Numerical Modelling and Neural Networks for Landmine Detection Using Ground Penetrating Radar

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***Abstract*—A numerical modelling case study is presented aiming to investigate aspects of the applicability of artificial neural networks (ANN) to the problem of landmine detection using ground penetrating radar (GPR). An essential requirement of ANN and machine learning in general, is an extensive training set. A good training set should include data from as many scenarios as possible. Therefore, a training set consisting of simulated data from a diverse range of models with varying: topography, soil inhomogeneity, landmines, false alarm targets, height of the antenna, depth of the landmines, has been produced and used. Previous approaches, have employed limited training sets and as a result they often have underestimated the capabilities of ANN. In this preliminary study, a 2D Finite-Difference Time-Domain (FDTD) model has been used as the training platform for ANN. Although a 2D approach is clearly a simplification that cannot directly translate to a practical application, it is a computationally efficient approach to examine the performance of ANN subject to an extensive training set. The results are promising and provide a good basis to further expand this approach in the future by employing even more realistic, but computationally expensive, 3D models and well-characterised, real data sets.**

I. Introduction

Since their first use in World War I [1], landmines (both anti-tank and anti-personnel (AP)) have been increasingly used giving rise to the so-called "landmine crisis" [1]. According to the International Committee of the Red Cross (ICRC), in the last fifty years more damage has been done from AP landmines than nuclear and chemical weapons combined [2]. Demining aims to tackle this problem and researchers in this field are trying to further develop the processes of demining in an attempt to improve its efficiency while maintaining its safety. A number of methods have been suggested over the years, from the frequently used and one of the first demining methods, metal detector (MD) [3] to trained dogs, chemical methods [4] and others. GPR is considered as a mature and well established approach for demining which has been extensively used and validated [5], [6], [7].

GPR for landmine detection is a multi-parametric problem. Landmines can be found in varied environments, e.g., in deserts, in urban environments, in jungles and many other, often complex, settings. As has been shown in [8], performance of GPR can be sensitive to scenario and currently no single automated processing and interpretation approach can be reliably used for every case. The great variation in the shape, location and characteristics of the targets as well as of the GPR transducers may result in substantially different outputs making the development of an integrated processing approach a very challenging task. However, this non-linearity and large diversity inherent in the demining problem makes it a suitable candidate for machine learning and specifically for ANN [9].

In [10], C-Scans measured from a specific minelane were used to train a feed-forward neural network. Principal component analysis (PCA) was also employed in order to reduce the dimensionality of the problem. Further results are given in [11] in which different methodologies were applied in an effort to reduce the dimensions of the model and increase its training efficiency. In [12], data from a single minelane were employed as a training platform for ANN. In contrast with [10] and [11] a single GPR trace was used in order to retain the applicability of the ANN to handheld devices that often do not offer accurate positioning information. B-Scans, after simple post-processing were used as inputs in [13], but again the training set was measured at a single minelane. In [14], a hybrid complex-valued ANN was employed in order to use both magnitude and phase information from eleven distinct frequencies (0.8-1.2 GHz) as inputs. It is interesting to note that in [14] a step by step classification strategy was used. This initially isolates targets from their background and subsequently a classification could take place between those targets. A single minelane was employed as a training platform, as for previous approaches

In order for ANN to assist landmine detection they must perform equally well in a variety of complex environments and not only on data from a single minelane. In that context, to our knowledge, no study has tried to illustrate the ability of ANN to address this problem. The present paper examines the performance of ANN subject to a large database of simulated GPR responses created in an attempt to adequately represent some of the key characteristics of complex environments that are often encountered in GPR landline detection. The responses are calculated using a 2D FDTD model. Although

