## **GPR** Target Signal Enhancement Using Least Square Fitting **Background and Multiple Clustering of Singular Values**

# Budiman P. A. Rohman<sup>1, 2, \*</sup> and Masahiko Nishimoto<sup>1</sup>

Abstract—Ground penetrating radar is an effective nondestructive method for exploring subsurface object information by exploiting the differences in electromagnetic characteristics. However, this task is negatively affected by the existence of ground clutter and noise especially if the object is weak or/and shallowly buried. Therefore, this paper proposes a novel method for suppressing the clutter and background noise simultaneously in both flat and rough surfaces. First, the ground clutter is removed mainly by applying a simplified least square fitting background method, which remains the residual random noise signal. The remaining signal is then decomposed by singular value decomposition, which assumes that the decomposed signal contains four main components including strong target, weak target, very weak target, and accumulated noise signals. The powered singular values and their differences are clustered by K-means to extract the target signal components. The simulation results indicate that the proposed method is able to enhance the target signal with satisfactory results under both flat and rough surfaces as well as in a high-level background noise. Besides, this method also shows its superiority to the latest existing proposed methods.

#### 1. INTRODUCTION

Ground penetrating radar (GPR) is a nondestructive method which is effectively used for detecting and obtaining buried object information. GPR has been applied to some applications such as geophysics, archaeology, remote sensing, civil engineering, and humanitarian demining [1]. However, the existences of ground surface reflection and high level contaminating noises are able to decrease the target signal clarity and its interpretation. Therefore, a robust signal enhancement of GPR signal is needed.

Different approaches have been introduced and proposed for both clutter and noise reduction such as background subtraction based method [2], clutter model approach [3, 4], wavelet transform approach [5, 6], and subspace projection based method [7-12]. Singular value decomposition (SVD) is a statistic based method of subspace projection which is considered by many researchers for building a robust GPR target signal enhancement as follows. In 2005, SVD was introduced for clutter reduction of stepped-frequency GPR by employing mean subtraction and an automatic threshold of singular values [7]. Then, in 2010, an auto-selected rule on principal component of the principal component algorithm was developed for de-noising the GPR signal [8]. In 2013, the method based on singular value decomposition and Fuzzy C-means (FCM) was proposed for GPR image enhancement [9]. Later, in 2017, the method proposed in [11] was able to select the principal component automatically according to its singular spectrum, its first difference and second difference singular values. According to both experimental and simulated results, this method can enhance signal against the presence on ground clutter and white Gaussian noise in flat surface condition.

Received 28 April 2018, Accepted 30 January 2019, Scheduled 15 April 2019

 <sup>\*</sup> Corresponding author: Budiman Putra Asma'ur Rohman (budi028@lipi.go.id).
 <sup>1</sup> Graduate School of Science and Technology, Kumamoto University, Japan.
 <sup>2</sup> Research Center for Electronics and Telecommunication, Indonesian Institute of Sciences, Indonesia.

Nevertheless, these methods mentioned above have limitations in some cases such as when the object is buried very shallowly and under the realistic rough surface condition. Therefore, this paper proposes a new approach by employing the least square fitting background and multiple clustered of subspace projection with the assumption of four main signal components considered: strong target, weak target, very weak target, and accumulated noise signals. Using this proposed method, both ground clutter and noise can be suppressed effectively so that the detail of target signal can be reconstructed well. This method is also reliable against both the flat and rough surface conditions as well as high-level background noise.

