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Different techniques in detection of buried objects using ground-penetrating radar

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ABSTRACT

The application of ground-penetrating radar (GPR) is addressed in this study, with the main application being the detection and classification of an underground target using GPR technology. This study focuses on the important task of GPR that needs to be done to improve the detection process, as well as ways to eliminate unwanted signals from the GPR image. The accuracy of detecting buried objects using GPR largely depends on the algorithms used, as smart algorithm technology has proven to be the most accurate, effective, and cost-effective.

1. Introduction

Many methods are used to discover and identify materials in the subsurface area. In recent years, ground-penetrating radar (GPR) has become an essential non-destructive device that detects and identifies a buried object. The GPR is a reliable tool used in many applications such as construction, mining, military, archaeological sites, tree roots, caves, land mines, civil and Geotechnical engineering[1]. The main parts of the GPR are the display, control box, transmitter (Tx) and receiver (Rx), Tx and Rx connected to the antenna, as shown in Figure (1). The average operating frequency range is from 10MHz to 4GHz, and the frequency is inversely proportional to the penetration depth and directly to the accuracy. The reflected signal is detected by the GPR system receiver and is the raw data that requires further processing for interpretation.

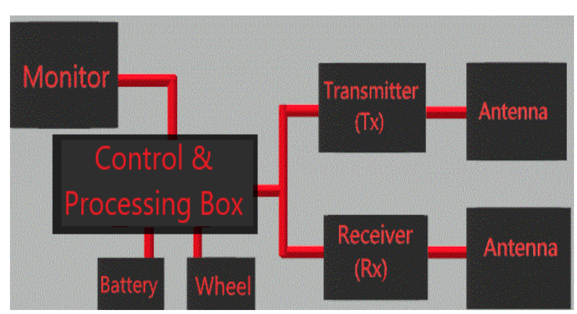

Figure 1. The main parts of the GPR

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There are three types of scans, A-scan, B-scan, and B-scan. The A-scan signal is one-dimensional and represents the electromagnetic fields reflected in one position, and the B-scan signal is two-dimensional. It is the sum of the A-scan signal, while the C-scan is the sum of the B-scan signal. The raw data is interpreted and analyzed to identify buried targets, where the raw data is analyzed either manually, semi-automatically, or by an automated algorithm[2].

This article conducts a comprehensive review of research papers on applying the Ground Penetrating Radar (GPR) system and is divided into five phases, as shown in Figure (2).

