GPR Signal Processing for Landmine Detection: A Comparative Study of Feature Extraction and Classification Algorithms

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Abstract: Landmine detection remains a critical challenge due to the difficulty of identifying buried threats. These hidden explosives pose a significant danger to human lives, hindering economic growth and development efforts. Traditional methods for landmine detection often need to be revised, relying on time-consuming manual techniques or needing more ability to identify non-metallic mines. Fortunately, advancements in technology offer various methods for locating buried landmines. Ground penetrating radar (GPR) has emerged as a powerful tool for subsurface exploration, emitting electromagnetic waves and recording reflections to create an image of buried objects. However, GPR data presents a complex picture, containing reflections from various underground features besides landmines. Effective landmine detection hinges on distinguishing these targets from background clutter. This paper delves into the comparative analysis of feature extraction and classification techniques employed in GPR-based landmine detection. The initial stage involves feature extraction, where algorithms identify and quantify characteristics within the GPR data that discriminate landmines from other objects. Various approaches exist, including image processing techniques like edge detection and statistical methods that analyze signal intensity variations. Machine learning algorithms, such as Support Vector Machines (SVMs) and k-nearest neighbors (k-NN), can learn these discriminatory features from labeled GPR data sets containing confirmed landmine locations. This paper meticulously compares the effectiveness of these techniques using performance metrics like probability of detection (Pd), accuracy, and false alarm rate (FAR). The paper aims to identify the optimal approach for accurate landmine detection by evaluating these metrics across different feature extraction and classification algorithms. This optimal approach should maximize Pd while minimizing FAR, ensuring landmines' safe and efficient identification for humanitarian demining efforts.

Keywords: Ground Penetrating Radar, Buried Object Detection, Clutter Reduction, Feature Extraction, Classification, Landmine Detection

1. INTRODUCTION

Landmines remain a significant global threat, threatening lives, hindering economic growth, and impeding development efforts. These explosive devices are buried underground and detonated upon contact with a person, vehicle, animal, or pressure [1]. The blast can cause direct and indirect damage through the explosive force and shrapnel. Beyond the immediate casualties, landmines also have a lasting impact, disrupting agricultural land use and harming the environment [2].

Effective landmine detection is a complex task influenced by various factors. These factors include the material used in the landmine, the soil's electromagnetic properties, the landmine's size, position, burial depth, shape, and environmental effects [3]. Landmine detectors are crucial for locating buried landmines and identifying the technology employed in their construction.

Researchers have made significant strides in developing automated landmine detection methods, primarily utilizing GPR technology. However, the performance of each technique varies depending on the type of explosive used, the landmine's shape, the properties of the soil, and the materials used in its construction. Researchers often employ surrogate landmines and non-mine objects buried at various depths during data collection to address this variability. This process helps researchers identify features that distinguish landmines based on size, shape, and casing type.

Landmines pose a life-threatening danger in many countries worldwide. Despite the global landmine ban, numerous countries retain the capability to produce them, and an estimated 80 countries remain affected by landmine contamination. These hidden explosives claim a devastating toll each year, with casualties ranging from 15,000 to 25,000 people killed or maimed [4]. Tragically, civilians, particularly children, represent a significant portion of landmine victims, accounting for approximately 80% of casualties.

Landmine detection is a critical issue for numerous countries. Landmine Monitor 2020 emphasizes the urgent need for complete landmine elimination. Fig. 1 shows the Landmine Contamination: Status 2020 report, as noted in [5]. International efforts are underway to eradicate landmines worldwide. Many countries have adopted the global landmine ban, and international funding supports demining operations. To date, 30 countries have achieved landmine-free status, with over 50 million landmines destroyed. However, experts estimate that complete landmine removal could take centuries due to the sheer number of devices buried globally.

The threat posed by buried unexploded ordnance remains a significant concern for human safety and environmental well-being. Landmine detection and clearance are inherently challenging, time-consuming, and often dangerous. Fortunately, advancements in sensor technology, coupled with image processing, machine learning, and neural networks, offer promising solutions for more effective landmine detection. The Ottawa Treaty enforces the Anti-Personnel Landmine Ban Convention, mandating landmine clearance by 2025 [6].

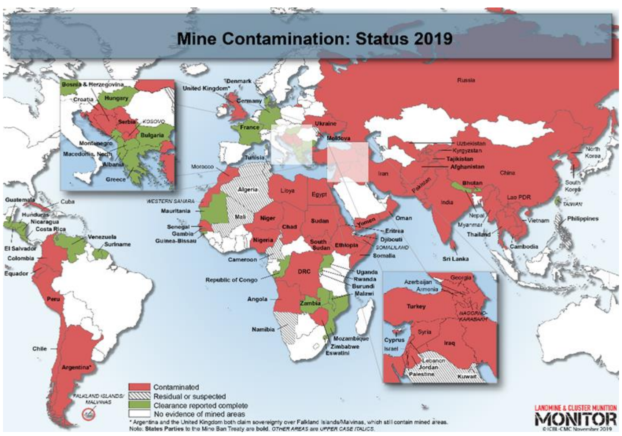

Figure 1. Landmine Contamination: Status 2020

2. Categories of Landmines and Demining

A. *Types of Landmines*

Landmines come in two distinct categories: Anti-Tank (AT) and Anti-Personnel (AP). AT landmines, also known as anti-vehicular landmines, typically have cylindrical or square shapes ranging from 150-300 mm in diameter and 50-90 mm in thickness. Landmines contain powerful explosives like TNT, Composition B, or RDX [4]. Landmines come in various shapes and sizes, utilizing metal, plastic, or wood casings to make them difficult to detect. They detonate when subjected to a minimum pressure of 200 kilograms, typically triggered by vehicles driving over them. Anti-tank landmines, primarily used on battlefields, are designed to destroy tanks and trucks. These weapons can cause casualties for people inside and around the targeted vehicle, posing a significant threat to civilians caught in conflict zones. Fig. 2 showcases various anti-tank landmines [7].

