Implementation of Wavelet Algorithm and Maximum Change-Point Method for the Detection of Ballast Substructure Using GPR



S. J. Savita, P. Anbazhagan, and Andhe Pallavi

1 Introduction

Ground-penetrating radar is a non-destructive geotechnical tool for detecting the subsurface targets. It consists of transmitting antenna, receiving antenna and display unit. The transmitting antenna transmits an electromagnetic pulse into the ground to detect and classify the various subsurface objects like metal, pipe and air cavity, and the reflected pulses are picked up by the receiving antenna. The reflections from the target depend on the different dielectric value of the object. According to the general principle, if the antenna frequency increases, then depth of penetration decreases with increase in resolution. The depth of penetration increases with decrease in the antenna frequency and resolution also decreases. To detect various patterns of different objects like metal, pipe and air cavity etc., various image and signal processing techniques can be utilized. GPR is widely used in various applications in landmine investigation, geotechnical, underground utilities, archaeology, etc. The interpretation of raw GPR radargram is a challenging task as it needs a better algorithm for improved visualization of the targets.

In this work, two contributions are carried out to map the subsurface targets. The wavelet transform with higher-order statistics method is implemented to map the subsurface targets. The change-point method [1] is also used to detect the abrupt

S. J. Savita · A. Pallavi

EIE Department, RNSIT, Bengaluru, India

e-mail: savita.s.j@rnsit.ac.in

A. Pallavi

e-mail: andhepallavi@rnsit.ac.in

P. Anbazhagan (⊠)

Department of Soil Mechanics, IISc, Bengaluru, India

e-mail: anbazhagan@iisc.ac.in

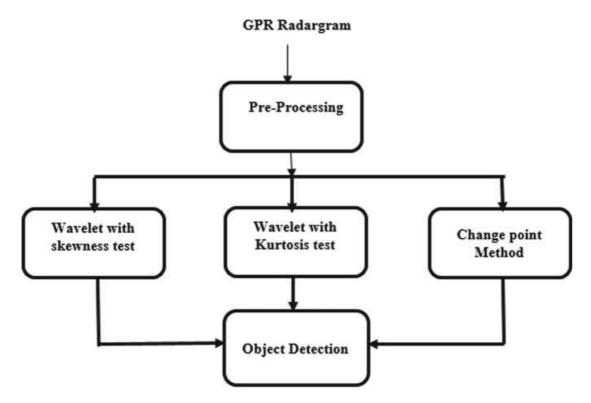


Fig. 1 GPR processing step

changes in the signal. By change-point algorithm, it is easy to detect the size of the object.

2 Methodology

Processing of raw GPR images [2] to map the subsurface targets is one of the difficult tasks. The subsurface targets are obscured with signal noise, echo, reflections from soil, etc. Hence, the interpretation of GPR image is one of the difficult techniques to differentiate between the target and the false target. An algorithm is implemented to detect the different signatures of the target from GPR images. The processing steps are firstly pre-processing of the GPR data, secondly applying the wavelets to the pre-processed signal and next is the detection of abrupt changes in the signal using a maximum change-point method. The block diagram of the processing steps is as shown in Fig. 1.

3 GPR Data Collection

The data sets are acquired from Mala GPR Machine at IISc Bangalore. The ground-coupled antenna with 800 MHz has been used to acquire the information of the

subsurface targets. In this work, a model railway track is built at IISc without the rails and sleepers. The underground objects used are metal (iron rod), M S steel and clean ballast. The length and width of the track are 4.8, 1.6 m. Ballast is used to construct a railway track. Ballast is irregular shaped stones, and the height of the ballast is 0.6 m. For all these targets, the reflections are different due to the dielectric value of the material.

