Tree Defect Reconstruction from Radar B-Scans via A Deep Learning Algorithm with Two-Stage Training

Nguyen T. Tin [(1)], Yee Hui Lee [(1)], Jiwei Qian [(1)], Kaixuan Cheng [(1)], Daryl Lee [(2)], Mohamed Lokman Mohd Yusof [(2)], and Abdulkadir C. Yucel [(1)]

(1) The School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, 639798 (thanhtin001@e.ntu.edu.sg, eyhlee@ntu.edu.sg, qian0069@e.ntu.edu.sg, chen1519@e.ntu.edu.sg, acyucel@ntu.edu.sg)

(2) National Parks Board, Singapore, 259569 (daryl_lee@nparks.gov.sg, mohamed_lokman_mohd_yusof@nparks.gov.sg)

***Abstract*—This study proposes a deep learning scheme with two-stage training for accurate reconstruction of the tree trunk defects from a radar B-scan. The proposed scheme leverages a U-Net model trained using a mean squared error (MSE) loss function followed by a hybrid structural similarity index (SSIM) loss function. In particular, after training with the MSE loss function, the scheme makes use of Canny edge detection algorithm to separate the domains enclosing the trunk and cavity in the reconstructed image. Then, the scheme uses the SSIMs of trunk and cavity domains separately for further training and enhancing the accuracy of the reconstructed image. Numerical tests on the simulated real tree trunk samples with four-layer structures show that the proposed scheme with two-stage training achieves very high accuracy compared to a traditional U-net model trained with conventional MSE loss function. While two-stage training approach is first proposed here for tree defect reconstruction, it is also applicable to other radar imaging techniques, e.g., subsurface imaging via ground penetrating radar.**

I. Introduction

Trees are indispensable for maintaining ecological balance, mitigating carbon emissions, and enhancing visual aesthetics. However, the structural integrity of trees can be compromised by internal defects, posing unforeseen risks to human safety. Regular assessments of tree health are imperative to proactively mitigate these risks. The radar system offers a straightforward method with the capability of tree defect imaging and classification. Conventional techniques involve scanning tree trunks with a radar system moved circularly around the trunk [1], followed by signal processing techniques, such as modified Kirchhoff migration [2] or full-waveform inversion [3] algorithms, to visualize tree defects (e.g., cavities or decay). However, these algorithms are either inaccurate or inefficient. Considering these algorithms' deficiencies, deep learning-based reconstruction algorithms have recently been proposed and particularly applied to subsurface imaging [4, 5]. These techniques can provide highly accurate images in real-time after proper training. That said, to the best of our knowledge, no deep learning algorithm is applied to reconstruct images of tree interiors from radar B-scans.

This paper proposes a deep learning algorithm to accurately reconstruct the tree trunk and tree defect from a B-scan obtained by moving the radar along a circular trajectory around the trunk. The proposed approach leverages a U-Net architecture [5], employing a two-stage training process: In the first stage of the training, the scheme uses a mean squared error (MSE) loss function and generates the image of the tree interior. Next, the scheme uses the Canny edge detector to distinguish the edges of the defect and trunk and consequently identify the tree trunk and defect regions. Finally, the scheme continues the training by using a hybrid structural similarity index (SSIM) loss function, which combines the SSIM losses of each region. By doing so, the proposed hybrid loss function can improve the reconstruction accuracy of trunk layer and defect without requiring dataset expansion, overcoming the plateaus encountered by traditional loss metrics such as MSE during training. The preliminary results show that the proposed scheme achieves an average SSIM of 90% for the trunk layer, meanwhile demonstrating a 10% improvement in the average cavity SSIM value and 42% improvement in mean absolute percentage error (MAPE) compared to the model trained using traditional MSE loss function.

