Journal of Applied Geophysics 93 (2013) 60–66

Contents lists available at SciVerse ScienceDirect

Journal of Applied Geophysics

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

Noncausal *f–x–y* regularized nonstationary prediction filtering for random noise attenuation on 3D seismic data

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ARTICLE INFO

Article history:
Received 10 February 2013
Accepted 15 March 2013
Available online 29 March 2013

Keywords:
Nonstationary autoregression
Regularization
Random noise attenuation
Least squares

ABSTRACT

Seismic noise attenuation is very important for seismic data analysis and interpretation, especially for 3D seismic data. In this paper, we propose a novel method for 3D seismic random noise attenuation by applying noncausal regularized nonstationary autoregression (NRNA) in *f–x–y* domain. The proposed method, 3D NRNA (*f–x–y* domain) is the extended version of 2D NRNA (*f–x* domain). *f–x–y* NRNA can adaptively estimate seismic events of which slopes vary in 3D space. The key idea of this paper is to consider that the central trace can be predicted by all around this trace from all directions in 3D seismic cube, while the 2D *f–x* NRNA just considers that the middle trace can be predicted by adjacent traces along one space direction. 3D *f–x–y* NRNA uses more information from circumjacent traces than 2D *f–x* NRNA to estimate signals. Shaping regularization technology guarantees that the nonstationary autoregression problem can be realizable in mathematics with high computational efficiency. Synthetic and field data examples demonstrate that, compared with *f–x* NRNA method, *f–x–y* NRNA can be more effective in suppressing random noise and improve trace-by-trace consistency, which are useful in conjunction with interactive interpretation and auto-picking tools such as automatic event tracking.

1. Introduction

Seismic noise attenuation is very important for seismic data processing and interpretation, especially for 3D seismic data. Among the methods of seismic noise attenuation, prediction filtering is one of the most effective and most commonly used methods (e.g., Galbraith, 1991; Gulunay, 1986; Gulunay et al., 1993; Sacchi and Kuehl, 2001). Prediction filtering can be implemented in *f–x* domain or *t–x* domain (Abma and Claerbout, 1995; Hornbostel, 1991). Abma and Claerbout (1995) compared *f–x* method and *t–x* method and gave the advantages and disadvantages of both these methods. The proposed method in our paper belongs to the category of *f–x* domain methods. The *f–x* prediction technique was introduced for random noise attenuation on 2D poststack data by Canales (1984) and further developed by Gulunay (1986). Wang and West (1991) and Hornbostel (1991) used noncausal filters for random noise attenuation on stacked seismic data and obtain a good result. Linear prediction filtering states that the signal can be described by an autoregressive (AR) model, which means that a superposition of linear events transforms into a superposition of complex sinusoids in the *f–x* domain. Sacchi and Kuehl (2001) utilized the autoregressive-moving average (ARMA) structure of the signal to estimate a prediction error filter (PEF) and applied ARMA model to attenuate random noise. Liu et al. (2009) applied ARMA-based noncausal spatial prediction filtering to avoid the model inconsistency.

As already noted, these above mentioned *f–x* methods assume that seismic section is composed of a finite number of linear events with constant dip in *t–x* domain. To cope with the assumption continuous changes dips, short temporal and spatial analysis windows are usually used in *f–x* prediction filtering. Except using windowing strategy, several nonstationary prediction filters are proposed and used in seismic noise attenuation and interpolation. Naghizadeh and Sacchi (2009) proposed an adaptive *f–x* prediction filter, which was used to interpolate waveforms that have spatially variant dips. Fomel (2009) developed a general method of regularized nonstationary autoregression (RNA) with shaping regularization (Fomel, 2007) for time domain inverse problems. Liu et al. (2012) propose a method for random noise attenuation in seismic data by applying noncausal regularized nonstationary autoregression (NRNA) in frequency domain, which is implemented for 2D seismic data. These nonstationary methods can control algorithm's adaptability to changes in local dip so that they can process curved events.

