

Article

Penetrating Radar on Unmanned Aerial Vehicle for the Inspection of Civilian Infrastructure: System Design, Modeling, and Analysis [†]

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Abstract

The increasing demand for noninvasive inspection (NII) of complex civil infrastructures requires overcoming the limitations of traditional ground-penetrating radar (GPR) systems in addressing diverse and large-scale applications. The solution proposed in this study focuses on an initial design that integrates a low-SWaP (Size, Weight, and Power) ultra-wideband (UWB) impulse radar with realistic electromagnetic modeling for deployment on unmanned aerial vehicles (UAVs). The system incorporates ultra-realistic antenna and propagation models, utilizing Finite Difference Time Domain (FDTD) solvers and multilayered media, to replicate realistic airborne sensing geometries. Verification and calibration are performed by comparing simulation outputs with laboratory measurements using varied material samples and target models. Custom signal processing algorithms are developed to extract meaningful features from complex electromagnetic environments and support anomaly detection. Additionally, machine learning (ML) techniques are trained on synthetic data to automate the identification of structural characteristics. The results demonstrate accurate agreement between simulations and measurements, as well as the potential for deploying this design in flight tests within realistic environments featuring complex electromagnetic interference.

Keywords: ultra-wideband impulse radar; UAV; radar penetration; imaging; FDTD



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1. Introduction

The need for the noninvasive inspection (NII) of various civilian infrastructures is becoming more diversified [1–3], so traditional ground-penetration radar (GPR) is no longer sufficient to meet these needs. Traditional GPR systems, while valuable, often fall short in addressing the increasing complexity and scale of modern infrastructure inspection tasks [4,5]. There are several key aspects that differ between conventional terrestrial GPR and UAV-based GPR systems. While ground-based systems typically offer a better signal-to-noise ratio, better depth penetration, and higher resolution due to the direct antenna–ground coupling, they are limited by terrain accessibility, surface conditions, and manual operation constraints. On the other hand, UAV-GPR systems face challenges such as higher electromagnetic noise, reduced resolution from higher standoff distances,

limited payload sizes, power consumption, and regulatory compliance [6–11]. Despite those limitations, these air-based systems offer enhanced mobility and coverage, especially in hazardous or hard-to-reach environments, by enabling contactless scanning [12,13]. For example, a complete automatic inspection of an airport facility that includes concrete structures, runway pavements, RF ground stations, and electromagnetic environments around these structures would be needed. To support the long-term integrity and safety of such critical systems, innovative sensing solutions capable of delivering comprehensive, high-resolution, and automated inspections are essential [14–18]. This study presents an advanced radar sensing system designed to meet these emerging challenges. It integrates a low-SWaP (Size, Weight, and Power) ultra-wideband (UWB) impulse radar, with the enhancements of physical structure models and a layered medium for multi-platform UAV (unmanned aerial vehicle) deployment [19], which has been proven to be an effective platform for fast and efficient monitoring [20–24]. Taking advantage of the benefits of temporal mobility, enhanced spatial coverage, and compact sensor payloads, the proposed system facilitates flexible and accurate inspection in various scenarios of civil infrastructure [25–29]. The system simulation and designing tool focused on building ultra-realistic multiple antenna and propagation models with Finite Difference Time Domain (FDTD) solvers [30–32], with the enhancements of physical structure models and a layered medium for airborne sensing geometries. The verification and calibration procedure compares the simulated profiles with lab measurements using different types of material samples and target models based on airborne-type A-Scan and B-Scan geometries [33]. Signal processing tools are developed, focusing on detecting anomalies from range profiles by identifying and mitigating interferences and artifacts in complex electromagnetic environments. The current results show that (1) the sensor has advantages based on the performance of the system payload, the power level, and accuracy. (2) A good match between measurements and simulation tests is achieved, even in complex electromagnetic environments. (3) With essential machine learning (ML) techniques, the detection of multiple structural characteristics in this type of infrastructure can be achieved with reasonable performance. (4) The next development step will enable flight tests of this sensor with more realistic data from traditionally hard-to-access locations.

2. Operation Concepts

2.1. *Noninvasive Inspection of Civil Infrastructure*

Even though radar technologies, such as ground-penetration radar (GPR) and synthetic aperture radars (SAR), have been investigated extensively in previous USDOT (US Department of Transportation) projects [34–49], based on the advantages of all-weather and surface-penetration sensing capabilities, a small, agile, and low-power version of such a radar as a payload for unmanned aerial vehicles (UAVs) or unmanned ground vehicles (UGVs) has not yet been demonstrated before. Another significant trend in bridge/road/pavement inspection is robot-based, automatic, multi-sensor integration from a distributed network [43–45,48,50,51]. Several manned ground-based platforms with cameras and other sensors (LIDAR, acoustic, piezoelectric, IR, RFID, etc.) have been reported before from DOT projects [40,50,52–62]. This includes machine learning (ML) processing methods to identify better structural and material health issues [37,53,63,64].

However, a more in-depth investigation is still needed to mature these algorithms. Transferring these R/D efforts to operational capabilities still depends on real-world challenges such as infrastructure accessibility, safety, environments, and the maturity of the sensor systems. The novel contribution of the new radar sensor package proposed in this project primarily lies in three aspects: (1) wideband microwave radar inspection, which offers better resolution and smaller sensor aperture sizes by leveraging the latest component

technology in radar sensors. (2) Enabling and implementing integration into a small UAS (Unmanned Aircraft System) platform, which has fewer restrictions from ground traffic, can access the problematic areas for human operators, and has been demonstrated through flight tests. (3) Introduction of a machine learning (ML) method based on high-fidelity physical modeling of the interactions between structures and microwave sensors and decision-tree-type sensor data models; thus, the ability to detect various types of defects in the 3D domain is improved compared to existing radar sensors. However, the UAS-based radar payload faces significant new challenges [65–67]. First, the standoff distance from the radar to the surface structure leads to a hybrid or heterogeneous propagation domain compared to existing GPRs. Second, extreme size, weight, and power constraints prohibit installation onto smaller platforms. Finally, there are legal regulations for deploying a UWB radar system over a UAV-based platform. In the US, the FCC (Federal Communications Commission) 02-48 describes that UWB GPR devices are only authorized for specific users (law enforcement, fire and rescue organizations, scientific research institutions, commercial mining companies, and construction companies) and must operate either below 960 MHz or within the 3.1–10.6 GHz band. These systems are only allowed when in contact with, or within close proximity of, the ground for the purpose of detecting, and with their energy intentionally directed down into the ground. Furthermore, all GPR systems must coordinate with the National Telecommunications and Information Administration (NTIA), but even airborne use is not authorized for such coordination. In Europe regulations (ETSI), GPR is allowed within a narrower 6–8.5 GHz band and strict power spectral density, but it is still not allowed for UAV-based platforms. Therefore, there are limitations for the legal deployment of UWB GPR on drones in the US and Europe [6–9].

2.2. Scanning and Data Collection Modes

The operation of UASs over the structure surface is similar to traditional GPR in the A-scan or B-scan modes. The A-scan usually involves 1D profiles, and the B-scan processes 2D profiles. The geometry of the near-field scanning mode is illustrated in Figure 1. This geometry is based on one scatterer (p_1) embedded in the concrete structure. A ray-tracing illustration [68] shows the expected scattering behaviors at the boundary between the air and the concrete materials.

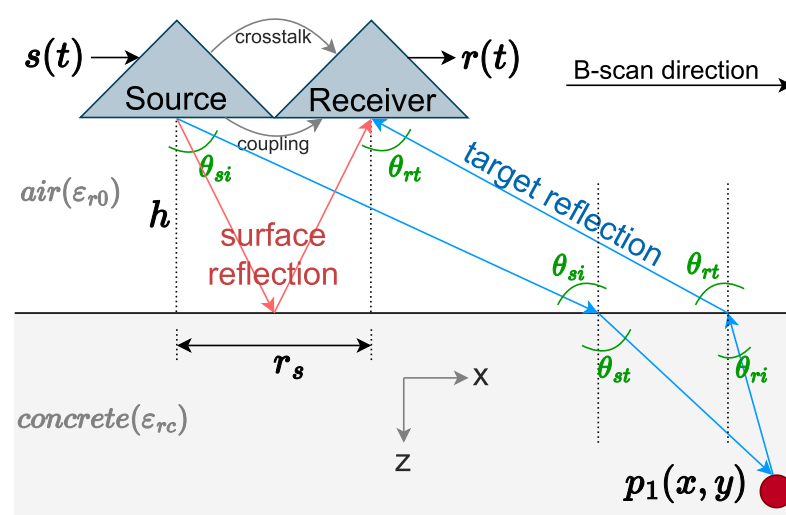


Figure 1. B-scan observation geometry representation and parameters.