4 Post-Processing Using Wavelets and Change-Point Method

4.1 Wavelet Transform

The algorithm used to filter out the noise in GPR data is discrete wavelet transform, after that a change-point method is applied to detect the abrupt changes in the signal. The wavelet transform is a multiresolution technique to extract the information content in the signal [3]. It is used to denoise the incoming signal. By choosing the wavelet coefficients at a particular value, we can convert the data into the wavelet domain. The coefficients chosen are from higher-order statistics method. In this method, we considered two tests, skewness test and kurtosis test. A signal is decomposed into 10 levels. The wavelet coefficients of a 2D wavelet transform are given by

$$WP_{x,s}^{m}(i) = WP_{x,s}^{n}(i) + WP_{x,s}^{o}(i)$$
 (1)

where $WP_{x,s}^m(i)$, $WP_{x,s}^n(i)$ and $WP_{x,s}^o(i)$ are wavelet packet coefficients of m, n and number of decomposition levels x = 1, 2, ..., x. number of scales are s = n, 1, 2, ..., i = 1, 2, ..., K, where K = L/2x. Where L is the length of the input signal.

The information content in the signal can be extracted by third and fourth-order moments, i.e. skewness and kurtosis test.

Skewness test. It is a distribution of asymmetry of the data. If the data are perfectly symmetrical, then its skewness value is zero. The value is positive if it is skewed to the left and negative for right side. It is given by the equation

$$S_3 = \sum_{i=1}^n \left(\frac{z_{i-}\sigma}{S}\right)^3 \tag{2}$$

where n = size of the sample, and S is the standard deviation. The third-order moment of a probability model is referred to as a skewness, so it is 3. The practical formula used for the skewness is,

Skewness =
$$\frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{z_{i-\sigma}}{s}\right)^3$$
 (3)

For large samples, the skewness distribution is normal with an error of $\sqrt{\frac{6}{n}}$. Hence,

Variance (Skewness) =
$$\frac{6}{n}$$
 (4)

The Chebyshev inequality for any random variable y is given by

$$\operatorname{Prob}(|S - E(S)| \ge t) \le \frac{\operatorname{Var}(S)}{t^2} \tag{5}$$

Using inequality of Eq. (5) the skewness test of Eq. (3) can be given as, a $\sqrt{\frac{6}{n}}$. where $a = 1/\sqrt{1-\delta}$.

$$-\frac{1}{\sqrt{1-\delta}} \le s \ge +\frac{1}{\sqrt{1-\delta}} \tag{6}$$

We have chosen a percentage of $\Phi = 90\%$.

Kurtosis test. Kurtosis is also called as a fourth-order moment, which is used to measure the peak reflections of the target. It is given by the equation

$$K_a = \sum_{i=1}^n \left(\frac{z_{i-\sigma}}{S}\right)^4 \tag{7}$$

If the distribution is flat and long tailed, then it has a higher kurtosis value and low kurtosis value for short-tailed distribution. The practical equation is given by

$$K_a = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^n \left(\frac{z_{i-\sigma}}{S}\right)^4$$
 (8)

For large samples, the distribution is normal with an error of $\sqrt{24/n}$. Using the inequality, the kurtosis with $a = \frac{1}{\sqrt{1-\delta}}$.

The kurtosis varies between $\pm \frac{1}{\sqrt{1-\delta}}$ Var (Ka).

4.2 Change-Point Method

It is a method used for the detection of the maximum number of abrupt changes in the GPR signal to calculate the size of a target [4]. In this, the GPR signal has been analysed by implementing a change-point method by following these steps.

- 1. It identifies the abrupt changes in the signal.
- 2. To find a signal change point, first, it chooses a point and divides the signal into segments [5].
- 3. Next, it computes an empirical estimate for the maximum number of changes for each section.
- 4. Within a section at each point, it calculates how much it deviates from empirical value and then adds the deviations for all the points.
- 5. Region of interest (ROI) of detected target is identified.
- 6. By this, the starting trace (position) and end trace (position) of the target are easily calculated.

