Inversion-based automatic processing of AEM data

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SUMMARY

Data processing is a mandatory step before inversion for any geophysical inversion, because data outliers significantly affect the inversion process, often forbidding to reach reasonable inversion models and misfits. In the processing of Airborne Electromagnetic (AEM) data, the specificity consists in the necessity to cull out capacitive and galvanic coupled data, with the latter more difficult to recognize in data space alone.
In this study I propose to use a generalization of the minimum support norm, namely the asymmetric generalized minimum support (AGMS) norm, for defining the data misfit in the objective function of an iterative reweighted least squared (IRLS) gauss-newton inversion. The AGMS norm in the data misfit puts a cap on the weight of non-fitting data points, allowing for the inversion to focus on the data points that can be fitted. Outliers can be identified after the AGMS inversion computing a classic L2 misfit from the final inversion model.
Inversions on AEM data with and without manual processing are compared, with the AGMS inversion able to recognize outliers in the same areas in which data are manually culled out because of coupling, with comparable final inversion models. Moreover, the processing scheme can recognize not only data which are affected by noise, but also data that are not modelled correctly, for instance because of the dimensionality of the forward response: in this case, it can be used for identifying the appropriateness of the modelling within the inversion area.
This inversion-based automatic processing scheme is very robust and works well also with a significant number of outliers; furthermore, it is fully general and can be applied not only to AEM data, but to any geophysical problem simply using the appropriate forward modelling.
Key words: processing, Airborne EM, coupling, noise, minimum support

INTRODUCTION

Data outliers significantly affect the inversion process, often forbidding to reach reasonable inversion models and misfits. For this reason, data processing is a mandatory step before inversion for any geophysical inversion. However, different norms can be used for the data misfit in the objective function of the inversion, with different effects of data errors: for instance, the L_1 norm is more forgiving for outliers than the L_2 norm, because the penalty grows linearly with the difference between data and forward response, instead of with the square of the difference.

In this study, I propose to use a generalization of the minimum support norm (Last and Kubik, 1983; Portniaquine and Zhdanov 1999), namely the asymmetric generalized minimum support AGMS norm (Fiandaca *et al.*, 2015), for inverting unprocessed AEM data. With this norm, tailored for data misfit in iteratively reweighted least squared inversion, the weight of outliers in the objective function is capped, and both capacitive coupled data and galvanic coupled data play a negligible role in the inversion, allowing to converge to an inversion model comparable to the one obtainable with processed data.

I present this approach in comparison to a classic manual data processing, both in terms of outlier recognition and model retrieval, on a SkyTem survey carried out in North Italy, in the vicinity of Brescia, for ground water characterization.

METHOD AND RESULTS

The classic L_2 data norm penalizes the square of the penalty $x = d - f$ between data and forward response:

$$\varphi(x) = (x)^2 \qquad (1)$$

The AGMS norm instead is expressed as:

$$\varphi(x) = \alpha^{-1}\left[(1-\beta)\frac{(x^2/\sigma^2)^{p_1}}{1+(x^2/\sigma^2)^{p_1}} + \beta\frac{(x^2/\sigma^2)^{p_2}}{1+(x^2/\sigma^2)^{p_2}}\right] \qquad (2)$$

where

$$\beta = \frac{(x^2/\sigma^2)^{\max(p_1,p_2)}}{1+(x^2/\sigma^2)^{\max(p_1,p_2)}} \qquad (3)$$

In Equation 1 and Equation 2, σ is the data standard deviation, p_1 and p_2 control the shape of the norm before and after $\frac{x}{\sigma} = 1$, and α determines the total weight of the penalty. Figure 1 shows the comparison between the L_2 penalty and the AGMS penalty with p_1=1, and p_2=0.5 and $\alpha = 0.5$.

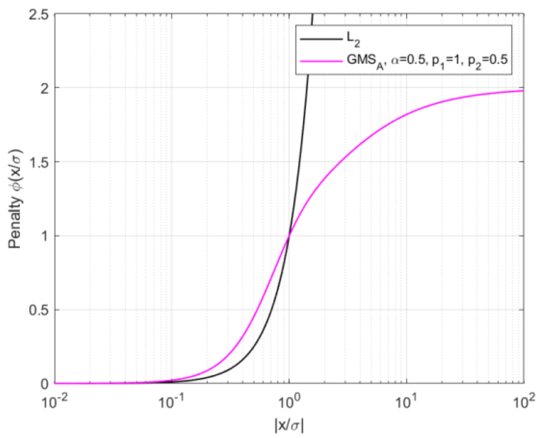

Figure 1. Penalty of the L_2 and AGMS norms as a function of the difference $x = d - f$ between data and forward response, weighted by the data standard deviation σ.