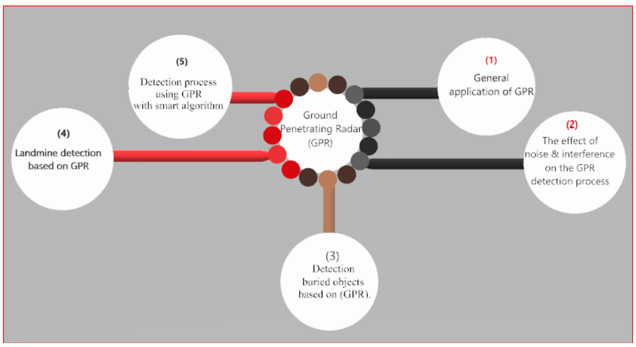

Figure 2. Summary of the five sections of the research paper

2. General application of ground-penetrating radar

This section summarizes the research papers that use the GPR system in general application. The researcher estimated soil change properties, coal seam thickness, tunnel defect treatment, plant root profile. In addition, methods for measuring the velocity of electromagnetic waves (EMW) in the medium, the thickness of the coal seams, etc., are found below. In Table 1 In [3], a simulation of the new hybrid algorithm based on the ground-penetrating radar (GPR) image is discussed, which provided technical guidance for tunnelling defects. In this simulation, a numerical experiment was performed on the finite element time-domain (FETD). This algorithm provided accuracy as well as efficiency information about tunnel defects. [4]discusses the detection of subsurface materials based on GPR images using various classification algorithms. A simulation software (gprMax) is used to obtain 180 GPR images of the target, where the shape and depth of the buried object determine the types of hyperbolae. Suggestion systems consist of four stages: preprocessing, feature extraction, feature reduction, and classification process. In[5], an experimental ultra-wideband of the bi-static synthetic aperture radar for design, implementation, and image analysis of plant root system architectures is discussed. It is a low-cost solution that provides important information about the system. The system consists of three parts, the first step is data processing, the second part is image processing, and the last step is to analyze the model. The simulation was carried out using MATLAB and the delay and sum beamforming algorithm used to generate a two-dimensional (2D) image from a one-dimensional (1D) image. The factors affecting the output results are soil condition, the relative permittivity of roots, and root sizes, while the problem in practical implementation is hardware limitations. [6]use ground-penetrating radar (GPR) data to provide approximate values for soil parameters. Simulated annealing (SA) is used as a global reflection method to obtain a one-dimensional (1D) full-wave response of finite difference (FD) for a typical ground response. The two basic steps of the SA method are to generate a random model, and then a decision is made based on an acceptance or rejection criterion. The test was obtained successfully, and the result of synthetic data and noise were added to it. The SA method can be summarized in two basic steps: the generation of a random model and a decision based on an acceptance or rejection criterion. [7] determine the electromagnetic wave (EMW) velocity of the sub-service material using Ground Penetrating Radar (GPR), which is required for the results of depth estimation, topographic correction, and buried object transmission. There are several common methods for estimating the velocity of an electromagnetic wave, such as velocity tables, scattered implants, hyperboloid fitting, and common midpoint (CMP), considered the most efficient treatment because they got better results than the rest.In [8], the operation of the GPR system has been analyzed using different buried objects and compared the results with different other frequencies (800MHz-250MHz). The frequency of the operation determines the distance and accuracy of the buried object. High resolution and shallow depth are obtained at 800MHz, while 250MHz is more suitable for lower resolution and greater penetration depth. [9] analyze different signal processing techniques by testing three spectrum characteristics to identify three types of materials. The operating frequency is 200MHz for the GPR system, and the type of materials used are metal, plastic, and concrete. Then evaluate the three buried objects in the frequency domain. The interface between matter and electromagnetic wave (EMW) was obtained using three spectral features, power spectral density (PSD) with short-range Fourier transform (STFT) as well as Wigner-Ville distribution (WVD). Simulation results and real data of the behavior of the spectral properties under different conditions, different electrical properties of the soil, and the dimensions of the buried object were compared. Environments and antenna frequency require further research to improve GPR image quality for plastic, concrete, and metal. [10]proposed an algorithm to identify hyperbolas in real-time GPR data. New technology has provided an efficient and accurate measurement of the depth and the volume of an underground object. It is more suitable for practical testing due to lower computational complexity than Hough transforms and simpler training data and neural network-based methods. It showed an accurate result for both the simulation data and the real GPR data. However, further, improvement is needed by increasing the GPR scanning with different types and positions of the buried objects. Regarding[11], an algorithm for coal thickness, The error rate of the detection results is about 3 cm. The new detection technology is applied to only one goal of reducing conventional symmetric filtration, and more research is needed to apply it to underground coal mining applications. In [12], an image retrieval algorithm of the reconstructed image with a new geometry has been proposed to reduce ground-based radar requirements and allow estimation of average permittivity. It can produce buried objects such as metal and plastic in highly wasted environments.

3. The effect of noise and interference on the detection process of ground-penetrating radar

The GPR antenna receives several signals from buried targets and other signals reflected by the internal and external sources that become part of the GPR image. The sources of unwanted signals are antennas, electronic parts, buildings, trees, and communication stations which increases the error rate in the detection process. The initial step of raw data analysis in the detection process is to remove unwanted signals such as noise and other reflected signals, as in the paper[13] that separates unwanted reflected signals from buried targets. The signal-to-noise ratio was improved in paper [14], and the effect of noise on the detection process was reduced using artificial neural networks (ANN). At the same time, in [15], better image discrimination and accuracy of raw data interpretation were obtained using a wavelet transfer process in noise isolation. The target signal is weaker than the unwanted signals because they are attenuated while passing through the medium; a specific procedure is required to separate them from the GPR image. Paper [16] discussed filters to separate the target signal from the unwanted signals. Another option is to compare images with and without the reflected electromagnetic wave (EMW). It is also described as a framework for de-cluttering GBR images by integrating a Multiscale Directional Bilateral Filter (MDBF) algorithm with GPR images. [17] Implemented various clutter removal methods. The method of mean subtraction, subspace projection or time gate based on entropy has problems determining local scattering in a given area or when buried objects are close to each other. The data is collected experimentally in different ways. The reflected signal of the buried object is represented as a hyperbola curve, while the received unwanted signal has a horizontal shape.

4. Detection of buried objects based on ground-penetrating

The GPR application is used to discover and identify the buried object, and there are many methods used in the detection process. The raw data must be interpreted using an algorithm. The factors that affect the detection process are accuracy, error rate, process complexity, uptime, material cost/time, and safety. Table 3 summarizes the different algorithms' research papers related to the detection process. [18] A powerful ground-penetrating radar detector was developed using the Adaptive Normalized Match Filter (ANMF) to detect buried tubes. The electromagnetic wave (EMW) signal is sent directly to the ground. The GPR image is a combination of the reflected signal of the buried object and the noise and chaos signal. The noise source can be any electronic or telecommunication equipment, and clutter is also the reflected signal of small objects buried underground. [19] use an algorithm to detect hyperbola in the GPR image automatically. This algorithm does not have prior knowledge of the properties of the medium. The method depends on the canny filter that recognizes the edge in the hyperbola curve. The first step is to use a filter to change the parameters of the buried object, and then the next step is to remove the redundancy. The new method is used with different types of antennas and operating frequencies. The results are acceptable compared to the semi-automatic detection of commercial software. The high error rate results from using a constant permittivity or ignoring the cross-section area of the buried object. In [20], a buried object is detected and segmented using the Specific Peaks Summarizing Traces (SPST) algorithm for GPR image preprocessing. This method compared the segmentation results with other methods using the mean square error (MSE) and root square error (RMSE) criteria. It is essential to have a dry medium to reduce the effect of reflection. [21] Represents automatic detection of hyperbolic signatures in b-scan. Histogram of Oriented Gradients (HOG) has developed a new method for enabling region reflection signals from a target and using a Supported Vector Machine (SVM) for classification and training. The average accuracy is 93.75% due to the detection goals of both synthetic and natural data tests. Operating frequency (250-700) MHz and synthetic data with less noise than real data test. [22] A GPR-based inverse tomography algorithm was used to reconstruct the geometrical features of the buried mineral material at different values of depth, soil, and material conditions. Simulation and experimentation results showed the correct localization of the buried objects despite noise on the data. [23] represented a multiple signal classification (MUSIC) algorithm for detecting a very closed buried object. The MUSIC algorithm suffers from a high error rate in the presence of noise and distortion. Then the W-MUSIC algorithm is the solution for a clear indication of targets in the presence of noise or distortion. The window of FFT music (W-MUSIC) is a new method to check a direct change in frequency with noise. [24] The buried body was identified and translated based on the GPR image with 3D random transformation (RT) and by a semi-automated approach algorithm. It is a robust and reliable algorithm with minimal human invasion. [25] studied the method of detecting non-metallic objects underground based on the GPR system and signal processing algorithm. The improvement in the detection process was obtained by increasing the signal-to-noise ratio of the received signal. This method used the cumulative energy distribution and the reflection of the buried object, which are related to each other. It is more efficient in the smooth ground such as path and road inspection, and the detection procedure is suffering a false detection with a different medium..