Let us consider a signal Y_1 , Y_2 , Y_3 , ..., Y_N , the function finds 'm' number of change points such that,

$$K = \sum_{i=1}^{m-1} (Yi - (Y)_1^{m-1})^2 + \sum_{i=m}^{N} (Yi - (Y)_m^N)^2$$

$$= \sum_{i=1}^{m-1} (Yi - \frac{1}{m-1} \sum_{j=1}^{m-1} Yj)^2 + \sum_{i=1}^{m} (Yi - \frac{1}{N-m+1} \sum_{j=m}^{N} Yj)^2$$

$$= m - 1 \text{var}([Y_1, \dots, Y_m - 1]) + N - m + 1 \text{Var}([Y_m, \dots, Y_N])$$
(9)

So findchangepts finds 'm' such that,

$$K(M) = \sum_{i=1}^{m-1} \Delta(Yi; X([Y_1, \dots, Y_m - 1])) + \sum_{i=1}^{m} \Delta(Yi; X([Y_m, \dots, Y_N]))$$
(10)

X is the empirical estimate, and Δ is the deviation from empirical value.

As the number of change points increases, residual error decreases. In this algorithm, a MATLAB function called findchangepts and MaxNumChanges is used to detect the abrupt changes in the GPR signal. MaxNumChanges uses an automatic threshold to detect a value of change point [6].

5 Results and Discussion

In this work, a GPR technique operates electromagnetic (EM) waves to provide a better resolution and non-destructive measurements of different dielectric contrasts in geological targets. When there is a target like metal or big sized ballast, it develops a strong reflection of electromagnetic waves because of the sharp objects present between the soil and the surrounding rock. The proposed algorithm is verified for different targets. The GPR data consists of a total number of 135 traces with a distance interval of 0.009712 m. The length of the metal piece buried underground is 1.2 m. The model track is constructed at IISc Bangalore as shown in Fig. 2. The length and breadth of the track are 4.8 and 1.6 m. The ballast filled at a height of 0.6 m. Ballast is a collection of big-sized stone which plays a very important role in maintaining a good condition of the track [7].

The signals reflected from the target are picked up by the receiving antenna. Further, it is processed using MATLAB. Figure 3 is the output after applying an average subtraction trace on the GPR raw data [8]. The pre-processed image is represented as a signal as shown in Fig. 4.

The comparison of wavelet with kurtosis and skewness test values for metal (iron rod), clean ballast and metal circular disc is analysed and tabulated.

Table 1 shows the comparison of various targets with skewness and kurtosis tests. It is clearly understood that dB3 performs better compared to the other mother wavelets. Kurtosis test performs better with respect to the higher values than skewness test.

In this Fig. 5, the GPR signal is partitioned into two segments. In each segment, the points are at a minimum distance from maximum number of changes. For metal targets, it accurately detected the target by considering two change points between the trace 25 and 45. By this, it is easy to calculate the size of the target which is discussed in Table 2. The targets used are metal 1 (iron rod), metal 2 (MS steel-large circular disc) and metal 3 (MS steel -small circular disc).

Fig. 2 Model track



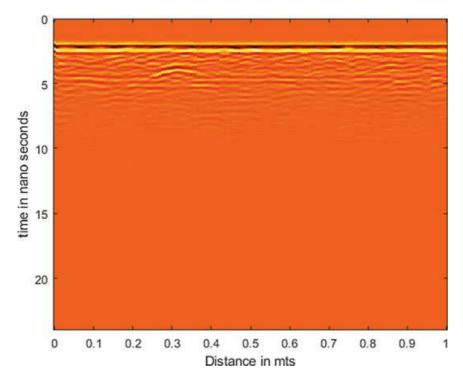


Fig. 3 GPR image

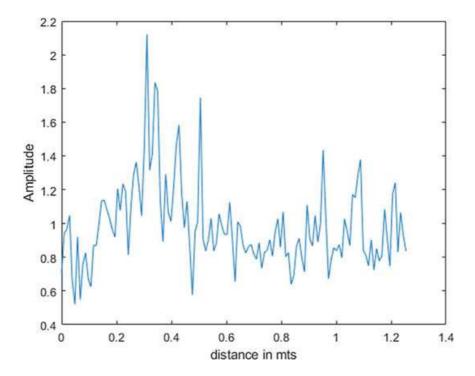


Fig. 4 Processed GPR signal in MATLAB

Table 1	Evaluation	of results usi	ng wavelets	(skewness a	nd kurtosis test)