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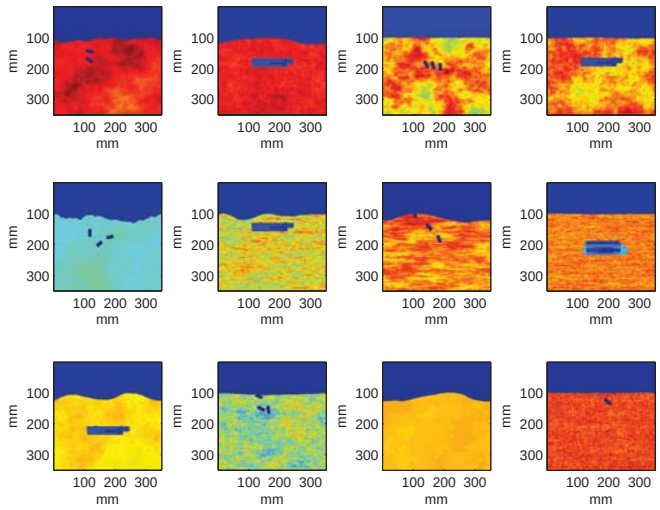

Fig. 1. A sample of the models used to synthetically evaluate the training set.

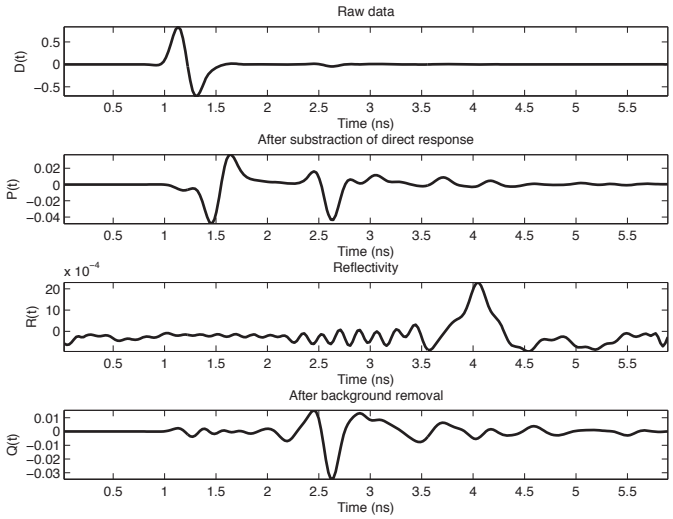

Fig. 2. Simulated data collected over a model of a PMN landmine. The first image illustrates the raw simulated data, in the second image the free-space response has been subtracted, in the third image the smoothed reflectivity (see (1)) is calculated and in the fourth the free of clutter A-Scan is illustrated (see (2) and (3)).

an ANN trained with a database of simulated responses from a 2D model is not directly applicable to real world cases, it can nonetheless provide an initial appraisal of the performance of ANN in a diverse set of different scenarios. The resulting simulated receiver operating characteristic (ROC) curves for the suggested ANN are found to be promising, reinforcing the view that a further expansion of this approach to the more computationally expensive, but more realistic, 3D case [8], and extensive testing using real data, should be pursued.

II. ANN TRAINING SET

One of the most important aspects of ANN is their training database [9]. To our knowledge, no published work has ever strongly focused on the quality of the training set. Limited data can result in a low resolution feature space. In addition, non-equally distributed data (e.g., imbalance between the number of data associated with the output patterns) can result in a low convergence rate of the training process and to an over-trained ANN biased to one pattern. To overcome this, Plett et. al. [12] replicated traces associated with landmines in an attempt to balance data with and without landmines. This brute force approach manages to overcome issues related with imbalanced data (low convergence, etc.) but the low resolution of the feature space still remains.

The training set we employed deals with both aforementioned problems using a 2D FDTD model [16]. The numerical scheme used is a 2D equivalent of the one suggested in [8]. Rough surface and soil inhomogeneity are simulated using fractals. Regarding the dielectric properties, a semi-empirical model suggested by [15] and used in [8] is employed. The GPR antenna is simulated as an idealised line source. The input pulse is a Gaussian modulated sinusoidal source with central frequency 1.2 GHz. The targets used in the simulations are 2D models of the AP landmines PMA-1 and PMN. Models of bullets are also included in an effort to add false alarm targets and increase the complexity of the simulated scenarios. Bullets are modelled as perfect electrical conductors (PEC). The discretisation step of the uniform 300×300 mm FDTD grid was $\Delta x = \Delta z = 1$ mm. The time step is equal to the Courant limit for the 2D case $\Delta t = 2.357$ ps. [16].

