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Critical Analysis of Background Subtraction Techniques on Real GPR Data

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ABSTRACT

Ground penetrating radar (GPR) is used to detect the underground buried objects for civil as well as defence applications under varying conditions of soil moisture content. The capability of detection depends upon soil moisture, target characteristics and subsurface characteristics, which are mainly responsible for contaminating the GPR images with clutter. Researchers earlier have used averaging, mean, median, Eigen values, etc. for subtracting the background from GPR images. To analyse the background subtraction or clutter reduction problems, in this paper, we have experimentally reviewed background subtraction techniques with or without target conditions to enhance the target detection under variable soil moisture content. Indigenously developed GPR has been used to collect the data for different soil conditions and several background subtraction signal processing techniques were critically reviewed like, mean, median, singular value decomposition (SVD), principal component analysis (PCA), independent component analysis (ICA) and training methods. The signal to clutter ratio (SCR) measurement has been used for performance evaluation of each technique. The relative merits and demerits of each technique has also been analysed. The background subtraction techniques have been appliedto experimental GPR data and it is observed that in comparison of mean, SVD, median, ICA, PCA, the training method shows the highest SCR with buried target. Finally, this review helps to select the comparatively better background subtraction technique to enhance the detection capability in GPR.

Keywords: Ground penetrating radar; Singular value decomposition; Principal component analysis; Independent component analysis; Training method, SCR; Generalised inner product; Generalised likelihood ratio

1. INTRODUCTION

Ground-penetrating radars (GPRs) is used to image the underground buried objects, which transmit then arrow electromagnetic pulses towards the predicted underground buried objects and get back the reflections[1]. Apart of other technologies, GPR is one of the most assuring technologies for detection and identification of buried objects in the underground imaging. The GPR technology provides the detection capability and identification capability of buried objects and it is best suitable technology for interpreting the target and the ground informations[1,2]. As compared to existing techniques, the GPR can speedily and non-incursively create high resolution image of underground buried objects[3-8]. In GPR, a challenging problem is to discriminate the buried target backscatter field from the rest of the backscatter field, which is outside the area of investigation. Since in GPR perspective, the background is much stronger than the useful signal, background subtraction methods are very useful to avoid the false occurrence of outcomes. Each measurement of GPR consists of noise due to hardware imperfection, specular reflection from ground surface, clutter and possibly target signal. Overall, the GPR background subtraction problem can be defined as 'blind signal detection. To process the collected GPR data, there is essential to select the useful data, therefore, the first step is to remove the ground bounce by some method. Another name of ground reflections are 'antenna characteristics and antenna to ground interface compensation', which terms as 'Background subtraction in GPR processing' or 'clutter reduction', each ground reflection may have more or less importance in GPR applications. There are various methods of ground bounce removal reported in the literature[9-17]. Researchers are applying various clutter removal techniques on stepped frequency continuous wave ground penetrating radar (SFCW-GPR) data and explored the importance of these techniques. The main clutter reduction techniques based on their operations are as statistical signal processing, classical filtering and neural network nonlinear signal processing. Clutter reduction based on statistical signal processing techniques such as PCA[13], ICA[12], mean subtraction[9], median removal[9], SVD[10] and non-linear training method[17] are being used in the present paper to remove or minimise the clutter. After processing data using these techniques, signal to clutter ratio (SCR) of images has been calculated with respect to raw image with soil moisture variations, and results are compared[22]. Therefore, in this paper, an attempt has been made to critically analyse the background subtraction techniques and compute the signal to clutter ratio for evaluating the performance of each technique.

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2. GPR SYSTEM DESCRIPTION

The GPR system[23], which has been developed indigenously using VNA for detecting underground buried objects as shown in Fig. 1. The vector network analyser (VNA) is used to generate the SFCW signal, which is amplified by power amplifier having a gain of 20 dB for transmission. The amplifier output is fed to a broadband (1–2 GHz) TEM Horn antenna. This broadband TEM Horn antenna has constant gain of 7 dB with frequency. Overall specifications of developed SFCW GPR system are shown in Table 1.

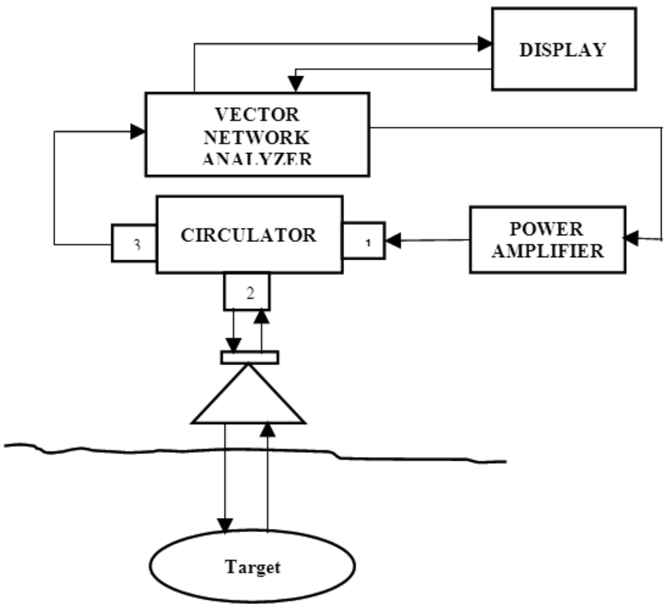

Figure 1. Monostatic ground penetrating radar system.

Table 1. SFCW –GPR specifications

Antenna	Double ridge horn
Vector network analyser	R&S FSH4
VNA power	1 mW (0 dBm)
Frequency range of operation	1 GHz to 2 GHz
Δf_o	1.58 MHz
No. of frequency points	631
Range resolution	15 cm
Investigated depth	≤1 m

3. SIGNAL PROCESSING AND DATA COLLECTION

When processing the GPR images, then several types of 'scans' associates in processing part. The 1D GPR range profile is called as A-scan, which is as shown in Fig. 2. In the present case, the A-scan range profile is a plot (1D) of range-amplitude, which is measured response of the echo signal over a single position as shown in Fig. 1 (GPR block diagram). In the plot obtained, peaks are represented as reflections from buried objects and locate the depth of the discontinuity. This A-Scan profile provides us the rough estimation of the location of the target and is termed as the detection stage. In Fig. 2, A-scan profile, the first peak is due to air-to-ground interface fixed reflection, second peak represents variable clutter reflection and third peak represents target reflection. A-scan profile after background subtraction, decreased the intensity of undesirable clutter peaks and enhanced the intensity of target peaks.

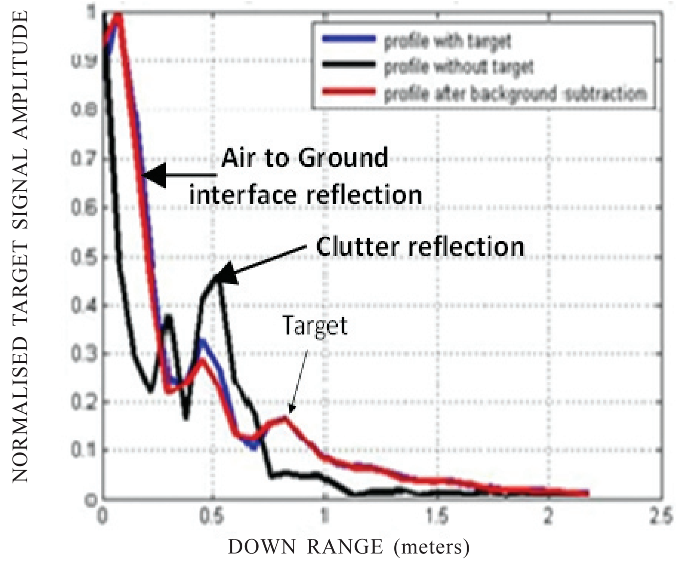

Figure 2. A scan range profile with target, without target and after background subtraction.

Usually, the number of A-scans are collected in the GPR data processing, which forms a 2D matrix of a GPR image of the area of interest and is known as B-scan, as shown in Fig. 3. In this matrix, each row represents a frequency point (or time) and column represents a cross range position. As is cleared from the previous discussion and from Fig. 4, the collected raw GPR data are in frequency domain B-scan with $M \times N$ data matrix. For further processing, domain of data is changed into the domain of data (i.e. frequency to time domain), which is also $M \times N$ using inverse Fourier transform. where M is frequency or time sample point and N is the cross range position. Further, to reduce the additive noise, windowing is applied. We have collected more than thousands of data with buried target

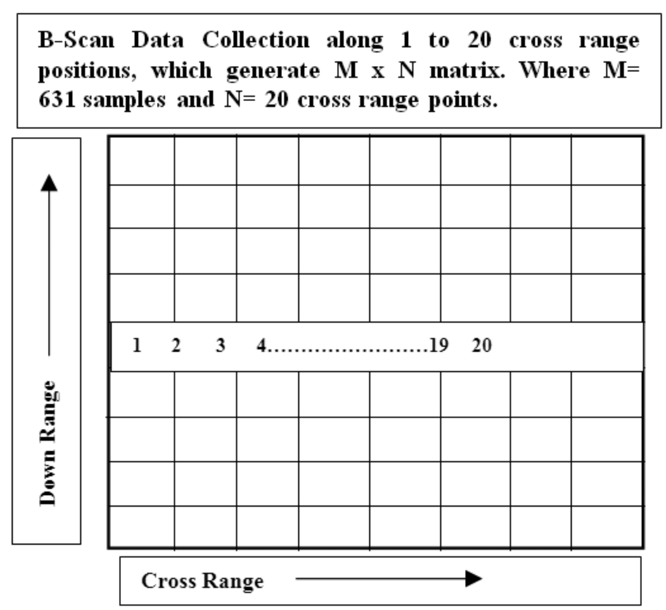

Figure 3. B-scan data collection as stacking of A-scan.