In this geometric observation model, $s(t)$ and $r(t)$ are the transmitted (TX) and receiving (RX) radar signals, respectively. θ_{si} and θ_{st} are the TX-signal's incidence and transmit angles at the boundary of concrete and air media. θ_{ri} and θ_{rt} are the RX-signal's incidence

and transmit angles. h is the flight altitude, ϵ_{r0} is the relative permittivity of the air, ϵ_{rc} is the relative permittivity of the concrete, and r_s is the separation of the antennas. One of the ray paths from the transmit source to the concrete surface, which reaches a single-point scatterer and then returns to the receiver, is also illustrated.

3. System Description and Observation Model

The UWB radar uses an impulse radar, based on the X4 [69] system-on-chip (SoC) chipset, and different antenna options to meet the UAS payload requirements. The payload of the UAS is designed to support downward-looking scans through the straight flight path. The images of this drone payload system are shown in Figure 2.

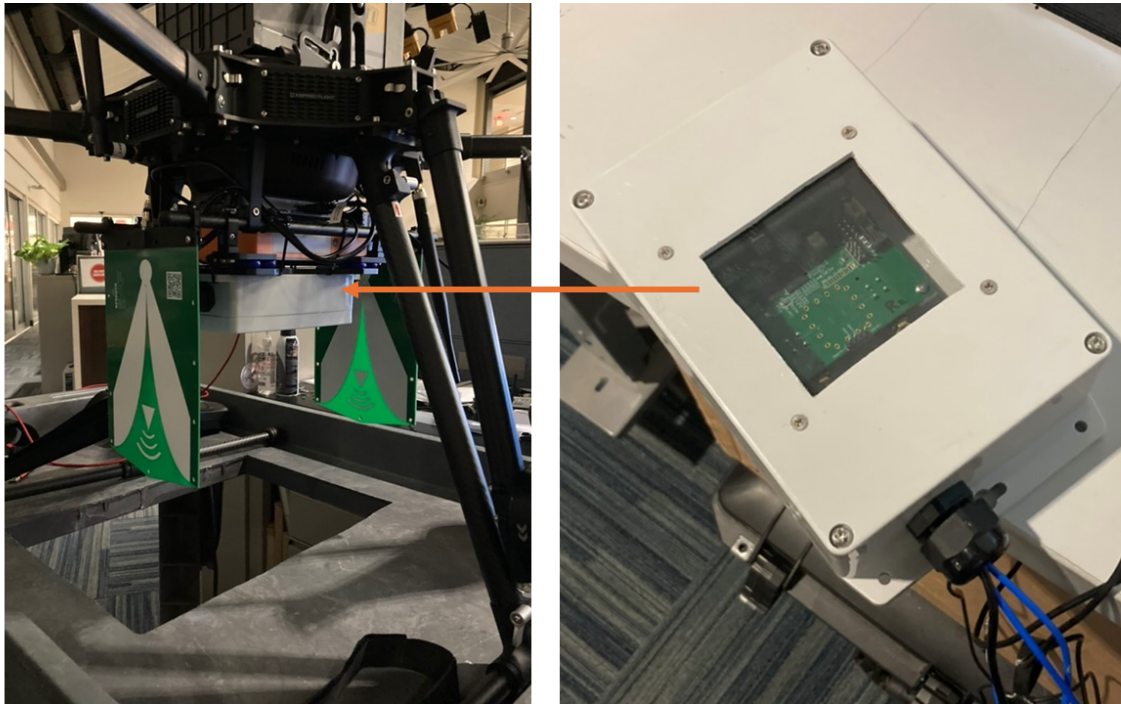


Figure 2. UWB impulse radar as a penetration radar for a drone payload.

Figure 3 shows an example of an A-scan range profile obtained using the radar payload through a concrete block, which suggests that the radar return signal, given the geometrical observation model in Figure 1, may be expressed as in Equation (1).

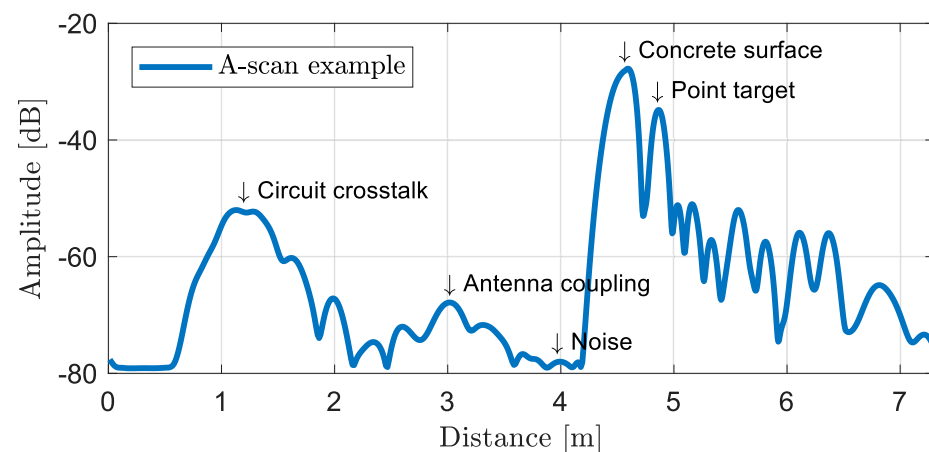


Figure 3. A-scan (range-profile) measurement of a concrete block using the radar mounted on the drone.

$$r(t, nx) = \sum_{n=1}^N \left\{ \sum_{p=1}^P [s_p(t, nx)] + s_{surface}(t) + s_{crosstalk}(t) \right\} + s_{noise}(t) \quad (1)$$

where t is the time, x is the horizontal step separation, $r(t, nx)$ is the signal measured on each position of the B-scan, s_p is the signal received from the point target (which also depends on parameters like the signal power radiated by the transmit and receive antennas and the radar cross-section of the scatterer point and its distance from the antennas), $s_{surface}$ is the signal received from the concrete surface, $s_{crosstalk}$ is the signal read due to the internal radar circuit cross-talk, s_{noise} denotes the additive white Gaussian noise, N is the number of A-scans, and P is the number of scatterers.

4. Overview of Simulation Methodology

This section outlines the simulation framework used to model and analyze the GPR system. It begins with a hyper-realistic modeling of the Vivaldi and Horn antennas for the FDTD gprMax solver [70]. Then, the UWB transmit Gaussian pulse is replicated in the simulator and verified against actual radar measurements. The propagation domain encompasses air and concrete, with consideration given to permittivity and conductivity. This domain is created by defining a 3D space where the TX/RX antennas, air, concrete, and targets are arranged (this 3D space is described in Section 5.1). Finally, an image correction process is developed to generate the 2D images of the underground targets, including key processes like signal power estimation, distance calibration, mitigation of concrete reflections, and compensation for heterogeneous propagation using ray-tracing corrections.

4.1. Antenna Modeling in FDTD Solver

The first step was to build realistic and detailed models in the FDTD tool (gprMax) of the two antennas used for the current radar, including a planar Vivaldi antenna [71] and a Horn antenna [72]. These models are illustrated in Figures 4 and 5. The digitized antenna model is obtained through the following steps for use with the FDTD tool: First, all the antenna dimensions are measured and used to create a CAD model. This CAD model is then imported into 3D electromagnetic (EM) analysis software gprMax 3.1.7 to verify its EM behavior. Subsequently, the model is voxelized, ensuring that the discretization space satisfies the CFL (Courant–Friedrichs–Lewy) condition [73] for the maximum frequency used. The antenna responses and radiation patterns at specific frequencies are simulated and verified by comparing them with the datasheet information. However, the goal is to compute the time-domain responses of these antennas to the specific UWB transmit waveforms, and the near-field radiation of both antennas was calculated using the time-domain FDTD solver.

