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Ground-Penetration Radar Signal Processing For Water Detection

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ABSTRACT

Ground penetration radar is very promising technology for underground or behind walls detection with high resolution. Recently various development has been introduced in GPR signal processing, multispectral sensors have been used over the years to collect the underground images. In the term of detecting and identify water underground GPR will detect water either by the voids created in the soil or by detecting the anomalies in the depth as the velocity of propagation changes due to the soil saturation with the water. The potential of ground penetration radar for water detection is affected by the type of soils, soil conductivity is an important factor, conductive soils like clay and moist tend to distort the signals which makes it hard to obtain good information about the underground structures.

In this study the aim was to detect underground water and removing clutter and noises represented by different soil situations, multiple signal processing methods has been implemented such as PCA, ICA, PICA and few filtering methods such as Gaussian, Median and compared their capabilities to find the best method in different soil situations.

I. INTRODUCTION

As known GPR technology has been widely used as a method of non-destructive testing of different subsurface observation. The vertical cross-section images obtained allow the identification of thickness and lithological horizons of different media. And over these years, GPR has been able to adjust to new areas [1]. Figure 1 shows the GPR principle. Recently, it has been successfully used to characterize and map subaqueous and anthropogenic soils. It has also been extensively used in hydro-pedological and hydro-geophysical investigations, finding landmines, water, oil, pipes and fused wires. During all GPR surveys, noise in general (either environmental or systematic) with other radio frequency signals interference can blur and damage the desired signal. Meanwhile, clutter which can be something such as a strong reflection from the antenna direct coupling and air-ground subsurface, the signature signals of the subsurface be masked [3- 9].

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A considerable number of researches in literature on GPR signal processing multiple signal enhancement and clutter removal methods for underground water detection has been under studying for many years a lot of fresh water is wasted (leaked) throughout the years. Moreover, a recorded response of the radar at a certain location is called an A-Scan waveform, which is explained as a measure of the amplitude in a reflected signal with respect to time. After combining all the collected A-scans by moving the radar antenna in a distinct direction the combined data forms what is called B-scan. In a B-scan image, EM wave transmission time (or penetration depth) is represented by the vertical axis and the horizontal axis represents the GPR spatial location [2].

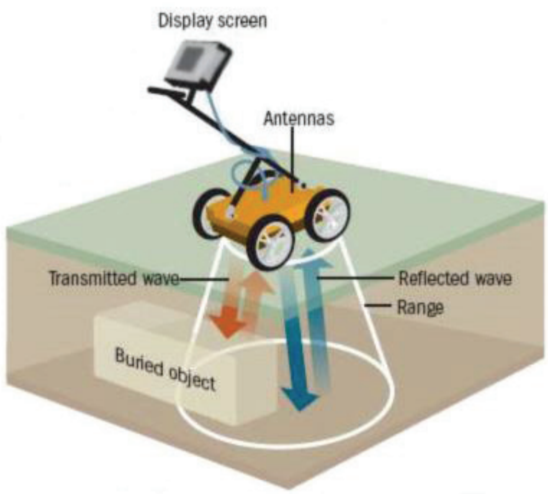


Figure 1: shows basic principle of GPR.

The efficiency of GPR is affected strongly by the soil's conductivity and its dielectric permittivity, since soils have different electrical characteristics so the scan depth is highly dependent on the specific target site. Clay soils, along with brackish or salty water will cause the radar signal to be absorbed or greatly attenuated. So, in certain soil types the GPR depth is limited [4]. So as known in GPR system, the reflected signal is a combination of the target, clutter and system noises. There are different approaches to remove or reduce cluttering in GPR images, the subspace methods such as principle component analysis (PCA) [10], independent component analysis (ICA) [11], singular value decomposition (SVD) [12], and the Probabilistic independent analysis (PICA) or noisy ICA [13]. Many researches were proved that the use of these methods is the best in obtaining the ideal target and they can successfully remove cluttering part from GPR images. GPR signals are almost of non-Gaussian distribution and above the second order moments, as a result ICA is effective to process these types of signals. Moreover, the PCA is simple and adequate for dimensionality reduction, therefore, combining PCA and ICA, i.e., PICA can produce an efficient method that handles both dimensionality reduction with suitable GPR clutter removal.

In this work a box filled with soil and fresh water was implemented inside, data was collected using GPRMax simulation the antenna scanned every 5mm, then roughness was added to the box, new data has been collected with the antenna scanning every 5mm. The last situation 300 blades of grass were implemented on top of this box again new data set was collected. The results of all these methods will be compared and showed to find the best method for these different soil situations.

II. THE PROPOSED STATISTICAL CLUTTER REDUCTION TECHNIQUES

In GPR systems, the transmitting and receiving antennas are moved in a linear way along the subsurface to transmit waves and detect the reflecting waves from the soil. This displacement produces a set of time or frequency signals named traces at each spatial step; N is the number of spatial samples and M is the number of time or frequency samples. Therefor the collected data can be expressed in a data matrix X ($M \times N$), where N<M; with a data sample X_{ij}, i is the frequency (time) index and j is the GPR position index.

Different methods have been employed to find such a linear representation, including conventional methods, singular value decomposition, principal components analysis, independent component analysis, etc. along with some filtering techniques such as Gaussian, Median, Wiener and Histogram are used in this research. The simplest conventional clutter removal algorithm is the mean subtraction (MS) which can be expressed as [14][15]:

$$X_{ij} = A_{ij} - \frac{1}{n}\sum_{j=1}^{n} A_{ij} \tag{1}$$

While A is also an $M \times N$ transformation matrix that has Eigen vectors in their decreasing order. After finding the matrix A, the subspace matrixes S_i, A_i and X can be formulated according to the subspace methods

PCA

$$X = \sum_{i=0}^{n} A_i^T S_i \tag{2}$$

ICA

$$X = \sum_{i=0}^{n} A_i S_i \tag{3}$$

SVD

$$X = UDV^T \tag{4}$$

Where $U_{m\times m}, V_{n\times n}$ are orthogonal matrices, $D_{m\times n}$ is a diagonal matrix with singular values arranged in descending order.

$$X = \sum_{i-0}^{n} D_i U_i V_i^T \tag{5}$$

III. IMAGE PROCESSING FILTERS

In image processing the term filtering is known as technique used for adjustment or image enhancement. As a simple example, you can use a filter on an image to focus on some specific features or disregard other features. So many image processing operations is performed with filtering which includes smoothen, edge enhancement, and sharpening of an image [16][17].

