Postprint: Research on Non-destructive Detection Methods for Soil Structure Using Ground Penetrating Radar

Authors: Wu Quan

Date: 2023-02-02T00:00:00+00:00

Abstract

Soil structure configuration exerts significant influence on soil moisture, solute transport processes, and crop growth. Conventional measurement methods rely on manual excavation of soil profiles and sampling followed by laboratory analytical testing, which are characterized by long cycle times and low efficiency. To address these limitations, this study proposes a non-destructive detection method for rapid measurement of soil structure configuration using Ground-Penetrating Radar (GPR) waveforms and images, focusing on the detection of soil structural attributes (stratification, layer thickness, and soil texture). The vertical gradient information derived from GPR waveform images can reflect soil stratification; therefore, the envelope detection method is employed to extract envelope signals from GPR echo signals, and Hilbert transform analysis of the instantaneous phase is utilized to determine layer boundaries. Given the relationship between soil dielectric constant and GPR echo amplitude, the amplitude of GPR echoes is used to invert the dielectric constant of each layer, from which the propagation velocity of radar waves in soil is calculated to obtain the thickness of each soil layer. Based on the quantitative relationship between image noise in GPR waveform images and the sand content ratio of soil, a Principal Component Analysis (PCA) method is proposed to perform noise estimation on the images of each soil layer to determine sand content, and Support Vector Machine (SVM) is subsequently employed to identify the soil texture of each layer. A knowledge base for soil structure configuration is established, encompassing geographic information, soil indices, detection data, and multi-feature fusion information from images, and an information system for rapid identification of soil structure configuration is developed. Field detection and validation were conducted using this method at two experimental sites with six sampling points and four soil structure configuration types in the vicinity of Hohhot, Inner Mongolia Autonomous Region. The research demonstrates that the identification accuracy of soil structure configuration within 1 m below the ground surface in the aforementioned areas exceeds 94%, and the relative measurement error of each soil layer thickness is less than 10%. This research method provides a novel mesoscale detection approach for rapid soil structure configuration detection applications.

Full Text

Nondestructive Inspection Method for Soil Profile Configuration Based on Ground Penetrating Radar

WU Quan[1], YAO Xijun[1], CHEN Xiaodong[2], ZHAO Min[2], ZHAO Huan[2], YUN Hao[1]

[1]Inner Mongolia Autonomous Region Territorial Space Planning Academy, Hohhot, Inner Mongolia 010000, China
[2]Inner Mongolia Dazhi Energy Technology Co., Ltd., Hohhot, Inner Mongolia 010000, China

Abstract

Soil profile configuration significantly influences soil moisture, solute transport processes, and crop growth. Conventional measurement methods rely on manual excavation of soil profiles and laboratory analysis, which are time-consuming and inefficient. To address these limitations, this study proposes a nondestructive detection method for rapidly measuring soil profile configuration using ground penetrating radar (GPR), focusing on GPR waveforms and their images to detect key attributes: stratification, layer thickness, and soil texture.

The longitudinal gradient information in GPR waveform images can reflect soil layering. An envelope detection method extracts the envelope signal from GPR echoes, and Hilbert transform analysis of the instantaneous phase determines layer boundaries. Given the relationship between soil dielectric constant and radar echo amplitude, this study inverts the dielectric constant of each layer from GPR echo amplitude, then calculates radar wave propagation velocity in soil from the dielectric constant to obtain layer thicknesses. Based on the quantitative relationship between image noise in GPR waveform maps and soil sand content, a principal component analysis method estimates image noise for each soil layer to determine sand content, combined with support vector machines to identify soil texture.

A knowledge base of soil profile configuration was established, encompassing regional information, soil indicators, detection parameters, and fused image multi-feature information. An information system for rapid soil profile identification was developed and validated through field testing at two experimental sites with six sampling points and four soil profile types around Hohhot, Inner Mongolia. Results demonstrate that the method achieves over 94% accuracy in identifying soil profile configuration within 1 m below the surface, with relative measurement errors of layer thickness less than 10%. This method provides a new mesoscopic detection approach for rapid soil profile assessment.