5. Landmine detection based on (GPR)

An unexploded ordnance devices can cause loss of life or injury and even a financial problem for the family directly or indirectly. There are different tools used in the detection process of unexploded ordnance such as landmines, and GPR equipment is the most common device used to detect underground landmines. However, there are still problems related to the detection of an underground landmine in comparison to other buried objects such as large types of landmines, a material made, whether it is plastic or not, safety issues, and weather conditions. Table 4 summarizes various research papers with various procedures used to detect and identify buried landmines. [26]The buried object is determined by linear segmentation and impedance change between soil layers, and the accuracy of the convolutional neural network (CNN) is increased by training the synthetic data. [27]It obtained an excellent penetrating signal with a high-accuracy detection system for metallic or non-metallic materials and improvised explosive devices (IEDs). The new method used a fast and accurate synthetic aperture radar (SAR) algorithm.[28]Presented applicable fast online algorithm for Dictionary Learning (DL) for a reverse construct of buried landmine. It is more accurate than another algorithm. At the same time, the operation time is practically high, and it is used with smaller mines. [29] This paper was used to compare the Energy Density Spectrum (EDS) of both the clutter detection signal and the target. This procedure has some difficulty in practice as Chaos objects can contain the same images created by the target object. Therefore, a high error alarm rate is possible in this algorithm, and it also cannot determine the size or shape of a land mine. [30] studied the identification of the buried object using the Simulated Correlation Algorithm (SIMCA) technique, which was used to locate the buried object. The combination of

GPR with SIMCA provided an excellent-resolution image. [31] Discuss the work of four algorithms in the process of detecting buried landmines. Using edge features in a hidden Markov model (HMM) and geometric features in a feed-forward command-weighted mean network.
The third uses spectral features, and the fourth is a block edge graph. Data collected from a vehicle-mounted ground-penetrating radar sensor, which distinguishes landmine data from chaotic objects. The automatic detection process is obtained in different locations, soils, and climatic conditions. [32] studied different sensor technology available to detect landmines. GPR used mine detection and still has limitations such as weather and noise. Each type of discovery has advantages and limitations. This paper is recommended for better results in landmine detection, as more sensors are required to improve the accuracy of the results and reduce scanning time. [33] comprised of different algorithmic methods for detecting and classifying landmines, where the error rate and accuracy are also essential for evaluating the correct algorithm. Other factors include algorithm types, target depth, soil propagation characteristics, and the physical shape of landmines. [34] Improved Landmine Detection for buried objects using the adaptive differential of gaussian (ADOG) methods. [35] The experimenter used a signaling process with multiple algorithms in parallel with GPR to detect the location of the landmine, using the Automatic Target Recognition (ATR) algorithm. Data is collected by Energy Focused GPR (EFGPR). The pilot test achieved a 96% accuracy rate and an error rate of about 0.017. The fuzzy inference system reduces false alarms and keeps detection rates at the same value..

6. Ground radar detection process with an intelligent algorithm.

The function of GPR is to detect a buried object, and in to obtain good results, new methods of interpretation of the raw data are required to reconstruct the buried object. Some of these methods are based on a complex numerical equation, and others are based on artificial algorithms such as Artificial Neural Network (ANN), Machine Learning (ML), and Deep Learning (DL) technology, which have obtained good accuracy and stability. It is also able to reduce calculation time[36]. Table 5 summarizes research papers for the use of new methods in the detection and identification process. [37] Improved buried target locating and detection using Multi-Target Genetic Algorithm (MOGA). The advantage of MOGA methods is faster, less complex, and reduced computational times for target identification compared to other classification methodologies. [38].

