A High-resolution GPR horizon extraction method based on local reflection and global correlation

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Abstract. Horizon extraction is a very basic and important part of ground penetrating radar (GPR) interpretation. Most GPR horizon extraction methods are based on local reflection of the GPR event such as the trace correlation algorithm, and hidden Markov model algorithm. These methods use only local structural characteristics of the GPR data and often fail to pick the layer correctly across discontinuous caused by faults and noise. In order to overcome shortcomings of the above methods, a novel method based on gradient structure tensor algorithm (GST) and dynamic time warping algorithm (DTW) is used in this paper to extract the horizon accurately which has been proved to be effective in the complex seismic data. GPR electromagnetic wave and seismic wave have certain similarity in kinematics and dynamics, we apply this method to realistic GPR data and prove its effectiveness.

1. Introduction

Ground penetrating radar (GPR) is a non-destructive and efficient shallow surface and underground detection equipment that has been widely used in civil engineering and road detection. The layer picking is one of the encountered problems when realizing the above applications which critically impacts the GPR data interpretation quality.

Numerous methods have been proposed to pick the layers from the GPR profile automatically or semi-automatically. Trace Correlation Algorithm makes use of the correlation characteristic between the adjacent traces intuitively and simply [5]. It can rapidly pick the expected layers especially for massive GPR data. However, the estimation errors may be accumulated as the algorithm iterates.

Hidden Markov model (HMM) and Bresenham algorithm is a delay estimation by exploiting the continuity of wavefronts modeled as a Markov chain [6]. The delay profiles can be tracked with any known method by assuming that the ordered sequence of signals is described by HMM. This method is very accurate but time-consuming and not suitable for real-time processing.

Some other methods are based on the local reflection slopes that estimate the geometric orientations of reflections. The local reflection slope can be estimated by using structure tensors [1] and the fitting effect of this method before and after fault is also not as expected.

The above methods only use local structural characteristics of the GPR data and often fail to pick the layer correctly across discontinuous such as faults and noise. To overcome the shortcomings of the above methods, a novel method based on gradient structure tensor algorithm (GST) and dynamic time warping algorithm (DTW) is used in this paper to extract the horizon accurately which has been proved to be effective in the complex seismic data [10]. We firstly use structure tensors to estimate the linearity and local slopes of local reflections, and then confirm a seed point and generate more seed
points evenly covering the entire horizon by DTW, and these seed points will be the constrain in the next step. At last, we compute the horizon in the least-square system.

2. Algorithm

2.1. Structure tensors

The structural tensors method was firstly proposed for image edge detection in digital image processing [8]. In the field of geophysics, structure tensors belong to the coherence cube techniques that were used to extract the attributes and characteristics of seismic data such as the faults and some special lithologic bodies.

Structure tensors are generally constructed as smoothed outer products of gradients I of an image. A structure tensor T(x) field at every image samples x can be computed as

\[
T(x) = \left[ \begin{array}{c}
< I_x \cdot I_x >, < I_x \cdot I_y > \\
< I_y \cdot I_x >, < I_y \cdot I_y > 
\end{array} \right],
\]

where \( I_x \) and \( I_y \) represent the horizontal and vertical gradients of 2-D GPR data, respectively. \(<<>\) represent a 2-D Gaussian smoothed filter with half-widths \( \sigma_1 = 6 \) (samples) and \( \sigma_2 = 2 \) (samples) in the vertical and inline directions, respectively. We use a larger half-width in the vertical direction because the waveform changes more frequently in the vertical direction.

The eigen-decomposition of each structure tensor \( T \) provides the measures of orientation and dimensionality that we require in structure-oriented filtering [2]. For 2D images, this eigen-decomposition is

\[
T = \lambda_u u u^T + \lambda_v v v^T,
\]

where \( \lambda_u \) and \( \lambda_v \) are the eigenvalues and \( u \) and \( v \) are the corresponding 2-D eigenvectors of \( T \). Assume that \( \lambda_u > \lambda_v \) and the direction of eigenvector \( u \) is orthogonal to the reflection. And correspondingly, the direction of eigenvector \( v \) is aligned with reflection. Therefore, we can compute the local slope by the eigenvector \( u \) or \( v \)

\[
s(x) = \frac{u_i(x)}{u_i(x)},
\]

where \( u_i(x) \), \( u_2(x) \), respectively, are components of the vectors \( u(x) \). \( s(x) \) is the local slopes in GPR profile. Figure 1(a) is GPR data, and Figure 1(b) is the local reflection slopes in the profile shown in the Figure 1(a). In the yellow rectangle of Figure 1(a), the W-shaped layer, correspondingly, the slopes in the yellow rectangle in Figure 1(b) alternates between positive and negative.