Keywords: soil; soil profile configuration; ground penetrating radar; nondestructive inspection

---

Introduction

Soil serves as the natural foundation and biological barrier for all terrestrial ecosystems. With accelerating industrialization and urbanization, conflicts between human activities and land resources have intensified, making soil quality and sustainable development critical research topics in soil science, agronomy, and environmental science. Soil quality detection methods typically fall into two categories: macroscopic and microscopic. Macroscopic approaches use satellite remote sensing to detect surface soil properties, monitoring parameters such as surface moisture, total nitrogen and phosphorus content, salinization, and heavy metal concentrations across broad spatial scales. While providing continuous surface information, these methods suffer from low spatial resolution. Microscopic approaches involve point measurements through profile excavation, augering, and sampling to obtain limited point data. Although accurate for small areas, these methods cannot capture spatial variability across larger regions. Both remote sensing and point measurements have spatial limitations, necessitating an objective, rapid, and accurate mesoscopic soil quality detection method.

Ground penetrating radar (GPR) is a geophysical method that uses high-frequency electromagnetic wave reflection to detect subsurface geological phenomena. Characterized by high efficiency, rapid deployment, continuous profiling, nondestructive operation, low cost, and high-resolution imaging, GPR has become an essential tool for nondestructive testing of layered infrastructure such as pavements, airport runways, tunnels, and embankments. Recent advances have extended GPR applications to soil detection, bridging the gap between macroscopic and microscopic scales. For instance, Wu et al. used GPR early-signal amplitude envelope methods to detect soil moisture before and after precipitation, achieving accuracy comparable to time-domain reflectometry. Hou et al. applied GPR to soil contamination detection, establishing relationships between dielectric constant, radar signals, and multiple contaminant parameters through neural networks. Zhao et al. demonstrated GPR' s effectiveness in detecting reclaimed soil layer thickness and structure. These studies either focused on GPR echo signals to establish soil-waveform relationships or investigated single soil properties such as moisture, thickness, distribution, or contaminant content.

This paper proposes a comprehensive nondestructive method for rapid soil profile configuration measurement using GPR. The approach analyzes both GPR waveforms and images, integrating waveform analysis algorithms, dielectric constant inversion, principal component-based image noise estimation, and support vector machines to investigate relationships between GPR signals and soil physical properties. The method simultaneously detects three primary soil profile attributes (stratification, thickness, and texture) for comprehensive soil configuration assessment. A rapid identification information system was developed and validated through field experiments, demonstrating efficient, nondestructive soil profile detection.

---

1. Study Area Overview

The study selected two typical regions in Inner Mongolia' s standard farming system zones: Tumed Left Banner in the Hetao Plain area and Dalad Banner in the loess hilly region [Figure 1: see original paper]. Tumed Left Banner, located in central-southern Inner Mongolia on the north bank of the Yellow River, experiences a continental semi-arid monsoon climate with high interannual precipitation variability and uneven seasonal distribution. The average annual precipitation is approximately 350 mm, with 60–70% occurring from July to September. The experimental site in Tumed Left Banner (109°54 44.3 E, 40°19 46.0 N) included three sampling points with typical soil profiles: loam-clay, sandy loam-clay, and loam.

Dalad Banner, situated at the northern end of the Ordos Plateau on the south bank of the Yellow River' s "Ji-shaped bend" in Inner Mongolia, has a typical semi-arid continental climate. Influenced by monsoon circulation, Dalad Banner experiences low spring precipitation and concentrated summer rainfall with occasional heavy storms. The uneven seasonal distribution leads to frequent drought and flood disasters, with average annual precipitation of about 300 mm. The experimental site near the Kubuqi Desert in Dalad Banner (109°53 40.2 E, 40°16 41.7 N) included three sampling points with typical profiles: sand-sandy loam, sand-clay, and uniform sand.

2.1 Data Collection

Four distinct soil profile types were selected for double-blind testing: loam-clay, sandy loam-clay, sand-sandy loam, and uniform sand. Parallel survey lines of 5 m length were established on uncultivated farmland without crop cover.

Point measurement sampling: Soil profiles were excavated at the midpoint of each survey line. Profile description was based on soil color, firmness, and particle size distribution. The depth and thickness of each textural layer were measured, and preliminary profile configuration was determined from the sequence and thickness of layers. Soil samples from each layer were collected for laboratory analysis.

