

## Article

# A Combined Wavelet–SVD Denoising and Wavelet Packet Decomposition Method for Quantitative GPR-Based Assessment of Compaction

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## Abstract

Ballast compaction is a critical factor influencing ballast bed condition and the operational safety of heavy-haul railways. However, existing quantitative evaluation methods often suffer from overly idealized simulation models and limitations in signal processing and assessment frameworks. To address these issues, this study proposes a quantitative analysis approach for ballast compaction by integrating non-uniform medium simulation modeling, wavelet–Singular Value Decomposition (SVD) joint denoising, frequency–wavenumber (F-K) migration imaging, and wavelet packet decomposition (WPD)-based feature extraction. Forward simulations were conducted based on the constructed model, and the proposed methodology was validated using 1.5 GHz (gigahertz, 1 GHz = 10<sup>9</sup> Hz) ground penetrating radar (GPR) data acquired from compaction experiments. The results demonstrate that wavelet–SVD joint denoising effectively suppresses deep coherent noise caused by strong reflections from sleepers, significantly enhancing the identification of deep effective signals and ensuring accurate localization and feature extraction of compaction zones. The Geometric Mean of WPD High/Low-Frequency Energy Ratio (GMHLFER) exhibits a strong positive correlation with the degree of compaction. In simulations, as the proportion of compacted material increased from 9% to 21%, the GMHLFER rose from 21.555 to 26.581. In field tests, the value increased from 22.012 to 26.012 as compaction severity progressed from slight to severe, demonstrating stable responses across full-gradient compaction conditions and indicating high robustness and sensitivity. The proposed method provides an effective approach for quantitative characterization of ballast compaction in heavy-haul railways, and offers a promising technical pathway for intelligent inspection and condition assessment of railway ballast beds.



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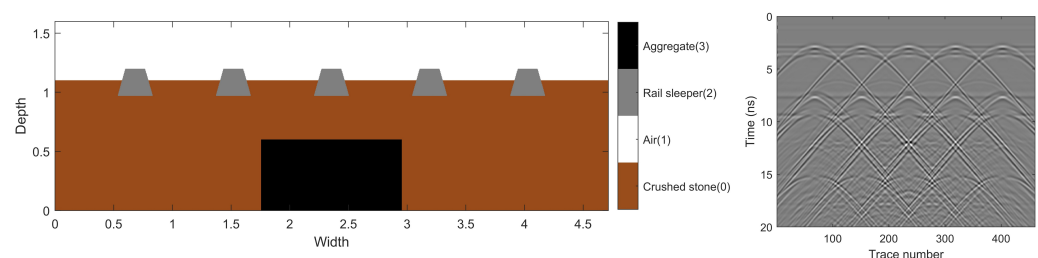
**Keywords:** ballast compaction; F-K migration; GPR; heavy-haul railway; wavelet–SVD joint denoising; WPD

## 1. Introduction

Railways undertake approximately 20% of the national passenger and freight turnover while consuming less than 10% of the total societal energy and producing a comparable proportion of emissions, highlighting their critical role in a comprehensive transportation

system. As a key component of the track structure, the ballast bed is primarily composed of clean aggregates, and its condition is closely related to railway operational safety. Defects such as moisture intrusion, loss of compaction, mud pumping, and slurry formation can degrade structural performance, alter the distribution of track stiffness, and adversely affect train running stability. Previous studies have shown that the deterioration of track structural performance is closely associated with the condition of the supporting structure, and that optimized maintenance strategies combined with condition-based assessment can effectively mitigate structural degradation and extend service life [1,2]. In particular, preventive maintenance and timely repair decision-making based on track condition evaluation play a crucial role in limiting defect accumulation and maintaining the mechanical integrity of the track system. Under long-term cyclic loading, ballast particles undergo continuous extrusion and friction, generating fine particles that gradually fill voids. Meanwhile, subgrade fines infiltrate into the ballast layer under rainfall and train-induced aerodynamic effects, further accelerating void clogging and reducing drainage capacity. With the accumulation of water, fine particles undergo fluidization and form a dense compacted layer under repeated train loading. This process weakens the elastic buffering capacity of the ballast bed, leading to increased wheel–rail dynamic interaction and more direct transmission of impact loads to the sleepers and the subgrade. As a result, track irregularities may be aggravated, the dynamic responses of the track structure are intensified, and fatigue damage of structural components is accelerated. In severe cases, these effects may compromise the stability of train operation and pose significant risks to railway operational safety. As a non-destructive testing technology, ground penetrating radar (GPR) has become an important tool for railway infrastructure assessment due to its high efficiency and non-invasive nature [3–5], and has been widely used to detect ballast defects such as moisture content, fouling, and compaction condition [6–8].

Most current research utilizing GPR for ballast bed evaluation relies on forward modeling results derived from simulation models. However, a critical limitation lies in the widespread assumption of homogeneous media in existing ballast bed models [9,10]. As illustrated in Figure 1, the compacted zone is typically idealized as a regular rectangular region classified as a single uniform medium. In reality, ballast bed compaction results from long-term particle crushing and compaction under cyclic loading, forming a multiphase mixture comprising broken ballast fragments, fine aggregates, and interstitial air. These idealized homogeneous models fail to incorporate random noise and exhibit substantial discrepancies from actual field conditions. Consequently, simulation outcomes struggle to reflect real-world scenarios, significantly limiting their engineering reference value.

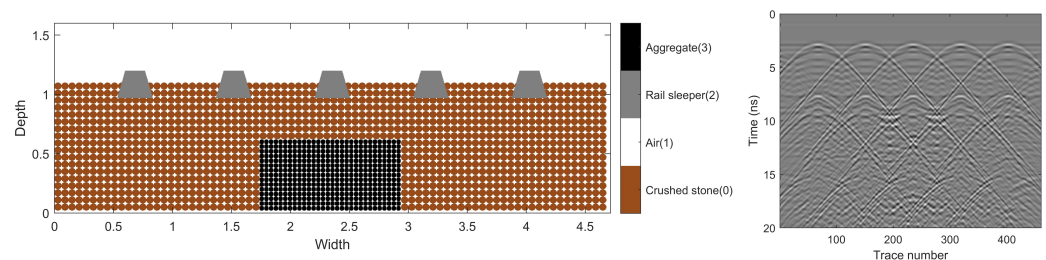


**Figure 1.** Uniform medium model.

Refined compaction models [11–14] represent ballast particles using two-dimensional disks or three-dimensional spheres (Figure 2). By simulating particle accumulation and rearrangement, these approaches capture the spatial structure and evolutionary process of compaction with markedly higher fidelity than their homogeneous counterparts. A key advantage lies in the adjustability of particle diameter to simulate progressive wear—smaller diameters indicate more severe degradation and indirectly reflect compaction degree. How-



ever, certain idealized limitations remain. First, ballast particles are simplified as regular circular shapes, which deviate from their actual geometrical characteristics. Second, a systematic set of quantitative indices for compaction severity is still lacking, making it difficult to support reliable quantitative evaluation.



**Figure 2.** Circular ballast model.

Existing studies have primarily focused on the relationship between GPR signal characteristics and subsurface medium conditions, aiming to achieve the identification and quantitative evaluation of ballast-related defects through signal analysis and feature extraction. On the one hand, at the level of signal mechanisms, previous studies have optimized the dominant frequency and bandwidth analysis of multi-frequency three-dimensional GPR signals to achieve precise localization of ballast contamination zones [15]. Building upon this, further investigations have examined the influence of crack width and different infill materials on GPR reflection characteristics, thereby revealing the variation patterns of signal responses under different medium conditions [16]. On the other hand, from an engineering application perspective, studies addressing ballast fouling and structural degradation have proposed rapid detection methods based on time-domain and frequency-domain response characteristics, enabling quantitative identification of coal dust thickness in heavy-haul railway ballast [17]. Meanwhile, by comparing the performance of different antenna types and operating frequencies, the influence of equipment parameters on detection accuracy has been systematically analyzed, providing guidance for antenna selection and parameter optimization in ballast layer inspection [18,19]. Overall, existing studies have contributed significantly to GPR-based ballast condition assessment from both signal mechanism analysis and engineering application perspectives.