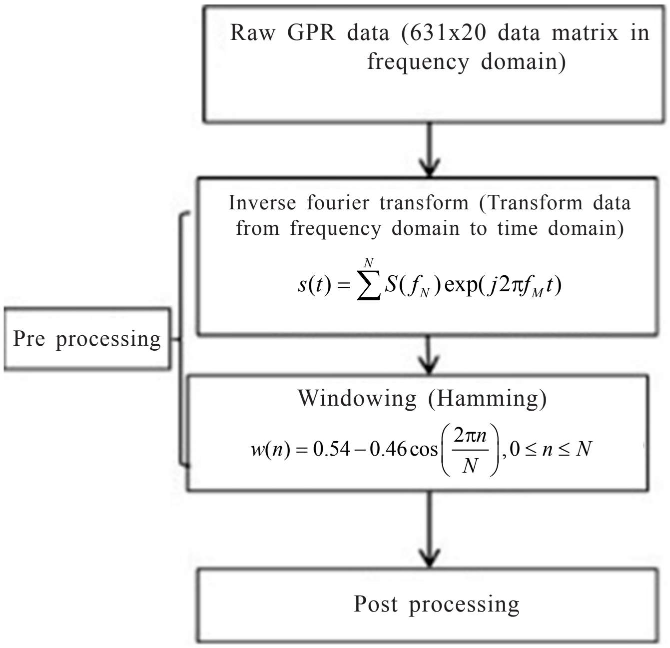

Figure 4. Flow diagram of GPR signal processing[24].

and without buried target (i.e., ground only) in various field conditions with 5 per cent - 15 per cent moisture variation. We have prepared field for specified moisture with the help moisture meter for collecting the data.

Raw B-Scan images with soil moisture variation have been plotted following the GPR signal processing steps shown in Fig. 4. The raw images without and with target for 5 % and 10 % soil moisture are as shown in Figs. 5(a-d),where, X-axis and Y-axis represent the cross-range and downrange respectively, blue colour represents the lowest intensity and brown colour represents the highest intensity. In all raw images, we cannot discriminate the target and clutter. Therefore, further processing is required to extract the target information and it is necessary to subtract the background to reduce the clutter.

4. BACKGROUND SUBTRACTION TECHNIQUES AND IMPLEMENTATION

In this section, some state-of-the-art background subtraction techniques are discussed for GPR applications. Background subtraction techniques can be classified mainly into three categories first, non-linear or pattern matching methods[19, 20] that use fuzzy set theory, genetic algorithm (GA) and neural

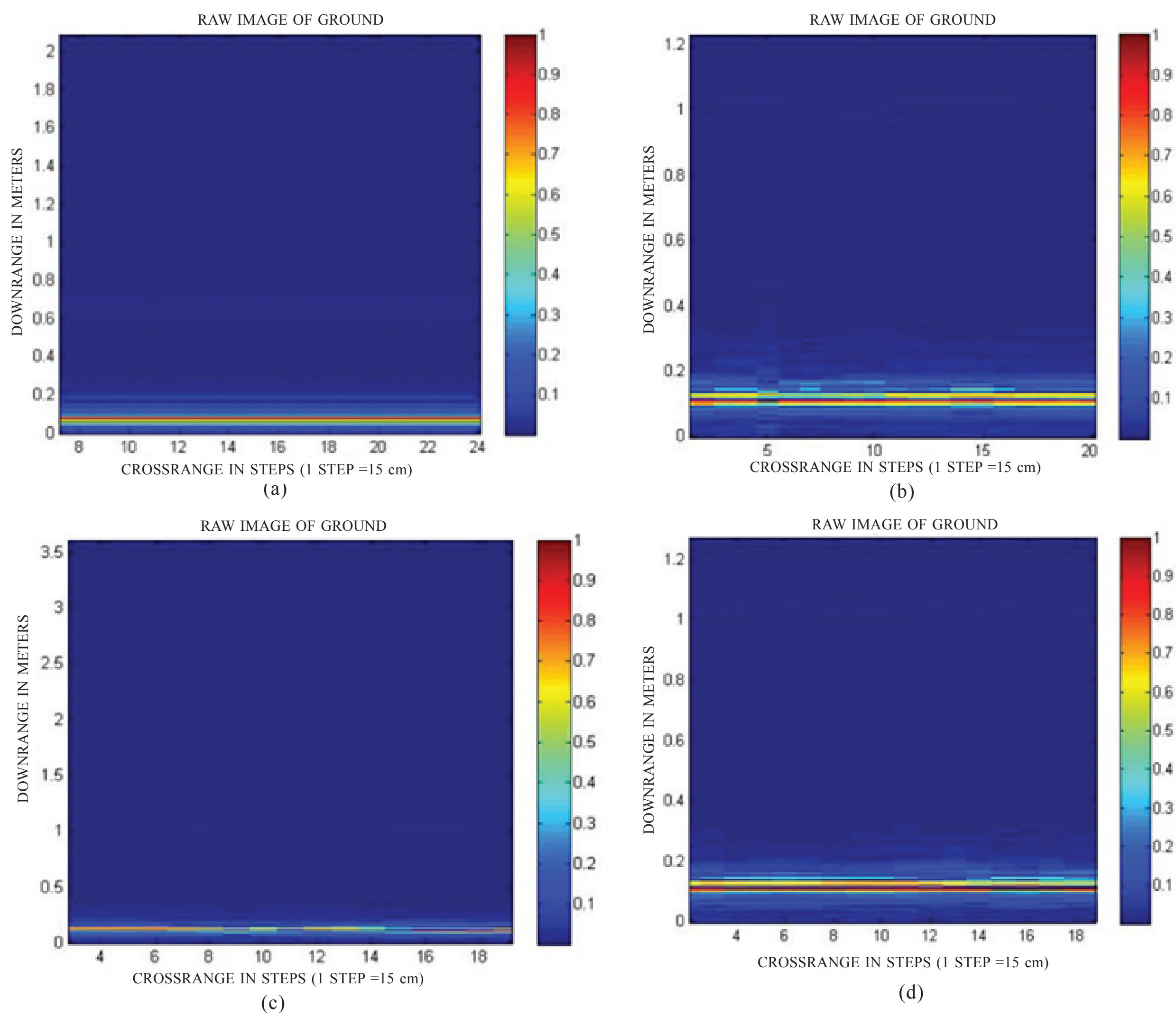

Figure 5. Raw images without and with target : (a) raw image without target (5 % moisture) (b) raw image without target (10 % moisture), (c) raw image with target (5 % moisture), and(d) raw image with target (10 % moisture).

networks to estimate the background and subtract it from the target data. The amount of the training burden, however limits the functionality of these methods otherwise their processing speed is fast. Second, image and detection techniques[21] using the near-field beam-forming approach for imaging the area of interest with appropriate background modelling, which is further-processed to detect the targets. These approaches generally require the parallel data slices of GPR to form an image and are thus not well suited to real time computations in which data is processed sequentially. A third method is statistical signal processing method[18], where some statistical hierarchy develops to remove the background using either probability of detection, variance, Eigen values or probability of false-alarm[16]. Selection criterion of background subtraction techniques are another major issue in GPR applications because of the following reasons:

- The mean removal method may be suitable to remove the steady background or random noise.
- The median method can be used to remove the abrupt internal noise, which is mostly dominant in a time series signal.
- Like metallic targets can be successfully detected by decomposing the signal and clutter using the singular value decomposition.
- Some components in our data may Gaussian distributed, linear and stationary. Therefore, Principal Component Analysis (PCA) is suitable for the signal, estimating process by forming the orthogonal subspace.
- ICA is followed higher order moments and is extracted independent components (IC's), which are statistically independent and non-Gaussian. Therefore ICA may show the better performance for removing the non-Gaussian components in GPR applications.
- Space variation include change in soil moisture and change in surface roughness, then selection criterion for subtracting the background is different. Space time adaptive processing with adaptive learning is a solution to incorporate the space variation in GPR data processing.

