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Subspace Clutter Removal Techniques in GPR Images

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Abstract—In many modern GPR systems, it is desired to detect the presence of targets in the interference which includes clutter and noise. Detection of water leaks using GPR has been aimed in this work. Pipe and soil are known as the clutter of data in this scenario. Various signal processing techniques like multivariate subspace-based algorithms are proposed to effectively suppress the clutter and increase the signal to interference ratio. Combining Independent Component Analysis (ICA) and Principal Component Analysis (PCA) as a unique algorithm has demonstrated the ability to eliminate the GPR clutter and extract the target signal.

1. INTRODUCTION

GPR is a non-destructive method that generates EM pulses to record, locate, and evaluate the depth of buried objects or subsurface features that cannot be seen visually. It is extensively used for target imaging, detection, and localization, health care applications, indoor motion detection, civil engineering applications, etc. [1].

It is well known that target detection process in GPR is highly affected by clutter. Clutter degrades the detection performance and may increase the false alarms in a non-target region, and it can be caused by the intervention between the transmitting and receiving antennas, reflection from the ground which is called ground bounce and scattering response from non-mine objects (roots, small rocks, non-uniform terrain and so on) [2]. Since the targets are buried near the surface which consist of minimum metal contents, clutter suppresses target signal because amplitude of reflected signal from the target is weaker than ground bounce. Therefore, clutter removal techniques can increase the detection probability of the buried objects.

In GPR system, the reflected signal is composed of target, clutter, and system noises. As the system noise has less importance than the other components, clutter reduction algorithms aim to decompose the reflected signal as target and clutter. There are different approaches that can remove the clutter in the GPR images. Among those, the subspace-based methods such as principal component analysis (PCA) [3–5], independent component analysis (ICA) [6, 7], singular value decomposition (SVD) [8–10], and the possible combination between them. These techniques are based on eigen values to perform matrix decomposition on the GPR image with different constraints. After the GPR image decomposes into multiple sub-images by these methods, the first sub-image (most dominant one) is prevailed as clutter, and the remaining ones construct the target components. PCA, ICA, and SVD indeed can construct multivariate subspace bases for separating the clutter from the target.

Many researches prove that subspace-based methods are the best to obtain an ideal target shape (hyperbola) [11, 12]. They can successfully remove clutter part of the GPR image.

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In addition to above clutter removal methods and in the case of rare inhomogeneous soil medium where its statistical properties vary with position along the surface, it can apply mean subtraction/removal (MS) [13], whereby the background signal is estimated as the mean of the unprocessed ensemble of GPR signals without a buried object [14]. MS is the simplest clutter reduction technique and is most effective if the ground is flat and uniform over the antenna path which is an ideal situation. However, subtracting the average may not lead to sufficient clutter reduction [15].

In this work, we have applied MS, SVD, PCA, ICA, and the combination of PCA/ICA which is called PICA methods on the B-scan GPR data. ICA based method components are reconstructed using corresponding Joint Approximate Diagonalization of Eigen matrices (JADE) [16]. GPR signals are almost of non-Gaussian distribution and above the second order moments, and as a result ICA is effective to process this type of signals. Moreover, 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. The results of all these methods will be compared and show that our new method is the best one.

2. MULTIVARIATE TECHNIQUES

Similar to speech, biomedical and seismic signals, GPR is a mixture of signals with unknown mixing coefficients. As a result, it needs to employ Blind Source Separation (BSS) [17, 18] approaches that can separate a set of signals called source signals from their mixture signals, without acquaintance of any information (or with very little information) about mixing background and sources. The most BSS problem is studied under the linear data model. Different methods have been employed to find such a linear representation, including conventional methods, singular value decomposition, principal components analysis, and independent component analysis.