Table 1. Summary of the research paper for the general application of GPR

Reference	Characteristics of paperwork	Result	Comments and Limitations
[3]	A hybrid algorithm for providing technical guidance and processing tunnel defects using frequency (400-600-900) MHz	Good results and accuracy with efficacy and efficiency.	Only simulation and practical testing are required.
[4]	Various classification algorithms are used for detection and classification.	High accuracy rate and results showing detection performance up to 91.7%	Performance depends on the number of GPR images and the classifier's training required.
[5]	Implementation and analysis of image plant root system architectures used at (3.1-5.3) GHz	Provided information about system parameters and factors limiting image features.	Many constraints include soil condition, relative root permittivity, root sizes, and hardware devices.
[6]	Using one dimension (1D) to get a typical response from the ground.	Obtain the approximate electrical conductivity, magnetic permeability, and dielectric constant values.	Advance information about the medium is required.
[7]	Determined the EM wave velocity; in the medium in different ways, CMP processing is the most efficient.	The velocity of the electromagnetic wave is required to estimate the depth of a buried object.	Incorrect estimation increases error rate, and the wavelength is governed by the operating frequency and the substrate velocity.
[8]	Results at two different frequencies (800MHz-250MHz using the RAMAC CU II system and Reflex W.	More suitable for low resolution and greater penetration depth.	The effect of weather on the accuracy of the results.
[9]	Determine the type of material, whether it is concrete, plastic or metal, with a frequency of 200MHz.	It is possible to distinguish between the three materials.	Environments and antenna frequency require further research.
[10]	The probability hyperbola mixture model used a robust orthogonal distance-fit algorithm applied to the GPR image.	Effective and accurate determination of the depth and volume of a buried object and less complexity in the calculation.	Further improvement by increasing GPR scanning with different types and positions of buried objects.
[11]	Coal thickness was developed using an estimation algorithm to optimize the detection and estimation stages at F = 800 MHz	Detect the object's depth with about a 3 cm error rate of the actual value.	The detection technique is only applied to one target, and more research is needed on the application of underground coal mining.
[12]	Image retrieval algorithm to reconstruct a new image geometry.	An approximation of the permittivity value.	Limited A to D to the 14-bit converter.

Table 2. Summarizes published papers for detecting and removing unwanted signals.

Reference	Characteristics of this paperwork	Result	Comments and Limitations
[13]	Analysis of the effect of noise on the GPR scan of shielded antennas at (200-400) MHz	Noise can blur the data, and external sources are powerful, which comes from the communication stations.	Discuss external noise without internal noise and detect buried objects.
[14]	Artificial Neural Networks (ANNs) are trained to optimize the target's reflected wave and improve the weak signal-to-noise ratio (SNR)	Noise separation as well as target signal optimization and signal-to-noise ratio improvement.	The results do not consider all types of noise, only white and colored Gaussian noises.
[15]	Wavelet transformation has been applied to improve the accuracy and resolution of the radar signal interpretations.	Increases image recognition and interpretation of raw data.	Noise removal and required thresholding with wavelet transform.
[16]	Separate the target from the unwanted signals by using filters or comparing images with and without the reflected electromagnetic wave (EMW).	Image reconstruction using a bidirectional multidirectional filter (MDBF) algorithm.	A problem in target detection or identification.
[17]	The Means subtraction and Subspace of the Projection are used for removal methods at frequency range (1 -2.3) GHz.	A different method was used to remove the clutter and any unwanted signals.	The problem to identify the clutter from the local area and to remove signal limited to a threshold value

The problem of misclassification and accuracy of the GPR image has been resolved by using a new Underground Cavity Detection Network (UcNet) to improve hollow classification and overcome holes in complex urban areas. UcNet develops a convolutional neural network (CNN) and a B-scan image. [36]Discuss a new algorithm to detect underground objects using artificial neural networks (ANN) and machine learning (ML).
These algorithms improve object localization and the location of multiple objects, improving accuracy and reducing the error rate. Buried object features are required to identify the buried object. However, large data storage space is required, which can cause instability. [39]A pre-trained network improves detection performance by reducing the amount of data required by Convolutional Neural Networks (CNNs). The loss of some information will increase the error rate, and the level of pretraining depends on the degree of similarity between the source and the target. The pretraining stages determine the accuracy of the detection process. [40] proposed an automatic interpretation of the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm, which is used to obtain geometric values of a target such as location, physical dimension, and buried object type. The performance of this algorithm is improved in detection, recognition, and accurate information with a lower error rate. The new methods were performed on real and synthetic data and compared with the Hough transformation. A new model with cylindrical bodies was implemented with different cross-sectional values. [41] . Developed an automated convolutional neural network (CNN) algorithm to detect buried threats (BTD) based on a GPR device. Both pretraining and data augmentation were run to overcome the limited training data of CNNs with GPR data. Three other CNN architectures were used to get better CNN detection results. [42]Determine the physical properties of soils using Finite-Time Domain Difference (FDTD). It determined the physical properties of soil based on GPR response in homogeneous soils. Soil parameters used in the time-domain-difference B-scan response are also improved using particle swarm optimization (IPSO) related to target object recognition with multiple depths. Various simulations occur with the change of depth, radius, and conductivity of the buried object. [43] It studied different mines at different depths and then automatically detected a landmine or unexploded ordnance (UXO) based on machine learning (ML). A neural network (NN) and logistic regression are used to identify and locate buried objects. The results of using NN are more accurate compared to the logistic regression result. The threshold value was set to be 0.25 or less for better detection. [44]The detection process is improved with a new procedure that removes noise and noise from the GPR image and then distinguishes the target from the background by setting a threshold level. Neural networks and curve-fitting approaches Whatever it is, this method increases the error rate at a threshold value close to or above the reflection signal.