Mainly, in this study, statistical methods have been investigated. On the basis of statistical properties, background subtraction techniques are categorised as statistical mean removal, median removal, singular value decomposition based on Eigen value, principal component analysis based on covariance or Eigen value, independent component analysis for a higher order statistical moment and a training method based on generalised inner product (GIP) and generalised likelihood ratio (GLR). Further, more details of these techniques have been discussed in the implementation part. Figure 6 shows the GPR data background subtraction flow for investigating the various background subtraction techniques. GPR preprocessed data is obtained as outlined in Fig. 4, and described.

A brief description of reviewed background reduction techniques for GPR are outlined as follows:

4.1 Mean Removal Method

Mean removal method[9,23]can be implemented by using Eqn (1):

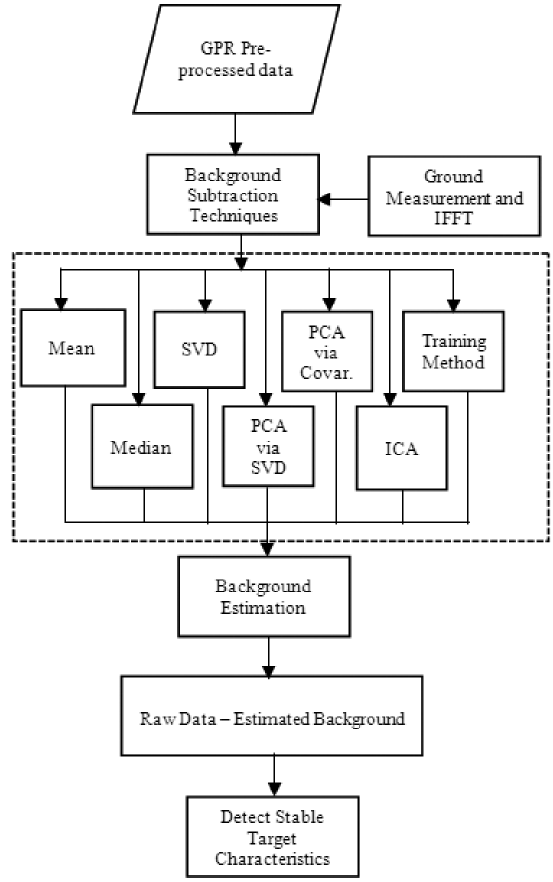

Figure 6. GPR data background subtraction flow.

$$X_{ave} = X_{raw} - \frac{1}{M}\sum_{i=1}^{M} X_i \tag{1}$$

where X_{raw} is the raw data, $\frac{1}{M}\sum_{i=1}^{M} X_i$ is mean data and X_{ave} is GPR data after mean is removed. In mean removal method subtract the mean from each total collected A-scans the "average single A-scan" as take account on all the collected ones. This is the simplest method to remove the ground interface bounces, which are located around the low frequency spatial spectrum. GPR pre-processed data are obtained from Fig. 4 and is applied to GPR data background subtraction flow as shown in Fig. 6 for both with or without target conditions. Now, we have been applying the mean removal method is then applied to estimate the background and subtract it using the Eqn (1).

Figures 7(a)-7(d) is shown as the results of implemented mean removal technique. As from Figs. 7(a)-7(b) mean removal removed most of the clutter components, which raw images are as shown in Figs. 5(a)-5(b) for without target case. Mean removal can eliminate most of the Homogeneous Ground Bounce. But many times this method filtered out the desire signal also. There is one more important observation that clutter components increase as soil moisture increases, which is clearly seen in Figs. 7(c)-7(d).

4.2 Median Based Ground Bounce Removal Method

Median based ground bounce method[9] can be implemented by using the following mathematical expression:

$$X_{med} = X_{raw} - median\left(X_{background}\right) \quad (2)$$

where X_{raw} is the raw data, $median\left(X_{background}\right)$ is median of background data and X_{med} is GPR data after median removal.

The median of a number of surrounding scans in GPR can be used to estimate the ground reflections. There are several different ways to perform the Median Subtraction, but, the preferred way is to gather the 'over all median single A-scan' and is to subtract from each total collected A-scans to remove the clutter. Again preprocessed data from Fig. 4 is applied to GPR data background subtraction flow (Fig. 6) for the median removal method. The estimated background was removed it with the help of Eqn (2). Experimental results of median based ground bounce removal method are as shown in Figs. 8 (a-d).

Results of median ground bounce removal method are similar to mean removal method, but target detection for 10% soil moisture is improved as compared to mean removal method, as shown in Fig. 8 (a). Many times median removal method removed the shallow buried target signal, otherwise this method is suitable for both smooth and rough surfaces.

4.3 Singular Value Decomposition

The collected 2D data (i.e. B-scan) in GPR applications is denoted by a matrix X, with dimension $\left(M \times N\right)$ and $\left(M \geq N\right)$, SVD[10,23] of the matrix may be

$$X = U * S * V^{T} \quad (3)$$

where, $U\left(M \times M\right)$ and $V\left(N \times N\right)$ are unitary matrices, respectively, $\sigma r's$ are Eigen values and

$S = \text{diag}(\sigma 1, \sigma 2, \sigma 3, ...\sigma r)$. Hence, X can be represented as:

$$X = X_{signal} + X_{clutter} \quad (4)$$

where, X_{signal} is target signal components and $X_{clutter}$ is clutter components. As from Eqn (4), data matrix is divided into signal and clutter part. The matrices constituted by higher and lower Eigen values are viewed as noise and are subtracted as

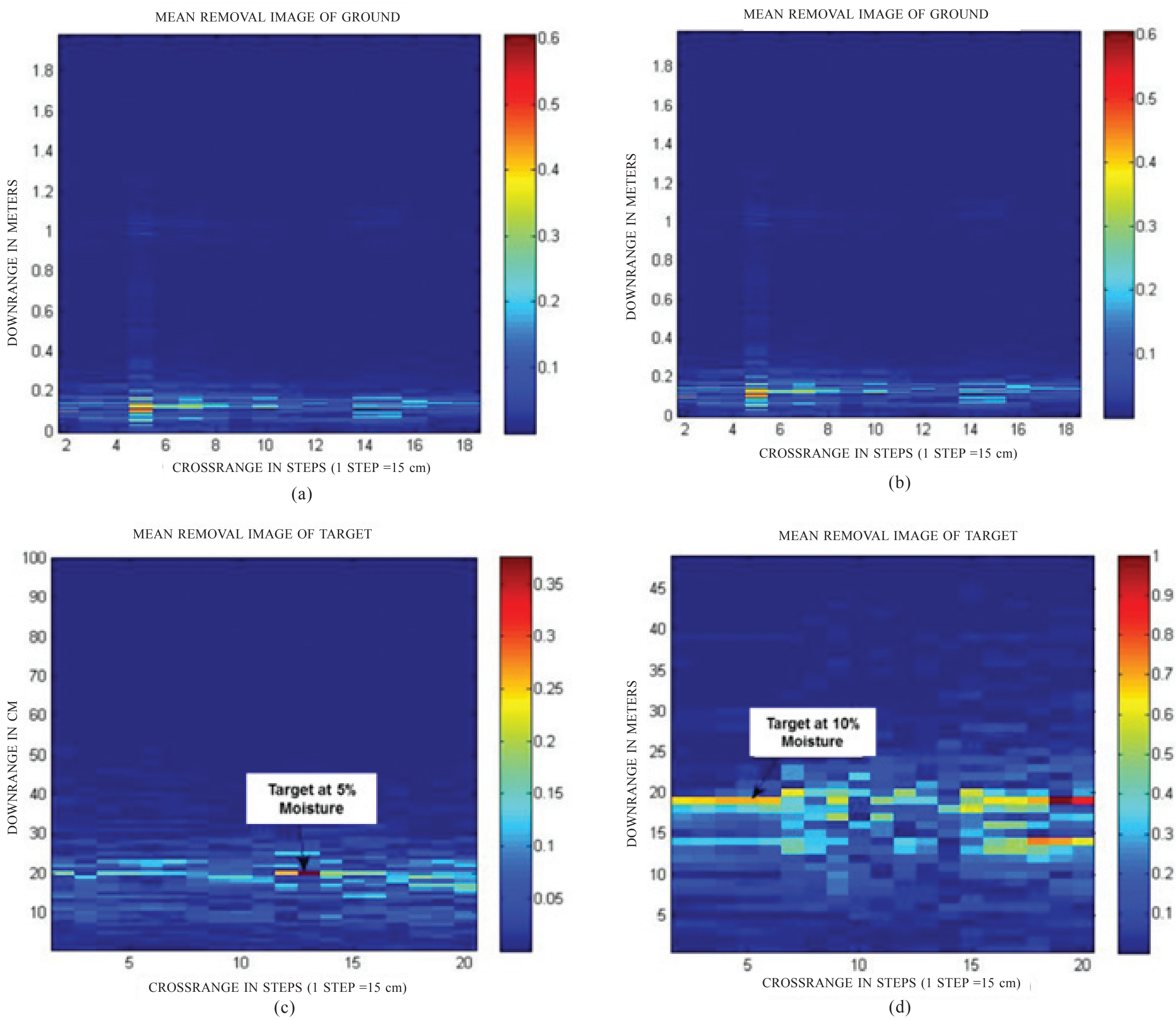

Figure 7. Mean removal method : (a) without target (5% moisture), (b) without target (10 % moisture), (c) with target at 35 cm (5% moisture), (d) with target at 35 cm (10% moisture).

clutter from the data. The matrices made by intermediate Eigen values are used to further processing. In present experiment, the 1st row and 1st column has been considered as dominant clutter values in the collected data matrix, so, at the time of implementation of SVD method, these row and column has been removed to reconstruct the clutter free signal. The signal reconstruction has been performed as follows:

$$X = U(:,2:end) * S(:,2:end) * V^T(2:end,:) \tag{5}$$

The GPR preprocessed data from Fig. 4 is processed through SVD based background subtraction process steps of Fig. 6. Using Eqns (3), (4), and (5), we have obtained background subtracted GPR data.