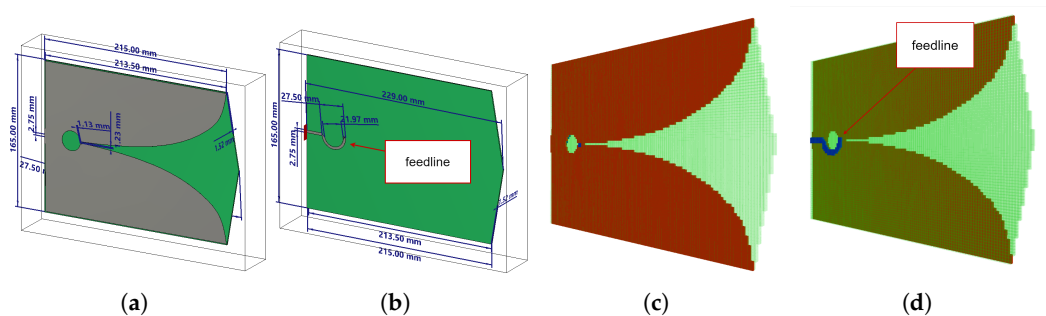


Figure 4. Digitized model of the TSA900 Vivali antenna. (a) Ground side of the CAD model. (b) Feedline side of the CAD model. (c) Ground side of the antenna voxelized. (d) Feedline side of the antenna voxelized.

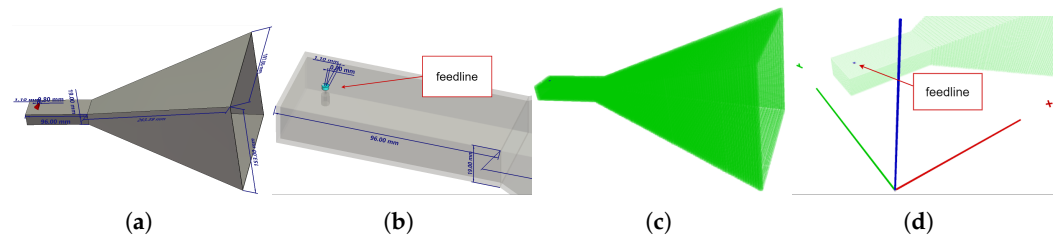


Figure 5. Digitized model of the WR137 horn antenna. (a) Ground side of the CAD model. (b) Feedline side of the CAD model. (c) Ground side of the antenna voxelized. (d) Feedline side of the antenna voxelized.

4.2. Waveform and Sensing Domain Modeling

Non-sinusoidal signals with narrow pulse widths play a critical role in modern data transmission, particularly within UWB systems. These impulses are characterized by their short duration and wide spectral content, enabling high temporal resolution and precise localization in both communication and radar applications [10,11]. The system proposed in this work uses an impulse signal with a carrier centered at 7.29 GHz. Figure 6 shows the time domain and frequency spectrum of the transmit impulse waveform used in the FDTD simulator, which was compared and is consistent with the measured transmit waveforms from the actual radar.

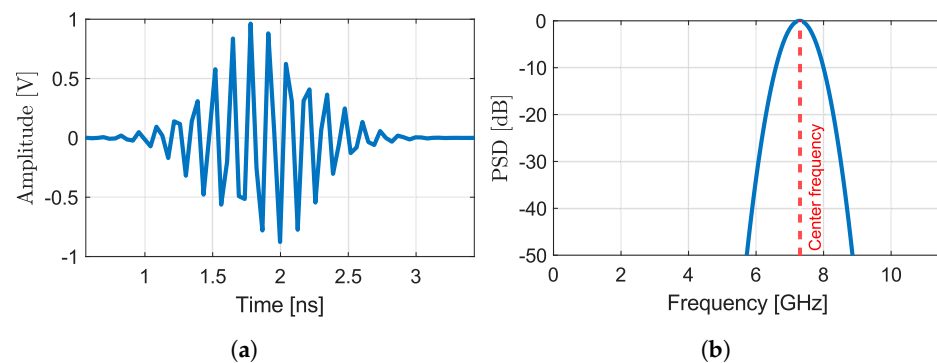


Figure 6. Waveform used in these experiments. (a) Impulse signal. (b) Power spectral density (PSD) of the signal used, centered at 7.29 GHz.

The sensing/computational domain was assumed to be uniform and isotropic first, then the two medium domains (air and concrete) were introduced. Concrete is a heterogeneous material comprising different aggregates with gaseous and liquid phases. Depending on the previous combination, its relative permittivity can change from 4 to 40, mainly determined by its moisture content (MC) [74–77]. Furthermore, the permittivity of the water changes according to frequency and temperature [78] (Figure 7a). These variations in the permittivity can result in frequency-dependent GPR spectral responses [79]. Concrete conductivity also changes due to frequency [77,80,81]. Although our simulation considered fixed values of $\epsilon_{r(\text{concrete})} = 5.24$ and $\sigma_{\text{concrete}} = 0.18$ S/m, we performed a numerical analysis to observe the effects of permittivity and conductivity changes over a frequency range (because of the ultra-wideband signal used). Through a harmonic decomposition of the signals for the frequency range of 5.8 to 8.8 GHz (Figure 7b), we verified that the variation in relative permittivity ≤ 0.5 and conductivity ≤ 0.2 S/m in the operational frequency band does not cause a significant change in the signal envelope and the group delay for pulse propagation (Figure 7c).

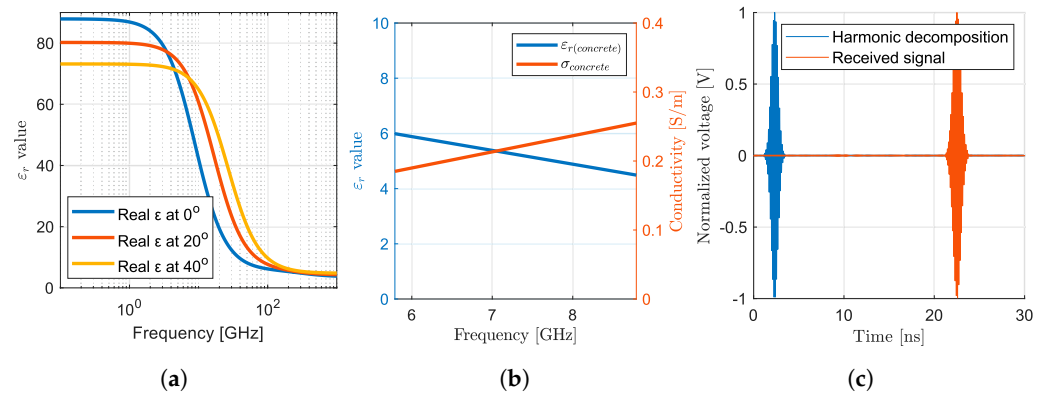


Figure 7. Normalized Harmonic decomposition analysis for relative permittivity and conductivity variations due to frequency change. (a) Relative water permittivity changes due to frequency and temperature. (b) Linear approximation of the permittivity and conductivity change for concrete within the range of 5.8 to 8.8 GHz. (c) Harmonic decomposition result of a simulated target 2 m away from the GPR (1 m air and 1 m concrete).

4.3. Algorithm Description

This section outlines the algorithm developed for 2D penetration imaging. The setup of the system consists of a radar positioned at a distance h above the concrete block. The radar moves horizontally to take the nadir measurements with a constant horizontal step. The known parameters are the distance to the concrete (h), the permittivity of the concrete ($\epsilon_{r(\text{concrete})}$), its conductivity (σ_c), and the separation of the antennas (r_s).

4.3.1. Estimate the Signal Power Radiated by the Transmit Antenna at the Target Locations

FDTD simulations were performed to estimate the transmission impulse signal power (the peak power of the impulses is used) in the 2D sensing space using high-fidelity antenna models (e.g., Figure 8a). These simulations were computationally expensive, requiring 3 h of computing time on our 6-K80 GPU server. This motivated the following equation to approximate this power distribution as a function of the angle and distance:

$$P_t = 10^{-4} \cos(3\theta) / d \quad (2)$$

where P_t is the radiation field power density level (W/m^2), θ is the off-boresight angle in radians from the center of the antenna aperture, and d is the distance in meters from the center of the aperture to the scatterer target. Figure 8a,b compare the near-field radiation power level mapping using FDTD simulation vs. the simplified analytical functions, respectively, and show that they are highly identical.