AP landmines, in contrast to AT landmines, target individuals. These disc-shaped devices are compact, typically measuring 20-125 mm in diameter, 50-100 mm in length, and weighing 30 grams. Common explosives used in AP landmines include TNT, Tetryl, and Comp B [4]. Detonation occurs under pressure as low as 2 kilograms or when someone steps on the mine. There are two main subcategories of AP landmines: blast and fragmentation.

Figure 2. Anti-Tank Landmine types

- Blast Landmines: Designed to cause severe injuries and infections upon detonation, primarily affecting people close to the blast.

- Fragmentation Landmines: Considered more dangerous than blast mines, these contain metal shrapnel that explodes outwards, inflicting casualties within a radius of approximately 200 meters when triggered [8].

Fig. 3 provides the various anti-personnel landmine products [10]. Landmines come in multiple shapes and sizes, utilizing metal, plastic, or wood casings to make them difficult to detect. Unexploded ordnance (UXO), which are explosive devices that fail to detonate as intended, also fall into this category [9]. The rise of improvised landmines further complicates detection efforts and increases civilian casualties. Landmine-triggering mechanisms also vary considerably. These include pressure-based activation systems, electronic triggers, remote detonation, light or sound sensitivity (acoustic/seismic fuses), and magnetic influences.

Figure 3. Anti-Personnel Landmine Types

B. *Types of Demining Methods*

Landmines can remain active for over five decades, necessitating demining efforts to prevent casualties. Demining refers to the process of removing landmines from contaminated areas. Two primary methods exist military and humanitarian demining.

- Military Demining: This method prioritizes speed over complete removal. It employs a brute force approach, utilizing vehicles to clear paths through minefields. While achieving an estimated 80% clearance rate, it accepts a certain level of casualties and leaves behind a significant portion of landmines.

- Humanitarian Demining: A more intricate and meticulous process, humanitarian demining focuses on safe and complete landmine removal with minimal environmental impact. It aims for a near-perfect 99.6% clearance rate. However, this safer method comes at a higher cost per landmine removed. It exposes deminers to risk, with an estimated one fatality for every 2,000 landmines cleared [4] [11].

3. EXPLOSIVE DETECTION

Researchers have explored various landmine detection techniques, each with advantages and limitations. This section explores six main categories of explosive detection methods: biological, electromagnetic, acoustic/seismic, mechanical, optical, and nuclear. We will discuss the sensor types, their requirements, performance capabilities, and challenges associated with each method.

A. Biological Detection

TABLE 1. THE REQUIREMENTS, PERFORMANCE, AND PROBLEMS OF BIOLOGICAL SENSORS

Sensors	Requirements	Performance	Problems
Rats [8]	Food reward training to locate explosives	Increased detection rate with more numbers of rats	Susceptible to tropical diseases
Dogs [12]	Extensive training in explosives	High success rate for detecting explosives	Mood, time, behavioral variations
Plants [13]	Genetically modified plant need a controlled environment	Detect explosives when nitrogen dioxide is present	Prone to false alarms
Ants [14]	No training is required, can self-deactivate	Capable of locating explosives back to the nest	Limited range and detection capabilities
Bacteria [15]	A genetically modified bacteria sprayed in the field	Covers large areas and detects TNT	Highly sensitive, leading to false positives
Bees [16]	Trained to associate a chemical odor with food reward	Effective at detecting landmines	Limited operation range due to temperature restrictions

Biological detection techniques utilize trained animals (rats, dogs) and insects (bees, ants) alongside plants and bacteria to sense the presence of explosive materials. While landmine detection using these biological sensors is possible, their effectiveness is often contingent on specific conditions. Table 1 compares each biological sensor's requirements, performance, and problems.

B. Electromagnetic Detection

The electromagnetic detection method identifies variations in the electromagnetic properties of buried objects compared to the surrounding ground surface. It utilizes electromagnetic sensors operating at different frequencies, employing transmitters and receivers. The transmitter emits signals within a specific frequency range, and the receiver interprets the reflected signals to detect anomalies. Table 2 details various electromagnetic detection sensors' requirements, performance, and problems.

TABLE 2. THE REQUIREMENTS, PERFORMANCE, AND PROBLEMS OF ELECTROMAGNETIC SENSORS

Sensors	Requirements	Performance	Problems
Metal Detector [17]	Measure the reflected current induced by the field	Prone to false alarms; Cannot detect non-metallic object	Difficult to detect in highly conductive soils
Ground Penetrating Radar [18]	Transmit and receive radio waves to detect reflected signals	Effective for metallic and non-metallic objects	Inconsistent in homogenous soil
Microwave Radar [19]	Transmit and receive micro waves to detect reflected signals	Can detect small and large objects	Performance can be slow in wet soil conditions
Millimeter-Wave Radar [20]	Send millimeter wave and collect reflected radiation	Penetrate on obstacles like clouds, smoke, and dry soil	Challenges faced across varying soil conditions
Electrical Impedance Tomography [21]	Measure current to map underground properties	Suitable for wet soil and detect all types of objects	Background noise can hamper performance
X-ray backscatter [22]	Pass x-ray photons and analyze	Effective for shallowly buried objects	Difficult to detect deep objects
Infrared [23]	Detect variations in temperature and light properties	Detect non-metallic landmines	Ineffective to detect deep objects

C. Acoustic Detection

Acoustic sensors project acoustic waves toward the ground. These waves reflect based on the acoustic properties of the materials they encounter, causing vibrations due to their mechanical properties. Table 3 presents acoustic sensor detection techniques, outlining their requirements, performance, and problems.