Figures 9(a)-9(d) presents the results of SVD based background subtraction method. The SVD automatically perform the Image compression method, because it will remove the selected Eigen value, which has contribution in the ground bounce and clutter. In without target case, SVD removed the least intensity part from data as shown in Fig. 9(a). The least intensity part is actually not clutter, but SVD is treated as clutter. In the present case, visual inspection of Figs. 9(c)-9(d), shows that the SVD method has not discriminated between target and clutter because estimated clutter via SVD is not capable to remove the clutter.

4.4 Principal Component Analysis via SVD

PCA[13] separate out the correlated and uncorrelated components in an image data matrix or B-scan matrix. A high correlation factor makes the algorithm more efficient. Uncorrelated components can be filtered out easily from the correlated components. The various applications of PCA are, such as signal processing, data compression, data visualisation, image analysis and pattern recognition. Dimensionality reduction is a big advantageous feature of the background subtraction technique. It is usually considered in the principal components computation, the largest singular values of the data matrix is considered as the ground reflection.

The estimated ground bounce is the principal components, which correspond to the l largest singular values, that is

$$g = \sum_{i=1}^{l} v_i \sigma_i \tag{6}$$

where g is the estimated background, l is the number of principal components, v_i is the Eigen vector matrix and σ_i is the Eigen value. The considered ground bounce can be tuned by varying the parameter l, which estimate the amount of ground bounce. The preprocessed data obtained from Fig. 4 as before, were applied to the GPR data background subtraction flow as shown in Fig. 6. Background was estimated with the help of

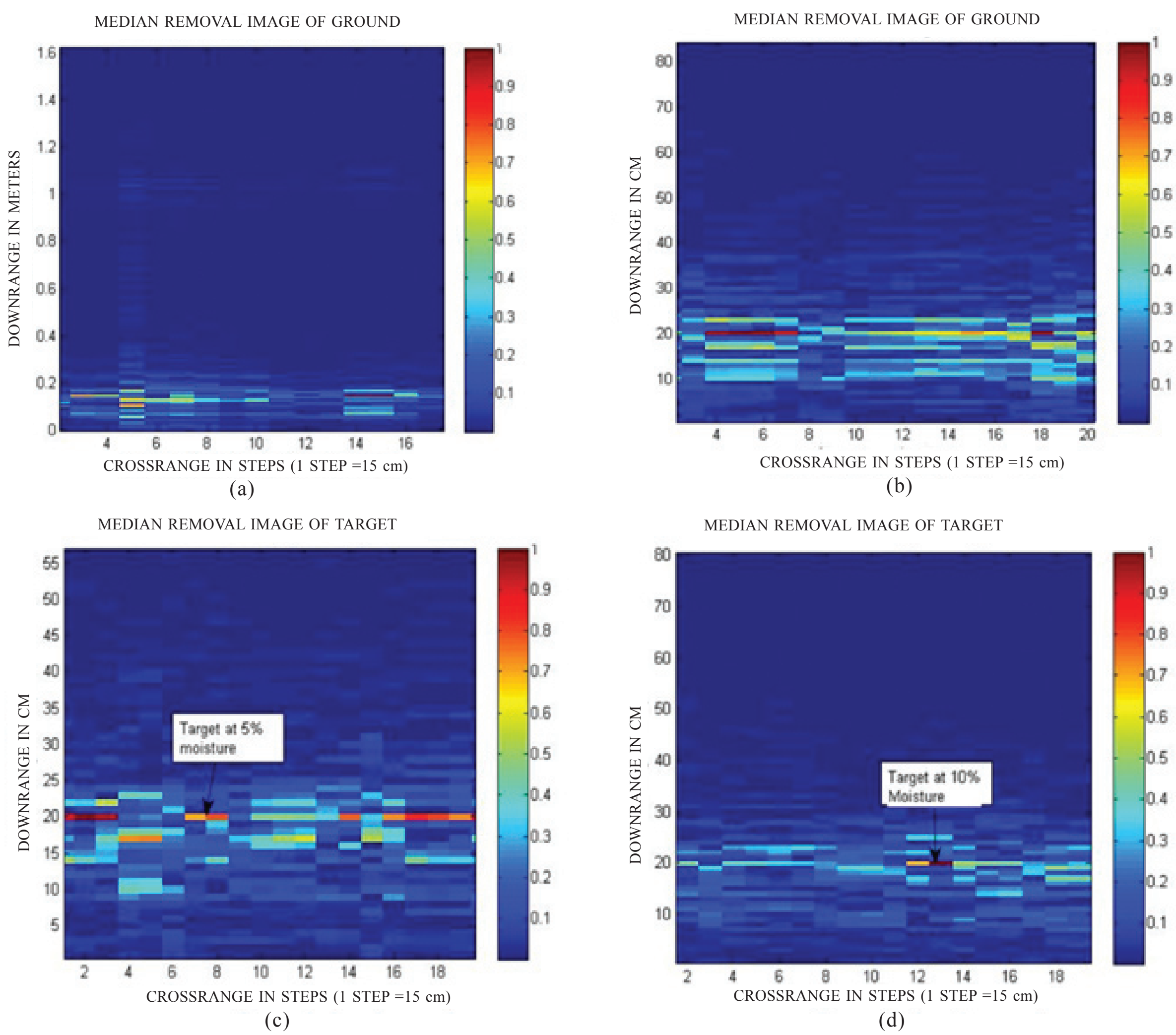

Figure 8. Median removal method: (a) without target (5% moisture) (b) without target (10 % moisture) (c) with target at 35 cm (5% moisture), and (d) with target at 35 cm (10% moisture).