## 2. GPR SIGNAL MODELLING AND PROPOSED METHOD

### 2.1. GPR Signal Model

Each trace of GPR signal is called as A-scan consisting of time domain signal x(t) with size  $N \times 1$ . The collection of A-scan, called B-scan, is considered as  $\mathbf{X} \in \mathbb{R}^{(M \times N)}$ , where M and N are sizes for space and time, respectively. Generally,  $\mathbf{X}$  consists of four main components including direct antenna coupling  $(\mathbf{X}_A)$ , ground surface reflection  $(\mathbf{X}_C)$ , target  $(\mathbf{X}_T)$ , and contaminating noise  $(\mathbf{X}_N)$  signals. Since the  $\mathbf{X}_A$  signal is measurable and repeatable in advance, so that in this study, this signal is omitted. Thus,  $\mathbf{X}$  can be expressed as Eq. (1),

$$\mathbf{X} = \mathbf{X}_C + \mathbf{X}_T + \mathbf{X}_N \tag{1}$$

## 2.2. Least Square Fitting Background

The proposed method consists of two main steps. The first step is removing the main ground clutter signal employing least square fitting background method. This is the simplified method of background subtraction introduced in [4]. This method is taken by determining the timing range of the ground surface reflection, calculating the scale factor based on the least square method, and then removing the predicted ground clutter. The detailed step is explained as follows. The A-scan of GPR x(t) is processed by cross-correlation function with a reference of ground surface reflection from a flat surface-homogeneous dry soil, s, resulting in C as expressed by Eq. (2).

$$C = \max_{t} \frac{1}{\|x\| \|s\|} \int s(\tau - t)x(\tau)d\tau$$
(2)

The maximum value of C above shows the highest similarity while the information of the lagged time, and t indicates the most possible timing of ground surface reflection. Starting from the lagged time, the range of ground clutter is assumed as long as determined sample length. Then, the scale factor of reference ground clutter signal is determined with respect to the amplitude of x(t) in corresponding time by using least-square method expressed by Eq. (3).

$$E = \min_{\alpha} \int (x(t) - \alpha s(t))dt$$
(3)

with E being the expectation residual signal value and  $\alpha$  the scale factor. The scale factor is searched so that the residual signal on the predicted timing of ground clutter signal is as minimum as possible indicated by minimum E value. The result of this subtraction process is denoted as  $x_O$  which B-scan of this computed signal is denoted as  $\mathbf{X}_O$ .

$$x_O(t) = x(t) - \alpha s(t) \tag{4}$$

#### 2.3. Multiple Clustering to Singular Values

Although the signal component of the ground clutter is mainly removed in the first step, the residual component still contains low-level random noise,  $\mathbf{X}_{CN}$ . Thus, the remaining signal  $\mathbf{X}_O$  can be expressed mathematically as follows:

$$\mathbf{X}_O = \mathbf{X}_T + \mathbf{X}_{NO} \tag{5}$$

$$\mathbf{X}_{NO} = \mathbf{X}_N + \mathbf{X}_{CN} \tag{6}$$

#### Progress In Electromagnetics Research Letters, Vol. 83, 2019

with  $\mathbf{X}_{NO}$  being a total of the residual noise produced by the first step processing,  $\mathbf{X}_{CN}$ , and the original noise,  $\mathbf{X}_N$  (Eq. (1)). In the second step, we employ the SVD to decompose the signal  $\mathbf{X}_O$  into its principal components as below,

$$\mathbf{X}_O = \mathbf{U}\mathbf{S}\mathbf{V}^T \tag{7}$$

where both matrices  $\mathbf{U} \in R^{(M \times M)}$  and  $\mathbf{V} \in R^{(N \times N)}$  are unitary matrices while **S** is singular matrix whose diagonal elements are singular values  $(\sigma_1, \sigma_2, \ldots, \sigma_r)$ , where r is smaller than M and N. Considering that  $\mathbf{u}_i$  and  $\mathbf{v}_i$  are the *i*-th component of matrices **U** and **V** with sizes  $M \times 1$  and  $N \times 1$ , respectively, the equation above can be written as,

$$\mathbf{X}_O = \mathbf{u}_1 \sigma_1 \mathbf{v}_1^T + \mathbf{u}_2 \sigma_2 \mathbf{v}_2^T + \ldots + \mathbf{u}_r \sigma_r \mathbf{v}_r^T$$
(8)

