

High resolution 3D nonlinear integrated inversion*

Li Yong¹, Wang Xuben¹, Li Zhirong², Li Qiong¹, and Li Zhengwen¹

Abstract: The high resolution 3D nonlinear integrated inversion method is based on nonlinear theory. Under layer control, the log data from several wells (or all wells) in the study area and seismic trace data adjacent to the wells are input to a network with multiple inputs and outputs and are integratedly trained to obtain an adaptive weight function of the entire study area. Integrated nonlinear mapping relationships are built and updated by the lateral and vertical geologic variations of the reservoirs. Therefore, the inversion process and its inversion results can be constrained and controlled and a stable seismic inversion section with high resolution with velocity inversion, impedance inversion, and density inversion sections, can be gained. Good geologic effects have been obtained in model computation tests and real data processing, which verified that this method has high precision, good practicality, and can be used for quantitative reservoir analysis.

Keywords: high resolution, integrated inversion, network with multiple input and output, hybrid intelligent learning algorithm

Introduction

Seismic inversion has become the core technique for reservoir prediction (Xiong, 2006) and as developed from direct inversion to model inversion and from linear to nonlinear inversion, so the precision and resolution of seismic inversion are greatly improved.

In order to improve the resolution and precision of the inversion sections, many studies and good results have been obtained, such as maximum entropy deconvolution (MED) and autoregressive recovery (AR) (Oldenburg et al., 1983; Walker and Ulrych, 1983), maximum-likelihood estimation (MLE) (Ursin and Holberg, 1985), Bayesian estimation deconvolution (BED) (Lavielle, 1991), and generalized linear inversion (GLI) (Cooke and Schneider, 1983). The typical commercial software is G-log of the Landmark Company. From late 1980, there were the band-constrained inversion

(BCI) technique and various optimization algorithms, the typical papers include the BCI method (Zhou and Zhou, 1993), the strata inversion method (Gluck et al, 1997), well constrained strata inversion (Carron and Schlumberger, 1988), strata model constrained inversion (Brac, 1988), and multiple parameter constrained inversion (Martinez et al, 1992). These methods improve the resolution of acoustic impedance inversion from different aspects and algorithms and reduce the uncertainty. Typical software includes Seislog, Parm, Strata, CCFY, I-SIS, Jason, and so on, which have played important roles in the exploration and production of many fields all around the world (Xiong, 2006).

In the respect to nonlinear inversion, chaos features of seismic traces and chaos controlling methods were discussed by Ulrych (1999), Yang (1993), and Li (1999). Li and An (2002) described a chaos neural network inversion method, which selects the proper strange absorbing factor by changing network parameters and

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realizes global optimization.

It is well known that log data has very high vertical resolution, which can reflect the formations, lithology, and physical parameters very near the well, but its extent is very limited. Seismic data has lower vertical resolution but its spatial extent is much wider and can be used for spatial control. Many seismic inversion techniques constrained with log data have been developed, which integrates seismic and log data (Li et al., 2007; Xiong, 2006). The high resolution 3D nonlinear integrated inversion method is composed of an adaptive Genetic Algorithm (GA) (Wang and Cao, 2002; Goldberg, 1989; Whitley et al., 1990), a multiple input and output adaptive network based on a fuzzy inference system (MIMO-ANFIS) (Li et al., 2007; Jang, 1993), and the Tabu Search algorithm (TS) (Glover, 1986) under the constraint of log data. This method can provide reservoir inversion sections with relatively high resolution and precision and can be used for quantitative reservoir analysis. This method can solve the problems of seismic inversion nonuniqueness and inversion extrapolation uncertainty well (Xiong, 2006).

Method and techniques

In this integrated reservoir inversion method, an adaptive Genetic Algorithm (GA), multiple input and output adaptive network based on fuzzy inference system (MIMO-ANFIS), and the Tabu Search algorithm (TS) are integrated into a hybrid intelligent learning algorithm which fully adopts the advantages of these three algorithms. The hybrid intelligent learning algorithm is a kind of robust search algorithm which is an improvement on traditional hybrid algorithms.

