DEEP LEARNING BASED EXPERT SYSTEM TO AUTOMATE TIME-DOMAIN ELECTROMAGNETIC DATA PROCESSING

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Transient Electromagnetic (TEM) methods are routinely used to obtain detailed understanding of the subsurface, which may be used for a variety of applications such as groundwater mapping and mineral exploration. Modern TEM surveys, employing driving or flying during data collection, result in large datasets that may contain thousands of line kilometers of data. Parts of these data will often be contaminated by interference from man-made conductors, e.g. fences, buried power lines, known as "couplings". If such disturbed data are inverted, the geological interpretation will be severely degraded in most cases. Therefore, couplings must be identified and removed from the data before inversion. The process of removing couplings is a time-consuming and highly sophisticated manual task. Machine learning based methods have been suggested as obvious automation tools, and the general approach has so far been to use large datasets of manually processed TEM data in a supervised learning approach. The problem with this is that it may be biased to local geological conditions and/or biased toward the individuals who perform the manual assessment (for instance a conservative versus optimistic coupling removal approach).

Here, we present an alternative approach where we consider coupling recognition as an anomaly detection problem. We employ an algorithm based on a deep convolutional autoencoder as an expert system to distinguish between coupled and uncoupled data in an automated manner. Since autoencoders are unsupervised learning methods, we make use of synthetic TEM data of a huge ensemble of realistic subsurface models for its training. The autoencoder is trained to learn an encoded representation of synthetic TEM data in a reduced dimensional space. A reconstruction part is also trained that decodes the encoded representation aiming to output a dataset similar to the original input. Therefore, if uncoupled data are observed by the autoencoder, it will reconstruct the data from its encoded representation with low error. However, when dealing with couplings, the reconstruction error will be elevated, indicating a non-geologic anomaly. We define the size of anomaly as the relative error between the input data and the reconstructed output normalized by the data standard deviation.

We test our expert system on data from more than 20 different areas mapped by a towed TEM (tTEM) system and show that the proposed approach displays high quality data processing within a fraction of a second. The proposed method gives most value in areas with significant infrastructure where manual processing is more demanding. Due to the unbiased nature of the training dataset, our algorithm is generalizable to practically any tTEM data set acquired worldwide. Most importantly, the complex data processing task has been eliminated and no highly skilled operator is required, which would make these systems more accessible to non-expert end-users. Here, the deep learning network is designed for the tTEM system, but it can be modified to any TEM system, airborne or ground-based, but it does require the building of a database with forward responses from realistic models using that particular system setup.

In the presentation, we will present the deep learning algorithm and show several case applications where the proposed approach is compared against the traditional manual processing.