In this proposed method, the remaining GPR signal is assumed to contain four components including strong target signal  $(\mathbf{X}_{TS})$ , weak target signal  $(\mathbf{X}_{TW})$ , very weak target signal  $(\mathbf{X}_{TV})$ , and contaminating noise  $(\mathbf{X}_{NO})$ . Therefore, we assume that the first two singular values correspond to the strong target signal as below,

$$\mathbf{X}_{TS} = \sum_{i=1}^{2} \mathbf{u}_i \sigma_i \mathbf{v}_i^T \tag{9}$$

The remaining singular values are then powered and processed by the simple K-means clustering algorithm to make two clusters for extracting  $\mathbf{X}_{TW}$ . K-means proceeds by selecting two initial cluster centers and then iteratively refining them using two steps: each singular value is assigned to its closest cluster center, and then each cluster center is updated to be the mean of its constituent instances. These steps run until there are no changes in the clustering process. The objective function J of this clustering process is expressed by

$$J = \sum_{j=1}^{m-2} \sum_{i=1}^{n-2} \left\| (\sigma_i^2)_{(j)} - c_j \right\|^2$$
(10)

where m is the number of cluster, n the number of data while  $c_j$  is the *j*th cluster centroid. Assuming that  $k_1$  is the last index from remaining descending ordered components corresponding to  $\mathbf{X}_{TW}$ .

$$\mathbf{X}_{TW} = \sum_{i=3}^{k_1} \mathbf{u}_i \sigma_i \mathbf{v}_i^T \tag{11}$$

Next, the second K-means clustering to the difference of remaining powered singular values  $\Delta_i$  as Eq. (12) is taken in order to separate  $\mathbf{X}_{TV}$  from contaminating noise component. Assuming that  $l_1$  is the number of component belonging to  $\mathbf{X}_{TW}$ , the objective function of this clustering is expressed by Eq. (13).

$$\Delta_i = \sigma_i^2 - \sigma_{i-1}^2 \tag{12}$$

$$J = \sum_{j=1}^{m-2} \sum_{i=1}^{n-2-i_1} \left\| (\Delta_i)_{(j)} - c_j \right\|^2$$
(13)

If  $k_2$  is the last index of component corresponding to the very weak target signal, we can obtain

$$\mathbf{X}_{TV} = \sum_{i=k_1+1}^{k_2} \mathbf{u}_i \sigma_i \mathbf{v}_i^T \tag{14}$$

Finally, by summing all of the extracted target signal components, we get the enhanced complete GPR target signal,  $\mathbf{X}'_{T}$ , which can be mathematically defined as below,

$$\mathbf{X}_{T}' = \sum_{i=1}^{2} \mathbf{u}_{i} \sigma_{i} \mathbf{v}_{i}^{T} + \sum_{i=3}^{k_{1}} \mathbf{u}_{i} \sigma_{i} \mathbf{v}_{i}^{T} + \sum_{i=k_{1}+1}^{k_{2}} \mathbf{u}_{i} \sigma_{i} \mathbf{v}_{i}^{T}$$
(15)

#### 3. RESEARCH METHODOLOGY

This study uses the synthetic data generated by finite-difference time-domain based software for electromagnetic propagation, gprMax [13, 14]. The targeted object considered in this study is a simplified model of anti-personnel landmine type-72 with 9 cm in width and 6 cm in height. For flat surface investigation, the landmine is buried in from 0.5 cm until 5 cm while in the rough surface, the depth is varied from 2 cm to 10 cm. The surrounding dry soil is homogeneous, and the uneven ground surface is realized randomly (See Fig. 1). The B-scan data contain 100 A-scans, and each scan contains 1697 sampling points. As incident pulse, we use a monocycle pulse with center frequency 5 GHz. The additive white Gaussian noise will be considered which signal to noise ratio (SNR) is 0 dB.

