Dynamic PCA-based Spatial Analysis for Accurate Localization of Multiple Landmines in GPR B-Scan Images

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Abstract -*Ground Penetrating Radar is a non-destructive technique used to locate buried utilities by examining the reflected signals from the underground that mainly depend on the contrast of the material. Clutters such as antenna crosstalk, air-ground interface, reflections from other subsurface materials, and noise hinder accurate landmine detection in GPR B-scan images. Various clutter removal techniques have been developed to identify and localize the buried objects, which distort the target signals and hinder accurate localization. After evaluating the merits and demerits of various PCA combinations, a new PCA-based method is proposed to enhance performance and address identified limitations. Dynamic PCA method filters and reduces the clutter from the GPR data using a dynamic sliding window to focus on the features and components for determining the exact location. Further, a noise reduction technique is applied to improve the quality of the clutter-removed GPR image, anda spatial localization technique determines the locations of the individual landmines. An investigation of several GPR B-scan data has revealed enhanced accuracy in the localization process result suggests that the simulation model can predict the target locations with reasonable accuracy, as the errors are relatively small. GPR-based landmine detection systems' dependability and effectiveness can be greatly increased by dynamic PCA, which will boost security in post-conflict regions.*
Keywords:*Clutter, Dynamic PCA, Ground Penetrating Radar, Landmine, Localization.*

INTRODUCTION

The landmines' presence in post-conflict regions requires detection and localization to promote security among humanitarians. GPR technique can detect landmines and other buried utilities non-invasively (Utsi, 2017). Landmines are difficult to identify and localize in GPR images because of clutter caused by natural and man-made objects, as well as environmental noise.In GPR, clutter refers to unwanted signal reflections that make it difficult to interpret subsurface data (Harry M. Jol, 2009). Air-ground interface, metallic debris, soil variations, and antenna noise are some of the sources of the interference. Traditional clutter reduction techniques like background subtraction (Singh, 2015) (Wu et al., 2022) and filtering techniques (Kumlu et al., 2020) (Gharamohammadi et al., 2021) have limitations in dynamically varying clutter conditions.

The Principal Component Analysis (PCA) reduced dimensionality and highlighted significant features in GPR B-scan images of landmines (Kabourek et al., 2012). Two-dimensional principal component analysis (2DPCA) identifies higher-order statistical dependencies in GPR signals, to improve clutter reduction while preserving essential target information (Vuksanovic, 2013). This technique has effectively distinguished subtle variations in buried object reflections from background clutter. PCA is useful in feature extraction from large raw data while at the same time reducing clutter reflections (Lin & Jiang, 2016). It has been improved using various methodologies to reduce clutter in GPR B-scan images, enabling improved detection of buried landmines.

In addition, by combining PCA with Independent component analysis (ICA) (Shehab et al., 2019), singular value decomposition (SVD) (Wang et al., 2015), and gradient magnitude (GM) (Lu et al., 2014) produced improved clutter separation in GPR images. Robust principal component analysis (RPCA) suppressed clutter in GPR images by decomposing into low-rank and sparse components and successfully separating target signals from clutter and noise, enhancing the reliability of detection algorithms (Song et al., 2017) (Yoon et al., 2019) (Liu et al., 2020). Figure 1 shows the various PCA-based clutter reduction methodologies in the GPR images of landmines.