GAUSSIAN FILTER

The Gaussian filters are linear filters with the chosen weights according to the gaussian function shape. So, the Gaussian smoothing filter is a quite good filter for removing noises drawn from normal distribution.

MEDIAN FILTER

The median filter (MF) is non-linear digital filtering technique that can be used to remove noises from images or signals. like a noise reduction method is a classical stage in preprocessing to amend the results of the processing such as, edge detection on an image. To be very specific, the MF replaces the pixel by the median instead of the average of all pixels in the neighborhood W:

$$y[m,n] = median\{x[i,j], (i,j) \in W \qquad (6)$$

Where W is representing the neighborhood, which is defined by the user, centered in the image around the location [m, n].

WINERE FILTER

The wiener filter is the type of filter to use to produce an estimate of the desired or random process of the target by linear time-invariant (LTI) filtering of these observed noisy process, assuming the known stationary signal and noise spectra, and additive noise. The wiener filtering is optimum in the manner of the mean square error. In other words, what can be said that the wiener reduces the overall error in the process of the inverse filtering and smoothen noise.

HISTOGRAM EQUALIZATION

The histogram equalization is one method used to process images by modifying the intensity distribution of histogram in order to adjust the contrast of these images. The main objective of this technique is to give a linear trend to the cumulative probability functions associated to the processed images.

As simply as it can be explained, the processing of the histogram equalization depends on the uses of the cumulative probability function (CDF). The CDF is a cumulative sum of all the probabilities in the domain is explained by:

$$cdf_x(i) = \sum_{j=0}^{i} P_x(j) \qquad (7)$$

The main idea of this processing step is it to give to the resulting image in a linear cumulative distribution function.

IV. EXPERIMENT AND RESULTS

For The simulated dataset is constructed by using gprMax simulation tool which has the ability of simulating real commercial antennas. In all simulations, Geophysical Survey Systems Inc. (GSSI) 1.5 GHz (Model 5100) antenna is used. It can implement various scenarios with different objects, different soil types, and different burial depths. Therefore, a huge dataset including many GPR images is easy constructed. Here, gprMax was implemented and study a simple and general case, which is:

- Our box is $480 \times 148 \times 170\ mm$, A sphere with a radius 10mm filled with water was placed at $240 \times 74 \times 100\ mm$ in that box.
- With GSSI 1.5 GHz antenna placed on top of the box 5mm height scanning every 5mm, during simulation the antenna moved approximately 56 times, each time an A-Scan was collected to form the B-scan data.
- The Fresh Water coefficients are the ε_r: 80.0, σ :0.5, μ_r: 1.0, Magnetic loss: 0.0.
- Different soil situations were implemented, the first scenario is having the box filled with sand and placing the sphere in it. With Sand coefficients having these values for this experiment: ε_r: 3, σ :0.001, μ_r: 1.0, Magnetic loss: 0.0.

- Second scenario some roughness has been added to the box (valleys are now up to 5mm deep and peaks are up to 5 mm tall), using soil Peplinski a soil and sand and clay fraction 0.5, bulk density $2g/[cm]^3$, sand practical density of $2.66\ g/[cm]^3$ and volumetric water fraction of 0.001-0.25 .
- Third scenario 300 blades of grass have been added on top of the same box with various heights between 30 to 50 mm with same soil properties as the second scenario.

In the GPR system to work as effective as possible, it is best to visit the area in question prior to any mapping or profiling for obtaining not only geological information but also historical and present land use. The main objective of this research is to enhance the GPR collected data and reducing the clutter and noises from other unwanted signals. PSNR (Peak- Signal to Noise Ratio) has been used to evaluate the difference made by these listed algorithms

So, the first step to calculate our PSNR, first the mean square error will be collected, then sum these mean square errors and divide them by the number of matrix elements (rows* columns) [18].

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I(i,j) - K(i,j)\|_2^2 \qquad (8)$$

Then PSNR is expressed by:

$$PSNR = 10\ \times \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad (9)$$

In GPRmax simulation the geometrical structure of the cases has been under study is shown in Figure. 2. During this simulation A-scan has been collected to provide the B-scan images by moving the antenna approximately 56 times.

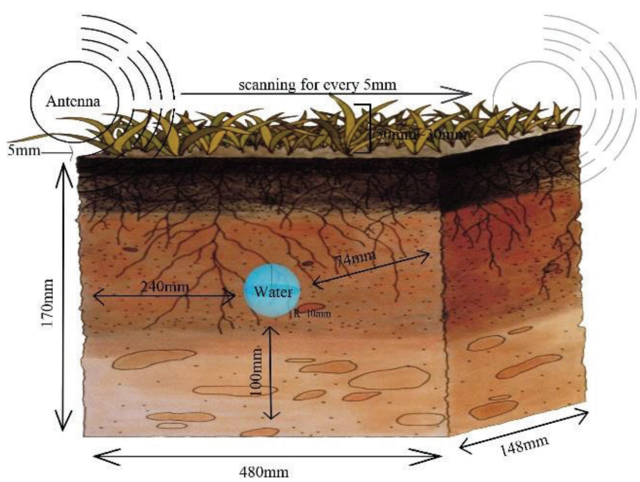


Figure 2: The geometric structure of the box.

The simulated B-scan soil and fresh water situation compared to the data collected from same box of soil without injecting water are shown in Figure. 3 below.