TABLE 3. THE REQUIREMENTS, PERFORMANCE, AND PROBLEMS OF ACOUSTIC SENSORs

Sensors	Requirements	Performance	Problems
Ultrasound [24]	Sound waves emitted by acoustic sensors reflect off the ground	Propagates in wet areas and underwater	Not efficient in sand
Acoustic to Seismic [25]	Generates acoustic or seismic waves and analyzes the vibration based on mechanical properties	Detect both types of landmines and give low false alarm rates	Detection speed is slow

D. *Mechanical Detection*

Mechanical detection of landmines utilizes physical interaction with the ground to locate buried explosives. Table 4 details mechanical detection techniques with requirements, performance, and problems.

TABLE 4. THE REQUIREMENTS, PERFORMANCE, AND PROBLEMS OF MECHANICAL DETECTION TECHNIQUES

Sensors	Requirements	Performance	Problems
Clearing Machines [11]	Clearing machines are rolling in the field to clear the path	Taking a short time to remove a landmine	Trigger the landmine when heavy-sized machines to clear it
Prodder and Probes [26]	Scans the shallow area at a 30-degree angle	Identifies the unusual object baesd on sound	Explode when prodding, so it is hazardous

E. *Optical Detection*

It penetrates the optical wave to the buried materials and measures the soil surface property. Table 5 displays optical detection techniques' requirements, performance, and problems.

TABLE 5. THE REQUIREMENTS, PERFORMANCE, AND PROBLEMS OF OPTICAL DETECTION TECHNIQUES

Sensors	Requirements	Performance	Problems
LIDAR [8]	Identifies the polarization changes in the backscattered energy	Detect metallic and non-metallic objects and cover large areas	Highly vegetated areas are not suitable
Light [10] [11]	Capturing light waves from the object	A large area scanned only on flat land in a shorter time	Less effective in poor lighting conditions

F. *Nuclear Detection*

The standard nuclear detection technique is nuclear quadrupole resonance (NQR), which uses radio-frequency and neutron-based techniques. Table 6 reports the nuclear detection techniques with requirements, performance, and problems.

Landmine detection remains a complex task due to limitations in current technologies. While widely used methods like metal detector (MD) and GPR offer some advantages, they also have drawbacks. Techniques like Bacterial and NQR show promise with low false alarm rates, but widespread adoption might be limited MDs are prone to false alarms when encountering even small amounts of metal debris.

TABLE 6. THE REQUIREMENTS, PERFORMANCE, AND PROBLEMS OF NUCLEAR DETECTION TECHNIQUES

Sensors	Requirements	Performance	Problems
Nuclear Quadrupole Resonance [28]	Used radio frequency and identify nitrogen atom nuclei in TNT	Effective in the detection of TNT or RDX explosive	Identify landmines with strong signal
Nuclear Magnetic Resonance [29]	Used along with a metal detector	Detect nitrogen present in TNT	Detect only landmine objects placed inside the coil

Ideally, a landmine detection system should be efficient, accurate, and have a minimal false alarm rate. Unfortunately, no single sensor or method can guarantee complete detection across all scenarios. Several factors hinder landmine identification, including:

- Obstacles like rocks or vegetation
- Presence of metallic debris
- Variations in temperature and humidity
- Different types of soil composition

Therefore, using multiple sensors is crucial. These sensors collect diverse data (heterogeneous information) to aid in decision-making. GPR, in particular, offers a variety of feature extraction and classification techniques. By analyzing these features, GPR can potentially identify landmines buried underground through proven classification algorithms.

4. REVIEW OF LANDMINE DETECTION METHODS USING GROUND-PENETRATING RADAR

GPR is a valuable tool for landmine detection. It uses electromagnetic pulses to image objects buried beneath the ground surface. The system has two key components: a transmitter antenna that sends the pulses and a receiver antenna that records the reflected energy. Differences in the electrical properties of subsurface objects cause anomalies in the received signal. The software then processes these anomalies to generate an image. Fig. 4 illustrates the process of landmine detection using ground-penetrating radar [30]. It also has a built-in memory to store data after the examination. Noninvasive subsurface sensing can detect metal, non-metal, and plastic landmine.

Significant research focuses on automating landmine detection using GPR data. GPR signals can potentially identify landmines, objects resembling landmines, and even the absence of landmines by analyzing features associated with them on the ground surface. However, challenges arise due to "clutter" in the data caused by surface scattering, target interaction, and variations in the subsurface. Fortunately, various algorithms and techniques can distinguish between landmines and clutter based on their specific characteristics. These methods extract features from GPR images to determine the presence or absence of landmines and similar objects. Soil composition can significantly impact the effectiveness of GPR-based landmine detection methods. These methods underscore the ongoing challenges in this field and the need for advancements in various detection techniques.

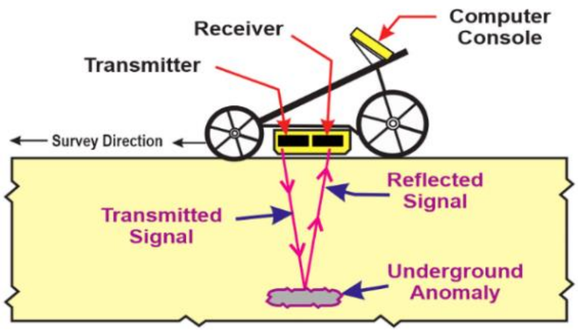

Figure 4. Ground Penetrating Radar Process

One example of a GPR-based landmine detection technique is the Energy-Focusing Ground-Penetrating Radar (EFGPR) developed by [31]. This system utilizes a fuzzy logic information fusion module for Automatic Target Recognition (ATR). The module analyzes a final set of features extracted from the GPR data and generates a system-level confidence value based on factors like blob length. Fig. 5 shows the process of the Mamdani Fuzzy Inference System with ATR structure [31].

