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Yapay Sinir Ağları Kullanılarak Yere Nüfuz Eden Radar Verilerinden Mayın Tespiti

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Özet

Kara mayını tespiti, ekonomik büyüme ve kalkınma zemininde kara mayınlarının insanların yaşamları üzerindeki olumsuz etkilerinin endişesi nedeniyle muazzam ve aslında büyüyen bir konu olmuştur. Bu makalede, yukarıda bahsedilen problemin üstesinden gelmek için yaygın olarak kullanılan bazı yapay sinir ağı yöntemleri incelenmiştir. Öncelikle yer radarlarından elde edilen veriler, yanıltıcı yer etkisi ve gürültünün azaltılması için işlenmiştir. Tek katmanlı ve çok katmanlı algılayıcılara ilişkin Adaline ve Madaline Yapay Sinir Ağı mimarileri, önceden işlenmiş veriler üzerinde gerçekleştirilmiştir. Gerçekleştirmenin sonucuna göre 208 bileşenden oluşan her bir girdi deseni için 60 veri işlenmiş ve işlem adımı öncesinde ileriye yayılma ve ardından geri yayılımdan yararlanılmıştır. Tek katmanlı Perceptron Yapay Sinir Ağı yöntemi %98.112 başarı oranı ile en iyi sonuçları vermiştir. Ayrıca sistemin tamamı, farklı öğrenme katsayıları, yineleme sayıları ve momentum sabitleri temelinde farklı Yapay Sinir Ağı mimarisiyle test edilmiştir. Bu problemin üstesinden gelmek için önerilen metodoloji, gömülü nesneler ve toprak tipi tespiti üzerinde yüksek doğruluk oranlarının elde edilmesiyle sonuçlanmıştır.

Anahtar Kelimeler: *Mayın tarama, Yere nüfuz eden radar, Yapay sinir ağları*

Mine Detection Through Ground Penetrating Radar Data Utilizing Artificial Neural Networks

Abstract

Landmine detection has been a tremendous and, in fact, growing issue due to the concern of land mines' adverse effect on people's lives on the ground of economic growth and development. In this article, some of the artificial neural network methods which are commonly used to tackle the afore-mentioned problem have been explored. First of all, data that have been obtained on ground penetrating radars have been processed so as to decrease the misleading ground effect and noise. Adaline and Madaline Artificial Neural Network architectures regarding single-layer and multi-layer perceptrons have been implemented on the pre-processed data. According to the result of the implementation, for each input pattern that consists of 208 components, 60 data have been processed and, prior to processing step, forward-propagation, followed by, back-propagation have been leveraged. Single-layer Perceptron Artificial Neural Network method have yielded the best results with the success rate of 98.112%. Furthermore, the overall system has been tested with different architecture of the Artificial Neural Network based on different learning coefficients, iteration numbers and

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momentum constants. The proposed methodology to tackle this problem has resulted in obtaining high accuracy rates on buried objects and soil type detection.