Railway track stiffness, which is significantly influenced by ballast compaction conditions, has been extensively investigated using various measurement methods. According to Wang et al. [20], existing track stiffness measurement approaches can be broadly classified into four categories: jack loading methods [21], impact hammer tests [22], falling weight deflectometer (FWD) methods [23], and track loading vehicle (TLV) methods [24]. These methods typically evaluate the overall stiffness characteristics of the track structure by applying static or dynamic loads and measuring the load–displacement response, and have been widely used in the analysis of the mechanical behavior of ballast and substructure layers. It has been shown that jack loading methods are suitable for localized stiffness measurements, impact-based methods can characterize dynamic structural responses, FWD methods enable rapid field assessment, and TLV systems allow continuous stiffness evaluation along railway lines.

However, it should be noted that the aforementioned methods are primarily based on mechanical response measurements and typically rely on external loading or vibration excitation. In comparison, studies on stiffness-related evaluation from a signal analysis perspective remain relatively limited, particularly in establishing the relationship between subsurface structural conditions (such as ballast compaction) and non-destructive signal features. Therefore, it is necessary to explore efficient and non-destructive signal-based approaches for the quantitative evaluation of ballast conditions.

GPR has demonstrated effectiveness in detecting subsurface anomalies and holds significant engineering value for identifying ballast fouling and compaction defects in railway infrastructure. However, the difficulty of obtaining high-quality measured data validated by excavation restricts the intelligent identification and detection of internal ballast defects [25–30]. In the quantitative evaluation of feature parameters, existing studies still lack a systematic mechanism for key parameter selection, leading to significant variability among features and limited quantitative capability, which makes it difficult to effectively support reliable determination of compaction levels. Furthermore, current ballast simulation models are predominantly constructed using homogeneous medium assumptions and regular geometric simplifications, neglecting the realistic shape of ballast particles and on-site noise interference. This leads to low fidelity with actual engineering conditions and limited reference value.

To address the above issues, this study proposes a quantitative evaluation method for ballast compaction based on GPR signal feature screening. The method achieves stable characterization and reliable discrimination of compaction conditions through the optimization of feature parameters and the construction of an optimal feature space. To this end, a non-uniform medium simulation modeling of the ballast bed, capable of representing the realistic random distribution characteristics of ballast particles, is first developed, thereby improving the engineering fidelity of the simulation results. In terms of signal processing, wavelet–Singular Value Decomposition (SVD) joint denoising and frequency–wavenumber (F–K) migration are employed to achieve noise suppression, feature preservation, and qualitative localization of compacted zones. On this basis, multiple feature parameters are systematically screened through comparative analysis between simulated and measured data, enabling the identification of optimal features for quantitative compaction evaluation. Conventional methods based on mechanical response are capable of measuring track stiffness and evaluating structural conditions; however, they typically rely on external loading and have limitations in directly characterizing ballast compaction. In contrast, the proposed method, while retaining the advantages of non-destructive testing, emphasizes feature screening and feature space construction, and is expected to improve the stability and consistency of evaluation results, enhance robustness against noise and environmental variability, and thereby provide more reliable support for railway condition assessment.

This study is based on the following scientific hypothesis: variations in ballast compaction conditions will induce systematic changes in GPR signal characteristics in both the time and frequency domains, and different feature parameters exhibit varying levels of sensitivity and stability in characterizing compaction conditions. By performing systematic screening and optimal combination of multiple feature parameters, a feature space with stable representation capability can be constructed, thereby enabling reliable quantitative evaluation of ballast compaction conditions. Based on this hypothesis, this study further develops the methodological framework and conducts validation analysis.

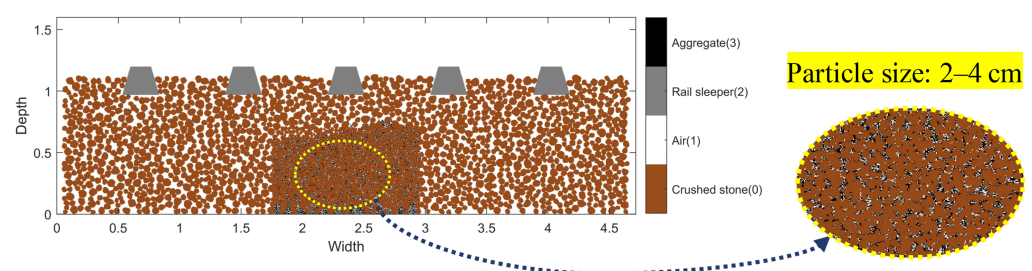
The remainder of this paper is organized as follows. Section 2 presents the proposed methodology, including the construction of the non-uniform ballast model, the wavelet–SVD joint denoising approach, F–K migration, and wavelet packet decomposition-based feature extraction. Section 3 describes the acquisition and preprocessing of both simulation and field GPR data. Section 4 provides the results and analysis, including model validation, signal processing performance, and feature evaluation for different compaction conditions. Finally, Section 5 summarizes the main conclusions and discusses the potential applications and future research directions.

## 2. Methodology

This section systematically introduces the overall methodology proposed in this study for the quantitative assessment of ballast compaction. It includes five core parts: non-uniform medium modeling of ballast bed, wavelet–SVD joint denoising, F-K migration imaging, WPD and feature parameter extraction. Through the integrated processing of modeling, noise suppression, imaging correction and feature quantification, this methodology aims to realize accurate identification and stable quantitative characterization of ballast compaction degrees in heavy-haul railways.

### 2.1. Modeling Methodology

This study proposes a method for establishing a ballast bed model by assigning values to an array, distinguishing medium types through numerical values. The electromagnetic properties of each medium are defined in an external material configuration file, with the integer values in the array directly corresponding to the sequential instruction numbers in the material text file, thereby enabling accurate mapping of material properties. Regarding the modeling of ballast particles, the irregular geometric morphology of ballast is reconstructed. The diameter of ballast particles in the clean ballast zone is controlled within the range of 0.04 m to 0.07 m. Following the ballast modeling process, the ballast region is progressively filled with particles. Particle positions are initialized using randomly generated centroid coordinates. To prevent the occurrence of suspended particles within the model, a settlement function is introduced to simulate gravitational effects. Ballast particles are continuously added until the designated ballast region reaches the specified filling density. The compacted defect zone is characterized using irregular geometries. The size of ballast particles filled within this zone is smaller than that in the clean ballast zone, with diameters controlled within the range of 0.02 m to 0.04 m. This reduction simulates the crushing effect induced by mutual extrusion and friction among ballast particles under long-term cyclic loading, ensuring that the formation mechanism of the compacted zone remains consistent with engineering reality. Concurrently, compacted aggregates are randomly distributed within the intergranular voids. Their volumetric proportion within the entire compacted region serves as a quantitative indicator of compaction severity. The resulting non-uniform medium ballast bed model is presented in Figure 3.



**Figure 3.** Non-uniform medium model.

Three quantitative indicators are introduced to assess the similarity between simulated and measured GPR data: spectral similarity, phase consistency, and image entropy similarity. These three indicators correspond respectively to the orthogonal amplitude and phase components of the Fourier transform, and jointly account for global statistical properties, local frequency characteristics, deterministic structural features, and stochastic variability. This multi-dimensional evaluation framework overcomes the inherent limitations of single-parameter assessments, enabling a comprehensive and objective quantification of model fidelity from three physically interpretable perspectives: those of frequency-domain charac-

teristics, spatial structural similarity, and information complexity. The spectral similarity is formulated as

$$S_{\text{spec}} = \max(0, \min(1, \rho[\log(|F(A)| + 1), \log(|F(B)| + 1)])) \quad (1)$$

where  $A$  and  $B$  are the two-dimensional matrices of the field data and model data,  $F(\cdot)$  is the two-dimensional Fourier transform, and  $\rho[\cdot, \cdot]$  is the Pearson correlation coefficient.

The phase consistency is formulated as

$$S_{\text{Phase}} = \frac{1}{MN} \sum_{i=1}^N \sum_{j=1}^M \left[ 1 - \frac{|\phi_A(i, j) - \phi_B(i, j)|}{\pi} \right] \quad (2)$$

where  $\phi_A(i, j)$  and  $\phi_B(i, j)$  are the phase values of the field data and model data at position  $(i, j)$ , respectively.