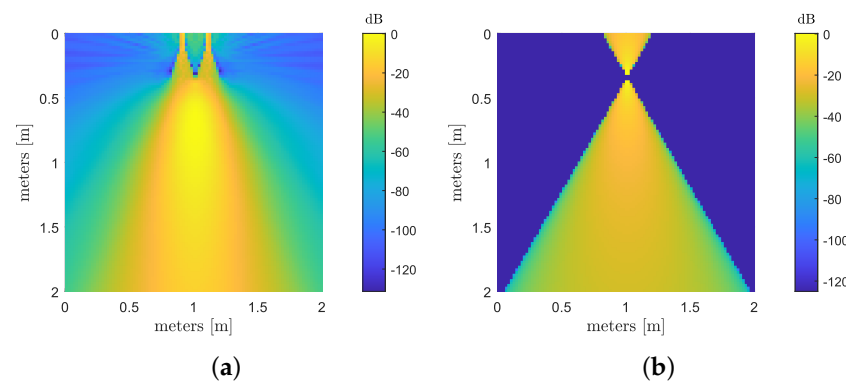


Figure 8. Signal power radiated. (a) Obtained by FDTD simulation. (b) Approximation using a simplified 2D function.

4.3.2. Distance Calibration

Calibration sets the system's zero-distance reference. To align all the equations with an arbitrary (0,0) point (radar center), it is necessary to find $time_{offset}$. This time is found by following the next steps:

- A point target is placed at a known distance (d) from the antenna system's boundaries (Figure 9a). As the antennas are close to each other, it is assumed that the distances from the TX antenna (d_t), the RX antenna (d_r), and the radar center (d_s) to the target are equal to each other ($d_t = d_r \approx d_s$).
- The target peak location, converted to the propagation time (pt_{time}), is measured (Figure 9b).
- The time offset is calculated by $time_{offset} = pt_{time} - 2d/c$, where c is the speed of light in the air. This offset is then applied to the radar-measured range values.

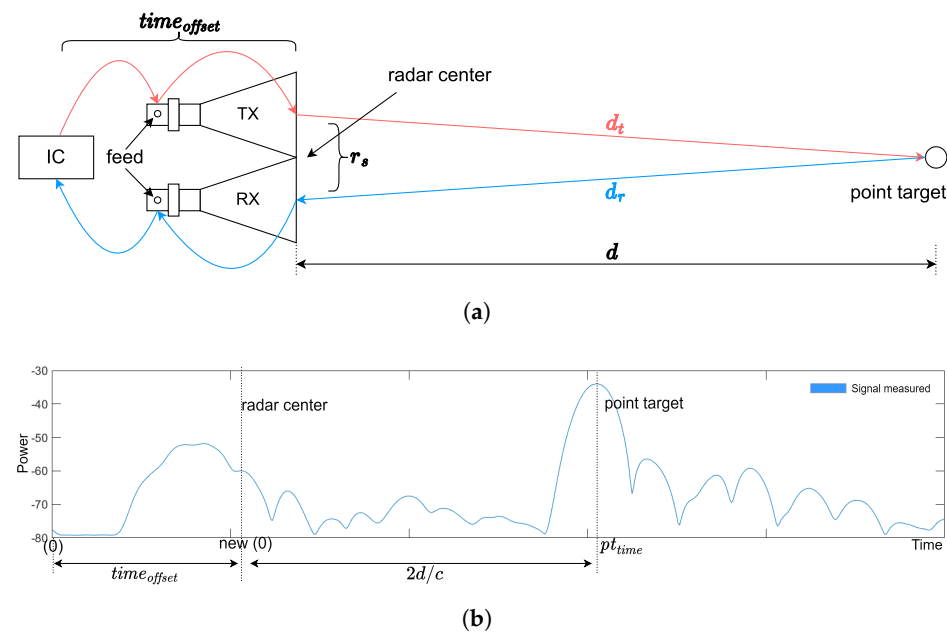


Figure 9. Distance calibration process. (a) Target placed far away from the system to obtain $d_t = d_r \ll r_s$, so it is assumed that $d_t = d_s \approx d$. (b) Example of a point target measurement. By finding the position of the target, the next equality is obtained: $time_{offset} = pt_{time} - 2d/c$.

4.3.3. Subtraction of Concrete Scattering Returns

The signal returned from the concrete medium could be substantial, especially at the surface of the concrete structures. To suppress this return, a subtraction of the measurement of a block of only concrete (without rebars or other objects inside) from all the A-scan is carried out. Figure 10 shows the example profiles after the subtraction.

4.3.4. Image Generation and Correction

A 2D approximation was used to model the imaging geometry. Correction is performed for two media (air and concrete) by performing a ray-tracing analysis, as shown in Figure 11. The point $p_s(0, -h)$ is the position of the antenna, $p_a(a, 0)$ is the interface reception, $p_k(a + b, m)$ is the target, and $p_n(a + b, nm)$ represents a virtual point in the same vertical line as p_k , the time t_3 of which (from the antenna) is considered, as it was only one medium (air) and equal to the propagation time from the antenna to p_k ($t_{3(air)} = t_{1(air)} + t_{2(concrete)}$). n is the vertical distance factor which relates p_k and p_n . ϵ_{r0} and ϵ_{rc} are the relative permittivity values of air and concrete, respectively. θ_i and θ_t are the incidence and transmission angles, respectively.

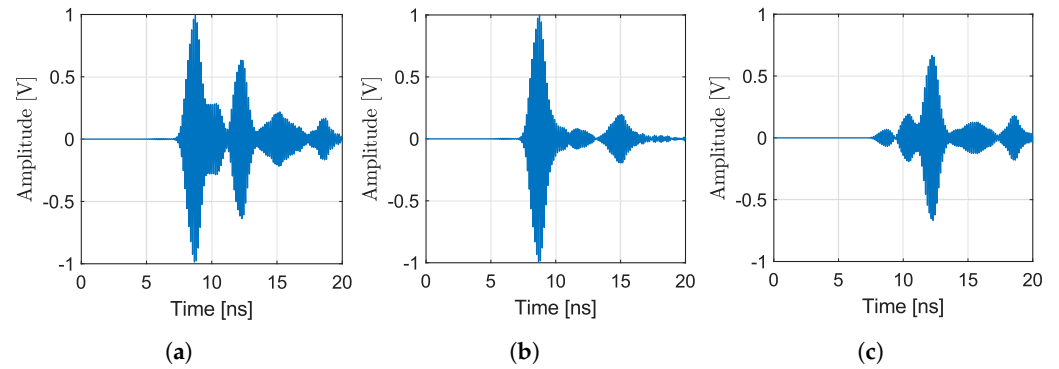


Figure 10. Concrete signature subtraction in an A-scan. (a) Example of an A-scan measurement. The first peak is mainly composed of the concrete surface. (b) Measurement of the concrete signature, which is carried out by measuring (from the same distance) a block of only concrete with no other objects inside. (c) Subtraction of the concrete signature from the A-scan. The concrete surface peak disappeared, and the information of targets inside the concrete increased.

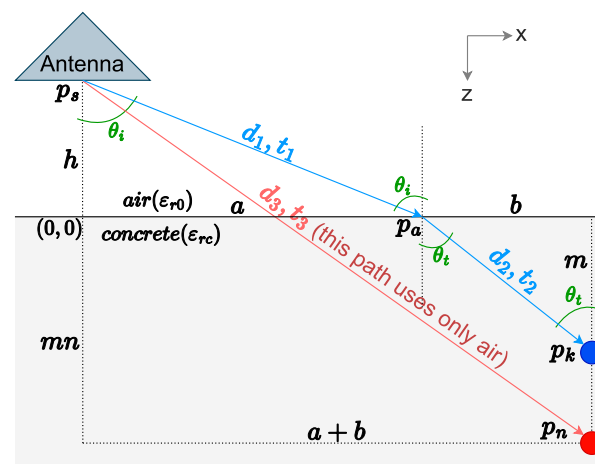


Figure 11. The approximate model used for the image generation processing. The idea is to find a virtual point (p_n) in the same vertical line as p_k , such as the propagation time $t_{3(air)}$ (assuming there is only air as the medium), which is equivalent to $t_{1(air)} + t_{2(concrete)}$.

