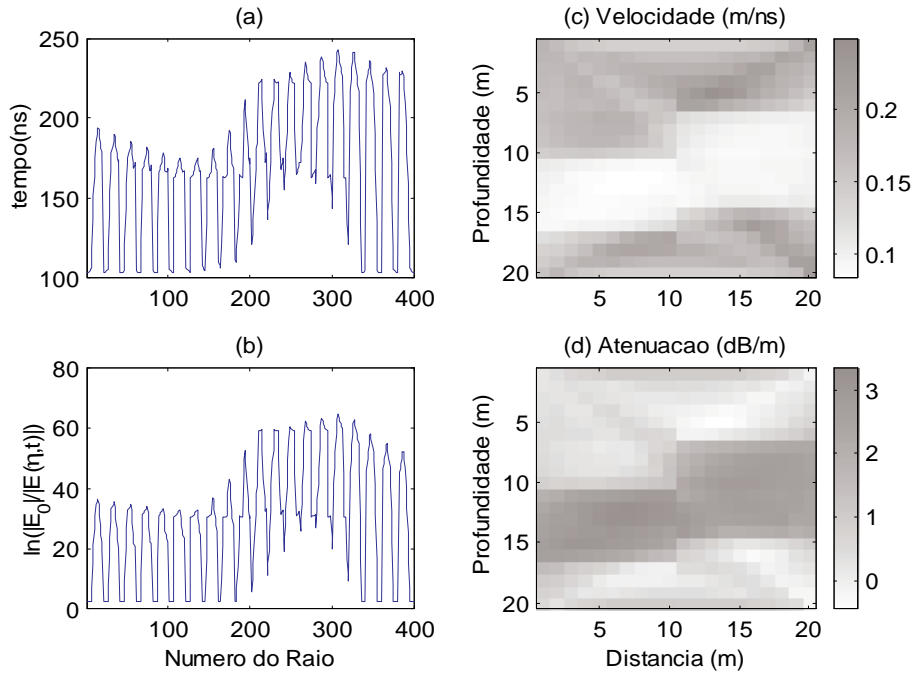


Figura 2: (a) Tempo de trânsito da EM ao longo dos raios cruzando a região entre os poços I e II; (b) Amplitude relativa logarítmica da onda eletromagnética ao longo de cada raio; (c) Resultado da reconstrução tomográfica ART da velocidade da onda EM e (d) Resultado da reconstrução tomográfica ART da atenuação da onda.

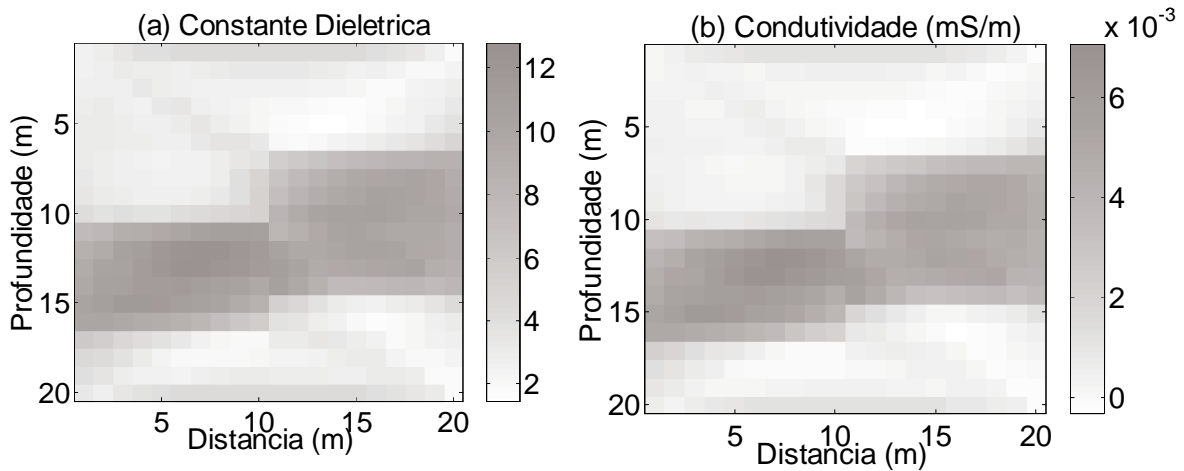


Figura 3 : (a) Reconstrução dos valores da parte real da constante dielétrica complexa resultante da aplicação da equação (7) aos dados da Figura 2(c); (b) Reconstrução dos valores da condutividade elétrica resultante da aplicação da equação (8) aos dados das Figuras 2(d) e 3(a).