Hale proposed a weight coefficient by eigenvalues \( \lambda_u \) and \( \lambda_v \) called linearity for quantitative analysis of the structure of the adjacent region of each point in the GPR profile. The formula as follows [3]:

\[
w(x) = \frac{\lambda_u(x) - \lambda_v(x)}{\lambda_v(x)}.
\]

As shown in the equation (4), when the \( \lambda_v \) is approximately close to zero, \( w(x) \) is close to being one. In this condition, the high value of linearity indicates that the image structure near this point is obvious and anisotropic. On the contrary, when \( \lambda_u \) is approximately equal to \( \lambda_v \), \( w(x) \) is close to zero, the little value of the linearity implies high noise and fault information near the point.
2.2. Dynamic time wrapping algorithm

The Dynamic Time Warping (DTW) algorithm finds an optimal match between two sequences by allowing for stretching and compression of sections. The problem of estimating relative time (or depth) shifts between two seismic images is ubiquitous in the GPR data processing. This problem is especially difficult where shifts are large and vary rapidly with time and space, and where images are contaminated with noise or for other reasons are not shifted versions of one another.

In GPR data, the cross-correlation of data between one trace and its adjacent trace is close to one. The waveforms of the two adjacent traces are nearly identical. However, the relative time (or depth) shifts may be obvious, and the two traces of data might have the same shape but there's some squeezing or stretching. DTW is robust to estimate correlation shifts in the presence of noise, and is often more accurate than windowed cross-correlation methods, especially in estimating rapidly varying shifts [4].

Supposed \( f = (f_1, f_2, ..., f_n) \) and \( g = (g_1, g_2, ..., g_n) \) are two sequences of the same GPR data. DTW can help to match points in the sequence \( g \) with \( f \), and get a shift sequence \( l = (l_1, l_2, ..., l_n) \). The DTW solves the following constrained minimization problem:

\[
\arg \min_{l} \sum_{i=2}^{n} (f_i + g_{l_{i-1}})^2 \quad \text{s.t.} \quad |l_i - l_{i-1}| \leq \varepsilon,
\]

where the shift strain \( \varepsilon \) represents the weight of squeezing or stretching. By DTW, we can compute the shift sequence \( l \) which will adjust the horizon. Figure 2 denotes the correlations of GPR data, which correctly connect the peaks of the GPR data of different traces.
where the green points are the initial horizon points. By DTW, we update the new red point and the yellow line represents the new horizon. Based on the seed point we determined at first, we can use DTW to obtain more seed points to control the accuracy of the layer globally. To increase the efficiency of estimating the global correlations, we do not correlate GPR traces within the whole time or depth window. Instead, we only correlate the traces in a small time or depth window centered at the iteratively updating horizon.

2.3. Horizon Extraction Method in least-square

We abstract the layer or the horizon as a curve $h(x)$. Now we can compute the local reflection slope $s(x)$ of the whole points in the GPR profile by structure tensors, and choose a seed-point $s_0$ that must be in the curve. We can derive the following equation

$$\frac{\partial h(x)}{\partial x} = s(x, h(x)), \quad s.t. \quad h(x_0) = h_0,$$

(6)

where the $s(x, h(x))$ denotes the slope in the curve $h(x)$. If we know the slope of a curve and a point in the curve, we can compute the curve by Euler Method quickly and efficiently as follow:

$$h(x_{i+1}) = h(x_i) + s(x_i) \quad s.t. \quad h(x_0) = h_0,$$

(7)

