APPLICATION OF AN ARTIFICIAL NEURAL NETWORK FOR AIRBORNE MAGNETIC DATA DISCRIMINATION

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Abstract

The objective of this work was to develop and apply an artificial neural network (ANN) to discriminate ordnance from non-ordnance based on input derived from airborne vertical magnetic gradient data. The project assessed whether more output classifications are beneficial and/or required for effective and consistent discrimination, e.g. large ordnance, small ordnance, scrap, and geology. While it may ultimately be possible to determine ordnance type using ANNs, for this project we got best results with the fundamental classification scheme: UXO or not UXO.

Introduction

Artificial neural networks (ANNs) are computational constructs that attempt to mimic the workings of the human brain with respect to the brain's ability to detect patterns. ANNs can be trained to determine which class an object belongs based on selected inputs. The inputs are weighted according to their relevance in determining the class of an object. This process is shown in **Figure 1** for a simple one layer neural network.

The set of weighting values (w) is determined by setting up a series of linear equations in which the inputs and outputs are known, and then finding the solution for w in a least squares sense. Once the weights have been established, the ANN can be tested on other data to see if the predicted output matches the known data class (Lawrence, 1994).

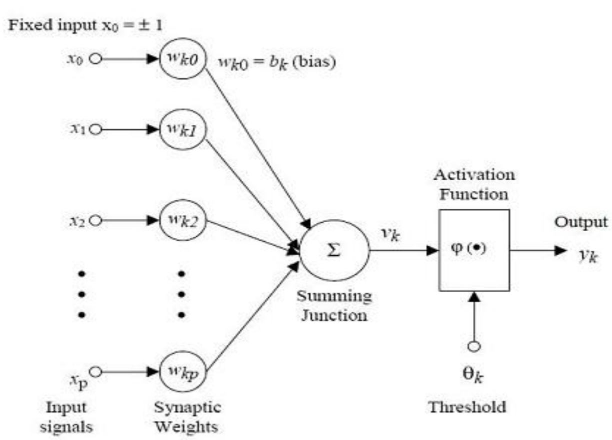

Figure 1: A one-layer artificial neural network showing major components: inputs x, weights w, summing function Σ, activation function φ, and output v.

In our specific case, we wanted to predict whether the source of a magnetic anomaly was produced by ordnance. The output classes fell into one of two categories. Either the item of interest was unexploded ordnance (UXO) or it was not unexploded ordnance (non-UXO). This latter category included geology, fragments from exploded ordnance, and non-ordnance items, for example: tools, bailing wire, automobile parts. The class of ordnance only included ordnance items that were 40mm or larger. The input consisted of anomaly amplitudes and parameters derived from least squares inversion of the magnetic data for a single dipole source—e.g., dipole magnetic moment, depth of burial of the source, orientation of the source dipole, and the least squares goodness of fit.

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Technical Approach

The first step in developing a ANN is to create a training set for consisting of existing airborne magnetic anomaly data acquired over known items, both ordnance and non-ordnance. A dipole inversion was used to estimate the depth, size, magnetic dipole moment and dipole orientation.

These parameters, along with the anomaly classification (UXO or not UXO) were fed into an ANN software packaged called BrainMaker, by California Scientific. The weighting coefficients were determined through an iterative process known as back-propagation. The sum of the multiplicative product of the inputs and the weighting coefficients was then entered into a universal function approximator. This approximator, a sigmoid function, provided probability output (i.e. chance of being UXO/not-UXO). The reliability of the ANN was verified and validated using a subset of data with known solutions that were not included in the original training set.

Our technical approach can be simply expressed in the following five step sequence:

1. Select magnetic data sets suitable for testing with ANN algorithm. 300-500 anomalies are needed for algorithm testing. Preferably, data have been collected with the Battelle VG-16 or VG-22 systems. The sources of the geophysical anomalies must be known and item descriptions provided.
2. Perform automated inversion on magnetic anomalies to obtain inputs for use in ANN (magnetic moment, orientation, depth of burial). Put together a database which includes item descriptions, inversion parameters, and any other parameters that might be useful in ANN classification.
3. Use a subset of ANN inputs from (4) to deduce appropriate weights for ANN classification algorithm.
4. Test accuracy of ANN classifier on the remaining ANN inputs.
5. Compare ANN classification with standard classification based on ordering of anomaly magnitude.