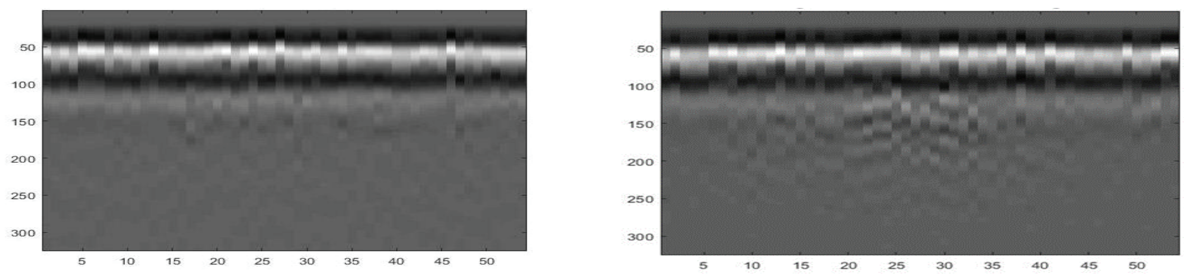


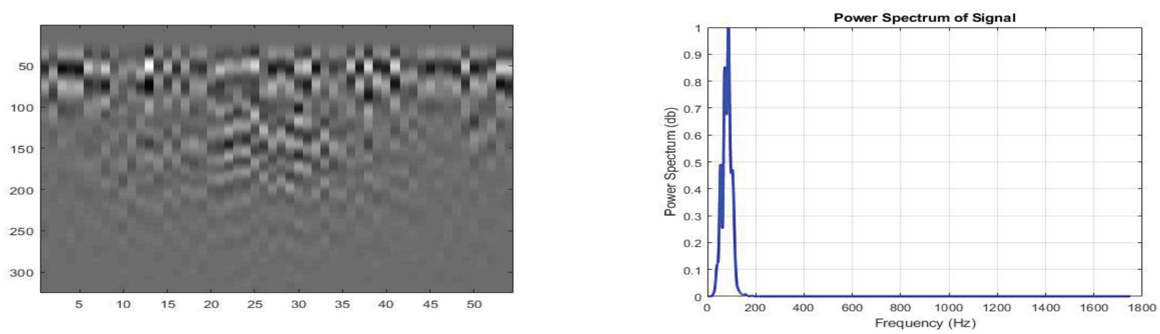
Figure 3: Shows the original image (B-Scan) of soil and soil with water sequentially.

The GPR Image data size is 325 with feature dimension 54, i.e., 325×54. And as known representation of the clutter component in GPR is stronger than the target. The simplest clutter removing method MS effect for soil and fresh water its corresponding power spectrum in Figure.4.

While Figure (5- 8) shows the decluttering results of SVD, PCA, ICA, and PICA and their power spectrum for the first data set of soil and fresh water scenario. While Figure 9 shows how the filters effect the GPR image.

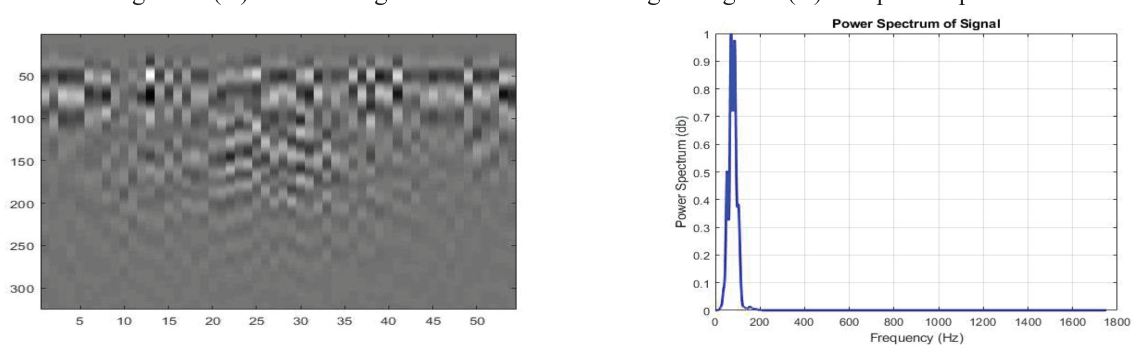
Table1 summarize the PSNR Performance for all Decluttering algorithms and filters.

The experimental result for this scenario shows that the PICA algorithm performance exceeded the other subspace clutter remove methods. While with filtering Histogram showed a much better performance than the other applied filters.



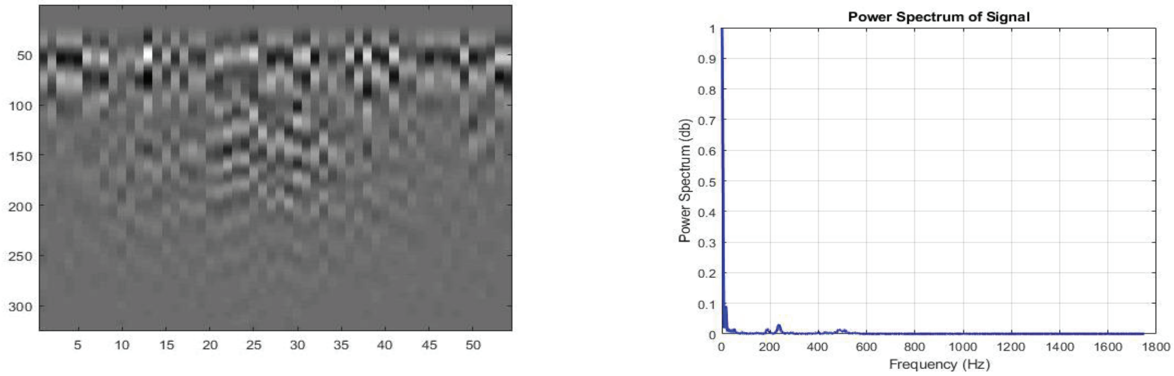
(A) (B)

Figure 4: (A) Decluttering soil and fresh water image using MS (B) The power spectrum



