Journal of Applied Geophysics 101 (2014) 95–107

Contents lists available at ScienceDirect

Journal of Applied Geophysics

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

Predicting 2D geotechnical parameter fields in near-surface sedimentary environments

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ARTICLE INFO

Article history:
Received 14 June 2013
Accepted 5 December 2013
Available online 12 December 2013

Keywords:
Crosshole tomography
Global inversion
Nonparametric statistics
Geotechnical parameters

ABSTRACT

For a detailed characterization of near-surface environments, geophysical techniques are increasingly used to support more conventional point-based techniques such as borehole and direct-push logging. Because the underlying parameter relations are often complex, site-specific, or even poorly understood, a remaining challenging task is to link the geophysical parameter models to the actual geotechnical target parameters measured only at selected points. We propose a workflow based on nonparametric regression to establish functional relationships between jointly inverted geophysical parameters and selected geotechnical parameters as measured, for example, by different borehole and direct-push tools. To illustrate our workflow, we present field data collected to characterize a near-surface sedimentary environment. Our field data base includes crosshole ground penetrating radar (GPR), seismic P-, and S-wave data sets collected between 25 m deep boreholes penetrating sand- and gravel dominated sediments. Furthermore, different typical borehole and direct-push logs are available. We perform a global joint inversion of traveltimes extracted from the crosshole geophysical data using a recently proposed approach based on particle swarm optimization. Our inversion strategy allows for generating consistent models of GPR, P-wave, and S-wave velocities including an appraisal of uncertainties. We analyze the observed complex relationships between geophysical velocities and target parameter logs using the alternating conditional expectation (ACE) algorithm. This nonparametric statistical tool allows us to perform multivariate regression analysis without assuming a specific functional relation between the variables. We are able to explain selected target parameters such as characteristic grain size values or natural gamma activity by our inverted geophysical data and to extrapolate these parameters to the inter-borehole plane covered by our crosshole experiments. We conclude that the ACE algorithm is a powerful tool to analyze a multivariate petrophysical data base and to develop an understanding of how a multi-parameter geophysical model can be linked and translated to selected geotechnical parameters.

1. Introduction

For various geotechnical and engineering purposes, a detailed characterization of the subsurface is required. In this context, geophysical techniques represent important tools because they are often the only means to delineate subsurface structures and to estimate physical properties in two or three dimensions. Especially, crosshole tomographic techniques (such as crosshole ground penetrating radar (GPR) or seismic tomography) are increasingly used because of their improved resolution capabilities compared to corresponding surface-based geophysical techniques. The most popular and robust approaches to analyze such crosshole GPR and seismic data sets are based on the inversion of first-break traveltimes. In various applications, recent studies have also illustrated the potential benefit when combining GPR travel time tomography with corresponding seismic techniques (e.g., Paasche et al., 2006; Linde et al., 2008; Paasche et al., 2008), because such multi-method exploration strategies can help to reduce uncertainties and ambiguities in data analysis and interpretation. To be effective, the data sets should be linked during the model-generation process using a cooperative or joint inversion approach (Lines et al., 1988). To invert for different parameters such as GPR and seismic velocities, it is common practice to use a structural link to couple the different geophysical data sets during inversion (e.g., Haber and Oldenburg, 1997; Gallardo and Meju, 2004; Paasche and Tronicke, 2007).

Most tomographic inversion approaches (including joint inversions) rely on linearized methods to reconstruct the underlying parameter fields (such as GPR and seismic velocities). In an iterative framework, a local optimization method is used to modify a user-defined starting model (e.g., Aster et al., 2005). Alternatively, global optimization (GO) approaches have been proposed for tomographic inversions including the inversion of traveltime data sets (e.g., Sen and Stoffa, 1995; Sambridge and Mosegaard, 2002). Compared to linearized inversion approaches, the advantages of GO approaches include the ability to produce results independent on the initial model, to explore the model space in more detail, and to generate an ensemble of acceptable solutions explaining the data equally well (e.g., Sen and Stoffa, 1995).

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http://dx.doi.org/10.1016/j.jappgeo.2013.12.002

Modern GO approaches such as particle swarm optimization (PSO; Kennedy and Eberhart, 1995) are computationally efficient and, thus, are potential tools to solve also complex or joint inverse problems in geophysics. Recently, the potential of the PSO approach to invert crosshole P-wave traveltimes has been demonstrated (Tronicke et al., 2011). Furthermore, using a synthetic example Tronicke et al. (2012) have presented a straight-forward implementation of a PSO based joint inversion framework.