Step 1 – Anomaly selection

Step 1 involved the identification of airborne magnetic data sets with suitable target documentation to use with the neural net algorithm. This required identification of the magnetic anomalies that were appropriately described as ordnance, fragments, magnetic rock or soil, or non-military objects. This was the most labor-intensive part of the project. We were able to identify about 500 magnetic anomalies from various magnetic data sets collected using Battelle's VG-16 and VG-22 boom-mounted helicopter systems. Shown in Figure 2 is a sample data set used in the project. The data are vertical magnetic gradient data from Battelle's West Jefferson UXO Test Site. At this site we have precise information on the type of ordnance buried. In addition to the West Jefferson data, we selected anomalies from Battelle surveys at Kirtland Air Force Base in Albuquerque, NM; Isleta, NM; Badlands Bombing Range, SD; Camp LeJeune, NC; and Twenty-Nine Palms, CA.

We were unable to obtain enough well-documented anomalies with vertical gradient data alone, so we chose additional anomalies from earlier total magnetic field surveys. It was necessary to mathematically generate vertical gradient data from the total field data. The transformation was necessary because we wanted to be consistent in Step 2 (inversion using vertical gradient data).

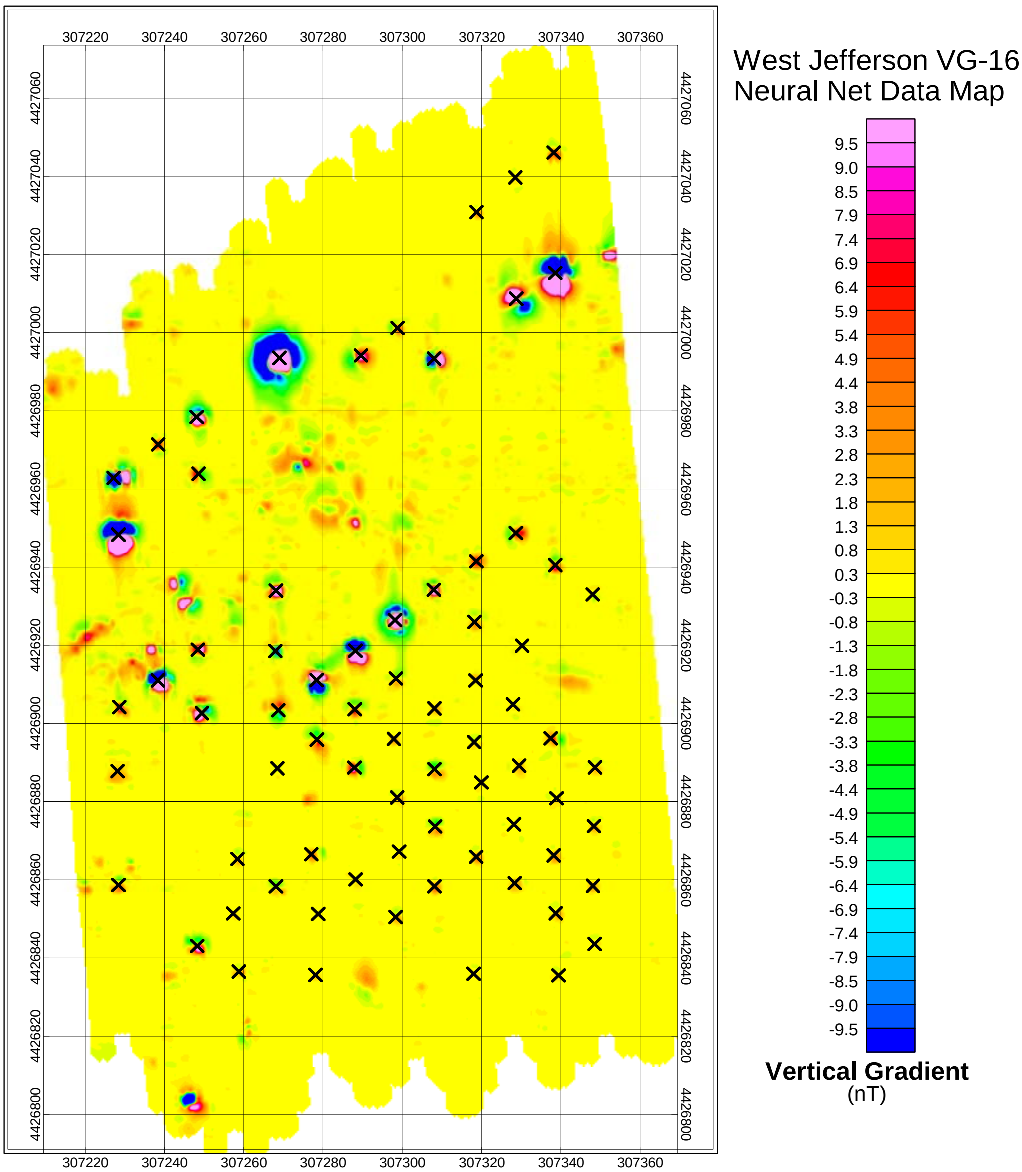

Figure 2: Airborne magnetic vertical gradient map of Battelle's UXO Test Site at West Jefferson.

Step 2 – Dipole inversion

Step 2 was to perform an automated inversion on the magnetic anomalies to obtain input parameters for use in ANN (magnetic moment, orientation, depth of burial) and to construct a database which included item descriptions, inversion parameters, and any other parameters that might be useful in ANN classification. A total of 1462 anomalies were inverted and included in this database.