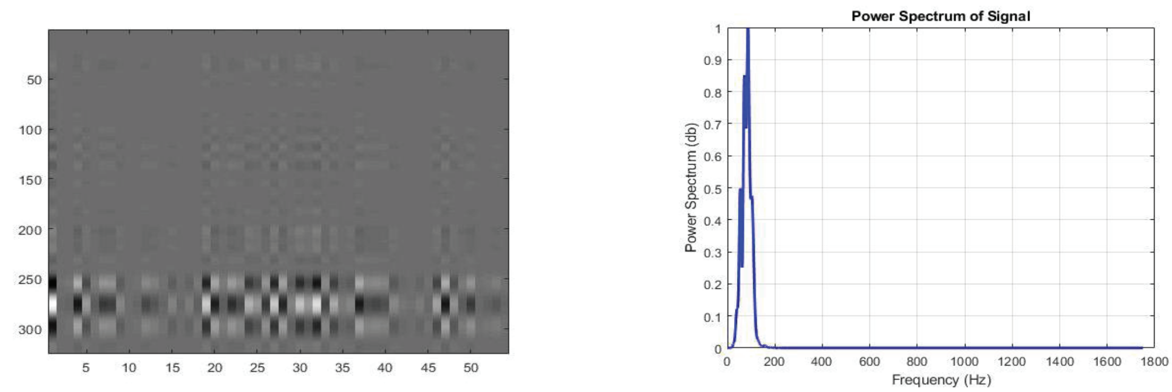
(A) (B)

Figure 5: (A) Decluttering soil and fresh water image using SVD (B) The power spectrum.



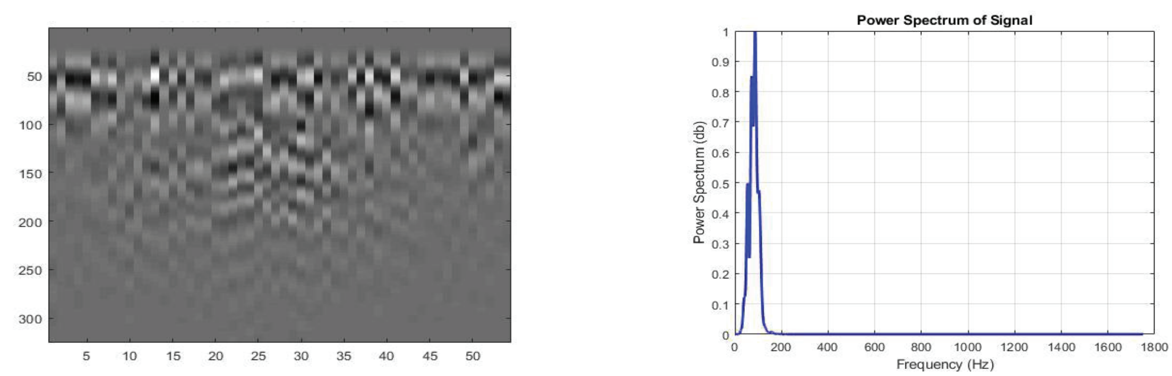
(A) (B)

Figure 6: (A) Decluttering soil and fresh water image using PCA (B) The power spectrum.



(A) (B)

Figure 7: (A) Decluttering soil and fresh water image using ICA (B) The power spectrum.



(A) (B)

Figure 8: 7: (A) Decluttering soil and fresh water image using PICA (B) The power spectrum.

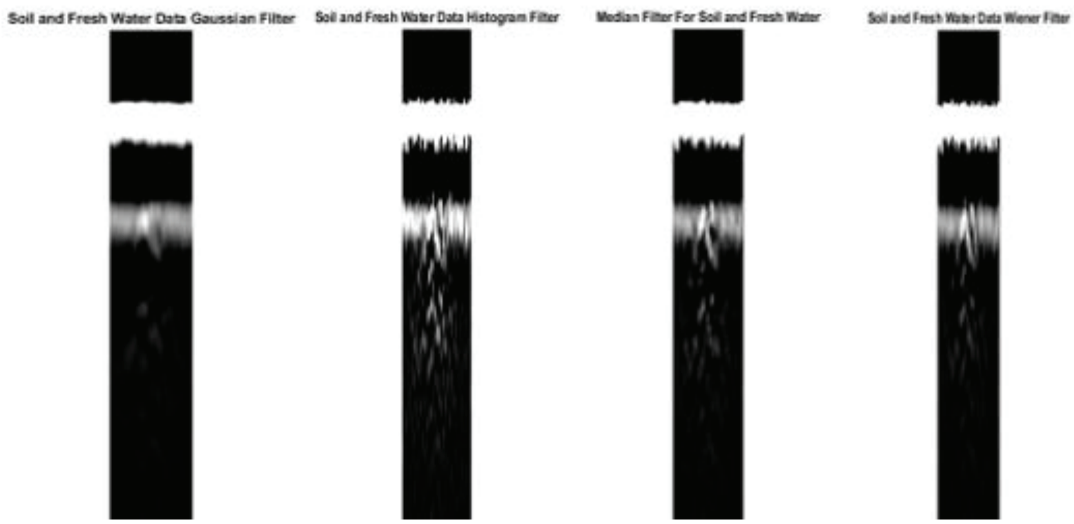


Figure 9: shows the effect of filtering over the soil and fresh water image.

TABLE 1: PSNR values for different described methods for soil and fresh water data

METHOD	PSNR	METHOD	PSNR
MS	57.1904	Gaussian	48.2118
SVD	64.4371	Median	48.0853
PCA	56.0816	Wiener	48.0106
ICA	64.7930	Histogram	52.9641
PICA	65.2304		

The simulated B-scan for soil roughness situation compared to the data collected from same box of soil without injecting water are shown in Figure. 10 below.

The simplest clutter removing method MS effect for soil and fresh water its corresponding power spectrum in Figure.11.

While Figure (12- 16) shows the decluttering results of SVD, PCA, ICA, and PICA and their power spectrum for the first data set of soil roughness and fresh water scenario. While Figure. 17 shows how the filters effect the GPR image.

Table 2 summarize the PSNR Performance for all Decluttering algorithms and filters for the soil roughness data set.

In the data set PCA and PICA with slit difference between them, their performance exceeded the other subspace clutter remove algorithms. While with filtering Histogram showed a much better performance than the other applied filters.