The image entropy similarity is formulated as

$$S_{\text{entropy}} = \exp\left(-\frac{|H(A) - H(B)|}{5}\right) \quad (3)$$

where  $H(I)$  is the Shannon entropy of image  $I$ .

## 2.2. Wavelet–SVD Joint Denoising Model

To effectively denoise GPR signals, a denoising model based on multi-scale decomposition and low-rank approximation is proposed. This model simultaneously constrains the signal in both the frequency domain and the matrix domain, achieving a balance between noise suppression and structural preservation. A two-dimensional wavelet decomposition with  $L$  levels is performed on the original image.

$$F \xrightarrow{w} \{A_L, H_k, V_k, D_k\} \quad (4)$$

In this decomposition,  $A_L$  is the  $L$ -level approximation coefficient matrix,  $H_k$  is the  $k$ -level horizontal detail coefficient matrix,  $V_k$  is the  $k$ -level vertical detail coefficient matrix, and  $D_k$  is the  $k$ -level diagonal detail coefficient matrix. Wavelet decomposition effectively separates information across different frequency scales, concentrating random noise predominantly within the high-frequency sub-bands while preserving the representation of subsurface structures in the low-frequency and relevant detail sub-bands. Singular Value Decomposition is performed on an arbitrary sub-band matrix  $W$ .

$$W = USV^T \quad (5)$$

where  $U$  is the left singular matrix,  $S$  is the singular value matrix, and  $V^T$  is the transpose of the right singular matrix. The singular values satisfy  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r \geq 0$ .

The cumulative energy ratio is defined as

$$\eta_k = \frac{\sum_{i=1}^k \sigma_i^2}{\sum_{i=1}^r \sigma_i^2} \quad (6)$$

where  $k$  is the number of retained singular values.  $\alpha$  is the preset energy retention ratio. When  $\eta_k \geq \alpha$  is satisfied, the first  $k$  singular values are retained while the remaining ones are set to zero, yielding the low-rank approximation

$$W_k = \sum_{i=1}^k \sigma_i u_i v_i^T \quad (7)$$

According to the Eckart–Young theorem [31], this low-rank reconstruction represents the optimal approximation in the sense of the Frobenius norm. Consequently, SVD truncation fundamentally constitutes an optimal energy compression process. All sub-bands processed by SVD are subsequently recombined, and the inverse wavelet transform is performed:

$$F_{\text{dénóise}} = W^{-1}(A'_L, H'_k, V'_k, D'_k) \quad (8)$$

The final denoised B-scan image is then obtained.

### 2.3. F-K Migration

F-K migration is a wavefield correction technique implemented in the frequency–wavenumber domain. The migration process relocates scattered wave energy from its apparent position to its true spatial position, thereby providing critical support for qualitative anomaly identification and spatial localization. This method is of significant importance for enhancing the detection accuracy of subsurface defects. Based on the electromagnetic wave equation, F-K migration achieves wavefield reconstruction through forward and inverse transformations between the time–space domain and the frequency–wavenumber domain. The two-dimensional Fourier transform is applied to the signal to convert the original signal from the  $t - x$  domain to the  $f - k_x$  domain, thereby mapping the signal from the time–space domain to the frequency–wavenumber domain. The transformation is formulated as

$$F(k_x, \omega) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, t) e^{-i(k_x x + \omega t)} dx dt \quad (9)$$

where  $f(x, t)$  is the original signal in the  $t - x$  domain,  $F(k_x, \omega)$  is the transformed signal in the  $f - k_x$  domain,  $f$  is the signal frequency,  $k_x$  is the spatial wavenumber, and  $\omega = 2\pi f$  is the angular frequency.

In the frequency–wavenumber domain, the propagation of electromagnetic waves along the depth direction of the ballast bed can be realized through wavefield extrapolation. The wavefield at depth  $z$  is expressed as

$$F(k_x, z, \omega) = F(k_x, z = 0, \omega) e^{ik_z z} \quad (10)$$

where  $F(k_x, z = 0, \omega)$  is the frequency–wavenumber domain signal at depth  $z = 0$  and  $k_z$  is the wavenumber in the depth direction, which can be derived from the electromagnetic wave dispersion relation as  $k_z = \sqrt{\left(\frac{\omega}{v}\right)^2 - k_x^2}$ , where  $v$  is the propagation velocity of the electromagnetic wave in the ballast medium, calculated from the dielectric constant  $\epsilon_r$  via  $v = c/\sqrt{\epsilon_r}$ , and  $c = 3 \times 10^8$  m/s is the speed of light in vacuum.

Electromagnetic waves undergo round-trip propagation from transmission to reception. The coordinate transformation of the frequency variable is performed via Stolt mapping to achieve accurate repositioning of reflected waves. A new frequency variable  $\omega'$  is introduced and satisfies

$$\omega' = v \sqrt{k_x^2 + k_z^2} \quad (11)$$

This mapping transforms the frequency–wavenumber domain coordinates from  $(k_x, \omega)$  to  $(k_x, k_z)$ . Through an interpolation algorithm, the transformed frequency points are matched to the original sampling grid, thereby achieving accurate phase correction of the wavefield.



The corrected frequency–wavenumber domain signal is transformed back to the time–space domain via the two-dimensional inverse Fourier transform, yielding the migrated signal.

$$f(x, z) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} F(k_x, k_z) e^{i(k_x x + k_z z)} dk_x dk_z \quad (12)$$

At this stage, the imaged position of the scatterer coincides with its actual spatial location, enabling the delineation of the defect region.

#### 2.4. Wavelet Packet Decomposition

Wavelet packet decomposition (WPD) is fundamentally based on quadrature mirror filters [32–34]. A wavelet function is selected, which corresponds to a pair of finite-length quadrature mirror filters satisfying the orthogonal condition as

$$g[k] = (-1)^k h[L - 1 - k] \quad (13)$$

where  $h[k]$  is the low-pass decomposition filter and  $g[k]$  is the high-pass decomposition filter.

WPD iteratively applies the aforementioned filters to decompose the signal. The total number of decomposition levels is set to  $J$ . Upon completion of the decomposition,  $2^J$  sub-bands are obtained at level  $J$  as terminal nodes. The wavelet packet coefficients at node  $(j, n)$  are denoted as  $c_j^n[m]$ , where  $j$  is the decomposition level,  $n$  is the node index within that level, and  $m$  is the sequence index of the coefficients at that node.

#### 2.5. Wavelet Packet Decomposition Feature Parameters

Layer 0 of WPD corresponds to the original signal itself. For each node at layer  $j - 1$ , it is decomposed into two new nodes at layer  $j$ .

The low-frequency child node  $(j, 2n)$  is expressed as

$$c_j^{2n}[m] = \sum_k h[k] c_{j-1}^n[2m - k] = (c_{j-1}^n * \bar{h}) \downarrow 2 \quad (14)$$

The high-frequency child node  $(j, 2n + 1)$  is expressed as

$$c_j^{2n+1}[m] = \sum_k g[k] c_{j-1}^n[2m - k] = (c_{j-1}^n * \bar{g}) \downarrow 2 \quad (15)$$

Upon completion of the decomposition, focus is placed on the  $N = 2^J$  terminal nodes at level  $J$ . Let the coefficients of node  $(J, i)$  be denoted as  $\{d_i[m]\}_{m=1}^M$ , where  $i = 0, 1, \dots, N - 1$ , and  $M$  is the length of the coefficient sequence at that node.

