Microwave Imaging of Voids in Oil Palm Trunk Applying UWB Antenna and Robust Time-Reversal Algorithm

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The oil palm trees in Southeast Asia face a great challenge due to voids within tree trunks. Besides, both plantations and the palm oil industry suffered considerable losses due to ineffective inspection of defective trees. Several techniques such as ultrasound, X-ray, capacitive volume, gamma computed tomography, and microwave tomography were applied to detect and control the decay of a trunk. However, all the techniques showed substantial drawbacks (such as limited resolution, tedious processing time, and use of bulky equipment with limited mobility) except for microwave tomography which overtook the other techniques by using a method that distinguishes the dielectric properties of healthy and diseased trunks. This work proposes ultra-wide-band (UWB) signal transmission and reception using antenna sensor arrays that record reflections from affected regions in the trunk. Various factors have been considered, such as different cylindrical arrays of 4, 8, 12, and 16 antennas; different positions of hollows; a heterogeneous trunk; multiple targets; and larger trunk samples (16–30 cm). To validate the system’s capabilities, two cylindrical wood samples with different diameters of 100 mm and 140 mm and with one hollow and three hollows within are 3D-printed, investigated, and then measured. The authors recommended a robust time-reversal algorithm (RTR) to reconstruct 2D images that successfully identified and localized cavities with the smallest diameter of 3.5 mm. Furthermore, reconstructed images of measured data verified a practical and reliable oil palm trunk imaging and sensing system with a high structural similarity index and resolution.

1. Introduction

Palm oil is a precious crop in SE Asia. Its importance is such that the improvement of Oil Palm Tree (OPT) husbandry and products is vital to the entire region. Fungal diseases that attack fruit and tree trunk are the greatest challenge to farmers. *Ganoderma* is a fungus that causes internal dry rot of the xylem which dramatically reduces osmosis. Initial symptoms manifest as pale green foliage [1–6]. As the dryness advances, hollows are formed within the trunk. Zonal monitoring by Unmanned Aerial Vehicles (UAV) as a recent monitoring method can monitor visual symptoms [7], but no internal damage can be monitored. Therefore, other technologies are used for deeper zonal analyses, especially since chemical methods that kill the fungus [8, 9] have serious environmental side effects.

Nondestructive testing (NDT) and nonintrusive inspection (NII) are techniques which can assist in the investigation of the internal condition of the oil palm tree trunk without any side effects on it. The specific associated instruments and machineries have been designed based on appropriate knowledge of the object’s physical and electrical properties. However, this designing procedure must be accurate, robust, fast, and inexpensive. Tomography, for example, is a reliable option to inspect defective and resin-containing trees. It is a method which has been utilized to create a cross-sectional
representation of the internal structure of an object under test (OUT) through the penetration of light, electromagnetic field, or electromagnetic waves [10]. The image reconstruction of an object is feasible through an entire projection of appropriate physical parameters. Moreover, the image can be achieved by either mapping out singular evaluated parameters or by using a tomographic technique using algorithms and superior computational practices for data collection and image reconstruction.

Several tomography techniques have been applied to investigate wooden media like an oil palm tree trunk. The "ultrasound" technique has limited resolution due to wavelength and transducer size because heterogeneous materials do not allow sound waves to travel in straight lines. Thus, it is difficult to locate the cavities in the xylem and difficult to distinguish between a single large hollow or a cluster [10–12]. The Electrical Capacitance Volume Tomography (ECTV) method yields inadequate spatial resolution with unfavourable nonlinear image reconstruction. Furthermore, the High-Resolution X-ray Computed Tomography (HRXCT) technique is tedious, dangerous, and dependent on system size and sample distance. The gamma computed tomography (CT) is also dangerously tedious and use bulky equipment which presents mobility issues [13, 14]. Therefore, a new alternative is required to face and resolve all the limitations that exist in the abovementioned techniques. Microwave tomography (imaging and sensing) is a non-destructive technique that promises and produces better results in terms of safety, cost, mobility, and processing time.

Microwave (MW) imaging and sensing systems are now ubiquitous and used for numerous applications. The most common applications can be mentioned as dielectric property extraction and localization. The first one contrasts dielectric properties in subject materials and/or performs the characterization of the subject under test [15–18]. For example, it can measure the permittivity of oil palm fruit and other tree components. A few researchers have used MW tomography to investigate the dielectric properties of a rubber leaf and oil palm leaf at the X-band [19], oil palm trunk core [20], oil palm natural rubber [21], and oil palm mesocarp [22]. Others have presented signal processing and analysis of OPT exposure to MW energy [23, 24]. In addition to these, the dielectric properties of a complete oil palm trunk were also investigated by the author under different conditions [25]. The second important application of microwave sensing is target finding and localization by applying the microwave radar technique. This method usually applies two or several low-power UWB/wide-band pulse antennas such as those presented in [26, 27]. Scattered fields can be received by source and receiver antennas. Besides, it has several advantages compared to other methods while detecting and sensing a target (hollow regions in an OPT trunk). It has low cost; has high image resolution; uses nonionizing radiation; and is mobile, safe, and easily applied.