Another approach is the iterative algorithm developed to give better results than the Early Time Subtraction (ETS) and combined ETS with a whitening filter. The total scattered field S(ω) received from the GPR has a clutter contribution H_c (ω), desired target T(ω), and noise n(ω) mentioned as equation (1). Based on the time delay and damping factor γˆ_r^(m,n) in the selected time window at the mth and nth iteration, the target was identified and represented in equation (2). Fig. 6 displays the steps involved in the iterative algorithm for clutter reduction [32].

$$S(\omega) = H_c(\omega) + T(\omega) + n(\omega) \quad (1)$$

$$\hat{T}^{m,n}(\omega) = \hat{A}_r^{m,n} e^{-\omega\hat{\gamma}_r^{m,n}} e^{-j\omega\hat{t}_r^{m,n}}\, T_r(\omega) \quad (2)$$

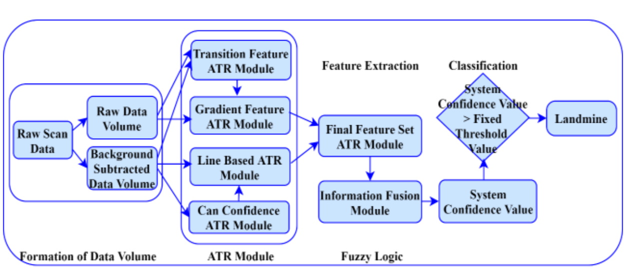

Figure 5. Mamdani Fuzzy Inference System with Automatic Target Recognition

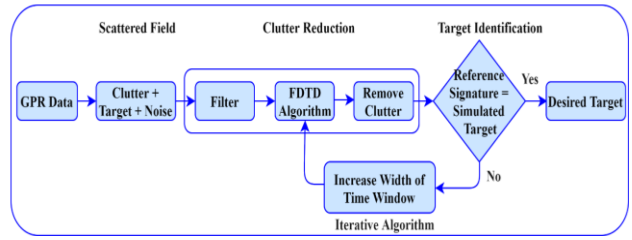

Figure 6. Clutter Reduction using Iterative Algorithm

[33] proposed a feature-level fusion for combining GPR and MD features. In decision-level fusion, MD features are retrieved using a weighted density distribution function (WDD) and given to a neural network for classification. Prony's Equation used to identify covered landmines based on GPR information. Using distance-based detectors, researchers compare Complex Natural Resonances (CNR) features from an unknown image with known objects in an object library. Fig. 7 displays the Complex Natural Resonance-based feature extraction process with distance-based detectors [34]. [35] recognized landmines through GPR feature-based rules, order statistics, and adaptive whitening (FROSAW) algorithm. FROSAW used depth-dependent features for anomaly detection from a constant false alarm rate (CFAR) detector and rule-based features to reject false alarms from mine-like objects.

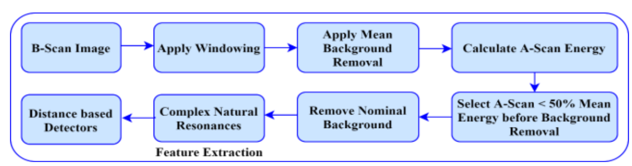

Figure 7. Complex Natural Resonances based feature extraction with distance-based detectors

The technique used a Seeded Region Growing Segmentation (SRGS) to extract and classify features through a Feed-Forward Neural Network (FFNN). The input xj mentioned in (3) gave to NN, and output y (4) ranked the pattern as a landmine or not where the length of the pattern n, activation function f. wi, and wij denoted the weight connected to the output neuron and hidden layer neuron. Fig. 8 shows the Seeded Region Growing Segmentation-oriented feature extraction and Feed Forward Neural Network as Classification [36].

$$x_j = I(j) \quad (3)$$

$$y = \int\left(\sum_{i=1}^{m} w_i f_i \sum_{j=1}^{n} w_{ij} x_j\right) \quad (4)$$

[37] compared and evaluated Hidden Markov Model (HMM), edge histogram descriptors (EHD), spectral correlation feature (SCF), and Geometric (GEOM) discrimination methodologies to recognize landmines and clutter objects using vehicle-mounted GPR information.

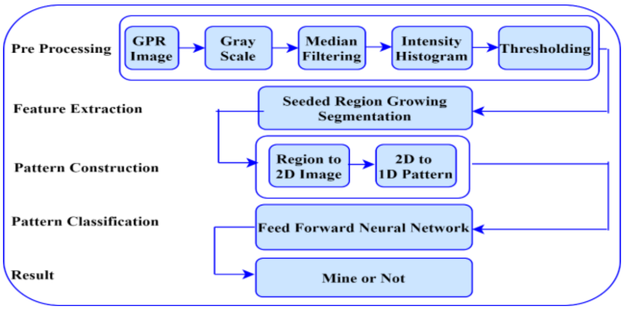

Figure 8. Seeded Region Growing Segmentation and Feed Forward Neural Network Architecture

[38] developed an algorithm for detecting anomalies and landmines. With the help of EHD, translation-invariant features were extracted from the identified regions of interest (ROI), and then a probabilistic K-Nearest Neighbors (KNN) was used to determine the confidence value (7) $Conf(S_T)$ using the mine class (5) $Conf^M(S_T)$ and the clutter class (6) $Conf^C(S_T)$ for accurate detection.

$$Conf^M(S_T) = \frac{1}{K}\sum_{k=1}^{K} \tilde{\mu}^M(R_k)\, w^p(S_T, R_k) \tag{5}$$

$$Conf^C(S_T) = \frac{1}{K}\sum_{k=1}^{K} \tilde{\mu}^C(R_k)\, w^p(S_T, R_k) \tag{6}$$

$$Conf(S_T) = \sqrt{Conf^M(S_T) \times (1 - Conf^C(S_T))} \tag{7}$$

HMM proved as effective in landmine detection through GPR data. This framework worked based on the gradient features extracted from GPR signatures. A k-nearest neighbor classier and bar histogram used EHD to retrieve the buried object's features. Fig. 9 shows the Hidden Markov Model for discrimination of landmine and Clutter Signatures [39].