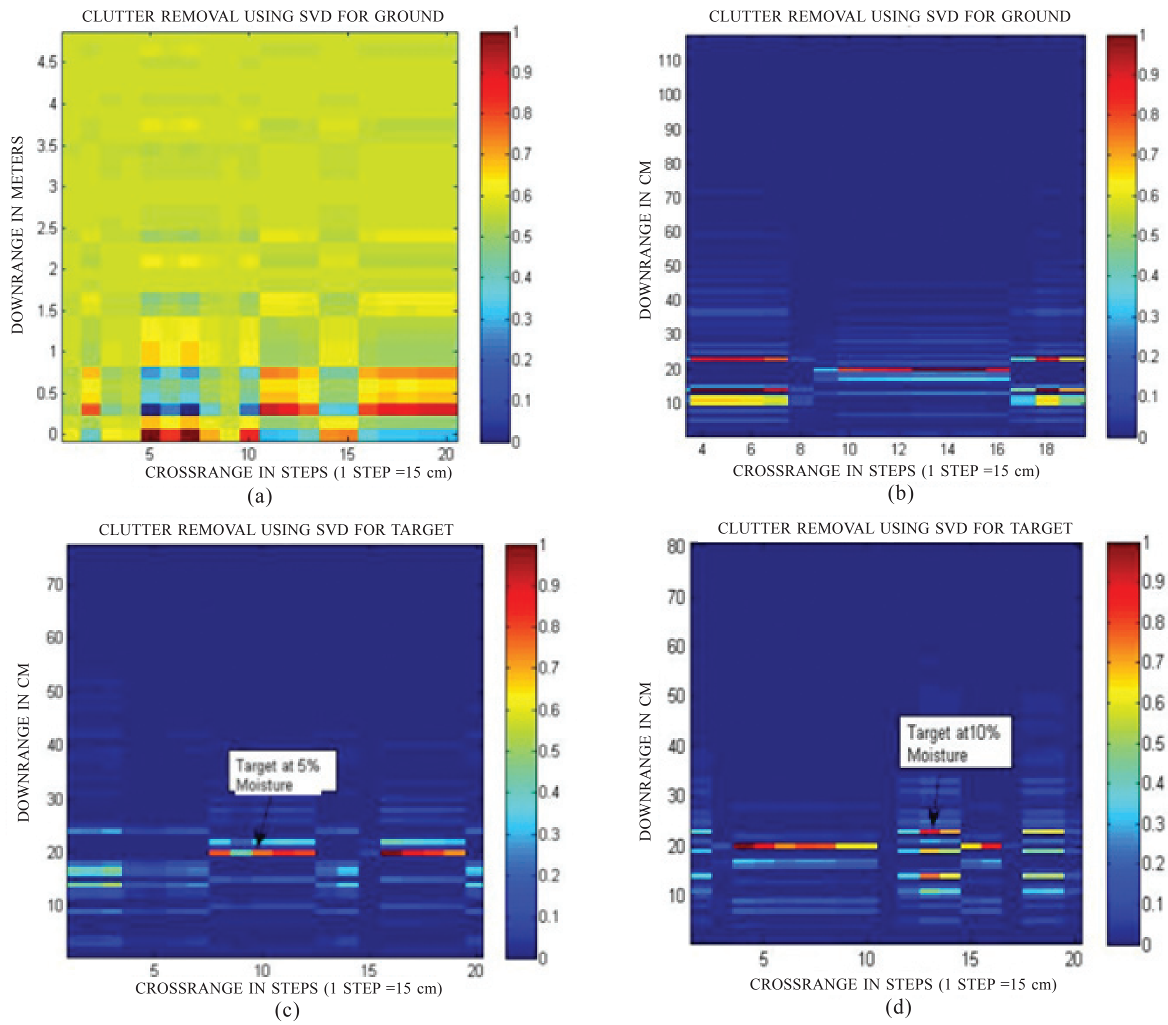

Figure 9. SVD based background subtraction method: (a) without target (5% moisture), (b) without target (10 % moisture), (c) with target at 35 cm (5% moisture), and(d) with target at 35 cm (10% moisture).

Eqn (6) and final results of PCA via SVD based ground bounce removal are as shown in Fig. 10 (a)-10(d).Target detection from PCA via SVD is improved, due to the much more reduction of clutter. Target shifting is a major problem in the PCA.

4.5 Principal component Analysis via Covariance

Mathematically, for background subtraction using PCA via covariance[13], in GPR, B-scan data can be represented by a $M \times N$. m = 1,2,…..,M ; n = 1,2,3,…..N) data matrix X_{mn}, where m is time or distance index and n is cross range or position index. Let N principal components of data matrix X be expressed as:

$$Y \;\; = B^T X \tag{7}$$

where $X=[x_1,x_2,x_3,.....,x_n]^T$ is the zero-mean input vector; $Y=[y_1,y_2,y_3,.....,y_n]^T$ is the transformed output vector of principal components and B is a $M \times N$ transformation matrix.

The PCA helps to express a relatively small number of decorrelated principal component of a set of random zero-mean variables without destroying the original useful information. Therefore, PCA reduces the dimensionality.

The main issue here is to, "How to interpret the PCA in GPR applications?" In PCA, transformed vector is computed with the assumption that transformation matrix is orthonormal, i.e. covariance matrix of transformed matrix Y is diagonalised. A mathematically covariance matrix C_x can be expressed as:

$$C_x = \frac{1}{N} XX^T \tag{8}$$

$$C_x\Phi = \Phi\Lambda \tag{9}$$

where C_x, Φ and Λ are Data matrix ,covariance , eigenvector and eigen value matrix respectively. The eigen values are arranged in decreasing order to estimate the transformation matrix B from N leading eigen values as given by following equation:

$$B = [\Phi_1, \Phi_2, \Phi_3, \ldots.., \Phi_N] \tag{10}$$

where B is the transformation matrix, which is composed of the Eigen vectors.

PCA matrix X_{PCA} can be calculated by Eqn (11):

$$X_{PCA} = B^T X \tag{11}$$

where X_{PCA} is the final output of PCA.

Results of PCA via covariance based ground bounce removal are as shown in Figs. 11 (a)-11(d). In this method, a covariance matrix is formed to calculate the Eigen values, these Eigen values depict as the principal components. After finding the principal components, the remaining methodology

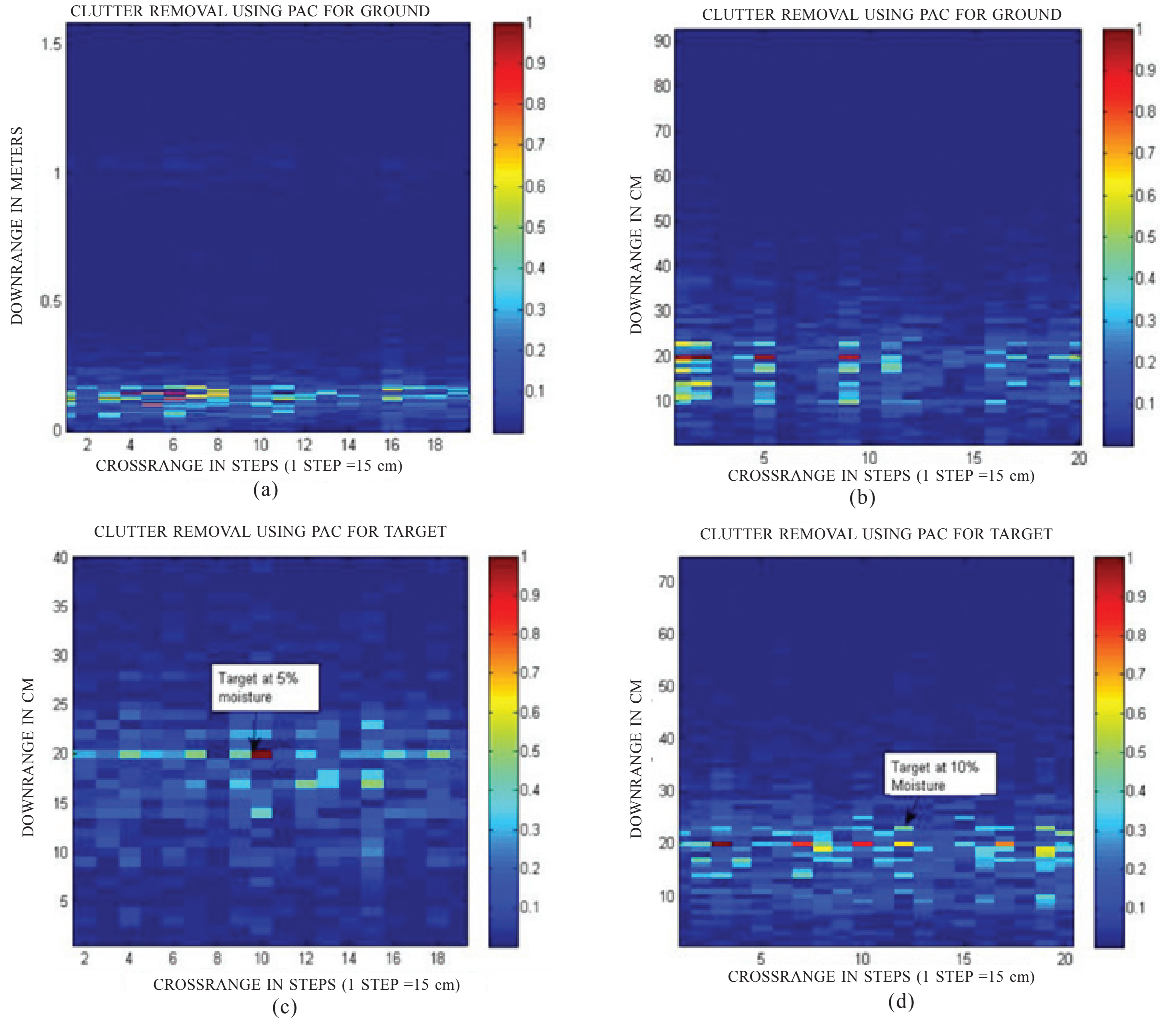

Figure 10. PCA via SVD method: (a) without target (5% moisture), (b) without target (10 % moisture), (c) with target at 35 cm (5% moisture), and (d) with target at 35 cm (10% moisture).

is same as for PCA via SVD. From Figs. 11(a)-11(d), it seems that the results are similar as for PCA via SVD, only that way of implementation is different. Another major aspect for both PCA implementation is 'principal component selection', which may create problem to discriminate the target and clutter.

4.6 Independent Component Analysis

Primarily, ICA[12] is used to remove the clutter, which follows the non-Gaussian characteristics. ICA separate out the GPR data into statistically independent components while other technique such as PCA is used to remove clutter which follows the Gaussian characteristics (i.e. Uncorrelatedness).

Since, uncorrelatedness is not sufficient to separate signals efficiently, therefore, ICA is used statistical independence. Higher order moments have been used to achieve the stronger statistical property than decorrelation. ICA has applications in feature extraction and background reduction from the images, in finding hidden factors from financial data and it is mostly used in telecommunications for separating the original source signal from interfering signals. In ICA statistics say that the raw data X_{raw} can be describes, by a linear process, $X_{raw} = AX$ where both the source X and mixing matrix A are unknown, i.e. statistically independent with few assumptions.