With respect to imaging in a wooden medium, some researches were carried out to detect trunk hollows or extract dielectric scatter from a wood slab to identify cavities. The backpropagation technique was performed to reconstruct the image of a hollow in a wooden trunk. However, the obtained constructed images showed that the hollow could not be detected clearly, and the images were blurry (their detected shapes were not the same) due to the noises and the single frequency measurement [28]. A wooden trunk was characterized combining the qualitative and quantitative microwave imaging techniques. Despite achieving good results, the system was complicated. Besides, the antenna sensors applied in the inspection of the trunk were large, and 30 of them were applied around the trunk. The process was more tedious since they did not possess prior information of the SUT, and they followed the multistatic technique to reconstruct the image (one transmitter sends and the other receives, and then the transmitter switches with the other one till the 30th array; however, if the reconstructed image uses improved TR, only one transmitter sends and the others receive, thus saving on processing time) [29]. Another imaging system has been used to characterize a wooden slab. Despite using iterative and backpropagation techniques and obtaining the reconstructed image, the system utilized a mechanical technique to move the antenna sensors horizontally and vertically around the trunk sample. Besides, only two large antenna sensors at a certain distance from the sample were used to send and receive the microwave pulses [30]. Furthermore, agarwood was potentially sensed and detected in a wooden trunk using MW tomography. Although six techniques were used to show the system’s imaging capability in the detection of agarwood, the obtained images failed the quality expectations since they could not achieve acceptable accuracy by evaluating the structural similarity index (SSIM) for each of these techniques (it did not exceed 47%) [31]. Therefore, a simpler, faster, and more accurate technique is required to compensate for the abovementioned drawbacks.

Before one can perform any image reconstruction of pathologic hollows, a MW antenna array is needed. Sensors are positioned in two different arrangements, planar and cylindrical. A planar array is initially used to demonstrate antenna sensor capability in wooden media [27]. Afterward, a cylindrical array is used for a thorough investigation of the OPT in this study.

This paper has six sections: an introduction of the challenges and methods of cavity detection in wooden media is followed by the selected MW techniques and algorithms. Then, the simulation studies and results are discussed. Finally, the study concluded.

2. Microwave Imaging Techniques

The three existing MW imaging techniques are passive, hybrid, and active. Passive imaging is based on MW heating of target cells that are detected by variations in regional temperature. In the hybrid method, microwave imaging and acoustic imaging are combined (more explanations about passive and hybrid techniques are presented in the Supplementary materials, section 1). Active techniques involve methods that rely on the significant electrical properties and contrast between malignant and normal tissues at microwave frequencies [32]. The active method applies MW pulses to illuminate a sample under test (SUT). This is accomplished either by tomography or by radar-based MW
imaging. In tomography, a target is detected because of its higher permittivity. Radar-based sensing detects a target when it has a strong scattered wave [33]. Several papers report detecting strong tumor-like scattering using a radar-based technique and data acquisition using the inverse process mathematically [34–38]. Each UWB antenna sends a UWB pulse in sequence. Scattered signals are received and analysed by an algorithm to detect and reconstruct an image. Any hollow and its surrounding region causes backscatter and can be compared to the other regions of the trunk; hence, cavities with different energy levels are used to reconstruct an image. Algorithm assistance should be sought to construct the image of the scatter in the testing medium.

Confocal Microwave Imaging (CMI) algorithms have been utilized over the last two decades. They usually combine and sum up all received signals to create an image that exploits differences in the intensity of dielectric scatter. During image reconstruction, an additional algorithm removes significant artifacts that affect the imaging algorithm’s performance. Artifact-removal algorithms should also suppress clutter. Most of the CMI algorithms are categorized as either Data Adaptive (DA) or Data Independent (DI). Both types are based on received backscattered radar signals illuminated by UWB pulses. In DI, the coherent addition is carried out based on an assumed propagated model. However, DA estimated this model by retrieving the signals and then applying some compensation factors. DA algorithms produce high-resolution images using array steering and provide excellent clutter removal compared to DI. Although DA algorithms obtain high-resolution images via array steering, which is difficult in real-time, open-source DI algorithms are preferred and have been improved by removing their faults [39–41]. Several algorithms are characterized by these two groups (Table 1 in Supplementary materials, section 2 shows a brief comparison).

3. Modelling of Microwave Imaging in Trunk

3.1. Antenna Array Configurations and Imaging Criteria Setup. Excitation, simulation, and measurement are performed when the UWB antennas are in contact with the trunk sample. A plastic tape support structure was designed made of polylactic acid (PLA) to hold the set of antenna arrays in the required locations. Figure 1 shows the simulated and modelled proposed antenna arrays presented in [27] along with the trunk and the plastic tape made of PLA. The tape is used to maintain the antennas oriented towards the sample, and it is completely fit and does not move during the experiment. The antennas illuminate the trunk once they touch it.

The system’s structure can adapt to a trunk sample with a minimum and a maximum radius of 50 mm ($R_{\text{min}}$) and 150 mm ($R_{\text{max}}$), respectively. Every two antennas are separated with a radial distance of 100 mm (300 mm for the larger sample), 15 mm vertically, and 22.5 degrees horizontally. Therefore, if $A$ is an antenna number from 1 to 16, then the position of the other arrays can be positioned according to the polar coordinate system as well:

$$\begin{align*}
\gamma &= R_{\text{max}} - d_r, \\
\theta &= \frac{(A - 1)\pi}{8},
\end{align*}$$

where $d_r$ is the radial displacement of arrays in terms of the maximum radius.