Table 3. Summary of the research papers for detection buried objects based on (GPR)

Reference	Characteristics of paperwork	Result	Comments and Limitations
[18]	A robust adaptive for the recognition process was tested in simulation and accurate data.	Detection and localization of the buried pipe, identify the hyperbola in the scan area.	The estimator is a big problem and practically has a small detection signal.
[19]	The algorithm has no prior knowledge of the medium, and a cunning filter recognizes the edge of the hyperbola, operating frequency at (400-900) MHz	Low computation time, good performance, and efficiency compared to commercial software.	False alarms are lab tested (0 to 20%) and undetected rate (0 to 28%).

Table 3 (cont.). Summary of the research papers for detection buried objects based on (GPR)

Reference	Characteristics of paperwork	Result	Comments and Limitations
[20]	Detection and segmentation of buried objects using the MALÅ GPR system at a frequency of (250-500) MHz	Good results in detection Buried objects compared to other segmentation methods such as MSE and RMSE standards.	The effect of a radio wave causes distortion.
[21]	Using the HOG algorithm for the detection process and SVM as a classifier and training at (250-700) MHz	The average result is 93.75% of detection targets for both synthetic and natural data tests.	During testing, the parameters of the HOG algorithm must be set.
[22]	Buried objects are located despite the noise, and the test frequency is (0.5-1.5) GHz.	The algorithm is used in different depths and conditions of soil and material.	Only metallic materials were used, and other materials required different locations.
[23]	Perform different algorithms like; (MUSIC), and W-MUSIC discovers buried objects close to each other.	The MUSIC algorithm reduces the error rate while W-MUSIC is affected by noise and changes with frequency.	The music algorithm suffered from a high error rate.
[24]	Determine the dispersion of buried objects using a 3D random transformation (RT).	Reliability in the detection process despite noise and clutter.	Memory is required to complete the detection and pattern recognition process.
[25]	The target detection energy correlation procedure used the GPR system at 1 GHz.	Average and background removal was used to improve the detection of non-metallic objects.	More process is required in object recognition.

Table 4. Summary of research papers on landmines detection based on GPR

Reference	Characteristics of paperwork	Result	Comments and Limitations
[26]	Linear partitioning and CNN are used to train synthetic data at 2GHz bandwidth. The pipeline used in landmine detection and its	Automated detection increased accuracy up to 95% with minimal detection preprocessing.	Accuracy decreases as the size of the CNN network decrease.
[27]	Fast and accurate SAR algorithm with Tx on vehicle and Rx mount as a drone. Simulations at (3.5-5.5) GHz	Improve penetration with high accuracy—detection of metallic or non-metallic materials.	The permittivity of the soil must be known or estimated.
[28]	GPR image representing the use of an online dictionary Learning that a support vector machine optimizes the extraction fracture of the buried object.	Develop mini-batch online dictionary learning, which can be used for correlation training data.	Practically high running time and less accurate results. False-alarm rates remain very high and are used with smaller mines.
[29]	Preprocessing and discrimination are used to remove clutter and characterize the energy density spectrum for landmines or clutter.	Improve detection and clutter discrimination.	A high error alarm rate is possible. It cannot identify the size or the shape of the landmine.
[30]	SIMCA is used to locate a buried object and uses a Pulse EKKO 1000 and REFLEXW package with an operating frequency of 450MHz	The integration of GPR with SIMCA provides the image with good accuracy and facilitates the interpretation of existing landmines.	High error rate due to accuracy problem as a result of the correction.
[31]	The results were obtained for three algorithms used for the detection of landmines.	Both EHD and HMM are good in a particular set of recognition processes.	The error rate increases due to the medium and the environmental change.
[32]	Various sensor technology is available to detect landmines, and GPR is the most common type.	Development is required in the image processing, the multi-sensing system, and the algorithm obtained.	Effects of weather and noise on detection. False alarms increase uncertainty and limit future research.

Table 4 (cont.). Summary of research papers on landmines detection based on GPR

Reference	Characteristics of paperwork	Result	Comments and Limitations
[33]	Error rate and accuracy are crucial performance-affected factors in the detection process, where the operating frequency is = 1 GHz.	Determining target depth, soil propagation characteristics, and landmine type depends on the types of detection used.	Plastic landmines require more research into the detection process than the metal type.
[34]	ADOG method for improving explosive device identification based on a B image.	ADOG output by subtracting the GPR image, the reflected signals of landmines are improved.	It is also difficult to recognize the high error rate while the signal passes through the medium.
[35]	The Automatic Target Recognition (ATR) algorithm, in parallel with GPR, determines the location of landmines.	The 96% of the recognition rate and false rate close to 0.017. Fuzzy logic reduced false alarms and changes in detection rates.	15 transmitter/receiver pairs were used, and each receiver power.

Table 5. Summarizes the research paper’s detection process using GPR with the smart algorithm.

