Focused attributes derived from AEM surveys using the continuous wavelet transform

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SUMMARY

Interpretation of a hydrogeophysical survey is a complex and comprehensive process. In addition to an areal coverage with AEM data, most often an interpretation involves additional data that are time consuming to collect and complicated to integrate into an overall model, e.g. borehole logs, borehole core samples, water chemistry, surface vegetation, satellite imagery plus the generally accepted geological background knowledge. Compared with the complexities of the interpretation process, the acquisition, QC and inversion of AEM survey data are a more straightforward affair and considerably less time consuming.

Interpretation basically has to do with identifying categories and finding boundaries between them so that depths, thicknesses, lithologies and a whole range of other model attributes can be estimated, qualitatively and quantitatively. To supplement the traditional product delivered by the inverter to the interpreter: inversion models displaying the distribution of subsurface electrical conductivity, I present two methods based on the Continuous Wavelet Transform that can deliver more focused attributes to assist in the interpretation. In the first method, layer boundaries in the smooth multi-layer models that are most often used in the inversion of large data sets are found. In the second method, the spatial distribution of the natural categories of the model parameter is found. Both methods are based on the inversion models and, evidently, they are useful to the extent that the variations in conductivity reflect geological / hydrogeological boundaries and categories - which is for the interpreter to decide.

Key words: Inversion, interpretation, derived attributes

INTRODUCTION

Planning, contracting, data acquisition and processing of a regional airborne electromagnetic (AEM) survey may take of the order of 3-5 months. The inverter's assessment of data quality, reliability of the contractors information on system parameters and noise model and experiments with inversion settings would take from a couple of weeks to a month. Computation time for the final inversion is of the order of days. All up, a total of 4-6 months is needed before the inverter can hand over the results to the interpreter. However, interpreting the product delivered by the inverter, i.e. the distribution of subsurface conductivity (which no one is interested in, really) in terms of geological formations and the most likely hydrogeological models is a much more complex and comprehensive process than collecting and inverting AEM data. An interpretation requires additional data that might be more time consuming to collect and considerably more complicated to integrate into an overall model, e.g. water chemistry, surface vegetation, satellite imagery, borehole logs, and borehole core samples, plus the generally accepted geological background knowledge. A complete picture with the required detail and reliability is only obtained after considerable effort (Lawrie and Christensen, 2015).

Two of the main tasks of the interpretation process are identifying categories and finding boundaries between them so that spatial extent parameters and a whole range of other model attributes can be quantitatively estimated. To assist in this process, tools and procedures that provide suggestions, subsequently to be edited and corrected by the interpreter using interactive visualisation software, would be desirable. There are mainly two approaches to developing such tools: a statistical / machine learning / artificial intelligence approach that, given certain training information provided by interpreter input, provides predictions / suggestions about the parameters in question. Another approach is a deterministic one that from the inversion models extracts attributes more directly useful for the interpreter than the distribution of conductivity, attributes that more directly address the interpreters efforts of categorizing and delimiting. Naturally these would be based on the conductivity distribution with the limitations that entails.

In this abstract I will develop some deterministic methods to derive attributes about layer boundaries and formation categories using the Continuous Wavelet Transform.

THE CONTINUOUS WAVELET TRANSFORM

In this section I will outline the basic principles of the Continuous Wavelet Transform (CWT) and illustrate its use with a traditional application of finding layer boundaries in an electrical log. More detailed presentations can be found in Cooper and Cowan (2009), Davis and Christensen (2013) and Mallat (1998).

A basic use of log information is to identify boundaries between different formations and thus assist the interpreter in a lithological interpretation. An automatic procedure could be useful in suggesting the position of layer boundaries in an objective way to assist in the interpretation, and if furthermore it could provide a hierarchy between the more important and the less important boundaries that would be even better. The CWT is an automatic procedure that does just that.

The CWT is defined as (Mallat, 1998)

$$W\left[f(u,s)\right] = \int_{-\infty}^{\infty} f(t)\,\frac{1}{\sqrt{s}}\,\Psi^*\left(\frac{t-u}{s}\right)dt \tag{1}$$

where s is the scale, u the position, Ψ is the wavelet used and * indicates complex conjugate.

The position of a boundary is now defined as the inflection points of the function, f, i.e. where the second derivative of the function is zero: $f'' = 0$. Using the so-called 'Mexican Hat' wavelet given as the second derivative of a Gaussian function the CWT will deliver the second derivative of f at different scales, s. In the presence of noise, the CWT of f at small scales will produce many more zeros than we are interested in. For increasing scale length, s, the CWT will provide a smoothed version of the second derivative, the number of zeros will decrease, and only the main boundaries will survive. Eventually the user must decide the scale length that is relevant for the situation.

