Available online at www.sciencedirect.com
ScienceDirect
Signal Processing 88 (2008) 1839–1851
SIGNAL PROCESSING
www.elsevier.com/locate/sigpro

Multichannel blind seismic deconvolution using dynamic programming ☆

Alon Heimer, Israel Cohen*

Department of Electrical Engineering, Technion– Israel Institute of Technology, Technion City, Haifa 32000, Israel

Received 14 December 2006; received in revised form 4 December 2007; accepted 20 January 2008
Available online 4 February 2008

Abstract

In this paper, we present an algorithm for multichannel blind deconvolution of seismic signals, which exploits lateral continuity of earth layers by dynamic programming approach. We assume that reflectors in consecutive channels, related to distinct layers, form continuous paths across channels. We introduce a quality measure for evaluating the quality of a continuous path, and iteratively apply dynamic programming to find the best continuous paths. The improved performance of the proposed algorithm and its robustness to noise, compared to a competitive algorithm, are demonstrated through simulations and real seismic data examples.

Keywords: Wavelet estimation; Multichannel blind deconvolution; Seismic signal; Sparse reflectivity; Reflectivity estimation

1. Introduction

In seismic exploration, a short duration seismic pulse is transmitted from the surface, reflected from boundaries between underground earth layers, and received by an array of sensors on the surface [1]. The received signals, called seismic traces, are analyzed to extract information about the underground structure of the layers in the explored area [2,3]. Pre-processing is applied to the raw data in order to increase the signal-to-noise ratio (SNR) and attenuate surface waves that are unrelated to the underground structure. Subsequently, the traces can be modeled under simplifying assumptions as noisy outcomes of convolutions between reflectivity sequences (channels) and an unknown wavelet. The objective of multichannel blind seismic deconvolution is to estimate both the wavelet and the reflectivity sequences from the measured traces.

Single-channel blind deconvolution is generally an ill-posed problem, and requires some a priori information about the channels or the wavelet. The reflectivity sequence is often modeled as a Bernoulli–Gaussian random sequence, and second-order statistics may be used to partially reconstruct the input signal. Several methods based on high-order statistics have been developed [4,5], which require very long data to properly estimate the output statistics. Alternatively, the wavelet can be modeled as an autoregressive moving-average (ARMA) process, and a maximum likelihood estimator for the reflectivity can be derived [6].

☆Part of this work was presented in [1].

*Corresponding author. Tel.: +972 4 8294731; fax: +972 4 8295757.
E-mail addresses: heimer@tx.technion.ac.il (A. Heimer), icohen@ee.technion.ac.il (I. Cohen).

0165-1684/$ - see front matter
doi:10.1016/j.sigpro.2008.01.022

Multichannel blind deconvolution (see [7] and references therein, [8,9]) is often more advantageous and more robust than single-channel blind deconvolution. Sparsity of the reflectivity sequences may be used to cope with the ill-posed nature of the basic blind deconvolution problem [10,11], and to improve the performance of non-blind deconvolution methods [12]. Channel sparsity has been used in [10], together with an assumption of short wavelet, to formulate an efficient channel estimation method suitable for relatively short traces (see also [13]). Lateral continuity of the reflectors across channels is also used to further improve the channel estimates. Idier and Goussard [14] model the two-dimensional structure of the underground reflectivity as a Markov–Bernoulli random field, and impose lateral continuity to generate deconvolution results that are far superior to those obtainable by single-channel deconvolution methods. However, their estimator of the two-dimensional reflectivity pattern is suboptimal, since the dependency between columns is treated locally, i.e., each column of the reflectivity is estimated separately, under prior distributions given by the previous column whose estimate is held fixed.

In this paper, lateral continuity of reflectors across channels is combined with the blind deconvolution algorithm of Kaaresen and Taxt [10]. We employ dynamic programming [15,16] to find the shortest continuous paths of reflectors across channels, and develop an improved multichannel blind deconvolution algorithm for seismic signals, which exploits the lateral continuity of earth layers. Rather than measuring the increase in the fit to the data each single reflector yields, versus the decrease in sparsity of the channel estimates, we measure the increase in the fit to the data obtained by a complete continuous path of reflectors, versus the decrease in the sparsity of paths. This approach is an attempt to look at the data as a whole, and account for dependency between all columns in the data, and not only adjacent ones. The improved performance of the proposed algorithm and its robustness to noise, compared to the blind deconvolution algorithm of Kaaresen and Taxt, are demonstrated by using simulated and real seismic data examples. The rest of this paper is organized as follows: In Section 2, we describe the signal model and briefly review the blind deconvolution algorithm presented in [10]. In Section 3, we describe a dynamic programming method for finding the shortest continuous path in an image. In Section 4, we introduce a multichannel blind deconvolution algorithm, which exploits the continuity of earth layers and utilizes the dynamic programming approach. In Section 5, the performance of the proposed algorithm is demonstrated on simulated and real seismic data, and compared to an existing algorithm. Finally, in Section 6 we discuss the additional complexity of the proposed algorithm.

2. Signal model and basic blind deconvolution process

2.1. Signal model

We assume M received signals (traces), each generated by a single input signal $h[n]$ passing through a channel $x^{(m)}[n]$ and corrupted by additive uncorrelated noise $e^{(m)}[n]$. The output signal of channel m can be written as

$$z^{(m)}[n] = \sum_{k=0}^{K-1} h[k]x^{(m)}[n-k] + e^{(m)}[n]$$
$$\text{for } m = 1,2,\ldots,M, \;\; n = 1,2,\ldots,N. \tag{1}$$

The following assumptions are made for the wavelet h and the channels:

(1) All channels are excited by the same wavelet h.
(2) The wavelet h has a finite support of length K, which is shorter than the channel.
(3) Each channel is sparse, i.e., the number of non-zero elements (reflectors) in a channel is small relative to the channel's length.
(4) The dependency between different channels is modeled as follows. Let $P = (n_1, n_2, \ldots, n_M)$ be a vector of M integer line numbers such that n_1 is uniformly distributed in the range $[1, N]$, and $n_m|n_{m-1}$ is uniformly distributed in the range $[n_{m-1} - 1, n_{m-1} + 1]$ for $m = 2, 3, \ldots, M$. We call the vector P the "location vector of a single layer". Let $\widetilde{\mathbf{a}}(P) = (\widetilde{a}_1^P, \widetilde{a}_2^P, \ldots, \widetilde{a}_M^P)$ denote a vector such that $\widetilde{a}_1^P$ is normally distributed with zero mean and standard deviation σ_a, and such that $\widetilde{a}_m^P|\widetilde{a}_{m-1}^P$ is normally distributed with mean $r\widetilde{a}_{m-1}^P$ and standard deviation $\sigma_a\sqrt{1-r^2}$ for some constant r close to 1 and $m = 2, 3, \ldots, M$. This is a Markov model for the amplitudes of the reflectors along the layer with locations P. The two-dimensional reflectivity pattern is the stacking of the M channels as columns in an $N*M$ matrix X. Let $\{P_1, P_2, \ldots, P_L\}$ be the location vectors of L single layers and