Abstract—Accurate detection of singular region using ground-penetrating radar (GPR) is very useful in assessing roadway pavement, bridge deck concrete structure, and railroad ballast conditions. To locate an object within the radargram involves extensive computational resources and time, especially when the data of interests only possess a small portion of the whole big data set. Therefore, an efficient GPR signal-processing technique is highly demanded. This paper proposes the use of 2-D entropy analysis to narrow down the data scope to the interested regions, which can considerably reduce computational cost for more sophisticated data postprocessing. Joint time-frequency analysis using short-time Fourier transform is then performed for singular region location detection and refinement. The proposed methodology is tested with different laboratory setups. The analysis results show good agreement with physical configurations.

Index Terms—Entropy, nondestructive testing, radar, radar detection, signal processing.

I. INTRODUCTION

MPULSE ground-penetrating radar (GPR) has been proven to be an effective tool in inspecting transportation infrastructures, including bridge deck [1]–[4], highway pavement, and railroad ballast [5], [6], because of its ability to extract subsurface information in a nondestructive manner. For GPR, one important and challenging design factor is signal processing, whose objective is to effectively analyze and extract meaningful information, and accurately interpret the measurement results. In this paper, a new signal-processing approach is developed to leverage GPR data analysis efficiency with a specific focus on singular region detection.

In transportation infrastructure survey, detecting sporadically located singular regions, such as embedded rebars is one of the basic functions for GPR subsurface structure examination. Many data-processing techniques have been developed for rebar detection. In [1], an energy function is used to model and detect rebar hyperbolic signature pattern and iterative hyperbola curve fitting is applied. Although this method is effective, the long computation time limits its applicability only to small-volume radar data set. Moreover, the curve-fitting method is only applicable when the characteristic pattern is already known, and is not valid for detecting a singular region of an arbitrary shape. In [2], an approximate linear scattering model is developed using the sparse nature of scatter to reconstruct the reflection signal. The reconstruction model is a double integral, and a minimization algorithm is implemented by loops of matrix multiplication. This method can precisely locate rebar. However, the processing procedures are relatively complicated. In [3]–[6], rebar GPR B-scan image signature curves are characterized through a series of image processing algorithms such as image segmentation, arc detection, and curve fitting. The same processing steps are performed throughout the entire scanning data even though the interested rebar data only populate a small portion of the data set. Although such approaches are meticulous, they are both costly and time consuming. Therefore, to develop a method to automate the detection of sporadically distributed singular regions of arbitrary shapes for facilitating sophisticated post-processing is highly desired.

In this paper, 2-D entropy analysis algorithm is developed to effectively reduce the data scope to the singular regions within the large background. In the information theory, entropy is a measure of the uncertainty associated with a random variable [7]. It has been used in several fields such as biomedical engineering [8], [9], speech [10], information data mining [11], front-wall clutter rejection [12], and color image enhancement [13]. However, to date, there has been no literature using entropy analysis on GPR image for detecting the sporadically distributed features. In this paper, 2-D entropy processing algorithm is developed for object extraction from the stationary background. As a result, the distinctive areas of interests can be rapidly identified, and the size of the data for postprocessing can be significantly reduced. For GPR data postprocessing, one important analytical approach is spectrum characterization with Fourier transform. However, the main limitation is that the signal time information is lost in transforming to the frequency domain. For a stationary signal analysis, where the processed signals do not change with time, this limitation is not an issue. While in GPR scans, the premise of stationary signal does not hold. During GPR operation, the scanning antennas move continuously, thus the subsurface features under inspection change dynamically, which lead to nonstationary reflection signals being collected. To obtain time and spectrum information from GPR signals, the joint time-frequency (JTF) signal decomposition is employed. JTF signal decomposition is a special form of spectral analysis that aims at precise tracking frequencies of nonstationary time-varying signals. However, the application of JTF analysis for GPR signal processing is very limited. A major barrier is the computational cost associated with the large data size, typically
over tens of giga-bytes (GBs). Directly performing complicate JTF analysis on such big data set is inefficient. In this paper, with the aid of entropy characterization to narrow down the data scope, the sophisticated JTF analysis cost is considerably reduced. In the literature, there exist a variety of JTF analysis approaches, such as Gabor, wavelet, and so on [14], [15], that can achieve high time and frequency characterization resolution and accuracy. Because singular region detection does not require extremely high characterization resolution, we choose to use the basic short-time Fourier transform (STFT) to fulfill the application goal, which produces marginal resolution but at a relatively lower computational cost. In this paper, the STFT analysis is applied upon 2-D entropy analysis to identify the right singular region while eliminate the false ones. Even though we use GPR rebar region detection and ballast moisture region assessment as the study cases, the proposed method can be extended and combined with other processing approaches to improve processing performance for other applications.

