Artificial Neural Networks and Machine Learning techniques applied to Ground Penetrating Radar: A review

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Abstract

Ground Penetrating Radar is a multidisciplinary Nondestructive Evaluation technique that requires knowledge of electromagnetic wave propagation, material properties and antenna theory. Under some circumstances this tool may require auxiliary algorithms to improve the interpretation of the collected data. Detection, location and definition of target's geometrical and physical properties with a low false alarm rate are the objectives of these signal post-processing methods. Basic approaches are focused in the first two objectives while more robust and complex techniques deal with all objectives at once. This work reviews the use of Artificial Neural Networks and Machine Learning for data interpretation of Ground Penetrating Radar surveys. We show that these computational techniques have progressed GPR forward from locating and testing to imaging and diagnosis approaches.

Keywords Ground Penetrating Radar, Artificial Neural Networks, Machine Learning, Review

Paper type Review Article

1. Introduction

Nondestructive Evaluation (NDE) is the process of inspecting, testing, or evaluating materials, components or assemblies for discontinuities, or variations in characteristics without affecting the serviceability of the system itself [1,2].

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There is a growing interest in using Ground Penetrating Radar (GPR) as an NDE tool considering different applications [3,4]. This is due to GPR's advantages over other techniques such as radiography, impact-echo and so on. Some outstanding advantages are (but not limited to): the portability of the equipment because of its moderate weight, relative low cost of the survey, reasonable budget of the initial investment, speed at which data can be acquired, allowing large areas to be surveyed in relative short time frames and high versatility in terms of application for different purposes and scenarios [5].

Since the technique is based on electromagnetic traveling waves it is possible to remotely access the subsurface and produce images that are highly correlated with the actual target condition [3–6]. Today, GPR is used not only for infrastructure maintenance but also for applications in geoscience studies, environmental investigations and archaeology surveys.

However, the physical principle of the GPR imposes an important drawback: the need of additional processing of the data collected during the survey to improve and interpret the assessment. In fact, the need for massive post-processing work for GPR comes from the low resolution of GPR signals (for instance the high sensitivity in centimeter-sized targets), as well as the nature of EM waves that GPR transmits and receives (quickly decaying amplitude and the loss of the higher frequency harmonics). Therefore, GPR data processing is intrinsically a challenge. Signal processing increase temporal resolution by deconvolution, denoising and improving the interpretation of GPR data raw [7]. While signal processing is used to separate (filter) useful information from noise and clutter, pattern recognition automating human interpretation to support efficient detection and characterization is needed.

Over the years, several different techniques were developed to facilitate the understanding of GPR raw data. Currently used in a wide range of applications, Artificial Neural Networks (ANNs) associated with Machine Learning (ML) techniques have been applied to improve the GPR NDE. This work discusses the ANN and ML techniques and their application to GPR.

2. Principles of GPR

GPR was first used in 1926 [8] and has a history of embracing change as new technologies arise. Annan et al presents a 30-year review of GPR applications corroborating the technique maturation [9]. In addition, this work [9] outlines the path to a more rigorous development in terms of standardization, accreditation and policy that are important issues considering the range of possible applications – more than 280 GPR different applications are described which represents several different scenarios and targets. Each scenario possesses its own properties concerning system specification, material properties, and environment condition.

Figure 1 depicts a GPR survey where the operation principle is the propagation and scattering of electromagnetic waves in solid matter. The GPR problem consists in retrieving the target signature in the received signal which is a convolution of several impulse responses. The input signal is a designed waveform that will suffer modification as it passes through several materials having different dielectric properties before returning to the receiver. The initial signal is then convolved with other impulse responses (e.g., the antenna or the host medium), considered as boundaries where reflection/transmission phenomena arise. In this context, real problems present convolution with non-linear materials [10].

The GPR ability to assess structures and the ability to indicate the state of deterioration are well known. For instance, the review done by [9] of GPR application in civil engineering shows improvements to assess buildings, roads, pavements, bridges, tunnels, geological/ geotechnical surveys, and others. Considering only the measurements, the success of the survey depends on the prior knowledge and experience of the user or on algorithm.