Um algoritmo combinado (Genético e Newton) aplicado à inversão de sondagem elétrica vertical

Alan O. Fernandes, Milton J. Porsani e Paul L. Stoffa

CPGG/UFBA, Institute for Geophysics - University of Texas at Austin

Abstract

In this paper we present a new inversion strategy which combines Newton's method with a genetic algorithm (GA). The combined algorithm explores the local convergence property of Newton's method and the global and random search property of the GA to find the global minimum. The pure GA and the combined algorithm were tested in the inversion of a vertical electrical sounding. A multidimensional interpolation scheme is used in Newton's method such that the computation of the forward modeling is not required. Two experiments using a population of 20 and 200 models were used for comparison purposes. Numerical results showed that the combined algorithm performs much better than the pure GA in both experiments. The new algorithm overcame two limitations: the need for a good starting model, that exists in Newton's (or Gauss-Newton's) method; and the need for a large population of models, that makes the pure GA time consuming and slowly convergent. The obtained results make the new algorithm very attractive for inversion of large geophysics problems where the computation time for the forward modeling is far too long.

Introdução

Algoritmos de busca local tal como o método de Newton ou de Gauss-Newton, são iterativos e utilizando propriedades do gradiente da função objetivo aprimoram sucessivamente o modelo corrente. Entretanto, a convergência para o mínimo global depende de um bom modelo inicial. Já os algoritmos de busca global, tal como o algoritmo genético não dependem de nenhum modelo inicial mas por outro lado convergem muito lentamente.

A implementação de um algoritmo híbrido pode ser feita com o AG combinado com um método de Newton ou com o método de Gauss-Newton (Porsani et al, (2000), Ferreira and Porsani (1997) e Chundururu et al. (1997)). Tais algoritmos combinados podem tirar proveito das vantagens individuais e ao mesmo tempo sobrepujar as limitações de cada um dos métodos de pesquisa local e global utilizados. Para análise da eficiência do novo algo-

ritmo utilizamos o problema de inversão de dados de sondagem elétrica vertical associada a modelos 1D de camadas planas e homogêneas, no qual os valores de resistividade aparente podem ser calculados através do emprego de filtros lineares [Ghosh (1971)].

Medida da qualidade do ajuste

Deixemos $\rho_a(s_j)$, $j = 1, \dots, M$ representar os valores de resistividade aparente observados nas posições s_j , e $\rho_a(\mathbf{m}, s_j)$ os correspondentes valores calculados para o modelo $\mathbf{m} = (m_1, \dots, m_N)^T$. Para cálculo da qualidade do ajuste associado a um dado modelo \mathbf{m} utilizamos a equação abaixo Porsani et al. (2000):

$$Q(\mathbf{m}) = 1 - \frac{2 \sum_{j=1}^M |\Delta d(\mathbf{m}, s_j)|^{1/2}}{\sum_{j=1}^M |\Delta d(\mathbf{m}, s_j)|^{1/2} + \sum_{j=1}^N |\Delta f(\mathbf{m}, s_j)|^{1/2}} \quad (1)$$

onde $\Delta f(\mathbf{m}, s_j) = \log_{10} \rho_a(s_j) + \log_{10} \rho_a(\mathbf{m}, s_j)$ e $\Delta d(\mathbf{m}, s_j) = \log_{10} \rho_a(s_j) - \log_{10} \rho_a(\mathbf{m}, s_j)$. Note que a concordância entre as resistividades aparentes observadas e calculadas implicam no valor máximo $Q(\mathbf{m}) = 1$.

Algoritmo Genético (AG)

O AG trabalha com uma população de modelos e faz uma analogia com o mecanismo de reprodução e seleção natural, utilizado na natureza pelos organismos vivos, para aprimoramento dos modelos. Para tanto utiliza uma medida de qualidade do ajuste (fitness) procurando diminuir a diferença entre as resistividades aparentes observadas e as calculadas. O AG tem um custo computacional tanto maior quanto maior for o número de modelos utilizados na população e a convergência pode ser lenta. A redução do número de modelos na população pode levar a uma convergência prematura para um mínimo local.

O algoritmo genético usado no presente trabalho é baseado no algoritmo descrito por

and Sen (1991) com uma modificação no processo de cruzamento sendo este efetuado em apenas um único parâmetro de cada modelo.