This paper is an extension of the work presented in [16]. In [16], a preliminary study is performed to show that entropy and STFT analysis feasibility. However, there are three critical limiting factors not addressed: 1) the entropy curve obtained contains high-frequency noise; 2) the determination of entropy threshold values for detecting singular regions is manual and subjective; and 3) upon 2-D entropy analysis, false singular region detection might be resulted. In this paper, solutions are developed to resolve these issues. First, moving average method is applied to alleviate entropy noise and smooth out entropy curve. Second, OTSU thresholding algorithm is developed so that singular regions identification is automated without requiring human intervention, which makes threshold determination an objective, generic, and efficient process. Third, STFT analysis is performed to identify the correct singular region and to eliminate the false regions that are not distinguishable with entropy characterization.

The remaining sections of this paper are organized as follows. Section II introduces data acquisition, including experimental setups and data preprocessing procedures. Section III describes in detail of two computational algorithms in use: 2-D entropy analysis and STFT. Section IV shows experimental results. The concluding remarks are drawn in Section V.

II. DATA ACQUISITION

A. System Setup

In this paper, the experimental data are collected with our impulse GPR system developed in [17]–[20]. Fig. 1(a) shows the system diagram. As shown, the GPR system hardware consists of five major functional units: 1) RF transmitter; 2) ultrawideband antennas; 3) data acquisition unit comprising of a high-speed real-time digitizer, high-speed data transmission and storage unit; 4) Quad-core computer (Intel core i7 3.4 GHz); and 5) field programmable gate array digital controller along with a wheel encoder.

The RF transmitter comprises of an ultrawide bandwidth (UWB) pulse generator that generates high amplitude (up to 18 V) 1 ns wide Gaussian pulse [Fig. 1(b)] whose pulse repetition frequency is set to 30 kHz. The digitizer employed is a high-speed real-time data acquisition unit (Agilent Acqiris U1065A module) of 8 Gsps sampling rate and 10-b resolution operating in simultaneous multibuffer acquisition and readout mode. The digitizer configuration details can be found in [17] and [18]. For impulse signal transmission and receiving, two identical tapered wideband horn antennas, as shown in Fig. 1(c), are designed. The antennas’ operating frequencies span from 0.6 to 6 GHz and S11 measurement result is shown in Fig. 1(d).

B. Test Setups

To evaluate the performance of our GPR data analysis approaches, GPR singular region detection experiments are
conducted with two types of setups. One is for rebar detections, while the other one is for ballast moisture region discovery.

For rebar detections, two different configurations are implemented: 1) a 30 mm diameter rebar is positioned in air and is placed 220 mm below antennas as shown in Fig. 2(a) and 2) two 20 mm diameter rebars spaced by 500 mm are buried 108 and 98.6 mm deep inside a concrete slab as shown in Fig. 2(b). Transmitter and receiver antennas [Fig. 2(c)] are packed inside a box which is placed 100 mm above the top surface of the concrete slab.

For ballast moisture region assessment, experiment is configured with contaminated ballasts. Fig. 3(a) shows the test platform developed emulating the railroad structure. One portion of the ballast region is contaminated with soil and water. Fig. 3(b) shows the subsurface structural configuration: 1) the ballast layer above the soil is 0.3 m thick and 2) 0.75 m apart from the left end of the platform, a region (highlighted in blue) of 0.45 m width and 0.2 m depth is filled with contaminated ballast mixed with soil and 2-gallon water, which is the fouled ballast region for GPR detection validation.

