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Novel approach for 1D resistivity inversion using the systematically-determined optimum number of layers.

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Summary

Determining the correct number of layers as input for 1D resistivity inversion is important for constructing a model that well represents the subsurface. In most electrical resistivity inversions, the number of layers is an arbitrary user-defined parameter, or it is determined through trial-and-error by running the inversion many times using different numbers of layers and choosing the number of layers that produces the best model-data fit. Here, we provide a method that solves the problem of choosing the correct number of layers. The method follows the two-steps approach suggested by Simms and Morgan (1992) to systematically resolve the optimum number of layers. The first step is to run a fixed layer thickness inversion. Then, we use the outcome of the first inversion to determine the optimum number of layers as an input parameter for the second step, which is a variable-thickness inversion (layer thicknesses and resistivities are inversion parameters) for the final resistivity model. Both steps use rescaled Ridge Trace least square regressions. The computer program for this method determines other the input parameters from the data file. The method utilizes an integrated program that performs the two inversion steps sequentially. The proposed method, which uses the robust Ridge Trace regression algorithm, has proven to be stable and accurate.

Introduction

Vertical electrical sounding (VES) is a geophysical method to determine the resistivity structure of the subsurface. The electrical resistivity data measured in $\Omega \cdot m$ is collected by taking surface measurements. A source of alternating current (AC) or a direct current (DC) sends current through a pair of *source* electrodes with spacing **L**. A resistivity meter connected to a pair of *potential* electrodes with spacing **A** measures the electrical resistivity data. The data consists of *apparent resistivity* that needs to be processed to obtain a VES profile of Earth resistivity versus depth. VES interpretations supported with other geophysical data provide significant insight into the geometry, lithology, and/or hydrology of the subsurface.

Methodology

First, let us examine the collected raw data. Apparent resistivity, ρ_a, is the ratio of measured voltage V to the applied current I, multiplied by a geometric constant k which depends on the survey geometry. The apparent resistivity can be written as: $\rho_a = k\,\frac{V}{I}$

Schlumberger Vertical Electrical Sounding

Using the Schlumberger array to acquire 1-D vertical electrical soundings has been used for decades and is still being used frequently despite the growing popularity of two-dimensional surveys with multi-electrode arrays.
After the apparent resistivity data is collected from the field, an inversion is performed to estimate the optimal number of layers, their thicknesses, and their ‘true’ resistivities.

The work of Simms and Morgan (1992) showed that the ‘variable parameter scheme’ (layer thicknesses and resistivities are inversion parameters) gives the most accurate inversion results. The number of layers sensed by the electrical survey is an arbitrary user input. The optimal number of layers is therefore a critical input to represent the surface in the most accurate yet simple way possible. It is worth noting that increasing the number of layers means increasing the number of inversion parameters, which will result in an inversion with less calculated error. However, this does not necessarily best represent the subsurface, for the decreased calculated error is just a by-product of the increase in number of parameters.

Here, a novel two-step approach for 1D resistivity inversion is adopted. This approach is an extension and simplification of the work done by Simms and Morgan (1992). The steps are:

1. Perform a fixed-thickness inversion with a large number of thin layers.
2. Obtain a model resistivity profile.
3. Integrate this resistivity curve.
4. Determine the number of layers from the points of change of slope of the integrated curve
5. Use the number of layers, so determined, for the variable-thickness inversion.

Integrating the curve of the resistivity profile with fixed-thickness layers yields a stable method to obtain the optimal number of layers that can represent the subsurface. This number of layers can be then used as an input for the variable-thickness inversion. This approach guarantees that the number of layers is not an arbitrary guess but rather a systematically determined parameter.

Determining the number of layers in 1D resistivity inversion

Ridge Trace Regression

The inversion scheme used is a damped non-linear least squares (NLLS). To avoid any singularity, the data has to be conditioned first. Correlation rescaling is used to condition the Jacobian matrix (Marquardt, 1975). The Ridge trace algorithm determines which damping values to use for each parameter (Hoerl and Kennard, 1970). After the data is conditioned, the range of damping values is between 0 and 1. This method provides a damping matrix instead of a single damping value for all inversion parameters.