The plastic tape was made of PLA to reduce the impacts on the electromagnetic (EM) field distribution. PLA has a dielectric constant near that of air; thus, it affects the EM fields minimally. To illuminate the trunk sample and collect the scattered electric fields and signals, a set of 16 monopole elliptical UWB antennas with dimensions of $15 \times 15 \text{mm}^2$ presented in [27] was utilized (Figure 1(b)) (when the antenna dimensions are also small, multiple antennas are permitted to gather more data from scattered signals). Besides, the microwave radar technique allows the reduction of clutter from highly scattered signals from targets (hollows) for image reconstruction [27, 33]). The antenna proposed here showed promising performance in the wooden area as shown in [27]. The antenna is designed on a substrate with a dielectric constant of 2.55 which is close to the $\varepsilon_r$ of most wooden materials in dry situations such as high-density wood, plywood, and even oil palm trunk. The proposed UWB antenna obtained a fractional BW of almost 17 GHz. Since the proposed antenna’s radiation characteristics have been evaluated considering a wooden slab as shown in [27], some of its radiation characteristics in the time domain and the frequency domain are presented in the presence of a cylindrical wooden media to show how the antenna arrays perform (Supplementary materials, section 4).

3.2. Modelling of Electromagnetic Behaviour and TR Algorithm. The time-reversal (TR) algorithm works with reciprocal properties of the wave equation, which means that both the electric and magnetic field components are backpropagated to focus on a source where transmitters and receivers join and mirror each other. TR is used in several applications, including US [42], and has demonstrated promising results in asymmetrical media and cluttered environments [43, 44] with profitable applications in electromagnetics [45, 46]. However, some projects require selective focusing and are tedious, expensive, and sensitive towards weak contrast with limited resolution [47]. Despite its exceptional promise, TR faces challenges during image reconstruction. These include calculating backscatter from the target, which requires a high-performance antenna with both a broad bandwidth and superior fidelity (the amount of pulse distortion is induced through the antenna, which is illustrated through the correlation coefficient between the transmitted signal and the received signal). For an impulse radio in UWB communications, a high degree of correlation must exist between the transmitted and received signals to avoid losing the modulated information [48]. Before applying the TR algorithm, the electromagnetic waves in the medium under test should be investigated. Thus, Maxwell’s equations are utilized. Maxwell’s equations (equation (2)) predict the propagation of electromagnetic energy away from time-varying sources (current and charge) in the form of waves. Consider a linear,
homogeneous, isotropic media characterized by \((\mu, \varepsilon, \sigma)\) in a source-free region; they can be expressed as follows:

\[
\nabla \times E = -\mu \frac{\partial H}{\partial t},
\]

\[
\nabla \times H = \sigma E + \frac{\partial E}{\partial t},
\]

\[
\nabla \cdot E = 0,
\]

\[
\nabla \cdot H = 0.
\]

The properties of an electromagnetic wave (direction of propagation, the velocity of propagation, wavelength, frequency, attenuation, etc.) can be determined by examining the solutions to the wave equations that define the electric and magnetic fields of the wave. In a lossless and symmetric medium, the wave equation can be simplified and presented using Maxwell’s equation as follows:

\[
\left(\nabla^2 - \frac{\mu}{\varepsilon} \frac{\partial^2}{\partial t^2}\right) A(r, t) = 0. \tag{3}
\]

Equation (3) gives two diverging and converging solutions as \(A(r, t)\) and \(A(r, -t)\). Therefore, the diverged wave from the point source is backpropagated using its genuine path in returning to the resource. \(A(r, -t)\) is the time-

**Figure 1:** (a) Modulated UWB antennas around a cylindrical media. (b) 16 simulated prototypes of the antennas around the sample. (c) The simulated prototype of the plastic tape and the trunk sample.

**Figure 2:** (a) Modulated Gaussian pulse as input. (b) UWB frequency response of the pulse.
Figure 3: Received signals.

Figure 4: A robust TR algorithm (RTR).
reversed field that is backpropagated in a tunable medium which gives a spatial concentration.

This paper presents an experimentally robust time-reversal technique that detects OPT trunk cavitation (hollows). An active TR is used to calculate targeted fields and reverse them after which the next two steps of simulation are numerically obtained. Simulation studies and models are based on a 2D finite difference time domain (FDTD) and performed by CST Studio 2019. UWB antenna sensors are modelled to send and receive signals. During the simulation process, the boundaries are considered as perfectly matched layers and then Maxwell’s equations shown in equation (2) are utilized to derive their boundary equations. After solving the FDTD equation, the time-reversed fields are backpropagated. Since the trunk sample is lossy and inhomogeneous, the wave equation for this new sample given by

$$\nabla^2 - \mu_0 \sigma \frac{\partial}{\partial t} - \mu_0 \frac{\partial^2}{\partial t^2} A(r, t) = 0,$$

where $\sigma$ is the material conductivity. Afterward, the time-reversed electric fields using the 2D FDTD is expressed by

$$E^{z+1}_z(i, j) = \frac{1}{1 + (\sigma \Delta t/2\epsilon)} E_z^z(i, j) - \frac{1}{1 - (\sigma \Delta t/2\epsilon)} \frac{\Delta t}{\Delta x} \times \left(H_y^{n+1/2}(i + \frac{1}{2}, j) - H_y^{n-1/2}(i - \frac{1}{2}, j) \right)$$

$$- H_x^{n+1/2}(i, j + \frac{1}{2}) + H_x^{n-1/2}(i, j - \frac{1}{2}),$$

where $\Delta x$ and $\Delta t$ are the FDTD cell size and time steps, respectively. However, the inhomogeneity does not affect equation (5) since it has been reversed to compensate the losses and attenuations [49].