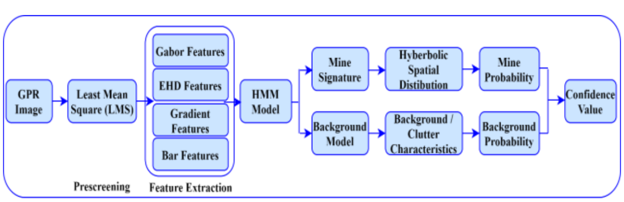

Figure 9. Hidden Markov Model for Discrimination of Landmine and Clutter Signatures

A supervised learning model used to retrieve spectral features from the identified Region of Interest (ROI) using the Least Mean Square (LMS) method. Equation (8) normalizes the Fourier-transformed data (Pk) magnitude to reduce its dependency on soil losses. This normalization is based on the N-point discrete Fourier transformed data (*S[k]*) and frequency *(k).* Fig. 10 displays Fourier Transform (FT) and SVM's feature extraction and classification process [40].

$$P_k = \frac{|S_k|}{\sum_{k=0}^{N-1} |S[k]|/N} \tag{8}$$

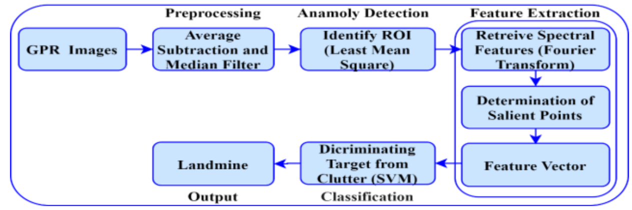

Figure 10. Feature Extraction and Classification using Fourier Transform and Support Vector Machine

Minimum Connected Component (MCC) method proposed to identify covered objects from the 2D GPR images based on graph theory. Fig. 11 illustrates the conversion process from the landmine matrix to MCC and MCCGray [41].

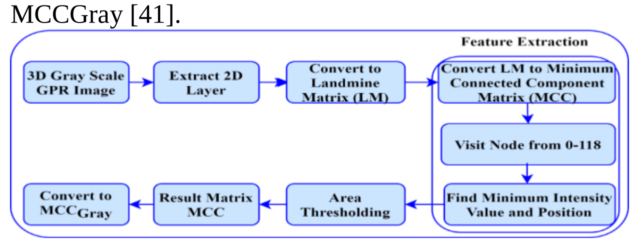

Figure 11. Minimum connected component-based feature extraction for landmine detection

Bag of Visual Words (BOV) and Fisher Vector (FV) used as the two modern feature-learning approaches used for Forward-Looking Ground Penetrating Radar (FLGPR) data processing. Based on the background mean μ and standard deviation σ, the normalized feature X' was extracted from image X using equation (9). In addition, the features retrieved from FLGPR data were BOV and FV applied with scale-invariant feature transform (SIFT) descriptors and raw pixel intensities under various soil conditions, data, classifiers, and techniques.

$$X' = \frac{|X| - \mu_{bg}}{\sigma_{bg}} \tag{9}$$

The final BOV and FV features were retrieved using equations (10) and (11) based on the dimensionality of raw and SIFT descriptors. Fig. 12 gives the Feature Learning approach steps for feature extraction using BOV and FV [42].

$$\psi_{BOV}(X|D) = \{\overset{max}{t}\ \{\gamma_t(k)\}; k = 1 \ldots K\} \tag{10}$$

$$\psi_{FV}(X|u_\lambda) = \{g_{\mu_k}^X,\ \ g_{\sigma_k}^X;\ k = 1 \ldots K\} \tag{11}$$

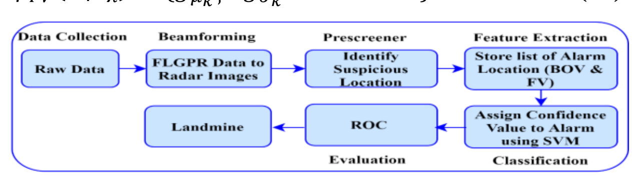

Figure 12. Feature Learning approach using Bag of Visual Words and Fisher Vector

Robust principal component analysis (RPCA) proposed to prescreen APM from GPR images. Initially, the technique received a productive RPCA method and used Decomposition (GoDec) to retrieve the target. Fig. 13 displays the process of RPCA-GoDec feature extraction and detection [43].

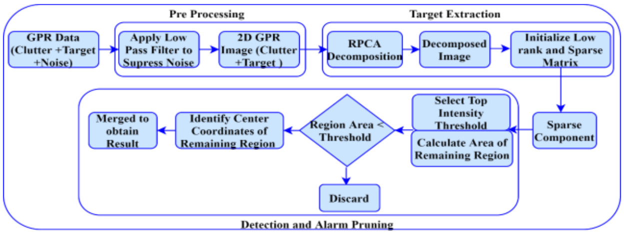

Figure 13. Robust Principal Component Analysis-Go Decomposition feature extraction and detection

The twin gray statistics sequence (TGSS) method developed to identify the twin vector and gray statistics. GPR features were classified using a B-scan image's row and column vector. Characteristics of image classified through TGSS method and dimension reduction through Gray Statistics Matrix (GSM). The gray statistics level h is defined using (12) and (13).

$$\left\{u_i(h) = \frac{1}{N}\sum_{y=1}^{N}\delta\left(G(i,y) = e_h\right)\right\} \tag{12}$$

$$\left\{v_i(h) = \frac{1}{M}\sum_{x=1}^{N}\delta\left(G(x,y) = e_h\right)\right\} \tag{13}$$

This process calculates the twin gray sequence for row vector *(i)* and column vector *(j)* from the image's gray statistics level. It then uses the Gray Level Co-occurrence Matrix (GLCM) to extend these local sequences and derive sequence coding for classification. Fig. 14 illustrates the feature classification using the Twin Gray Statistics Sequence [44].

