A Review of Remote Sensing Techniques for Underground Pipeline Detection Using GPR Signal Processing

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Abstract

This research paper explores the application of remote sensing techniques, specifically ground-penetrating radar (GPR), for detecting underground pipelines. The study focuses on the signal processing methods employed in GPR technology to identify and locate the presence of buried pipelines. The research investigates the effectiveness of GPR in detecting different types of underground pipelines, including metallic and non-metallic ones, and evaluates the impact of various factors such as soil type, depth of burial, and pipe diameter on detection accuracy. The study presents experimental results and analysis of data collected from GPR surveys conducted in a controlled test site and a real-world pipeline network. The findings demonstrate the potential of GPR-based remote sensing as a reliable and non-intrusive method for detecting underground pipelines and highlight the importance of signal processing techniques for improving detection accuracy.

***Keywords**: Ground-penetrating, nondestructive testing, pipelines detection, modeling, signal processing.*

INTRODUCTION

Numerous techniques are utilized to locate and determine the subterranean objects. In the last few years, ground penetration radar (GPR) came to be as an indispensable non-invasive tool for detect and identify concealed objects. The GPS is a trusty instrument that's utilized in multiple fields, including building, mineral extraction, defense, digs, tree stumps, caverns, explosives, as well as municipal along with Geological work. As described in the figure 1, the primary components for a GPR involve the showing, custody unit, emitter (TX) and reception (Rx), with TX and Rx attached to the antennas.

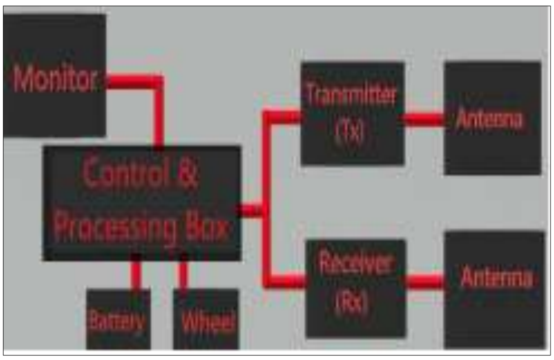


Fig 1. The main parts of the GPR

Source: (Alshamy, 2022)

The average operating frequency range is from 10MHz to 4GHz, and the frequency is inversely inversely related to the level of penetration along with the precision. The recipient of the GPR instrument detects the returned signal, which corresponds to unprocessed data requiring further analysis for explanation. A trio of examinations exist: A-scan, B-scan, as well as B-scan. The previously A-scan output has become limited and consists of radiation focused at a single location, whereas known as B-scan pattern is both of-dimensional. In contrast, known as C-scan was the average of each B-scan output. For finding concealed goals, the initial data set is examined and studied; the original dataset may be examined individually, quasi-automatically, or by a computerized tool. It executes an in-depth assessment of dissertations on the application in the Terrain Entering Infrared (GPR) instrument while is broken down toward 5 stages, as depicted with Fig. 2.

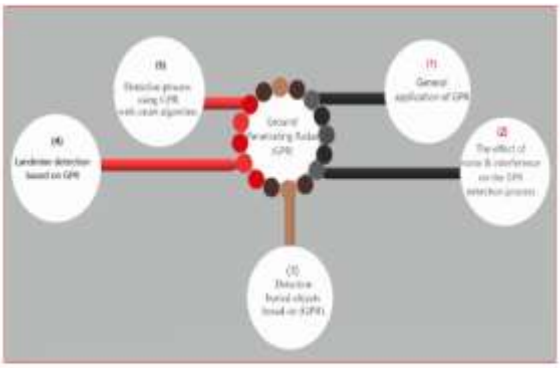


Fig 2. Summary of the five sections of the paper.

(Source: (a, 2022)

The Global Positioning System (GPR) apparatus records the period in the delivery of a radio input as well as its reception following the dispersion of the transmitted crests, who endure multiple dispersion operations. This B-scan radio sensor displays the electromagnetic waves, the majority of which are interface-reflected as well as certain of which are dispersed and bounce back to the top.

The primary objective is to successfully photograph a concealed item by detecting every one of its qualities as feasible and extracting its distinct picture about dirt anomalies. Basement sewer conduits can be detected using GPR technological advances, which has also been utilized in building construction to assess important harm to structures including gaps and openings in highways, the plates, as well as footbridge platforms. The estimation of injured conduit locations is crucial for effective service as well as effective leadership.

