A Deep Learning Scheme for Rapidly Reconstructing 3D Permittivity Maps from GPR C-scans

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***Abstract*—In this paper, we propose a deep learning-based scheme for rapidly reconstructing subsurface 3D permittivity maps from ground-penetrating radar (GPR) C-scans. In this approach, a U-shaped deep convolutional neural network (CNN), 3D U-Net, is adopted to build the mapping relationship between GPR C-scans and 3D permittivity maps. The network consists of an encoder and a decoder with skip connections. A set of C-scans and their corresponding permittivity maps from random subsurface scenarios are produced to train and test the 3D U-Net based on mean square error loss. Our preliminary results show that the mean absolute percentage error and structural similarity achieved on the testing data are 0.0994% and 0.9980, respectively. The computation time required for estimating one permittivity map for a given C-scan via the proposed scheme is only 2.9 ms. Note that even computation of one C-scan in the classical reconstruction schemes takes 40 minutes. This makes the proposed method at least 800,000x faster than the classical reconstruction schemes. The results clearly demonstrate that our proposed methodology allows accurate and super-efficient reconstruction of the subsurface 3D permittivity maps from GPR C-scans.**

Keywords—Convolutional neural network (CNN), C-scan, deep learning, ground-penetrating radar (GPR), permittivity map.

I. INTRODUCTION

Ground-penetrating radar (GPR) has been widely used as a non-destructive technique for detecting or imaging subsurface structures and extracting their characteristics. The reconstruction of the 3D permittivity map, which includes the shape, size, location, orientation, and permittivity information of the object, from GPR data is of great significance for the subsurface mapping and health monitoring of tree roots. Traditional migration-based methods can only approximately recover the object's shape and position but not the permittivity. On the other hand, full-wave inversion (FWI) algorithms are capable of reconstructing the permittivity maps, but they require many forward full-wave simulations in every iteration, which leads to a very high computation cost. For example, the FWI algorithm presented in [1] requires a week for reconstructing one 3D permittivity map. Therefore, FWI algorithms is still not practical to be applied to 3D scenarios for monitoring the subsurface structures real-time. In [2], deep learning-based methods are proposed to reconstruct the 2D permittivity maps from given GPR B-scans. However, 2D permittivity maps only restore a slice of the 3D permittivity map of the subsurface object are not capable of extracting important features of the object, such as orientation and complete shape of the object.

In this paper, for the first time, a deep learning-based methodology for reconstructing the 3D permittivity maps of the subsurface objects from the GPR C-scans is proposed. The main strategy in this methodology is to build an optimal mapping between the GPR C-scans and the permittivity maps via a U-shaped deep convolutional neural network, called U-net. The network consists of an encoder for extracting the features from the C-scan and a decoder with skip connections for reconstructing the permittivity map. A large set of C-scans and the 3D permittivity maps are generated to train and test the U-net using a mean square error (MSE) loss function. After testing, a mean absolute percentage error (MAPE) of 0.0994% and a structural similarity (SSIM) of 0.9980 are achieved. The computation time required to estimate one permittivity map for a given C-scan is only 2.9 ms. Note that one iteration of FWI requires computing the C-scan for a given permittivity map, which takes more than 40 minutes. By considering this, the proposed method is at least 800,000x faster than FWI. (Note: FWI often requires more than one iterations, but here we consider the most conservative scenario.) This makes our scheme highly suitable for the (near) real-time reconstruction of 3D permittivity maps of subsurface scenarios.

II. METHODOLOGY

Assume that a 3D permittivity map of a subsurface scenario and its corresponding C-scan are denoted by X and Y, respectively [Fig. 1]. The GPR measurements performed on the surface yield a C-scan via $Y = H(X)$, where the forward operator $H(\cdot)$ maps from permittivity map to the C-scan. In contrary, the inverse operator $H^{-1}(\cdot)$ reconstructs the permittivity map for a given C-scan via $X = H^{-1}(Y)$, where the inverse operator H^{-1} is highly non-linear and approximated by the proposed deep learning methodology in this study.

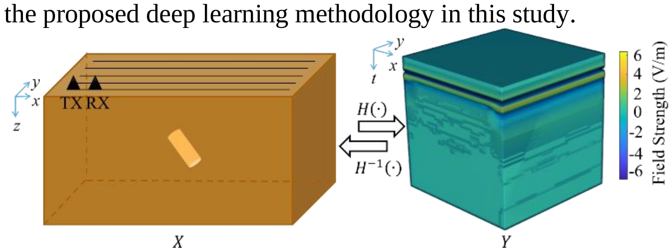

Fig.1. The forward and inverse relations between the 3D subsurface scenario and 3D permittivity map.

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In our methodology, the 3D U-Net [3], which achieves precise medical image segmentation based on the fully convolutional network, is employed to describe H^{-1}. The implementation of the proposed scheme is shown in Fig. 2. In the training stage of the proposed scheme [Fig. 2(a)], a set of data pairs including the C-scans and permittivity maps are used to train the 3D U-Net. The parameters of the 3D U-Net are updated for reducing the MSE loss between the output permittivity maps and the actual (ground truth) permittivity maps. In the testing stage [Fig. 2(b)], the well-trained model is used to predict 3D permittivity maps of new input C-scans.

