MINE DETECTION USING GPRMAX AND IMAGE PROCESSING OF B SCANS FOR HOMOGENEOUS AND HETEROGENEOUS SOILS

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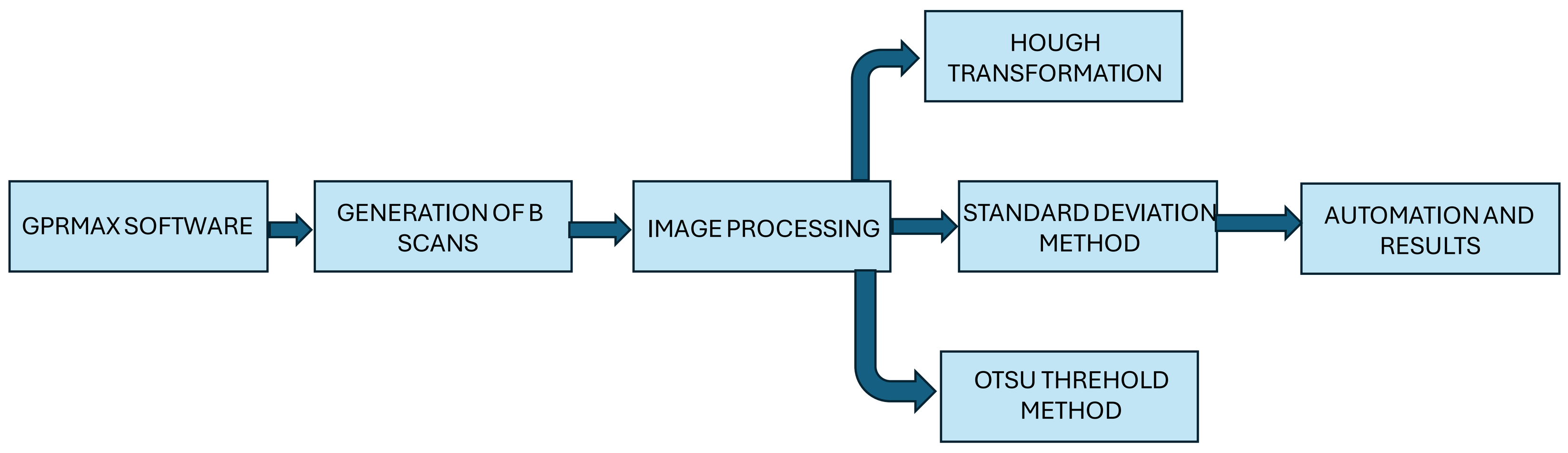
Abstract:
The project makes us to utilize Ground Penetrating Radar (GPR) technology to provide a dependable, effective, and secure approach for landmine detection. With a variety of soil types, GPR is a non-invasive subsurface sensing device that can identify metallic and non-metallic mines. In this procedure we modelled heterogeneous soil with stochastic properties and then we aimed to evaluate the B Scan images for Homogeneous and Heterogeneous realistic soils via various image processing algorithms such as Hough Transformation, Standard Deviation Method, etc. for better efficiency of landmine detection.

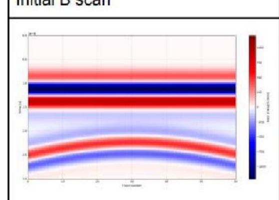
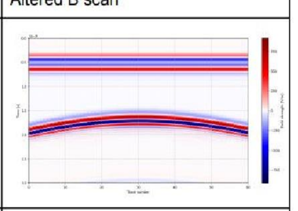
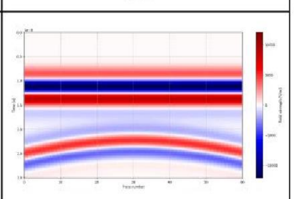
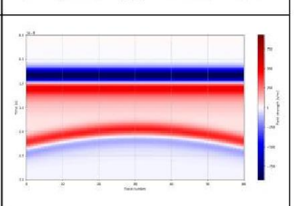
Objective:

