Journal of Applied Geophysics 122 (2015) 159–166

Contents lists available at ScienceDirect

Journal of Applied Geophysics

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

Wavelet phase estimation using ant colony optimization algorithm

Shangxu Wang [a], Sanyi Yuan [a,*], Ming Ma [a], Rui Zhang [b], Chunmei Luo [a]

[a] State Key Laboratory of Petroleum Resources and Prospecting, CNPC Key Laboratory of Geophysical Exploration, China University of Petroleum, Changping 102249, Beijing, China
[b] Geology School of Geosciences, University of Louisiana at Lafayette, LA 70504-4650, United States

A R T I C L E   I N F O

Article history:
Received 21 January 2015
Received in revised form 3 August 2015
Accepted 17 September 2015
Available online 21 September 2015

Keywords:
Wavelet phase estimation
Ant colony optimization algorithm
Mixed-phase wavelet
Deconvolution
Weak signal

A B S T R A C T

Eliminating seismic wavelet is important in seismic high-resolution processing. However, artifacts may arise in seismic interpretation when the wavelet phase is inaccurately estimated. Therefore, we propose a frequency-dependent wavelet phase estimation method based on the ant colony optimization (ACO) algorithm with global optimization capacity. The wavelet phase can be optimized with the ACO algorithm by fitting nearby-well seismic traces with well-log data. Our proposed method can rapidly produce a frequency-dependent wavelet phase and optimize the seismic-to-well tie, particularly for weak signals. Synthetic examples demonstrate the effectiveness of the proposed ACO-based wavelet phase estimation method, even in the presence of a colored noise. Real data example illustrates that seismic deconvolution using an optimum mixed-phase wavelet can provide more information than that using an optimum constant-phase wavelet.

1. Introduction

The post-stack seismogram can be described using the convolution of a reflectivity series model with a seismic wavelet (Robinson and Treitel, 2000). A major aim of seismic deconvolution is to eliminate the wavelet from seismogram, so as to recover the reflectivity series and interpret subsurface geometries (e.g., Yilmaz, 2001; Oliveira and Lupinacci, 2013). In the frequency domain, a wavelet is determined by the amplitude and phase spectra. Therefore, wavelet elimination requires removing both its amplitude and phase spectra. In general, the frequency band of seismic data is broadened after the wavelet amplitude spectrum is removed. The seismic trace can be corrected to its zero-phase through the phase spectrum to eliminate wavelet. In this case, the positions of wavelet peaks accurately correspond to the interfaces between two layers and thus help to understand seismic interpretation. In addition, the impact of wavelet side lobes on seismic resolution decreases, and the lateral continuity of seismic events improves (e.g., Zhang and Castagna, 2011; Yuan and Wang, 2013). However, inaccurate wavelet phase estimation will result in poor deconvolution, poor sparse–spike reflectivity inversion or poor impedance inversion (e.g., Brown, 2004; Delprat-Jannaud and Lailly, 2005; Oliveira et al., 2009; Yuan and Wang, 2011; Zhang et al., 2013). For instance, the artifacts of "adjoint events" induced by non-zero phase wavelet may be interpreted as effective events.

Spiking deconvolution or Wiener–Levinson (WL) deconvolution technique (e.g., Leinbach, 1993; Robinson and Treitel, 2000) has been broadly applied to remove a minimum-phase wavelet. Aside from the minimum-phase wavelet assumption, the method requires reflectivity to be a white random sequence. However, the real wavelet phase is not often minimum phase, and a minimum-phase equivalent of the wavelet can be eliminated using spiking deconvolution. The residual phase, that is, the phase difference between real mixed-phase wavelet and estimated minimum-phase wavelet by spiking deconvolution may cause severe waveform distortion in deconvolution results (e.g., Yuan and Wang, 2011).

Considering that underground reflectivity obeys a non-Gaussian distribution, Wiggins (1978) employs the entropy (or disorder) minimization or equivalent kurtosis maximization criterion to describe the non-Gaussianity features of data and proposes a minimum entropy deconvolution approach. The basic idea of this method is to make the non-Gaussianity of deconvolution result using an arbitrary mixed-phase wavelet maximum. The method extends the application by eliminating the white reflectivity and minimum-phase wavelet assumptions. However, it magnifies strong reflection and suppresses weak reflection (e.g., Ooe and Ulrych, 1979; Walden, 1985). In addition, it cannot avoid instability in the presence of noise (e.g., Longbottom et al., 1988; Wiggins, 1985). Minimum entropy deconvolution approach fails when the center frequency is larger than the bandwidth (e.g., White, 1988; Xu et al., 2012). This approach is also readily trapped into a local solution when the initial model does not belong to a locally convex space of the true model (e.g., Wiggins, 1985).

