A Deep Learning-Based Framework for Estimating Tree Defect Parameters via a Stand-off Radar

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***Abstract*—Radar has recently become highly preferable for detecting and imaging tree defects (cavities/decays) within tree trunks. This paper proposes a framework for rapidly estimating the parameters of the tree defects from the radar B-scan of the tree trunk. The scheme uses the B-scan obtained while the radar is moved on a straight trajectory, away from the tree's surface, in a stand-off configuration. It processes the B-scan with a Hessian ridge detection and inputs it to a deep learning algorithm. The developed deep learning algorithm leverages an encoder-decoder convolutional neural network (ED-CNN) and a novel loss function with mean square error and area of difference. The scheme finally outputs the radius and center coordinates of the defect with rough boundaries, assumed to be approximated by a circular shape. The proposed scheme estimates the center coordinates and radius of defects with a mean relative error of 0.03 and 0.09, respectively. The proposed scheme is the first and foremost tool for estimating the parameters of the tree defects by processing the radargram obtained by moving the radar away from the tree surface on a straight trajectory.**

I. Introduction

Radar systems have been used for detecting tree defects inside tree trunks and reconstructing the images of their shapes and permittivity maps. Existing radars used for this purpose require data collection on a circular trajectory around the trees, which is a time-consuming and labour-intensive process. In addition, the full-waveform inversion and migration techniques used for permittivity and/or shape reconstruction of tree defects are computationally expensive and inaccurate, respectively. To this end, current data collection and processing techniques for tree defect detection are not practical for accurate defect detection for a large number of trees in a short period of time. Recently, a stand-off radar system was proposed for rapidly scanning the tree trunks from a distance and accurately detecting the tree defects [1]. That said, this study only focuses on detecting defects' signatures in B-scans, lacking in estimating defect parameters, such as their sizes and positions, which are significant for assessing the severities of defects and performing necessary actions.

Deep learning-based algorithms have been developed for parameter estimation and imaging of subsurface objects [2, 3]. However, these algorithms are not accurate when directly applied to the estimation of the tree defect parameters as the scenario considered in tree defect detection is different and challenging compared to subsurface imaging. The unique challenges of tree defect detection result from the clutter in B-scans due to strong and diffuse reflection from rough trunk surfaces and multiple reflections among the concentric wood layers. This clutter makes the tree defect signature indistinguishable and uninterpretable for parameter extraction. To this end, robust deep learning frameworks are needed for estimating the defects' parameters.

This paper presents a deep learning framework to simultaneously predict the defect's center coordinates and radius from the B-scan, collected while moving the radar on a straight trajectory away from the trunk surface. Initially, the framework processes the B-scan by enhancing the signatures of the signals reflected from the defect via the ridge detection algorithm. Then, the processed B-scan is fed into a developed encoder-decoder convolutional neural network (ED-CNN) to extract the high-level semantic features, interpret them, and obtain the defect parameters. The developed ED-CNN is trained by a properly designed hybrid loss function that combines the mean square error (MSE) with the area of difference (AoD). The proposed framework accurately estimates the defects' coordinates and sizes with a mean relative error (MRE) of 0.03 and 0.09, respectively. Furthermore, the accuracy of the bounding circles generated by the predicted parameters is quantified by an intersection over union (IoU) as 0.77, also showing the framework's high accuracy.

II. Methodology

The flowchart of the proposed scheme is shown in Fig. 1(a). First, the tree trunk is scanned by moving the antenna along a 1.5-meter long straight trajectory away from the tree trunk and recording the reflected signal at each position [Fig. 1(b)]. Then, the collected signals are spatially stacked to generate a raw B-scan [Fig. 1(c)]. Antenna calibration is subsequently applied to the raw B-scan to remove the direct coupling between the transmitter and the receiver, revealing only the hyperbolas due to the reflections from the tree's internal structure [Fig. 1(d)].

To further enhance the signatures of defects in the B-scan, local maxima ridge detection is applied by calculating two eigenvalues λ_1, λ_2 $(\lambda_1 < \lambda_2)$ of the 2x2 second-order derivative (Hessian) matrix for each pixel in the image [4]. The enhanced B-scan, generated by assigning the brightness of each pixel equal to its corresponding λ_1 if $\lambda_1 < 0$, or 0 if λ_1 is positive, has noticeably higher contrast between the hyperbolas and the background of the B-scan [Fig. 1(e)].

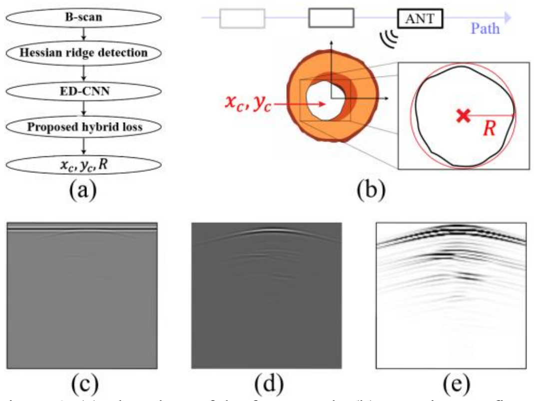

Figure 1. (a) Flowchart of the framework, (b) scanning configuration, definition of defect parameters: center coordinates and radius, and corresponding bounding circle, (c) raw B-scan, and processed B-scans after applying (d) antenna calibration and (e) ridge detection.

