Journal of Petroleum Science and Engineering 171 (2018) 1159–1170

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

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

Cognitive seismic data modelling based successive differential evolution algorithm for effective exploration of oil-gas reservoirs

Jing Zhao[a], Jinchang Ren[b,c,*], Jaime Zabalza[c], Jinghuai Gao[d], Xinying Xu[c,**], Gang Xie[e]

[a] School of Earth Science and Engineering, Xi'an Shiyou University, Xi'an, China
[b] School of Electrical and Power Engineering, Taiyuan University of Technology, Taiyuan, China
[c] Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow, UK
[d] Institute of Wave & Information, School of Electronic and Information Engineering, Xi'an Jiaotong University, Xi'an, China
[e] Taiyuan University of Science and Technology, Taiyuan, China

ARTICLE INFO

Keywords:
Successive differential evolution algorithm
VSP data
High dimensional data
Velocity and *Q* inversion

ABSTRACT

A cognitive modelling based new inversion method, the successive differential evolution (DE-S) algorithm, is proposed to estimate the Q factor and velocity from the zero-offset vertical seismic profile (VSP) record for oil-gas reservoir exploration. The DE algorithm seeks optimal solutions by simulating the natural species evolution processes and makes the individuals become optimal. This algorithm is suitable for the high-dimensional nonseparable model space where the inversion leads to recognition and prediction of hydrocarbon reservoirs. The viscoelastic medium is split into layers whose thicknesses equal to the space between two successive VSP geophones, and the estimated parameters of each layer span the related subspace. All estimated parameters span to a high dimensional nonseparable model space. We develop bottom-up workflow, in which the Q factor and the velocity are estimated using the DE algorithm layer by layer. In order to improve the inversion precision, the crossover strategy is discarded and we derive the weighted mutation strategy. Additionally, two kinds of stopping criteria for effective iteration are proposed to speed up the computation. The new method has fast speed, good convergence and is no longer dependent on the initial values of model parameters. Experimental results on both synthetic and real zero-offset VSP data indicate that this method is noise robust and has great potential to derive reliable seismic attenuation and velocity, which is an important diagnostic tool for reservoir characterization.

1. Introduction

The exploration targets are turning from conventional to unconventional reservoirs with the development of oil-gas exploration technology (Zhou et al., 2012). How to finely describe the medium structure, lithology and saturation of fluids is a critical problem in exploration geophysics. Seismic waves propagating through the earth suffer attenuation and dispersion due to the viscosity of the media. The inherent attenuation of the medium is usually quantified by the quality factor Q which is a diagnostic tool for hydrocarbon detection and reservoir characterization. Meanwhile, velocity is one of the most important earth parameters that determine the accuracy of seismic imaging in exploration geophysics. Therefore, Q and velocity estimation are of great importance.

Direct estimation methods and inversion methods are usually two different approaches to estimate the Q factor and velocity. On one hand, the direct estimation approaches can be divided into time domain, frequency domain, and time-frequency domain methods. On the other hand, there are also many inversion estimation methods such as waveform inversion and tomography. This paper focuses on the waveform inversion methods.

Researchers have already developed various waveform inversion approaches such as local optimization waveform inversion and global optimization. In local optimization, the minimum of the objective function can be determined by gradient, conjugate gradient, Newton, Gauss-Newton, and quasi-Newton methods. Among these, the gradient-based waveform inversion methods have got some success, but they have the limitation of nonlinearity of the inversion and dependence on the initial model. In fact, Virieux (Virieux and Operto, 2009) pointed out that some challenges of waveform inversion are related to building exact initial models, defining new minimization criterion and improving multi-parameter inversion capability.

* Corresponding author. School of Electrical and Power Engineering, Taiyuan University of Technology, Taiyuan, China.
** Corresponding author.
E-mail address: jinchang.ren@strath.ac.uk (J. Ren).

https://doi.org/10.1016/j.petrol.2018.08.044
Received 1 April 2018; Received in revised form 10 August 2018; Accepted 14 August 2018
Available online 21 August 2018
0920-4105/

On the other hand, there are many global optimization methods such as evolutionary algorithm (EA) (Price, 1996), simulated annealing algorithm (Corana et al., 1987) and the Monte Carlo method (Press, 1968). Moreover, EA can be divided into differential evolution (DE), genetic algorithm (GA), ant algorithm, and so on. Compared with the gradient-based waveform inversion method, the global optimization methodology is less dependent on the initial values and requires no gradient. However, it needs a large amount of computation. Despite this fact, it is widely used in recent years with the development of high performance computing.

On a different note, cognitive computing can handle human problems. It has the capability in studying, reasoning, and solving specific problems. Cognitive systems can understand the problems adequately and model the thought process as computing models. Their ability of studying abstract features is similar to the study processing of the brain. Hence the cognitive computing can enhance the human intellectual and decision-making capacity.

