Global optimization of data quality checks on 2-D and 3-D networks of GPR cross-well tomographic data for automatic correction of unknown well deviations

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Summary

Mislocation of the transmitter and receiver stations of GPR cross-well tomography data sets can lead to serious imaging artifacts if not accounted for prior to inversion. Previously, problems with tomograms have been treated manually prior to inversion. In large data sets and/or networks of tomographic data sets, trial and error changes to well geometries become increasingly difficult and ineffective. Our approach is to use cross-well data quality checks and a simplified model of borehole deviation with particle swarm optimization (PSO) to automatically correct for source and receiver locations prior to tomographic inversion. We present a simple model of well deviation, which is designed to minimize potential corruption of actual data trends. We also provide quantitative quality control measures based on minimizing correlations between take-off angle and apparent velocity, and a quality check on the continuity of velocity between adjacent wells. This methodology is shown to be accurate and robust for simple 2-D synthetic test cases. Plus, we demonstrate the method on actual field data where it is compared to deviation logs. This study shows the promise for automatic correction of well deviations in GPR tomographic data. Analysis of synthetic data shows that very precise estimates of well deviation can be made for small deviations, even in the presence of static data errors. However, the analysis of the synthetic data and the application of the method to a large network of field data show that the technique is sensitive to data errors varying between neighboring tomograms.

Introduction

Significant errors related to poor time zero estimation, well deviation or mislocation of the transmitter (TX) and receiver (RX) stations can render even the most sophisticated modeling and inversion routine useless. Previous examples of methods for the analysis and correction of data errors in geophysical tomography include the works of Maurer and Green (1997), Squires et al. (1992) and Peterson (2001). Here we follow the analysis and techniques of Peterson (2001) for data quality control and error correction. Through our data acquisition and quality control procedures we have very accurate control on the surface locations of wells, the travel distance of both the transmitter and receiver within the boreholes, and the change in apparent zero time. However, we often have poor control on well deviations, either because of economic constraints or the nature of the borehole itself prevented the acquisition of well deviation logs. Also, well deviation logs can sometimes have significant errors.

Problems with borehole deviations can be diagnosed prior to inversion of travel-time tomography data sets by plotting the apparent velocity of a straight ray connecting a transmitter (TX) to a receiver (RX) against the take-off angle of the ray (Figure 1).

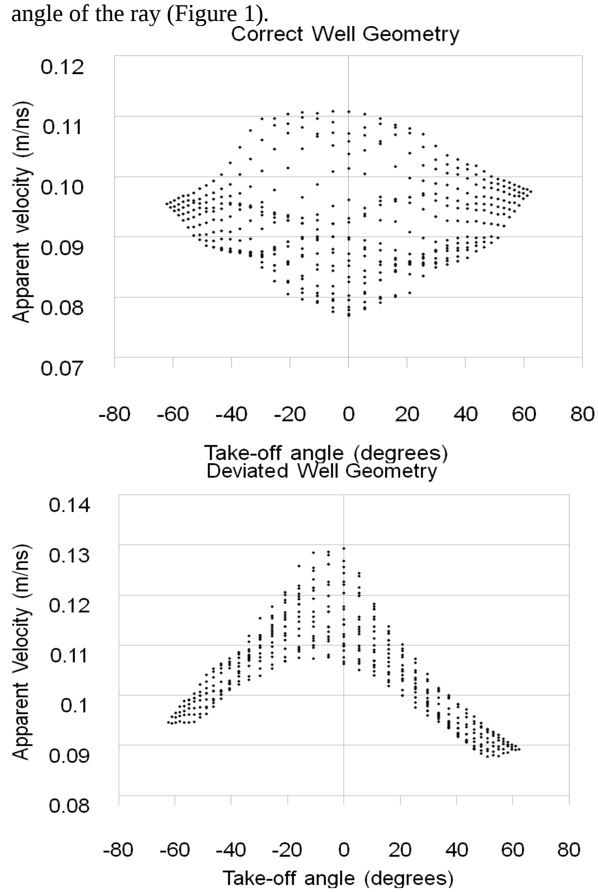

Figure1. Scatter plots of the calculated velocity of a straight ray between source and receiver pairs verses the take-off angle. The QC scatter plots for the correct well geometry without static errors (A), and a for a deviated well (B) show variations in correlation between apparent velocity and take-off angle.

Issues with the time-zero pick or distances between wells appear as symmetric smiles or frown in these QC plots. Well deviation or dipping-strong anisotropy will result in an asymmetric correlation between apparent velocity and take-off angle (Figure 1-B). In addition, when a network of interconnected GPR tomography data is available, one has the additional quality constraint of insuring that there is continuity in velocity between immediately adjacent tomograms. A sudden shift in the mean velocity indicates that either position deviations are present or there is a shift in the pick times.