The antenna sensor input is a modulated UWB Gaussian pulse with a modulating frequency $(f_r)$ of 1.3 GHz, given as follows:

$$S(t) = e^{-(t-t_0)^2/2\omega^2} \cos (2\pi f_r t),$$

where the pulse center is $t_0$; $\omega$ has a pulse width of 86.1 ps associated with a half-power bandwidth of 27 GHz as shown in Figure 2.

**Figure 5:** The ETC (a) and gated windowed signals (b).

**Figure 6:** The wave diagram that defines the early and late time instants.
Before beginning the simulation, total fields, with and without a hollow, need to be subtracted to obtain the cavity’s contribution to each receiver array. Figure 3 shows total received signals for both conditions when array A1 transmits a signal to 15 receivers. To obtain the received signal between every two array antennas, the arrays are located around the OPT cylinder with a radial distance of 100 mm; for the unhealthy sample, a spherical hollow (diameter = 8 mm) is located at the center of the cylinder as well. Afterward, the transmitter sends the Gaussian pulse presented by equation (6) and Figure 2, and the receivers receive the signals shown in Figure 3.

4. Image Reconstruction Algorithm and Procedures

Several types of researches have used planar arrays with different numbers of antennas to detect breast tumours [50, 51]. For our purposes, we initially used 10 planar sensor arrays to show the capability of the antenna arrays [27]. An integrated cylindrical array was used to simulate the OPT shape for this first study of MW imaging of pathological OPT hollows. The cylinder’s dimensions are 100 mm diameter × 55 mm thickness, which matches the average ten-year growth of an OPT trunk intending to detect cavities at an early stage in young trees. The hollow (8 mm in diameter) is at the center of the simulated trunk. Dielectric properties were previously measured and recorded from plantation samples of healthy and unhealthy trees presented by Tale et al. [25]. Therefore, referenced dielectric constants associated with both healthy and pathologic samples were available for simulation studies. A healthy dielectric constant has ~10% moisture content. These constants are 5 and 3, respectively [20, 25]. Since the TR algorithm was used, an additional phase shift coherently compensated for all BW, especially during backpropagation, as part of the proposed robust TR algorithm. Although we did assess effects on multilayered OPT, characteristic TR processing also showed promise for multilayered and cluttered media.

Tale et al. [27] established the feasibility of this imaging system and planar array for the detection of hollows in wood.
media. Hence, signal processing was initiated sequentially like a conventional time-reversal algorithm to forward signals with and without targets to obtain deviations. However, signals were then reversed in time and backpropagated to concentrate on targeted loci; the goal is to calculate and extract a hollowness response from the total field after clutter and artifact removal. Such processing is significant since a target’s response is dominated by reflections from other layers in a sample, to include all inhomogeneities. Hence, our signal processing algorithm was devised and extended to minimize clutter and extract the hollowness response from the totality of scattering fields and signals. Figure 4 illustrates the algorithm diagram ($S_1$–$S_{16}$ are the calibrated received signals).

Following the proposed algorithm shown in Figure 4, each section of the imaging algorithm is presented accordingly.

4.1. Subtraction of Background. Apart from hollowness effects on scattered signals, such signals contain clutter from various sources, including side-lobe coupling, which should be reduced as much as possible. Background signals ($E_{bg,s,m}(t)$ when no trunk phantom exists) are thus subtracted from scattered signals ($E_{ss,s,m}(t)$) to obtain the true background signal ($E_{Rx,s,m}(t)$) (its clutter has been removed) for the $s$ th view ($s = 1, \cdots, S$) at the measurement points of the antenna arrays given as follows:

$$E_{Rx,s,m}(t) = E_{ss,s,m}(t) - E_{bg,s,m}(t),$$

where $N = 16$ is the maximum number of antenna sensors. Thus, the output from equation (7) yields reduced clutter.

4.2. Removing Early Time Content (ETC). Early Time Content (ETC) are signal reflections with higher magnitudes compared to scatter from a hollow. ETC should also be removed so that it will not mask a hollow’s scatter. Therefore,
ETC is subtracted from Late Time Content (LTC) or hollow backscatter signals. This is done by subtracting the average of all scattered signals \( E_{\text{ave},m}(t) \) from each scattered signal \( E_{s,m}(t) \) given by

\[
E_{1,s,m}(t) = E_{s,m}(t) - E_{\text{ave},m}(t),
\]

where

\[
E_{\text{ave},m}(t) = \frac{1}{s} \sum_{i=1}^{s} E_{i,s,m}(t) + \frac{1}{s} \sum_{i=1}^{s} n_{i}(t),
\]

where \( n_{i}(t) \) is a zero-mean noise.