Signal processing techniques can be used to improve the signal integrity. Over the years, several techniques have been developed or adapted to this goal. Some of them are related to radar detection in military applications. Benedetto et al presents a signal processing review

Figure 1.
GPR survey.

related to GPR systems [11]. This work [11] also discusses the main techniques employed, theoretical insights and instructions on the proper use of the processing in relation to the quality of the data acquired and the purposes of the surveys. Data editing, zero-time correction, zero offset removal, band-pass filtering, time-varying gain and resolution improvement methods for 1D, 2D and 3D scan results are among the techniques described.

However, even after signal processing techniques, it may be difficult to distinguish between several types of targets which, in turn, can differ in geometry and composition [12–14].

The need of auxiliary tools for interpretation comes from the GPR physical principle which is the electromagnetic propagation at radio or microwave frequencies. Real world scattering electromagnetic phenomena is a non-linear problem [5,6]. Thus, the antennas, their coupling with the ground and consequently the entire GPR system have non-linear behavior. Therefore, even after the use of signal processing techniques, targets can still be blurred. There are certainly many benefits gained from using intelligent systems to fix that problem since it may be too expensive or inefficient for humans to execute this task.

In the GPR pattern recognition, we are given a training set (recording from the receiving antenna) and attempt to predict the sources that created those reflections (targets) for a given GPR scenario. This can be considered an inverse problem. Electromagnetic wave propagation inverse problems are typically ill-posed, as contrary to the well-posed problems more typical when modeling physical situations where the model parameters or material properties are known [5,6].

For the NDE use of GPR, pattern recognition aims at determining a finite number of parameters. These are the parameters needed to characterize targets in a given medium by identifying electrical and geometric properties. In general, this is a difficult problem because information obtained in the assessment is not sufficient for estimation, which requires some a priori information about the problem. On the other hand, a large number of data can bring instability. This instability, called 'the curse of dimensionality', is a phenomenon that takes place in high dimensional data space with the sparsity of the sample points [15]. Another problem that takes place in high dimensional problems is the rise of the computational effort.

Therefore, the current approach can improve the GPR assessment and diminish the importance of human interpretation by solving the inverse problem. In general, it is applied after signal processing has been used. To be effective, pattern recognition techniques should be efficient, adaptable to different applications, give a fast response for large amounts of data and provide a desirable false alarm response or probability of detection.

Considering the purpose of using GPR for NDE we assume that it is impossible to develop a technique that can classify and distinguish buried targets for all types of GPR assessments. Machine Learning (ML) and Artificial Neural Networks (ANN) are among the most frequent solutions applied to GPR inverse problem. The background on the use of those techniques is discussed next.

3. Background: ANN and ML for GPR

As Section 2 suggests, GPR has evolved during the years absorbing technology to enhance efficiency, improve user's convenience and support the ever-increasing number of applications. Various imaging or inversion techniques have been developed to reconstruct the scattered signals back to their true spatial location. Most of them were based on the numerical inversion of integral equations, such as [12–14]. All these techniques are characterized by a high level of complexity, accuracy, and a significant computational burden.

Consequently, the imaging of typical field data may be difficult due to problems like limited coverage, noisy data, or nonlinear relations between observed quantities and physical parameters to be reconstructed. Therefore, it has become necessary to use more efficient analysis for interpretation of raw-data. Such analysis requires algorithms by which problems having complex scattering properties can be solved as accurately and as fast as possible. This requirement is tough to reach when dealing with iteratively solved algorithms categorized by a forward solver as part of the loop, which often makes the resolution process computationally unreasonable for large problems. ANNs has been proven to be a consistent option [16,17]. Such an algorithm learns (i.e. progressively improves performance) tasks by considering examples, generally without task-specific programming.

Some reviews about transcribing and transform GPR images into format useful for assessments can be found in the literature [18,19]. A review of fault and error tolerance in ANN is presented in [20] where the main passive techniques used for improving the fault tolerance of ANN are presented.