GA in the hybrid intelligent learning algorithm

The GA algorithm is an iteration process based on an adaptation function which implements genetic operations on species individuals to realize a structural reconstruction of the species individual. In the iteration process, the species individuals are optimized and gradually approach to the optimum solutions. GA is an intelligent search algorithm, whose basic operations include selection, chiasma, and aberrance. Therefore, GA has the characteristics of robust adaptation and global optimization, which are lacking in other algorithms. GA consists of chromosome coding, individual adaptation evaluation, a genetic operator, and running parameters. The objective problems are coded as chromosomes and individual adaptation may correspond to the objective

functions. The genetic operator includes a selection operator (or scale operator), chiasma operator (single point chiasma operator), and aberrance operator (basic aberrance operator). Running parameters consist of species size, number of termination evolution generations, chiasma probability $P_c = 0.4 - 0.99$, and aberrance probability $P_m = 0.0001 - 0.1$.

The MIMO-ANFIS learning algorithm in the hybrid intelligent learning algorithm

In the ANFIS network structure, the ANFIS learning algorithm mainly applies a hybrid learning algorithm combining a gradient decrease-based algorithm (GD) and least squares estimation (LSE).

In the ANFIS network, the conclusion parameter is linear and the premise parameter is nonlinear. We update the ANFIS network parameters with two steps: the conclusion parameters are optimized using LSE and the premise parameters are optimized using GD. Specifically, the hybrid learning algorithm is divided into forward and feedback channels. In the forward channel, the premise parameter is constant and a signal is input to each layer for computation, up to the fifth layer, where the conclusion parameter is distinguished using LSE. Then, in the feedback channel, the conclusion parameter is constant and the error signal is backward propagated to the second layer, where the premise parameter is updated using GD. When the premise parameter is constant, the optimum conclusion parameter can be found. The hybrid learning algorithm reduces the searching space dimensions for the feedback propagation algorithm, so it can reach convergence rapidly. In the hybrid learning algorithm, the update formula for the premise and conclusion parameters are separated, so the learning speed of premise parameter can be increased by various GD transforms or other optimization techniques, such as the conjugate gradient method, second order feedback propagation method, rapid feedback propagation method, and so on. Table 1 summarizes the activities in each channel of the hybrid learning algorithm.

Table 1 Two channels in ANFIS hybrid learning process

	Forward channel	Backward channel
Premise parameter	constant	Gradient decrease
Conclusion parameter	LSE	Constant
signal	Node output	Error signal

The tabu search algorithm in the hybrid intelligent learning algorithm

Tabu search (TS) is a kind of sub-heuristic search algorithm. The TS algorithm can avoid circuitous

searches by introducing a feasible memory structure and the corresponding tabu rule and absolve some good status tabooed by the deprecating rule in order to ensure diversified and effective searches to realize global optimization. Moreover, the TS algorithm has memory capability and can greatly improve computation speed.

The tabu search includes the following steps:

- 1: determine network parameters;
- 2: generate an initial solution x^{now} and give a tabu table $H=\Phi$;
- 3: determine the neighborhood standard δ and neighborhood size and generate each component in the neighborhood $N(x^{now})$ by adding a random value in the interval $[-\delta, +\delta]$ to each component of x^{now} ;
- 4: if the optimum solution x^{N-best} in neighborhood $N(x^{now})$ meets the amnesty rule, let $x^{now}=x^{N-best}$ and go to the sixth step;
- 5: choose candidate set $Can-N(x^{now})$ meeting the tabu conditions in neighborhood $N(x^{now})$ and an choose optimum solution $x^{Can-best}$ in $Can-N(x^{now})$ and let $x^{now}=x^{Can-best}$;
- 6: let $x^{now}=x^{next}$, and update tabu table H ; and
- 7: repeat the third step, until the final conditions are met.

Techniques for integrated inversion implementation

Inversion objective function

Conventional seismic inversion methods are based on the forward modeling computation method, which searches for the optimum least square fit between the forward modeling traces and the real seismic traces. In order to overcome the problems caused from the seismic model, our method doesn't use a seismic model but assumes there is a nonlinear mapping relationship between seismic signals and log data (Wang and Cao, 2002). The assumption is tenable for acoustic impedance, velocity, density, and porosity. In this paper, we assume there is a nonlinear mapping relationship between seismic signal S and log data W . The input is seismic data adjacent to the wells and the output (teacher signal) is log data (acoustic impedance, velocity, density, porosity, and etc.). The integrated nonlinear mapping relationship in the study area, called the study area function F , has a mapping relationship described by:

$F: x \rightarrow y$, with $x \in S$ and $y \in W$.