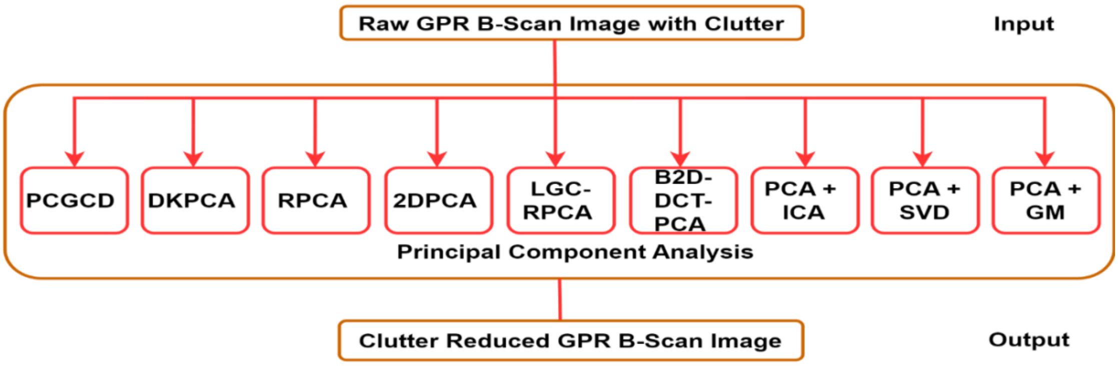

Figure 1PCA-based Clutter Reduction Methodologies in GPR Images

Linear-Gain-Compensation-Robust-PCA (LGC-RPCA) and Bilateral 2-D-discrete cosine transform PCA (B2D-DCT-PCA) (Hahm et al., 2020) approaches focused on reconstructing landmines with background interactions and employing spatial transformations to enhance signal clarity and suppress noise (Sun et al., 2019) (Yang et al., 2020). Principal components gaussian curvature decomposition (PCGCD) (Su et al., 2022) analyzed the location and removal of all unrelated features from the important features andincreased the signal-to-noise ratio. Deep Kernel PCA (DKPCA) extracted the components for the analysis of high dimensions of GPR data and performed well in clutter-prone areas (Tonin et al., 2024). Figure 2 displays the stages involved in principal component analysis based on clutter reduction.

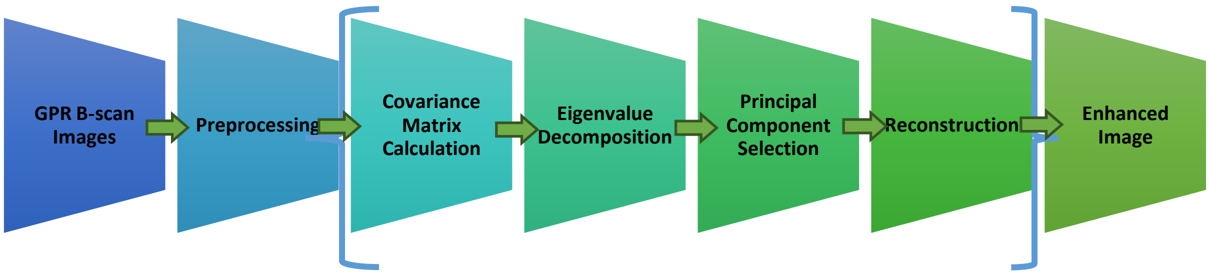

Figure2Stages in Principal Component Analysis(SimpliLearn, n.d.)

Researchers have developed many techniques by integrating PCA to reduce clutter in GPR B-scan images and to achieve robust clutter reduction and landmine localization. However, PCA may not sufficiently capture clutter variability throughareas of a GPRimage. This article proposes a dynamic PCA method to reduce clutter and identify the precise location of materials in GPR B-scan images. Unlike PCA, Dynamic PCA (Kwon et al., 2020) adapts to work on varying clutter conditions to differentiate landmine signals from background noise. Further, the clarity of images is improved by noise reduction techniques, and advanced contour detection and spatial localization algorithms are then used to identify the landmine positions. The GPR detection rate and localization accuracy improved significantly across diverse datasets, and distinguishing landmine composition as metal or plastic. In this study, Dynamic PCA is demonstrated to improve the reliability and efficiency of landmine detection systems through GPR.

DYNAMIC PCA FOR CLUTTER REDUCTION IN LANDMINE GPR IMAGES

Dynamic PCA is the improved version of the PCA technique, which is suitable for analysis of the time or spatially varying data, analyzing the segments or regions of data. While the standard PCA calculates all the principal components of the entire dataset at one time, the Dynamic PCA calculates it on the windows or subsets of the data making it useful for application areas like GPR B-scan images of landmine, signal processing, and time series analysis. Figure 3 illustrates the steps involved in Dynamic principal component analysis.