Step 3 – ANN training

In this step we used a subset of ANN inputs from Step 2 to deduce appropriate weights for ANN classification algorithm. Of 1462 total targets, 1170 (80%) were used to train the neural network. A screenshot of the network training is shown in Figure 3. The histogram shows the distribution of misfits between the desired output (1 for UXO item, 0 for non-UXO) and the actual output. While intuition would dictate that the ideally trained network would have all the misfit values at or very close to zero, this is actually not the case. If a network is trained to the degree that it works perfectly for all the training data points, then it will not be able to generalize to future data. To put it in human terms, the network will simply memorize the correct answers instead of learning the more generally applicable patterns that will allow it to perform well on future data that was not part of the training set. There is no exact rule for how far to train a network; numerous trained networks have to be applied to test data in order to find the optimal training level for any particular application.

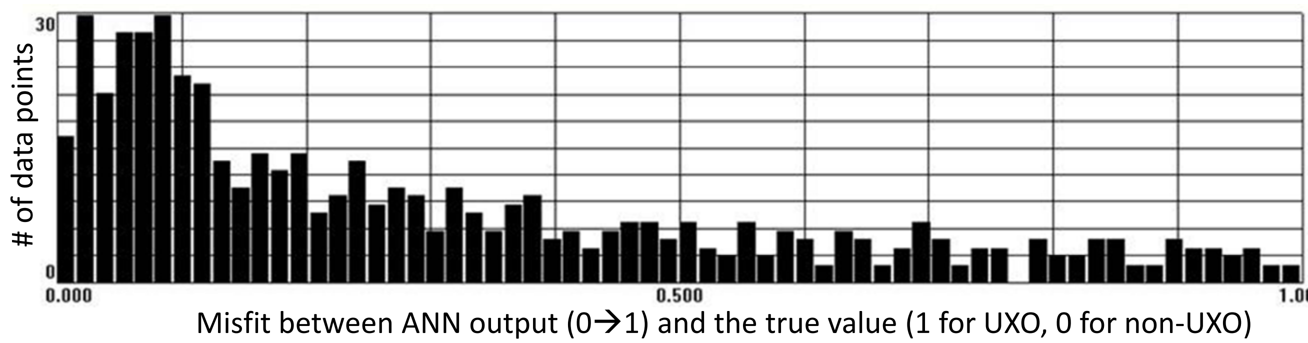

Figure 3: Distribution of misfits between the desired output and the actual output.

Step 4 – Testing the trained network

In order to test the accuracy of the ANN classifier we applied the trained network to the remaining ANN inputs. Results show that the ANN significantly improves the capability to predict whether the source of an anomaly is intact ordnance or non-ordnance (magnetic geology, exploded scrap, non-ordnance metallic objects). The ANN result shows that ordering by neural network probability of being UXO places the seed items--all of which are ordnance--high in the list, and non-seeds (mostly exploded fragments) low in the list. This is summarized in Figure 6.