The inversion objective function is $E = \frac{1}{N} \sum_{i=1}^N |W_i - F(S_i)|$,

where N is the well number in the study area, W is well data, S is seismic data, and F is the function for the study area.

The forward modeling problems are avoided by using the inversion objective function. As the study

area function matches with the well data in the study area, the mapping relationship between seismic signals and inversion objective is very reliable. Hence, we can assume the study area function covers the whole seismic data space.

Techniques in reservoir 3D integrated inversion

During the seismic inversion, after preprocessing (Shen et al., 2007), the log data from several or all wells and seismic data adjacent to the wells in the study area are input into the network and are integrated and trained so the adaptive weight function in the study area can be obtained and integrated nonlinear mapping relationship can be built and updated based on the lateral and vertical geologic variations in the reservoir. Thus, the inversion process and results can be constrained and controlled to realize the integrated inversion and the inverted data volume can be produced. Figure 1 shows a flow chart of the high resolution 3D nonlinear integrated inversion.

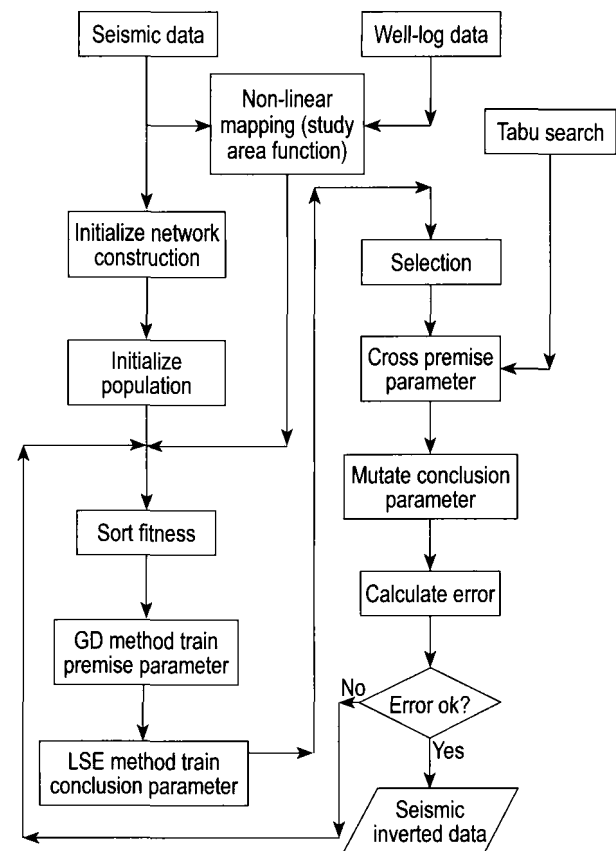


Fig. 1 Flow chart of high resolution 3D nonlinear integrated inversion

Model inversion and application examples

First, we used theoretical seismograms to test if the algorithm can recover the given models and then we used

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real seismic data to verify the validity of this method.

Wedge model inversion

The geologic model is a wedge with velocity of 2000 m/s in the middle of the model surrounded by a velocity of 3000 m/s as shown in Figure. 2. The objective of the inversion is to test if the low velocity wedge body can be detected. Figure 3 shows the synthetic seismograms from forward modeling. The wavelet is a 30 Hz zero phase wavelet and a total of 100 traces were computed with a the time interval of 0 to 250 ms. During seismic inversion, the model at the first and 100th traces are taken as constraining log curves. First, the study area function F is computed and then the inverted section is computed and shown in Figure 4. A comparison of Figures 2 and 4 shows that the inverted section is basically consistent with the geologic model.

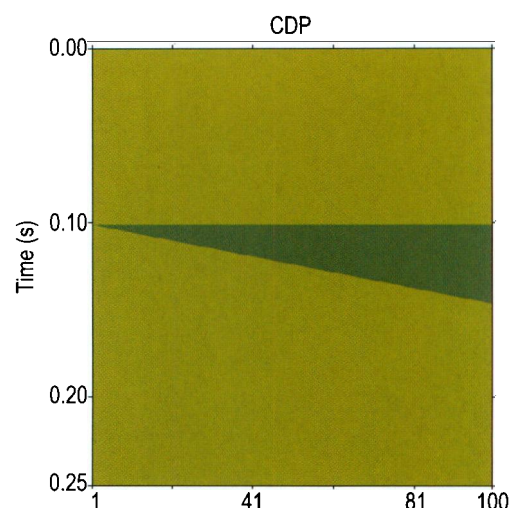


Fig. 2 Wedge model with a velocity in the wedge of 2000 m/s and 3000 m/s in the surrounding rock.