Other techniques for image recognition and classification have been used, regardless of their association or not with the ANNs. ML are algorithms that evolved from the study of computational learning theory in artificial intelligence [21,22]. The ML algorithms are constructed in such a way as to learn and make predictions from the data unlike the static programming algorithms that need explicit human instruction. Remark: at the present, the usual is to consider ANN as a ML technique. Here, we assume that they are two different categories of algorithms. The single objective is to simplify the organization and the text understanding. However, this debate can take a place [23]. For instance, Intel Artificial Intelligence Academy [24] calls ML for regression and classification algorithms; and ANN as 'deep learning' for multilayer perceptron, convolution neural networks, cost functions, and back propagation algorithms. In this paper, we suggest to use the ANN for image segmentation (classify areas potentially containing object reflections) and after diagnosis using ML techniques to identify patterns.

Recent studies provide a general comparison among several different ML algorithms [25,26]. Theoretical and experimental data-modeling is discussed in [27] in large-scale data-intensive fields, relating to: (1) model efficiency, including computational requirements in learning, and data-intensive areas' structure and design, and introduces (2) new algorithmic approaches with the least memory requirements and processing to minimize computational cost, while maintaining/improving its predictive/classification accuracy and stability.

The possible first application of ANN for GPR is presented in [28]. The method presented an algorithm that adapts the input data for searching objects' signatures that are successively identified by means of a recognition step using a back-propagation neural network. They sustain those results on data showing buried pipe signatures with a degree of accuracy similar to those performed by a human operator.

Figure 2 and Table 1 show a study performed on online databases (Scopus, Open Science Elsevier, Researchgate, Google and IEEExplore – showing number of papers x year) about the use of ANN and ML for GPR. Several applications were found. Applications are reported (but not limited to): engineering and computer science (47%), physics and astronomy (13%), materials science (12%) and earth and planetary sciences (11%). The investigation suggests that ANN were first used to identify hyperbolic signatures late in the last century. The procedure then evolved to the use of Fuzzy Logic for the detection and localization of targets. That period corresponds to the growth of the GPR as an NDE technique. As more applications were tested, more complex the data became with a higher false alarm rate. More robust algorithms were necessary to cope with this issue. During the 2000s, more publications related with stochastic methods were published. The scientific publication rate has been found to increase until the appearance of the Multiobjective Neural Network (MNN) implementation. Since then the number of publications has been almost stable with various different methods applied.

A relevant discussion about ANN and/or ML techniques for GPR is the training data. Historically most training data has usually come from a relatively limited set of measured GPR raw data. In the current context of faster full-waveform forward solvers, and improved

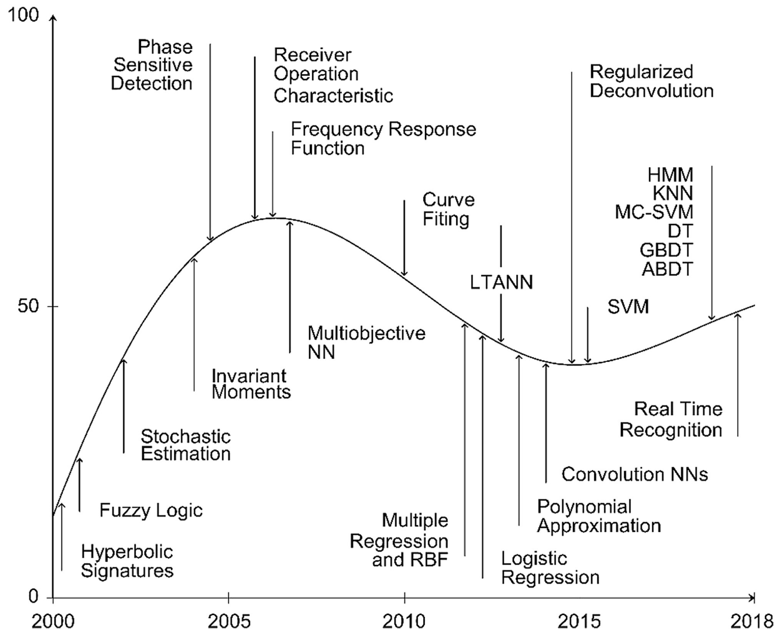

Figure 2.
An extract of the state-of-the-art of techniques that has progressed GPR forward from locating and testing to imaging and diagnosis.