With this choice of values for the norm settings the AGMS norm gives misfit 1 for $\frac{x}{\sigma} = 1$ (i.e. the same value of the L_2 norm), with similar penalty for low misfit (because of p_1=1) and a slow growth of the penalty when $\frac{x}{\sigma} > 1$ (because of p_2=0.5). This slow growth allows for applying the AGMS norm in an iterative minimization process, because a decrease in $\frac{x}{\sigma}$ gives a measurable penalty reduction.

This data norm is applied in an IRLS inversion composed of two inversion cycles: firstly, a cycle with the AGMS norm is carried out; secondly, the data norm is switched to the classic L_2 norm, data above a misfit threshold are rejected, and the inversion is continued until a new minimum is reached. The inversion is carried out following Christiansen *et al.* (2017), i.e. inverting the model resistivity in a regular inversion grid decoupled from the sounding positions.

This new automatic, inversion-based processing scheme is tested on a SkyTem dataset acquired in Brescia (North Italy), for ground water characterization. Data were manually processed in Aarhus Workbench following Auken *et al.* (2009), for culling out both galvanic coupled data and capacitive coupled data, with 6111 soundings (and 108153 total data) kept after processing out of the original 9596 soundings (and 215643 data). No automatic filter nor manual culling were carried out on the data for automatic processing, the only exception being the trapezoidal averaging filter applied for increasing the signal to noise ratio. A uniform 40 m x 40 m xy horizontal discretization and log-increasing depths from 5 m to 400 m were used for inverting both processed and unprocessed data.

The automatic data processing rejected 17.7% of the data, i.e. 38116 data, keeping 177527 data, in comparison to the 108153 data kept after manual processing (+65%). Figure 2 presents the comparison of the number of gates kept after processing, for both low-moment and high-moment data, for automatic and manual processing. Furthermore, a data stripe in the East part of the acquisition area (highlighted by a magenta rectangle in Figure 2) is presented in Figure 3, together with the result of the automatic processing.

The areas of low gate numbers of the manual processing are the same areas in which the automatic processing removes the data, for both low- and high-moment. This happens both where clear noise is present, being it capacitive or random, and where galvanic noise affects the data. The ability to detect galvanic noise depends on the spatial regularization of the inversion: only data that can be modelled by a spatially consistent model are kept by the automatic processing. Furthermore, smooth data that cannot be fitted also in the manual-processed dataset in correspondence to topographical variations are also flagged out as outliers.

Finally, Figure 4 shows a comparison of two depth slices of the inversion models of the manually- and automatically-processed data, at 50 m and 120 m: similar results are achieved, without any clear evidence of artifacts in the inversion of the automatically-processed data.

CONCLUSIONS

The inversion-based automatic processing scheme proposed in this study is very robust and works well also with a significant number of outliers. Despite it cannot fully substitute the manual processing step in AEM data interpretation, it can be an extremely valuable tool both for achieving preliminary results, e.g. in real time, and for helping/guiding the manual data processing, telling to the user when data can be fitted by a smooth inversion model. Furthermore, the automatic processing is fully general and can be applied not only to AEM data, but to any geophysical problem simply using the appropriate forward modelling