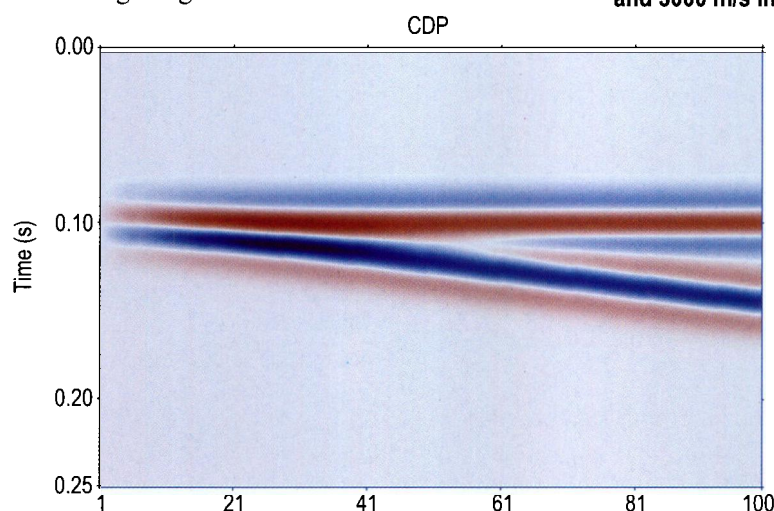


Fig.3 Synthetic seismograms generated from the wedge model in Figure 2. The trace data is from CDP 1 to 100 and the time interval is from 0 to 0.25 s.

3D Integrated seismic inversions of the real seismic data

We performed velocity inversion with the method described in this paper for real 3D seismic data with an area of 488 km² and obtained the 3D velocity volume shown in Figure 5. The integrated inversion was performed under the constraint of log data from three wells (CS2, CS6, and XU15). The inverted velocity data has high resolution and precision, comparable to the resolution of real log curves. Figure 6 is a velocity section through well CS6 extracted from the 3D velocity volume. The velocity section indicates that the velocity variations of the volcanics in the Yingcheng formation in the XX area are: the velocity generally increases with depth, the velocity of the layer between T4 to T4C ranges from 5100 m/s to 5500 m/s and averages about 5200 m/s, and the velocity of the layer between T4C to T41 is higher, ranging from 5600 m/s to 6000 m/s. This kind of velocity feature reflects the variations of the Yingcheng formation downward.

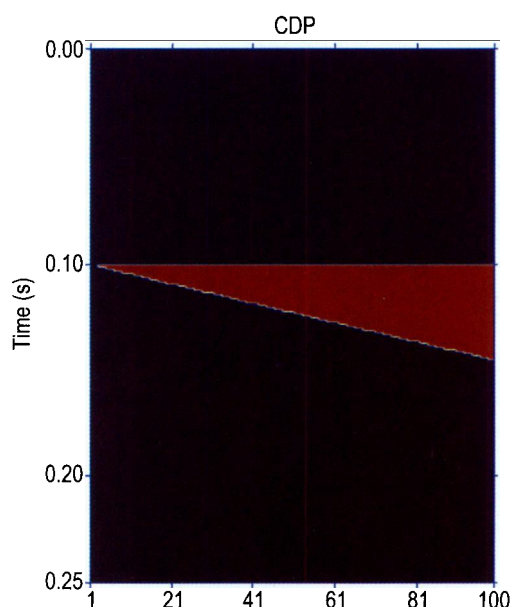


Fig. 4 Velocity inversion section obtained with our seismic inversion method and the synthetic traces in Figure 3.

Error analysis and evaluation

Figures 7 - 9 show a comparison between the inverted velocity and sonic velocity curves at the three wells. The two curves are consistent with each other, with comparable shape and trend. The resolution of the inverted velocity curve approaches that of the sonic velocity curve. Thus, we conclude that the inversion results are reliable. Table 2 shows a numerical comparison between log velocity and inverted velocity. The velocity error ranges from 0.01 % to 1.20 %. Therefore, seismic inversion sections with high resolution and precision can form the basis for reservoir prediction.