Further, for GPR applications, useful information can be obtained from ICA linear process by selecting the target information component and other components are discarded as background. Figures 12(a)-12(d) shows the results of ICA method, in which ICA removes all lower intensity components and enhances clutter components. It is not possible, discriminate target and clutter signature as shown in Figs. 12(c)-12(d), because the ICA method follows linear process, which is statistically independent, but in actual GPR data is statistically dependent. Therefore, target component selection using ICA is not possible in the GPR data scenario.

4.7 Training Method

Training Method[17,23] is also used to remove the Ground reflection in Ground Penetrating Radar. The ground reflections depends on the surface roughness and on the soil conditions, which degrade the performance of background subtraction techniques. The Space-time adaptive processing (STAP) has been used to select the training data in the radar based target detection.

In this method, a set of independent identically distributed (iid) target-free data has been formed by non-homogeneous detector (NHD). There are two methods used to select

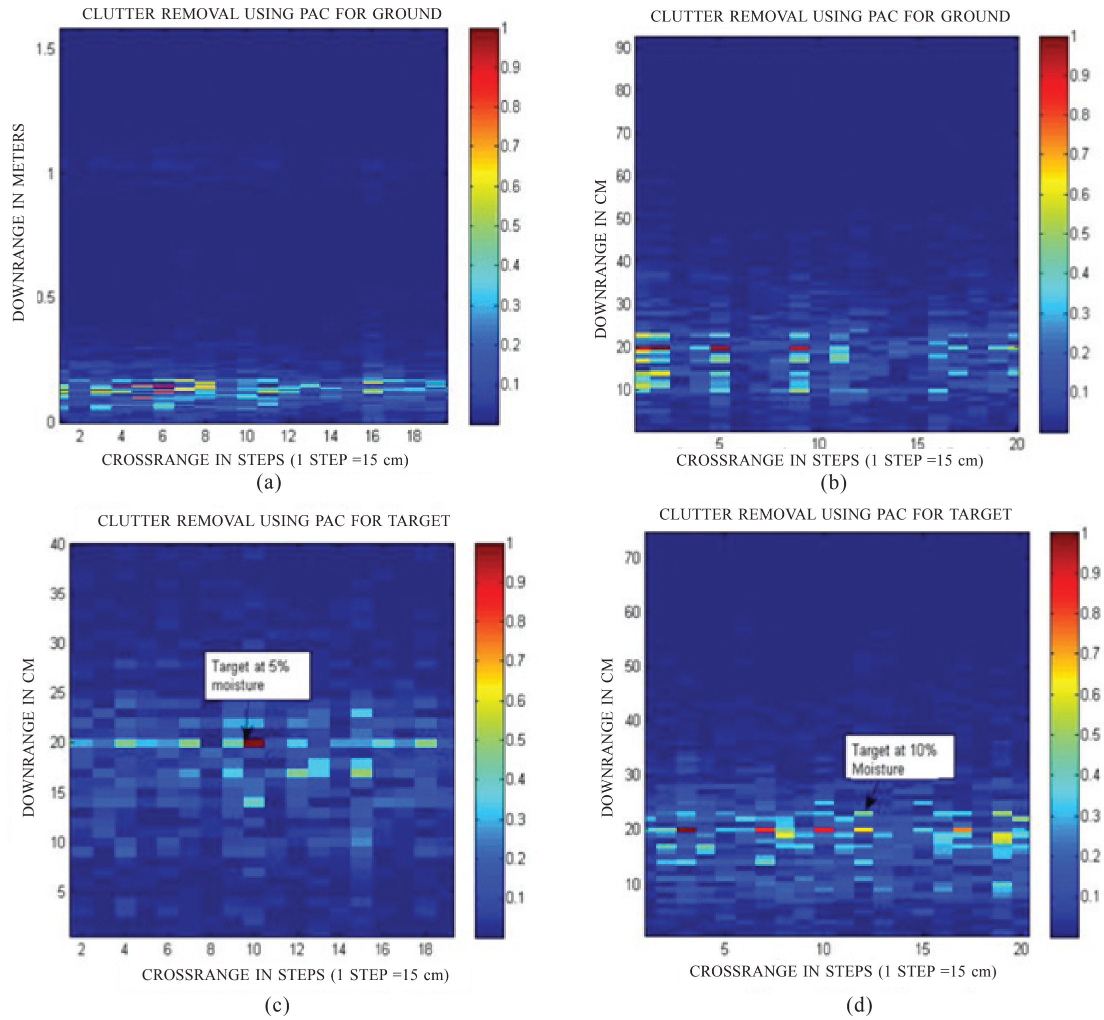

Figure 11. PCA via covariance method: (a) without target (5% moisture), (b) without target (10 % moisture), (c) with target at 35 cm (5% moisture), (d) with target at 35 cm (10% moisture).

the reference, which are general inner product (GIP) and generalised likelihood ratio (GLR). GIP is a non-uniformity detection method that was originally developed for the selection of uniform secondary clutter data in space-time adaptive processing for airborne early-warning radar. The GIP computes the whitened output $Y_{GIP}(n)$ for each sample X_n in the training data set and $Y_{GIP}(n)$ is given by:

$$Y_{GIP}(n) = X_n^T C_x^{-1} X_n \tag{12}$$

where C_x^{-1} is the inverse of the covariance matrix of training data. Similarly, the GLR method was also developed for airborne radar and given by:

$$Y_{GLR}(n) = \frac{\left(X_{gnd}^T C_x^{-1} X_{gnd}\right)\left(1 + X_n^T C_x^{-1} X_n\right)}{X_{gnd}^T C_x^{-1} X_n} \tag{13}$$

The where X_{gnd} is dominant ground reflection vector estimated by averaging the GPR raw data, C_x is covariance matrix of reference data. Figures 13 (a)-13(d) shows the results of implementing training methods for background subtraction.

For both methods, lower and upper thresholds are selected by selecting the suitable weight factor α. The lower threshold T_1 is for homogeneous background subtraction and the upper threshold T_2 is for non-homogeneous background subtraction.

$$T_1 = mean\left(Y_{GIP}\right) + \alpha\sigma \;; \alpha > 0 \tag{14}$$

$$T_2 = mean\left(Y_{GLR}\right) + \alpha\sigma ; \alpha > 0 \tag{15}$$

Here σ is standard deviation. The main issue in this algorithm is to set the optimal value of α. Typically the value of α is in between 0 and 1. Dependency of α and training time are major demerits of this method.

5. PERFORMANCE AND DISCUSSION

The complete GPR signal processing flow for investigating background subtraction methods are as shown in Fig. 4 and Fig. 6, respectively. Range profile without target, with target and after background subtraction are as shown in Fig. 2, where the first dominant peak is from ground reflection. Antenna to ground distance is 15 cm, which is always added to target depth. After, applying background subtraction, target peak is clearly visualised as shown in Fig. 2. To evaluate the performance of the investigated method, the signal to clutter ratio is calculated, which is given by