Signal averaging provides ETC because antenna sensors are aligned and located symmetrically around the test sample and because of the generally spherical shape of the targeted cavities. Moreover, performing the time gating later will improve the outcomes when the sample is asymmetrical such as a real OPT trunk which is not symmetrical. Besides, applying the time gating (using windowed gating function) offered smoother signals [52]. Figure 5 illustrates the output for ETC stage and time gating of the signal.

4.3. Paired Multiplying Scattered Output. ETC output \( E_{1,s,m}(t) \) for each scattered signal from each sensor is paired multiplied to increase scattered data for more accurate detection and localization (DMAS [53]). Paring multiplication of four scattered signals \( u_1, u_2, u_3, \) and \( u_4 \) is performed as follows \( (u_1 \rightarrow u_4 \) are mentioned just as an example to show how pairing multiplication works):

\[
\begin{align*}
u_1 &= E_{1,s,1}(t), \\
u_2 &= E_{2,s,1}(t), \\
&\vdots \\
u_{16} &= E_{16,s,1}(t), \\
m &= 1, 2, \ldots, 16.
\end{align*}
\]
Since presenting $E_{2s,m}(t)$ for all the 16 arrays is lengthy, we show $E_{2s,m}(t)$ for only $m = 4$. Therefore, the output for $E_{2s,m}(t)$ is presented accordingly:

\begin{align*}
    y_1 &= u_1 \cdot u_2, \\
    y_2 &= u_1 \cdot u_3, \\
    y_3 &= u_1 \cdot u_4, \\
    y_4 &= u_2 \cdot u_3, \\
    y_5 &= u_2 \cdot u_4, \\
    y_6 &= u_3 \cdot u_4.
\end{align*}

Therefore,

\begin{equation}
    E_{2s,m}(t) = [y_1 y_2 y_3 y_4 y_5 y_6],
\end{equation}

where $y_1$, $y_2$, $y_3$, $y_4$, $y_5$, and $y_6$ are column matrixes.

Multiplied scattered signals are then averaged to remove clutter and artifact further ($E_{2s,m}(t)$) and improve the hollow detection.

4.4. Time of Arrival (TOA). TOA is determined to perform time grating and detect hollowness response. It measures the time between a wave’s touching a sample’s front and back walls: early time ($t_E$) and late time ($t_L$), respectively. TOA provides a helpful window that further reduces clutter that
is reflected from a back wall. This windowed signal \( E_{3,m}(t) \) is determined as follows:

\[
E_{3,m}(t) = \begin{cases} 
E_{2,m}(t), & \text{if } t_f < t < t_L, \\
0, & \text{otherwise}. 
\end{cases} 
\] \( (13) \)

The procedure for calculating TOA is presented in Figure 6 (more details and explanation are depicted in Supplementary materials, section 3).

4.5. Time Gating and Windowing. The next step is to window the obtained TOA signal by multiplying it with a short Gaussian pulse \( E_4 \). This, when compared to the wavelength, helps detect smaller hollows. Equation (14) shows that windowing leaves both amplitude and phase unchanged for all required signals:

\[
E_{4,m}(t) = E_{3,m}(t) \cdot e^{-((t-t_p)/\tau)^2}, 
\] \( (14) \)

where \( t_p \) and \( \tau \) represent the apex and a factor for tapering the Gaussian window, respectively (the behavior is like that of a matched filter which provides an apex at the point where \( E_3 \) concentrates more); \( E_{4,m}(t) \) is the output obtained in robust TR simulation.
5. Reconstructed Images Using Simulated and Measured Results

Four separate trials demonstrated the robustness of this approach to detect simulated OPT hollows. Before discussing image reconstruction, it is informative to illustrate parameters that affect the integrated cylindrical array. Please note that this antenna array’s ability to work on wood media had been previously demonstrated by Tale et al. [27]. Received signals from different sensors and angles, plus the fidelity factor and sensor coupling, are now discussed (Supplementary materials, section 4).

After investigating factors such as received signals, fidelity, and coupling effects, received signals were extracted from CST Studio 2019 then imported to reconstruct an image of the hollow. Several factors were considered in the image reconstruction process. These include the number of sensors, different target locations (hollows), smaller hollows, multiple targets, larger OPT diameters (16 and 30 cm), and OPT asymmetry. Furthermore, a hollow diameter of 8 mm was presented for all cases except for one of 5 mm. OPT diameter was 100 mm for all trials except those of 16 and 30 cm diameters.

To reconstruct the image, all the imported signals and reconstruction procedures presented above are utilized to get the output. Then, time delay for every focal point is calculated. The antenna sensors’ positions are introduced, and the distances are calculated. Afterward, the output data is interpolated and intensity values for each focal point determined. Finally, the images are reconstructed based on the intensity of each focal point.

The first trial investigated the effects of sensor numbers on detection accuracy and localization. We comparatively assessed the new RTR algorithm’s ability to reconstruct an image against three conventional algorithms: DAS, DMAS, and standard TR.

