A Deep Learning-Based Methodology for Rapidly Detecting the Defects inside Tree Trunks via GPR

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***Abstract*—This paper proposes a deep learning-based approach for rapidly detecting the defects inside tree trunks via ground penetrating radar (GPR) technology. In this approach, GPR measurements are performed centimeters-away from the surface of tree trunk on a straight trajectory. Then the B-scans obtained from GPR measurements are processed via a deep learning algorithm to detect the defects inside the tree trunks, classify their types, and estimate their sizes/severities. An open-source finite-difference time-domain (FDTD) simulator is used to produce a large set of B-scans from random realizations of realistic 2D tree trunk cross-sections without and with different size of defects (cavities, decays, and cracks). The data set is then used to train and test a six-layer convolutional neural network (CNN) with drop-out layers and weight regularization to avoid overfitting. Our preliminary results show that the testing accuracy of the CNN algorithm is more than 90%. The testing results demonstrate that the current methodology allows accurately detecting the types and sizes of defects inside tree trunks to monitor the health condition of trees.**

Keywords— convolutional neural network (CNN), deep learning, defect detection, ground-penetrating radar (GPR), tree health monitoring.

I. Introduction

The non-destructive techniques such as microwave tomography and ground penetrating radar (GPR) are becoming increasingly popular for the health monitoring of trees. These techniques allow imaging inside the trunks of the health and unhealthy trees with defects (e.g., decays, cavities, cracks) and assessing their health conditions. The microwave tomography requires transmitting and receiving electromagnetic (EM) signals via multiple antennas positioned around the tree trunk and processing of these signals via a computationally costly reconstruction algorithm [1]. The GPRs often leverage a set of transmitter and receiver antennas and make use of advanced signal processing techniques to image the interiors of tree trunks [2]. All these techniques necessitate measurements in contact with the surface of the tree trunks, require excessive resources, and are time-consuming even for a single tree. To this end, their applicability to the massive health screening of trees in large forests is not feasible.

In this paper, a convolutional neural network (CNN)-based methodology for rapidly detecting defects inside tree trunks via GPR technology is proposed. In this methodology, the main strategy is scanning the tree trunks centimeters-away from their surfaces on a straight trajectory via a GPR. By doing so, the GPR measurements can be performed very fast and a cluster of trees can be scanned in a short time. Next, the B-scans of trees are simultaneously processed via a trained CNN to detect the defects and identify their types and sizes. The numerical tests clearly demonstrate the feasibility and detection accuracy of the proposed methodology.

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II. Methodology

The proposed methodology extracts the features of the received EM signals, particularly B-scans, while moving a set of transmitter and receiver on a straight trajectory centimeters-away from the tree trunk. (Note: The straight trajectory and transmitter/receiver are shown with thick black line and dots in Fig 1(a), respectively). At selected measurement locations on the trajectory, the transmitter emits an EM signal and the receiver collects the EM signals reflected from the tree trunk. The time history of the received EM signals at the selected locations on trajectory, A-scans, are stacked together to form B-scans. The B-scans of the trees with defects clearly show the distinct scattering signatures of the defects via different numbers of hyperbolas with differing apexes and local distortions due to multiple reflections in defects with different material properties. These signatures can be detected by the human eye in the example scenario below and also by the machine via a CNN algorithm even in the scenarios where those can not be detected by the human eye.

In the example scenario, a realistic tree trunk model with and without defects is simulated using an open-source 2D finite-difference time-domain (FDTD) simulator [3] to show the distinct scattering signatures of the defects. In this scenario, a Hertzian dipole transmits a Gaussian signal with the center frequency of 1 GHz. A probe positioned 30 cm away from the dipole collects the reflected signals. Both dipole and probe, shown with dots in Fig. 1(a), are moved along three meter-long straight trajectory, 15 cm away from the nearest point on the tree trunk surface. The A-scans are obtained at every 4 cm. First, a healthy tree trunk with relative permittivity 6 is simulated [Fig. 1(a)]. Its B-scan clearly shows the reflections from the top surface of the trunk (the hyperbola at the upper part) and the bottom surface of the trunk (the hyperbola at the lower part). The tree trunks with cavity [Fig. 1(c)], decay with relative permittivity 16 [Fig. 1(e)], and crack [Fig. 1(g)] are simulated. Their corresponding B-scans [Figs. 1(d),(f),(h)] clearly show the distinct scattering signatures of the defects. In particular, the cavity introduces a hyperbola in between two hyperbolas [Fig. 1(d)], while the decay and crack produce a pair of hyperbolas [Fig. 1(f)] and a short segment [Fig. 1(h)], respectively.