Similar to minimum entropy deconvolution, two other approaches to obtain the global solution have been developed. One is the constant-phase rotation method based on the maximum non-Gaussianity of deconvolution results (e.g., Levy and Oldenburg, 1987; Longbottom et al., 1988; White, 1988; Economou and Vafidis, 2012; Wang et al., 2014). This method supposes that the wavelet or residual wavelet phase is constant, which significantly restricts the range of

* Corresponding author.
E-mail address: yuansy@cup.edu.cn (S.Y. Yuan).

http://dx.doi.org/10.1016/j.jappgeo.2015.09.013
0926-9851/

model space. Constant-phase rotation is commonly applied to improve the resolution of stationary seismic data. It is also extended to process non-stationary seismic data (van der Baan, 2008; van der Baan and Fomel, 2009; Edgar and van der Baan, 2011; Fomel and van der Baan, 2014) by dividing the data into partly overlapping sequences. The other method is the mixed-phase wavelet scanning method, which is also based on the maximum non-Gaussianity of deconvolution results. With the given wavelet amplitude spectrum, this approach identifies an optimum wavelet phase or all-pass filter via the exhaustive algorithm (e.g., Porsani and Ursin, 1998; Ursin and Porsani, 2000) or via a global optimization algorithm such as simulated annealing algorithm (e.g., Wood, 1999) or genetic algorithm (e.g., Caraballo and Porsani, 2011), to ensure that the method can stably search for a global optimization result. However, both approaches are limited by the geological model and processing data bandwidth. Moreover, noise can further deteriorate the wavelet phase estimation.

Regularized inversion or Bayesian inversion method is proposed to simultaneously estimate the wavelet and sparse reflectivity series, with the assumption that the subsurface reflectivity series is sparse within an infinite band. Velis (2008) introduces a simulated annealing technique to eliminate the influence of wavelet phase and to obtain a sparse–spike reflectivity based on the constant-phase wavelet assumption. The inverted spikes can be utilized to interpret layer thickness or even identify thin layers below tuning thickness (e.g., Puryear and Castagna, 2008; Yuan and Wang, 2013; Sen and Biswas, 2015). Under the condition of smooth wavelet in the time or transform domain and continuous reflectivity in the space direction(s), the linearized technique is adopted to obtain an optimum sparse deconvolution result and enhance seismic resolution (e.g., Kaaresen and Taxt, 1998; Gholami and Sacchi, 2013). However, regularized inversion and Bayesian inversion approaches strongly depend on the choice of the regularization parameter(s), such as the relative weight between fitness of data and sparseness of reflectivity series.

These above statistical deconvolution or data-dependent deconvolution methods have been used to remove wavelet effect or estimate wavelet with various ranges of success. However, these conventional methods require assumption about reflectivity. For instance, reflectivity is assumed to be subject to non-Gaussian distribution, Laplacian distribution, Student's T distribution or Cauchy distribution (Li et al., 2013). To establish a quality control standard for statistical deconvolution, well-log data is often used to replace the priori statistical distribution assumption. Conventional constant-phase rotation technique based on a seismic-to-well match criterion (White and Simm, 2003) has been applied to high-resolution processing (e.g., Edgar and van der Baan, 2011) and seismic inversion (e.g., Zhang and Castagna, 2011). In the present study, a frequency-dependent wavelet phase scanning technique with the same criterion is presented to search for an optimum mixed phase or an optimum root combination from a limited number of solutions. The complex nonlinear process can be mapped into ant colony to search the shortest path to food. Therefore, an ant colony optimization (ACO) algorithm (Dorigo et al., 1996; Yuan et al., 2009; Liu et al., 2015) can be used to solve the nonlinear problem. Specifically, a smooth amplitude spectrum of wavelet can be achieved from seismic data and applied to build a minimum-phase wavelet having finite length. By combining nearby-well seismic data with well-log data, we can use the new ACO algorithm to determine an optimum wavelet phase or mixed-phase wavelet in a finite phase or root space. For convenience, the proposed method is named as ACO-based wavelet phase estimation (AWPE). Without the statistical assumption of reflectivity, the evaluation criterion adopts convolution instead of deconvolution or inversion to get rid of ill-posedness issues in inverse problem. It can also optimize seismic-to-well tie, particularly for weak reflection signals. Moreover, the method avoids the need to select the regularization parameters.

