STATISTICAL AND NEURAL TECHNIQUES FOR PROCESSING OF NONPARAMETRIC GEOPHYSICAL MINE DATA

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ABSTRACT

This paper analyzes the effectiveness of combining certain statistical techniques with a neural network to improve land mine detection. The detection method must not only detect the majority of landmines in the ground, it must also filter out as many of the false alarms as possible. This is the true challenge to developing landmine detection algorithms. Our approach combines a Back-Propagation Neural Network (BPNN) with statistical techniques and compares the performance of mine detection against the performance of simple statistical techniques such as the energy detection method and the stand-alone statistical techniques. Our results show that the combination of these techniques with a neural network improves performance over these alone.

Key-words: Geophysical signal processing, mine detection, artificial neural networks.

1. INTRODUCTION

Antipersonnel landmines are devastating weapons of war, but they are equally devastating after a war. The vast majority of landmines in use today around the world have no means of self-neutralization or self-destruction. Millions of antipersonnel mines are estimated to be buried in the ground of forty countries. They kill or maim more than 2000 civilians per month and prevent the return to productive activities of vast areas of land. Demining activities are supported by several humanitarian organizations, at an estimated cost of $800 per mine found [4]. Therefore there is a real need for technologies which can render demining more effective, more cost-effective and safer. Unexploded ordnance (UXO) creates very similar problems, both in areas where armed conflicts have taken place, and in military bases and training areas which need to be returned to civilian usage.

A number of novel technical approaches to the demining problem have recently emerged based on various sensor technologies, and recent research has been directed at making effective use of these technologies to obtain greater accuracy in mine detection and in organizing searches through the minefield [1, 5, 6, 7, 8, 9]. The whole field of mine detection is now poised to achieve significant scientific developments. All technical approaches which have been recently proposed for accurately detecting mines and minimizing false alarms are based on obtaining better sensors, and on exploiting sensory data using on-line or off-line algorithmic processing of data from single or multiple sensors. Data fusion techniques that can take advantage of the complementary characteristics of different sensors are also of interest. The recent availability of multisensory data [2] from calibrated minefields, and from minefields which actually represent a real challenge to detection algorithms, are particularly useful.

The sensory data measured in the minefield is corrupted by clutter due to a variety of man made artifacts, but it is also affected in an unpredictable manner by inaccuracies in registration (which refers to the exact positioning of the sensory measurements with respect to the known location of the target), by the naturally inhomogenous nature of the terrain, and by a variety of natural occurring objects (such as rocks) or local irregularities in the terrain. Thus, sensory data is naturally or artificially very noisy, and this is both a source for errors in mine detection and for a very large number of false alarms. As a result, the sensory data contains errors which cannot easily be characterized using a standard statistical representation.

In [1] a new approach (the -Technique) based on measuring differences in reflected (or induced) energy in contiguous areas, was shown to be an effective and computationally very fast approach to accurately detecting mines and significantly reducing false alarms. In this paper, we consider improvements on this approach using neural network techniques and an additional measured statistic which we will call the *S*-Statistic. The *S*-Statistic is combined with the -technique and a learning Back-Propagation Neural Network (BPNN) [10] to obtain significantly improved mine detection algorithms.

We propose a BPNN architecture, denoted *BPNN*(,*S*), which is a feedforward neural network model. The network is trained on two features extracted from the data in the mine field: the -value and the *S*-Statistic. This approach uses data from a small calibrated area to train the network, which is then used for mine detection over much larger areas. Our experimental evaluation using available sensory data [2] shows that the trained network architecture can be effectively used in areas which are geographically remote from the calibration area. It is also effective when tested with sensory data obtained with EMI sensors which have different characteristics from those which were used to collect the network training data.