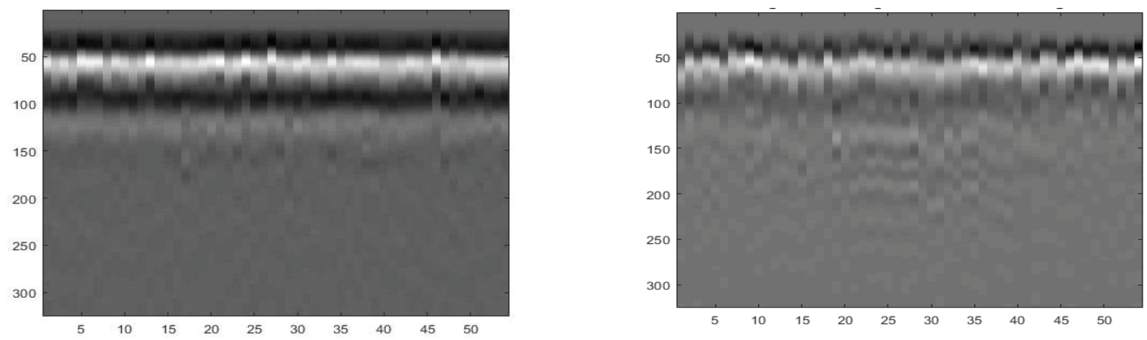
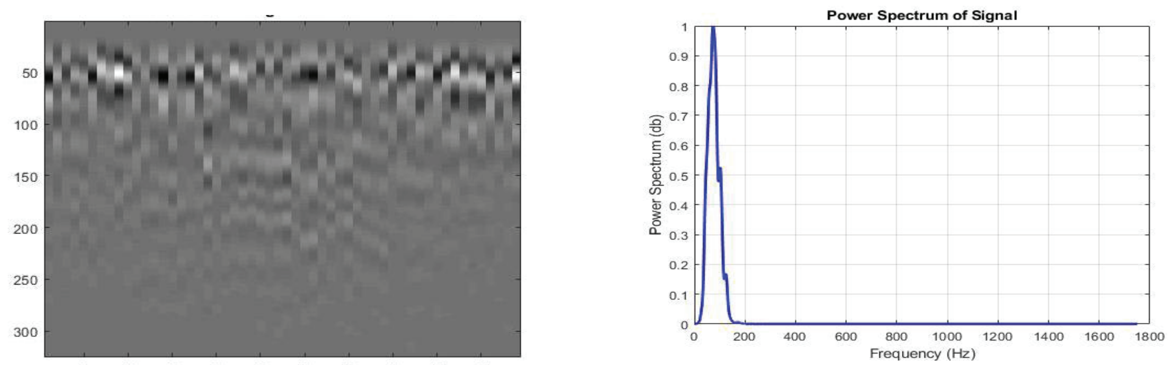


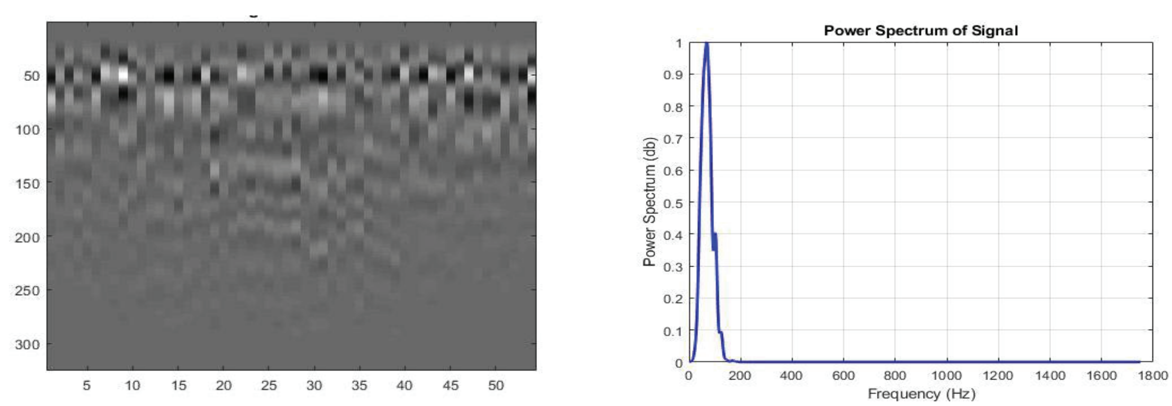
Figure 10: Shows the soil image and the soil and fresh water after adding some roughness.

As its obvious the after adding some roughness to our box the signal we received is a bit distorted which leads to have unclear image because of new soil properties.



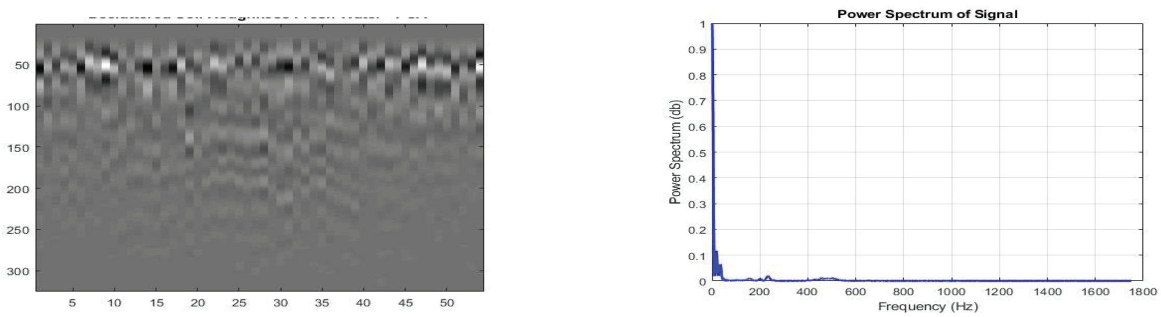
(A) (B)

Figure 11: (A) Decluttered soil roughness image using MS (B) The Power spectrum.