The simplest conventional clutter removal algorithm is the mean subtraction (MS) which can be expressed as Eq. (1)

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

The subspace-based methods are non-parametric methods that can extract significant features from a mixture of data and convert the correlated mixture data variables into a set of linearly uncorrelated variables. GPR image can be represented as a matrix X with $m \times n$ dimension that includes both clutter and target signals, i.e., $X = X_{\text{clutter}} + X_{\text{target}}$.

A is also an $m \times n$ transformation matrix that contains eigen vectors in decreasing order. After the transformation matrix A is found depending on some rules like orthogonality, the subspace matrices S_i, A_i, and X can be decomposed and formulated according to the subspace method as:

PCA

$$X = A_1^T S_1 + \sum_{i=2}^{n} A_i^T S_i \tag{2}$$

ICA

$$X = A_1 S_1 + \sum_{i=2}^{n} A_i S_i \tag{3}$$

SVD

Since $X = UDV^T$, where $U^{m\times m}$, $V^{n\times n}$ are orthogonal matrices, and $D^{m\times n}$ is a diagonal matrix with singular values arranged in descending order of magnitude, i.e., $D = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_n)$.

$$X = \sum_{i=1}^{n} \sigma_i u_i v_i^T = \sigma_1 u_1 v_1^T + \sum_{i=2}^{n} \sigma_i u_i v_i^T \tag{4}$$

For Eqs. (2)–(4), the first part represents X_{clutter}, while the remaining parts are associated with X_{target}.

3. EXPERIMENTAL RESULTS

The main objective of this work is to reduce the amount of clutter and other unwanted signals present in the GPR data which are not related to the target characteristics. Two metrics are used to evaluate performance of the proposed algorithms, which are Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

SNR is the ratio of average energy of the image matrix after removing the clutter and noise to the average of matrix containing clutter and noise:

$$\mathrm{SNR} = \frac{P_{\text{clutter and noise removal}}}{P_{\text{clutter and noise}}} \tag{5}$$

SSIM indicates and assesses the similarity between the base image and the processed image with values between 0 and 1, where 1 represents the identical images.

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 easily constructed. Here, we use gprMax to implement and study a simple and general case, which is:

- ✓ A wet sandy box with (x, y, z) dimension (480 mm, 148 mm, 170 mm).
- ✓ A metallic pipe which starts at (0 mm, 74 mm, 80 mm), ends at (480 mm, 74 mm, 80 mm) coordinate along x-axis with 10 mm radius.
- ✓ Antenna 5 mm upper than sandy box and 5 mm distance scan.
- ✓ GSSI 1.5 GHz antenna frequency.

The gprMax commands are:

Figure 1 depicts the geometrical structure of the case under studying.

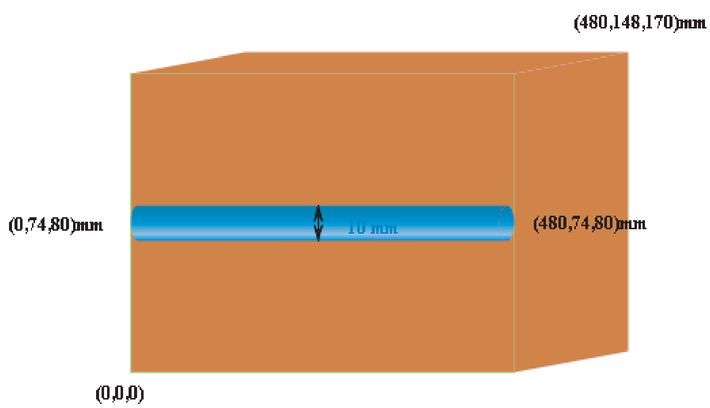


Figure 1. The geometrical structure of the GPR model.