C. GPR Data Preprocessing

During rebar scan test, GPR antennas are moved horizontally above the rebar for reflection signal collection. The obtained raw B-scan images are shown in Fig. 4. In these B-scan images, x-axis indicates scan distance whereas y-axis specifies the radar signal travel time. The raw images contain significant background noise including floor surface reflection signal and transmitter/receiver antennas direct coupling interference signal located between time indexes 0 and 2 ns. To remove these undesired signals, the following data preprocessing steps are implemented.

1) Subtracting the first sampling trace from all subsequent traces to eliminate the stationary systematic interference signal.
2) Applying a fifth-order 1 GHz finite impulse response low-pass filter to remove off-band noise. Using rebar-in-air image as the example, the resulting images upon these processing are shown in Fig. 5(a).
3) Applying averaging operations (stacking) among every 100 traces to further alleviate random noise and to improve signal to noise ratio. The final image is shown in Fig. 5(b). Note the averaging factor of 100 is selected for its effectiveness in removing noise while maintaining good image resolution.

For the ballast setup configuration, Fig. 6(a) is the raw image, and Fig. 6(b) is the image obtained upon preprocessing. For all test configurations, 2-D entropy and STFT analysis described below are applied to detect the singular regions, which are rebar region and fouled ballast region, respectively.

III. COMPUTATIONAL ALGORITHMS: 2-D Entropy and Short-Time Fourier Transform

A. Windowing 2-D Entropy Method

In information theory, entropy is a measure of the uncertainty associated with a random variable. It quantifies the expected value of the information contained in a message. For our GPR data processing, entropy characterization is
explored to identify the singular region within a large data set. In particular, a high entropy value indicates high degree of data similarity whereas a low entropy value highlights high degree of data singularity. In the following, we will elaborate our GPR data entropy analysis algorithm.

The received GPR reflection signal \( Y(t) \) can be modeled with the following equation:

\[
Y(t) = D(t) + S(t)
\]  

where \( D(t) \) represents the reflection signal from the object of interest; \( S(t) \) models interference and noise, including reflection signals from the background such as the concrete slab surface, transmitter and receiver antennas direct coupling signals, and so on. In calculation, power normalization is first performed with the summation of the power of the same time index data points on different traces. The normalization equation is expressed as

\[
y_i(t) = \frac{\|Y_i(t)\|}{\sum_{i=1}^{M} \|Y_i(t)\|}
\]  

where \( y_i(t) \) is the normalized signal, \( i \) is the trace index, \( M \) is the total number of traces included, and \( t \) is the time index of pulse data on each reflection trace waveform.

Upon power normalization, a generalized Renyi’s entropy [21] is applied to assess data singularity

\[
E_\alpha(t) = \frac{1}{1 - \alpha} \log \left( \sum_{i=1}^{M} [y_i(t)]^\alpha \right)
\]  

where \( E_\alpha(t) \) is the entropy quantification and \( \alpha \) is the entropy order. When \( \alpha = 1 \), (3) transforms to the basic Shannon entropy. For analysis demonstration, Fig. 7 shows different trace waveforms for scanning rebar-in-air setup. The scanning trace indexes are \( i = 1000, 1200, 1400, 1600, 1800, 2000, \) and \( 2200 \), respectively. Note, because rebar is a metal structure, comparing with background objects, it produces the strongest reflection corresponding to the peak pulse point on each trace waveform.

As the scanning trace index increases from \( i = 1000–2200 \), the rebar reflection causes the time index of the peak point to initially shift toward the lower numbers and then shift back to higher ones. The lower index implies shorter signal travel distance between rebar and transceiver antennas.