Keywords: *Mine detection, Ground Penetrating Radar, Artificial neural networks*

1 Introduction

Landmines have 2 different types: Anti-personnel (AP) and Anti-tank (AT) which are some of the most prominently used war materials [1]. According to the allegation made by the United Nations, as of 2000, there are 70 million landmines that have been laid across the world [2]. It is argued that it is a highly consequential matter for most of the countries to deactivate these landmines. However, the fact the process is not only about deactivating the mines but, maybe more importantly, finding out where these mines are makes landmine detection play a key role within the context. Along with expressing how significant detecting these mines are, it is required to discuss that detection processes can be very hazardous due to the explosions that can occur if the detection is somehow tried to be done through direct contact with the mines. This is exactly why contact-free detection methods come into play with a huge value with them. These methods, basically, leverage the data collected from several sensor types such as metal detectors and radars which have no direct contact with the mines. Among these methods, ground penetrating radars (GPR) come out to be more preferable as it can also be used as a totally independent sensor and a complementary source for metal detectors, which makes both metal and non-metal (plastic, wood etc.) detection feasible [3]. GPR, standard Electromagnetic Induction (EMI) has considerable advantages against the other alternatives due to its capability of differentiating and detecting even the smallest metal pieces [4]. Within the scope of this work, while processing the data obtained through GPR by making use of artificial neural networks (ANN), the advantages mentioned have paved the way for considerable decrease in duration of the detection. Moreover, the main reason for ANN to be more preferable compared to the other alternatives is that its algorithm has great preposition to take even the subtlest failure scenarios (negative outcomes) that can happen on the field into consideration, which brings about enormous potential to be successful in performing well for even the most complex scenarios [5]. Many studies have been carried out on mine detection. In one of them, Swydan et al. proposed an anti-personnel landmine detection system, which was mainly based on non-metallic mine detection without direct contact and observing changes in the signal representing reflected wave properties. Within the study, an electromagnetic sensor with a rectangular waveguide transition is used in the scanning process. Scanning was basically carried out in the near field with continuous electromagnetic waves transmitted in the lower frequency range. In this method, the presence of mines is demonstrated by detecting the reflected signals and creating images for the scanned area. It is aimed to minimize the error in the scanned area by using ANN to evaluate the presence of mines. They designed the system to be able to make decisions even under the circumstances including different buried objects and different surface conditions. That is, the main target of ANN is to basically minimize the false-positive probability while keeping the false-negative probability at zero [6]. As a result of the study, Groenenboom and Yarovoy observed that it is much easier to obtain an overview of the locations of possible landmines in the area by comparing the images obtained from the GPR system with the cross-sectional drawings of the previously processed data. In this process, moving average subtraction and diffraction stack algorithms were applied in three dimensions, which yielded much better results than using their two-dimensional equivalents, that is, processing the lines separately [7]. Achkar and Owayjan investigated different detection techniques which are image processing techniques, classification techniques in their mine detection and a couple of classification studies. In the system they designed, a camera was used to capture real-time images of the scanned image. After processing the captured images, data were used as input to be classified in an ANN, which was the backbone of the anti-tank landmines detection. However, they claim that the camera cannot be functional in this scenario and to improve the system further, ultrasonic sensors should be used [8]. György et al. have designed a robot that can find certain types of mines by relying on their geometric properties. The necessary information for this has been acquired through methods based on ANN. At the end of the studies, the robot they designed managed to achieve satisfactory results by using a pattern recognition algorithm. Moreover, according to the results of the study, about half of the mines with a small neural network were correctly detected. When they increased the number of neurons to the appropriate and required level, that is, when the complexity was increased, there has been a realizable performance improvement on the learning speed but not on the accuracy level [9]. What's more, Zhang et al. carried out a study for landmine detection with simultaneous feature and hidden markov model (HMM) using GPR. In this study, experiments were performed on images obtained from an arid test area with GPR. The dataset they created contained two classes: mines and non-mines. In the study, they first processed the data so that each image was normalized and scaled to the range of [0, 1]. Then the images are binarized to get the clean gray level image. Next, a 5x5 frame was moved along the x-axis to obtain the image sequences, then, they extracted an image sequence for each data sample of 9 images. As a result, they achieved higher than 90% accuracy [10]. Yuksel et al. compared standard HMM and MI-HMM (Multiple Instance Hidden Markov Models) algorithms using landmine data. Standard HMM uses indiscrete arrays as input. Both algorithms use a Gibbs sampling optimization program. While the MI-HMM algorithm uses a MIL (multiple instance learning) target; standard HMM uses a common probability target. MI-HMM training is as follows: For each target image, 5 equally spaced arrays are selected from the MRF (Markov random field) bounding box and placed in positive bags, and five randomly selected arrays are selected from non-target images and placed in negative bags. The standard HMM algorithm, on the other hand, uses 2 HMM training. It trains the target HMM using a set of training sequences from target images and trains the non-target HMM using a set of training sequences from non-target images. As a result; When the sequence screener algorithm is used, both models have shown similar performances. This indicates that the standard HMM algorithm has the same potential performance cap as MI-HMM but fails to achieve similar performance results. On the other hand, they have shown that MI-HMM can perform close to the real result even without the Oracle algorithm [11]. In this study, first, mine detection, ground penetrating radar and artificial neural network methods are mentioned as a concept and the algorithms used for mine detection are examined in the introduction part. In the second part of the study, information about ground penetrating radar systems is given and the operating logic of the artificial neural network method applied within the scope of this study is observed. In the third section, the overall method presented is profoundly explained. Furthermore, the results of the study and the evaluation of these results are presented in the fourth section. In the last part of the study, these evaluation results were taken into consideration and a conclusion is reached. According to these results, suggestions about the current system are made.