5.1. Reconstructed Images Using Simulation Data. Figure 7 shows the impact from different numbers of sensors (4, 8, 12, and 16) on hollowness detection (center of sample disc) using the DAS algorithm. When the array’s number of sensors increases, so does clarity, accuracy, and clutter...
removal. This is likely due to increased signal scattering. An array’s number of sensors also impacted image reconstruction as seen in Figure 8. The same trend appears for DMAS results but with greater accuracy and clutter removal for all arrays (Figure 8). Array (d) produced the best outcome. Also, larger arrays increased contrast at the center for both X and Y axes.

Figures 9 and 10 show image reconstructions using conventional and proposed TR algorithms, respectively, with a similar trend (DAS versus DMAS). Conventional TR images of the hollow were more accurate and had less clutter compared to DAS and DMAS results. RTR produced superior outcomes in terms of accuracy in localization and image quality. All arrays with 16 sensors yielded better results for each algorithm. However, the proposed robust TR achieved superior results even with 4 sensors. This is because it uses the paring multiplication method, which enhances the scattered data in the imaging area, to achieve an acceptable artifact and clutter removal.

After this, we turned to robust TR image reconstructions of off-center hollows. Figure 11 shows reconstructions of 8 mm off-center cavities at $X = -20$ mm/$Y = 0$ mm and $X = 10$ mm/$Y = -30$ mm, respectively, achieved with a 16-sensor array. Artifacts noted are due to unequal distances between sensors and hollow, although the recommended robust time-reversal algorithm obtained high accuracy in detection and localization.

The image in Figure 12 is of a much smaller 5 mm hollow. Improved image quality and accurate localization demonstrate the robust TR’s capability, especially considering far less clutter and artifacts.

Image reconstruction of three off-center hollows is shown in Figure 13. All algorithms detected all three hollows but with slight shifts in position except for the robust TR, which showed superior localization.

Figure 14 illustrates reconstructed images of central hollows in much larger OPT samples with diameters of 160 and 300 mm. The proposed detection and reconstruction system removes and suppresses clutter better than conventional DAS, DMAS, and TR algorithms. What clutter remains at the center is due to increased delays and distance between cavities and each antenna.

Figure 15 shows a nonhomogeneous sphere as seen in a prior investigation. The test sample appears heterogeneous after adding two elliptical cylinders. Total length and width from X to Y axes are 130 and 100 mm, respectively, with a hollow at $X = -10$ and $Y = 0$. This image demonstrates that the proposed system and RTR readily detect hollows in nonhomogeneous trunk samples with excellent clutter and artifact removal. Some clutter remains to the right of the hollow, likely due to the unequal distribution of sensors causing signal delays from sensors on the left.
5.2. Reconstructed Images Using Measured Data. The authors use measured data to perform an additional assay and compile data for further coding. Before that, two cylindrical wooden shapes with different diameters of 100 mm and 140 mm representing healthy and unhealthy OPT xylem (a total of four samples) are fabricated with a 3D printer filled with wooden material of 40% wood [54]. Also, a plastic tape made of PLA was 3D printed to fasten all sensors to the cylinder. An aspherical hollow was centrally positioned. The samples’ dimensions were 100 × 55 mm and 100 × 140 mm (diameter/thickness), with a 5 mm diameter hollow. For logistical reasons and expense, the sample was 3D printed due to the unavailability of live young trees (<10 y). No plantation manager would agree to cut a tree for our use. The authors, therefore, fabricated a sample to assess simulation results before taking a portable system (VNA) to a plantation for in vivo validation. Besides, a similar tendency in the dielectric properties of this printed sample with those of the OPT sample presented in [20, 25] will be presented later. Figure 16 depicts the sensor array used for the 3D-printed simulated trunk for two different dimensions of 100 mm and 140 mm diameters. All components are depicted.

Before 3D printing the cylinder, a 3D cube was printed (same dimensions as [27]) to measure the dielectric properties at 2.45-3.26 GHz with a moisture content of 0-10% as presented by [20]. Dielectric measurements of the 3D-printed sample in Figure 17 show the same trend obtained in [20]. The investigations are performed in three structural directions such as cross-sectional, radial, and tangential to analyze the impacts of these directions on dielectric specifications of the samples. Before starting the measurements, the wooden cube is polished with sandpaper to make the sample’s surface smooth and to reduce any possibility of air bubble existence between the sample and the probe. Because the presence of an air gap between the sample surface and the probe can lead us to an incorrect and false measurement result. The dielectric properties of the OPT chunk are measured by applying an open-ended coaxial probe which is connected to a Vector Network Analyzer (VNA) model HP 85070-D. As aforementioned, microwave heating and microwave imaging are nondestructive measuring methods.

![Figure 18: RTR-reconstructed image using measured data for the sample with a diameter of 100 mm: (a) DAS, (b) DMAS, (c) TR, and (d) RTR.](image-url)
Besides, their low-power measurements do not cause any harm and alteration either in the biomass characteristics or in the human body during the test. Thus, a 3.5 mm diameter open-ended probe is used to touch the sample surface based on the previous method. The applied method of the measurement relies on the reflection coefficient of the coaxial probe when it reaches the sample surface. Hence, the dielectric properties of the log are measured concerning the magnitude and the phase of the reflection coefficient at each frequency of the band. Besides, all the locations on the sample are under test from the central part to the edge of the bark and cortex; however, the sample is divided into five parts and only the best outcome is chosen [25].