As antennas move away from the rebar, the pulse peak shifts to higher time indexes, indicating longer travel time. To identify the time index region that contains singular features such as peak shifting, entropy values are computed using (2) and (3) with \( M = 4088 \) scanning traces, where \( \alpha \) is set to 3 [8], [21]. The resulting entropy curve is shown in Fig. 8.

### B. Entropy Curve Smoothing Using Moving Average

To alleviate entropy value fluctuations, moving average (SMA) operation is performed to smooth out the entropy data [22]. Denoting the entropy value at index \( n \) as \( E(n) \) in entropy data sequence, SMA calculates the mean of every \( m \) data points. In this paper, \( m \) is selected to be 5\% of the number of data points in \( E(n) \), that is, \( m = n/20 \)

\[
E_{\text{smooth}}(n) = \frac{1}{m} \sum_{i=n-m+1}^{n} E(i).
\]

### C. Adaptive Entropy Threshold Determination

Depending on the data homogeneity, the B-scan image can be segmented into three classes of regions: singular region, stationary background region, and the transition region in-between. The classification process can be made through
assessing region’s entropy values against two selected thresholds \( K_1 \) and \( K_2 \), where \( K_1 < K_2 \). The singular region entropy values are lower than threshold \( K_1 \), the stationary background region entropy values are higher than \( K_2 \). While for the transitioning region, its entropy values are between these two thresholds.

To appropriately determine threshold values \( K_1 \) and \( K_2 \), the automatic OTSU thresholding method [23] is employed. OTSU method is a classic image segmentation technique for extracting an object from its background. In principle, an image can be divided into nonoverlapping regions by evaluating region’s homogeneity through intensity values (i.e., pixel magnitude) variance assessment. For region classification, the intraclass intensity values are close to each other with small variances, whereas the interclasses intensity values are significantly different with large variances. OTSU method performs statistical analysis to identify appropriate thresholds so as to segment image into different regions accomplishing the criteria: the intensity values variances of the same region is minimized while the variances of different regions are maximized.

When applying OTSU method to determine GPR B-scan image segmentation thresholds, the entropy is chosen as the intensity value. Recording the number of entropy points whose values are \( E_i \) as \( n_i \), the total number of entropy points is \( N = \sum E_i \in [E_{\text{min}}, E_{\text{max}}] \) \( n_i \), where \( E_{\text{min}} \) and \( E_{\text{max}} \) specify the minimum and the maximum entropy values, respectively. Statistical normalization is then performed

\[
p_i = \frac{n_i}{N}, \quad p_i \geq 0, \quad \sum_{E_i \in [E_{\text{min}}, E_{\text{max}}]} p_i = 1 \tag{5}\
\]

where \( p_i \) specifies \( E_i \) value occurrence frequency or the normalized probability. With two thresholds \( K_1 \) and \( K_2 \), the entropy data set is divided into three subgroups: group \( C_0: [E_{\text{min}}, K_1] \), group \( C_1: (K_1, K_2) \), group \( C_2: [K_2, E_{\text{max}}] \). The occurrence frequency of each subgroup can be calculated as

\[
\omega_0 = P(C_0) = \sum_{E_i \in [E_{\text{min}}, K_1]} p_i
\]

\[
\omega_1 = P(C_1) = \sum_{E_i \in (K_1, K_2)} p_i
\]

\[
\omega_2 = P(C_2) = \sum_{E_i \in [K_2, E_{\text{max}}]} p_i \tag{6}\
\]

and the group mean values are

\[
\mu_0 = \sum_{E_i \in [E_{\text{min}}, K_1]} E_i P(E_i | C_0) = \sum_{E_i \in [E_{\text{min}}, K_1]} E_i \frac{p_i}{\omega_0}
\]

\[
\mu_1 = \sum_{E_i \in (K_1, K_2)} E_i P(E_i | C_1) = \sum_{E_i \in (K_1, K_2)} E_i \frac{p_i}{\omega_1}
\]

\[
\mu_2 = \sum_{E_i \in [K_2, E_{\text{max}}]} E_i P(E_i | C_2) = \sum_{E_i \in [K_2, E_{\text{max}}]} E_i \frac{p_i}{\omega_2} \tag{7}\
\]