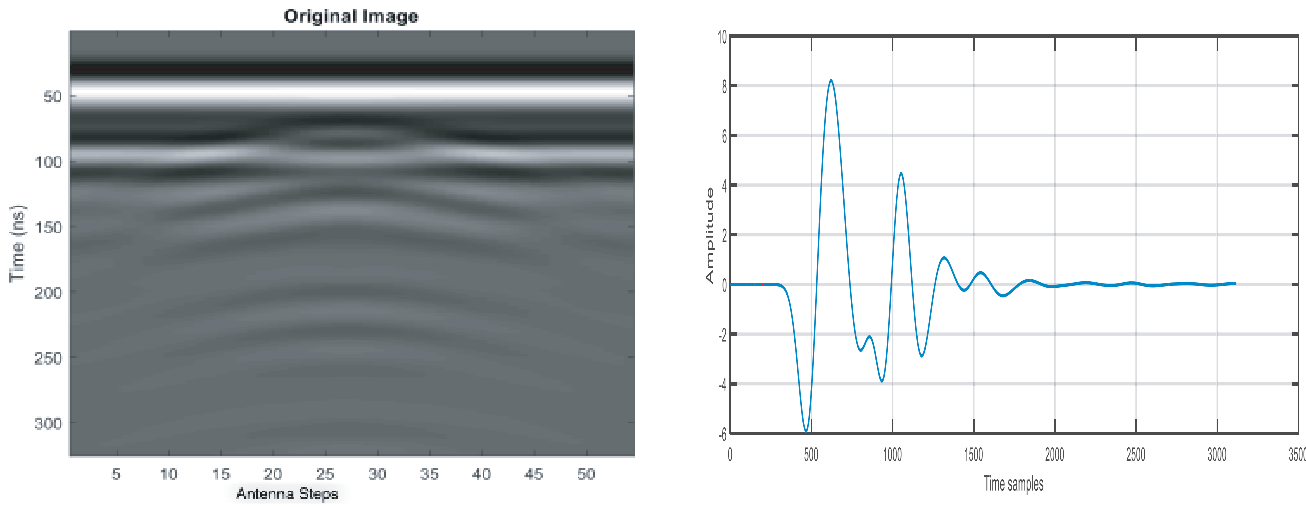
During simulation, the antenna has been moved 54 times for scanning the whole box. In each step, A-scan data have been collected to provide the row B-scan data.

The simulated B-scan and A-scan the GPR model are shown in Fig. 2.

The pipe is the most prominent background of our row data that should be subtracted.

Utilizing FFT, the power spectrum of the whole data can be estimated as shown in Fig. 3. It is obvious that the spectrum is composed of two peaks with different amplitudes and frequencies which are corresponding to the background with the surface barrier and metallic pipe.

The GPR image data size is 325, and feature dimension is 54, i.e., 325 × 54. It can exploit the principle of the eigen values and vectors to measure the appropriate feature reduction. Also the representation of the clutter in GPR is much stronger than the target component, and it can be reconstructed by the use of the eigen vector corresponding to the largest eigen value of the correlation



(a) (b)

Figure 2. GPR (a) B-scan and (b) A-scan signal.

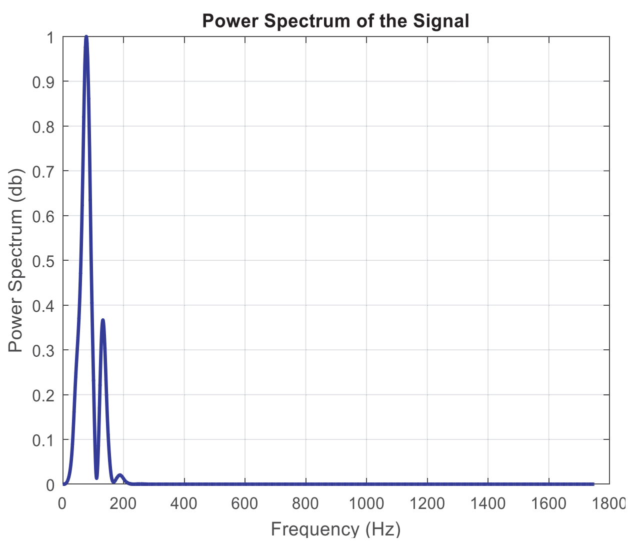


Figure 3. The power spectrum of the GPR signal.