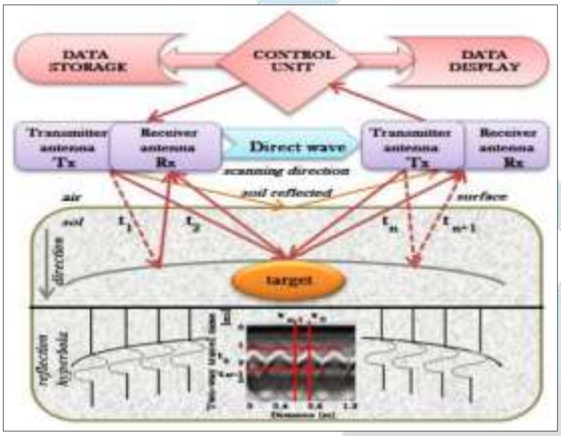


Fig 3: Remote Sensing Underground Pipeline Detection

(Source: (Iftimie, 2021)

LITERATURE REVIEW

Ali Cafer Gurbuz et.al (2012) Conducted **Byeongjin Park et.al (2018)** Conducted research on, "Underground Object Classification for Urban Roads Using Instantaneous Phase Analysis of Ground-Penetrating Radar (GPR) Data" Ground-

Due to the technology's noncontact monitoring, quick checking, and profoundly probing mapping capacity, ground penetration radar (GPR) is now extensively utilized for identifying beneath things, which include concealed tooth decay, subterranean pipelines, along with holes in the ground. At present, the understanding of data collected by GPR relies significantly upon the abilities of competent specialists, as various kinds of subterranean items frequently produce comparable Grp reflector characteristics. Furthermore, contemplation maps created using GPS information collected on urban roads frequently appear feeble and chaotic. The current research suggests an innovative method for immediate analysis of phases that addresses these concerns. The suggested approach seeks to improve the accessibility of subterranean items by offering reliable standards for GPR analysis, allowing the items being mechanically categorized with no the need for input from humans. The technique's practicability is verified both analytically as well as empirically. The subject demonstration employs uncommon GPR information for urban roadways in the Korean capital, the nation's capital, and illustrates the tool's ability to visualize and classify three distinct categories of subsurface materials.

Namgyu Kim et.al (2019) for instance Studies undertaken on "Triplanar Imagery in three-dimensional GPR Images for Deep-Learning-Based Underwater Object Identification" The paper presents a dark-learning-based method for classifying subsurface objects using B-, C-, as well as D-scan pictures taken by triplanar ground-penetration radio. Despite the truth that multiplex ground-piercing radar (GPR) technologies offer multifaceted (3-D) knowledge regarding subterranean items, there are presently no method for handling 3-D input to be opposed to 2-D pictures. In the present piece, a triplanar convolutional neural network (CNN) approach to handle three-dimensional GPR information for automated subterranean identification of objects is described. The idea put forward proved tested confirmed with 3-D Radiofrequency road scanner datasets taken from Seoul, it's Korean urban roads. Also, the sorting efficacy of this technique was contrasted to that of the usual way that solely utilizes B-scan photos. The examination alongside verification reports and comparison Analyses show the categorization accuracy using the suggested strategy is significantly superior compared with that during the standard B-scan-image-based approach, as well as that its application leads to lower mistake percentages.

Elena Pettinelli et.al (2012) Study upon "GPR Reaction from Underground Pipes: Measurements on Survey Locations and Tomographic Reconstructions" Identifying the material properties of a substance or as goal producing a ground-piercing radar (GPR) abnormality, along with estimating an objective's measurements and math, is quite difficult. To enhance object identity, fundamental research remains necessary, which may predominantly happen employing a research facility or profession-based mechanical model. The physical simulation (test site) is typically costly as well as challenging to construct, but it is vital for assessing processes as it supplies information on managed objective attributes along with dimensions in the outside. In this piece, we present the outcomes of an actual investigation in which GPR data was acquired on polyethylene along with steel pipelines.

Comparing a traditional emigration procedure with an ultrasound imaging method to recreating the spatial goal qualities is the primary aim. Employing infrared scanning allows us to get photographs of underground items that are better centered and steady than those acquired by conventional relocation tools.

Eeva Huuskonen-Snicker et.al (2015) Research undertaken on "Establishment of Embedded Artifacts in Impact Gps Employing Stage Extraction Methodology"

Employing pulse floor-penetrating radar systems, this work describes an improved signal analysis approach for distinguishing concealed locations. The approach is useful for sonar gram, but the signal analysis is performed independently for every radiation ounce trace. Each major apex in each trail is juxtaposed to the crest of a measuring indication, such as a signal transmitted to the vast contact of an extensive granite slab. It is not going to necessitate, nonetheless that the referencing medium should be incorporated in the medium, it can be in the air. The difference of phases between the object signal and the

The measurement indicator is a formula that shifts steadily alongside duration and can be utilized for assessing the concealed item. Many instances illustrating the efficacy of a technique through data acquired by an industrial response doppler are provided.