1.1 The Geophysical Minefield Data

The minefield data we use in the present study is based on measurements provided by DARPA [2], with two different electromagnetic induction sensor systems, at a variety of geographic locations. This data has been collected in a series of systematic minefield sensing experiments conducted at multiple locations implanted with decoy mines and mine-like objects, with a variety of sensors. The first sensing system considered is a Geonics EM61-3D [13] three-component time domain sensor. It consists of a multichannel pulsed induction system having a 1 m square transmitter coil and three orthogonal 0.5 m receiver coils which are positioned approximately 0.3 m above the ground. The second system consists of a 0.5 m Geonics EM61 pulsed induction sensor equipped with two co-planar 0.5 m coils with a vertical spacing of 0.4 m. The sensor height above ground level is again approximately 0.3 m. Specifically, the data we will use represents the measurements collected in a roughly 100×100 square meter area for four different regions. In order to be consistent with the description provided in [2], we will use the following names for these regions which have significantly different clutter characteristics, as well as different target (decoy mine) locations. They will be referred to as Firing Point (FP) 20, Seabee and Turkey Creek. An example of EMI energy data is shown on Figure 1, for 1m Z Coil measurements obtained by DARPA [2]. The area which appears to have zero energy is simply one for which we do not have any data (e.g. it may just not have been surveyed). Inspection of the figure shows the significant amount of clutter.

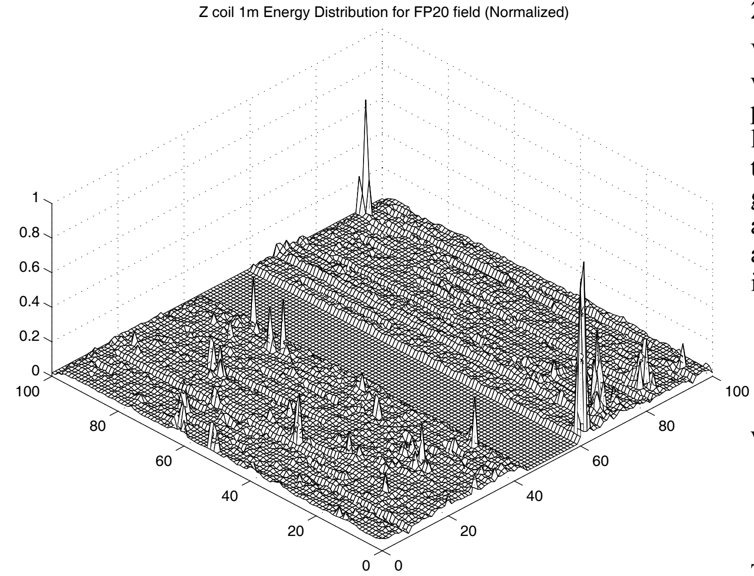

Figure 1: Geonics EM61-3D sensor Z coil 1m resolution data at FP 20. The z-axis show the normalized energy value of the coil, and x and y axes are x and y positions in the minefield.

2. THE ENERGY DETECTOR, THE -TECHNIQUE AND THE *S*-STATISTIC

An energy detector is a simple and useful detection technique which will report an “alarm” – i.e. a location which may possibly contain a mine – on the basis of some measured response energy value which exceeds some given threshold [2, 3]. Since it is the simplest possible detection technique, we will use it as a basis for comparison with other methods. With a low enough threshold energy value, an energy detector will yield very high probabilities of detection of mines but will also lead to unacceptably high false alarm rates. Handling false alarms in the minefield can be almost as expensive as removing a real mine. Since thousands of false alarms can occur in sweeping a relatively small minefield, it is important to be able to devise techniques which provide a high probability of detection, with false alarm rates which are much lower than those resulting from the energy detector.

One such improved detection technique is the -Technique reported in an earlier paper [1] which significantly reduces false alarm rates by making use of neighborhood or area information around each location. It uses the following statistic of the $Z - coil$ data from an electromagnetic induction (EMI) sensor:

$$D_n(p) = \frac{E(p) - E(p_n)}{E(p)}, \quad (1)$$

where p is any point in the minefield, $E(p)$ is the EMI energy level measured by the $Z - coil$ at point p, and $E(p_n)$ is the energy level measured at an immediate neighbor p_n (there are 8 of them) of point p. The idea in using this statistic is to stress that relative energy values are more significant indicators of the presence of a target, than absolute levels or differences in energy. We call D_n the *Local Relative Energy*. Notice that $D_n(p) \leq 1$, and that it can take unbounded negative values.

2.1 The *S*-Statistic

When we analyze the energy profiles at the mine locations, we realize that the energy is higher than that at neighboring points. If we assume that this is generally true for most mine locations, and we further assume that in non-mine locations this property does not hold true, then we would have a very good indicator that will help us identify mine locations. Just as the -Technique exploits this property, we propose a new and very effective statistic using this type of local difference information, which we call the <u>*S*-Statistic</u>, where:

$$S = \frac{E(p) - (8-m)/8 \quad {}_{All\ p_n} E(p_n)}{E(p)} \quad (2)$$

where $m = 7$ or $m = 8$.