Método de Newton

O problema inverso proposto consiste em minimizar a equação seguinte:

$$\Phi(\mathbf{m}) = 1 - Q(\mathbf{m}) \quad (2)$$

Podemos quase linearizar a equação (2) utilizando a expansão de Taylor de ordem 2 ao redor do modelo, $\mathbf{m}_{k,j}$, obtendo assim a expressão da forma quadrática $\tilde{\Phi}(\mathbf{m})$. Derivando a forma quadrática assim gerada, com relação aos parâmetros do modelo obtém-se o sistema de equações a ser resolvido,

$$\begin{vmatrix} \frac{\partial^2 \tilde{\Phi}}{\partial m_1^2} & \cdots & \frac{\partial^2 \tilde{\Phi}}{\partial m_1 \partial m_N} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 \tilde{\Phi}}{\partial m_N \partial m_1} & \cdots & \frac{\partial^2 \tilde{\Phi}}{\partial m_N^2} \end{vmatrix} \begin{vmatrix} m_1 - m_{k,j} \\ \vdots \\ m_N - m_{k,j} \end{vmatrix} = \begin{vmatrix} \frac{\partial \tilde{\Phi}}{\partial m_1} \\ \vdots \\ \frac{\partial \tilde{\Phi}}{\partial m_N} \end{vmatrix}$$

As derivadas de primeira e segunda ordem que aparecem no sistema acima podem ser avaliadas numericamente.

O sistema pode ser resolvido com o algoritmo gradiente conjugado. Conhecido o vetor solução $\Delta \mathbf{m}$ atualizamos o modelo corrente $\mathbf{m}_{k+1} = \mathbf{m}_k + \Delta \mathbf{m}$.

Algoritmo híbrido

O algoritmo Genético-Newton pode ser estruturado de acordo com a Figura (1) onde as derivadas podem ser calculadas usando valores da função objetivo interpolados na vizinhança do melhor modelo ao estágio k do AG. Os valores na vizinhança do modelo \mathbf{m}_k e necessários para cálculo das derivadas, podem ser interpolados a partir de $\Phi(\mathbf{m})$ dos modelos gerados no AG e disponíveis. A interpolação multidimensional utilizada nos exemplos apresentados foi desenvolvida com base no algoritmo tipo-Levinson apresentado em Porsani (1986).

Inversão de dados sintéticos

Para explorar o fato de que nem sempre é possível trabalhar com grandes populações, testamos o algoritmo genético e o algoritmo híbrido com dois tamanhos de população ($n_{pop} = 200$ e $n_{pop} = 20$). Para o teste dos algoritmos foi gerado um modelo sintético de três camadas. Este modelo, a função guia usada pelos algoritmos para a busca bem como os modelos invertidos estão representados nas tabelas [1] e [2].

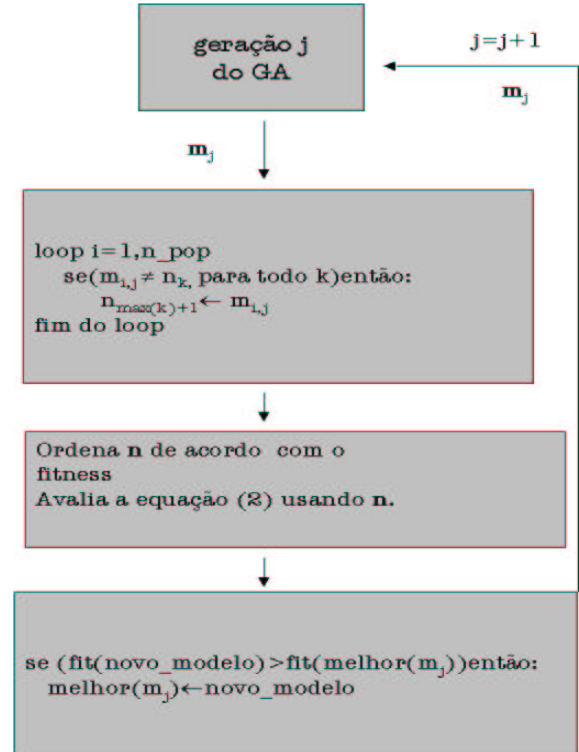


Figura 1: Representação esquemática do algoritmo híbrido (Genético-Newton) usado neste trabalho.