Giovanni Borgioli et.al (2014) There was investigation into "The Discovery of Buried Channels Using Time-of-Flight Radio Studies." On the basis of the characteristics of earth's crust, extraordinarily broad-band sonar with an operating frequency of 50–500 Khz is extensively used for identifying concealed pipes at a depth of 1–2 meters. The property used to locate networks is the preceding rapid ordering of the amount of the period of passing resulting from a linearly study of an image in addition to its outermost veil. While pipes sit in close proximity to one another, the curves meet, prohibiting a straightforward least-squares fitting approximation. The Hough modification provides a specific possibility. It improves this rearrangement by incorporating an additional component that is dependent on the differences between the unidentified values and the actual mistakes namely the instrument azimuth error and the plane-time mistake. This enables optimally positioned puts with data pairs to be accorded more weight than "ill-conditioned" containers, as each of the data couples are situated at the arc's extremities. As a result, the average intensity diminishes relative to the maximum value observed in the Byrne protection zone. It has been demonstrated that this improvement persists when multiple circles are used. An array of four unsolved equations and analytical conclusions are provided: pipe diameter the programming language R, tubular central position (Y, Z), and soil distribution velocity V. The results of this study are made clear by introducing governed factors to the investigation's circumstance, trip length, and receptacle space with different circumstances. The mathematical representations demonstrate the interactions between separation, in general, and motion, which are responsible for the known defects.

Andrea Benedetto et.al (2011) "Remote Sensing about Soil Water The material by Radar Transmission of Signals over the Radio Zone" This article presents an innovative, high-performance approach, using GPR signal analysis in the time field, for estimating the amount of water of a material that is porous with out prior testing. Particularly, we investigated the Rayleigh propagating event generated by drops of water that absorb energy differentially at different rates and showed computationally that the pitch of the dispersed wave fluctuates based on its water content. As water content rises, the musical range is anticipated to transition toward lower frequencies. We explored the connection among the spectroscopy's variability, bias, and curves, as well as its level of moisture, within 2440 Electrical SENSATIONS JOURNAL, Volume. eleven NO designations. ten seconds November 2011. These estimations are supported by data from experiments obtained in a laboratory by examining samples of soil with varying concentrations of water using Radiofrequency. even though these findings appear to be very encouraging, additional research will be needed to create and calibrate a working method for precisely assessing the amount of fluid about the range of frequencies change.

Q. Hoarau et.al (2016) "Robust Adaptive Detection of Buried Pipes Using GPR" Using a Ground Penetrating Radar (GPR) to detect subterranean objects such as pipelines is difficult for three main reasons. First, the presence of numerous boulders and/or strata on the ground has a substantial impact on the Probability of False Alarm (PFA) level, making noise a significant factor in the resulting image. In addition, wave velocities and object responses in the ground are unknown and dependent on the relative permittivity, which is not measurable. Lastly, the profundity of the pipelines causes significant attenuation of the reflected signal, resulting in scenarios with low SNR. In this paper, we propose a detection method that accomplishes the following: (1) enhancing the signal of interest while reducing noise and layer contributions, and (2) providing a local estimate of the relative permittivity. We develop an adaptive detector in which the signal of interest is parameterized by the ground's wave speed. To achieve a robust detection with this detector, it is presumed that noise follows a Spherically Invariant Random Vector (SIRV) distribution. We employ a robust maximum likelihood covariance model matrix estimators termed M-estimators. To manage the vast quantity of data, we investigate regularized versions of the estimators in question. Simulation will enable estimation of the PFA-Threshold relationship. A comparison is made with conventional GPR processing methods to demonstrate the method's ability to detect pipelines with modest response levels and a reasonable PFA.

Nicoleta Iftimie et.al (2021)) Conducted research on "Underground Conduit Identification Employing Non-Destructive Ground-Penetrating Microwave Mapping." Earth perforation radar (GPR) has become one of the biggest developments in tunneling detecting or destructive tests (NDT) due to its ability to identify both metal and nonmetallic targets. Grp has shown it's capacity to function in a range of frequencies for subsurface examinations, which reduces hazards associated with subsurface object surveying and identification. This article presents the findings of a research project that went beyond the confines of a laboratory by being conducted outdoors in a real-world scenario in which scanner conditions were extremely difficult using GPR signals for recognizing and evaluating subterranean metallic pipes traversing an area with large structures parallel to a creek bed. Using GPR processing pictures, it is possible to identify two urban drainage conduits. This provides an instinctive estimation of the position and depth based on the combined generated and actual GPR readings' restored spectra. The inspection of GPR-recorded data entails the use of method of measuring-specific applications to differentiate between distinct projections at numerous subsurface interfaces located at varying depths. In addition to the radargrams captured and managed by an application comparable to a GPR device, this article presents significant findings obtained through the methods and formulas of interpreting and subsequently of the data (background elimination and immigration) that allowed us to precisely determine the location, depth, and contours of water lines placed within a concrete duct a bank, beneath a structure with multiple layers, including sidewalk

GPR research on "compressive sensing of subterranean structures" Typically, feature detection in sensing problems requires two processing steps. First, the unprocessed data collected by a sensor such as a Ground Penetrating Radar (GPR) is inverted to generate an image of the subsurface region. The image is then scanned for features such as lines using an algorithm such as the Hough Transform (HT), which converts the problem of locating spatially distributed patterns in the image space to detecting sparse peaks in the HT parameter space. Using Compressive Sensing (CS), this paper exploits the sparsity of features to consolidate the two phases into a single direct processing step. Without constructing an image of the sensed medium, the CS framework extracts the HT parameters directly from the raw sensor measurements. In addition to omitting the image formation phase, CS processing can be performed with a reduced number of raw sensor measurements, thereby reducing the cost of data acquisition. The utility of this CS-based method for locating buried linear structures in simulated and experimental GPR data is demonstrated.