The sub-band energy is calculated as

$$E_i = \sum_{m=0}^M |d_i[m]|, \quad i = 0, 1, \dots, N - 1 \quad (16)$$

The energy distribution probability is formulated as

$$P_i = \frac{E_i}{E_{\text{total}}} \quad (17)$$

where  $E_{\text{total}}$  is the total energy. Wavelet packet energy entropy (WPEE) quantifies the uniformity or randomness of signal energy distribution across frequency sub-bands. As compaction severity increases, numerous random scatterers are introduced, redistributing

energy into higher-frequency sub-bands. This intensifies signal randomness and leads to an increase in entropy. WPEE is calculated as follows

$$\text{WPEE} = \frac{\sum_{i=0}^{N-1} P_i \ln\left(\frac{P_i}{U_i}\right)}{\ln(q)} = \frac{\sum_{i=0}^{N-1} P_i \ln(P_i) - \sum_{i=0}^{N-1} P_i \ln(1/N)}{\ln(q)} \quad (18)$$

Since  $\sum P_i = 1$  and  $\ln(1/N) = -\ln(N)$ , the above equation can be simplified as

$$\text{WPEE} = \frac{\sum_{i=0}^{N-1} P_i \ln(P_i) + \ln(N)}{\ln(q)} \quad (19)$$

Wavelet Packet Sub-band Energy Kurtosis (WPSEK) is adopted to evaluate whether the energy distribution across sub-bands exhibits sharp-peak and heavy-tail characteristics—specifically, the presence of frequency bands with exceptionally concentrated energy. When ballast compaction occurs, reflected wave energy becomes concentrated within a limited number of frequency bands, producing distinct sharp peaks in the energy distribution spectrum. This phenomenon directly indicates the formation of a strong reflecting interface induced by compaction. The WPSEK is calculated as follows

$$\text{WPSEK} = \frac{1}{N} \sum_{i=0}^{N-1} \left( \frac{l_i - \mu_l}{\sigma_l} \right)^4 \quad (20)$$

where  $l_i = \ln(E_i + \text{eps})$  is the logarithmic value of the energy,  $\mu_l = \frac{1}{N} \sum_{i=0}^{N-1} l_i$  is the mean, and  $\sigma_l = \sqrt{\frac{1}{N} \sum_{i=0}^{N-1} (l_i - \mu_l)^2}$  is the standard deviation.

The compacted layer tends to retain more moisture, leading to an increase in the dielectric constant. As electromagnetic waves propagate through this medium, high-frequency components attenuate more rapidly, resulting in a relative reduction in high-frequency energy and a corresponding increase in the low-frequency-to-high-frequency energy ratio. Geometric Mean of WPD High/Low-Frequency Energy Ratio (GMIHLFER) quantifies the shift of the signal spectrum centroid toward lower frequencies.

$$\text{GMIHLFER} = \ln\left(\frac{E_{\text{low}}}{E_{\text{high}} + \text{eps}}\right) \quad (21)$$

### 3. Data Acquisition

This section describes the source and preprocessing flow of the data used in this study, including simulation data and field measured GPR data. The simulation data were generated based on the established non-uniform medium model with different compaction ratios, while the field data were collected from an in-service heavy-haul railway line with verified compaction grades. Standard preprocessing procedures were applied to ensure the reliability of subsequent signal analysis and feature extraction.

#### 3.1. Simulation Data

Forward simulations were conducted using gprMaxv3.1.7 to generate GPR data based on the non-uniform medium ballast model proposed in the preceding section. The model geometry was imported via an external H5 file, together with the corresponding material configuration file. A total of five simulation models were established, with the proportion of compacted material ranging from 9% to 21% at incremental steps of 3%. The forward modeling parameters are summarized in Table 1.

When analyzing ballast compaction defects, individual A-scan signals often contain random noise and locally scattered high-frequency components that are spatially inco-

herent, making it difficult for single-trace data to reliably represent the overall structural response of the medium. Therefore, an averaging process is introduced to stack multiple traces, which preserves spatially coherent signal components while effectively suppressing random noise, thereby improving the signal-to-noise ratio and making the results more representative to some extent. Specifically, traces within the range of 160–280 were averaged, and representative traces (Nos. 190, 220, 250, and 280) were selected for comparison. All signals were normalized prior to analysis. As shown in the normalized A-scan comparison (Figure 4), the selected traces exhibit similar oscillatory patterns within the main time windows, which provides support for the rationality of the averaging approach.

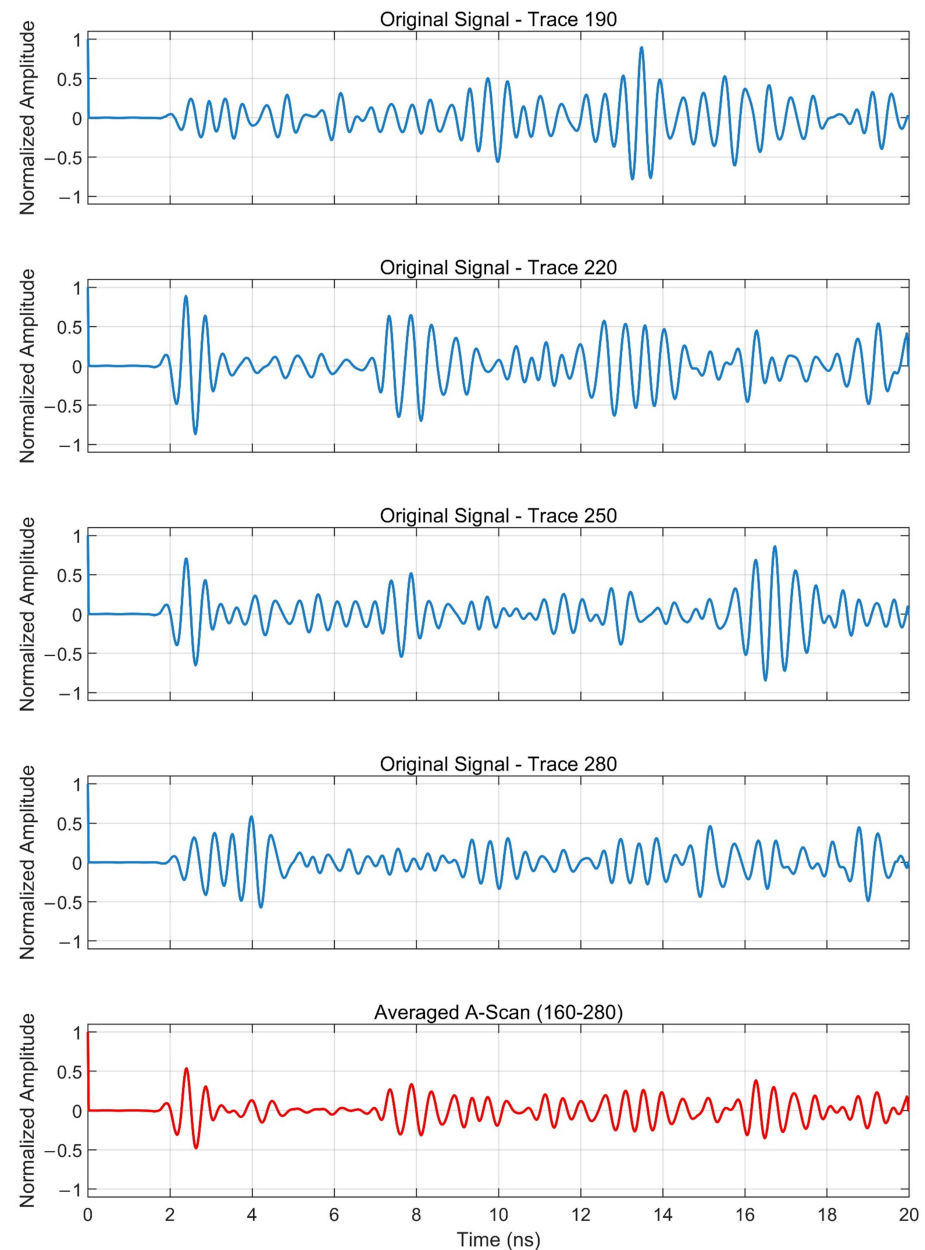
**Table 1.** Summary of forward modeling parameters.

| Parameters                   | Values                                  | Unit |
|------------------------------|-----------------------------------------|------|
| Model size                   | $4.716 \times 1.600$                    | m    |
| Central frequency            | 1.5                                     | GHz  |
| Grid size                    | $\Delta x = \Delta y = \Delta z = 0.02$ | m    |
| Time window                  | 20                                      | ns   |
| Scan interval                | 0.01                                    | m    |
| Antenna distance (TX and RX) | 0.01                                    | m    |
| Excitation wave type         | Ricker                                  | -    |
| Trace number                 | 460                                     | -    |

The averaged results indicate that the waveform still retains the fundamental oscillatory structure within the primary time windows. In particular, the oscillation patterns in the ranges of 2–4 ns, 7–10 ns, and 13–17 ns are preserved to a large extent, suggesting that the averaging process maintains the dominant frequency characteristics of the signal to some degree. Meanwhile, high-frequency details are significantly reduced, resulting in a smoother overall waveform. This phenomenon can be regarded, to some extent, as analogous to a spatial low-pass filtering effect. Therefore, the averaging method is suitable for the overall evaluation of ballast compaction conditions, as it helps to highlight the main reflection characteristics associated with the subsurface structure.

