A Deep Learning-Based Imaging of Tree Interiors via a Standoff Radar System

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Abstract— **This paper proposes a deep learning scheme for reconstructing the images of tree interiors via a standoff radar configuration. The radar is used to collect the signals reflected from the tree trunk while moving it along a straight trajectory distanced away from the surface of the trunk. Collected signals, stored as B-scans, are then processed and used as training and testing data for a modified U-Net model, which reconstructs the images of the tree trunk interiors. A novel hybrid loss function, consisting of segmental average structural dissimilarity index measure (SA-SSIM) and binary cross entropy (BCE), is proposed to increase the accuracy of reconstructing the fine details on the defect and trunk boundaries. A dataset containing diverse random 3D tree trunk and defect shapes and their corresponding B-scans is generated to train and test the proposed network. The preliminary results show that the proposed scheme achieves a very high accuracy in reconstructing the images of tree interiors. The proposed scheme is the first and foremost imaging technique for monitoring the interiors of tree trunks with defects while moving the radar on a straight trajectory in a standoff configuration.**

I. Introduction

The radar system has been commonly used during the health assessments of trees. In particular, the radar is instrumental in reconstructing the images of the tree interiors and displaying the defects inside the tree trunks. For this purpose, traditional migration techniques, e.g., the modified Kirchhoff migration algorithm [1], have been used to reconstruct the images of tree interiors after the B-scans are collected by moving the radar around the tree trunk while in contact with its surface. However, such reconstruction and data collection is highly time-consuming, labor-intensive, and not applicable to the health monitoring of a large number of trees in forests or urban areas. To overcome this issue, a standoff radar system, moved along a straight trajectory distanced away from the surface of the trunk, has been proposed [2] and used to detect tree defects (cavities or decays). Nevertheless, this standoff radar configuration has never been used to reconstruct the images of the tree interiors, particularly the positions and shapes of tree defects. Additionally, while deep learning-based reconstruction has recently been applied to traditional ground penetration radar applications, e.g, imaging subsurface objects [3], [4] , it has never been investigated for imaging the interiors of trees with defects.

This paper proposes a deep learning scheme for reconstructing the images of the tree interiors via a standoff radar system. In the proposed scheme, the B-scan is collected along a 1.5-meter straight trajectory away from the tree trunk, processed by antenna calibration, and inputted to a modified U-shaped convolutional neural network, called U-Net. The modified U-net leverages a novel hybrid loss function combining BCE and SA-SSIM: While the BCE ensures the accuracy of the global shape reconstruction, the SA-SSIM enhances the fine detail reconstruction by partitioning the cross-sectional image into segments and evaluating the structural dissimilarity index measure (DSSIM). By carefully assigning the weights to the components of the loss function, the proposed network achieves a high accuracy in reconstruction with a structural similarity index measure (SSIM) of 0.9279, a mean squared error (MSE) of 0.0143, and a mean absolute error (MAE) of 0.0178.

II. The Proposed Scheme

The proposed scheme employs a standoff radar system moving along a straight trajectory for data collection [Fig. 1(a)]. The data consists of a B-scan formed by spatially stacking all A-scans obtained at each radar position. This B-scan is then processed by antenna calibration and inputted to the modified U-Net model, which can successfully reconstruct the image of the tree interior. The measurement configuration is shown in Fig. 1(b), where a pair of transmitter (Tx) and receiver (Rx) with an interspacing of 10 cm is moved with 3cm steps along a 1.5-meter-long straight trajectory, positioned 15 cm away from the trunk's surface.

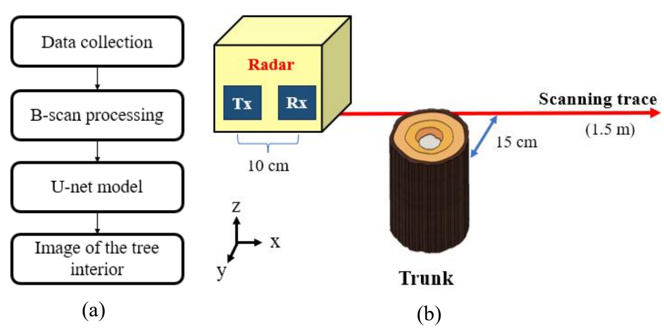

Figure 1. (a) The flowchart of the proposed scheme and (b) the configuration of the data collection setup.

A signal processing technique leveraging antenna calibration is used to remove the direct coupling between the Tx and Rx in the B-scan and to reveal the signatures of the defects in the B-scan. Then, the processed B-scans as well as the ground-truth tree interior images are used to train the U-net model. The well-trained U-net is used to image the tree interior with defect for provided B-scan. The proposed U-net leverages a modified version of the DMRF-UNet [4]. This network employs a multi-layered encoder to extract details from the processed B-scans and ground-truth images efficiently. The decoder component plays a crucial role in reconstructing the defects with accurate shapes and positions. Skip connections are introduced to enhance the capacity to preserve fine-grained details and maintain context awareness during the reconstruction process.