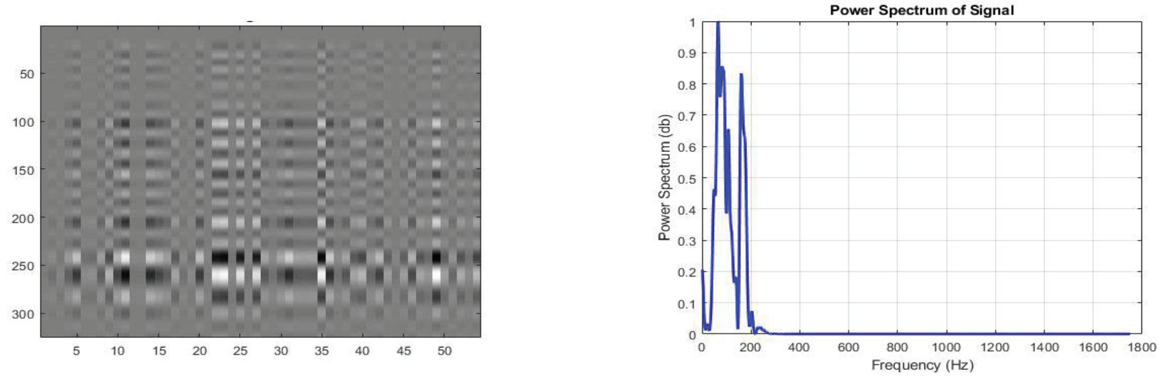
(A) (B)

Figure 12: (A) Decluttered soil roughness image using SVD (B) The power spectrum.



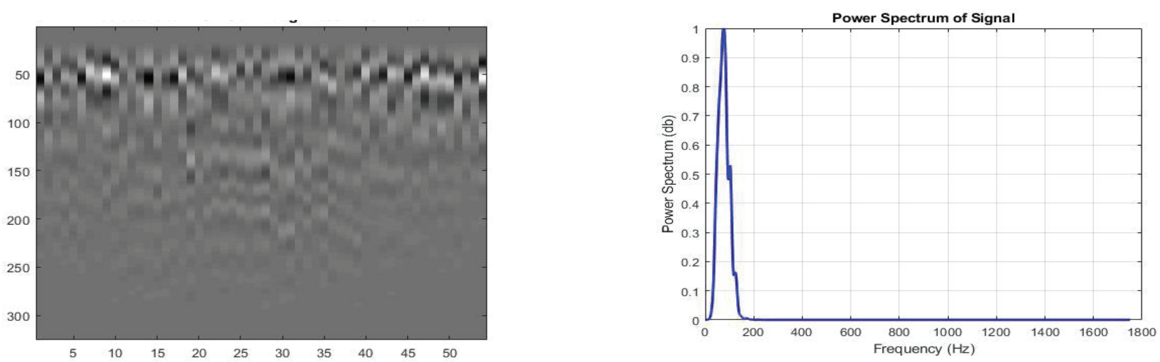
(A) (B)

Figure 14: (A) Decluttered soil roughness image using PCA (B) The power spectrum.



(A) (B)

Figure 14: (A) Decluttered soil roughness image using ICA (B) The power spectrum.



(A) (B)

Figure 15: (A) Decluttered soil roughness image using PICA (B) The power spectrum.

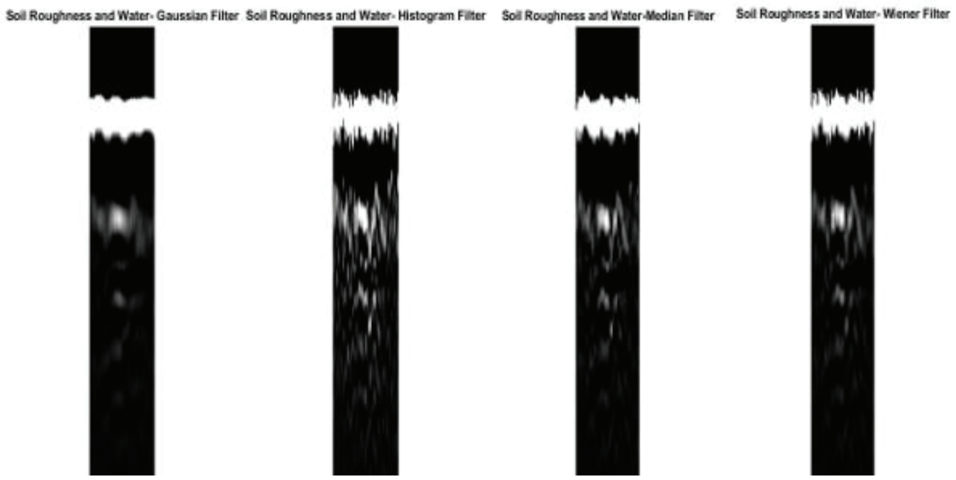


Figure 16: Shows the effect of the filters on the soil roughness image.

TABLE 2: PSNR values for different methods of the soil roughness data.

METHOD	PSNR	METHOD	PSNR
MS	58.9175	Gaussian	48.7414
SVD	69.3546	Median	48.4714
PCA	70.5059	Wiener	48.2815
ICA	66.6977	Histogram	53.4258
PICA	70.4988		

The simulated B-scan for grass soil situation compared to the data collected from same box of soil without injecting water are shown in Figure. 17 below.

The simplest clutter removing method MS effect for soil and fresh water its corresponding power spectrum in Figure.18.

While Figure (19- 22) shows the decluttering results of SVD, PCA, ICA, and PICA and their power spectrum for the first data set of soil roughness and fresh water scenario. While Figure. 23 shows how the filters effect the GPR image. Table 3 summarize the PSNR Performance for all Decluttering algorithms and filters for the soil roughness data set.