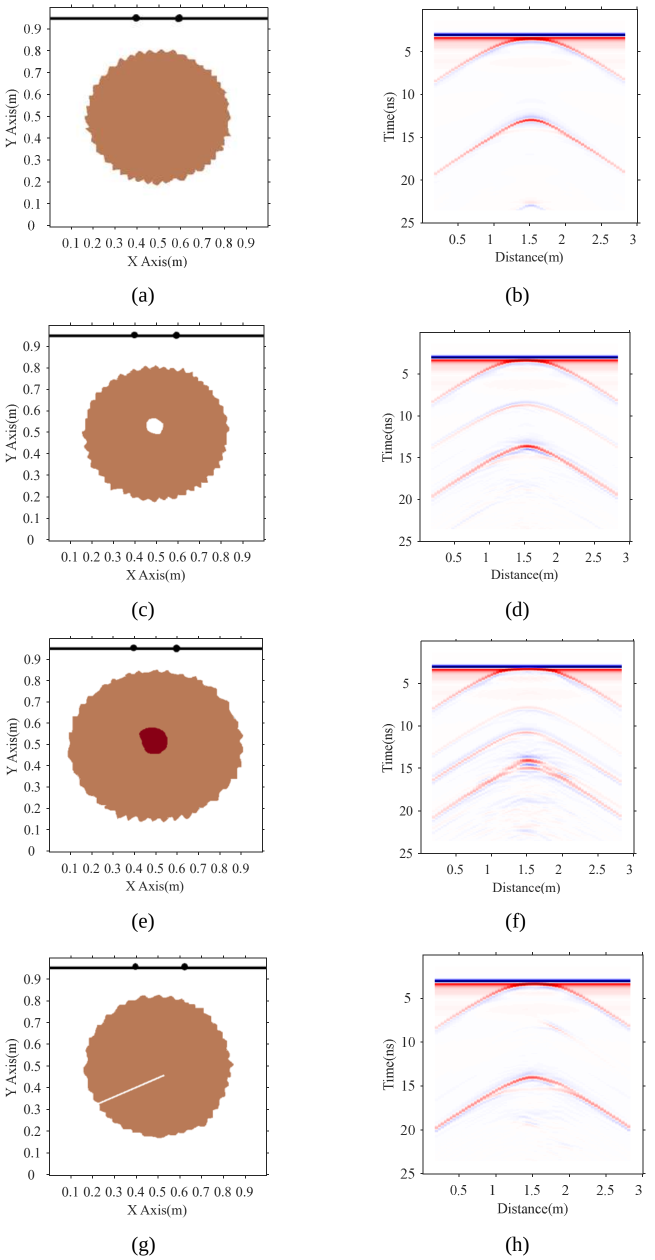

Fig.1. (a) The simulation model and (b) B-scan of a healthy tree trunk. (c) The simulation model and (d) B-scan of a tree trunk with cavity. (e) The simulation model and (f) B-scan of a tree trunk with decay. (c) The simulation model and (d) B-scan of a tree trunk with crack.

To detect the distinct signatures of defects and classify their types and severity via a CNN, 500 random scenarios and their corresponding B-scans are generated. In these randomly generated realistic scenarios, the tree trunks with random rough surfaces have relative permittivities varying from 5 and 10. The major and minor axis of the ellipse-shaped trunks are randomly chosen from intervals [0.3, 0.4] m and [0.2, 0.4] m, respectively. Seven different classes are introduced using these randomly generated scenarios. These classes include the healthy trunks, the trunks with minor and major cavities (with radii randomly selected in [0.03, 0.075) m and [0.075, 0.15] m, respectively), the trunks with minor and major decays (with radii randomly selected in [0.03, 0.075) m and [0.075, 0.15] m, respectively), and the trunks with minor and major cracks (with lengths randomly selected in [0.15, 0.3) m and [0.3, 0.55] m, respectively). The B-scans of these seven classes are scaled, transformed to grey-scale, and resized to train CNN; while a quarter of B-scans are used for testing, the rest is used for training. The trained CNN consists of six convolutional layers, six max-pooling layers and two full-connected layers. A drop-out layer is added after the second fully-connected layer to avoid over-fitting. The output of seven neurons is used to predict the class of each B-scan. The details of the CNN will be provided in the talk.

III. Results And Discussions

After the model fitting via training and testing samples, the final average testing accuracy approaches 91%, as shown in Table I. The accuracy for classifying the severity of cracks is higher than the other two types with more complex patterns. These results have proven the potential of the proposed methodology for accurately detecting the defects inside tree trunks and classify their severities. A large amount of samples will be generated to train and test the proposed network in the future.

TABLE I. CLASSIFICATION ACCURACY

Class	Health trunk	Minor cavity	Major cavity	Minor decay	Major decay	Minor crack	Major crack	
Accuracy (%)	94	93	76	83	84	100	100	91 (ave)

IV. Conclusions

In this study, a deep CNN-based methodology for detecting tree defects with various severities was proposed for rapidly monitoring the health conditions of a cluster of trees via GPR measurements performed centimeters-away from the surfaces of the tree trunks. The numerical tests showed the feasibility and high detection accuracy of such methodology. Training of the CNN algorithm via B-scans of realistic 3D tree trunk models are currently underway.

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