



How to enhance Magnetotellurics resistivity model resolution using passive seismic HVSR to identify the cover-basement interface.

Nuwan Suriyaarachchi

¹Centre of Exploration Targeting,
School of Earth Sciences
University of Western Australia
35 Stirling Highway,
Perth 6009 WA,
Australia.
nuwan.suriyaarachchi@
research.uwa.edu.au

²Mineral Exploration
Cooperative Research
Centre, School of Earth
Sciences, University of
Western Australia
35 Stirling Highway,
Perth 6009 WA,
Australia.

Vitaliy Ogarko

¹International Centre for Radio Astronomy
Research,
University of Western Australia,
35 Stirling Highway,
Perth 6009 WA,
Australia.
vitaliy.ogarko@uwa.edu.au

Jeremie Giraud

¹Centre of Exploration Targeting,
School of Earth Sciences
University of Western Australia
35 Stirling Highway,
Perth 6009 WA,
Australia.
jeremie.giraud@uwa.edu.au

²Mineral Exploration
Cooperative Research
Centre, School of Earth
Sciences, University of
Western Australia,
35 Stirling Highway,
Perth 6009 WA,
Australia.

Lachlan Hennessy

¹4 Anglo American
Group Discovery and Geosciences,
201 Charlotte Street,
Brisbane 4000 QLD,
Australia.
lachlan.hennessy@angloamerican.com

Hoel Seille

¹CSIRO, Deep Earth
Imaging FSP,
Australian Resources
Research Centre,
26 Dick Perry Avenue,
Kensington WA 6151,
Australia.
hoel.seille@csiro.au

Mark Lindsay

¹Centre of Exploration Targeting,
School of Earth Sciences
University of Western Australia
35 Stirling Highway,
Perth 6009 WA,
Australia.
mark.lindsay@uwa.edu.au

²Mineral Exploration
Cooperative Research
Centre, School of Earth
Sciences, University of
Western Australia,
35 Stirling Highway,
Perth 6009 WA,
Australia.

Mark Jessell

¹Centre of Exploration Targeting,
School of Earth Sciences
University of Western Australia
35 Stirling Highway,
Perth 6009 WA,
Australia.
mark.jessell@uwa.edu.au

²Mineral Exploration
Cooperative Research
Centre, School of Earth
Sciences, University of
Western Australia,
35 Stirling Highway,
Perth 6009 WA,
Australia.

SUMMARY

Magnetotelluric (MT) and the passive seismic Horizontal to Vertical Spectral Ratio (HVSR) methods are commonly used to characterize cover thickness. While MT is sensitive to resistivity contrasts in the subsurface, the MT data inversion process is affected by non-uniqueness, noise, and sometimes sparsely sampled data, all which tend to increase uncertainty in the inverted models. Likewise, HVSR models are also affected by uncertainty.

In this study, we test a new approach to exploit the complementarity between HVSR and MT modelling, using structural information from HVSR to reduce the uncertainty on the cover thickness recovered using MT data inversion. To this end, we adjust the roughness constraints applied to MT inversion using the depth range predicted by the HVSR method.

New approach can recover sharp resistivity contrasts at the cover-basement interface and the cover depth estimation uncertainty could be reduced to 5%.

Key words: Magnetotellurics, Passive seismic, inversion, integration, cover thickness

INTRODUCTION

The magnetotelluric (MT) method is an electromagnetic method that can be used to characterize the interface between the sedimentary cover and the crystalline basement. This in turn can provide valuable information for mineral and geothermal energy prospectivity mapping and groundwater modelling at a fraction of cost the drilling. In this abstract, we present two new approaches to use depth constraints from passive seismic HVSR models to enhance MT resistivity model resolution and to reduce the uncertainty in the recovered cover thickness.

The inversion of MT data usually yields the smoothest resistivity model, which is demanded by the smoothness regularization terms of the inversion. This limits the detection of localized resistivity features such as sharp resistivity contrasts. On the other hand, purely data-driven inversions would create unrealistic resistivity models. This research attempts to find realistic models which could represent the contrast in resistivity between the conductive cover and the resistive basement, while maintaining geological plausibility.

