Using convolutional neural networks to classify UXO with multicomponent electromagnetic induction data

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Summary

Electromagnetic induction (EMI) methods are commonly used to classify unexploded ordnance (UXO) in both terrestrial and marine settings. Modern time-domain systems used for classification are multicomponent which means they acquire many transmitter-receiver pairs at multiple time-channels. We developed a convolutional neural network (CNN) that classifies UXO directly from EMI data. Analogous to an image segmentation problem, our CNN preserves the spatial dimensions of the input and produces a high-resolution classification map. The CNN is trained using synthetic data generated with a dipole forward model considering all possible UXO and clutter objects. A physics-based parameterization of the clutter classes is used to maximize clutter discrimination. Our approach was tested on data acquired with the UltraTEMA-4 system in the Sequim Bay marine test site. Including spatially correlated noise in our training dataset significantly improved our classification results for field data. For this test dataset, our CNN-based approach detects all UXOs and discriminates ∼70% of the clutter.

Keywords: electromagnetic induction, UXO classification, convolutional neural network

Introduction

The use of EMI systems to detect and classify UXO on land is well established. Recently, systems such as the UltraTEMA-4 (Funk et al., 2022) have also been designed for underwater munitions. Advanced systems aim to reduce costs related to excavation and interrogation by discriminating non-UXO objects in a single pass. These systems usually rely on many sources and receivers and create spatially dense data which has high information content since the targets are illuminated from different angles.

The usual workflow for clearing a site consists of generating a map from EMI data from which anomalies of interest are picked, then classification is done for each of these anomalies and a target list is obtained. Picking anomalies from a gridded image created from sensor data is done by setting some threshold value of amplitude chosen to maximize the detection of ordnance expected at the site without including anomalies from sensor noise or smaller items. Once the anomalies are picked, classification is done using a physics-based inversion approach where polarizability curves are estimated from the EMI data. These curves are then compared with those in a library to look for a match based on some misfit and a class is assigned (see e.g. Pasion et al., 2007).

In this work, we develop a workflow that takes EMI data directly and produces a classification map using two CNNs from which a final single class may be assigned to each anomaly detected. Both CNNs have the same architecture but the first one is only used to detect anomalies from metallic objects while the second creates the classification map.

Methods

We use two CNNs to detect and classify UXOs from EMI data. The input for the CNNs was defined as a two-dimensional data map considering a fixed number of transmitter cycles in the along-track direction and the spatial extent of the receivers in the cross-track direction. Analogous to an image segmentation problem, our CNN outputs a classification map that preserves the spatial dimensions of the input (Figure 2). The label masks used for training are defined using the magnitude of dB/dt (computed from x,y,z components measured at receivers), adding them up for all the transmitters and thresholding this sum at a specific value (Figure 3). Data is processed per-line using a fixed sliding window with steps equal to one and a simple voting scheme is used to get a single class value per receiver location.

We train the CNNs using synthetic data generated with a dipole forward model considering all possible UXO and clutter objects. This forward model uses polarizability curves from a library; each object in the library has three polarizability curves associated with three orthogonal axes aligned with its geometry. This dipole model has been shown to be accurate for compact objects such as UXOs. The clutter objects were designed based on the following physics-based parameterization for the polarizability curves (Pasion & Oldenburg, 2001):

$$L(t) = kt^{-\beta} \exp\left(-t/\gamma\right) \tag{1}$$

Where $L(t)$ denotes the polarizability as a function of time t and k, β and γ are parameters related to the decay of the EM signal in the object. Using this model, we estimate the values of k, β and γ for the UXOs in the library. Since we have a polarizability curve $L(t)$ for each of the three axes, there are a total of 9 parameters to be estimated. Then, we set a distance threshold value, above which, the remaining parameter space is filled with values that we attribute to clutter (Figure 1).

