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Bayesian frequency-domain blind deconvolution of ground-penetrating radar data

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ABSTRACT

Enhancing the resolution and accuracy of surface ground-penetrating radar (GPR) reflection data by inverse filtering to recover a zero-phased band-limited reflectivity image requires a deconvolution technique that takes the mixed-phase character of the embedded wavelet into account. In contrast, standard stochastic deconvolution techniques assume that the wavelet is minimum phase and, hence, often meet with limited success when applied to GPR data. We present a new general-purpose blind deconvolution algorithm for mixed-phase wavelet estimation and deconvolution that (1) uses the parametrization of a mixed-phase wavelet as the convolution of the wavelet's minimum-phase equivalent with a dispersive all-pass filter, (2) includes prior information about the wavelet to be estimated in a Bayesian framework, and (3) relies on the assumption of a sparse reflectivity. Solving the normal equations using the data autocorrelation function provides an inverse filter that optimally removes the minimum-phase equivalent of the wavelet from the data, which leaves traces with a balanced amplitude spectrum but distorted phase. To compensate for the remaining phase errors, we invert in the frequency domain for an all-pass filter thereby taking advantage of the fact that the action of the all-pass filter is exclusively contained in its phase spectrum. A key element of our algorithm and a novelty in blind deconvolution is the inclusion of prior information that allows resolving ambiguities in polarity and timing that cannot be resolved using the sparseness measure alone. We employ a global inversion approach for non-linear optimization to find the all-pass filter phase values for each signal frequency. We tested the robustness and reliability of our algorithm on synthetic data with different wavelets, 1-D reflectivity models of different complexity, varying levels of added noise, and different types of prior information. When applied to realistic synthetic 2-D data and 2-D field data, we obtain images with increased temporal resolution compared to the results of standard processing.

1. Introduction

Surface ground penetrating radar (GPR) reflection surveying has become a widely used tool for high-resolution imaging of the shallow subsurface for environmental, geological, archeological, and engineering applications (e.g., Annan, 2005; Neal, 2004; Slob et al., 2010). The detailed interpretation of subtle stratigraphic features and the identification of closely spaced subsurface targets in GPR reflection data critically depend on the accuracy and optimized temporal resolution of the images. However, the unprocessed GPR reflection data provide a blurred and incorrect image of the true subsurface reflectivity structure due to the shape and causal nature of the wavelet embedded in the reflection data (e.g., van Dam and Schlager, 2000). This embedded wavelet has been affected by the source-pulse shape (e.g., Streich and van der Kruk, 2007), the antenna-coupling response (e.g., Lampe and Holliger, 2003) and the earth filter, which introduce amplitude distortions and time delays relative to the earth's reflectivity structure. In this paper, we present a novel blind-deconvolution algorithm that we employ in a new approach to deconvolution for GPR.

Deconvolution is an inverse filtering procedure that aims at increasing the temporal resolution of reflection data and retrieving a band-limited version of the earth's reflectivity function by removing the embedded wavelet (Robinson and Treitel, 2000). In seismic-reflection processing, deconvolution is widely considered to be a key procedure for resolution enhancement and has a critical impact on image quality and data interpretability (e.g., Yilmaz, 2001). Ideally, the remaining wavelet after deconvolution (i.e., the embedded wavelet convolved with the estimated inverse filter) is a short zero-phase pulse, which means that the reflection amplitudes in the deconvolved data are observed at the true reflection travel times. The image resolution is increased because a zero-phase wavelet is shorter in time duration than other wavelets with the same amplitude spectrum (Berkhout, 1974). Despite the popularity of GPR reflection imaging, only few reports of successful deconvolution applications to GPR data have been published to date (e.g., Arcone et al., 1998; Chen and Chow, 2007; Fisher et al., 1996; Lafleche et al., 1991; Moran et al., 2000; Xia et al., 2003; Xia et al., 2004). The lack of reliable deconvolution approaches to GPR data is unsatisfactory as the image accuracy and

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temporal resolution of many GPR data sets may be suboptimal. Deconvolution also includes estimating the embedded wavelet, which when known can aid in the data interpretation and may serve as input parameter for waveform modeling.

Standard stochastic deconvolution algorithms (spiking and predictive deconvolution algorithms; e.g., Robinson and Treitel, 1967, 2000) as for example applied to GPR data by Arcone et al. (1998), Belina et al. (2009) and Lafleche et al. (1991) perform best for minimum-phase wavelets. However, GPR systems radiate mixed-phase wavelets with their maximum amplitudes generally observed in the center of the wavelet (Annan, 2005), whereas minimum-phase wavelets are characterized by as much front-loaded energy distribution as possible. This discrepancy in energy distribution (phase characteristics) is likely responsible for the often poor performance reported for deconvolution applied to GPR data. If an estimate of the embedded wavelet is available, deterministic deconvolution (wavelet deconvolution; e.g., Berkhout, 1977) may be an alternative approach (e.g., Gottsche et al., 1994; Neves and Miller, 1996; Xia et al., 2003, 2004). Wavelet estimates have been obtained by measuring the pulse traveling through the air while holding the source and receiver antennas facing each other (e.g., Xia et al., 2003, 2004) or estimated from prominent isolated reflections (e.g., Gottsche et al., 1994). Belina et al. (2009) pointed out that airwave measurements using lifted antennas ignore antenna-ground coupling effects (Lampe and Holliger, 2003) and, hence, give unrealistic estimates of the wavelet that propagated through the subsurface. As an alternative method for resolution improvement, Belina et al. (2009) discussed band-limited spectral whitening and spectral blueing, which balance the amplitude spectrum without phase correction and imply that the embedded wavelet is zero phase (Yilmaz, 2001). Other approaches to enhance the GPR image resolution by reducing attenuation and dispersion effects without removing the embedded wavelet (e.g., Bradford, 2007; Irving and Knight, 2003; Turner, 1994) result in sharper images, but the distortions of the data phase (e.g., misallocation of reflections in time) remain.