However, it should be noted that averaging also has certain limitations in representing localized features. For anomalies that appear only in a few traces or have limited spatial extent, their high-frequency characteristics may be weakened or even lost during the averaging process, thereby reducing their detectability. Consequently, while averaging is effective for extracting spatially consistent background information, it is relatively limited in characterizing localized anomalies and should be complemented with other analysis methods.

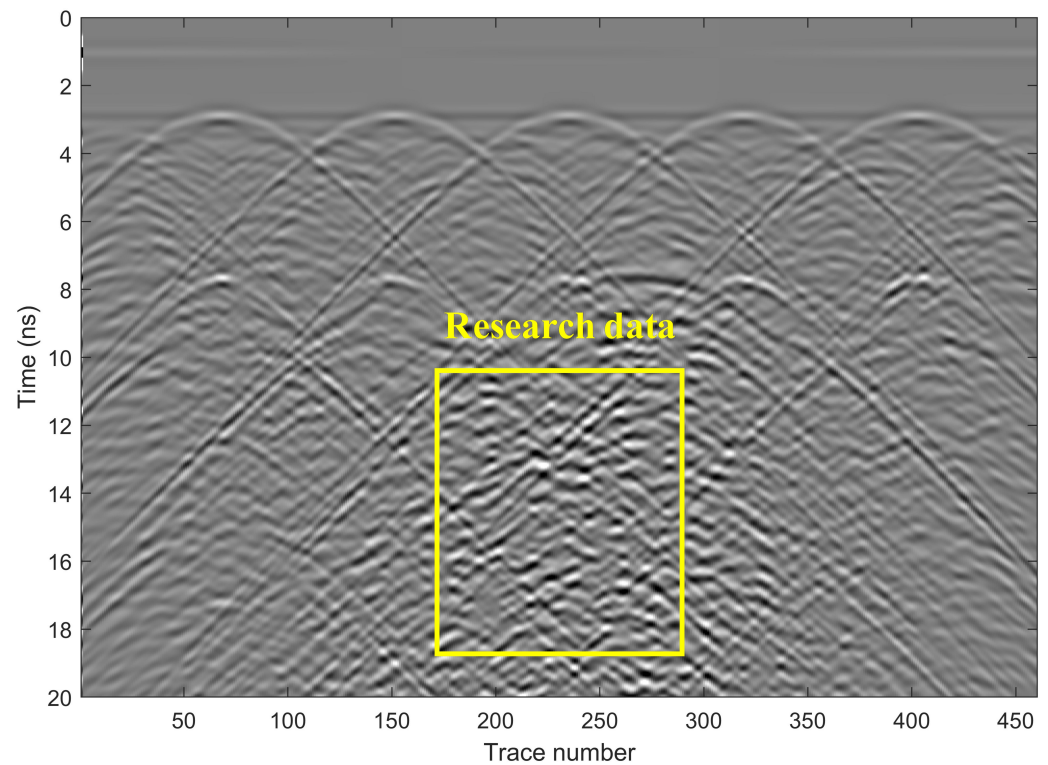
For the simulation data, scan traces containing the compaction defect region were extracted by selecting an appropriate trace number range. Considering that strong reflections from sleepers can significantly interfere with the analysis of deeper signals within the ballast bed, the time sampling window was further constrained during preprocessing to remove these high-amplitude reflections. Specifically, the selected trace range was 160–280, and the time sampling range was 2400–4000, corresponding to approximately 11–18 ns. The signal within the highlighted box in Figure 5 represents the selected dataset. The retained data were then averaged, and the mean waveform was taken as the final dataset for subsequent analysis.



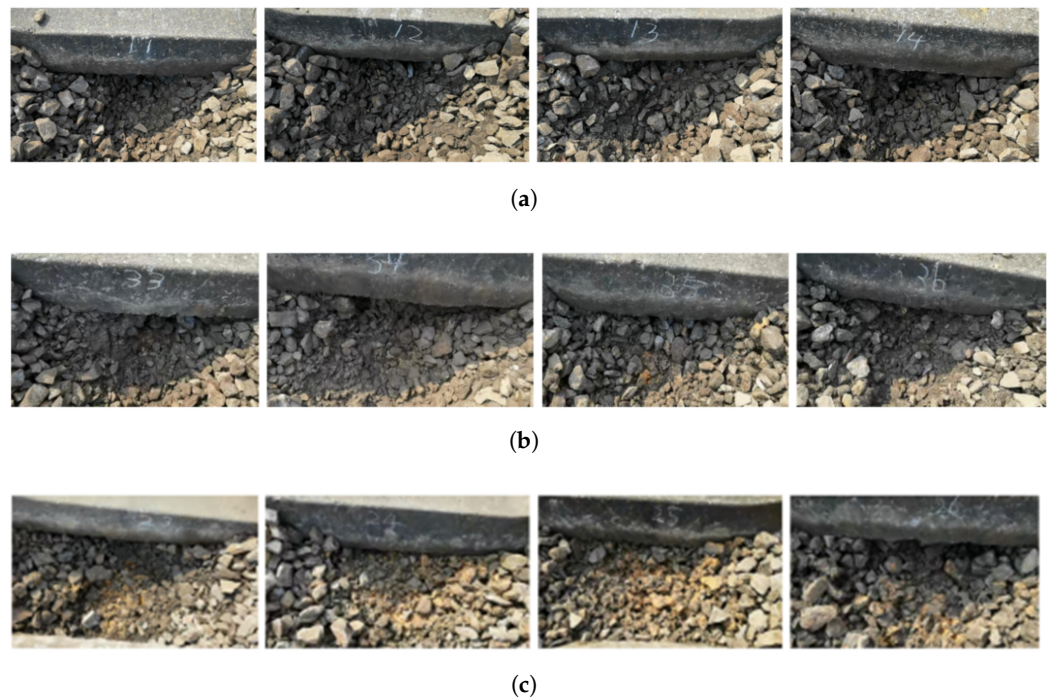
**Figure 4.** Comparison of normalized A-scan signals and averaged waveform (traces 160–280).

### 3.2. Field Data

Field investigations were conducted along a heavy-haul railway line in China. A 1.5 GHz ground penetrating radar (GPR) system was used to acquire data at a height of 30 cm above the sleeper surface, with a trace interval of 0.0225 m and a time window of 18 ns. After data acquisition, excavations were carried out at the center position between every two sleepers, and each excavated pit was labeled. Based on visual inspection, the severity of ballast compaction was empirically classified into three grades: slight, moderate, and severe. To minimize data variability, four consecutive excavated pits with consistent compaction severity were selected for each grade. Photographs of the excavated pits and their corresponding labels are presented in Figure 6.



**Figure 5.** Forward-simulated B-scan image of the simulation model.

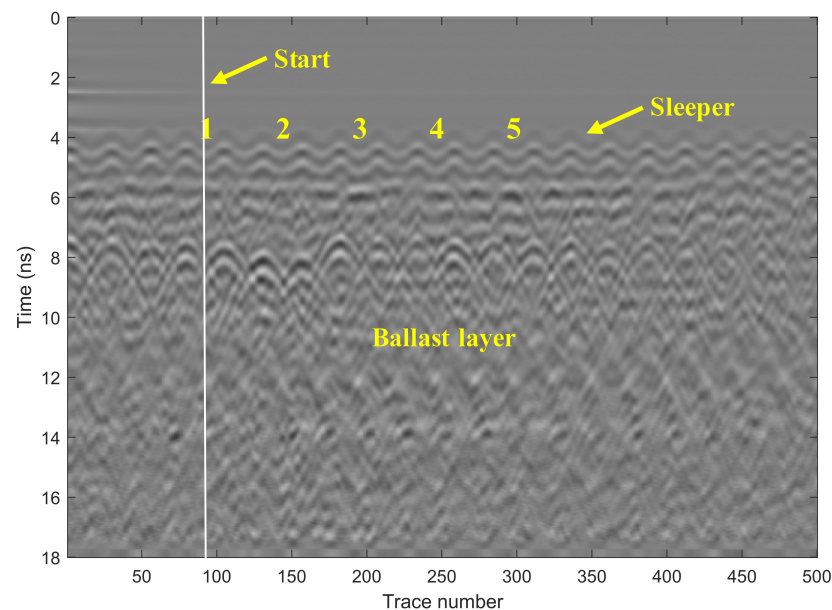


**Figure 6.** Field photographs of ballast compaction defects: (a) Field photograph of slight compaction; (b) field photograph of moderate compaction; (c) field photograph of severe compaction.