The EAs are a kind of cognitive computing, they simulate the natural species evolution processes by computers, and make the individual become optimal. However, the conventional EAs often lose their effectiveness when applied to high-dimensional problems. Z. Pan (Pan et al., 2015) proposed CRsADE method which use individual crossover rate and subcomponent crossover rate to adaptively improve the efficiency of crossover operation. C. Wang proposed DE with cooperative coevolution selection (DE-CCS) (Wang and Gao, 2010) and DE with cooperative coevolution mutation (DE-CCM) (Wang and Gao, 2012). These methods divided the high-dimension problem to several subproblems and judged the subproblems by local fitness functions. R. Chandra (Chandra et al., 2017) proposed coevolutionary multi-task learning used for multi-step chaotic time series prediction. This paper presents a network architecture which is capable predict multi-step. Z. Gao (Gao et al., 2014) proposed a highly efficient DE algorithm (HEDE) which used a new population evolution strategy to decrease the population size. A new multimutation scheme was later proposed to converge quickly. (Gao et al., 2016). X. Cui (Cui et al., 2016) improved particle swarm optimization used for poststack impedance inversion. This method combined the swarm intelligence and probabilistic theory for global optimization. S. Mahdavip (Mahdavi et al., 2015) reviewed metaheuristics in large-scale global continues optimization, including large-scale global optimization (LSGO), evolutionary algorithm (EAs), cooperative coevolution (CC). Although lots of DEs such as cooperative coevolution (CC) (Govindan et al., 2011), ND-CC (Gomes et al., 2017) and Co-evolutionary multi-task learning were proposed to solve high-dimensional optimization problems, they only work well with the separable problem, i.e., the existing CCs often lose their advantages when applied to high-dimensional nonseparable model space. Meanwhile, most existing methods have the problems of “dimensional bottleneck”. The optimizing ability of these methods declined sharply with the increasing of the dimensions. To make the fine subsurface medium, we need to divide the medium into small pieces which let the parameters of the model to be huge. To inverse thousands of parameters can result in the existing CCs becoming invalid or making a large number of iterations.

In this paper, we propose a new DE to derive Q and velocity from zero-offset vertical seismic profiling (VSP) data. Compared with reflection seismic data, VSP data has high signal-to-noise ratio (SNR), high resolution, and can provide more information about medium layers and signal frequency. As the upgoing primary reflection of the VSP record is much stronger than the related multiples, our research will focus on the direct downgoing wave and upgoing primary reflection.

By considering the property of viscoelastic media and the examples of DE-CCM, we estimate the Q factor and velocity using the DE algorithm along successive medium layers from bottom to top. Another innovation is that a weighted mutation strategy and a stopping criteria are introduced to speed up the computation. We name the new DE as successive differential evolution (DE-S), where the validity of our proposed method is tested using both synthetic model and real record.

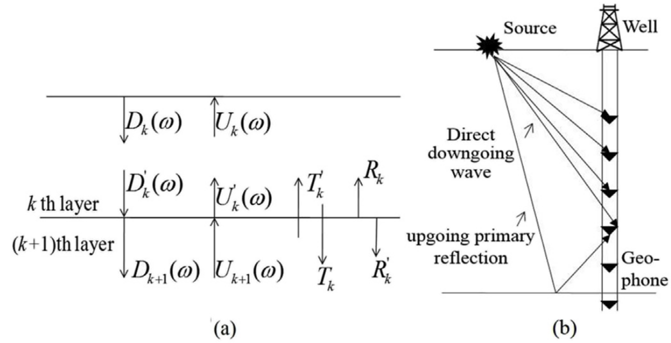

Fig. 1. (a) The relationship between the downgoing and the upgoing wave. (b) The diagram of the zero-offset VSP record including the direct downgoing wave and upgoing primary reflection.

2. Our proposed DE-S method

2.1. The conventional DE method and its disadvantages

The Q factor and velocity of the viscoelastic medium that need to be estimated, span the related nonseparable model parameter space. Fig. 1(a) shows the relationship between the downgoing and the upgoing wave at a given interface and at the top and the bottom of a layer. $D_k'(\omega)$ and $D_k(\omega)$ are the spectrum of the downgoing wave at the bottom and the top of layer k, respectively. Similarly, $U_k'(\omega)$ and $U_k(\omega)$ correspond to the spectrum of the upgoing wave. Fig. 1(b) is the zero-offset VSP model diagram. The space between two successive geophones is defined as a layer. The parameters of each layer span the subspace and the parameters are defined as subcomponents.

VSP is a kind of seismic observation method. As shown in Fig. 1(b), the source of the VSP excites the seismic waves at some points at the surface, but receives the seismic signals by geophones which are vertically settled at various depths along the well. The received seismic waves include downgoing waves propagating from up to down and upgoing waves propagating from down to up. The record received by a geophone is called a trace of record. Thousands of traces construct a VSP data. For a trace of VSP data, the amplitude, phase and frequency of the direct downgoing wave changes because of the attenuation when seismic wave propagates from the source to the geophones in the viscoelastic medium.

Thus the direct downgoing wave is a function of the parameters of the upper layers over the geophone. The downgoing wave is reflected on each reflecting interface and then it arrives to the geophones to form the upgoing wave. Thus, the upgoing wave is a function of the parameters of all layers. Finally, the trace of record is a function of all the estimated parameters. Therefore, the model space spanned by the estimated parameters is nonseparable along both time and depth directions, so it is not possible to estimate the subcomponents (parameters) independently and simultaneously.

Storn (Storn and Price, 1996) first proposed the DE algorithm for global optimization, which has three operations. First, it creates the mutant individual by adding a weighted difference vector between two individuals to a third individual. Then, it creates the trial individual by crossing the mutated individual and the original individual. Finally, it selects the next generation according to the fitness values of the parent individual and the trial individual. DE-CCM incorporates the decomposition strategy of cooperative coevolution into DE to decompose the large-size individual into subcomponents in the mutation step.

We can estimate the Q factor by using DE-CCM to show the disadvantages of the existing methods. Take the VSP direct downgoing wave as an example. We get the forward simulation from the method