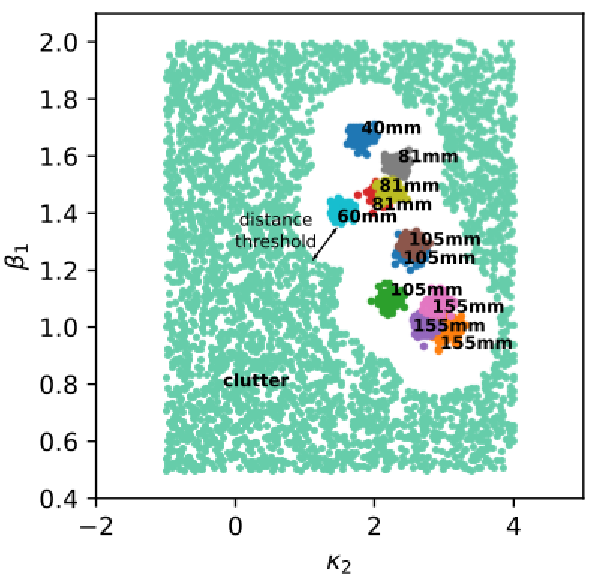

Figure 1: Parameter space depicting clutter design strategy; shown is a simplified 2D parameter space while our approach uses a 9-dimensional parameter space.

The architecture of both CNNs is the same but the first one is trained as a binary classifier that outputs a map which labels data as either background or TOI (target of interest) whereas the second one is a multi-class classifier that outputs a map with UXO type class. This two-step approach is mainly done due to the need to separate anomalies and background data in order to estimate spatially correlated noise from the field data and add it to the training data. This step was found crucial to improve classification results of field data with our CNN.

The output of the second CNN is a classification map which may also be expressed as a set of probability maps, each showing the data points likelihood of belonging to a certain class. To obtain a single class for each anomaly identified, we simply take the average probability values for all data points within a certain cell surrounding the anomaly (such cells are picked manually from the previous binary map) and select the class with the highest average probability (Figure 4).

Test data

We tested our approach using field data acquired with the UltraTEMA-4 system in the Sequim Bay marine test site (Funk et al., 2022). The first CNN of our workflow was trained with 20,000 examples of synthetic data and binary label masks, while the second CNN was trained with 400,000 examples of data and multi-class label masks. Classification results for the field data show that our approach detects all UXOs and discriminates ~70% of the clutter (Figure 5).

A preprocessing step was used to remove the EM response of conductive seawater and sediments but some spatially correlated noise still remains in the data. Our workflow is able to cope with this by using the first CNN to separate background signal from anomalies in the field data. Then, we randomly sample pieces of this background signal and add them to the training dataset of the second CNN.

Discussion

A key feature of our CNN is its segmentation-like architecture. Compared to a first version of the CNN (Heagy et al., 2020), this new architecture is able to provide higher-resolution classification maps which do not require interpolation and therefore is less likely to miss small objects. However, our CNN has not been trained for multi-target scenarios (two objects close together i.e. in the same spatial window) hence it may lead to errors for such cases. In future work, we plan to explore this multi-target scenario by including these cases in the training dataset of our CNN.

The clutter design is also an important part of our approach. As with any machine learning approach, the CNN needs to be trained with examples not only of all UXOs but also with all possible clutter objects. The physics-based parameterization used here (Equation 1) attempts to exhaustively cover all possible clutter objects by setting a distance in the parameter space. The value for this distance has to be tuned in order to maximize clutter discrimination without decreasing UXO detection. This distance may be chosen using a line of synthetic data that includes both UXOs and objects with the expected dimensions of clutter and/or with a field calibration line that is usually available for UXO clearance projects.

Other choices such as grouping the UXO objects, adding random noise to the training dataset and averaging probabilities for overlapping (sliding) windows have also slightly improved the performance of our second CNN.

Conclusion

Modern EMI systems used for UXO classification collect spatially dense data with sufficient information to classify different types of UXO and discriminate clutter. The traditional approach for classification is based on inversion and polarizability curve matching. We developed a CNN-based approach for UXO classification directly from EMI data. Our approach uses two CNNs, the first one for anomaly detection and the second one for classification. Their architectures follow an image segmentation structure where the output preserves spatial dimensions of the input and therefore produce high resolution classification maps. The CNNs were trained with synthetic data using a dipole model and considering UXOs and all possible clutter objects, which were designed in a physics-based parameter space. Spatially and temporally correlated noise that is consistent with that of the field is also added to the training dataset to improve classification results. Our workflow was applied to marine EMI dataset from a test site where it successfully detected all of the UXOs while discriminating ~70% of the clutter.