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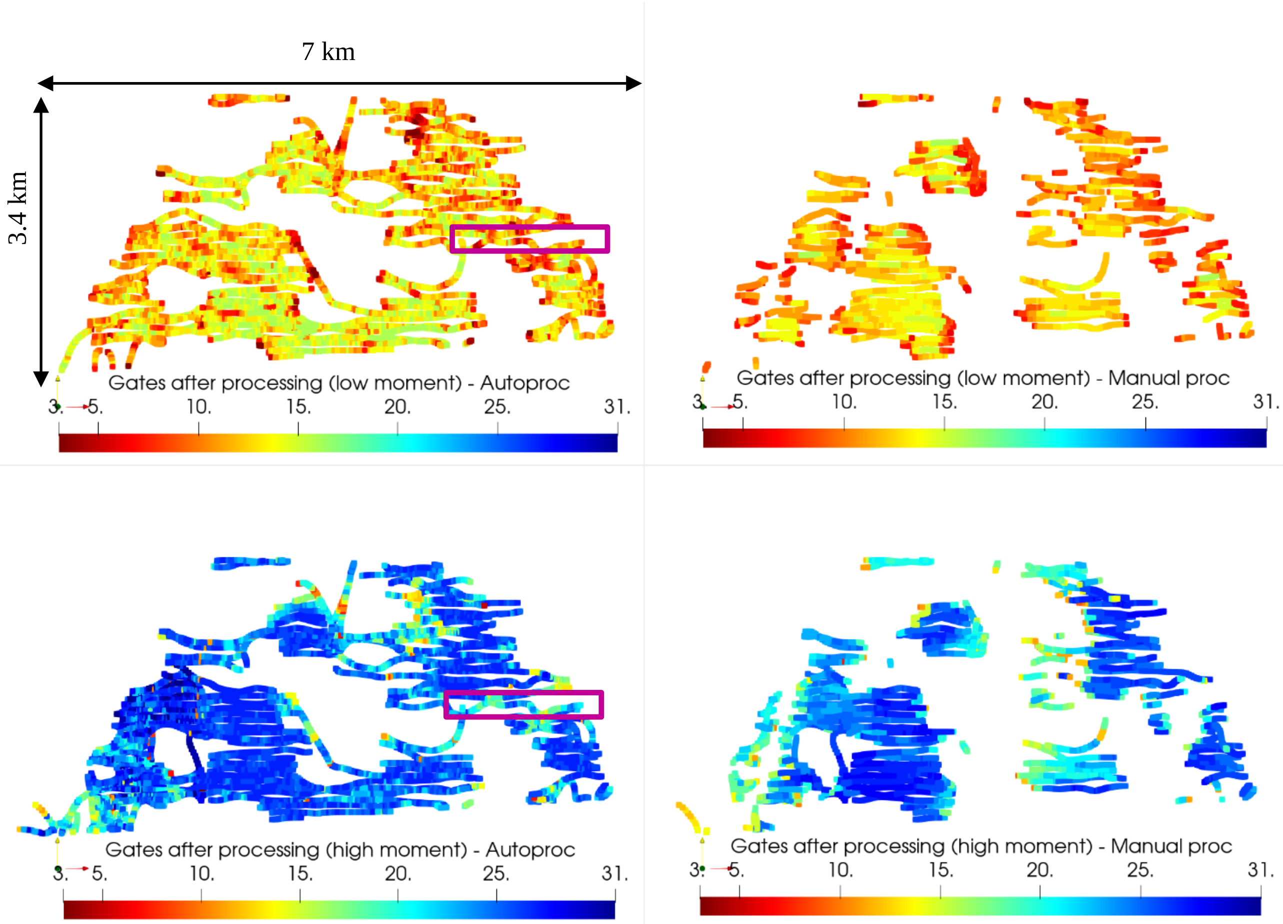

Figure 2. Number of gates after automatic processing (left) and manual processing (right), for low-moment data (top) and high-moment data (bottom) acquired in a SkyTem survey in Brescia (Italy). The magenta rectangles highlight the soundings depicted in Figure 3.

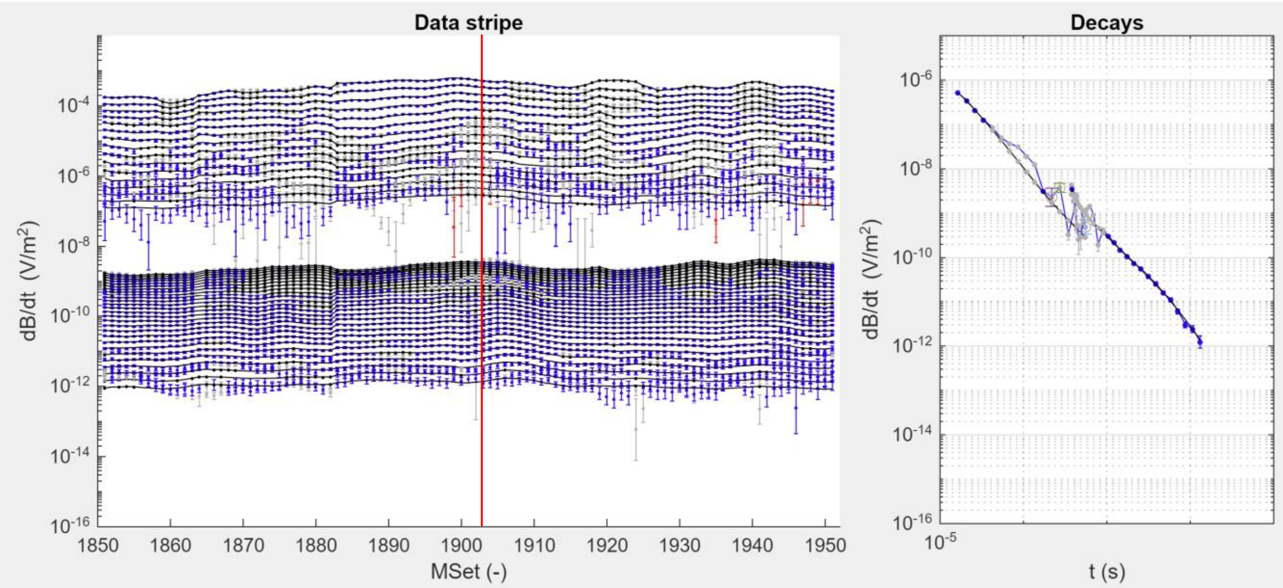

Figure 3. Data stripe and exemplar sounding in correspondence to the magenta rectangle of Figure 2, with positive data (blue markers), negative data (red markers), data fit (black lines) and rejected data (grey markers). The red line in the left panel shows the position of the exemplar sounding shown in the right panel.