By aligning the marked starting position of data acquisition with the periodic strong reflection signals generated by sleepers, the radar data traces corresponding to each labeled excavation pit were precisely identified. As illustrated in Figure 7, taking pits 1 to 5 as an example, the starting position corresponds to pit 1, and each subsequent pit is located at the position every two strong reflection signals. This method enables the accurate localization of GPR signals corresponding to different levels of ballast compaction. The selected field



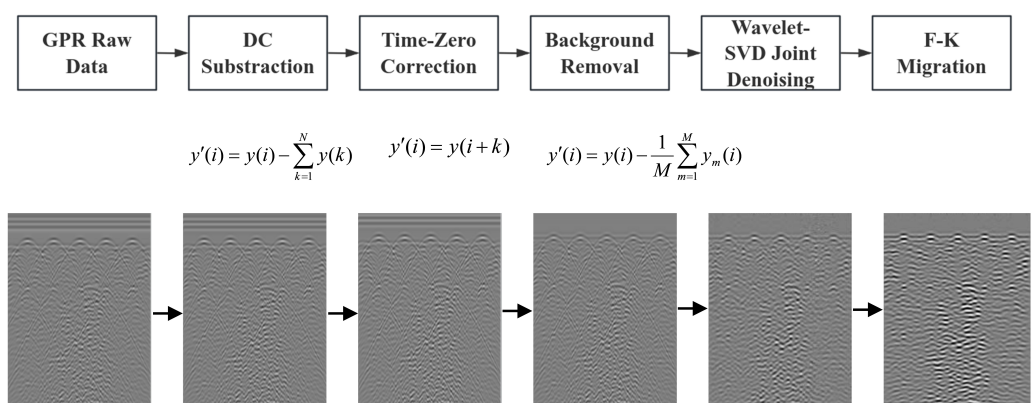
data were processed using the same workflow as the simulation data to remove sleeper reflections. To minimize randomness, the processed traces were averaged, and the resulting data were used as the final research dataset.



**Figure 7.** B-scan example of field data.

### 3.3. Data Preprocessing

GPR data are subject to multiple interferences, including environmental noise, strong sleeper reflections, and medium heterogeneity. In addition, issues such as DC offset and baseline drift further exacerbate the aliasing of reflection signals from compacted areas, impairing both visual interpretation and defect localization. To address these challenges, a preprocessing workflow was implemented to enable qualitative identification of compaction defects, as illustrated in Figure 8. The procedure comprises five steps: (1) DC Subtraction, (2) Time-Zero Correction, (3) Background Removal, (4) Wavelet-SVD Joint Denoising, and (5) F-K Migration. Throughout the entire preprocessing workflow, the signal gain remains constant to ensure that amplitude variations reflect only subsurface physical properties rather than artificial scaling. The resulting B-scan image accurately delineates the spatial distribution of compacted regions, providing a reference for the extraction range of the research data.



**Figure 8.** Flowchart of signal preprocessing.

#### 4. Results and Analysis

A subset of field measurements was randomly selected to evaluate the fidelity of the three simulation models. It should be noted that, to ensure a fair comparison, all models were constructed within a unified simulation framework, including identical mesh discretization, time window settings, computational domain, and signal processing procedures. The only distinction among the models lies in the representation of the internal ballast structure. Therefore, the variations observed in the normalized metrics—spectral similarity, phase consistency, and image entropy—primarily reflect differences in structural characteristics. The specific results are presented in Table 2.

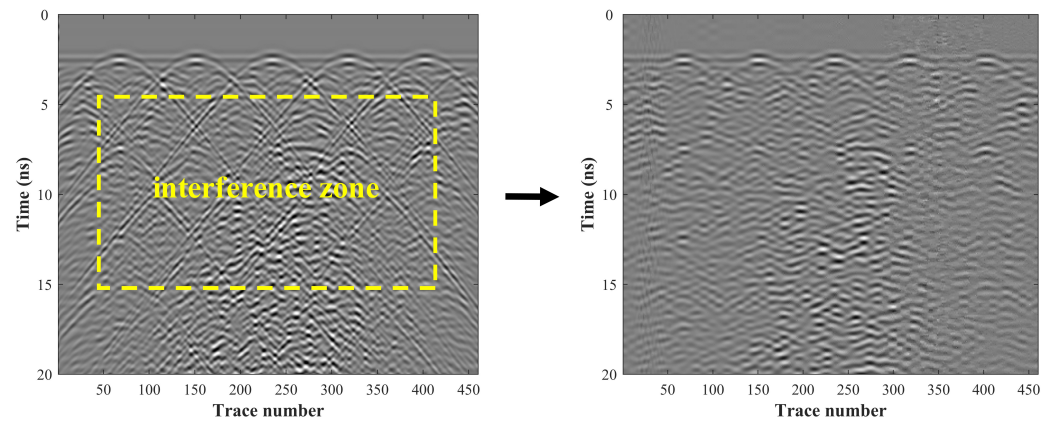
In terms of spectral similarity, the non-uniform medium model achieved a score of 0.546, surpassing both the homogeneous medium model (0.467) and the circular ballast model (0.519), representing improvements of approximately 16.9% and 5.2%, respectively. Regarding phase consistency, the non-uniform medium model attained a score of 0.428, closely matching the homogeneous medium model (0.424) while significantly outperforming the circular ballast model (0.233). For image entropy similarity, the non-uniform medium model scored 0.920, exceeding the circular ballast model (0.909) and substantially outperforming the homogeneous medium model (0.690), corresponding to an improvement of approximately 33.3%.

The comprehensive evaluation of these three indicators demonstrates that the non-uniform medium model exhibits optimal performance in terms of spectral structure, phase characteristics, and image information distribution, achieving the highest consistency with field measurements. These results indicate that the proposed model possesses superior capability in replicating actual detection scenarios and achieves stronger agreement with engineering field conditions.

**Table 2.** Similarity scores of three simulation models.

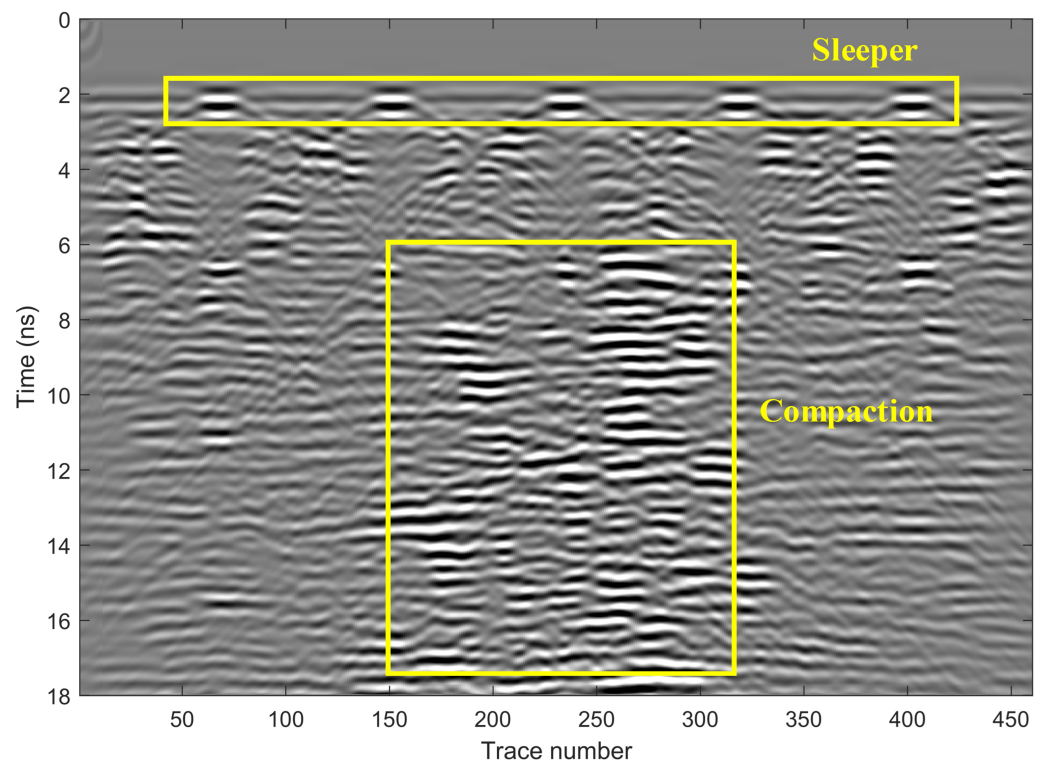
| Model                    | Spectral Similarity | Phase Consistency | Image Entropy Similarity |
|--------------------------|---------------------|-------------------|--------------------------|
| Homogeneous medium model | 0.467               | 0.424             | 0.690                    |
| Circular ballast model   | 0.519               | 0.233             | 0.909                    |
| Non-uniform medium model | 0.546               | 0.428             | 0.920                    |

