



Investigating motion blur and temporal aliasing from time-lapse electrical resistivity

Dale Rucker

hydroGEOPHYSICS, Inc, 2302 N Forbes Blvd, Tucson, AZ 85745, United States



ARTICLE INFO

Article history:

Received 4 May 2014

Accepted 17 September 2014

Available online 6 October 2014

Keywords:

Electrical resistivity

Monitoring

Time-lapse

Moment analysis

Image appraisal

ABSTRACT

Geophysical monitoring through time-lapsed resistivity imaging is investigated to determine detrimental effects resulting from temporal smear. Temporal smear can be divided into motion blur and temporal aliasing, with motion blur attributed to an extended sample integration time relative to the velocity of a moving target, thus giving rise to reproduced targets that are distorted versions of the real target shape. Aliasing results from undersampling across time and may give a discontinuous movement. The degree to which each aspect of smear affects target properties described by spatial moment analysis depends on the spatial resolution of the imaging method and the degree to which temporal degradation is applied. For synthetic models with relatively high spatial resolution, aliasing effects were slight except in cases where the minimal number of snapshots was acquired to understand the end state condition of the target. Motion blur, on the other hand, had progressive detrimental effects with each level of additional smearing. For field data acquired during subsurface injection with a lower resolution array, the damaging effects from motion blur and temporal aliasing were equivalent. Both aspects showed progressive degeneration of spatial moments with each level of degradation. To combat this problem in the short term, it is recommended to acquire resistivity data as rapidly as possible and sacrifice some spatial resolution to enhance temporal resolution. In the future, there may be methods adopted from motion photography to deblur target motion by using the point spread function. Aliasing, however, can only be solved through continuous sampling.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

The electrical resistivity geophysical method is a popular means by which to remotely monitor hydrogeological changes, owing to major advances in instrumentation, survey design, and data inversion techniques (Loke et al., 2013). The temporal variability in resistivity has been directly linked to changes in moisture content (Michot et al., 2003), contaminant concentration (Wilkinson et al., 2010), and temperature-related processes (Hauck, 2002). Quantitatively, the use of time-lapse resistivity to estimate hydraulic parameters has also been extensively applied. For the hydraulic parameter estimation procedure, the subsurface undergoes a significant change by introducing an electrically conductive tracer at a source (Camporese et al., 2011; Monego et al., 2010), which is often followed by an extraction at a nearby sink (e.g., Oldenborger and Routh, 2009; Singha and Gorelick, 2005). Over this period, a set of snapshots are gathered and processed using specialized inverse modeling algorithms to reproduce the subsurface electrical conductivity distribution. In turn, the calculated electrical conductivity is used to estimate the time history of the injected tracer, and

attributes of the reproduced anomaly are compared to attributes from a separate flow and transport model for parameter estimation. Overall, the geophysical data and the hydrogeologically-based models tend to agree with reasonable fidelity. However, several have noted a few problems of the estimation procedure including mass underestimation in the electrical conductivity data by up to 75% and inaccuracies in the location and the degree of spread of the geophysical anomaly (Singha and Gorelick, 2005). Reasons for the underperformance of the resistivity method have been placed on low or nonuniform spatial resolution, regularization, and homogenized petrophysical relations.

With the time-lapse resistivity method, a snapshot of the earth is taken periodically, where each snapshot samples a set of potential measurements taken from combinations within a network of electrodes. Depending on the size of the network, the sampling time over which to complete a single snapshot can be significant. Many have tried to minimize this time to avoid “temporal smear” by either reducing the total number of samples within a snapshot (e.g., Singha and Gorelick, 2005; Ward et al., 2010), reducing the size of the network (Pidlisecky and Knight, 2011; Rucker, 2009), or by developing rapid acquisition systems (Ogilvy et al., 2009; Rucker et al., 2014). While the previous studies tackled the problem from the standpoint of acquisition, several others have tried reducing blur during modeling. Kim et al. (2009) tracked the measurement time of each data sequence and

E-mail addresses: drucker@hgiworld.com, druck8240@gmail.com.

inverted images on a discretized time line. Kuras et al. (2009) used an approach to reduce temporal smear by reorganizing the measurement sequence to ensure measurements with similar spatial sensitivity were as close together in time as possible. Doetsch et al. (2012) accommodated temporal smear through spline interpolation of the potential data to estimate hypothetical values back to a fixed point in time.

One potential reason for the underperformance of the hydrogeophysical modeling that has not been given adequate attention is the effects that arise from temporal smearing. Here, temporal smearing is separated into two related components that include motion blur and temporal aliasing, with motion blur attributed to extended sampling integration time relative to target velocity and aliasing resulting from a large time lag between snapshots. To put it in terms of motion photography, blur results from large exposure times, whereby the shutter is open too long relative to the motion of the target. Temporal aliasing is due to a low frame rate and will produce a target motion that appears discontinuous. Both aspects can affect spatially-derived geometric attributes as estimated from time-lapse inverse modeling. In this work we investigate the issue of temporal smear using both synthetic and field-based resistivity surveys as test cases. The synthetic test cases use either moving or growing conductive targets in a homogeneous background. The field based surveys were conducted during shallow subsurface injections. Spatial moments were then computed to compare results within each test case. The results will show the degree to which each aspect of temporal smearing may give rise to similar observations of inaccurate target reproduction noted in the earlier references.