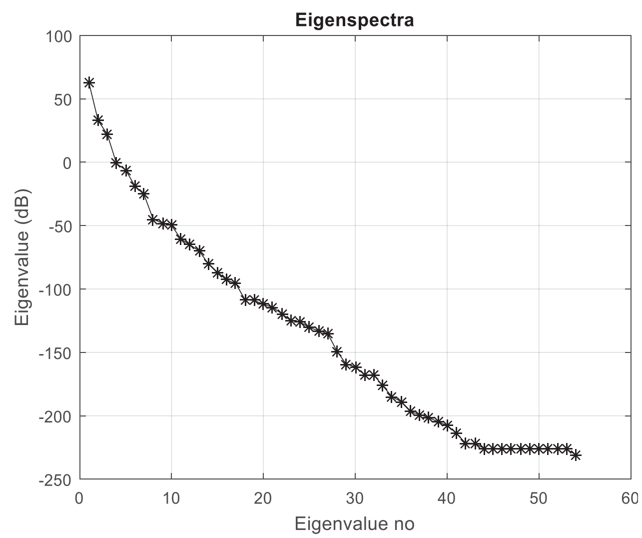
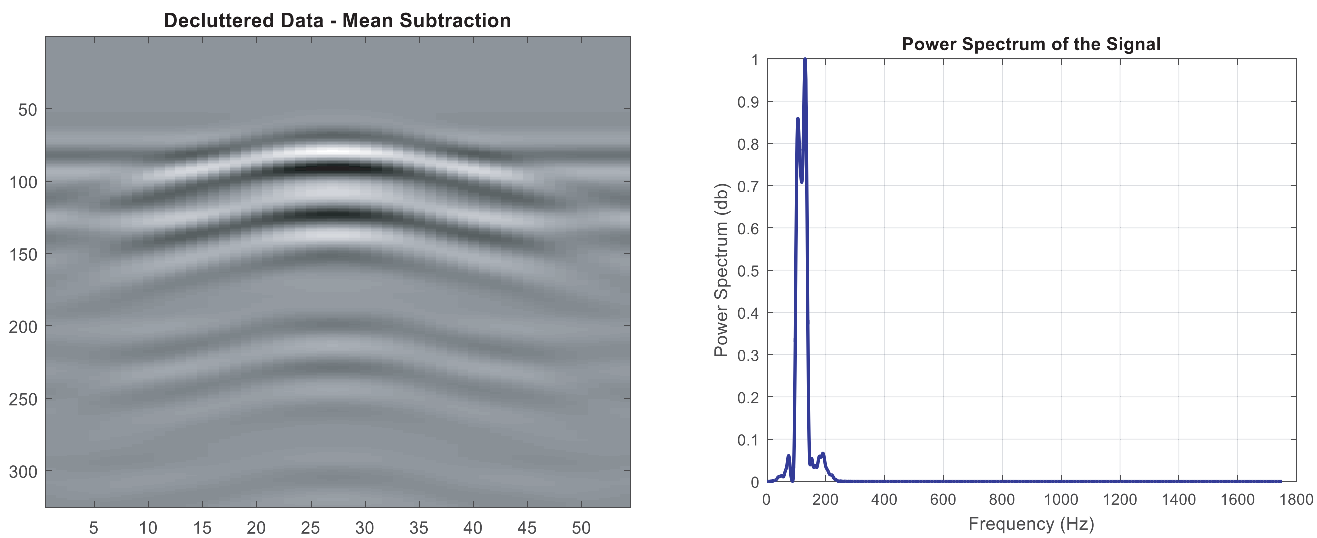


Figure 4. Eigen spectra of the GPR signal.

