AEM imaging based on deep neural network system

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\section*{SUMMARY}

Due to huge amount of airborne EM survey data in time-domain, one generally uses imaging to process the data or invert them based on one-dimensional models. Traditional imaging methods cannot be both fast and accurate. To solve this problem, we present in this paper an imaging method based on deep neural network system. The deep neural network learns the functions between the model and the response through the training set and approaches this function by updating the parameter matrix. Compared with traditional neural networks, deep neural networks use a deeper hierarchical structure with a larger parameter matrix that are more suitable for solving complex nonlinear problems. To check the effectiveness of our deep neural network system, we test our imaging algorithm both on synthetic and survey data.

\textbf{Keywords:} Airborne EM, Deep Neural Networks, imaging, inversion

\section*{INTRODUCTION}

Imaging is a special 'inversion' method that does not require initial models and optimization algorithms to regularize the model solutions. The current imaging methods mostly convert the survey data into some intermediate parameters like apparent conductivity and apparent depth, such as in CDI, CDT, EMflow (Huang and Rudd, 2008; Fraser,1978; Macnac et al.,1998). These parameters have certain physical meanings and they can be plotted at different depths to obtain sections that mimics inversion results (Yin et al.,2015). As the imaging method is fast and suitable for processing big dataset, the research on imaging method is particularly important in the field of airborne EM.

Deep learning is a method of machine learning, with powerful ability and flexibility that has been widely used in the fields of image recognition, natural language processing and retrieval engine. As with traditional imaging methods, deep neural network imaging does not require initial models and optimization algorithms. The difference, however, is that one needs to build training sets and test sets for neural networks. The training set is used to update the system parameters, while the test set is used to test the system performance. Traditional neural network technique has been applied in imaging field, e.g. by Zhu et al. (2010). However, due to the relatively low precision of traditional neural network imaging technology, its application is limited. Deep neural network uses the concept of hierarchy to gradually analyze the input of the network, its huge parameter matrix is more suitable for the prediction of complex underground conditions. In this paper, we adopt a network structure that combines CNN (Convolution neural network) and RNN (Recurrent neural network). We use LSTM (Long Short-Term Memory) module in RNN that makes RNN performance even more powerful (Hochreiter and Schmidhuber,1997). We will use both theoretical and field data to test our deep neural network technique.

\section*{METHODS}

We first use the forward modeling program to get the training set and test set for the deep neural network. The training set contains 1 million models with corresponding EM responses, while the test set contains 8,000 models with corresponding EM responses. Since the size of the input matrix for the neural network is fixed, we use the model with fixed number of layers and layer thicknesses. Figure 1 gives the network structure.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{network_structure.png}
\caption{Structure of deep neural network system}
\end{figure}

The network contains five CNNs and one RNN. CNNs are used to extract data features and input to the RNN according in a certain sequence. At Moment (1), RNN predicts the resistivity of the deepest part of the underground formation through the information given by CNN\textsubscript{1}. At Moment (2), RNN...
predicts the resistivity of deeper parts of the underground through the information given by $\text{CNN}_2$ and the information of the previous moment. The process is repeated. RNN obtains the shallowest resistivity of the underground formation at Moment (5).

The input of the network is the normalized EM signal and the flight altitude, the output is the normalized resistivities for each layer (20 layers in total). The response signal and the flight altitude are two completely different physical parameters, and they have different weights on the final imaging results. In fact, the flight altitude is the so-called ‘first-order’ parameter, meaning that it is mostly sensitive to and has large influence on AEM responses. We use the technique shown in Figure 2 to input the flight height. That is to increase the influence weight of flight height on the final imaging result, we copy the flight height information multiple times and input it into the fully connected layer of the convolutional neural network. In this way, the network can access and thus learn the information on flight height.

![Figure 2. Local structure of CNN. The flight height is input multiple times for large influence weight.](image)

**RESULTS**

To demonstrate the effectiveness of our algorithm, we first test the deep neural network imaging method on synthetic model. For comparison purpose, we also calculate the EM responses respectively for a half-sine and a trapezoid transmitting wave. From the randomly selected inversion results shown in Figure 3, we can see that our imaging algorithm works well. Moreover, we also calculate the root mean square (RMS) errors of the entire test set and display them in Figure 4. Based on the statistics, 80% of samples have RMS less than 0.02, and 95% of samples have RMS less than 0.03. This implies that the deep neural network system performs well throughout the test set.

![Figure 4. Error distribution for test set.](image)

**CONCLUSIONS**

Deep neural network system imaging is accurate, fast with a high resolution. The imaging results from our deep neural network system method can well match the results of traditional Occam’s inversion. Combining the techniques of CNN and RNN, the network can finish training at a high speed, so that it can complete the processing of AEM data even for large survey area.

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Figure 3. Imaging results using deep neural network method in comparison with real model. The models are randomly selected from test set. For each model, the right side shows the comparison of AEM responses.

Figure 5. Comparison of deep neural network imaging and Occam’s inversion results