Synthetic Example

The forward 1D resistivity model is used to create synthetic data of apparent resistivity using the input parameters shown in Table 1. Then, from the apparent resistivity and the survey geometry, the layers thicknesses and resistivities are inverted for (Figures 1-4). The number of layers (3 layers) is recovered accurately and the results of the inversion are shown in Table 1.

Type	Input	Output
ρ [Ω·m]	1000, 2000, 200, 500	1000, 2013, 170, 506
Thickness [m]	10, 20, 40	10, 19 , 36.5
Num. of measurements	18	

Table 1: Input parameters used in the forward model and the inverted parameters (output).

Real Data Example
Saint Lucia , Roseau (Vanard) Watershed

This data is part of work jointly done by Frank Dale Morgan (MIT) with members of the Water Resources Management Agency (WRMA) in Saint Lucia in 2014. The studies were aimed at conducting geophysical exploration for possible potable groundwater resources in one or two watersheds of St Lucia. The Vanard area of the Roseau watershed of North-West Saint Lucia was thoroughly investigated.

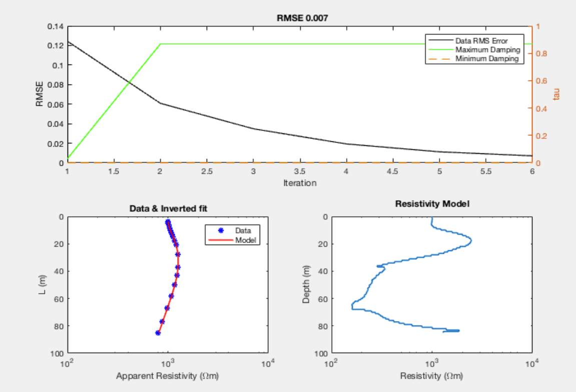

Figure 1: Fixed-thickness inversion. Top plot shows the RMS error and damping parameters (maximum and minimum values). Bottom-left plot shows the data and inverted fit. Bottom-right plot shows the resistivity model versus depth.

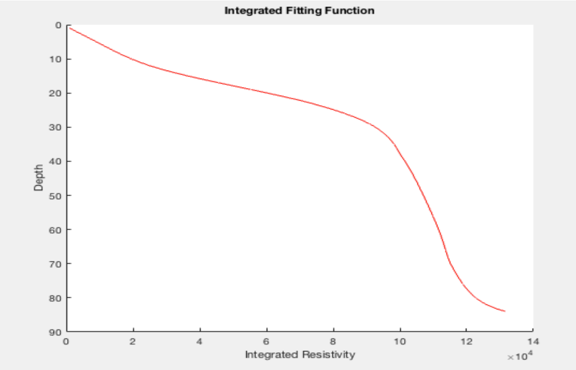

Figure 2: The result of integrating the resistivity model. From this curve, we extracted the number of layers (3 layers) plus half space.

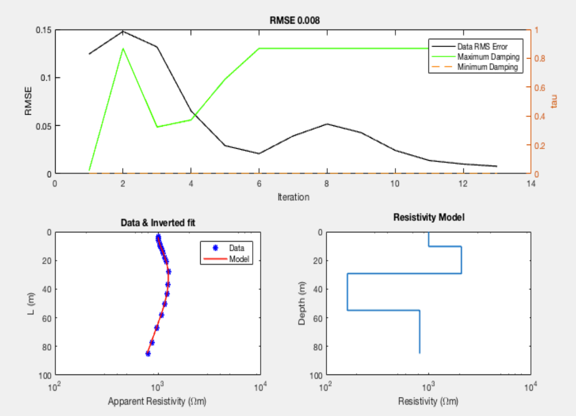

Figure 3: The result of the variable-thickness inversion.