Ref.	Main Contributions
[28,29]	ANN perform with the same accuracy as a human operator.
[30,31]	Detection algorithms are combined using fuzzy logic and ANNs.
[32,33]	ANN operates with 3D images to locate targets.
[34]	Stochastic estimation is combined with ANNs.
[35]	Invariant moments as a feature extraction for ANNs.
[36,37]	ANN-based reconstruction based on EM-fields.
[38]	Receiver operating characteristic (ROC) curves to train ANNs.
[39]	Principal component analysis (PCA) to train ANNs.
[40]	Frequency response function (FRF) and ANN.
[41]	Multiobjective neural networks (MNNs).
[42]	ANNs and curve fitting techniques.
[43]	Multiple regression and the radial basis function neural network
[44]	ANNs and logistic regression algorithms.
[45]	Laplace Transform instead of ordinary weights (LTANN).
[46]	Polynomial approximation (the feature vector) are ANN inputs.
[47,48]	The benefit of using a Convolutional NN (CNNs) is that features extracted from the data are a learned parameter of the system.
[49]	Regularized deconvolution is utilized to increase range resolution.
[50]	CNNs configuration to extract data from multiple sources.
[51–53]	ML approaches are used to detect signatures with ANNs.
[54]	Real-time hyperbolae recognition and fitting in GPR data.
[55]	A Multi-task spatio-temporal ANNs that combines 3D ConvNets and Recurrent Neural Networks (RNNs)

Table 1.
An extract of the state-of-the-art for ANN and ML for GPR applications.

analytical methods, there is a necessary discussion around the use of simulated results as training data.

Realistic simulated data can offer the possibility of providing a more diverse set of training data, than solely measured results. For instance, one well known limitation of CNNs is that they require large amounts of data for training (parameter inference) to avoid overfitting (poor generalization). Bralich et al. [48] investigated several different variations of realistic simulated pre-training data. The results indicate that pre-training can lead to improved detection performance. However, some configurations also cause a deterioration in performance. Accordingly, an examination of the volume and diversity of training data necessary to obtain a robust ANN and ML GPR system is still needed.

Another approach is to use techniques for training data augmentation [56,57]. Reichmann et al. [58] investigate the initialization step of pretraining and propose a dataset augmentation protocol. The efficacy of these approaches is evaluated on several architectures with a relatively similar number of network parameters to learn. The results indicate that both pretraining and dataset augmentation help achieve higher GPR detection performance.

Also, it is important to discuss the restriction of ML to specific GPR application areas, such as rebar diameter estimation, cylinder location, or detection of small asymmetrical cracks. The measures of ‘condition positive’, ‘condition negative’, ‘true positives’, ‘true negatives’, ‘false positives’, ‘false negatives’ are used measure the accuracy of the classifier. Ajithkumar et al. [53] establishes criteria and tests ML techniques applied to GPR landmine detection. They are: misclassification rate (indicates the probability of the classifier being wrong); true positive rate (indicates how it often predicts positive. Also, known as sensitivity or recall); false positive rate (indicates how often it predicts positive when it is negative); specificity (indicates how often it predicts negative when it is negative); precision (indicates the classifier’s correctness when it predicts positive); false negative (indicates the classifier’s incorrectness when it predicts negative); F score (this is a weighted average of the true positive rate and precision); safety factor (it is the probability of a mine being detected is not a mine).

3.1 Generic implementation

In general, a typical GPR procedure to detect underground targets can be summarized as: the received time waveform can be described as the convolution of a number of time functions each representing the impulse response of some component of the radar system in addition to noise contributions [5,41]. It is possible to simplify a GPR received time waveform as follows:

$$f_r(t) = f_a(t) + f_s(t) + sg(t) + ns(t) \tag{1}$$

where $f_a(t)$ represents the antenna interference, $f_s(t)$ the reflections from the ground surface, $sg(t)$ is the signal from underground targets, and $ns(t)$ the noise. $f_a(t) + f_s(t)$ is called direct wave (or clutter) in GPR measurements. The main features to conduct this characterization can be: 1) the peak amplitude of the reflected field; 2) the delay of the first reflected echo, calculated with respect to the time of arrival, at the receiving point, of the direct field); and 3) a measure of the duration of the scattered field. It can be added here the imperfections of the antennas operation as well as their coupling with the air and/or the surface of the solid under study [41].

