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Editorial

Special Issue on Ground Penetrating Radar: Theory, Methods, and Applications

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Ground penetrating radar (GPR), geophysics exploring technology, could non-destructively acquire high-precision information about the shallow subsurface. GPR has played a crucial role in the detection of urban engineering [1], geological disasters [2], archaeological studies [3], and military affairs [4], with various advantages such as fast speeds, convenience, robust immunity to interference, and light weight [5]. In the modern epoch, equipment for GPR data acquisition is well established, but the explication of GPR data still relies on artificial judgment and experience, lacking automation. With the further exploration of urban underground spaces, it is difficult for traditional GPR interpretation methodologies to meet the current demand for efficiency and precision. Meanwhile, the diversification of explored objects presents novel challenges to the application scenes of GPR. This Special Issue aims to introduce and report on recent advancements in GPR, encompassing aspects such as numerical simulation, inversion imaging, data processing methodologies, and various domains of GPR application.

GPR numerical simulation algorithms are advancing along two primary dimensions: the refinement of modeling precision, and the enhancement of simulation accuracy and efficiency. Various forward modeling algorithms, medium models, mesh generation techniques, and boundary conditions are the hot spots discussed by scholars. In response to the evolving requirements of finely detailed engineering prospecting and the escalating complexity of simulated geometric entities, a concomitant pursuit of the equilibrium between algorithmic computational efficacy and precision has led to the introduction of novel algorithms into GPR forward simulations. These contain methodologies such as the Discontinuous Galerkin finite element method [6], the spectral element method [7], and the symplectic Euler method [8]. Simultaneously, the intrinsic quality of GPR data impacts the accuracy and precision of data interpretation. Given the intricate nature of the explored environment, in which electromagnetic waves are prone to phenomena such as scattering and diffraction during propagation, distinguishing meaningful information from interfering signals within real-time recorded images becomes a formidable challenge. Therefore, the utilization of data processing techniques to suppress noise, extract salient information, and deduce relevant parameters is necessary. Traditional data processing workflows encompass operations such as digital filtering, deconvolution, gain recovery, and time-delay correction.

In recent years, the requirements of visualization and real-time capabilities in exploration have propelled inversion imaging into extensive discourse among numerous scholars. Migration is among the topics under consideration, including Kirchhoff integral migration, finite-difference migration, frequency-wavenumber migration, and reverse-time migration [9,10]. However, conventional migration algorithms predominantly focus on geometric structural imaging, and are difficult to use to describe high-precision reflectivity parameters. In contrast, least-squares reverse-time migration formulates imaging as a least-squares inversion problem [11], demonstrating a robustness to irregular data, elevated imaging precision, and superior amplitude fidelity. Furthermore, full-waveform inversion (FWI) represents a promising tool for attaining high-resolution underground images, directly depicting precise information concerning target material, location, size, and other parameters. FWI concurrently utilizes kinematic and dynamic information, thus serving as a robust instrument for reconstructing intricate geological structures and anomalous bodies. Recently, scholars have embarked upon research endeavors encompassing regularization, multiscale strategies, stochastic sources, and cross-constraints [12–14], aiming to enhance the accuracy and increase the inversion speed of FWI. These endeavors have effectively promoted the practical application of FWI.

Given the formidable capabilities exhibited by deep learning across a variety of domains, a series of advancements in GPR technology, based on deep learning methodologies [15], has recently been achieved. Researchers have harnessed machine learning techniques to automatically extract and identify anomalies associated with structural defects through the extraction of hyperbolic features or high-dimensional image characteristics from GPR data, accounting for differences in image and signal attributes [16,17]. Some scholars have sought to integrate deep learning into auxiliary roles for GPR forward simulation and inversion solution processes [18] to improve efficiency and precision. Offline training and online prediction using deep learning could construct a system that maps from the model to the forward profile, considerably accelerating the forward simulation speed. Novel methodologies based on convolutional neural networks enable the rapid solution of highly nonlinear physical governing equations in less time, providing inversion practitioners with new research approaches.

The diversification of objects detected by GPR has ranged from traditional realms, encompassing urban engineering, railways, water resources, mining, tunnels, and archaeology, to include diverse fields such as lunar soil investigation [19], Mars exploration [20], tree defect detection [21], soil moisture content assessment [22], and pollutant leakage detection [23]. This expansion underscores the robust vitality of GPR and its increasingly expansive prospects across a wider spectrum of applications.

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