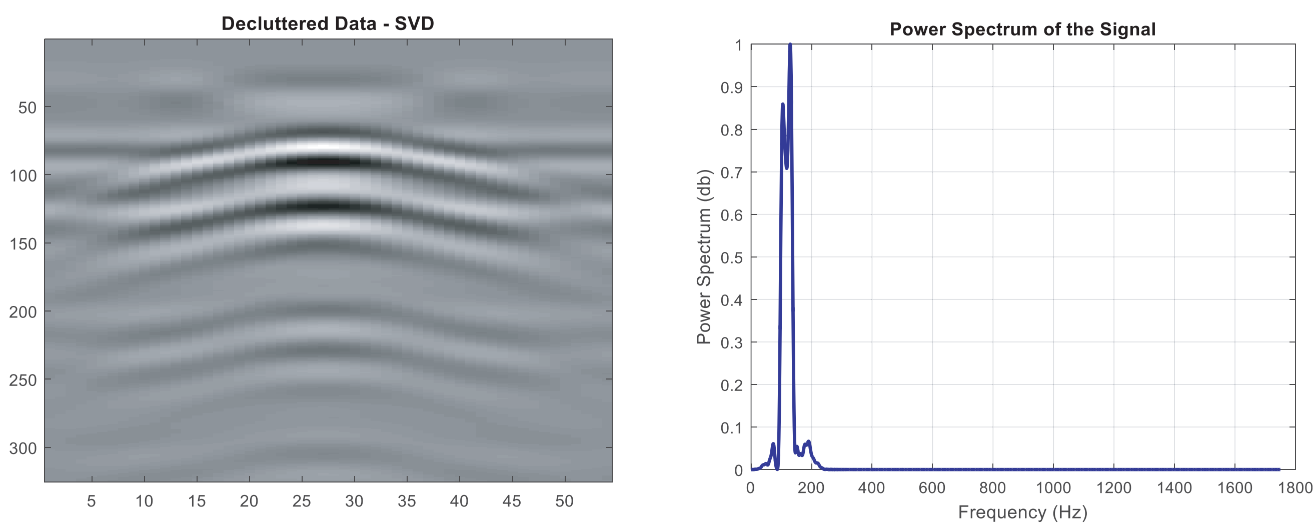
Table 1. PSNR and SSIM values for the different described clutter reduction algorithms.

Algorithm	PSNR	SSIM
MS	14.632	0.0022
SVD	**14.712**	**0.0035**
PCA	14.344	0.0028
ICA (3rd subspace)	**14.702**	0.0014
PICA	**15.210**	**0.0037**



(a) (b)

Figure 5. (a) Decluttered image using MS, (b) the power spectrum.



(a) (b)

Figure 6. (a) Decluttered image using SVD, (b) power spectrum.

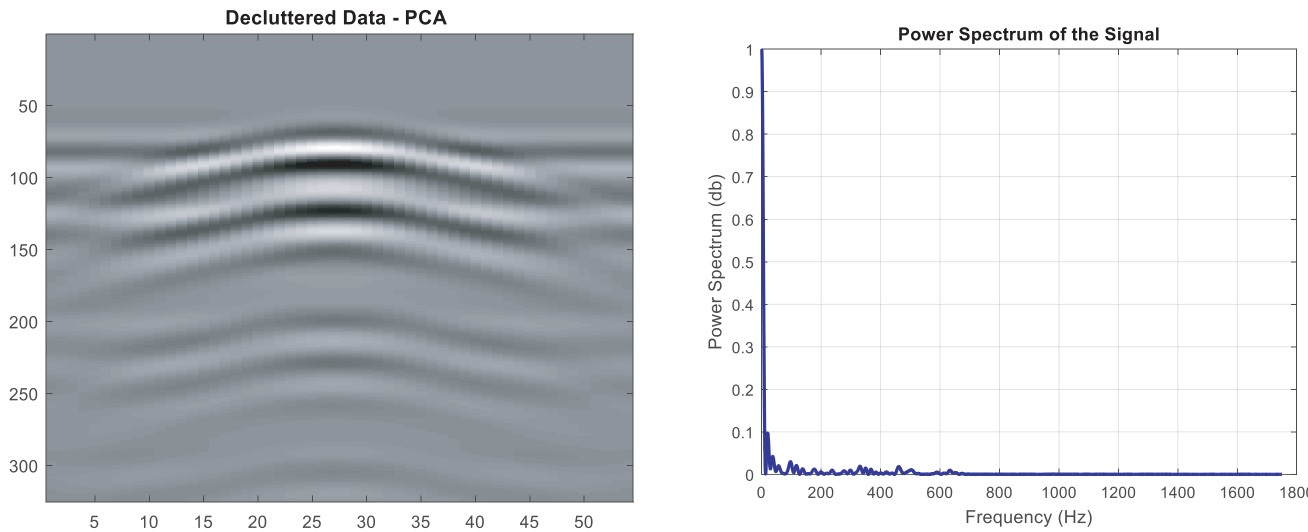
matrix of the GPR image in SVD method or the first principal component in the PCA and ICA based methods. Fig. 4 illustrates that the most discriminative features are within the first 20 dimensions; therefore, it can ignore the low significant features of the GPR image and reduce the dimension of the data to 325×20.