2 Material and Method

This section includes methods on ground penetrating radar systems, scanning methods and classification algorithms.

2.1 Ground Penetrating Radar System

Ground-penetrating radar (GPR) systems are a type of radar that can provide remote detection of targets hidden behind obstacles such as soil, concrete, brick, or trees by using electromagnetic waves in the fields of archeology, geology, civil engineering and defense [12]. Engineering applications of this system include finding and testing buried structures, tunnels, dumps and pollutant clouds. The choice of a set of frequency treatments depends on several factors, including the particular modulation scheme, antenna type and polarization, size and shape of the target, transmission characteristics of the intervening medium, and operational requirements [13-14]. Some studies have conducted to examine the characteristics of a particular system type, and various factors affecting the detection and resolution. For the system to work in a successful manner, GPR must satisfy the following conditions:

1) An adequate signal / clutter ratio

2) An adequate signal / noise ratio

3) A sufficient spatial resolution of the target

4) A sufficient depth resolution of the target.

Although forward transmission methods are used in GPR, most GPR systems detect the signal backscattered from the target. Figure 1 shows how the GPR system works.

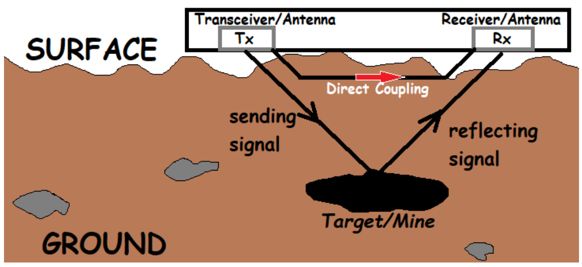

Figure 1. GPR simple operation diagram

An initial estimation of the radar's range performance can be made by considering some factors such as losses on the road, target reflection, clutter and the dynamic range of the system. The spatial resolution of the radar can be determined by considering the depth and plane resolution separately. Most GPR systems use a pulse time domain waveform and receive the reflected signal at a sampling receiver, however, Frequency Modulated (Stepped) Continuous Wave Radar (FSCR) and stepped frequency radar modulation schemes have been recently more commonly used [15]. As the cost of components decreases, more use of these systems is expected as they can be designed to have dynamic ranges.

2.1.1 Frequency Stepping Continuous Radar

In this study, frequency stepping continuous radar (FSCR) was used for GPR. This method can be defined as a way to emit electromagnetic waves in a certain frequency range underground, this way, it can perform imaging by measuring the phase difference of the reflected signal and the reflection coefficient of the target. Although systems operating in the frequency domain are easier to achieve high signal-to-noise ratios, they are more expensive and more complex in design than systems operating in the time domain of pulse wave generation [16-17]. The FSCR radar system sends the continuously changing carrier wave with the selected frequency over the voltage-controlled oscillator. The received signal is mixed with the transmitted waveform, resulting in a different frequency associated with the phase of the received signal. In FSCR, the transmitter changes as a function of time. If the change is linear and it is assumed that it returns from the target in time *T(d)*;

$$T(d) = 2R/C \quad (1)$$

is obtained, Here, R is the range, C is the speed of light [18].