The pre-processed inputs to the ANN are simple traces (A-Scans) similar to [12]. The source is placed at the centre of the model at a variable height above the interface. In the model, the fractal dimensions of the soil's moisture distribution, the roughness of the surface, the height of the transmitter, the existence or not of landmines, the type and the depth of the landmines – when present in the model – and the number of any simulated bullets, are randomly chosen in an effort to keep the training set equally distributed while increasing its size. With such an approach, a diverse set of realistic models are part of the training set. Fig. 1 illustrates a sample of the models used as the training platform for the ANN. The actual training set consisted of 4,000 traces from an equally distributed set of models covering a wide range of possible scenarios. Note that landmines were always placed in the centre of the model. This was deliberate in order to avoid the so-called "outliers" – obtained when the antenna is placed over the edge of a landmine – which reduce the performance of ANN [12], [14].

III. PRE-PROCESSING

Apart from the quality of the training data, another equally important parameter of ANN is data pre-processing. The raw simulated data contain all the information available, nonetheless, this information is not trivially accessible to ANN. Pre-processing addresses this problem by making the input data more readable, increasing the resolution of the feature space.

We have applied a processing scheme based on deterministic deconvolution for the classification between PMA-1 and PMN. Initially, the free-space response is subtracted from the raw data in an effort to eliminate the direct wave. Subsequently, deterministic deconvolution is applied to retrieve

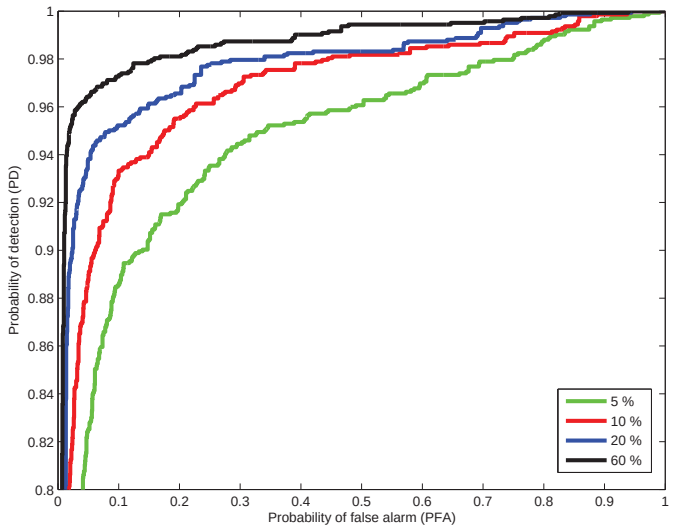

Fig. 3. ROC curves using as data set A-Scans from both AP landmines PMN and PMA-1 as targets of interest, and from background scattered fields from bullets, soil inhomogeneity, rough surface, etc., classified as false alarm targets, obtained using 5%, 10%, 20% and 60% of the available data as training set. A linear combination of ten randomly selected traces is employed in an effort to decrease the clutter from the input data (after the direct response is removed).