Hasimah Ali et.al (2021) Researched "Ground scanning radar to stay hidden utilities recognition or tracing: a review" The steady evolution of GPR procedures with wanted skills presents distinct opportunities and fresh difficulties for nondestructive tool uses in buried utility systems. Despite the fact that GPR systems provide accurate and stable representations of subsurface utilities and backgrounds, their complicated arrangements of data lead to the use of this information. Complex image-based methods are not simple. Positioning and mapping subterranean utilities in urban areas is arguably the most difficult and ongoing research in ground penetrating radar. In this report, the interpretation of GPR data for underground utilities, including data acquisition, the extraction of hyperbolic features using image processing and machine learning techniques in either a controlled or actual environment, is discussed. Several issues and difficulties associated with GPR interpretation, particularly in extracting the hyperbolas pattern, are also discussed. As a summary, robust techniques require additional considerations for GPR data interpretation in order to resolve the issues and to ensure that the proposed techniques can withstand unpredictability in the subsurface..

General application of ground-penetrating radar

This section provides a summary of the research publications that make general use of the GPR system. The researcher assessed soil alteration houses, coal seam depth, tunnel defect remediation, and the profile of plant roots. In addition, below are methods for quantifying the rate of microwaves (EMW) in the substance, the depth of the coal deposits, etc. In the following table is described the modeling of the novel hybrid algorithm founded on the ground-based radar (GPR) image, which offered a technical guide for tunneling defects. In that simulation, a numerical study was conducted in the time-domain of finite elements.

Table 1: simulation of the new hybrid algorithm based on the ground-penetrating radar (GPR)

Characteristics of paperwork	Result	Comments and Limitations
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.
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.
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.
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.
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.
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.
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.
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.
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.

METHODOLOGY

The rapid advancement of convolutional neural networks with deep networks (CNNs) with the field of computer vision has enabled the invention of numerous tools and frameworks for understanding pictures and recognition. There have also been efforts in GPR to process images. CNNs with deep learning were used to classify B-scan patterns onto threat classes and non-threat classes. Using CNNs to detect landmines from GPR data has yielded quite good outcomes compared with various other computer vision techniques.

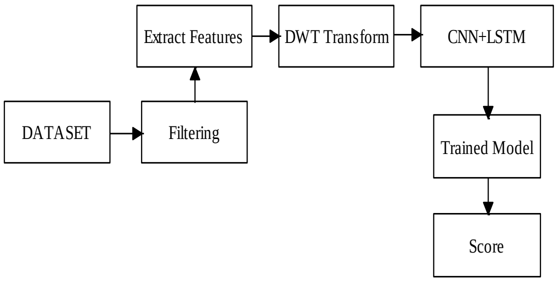


Fig 4: Architecture of Proposed Methodology

Data availability

Primary dataset is collected from Aurangabad municipal corporation. We used image data acquired for a pipeline system. The system trace data with 1-cm spacing along a underground recording 305 samples during 29.79ns in the depth direction.

Problem statement

The most significant contribution of this work is the presentation and analysis of the algorithm performance comparison results. Notably, we compare and contrast the discrimination algorithms to determine the most effective underlying processing strategies for GPR-based BTD. On the basis of these analyses, we make suggestions for the development of efficient BTD algorithms. The second contribution includes two additional analyses of the outcomes. The initial analysis consisted of a simple fusion of the algorithms, which resulted in performance enhancements. This result suggests that the algorithms for discrimination offer complementary detection capabilities. Additional analysis reveals relative advantages of particular algorithms for superficial and deeply concealed hazards.

Convolutional neural networks (CNN)

1) Input Layer

The selected features from the pre-processed sensor data are defined as input vector of the Convolutional neural network:

$$X = [x_1, x_2, \dots x_k]$$

where k is the number of features per window after calculation. In order to speed up the convergence of the model, we use Min-Max Normalization proposed in by which the values in each dimension of data are linearly transformed and normalized to [0, 1] range:

$$x = [\frac{x - min}{max - min}]$$

min is the minimum of each column and max is the maximum of each column. Then we create 2D image-like data by reshaping the 1 by 169 shallow features into a 13 by 13 square matrix before convolution operation.