2.2 Scanning Method

In this study, A-Scan was used as the scanning method. A single data waveform d (xi, yj, t) recorded with antennas at a fixed scan position (xi, yj) is referred to as an A-scan. An example A-scan for GPR is shown in Figure 2. Since the scan position is a fixed A-scan, this is only a function of time and the delay that is related to the depth of the target. A-scans and energies are generally used for target detection tests at respective scan positions [19].

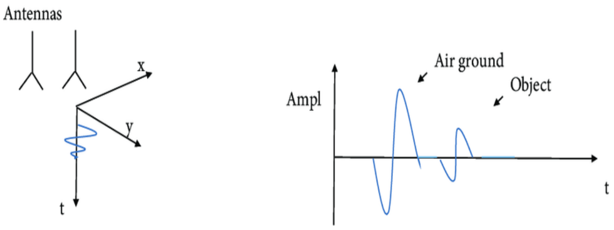

Figure 2. A-scan and A-scan signal [19].

2.3 Classification Algorithms

In this study, an ANN-based classification application was carried out to detect the underground mines. Based on the main motivation of ANN which is to produce output according to the given input, the data is used to train the model, which can be addressed as the learning of the network. There are multiple methods of this learning process. Artificial neural networks are divided into three as supervised, unsupervised and reinforcement (supportive) learning according to training algorithms. In addition, if at least two of these training algorithms are used hand in hand, a hybrid training algorithm can be claimed to come into play. In the supervised training algorithm used in this study, output values are also given for the input values given to the network. By calculating the error between the output of the network and the expected output, the new weights of the network are arranged according to this margin of error.

2.3.1 Multi-Layer Artificial Neural Networks

Multilayer artificial neural networks (MLP) are neural networks with one or more hidden layers. Generally, this network consists of an input layer, at least one hidden layer, and an output layer. The reason for the need for hidden layers is to determine the properties of the generally unprocessed signals coming from the input layers, to weight them and to direct the results to the output layer [20]. Examples are the Hopfield network model and the Kohonen feature map. The Hopfield model contains a cluster of neurons, each connected to another. No distinction is made between input and output cells. The MLP model is shown in Figure 3.

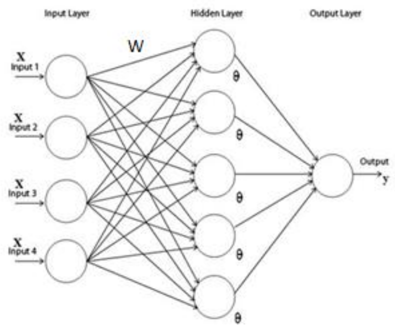

Figure 3. MLP network model

Here; X is input, W is weights, θ is activation function and Y is output. In MLP, the following operation (Eq. 2) is performed for each neuron in the layers.

$$NET_j^a = \sum_{i=1}^{n} X * W \qquad (2)$$

2.3.2 Propagation Methods

In this study, two different propagation methods, namely forward-propagation neural networks (FPNN) and back-propagation neural networks (BPNN), which will affect the success rate, are included. In FPNN method, the input nodes are those that do not have ties to themselves and the output nodes have no ties far from them. Neurons are in the form of regular layers from the input to the output, there is only a connection from one layer to the next layers. All other nodes are hidden nodes [21]. Once the states of all input nodes are set, all other nodes in the network can also set their states as values propagated throughout the network. The work of Forward - Propagation Neural Networks (FPNN) is about calculating a series of inputs and outputs given a way. A multi-layer FPNN is a network where any path from an input node to an output node recognizes the same number of arcs. The nth layer of such a network consists of all nodes with n arc transitions from an input node. The aforementioned hidden layer is the layer containing hidden nodes. FPNNs have become very popular in recent years. They have been found to generalize well in practice, meaning that when trained on a relatively sparse set of data points they will generally provide the correct output for an input not in the training set [22]. The processing of information in FPNN begins with the display of data in the training set to the network at the input layer. Incoming inputs are sent to the middleware without any changes. This situation is represented by the equation below.