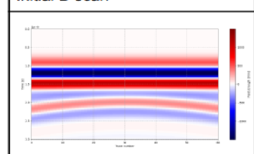
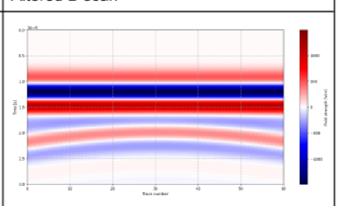
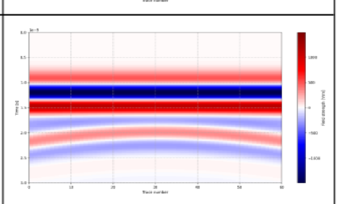
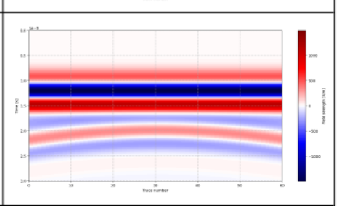
- We aimed to acquire a foundational understanding of electromagnetic waves, focusing on their fundamental properties, including propagation, skin depth in various environment, and their practical applications.
- To understand the use of Gprmax software for the detection of mines which also include changing of different physical parameters of the buried object and waveform for plotting B Scans.
- To investigate the use of image processing algorithms for enhancing the detection of buried objects in B-scan images, with reducing noise for improved accuracy and reliability.
- To understand the use of various methods for Image Processing such as Hough Transform, Standard Deviation Method, OTSU Threshold Method, etc.

Methodology:



Generation of B Scan by altering the Material Properties and Waveform Parameters:

Initial B scan	Altered	Altered B scan
	Case1: #waveform: ricker 1 5e8 my_ricker (decreasing frequency)	
	Case2: #waveform: ricker 10 1.5e9 my_ricker (increasing maximum amplitude)	
	Case3: #waveform: gaussian 1 1.5e9 my_gaussian (changing waveform)	

Initial B scan	Altered	Altered B scan
 #material: 3 0.01 1 0 my_sand #soil_peplinski: 0.5 0.5 2.0 2.66 0.001 0.25 my_sand #waveform: ricker 1 1.3e9 my_ricker	Greater sand fraction: 0.8	
	Greater clay fraction: 0.8	
	Increasing water content to 0.5 to 0.7	

Quantification of B Scan Heat Maps:

Initial case	Altered case 1
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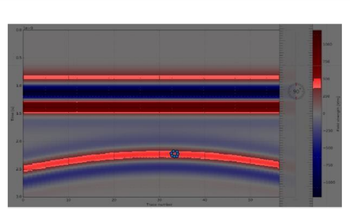
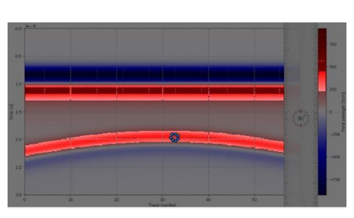
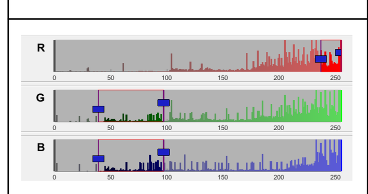
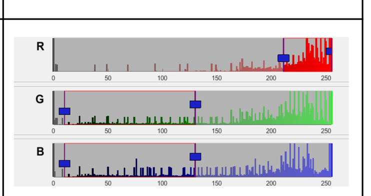
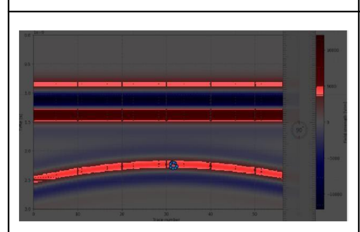
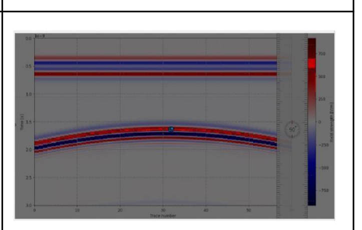
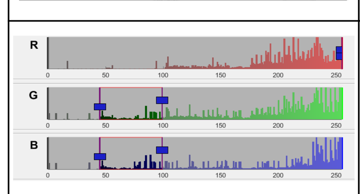
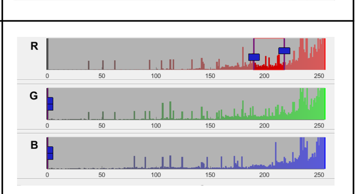
	