Reference	Characteristics of paperwork	Result	Comments and Limitations
[37]	MOGA model is less complex and much faster than VSM and CNN models.	Improved the localization & detection based on the MOGA method.	The real-time implementation method takes a longer time & more architecture is required for implementation.
[38]	New methods UcNet developed based on a convolutional neural network (CNN) combined with phase analysis of super-resolution (SR) GPR images.	Overcome the sinkholes in complex urban roads. Image-based 3D Ground Penetrating Radar (GPR) Network for Underground Cavity Detection (UcNet) prevents sinkholes in complex urban roads.	GPR image inaccuracy may cause false alarms during phase analysis.
[36]	New algorithms from ANN and ML are used for the underground object.	Improve the localization of the buried object reduces the error rate.	Large data is required, which increases cost and can lead to instability.
[39]	Automatic algorithm of a (CNN) used to detect a buried threat detection (BTD).	Pretraining brought higher detection performance and improvements in detection performance for CNNs.	CNN's limited training data results in poor detection performance.
[40]	Obtaining the physical properties of the soil from the A-scan and then inverting these parameters using the FDTD and IPSO methods in the B-scan	Simulations were obtained with different values of cross-sectional radius, depth, and conductivity.	It is required with many simulated cases in different cross-sectional areas.
[41]	A new method for detecting unexploded ordnance using machine learning techniques of artificial neural networks, transmitter frequency (1-2.3) GHz.	Both ANN and logistic regression algorithms estimate the location of a buried object and ANN is more accurate in the results.	Results are limited by specific experimental design options such as GPR image patches' size and a particular cross-validation procedure.
[42]	The coupling of the IPSO algorithm to the FDTD analysis method to identify and localize the underground object.	A B-scan image with the algorithm was used to locate and identify buried objects (plastic and metal) at different depths.	The error rate is inversely proportional to the iteration number of algorithms.
[43]	• Automatically detects a landmine or unexploded ordnance (UXO) using a neural network (NN) and a logistic regression at the transmitter frequency (1-2.3 GHz).	Neural networks and logistic regression algorithms distinguish between targets and clutter, where neural networks have more accurate results.	The system is trained on one type of soil, and a more extensive set of training samples is needed to distinguish between different targets and chaos.
[44]	Determining the hyperbolic pattern in GPR images and locating buried objects using neural networks and curve-fitting techniques.	Automatic detection and location of buried objects by using the neural network is used to detect a buried object after estimating the position of the buried objects using curve fitting.	Error rate increase when the threshold value is close or higher than the reflection signal and accurate result techniques are required.

Conclusion

This paper summarizes the different algorithms used in detecting buried objects based on the ground-penetrating radar (GPR) as well as the interpretation of GPR images using four stages of the detection process which are preprocessing, feature extraction, feature reduction, and classification stages. It also distinguishes between an unwanted reflected signal such as noise and a direct wave from the desired signal of a buried target. Then compare A, B, and C scans, while B-scan is the most common type of detection.

The paper concluded that the intelligent smart algorithm is the most efficient and accurate compared to other algorithms. Whoever is searching for new intelligent algorithms to improve the detection and recognition process. Most research papers also rely on a single buried object, while more research is needed to discover more than one target.

REFERENCES

[1] S. Irisa and F.-V. France, "BURIED OBJECT DETECTION FROM B-SCAN GROUND PENETRATING RADAR DATA USING FASTER-RCNN Minh-Tan Pham , S ´ ebastien Lef ` evre Universit ´," pp. 6808–6811, 2018.

[2] R. J. Yelf, "Application of Ground Penetrating Radar to Civil and Geotechnical Engineering," Electromagn. Phenom., vol. V.7, no. №1 (18), 2007.

[3] D. Feng, X. Wang, and B. Zhang, "Specific evaluation of tunnel lining multi-defects by all-refined GPR simulation method using hybrid algorithm of FETD and FDTD," Constr. Build. Mater., vol. 185, pp. 220–229, 2018, DOI: 10.1016/j.conbuildmat.2018.07.039.

[4] L. Seyfi, "A Hybrid Pattern Recognition System for Detecting Buried Object in GPR Images," Helix, vol. 8, no. 2, pp. 3151–3159, 2018, DOI: 10.29042/2018-3151-3159.

[5] T. Truong, A. Dinh, and K. Wahid, "An ultra-wideband frequency system for non-destructive root imaging," Sensors (Switzerland), vol. 18, no. 8, 2018, DOI: 10.3390/s18082438.

[6] K. B. Kara and E. Pekşen, "1D full-waveform optimization using GPR data," 9th Congr. Baulk. Geophys. Soc. BGS 2017, vol. 2017-Novem, no. December 2017, DOI: 10.3997/2214-4609.201702521.

[7] R. W. Jacob and T. M. Urban, "Ground-Penetrating Radar Velocity Determination and Precision Estimates Using Common-Midpoint (CMP) Collection with Hand-Picking, Semblance Analysis and Cross-Correlation Analysis: A Case Study and Tutorial for Archaeologists," Archaeometry, vol. 58, no. 6, pp. 987–1002, 2016, DOI: 10.1111/arcm.12214.

[8] D. Toksoz, I. Yilmaz, A. Seren, and I. Mataraci, "A Study on the Performance of GPR for Detection of Different Types of Buried Objects," Procedia Eng., vol. 161, pp. 399–406, 2016, DOI: 10.1016/j.proeng.2016.08.581.

[9] V. R. N. do. Santos, W. Al-Nuaimy, J. L. Porsani, N. S. T. Hirata, and H. S. Alzubi, "Spectral analysis of ground penetrating radar signals in concrete, metallic and plastic targets," J. Appl. Geophys., vol. 100, pp. 32–43, 2014, doi: 10.1016/j.jappgeo.2013.10.002.