Standard stochastic and deterministic deconvolution routines either involve the estimation of the embedded wavelet from the data assuming it is minimum-phase or require that the wavelet is known. In contrast, blind deconvolution routines aim at retrieving both the embedded wavelet and the underlying reflectivity series from the data without making a priori assumptions about the phase spectrum of the wavelet (e.g., Sacchi and Ulrych, 2000). Instead, blind deconvolution approaches generally are based on more restrictive assumptions about the reflectivity than standard stochastic deconvolution. For example, the reflectivity may be assumed to exhibit a non-Gaussian amplitude distribution (e.g., Walden, 1985). Non-Gaussian in this context means that a distribution is sparse or leptokurtic, exhibiting a higher probability of extreme values than a Gaussian distribution.

As a consequence of the Central Limit Theorem, convolving a leptokurtic reflectivity series with an arbitrary wavelet produces an output with a distribution closer to Gaussian (Donoho, 1981). Hence, maximizing some measure of the deviation from a Gaussian distribution of the deconvolution output such as the kurtosis potentially allows recovering the original reflectivity series. Other blind deconvolution approaches are based on, for example, matching higher-order cumulants between the data and the wavelet (e.g., Velis and Ulrych, 1996), maximization of whiteness measures of the deconvolution output (van der Baan and Pham, 2008), or separating the wavelet and reflectivity using the complex cepstrum (e.g., homomorphic deconvolution; Ulrych, 1971).

In reflection seismology, Wiggins (1978) introduced the first blind deconvolution algorithm based on kurtosis maximization termed "minimum entropy deconvolution" (MED). Even though the kurtosis proved to be a robust measure for detecting phase changes (e.g., Longbottom et al., 1988; van der Baan, 2008; van der Baan and Fomel, 2009), some of the main disadvantages of kurtosis maximization and MED applications are that they are associated with a non-linear and multi-modal objective function (Wiggins, 1985) and that kurtosis is insensitive to timing and polarity (Longbottom et al., 1988; Wiggins, 1978).

In addition to the MED technique, a series of other mixed-phase wavelet estimation and deconvolution algorithms that rely on the assumption of a non-Gaussian reflectivity distribution have been presented. Wood (1999) proposed a simultaneous deconvolution and wavelet estimation technique that inverts in the frequency domain for the wavelet phase spectrum given the wavelet's amplitude spectrum. The decomposition of a mixed-phase wavelet into a minimum-phase and maximum-phase component (Eisner and Hampson, 1990), or reformulated, the parametrization of a mixed-phase wavelet as the convolution of the wavelet's minimum-phase equivalent with an all-pass filter (Claerbout, 1985) was used by Misra and Sacchi (2007), Porsani and Ursin (1998), and Ursin and Porsani (2000) to estimate mixed-phase wavelets. Porsani and Ursin (1998) and Ursin and Porsani (2000) estimated an optimum all-pass filter by solving extended normal equations in an exhaustive search manner. Porsani and Ursin (1996) applied this approach also to GPR data. Misra and Sacchi (2007) inverted for the all-pass filter using fourth-order cumulant matching and employed a global non-linear optimization scheme for computing the all-pass filter coefficients.

In summary, standard deconvolution routines have rarely been applied successfully to GPR data, which we primarily attribute to the mixed-phase characteristics of the GPR source wavelet. We present a novel general-purpose mixed-phase wavelet estimation and deconvolution algorithm to enhance surface GPR reflection data. First, we discuss the pertinent theoretical aspects and then present the details of the implementation with regard to the frequency-domain filter design and the time-domain objective function evaluation. A novel contribution to the blind-deconvolution problem and key element of our algorithm is the inclusion of prior information in a Bayesian framework, which allows constraining the polarity and timing of the wavelet to be estimated. In order to solve the non-linear deconvolution problem, we employ a global optimization scheme. We assess the robustness and limitations of our deconvolution algorithm with regard to the input parameters and noise using different 1-D synthetic data sets. Finally, we explore the potential of our new deconvolution scheme on realistic 2-D synthetic data and a 2-D field GPR profile. A list of mathematical symbols and a glossary of the most important terms are presented in Appendix **A** and Appendix **B**, respectively.

2. Theoretical background

We assume that a GPR trace $x(t)$ represents the recording of far-field plane-wave reflections and can be modeled as the convolution of a reflectivity series $r(t)$, which is a function of the impedance contrasts, with a stationary wavelet $w(t)$ plus some superposed noise $n(t)$ such that

$$x(t) = r(t) * w(t) + n(t), \tag{1}$$

where $*$ denotes convolution and t represents time. For our further analysis, we assume that (1) $r(t)$ is a stationary non-Gaussian white series, (2) that $n(t)$ and $r(t)$ are uncorrelated and (3) that the variance of $n(t)$ is much smaller than the variance of $r(t)$ (e.g., Robinson and Treitel, 2000).

For electromagnetic waves, the impedance is the scalar ratio of the transverse components of the electric and magnetic fields **E** and **H**, respectively, and may be expressed in the frequency domain as (e.g., Ward and Hohmann, 2006)

$$I = \frac{|\mathbf{E}|}{|\mathbf{H}|} = \sqrt{\frac{\mu}{\epsilon + i\frac{\sigma}{\omega}}}, \tag{2}$$

where ϵ, σ, and μ are the dielectric permittivity, electrical conductivity, and magnetic permeability, respectively, which are assumed