	
Field Strength (V/m): 446	Field Strength (V/m): 341

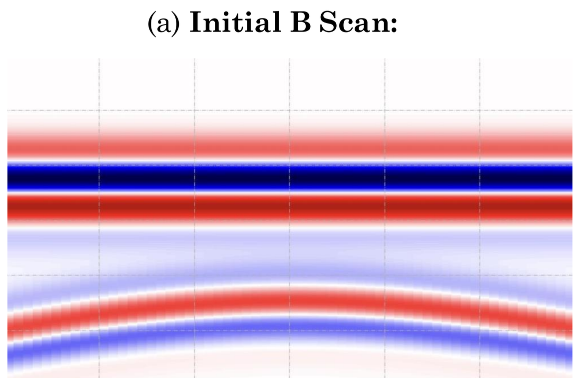
Altered case 2	Altered case 3
#waveform: ricker 10 1.5e9 my_ricker (increasing maximum amplitude)	#waveform: ricker 1 5e8 my_ricker (decreasing frequency)
	
	
Field Strength (V/m): 4118	Field Strength (V/m): 660

Enhancing Signal Extraction from B-Scans:

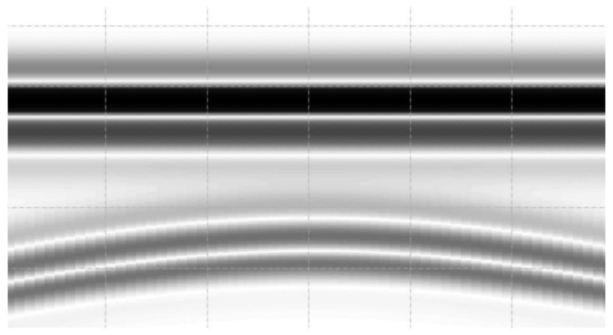
1. Standard Deviation Method:

In the process of extracting hyperbolas and removing background noise from B-scan images using image processing, the standard deviation in the RGB values of pixels plays a crucial role. This method aims to ensure efficiency and consistency in the analysis. Steps involved in this method are as follows:-

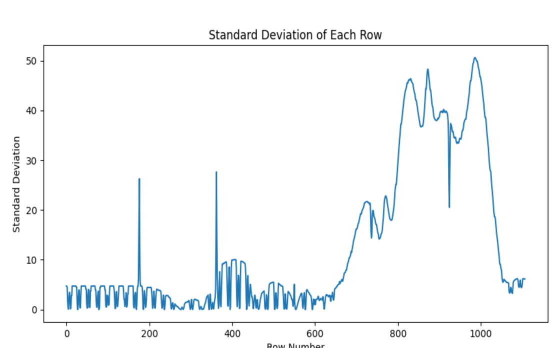
(a) **Initial B Scan:**



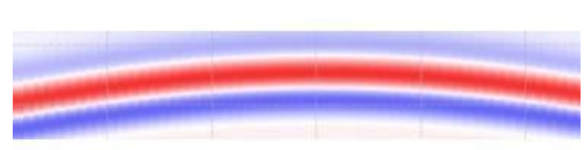
(b) Modified Greyscale Image



(c) Standard Deviation of Each Row



(d) Masked and Post-Processed Image



Firstly Converting an image to grayscale involves reducing the three RGB (Red, Green, Blue) color channels into a single intensity channel. This process simplifies the image representation, focusing solely on intensity variations irrespective of color. Then we segment the image into over a thousand horizontal slices. For each slice, we calculate the standard deviation, a statistical measure that quantifies variation in brightness across the slice, and then we set a threshold and mask the image area where the standard deviation is below that threshold value and the remaining parts of the image, which show higher brightness variation, are preserved for further analysis.