$$SCR = 20\log_{10}\frac{S}{C} \tag{16}$$

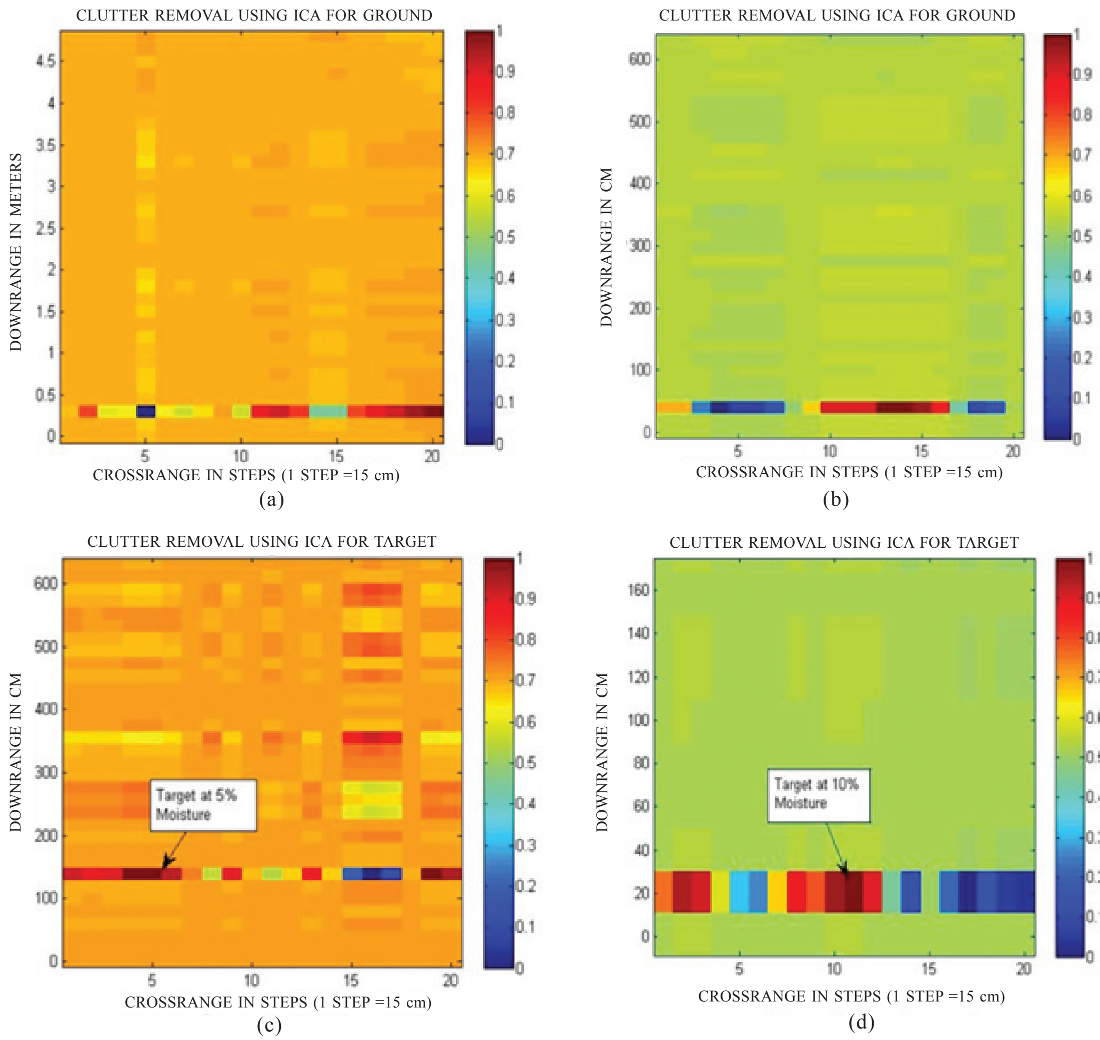

Figure 12. ICA method: (a) without target (5% moisture), (b) without target (10 % moisture), (c) with target at 35 cm (5% moisture), and (d) with target at 35 cm (10% moisture).

where SCR denotes signal to clutter ratio, S is peak signal and C is estimated clutter by standard deviation.

Known target location and depth information is available; the signal to clutter ratio is calculated using Eqn (16). Data is collected for moisture levels between 5 per cent - 10 per cent for with the metal target (at 35 cm) and without target condition. As seen from Figs. 5(a) and 5(b), raw image contrasts are similar for both 5 per cent and 10 per cent moisture content for without target case, respectively. It has mixed signal proportion of background and target like signal. To remove the background, mostly statistical methods are applied to the raw data.

Table 2 describes the SCR (dB) for without target case for 5 per cent and 10 per cent soil moisture. The following observations have been mad.

(i) Mean removal method, median method and PCA give almost similar signal to clutter ratio for both 5 per cent and 10 per cent soil moisture, respectively. Most of the homogenous clutter components have been removed by all the three methods, but target like clutter remain present, which are shown in Figs. 7(a)-7(b), 8(a)-8(b), 10(a)-10(b), and 11(a)-11(b).

(ii) In training method, training factor α decides the effectiveness of the method. α should be in between 0 and 1. We have taken 0.01 as the value of α and evaluated the effectiveness of the method. Training method signal to clutter ratio is better than for SVD and ICA methods for both 5 per cent and 10 per cent moisture content. As seen from Eqns. (14) and (15) and from Figs. 13 (a)-13(b),

Table 2. Signal to clutter ratio calculation for without target

Method	Moisture (%)	Signal to clutter ratio (dB)
Mean removal	5	43.1230
	10	31.5264
Median	5	42.9703
	10	31.7852
Singular value decomposition	5	18.1632
	10	16.9892
Principal component analysis	5	41.3491
	10	31.8468
Independent component analysis	5	16.5975
	10	18.9702
Training method	5	23.3593
	10	28.1966

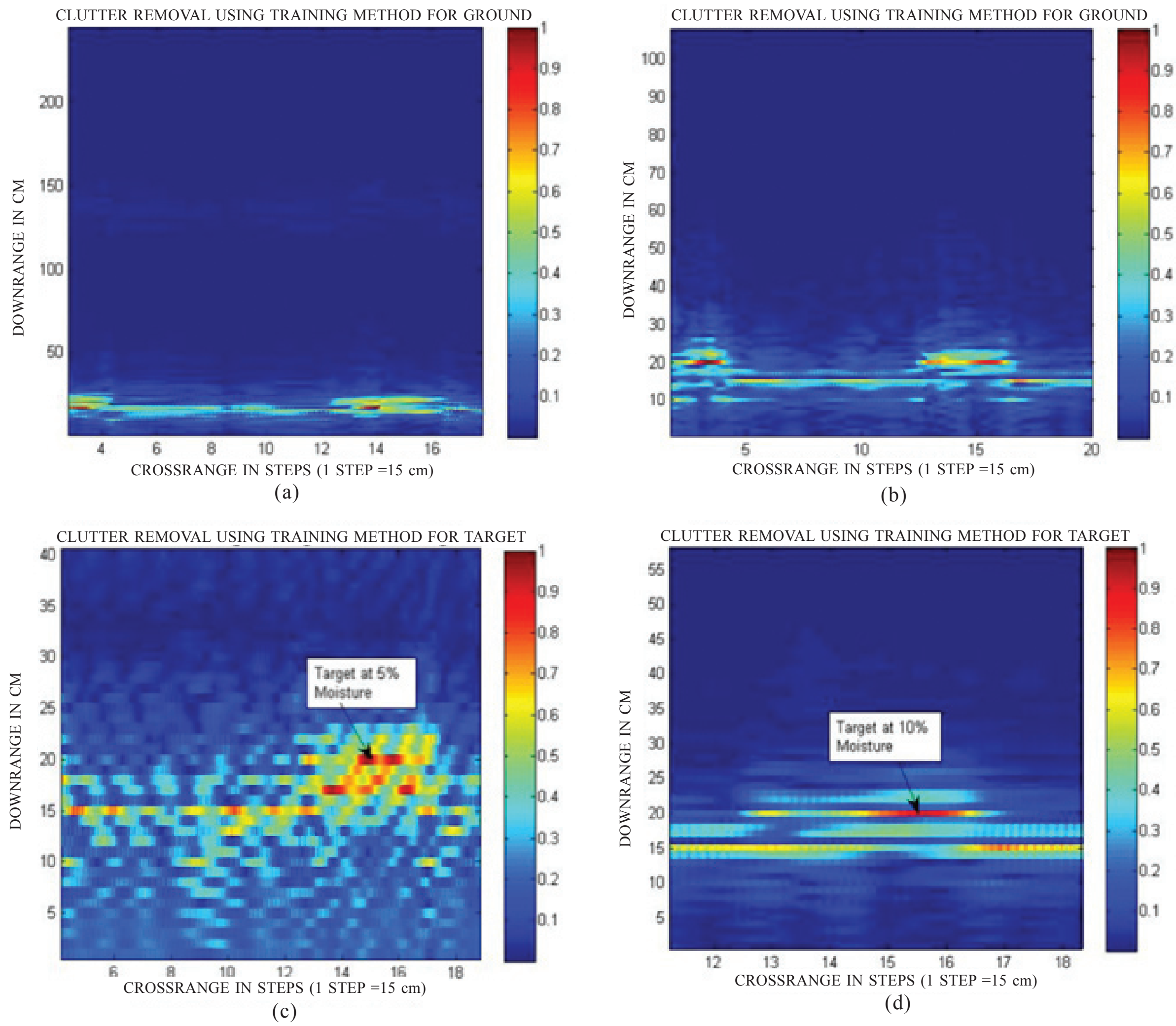

Figure 13. Training method: (a) without target (5% moisture), (b) without target (10 % moisture), (c) with target at 35 cm (5% moisture), and (d) with target at 35 cm (10% moisture)

using two threshold values, enhances the capability of this method for both homogenous as well as non-homogeneous background removal.

For with target case, the following observations are made from Table 3.

Table 3. Signal to clutter ratio calculation for with target

Method	Moisture (%)	Signal to clutter ratio (dB)
Mean removal	5	50.9838
	10	42.3701
Median	5	51.8527
	10	42.9463
Singular value decomposition	5	21.7838
	10	21.9916
Principal component analysis	5	53.2104
	10	45.9386
Independent component analysis	5	10.0666
	10	21.4041
Training method	5	70.6971
	10	80.5989

(a) Signal to clutter ratio for mean removal method, median method and PCA method have almost the same value for both 5 per cent and 10 per cent soil moisture. All three methods have good target feature extraction capability for homogeneous ground, which is as shown by their SCR values. As seen from Figs.7(c)-7(d), 8 (c)-8(d), 10(c)-10(d), and 11 (c)-11(d) the methods successfully detected the metal target (dark brown region) after background subtraction. But under many circumstances, these methods removed the target information during background subtraction, especially in shallow buried target conditions. Also, PCA method has a target position shifting problem due to improper projection of the data.