3. A NEURAL NETWORK MINE DETECTOR USING THE -TECHNIQUE AND THE *S*-STATISTIC

The neural network approach we propose compensates for clutter by making use of neighborhood information. Thus the advantages of using a neural network include the following: real-time operation (depends on the neural network structure - the one used in this paper supports it), adaptability to unstructured and not previously known environments, robustness to the presence of non-standard noise, fault tolerance via adaptivity, parallel processing of sensor data and capability for direct hardware implementation.

In this section we combine the *S*-Statistic with the -Technique in a neural network design. The approach we propose is based on learning. It exploits data from a small calibrated area to train a neural network which can then be used for mine detection over much larger areas. We will show that the trained network can be robustly used in areas which are geographically remote from the calibration area, and that it can even be used for mine detection with EMI sensors which are different from those which produced the training data.

3.1 The *BPNN*(,*S*) Structure

We will now discuss the specific neural network architecture which will be used for mine detection, and the learning procedure which uses calibration area data based on the S-Statistic and the -Technique. The network is only trained with Z-coil $1m$ data from the $30m \times 15m$ calibration area of a site known as Firing Point 20 (FP20) [2].

We use a three layer feedforward back-propagation neural network (BPNN) to detect mines and reject false alarms (see Figure 2). The network has two input neurons. When the network is either trained for some location p, or when it is asked to provide a decision (mine or non-mine) for the location p, one input neuron receives the input $s = \frac{E(p)-(8-m)/8 \quad E(p_n)}{E(p)}$ and the other receives $= m/8$ where is the -Technique parameter and m is the number of immediate neighbors required whose energy values are strictly less than the center point's energy value.

In the network's output layer, there are two neurons which are used to decide between the two hypotheses (mine or a non-mine) for the location for which input data is presented. The network has six intermediate (hidden) layer neurons.

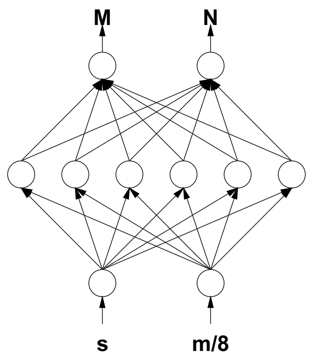

Figure 2: BPNN Detector with inputs s and $= m/8$ (BPNN($, s$)

In the training phase, one output designated as M is trained to produce the value 1.0 for mine locations and the value 0.0 at non-mine locations, while the other output designated N is trained for the opposite result. Since the output neurons M and N will take values between 0 and 1 according to the BPNN model, we use the ratio of M to N to make a decision, as described below.

The calibration data consists of registration targets, other targets for calibration, and the so-called system "stressing" targets [2]. The first two target groups have been designed to calibrate radar and EMI systems (we only deal with the latter in this paper), and the stressing targets are used to determine whether these sensors are achieving the desired sensitivity and effectiveness.

The network is trained using the BPNN learning algorithm [10]. The weights from the input neurons to the intermediate layer, and from the intermediate (or hidden layer) to the output neurons, are adjusted so as to minimize the cost function:

$$E = \frac{1}{2}[(R-M)^2 + ((1-R)-N)^2] \quad (3)$$

where R is the ground truth information about the location being searched. For training, R has a value of 1 if there is a mine, and 0 if not and this training is carried out over all locations p in the calibration area.

In the decision phase when the network is being applied to data it has not observed previously, we use the decision variable:

$$D = \frac{M}{N} \quad (4)$$

When the input values s and for a given location are presented to the network and if $D > 1$ the location is declared to contain a mine; otherwise it is declared not to contain a mine. Clearly, just as with any other detection algorithm, the neural network is not "perfect" so that the probability of a false alarm is not 0, and the probability of correct detection of a mine is not 1. However, as we shall see below, its performance is remarkably good with little training and across different EMI sensors.

4. EXPERIMENTAL RESULTS

This section summarizes the performance achieved using the Back-Propagation Neural Network for land-mine detection.

After training the BPNN network on the calibration data, it was tested for all available data which includes measurements from both $1m$ and $0.5m$ EMI sensor systems (6 separate sets), for all the data including calibration and "center square" areas. The center square is a $100m \times 100m$ area in which registration targets are placed. Since the energy measurements vary from one site to another and also for different sensory systems, we prepare the results with zero threshold energy level. We report the results of the energy detector and the $BPNN($ $,S)$ applied after $= 7/8$ and $= 7/8$.

