Localized Parametric Electromagnetic Inversion for Pavement Profiling with Ground Penetrating Radar

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Abstract

Ground penetrating radar (GPR) has proven to be an effective non-destructive tool for pavement profiling. Layer-stripping algorithm and parametric electromagnetic (EM) inversion algorithm (referred to as EMI algorithm) are two inverse scattering approaches to estimate multilayered media properties using monostatic GPR. In this paper, a localized parametric EM inversion approach (referred to as NHD-EMI algorithm) is proposed for analyzing pavements with spatial varying characteristics. A non-homogeneous detector (NHD) is first used to divide the whole data into multiple subsegments with similar media properties. Then EMI is applied to each segment with layer-stripping technique to provide the initial model parameter estimates needed by the EMI algorithm. Numerical results show that the proposed NHD-EMI algorithm exhibits better performance over the existing EMI algorithm for nonhomogeneous pavements.

Introduction

The estimation of layer thickness and permittivity is very important for the routine maintenance of the road, highway, and airport runways. Ground penetrating radar (GPR) has proven to be an effective non-destructive tool for pavement profiling. It transmitted high frequency and ultra-wideband pulse which can be reflected due to variations in the electrical properties of the investigated medium [1]. The returned echoes of the GPR signal reflect the structure characteristic (pavement-layer thickness and the permittivity of each layer). GPR is a nondestructive way which has superior penetrability and high resolution and it has presently been used in many fields such as nondestructive tests in civil engineering [2], object detection and classification etc.

\[ s(x, t) = \sum_{k=1}^{L(x)} A_k(x) w(t - \tau_k(x)) + e(x, t) \] (1)

where \( x \) denotes the scan position, \( w(t) \) denotes the transmitted pulse, \( A_k(x) \) and \( \tau_k(x) \) denotes the amplitude and time delay of the pulse reflected from the Layer \( k \), respectively, \( L(x) \) denotes the number of layers at the scan position \( x \), and \( e(x, t) \) denotes unmodeled clutter and noise.

We can estimate the delays and amplitudes of the returned echoes reflected from the different dielectric media by matched filter and high resolution parameter estimation techniques (such as WRELAX [3]). Then the
permittivity profile (layer thickness and permittivity) can be calculated from the estimation of the amplitude \( A_k(x) \) and the time delay \( \tau_k(x) \). This is the layer stripping inversion approach [4][5].

Another approach is the parametric EM inversion (referred to as EMI for convenience) [4][5]. Layer-stripping is based on tracking and analyzing the estimates of amplitude and time of delay of reflected echoes, while EMI is based on minimizing a cost function based on the difference between measured and modeled data in every spatial location. Layer-stripping is less accurate but is computationally more efficient than EMI. In practice, layer-stripping is used as a prescreening method for rough inspection of a large area, and EMI is used for fine inspection of some interested small area. Layer-stripping can also be used to provide the initial estimates of the model parameters needed by the EMI algorithm to fasten the convergence speed.

**The NHD-EMI Algorithm**

The conventional EMI algorithm assumes horizontal model, which means EMI can only work well when the permittivity changes very slowly in the lateral direction. We propose to use EMI in combination with a non-homogeneous detector (NHD) [6], which was originally designated as a secondary data selection method for space-time adaptive processing in airborne radar. We call this modified EMI algorithm as NHD-EMI.

Assume laterally continuous scan locations are described by \( \{x_i\}_{i=1}^N \), and the data vector at position \( x_i \) is denoted by \( s_i \) (called A-scan) with dimension \( N \times 1 \), where \( N_x \) and \( N \) denote the number of scan positions and data samples in the vertical direction, respectively. Define generalized inner product [6] of each A-scan (\( s_i \)) as the output of the NHD, which has the form

\[
y_i(GIP) = s_i^H \mathbf{R}_c^{-1} s_i
\]

where \( [\cdot]^H \) denotes conjugate transpose and \( \mathbf{R}_c \) denotes the covariance matrix of the clutter plus noise for the B-scan. The estimate of \( \mathbf{R}_c \) is given by

\[
\hat{\mathbf{R}}_c = \frac{1}{N_x} \sum_{i=1}^{N_x} s_i s_i^H
\]

By using NHD, we can divide the whole data into multiple subsegments satisfying horizontal models. Then EMI can be applied to each subsegment individually instead of using the whole data for EM inversion. To make the paper self-contained, below we briefly summarize the EMI algorithm [4].