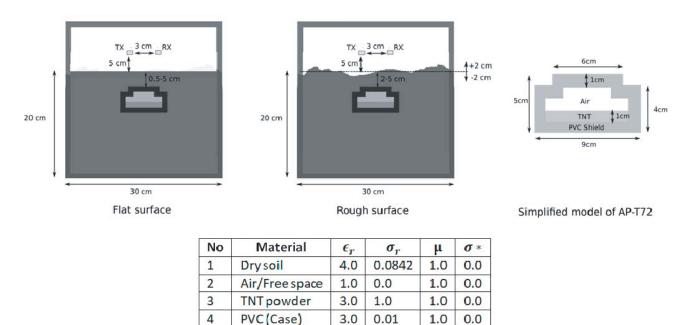


Figure 1. Simulation model and employed electromagnetic constants.

For evaluation step, results of the proposed method, both A-scan and B-scan, are employed for analysis. The comparison and numerical analysis to the existing SVD based methods [9, 11] are conducted in the perspective of the signal-to-clutter-plus-noise-ratio (SCNR) and root-mean-squareerror (RMSE) in both flat and rough surfaces. SCNR is needed to evaluate the quality of the enhanced target signal while RMSE is important for investigating the similarity of the enhanced signal with the reference signal. The reference signal is produced by subtracting the B-scan containing landmine with B-scan without landmine in the same given soil conditions and parameters. In other words, the reference signal is a landmine-only signal in various soil conditions. Both of these evaluation parameters are expressed by following equations, respectively,

$$SCNR = 10 \cdot \log_{10} \left( \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} [r(i,j)^{2}]}{\sum_{i=1}^{M} \sum_{j=1}^{N} [r(i,j) - t(i,j)]^{2}} \right)$$
(16)  
$$RMSE = \sqrt{\left( \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [r(i,j) - t(i,j)]^{2} \right)}$$
(17)

where r is the enhanced target image, and t is the reference image while i and j are the indices of image pixels.

#### 4. RESULT AND DISCUSSION

#### 4.1. Analysis of the A-Scan Data

Figure 2 shows the result of target signal enhancement using the proposed method in the very shallowly buried landmine. It can be seen clearly that the proposed method provides the result with low residual background noise. Moreover, although the signal is overlapped partly with the ground clutter, the proposed method is able to enhance and reconstruct the main component of target signal.

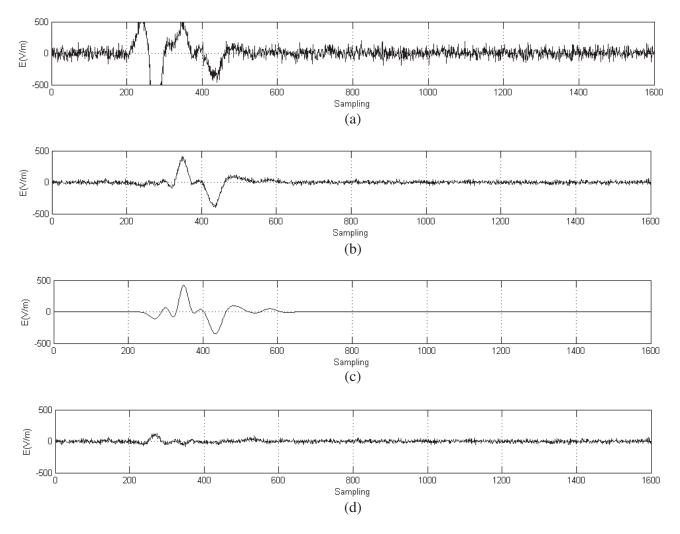


Figure 2. Results of enhanced GPR target signal using proposed method under rough surface with SNR = 0 dB, landmine depth = 0.5 cm: (a) original signal contaminated with ground clutter and background noise SNR = 0 dB, (b) enhanced signal using proposed method, (c) reference signal (landmine only), (d) residual signal produced by subtract signal (c) to (b).