We present numerical investigations using a synthetic model. First, we computed the responses of a 1D two-layer cover basement model to test our approaches. Then, assuming that collocated passive seismic measurements analysed using the HVSR technique could detect the cover-basement interface within a certain depth range, we defined constraints for the MT inversions. Finally, we analyse the results of unconstrained and constrained inversions of MT data to determine the most effective constraints.

METHODOLOGY

Forward problem

In this study we assume a sedimentary cover resistivity of 20 Ω m, a basement resistivity of 1000 Ω m and a cover thickness of 1000 m (Figure 1a). We assume a 1D model with homogenous layers.

The forward response of this model was calculated using the impedance recursive approach (Wait 1954). The responses were calculated at 56 frequencies ranging from 10⁻³ to 10⁴ Hz having 8 frequencies per decade. 5% random noise was added to the response to simulate real data (Figure 1b).

According to Mulargia (2016) and Castellaro (2012), the modelling of HVSR data would produce models where the estimation of the depth to an interface has uncertainties ranging from 10% to 25%. In this synthetic study, we consider that an estimation of the depth of the cover basement interface using HVSR has 25% uncertainty and the true interface resistivity signature sensed by MT would locate within that depth range.

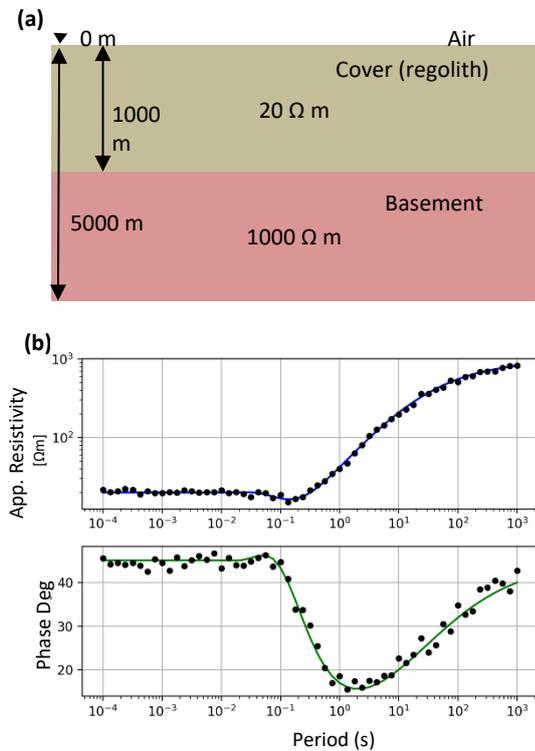


Figure 1 a) Initial cover basement model and b) MT response

INVERSION METHOD AND CONSTRAINTS

Within the Occam’s inversion scheme (Constable, Parker et al. 1987), the objective function U is minimized (Equation 1):

$$U = \|\partial m\|^2 + \|P(m - m_*)\|^2 + \mu^{-1} \left[\|C(d - F(m))\|^2 - \chi_*^2 \right]$$

Equation 1. Unconstrained regularization function (Constable, Parker et al. 1987)

The first term (∂m) is the model roughness. It applies the differentiation operator ∂ to the model vector m (see subsection below for details). The second term is the measurement of the difference between the model m and the prior model m_* . P is a diagonal matrix that determines the relative weighting between model roughness and closeness to the prior model. The third term is a measure of the misfit of the models’ forward response $F(m)$ to the data d . C is the data covariance and defines the error estimate for each data point. It is a diagonal matrix; χ_*^2 is the target misfit; μ^{-1} is a Lagrange multiplier that balances the trade-off between the data fit and the regularisation terms (Constable, Parker et al. 1987).

In this framework, ∂m , P and m_* can be defined using external information. Here, the interface depth estimation from the HVSR modelling was only used to constrain the model roughness term.