GPR sampling: A GER-10 pulsed GPR system from Qingdao Zhongdian Zhongyi Intelligent Technology Development Co., Ltd. was used [Figure 2: see original paper]. Considering the cultivated soil thickness of approximately 0.5–1.5 m and the minimum range affected by soil texture on electromagnetic properties, a 900 MHz antenna was selected. Specific parameters are listed in .

Parameter settings include time window size, scan sample points, scans per second, gain points, etc. Proper parameter setting is crucial as it directly affects data quality.

1) **Detection depth and time window:** The detection depth should be 1.5 times the target depth to avoid data loss or reduced vertical resolution. For the 1.5 m target depth in this study, the time window length (Range) was calculated as:

$$\text{Range} = 2 \times H \times \sqrt{\varepsilon}$$

where H is detection depth and ε is dielectric constant. For sandy loam in Dalad Banner with $\varepsilon = 6.6$, the time window was set to 40 ns with adequate margin.

2) **Sampling resolution:** The analog-to-digital conversion bit depth was set to 16 Bit for balanced acquisition speed.

3) **Acquisition mode and scan samples:** Distance mode was selected, where GPR collects data at equal distance intervals. The number of scan samples (Samples) must satisfy:

$$\text{Samples} \geq 10^{-8} \times \text{Range} \times F_a$$

where F_a is the antenna center frequency. For the 900 MHz antenna with 40 ns time window, Samples was set to 512 to ensure high vertical resolution.

4) **Scan rate:** The GER-10 system automatically sets the maximum scan rate for the current sample points. With the 900 MHz antenna and 512 samples, the scan rate was 512 traces/s, with a distance wheel interval of 5 mm. The maximum acquisition speed was 36.86 km/h; exceeding this speed increases horizontal distance errors.

Before field measurement, a Pereometer dielectric constant meter and a soil moisture meter were used to survey the site and set GPR parameters. Data collection was interrupted in uneven terrain to avoid air wave interference. Each survey line collected 1000 sets of GPR waveform data.

2.2.1 Image Preprocessing

All subsurface objects and medium inhomogeneities generate echo signals. Soil particle size, compaction, moisture content, and ground slope create geometric non-uniformities, resulting in GPR echo signals containing various random noises and clutter. Signal processing algorithms including mean filtering, band-pass filtering, median filtering, and exponential gain adjustment were applied to remove background effects, high-frequency clutter, direct ground waves, and enhance signals to improve signal-to-noise ratio.

2.2.2 Soil Layer Identification Based on Envelope Detection

GPR electromagnetic waves produce echoes with different amplitudes and phases when encountering different soil textures. Waveform peaks are identified in white and black (or grayscale/color) to represent subsurface reflectors, with co-phase axes or equal grayscale/color lines characterizing underground reflection surfaces. The clarity of reflected pulse waveforms is crucial for geological interpretation of GPR images.

To suppress noise interference, the Hilbert transform-based envelope detection method extracts envelope signals from GPR echoes to determine soil interface positions. The GPR echo signal $x(t)$ undergoes Hilbert transform:

$$\hat{X}(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau = x(t) * \frac{1}{\pi t}$$

where $\hat{X}(t)$ is the transformed result and $*$ denotes convolution. The analytic signal is constructed as:

$$x_a(t) = x(t) + j\hat{X}(t)$$

The time-domain amplitude envelope $A(t)$ and instantaneous phase $\phi(t)$ are:

$$A(t) = \sqrt{x^2(t) + \hat{X}^2(t)}$$

$$\phi(t) = \arctan\frac{\hat{X}(t)}{x(t)}$$

The instantaneous phase signal $\phi(t)$ undergoes high-order least squares fitting. Through repeated experiments, when the order is set to 8, the inflection points of the fitted curve closely match actual soil interface positions. These convex/concave inflection points are identified as soil interface locations in the time domain.