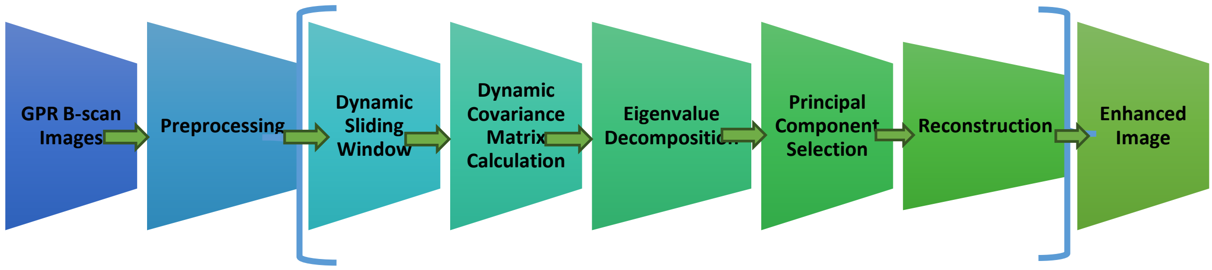

Figure3 Steps Involved in Dynamic Principal Component Analysis

GPR B-Scan Images

The GPR data consists of raw B-scan images as the input to preprocess. These images contain the desired signal of landmine reflections and clutter/noise. Table 1 displays the input parameter for the simulation of metal and plastic landmines. Figures 4and 5 show the Paraview simulation images of metal, plastic, water puddles, and stone and the corresponding B-scan image of the simulation. Table 2 summarizes the steps involved in Dynamic PCA-based clutter reduction.

Table 1 Input Parameter for Simulation of Metal and Plastic Landmine

Simulation Parameter	Value
Domain Dimensions	(6.00, 2.00, 0.002)m in (x, y, z)

Grid Spacing	(0.002, 0.002, 0.002) m in (x, y, z)
Source Antenna Position	(2.3, 1.80, 0)m
Receiver Antenna Position	(2.35, 1.80, 0)m
Source-Receiver Movement	0.023 m in the x-direction
Domain Box	(0, 0, 0) to (6.0, 1.75, 0.002)m
Material	Metal Pipe (PEC), Plastic Box (PVC), Water Puddle, Stone
Scanning Process	100 A-scans to1 B-scan