#### 4.2. Analysis of the B-Scan Data

Figure 3 shows the comparison of the signal in the case of flat surface with landmine depth from 0.5 cm until 5 cm. According to Fig. 3(a), it can be seen clearly that the proposed method can suppress the

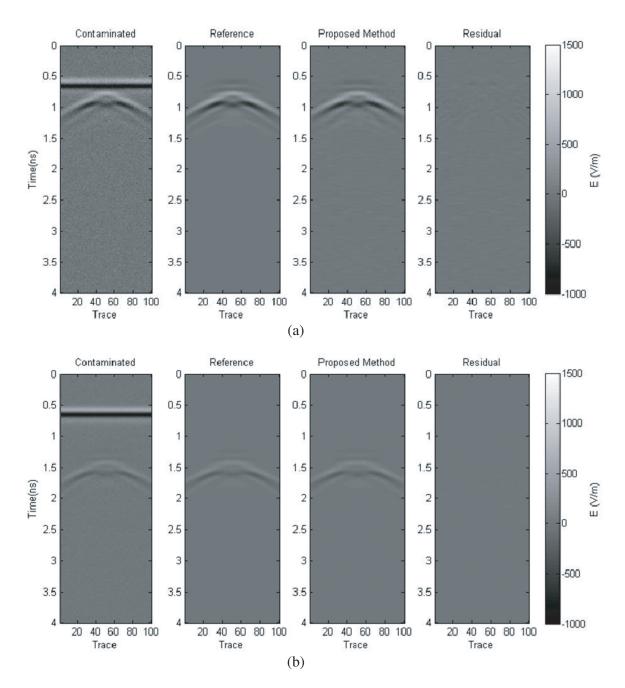


Figure 3. Results of enhanced GPR target signal using proposed method under flat surface with SNR = 0 dB and its comparison with the reference signal (landmine only): (a) landmine depth is 0.5 cm, (b) landmine depth is 5 cm.

clutter and noise to their very minimum values even if the landmine is buried very shallowly, and the signal quality is very low. Although there are some residual signals which can influence the clarity of target signal, the main features of the target signal can be maintained. Moreover, the part of target signal that is overlapped with ground clutter can be reconstructed. In other words, the target signal can be extracted well. Then, Fig. 3(b) shows us that in the depth 5 cm under the flat ground surface, the method can easily extract the detail of target signal and suppress the noise well.

Figure 4 shows the enhanced signal using proposed method under the rough ground surface. When the distance between the landmine and surface is very short (Fig. 4(a)), the proposed method can



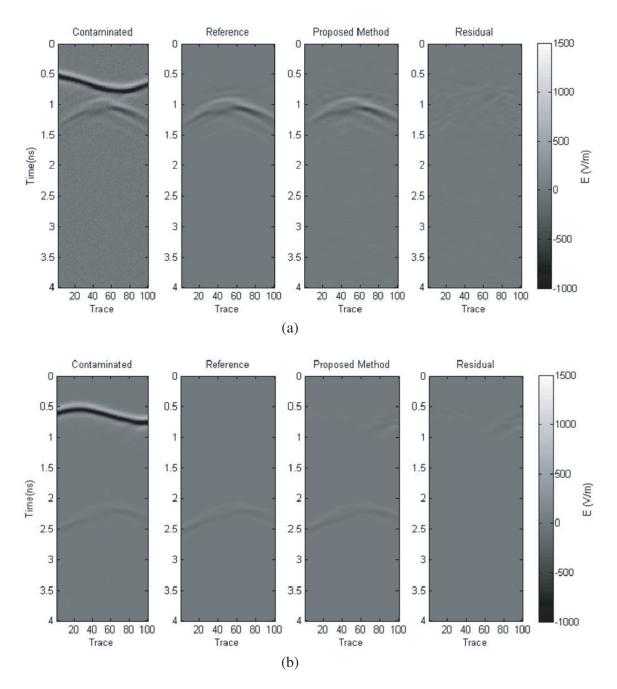


Figure 4. Then please change the figure and caption syntax as below, Results of enhanced GPR target signal using proposed method under rough surface with SNR = 0 dB and its comparison with the reference signal (landmine only): (a) landmine depth is 2 cm, (b) landmine depth is 10 cm.

extract target without distracting the target signal features. Although the scattered signals still exist surrounding the target signal, the overall landmine signal features can be preserved. Similarly, Fig. 4(b) reveals that in the deeply buried object, the target signal can be reconstructed well.