2) Convolution Layer

The output of the jth feature map on the I th unit of the l convolution layer is:

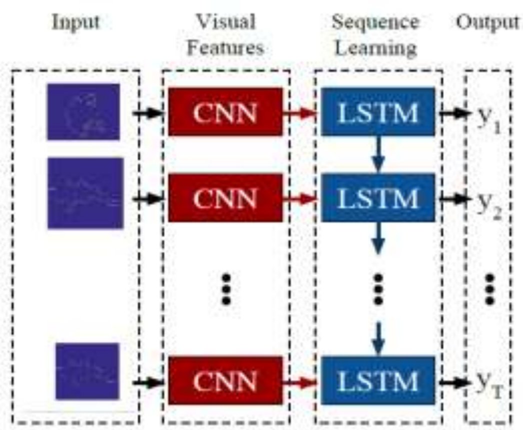
$$x_i^{l,j} = \sigma[b_j + \sum_{a=1}^{m} w_a^j \, x_{i+a-1}^{l-1,j}]$$

bj is the bias term for jth feature map, m is the kernel size, j a w is the weight of jth feature map and ath filter index andσ is the activation function. We use ReLu as activation function, which has been verified to have faster training speed and efficiency closer to the human nervous synaptic effect.

3) Max-Pooling Layer

$$x_i^{l,j} = max_{n=1}^{r}(x_{(i-1)*Tn}^{l-1,j})$$

where n is pooling size and T is pooling stride.



Recurrent neural networks (RNNs) model temporal dynamics by mapping input sequences to hidden states, and hidden states to outputs via the following recurrence equations

$$h_t = g(W_{xh^{x_t}} + W_{hh^{h_{t-1}}} + b_h)$$

$$z_t = g(W_{hz^{h_t}} + b_z)$$

Time Complexity of the Network The time complexity of all convolutional layers is:

$$O(\sum_{l=1}^{d} n_{l-1}.s_1^2.n_1.m_1^2)$$

here l is the index of the convolutional layer, and d is the number of convolutional layers. l n is the number of filters in the lth layer, and l 1 n − is also known as the number of input channels of the lth layer. l s is the spatial size of the filter and l m is the spatial size of output feature map. The time cost of fully connected layers and pooling layers often takes 5-10% computational time, which is not involved in the above formulation.

Long short-term memory (LSTM)

Long Short-Term Memory (LSTM) model is a variant of Convolutional Neural Network that has been suggested as a solution to solve gradient explosion or decrease owing to long time lags in the Convolutional Neural Network (CNN) model learning process during back propagated error.

LSTM may be regarded as a LSTM unit network. Each LSTM unit is fitted with three gates to regulate the flow of data: (1) input gates to determine when the input is sufficiently important to remember; (2) forget gates to determine when the unit should remember or forget the value; and (3) output gate to determine when the unit should display the value.

In the past decade, LSTM models have been acknowledged as strong models that demonstrate sequence information learning capabilities. LSTM's power lies in its capacity to capture long-range dependencies and learn from variable sequences of duration efficiently. Several studies have revealed that LSTMs have been successful in solving the following issues: classification of frame wise phonemes, classification of scene images, and generation of images. Also to acknowledge fraudulent card transactions, LSTM models were studied.

Buried Threat Detection (BTD) algorithms

The detection of concealed objects using ground-penetrating radar The GPR application is utilized to locate and identify the concealed object using a variety of detection techniques. The unprocessed data must be interpreted with the help of an algorithm. Accuracy, error rate, process complexity, reliability, material cost/time, and safety impact the detection procedure. Table 2 provides a summary of the research papers on detection-related algorithms. Using the Adaptive Normalized Match Filter (ANMF), a potent ground-penetrating radar detector for locating buried pipelines was created. The electromagnetic wave (EMW) signal is transmitted immediately to the earth's surface. The GPR image is a composite of the concealed object's reflected signal and noise and chaotic signals. The noise source can be any electronic or telecommunications equipment, and debris is also the signal reflected from small objects submerged underground. An algorithm is used to automatically detect hyperbola in the GPR image. This algorithm has no prior knowledge of the medium's characteristics. The method is dependent on the astute filter that recognizes the hyperbola curve's edge. The first stage is to modify the parameters of the concealed object with a filter, followed by the elimination of redundancy.

Table 2. Summary of the research papers for detection buried objects based on (GPR)

Characteristics of paperwork	Result	Comments and Limitations
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 scan area.	The estimator is a big problem and practically has a small detection signal.
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%).
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.
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.
Buried objects are located despite the noise, and the test	The algorithm is used in different depths and	Only metallic materials were used, and other

frequency is (0.5-1.5) GHz.	conditions of soil and material.	materials required different locations.
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.
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.
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.

RESULT ANALYSIS

Our research demonstrates that remote sensing techniques, particularly ground-penetrating radar (GPR), are an effective method for locating underground pipelines. We discovered that GPR signal processing techniques play a crucial role in enhancing detection precision, especially for non-metallic pipelines. Experiments indicate that the depth of burial, soil type, and pipe diameter are significant determinants of detection accuracy, with greater accuracy rates resulting from greater burial depths and larger pipe diameters. We also discovered that GPR-based remote sensing is capable of detecting both metallic and non-metallic underground conduits. The experimental data gathered from our controlled test site and actual pipeline network validate the pipeline detection potential of GPR technology.