Small errors in well geometry may be effectively treated during inversion by including weighting, or relaxation, parameters into the inversion (e.g. Bautu et al., 2006). In the technique of algebraic reconstruction tomography (ART), which is used herein for the travel time inversion (Peterson et al., 1985), a small relaxation parameter will smooth imaging artifacts caused by data errors at the expense of resolution and contrast (Figure 2). However, large data errors such as unaccounted well deviations cannot be adequately suppressed through inversion weighting schemes. Previously, problems with tomograms were treated manually. However, in large data sets and/or networks of data sets, trial and error changes to well geometries become increasingly difficult and ineffective.

Methods

Our method consist of three parts: 1) a forward model to describe a deviated well in Cartesian coordinates, 2) the calculation of a merit function related to QC of well deviation, and 3) a global optimization method to minimize the merit function.

In selecting a model for well deviation we considered that many of our GPR data sets are from within shallow aquifers, where the overall length of wells are relatively small. We also assumed that deviations would be relatively small over the length of the well with no sudden changes in direction. Complicated models of well deviation that includes several changes in azimuth and dip were purposely

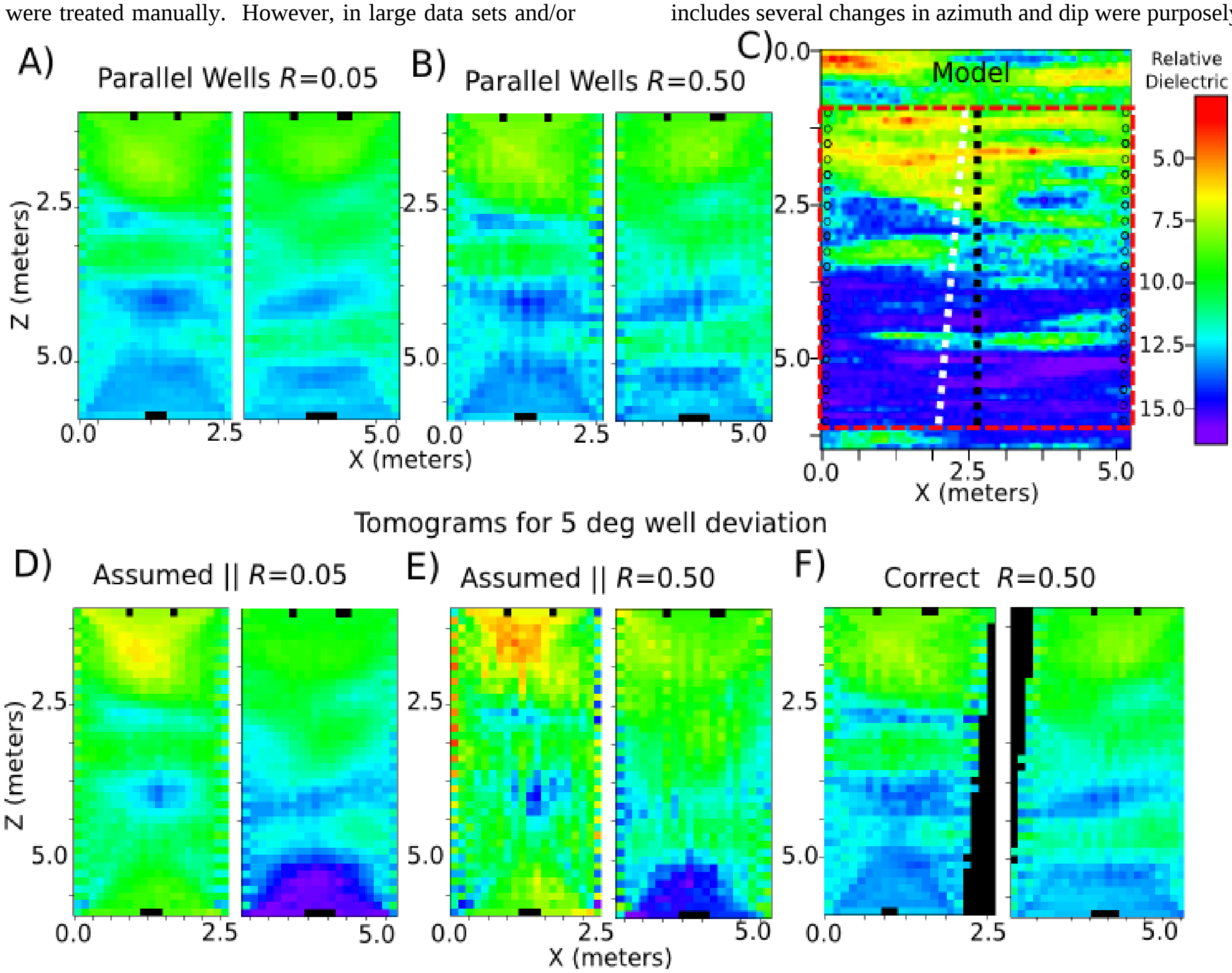

Figure 2. Inversion results generated from travel time picks from FDTD simulation of a geostatisical model of dielectric properties (C). Panels A and B show the results for a pair of parallel tomograms with a relaxation weight *R* of 0.05 and 0.5, respectively. Panels D and E show the effects of a deviated well when the wells are assumed to be parallel for a relaxation weight *R* of 0.05 and 0.5, respectively. Panel F show the inversion results when the correct well geometry is used for the deviated well.

avoided to prevent the possibility of inadvertently removing natural heterogeneity trends. Our model is a simple straight well with a single deviation angle with the pivot point located at the surface location of the well.

The model of a network of interconnected tomograms is most efficiently described in terms of network notation. Two and three-dimensional networks of GPR tomograms are described by set of nodes and connections, or edges, where the nodes represent the boreholes of the GPR TX's and RX's, and the tomography data represents the connections between the nodes.

The coordinate of each transmitter and receiver (x'_n,y'_n,z'_n) is given by

$$x'_n = R_n \sin(\theta_n)\cos(\phi_n) + x_n$$

$$y'_n = R_n \sin(\theta_n)\cos(\phi_n) + y_n$$

$$z'_n = R_n \cos(\theta_n)$$