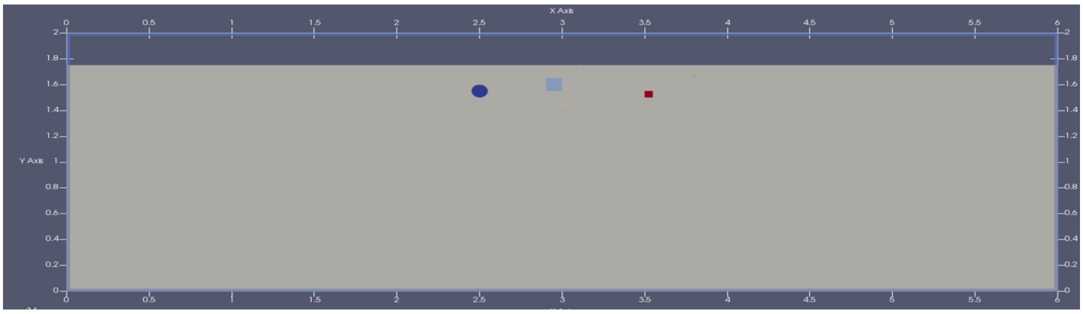

Figure 4Paraview Simulation Images of Metal, Plastic, Water Puddle, and Stone

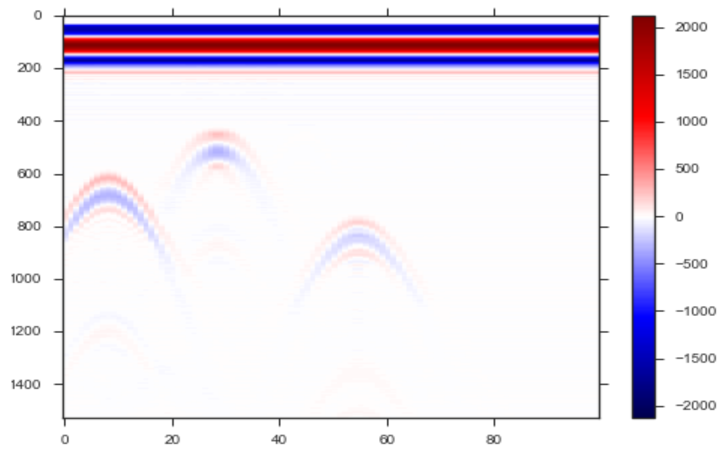

Figure5 GPR B-Scan Image of Metal, Plastic, WaterPuddle and Stone

Table 2 Function for Dynamic PCA-based Clutter Reduction

Function dynamic_pca(image, win_size, num_comp):
 # Step 1: Preprocess the image denoised_image = denoise_gaussian(image) normalized_image = normalize_zeromean(denoised_image) **# Step 2: Sliding window approach to preprocessed image** window=normalized_image[win_size x win_size] **# Step 3: Compute the covariance matrix for the window** covari_matrix = np.cov(window) **# Step 4: Perform Eigenvalue decomposition** eigenvalues, eigenvectors = np.linalg.eigh(covari_matrix)

```
sorted_indices = np.argsort(eigenvalues)
# Step 5: Select the top principal components
principal_comp = eigenvectors[sorted_indices[num_comp]]
# Step 6: Project the window data onto the principal components
window_redu=np.dot(window-window.mean,principal_comp)
window_reconst=np.dot(window_redu,principal_comp.T)+window.mean()
# Step 7: Insert the reconstructed window into the enhanced image
enhanced_image[win_size, win_size] = window_reconst
```

Preprocessing

Preprocessing reduces noise using formula (1) and removes uniform clutterusing formula (2) to isolate required signals, as every row in the denoised image contains only zero.

$$denoised_{image} = f_{denoise}\,(image) \tag{1}$$

$$normalized_{image} = \frac{denoise\ d_{image} - \mu}{\sigma} \tag{2}$$

Dynamic Sliding Window

In contrast to PCA, which is applied to the entire signal, Dynamic PCA sectioned the GPR image into a set of overlapping windows. It is important to perform covariance computation for each segment of the images to capture variable information locally.A fixed size of the selectedwindow is identified to move. The window then translates across the image, at each position, it extracts a local patch of data.The window covers the adjacent regions to identify the transitioning features between regions using formula (3).

$$window = normalized\_image[\mathrm{win_{size}}\ \mathrm{x}\ \mathrm{win_{size}}] \tag{3}$$

Dynamic Covariance Matrix for Each Window

The covariance matrix is computed using formula (4)to capture the influences between the different points in the localized region usingthe characteristics of the data of principal features. Each window results in a covariance matrix that gives the measure of how the pixel values in a window are correlated.

$$covari_{matrix} = \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)\,(X_i - \mu)^T \tag{4}$$

X_i is the pixel values of the image at position i , μ is the average of all the pixel values within the window and n is the number of data points in the window.

Eigenvalue Decomposition

Each window decomposes into its eigenvalues (λ) which indicates the amount of variance in the direction of the corresponding eigenvector, and eigenvectors (υ) represent the directions of principal components in which the data varies the most calculated using formula (5) and (6).

$$covari_{matrix} . v_i = \lambda_i . v_i \quad (5)$$

$$sorted_{indices} = \mathrm{argsort}(\lambda) \quad (6)$$

Principal Components Selection

For each window, this data is then transformed to its principal component space (7)containing the most important eigenvectors which are, in turn, those that define the greater eigenvalues.

$$\mathrm{principal}_{\mathrm{comp}} = v\,[sorted_{indices}\,[\mathrm{num}_{\mathrm{comp}}\,]] \quad (7)$$

Reconstruction

It brings the data back to the original space using formulas (8) and (9) while making only the principal features are accentuated and all noise is removed.

$$\mathrm{window}_{\mathrm{redu}} = (\mathrm{window} - \mu) \cdot \mathrm{principal}_{\mathrm{comp}} \quad (8)$$

$$\mathrm{window}_{\mathrm{reconst}} = \mathrm{window}_{\mathrm{redu}} \cdot \mathrm{principal}_{\mathrm{comp}}^{T} + \mu \quad (9)$$