Table 2 Comparisons between sonic log velocity and inverted velocity at well XU15

Log velocity	Inverted velocity	Error (%)
5075.08	5081.25	0.12
5067.23	5025.75	-0.82
4954.01	4955.65	0.03
4996.86	5002.92	0.12
5013.3	4953.24	-1.20
4971.35	4974.79	0.07
5038.83	5095.29	1.12
5203.99	5193.35	-0.20
5216.53	5216.72	0.01
4239.41	5238.54	-0.02
5227.48	5272.25	0.86
5243.1	5236.8	-0.12
5123.72	5146.42	0.44
5103.29	5123.18	0.39
5064.39	5062.14	-0.04
5054.09	5043.68	-0.03

Conclusions

The inversion method presented in this paper is a new nonlinear seismic inversion method based on a nonlinear algorithm. This method improves the flow of the entire inversion technique and fully integrates the advantages of

genetic, chaos, ANFIS, and tabu search algorithms and overcomes the defects of each algorithm. In the probability search process, the probability changes adaptively to realize the uniformity of the hybrid algorithm and the inversion system is convergent to the global optimum solution adaptively. Hence, the inversion results are improved greatly. Under the constraint of multiple wells, this method trains the ANFIS network with multiple input and output and builds an adaptive weight function. The integrated nonlinear mapping relationships with automatic updating constrains

and controls the inversion progress and greatly improves the inversion precision and resolution. Seismic inversion sections with high resolution can show the vertical and lateral variations of the reservoir clearly. The nonlinear seismic inversion based on the hybrid intelligent algorithm is a multiple seismic attribute inversion method.

The results from model and real 3D seismic data inversion indicate that the method presented in this paper is independent of the model, which can avoid the artificial factors caused by different geologic models

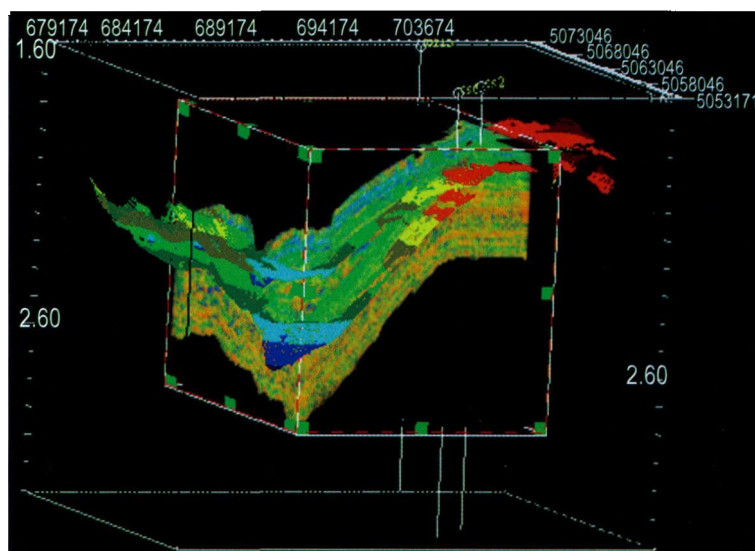


Fig. 5 3D velocity inversion volume, indicating spatial variations of the velocity in the Yingcheng formation (T4-T41)

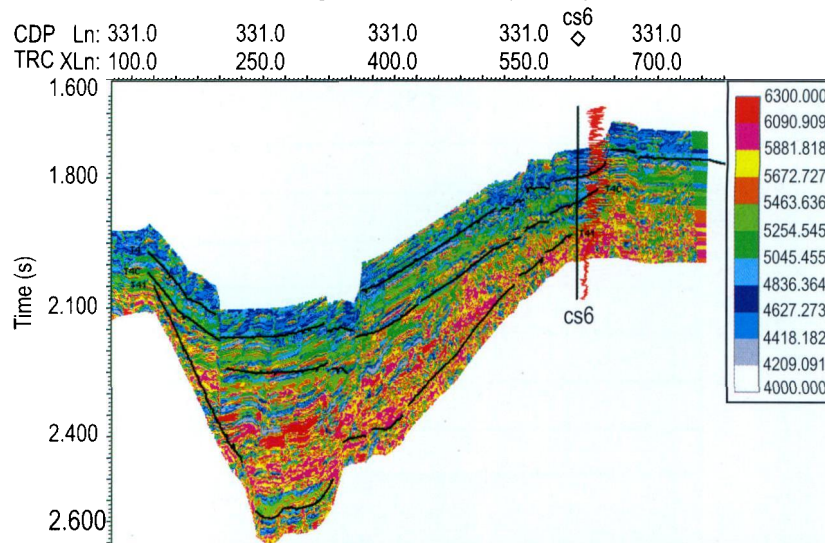


Fig. 6 Velocity section of inline 331 crossing well CS6 with relatively high resolution, reflecting the lithologic variation and structural features of the volcanics.