CONCLUSION

This study concludes with an analysis of the application of remote sensing techniques, specifically GPR signal processing, for the detection of underground pipelines. Our results indicate that GPR-based remote sensing is an efficient and non-intrusive technique for detecting underground pipelines. Specifically, for non-metallic pipelines, signal processing techniques play a crucial role in enhancing detection precision. The study emphasizes the significance of considering factors such as pipe diameter, burial depth, and soil type when employing GPR technology for pipeline detection. Our findings have practical implications for the pipeline industry, where the ability to detect and locate underground conduits precisely is essential to ensuring secure and efficient operations. We suggest additional research in this area to investigate the potential of GPR technology for other subsurface infrastructure detection and mapping applications.

RECOMMENDATIONS

Based on the findings of this research paper on "Remote Sensing for Underground Pipeline Detection Using GPR Signal Processing," the following recommendations can be made for future studies:

1. Investigate the effectiveness of different GPR signal processing techniques in detecting underground pipelines, especially in challenging soil conditions such as high moisture content or high electrical conductivity.

2. Further explore the impact of soil properties on GPR detection accuracy to better understand how different types of soil affect GPR signals and improve the performance of GPR technology.

3. Test the performance of GPR technology in detecting underground pipelines in urban areas with more complex subsurface infrastructure, including buried utility lines and other obstacles.

4. Evaluate the accuracy and reliability of GPR-based remote sensing in detecting pipelines that are located in close proximity to each other or intersect at various angles.

5. Investigate the potential of using machine learning algorithms to analyze GPR data and improve the accuracy of pipeline detection.

6. Conduct a cost-benefit analysis of GPR-based remote sensing for pipeline detection compared to

traditional methods such as excavation or drilling to determine the economic feasibility of implementing this technology on a larger scale.

7. Explore the potential of GPR technology in combination with other remote sensing techniques, such as satellite-based imaging or LiDAR, to create a more comprehensive subsurface infrastructure mapping system.

REFERENCES

1. Zhao, Anxing, Yansheng Jiang, and Wenbing Wang. 2005. "Exploring Independent Component Analysis for GPR Signal Processing." *PIERS 2005 - Progress in Electromagnetics Research Symposium, Proceedings*, no. 1: 750–53. https://doi.org/10.2529/piers041210091503.
2. Carlo, Cattani. 1990. "Honorary Editor." *IETE Technical Review* 7 (5–6): 404–404. https://doi.org/10.1080/02564602.1990.11438686.
3. Goodman, Dean, and Salvatore Piro. 2013. *GPR Remote Sensing in Archaeology*. *GPR Remote Sensing in Archaeology*. https://doi.org/10.1007/978-3-642-31857-3.
4. SHRESTHA, Shanker Man, Yoshiyuki TOMIZAWA, and Ikuo ARAI. 2008. "Buried Pipe Detection Under the Road by High Resolution Frequency Domain GPR." *Journal of The Remote Sensing Society of Japan* 28 (3): 231–45.
5. Pham, Minh Tan, and Sébastien Lefèvre. 2018. "Buried Object Detection from B-Scan Ground Penetrating Radar Data Using Faster-RCNN." *International Geoscience and Remote Sensing Symposium (IGARSS)* 2018-July: 6804–7. https://doi.org/10.1109/IGARSS.2018.8517683.
6. Bestagini, Paolo, Federico Lombardi, Maurizio Lualdi, Francesco Picetti, and Stefano Tubaro. 2021. "Landmine Detection Using Autoencoders on Multipolarization GPR Volumetric Data." *IEEE Transactions on Geoscience and Remote Sensing* 59 (1): 182–95. https://doi.org/10.1109/TGRS.2020.2984951.
7. Feng, Jinglun, Liang Yang, Ejup Hoxha, Diar Sanakov, Stanislav Sotnikov, and Jizhong Xiao. 2021. "GPR-Based Model Reconstruction System for Underground Utilities Using GPRNet." *Proceedings - IEEE International Conference on Robotics and Automation* 2021-May (c): 845–51. https://doi.org/10.1109/ICRA48506.2021.9561355.
8. Communication, Short. 2021. "Ce Pt Ve r Si o n Ac Ce Pt Ve R."
9. Nfl-tbs, The, Chambaud Jo, Eyer Pii, and International Journal. 2013. "Ac Ce Pt e d Cr." *Drug and Alcohol Dependence*, 1996–2010. http://dx.doi.org/10.1016/j.drugalcdep.2015.01.009.
10. Zhou, Xiren, Qiuju Chen, Shengfei Lyu, and Huanhuan Chen. 2022. "Mapping the Buried Cable by Ground Penetrating Radar and Gaussian-Process Regression." *IEEE Transactions on Geoscience and Remote Sensing* 60: 1–10. https://doi.org/10.1109/TGRS.2022.3181380.
11. Singh, Navneet P., and Manisha J. Nene. 2013. "Buried Object Detection and Analysis of GPR Images: Using Neural Network and Curve Fitting." *2013 Annual International Conference on Emerging Research Areas, AICERA 2013 and 2013 International Conference on Microelectronics, Communications and Renewable Energy, ICMiCR 2013 - Proceedings*, no. June 2014. https://doi.org/10.1109/AICERA-ICMiCR.2013.6576024.
12. Jin, Yang, and Yunling Duan. 2020. "Identification of Unstable Subsurface Rock Structure Using Ground Penetrating Radar: An Eemd-Based Processing Method." *Applied Sciences (Switzerland)* 10 (23): 1–19. https://doi.org/10.3390/app10238499.
13. Pasolli, Edoardo, Farid Melgani, and Massimo Donelli. 2009. "Automatic Analysis of GPR Images: A Pattern-Recognition Approach." *IEEE Transactions on Geoscience and Remote Sensing* 47 (7): 2206–17. https://doi.org/10.1109/TGRS.2009.2012701.
14. Mumtaiz, Hussain, Jafar W Abdul, and Thamir R Saeed. 2022. "Different Techniques in Detection of Buried Objects Using Ground- Penetrating Radar : A Review" 14: 232–40.
15. Srinivas, Chalasani, and Tumma Srinivasarao. 2018. "BURIED PIPES DETECTION THROUGH," no. December 2017.
16. Ni, Zhi Kang, Jun Pan, Cheng Shi, Shengbo Ye, Di Zhao, and Guangyou Fang. 2022. "DL-Based Clutter Removal in Migrated GPR Data for Detection of Buried Target." *IEEE Geoscience and Remote Sensing Letters* 19 (October). https://doi.org/10.1109/LGRS.2021.3089246.
17. Rabus, D., L. Arapan, T. Pierre, J. M. Friedt, and F. Cherioux. 2022. "Sampling Frequency Fluctuations of the Sensors and Software SPIDAR Ground Penetrating Radar: Impact on Probing Passive Surface Acoustic Wave Delay Lines for Pollution Sensing." *IEEE Geoscience and Remote Sensing Letters* 19.