[10] H. Chen and A. G. Cohn, "Probabilistic robust hyperbola mixture model for interpreting ground penetrating radar data," Proc. Int. Jt. Conf. Neural Networks, 2010, DOI: 10.1109/IJCNN.2010.5596298.

[11] A. Strange, V. Chandran, and J. Ralston, "Signal processing to improve target detection using ground penetrating radar," Res. Conc. Speech, Audio Video Technol. Qld Univ. Technol., no. June 2014, pp. 3–6, 2002, [Online]. Available: https://eprints.qut.edu.au/2994/%0Ahttp://onlinelibrary.wiley.com/doi/10.1002/0471654507.eme152/full%5Cnhttp://eprints.qut.edu.au/2994/.

[12] G. Junkin and S. P. Kingsley, "New strategy to locate buried object," no. 6, 1995.

[13] A. M. M. Mostapha, A. Faize, G. Alsharahi, M. Louzazni, and A. Driouach, "Effect of external noise on ground penetrating radar ability to detect objects," Int. J. Microw. Opt. Technol., vol. 14, no. 2, pp. 124–131, 2019.

[14] X. L. Travassos, D. A. G. Vieira, V. Palade, and A. Nicolas, "Noise reduction in a non-homogenous ground penetrating radar problem by multiobjective neural networks," IEEE Trans. Magn., vol. 45, no. 3, pp. 1454–1457, 2009, DOI: 10.1109/TMAG.2009.2012677.

[15] J. Zhu, Y. Xue, N. Zhang, Z. Li, Y. Tao, and D. Qiu, "A noise reduction method for Ground Penetrating Radar signal based on wavelet transform and application in tunnel lining," IOP Conf. Ser. Earth Environ. Sci., vol. 61, no. 1, 2017, DOI: 10.1088/1755-1315/61/1/012088.

[16] D. Ri et al., "Multiscale Directional Bilateral Filter Based Clutter Removal in Gpr Image Analysis ' Hql] . Xpox Dqg , Vlq (Uhu," pp. 0–3.

[17] R. Solimene, A. Cuccaro, A. Dell'Aversano, I. Catapano, and F. Soldovieri, "Ground clutter removal in GPR surveys," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 7, no. 3, pp. 792–798, 2014, doi: 10.1109/JSTARS.2013.2287016.

[18] Q. Hoarau, G. Ginolhac, A. M. Atto, J. M. Nicolas, and J. P. Ovarlez, "Robust adaptive detection of buried pipes using GPR," Eur. Signal Process. Conf., vol. 2016-Novem, no. March 2018, pp. 533–537, 2016, DOI: 10.1109/EUSIPCO.2016.7760305.

[19] L. Mertens, R. Persico, L. Matera, and S. Lambot, "Automated Detection of Reflection Hyperbolas in Complex GPR Images with No A Priori Knowledge on the Medium," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 1, pp. 580–596, 2016, DOI: 10.1109/TGRS.2015.2462727.

[20] I. J. Muhsin and N. J. T, "Buried Objects Detection and Segmentation Using a Semi-Automatic Technique Called Selected Peaks of Summing up Traces (SPST) Buried Objects Detection and Segmentation Using a Semi-Automatic Technique Called Selected Peaks of Summing up Traces (SPST)," no. September 2019, 2016.

[21] K. L. Lee and M. M. Mokji, "Automatic target detection in GPR images using Histogram of Oriented Gradients (HOG)," 2014 2nd Int. Conf. Electron. Des. ICED 2014, no. 1, pp. 181–186, 2014, DOI: 10.1109/ICED.2014.7015795.

[22] F. Soldovieri et al., "Gpr estimation of the geometrical features of buried metallic targets in testing conditions," Prog. Electromagn. Res. B, vol. 49, no. 49, pp. 339–362, 2013, DOI: 10.2528/PIERB12120508.

[23] W. Jiang, S. Pennock, and P. Shepherd, "A novel W-MUSIC algorithm for GPR target detection in noisy and distorted signals," IEEE Natl. Radar Conf. - Proc., pp. 1–6, 2009, DOI: 10.1109/RADAR.2009.4977050.

[24] A. Dell'Acqua, A. Sarti, S. Tubaro, and L. Zanzi, "Detection of linear objects in GPR data," Signal Processing, vol. 84, no. 4, pp. 785–799, 2004, DOI: 10.1016/j.sigpro.2003.12.010.

[25] M. Sezgin, F. Kurugollu, I. Tasdelen, and S. Ozturk, "Real-time detection of buried objects by using GPR," Detect. Remediate. Technol. Mines Minelike Targets IX, vol. 5415, no. January 2004, p. 447, 2004, DOI: 10.1117/12.541128.

[26] S. Lameri, F. Lombardi, P. Bestagini, M. Lualdi, and S. Tubaro, "Landmine detection from GPR data using convolutional neural networks," 25th Eur. Signal Process. Conf. EUSIPCO 2017, vol. 2017-Janua, pp. 508–512, 2017, DOI: 10.23919/EUSIPCO.2017.8081259.

[27] M. Garcia-Fernandez, A. Morgenthaler, Y. Alvarez-Lopez, F. Las Heras, and C. Rappaport, "Bistatic landmine and IED detection combining vehicle and drone mounted GPR sensors," Remote Sens., vol. 11, no. 19, pp. 1–14, 2019, DOI: 10.3390/rs11192299.