II. The Deep Learning Network Design

A U-Net model is implemented to reconstruct the interiors of tree trunks. The model is trained by tree trunk models with and without defects and their corresponding B-scans. The B-scans are generated by an open-source 3D finite-difference time-domain (FDTD) simulator [6]. A 1.5GHz GSSI antenna model is used as the transmitter (Tx) and receiver (Rx) and positioned 15 cm stationary from the nearest tree trunk point while the tree layer is rotated, mimicking a circular trajectory. To increase the diversity of the dataset, the tree trunk model varies in radius from 20 to 40 cm and has diverse permittivity ranges across its layers: bark [5-7.5], cadmium [10-15], sapwood [10-15], and heartwood [5-7.5]. A-scans are captured at 10-degree intervals and spatially stacked into one B-scan.

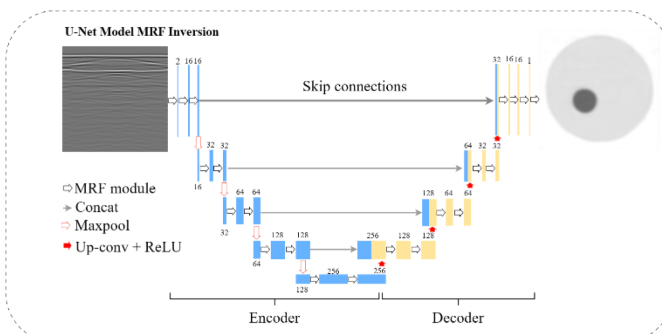


Figure 1. The U-Net model with MRF modules [5].

The network employs an encoder-decoder framework with skip connections. As shown in Fig. 1, the encoder comprises five stages, integrating two multi-receptive field (MRF) modules succeeded by 2x2 max-pooling layers to condense spatial dimensions. It employs convolutional layers with incremental filter levels for effective feature extraction. To recover information lost during downsampling, four skip connections combine decoder features with corresponding encoder features. The decoder section incorporates four up-convolutional layers and two MRF modules, progressively reducing filter levels. In the final stage, a 1×1 convolutional layer, followed by the exponential linear unit activation, produces the combined image of the trunk layer with the cavity.

The training process is divided into two stages. In the first stage, MSE loss is employed to scrutinize the base trunk layer, including the defect, resulting in enhanced clarity of the overall trunk layer structure. Following this initial stage and after around 100 epochs, as the MSE loss reaches a plateau, the scheme proceeds to a subsequent stage, spanning 50-100 epochs. In the second stage, the scheme uses a hybrid loss function, combining the SSIMs of the trunk and cavity layers. Such SSIMs are combined in such a way that attention is directed to the accuracy/SSIM of the trunk layer since it inherently includes the cavity. The local SSIMs are computed after utilizing the Canny edge detection algorithm.

The Canny edge detection technique is used to identify the edges and transitions in grayscale tree layer images. Based on the calculation of the gradient magnitude and direction, it applies the distinct threshold range from weak edge and strong edge, as shown in Fig. 2, customized for trunk [25-100] and defect [140-200], enabling the isolation and precise localization of trunk region and defect region within trunk.

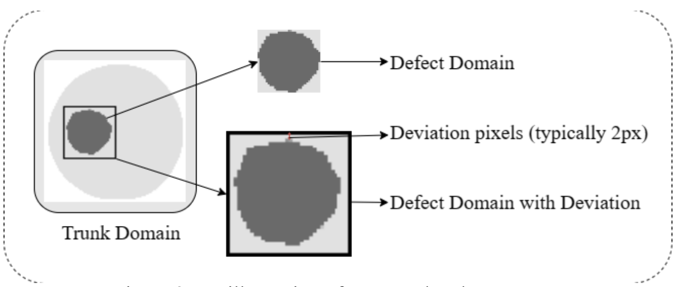


Figure 2. An illustration of Canny edge detector's output.