The overall entropy mean equals

\[
\mu_T = \mu(L) = \sum_{E_i \in [E_{\text{min}}, E_{\text{max}}]} E_i p_i. \tag{8}\
\]

The intraclass variances can be calculated as

\[
\sigma_0^2 = \sum_{E_i \in [E_{\text{min}}, K_1]} (E_i - \mu_0)^2 \frac{P(E_i | C_0)}{\omega_0}
\]

\[
\sigma_1^2 = \sum_{E_i \in (K_1, K_2)} (E_i - \mu_1)^2 \frac{P(E_i | C_1)}{\omega_1}
\]

\[
\sigma_2^2 = \sum_{E_i \in [K_2, E_{\text{max}}]} (E_i - \mu_2)^2 \frac{P(E_i | C_2)}{\omega_2}. \tag{9}\
\]

The interclass variance can be measured by the following discriminate criterion:

\[
\sigma_B^2 = \omega_0 (\mu_0 - \mu_T)^2 + \omega_1 (\mu_1 - \mu_T)^2 + \omega_2 (\mu_2 - \mu_T)^2 = \omega_0 \omega_1 (\mu_0 - \mu_1)^2 + \omega_1 \omega_2 (\mu_1 - \mu_2)^2 + \omega_2 \omega_0 (\mu_2 - \mu_0)^2 \tag{10}\
\]

which is a function of threshold variables \( K_1 \) and \( K_2 \). The optimal thresholds \( K_1^o \) and \( K_2^o \) can be determined by maximizing \( \sigma_B^2 \) [23]

\[
\sigma_B^2(k_1^o, k_2^o) = \max_{k_1, k_2 \in [E_{\text{min}}, E_{\text{max}}]} \sigma_B^2(k_1, k_2). \tag{11}\
\]

The adoption of these two optimal thresholds can maximize intergroup entropy variance. In the meantime, the intragroup entropy values variance is minimized [23].

D. Short-Time Fourier Transform

In essence, STFT implements local Fourier transform on data that are evenly divided into smaller time windows. Mathematically, STFT algorithm is expressed as below

\[
X(\tau, \Omega) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-j\Omega t}dt \tag{12}\
\]

where \( x \) is the received GPR signal, \( \Omega \) is the radial frequency whose resolution (\( \Delta \Omega = 2\pi/N \)) is determined by the number of points \( N \) adopted for FFT computation. In this analysis, \( N = 256 \) is the time resolution. Because our GPR digitizer’s sampling frequency is 8 Gsps, \( \tau \) equals 125 ps. \( w(t) \) is the window function. Here a Hamming window is employed. In STFT analysis, there exists a tradeoff between time and frequency resolution when determining the window size. Through a series of iterative experiments, we select 1/10 the total number of time index to set the window size, which is proven effective in achieving a good balance between frequency and time resolution for rebar detection.

IV. EXPERIMENT RESULTS AND DISCUSSION

A. Rebar Test Results

With entropy and STFT characteristics analyzed above, this paper proposes to perform 2-D entropy analysis first to narrow down data scope to distinctive regions, and then uses STFT
to refine true singular region detection. For rebar in-air setup, entropy analysis (3) with $\alpha = 3$ is first applied to B-scan image along y-axis (as shown in Fig. 9). The obtained smooth entropy curve is shown in Fig. 9(b). Using OTSU thresholding method, two threshold values $K_1^* = 28.96$ and $K_2^* = 31.08$ are calculated. The region between 0 and $K_1^*$ is the singular region, while the region between $K_1^*$ and $K_2^*$ is the transition region. In this paper, for not to miss detecting the areas of interests, we take a conservative approach by searching for both the singular region and the transition region, where both regions have entropy values below the higher threshold $K_2^* = 31.08$. As shown in Fig. 9(b), there are two regions whose entropy values are below this threshold. One locates between $t = 1.625$ ns and $5.75$ ns and the other one locates between $t = 7.75$ and 8.625 ns.