Model roughness term (∂m) is product of roughness penalty weight (first matrix with weights w), the first-order difference roughness operator (second matrix) and the model vector (third matrix) (Equation 2). This has illustrated using a 5-layer example below. Air layer considered as a fixed resistivity layer ($\sim 10^{12}$ Ω m) assigned 0 penalty weight by nullifying the first row of the difference operator matrix.

$$\partial m = \begin{bmatrix} w_1 & 0 & 0 & 0 & 0 \\ 0 & w_2 & 0 & 0 & 0 \\ 0 & 0 & w_3 & 0 & 0 \\ 0 & 0 & 0 & w_4 & 0 \\ 0 & 0 & 0 & 0 & w_5 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ -1 & 1 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & 0 & -1 & 1 \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ m_5 \end{bmatrix}$$

Equation 2. Expanded model roughness term (Key 2010)

New approach was tested to assign penalty values in roughness penalty weight diagonal matrix (first matrix in equation 2) using prior HVSR information. This approach was tested against the unconstrained methods (minimum gradient support regularization and depth weighted regularization). In what follows, unconstrained inversions refer to the case where no HVSR information is used and the roughness penalty weights (w_i) are all equal to 1.

Constraining approach

Here we test the utilisation of a sliding window within a specified interval around the depth predicted by HVSR, d_{pred} . The weights assigned to the roughness are calculated as follows:

$$W_i = \begin{cases} 1, & |d| > d_{pred} + \delta d \\ w_i, & |d| = d_{pred} \\ 1, & |d| < d_{pred} - \delta d \end{cases}$$

Equation 3. Square constrain window

This constrained approach uses (flat) roughness penalty value (w_i) from minimum (0) to maximum (1) in 0.05 steps for the depth window within the depth uncertainty estimated by HVSR model.

The width of the sliding depth window (δd) for this test was set to 5% of the estimated interface depth from HVSR. Approximately 20 depth predictions (d_{pred}) values were linearly placed within the cover depth range.

Recovered models were examined in model space and data space and compared with the results of unconstrained inversions.

RESULTS AND DISCUSSION

Unconstrained inversion

Both minimum gradient support regularization results (Figure 2 a) and depth weighted regularization results (Figure 2b) revealed a smoothed resistivity model for the initial model. Resistivity contrast for the cover-basement boundary is not clearly visible in either models.

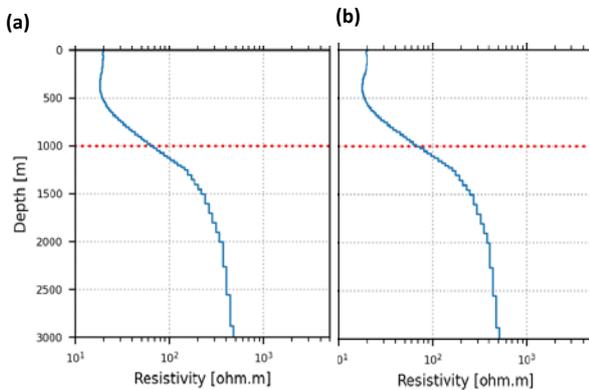


Figure 2. Inverted resistivity model from unconstrained inversion, (a) first difference penalty method, (b) depth weighted penalty method

Constrained inversion

Figure 3 shows the inverted resistivity models from depth range constraining (square window) method.

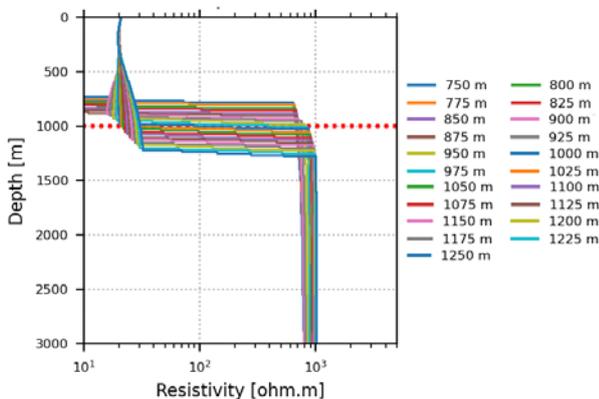


Figure 3. Inverted resistivity models different depth predictions, depth range sliding window method

In this approach, minimum roughness penalty (0) could not converge into a final solution. Next plausible lowest roughness

penalty 0.05 was used to recover the highest resistivity contrast for the cover-basement interface.

Low depth predictions (from 750 to 850 m) could create unrealistic resistivity model fluctuations at the cover-basement interface prediction depth (Figure 4). Possible reasons are discussed further in next section.

