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Artificial neural networks for efficient removal of coupled airborne transient electromagnetic data

Kristoffer K. Andersen
Aarhus University
C.F.Møllers Alle 4
8000 Aarhus C
Denmark
kka@phys.au.dk

Casper Kirkegaard
Aarhus University
C.F.Møllers Alle 4
8000 Aarhus C
Denmark
casperk@geo.au.dk

Nikolaj Foged
Aarhus University
C.F.Møllers Alle 4
8000 Aarhus C
Denmark
nikolaj.foged@geo.au.dk

Esben Auken
Aarhus University
C.F.Møllers Alle 4
8000 Aarhus C
Denmark
esben.auken@geo.au.dk

SUMMARY

Modern airborne transient electromagnetic (ATEM) surveys typically span thousands of line kilometres requireing careful data processing. When surveys are flown in populated areas data processing becomes particularly time consuming, since the acquired data is contaminated by couplings to man made conductors (power lines, fences, pipes, etc). Coupled soundings must be removed from the dataset prior to inversion, but since the signature of couplings can be subtle and difficult to describe in general terms it has so far remained mostly a manual task.

Here we train an artificial neural network (ANN) to recognize coupled soundings in previously processed data and use this network to identify couplings in other data. The approach provides a dramatic reduction in the time required for data processing, since one can directly apply the network to the raw data. We describe the neural network we use and present the inputs and normalizations required for maximizing the effectiveness of the network. We present the training state and performance of the network and finally compare inversions based on manually processed data and ANN processed data. The results show that a well trained network can produce a high quality processing of ATEM data, which is either ready for inversion or in need of minimal manual processing. The results are very promising and can significantly reduce the processing time and cost of large ATEM surveys.

Key words: Artificial neural networks, AEM, couplings, data processing

INTRODUCTION

When large airborne transient electromagnetic surveys are conducted in densely populated parts of the world, couplings to man-made conductors pose a significant problem in terms of data processing. Most steps of a data processing workflow can be fully automated (Auken *et al.*, 2009), however, removal of these couplings remains a subtle problem that require manual user intervention. Couplings influence the signal to a degree that all coupled data have to be removed from the dataset in order not to introduce model error during inversion. However, since the signature of couplings is hard to describe in general programmatic terms, it is a challenging process to automate. Currently, the process is conducted manually by human visual inspection of all raw data in a survey. This procedure takes up a very large fraction, 50 – 70 %, of the total time spend on the full workflow from data acquisition to final inversion and presentation. Rather than try to describe the behaviour of a coupled sounding in programmatic terms, we now try to produce a collection of coupled and uncoupled soundings and *train* an artificial neural network (ANN) to automatically recognise the differences for us. ANNs are used for many different purposes such as detecting credit card fraud and performing speech recognition. They have also been applied in geophysics with a review of applications given by Poulton (2002). Notably, ANNs were suggested for inversion of EM data as early as the beginning of the 90's (Raiche, 1991) and used recently to invert ATEM data (Zhu *et al.*, 2012) for a simple 2 layer model of the earth. This is however a very restrictive model and of very limited usage.

Apart from some simple analytic methods presented by Auken *et al.* (2009), Reninger *et al.* (2011) have tried to use singular value decomposition for removal of couplings and conclude that it can make the processing less time consuming and subjective. Couplings can generally be divided into so-called galvanic and capacitive couplings (Danielsen *et al.*, 2003). Galvanic couplings are present for example in connection with overhead power lines and give rise to an LR circuit with an exponential decay. The capacitive couplings coming from for example buried cables give rise to LRC circuits with an oscillating part which is exponentially decaying. These couplings are very distinctive and fairly easy to identify on the contrary to the smooth galvanic couplings.

We here train an ANN on previously processed data and use this network to process other ATEM data. With an appropriate network one can readily use the processing obtained by applying the network for inversion, and thereby obtain a high quality inversion result with minimal user intervention. However, one should be careful that the network has been trained on data from a setting similar to what is being investigated, since it will not necessarily respond well to patterns it has never seen before. This problem can be overcome by using a network that has been trained on data from many different locations, or by performing a manual processing of a small part of a large survey and train a neural network on these.

METHOD AND RESULTS

Artificial neural networks are inspired - as the name suggests - by the structure of the brain and capable of some of the same things as the brain such as e.g. pattern recognition. We use a simple feedforward network consisting of ~40 inputs, ~20 neurons in a so-called hidden layer and a single scalar output ranging from -1 to 1. Consider a neuron in the hidden layer, *i*. A weighted sum is made of all the inputs, a bias is added and a transfer function applied. In mathematical terms

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_j + b_i\right),$$

where w_{ij} are weight factors, x_j the inputs, b_j a bias and f_i is the transfer function. There are several choices for the transfer function, but we will exclusively use the tan-sigmoid function

$$f(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}},$$

which smoothly approaches -1 as *t* goes to -∞ and 1 when *t* goes to ∞.

The choice of inputs is crucial since one wants to supply the network with sufficient data to make the correct decision but also avoid supplying superfluous and unnecessary information which might "disturb" the network. To determine if a sounding is coupled we use as an input the derivative of the magnetic field, dB/dt, for 11 time gates, the dB/dt values of the neighbouring soundings (the previous and the next) and the derivative of the flight height before and after the sounding.