2. Monitoring strategies

A great deal of our understanding of subsurface processes, and in particular those processes that involve mass and energy transport in porous and fractured media, comes from observing them over a finite time window. The frequency at which observations are conducted, however, tend not to be linked to a temporal scale related to appreciable changes for many state variables describing transport. Rather, the frequency of acquisition is likely conducted ad hoc, with a mindset that oversampling is superior to undersampling and data can simply be filtered or reduced to better understand their implications. Networks of environmental sensors deployed to make our observations are now commonly installed with high frequency acquisition rates to collect moisture, temperature, pressure, etc., with little to no additional expense over low frequency equivalents. The only limitations to deployment appear to be continuous reliable power and data storage. The latter may have been solved with the advent of an intelligent web of sensors, which comprise a network of sensor nodes and communications systems that actively transmit their data to a central server (Delin et al., 2005; Hart and Martinez, 2006).

Monitoring the subsurface with geophysical methods is more temporally constrained compared to a network of independent environmental sensors. Each measurement from a pair of electrodes is interdependent upon measurement at other electrodes. While geophysical methods have proven valuable at yielding information regarding the transient nature of water movement in the subsurface, applying the techniques can be relatively expensive and unwieldy, reducing the rate of acquisition to perhaps one or two snapshots over the course of study relative to hundreds or thousands of snapshots that can be acquired with a sensor. For example, only a few practitioners can dedicate a direct-current (DC) electrical resistivity system to a single long-term project and acquire a sufficient temporal perspective to rival its sensor counterpart (e.g., Calendine et al., 2011; Hilbich et al., 2008; Ogilvy et al., 2009; Sjö Dahl et al., 2008; Versteeg et al., 2004). The expense of dedicated computer hardware, cabling, electrodes, and a processing hub is arguably 10 to 100 times greater than a datalogger with an equal number of sensors to electrodes. Yet, in each case cited above,

the geophysical dataset provided a spatially continuous view that allowed a more complete understanding of subsurface processes than could have been likely provided by a more sparsely distributed set of sensors, regardless of sampling frequency. For the remaining group of geophysicists that cannot dedicate resources for long periods of time, conducting a monitoring study is often opportunistic. Due to time and cost constraints, the studies may be shortened or acquired sporadically.

Extensive investigation into applications of resistivity monitoring for a large degree of problem types have revealed a broad range of monitoring strategies, which have been summarized in Fig. 1. The summary involved defining an order (n) for the approximate number of snapshots within a study equating to 2^n . The timing of acquisition is sometimes synchronous, where snapshots are planned to a specific event such as end state capture. Alternatively, acquisition can be more informal and asynchronous, where data are collected regardless of the condition of the subsurface. Most surveys involve either orders 0 or 1 and it is very rare to find an n^{th} order survey (e.g., Rucker et al., 2014). Acquiring and processing data sufficiently fast have large hardware requirements. However, processing of an n^{th} order survey would likely not involve inverse modeling.

Fig. 2 shows graphically the times at which a resistivity snapshot would likely be acquired for both natural and artificial environmental stimuli. A natural stimulus including precipitation or diurnal heating usually has a periodicity in the environmental variable of interest (e.g., moisture or temperature) and examples are shown for monitoring applications of orders 0, 2, or n . Notice that if a low number of snapshots are acquired relatively to the frequency content of the environmental variable, information will be lost associated with temporal aliasing. For artificial stimulus, such as a subsurface injection, several strategies have been used including simple end state capture, semi-continuous, and continuous acquisition. Together, Figs. 1 and 2 outline a systematic means of applying geophysical monitoring and a full understanding of the final monitoring goal may improve survey design and results while reducing costs. However, as will be demonstrated later, a reduced survey cost through lower coverage may increase the uncertainty in the subsurface properties.

3. Theoretical methodology

The time dependent nature of investigating temporal smearing required the use of time-lapse electrical resistivity tomography (ERT). Several have investigated and compared different means by which to conduct time-lapse ERT (e.g., Hayley et al., 2011; Oldenborger et al., 2007). Noted advantages for a temporally constrained time-lapse inversion include penalizing differences across multiple models allowing a smooth transition of target features through time, while also minimizing artifacts of the background (Hayley et al., 2011). In this work, temporally constrained time-lapse inversion is implemented as described in Loke et al. (2014a), which is available in the commercial inversion code RES3DINVx64.

Borrowing from the descriptions in Rucker et al. (2011) and Loke et al. (2014a), the equation for the constrained optimization method describes the relationship between model parameters and measured data. Here, the model parameters in vector \mathbf{r} are the electrical resistivity values at each discretized cell within the model domain. Given the large range over which electrical resistivity may vary and the nonphysical meaning of most negative electrical resistivity, \mathbf{r} usually represents the logarithm of the model resistivity values. The optimization procedure marches along a piece-wise linear path on the error surface using a model updating procedure to calculate a $\Delta \mathbf{r}_i$ at iteration i using information about \mathbf{r}_{i-1} and the sensitivity matrix, \mathbf{J} , containing the partial derivative of data measurements relative to the model parameters. To dampen the effects of noise being amplified through the modeling procedure, various matrix roughness filters in time (\mathbf{M}) and space (\mathbf{W}), as well as data and model weighting matrices \mathbf{R}_d and \mathbf{R}_m ,

Download English Version:

<https://daneshyari.com/en/article/4740083>

Download Persian Version:

<https://daneshyari.com/article/4740083>

[Daneshyari.com](https://daneshyari.com)