Without using any prior information, the easiest clutter removal method is the mean subtraction (MS) method. Figs. 5(a) and 5(b) explain the decluttered GPR and its corresponding power spectrum using mean subtraction method.

Figures 6–9 show the performance results of the SVD, PCA, 3rd principal of ICA, and the proposed PICA clutter removal methods on the real data. The signal reconstruction using 20-ICA Eigen image components is illustrated in Fig. 10.

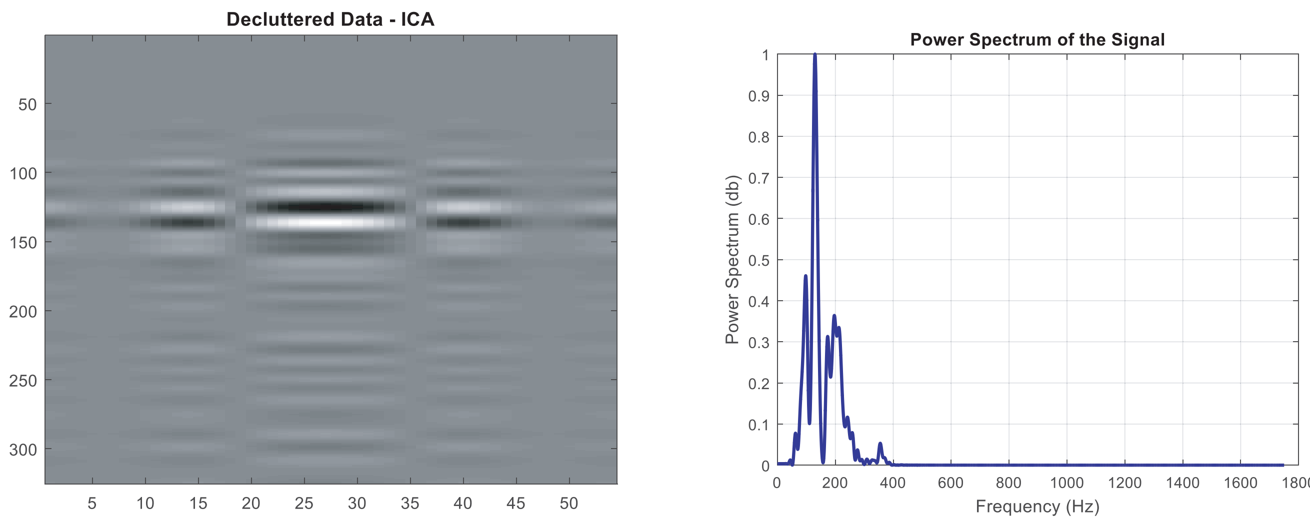
Table 1 summarizes the PSNR and SSIM performances of all decluttering techniques.