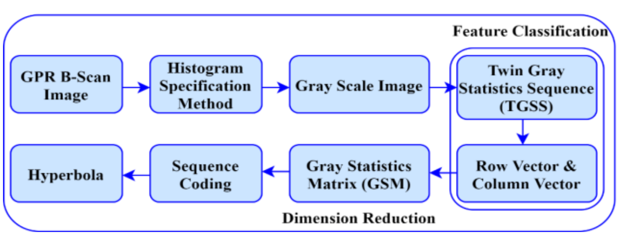

Figure 14. Feature classification using Twin Gray Statistics Sequence

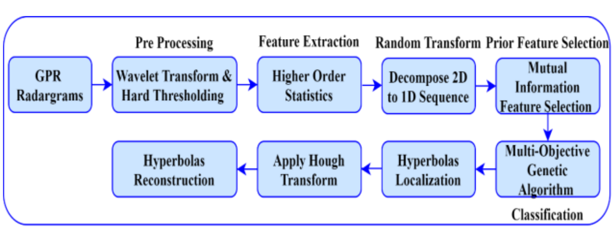

Figure 15. Process of Classification through Multi-Objective Genetic Algorithm

The classification method as Multi-Objective Genetic Algorithm (MOGA) was proposed. The MOGA classifier utilizes features retrieved using Higher-Order Statistics (HOS) and Mutual Information Feature Selection (MIFS). Fig. 15 details the classification process involving the Multi-Objective Genetic Algorithm [45].

The synthetic information from the GprMax program is utilized. The feature vector was calculated for row r and column c indices using Equations (14) and (15) for the data x.

$$Feature_c = \sqrt{\sum_{r=2}^{Rows}\left(x_{rc} - x(r-1)c\right)^2} \tag{14}$$

$$Feature_r = \sqrt{\sum_{c=2}^{Cols}\left(x_{rc} - x_r(c-1)\right)^2} \tag{15}$$

$$FV_{rc} = [Feature_r Feature_c] \tag{16}$$

The final FV combined features derived from rows and columns mentioned in (16). Fig. 16 shows the Feature Vector retrieval process for Underground Object Detection from GprMax [46].

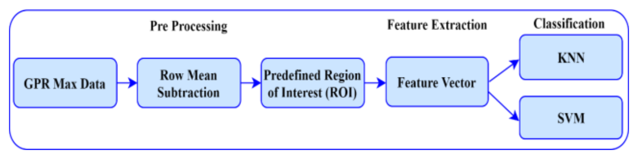

Figure 16. Feature Vector for Underground Object Detection from GprMax

Supervised machine-learning technique focused to identify landmines. The approach extracted three and five feature datasets from GPR images of landmines and classified them via support vector machine (SVM) and neural network (NN). Fig. 17 displays three and five features of feature extraction with a neural network classifier [47].

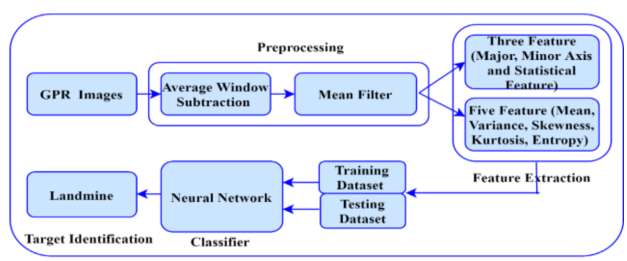

Figure 17. Five Features of Feature Extraction with Neural Network Classifier

[48] calculated a correlation coefficient between the main case's Scattering parameter (S-parameter) and whitening Algorithm to detect the anomaly. The landmine and clutter have varying scattering parameters due to different Ultra-Wide Band (UWB) signal compositions. The RPCA observed the data matrix X (17) from where the low-rank component G, sparse component S, and noise N.

$$X = G + S + N \tag{17}$$

The initial values of the low-rank matrix G_0 and the sparse matrix S_0 were calculated using Equations (18) and (19) based on data matrix X and transposition vector T.

$$G_0 = \left(\frac{1}{N}\sum_{i=1}^{N} x_i\right) 1_{N\times 1}^{T} \tag{18}$$

$$S_0 = X - G_0 \tag{19}$$

[49] proposed an intelligent system using a multi-agent hardware structure with different sensors. The agent worked independently to reach optimal acquisition, get Local Decision-Making (LDM), and share the information with another agent. The final decision on collaborative details shared by the agent will emerge in the Cooperative Decision-Making (CDM) system. Features vector calculated for Visible Spectrum (VS), Infrared (IR), and ultraviolet (UV) sensors using equation (20).

$$\Gamma = [\Lambda,\ \lambda,\ \mu,\ \sigma_M\ ,\xi,\ K,\ \zeta,\ \rho,\ \epsilon,\ \phi\ ] \tag{20}$$

[50] proposed a likelihood-ratio test (LRT) using Full-Length Ground Penetrating Radar (FLGPR). The LRT constructs a band of feasible probability densities for each hypothesis. developed a likelihood-ratio test (LRT) using FLGPR. Gradient magnitude with thresholding method employed for removing unwanted clutters and wavelet-based denoising to eliminate noise from the GPR images. The approach measured the peak signal-to-noise ratio (PSNR) using equation (21) based on mean square error (MSE) and image entropy (IE) using equation (22). Fig. 18 displays the process of clutter suppression and denoised data for further classification [51].

$$PSNR\ (dB) = 10 \log_{10} \frac{L^2}{MSE} \tag{21}$$

$$H = \frac{\left(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} B^2(m,n)\right)^2}{\left(\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} B^4(m,n)\right)} \tag{22}$$