I use discrete binomial filters in the discrete numerical implementation of the CWT. The double differentiation is implemented by discrete convolution with the filter: [1, -2, 1]/4. This gives the second derivative at the lowest averaging level. The subsequent averaging is implemented by repeated iterative convolution with the averaging filter: [1, 2, 1]/4. On every averaging level, the values of the second derivative are stored and the zeros found. The two-dimensional array spanned by the sample numbers of the input array and the averaging level constitute the CWT spectrum. When the averaging process is completed, the zeros of the CWT spectrum are contoured, see Figure 1. Now it is up to the user to choose the appropriate averaging level or - equivalently - the number of boundaries. This is the only parameter that needs to be provided by the user. Finally the original values between the boundaries are averaged to give a mean value of the input array between the boundaries, i.e. the mean layer parameter.

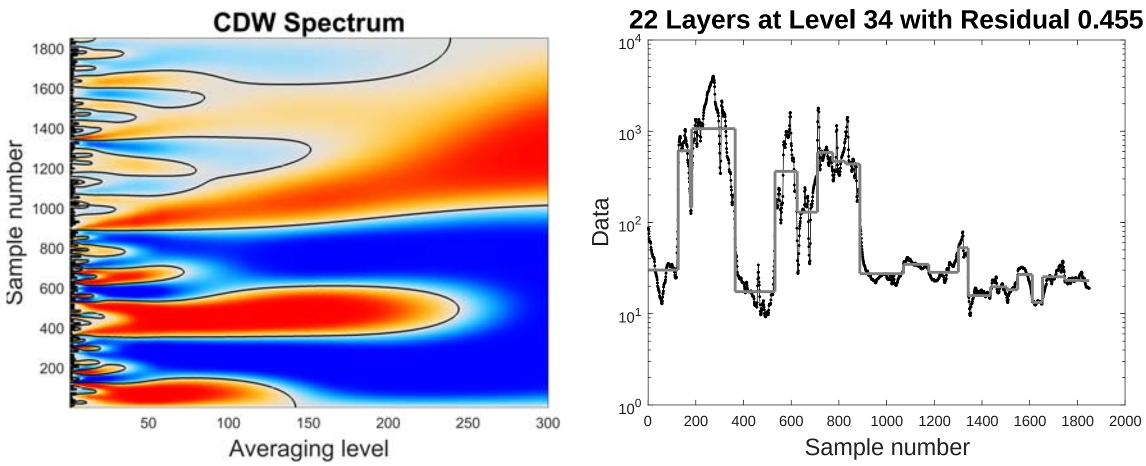

Figure 1: Left frame: The CWT spectrum of the Beder F log. Right frame: A 22-layer piecewise constant approximation obtained using the CWT.

When the user has chosen the number of relevant boundaries by choosing the proper averaging level, the position of the boundaries are chosen *not* as the actual position of the zeros at that averaging level, but by following the zero contours to the zero position at the lowest averaging level. This ensures that the position is found with the best possible precision and that the boundary does not change when more boundaries are added. This establishes a unique hierarchy between the boundaries and ensures that increasing model complexity comes as a subdivision of existing intervals. This is a prominent and very desirable property of the CWT analysis.

Figure 1 shows the CWT spectrum of an electrical log, Beder F, recorded with the Ellog measure-while-drilling auger tool (Sørensen 1999) in East Jutland, Denmark, together with the piecewise constant approximation to the log obtained by choosing 22 boundaries, corresponding to the averaging level with number 34.

USING THE CWT TO FIND LAYER BOUNDARIES IN A MULTI-LAYER MODEL

Conductivity models delivered to the interpreter form the basis for the geological and hydrogeological interpretation which consists in a quantitative delineation of depths to layer boundaries and a qualitative identification of different lithologies. The most often used model for inversion of large AEM data sets is a multi-layer model (MLM), but in modern-day vertically and laterally correlated inversion, conductivity changes appear as gradual and formation boundaries are not immediately evident.