Acknowledgments

This work is supported by SERDP project MR22-3487.

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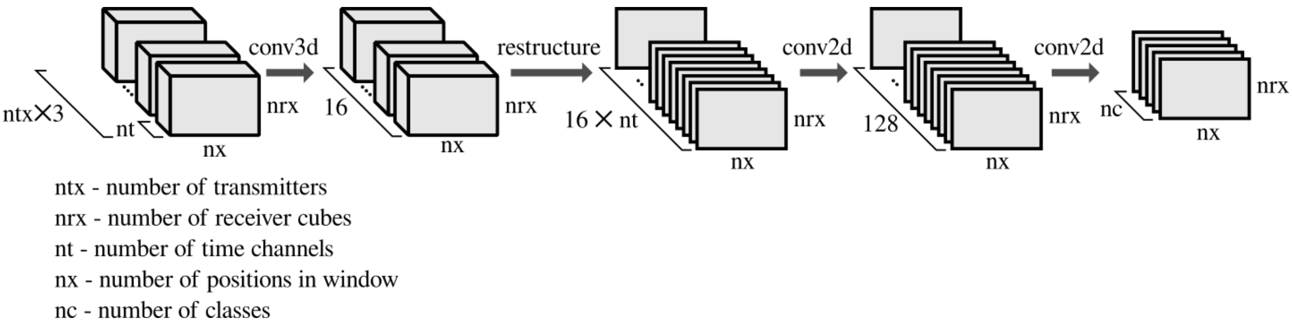

Figure 2: Proposed CNN architecture to detect and classify UXO directly from EMI data.

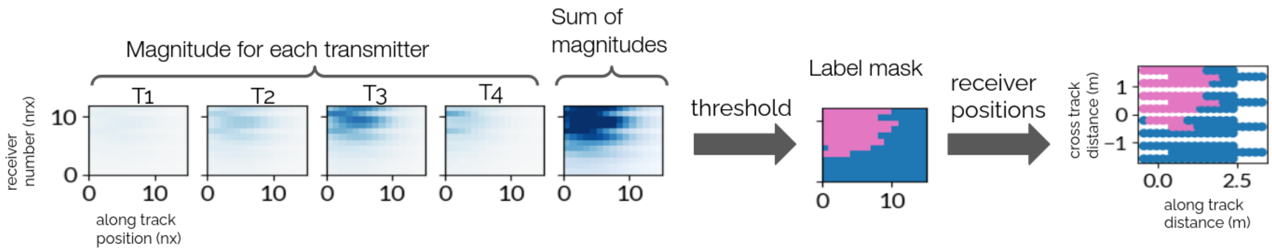

Figure 3: Defining label masks from EMI data.

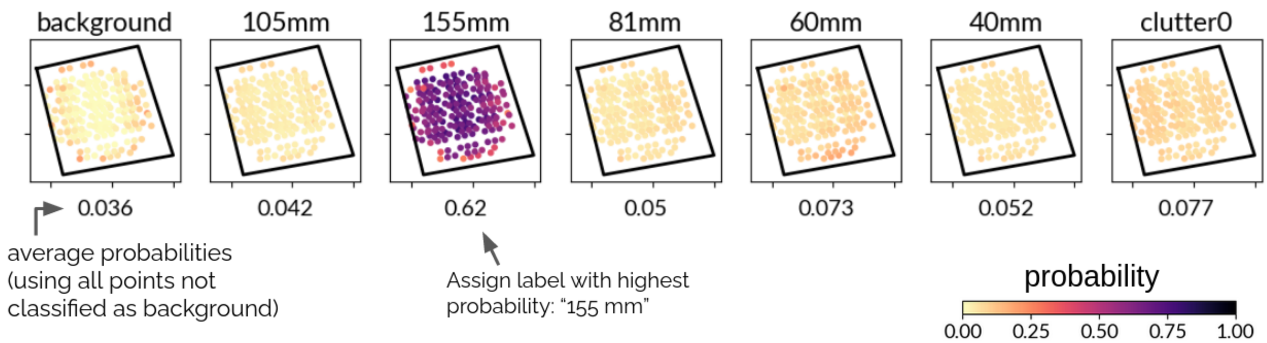

Figure 4: Computing average probabilities to assign a final label from the CNN output.