2.2.3 Soil Dielectric Constant and Layer Thickness Calculation

GPR echo amplitude inversion determines the relationship between layer dielectric constant and echo amplitude:

$$\varepsilon_i = \varepsilon_{i-1}\left[\frac{1+R_i}{1-R_i}\right]^2, \quad i = 1, 2, \dots, N$$

where ε_i is the dielectric constant of layer i, ε_{i-1} is the overlying layer's constant, R_i is the reflection coefficient, and N is the total number of layers. The reflection coefficient is calculated as:

$$R_i = \frac{A_i}{A_m}$$

where A_i is the reflected wave amplitude and A_m is the full reflection amplitude obtained from metal plate testing. Starting with air ($\varepsilon_0 = 1$) as the surface medium, each soil layer' s dielectric constant can be derived sequentially.

For soil with dielectric constant ε_i, electromagnetic wave propagation velocity v_i is:

$$v_i = \frac{c}{\sqrt{\varepsilon_i}}$$

where c is the speed of light in vacuum (3×10^8 m/s). Layer thickness H_i is calculated from two-way travel time t_i:

$$H_i = \frac{v_i \times \Delta t_i}{2}$$

2.2.4 Soil Texture Identification Method

1) Image noise estimation based on principal component analysis: Soil properties including particle size, density, porosity, permeability, and magnetism affect echo signal images. Chen et al. demonstrated that GPR image noise variance correlates positively with soil sand content. The noisy image f can be modeled as:

$$f = r + n$$

where r is the noise-free image and n is additive white Gaussian noise with zero mean and variance σ_n^2. The covariance matrix relationship is:

$$C(f) = C(r) + \sigma_n^2 I$$

where $C(f)$ and $C(r)$ are covariance matrices of f and r, and I is the identity matrix. Since real images have limited principal components, $C(r) \approx 0$, simplifying to:

$$\sigma_n^2 = \min(\lambda_i)$$

where λ_i are eigenvalues of $C(f)$. The noise variance is estimated for each layer' s image as a feature parameter reflecting sand content.

2) Soil moisture content: Under identical precipitation or irrigation conditions, different soil textures exhibit varying moisture content due to differences in permeability. Soil moisture θ is calculated using the Topp equation:

$$\theta = -5.3 \times 10^{-2} + 2.92 \times 10^{-2}\varepsilon_i - 5.5 \times 10^{-4}\varepsilon_i^2 + 4.3 \times 10^{-6}\varepsilon_i^3$$

3) Support vector machine for texture identification: Feature vectors for each layer are constructed from noise variance σ_n^2, moisture content θ, average grayscale, third central moment, and one-dimensional entropy H (representing grayscale distribution information). These features establish a soil texture library for SVM training and layer identification.

3.1 Indoor Experimental Analysis

A soil analysis test chamber was designed with three-layer configurations: upper layers of sandy loam with particle sizes 0.5–1 cm and 1–2 cm, and a lower clay layer [Figure 3: see original paper]. Raw and preprocessed images show depth on the vertical axis and GPR trace number on the horizontal axis.

Each trace' s data was averaged along the survey direction, normalized, and DC components removed. Hilbert transform produced upper (red) and lower (green) envelope curves [Figure 4: see original paper]. The instantaneous phase signal was least-squares fitted to obtain the phase curve. Inflection points (green circles in [Figure 5: see original paper]) identify layer boundaries, yielding the stratified image [Figure 6: see original paper].

compares traditional measurements (measured values) with method calculations (calculated values). Results show relative errors of 6.16–9.57% for dielectric constant, 7.58–9.69% for layer thickness, and 8.46–9.13% for moisture content. Higher noise variance correlates with higher sand content, with significant variance differences between layers enabling accurate profile identification.

3.2 Knowledge Base Creation and System Development

A comprehensive knowledge base was established covering regional information (county, coordinates, climate), soil properties (texture, moisture, bulk density, porosity), detection parameters (GPR settings, survey time, line orientation, waveforms), and fused image features (noise variance, average grayscale, third central moment, one-dimensional entropy). This database forms the foundation for intelligent soil profile analysis.

A rapid detection system was developed with functions including GPR waveform preprocessing (direct wave removal, median/Gaussian filtering, gain adjustment), data analysis (import, screening, detection, calculation, visualization), intelligent detection (profile analysis and indicator output), and automatic report generation.