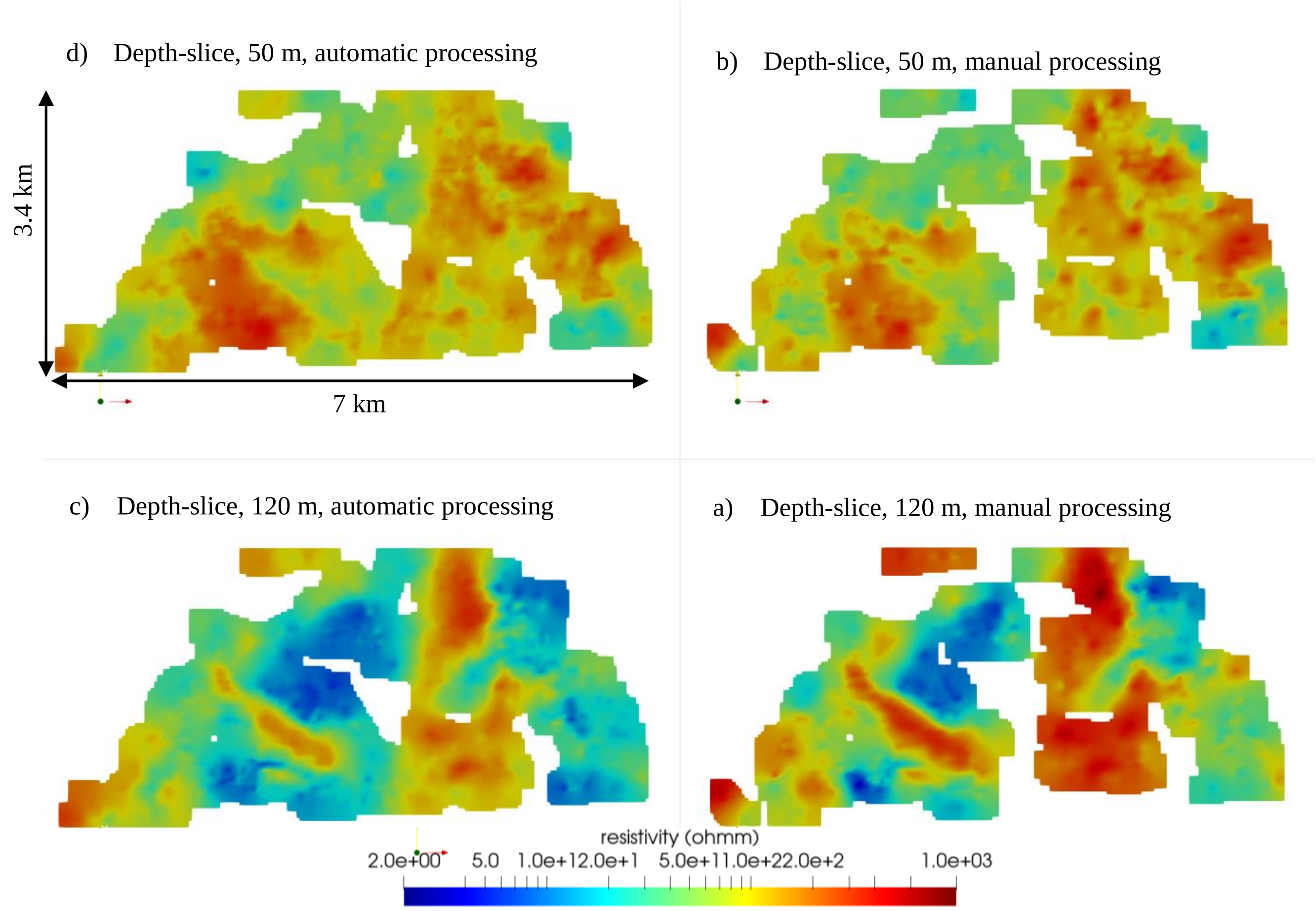

Figure 4. Horizontal depth slices of the resistivity inversion models for automatic processing (left) and manual processing (right) of a SkyTem survey acquired in Brescia (Italy).