https://doi.org/10.1109/LGRS.2020.3048084.

18. Ghozzi, Rim, Samer Lahouar, Sony Achmad Louis, Chokri Souani, and Kamel Besbes. 2017. "Extraction of Geometric Parameters of Underground Tube Using GPR." *2017 International Conference on Control, Automation and Diagnosis, ICCAD 2017*, 60–63. https://doi.org/10.1109/CADIAG.2017.8075631.
19. Feng, Jinglun, Liang Yang, Haiyan Wang, Yingli Tian, and Jizhong Xiao. 2021. "Subsurface Pipes Detection Using DNN-Based Back Projection on GPR Data." *Proceedings - 2021 IEEE Winter Conference on Applications of Computer Vision, WACV 2021*, 266–75. https://doi.org/10.1109/WACV48630.2021.00031.
20. Hoarau, Q, G Ginolhac, A Atto, Jean-marie Nicolas, Jean-philippe Ovarlez, Q Hoarau, G Ginolhac, Jean-marie Nicolas, Jean-philippe Ovarlez Robust Adaptive Detec-, and August Robust. 2016. "Robust Adaptive Detection of Buried Pipes Using GPR To Cite This Version : HAL Id : Hal-01323391 Robust Adaptive Detection of Buried Pipes Using," no. Eusipco.
21. Hoarau, Q, G Ginolhac, A Atto, Jean-marie Nicolas, Jean-philippe Ovarlez, Q Hoarau, G Ginolhac, Jean-marie Nicolas, Jean-philippe Ovarlez Robust Adaptive Detec-, and August Robust. 2016. "Robust Adaptive Detection of Buried Pipes Using GPR To Cite This Version : HAL Id : Hal-01323391 Robust Adaptive Detection of Buried Pipes Using," no. Eusipco: 293–305.
22. Gallet, Matthieu, Ammar Mian, Guillaume Ginolhac, and Nickolas Stelzenmuller. 2022. "CLASSIFICATION OF GPR SIGNALS VIA COVARIANCE POOLING ON CNN FEATURES WITHIN A RIEMANNIAN FRAMEWORK : Universit ´ e Savoie Mont Blanc , LISTIC , Annecy France Contact : { Firstname . Lastname } @ Univ-Smb . Fr : G ´ Eolithe , Contact : Nickolas.Stelzenmull," 365–68.
23. Santos, Vinicius Rafael N., and Fernando L. Teixeira. 2017. "Study of Time-Reversal-Based Signal Processing Applied to Polarimetric GPR Detection of Elongated Targets." *Journal of Applied Geophysics* 139: 257–68. https://doi.org/10.1016/j.jappgeo.2017.02.025.
24. Khan, Umar S., Waleed Al-Nuaimy, and Fathi E. Abd El-Samie. 2010. "Detection of Landmines and Underground Utilities from Acoustic and GPR Images with a Cepstral Approach." *Journal of Visual Communication and Image Representation* 21 (7): 731–40. https://doi.org/10.1016/j.jvcir.2010.05.007.
25. Reddy, P. Kiran Kumar. 2017. "GPR System to Inspect Underground Distribution Systems." *IOSR Journal of Computer Engineering* 19 (04): 53–59. https://doi.org/10.9790/0661-1904025359.
26. El-Mahallawy, Mohamed S., and Mazlan Hashim. 2013. "Material Classification of Underground Utilities from GPR Images Using DCT-Based SVM Approach." *IEEE Geoscience and Remote Sensing Letters* 10 (6): 1542–46. https://doi.org/10.1109/LGRS.2013.2261796.
27. Rogers, Chris, David Chapman, Nicole Metje, and Mehran Eskandari Torbaghan. 2020. "Assessing the Underworld - A Three-Infrastructure Approach to Remote Sensing." *37th International NO-DIG Conference and Exhibition 2019*, no. October.
28. Rogers, Chris, David Chapman, Nicole Metje, and Mehran Eskandari Torbaghan. 2020. "Assessing the Underworld - A Three-Infrastructure Approach to Remote Sensing." *37th International NO-DIG Conference and Exhibition 2019*, no. October.
29. Dutta, Arnab, and Sameer Saran. 2016. "Short Note 3D Modeling of Subsurface Utilities Using Ground Penetrating Radar (GPR) Data." *Journal of Geomatics* 10 (2): 217–21.
30. Chandra, G. Ramesh, K. Rajiv, and B. Basaveswara Rao. 2019. "Detecting Radius of Pipe in GPR Images and Comparing with 3D Synthetic Data." *Proceedings of the IEEE International Conference Image Information Processing* 2019-November (September 2020): 7–10. https://doi.org/10.1109/ICIIP47207.2019.8985761.
31. Dou, Qingxu, Lijun Wei, Derek R. Magee, and Anthony G. Cohn. 2017. "Real-Time Hyperbola Recognition and Fitting in GPR Data." *IEEE Transactions on Geoscience and Remote Sensing* 55 (1): 51–62. https://doi.org/10.1109/TGRS.2016.2592679.
32. Kang, Man Sung, Namgyu Kim, Seok Been Im, Jong Jae Lee, and Yun Kyu An. 2019. "3D GPR Image-Based UcNet for Enhancing Underground Cavity Detectability." *Remote Sensing* 11 (21): 1–18. https://doi.org/10.3390/rs11212545.
33. Hartshorn, Caylin A., Sven D. Isaacson, Benjamin E. Barrowes, Lee J. Perren, David Lozano, and Fridon Shubitidze. 2022. "Analysis of the Feasibility of UAS-Based EMI Sensing for Underground Utilities Detection and Mapping." *Remote Sensing* 14 (16): 3973. https://doi.org/10.3390/rs14163973.
34. Šarlah, Nikolaj, Tomaž Podobnikar, Domen Mongus, Tomaž Ambrožič, and Branko Mušič. 2019. "Kinematic GPR-TPS Model for Infrastructure Asset Identification with High 3D Georeference Accuracy Developed in a Real Urban Test