Wavelets	Metal track target	No target (ballast)	Metal circular disc (large)	Metal track target	Metal circular disc (large)	No target	
	Skewness			Kurtosis			
Haar	1.1954	0.055802	1.32125	5.3774	3.6417	1.7909	
dB2	1.2128	0.20548	1.30761	4.288	4.1728	1.6484	
dB3	1.3041	0.26402	1.18864	4.7827	3.5847	1.6569	
Sym2	1.2128	0.20548	1.30761	4.288	4.1728	1.6484	

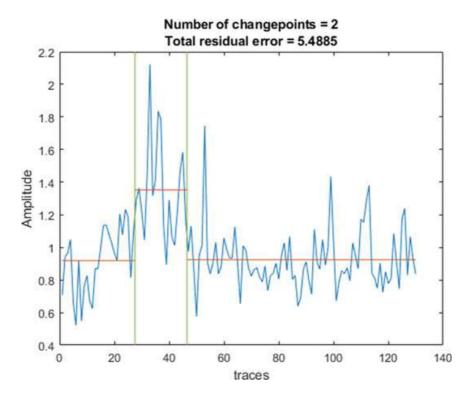


Fig. 5 Applied change-point method (target–metal 1)

Table 2 Comparison of results using change-point method

Object	Traces	Distance interval	Actual value	Obtained value-(change-point method)	Error in %	SNR	Resolution
Metal 1	135	0.009712	0.2 m	0.19 m	5	47	1.0296
Metal 2	42	0.009712	0.12 m (Dia)	0.11 m	8.3	38	1.0296
Metal 3	37	0.009712	0.08 m (Dia)	0.072 m	10.05	36	0.8261

By implementation of maximum change-point algorithm, it is accurately identified the size of the target in all the three cases with error of 5% and resolution of approximately 1.0.

6 Conclusion

The application of GPR in the field of geotechnical engineering gives a better result in interpretation of radargrams by implementing a wavelet algorithm with higher-order statistics and change-point method for detection of the various target. Wavelet transform is applied on raw GPR data to remove the unwanted noise. Haar, dB2, dB3, Sym2 and Sym8 mother wavelets are applied on GPR data to extract the useful information. The two tests called skewness and kurtosis are carried out. In this, kurtosis performs better compared to the skewness test. Later, a change-point method is implemented to identify the size of the target. A MATLAB function called find-changept is used accurately to find the total number of traces in which the object is buried underground. The change-point method works better to estimate the size of the target.

References

- 1. Chakar, S., Lebarbier, E., Levy-Leduc, C., Robin, S.: A robust approach for estimating change-points in the mean of an AR (1) process. Bernoulli Soc. Math. Stat. Prob. **23**(2), 1408–1447 (2017)
- 2. Jol, H.: Ground Penetrating Radar: Theory and Applications, 2nd edn. ISBN: 9780128159774, Elsevier (2019)
- 3. Javadi, M., Ghasemzadeh, H.: Wavelet analysis for ground penetrating radar applications: a case study. J. Geophys. Eng. 1189–1202 (2017)
- 4. Lavielle, M.: Using penalized contrasts for the change-point problem. Sig Process **85**(8), 1501–1510 (2005)
- 5. Nilsen, M.: A Study on Change Point Detection Methods Applied to Beam Offset Detection in Laser Welding. Elsevier Science Direct, (NOLAMP17) (2019)
- 6. Killick, R., Fearnhead, P., Eckley, I.A.: Optimal detection of changepoints with a linear computational cost. J. Am. Stat. Assoc. **107**(500), 1590–1598 (2012)
- 7. Vidyaranya, B., Anbazhagan, P., Divyesh, R., Athul.: Identification of heterogeneities in lateritic soils. In: Proceedings of Fifth International Conference on Forensic Geotechnical Engineering (2016)
- 8. Daniels, D.J.: Ground Penetrating Radar, 2nd edn. London Institution of Electrical Engineers. ISBN 978-0-86341-360-5 (2004)