$$t_1 + t_2 = \frac{d_1}{c} + \frac{d_2 \sqrt{\epsilon_{rc}}}{c} = \frac{1}{c} \sqrt{(d_1 + d_2 \sqrt{\epsilon_{rc}})^2} = \frac{1}{c} \sqrt{d_1^2 + 2d_1 d_2 \sqrt{\epsilon_{rc}} + d_2^2 \epsilon_{rc}} \quad (3)$$

$$t_3 = \frac{\sqrt{d_1^2 + 2d_1 d_2 (\sin(\theta_i) \sin(\theta_t) + n \cos(\theta_i) \cos(\theta_t)) + d_2^2 (\sin^2(\theta_t) + n^2 \cos^2(\theta_t))}}{c} \quad (4)$$

$$d_1^2 + 2d_1 d_2 \sqrt{\epsilon_{rc}} + d_2^2 \epsilon_{rc} = d_1^2 + 2d_1 d_2 (\sin(\theta_i) \sin(\theta_t) + n \cos(\theta_i) \cos(\theta_t)) + d_2^2 (\sin^2(\theta_t) + \epsilon_{rc} \cos^2(\theta_t)) \quad (5)$$

First, t_1 and t_2 are calculated in Equation (3), while t_3 is calculated in Equation (4), and the equality between them is shown in Equation (5). The vertical distance ratio n between p_k and p_n was found to be approximately equal to $n \approx \sqrt{\epsilon_{rc}}$. A numerical analysis was performed to determine the error of this approximation, and the results can be observed in Figure 12. The error of the vertical distance factor $n \approx \sqrt{\epsilon_{rc}}$ in the proposed approximation increases while the incidence angle increases, and the error is close to zero when the relative permittivity of the second medium is close to one. The ratio between altitude h and target depth m is expressed as m/h , showing that the error of the vertical

distance factor approximation ($n \approx \sqrt{\varepsilon_{rc}}$) for objects near the surface is smaller than for deeper objects.

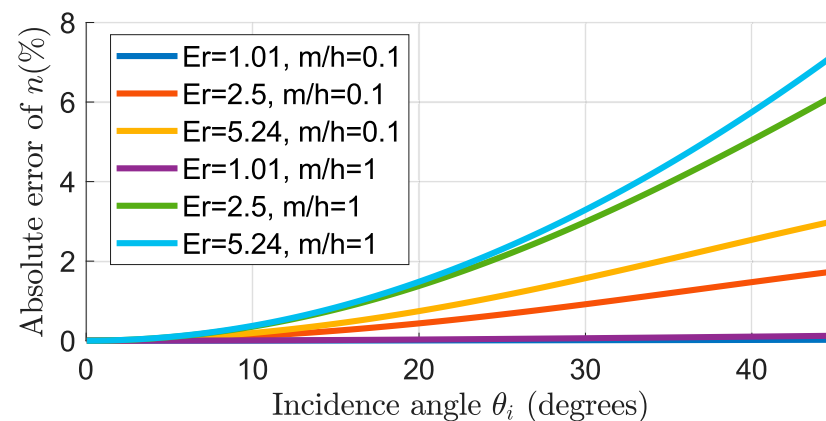


Figure 12. Numerical error analysis for the vertical distance factor approximation $n \approx \sqrt{\varepsilon_{rc}}$.

For the previous approximation, the 2D image is generated by performing the following steps.

- Generating a B-Scan matrix. As the radar moves horizontally, it records A-scan measurements at each position. These are stored in a matrix (B-scan) alongside their corresponding time arrays and antenna positions. This matrix forms the basis for further processing.
- Creating a 2D space. The next step is to define the boundaries and resolution of a 2D space by using a data matrix. Proper limits ensure that the space encompasses all relevant data, while resolution affects computational cost and detail. Higher resolution provides finer detail but increases processing demands.
- Iterative processing. The iterative stage converts A-scan data into the 2D space. Figure 13 shows this process.

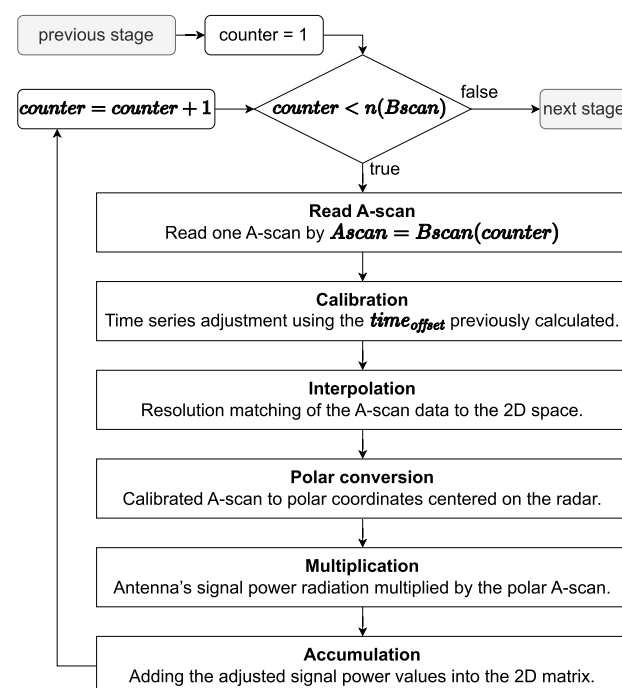


Figure 13. A-scan imaging signal processing flow and iteration.

- (d) Final 2D space conversion. The final steps involve first filtering the signal in the base band and then translating the 2D space into the concrete domain by applying the approximation $n \approx \sqrt{\epsilon_{rc}}$. This adjustment simplifies the calculations by deferring permittivity corrections to this stage.

5. Detection of Rebars and Cracks

This section presents simulation and experimental validation of the imaging process for detecting rebars and internal features within concrete structures. Simulations performed using gprMax examine two concrete conductivities ($\sigma_c = 0.02$ S/m and 0.18 S/m), illustrating how increasing the conductivity reduces the maximum detectable rebar depth due to attenuation of the electromagnetic waves. A setup with progressively deeper barbed rebars confirmed the limitations of post-processing depth. Laboratory experiments carried out in an anechoic chamber with rebars suspended in the air validate the one-media image processing capability to distinguish multiple targets. Finally, real-world measurements on a full-size concrete block demonstrated the effectiveness of the algorithm in reconstructing the block structure, and the results align well with the physical configuration.

5.1. Simulation Results

A 3D domain (Figure 14a) is defined for simulation using the FDTD solver software gprMax v3.1.7. This 3D space is defined by a rectangular prism of $2000 \times 1508 \times 252$ mm, discretized with a resolution of 2 mm, having approximately 95×10^6 grid points. It also includes 25 PML (Perfectly Matched Layer) cells on each side of the rectangular prism for the absorbing boundary conditions. The setup was sized to define two regions, the upper region filled with air, and the lower region representing a concrete block of $2000 \times 608 \times 252$ mm containing 11 rebars (arranged according to a current rebar distribution of an actual concrete block presented later on in Figure 23) and two simulated cracks (one vertical and one horizontal) inside. Each rebar is defined by a metal cylinder of 12 mm in diameter and 252 mm in length, while the cracks were defined with a thin 2 mm-thick dielectric rectangular prism. The included antennas are two hyper-realistic horn antennas (described in Section 4.1) where a Gaussian pulse (described in Section 4.2) is injected in the feed of the TX antenna as the voltage source. They are defined in the air, positioned 512 mm over the concrete block, to simulate a drone flight. The antennas' position is moved horizontally through 36 positions to obtain the B-scan. Figure 14b shows the resulting image produced by gprMax using the described parameters.

Using the FDTD method, two simulations were performed using the same concrete permittivity of $\epsilon_{rc} = 5.24$ but different concrete conductivity (σ_c). The first used a concrete conductivity of $\sigma_c = 0.02$ S/m. Figures 15 and 16 show the image processing for this conductivity. Figure 15a shows the raw B-scan measurement, where the strongest reflection comes from the concrete surface and obscures the signatures of the rebars inside. Figure 15b shows the resulting image obtained by removing the concrete signature. It is possible to distinguish reflections within the concrete, but not to distinguish the positions of the bars or cracks. Figure 16a shows the raw result of the image processing with uncorrected distance, without baseband filtering or the second medium correction (correction described in Section 4.3.4). The result of the algorithm is shown in Figure 16b, where red crosses represent the locations of each rebar. All rebars, as well as horizontal and vertical cracks, are detected. The lower limit at the bottom of the figure occurs because the propagation correction processing for the second medium compresses the size of the image.