Enhanced Image

The enhanced GPR datausing formula (10) produced a clearer view of important objects such as landmines easily distinguishable.

$$\mathrm{enhanced}_{\mathrm{image}}\,[\mathrm{win}_{\mathrm{size}}\,, \mathrm{win}_{\mathrm{size}}\,] = \mathrm{window}_{\mathrm{reconst}} \quad (10)$$

Results and Discussion

Localization

After the Dynamic PCA, Binary thresholding is applied to the enhanced image to differentiate between the possible range of landmine signals and the background noise which is then smoothed by morphological operations and column-wise filtering. By contour detection, possible areas with buried landmines are detected and the spatial coordinates are then computed for enhanced localization of the objects. Figure 6 displays the identified location of metal and plastic landmines in GPR B-scan images.Table 3. displays the comparison of results of simulated and predicted target location differences in metres.

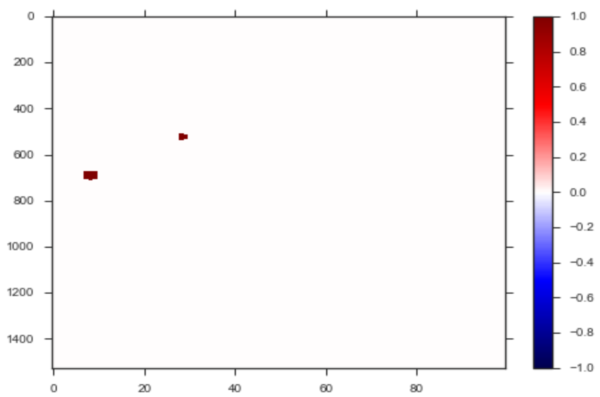

Figure 6 The Precise Location of Metal and Plastic in GPR B-Scan Images

Ourresults demonstrate the proposed approach's effectiveness in enhancing landmine localization accuracy, leveraging Dynamic PCA basedspatial analysis through clutter reduction in GPR images.

Table 3 Comparison of Results of Simulated and Predicted Target

Simulation	Target	Simulated Target Location in metres				Predicted Target Location in metres				Error in meters			
		X1	Y1	X2	Y2	X1	Y1	X2	Y2	X1	Y1	X2	Y2
Sim 1	Metal 1	2.75	1.65	2.57	1.52	2.80	1.60	2.53	1.48	**0.05**	**-0.05**	**-0.04**	**-0.04**
	Plastic 1	2.95	1.53	3.05	1.58	2.97	1.52	3.00	1.52	**0.02**	**-0.01**	**-0.05**	**-0.06**
Sim 2	Metal 2	3.00	1.55	3.20	1.65	3.04	1.53	3.22	1.52	**0.04**	**-0.02**	**0.02**	**-0.13**
	Plastic 2	4.00	1.55	4.20	1.65	4.10	1.53	4.28	1.51	**0.10**	**-0.02**	**0.08**	**0.14**

Clutter Reduction Performance

Investigations reveal improvements in the Dynamic PCA algorithm, in which key clutter components that interfere with the perception of the landmine signatures are well isolated and eliminated.

Localization Accuracy

We observe a notable improvement in landmine localization accuracy with the proposed methodology leads to negligible error between simulated and predicted target locations. We can precisely determine the positions of detected landmines within the GPR images by employing contour detection and spatial localization techniques.

CONCLUSION

Dynamic PCA methodemployed to reduce clutter,and noise and identifies the landmine location from GPR B-scan images. It reduces clutter using dynamic PCA and through contour detection and spatial localization techniques, the locations of landminesare detected.

The results of our experimental assessments show that the presented approach is effective, and the detection rate and localization accuracy exceed those of conventional techniques. An analysis of several GPR B-scan data indicates improved precision in the localization procedure result indicates that the simulation model can accurately estimate the target's position as the errors are reasonably small., which would allow for the benefits of dynamic PCA and thus create a platform for further exploration of real-time GPR-based landmine detection systems.

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