(b) Signal to clutter ratio for SVD and ICA are least as compared to all other methods described in this paper. In these methods target feature extraction effectiveness is also unpredictable as shown in Figs. 9(c)-9(d) and in Figs. 12(c)-12(d), respectively. SVD method is based on Eigen values as seen from Eqn (3); many times the wrong selection of background Eigen value give rises to clutter components and may remove the target information particularly in GPR applications. When clutter and target data share the same spectrum, then GPR data have statistical dependency, which is an undesirable property for ICA method. Therefore, ICA method is not suitable in GPR applications.

(c) Training method efficiency depends on the training factor tuning. But from the target detection point of view, once training factor has been decided, the detection is very good. Signal to clutter ratio for training method is highest as compared to all other methods. We have taken 0.01 for the value of α and got stable target feature (dark brown region) as shown in Figs. 13(c)-13(d). Decision of α is a critical issue in training method, because two threshold values as from Eqns (14) and (15) depend on the value of α.

6. CONCLUSIONS AND FURTHER WORKS

In this paper, experimentally various background subtraction methods have been critically analysed for GPR signal processing applications to enhance the target detection and reduction of unwanted clutter or signal. Mean removal, Median removal, PCA method and Training method successfully detected metal target by using indigenously developed GPR. However, the results show that reviewed background subtraction methods have choice to remove the unwanted signals or clutter for both smooth and rough surface. Signal to clutter ratio evaluated for each method. SVD and ICA method optimisation is a crucial issue in GPR application, therefore both methods are not suitable for GPR signal processing in our case. Training method is well suited to attempt the challenge to remove the rough surface. But in this method manual intervention is more because surface to surface reference / threshold value will be changed and it is a slow method. Therefore, much more the focus of the researcher will be required on background subtraction techniques for non-homogeneous surface/ rough surface that have adaptive feature and are better SCR. In future, there may be possible, that the artificial neural network (ANN) can become a new promising technique for background subtraction in GPR applications because once ANN is trained for large amount of GPR experimental data, then the background and foreground separation can easily be achieved. Lastly, the various types of are buried targets are not limited and the subsurface keeps on changing in aspects like dielectric behavior of medium, roughness, moisture content and hence, GPR system needs to be accustomed to these changes repeatedly.

REFERENCES

1. Daniels, D.J. Ed., Ground Penetrating Radar, 2nd ed. Inst. Electr. Eng.,London, U.K., 2004. doi: 10.1049/PBRA015E
2. Bruschini, Claudio. Guidebook on Detection Technologies and Systems for Humanitarian Demining, GICHD, Geneva, March 2006. ISBN 2-88487-045-8.
3. Gader, P.; Mystkowski, M. & Zhao, Y. Landmine detection with ground penetrating radar using hidden Markov models. *IEEE Trans. Geosci. Remote Sens.,* 2001, **39**(6), 1231–1244. doi: 10.1109/36.927446
4. Xu, X.; Miller, E.L.; Rappaport, C.M. & Sower, G.D. Statistical method to detect subsurface objects using array ground-penetrating radar data. *IEEE Trans. Geosci. Remote Sens*., 2002, **40**(4), 963–976. doi: 10.1109/TGRS.2002.1006391
5. Narayanan, R.M.; Pardipuram, R. & Rundquist, D.C. Statistical characteristics of simulated radar imagery from bare soil surfaces: Effects of surface roughness and soil moisture variability. *IEEE Trans. Geosci. Remote Sens.,* 1994, **32**(1), 159–168. doi: 10.1109/36.285198
6. Lopez-Sanchez J.M. & Fortuny-Guasch, J. 3-D radar imaging using range migration techniques. *IEEE Trans. Antennas Propag*., 2000, **48**(5), 728–737. doi: 10.1109/8.855491
7. Monte, L. Lo; Erricolo, D.; Soldovieri, F. & Wicks, M.C. Radio frequency tomography for tunnel detection, *IEEE Trans. Geosci. Remote Sens.,* 2010, **48**(3), 1128–1137. doi: 10.1109/TGRS.2009.2029341
8. Brenner, A.R. & Roessing, L. Radar imaging of urban areas by means of very high-resolution SAR and interferometric SAR. *IEEE Trans. Geosci. Remote Sens.*, 2010, **46**(10), pp. 2971–2982. doi: 10.1109/TGRS.2008.920911
9. SigveTjora, EgilEide, Evaluation of methods for ground bounce removal in GPR utility mapping. *In* proceeding of 10th International Conference on Ground Penetrating Radar, The Netherlands 2004, ISBN: 90-9017959-3.
10. Solimene, Raffaele; Cuccaro, A.; 'Aversano, A. Dell ; Catapano, Ilaria & Soldovieri, Francesco. Ground clutter removal in GPR surveys. *IEEE J. Selected Topics Applied Earth Observations Remote Sensing*, 2013,. doi: 10.1109/JSTARS.2013.2287016
11. Wu, R.; Clement, A.; Li, J.; Larsson, E.G.; Bradley, M.; Habersat, J. & Maksymonko, G. Adaptive ground bounce removal. *Electronics Letters*, 2001, **37**(20), 1250-1252. doi: 10.1049/el: 20010855
12. Gao, Qian Li, Tang & Wu, Renbiao A novel KICA method for ground bounce removal with GPR. *In* Proceeding of International Conference on Radar, 2006 CIE '06. doi: 10.1109/ICR.2006.343273
13. Mayordomo, alvaro muñoz & yarovoy, alexander. optimal background subtraction in gpr for humanitarian demining. *In* Proceedings of the 5th European Radar conference, Amsterdam, The Netherlands, October 2008, ISBN: 978-2-87487-009-5.
14. Khan, Umar Shahbaz & Al-Nuaimy, Waleed. Background removal from GPR data using eigenvalues. *In* Proceeding of 13th International Conference on Ground Penetrating Radar (GPR), 2010. doi: 10.1109/ICGPR.2010.5550079
15. Solimene, R.; Cuccaro, A.; 'Aversano, A. Dell; Catapano, I. & Soldovieri, F. Background removal methods in GPR prospecting. *In* proceedings of the 10th European Microwave Conference. Nuremberg, Germany, Oct 2013. ISBN: 978-2-87487-033-0.
16. VanKempen, L. & Sahli, H. Signal processing techniques for clutter parameters estimation and clutter removal in GPR data for landmine detection. *In* Proceeding of 11th IEEE Signal Processing Workshop on Statistical Signal

Processing, 2001, pp. 158-161.
doi: 10.1109/SSP.2001.955246
17. Liu, Jiaxue & Wu, Renbiao. Training method for ground bounce removal with ground penetrating radar. *In* Proceeding of IEEE Radar Conference, 2007.
doi: 10.1109/RADAR.2007.374335
18. Xu, X.; Miller, E.L.; Rappaport, C.M. & Sower, G.D. Statistical method to detect subsurface objects using array ground-penetrating radar data. *IEEE Trans. Geosci. Remote Sensing*, 2002, **40**, 963-976.
doi: 10.1109/TGRS.2002.1006391
19. Vicen-Bueno, R.; Carrasco-lvarez, R.; Rosa-Zurera, M. & Nieto-Borge, J.C. Sea clutter reduction and target enhancement by neural networks in a marine radar system. *Sensors*, **9**, 1913-1936, 2009.
doi: 10.3390/s90301913
20. Chan, L.A.; Nasrabadi, N.M. & Torrieri, D. Eigen space transformation for automatic clutter rejection. *Optical Engineering*, 2001, **40**(4), 564-573.
doi: 10.1117/1.1355258
21. Bradley, M.R.; Witten, T.R.; Cummins, R.M.C.; Crowe, M.; Stewart, S. & Duncan, M. Mine detection with a multi-channel stepped-frequency ground-penetrating radar. *In* Proceeding SPIE, 3710, Aero Sense Detection and Remediation Technologies for Mines and Mine like Targets IV, 1999, pp. 953–960.
doi: 10.1117/12.357115
22. Verma, P.K.; Gaikwad, A.K.; Singh, D. & Nigam, M.J. Analysis of clutter reduction techniques for through wall imaging in UWB range. *Progress Electromag. Res. B*, 2009, **17**, 29-48.
doi: 10.2528/PIERB09060903
23. Sharma, Prabhat; Gaba, S.P. & Singh, Dharmendra. Study of background subtraction for ground penetrating radar. *In* National conference on recent advances in Electronics and Computer engineering, 2015.
doi: 10.1109/RAECE.2015.7510234
24. Sharma, Prabhat; , Kumar, Bambam & Singh, Dharmendra Non-metallic pipe detection using SF-GPR: A new approach using neural network. *In* IEEE International Geoscience and Remote sensing symposium, 2016.
doi: 10.1109/IGARSS.2016.7730726

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