The second simulation is executed considering $\sigma_c = 0.18$ S/m to highlight the effects of conductivity. Figures 17 and 18 show the image processing for this conductivity. Figure 17a shows the B-scan measurements. Most of the radar scatters are due to the concrete surface, and it is not possible to distinguish other elements inside the concrete.

Figure 17b shows the 2D image after subtracting the concrete signature. Figure 18a shows the raw result of the image processing with an uncorrected distance, and without baseband filtering or applying the second medium correction. The final processed image is shown in Figure 18b. Due to the increase in conductivity, the return signals decreased in amplitude, but it is still possible to distinguish the rebars and the cracks.

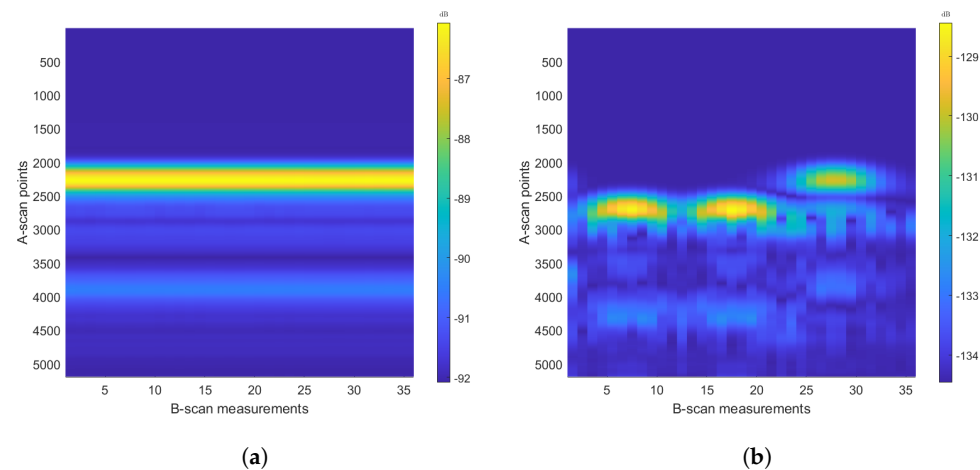


Figure 17. B-scan simulation measurement produced by gprMax with $\epsilon_{rc} = 5.24$ and $\sigma_c = 0.18$ S/m using the setup described in Figure 14. Power scale adjusted to enhance visualization. (a) Raw B-scan measurement. (b) B-scan measurement with the concrete signature removed.

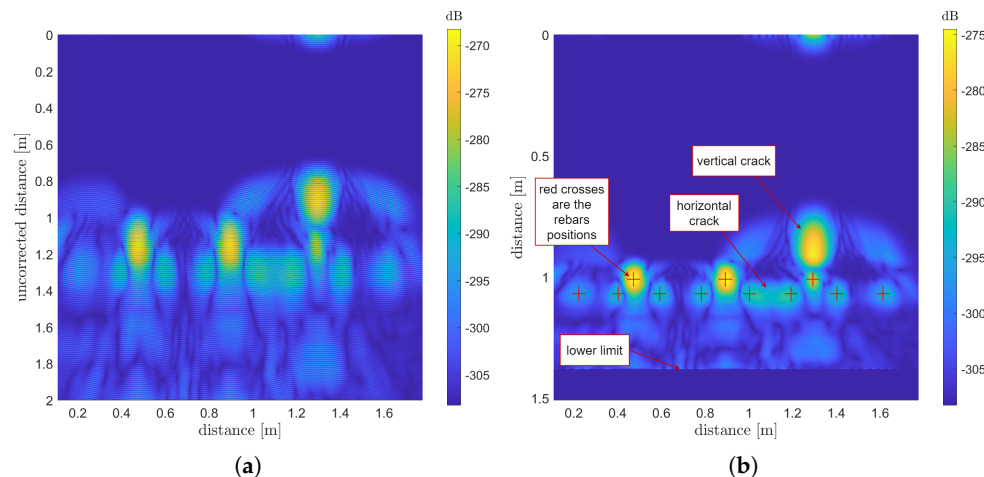


Figure 18. Imaging processing result for $\epsilon_{rc} = 5.24$ and $\sigma_c = 0.18$ S/m. Power scale adjusted to enhance visualization. (a) Raw image result without applying the second medium correction of $\sqrt{\epsilon_{rc}}$. (b) Result after applying baseband filtering, distance correction, and conversion to dB. Red crosses indicate the position of the rebars.

Two additional simulations were performed to determine the maximum detectable depth for both conductivities ($\sigma_c = 0.02$ S/m and $\sigma_c = 0.18$ S/m). Figure 19 illustrates a setup where the depths of the rebars progressively increase, allowing their discrimination based on depth. Figure 20 presents the image processing results for both cases. As shown in Figure 20, an increase in the conductivity of the material leads to a reduction in the maximum detectable depth of a rebar. This occurs because the electromagnetic waves lose amplitude as they propagate through the medium. A measure of how deeply an electromagnetic wave can

penetrate a material before its amplitude is significantly reduced is the depth of the skin. It depends on various material and wave parameters and is defined in Equation (6) [82].

$$\delta = \frac{1}{2\pi f \sqrt{\frac{\mu\epsilon}{2} \left[\sqrt{1 + \left(\frac{\sigma}{2\pi f \epsilon} \right)^2} - 1 \right]}} \quad (6)$$

where δ is the skin depth in meters, f is the frequency in Hz, μ is the permeability in H/m, ϵ is the permittivity in F/m, and σ is the conductivity in S/m. Table 1 summarizes the skin depth and the post-processing maximum detectable rebar depth for the values utilized.

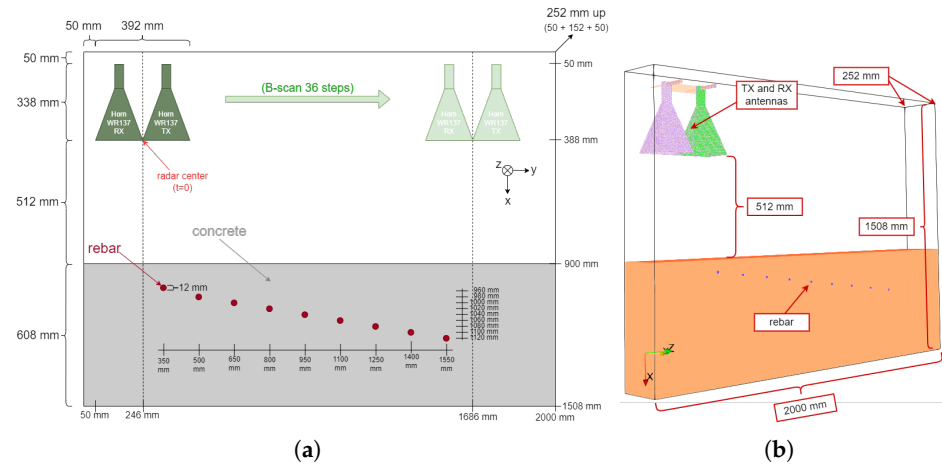


Figure 19. Setup for finding out the post-processing maximum detectable rebar depth in concrete with conductivities of $\sigma_c = 0.02$ S/m and $\sigma_c = 0.18$ S/m. (a) Setup dimensions. (b) Resulting 3D image obtained with gprMax.