To compensate for the blurry definition of formations in MLMs, I will use the CWT to find the layer boundaries. Figure 2 shows a plot of a typical MLM with 30 layers from an AEM survey. At each MLM layer boundary, the second derivative, taken at the middle point, of the model is found as the third derivative of the 5th degree polynomial defined by 5 consecutive points of the integrated model. A dense equidistant sampling of the piecewise linear function that passes through the values thus defined will then provide the input array to the CWT. Figure 2 shows the CWT spectrum of a MLM and the resulting few-layer model (FLM), and Figure 3 shows a model section of the FLMs created this way together with the original MLM section.

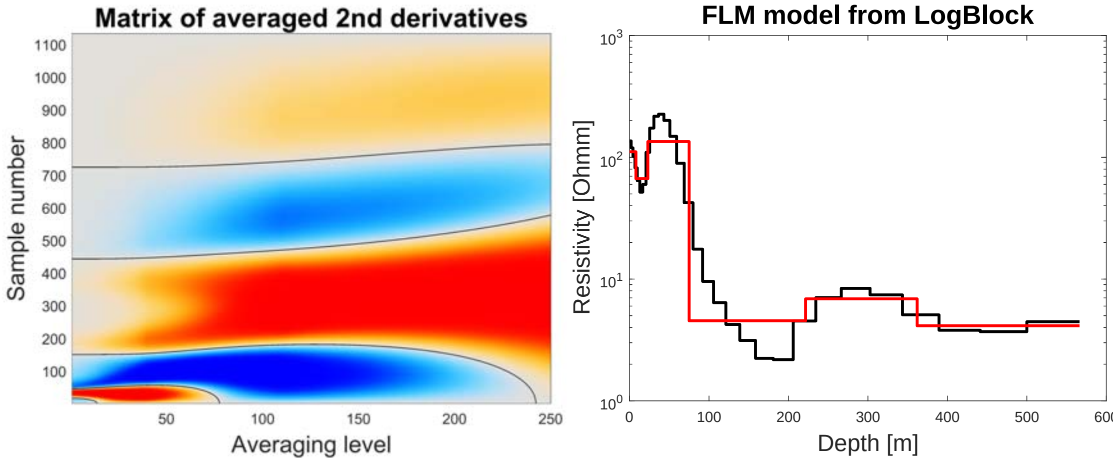

Figure 2: Left is the CWT spectrum of the model log(resistivity) of the MLM shown on the right together with a 6-layer FLM.

USING A CWT ANALYSIS TO IDENTIFY PARAMETER CATEGORIES

The CWT analysis of the previous section is focused on finding boundaries and works on one inversion model at a time. However, in this approach there is no focus on what is actually delineated with the boundaries. It would be desirable to have a method of identifying the basic formations as defined by the parameter values taking a whole survey, or part thereof, into account. In this section I develop a method based on a CWT analysis of finding the clusters / categories / bins for all parameter values of a survey. The procedure is the following: (1) Collect all layer parameters (conductivities | log(conductivities)) from all models of the survey area into one one-dimensional array; (2) Sort the array; (3) Use the sorted array as input array to the CWT analysis. The boundaries found in the CWT analysis are now used to define the end points of the 'natural' intervals of the sorted array values. As seen in the previous sections, the CWT analysis thereby defines a hierarchy between the number of bins. As before, the only user-selected parameter is the number of bins to be used.

Figure 3 shows the original MLM inversion model section of a line from an Australian survey together with the model sections resulting from the layer boundary procedure of the previous section and with the model sections produced using 4 and 7 bins. It is quite obvious that increasing the number of bins results in a subdivision of the already existing bins. Data were recorded with the SkyTEM312 system and the inversion was implemented with a hybrid approach using both the approximate inversion (Christensen, 2016a) and full accuracy calculations. Laterally correlated models were produced using a strictly horizontal Lateral Parameter Correlation procedure (Christensen, 2016b). As can be seen the simplifications obtained by binning are close to what one would expect from a manual categorization of the model section.

CONCLUSIONS

This extended abstract presents the CWT analysis method as a flexible tool for finding attributes in the volume of inversion models from an AEM survey that may be of assistance in the geological and hydrogeological interpretation. Two methods have been developed: The first one focuses on finding the depths to boundaries in the MLM inversion models and ascribes the mean value of the original MLM parameter to the model layers of the resulting FLM; The second categorizes all layer parameters of (parts of) a survey into 'natural' bins as defined by the hierarchical structure of the CWT analysis. In both methods, the CWT analysis offers a hierarchy of boundaries / bins. Naturally, both methods are based on the conductivity distribution only, and the boundaries and categories can only be identified with geological/hydrogeological boundaries and categories to the extent that these depend only on the conductivity - which is by no means always the case. The attributes produced with these two approaches must of course be scrutinised and edited by the interpreter, and they both offer the option of imposing post-processing conditions on the results, e.g. minimum layer thicknesses and minimum contrasts across layer boundaries.