A função guia foi definida usando um espaçamento logarítmico equidistante do modelo verdadeiro. Cada parâmetro foi decodificado em 7 bits tendo portanto uma resolução máxima de 127 pontos. Todos os parâmetros do algoritmo genético foram mantidos constantes durante os testes, a probabilidade de mutação (probabilidade de um modelo sofrer uma alteração em um de seus bits) usada foi igual a 5%, a probabilidade de cruzamento usada foi de 100%, e a probabilidade de atualização igual a 80%.

Para o algoritmo híbrido sempre foram usados os 200 melhores modelos em n para fazer a interpolação da função objetivo e calcular as derivadas.

Conclusões

O algoritmo híbrido se mostrou mais eficiente que o AG puro para as duas populações achando um mínimo local melhor no caso de $n_{pop} = 20$ e achando o mínimo global para o caso de $n_{pop} = 200$, como podemos constatar na Figura (2) pelos valores do fitness e pela concordância entre os modelos verdadeiro e invertidos [Figura 3(a), (b), (c) e (d)]. Portanto o algoritmo de Newton pode ser usado pa-

Algoritmo híbrido

ra aperfeiçoar o melhor modelo fornecido pelo AG e também, caso não melhore o modelo corrente, atua de forma similar ao operador genético de mutação gerando um modelo com características diferentes na população. O novo método apresentado pode ser utilizado em qualquer problema de otimização onde a função a ser otimizada tem a segunda derivada contínua. O fato de não ser necessário calcular o campo associado aos modelos, ou mesmo calcular a matriz sensibilidade, como no método de Gauss-Newton, faz do novo algoritmo uma boa alternativa para os problemas de inversão não-linear onde o cálculo do modelo direto é pesado computacionalmente.

Agradecimentos

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Tabela 1: Valores das resistividades (ρ) e espessuras (Δz) do modelo verdadeiro e correspondentes valores máximos e mínimos utilizados na função guia do AG.

Modelo Verdadeiro		Função Guia			
$\rho(\Omega m)$	$\Delta z(m)$	Mínimo		Máximo	
		$\rho(\Omega m)$	$\Delta z(m)$	$\rho(\Omega m)$	$\Delta z(m)$
94.0	2.0	50.0	1.0	200.0	5.0
470.0	9.0	100.0	5.0	1000.0	20.0
165.0	99.0	50.0	50.0	500.0	200.0
360.0		100.0		600.0	

Tabela 2: Valores das resistividades (ρ) e espessuras (Δz) dos modelos invertidos com o AG e o algoritmo combinado Genético-Newton.

Genético				Genético-Newton			
$n_{pop} = 20$		$n_{pop} = 200$		$n_{pop} = 20$		$n_{pop} = 200$	
$\rho(\Omega m)$	$\Delta z(m)$	$\rho(\Omega m)$	$\Delta z(m)$	$\rho(\Omega m)$	$\Delta z(m)$	$\rho(\Omega m)$	$\Delta z(m)$
139.50	4.69	100.55	2.53	113.37	2.50	95.21	2.12
368.92	19.36	761.89	5.00	355.78	18.33	520.49	7.65
133.10	73.26	168.47	123.72	133.10	64.97	168.46	106.18
392.95		409.94		351.01		366.14	

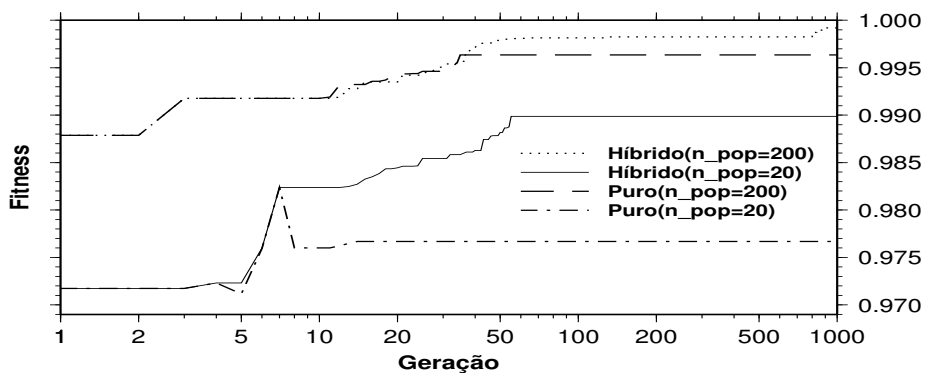


Figura 2: Evolução do fitness do melhor modelo no AG puro e algoritmo combinado Genético-Newton.