## 4.3. Comparison of Numerical Evaluation

Table 1 compares the results before and after the signal is processed by the proposed method and other existing methods on a flat surface. Based on the SCNR values, we can simply conclude that the

#### Rohman and Nishimoto

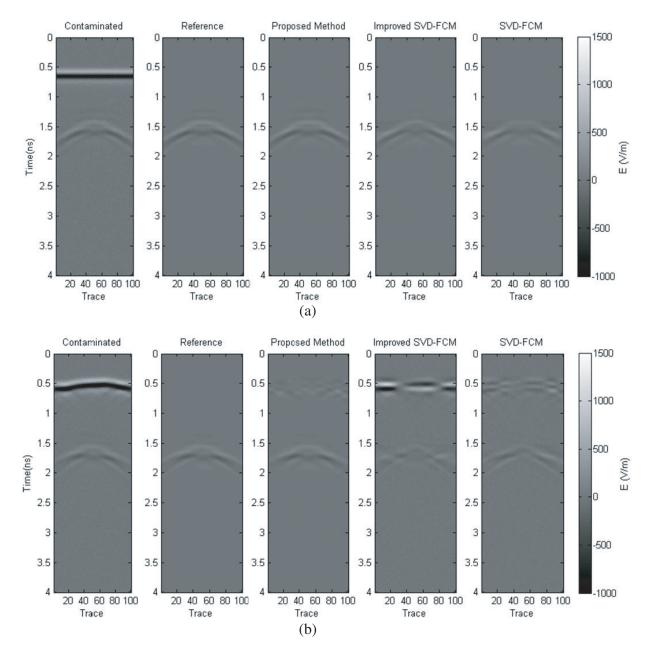


Figure 5. Comparison of enhanced GPR target signal using proposed method and two existing methods with landmine depth 5.0 cm and SNR = 0 dB: (a) at surface, (b) rough surface.

**Table 1.** Comparison performance under flat surface SNR = 0 dB.

Depth	SCNR	Proposed Method		Improved SVD-FCM [11]		SVD-FCM $[9]$	
(cm)	(dB)	SCNR (dB)	RMSE	SCNR (dB)	RMSE	SCNR (dB)	RMSE
0.5	-6.69	11.04	17.67	5.40	33.79	5.36	33.94
1.0	-7.39	11.25	15.59	5.67	29.65	5.54	30.08
2.0	-8.71	11.51	12.63	6.00	23.80	5.83	24.27
5.0	-13.35	11.57	6.99	5.97	13.33	6.17	13.05

#### Progress In Electromagnetics Research Letters, Vol. 83, 2019

proposed method can improve the quality signal up to 20 dB, higher than the other methods. Then, based on the RMSE values, the proposed method can preserve the target signal waveform better than other compared methods. Table 2 gives almost similar information to Table 1. Generally, according to these data, on the rough surface, the problem is more challenging so that the SCNR improvement in all of the methods is lower than the flat surface case. However, the proposed method is able to suppress both ground clutter and background noise and also maintains the target signal for both rough and flat surface conditions better than the existing methods. These comparison results are confirmed well by Fig. 5.