where R_n is the distance down the borehole of the TX or RX station, θ_n is the angle of deviation of well n, and φ_n is the azimuth of the deviation, and (x_n,y_n,z_n) are the coordinates of the station when perfectly vertical wells are assumed. The angle of deviation θ_n for each well is constrained to less than or equal to 10º, while the azimuth is free to rotate though all 360º. In the case of a 2-D network φ_n is held constant.

The merit function of the optimization consists of quantitative checks on the continuity of velocity between connections of the network, and checks to ensure that there is minimal correlation between apparent velocity and the take-off angle. The first quality control is given by,

$$QC_1 = \sum_{n \in N} \sum_{i \in C_n} \frac{v_i - \bar{v}_n}{\bar{v}_n} ,$$

where v_n^- is the mean apparent velocity of the subset of the tomography data C_n connected to node n, v_i is the velocity of connection i of the subset $C_{n,}$ and N is the total number of nodes. The second quality control is given by,

$$QC_2 = \sum_{c=1}^{C} |R_c^u| + |R_c^d| ,$$

where R_c^u is the correlation coefficient of connection c for upgoing take off angles versus apparent velocity and R_c^d is the correlation coefficient of connection c for the down going rays. The sum of these two measures of data quality defines the merit function. Together the two measures provide counter-weight between continuity of velocity between tomograms and the quality of individual tomograms. To minimize this merit function, and thus maximize quality, we utilize a global optimization algorithm known as particle swarm optimization (PSO).

The PSO algorithm of Kennedy and Eberhart (1995) is a technique based loosely on the observed behavior of large swarms. This algorithm optimizes the quality control merit function by moving "particles", or solutions of the merit function, around in a search space towards the optimal solution. The movements of the particles are controlled by communication between the particles of the best solution of all of the particle's past positions, and the best current solution. We utilized the PSO FORTRAN code of Mishra (2006), which has been extensively tested for finding global minima of complicated test functions.

Validation on synthetic data for a 2-D network

To test our method we utilized travel-times picked from a numerical model of electromagnetic propagation through a geostatistical model of the distribution of dielectric permittivity and electrical conductivity (Figure 3). The numerical model is a 2-D TE mode implementation the ADI-FDTD algorithm of Namiki (1999), and the travel times were automatically picked with the algorithm of Crosson and Hesser (1983). The structure and variance of the geostatistical model is based on high resolution geophysical logs acquired at our test field site. Source positions were situated at the location of the open circled on the edges and the RX locations were situated along the black lines in figure 3.

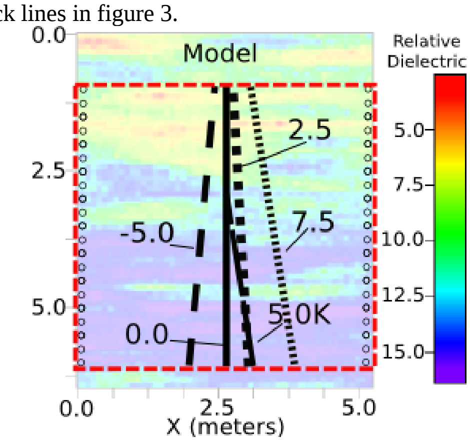

Figure 3. The geometry of deviated wells between two vertical wells.