$$Çk = Gk \qquad (3)$$

In BPNN, unlike FPNN, the output of a neuron is not only given as an input to the next neuron layer. It can be connected to any neuron in the previous layer or its own layer as an input. Thanks to this structure, BPNN shows a non-linear dynamic behavior. Based on the type of the connections that give the feedback feature, with the same artificial neural network, it is possible to obtain back-propagation ANN's with different behavior and structure [23-24]. In general, the purpose of BPNN is to compare the input and output entering the network and to reduce the error in this comparison. Error values are obtained with the equations given below and weights are changed according to these values.

$$Em = \mathrm{Bm} + \mathrm{Cm} \qquad (4)$$

If the error in the output layer is accepted as *Eh*;

$$Eh = 1/2 \sum\nolimits_{m} 2 \qquad (5)$$

Thus, changing the weights would be as follows;

$$\Delta A_{jm}^{a}(\mathrm{t}) = \lambda\delta\mathrm{m}Ç_j^a + \alpha\Delta A_{jm}^{a}(t-1) \qquad (6)$$

Here; λ is the learning coefficient, α represents the momentum coefficient and δm indicates the error of the output unit m.

3 Experimental Results

In this study, an ANN-based classification application was carried out to detect the underground mines. A-Scan was used as the scanning method. A single data waveform d (xi, yj, t) recorded with antennas at a fixed scan position (xi, yj) is referred to as an A-scan. An example A-scan for GPR is shown in Figure 4. The dataset file used in this study, imported from Kaggle (Machine Learning and Data Science Community), contains 111 patterns obtained by bouncing signals sent with the GPR system from various angles and under various conditions. These data were obtained by A-scan with adequate resolution and bandwidth. The dataset file also contains 97 more patterns obtained from rocks under similar conditions

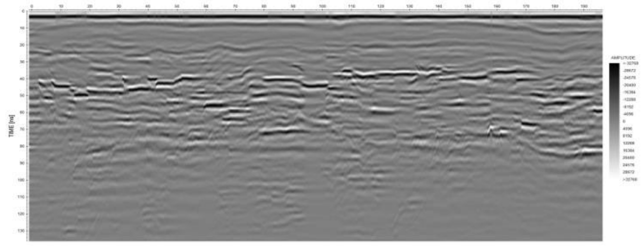

Figure 4. A visual obtained via the GPR system

The transmitted signal is a frequency modulated chirp that rises in frequency. The dataset contains signals from various aspect angles of 90 degrees for cylinder and of 180 degrees for rock. Each pattern is a set of 60 numbers in the range of 0.0 to 1.0. Since there are 208 designs in total, the total number of data in the dataset is 12480. Each data represents the energy within a specific frequency band integrated over a specific time period. The label associated with each record contains the letter "R" if the object is a rock; and the letter "M" if it is a mine. The numbers on the labels are according to the increasing aspect angle [25]. For this operation, C/C++ programming language and MATLAB development environment were used. First of all, the data file has been converted from .dat to .xls to obey the required format. Then, in order to classify the data, the algorithms of ANN mentioned in the fourth section (individually-individually and in hybrid forms) were utilized. In this application, a network (NET) is created first and inputs, output (target), hidden layers, training rate and learning rate variables have been added to this network. Inputs and outputs are divided into training and testing data sets. Network training was completed using training inputs and outputs. The inputs and outputs used for testing are given into the network, and thus the outputs obtained from the trained network enabled the comparison of these results with the actual outputs. The training, validation and testing percentages were determined as 70%, 15% and 15%, respectively. The learning coefficient was found by error method, and determined as 0,85. Since the training percentage is 70% and each design consists of 60 data, the number of entries to be trained is 42, the number of test entries is 6, and the number of validation entries is 12. In the MATLAB software platform, firstly, the data structure has been transposed, since the entered data was taken as a column. Since the obtained data were in the range of 0-1, there was no need to normalize them. Then, the maximum number of iterations (epochs) was assigned to the created network. Iteration was done for convergence. The number of iterations was determined as 10000 by trial and error. In this way, all parameters of the application were determined and training and testing processes were carried out. Three different methods were applied for the performance evaluation of the application. These; It was determined as MAPE (mean absolute percent deviation), SStotal (mean deviation sum) and SSerror (sum of deviation of error). Equations of these methods are given below.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{A(t) - F(t)}{A(t)}\right| \tag{7}$$