A sixteen-sensor array was assembled then positioned after soldering ports to the SMA ports. The model HP 85070-D Vector Network Analyzer (VNA) was calibrated and used for all measurements. Two cables were connected, one to the first terminal and the other to sensors 2 through 16. S-parameters were extracted from the VNA then imported to MATLAB for image reconstruction. The inverse Fourier transformation ($S_{21}$) was calculated for all received signals after transmission. Finally, the proposed RTR algorithm reconstructed the image (Figures 18 and 19). Figures 18 and 19 indicate the experimental reconstructed images using the RTR algorithm for two 3D-printed wooden samples shown in Figure 16. The experimental reconstructed images show that the spherical hollow with a diameter of 5 mm in the fabricated samples is perfectly detected (same as in the simulation, where the background signal appears when no trunk phantom exists). However, some negligible clutters are also noticed for both 100 mm and 140 mm diameter samples.

To conduct further evaluation and to show the antenna’s capability through measurements, more wooden samples with three hollows are 3D printed. Two more samples are printed, one with a diameter of 100 mm and the other with a diameter of 140 mm, each with three hollows (5 mm diameter) within. These targets are located at (0, 0), (-30, 20), and (-45, -10) for the one with a diameter of 100 mm and (-10, -5), (-25, -15), and (20, 40) for the other one with a diameter of 140 mm. Figures 20 and 21 depict the reconstructed images of the sample with a 100 mm diameter and the sample

![Figure 19: RTR-reconstructed image using measured data for the sample with a diameter of 140 mm: (a) DAS, (b) DMAS, (c) TR, and (d) RTR.](image-url)
with a 140 mm diameter, respectively. They show that all three hollows were detected using RTR. However, more clutter was noticed compared to the time when the samples had only one hollow. Besides, as the diameter increased to 140 mm, less accuracy was obtained compared to when the diameter was 100 mm, although it was detected that only one of the targets was misplaced slightly in the reconstructed image of the sample with a diameter of 140 mm.

5.3. Structural Similarity Index (SSIM) and Image Resolution.
In full-reference image quality assessment methods, the quality of a test image is evaluated by comparing it with a reference image that is assumed to have a perfect quality. The goal of image quality assessment research is to design methods that quantify the strength of the perceptual similarity (or difference) between the test and the reference images. Besides, the similarity index is acquired by checking the images’ luminance, contrast, and structure. More details on how it is done are presented in [55] (the formulas for resolution calculations are presented in Supplementary materials, section 5).

The reference image is an image that shows a sphere with a dimension of 8 mm (in simulated investigations) located at the center of the imaging area with the mean squared error (MSE) of 0 and SSIM of 1. This reference image does not show any clutters and artifacts; the clutters and artifacts are perfectly removed. Table 1 presents the MSE and SSIM for all the reconstructed images. Figures 7–15 and Figures 18–21 cited in Table 1 show the results of the 16 arrays. It is observed that the reconstructed image using the recommended RTR obtained the highest SSIM score and the lowest MSE. Table 1 shows that the RTR algorithm offers the highest SSIM and the lowest MSE in Figures 7–15 and Figures 18–21 except when trunk sample’s diameter is 300 mm as the MSE is slightly lower compared to the conventional techniques like DAS and DMAS.

Table 2 indicates the comparison of the proposed imaging system with other researches using microwave imaging and ultrasound methods. In addition, it shows that the proposed system applying the microwave technique can achieve better results in terms of resolution and can detect the smallest hollow with a diameter of 3.5 mm in any location within the trunk.
6. Conclusions

Oil palm trees are important to SE Asia’s economy. Their health is challenged by a fungus that destroys the OPT trunk xylem and leaf hollows. This degrades productivity and eventually kills the tree. The plantation owners and the oil palm industry have failed to inspect their trees effectively. Therefore, they approached tomography techniques as a solution to their losses. Although several tomography methods have been suggested over the years, MW imaging and sensing shows promise with negligible side effects. This paper introduced a noninvasive system that detects fungal-induced cavitation at an early stage. The proposed UWB antenna array effectively works in wood media for both planar and cylindrical configurations. They are used to send and receive UWB pulses. Various conditions were considered for the examinations such as different array arrangements of 4, 8, 12, and 16 sensors; a smaller cavity of 5 mm diameter; multiple hollows (center and off-center); larger 16 and 30 cm diameter trunks; and a heterogeneous trunk sample. Then, the image reconstruction of the received data using three conventional algorithms (DAS, DMAS, and TR) was compared with the proposed RTR processing and showed improved quality and accuracy. The simulated OPT trunk samples were 3D printed (100 mm, 140 mm) to represent healthy and unhealthy trees (eight samples in total: four healthy and four unhealthy samples, two with a centrally located spherical hollow of 5 mm diameter and two with three targets of 5 mm diameter). The simulated and experimental reconstructed images using the proposed array and RTR algorithm demonstrated more accuracy and image quality compared to conventional algorithms. The proposed system utilizing the robust time-reversal algorithm is capable of detecting a hollow with a minimum diameter of 3.5 mm (the range, cross-range, and spatial resolution are 5.5 mm, 7.5 mm, and ~3.5 mm, respectively) at any location within a trunk that has a diameter of 30 cm. In addition, the Structural Similarity Index investigation of the reconstructed images indicated that the proposed RTR

![Figure 21: RTR-reconstructed image using measured data for the sample with a diameter of 140 mm and three targets: (a) DAS, (b) DMAS, (c) TR, and (d) RTR.](image-url)
algorithm achieves the highest value in comparison with the conventional algorithms presented here and those applied for imaging of agarwood in the literature. Therefore, the proposed system can be an adequate imaging system to detect hollowness in wood media as OPT. Furthermore, it can be extended and applied in plantations for deep zonal monitoring of the trees.