3.3 Field Experimental Analysis

Field double-blind tests were conducted in Tumed Left Banner and Dalad Banner in October 2021 on four profile types: loam-clay, sand-clay, and sand-sandy loam. [Figure 6: see original paper] shows comparative results between calculated layers and actual profiles. The method accurately identified layer numbers and textures, with thickness errors of 2–6 cm for loam-clay and 1–6 cm for sand-sandy loam, achieving approximately 94% accuracy .

---

4. Discussion

The field-tested four profile types showed 3–5 layers, with each layer approximately 20–30 cm thick (except for obstructive layers). Adjacent layers exhibited similar textures. The method accurately detected stratification and thickness within 10% error compared to manual excavation. Soil texture results matched manual analysis, with overall accurate profile identification.

This study innovatively combines GPR waveform and image analysis, integrating traditional instruments with GPR for comprehensive soil property detection. Unlike previous work focusing on single properties, this method simultaneously analyzes stratification, thickness, and texture, validated through controlled and field experiments.

GPR pulse signals are sensitive to surface vegetation and underground root systems, which affect signal precision when the distance from ground surface exceeds a certain range. Field surveys should avoid vegetated periods or locations. GPR signals are significantly affected by water, with saturated soils masking other properties. Measurements should be conducted during dry surface conditions, with parameters adjusted based on soil viscosity and moisture. Obstructive layers with relatively high moisture content can be detected using the GPR-water relationship.

While validated in typical regions, China' s vast territory exhibits diverse soil profiles with varying GPR penetration and interference characteristics. Extension to other regions requires further research.

---

5. Conclusions

1) The envelope detection method produces clear stratification images, revealing subsurface layering characteristics. Dielectric constant inversion from GPR amplitude and thickness estimation show measurement errors but generally match field measurements.
2) Soil sand content correlates with GPR reflection intensity and image noise. Clay, loam, sandy loam, and sand show progressively increasing noise due to increasing sand content.

3) The Topp polynomial calculates soil moisture, PCA-based image noise estimation indirectly determines sand content, and SVM identifies soil texture using feature vectors combining moisture, noise variance, and image features, achieving correct identification.
4) This method provides a new mesoscopic detection approach for rapid soil profile assessment, offering nondestructive, efficient, and accurate analysis compared to manual excavation.

References

[1] Li Binbin, Xu Mingxiang, Gong Chen, et al. Hotspots and trends in international soil quality research based on Citespace visual analysis of big data[J]. Journal of Natural Resources, 2017, 32(11): 1983-1998.

[2] Chen Guoqian, Zhu Cunxiong, Li Suyun, et al. Remote sensing model construction and spatial-temporal changes of soil moisture in the Three River Headwaters region[J]. Acta Agrestia Sinica, 2021, 29(Suppl. 1): 199-207.

[3] Ma Chi. Accuracy comparison of soil total nitrogen content inversion based on HJ-1A HSI and Sentinel-2A remote sensing data[J]. Radio Engineering, 2021, 51(12): 1540-1548.

[4] Qiao Lu, Chen Lixin, Dong Chengming. Estimates of soil N, P, K concentration by using hyperspectral remote sensing technology[J]. Forest Engineering, 2018, 34(6): 25-31, 71.

[5] Wang Shuang, Ding Jianli, Wang Lu, et al. Remote sensing monitoring of soil salinization based on surface spectral modeling[J]. Arid Land Geography, 2016, 39(1): 190-198.

[6] Cheng Yongsheng, Zhou Yao. Research progress and trend of quantitative monitoring of hyperspectral remote sensing for heavy metals in soil[J]. The Chinese Journal of Nonferrous Metals, 2021, 31(11): 3450-3467.

[7] Ye Lingwei, Bai Yongping, Yang Xuedi, et al. Application of hyperspectral remote sensing in monitoring heavy metals in soil[J]. The Administration and Technique of Environmental Monitoring, 2018, 30(6): 1-5, 60.

[8] Wang Sinan, Li Ruiping, Han Gang, et al. Characteristics of the landscape changes under the hinterland drought conditions in Mu Us Sandland[J]. Arid Land Geography, 2018, 41(5): 1080-1087.