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provided by different interpreters. The computation speed is fast. It only takes about 4 hours and 50 minutes to perform the velocity inversion of 488 km² of 3D seismic data using an IBM T42 computer with a main frequency

of 1.7G. This method overcomes the problems of nonuniqueness in seismic inversion and uncertainty in inversion extrapolation. The inversion results are stable and are consistent with actual drilling data.

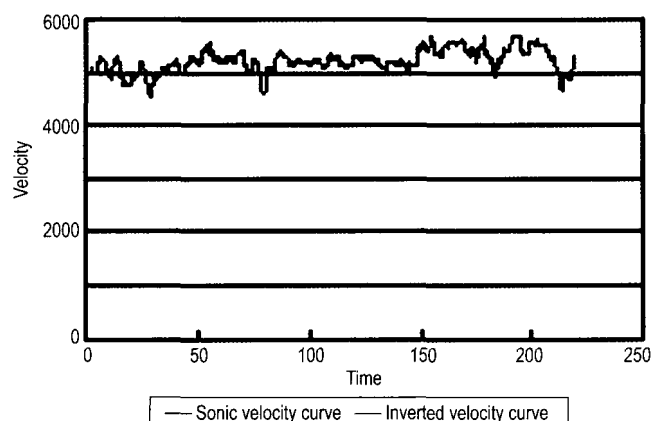


Fig. 7 A comparison between the inverted velocity curve and sonic velocity curve at well CS2.

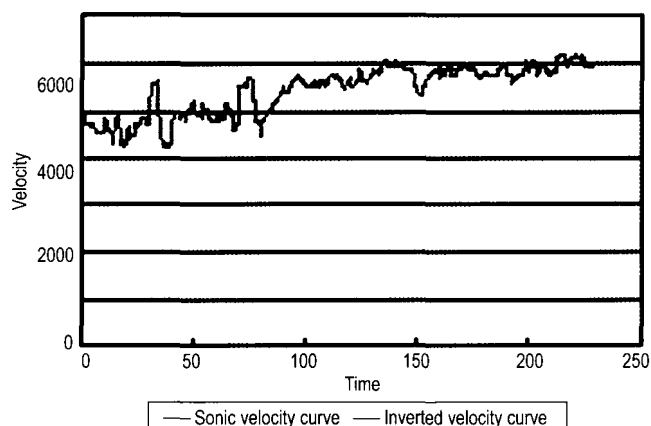


Fig. 8 A comparison between the inverted velocity curve and sonic velocity curve at well CS6.

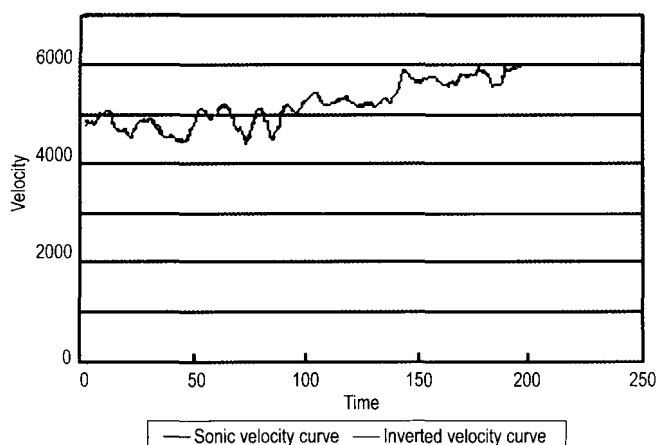


Fig. 9 A comparison between the inverted velocity curve and sonic velocity curve at well XU15.