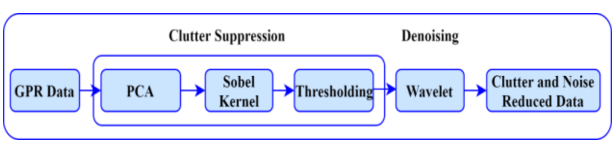

Figure 18. Gradient-based clutter suppression and Wavelet-based Denoising

[52] analyzed the framework trained on GPR data captured in landmine-free areas using autoencoders. It used different polarizations to analyze GPR data but required improvement in localizing the anomaly. [53] proposed an autonomous cognitive GPR (AC-GPR) based on deep reinforcement learning (DRL) that uses a rewarding method for both Region of Interest (RoI) detection and object classification. Researchers developed Deep Q-learning networks (DQNs) to address the dimensionality challenge in state space and enable them to learn policy directions. Gauss gradient and the Speeded Up Robust Feature (SURF) descriptor method was presented. Gauss gradient algorithm estimated the cumulative HOG (23) using the image details D_{fx} and D_{fy}. SURF detector identified the feature vector v using equation (24) from the 4x4 sub-region in horizontal direction d_x and vertical direction d_y.

$$D_{fxy} = |D_{fx}| + |D_{fy}| \tag{23}$$

$$v = \left[\sum d_x, \sum |d_x|, \sum d_y, \sum |d_y|\right] \tag{24}$$

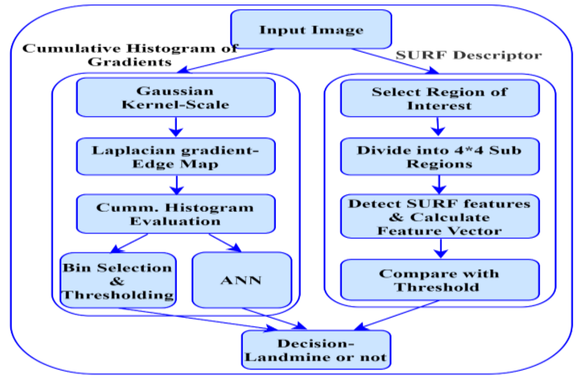

Figure 19. Feature Extraction using Cumulative Histogram of Oriented Gradients and SURF Descriptor

Fig. 19 illustrates the entire process of landmine detection using the Cumulative Histogram of Oriented Gradients (HOG) and SURF Descriptor method for feature extraction [54].

Convolutional Auto-Encoder (CAE) used to remove clutter from the GPR image and produce the target component directly. The filter coefficient of the encoder and decoder in CAE depended on the kernel size and the number of filters used in the encoder and decoder. Signal-to-clutter ratio (SCR) measured the effectiveness of the CAE method on actual data. Fig. 20 displays the Convolutional Auto-Encoder architecture to remove clutter from the GPR image [55].

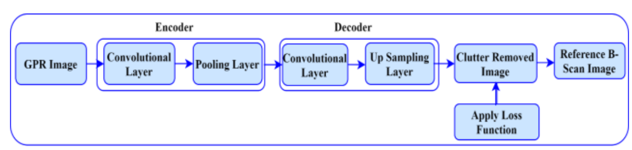

Figure 20. Convolutional Auto-Encoder Architecture to remove clutter

[56] used a CNN to extract information from B-scans and RNN to model the differential data and retrieve features amongst scans from down and cross-track networks. [57] used the You Only Look Once version 3 (YOLOv3) model to identify pipelines under the subsurface. The iterative thresholding method transformed the hyperbolic response into a binary image to determine a pipeline's buried position and depth. [58] used key point–regression mode to identify the region of interest and hyperbola detection.

5. Discussion on Comparison of GPR Sensors Data with Algorithm, Features, Advantages, Limitations, Dataset, and Accuracy

The comparison Table 7 shows the information related to GPR data processed through many algorithms and retrieved a specific feature for classification to identify landmines. Each technique has advantages and limitations, and the dataset used for implementation shows accuracy in the probability detection and false alarm rate.

TABLE 7 COMPARISON OF GPR SENSORS DATA WITH AN ALGORITHM, FEATURES, ADVANTAGES, LIMITATIONS, DATASET, AND ACCURACY

Algorithm	Features	Advantages	Limitations	Dataset	Metrics
Mamdani fuzzy inference system [31]	ATR Confidence Value	Information fusion maximizes the strengths of independent modules and minimizes their weaknesses	Gradient and line-based feature algorithms gave a high false alarm rate	Calibration lane	Pd-96% FAR-0.017
Iterative Algorithm [32]	Scatter	Effectively reduced the clutter, which leads to a decreased false alarm rate	Detected only anti-personnel mines	Dr. Chen's GPR data	FAR-11% For SNR-40dB
Feature and Decision-Level Fusion [33]	Spatial	Feature-level fusion produced reduced FAR	Investigation needed in WDD functions	US Dataset	Pd-83.97 (MD) Pd-52.92 (GPR)
Prony's Algorithm, Distance-based detectors [34]	CNR	Better performance with good probability detection achieved with CNR and multiple distance-based detectors	CNR analysis requires removing the nominal background from the A-Scan	Demining Technology Center	Pd-100% for higher SNR
FROSAW [35]	Depth-Dependent and Rule-Based Feature	FROSAW achieved a reduced FAR at high PD than CFAR	The return signal from clutter objects was similar to mine signals	NIITEK data	Pd-91 to 100 FAR-0.0338
Median Filtering, SRGS, FFNN [36]	Region-based Segmentation	An efficient method and more reliable for detecting and classifying anti-personnel landmines with more accuracy	Tested on a small amount of actual data	DeTeC at the EPFL, Switzerland	Pd-80%
HMM, GEOM, SCF, EHD [37]	Edge, Geom, Spectral, Edge	An HMM, edge-based algorithm provided the highest performance over the entire data collection	Compared to EHD, HMM algorithms require about five times more processing time per alarm	NIITEK data	Pd-90% FAR-0.00232 (HMM)
EHD, KNN [38]	Edge	Fuzzy techniques distinguished false alarms from accurate detections	Factors appear to be influenced by geography and the environment	NIITEK data	Pd - 90%
HMM [39]	Gradient, Gabor, Edge, Bar Histogram	Model encountered 13 different AT landmines	EHD was not as effective as Gabor, bar, and gradient algorithms	NIITEK data	EHD Pd-95% FAR-0.01181
LMS, FT, SVM, and Median filters [40]	Spectral	The spectral feature method gave a better performance for landmine detection compared to edge and gradient features	Multiple features can include improving the classification accuracy	Real-world data	Accuracy-0.83
MCC [41]	High-Intensity Valued Edges	The efficient performance achieved in landmine detection by using grayscale images	The feature extracting efficacy was not a significant property for landmine detection.	Grayscale landmine image	Confidence Level-95%
SVM, SIFT Descriptor [42]	BOV, FV	Performed well on feature learning methods BOV and FV applied to the FLGPR images on HH polarization	Feature learning did not perform well for other feature sets in all polarizations	Western U.S. Army Data	FAR-0.02
RPCA-GoDec [43]	Sparse Component	GoDec with thresholds has fast computation and robustness against clutter and noise	Target discrimination had to be focused more	Georgia Technology Institute	Pd- 99%
TGSS [44]	Twin Feature	The twin method performed well in robustness and dimension reduction	The accuracy rate fluctuated as the training sample set changes	Real data	Accuracy-82.77%