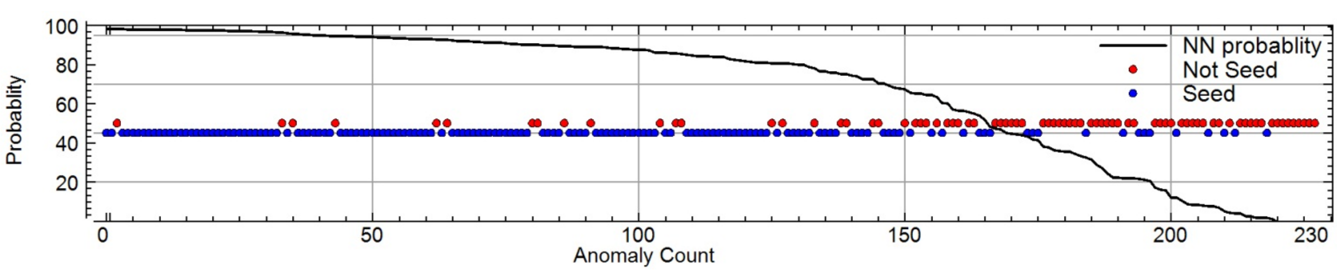

Figure 6: All test anomalies, sorted by the ANN determined probability of being UXO items. There is an obvious grouping of non-seeded (mostly exploded fragments) to the lower probably end of the plot.

Step 5 – Comparison to anomaly amplitude sorting

The final step was to compare ANN classification with standard classification, which is based on anomaly magnitude. An industry standard for determining the effectiveness of an anomaly classification scheme is a Receiver Operating Characteristic (ROC) curve. This is a plot of the total true UXO items picked versus the total number of false picks generated. Thus the ideal curve would be as marked, a vertical line at the far left switching to a horizontal line across the top representing 100% total detection at the start of the list with no false positives. This is not generally achievable, so the goal is to get as close as possible to this line. As shown in the image, the Neural Net based prioritization is closer to the ideal line than the line that represents sorting by amplitude alone.

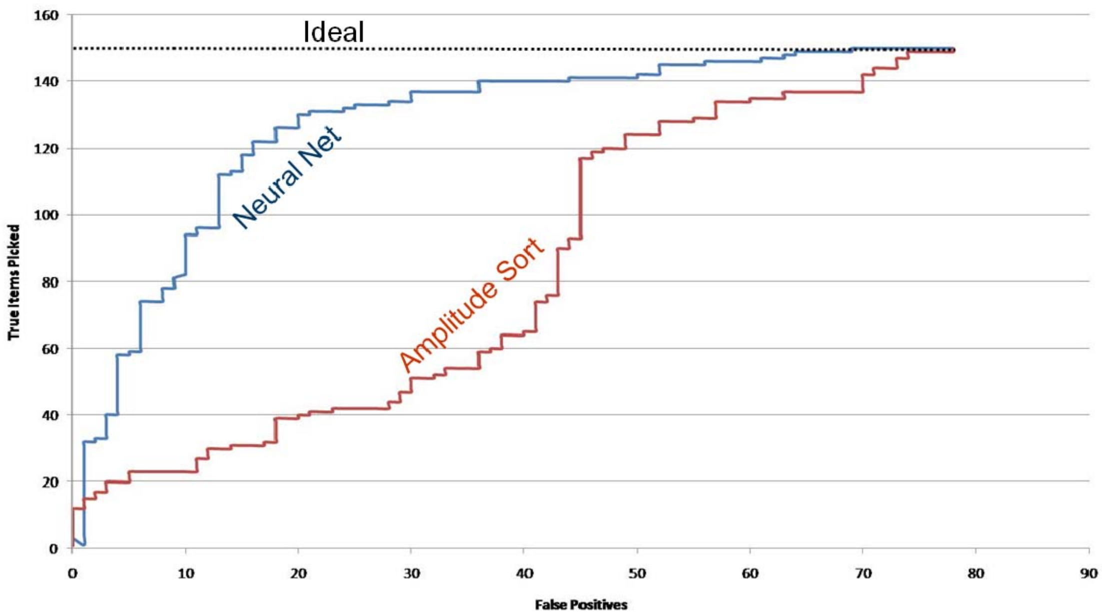

Figure 7: ROC curves for test data set sorted by the neural net ranking (blue) and anomaly amplitude (red). The black dashed line represents the ideal discrimination, where all items of interest are detected with zero false positives.

Conclusions

We have successfully trained and tested an artificial neural net for use in discriminating between intact UXO items and other magnetically responsive items, ranging from geology to UXO fragments. The significant improvement in discrimination over using anomaly amplitude alone has been clearly demonstrated. This should help reduce the number of picks that require intrusive sampling, which in turn will save time and money during the remediation phase of UXO remediation.

References

Lawrence, J., Introduction to Neural Networks: Design, Theory, and Applications. http://www.calsci.com California Scientific, 1994.