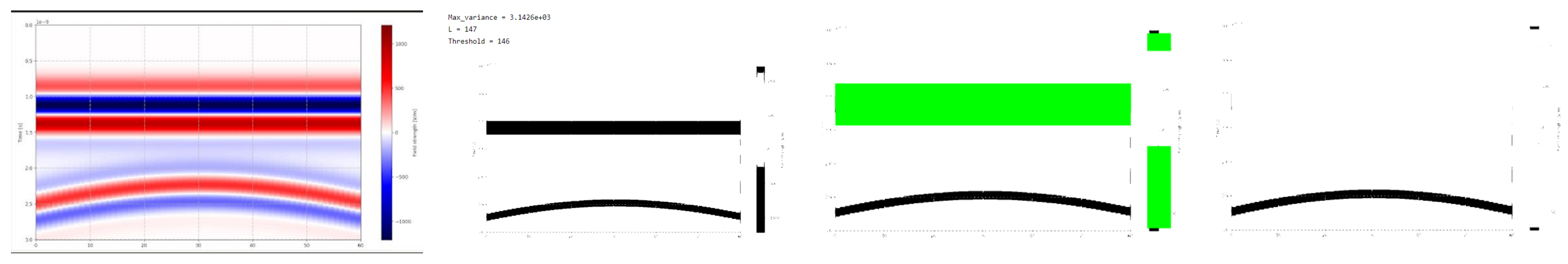
2. Fitting Method-Image Processing Algorithm Approach

In our project, we enhance GPR images to buried objects by focusing on the red color channel, which helps distinguish soil from other elements. We use the Otsu threshold method to separate these components based on brightness. Then, we apply the Hough Transformation to identify and highlight linear features, simplifying the detection of hyperbolas—curves in the images that indicate where objects are buried. This method effectively focuses our analysis on key areas, making it easier to identify and study buried objects.

(a) **OTSU Threshold:**
- It performs automatic image thresholding, the algorithm returns a single intensity threshold that separates pixels into two classes, foreground and background. This threshold is determined by maximizing inter-class variance.
- The pixels are divided into two classes as C0 and C1 at gray level t.

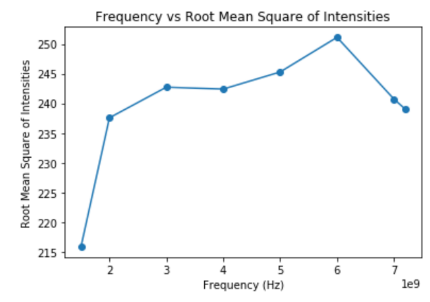
$$\sigma_B^2(t) = \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2$$

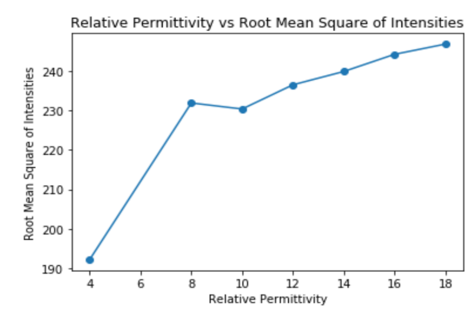
(b) Hough Transformation:
- Hough Transform is characterized by the robustness against noise and partial occlusion of features. It has many formulations, the simplest being Hough Lines (line detection).



Initial Image of B scan | Otsu Threshold Red Ch. | Line Det. Using Hough | Image of Hyperbola

Using the code to find the intensity variation by changing the GPR input parameters we plotted Frequency vs Root Mean Square of Intensities and Relative Permittivity vs Root Mean Square of Intensities



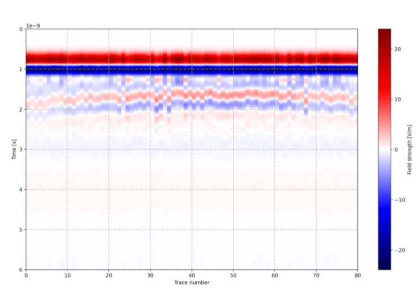


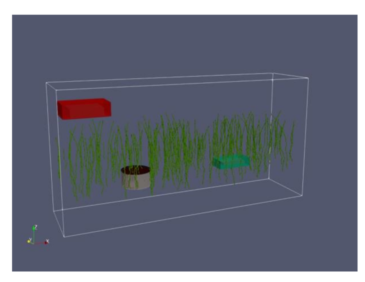
Automation of Signal Extraction from B Scan:

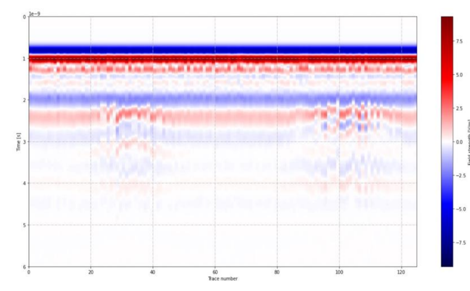
As we know that we will be provided with many B Scans so we need to do the automation of this process because we cannot do the procedure on every image individually. Automating makes everything faster, more reliable, and easier. Instead of doing the same tasks over and over again, computers can do it quickly and accurately. This helps ensure that the analysis is consistent and doesn't miss any important details. Automated analysis also lets us handle huge amounts of data easily, and it can even help us spot problems in real-time, like issues with structures or changes in the ground. Overall, automation is like having a super-efficient assistant that helps us get the most out of GPR data without the hassle. For automation we developed a script using python programming libraries such as cv2, NumPy, os and tqdm.

Modeling of Soil using Stochastic Distribution of Properties:

To model realistic soils in Gpr Max we need to use stochastic distribution of dielectric properties that involve simulating soil conditions that reflect the variability found in natural environments. This is achieved by incorporating stochastic, or random, distribution of dielectric properties within the GPRMAX simulation framework.







Results:

- Lower frequencies provide less resolution but penetrate deeper. Higher frequencies, on the other hand, offer shorter penetration but better resolution. Depending on the goal depth and size, varying frequency helps in achieving a balance between depth and resolution.
- Higher permittivity materials slow down the radar wave and Higher conductivity absorbs and attenuates radar waves, which can limit depth penetration.
- Applying the Otsu threshold method for image segmentation helped in distinguishing between the foreground, likely areas with potential mines, and the background effectively.
- The Hough Transform is crucial in isolating linear features and enhancing the visibility of hyperbolic patterns associated with buried objects.
- Automation of the image processing workflow allowed for consistent, efficient analysis of multiple B-Scan images.
- Graphs showing standard deviations and thresholding results clearly showed the distinction between noise and meaningful data.
- Different stochastic soil models showed varying effects on the penetration depth and reflection patterns of GPR signals. Soils with higher permittivity and conductivities demonstrated more pronounced signal attenuation, affecting the detection depth and clarity of subsurface objects.
- VTK files viewed in Para View software, offered detailed variability of soil.

Conclusion:

Our project, titled "Development of Mine Detection Tool using GPR and Study of the Behavior of Electromagnetic Waves in Different Conditions," has significantly improved how we explore below the surface and detect mines. We used Ground Penetrating Radar (GPR) along with advanced image and signal processing techniques to better identify and analyze buried mines. Major improvements include better image processing using methods like Otsu's threshold and Hough Transform, which help us recognize the specific patterns made by buried objects in noisy data. We also created an automated system to process B-Scan images, which allows us to analyze large amounts of data quickly and accurately, important for use in the field. Additionally, our use of stochastic soil modeling, which simulates more realistic soil conditions, has improved the accuracy of our GPR signal predictions. This project not only shows how effective GPR can be in finding mines but also provides a model that can be adapted for other geophysical and engineering uses.

Future Scope:

- First, improving the capabilities of the Ground Penetrating Radar (GPR) technology to handle a wider range of soil types and environmental conditions could increase its applicability, ensuring more reliable detection across diverse geographies.
- Enhancing image processing algorithms, especially in automated and real-time settings, will improve the speed and accuracy of mine detection.
- We can further study about that how we can differentiate between buried object and landmine and train a model for identification more accurately.
- We can test more image processing models and find the best suitable for accurate identification.
- We can also go further to use Neural network Frameworks for processing of B Scans that are generated from heterogeneous realistic soil models.

References:
[1] X. Zhou, H. Chen and J. Li, "An Automatic GPR B-Scan Image Interpreting Model," in IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 6, pp. 3398-3412, June 2018, doi: 10.1109/TGRS.2018.2799586.
S. Shihab, W. Al-Nuaimy and A. Eriksen, "Radius estimation for subsurface cylindrical objects detected by ground penetrating radar," Proceedings of the Tenth International Conference on Grounds Penetrating Radar, 2004. GPR 2004., Delft, Netherlands, 2004, pp. 319-322
https://docs.gprmax.com/en/latest/