$$SStotal = \frac{\sum \left|X(i) - X'\right|}{n} \tag{8}$$

$$SSerror = \sum (Y - X) \tag{9}$$

$$R2 = 1 - \left(\frac{SSerror}{SStotal}\right) \tag{10}$$

In this study, classification was made using Single-Layer and Multi-Layer perceptron and Adaline and Madaline artificial neural network architectures. The achievements of the methods are as in Table 1 and the application output of the proposed method is as in Figure 6. Although the results obtained in the generally applied methods are close to each other, the results obtained in the multilayer ANN model with the back-propagation algorithm gave more efficient results than other methods.

Table 1. Success percentages of all methods

Model	Training (%)	Test (%)	Validation (%)	R (%)
MLP	**99.995**	**94.142**	85.519	**98.112**
SLP	98.165	90.348	**89.774**	93.288
ADALINE/ MADELINE	94.636	86.573	81.240	89.732

Training success which can be defined as performance while training, test results and R value, respectively, are given in Figure 5, with the application realized with a multilayer perceptron without installing a hybrid algorithm.

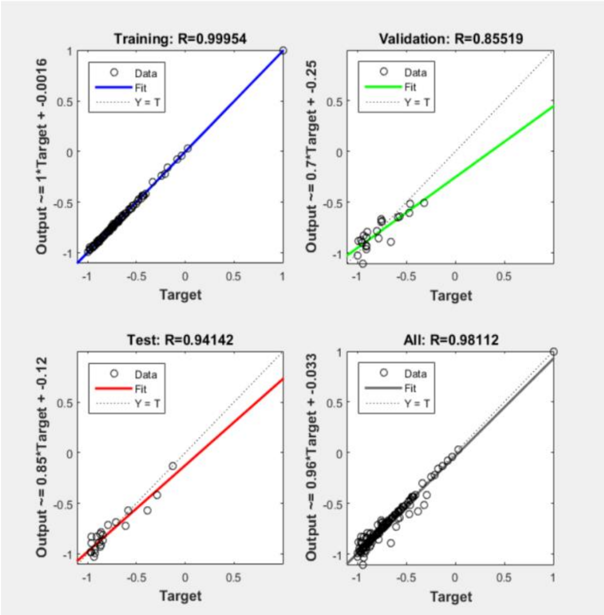

Figure 5. ANN processing outputs

4 Conclusion and Discussion

In this study, a solution has been produced for mine detection by processing ground-penetrating radar data and using various algorithms of artificial neural networks. In this solution, forward propagation algorithm was used beforehand, and then back propagation algorithm was used, while it achieved the highest success rate with 98.112% with Multilayer Artificial Neural Networks, 93.288% success rate with Single Layer Artificial Neural Networks and Adaline/Madaline algorithm with 89.732%. had low success. In addition, the proposed artificial neural network techniques are mentioned, the types of radar penetrating the ground and scanning types are compared and information about these issues is given. In the light of future studies, first of all, the data set can be balanced due to the imbalance of the number of rocks and mines in the data set, and at the same time, the success rates can be compared by performing the normalization process to ensure that each attribute in the data set affects the classification at the same rate. Thus, the proposed system can be used in real time with a multilayer artificial neural network structure with the highest.

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