Subsequently, Renyi’s entropy calculation is applied to scanning traces along x-axis. Fig. 10(b) shows the entropy curve. Using OTSU thresholding method, two threshold values $K_3^* = 10.25$ and $K_4^* = 12.01$ are obtained to identify the distinctive data region in X-direction. Like the analysis along y-axis, the region containing rebar reflection information is within the region below threshold $K_4^*$, which is found between $x = 0.55$ m and $x = 1.95$ m.

By combining both x-axis and y-axis entropy analysis results, the intersection regions are obtained. For rebar-in-air setup, the extracted regions are shown in Fig. 11(a), while for rebars-in-concrete-slab setup, the extraction regions are highlighted in Fig. 11(b). In both cases, a false region below 7 ns is also extracted. STFT analysis is then performed to refine the extraction result and eliminate the false region.

For one-rebar-in-air data, STFT analysis is performed on the selected signal trace at $x = 1.1$ m across the extracted regions shown in Fig. 11(a). The obtained time-spectrum is shown in Fig. 12(a). As shown, no strong reflection occurs between 8 and 10 ns, which means the second region (8–9 ns) shown in Fig. 11(a) is the false singular region that should be eliminated. The corrected singular region extraction result is shown in Fig. 13(a). Similarly for two-rebar-in-concrete slab data, STFT analysis on the signal trace locating at $x = 1.5$ m is performed and the result is shown in Fig. 12(b). As shown, no strong reflection exists between 6 and 10 ns, which indicates
the second region (between 7 and 9 ns) shown in Fig. 11(b) is also a false region and should be eliminated. The corrected singular region extraction result is shown as Fig. 13(b). In both cases, the extracted rebar region comprises less than 40% of the entire scanning data volume.

Further, STFT is operated on trace signals selected from the left side, the middle, and the right side of the rebar region, respectively. The corresponding STFT analysis results are shown in Fig. 14(b)–(d).

In Fig. 14(b), a strong peak occurs at 2.8 ns on the trace of $x = 0.75$ m when antennas are on the left side. Fig. 14(c) shows when the antennas are right above the rebar (the trace of $x = 1.1$ m), a strong peak pulse is produced at 1.9 ns. Fig. 14(d) shows a strong peak at 2.8 ns on trace of $x = 1.5$ m when antennas are on the right side. In our experiments, we are able to find out that the 2.8 ns peak pulse is the reflection signal from the floor surface underneath rebar with the use of a large metal sheet. By covering the floor surface with a large metal sheet, a stronger reflection pulse is observed occurring at exactly the same time instant (2.8 ns), which validates the floor as the reflection source. With reference to Fig. 4(a), the distance between antennas and the rebar can be determined through the following calculations: 1) subtracting the time offset between antennas direct coupling pulse ($t = 0.5$ ns) (the transmitter antenna and receiver antenna are packed together inside of a box, the direct coupling pulse time is thus used as the reference time point) and the strongest STFT peak point ($t = 1.9$ ns), obtains time offset $\Delta t = 1.4$ ns and 2) inserting $\Delta t$ to the following equation:

$$V = \frac{d}{(\Delta t/2)}$$

where $d$ is the distance, $V$ is the speed of light in air ($3 \times 10^8$ m/s), and $(\Delta t/2)$ indicates one-way signal travel time from rebar to the receiver antenna. The distance $d$ is thus calculated to be 210 mm, which agrees well with the physical setup described in Section II-A, where antennas are placed 220 mm above the rebar.