In this data set PICA algorithm performance exceeded the other subspace clutter remove algorithms. While with filtering Histogram showed a much better performance than the other applied filters

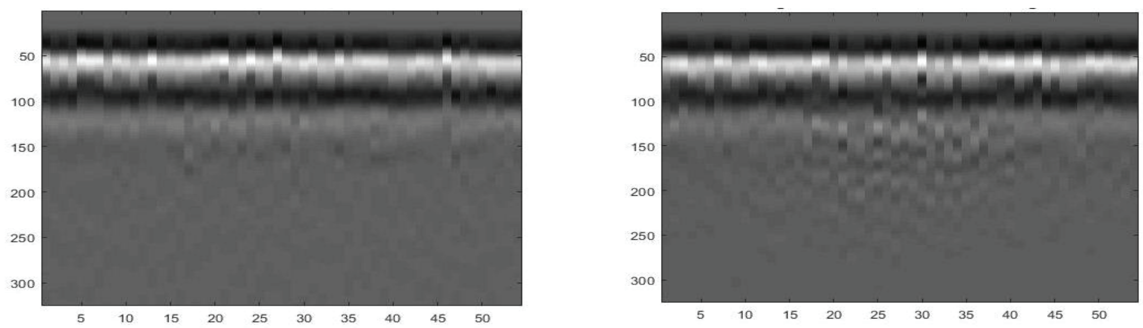
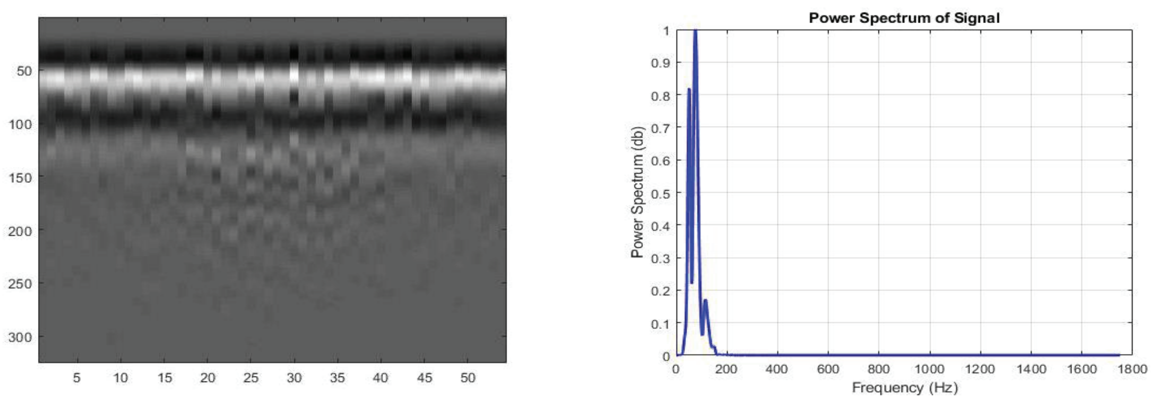
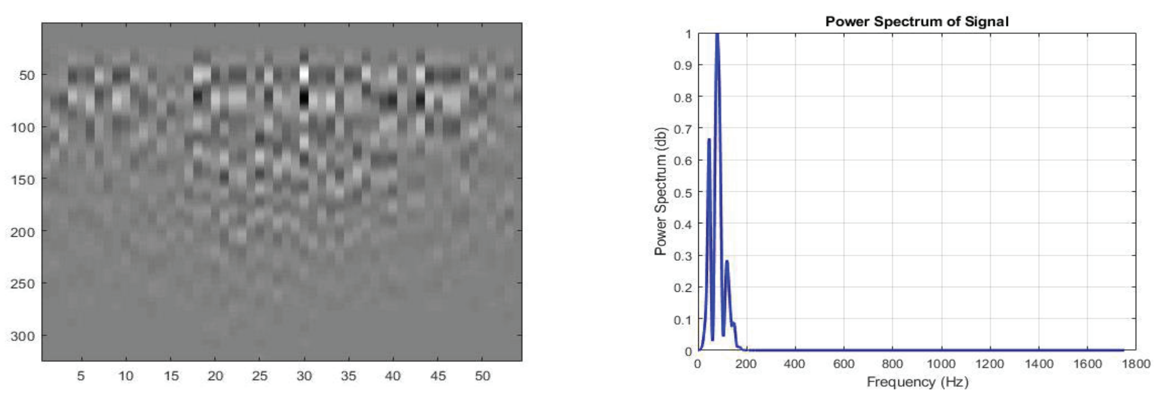


Figure 17: Shows the soil image and the soil and fresh water after adding grass on top.



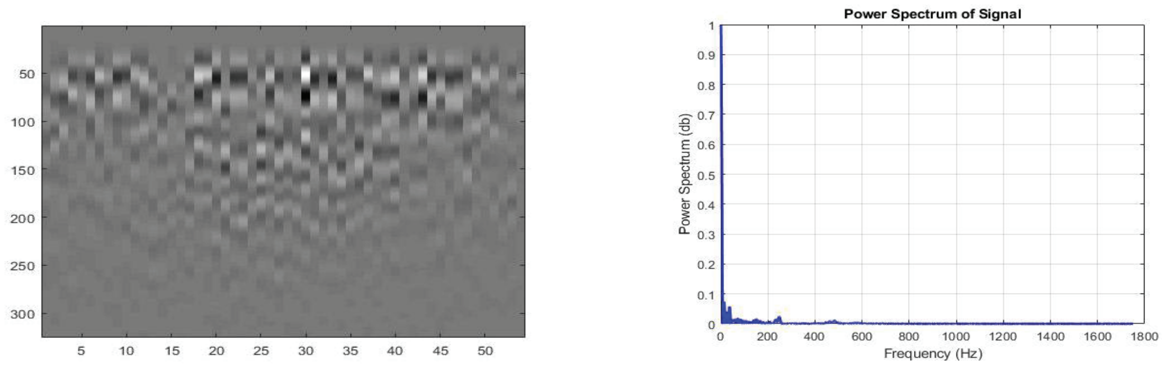
(A) (B)

Figure 18: (A) Decluttered grass soil image using MS (B) The power spectrum.