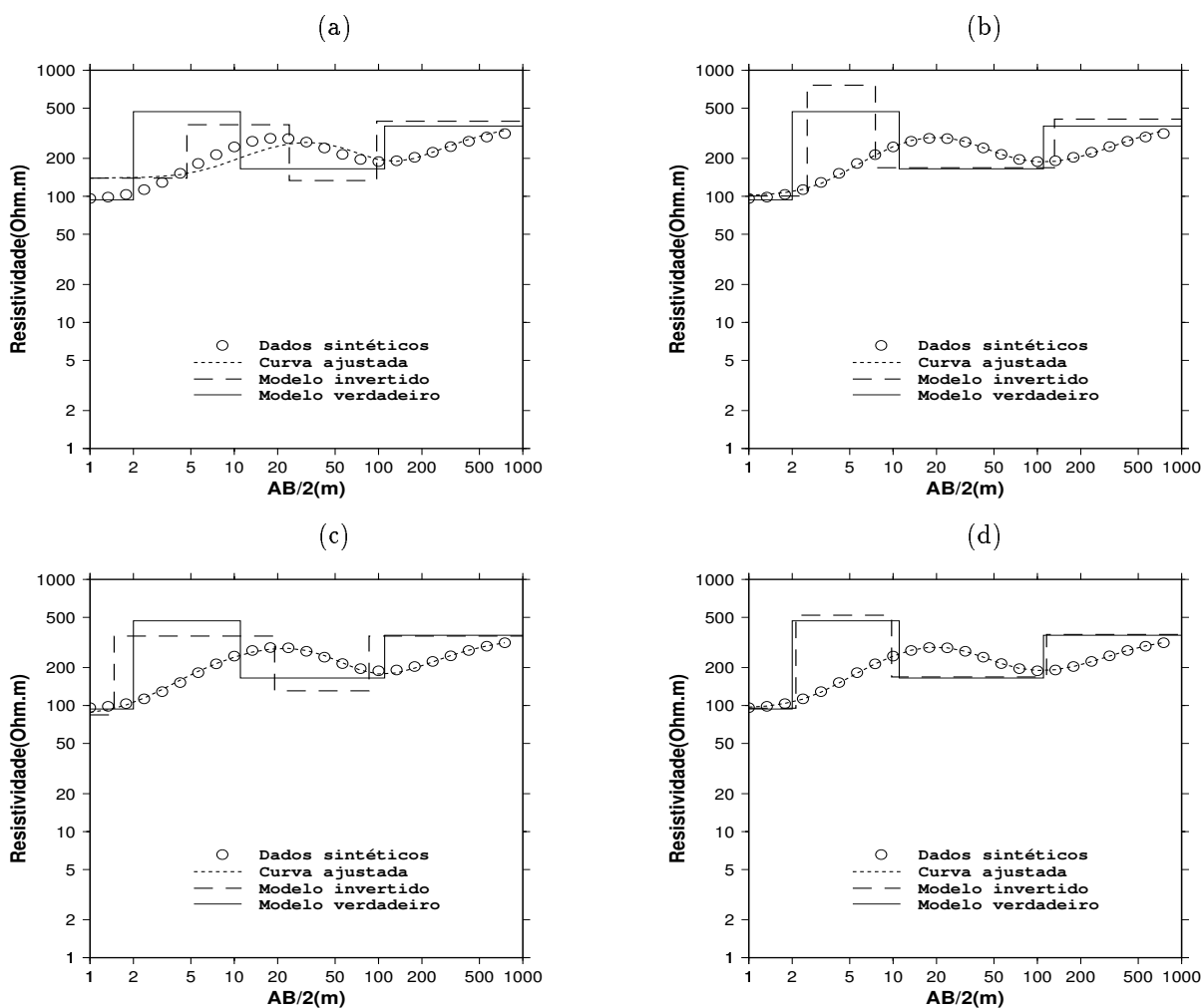


Figura 3: Comparação entre modelos verdadeiros e invertidos e entre os dados de resistividade aparente calculados e observados. Resultados obtidos com o algoritmo genético puro com $n_{pop} = 20$ em (a), com $n_{pop} = 200$ em (b). Algoritmo híbrido com $n_{pop} = 20$ em (c) e com $n_{pop} = 200$ em (d).