The experimental results confirm that the PICA approach outperforms other subspace state-of-



(a) (b)

Figure 7. (a) Decluttered image using PCA, (b) power spectrum.



(a) (b)

Figure 8. (a) Decluttered image of the 3rd component using ICA, (b) power spectrum.

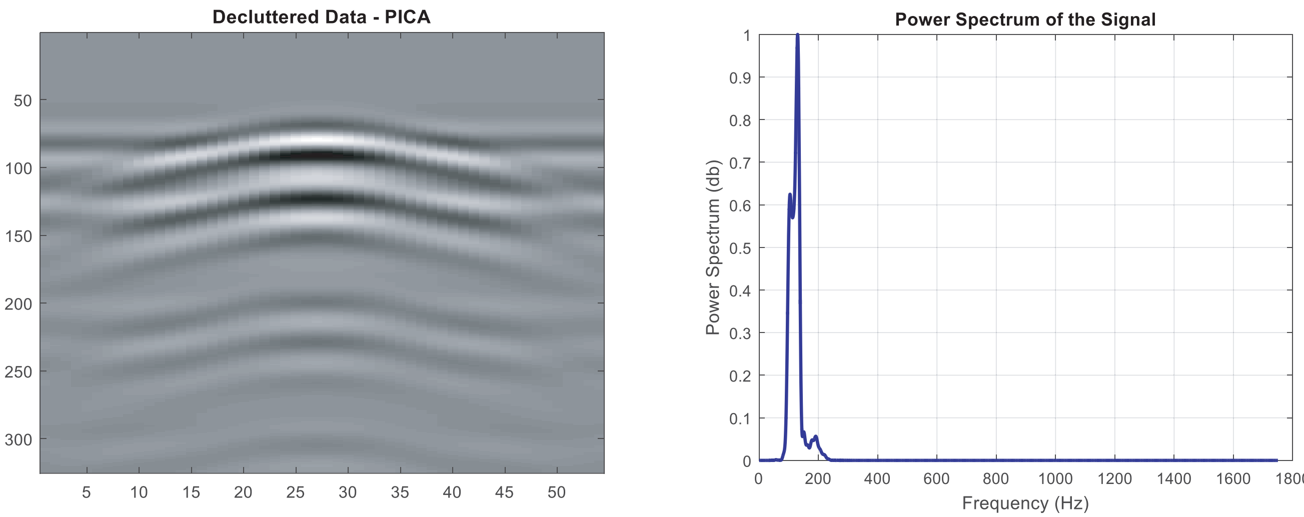
the-art clutter removal methods.

All subspace algorithms are simulated and realized using MATLAB 8.6 (R2015b) software tool and performed on an (Intel Core i5, 2.4 GHz CPU, 4GB RAM) computer.

The running time performance of the all subspace-based GPR clutter removal algorithm is as shown in Table 2.

Table 2. Time performance of the different clutter reduction algorithms.

Algorithm	Time (msec)
SVD	3.73
PCA	4.10
ICA (3rd subspace)	6.78
PICA	11.05



(a) (b)

Figure 9. (a) Decluttered image using PICA, (b) power spectrum.