The denoising effect of the joint wavelet–SVD method is illustrated in Figure 9. A comparison of the profiles before and after processing reveals that, in the raw data, strong reflection energy generated by sleepers extends downward along the time axis, forming a relatively continuous interference zone in the deeper region. This significantly impacts the identification and interpretation of deep effective reflection signals, partially masking genuine geological responses. Following wavelet–SVD processing, the deep interference caused by high-amplitude sleeper reflections is substantially attenuated. The vertical continuity of anomalous energy is effectively suppressed, and the visibility of deep effective signals is notably enhanced, without exhibiting excessive smoothing or waveform distortion. These results demonstrate that wavelet decomposition enables the separation and localization of locally anomalous high-amplitude responses within the multi-scale domain. Subsequently, SVD low-rank reconstruction further mitigates the non-target coherent interference energy arising from strong sleeper scattering through optimization of the singular value structure of the data matrix, thereby achieving reasonable suppression of anomaly-dominant singular components. While preserving the principal reflection structural features, this approach effectively controls strong reflection artifacts, consequently improving overall data quality.



**Figure 9.** Denoising effect comparison of wavelet-SVD joint method.

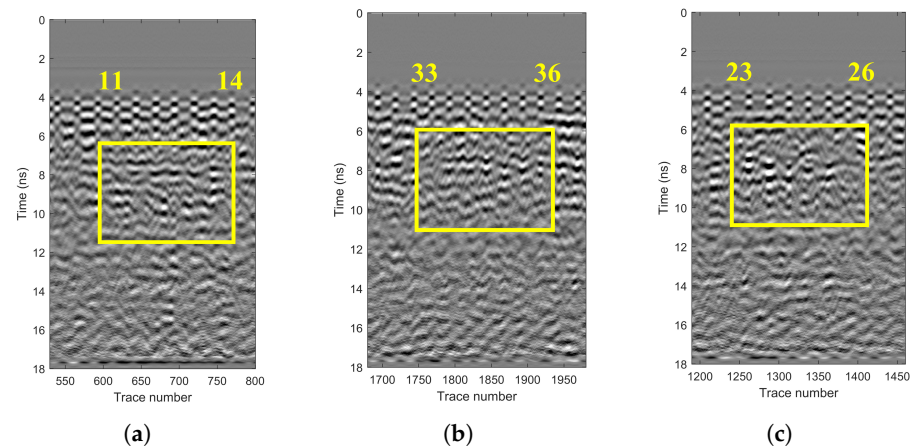
Following preprocessing via DC Subtraction, Time-Zero Correction, Background Removal, Noise Removal, and F-K Migration, geometric distortions in the GPR signals were effectively corrected. The spatial contours and boundary positions of the compacted defect areas were clearly delineated. The qualitative identification performance is analyzed below using both simulated and field data. Figure 10 presents the simulated data after the series of preprocessing steps, in which the contour and boundary of the compacted defect area are distinctly highlighted. This provides a solid foundation for the subsequent accurate extraction of data related to compaction defects.



**Figure 10.** Processed simulation data.

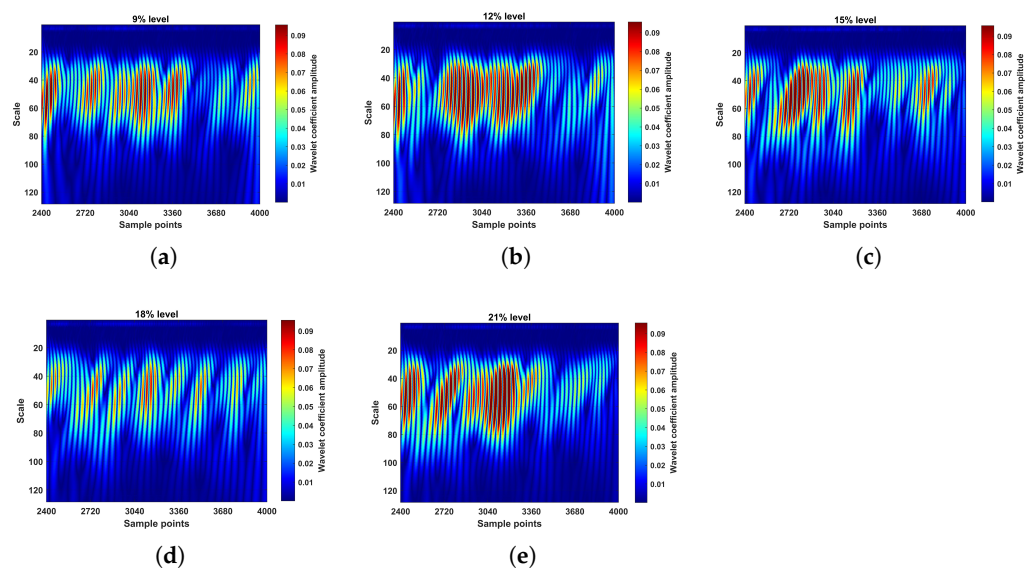
Field GPR data are subject to environmental noise and medium heterogeneity, often leading to aliasing of reflected signals from compacted areas. Following a series of preprocessing steps and F-K migration, the contour features of the compacted zones were delineated. Figure 11 indicates the locations of the numbered excavation pits. The area between pits 11–14 corresponds to slight compaction, the area between pits 33–36 corresponds

to moderate compaction, and the area between pits 23–26 corresponds to severe compaction. After F-K migration, the compacted defect areas can be identified with improved clarity.



**Figure 11.** Processed field data: (a) slight compaction; (b) moderate compaction; (c) severe compaction.

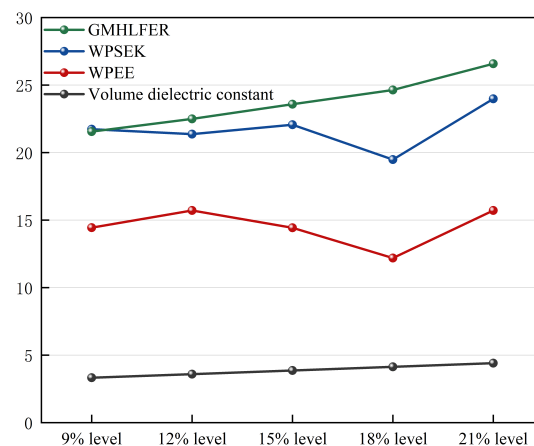
Wavelet packet decomposition was applied to the forward simulation data proposed in this study to generate visualized results of signal energy distribution. Figure 12 presents the energy distribution maps of GPR signals under varying proportions of compacted material. The left side of each image represents the frequency scale axis, where high frequencies correspond to small scales and low frequencies to large scales. As the degree of ballast compaction intensifies, the signal energy distribution becomes increasingly concentrated and predominantly converges in shallow regions characterized by smaller time-domain sampling points. For compaction levels of 9% and 12%, signal energy is concentrated before time sampling point 3600. With increasing compaction severity, the majority of energy becomes concentrated before time sampling point 3300. In contrast, deeper regions corresponding to larger time-domain sampling points exhibit a pronounced attenuation trend, with signal energy for compaction levels of 18% and 21% being sparsely distributed beyond sampling point 3400.