Subsequently, an ED-CNN is designed to predict the defect's radius R and center coordinates (x_c, y_c) w.r.t to the trunk's mass center. Particularly, encoder extracts high-level features of defects from the B-scan, and decoder interprets the features and passes them to fully connected layers which finalize the regression task. To train the model for predicting three parameters, the conventional MSE loss function, i.e.,

$$loss_{\mathrm{MSE}} = loss_{\mathrm{MSE}_{x_c}} + loss_{\mathrm{MSE}_{y_c}} + loss_{\mathrm{MSE}_R} \quad (1)$$

only evaluates the combined errors in terms of the values of parameters without considering their geometrical meaning, and thereby is unreliable. For example, two sets of predictions provided in Fig. 2(a), achieving the same $loss_{\mathrm{MSE}}$ for the same ground truth, can generate totally different bounding circles using the predicted parameters (blue). This is because although the sum in (1) is the same, each individual MSE loss component can be vastly different [Fig. 2 (a)]. To address this issue, the loss function is enhanced by adding a term evaluating the AoD between the ground-truth and predicted bounding circles [Fig. 2 (b)]. The corresponding loss term $loss_{\mathrm{AoD}}$ is

$$loss_{\mathrm{AoD}} = S_{\mathrm{truth}} + S_{\mathrm{pred}} - 2S_{\mathrm{intersection}} \quad (2)$$

where S_{truth}, S_{pred}, and $S_{\mathrm{intersection}}$ stand for the calculated area of the ground truth, predicted bounding circles, and the overlapping region between them, respectively. Consequently, the proposed hybrid loss function using both MSE and AoD losses is written as

$$loss_{\mathrm{hybrid}} = \alpha\, loss_{\mathrm{MSE}} + \beta\, loss_{\mathrm{AoD}} \quad (3)$$

where α and β are the weights associated with the MSE and AoD losses set to be 1 and 0.5 in this study, respectively.

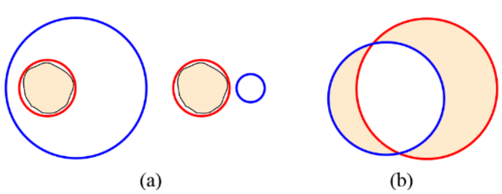

Figure 2. (a) Two predicted bounding circles (blue) generating the same MSE loss for the same ground truth (red) and (b) visualization of AoD highlighted.

III. Results and Discussion

The proposed framework is trained and tested with a dataset of 600 pairs of 3-D layered tree trunks with internal cavities and their corresponding B-scans generated by an open-source forward solver. The antenna is modeled by a Hertzian dipole transmitting a Ricker signal at a center frequency of 1 GHz. Fig. 3 shows bounding circles generated by the predicted parameters in three tree trunk samples with various cavity sizes and positions in the test dataset. The estimated parameters of the cavities are highly accurate as corresponding bounding circles are very close to the ground-truth cavity, proving the capability of the current framework for precise predictions of the cavity's parameters. An ablation study is performed to demonstrate the necessity of each unique component of the proposed framework. As shown in Table I, both ridge detection and the proposed hybrid loss function are needed to achieve the highest IoU and lowest MREs of x_c, y_c, and R.

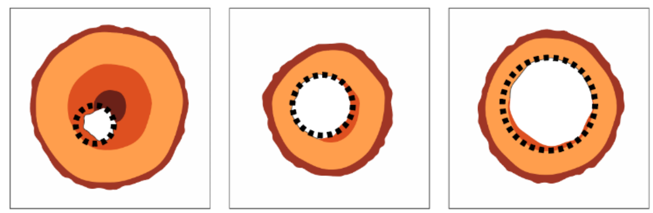

Figure 3. Three examples of tree trunks with cavities in the testing dataset with the predicted bounding circles (black).

Table I. Ablation Study of The Proposed Scheme

	IoU	MRE_{x_c}	MRE_{y_c}	MRE_R
w/o hybrid loss + w/o ridge detection	0.59	0.066	0.038	0.176
w/o hybrid loss	0.64	0.056	0.037	0.168
w/o ridge detection	0.63	0.053	0.035	0.117
Proposed scheme	**0.77**	**0.031**	**0.027**	**0.085**

IV. Conclusion

This study proposed a deep learning framework combining ridge detection and ED-CNN with a hybrid loss function to rapidly estimate the parameters of tree defects. The numerical results demonstrated the capability and accuracy of the proposed framework.

V. References

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