Determining the number of layers in 1D resistivity inversion

Field Methods and Data Processing

In order to ascertain the hydrogeology of the Roseau watershed, geophysical methods were employed for in-field data collection. The data was then analyzed using 1D resistivity codes developed at the Earth Resources Laboratory, MIT.

Shown here is one VES reprocessed using the two-step approach explained earlier (Figures 5-6). The algorithms succeeded in resolving the number of layers (5 layers) and inverting for their thicknesses and 'true' resistivity values that are essential for water explorations in that area.

Conclusion

The solution of the electrical resistivity profile from apparent resistivity is non unique. Also, most inversion algorithms require user-input parameters, including the number of layers, which can be arbitrary and increase the uncertainty of the result. Here, we have provided a robust approach that chooses the inversion parameters and determines the optimum number of layers. The inversion algorithm uses an activation function, correlation rescaling and ridge trace regression which insure robustness and functionality of the algorithm and avoid singularity. The method is computationally fast, user-friendly and yields a high degree of accuracy.

Acknowledgment

The authors would like to thank Dr Darrell Coles for providing his forward model code used in the inversion of the thicknesses and resistivities. We also gratefully acknowledge the support of Morgan's group at MIT.

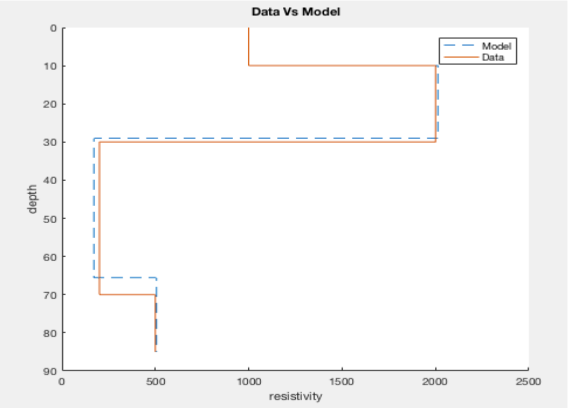

Figure 4: Comparison between synthetic and inverted models

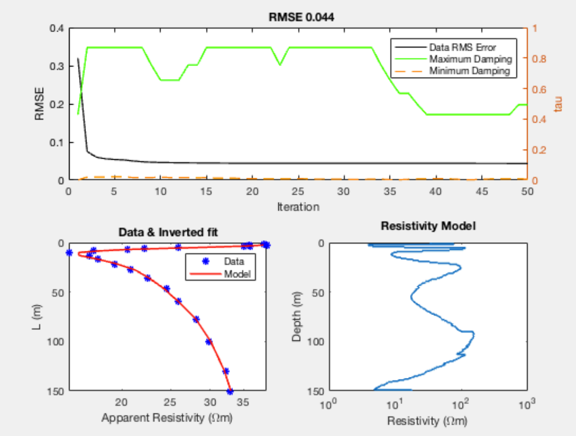

Figure 5: Fixed-thickness inversion of VES acquired in Saint Lucia. From the resistivity model, we extracted the number of layers.

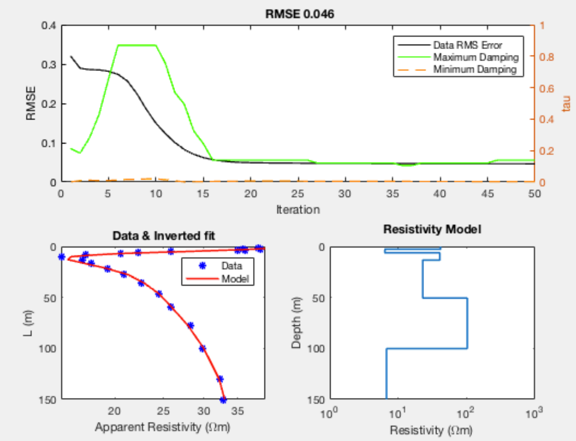

Figure 6: Variable-thickness inversion of VES acquired in Saint Lucia.