The results for the three minefield sites with two different sensors used, are given in Table 1. For all sites we observe that the BPNN based techniques achieve substantial reduction in probability of false alarms over the -Technique and the energy detector, though it may not find as many actual targets as the -Technique.

Location Names	FP 20		Seabee		Turkey Creek	
Data Sensor	1m	0.5m	1m	0.5m	1m	0.5m
Points searched	8406	7896	11134	10395	8109	7945
No. of Mines	21	24	24	24	24	24
FA detected: Energy det.	8385	7872	11110	10371	8085	7921
Mines detected: Energy det.	21	24	24	24	24	24
FA detected: = 7/8	2067	1381	2628	1746	2014	1463
Mines detected: = 7/8	21	23	24	24	24	24
FA detected: $BPNN($ $,S)$	978	588	1291	853	985	719
Mines detected: $BPNN($ $,S)$	20	23	24	23	24	24

Table 1: ANN Improvement for Reducing False Alarms for Different Sites with 1m and 0.5m Z-coil Data

The Receiver Operating Characteristic (ROC) for FP20 is plotted as shown in Figure 3. Each ROC curve represents the relation between the probability of detection and the probability of false alarms for a certain detector. Three ROC curves are plotted: (i) for the pure energy detector, (ii) for the -Technique, and (iii) for the $BPNN($ $,S)$.

It can be seen that the BPNN detector provides better performance than the -Technique, and both have significantly better performance than the pure energy detector. For example, from Figure 3 to obtain a 0.08 false alarm probability, the probability of detection will be 0.5 for the pure energy detector , 0.57 for the -Technique, and 0.80 for the $BPNN($ $,S)$.

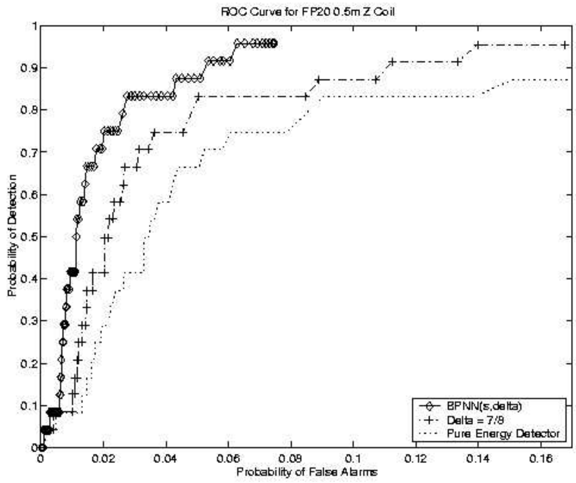

Figure 3: ROC curve for FP20 using 0.5m Z coil data

We noticed similar improvements for the data from the other sites.

Of course, the ANN based technique requires training, and is therefore more complex and computationally more costly than the -Technique. Notice also that for a certain value of the probability of detection, there may be multiple values of the percentage of false alarm reduction. This is because it sometimes occurs that, as we vary the energy threshold, the probability of detection remains unchanged while the false alarm probability varies.

5. CONCLUSIONS

In this paper we have proposed a back-propagation neural network based algorithm for mine detection and false alarm filtering. It is shown through the use of experimental data that the proposed network is very effective in detecting mines and rejecting false alarms.

Although BPNN training needs to be conducted off-line and is computationally costly, the actual exploitation of the algorithm by feeding point-by-point data and obtaining the network's output is a real time computation. Both of these aspects can be carried out on a low cost portable personal computer. Furthermore, the learning phase can be significantly accelerated by a hardware implementation.

All experimental results we present here, based on all available data from EMI sensors provided in [2], both with $1m$ and $0.5m$ sensors from two different instruments, support the following claims:

- A BPNN detector offers a robust non-parametric technique for mine detection. It out-performs the – *Technique* and the energy detector significantly.
- The BPNN mine detector can be trained on limited calibration data, and the trained network then performs in a robust manner in a wide variety of geographic locations with measurement data which it has not 'seen' before, and with data from sites with very different clutter conditions.
- The BPNN detector's robustness appears to transcend the particular sensor (and resolution) used. Specifically, a BPNN detector trained with limited $1m$ data at one site performs accurately at all sites, even with $0.5m$ data obtained with another sensor.

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