In this paper, we describe the AWPE method, which includes the decomposition of wavelet, the incorporation of the ACO algorithm into wavelet phase estimation and the implementation of the ACO algorithm. Three synthetic examples and a well-through real data example are adopted to evaluate the performance of the proposed method.

2. Method

2.1. Wavelet decomposition

In the following descriptions, we assume that a discrete wavelet $w(t)$ can be represented as $(w_0, w_1, \cdots, w_N)$. On the basis of the properties of forward Z transform and inverse Z transform (Sitton et al., 2003), the discrete wavelet is expressed as

$$\begin{aligned} w(t) &= Z^{-1}[w_N(z-\alpha_1)(z-\alpha_2)\cdots(z-\alpha_N)] \\ &= w_N(-\alpha_1, 1) * (-\alpha_2, 1) * \cdots * (-\alpha_N, 1), \end{aligned} \tag{1}$$

where $\alpha_n (n = 1, 2, \cdots, N)$ represents the roots (or the zeros) of the Z transform polynomial for wavelet $(w_0, w_1, \cdots, w_N)$, * represents the convolution operator and $Z^{-1}[\bullet]$ represents the inverse Z transform. The wavelet sequence $(w_0, w_1, \cdots, w_N)$ can be reconstructed using the convolution of a series of two-term wavelets $(-\alpha_n, 1)$. In the frequency domain, the wavelet phase spectrum is described using the sum of the phases of all two-term wavelets. Therefore, the phase of the reconstructed wavelet changes when a real root or a pair of conjugate complex roots varies. If only the symmetric movement of these roots in z plane with respect to the unit circle is considered, i.e., the two-term wavelets $(-\alpha_n, 1)$ are replaced by the corresponding two-term wavelets $|\bar{\alpha_n}|(-\frac{1}{\bar{\alpha_n}}, 1)$, the new reconstructed wavelet can have the same amplitude spectrum as the original wavelet but different phase spectra. Through various combinations of these roots and their counterparts, a series of reconstructed wavelets that have a same amplitude spectrum but different phase spectra can be produced. The number of reconstructed wavelets is up to 2^{Nr+Nc}, where Nr is the number of real roots and Nc is the number of conjugate complex roots pairs.

2.2. Encoding and decoding for wavelet phase estimation

When the amplitude spectrum of a wavelet and its length are given, a minimum-phase wavelet can be obtained via Hilbert transform or Kolmogoroff technique (Claerbout, 1985). We assume that the real roots and complex roots, whose imaginary parts are not less than zero, are $(\beta_1, \beta_2, \cdots, \beta_{Nr})$ and $(\gamma_1, \gamma_2, \cdots, \gamma_{Nc})$ respectively. A wavelet library having 2^{Nr+Nc} wavelets that share the same amplitude spectrum but different phase spectra can be constructed by simply transforming the root β_i and/or γ_i into $1/\beta_i$ and/or $1/\gamma_i$. Therefore, wavelet phase estimation can be described as the search for the optimum root combination that leads to the best seismic-to-well tie. In general, the sum of Nr and Nc is more than 30. At least, 2^{30} wavelets or root combinations must be scanned and evaluated using the exhaustive search technique. Hence, the computation cost is highly expensive. In fact, the process for seeking the optimum wavelet phase can be regarded as a combinational optimization problem for searching $Nr + Nc$ roots from the set $\{(\beta_1, 1/\beta_1), \ldots, (\beta_{Nr}, 1/\beta_{Nr}), (\gamma_1, 1/\gamma_1), \ldots, (\gamma_{Nc}, 1/\gamma_{Nc})\}$. It is worth noting that one root from each pair of symmetric roots is chosen. This procedure is similar to the process of foraging ants searching for the shortest path. Root combination optimization can be achieved by simulating the ant colony cooperation behavior, and thus an optimum mixed-phase wavelet can be estimated. By means of heuristic search controlled by pheromone, the ACO algorithm can rapidly converge to the global solution. An encoding operation is necessary to map the wavelet phase estimation problem to the root combination optimization problem, which can be implemented by ACO algorithm. Conversely, a decoding operation is also required to transform the sub-paths where ant passes into a discrete wavelet series.