Besides producing helpful attributes - hopefully - the method offers itself to be integrated into machine learning approaches, providing a first deterministic suggestion of formation boundaries which, together with user input, can be used in a machine prediction process.

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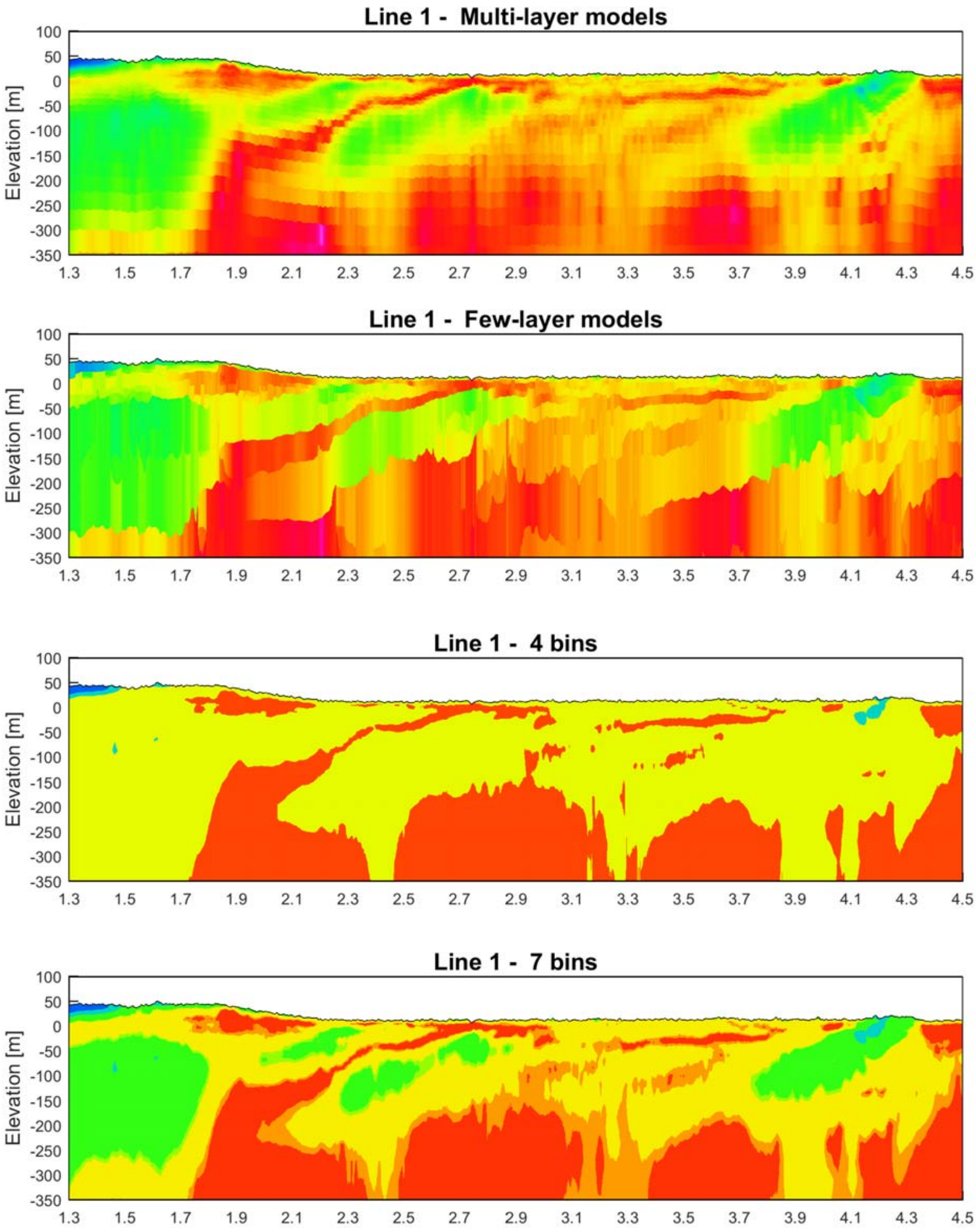

Figure 3: Top left: The multi-layer model section. Top right: The few-layer section from finding layer boundaries. Bottom left: Binned section with 4 bins. Bottom right: Binned section with 7 bins.

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