[28] F. Giovanneschi, K. V. Mishra, M. A. Gonzalez-Huici, Y. C. Eldar, and J. H. G. Ender, "Dictionary learning for adaptive GPR landmine classification," IEEE Trans. Geosci. Remote Sens., vol. 57, no. 12, pp. 10036–10055, 2019, DOI: 10.1109/TGRS.2019.2931134.

[29] P. M.P, "Buried Object Discrimination in a Ground Penetrating Radar Radargram," Bonfring Int. J. Adv. Image Process., vol. 3, no. 1, pp. 08–12, 2013, DOI: 10.9756/bijaip.10188.

[30] A. Sengodan and W. P. Cockshott, "The SIMCA algorithm for processing ground penetrating radar data and its use in landmine detection," 2012 11th Int. Conf. Inf. Sci. Signal Process. their Appl. ISSPA 2012, no. May 2011, pp. 983–988, 2012, DOI: 10.1109/ISSPA.2012.6310699.

[31] A. Karem, A. Fadeev, H. Frigui, and P. Gader, "Comparison of different classification algorithms for landmine detection using GPR," Detect. Sens. Mines, Explos. Objects, Obs. Targets XV, vol. 7664, no. April, p. 76642K, 2010, DOI: 10.1117/12.852257.

[32] L. Robledo, M. Carrasco, and D. Mery, "A survey of land mine detection technology," Int. J. Remote Sens., vol. 30, no. 9, pp. 2399–2410, 2009, DOI: 10.1080/01431160802549435.

[33] D. J. Daniels, "A review of landmine detection using GPR," 2008 5th Eur. Radar Conf. Proceedings, EuRAD 2008, vol. 44, no. 0, pp. 280–283, 2008.

[34] X. Xu and E. L. Miller, "Adaptive difference of Gaussians to improve subsurface object detection using GPR imagery," IEEE Int. Conf. Image Process., vol. 2, pp. 457–460, 2002, DOI: 10.1109/icip.2002.1039986.

[35] P. D. Gader, B. N. Nelson, H. Frigui, G. Veillette, and J. M. Keller, "Fuzzy logic detection of landmines with ground penetrating radar," Signal Processing, vol. 80, no. 6, pp. 1069–1084, 2000, DOI: 10.1016/S0165-1684(00)00020-7.

[36] X. L. Travassos, S. L. Avila, and N. Ida, "Artificial Neural Networks and Machine Learning techniques applied to Ground Penetrating Radar: A review," Appl. Comput. Informatics, no. October, 2018, DOI: 10.1016/j.aci.2018.10.001.

[37] H. Harkat, A. E. Ruano, M. G. Ruano, and S. D. Bennani, "GPR target detection using a neural network classifier designed by a multiobjective genetic algorithm," Appl. Soft Comput. J., vol. 79, pp. 310–325, 2019, DOI: 10.1016/j.asoc.2019.03.030.

[38] M. S. Kang, N. Kim, S. B. Im, J. J. Lee, and Y. K. An, "3D GPR image-based UcNet for enhancing underground cavity detectability," Remote Sens., vol. 11, no. 21, pp. 1–18, 2019, DOI: 10.3390/rs11212545.

[39] J. Bralich, D. Reichman, L. M. Collins, and J. M. Malouf, "Improving convolutional neural networks for buried target detection in ground penetrating radar using transfer learning via pretraining," Detect. Sens. Mines, Explos. Objects, Obs. Targets XXII, vol. 10182, p. 101820X, 2017, DOI: 10.1117/12.2263112.

[40] B. Jafrasteh and N. Fathianpour, "Automatic extraction of geometrical characteristics hidden in ground-penetrating radar sectional images using simultaneous perturbation artificial bee colony algorithm," Geophys. Prospect., vol. 65, no. 1, pp. 324–336, 2017, DOI: 10.1111/1365-2478.12413.

[41] D. Reichman, L. M. Collins, and J. M. Malouf, "Some good practices for applying convolutional neural networks to buried threat detection in Ground Penetrating Radar," 2017 9th Int. Work. Adv. Gr. Penetrating Radar, IWAGPR 2017 - Proc., 2017, DOI: 10.1109/IWAGPR.2017.7996100.

[42] Y. Matriche, M. Feliachi, A. Zaoui, and M. Abdellah, "FDTD and improved PSO methods of coupling for identification and localization of buried objects using GPR B-scan response," Int. J. Remote Sens., vol. 35, no. 21, pp. 7499–7518, 2014, DOI: 10.1080/01431161.2014.968689.

[43] X. Núñez-Nieto, M. Solla, P. Gómez-Pérez, and H. Lorenzo, "GPR signal characterization for automated landmine and UXO detection based on machine learning techniques," Remote Sens., vol. 6, no. 10, pp. 9729–9748, 2014, doi: 10.3390/rs6109729.

[44] N. P. Singh and M. J. Nene, "Buried object detection and analysis of GPR images: Using neural network and curve fitting," 2013 Annu. Int. Conf. Emerg. Res. Areas, AICERA 2013 2013 Int. Conf. Microelectron. Commun. Renew. Energy, ICMiCR 2013 - Proc., no. June, 2013, doi: 10.1109/AICERA-ICMiCR.2013.6576024.