To train and test the 3D U-Net, a set of C-scans and subsurface permittivity maps are generated using an open-source 3D finite-difference time-domain simulator [4]. In one subsurface scenario, as shown in Fig. 1, one object is buried in the $1\times1\times0.26$ m^3 soil environment. The permittivity of the soil is set to 4. A Hertzian dipole transmits a Gaussian signal with the center frequency of 1 GHz. A probe positioned 10 cm away from the dipole measures the reflected signals. Both dipole and probe are 2 cm away from the ground and moved along the x and y directions in the xy plane. The scanning steps along the x and y directions are 10 cm and 12 cm, respectively. The object is randomly selected as a cylinder, sphere, or box with a random size. The object's relative permittivity is randomly chosen in interval [8, 27]. The object is randomly positioned in a region of $0.4\times0.4\times0.26$ m^3. In total, 2000 random 3D permittivity maps and C-scans are produced.

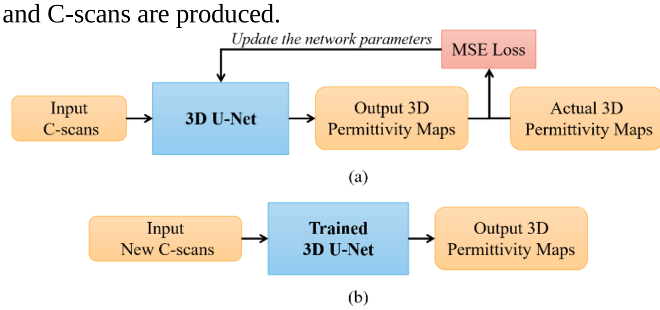

Fig.2. The (a) training and (b) testing stages of our proposed scheme for reconstructing 3D permittivity maps from GPR C-scans.

Both the input C-scans and output permittivity maps are normalized and resized to $64\times64\times64$. The 3D U-Net consists of an encoder for extracting the features in the C-scans and a decoder for reconstructing the desired permittivity maps. The skip connections between the encoder and decoder avoid information loss in the down-sampling process. The details of the network will be provided in the talk.

III. Reconstruction Results

Three examples of the predicted maps are visualized in Fig. 3. Fig. 3(a) compares the ground truth and the prediction of a cylinder, box, and sphere buried in the soil with random size, position, shape, orientation, and permittivity. Fig. 3(b) presents the one-slice of permittivity maps in the xz plane. We can observe that both the predicted subsurface geometry and corresponding permittivity map are very close to the ground truth. These results have proven the potential of the proposed methodology for accurately and rapidly reconstructing the 3D permittivity map from the GPR C-scan.

IV. Conclusions

In this study, a deep learning-based methodology for reconstructing the 3D subsurface permittivity map from GPR C-scan is proposed. The numerical results verify the capability of the proposed method in achieving very high accuracy and ultra-high efficiency when reconstructing 3D permittivity maps.

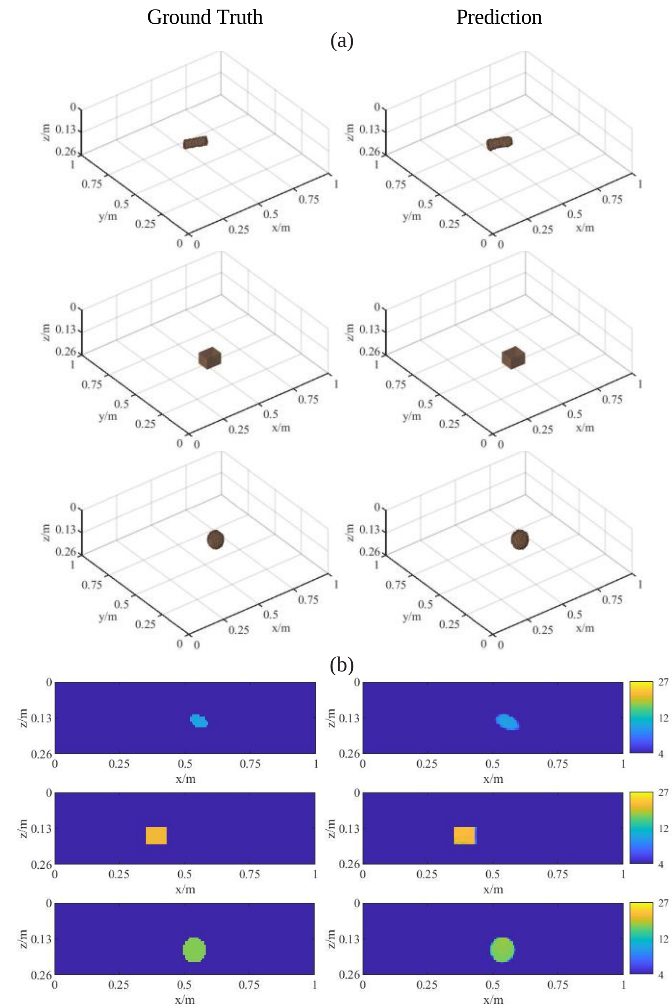

Fig. 3. (a) Reconstructed cylinder, box, and sphere buried in the soil via the proposed scheme and their ground truths and (b) one slice of their permittivity maps in the *xz* plane.

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