TABLE 7 Continue

Algorithm	Features	Advantages	Limitations	Dataset	Metrics
MOGA [45]	HOS	MOGA outperformed in the training set and achieved a good result in the validation and testing data	MOGA's design time was higher than the use of neural networks but faster than SVM	Maas and Schmalzl Data	Accuracy-91.03%
GPR Max, KNN, SVM, HOG [46]	Gradient	HOG produced better results when KNN used	Reduced the noise level in signals	Synthetic Data from GPR Max	Average Performance-92.6%
SVM and NN Classifier [47]	Five Feature Set	The NN method produced better performance compared to the SVM	Not included various types of soil and moisture content levels	Surrogate landmines and non-mines	Accuracy NN-95% SVM-85%
Whitening Algorithm [48]	S-Parameter	ZCA-correlation whitening algorithm performed well on the simulated database	The simulation did not consider soil inhomogeneity	Georgia Tech	Correlation Coefficient-89.74%
CDM [49]	LDM and CDM	The system detected IEDs of any shape, material, and type	GPR and TS sensors were less performing than the VS and improved only in CDM	Fabio Caraffini Data	Acc-0.7778 (IR)
LRT in Density Band and Outlier Model [50]	Feasible probability density	LRT detector reduced the False alarm and missed detection in robust outlier model	A robust hypothesis test is needed to assess the accuracy of the LRT detector adequately	Dr.Traian Dogaru of US Army	FA-8 MD-2
PCA, Wavelet denoising [51]	Gradient	Worked well in clutter suppression, PSNR, and entropy under homogeneous medium	Testing in heterogeneous soil and rough surface conditions is necessary	Synthetic and measured data	PSNR-37.28, IE-698.4
Autoencoder [52]	Multipolarization	Horizontal and vertical polarization achieved better accuracy	Autoencoder enabled only a limited amount of data.	Real data	Accuracy - 93%
DRL [53]	DQN	Performed well in object detection and classification accuracy	Worked only in a homogeneous environment	Simulated (gprMax)	Classification -7.12X 10^3
Cumulative HOG, SURF Descriptor [54]	Gradient and SURF	The SURF method produced more detection probability with no false alarm compared to gauss gradients	The interpolation retrieved the original image when decimation was applied to reduce the size of an image	Real data	Accuracy-89%
CAE, DCAE [55]	Texture	The clutter removal method CAE and DCAE directly provided the target component and worked well in simulated data	The process was slightly behind in the performance of real data compared to LRSD-based methods	Vrije Universiteit Brussel	Clutter-0.119(CAE) 0.197(DCAE)
CNN-RNN [56]	LSTM	Feature extracted using both CNN and RNN	Possible only when using deep learning algorithms	Real	Pd-0.9
R-CNN [57]	YOLOv3	The YOLOv3 model recognized the regions of the pipeline	Took more time to divide the image into interest areas of the region	Real	Precision-95.6%
End-End DL [58]	Key point–regression mode	Support good accuracy and maintain operating speed	Parameters cannot be optimized using deep learning methods	Real and simulated-Gprmax	Accuracy-97.01%

CONCLUSION

This study compared various feature extraction and classification algorithms for landmine detection using Ground Penetrating Radar (GPR) data. The goal was to identify the most effective approach for accurate landmine detection, minimizing false alarms while maximizing the probability of detection. The analysis revealed that clutter in GPR data, caused by buried objects and soil variations, significantly impacted landmine identification. To address this challenge, researchers explored various clutter reduction algorithms like SURF descriptors and machine learning features (Five feature sets, BOV, FV, and CAE). These techniques aimed to extract salient features and reduce clutter, ultimately improving landmine detection accuracy.

Furthermore, the study investigated the effectiveness of different classification algorithms (SVM, NN, KNN, and FFNN) in differentiating between clutter and landmines. Spectral feature-based classifiers, particularly SVM, demonstrated superior performance in distinguishing landmines from non-mines within GPR data compared to NN classifiers, which rely on edge and gradient features. This comparative analysis underlines the importance of clutter reduction and feature extraction in GPR-based landmine detection. The superior performance of SVM classifiers using spectral features highlights their potential for real-world applications. This research will explore the integration of deep learning algorithms as classifiers. Additionally, it will investigate the effectiveness of these methods in diverse environments with varying clutter characteristics.

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