



Robust estimation of temporal resistivity variations: Changes from the 2010 Mexicali, M_w 7.2 earthquake and first results of continuous monitoring

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ABSTRACT

The magnetotelluric (MT) method is a well-known geophysical technique in tectonic and reservoir exploration studies. In recent years, several works have proven that the MT method is a valuable tool for monitoring fluid injection for enhanced geothermal systems and CO₂ sequestration due to its sensitivity to resistivity changes. However, most of these works report variations only in apparent resistivity and phase data, without estimating changes in the underground structure. Few studies have tried to deal with this problem. Efforts were made for DC-resistivity time-lapse monitoring (Goldstein et al., 1985a) and for the MT case using theoretical examples (Sholpo, 2006, 2010). Promising results had been obtained, but with scarce application to real scenarios.

We propose a methodology to estimate resistivity variations in the underground geo-electrical structure by applying a linearized iterative nonlinear least-square inversion scheme using the Marquardt-Levenberg method to stabilize the inversion. The method is tested first with synthetic MT data, then with data registered on a permanent MT station in the Mexicali Valley, Mexico; and finally, with data measured before and after a M_w 7.2 earthquake, also in the Mexicali Valley. We propose a strategy to define and apply a reference model for situations where the available constraining information is not enough. Our method seems to produce stable and coherent results, as long as the ground resistivity change is able to produce response differences larger than the data uncertainty.

1. Introduction

The magnetotelluric (MT) method is recognized as a valuable geophysical tool for obtaining information about lateral and vertical variations in electrical conductivity, which can be related to the occurrence of natural resources and/or other geological processes (Chave and Jones, 2012). In the last decades, developments in data processing techniques and improvements in equipment made it possible to implement MT analysis studies where natural or man-related processes need to be monitored periodically. MT monitoring has been applied mainly in studies of tectonically active regions, with the intention of enlarging the information obtained by other methodologies (Svetov et al., 1997; Balasco et al., 2008; Aizawa et al., 2010; Aizawa et al., 2011; Aizawa et al., 2013; Romano et al., 2014). In recent years, the use of magnetotelluric monitoring has also provided promising results in projects where ground resistivity changes are expected due to injection or extraction of fluids. Peacock et al. (2013) compared data sets measured before and after fluid injection in an enhanced geothermal system (EGS) in Paralana, Australia. They estimated the direction of fluid

migration from the observed variations in apparent resistivity and phase data. Likewise, Didana et al. (2015) used two time-lapse MT surveys to monitor changes before and after a fluid injection operation in Habanero EGS project. On the other hand, Abdelfettah et al. (2014) used continuous MT monitoring during a chemical and hydraulic stimulation of a production well in the Rittershoffen geothermal field in France. They reported small variations in the phase tensor values, possibly associated with changes in subsurface permeability during the hydraulic stimulation.

While these studies identified time variations in apparent resistivity and phase values measured at the surface, they did not explore what kind of changes occurred in the underground geo-electrical structure that may originate the variations on the data. This, of course, is not a trivial task because there must be a well-established knowledge of the electrical properties of a structure before being able to estimate any change on it.

Despite this disadvantage, efforts have been made to estimate resistivity changes in geo-electric structures. Goldstein et al. (1985a) reported variations in time-lapse DC resistivity data along a profile in a

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geothermal field in Mexico. They used a least-squares solution of a linear problem to relate the observed apparent resistivity changes with the ground resistivity changes. Correspondingly, Sholpo (2006, 2010) proposed a similar methodology to estimate ground resistivity changes from magnetotelluric apparent resistivity variations, estimated from synthetic models. She assumed a well-known reference model and explored the effect of resistivity variations in specific layers of a 1D model or specific cells in a 2D model. This implementation requires data with a very low uncertainty as well as a good estimation of the sensitivity matrix relating data variations with ground resistivity variations. In addition, the areas at depth where changes may occur should be defined *a priori*, a case often beyond the reach of typical field studies.

More recently, Rees et al. (2016) applied continuous MT monitoring in Australia to investigate subsurface resistivity changes caused by depressurization of coal-seam layers during methane extraction operations. They also applied continuous MT as a fracture detection tool in shale-gas hydraulic stimulation. In both cases they were able to detect small resistivity time-changes at depth associated with fluid extraction or injection operations. The temporal changes on the geo-electric structures are estimated by time-lapse 2D modeling, as well as by 1D inversion of daily data at a given station.

We are interested in investigating temporal variations of the ground resistivity structure produced by permeability and fluid flow changes in the subsurface, caused by tectonic events or fluid extraction/injection from a geothermal reservoir. In this paper we propose a methodology that can be applied to time-lapse data as well as continuous monitoring data sets. This methodology allows us to estimate ground resistivity changes from MT data changes by using a regularized inversion scheme. We test this technique first with apparent resistivity and phase data using 1D synthetic models. Then, we apply our methodology on data that was monitored during several months at a selected site in Mexicali Valley, Mexico. Finally, we use field data registered before and after a M_w 7.2 earthquake in the same region, to explore time-lapse 2D variations of the ground resistivity that could be associated to fluid flow or permeability changes.