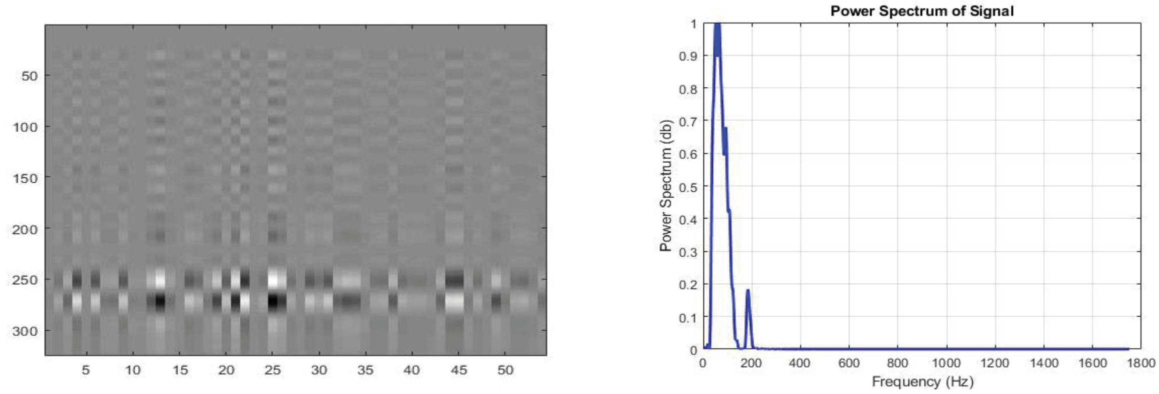
(A) (B)

Figure 19: (A) Decluttered grass soil image using SVD (B) The power spectrum.



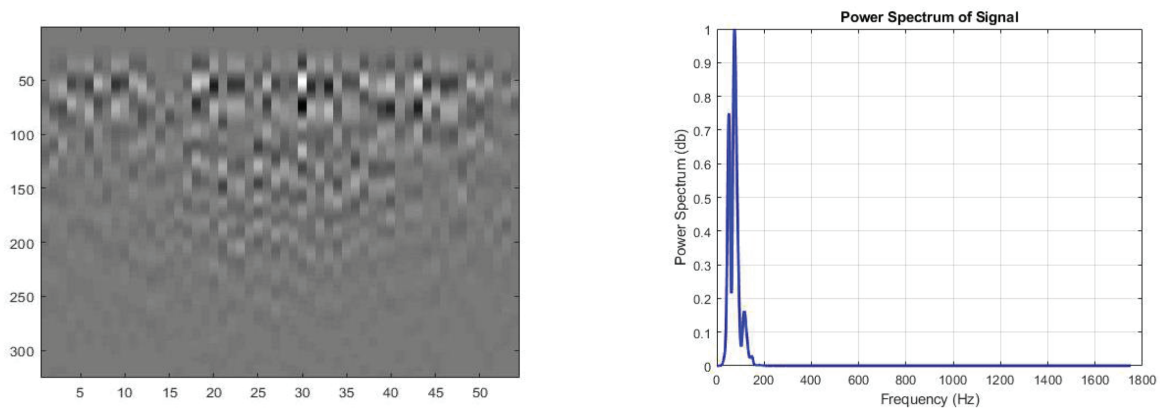
(A) (B)

Figure 20: (A) Decluttered grass soil image using PCA (B) The power spectrum.



(A) (B)

Figure 21: (A) Decluttered grass soil image using ICA (B) The power spectrum.



(A) (B)

Figure 22: (A) Decluttered grass soil image using PICA (B) The power spectrum.

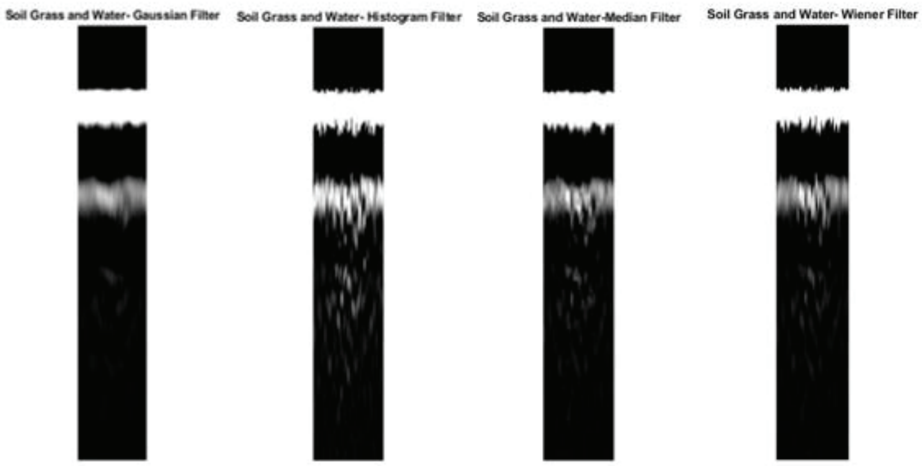


Figure 23: Shows the effect of filters on the Grass soil image.

TABLE 3: PSNR values for different methods on the grass soil data.

METHOD	PSNR	METHOD	PSNR
MS	57.3919	Gaussian	48.3540
SVD	62.7766	Median	48.2273
PCA	56.3077	Wiener	48.1700
ICA	61.4543	Histogram	53.0424
PICA	64.1537		

All subspace algorithms and filters are simulated using MATLAB (R2017b) software tool. For all the decomposition methods, the results are satisfactory and they can remove the background and surface clutter successfully. In addition, it can reduce the dimensionality of the processed data. Meanwhile filtering the GPR image alone can be sometimes not enough.

V. CONCLUION

The signal processing is required to analyze the collected signals, here different methods to analyze and find water with the best method used in different soil situation some methods like mean subtraction (MS), singular value decomposition (SVD), principal component analysis (PCA), independent component analysis (ICA), and the combination (PICA) were tested and examined for the GPR clutter reduction purpose and image enhancement filters such as Gaussian, Median, Wiener, Histogram. They have been applied to GPR data with the aim to improve image quality by removing target unwanted features from the image and presents reduced data for further processes like classification tasks which is known to be the next stage after clutter reduction. As demonstrated earlier these methods have shown satisfying results in the term of clutter and noise removing. In the first soil situation methods like SVD, ICA and PICA have provided better results, while after adding some roughness SVD, PCA, and PICA, after adding the grass on top results showed that SVD and PICA were much better. We can conclude that PICA was our optimal algorithm regarding these soil situations. Meanwhile in filtering Histogram showed a much more satisfying result than the other filters.

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