Regardless of the used inversion approach, the resulting parameter models (e.g., GPR and seismic velocity models) have to be interpreted in terms of the target structures and/or target parameter distributions. Usually, the resulting tomographic velocity models are interpreted manually considering available background information such as core or geophysical logging data. However, for a detailed site characterization, the geophysical parameters have to be translated into the corresponding hydrological, geotechnical, or engineering parameters. Here, the basic idea is to establish a parametric link to inter- or extrapolate sparsely sampled 1D borehole or direct-push (DP) parameters using 2D or 3D geophysical models. However, formulating such a translation remains a challenging task because the observed parameter relations are often complex, site-specific, and sometimes also poorly understood. Commonly, existing petrophysical or empirical relations established between borehole data and parameters in the vicinity of the borehole are used (e.g., Yamamoto et al., 1994; Angioni et al., 2003). When using existing petrophysical relations to translate geophysical parameters into target parameters, problems might arise because these relations are usually derived from laboratory measurements under non in-situ conditions and, thus, they might not be applicable universally and site-specific petrophysical relations are required (e.g., Hubbard and Rubin, 2000; Hyndman et al., 2000). To overcome the limitations of preconceived relations and to account for uncertain and nonunique parameter relations, also different statistical and geostatistical frameworks have been proposed. Cassiani et al. (1998), for example, used a geostatistical framework based on co-kriging to estimate hydraulic conductivity from seismic velocities and sonic log data. Tronicke and Holliger (2005) and Dafflon et al. (2009) proposed conditional stochastic simulation approaches based on simulated annealing to integrate a typical hydrogeophysical database for hydrological site characterization. Such conditional stochastic simulations are considered as a powerful tool for data integration because they are conceptually simple and flexible with regard to imposing constraints (e.g., Deutsch and Wen, 1998, 2000). Furthermore, Doyen and Boer (1996) proposed a multivariate stochastic approach using Bayesian simulation to simulate sparsely sampled target variables from denser sampled variables. This approach was originally applied to inter- and extrapolate lithological data, but was used in various fields including reservoir and hydrological characterization (e.g., Ezzedine et al., 1999; Chen et al., 2001; Bosch et al., 2010; Dubreuil-Boisclair et al., 2011; Ruggeri et al., 2013). Clustering methods are another statistical approach to model a target parameter by the integration of various geophysical data. For example, Paasche et al. (2006) used a clustering method to derive hydrological parameter models from crosshole surveys.

Another promising statistical approach, which until today has been rarely used in Earth Sciences, was introduced by Breiman and Friedman (1985). Their alternating conditional expectation (ACE) approach is a nonparametric multiple regression method, which was developed to find functional relationships between a dependent variable and one or more independent variables without any a priori information regarding the model (e.g., linear dependencies). Recent studies have shown the potential of this approach for analyzing geoscientific data. For example, Xue et al. (1997) used the ACE algorithm for permeability estimation from well logs. Furthermore, Nashawi and Malallah (2006) related pressure gradient data and rock density to fracture gradients using the ACE approach, whereas Scuzs and Horne (2009) used the ACE approach to define functional relationships between different parameters in a hydrological data set. These studies have shown that the ACE approach is a versatile tool to analyze rather typical geoscientific data sets when the underlying functional relationships between dependent and independent variables are unknown.

In this study, we investigate the potential of the ACE approach to link jointly inverted models of GPR, P-wave, and S-wave velocities to different sparsely sampled 1D borehole and DP parameter logs. After presenting the methodological basics of our GO joint inversion strategy and the ACE algorithm, we describe our field site and our data base which includes crosshole GPR and seismic data as well as a variety of borehole and DP logs. Then, we present the resulting velocity models and the ACE derived optimal transformations which allow us to link our geophysical velocities to target logging parameters (sleeve friction f_s, effective grain size d_{10}, and gamma ray activity GR) and to extrapolate these parameters across the entire inter-borehole plane.

2. Methodology

In this section, we present the fundamental methodological details regarding data inversion and statistical analysis. After describing our joint inversion strategy based on particle swarm optimization (PSO), we present the alternating conditional expectation (ACE) method which is used to link our inverted velocities to existing borehole and DP logs.

2.1. Particle swarm optimization

PSO is a recently developed GO approach inspired by the social behavior of animals (Kennedy and Eberhart, 1995). Although PSO has proven to provide excellent convergence rates in different optimization problems, it has seldom been applied to invert geophysical data (e.g., Fernández Martínez et al., 2010). Here, we have adapted the PSO approach of Tronicke et al. (2011, Fig. 1) and apply it the first time to

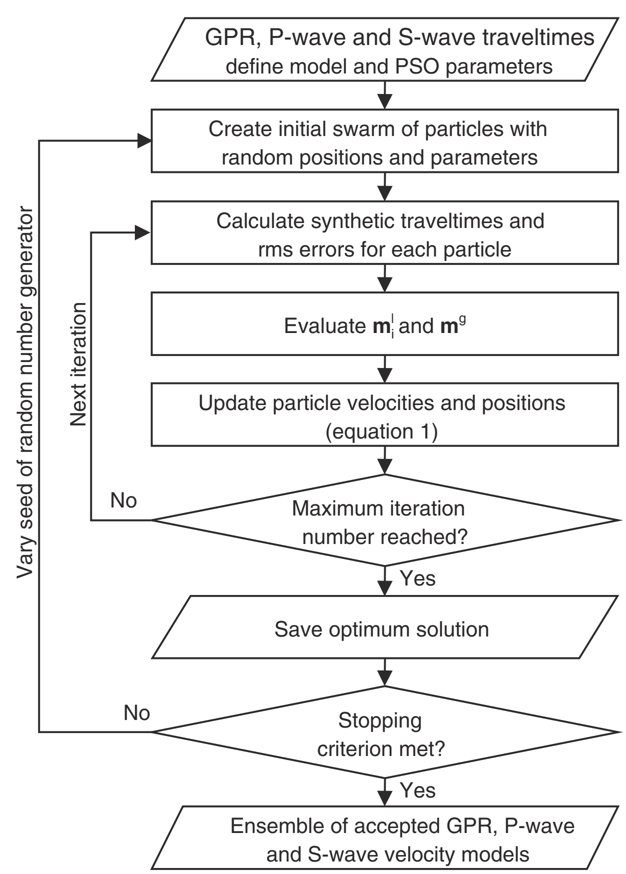

Fig. 1. Flow chart illustrating the key steps of the used PSO based joint inversion procedure (modified after Tronicke et al., 2011).