ANNs and/or MLs can be used for solve this inverse scattering problem. The system must do a combination of signal processing techniques to provide a high-resolution image of the subsurface in near real-time enabling straightforward data interpretation and providing accurate depth and azimuth location information.

Figure 2 and Table 1 suggest that GPR has systematically progressed forward from locating and testing to imaging and diagnosis. It is often required not only to detect possible buried objects but also to reconstruct their geometric and physical characteristics.

The three major stages for implementing these techniques for GPR are: preprocessing (raw data acquisition and treatment), image segmentation (ANN) and pattern recognition (ML). First, features are detected from GPR data raw by sensing salient local image regions. Second, improve the invariance by extracting salient local image regions as feature to replace the whole image to deal with large changes of GPR images. And the number of interest points is reduced effectively, which makes the processing easier. Then, features matching is done by comparing the detecting feature and the template feature. These three software stages work together in the cited order to achieve the highest resolution and accuracy possible within the limitations of real-time GPR operation. Sections 4 presents in detail this proposed workflow.

4. Imaging and diagnosis procedure for GPR applications

The success rate of any GPR system is limited by the sensing aspects of each individual application, and tends to produce high false alarm rates when the situation is generalized. Techniques and algorithms have been developed to improve GPR success rates, as discussed at Section 3. While extremely useful, these algorithms need some computational effort, but they are improving their skills and usefulness based on large datasets. These are some of the tasks performed by recent imaging and diagnosis algorithms for GPR (Figure 3):

I. preprocessing step to reduce noise and undesired electromagnetics system effects (signal processing);

II. image segmentation with an ANN to classify areas potentially containing object reflections;

III. diagnosis by ML techniques to identify patterns.

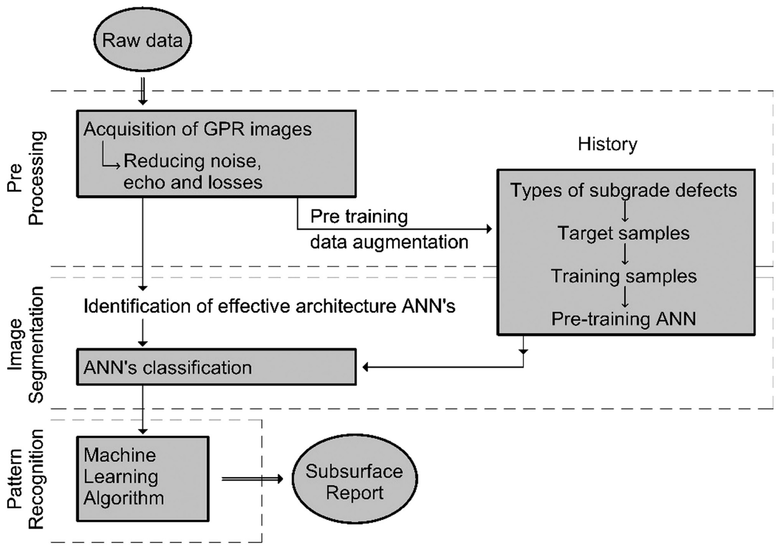

Figure 3. Main stages of GPR imaging and diagnosis system.

In the first segment, a preprocessing procedure has the task to: reduce noise; eliminate the undesired presence of the ground surface echo; and compensate for electromagnetic propagation losses [11,59].

Computational time and effort are required in analyzing the data collected before the processing, focusing on the main requirements, expected outcomes, and to set the most effective strategy for reaching the surveys' objective. The quality of the dataset influences the intensity of the processing needed for increasing the data readability. At the same time, the level of noise and the compromise between frequency, resolution and range in line with the nature of the target may also represent a limit to the performance of the processing phase.

For image segmentation, the use of convolutional neural network (CNN) for GPR is flourishing. The CNN (or ConvNet) is a class of deep, feed-forward ANNs [60]. A review of object detection based on CNN can be found in [19,61]. The objective is to make a map of all detected diverse areas on the image. Mainly, every pixel needs to have a label related with it. For that, the last fully connected layer is replaced by another convolution layer with a large receptive field. The idea is to capture the global context of the image. If we choose our new last convolution layer big enough we will have this localization effect scaled up to our input image.