**Figure 12.** Visualization of wavelet packet decomposition energy distribution for forward simulation data: (a) 9% compacted material filling; (b) 12% compacted material filling; (c) 15% compacted material filling; (d) 18% compacted material filling; (e) 21% compacted material filling.



The characteristic parameters extracted from the simulation data are analyzed in Figure 13 and summarized in Table 3. The equivalent volumetric dielectric constant increases monotonically from 3.324 to 4.404 as the compaction level rises from 9% to 21%, consistent with the physical mechanism of reduced ballast porosity and increased solid particle filling. The GMHLFER exhibits the most stable and continuously increasing trend, gradually rising from 21.555 to 26.581, demonstrating highly consistent responsiveness to compaction severity. In contrast, the WPEE remains within the range of 14.430–15.711 between 9% and 15% compaction, drops sharply to 12.189 at the 18% level, and subsequently rebounds to 15.711 at 21%, indicating insufficient overall stability. The WPSEK shows slight fluctuations within the 12–15% interval, decreases significantly to 19.482 at the 18% compaction level, and then recovers to 23.982 at 21%, with regular responses observed only at the 9%, 15%, and 21% levels. Overall, the GMHLFER demonstrates a monotonically increasing and stable response across the full compaction gradient, establishing it as the most robust quantitative indicator among all evaluated parameters. In contrast, the quantification capability of WPEE and WPSEK is limited due to abnormal fluctuations at moderate to high compaction levels. This conclusion requires further validation using field measurement data.



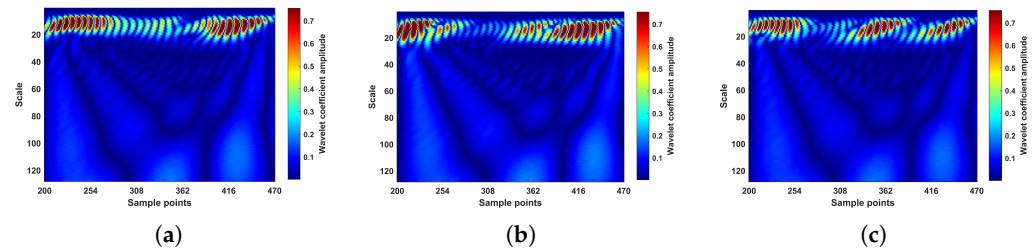
**Figure 13.** Characteristic parameter curves of forward simulation data.

**Table 3.** Summary of characteristic parameter values for forward simulation data.

| Data Number | Volume Dielectric Constant | WPEE   | WPSEK  | GMHLFER |
|-------------|----------------------------|--------|--------|---------|
| 9% level    | 3.324                      | 14.439 | 21.732 | 21.555  |
| 12% level   | 3.594                      | 15.709 | 21.369 | 22.495  |
| 15% level   | 3.864                      | 14.430 | 22.060 | 23.581  |
| 18% level   | 4.134                      | 12.189 | 19.482 | 24.632  |
| 21% level   | 4.404                      | 15.711 | 23.982 | 26.581  |

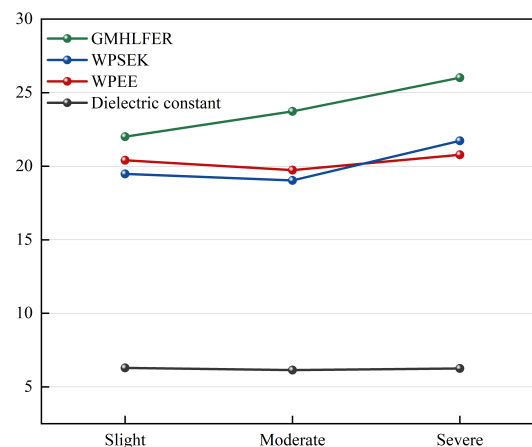
Raw GPR data corresponding to slight, moderate, and severe compaction conditions were extracted from field measurements. Strong reflection interference from sleepers was removed through signal preprocessing, yielding a purified dataset for analysis. Figure 14 presents the energy distribution maps for the three compaction levels derived from wavelet packet decomposition. As evident from the corresponding energy distribution maps, signal energy under severe compaction conditions is significantly attenuated between time sampling points 370 and 470. This phenomenon is attributed to the accelerated energy attenuation rate of electromagnetic waves propagating through the compacted medium. The observed variation pattern is consistent with the characteristics exhibited by the simulation data, thereby validating the fidelity of the proposed model and the reliability of the field data.





**Figure 14.** Visualization of wavelet packet decomposition energy distribution for field data: (a) slight compaction; (b) moderate compaction; (c) severe compaction.

The characteristic parameters extracted from the field data are presented in Figure 15 and summarized in Table 4. The dielectric constant exhibits no discernible trend across different compaction levels. The WPEE fluctuates between 19.734 and 20.780, while the WPSEK varies between 19.037 and 21.726. Neither parameter demonstrates a significant correlation with compaction severity. In contrast, the GMHLFER exhibits a consistent increase from 22.012 under slight compaction to 26.012 under severe compaction, demonstrating well-defined regularity.



**Figure 15.** Characteristic parameter curves of field simulation data.

**Table 4.** Summary of characteristic parameter values for field data.

| Level    | Dielectric Constant | WPEE   | WPSEK  | GMHLFER |
|----------|---------------------|--------|--------|---------|
| Slight   | 6.291               | 20.408 | 19.476 | 22.012  |
| Moderate | 6.143               | 19.734 | 19.037 | 23.729  |
| Severe   | 6.252               | 20.780 | 21.726 | 26.012  |

Based on the above, a combined analysis of simulation data and field measurements indicates that the GMHLFRE corresponds to relatively stable numerical ranges under different compaction levels. Specifically, under slight compaction conditions, the parameter is generally distributed below 23, while it gradually increases with increasing compaction degree, typically exceeding 25 under severe compaction conditions. These results suggest that when the GMHLFRE exceeds 25, it can be used as a reference criterion for identifying severe compaction, thereby enabling quantitative grading evaluation of ballast compaction conditions.

It should be noted that the above numerical ranges are derived from statistical results based on the current simulation and field data. Due to the influence of field conditions, moisture content, and particle composition, the specific thresholds may still exhibit certain variability. Therefore, the proposed method is more suitable for providing quantitatively in-

dicative intervals with engineering relevance, while the determination of precise thresholds still requires further calibration with additional field data and physical parameters.

## 5. Conclusions

This study proposes a feature-screening-based framework for the quantitative evaluation of ballast compaction in heavy-haul railways. The results indicate that the GMHLFER can serve as a stable core indicator for compaction characterization, exhibiting a consistent increasing trend with compaction degree in both simulation and field measurements, and demonstrating good sensitivity and stability. These findings suggest that, under complex heterogeneous medium conditions, feature screening can effectively extract key information representative of compaction states.

Under simulation conditions, the GMHLFER increases from 21.555 to 26.581 as the compaction proportion rises from 9% to 21%. In field measurements, the corresponding values range from 22.012 to 26.012 as compaction progresses from slight to severe. These results indicate that the GMHLFER can effectively respond to variations in compaction conditions and shows potential for engineering application. Compared with approaches relying on single features or empirical indicators, the proposed evaluation strategy based on feature screening and feature space construction reduces the influence of feature variability and improves the consistency and stability of compaction characterization.

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## Abbreviations

The following abbreviations are used in this manuscript:

|         |                                                       |
|---------|-------------------------------------------------------|
| GPR     | Ground Penetrating Radar                              |
| F-K     | Frequency–Wavenumber                                  |
| SVD     | Singular Value Decomposition                          |
| WPD     | Wavelet Packet Decomposition                          |
| GMHLFER | Geometric Mean of WPD High/Low-Frequency Energy Ratio |
| WPEE    | Wavelet Packet Energy Entropy                         |
| WPSEK   | Wavelet Packet Sub-band Energy Kurtosis               |

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