In using *f–x* prediction filter to suppress random noise on 3D seismic data, one needs to run the 2D algorithm slice by slice (along inline *x* or crossline *y*). To use more information to predict the effective signal in 3D data, several geophysicists extended *f–x* prediction filtering to 3D case. Chase (1992) designs and applies 2-D prediction filters in the plane defined by the inline and crossline directions for each temporal frequency slice of the 3-D data volume. Ozdemir et al. (1999) applied *f–x–y* projection filtering to attenuate random noise of seismic data with low poor signal to noise ratio (SNR), in which the crucial step of 2-D spectral factorization is achieved through the causal helical

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0926-9851/$ – see front matter
http://dx.doi.org/10.1016/j.jappgeo.2013.03.007

filter. Gulunay (2000) proposed using full-plane noncausal prediction filters to process each frequency slice of the 3-D data. Wang (2002) applied *f–x–y* 3D prediction filter to implement seismic data interpolation and gave a good result. Hodgson et al. (2002) presented a novel method of noise attenuation for 3D seismic data, which applies a smoothing filter to each targeted frequency slice and allows targeted filtering of selected parts of the frequency spectrum.

In this paper, we extend *f–x* NRNA method (Liu et al., 2012) to *f–x–y* case and use *f–x–y* NRNA to attenuate random noise for 3D seismic data. The coefficients of 3D NRNA method are smooth along two space coordinates (x and y) in *f–x–y* domain. This paper is organized as follows: First, we provide the theory for random noise on 3D seismic data, paying particular attention to establishment of *f–x–y* NRNA equations with constraints and implementation of it with shaping regularization. Then we evaluate and compare the proposed method with *f–x* NRNA using synthetic and real data examples and discuss the parameter selection problem associated with our algorithm.

2. Methodology

2.1. The review of f–x NRNA

Seismic section $S(t,x)$ in *f–x* domain is predictable if it only includes linear events in *t–x* domain. The relationship between the n-th trace and (n–i)-th trace can be easily described as

$$S_n(f) = \sum_{i=1}^{M} a_i(f) S_{n-i}(f), \tag{1}$$

where M is the number of events in 2D seismic section. Eq. (1) describes forward prediction equations, namely causal prediction filtering equations (Gulunay, 2000). In the case of both forward and backward prediction equations (noncausal prediction filter), Eq. (1) can be written as (Gulunay, 2000; Liu et al., 2012; Naghizadeh and Sacchi, 2009; Spitz, 1991)

$$S_n(f) = \sum_{i=1}^{M} a_i S_{n-i}(f) + \sum_{i=-1}^{-M} a_i S_{n-i}(f), \tag{2}$$

where M is the parameter related to the number of events. Note that Eq. (2) implies the assumption $\sum_{i=1}^{M} a_i S_{n-i}(f) = 0.5 S_n(f)$ and $\sum_{i=-1}^{-M} a_i S_{n-i}(f) = 0.5 S_n(f)$. Theoretically, a_i in forward prediction equations is the complex conjugation of a_{-i} in backward equations (Galbraith, 1991). Gulunay (2000) pointed that it is possible to reduce the order of the normal equations from $2M$ to M because the coefficients of noncausal prediction filter have conjugate symmetry.

f–x prediction filtering has the assumption that the events of seismic section are linear. If seismic events are not linear, or the amplitudes of wavelet are varying, they no longer follow linear or stationary assumptions (Canales, 1984). One needs to perform *f–x* prediction filtering over a short sliding window in time and space to cope with continuous changes in dips (Naghizadeh and Sacchi, 2009). Fomel (2009) developed a general method of RNA using shaping regularization technology, which is implemented for real number. Liu et al. (2012) extended the RNA method to *f–x* domain for complex numbers and applied it to seismic random noise attenuation for 2D seismic data. The *f–x* NRNA is defined as (Liu et al., 2012)

$$\varepsilon_n(f) = S_n(f) - \sum_{i=1}^{M} a_{n,i}(f) S_{n-i}(f) - \sum_{i=-1}^{-M} a_{n,i}(f) S_{n-i}(f). \tag{3}$$