As mentioned above, it is difficult to extract the horizon correctly by using only the local reflection slope, especially when the noise is large or there are faults in the horizon because errors are accumulated with the layer extraction process progresses. To solve this problem, we take the layer obtained by the above equation as the initial layer called $h_0$ and then improve the correlation of the different trace by DTW algorithm, finally compute the new layer in a least-square system with the preconditioned conjugate gradient method with more seed points constraints. We can further impose smooth regularizations on the horizon and build the following equations for the 2D slope-based horizon extraction

$$\left[w(x, h(x)) \frac{\partial h(x)}{\partial x}\right] \approx \left[w(x, h(x))s(x, h(x))\right],$$

(8)

where $w(x, h(x))$ denotes the linearity. We put $w(x, h)$ to the equation (8) so that we can control the influence of the noise and fault. $h(x)$ is the initial horizon computed by the equation (7). We can rewrite the equation in an iterative way as follow

$$W_i h_{i+1} \approx W_i s_i,$$

(9)

where the diagonal matrix $W_i$ is the i-th iteration horizon’s linearity matrix and the $D_x$ represent finite-difference approximations of the first derivatives, $h_{i+1}$ is the horizon we compute, and $s_i$ represent the i-th iteration horizon’s slope. We use approximate equalities in equations (9) because we compute the least-squares solution by solving the normal equation of equation (10):

$$D_j^TW_j^*D_j h_{i+1} = D_j^TW_j^*s_i,$$

(10)

s.t. $h(x_j) = h_j, \quad j = 1, 2, ..., m$

where $j$ is the number of the seed points computed by DTW. We can use conjugate gradient solver with a constraint preconditioner and starting with an initial horizon $h_0$ passing through the control points [9]. The layer picking technique can be summarized by the following algorithm:

Step1: Compute the local reflection slopes $s(x)$ of the GPR data by structure tensors.
Step2: Confirm the seed point $h_0$ as the start point to extract the horizon.
Step3: Initialize the horizon. Compute the initial horizon using the equation (7).
Step4: Generate more seed points evenly covering the entire horizon by DTW, and these seed points will be the constraint in the next step.
Step 5: Compute the equation (10) iteratively with the seed points as hard constrain until the average updating is smaller than some small threshold \( \frac{1}{N} \sum_{n=1}^{N} |h_{i+1}(x_n) - h_i(x_n)| < \theta \).

Step 6: Smooth the horizon and output the horizon.

2.4. Algorithm instance

We have used python language to realize the proposed method, which has a good effect on the verification of examples. We applied the proposed methodology to a real GPR profile section. The profile (512*1500) was obtained in the plastic waterproof runway of Xi'an Jiaotong University and we use the GSSI system equipped with a central frequency 900MHz antenna. The recorded raw GPR data are shown in Figure 3(a). Figure 3(b) shows the horizon only used the local reflection slopes. Figure 3(c) demonstrates the horizon extracted by the above algorithms. Figure 3(b) indicates that the stratification level is generally low and the further away from the seed point, the greater the error accumulation. By contrast, our method is more accurate.

Figure 3. A GPR profile (a) with two horizons extracted by local reflection slopes only (b) and local reflection slopes and global correlation (c).

We extracted horizontally sparse (one for every 200 traces) traces within vertical short windows that are centered at the horizon. There traces are flattened by the updated horizon. Figure 4(a) and Figure 4(b) represent the first yellow layer in the Figure 3(b) and Figure 3(c), respectively. Figure 4(c) and Figure 4(d) represent the second red layer in the Figure 3(b) and Figure 3(c), respectively. In the Figure 4(a) and Figure 4(b), all the traces are vertically aligned and the flattened horizon in the middle consistently passes through all the throughs because the first layer is smooth. Compared to the Figure 4(c), the horizon in the Figure 4(d) passes the peaks accurately.
3. Conclusions
We presented an iterative horizon extraction method for GPR data based on local reflection slopes and global correlations. We fit the horizon in a least-square system. The method has achieved good results in practice. The main advantage of the methodology is its robustness because more global characteristics were used when tracking the horizon. The comparison with common method based on coherence and similarity shows that the proposed method has high stability in automatic horizon tracking. In the following scientific research, we will continue to optimize the algorithm to make use of more waveform features in GPR data so that the algorithm can better match the layers, especially on both sides of the fault.

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