Assume \( \mathbf{S}_0 \) denotes data matrix of a selected subsegment after NHD processing with each column corresponding to a A-scan data vector (some \( s_i \)). The permittivity profile \( \varepsilon(x, z) \) can be parameterized as a continuous function using a basis of cubic B-splines. Permittivity thus can be model as

\[
\varepsilon(x, z) \approx \varepsilon(x, z, m) = \sum_{i=1}^{N} m_i f_x(x - x_i^{(m)}) f_z(z - z_i^{(m)})
\]

where \( m = [m_1, m_2, ..., m_N]^T \) denotes the unknown model vector that defines the amplitudes of the B-spline functions \( f_x(x) \) and \( f_z(z) \) centered at the grid \( (x_i^{(m)}, z_i^{(m)}) \), and \( (\cdot)^T \) denotes transpose. Let \( \mathbf{S}(m) \) be data estimated by the forward modeling for model \( m \). Then the estimate of the model parameters can be found by minimizing the following cost function

\[
Q(m) = \| \mathbf{S}_0 - \mathbf{S}(m) \|^2
\]

defined as the difference between the observed and modeled data. The minimization of the above cost function is a nonlinear optimization problem and can be solved by using iterative Gauss-Newton method that linearizes \( \mathbf{S}(m) \) about the current model \( m_c \)

\[
\mathbf{S}(m) \approx \mathbf{S}(m_c) + \nabla_m [\mathbf{S}(m_c)] (m - m_c)
\]

Then the estimate of the model parameter can be approximately given by

\[
m - m_c \approx [\nabla_m \mathbf{S}(m_c)]^+ [\mathbf{S}_0 - \mathbf{S}(m_c)]
\]

where \( [\cdot]^+ \) denotes pseudo-inverse operator. \( m_c \) can be obtained via the less accurate layer-stripping approach [5]. Further details about the EMI algorithm can be found in [4].
Experimental Results

In this section, we present some numerical examples to illustrate the performance of the proposed algorithms.

![Figure 2: Original permittivity profile](image1)

![Figure 3: Output of GIP based NHD](image2)

Figure 2: Original permittivity profile

Figure 3: Output of GIP based NHD

![Figure 4: Comparison of the estimation performance between EMI (solid line) and NHD-EMI (dashed line)](image3)

(a) Layer 1

(b) Layer 2

Figure 4: Comparison of the estimation performance between EMI (solid line) and NHD-EMI (dashed line)

In the following examples, the transmitted signal is a Gaussian pulse \[ T_w = 0.7\,ns \] with a pulse width \[ T_w = 0.7\,ns \], the sampling period is \[ 0.07\,ns \], the total sample points along the scan direction is \[ N_x = 50 \]. The original permittivity profile is shown in Figure 2. Gradual change exists in the horizontal direction for Layers 2. In the EM inversion step, the vertical and horizontal grid spacings for the EM model parameterization are \[ \Delta z^{(m)} = 0.4\,cm \] and \[ \Delta x^{(m)} = 3\,cm \], respectively. The signal-to-noise ratio (SNR) is defined as the averaged power of the transmitted signal over the noise power and is set to 20 dB in the following examples.

Figure 3 shows the output of GIP based NHD, from which it can be noted that the horizontal change of the second layer was detected correctly and we must divide the whole data into three subsegments accordingly before applying EMI.

The estimation performance of the permittivity profile obtained via EMI (solid line) and NHD-EMI (dashed line) is shown in Figure 4. In Figure 4, the horizontal axis denotes the scan position, and the vertical axis is the averaged mean squared error (MSE) in dB of each layer at each scan position obtained via 100 Monte Carlo trials. Figures 4(a) and (b) show the results for the first and second layers, respectively. From Figure 4 it can be noted that NHD-EMI exhibits better performance over GEM, especially for those layers that are non-homogeneous in the lateral direction.
Conclusion

In this paper, a localized parametric EM inversion approach (referred to as NHD-EMI algorithm) is proposed for analyzing pavements with spatial varying characteristics, which combines a non-homogeneous detector (NHD) with existing EMI algorithms. Numerical results show that the proposed NHD-EMI algorithm exhibits better performance over the existing EMI algorithm for nonhomogeneous pavements.

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