Field." *Remote Sensing* 11 (12). https://doi.org/10.3390/rs11121457.

35. Jin, Yang, and Yunling Duan. 2020. "Wavelet Scattering Network-Based Machine Learning for Ground Penetrating Radar Imaging: Application in Pipeline Identification." *Remote Sensing* 12 (21): 1–24. https://doi.org/10.3390/rs12213655.
36. Qiao, Lihong, Yao Qin, Xiaozhen Ren, and Qifu Wang. 2015. "Identification of Buried Objects in Gpr Using Amplitude Modulated Signals Extracted from Multiresolution Monogenic Signal Analysis." *Sensors (Switzerland)* 15 (12): 30340–50. https://doi.org/10.3390/s151229801.
37. Liu, Hai, Zhijun Long, Bo Tian, Feng Han, Guangyou Fang, and Qing Huo Liu. 2017. "Two-Dimensional Reverse-Time Migration Applied to GPR with a 3-D-to-2-D Data Conversion." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 10 (10): 4313–20. https://doi.org/10.1109/JSTARS.2017.2734098.
38. Gurbuz, Ali Cafer, James H. McClellan, and Waymond R. Scott. 2012. "Compressive Sensing of Underground Structures Using GPR." *Digital Signal Processing: A Review Journal* 22 (1): 66–73. https://doi.org/10.1016/j.dsp.2010.11.003.
39. Bernold, L., L. Venkatesan, and S. Suvarna. 2017. "A Multi-Sensory Approach to 3-D Mapping of Underground Utilities." *Proceedings of the 19th International Symposium on Automation and Robotics in Construction (ISARC)*, 1–6. https://doi.org/10.22260/isarc2002/0082.
40. Park, Byeongjin, Jeongguk Kim, Jaesun Lee, Man Sung Kang, and Yun Kyu An. 2018. "Underground Object Classification for Urban Roads Using Instantaneous Phase Analysis of Ground-Penetrating Radar (GPR) Data." *Remote Sensing* 10 (9). https://doi.org/10.3390/rs10091417.