[9] Li Mingliang, Yang Mengli, Liu Chunyu, et al. Dynamic evolution and regional differences of sustainable development in Jiziwan of the Yellow River[J]. Arid Land Geography, 2022, 45(2): 639-649.

[10] Deng Shikun. On the basic principles for the choice of GPR field survey parameters[J]. Chinese Journal of Engineering Geophysics, 2005, 2(5): 323-329.

[11] Xie Guolan. Analysis of soil water content based on ground penetrating radar[D]. Nanchang: Nanchang University, 2009.

[12] Yang Zhaoliang. Ground penetrating radar signal processing and software development[D]. Chengdu: University of Electronic Science and Technology of China, 2005.

[13] Yan Yongbin. Ground penetrating radar image recognition and processing[D]. Beijing: Beijing University of Chemical Technology, 2008.

[14] Zhou Chunxiao, Chen Ye. The progress of ground penetrating radar[J]. Journal of Nanjing Normal University (Natural Science Edition), 1998, 21(1): 111-115.

[15] He Ruizhen, Hu Zhenqi, Wang Jin, et al. The progress of using ground penetrating radar to detect the soil quality[J]. Progress in Geophysics, 2009, 24(4): 1483-1492.

[16] Shi Rong, Deng Ke, Yan Jian. Relationship and capability analysis on two pulse signal envelope extraction methods[J]. Radio Engineering, 2021, 51(1): 1-7.

[17] He Lingsong, Yang Shuzi. Envelop estimation by a pair of digital filters[J]. Journal of Vibration Engineering, 1997(3): 116-121.

[18] Liao Binbin. Research on the application of deep learning in target recognition of ground penetrating radar[D]. Chengdu: University of Electronic Science and Technology of China, 2019.

[19] Wu Zhiyuan, Du Wenfeng, Nie Junli, et al. Detection of cohesive soil water content based on early signal amplitude envelope of ground penetrating radar[J]. Transactions of the Chinese Society of Agricultural Engineering, 2019, 35(22): 115-121.

[20] Wang Yiyou, Hu Yongfeng, Wang Yajie, et al. Bearing fault diagnosis based on Hilbert envelope and order analysis[J]. Automobile Parts, 2022(7): 74-78.

[21] Ding Ying, Sui Shunqi, Wang Kaiyun, et al. Wheel tread flat diagnosis of railway freight wagons based on Hilbert envelope analysis[J]. Rolling Stock, 2022, 60(2): 52-55.

[22] Qin Yanfang. Precision analysis of soil moisture retrieval based on ground penetrating radar in arid region[J]. Resource Information and Engineering, 2018, 33(6): 130-133, 135.

[23] Haukalid K, Folgero K. Broad band permittivity measurements of gas hydrate formation using open ended coaxial probes[J]. Energy & Fuels, 2016, 30(9): 7196-7205.

[24] Liu X H, Tanaka M, Okutomi M. Single image noise level estimation for blind denoising[J]. IEEE Transactions on Image Processing, 2013, 22(12): 5226-5237.

[25] Li Kaili, Tan Manzhi, Mi Shuxiao, et al. Evaluating soil quality with texture profile configuration: A case study of Fenqiu, Henan[J]. Soil, 2016, 48(6): 1253-1260.

[26] Li Huijun, Zhong Ruofei. Numerical study on the relationship between amplitudes of ground penetrating radar wave and water content in soil[J]. Journal of Applied Sciences, 2015, 33(1): 41-49.

[27] Topp G C, Davis J L. Time domain reflectometry (TDR) and its application to irrigation scheduling[J]. Advances in Irrigation, 1985(3): 107-127.

[28] Zhao Yanling, Wang Jin, Gong Xiaoguang, et al. Nondestructive detection of soil layer based on GPR[J]. Science & Technology Review, 2009, 27(17): 35-37.

[29] Chen Xiaodong, Yao Xijun, Yun Hao, et al. Rapid detection of surface soil texture based on noise estimation[J]. China Resources Comprehensive Utilization, 2022, 40(2): 38-40.

Note: Figure translations are in progress. See original paper for figures.