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计算公式由于包含有速度横向导数项,在速度横向变化大的介质中,也能有较高的聚焦效果,而且也走时计算提供了精确的相对振幅保持系数。本文对推导的方法进行模型测试并进行实际数据的试算,其结果证明非对称走时方法的成像精度远高于对称走时计算方法。

关键词: 单程波算子, 走时公式, 李代数, 拟微分算子

二阶精度广义非线性全局最优的偏移速度反演方法 // A quadratic precision generalized nonlinear global optimization migration velocity inversion method, 赵太银¹, 胡光岷¹, 贺振华², 黄德济², APPLIED GEOPHYSICS, 6(2), P. 138 - 149

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摘要: 如何快速、精确地利用叠前深度偏移进行偏移速度分析是勘探地震学的一项重要研究内容,针对该问题,本文提出一种二阶精度广义非线性全局最优的偏移速度反演方法。我们将首先去掉速度模型修正量与成像深度呈线性关系的假设,推导出具有二阶精度的速度模型修正量计算公式,使每一次迭代得到的速度模型尽可能地接近实际模型;然后采用广义非线性反演方法反演获得对所有道集的全局最优的速度模型修正量,不仅极大地加快了收敛速度,而且反演过程中陷入局部极小的可能性也减小了。理论模型和Marmousi模型的处理结果表明:本方法精度高、处理速度快,提高了偏移速度分析方法的实用性和对复杂构造成像的准确性。

关键词: 叠前深度偏移, 偏移速度分析, 广义非线性反演, 共成像道集

零偏VSP资料波阻抗反演方法研究 // Acoustic impedance inversion of zero-offset VSP data, 王静^{1,2}, 刘洋^{1,2}, 孙哲^{1,2}, 田洪³, 苏华³, 赵前华³, 刘颖宇³, APPLIED GEOPHYSICS, 6(2), P. 150 - 158

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摘要: VSP资料钻前预测的关键在于高精度的波阻抗反演,本文针对VSP资料高分辨率、高信噪比以及能精确地分离出上、下行波的特点,提出了一种利用VSP资料进行井底以下钻头前方地层波阻抗反演的方法。该方法

首先对VSP走廊叠加记录采用非线性迭代反演方法反演地下地层的波阻抗;通过在迭代过程中不断修改阻尼因子,以及引入预条件共轭梯度法求解方程组,增强了解的稳定性和收敛速度。理论模型与实际资料的处理结果表明该方法具有较好的效果,并在VSP资料钻前预测研究中具有良好的应用前景。

关键词: 零偏VSP, 波阻抗反演, 非线性迭代反演, 阻尼因子, 预条件共轭梯度法

高分辨率非线性三维整体反演研究 // High resolution 3D nonlinear integrated inversion, 李勇¹, 王绪本¹, 李志荣², 李琼¹, 李正文¹, APPLIED GEOPHYSICS, 6(2), P. 159 - 165

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摘要: 高分辨率非线性三维整体反演方法是基于非线性理论,在层位控制下,将工区多井(或全部井)的测井数据与井旁地震道数据输入具有多输入多输出的网络,同时进行整体训练,可获得整个工区的自适应权函数,并建立综合非线性映射关系,并根据储层在纵横方向上的地质变化特征更新这种非线性映射关系,这样,就能对反演过程及其反演结果起到约束和控制的作用,从而获得稳定且分辨率高的地震反演剖面(速度反演剖面/波阻抗反演剖面/密度反演剖面),实现整体反演,该方法通过模型试算和实际资料处理,获得较好的地质效果,证明该方法精度高、实用性强,可用于储层的定量分析。

关键词: 高分辨率, 整体反演, 多输入多输出网络, 混合智能学习算法

地球物理资料群体智能反演 // Swarm intelligence optimization and its application in geophysical data inversion, 袁三一, 王尚旭, 田楠, APPLIED GEOPHYSICS, 6(2), P. 166 - 174

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摘要: 复杂地球物理资料的反演问题往往是一个求解多参数非线性多极值的最优解问题。而鸟和蚂蚁等群体觅食的过程,正好与寻找地球物理反演最优解的过程相似。基于自然界群体协调寻优的思想,本文提出了交叉学科的群体智能地球物理资料反演方法,并给出了其对应的数学模型。用一个有无限多个局部最优解的已知模型对该类方法进行了试验。然后,将它们应用到了不同的复杂地球物理反演问题中:(1)对噪声敏感的线性问题;(2)非线性和线性同步反演问