2. Theory

2.1. Antecedents

Estimation of temporal variations of a subsurface structure based on measurements at the Earth's surface is a main goal in geophysical monitoring. In particular, numerical solutions to solve ground resistivity changes from apparent resistivity data have been explored in the past. Goldstein et al. (1985a) estimated percentage variations of the subsurface resistivity across a geothermal field in Mexico, using DC resistivity data observed during a period of four years (1979, spring 1980, fall 1980, fall 1981 and spring 1983), along the same dipole–dipole profile. Assuming small changes in the subsurface resistivity, they used a Taylor series to set a linear relationship between the change in measured data (apparent resistivity) and changes in ground resistivity

$$\Delta \rho_a \approx \sum_{j=1}^M \frac{\partial \rho_a}{\partial \rho_j} \Delta \rho_j, \quad (1)$$

where $\Delta \rho_j$ is the change in ground resistivity at each cell of a 2D model consisting of M cells, $\Delta \rho_a$ is the observed change in apparent resistivity measured along the profile as a function of the transmitter-receiver separation, and $\frac{\partial \rho_a}{\partial \rho_j}$ are partial derivatives relating the apparent resistivity data with the ground resistivity, at each model cell.

Using the fact that

$$\frac{\partial \ln \rho_a}{\partial \ln \rho_j} = \frac{\rho_j}{\rho_a} \frac{\partial \rho_a}{\partial \rho_j}, \quad (2)$$

Eq. (1) can be written as

$$\frac{\Delta \rho_a}{\rho_a} \approx \sum_{j=1}^M \frac{\partial \ln \rho_a}{\partial \ln \rho_j} \frac{\Delta \rho_j}{\rho_j}. \quad (3)$$

A least-squares method was then used to solve Eq. (3) for the unknown parameters $\frac{\Delta \rho_j}{\rho_j}$. They used the data measured in 1979 as base line to estimate subsequent changes in the model cells, and found increasing and decreasing resistivity changes at different subsurface locations.

Sholpo (2006) proposed a method for direct conversion of time-lapse magnetotelluric apparent resistivity to changes in ground resistivity of a 1D structure. She considered a layered model with n layers, being ρ_j ($j = 1, \dots, n$) the resistivity of each layer, and a second model with the same number of layers and thicknesses, but with different resistivity values, thus the second model can be regarded as a variation in time of the first. The apparent resistivity values are estimated for a set of m frequencies ρ_{ai} ($i = 1, \dots, m$), where $m \geq n$. Therefore, the relationship between model changes and corresponding apparent resistivity changes is defined as

$$\Delta \ln \rho_{ai} = \sum_{j=1}^n \frac{\partial \ln \rho_{ai}}{\partial \ln \rho_j} \Delta \ln \rho_j \quad i = 1, \dots, m, \quad (4)$$

where $\Delta \ln \rho_j = \ln \left(\frac{\rho_{1j}}{\rho_{0j}} \right)$ and $\Delta \ln \rho_{ai} = \ln \left(\frac{\rho_{ai}}{\rho_{a0i}} \right)$ are relative changes of ground resistivity and apparent resistivity, respectively. By this, Eq. (4) becomes

$$\ln \left(\frac{\rho_{ai}}{\rho_{a0i}} \right) = \sum_j^n a_{ij} \ln \left(\frac{\rho_{1j}}{\rho_{0j}} \right), \quad i = 1, \dots, m, \quad (5)$$

where $a_{ij} = \frac{\partial \ln \rho_{ai}}{\partial \ln \rho_j}$. Thus, the unknown ground resistivity change in Eq. (5) is solved by least-squares estimation. The author concluded that, using apparent resistivity variations, it is possible to monitor ground resistivity variations in a given layer, provided that the layer's resistivity and its variation range are well known. In a second paper (Sholpo, 2010) she extends her procedure to a 2D model reaching a similar conclusion.

One can realize that the requirement above is often beyond the reach in real cases, where the structure at depth is not always well known, neither the depth location of probable resistivity variations. Moreover, the observed data might be inaccurate or insufficient.

2.2. Our approach

In this work we apply a methodology based on a linearized iterative nonlinear least-square algorithm to calculate the temporal variations in ground resistivity by inverting changes in observed data. Consider a reference 1D model consisting of n layers with resistivity ρ_{0j} ($j = 1, \dots, n$), as well as a perturbed model represented by ρ_{1j} ($j = 1, \dots, n$). Correspondingly, we have two magnetotelluric data sets: one associated with a reference model (ρ_{a0} , ϕ_0) and the other with a perturbed model (ρ_{a1} , ϕ_1). We are interested in estimating the model perturbation by using the changes in the observed data, along a given frequency or period range f_i ($i = 1, \dots, m$). We define a relative apparent resistivity change $\ln \left(\frac{\rho_{a1i}}{\rho_{a0i}} \right)$, $i = 1, \dots, m$ as well as an absolute change in the impedance phase $\phi_{1i} - \phi_{0i}$, $i = 1, \dots, m$.

$$b_i = \ln \left(\frac{\rho_{a1i}}{\rho_{a0i}} \right), \quad i = 1, \dots, m$$

Therefore, we define a data array \mathbf{b} , composed by , the relative changes in apparent resistivity, and , the absolute changes in phase data.

The sensitivity matrix \mathbf{A} relates the resistivity model \mathbf{x} with the data array \mathbf{b} , giving a way to iteratively approximate the model, as explained below

$$\mathbf{Ax} = \mathbf{b}, \quad (6)$$

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