Depth	SCNR	Proposed Method		Improved SVD-FCM [11]		SVD-FCM $[9]$	
(cm)	(dB)	SCNR (dB)	RMSE	SCNR (dB)	RMSE	SCNR (dB)	RMSE
2.0	-9.90	7.78	18.61	-5.82	86.17	-5.61	84.31
5.0	-14.42	4.66	15.65	-10.02	79.74	-9.98	79.54
8.0	-19.21	0.49	14.88	-14.86	78.97	-14.75	78.23
10	-22.29	-1.53	12.99	-17.79	77.04	-17.82	77.68

Table 2.	Comparison	performance	under	rough	surface	SNR =	$0\mathrm{dB}.$
----------	------------	-------------	-------	-------	---------	-------	-----------------

## 5. CONCLUSION

We have described a novel approach of GPR signal enhancement using least square fitting method and multiple clustering to singular values with assumption of four signal components included. The studied target object is a simplified model of anti-personnel landmine T-72. The depth of the target is varied between 0.5 cm and 10 cm under both flat and rough surfaces while the background noise considered is  $SNR = 0 \, dB$ . According to the simulation results, the proposed method is able to suppress both clutter and noise so that the target signal can be extracted and maintained well enough. Moreover, compared to the recent existing SVD based methods, the proposed method provides better results in overall given environments.

## REFERENCES

- 1. Jol, H. M., Ground Penetrating Radar Theory and Applications, Elsevier, 2008.
- 2. Mayordomo, A. M. and A. Yarovoy, "Optimal background subtraction in GPR for humanitarian demining," *IEEE Radar Conference, 2008, EuRAD 2008*, 48–51, European, 2008.
- 3. Brooks, J. W., L. M. van Kempen, and H. Sahli, "Primary study in adaptive clutter reduction and buried minelike target enhancement from GPR data," *Detection and Remediation Technologies for Mines and Minelike Targets V*, Vol. 4038, 1183–1193, International Society for Optics and Photonics, 2000.
- 4. Brunzell, H., "Detection of shallowly buried objects using impulse radar," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 37, No. 2, 875–886, 1999.
- Carevic, D., "Wavelet-based method for detection of shallowly buried objects from GPR data," Information, Decision and Control, 1999, IDC 99, Proceedings, 201–206, IEEE, 1999.
- Baili, J., S. Lahouar, M. Hergli, I. L. Al-Qadi, and K. Besbes, "GPR signal de-noising by discrete wavelet transform," Ndt & E International, Vol. 42, No. 8, 696–703, 2009.
- Abujarad, F., G. Nadim, and A. Omar, "Clutter reduction and detection of landmine objects in ground penetrating radar data using singular value decomposition (svd)," *Proceedings of the 3rd International Workshop on Advanced Ground Penetrating Radar, 2005, IWAGPR 2005, 37-42,* IEEE, 2005.
- 8. Shen, J.-Q., H.-Z. Yan, and C.-Z. Hu, "Auto-selected rule on principal component analysis in ground penetrating radar signal denoising," *Chinese Journal of Radio Science*, Vol. 1, 17, 2010.

- Riaz, M. M. and A. Ghafoor, "Ground penetrating radar image enhancement using singular value decomposition," 2013 IEEE International Symposium on Circuits and Systems (ISCAS), 2388– 2391, IEEE, 2013.
- Liu, C., C. Song, and Q. Lu, "Random noise de-noising and direct wave eliminating based on svd method for ground penetrating radar signals," *Journal of Applied Geophysics*, Vol. 144, 125–133, 2017.
- 11. Zhu, J., W. Xue, X. Rong, and Y. Yu, "A clutter suppression method based on improved principal component selection rule for ground penetrating radar," *Progress In Electromagnetics Research M*, Vol. 53, 29–39, 2017.
- Soldovieri, F., A. F. Morabito, F. D'Agostino, S. I. Ivashov, V. V. Razevig, and I. A. Vasilyev, "A simple processing approach for holographic rascan data," *Progress In Electromagnetics Research*, Vol. 107, 315–330, 2010.
- 13. Warren, C., A. Giannopoulos, and I. Giannakis, "gprmax: Open source software to simulate electromagnetic wave propagation for ground penetrating radar," *Computer Physics Communications*, Vol. 209, 163–170, 2016.
- 14. Giannakis, I., A. Giannopoulos, and C. Warren, "A realistic fdtd numerical modeling framework of ground penetrating radar for landmine detection," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 9, No. 1, 37–51, 2016.