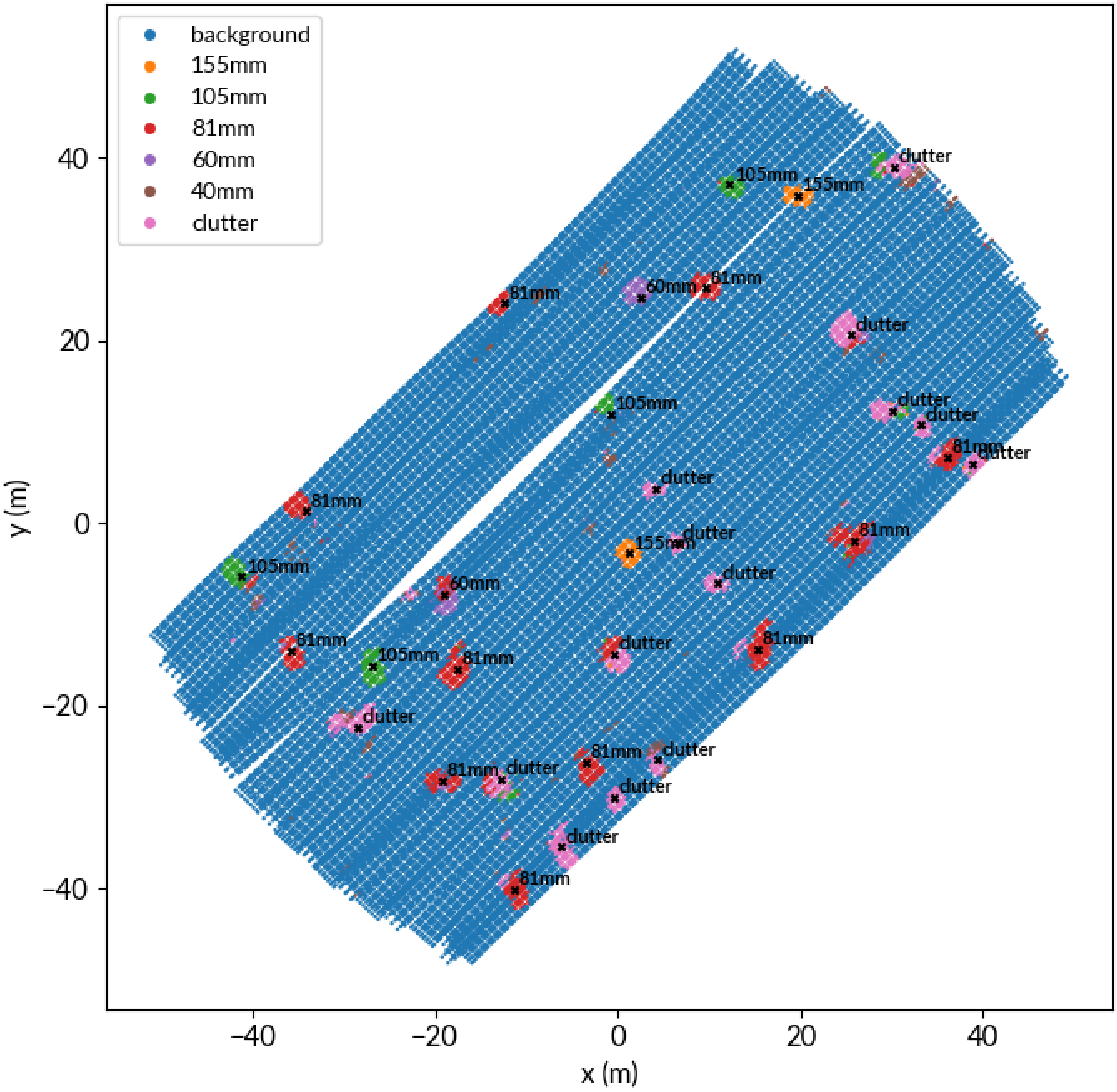

Figure 5: Classification for Sequim Bay field data (2021), colors indicate the classification map produced by the CNN and shown labels are given by our voting system.