In this tomography network the two end wells are unconstrained by neighboring tomography data. Therefore, the geometry of these end wells was held constant, and only the central well was allowed to update during the inversion. The results of our inversion method are summarized in table 1. To check how robust the technique is to the presence of other data errors such as static time-zero shifts, anisotropy, and incorrect estimation of well separation, additional constant time shifts were added to the data in subsequent test. Additionally, the possibility of a change in time-zero between the two tomography data sets was tested with a +1 ns and -1 ns shift in the time-picks of the two wells.

Table 1. Inverted well deviation angles compared to the angle of deviation used to generate synthetic data (see figure 3). Each comparison is repeated with static shifts in time-zero to estimate the sensitivity to uncorrected static errors.

Zero Time	Well Deviations Angles				
Shift (ns)	0^o	2.5^o	-5^o	7.5^o	5.0K
no shift	0.294	2.519	-4.686	9.804	1.592
2	0.295	2.400	-4.415	9.273	1.531
-2	0.292	2.651	-4.994	10.408	1.658
-1 and +1	2.070	4.300	-6.462	7.988	-0.191

The results show that the technique is precise for low angles of deviation, and tolerant of constant data errors, with decreasing precision at larger deviation angles and more complicated geometries. However, the technique is sensitive to changes in time picks between tomography data sets (eg. -1 and +1 ns). Our experience is that shifts of this nature are rare, and we acquire travel times in free space before and after each tomography data set to ensure that any drift or change in time-zero has not occurred.

Application to field data

Here we are attempting to use the well deviation inversion technique to correct data collected at the Department of Energy's Integrated Field Research Challenge (IFRC) site near Rifle, Colorado. At the site we have a network of GPR tomography data sets consisting of 12 wells interconnected by 16 2-D inverted tomograms. Initial inspection of neighboring tomograms showed significant discontinuities in velocity and structure. Because of the tight controls on other data errors that could lead to these sudden shifts, deviated wells were suspected and motivated this study. Subsequently 9 of the 12 wells have been logged for deviation to compare with our inversion results. The 2-D map view plots of the inversion estimated deviations and logged deviations are shown figure 4.

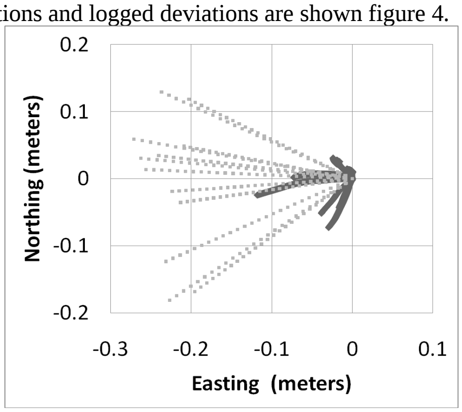

Figure 4. Plot of well deviations estimated from the inversion method (gray) and the plot of well deviations derived from deviation logs (black).

While, the inverted deviations are nearly twice as large as the recorded deviations, both data sets show a systematic drift to the west. The lack of better agreement may come from the model trying to correct data quality issues that stem from a series of small errors not obvious in the data quality control methods.

Discussion and Conclusions

This study has shown promise for automatic correction of well deviations in GPR tomography data. The analysis of synthetic data shows that very precise estimates of well deviation can be made for even with constant data errors. However, the analysis of the synthetics and the application of the method to a large network of field data show that the technique is sensitive to varying data errors between neighboring tomograms. We are investigating more sophisticated models including deviation bends, time-zero shifts, and anisotropy. Our current attempts to deal with these additional complexities are complicated by their strong correlation with our QC measures, leading to incorrect solutions. We need QC measures that uniquely indicate particular data problems in the presence of noise and heterogeneity.

The simplicity of our model will not remove all artifacts of deviation from the inverted tomograms. This residual deviation may be corrected with the method proposed of Cordua et al. (2008) and Cordua et al. (2009). Their work on accounting for correlated data errors during inversion, using a non-diagonalized covariance matrix, demonstrated the ability to remove small spatially correlated data errors without losing resolution. We feel that this method is a perfect complement to our approach in that we are attempting to remove only large general trends and leave small spatially correlated data errors untouched to avoid corrupting real information. The eventual hope is that data errors in large networks of GPR tomography data sets can be mitigated to allow for 3-D monitoring of subtle changes in subsurface properties during field experiments.

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