**Data Availability**

The data (measured data and codes) used to support the findings of this study are available from the corresponding author upon request and with the institute’s permission.

**Conflicts of Interest**

The authors declare that there is no conflict of interest regarding the publication of this paper.

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**Table 1: The MSE and SSIM comparison of the reconstructed images.**

| Images               | MSE    | SSIM  | Images               | MSE    | SSIM  |
|---------------------|--------|-------|---------------------|--------|-------|
| Figures 7–10, RTR   | 255.005| 0.9775| Figure 14(b), RTR   | 213.6472| 0.9818 |
| Figures 7–10, TR    | 295.233| 0.8756| Figure 14(b), TR    | 216.744 | 0.9752 |
| Figures 7–10, DMAS  | 458.56 | 0.8021| Figure 14(b), DMAS  | 201.002 | 0.9872 |
| Figures 7–10, DAS   | 580.56 | 0.7898| Figure 14(b), DAS   | 198.9320| 0.9832 |
| Figure 11(a), RTR   | 290.23 | 0.9687| Figure 15, RTR      | 113.05  | 0.9921 |
| Figure 11(a), TR    | 311.65 | 0.8567| Figure 15, TR       | 122.35  | 0.9811 |
| Figure 11(a), DMAS  | 384.221| 0.8187| Figure 15, DMAS     | 146.52  | 0.9750 |
| Figure 11(a), DAS   | 488.32 | 0.7923| Figure 15, DAS      | 178.23  | 0.9115 |
| Figure 11(b), RTR   | 135.25 | 0.9843| Figure 18, RTR      | 189.8103| 0.9833 |
| Figure 11(b), TR    | 158.36 | 0.9278| Figure 18, TR       | 192.6819| 0.9826 |
| Figure 11(b), DMAS  | 256.58 | 0.8722| Figure 18, DMAS     | 196.0304| 0.9824 |
| Figure 11(b), DAS   | 399.58 | 0.8055| Figure 18, DAS      | 202.9246| 0.9816 |
| Figure 12, RTR      | 129.15 | 0.9899| Figure 19, RTR      | 187.7792| 0.9838 |
| Figure 12, TR       | 294.56 | 0.9679| Figure 19, TR       | 226.4809| 0.9807 |
| Figure 12, DMAS     | 390.57 | 0.8943| Figure 19, DMAS     | 254.3981| 0.9793 |
| Figure 12, DAS      | 530.48 | 0.74  | Figure 19, DAS      | 411.2105| 0.9688 |
| Figure 13, RTR      | 125.36 | 0.9625| Figure 20, RTR      | 102.244 | 0.9901 |
| Figure 13, TR       | 255.349| 85.258| Figure 20, TR       | 351.9688| 0.9672 |
| Figure 13, DMAS     | 288.98 | 80.522| Figure 20, DMAS     | 421.3549| 0.9598 |
| Figure 13, DAS      | 321.005| 78.85 | Figure 20, DAS      | 605.5244| 0.9456 |
| Figure 14(a), RTR   | 110.32 | 0.9978| Figure 21, RTR      | 105.511 | 0.9956 |
| Figure 14(a), TR    | 243.2801| 0.9802| Figure 21, TR       | 286.2467| 0.9646 |
| Figure 14(a), DMAS  | 277.9802| 0.975 | Figure 21, DMAS     | 353.9807| 0.9696 |
| Figure 14(a), DAS   | 390.6024| 0.9658| Figure 21, DAS      | 355.2921| 0.9678 |

**Table 2: Comparison of the proposed system with similar recent works.**

| References | Methods                                         | Maximum trunk size (mm) | Minimum size of detected void (mm) |
|------------|------------------------------------------------|------------------------|-----------------------------------|
| [28]       | Microwave imaging (single frequency)           | 300                    | 50                                |
| [29]       | Microwave imaging (single frequency)           | 300                    | 50                                |
| [31]       | Microwave imaging (single frequency)           | 230                    | 60                                |
| [56]       | Ultrasound                                      | 250                    | 23.6                              |
| [57]       | Ultrasound                                      | 495 $\times$ 301 $\times$ 145 | 75 $\times$ 43                    |
| [58]       | Ultrasound                                      | 300                    | 25                                |
| Proposed   | Microwave imaging                              | 300                    | 3.5                               |
Supplementary Materials

The supplementary material section consists of five parts showing extra explanation for the previous section from the manuscript. These parts are cited in the main text and are identifiable through supplementary section numbers [33, 59–64]. (Supplementary Materials)

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