To accurately reconstruct the intricate details, a hybrid loss function, consisting of SA-SSIM and BCE, has been proposed. Traditional loss functions, such as MSE and BCE, often prioritize the global accuracy of the image and thereby overlook the accurate reconstruction of the fine details on the boundaries. To this end, in addition BCE, SA-SSIM is used in hybrid loss function as $loss_{hybrid}$ = α×$loss_{BCE}$ +β× $loss_{SA-SSIM}$, where α and β represent the weights allocated to BCE loss ($loss_{BCE}$) and SA-SSIM loss ($loss_{SA-SSIM}$) and are set to 0.7 and 0.3, respectively. $loss_{BCE}$ is computed via

$$loss_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \times \log(p(y_i)) + (1-y_i) \times \log(1-p(y_i))], \quad (1)$$

where N is the number of pixels in each image, y_i is the true label for the ith pixel (either 0 for air/decay or 1 for wood), and $p(y_i)$ is the predicted probability of the positive class (class 1, wood) for the ith pixel. While computing the SA-SSIM, the ground-truth and predicted images are divided into 64 segments and DSSIM is computed for each segment [Fig. 2]. The average of all DSSIMs for all segments is assigned as $loss_{SA-SSIM}$.

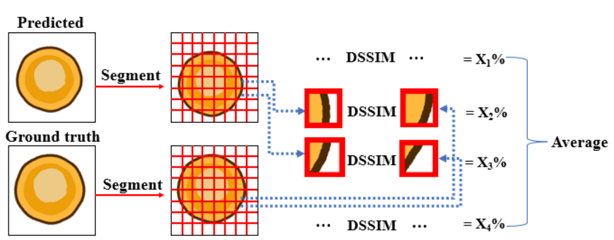

Figure 2. The illustration of SA-SSIM loss function.

III. Results and Discussions

A dataset consisting of 1800 random trunk/defect shapes and their corresponding B-scans is generated using an open-source finite-difference time-domain simulator [5]. For each data point, a Hertzian dipole (TX) operated at a center frequency of 1 GHz, transmitting a Gaussian signal, and a probe is assumed as RX. The 3D tree trunk is realized by a four-layer trunk model with bark, outer sapwood, inner sapwood and heartwood layers; some trunks with defects included in the set are demonstrated in Fig.3(a). Table I compares the performance metrics of the training via traditional loss functions (MSE and BCE) and the proposed hybrid loss function. Clearly, the model trained with the proposed hybrid loss function (SASSIM-BCE) outperforms others, especially in SSIM metrics with 92.79% accuracy. This superiority is also evident in other performance metrics. Furthermore, the reconstructed images obtained by the models trained with the traditional and proposed hybrid loss functions are provided in Fig. 3(b)-(e). Apparently, the U-net model with proposed hybrid loss function (SASSIM-BCE) can accurately reconstruct the shapes of the defect and trunk, while the models with traditional loss functions (MSE and BCE) cannot.

Table I. Performance Comparison of the Models Trained with Different Loss Functions

Loss functions	SSIM (↑)	MSE (↓)	MAE (↓)
MSE	0.8772	0.0480	0.0246
BCE	0.9034	0.0168	0.0215
SASSIM-BCE	**0.9279**	**0.0143**	**0.0178**

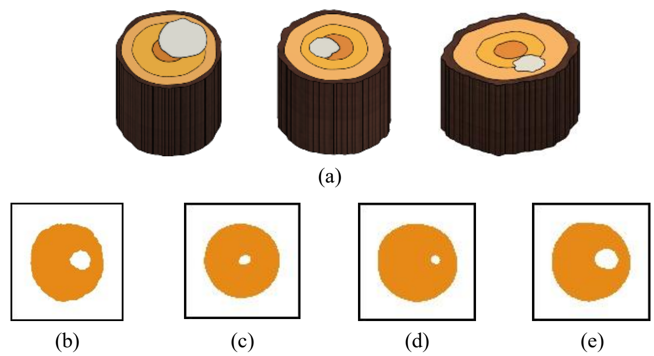

Figure 3. (a) Some of the 3D trunk samples used in dataset. (b) Ground-truth tree interior and reconstructed tree interior via the model with (c) MSE and (d) BCE loss functions and the proposed (e) SASSIM-BCE loss function.

IV. Conclusions

In this paper, a deep learning-based scheme was proposed for reconstructing the tree interiors. The scheme leveraged a modified U-Net with a hybrid loss function, trained/tested with a large dataset, achieved a very high reconstruction accuracy, and is currently trained with real measurement data.

Acknowledgment

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