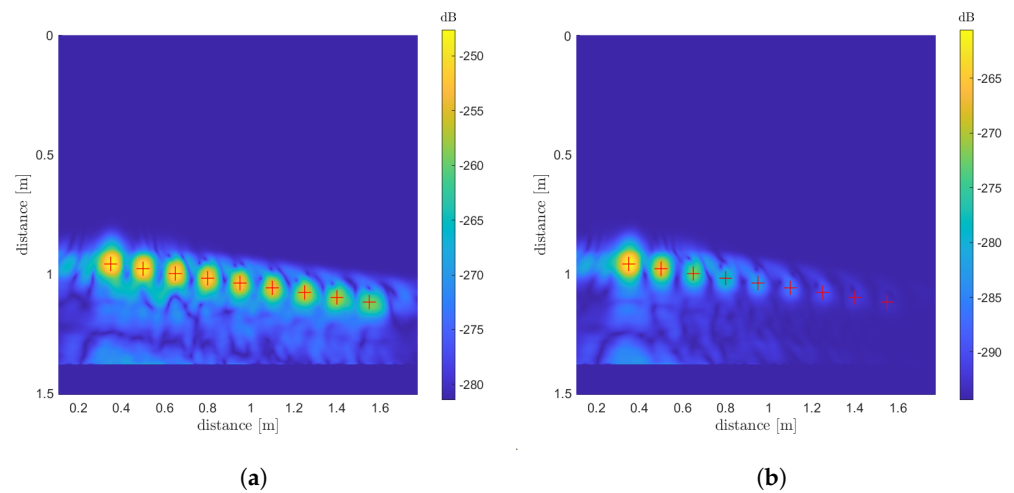


Figure 20. Resulting image process simulation for two concrete conductivities. Power scale adjusted to enhance visualization. (a) Resulting image for $\sigma_c = 0.02$ S/m. (b) Resulting image for $\sigma_c = 0.18$ S/m.

Table 1. Skin depth.

f (GHz)	μ_r	ϵ_r	σ (S/m)	δ (mm)	Post-Processing Maximum Detectable Rebar Depth (mm)
7.29	1	5.24	0.02	607.62	>220
7.29	1	5.24	0.18	6.76	180

5.2. Laboratory Measurements

Experimental measurements were carried out to validate one medium image processing in an anechoic chamber with suspended rebars in the air to validate the image processing capability to distinguish multiple targets. Figure 21 shows the setup for the measurements inside an anechoic chamber with the system pointing upward. Four horizontal rebars, separated 200 mm from each other, were held by two foam columns. The GPR took measurements pointing upward while it moved horizontally over the ruler attached to the floor. Figure 21a shows the front view of the setup, while Figure 21b shows its side view. Distance calibration was carried out by placing a single point target (a horizontal rebar was used) at a known distance sufficiently far from the system, as can be seen in Figure 21c.

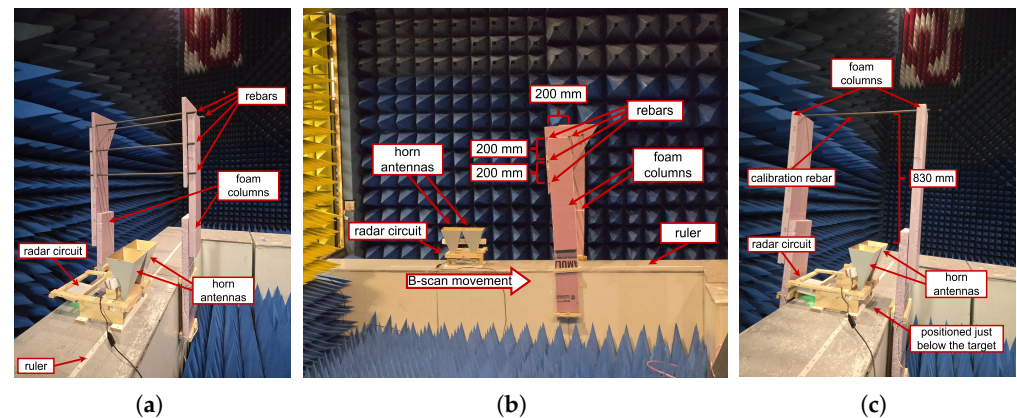


Figure 21. Chamber measurement setup. (a) Front view of the setup. (b) Side view of the setup. (c) Calibration setup.

Figure 22a shows the raw B-scan consisting of 41 A-scan measurements separated by 5 cm along 2 m. Figure 22b shows the resulting image of the algorithm for one medium (air), where the red crosses represent the places of the rebars. Even though the scatter of the closer rebar obscures the rebars behind, it is possible to distinguish them, and the separation found in the 2D image agrees with the physical measurements.

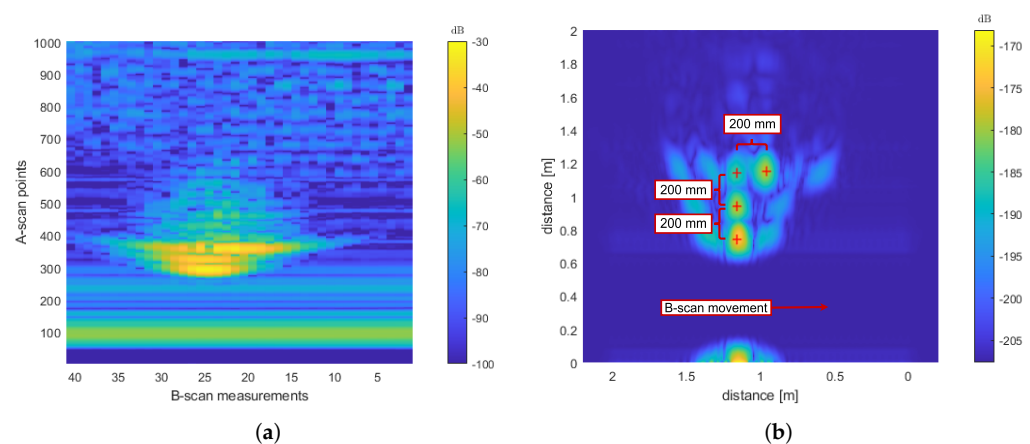


Figure 22. Image obtained by processing the data collected inside the anechoic chamber. Power scale adjusted to enhance visualization. (a) B-scan obtained with 41 A-scan measurements separated by 5 cm along 2 m. (b) Imaging results after processing using the proposed algorithm.

5.3. Measurement of an Actual Concrete Block

Another experimental measurement was carried out, but outside the laboratory. Figure 23a shows the setup of the measurements of an actual concrete block. The radar was mounted on a rail attached to a wooden crossbar supported by two wooden columns and was pointed downward to measure the concrete block. The dimensions of the concrete block (Figure 23b) are $1.55 \times 0.22 \times 0.41$ m and were seated over a concrete base, leaving a 79 mm air gap.

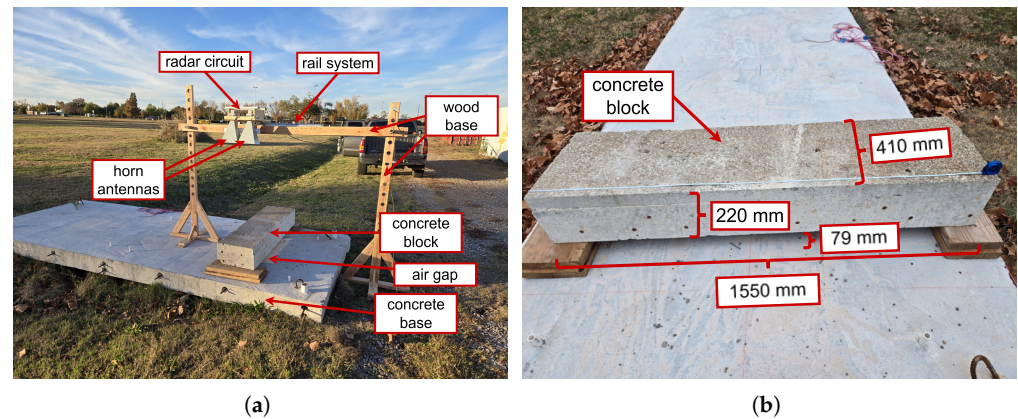


Figure 23. Setup of the measurement of an actual concrete block. (a) Front view of the setup. (b) Dimensions of the concrete block.

Figure 24a shows the measurement of the B-scan composed using 15 A-scans. Figure 24b shows the image output of the processing, where a side cut of the concrete, the air separation, and the concrete base can be identified. The results show good agreement with the actual measurements.