For two rebars in a concrete slab setup, Fig. 15(a) extracts the intersected B-scan image section that focuses on rebars. Both STFT images of the left side trace (the trace at $x = 1.25$ m) [Fig. 15(b)] and right side trace (the trace at $x = 1.7$ m) [Fig. 15(c)] show two strong peaks (in red color) at 1.75 and 3.125 ns. These peak time values are used to compute rebars burying depths inside the concrete slab. The radar signal two-way travel time between concrete and rebars is calculated
to be $3.125 - 1.75 = 1.375$ ns. The electromagnetic (EM) wave travel velocity $V_c$ inside concrete needs to be considered, which equals

$$V_c = V / \sqrt{\varepsilon_c}$$  \hspace{1cm} (14)$$

where $\varepsilon_c$ is the relative dielectric constant of the concrete which equals about 4.1 according to our measurements conducted in [17]–[20]. $V$ is the speed of light in air, $V_c$ is calculated to be $1.48 \times 10^8$ m/s. Using (13) with $\Delta t = 1.375$ ns, the rebar burying depth from concrete surface is computed to be 102 mm approximately, which is in good agreement with the physical setups (98.6/108 mm depths) described in Section II.

B. Ballast Test Results

For ballast platform setup, entropy analysis is first applied to the B-scan image along $y$-axis, as shown in Fig. 16(a). Using OTSU thresholding method, two threshold values $K1^* = 5.08$ and $K2^* = 5.92$ are calculated. The singular regions have entropy values below threshold $K1^*$. As shown in Fig. 16(a), there are three regions whose entropy values are below this threshold. The first one locates between $t = 5.125$ and 6.00 ns, the second locates between $t = 11.00$ and 12.50 ns, and the third one locates between $t = 14.25$ and 17.50 ns.

Subsequently, Renyi’s entropy is computed along $x$-axis. Fig. 16(b) shows the obtained curve. Using OTSU thresholding method, two threshold values $K3^* = 4.88$ and $K4^* = 5.43$ are obtained. Similar to the analysis along $y$-axis, the singular region is below threshold $K3^*$, which locates between $x = 2.35$ m and $x = 2.75$ m. By combining both the $x$-axis and $y$-axis entropy analysis results, the intersection regions in the B-scan image are obtained. For the ballast platform setup, the extracted region is shown in Fig. 17.

To refine region identification, windowing STFT analysis is performed on a trace signal across three regions locating at $x = 2.5$ m. The corresponding STFT analysis result is shown in Fig. 18. As shown in Fig. 18, a strong peak occurs only between 11 and 12 ns. This result indicates that region 2 in Fig. 17 is the true singular region while regions 1 and 3 are false ones. Combining the results of entropy analysis and STFT analysis, the correct fouled ballast region is singled out as shown in Fig. 19. In this test case, the extracted region comprises less than 5% of the entire scanning data volume.

To validate the detection result, the fouled ballast region depth is computed in a similar way as in the rebar test. The ground surface reflection signal locates at $t = 8.5$ ns as shown in Fig. 6(a), and the detected region top side locates at $t = 11.0$ ns; therefore, the two-way travel time of radar incident signal between ground surface and moisture region is

![Fig. 16](image1.png)

![Fig. 17](image2.png)

![Fig. 18](image3.png)
Fig. 19. Final moisture region detection result based on entropy and STFT analysis.

11.0–8.5 = 2.5 ns. Substituting the measured dielectric constant of clean ballast into (14), \( V_c \) is calculated as 1.73 × 10^8 m/s. Using (13) with \( \Delta t = 1.25 \) ns, the depth of the fouled ballast region is computed as 0.216 m approximately. This value agrees well with the actual physical setups (0.2 m depth).

V. CONCLUSION

This paper has demonstrated the integration of 2-D entropy and STFT analytical methods to leverage GPR data-processing efficiency. By computing radargram 2-D entropy and OTSU thresholds, singular areas within large background data can be effectively extracted. The use of entropy analysis effectively reduces the data volume for implementing more sophisticated postprocessing algorithms. In our test experiments, around 60% data compression rate is achieved for rebar detection and 95% data compression rate is achieved for fouled ballast region detection. STFT is then applied for time-frequency characterization to leverage region detection accuracy and screen out false results. Note there are other more sophisticated JTF analysis methods, such as Gabor transform, wavelet, fractional Fourier transform, and so on, that are capable of more advanced characterizations when the data scope is more focused with the assistance of entropy calculation. STFT is generally sufficient for these applications that require marginal detection resolutions.

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