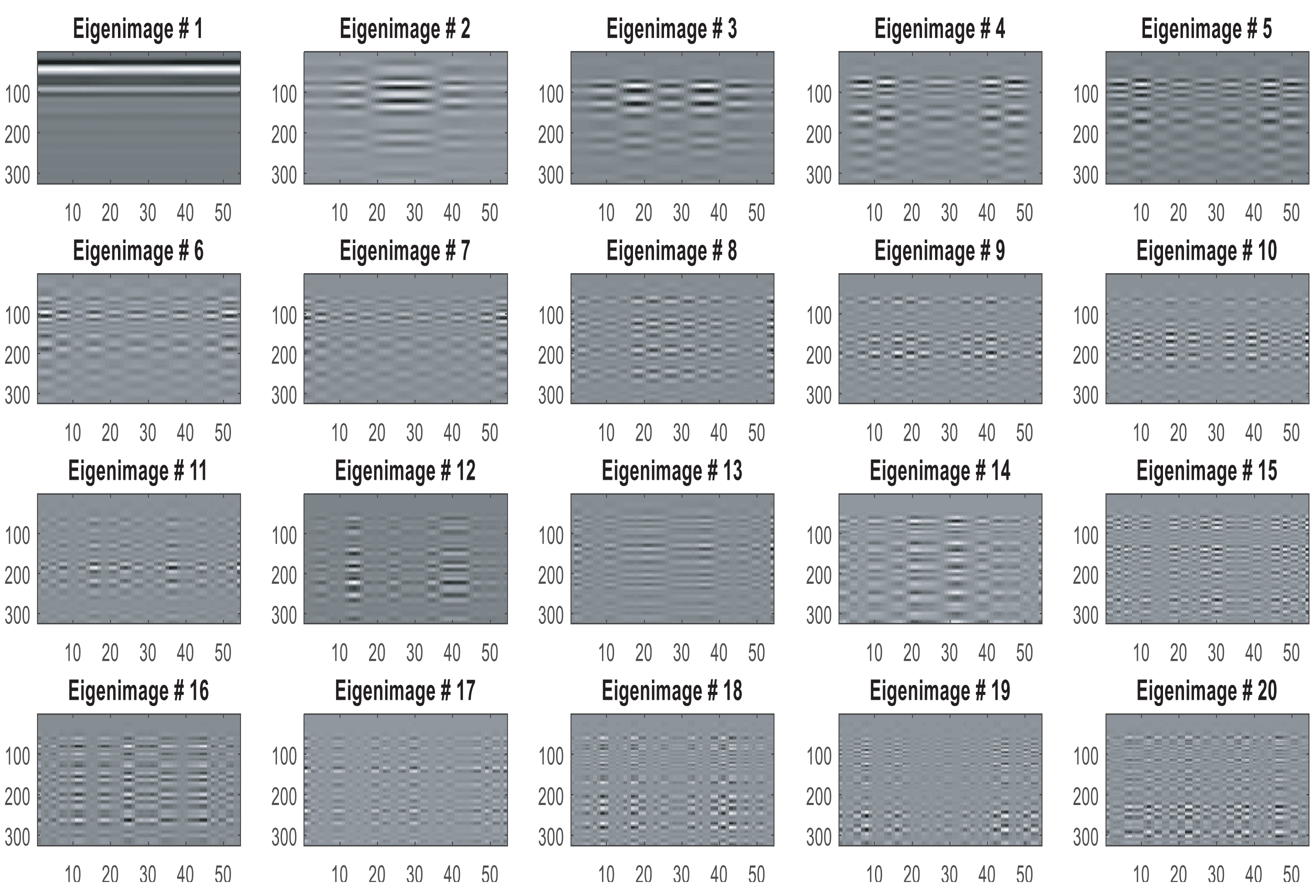


Figure 10. The 20-ICA Eigen image components.

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.

4. CONCLUSION

Various well-known approaches such as mean subtraction (MS), singular value decomposition (SVD), principal component analysis (PCA), independent component analysis (ICA), and the combination (PICA) are tested and examined for GPR clutter reduction purpose. They have been applied to GPR data with the aim to improve image quality by removing target uncorrelated features from the image and prepare reduced data for further processes like the classification tasks which is envisaged to be the next stage after clutter reduction. Consequently, the data representations handled by various feature spaces in GPR significantly enhance the trace and object detection efficiency.

For various GPR data samples, PCA, SVD, and PICA methods demonstrate that they are suitable for the uniform or near to uniform clutter reduction. Meanwhile, for the non-uniform clutter reduction, PCA, ICA, and PICA are also significant algorithms.

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