A Signal Processing Algorithms-Assisted Deep Learning Scheme for Ground-Penetrating Radar Imaging

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Ground-penetrating radar (GPR) has been widely used for the non-destructive inspection of subsurface structures in geophysical and civil engineering. The reconstruction of subsurface permittivity maps from GPR B-scans allows retrieving subsurface objects' size, shape, location, and permittivity information. Traditional imaging algorithms developed for this purpose suffer from high computational cost and low accuracy when applied to complex scenarios. To tackle these issues, deep learning-based methods have been proposed to characterize the mappings from B-scans to permittivity maps (B. Liu, Y. Ren, H. Liu, H. Xu, Z. Wang, A. G. Cohn, and P. Jiang, "GPRInvNet: Deep Learning-Based Ground-Penetrating Radar Data Inversion for Tunnel Linings," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 10, pp. 8305-8325, Oct. 2021) (Q. Dai, Y. H. Lee, H. -H. Sun, G. Ow, M. L. M. Yusof, and A. C. Yucel, "DMRF-UNet: A Two-Stage Deep Learning Scheme for GPR Data Inversion Under Heterogeneous Soil Conditions," *IEEE Trans. Antennas Propag.*, vol. 70, no. 8, pp. 6313-6328, Aug. 2022). These deep learning-based methods are trained with a diverse set of input B-scans and output permittivity maps. However, since all these techniques are fully data-driven and strongly dependent on the training dataset, their accuracy degrades when applied to GPR imaging of new scenarios with targets buried in different soil environments. This is because noise and clutter in B-scans due to the heterogeneity of the new soil environments are totally different from those in the scenarios included in the training dataset. To this end, innovative deep learning approaches, which will be less prone to noise and clutter due to the heterogeneity of the different subsurface environments, are called for. Such approaches should have less dependence on the available datasets and be more accurate for any subsurface scenario under different soil conditions.

This study proposes a deep learning scheme exploiting the strengths of conventional signal processing techniques and advanced deep learning methods. The proposed deep learning scheme is assisted by column-connection clustering (C3) and traditional migration algorithms for reconstructing the subsurface permittivity maps from the GPR B-scans. In particular, the noisy B-scans measured under heterogeneous soil conditions are first processed by the C3 algorithm, which extracts the hyperbolic signatures of the subsurface objects into new B-scans while removing the environmental noise and clutter. Next, new B-scans containing only the object signatures are processed by a fast migration algorithm to extract the locations of the subsurface objects. The C3 and migration algorithms-processed data, along with the original noisy B-scan, are inputted to a U-shaped convolutional neural network, which consists of an encoder and a decoder with skip connections. The C3 and migration algorithms-processed data guide the encoder to learn key features of the object signatures, while the noisy B-scans provide the complete information of the subsurface scenario to avoid information loss. Using the feature representations learnt by the encoder, the subsequent decoder constructs the subsurface permittivity maps. Convolutional layers with multiple receptive fields are employed in both the encoder and decoder to extract multi-scale features of multiple objects with various properties. A real measurement dataset consisting of noisy B-scans is used to train and test the proposed deep learning scheme. Compared to a conventional fully data-driven deep learning scheme that only considers noisy B-scans, the proposed deep learning scheme has improved the imaging accuracy. More importantly, the required amount of B-scans for training the proposed network is reduced since C3 and migration algorithms-processed data assists the network in extracting features of object signatures more effectively. In the talk, we will present the comparison results with existing fully data-driven deep learning-based methods and the generalization capability of the proposed scheme for new scenarios.