Eq. (3) indicates that one trace noise-free in *f–x* domain can be predicted by adjacent traces with the different weights $a_{n,i}(f)$. Note that the weight $a_{n,i}(f)$ is varying along the space direction, which is indicated by subscript i in $a_{n,i}(f)$. In Eq. (3), the coefficient a is the function of space i, but it is not in Eq. (2). When applying *f–x* NRNA to seismic noise attenuation, we assume that the prediction error $\varepsilon_n(f)$ is the random noise and the predictable part $\sum_{i=1}^{M} a_{n,i}(f) S_{n-i}(f) + \sum_{i=-1}^{-M} a_{n,i}(f) S_{n-i}(f)$ is the signal. Finding spatial-varying coefficients $a_{n,i}(f)$ forming Eq. (3) is ill-posed problem because there are more unknown variables than constraint equations. To obtain the coefficients, we should add constraint equations. Shaping regularization (Fomel, 2009) can be used to solve the under-constrained problem (Liu et al., 2012). The RNA method can also be used for seismic data processing in *t–x–y* domain, such as seismic data interpolation (Liu and Fomel, 2011).

2.2. f–x–y NRNA for random noise attenuation

Two dimensional *f–x* NRNA only considers one space coordinate x. If we use *f–x* NRNA on 3D seismic cube, we usually apply *f–x* RNA in one space slice. *f–x* NRNA reduces the effectiveness because the plane event in 3D cube is predictable along different directions rather than only one direction. Therefore, we should develop 3D *f–x–y* NRNA to suppress random noise for 3D seismic data.

Next, we use Fig. 1 to illustrate the idea of *f–x–y* NRNA. The middle trace T_{33} is the one we want to predict. Trace T_{33} can be predicted from circumjacent traces $T_{11} \sim T_{55}$ (except itself T_{33}). The prediction process includes all different directions. For example, if we use T_{21} to predict T_{33}, we can estimate a corresponding coefficient using the described algorithm in the following. *f–x–y* NRNA uses all around traces to predict the middle trace. Therefore, the prediction uses more information than *f–x* NRNA. For all the traces in 3D cube, similar

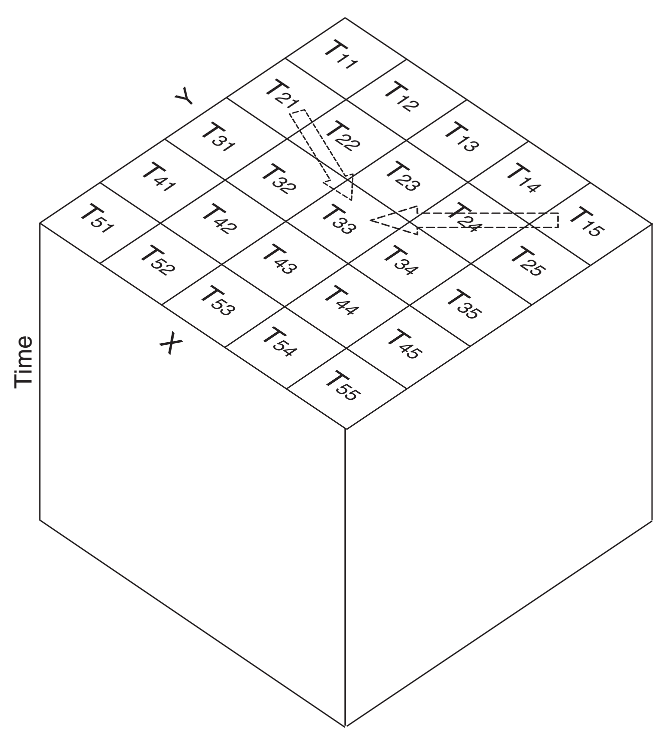

Fig. 1. The *f–x–y* prediction filter. The trace T_{33} is predicted from circumjacent traces T_{11}–T_{55}(except itself T_{33}).