The use of some kind of ANN to train an end-to-end learning system is increasingly possible. A learning system with independent learning competence, can take the initiative to learn the relevant representation features. At the moment, research combined with deep learning and intensive learning is still in its beginning, but some research in this area has achieved good performance in multiobjective recognition tasks [19,58,61]. So far, ML is indeed a method to adjust the parameters inside a system so that the system will have better predictions or estimations when the learning process is continued. However, up to the present, ANN has more independent learning competence. It means the ANN extraction can be further optimized so that it can more easily to express the segmentation features. The depth of learning will help to achieve greater progress. Consequently, CNN outperform the ML algorithm for image segmentation [58,61].

The benefit of using a CNN is that features extracted from the data are a learned parameter of the system. The multilayer structure can be used to achieve minimal preprocessing. Procedures to improve the implementation of CNN for GPR data are presented in [58]. The main steps can be described as:

I. smaller convolutional filters: to reduce the number of parameters to learn, the suggestion is to split larger filters into several smaller filters in series;

II. network pre-training: the filters of one network can be used to initialize a network on a different task, leading to improved performance. Using a pre-trained network would increase the effective number of data points the network has seen;

III. training data augmentation: another option to increase the dataset size is to augment it with data transformations. For example, in natural images, objects can appear rotated or at different scales of illumination and therefore, adding rotated and scaled patches to the dataset has been shown to improve classification performance;

IV. the identification of effective architectures for the problem under consideration: comparison of different architectures (HOG, RNN, HMM, LTANN, regularized deconvolution, etc.) must be done considering the specific GPR problem.

The last segment is pattern recognition. Support Vector Machine (SVM), Hidden Markov Model (HMM), K-Nearest Neighbour (KNN), Multi-Class Support Vector Machine (MC-SVM), Decision Tree (DT), Gradient Boosted Decision Tree (GBDT), Adaptive Boosted Decision Trees (ABDT) and others ML techniques have been used as pattern recognition technique to identify the hyperbolic anomalies associated with buried targets, generating information for decision making action [51–53]. It has been found that the performance of classifiers depends on the metric of targets to non-targets in the training dataset. For that reason, the choice can also be made only by considering these factors.

The main difference between SVM and Decision Trees is that SVM uses a function called Kernel. A Kernel function $k(x, x')$ characterizes the similarity between classes of objects. In the GPR context, the objects are the received samples (time-domain) or patterns in the image (space-domain). Decision Trees split the input space into hyper-rectangles according to the target.

An HMM is a tool for representing probability distributions over sequences of observations. Considering GPR, it can be used to automatically divide the received waveform into multiple sequence patterns. Understanding the advantages and drawbacks of each technique is necessary to apply those algorithms to the GPR problem. Even with the right choices of those configurations, the ability to predict and detect targets requires considerable expertise as well as a set of specialized post-processing tools.

5. Conclusion

GPR has attracted considerable interest from the NDE community. As more applications for GPR as an NDE tool appears, the complexity of the postprocessing algorithm grows. The use of ANN and ML techniques is a significant milestone because the new approach tackles an important problem: how to interpret GPR data without human assistance. One challenge is to design algorithms that can resolve uncertainty about false positives and false negatives. Another common challenge is improving object localization and handling of multiple objects.

This review presented a brief discussion about attempts to automate the process of understanding GPR readings and the algorithms have been used to this aim. After some background, it is possible to state that the GPR problem is becoming more complex. For these new scenarios, an algorithm is given the rules and then decides how to classify the target.

Whether these new scenarios will be as amenable to this approach is not clear yet. However, it is important to understand how this methodology evolved with time.

Overall it has been a complex project on many levels. There are some challenges ahead:

I. false positives vs false negatives. How to handle this based on the complexity of some applications, such as the wide variety of soil characteristics, for instance;

II. nowadays the focus is still on 2D radargrams or vertical depth profiles. What is needed to transition to horizontal profiles and full 3D volumes? That adds a whole new level of complexity;

III. improved object localization and handling of multiple objects;

IV. increase the scenario complexity, as weather, vegetation and terrain as example;

V. fuse data with different sensor modalities.

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