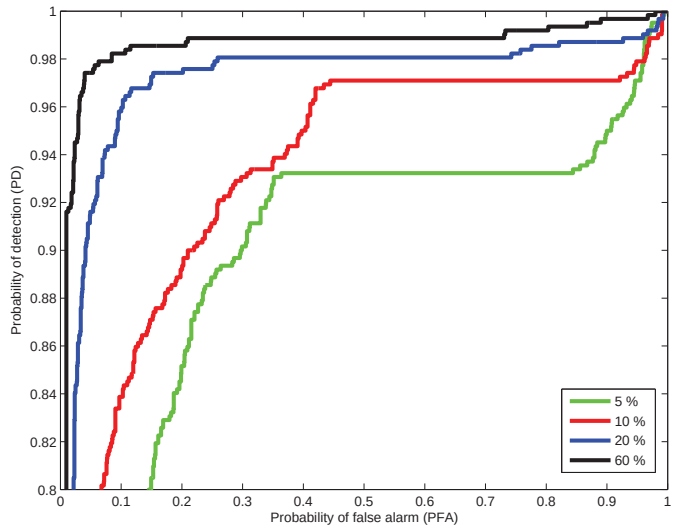

Fig. 4. ROC curves using as data set only A-Scans from AP landmines PMN and PMA-1 located in a diverse range of media, obtained using 5%, 10%, 20% and 60% of the available data as training set. The pre-processing consists of a deterministic deconvolution (1) (after the direct response is removed).

the reflectivity of the model (1)

$$R(\omega) = \frac{D(\omega) - F(\omega)}{F(\omega) + e^2} = \frac{P(\omega)}{F(\omega) + e^2}, \tag{1}$$

where R is the reflectivity, F is the direct response, D is the raw data, P is the data after the removal of the direct response and e is a damping factor used to overcome any instabilities due to possible division by zero (ω indicates that the operations in (1) take place in the frequency domain). Lastly, a moving average filter is employed in order to remove the unnatural high-frequency content of the reflectivity due to deconvolution artefacts.

Another pre-processing approach is employed to detect landmines against false alarm targets. Ten traces containing information from false alarms (soil inhomogeneity, bullets and rough surface) are randomly selected. We then define the matrix $\mathbf{G} = [\mathbf{g}_1,\ \mathbf{g}_2,\ \ldots\ \mathbf{g}_{10}]$, where $\mathbf{g}_q = [g_q(1),\ g_q(2),\ \ldots\ g_q(t)]^T$ is the $q$ith randomly selected trace (t indicates time). Subsequently, we approximate the background clutter which occurs in each trace (either it has a landmine or not) with a linear combination of the randomly selected traces

$$\mathbf{w} = \left(\mathbf{G}^T\mathbf{G}\right)^{-1}\mathbf{G}^T\mathbf{P} \tag{2}$$

$$\mathbf{Q} = \mathbf{P} - \mathbf{G}\cdot\mathbf{w}, \tag{3}$$

where $\mathbf{P} = [P(1),\ P(2),\ \ldots\ P(t)]^T$ is the raw data after removing the direct response and $\mathbf{w} = [w(1),\ w(2), \ldots\ w(10)]^T$ is the weight vector. The predicted clutter is then subtracted from $\mathbf{P}$. The new trace $\mathbf{Q} = [Q(1),\ Q(2),\ \ldots\ Q(t)]^T$ is used as training set to discriminate between landmines and false alarms. Fig. 2 illustrates an example of how raw simulated data are transformed to reflectivity, for classification between landmines, and to a clutter-free A-Scan for isolating landmines from false alarms.

IV. Neural Networks Structure

A traditional two-layered feed-forward back-propagation ANN [9], [17] was used in the proposed classification scheme. Through trial and error, it was found that increasing the complexity of the neural structure did not increase the performance of the ANN. Two-layer ANNs, with 50 and 30 neurones respectively were found to maximise performance without introducing undue complexity. Sigmoids were used as activation functions. The optimisation employed in the training process is the scaled conjugate gradient method [18]. The training set consisted of 4,000 different A-Scans resulting from 4,000 different and diverse models, 20 % of the training set (randomly selected) was used for testing the ANN performance and 20 % used as a validation set. The training process was supervised, thus, it was up to the user to define the targets of interest.

A step by step strategy, similar to the one suggested in [14], was employed in the present classification scheme. Initially, a classification between landmines and false alarms isolated the traces of interest which subsequently were further examined in an effort to recognise their type. As a result, the complexity of the feature space was decreased making detection and classification more accurate. The ANN used in each step are supervised accordingly. Figs. 3 and 4 illustrate the resulting ROC curves for each step. It is evident that increasing the size of the training set – while retaining its inclusivity – increases the performance of ANN, especially when classification between similar targets needs to be achieved. The ROC curves are calculated using the test set, i.e., 20 % of the initial data that are not used during the training process.