Since the networks are generally trained from an initial state with random weight factors between -1 and 1, one has to suitably normalize the data. For the dB/dt values we normalize by

$$x' = sign(x) \cdot log(|x|),$$

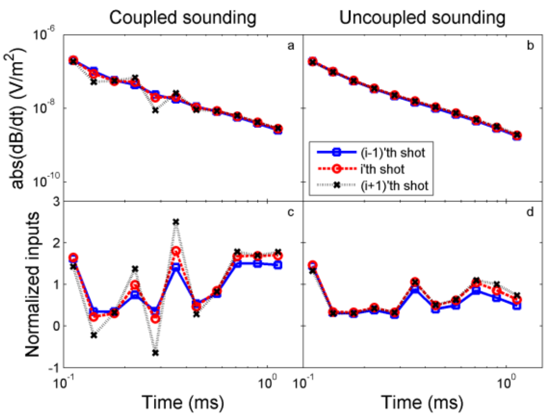

Figure 1. Raw input data for a coupled (a) and uncoupled (b) sounding. Each input contains three soundings, the current and the neighbouring, and two flight height derivatives (not shown here). In (c) and (d) are shown the normalized inputs, which are of order 1.

and afterwards for all inputs we subtract the mean and divide by the standard deviation. The unnormalized and normalized data for a coupled and uncoupled sounding is shown in Fig. 1. Whereas the raw input data covers several decades, the normalized data are in the range +/- 5 and all around 1.

The network is trained on previously processed data, where an experienced geophysicist has already determined whether a given sounding is coupled or uncoupled. Coupled data are assigned the value -1 and uncoupled 1. The output of the network thus becomes is a number between -1 and 1. For the training set the network output and the target is shown in Fig. 2. The output of the network is highly peaked around -1 and 1 and we find an optimal division between the two cases around an output of 0 as expected. Only a few soundings are in the grey zone around the optimal cut. Generally the agreement between the network and manually processed data is around 90 %. This agreement also reflects variations in the way data are processed manually, in particular with respect to how grey area soundings are treated.

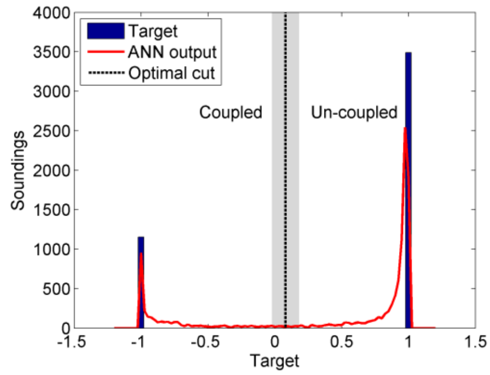

Figure 2. The output of the network compared to the manually found target which it is trained to match. The optimal cut shows where one should divide between coupled and uncoupled to get the best agreement between the target and ANN output.

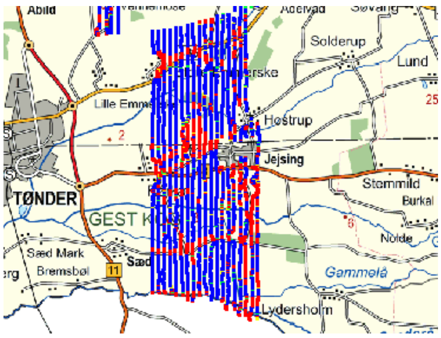

Figure 3. ANN processing of a field example. The blue dots are uncoupled data, red dots are coupled, and green dots are in the grey area. The coupled data lie along infrastructure such as roads as expected.

In Fig. 3 is shown the output of the network when applied to a field example. The red dots are the coupled data. These generally lie along roads and other infrastructure as expected. With this processing one can directly invert the data and get a good result. Such an inversion is shown in Fig. 4 together with the manually processed data. The agreement between the two inversions is very good and the ANN processing actually uses more of the data compared to the manually processed. I.e. it is generally less strict.

CONCLUSIONS

We show that artificial neural networks can conveniently be used to process large ATEM data set. With a suitable network couplings to man-made conductors can be identified in the data and afterwards one can directly invert the data with a good result. Hence, we can significantly reduce the time needed to process ATEM data and hence reduce the cost of a survey. However, one has to choose the network with care and make sure that it has been trained on sufficient data before applying the ANN naively.

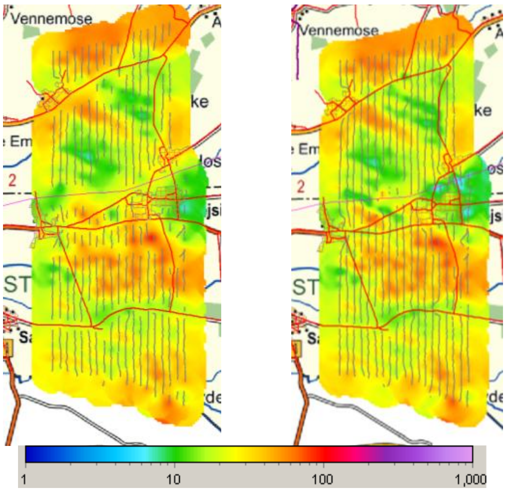

Figure 4. Inversion of manually processed (left) and ANN processed data (right). The resistivities are shown at a depth of 35 m.

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