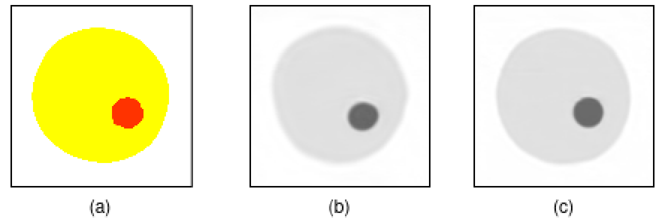
Visual representations and SSIM calculations of detected contours are illustrated and computed through bounding rectangles, typically deviating by a slight pixel value (2 pixels).

III. Results and Discussion

The proposed network was trained and tested on a limited dataset with 500 samples. Fig. 3 presents a ground truth sample in the testing dataset and its reconstruction by the models trained with conventional MSE loss function and proposed hybrid loss function. Clearly, the proposed scheme achieves a remarkable improvement compared to the conventional scheme in preserving structural details despite dataset limitations. Furthermore, Table I quantitatively supports these findings, comparing metrics between conventional MSE training and the proposed two-stage training with MSE + Hybrid Loss Function. Trunk SSIM increases from 0.8684 to 0.902, and cavity SSIM improves from 0.65795 to 0.759. The reduction in MAPE to 1.497%, coupled with a reduction in MRE, underscores the model's accuracy. This aligns with the visual enhancements in Fig. 3, highlighting the method's efficiency in achieving precise and visually improved results.

Figure 3. (a) Ground-truth tree interior and reconstructed tree interior via U-net Model trained by (b) MSE and the proposed (c) Hy_{loss}.

Table I. The Performance Metrics of the Model with Proposed Two-Stage Training (MSE+Hybrid) and Conventional Training (MSE)



U-net model trained by	Average value on the test set			
	Trunk SSIM	***Cavity SSIM***	***MRE (%)***	***MAPE (%)***
MSE	0.8684	0.65795	0.01025	2.5769
MSE + Hybrid Loss Function	0.902	0.759	0.009	1.497

IV. Conclusions

This paper proposes a deep learning algorithm with a two-stage training approach for reconstructing the tree defects using the B-scans obtained on a circular trajectory around the tree trunk. The scheme leverages a U-Net model with a hybrid SSIM-based loss function, integrating Canny edge detection. It is trained and tested with a limited dataset, achieving high accuracy in defect imaging and localization.

Acknowledgements

This work was supported by the Ministry of National Development under the Cities of Tomorrow (CoT) R&D Programme with Award No. COT-V4-2020-6.

References

[1] C. Özdemir, Ş. Demirci, E. Yiğit, and B. Yılmaz, "A review on migration methods in B-Scan ground penetrating radar imaging," *Mathematical Problems in Engineering*, vol. 2014, pp. 1–16, Jan. 2014.

[2] I. Giannakis, F. Tosti, L. Lantini, and A. M. Alani, "Health monitoring of tree trunks using ground penetrating radar," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 10, pp. 8317–8326, Oct. 2019.

[3] D. Feng, Y. Liu, X. Wang, B. Zhang, S. Ding, T. Yu, B. Li, and Z. Feng, "Inspection and imaging of tree trunk defects using GPR multifrequency Full-Waveform Dual-Parameter inversion," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, pp. 1–15, Jan. 2023.

[4] Q. Dai, Yee Hui Lee, H.-H. Sun, G. Ow, M. Lokman, and A. C. Yucel, "3DInvNet: A Deep Learning-Based 3D Ground-Penetrating Radar Data Inversion," *IEEE Trans. Geosci. Remote Sens.*, 61, pp. 1–16, Jan. 2023

[5] 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 Propagat.*, vol. 70, no. 8, pp. 6313–6328, Aug. 2022.

[6] C. Warren, A. Giannopoulos, and I. Giannakis, "gprMax: Open source software to simulate electromagnetic wave propagation for Ground Penetrating Radar," *Computer Physics Communications*, vol. 209, pp. 163–170, Dec. 2016.