A 2D case study, as presented in Fig. 5, is used to illustrate the performance of the suggested classification scheme. Both PMA-1 and PMN landmines are employed and bullets are added in an effort to increase the complexity of the model. The soil varies stochastically as well as the rough surface. The electric permittivity is a frequency-dependent function

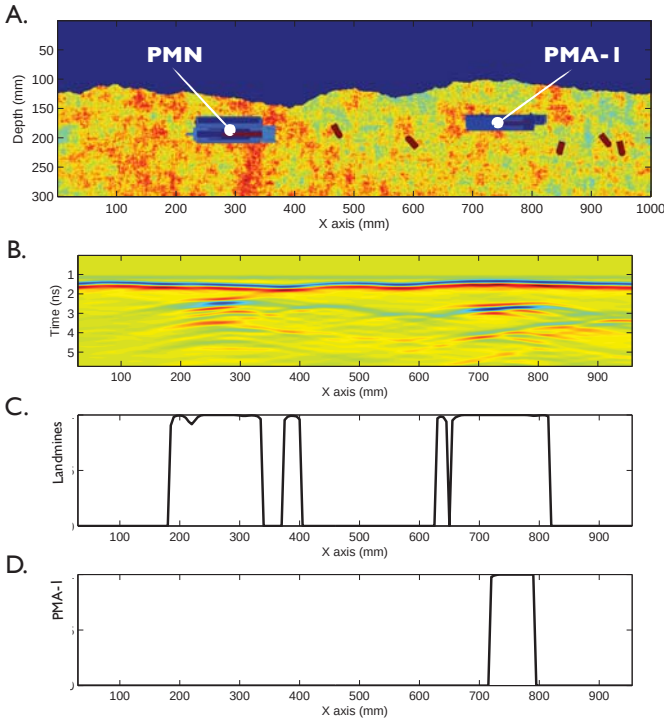

Fig. 5. A) A 2D model with a stochastic variation of soil's properties and rough surface. Both AP landmines (PMA-1 and PMN) as well as bullets were buried in along the x axis. B) B-Scan after the removal of the direct response (no gain is applied). C) Classification between landmines and false-alarms (soil inhomogeneity and bullets). Both landmines were successfully detected. D) Traces that were categorised as landmines were further examined in order to specifically detect PMA-1.

simulated with a conductive and a Debye term [8]. The classification scheme uses the clutter-free responses of the traces in order to isolate the landmines over the false alarm targets. Subsequently, the traces that are classified as landmines are further examined. The reflectivity of each trace is used in order to detect a specific type of landmine. In the present example the objective was set to detect the PMA-1. The outputs of the suggested scheme in each trace can be either 0 or 1 (landmines or no-landmines, PMA-1 or PMN), the value 0.9 is chosen as threshold, the traces which fall below 0.9 are neglected as no targets of interest. As it is shown in Fig. 5, landmines are successfully detected against false alarm targets. In addition, the proposed detection proved to be capable to distinguish between similar targets like PMA-1 and PMN.

V. Conclusions

This initial 2D modelling study illustrates that a sufficiently large and diverse dataset is an essential and basic requirement for an ANN to operate effectively and equally well in a variety of scenarios. This was demonstrated using simulated ROC curves obtained by utilising different amount of data in the ANN process. The proposed ANN approach results in a two-step classification process. First landmines are isolated from false alarms and then the type of the each landmine is recognised. Different pre-processing approaches are used in each step. For discrimination between landmines and false alarms a clutter-removal technique is proposed approximating unwanted clutter via a linear combination of randomly selected traces. The reflectivity calculated by deterministic deconvolution can then be used for identifying specific types of landmines. It is suggested that further work employing realistic 3D models and real data could result in an efficient ANN classification process to be tested in the field.

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