We calculated the numerical sum of the (absolute) gradients of resistivity model to quantify model fluctuations. Result showed minimum value (sum) close to the correct depth prediction (Figure 4). Assuming lowest sum of gradients was given at the most probable interface depth, cover-basement depth for this approach would be 1025 m with 5% (25 m) uncertainty.

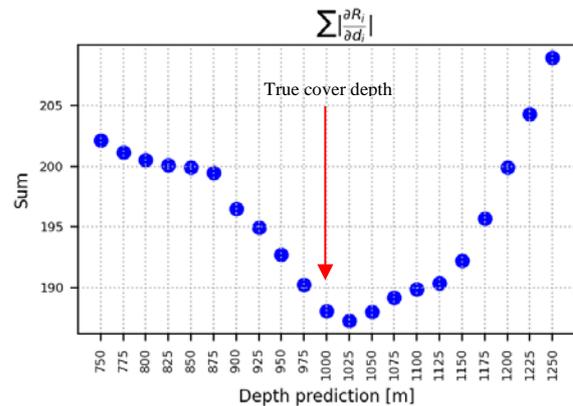


Figure 4. Numerical sum of absolute values of gradients, depth range constrain approach

DISCUSSION AND CONCLUSIONS

There are two possibilities that lowered model roughness penalties could cause sharp resistivity gradients in MT inversion results. When the depth prediction is correct, the model could fit with observations (data) to achieve an appropriate resistivity gradient within the (roughness) relaxed depth range. If the depth prediction is incorrect, the model is trying to describe observations while having unrealistic resistivity model fluctuations inside the relaxed depth window. This model fluctuations could be influenced by the random data noise which is introduced at the beginning of forward modelling to simulate real data.

Initial cover basement interface estimation from HVSR and its uncertainty estimation is central for the constrained MT inversion stability. Therefore, any interface predictions should be based on robust geological-geophysical prior information. With reasonable interface depth predictions with reasonable uncertainty, we could apply this new approach successfully to recover accurate resistivity models and describe the observations within acceptable RMS.

The numerical sum of the resistivity gradient successfully quantified the total gradient changes (model oscillations) in the inverted model. When the depth prediction was close to the true cover depth, inverted models showed the lowest value for the sum of the gradients in relation to the other predictions.

Based on the results and observations mentioned above, we can remark the following conclusions for new constraint approach. Sliding constraints windows could use to draw reasonable depth predictions for cover depth. In this synthetic test, the depth

prediction uncertainty was reduced to 5% of the cover depth estimation initially given by the HVSR.

Smaller sliding window and multilayer stratigraphy scenarios must be checked for the robustness of the new approach.

ACKNOWLEDGMENTS

This abstract is part of a PhD research conducted at Centre of Exploration Targeting, University of Western Australia.

We acknowledge the support of the MinEx CRC and the Loop: Enabling Stochastic 3D Geological Modelling (LP170100985) consortia. MDL is supported by ARC DECRA DE190100431. This work has been supported by the Mineral Exploration Cooperative Research Centre whose activities are funded by the Australian Government's Cooperative Research Centre Programme. This is MinEx CRC Document 2021/24.

REFERENCES

- Castellaro, S. and F. Mulargia (2012). "A statistical low noise model of the Earth." *Seismological Research Letters* **83**(1): 39-48.
- Constable, S. C., R. L. Parker and C. G. Constable (1987). "Occam's inversion: A practical algorithm for generating smooth models from electromagnetic sounding data." *Geophysics* **52**(3): 289-300.
- Key, K., Ed. (2010). *OCCAM1DCSEM: An Open-Source Inversion Program for Generating Smooth 1D Models from Controlled-Source Electromagnetic and Magnetotelluric Data.*, Scripps Institution of Oceanography, University of California, San Diego.
- Mulargia, F. and S. Castellaro (2016). "HVSR deep mapping tested down to ~ 1.8 km in Po Plane Valley, Italy." *Physics of the Earth and Planetary Interiors* **261**: 17-23.
- Wait, J. R. (1954). "On the relation between telluric currents and the Earth's magnetic field." *Geophysics* **19**(2): 281-289.