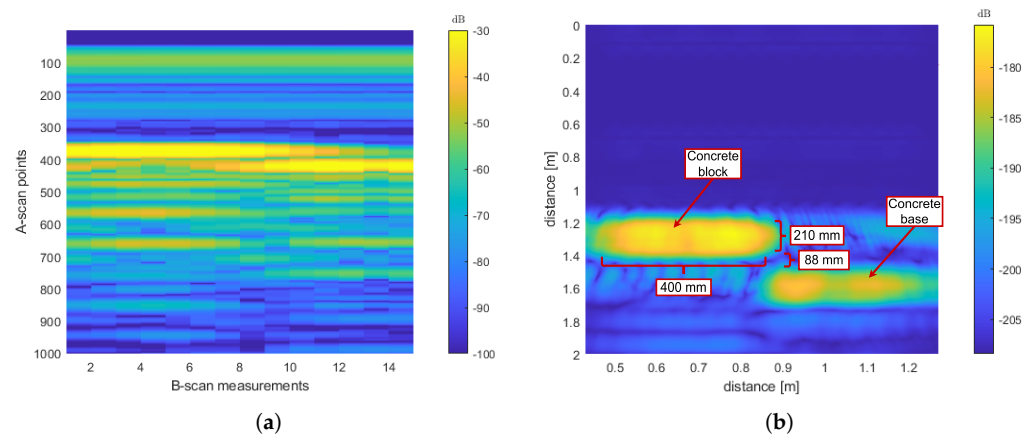


Figure 24. Preliminary imaging results based on an actual concrete block. Power scale adjusted to enhance visualization. (a) B-scan composed of 15 A-scans. (b) Image output after the processing using the proposed algorithm, which shows the exterior profile of the concrete block.

6. Machine Learning Processing

In this section, we present a machine learning approach as an initial step toward utilizing the images generated through the image processing methods described above. The primary goal at this stage is to detect rebars, with their positions being the only parameter that varies between images. This preliminary work lays the foundation for future developments, where more detailed characteristics, such as varying permittivity, conductivity, and additional material properties, will be incorporated into the input data. The object detection framework presented in this section employs deep learning techniques, specifi-

cally the YOLOv4 (You Only Look Once, version 4 [83]) architecture, to detect and locate the rebars within simulated construction scenes. These scenes, generated through FDTD electromagnetic simulations, visually represent reinforced concrete structures, with rebars as the primary targets of interest.

6.1. Dataset Preparation

Synthetic B-scan data were generated with their respective image processing for training and evaluation. Each image corresponds to a simulated scene that contains multiple rebars embedded in a concrete block. This approach provides precise control over the physical parameters and the distribution of the bars, enabling a systematic assessment of the detection method.

Each simulation scene is represented as an object containing the rebar coordinates (in meters), the dielectric permittivity (ϵ_c) and electrical conductivity (σ_c) of the concrete, the distance from the antennas to the concrete surface (h), the processed B-scan image matrix, and the applied color scale limits. To ensure uniformity, the simulation parameters were kept constant, with a concrete permittivity of $\epsilon_c = 5.24$, conductivity of $\sigma_c = 0.18$ S/m, a rebar diameter of $d_r = 12$ mm, and a distance from the antenna to the surface of $h = 512$ mm. No cracks or additional heterogeneities were introduced to ensure a highly controlled training environment without external artifacts.

The bars were randomly placed within each scene under controlled distribution constraints at a depth between 40 and 200 mm and separated by at least 67 mm to avoid overlap. The horizontal resolution was fixed at 40 mm per A-scan, resulting in 36 A-scans per image. The general simulation setup and a sample distribution of the bar are illustrated in Figure 25.

Standardized image processing was applied to the B-scan images. A fixed color scale was used across all images to maintain consistency and reduce domain shift during model training. The ground truth positions of the barbed wire were extracted from the metadata of each simulation object and transformed into pixel coordinates. Based on these, rectangular bounding boxes were generated to annotate the visible rebar signatures in each image, as shown in Figure 26.

The dataset consists of images, each with a resolution of 512×512 pixels. On average, each image contains between 5 and 7 rebars, with slight variations due to randomization. The dataset was partitioned into training, validation, and test subsets following a 70%/10%/20% split, respectively. A summary of the dataset parameters is provided in Table 2.

Table 2. Dataset parameters.

Attribute	Value
Image Resolution	512×512 pixels
Average Rebars Per Image	5–7
Train/Validation/Test Split	70%/10%/20%
Concrete Permittivity (ϵ_c)	5.24
Concrete Conductivity (σ_c)	0.18 S/m
Rebar Diameter (d_r)	12 mm
Antenna Height (h)	512 mm

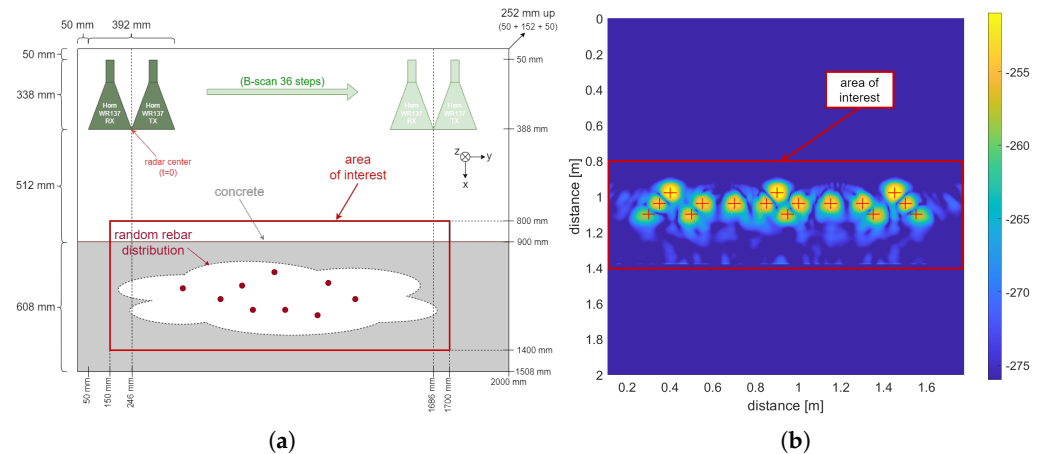


Figure 25. Setup for testing the ML processing. (a) Geometries and locations of the rebars. (b) An example result of the image formation, showing the area of interest.

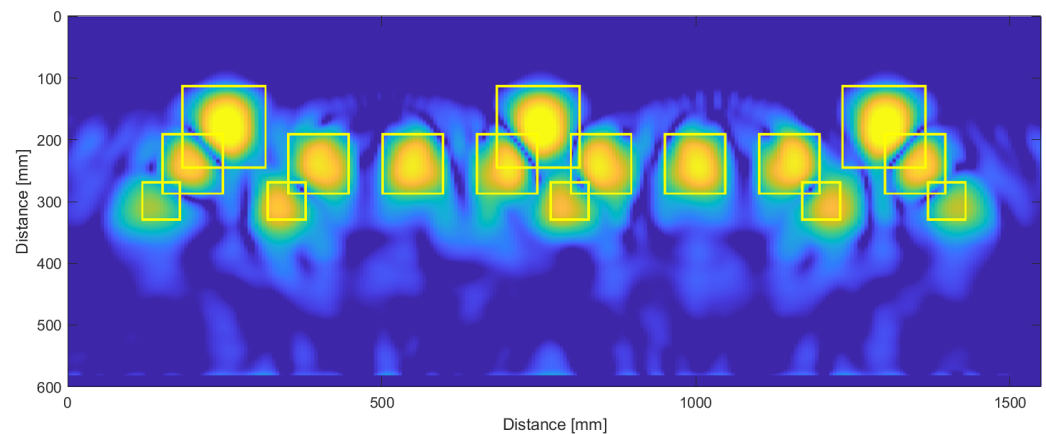


Figure 26. Sample of an annotated training image. The yellow bounding boxes indicate the labeled position of the rebars.

6.2. Data Preprocessing and Augmentation

All B-scan images were resized to 416×416 pixels to match the input requirements of the YOLOv4-tiny network [84], with pixel values normalized to the [0, 1] range for numerical stability. Bounding-box coordinates were adjusted proportionally during resizing to preserve annotation accuracy.

To improve model generalization and mitigate overfitting, data augmentation techniques [85] were applied. The images and corresponding bounding boxes were randomly rotated horizontally, scaled in a range of 1.0 to 1.05, and small random rotations within ± 5 degrees. Brightness and contrast adjustments were also made to introduce variability in image intensity. Bounding boxes were dynamically updated, with a 0.25 intersection over Union (IoU) threshold enforced to remove degenerate cases.

The anchor boxes were determined using clustering k-means in the training set, with six clusters selected according to common practice for two-stage YOLO architectures. The larger anchors were assigned to the first detection head, and the smaller anchors to the second, aligned with the YOLOv4 tiny structure. Figure 27 shows some samples of the augmentation process.

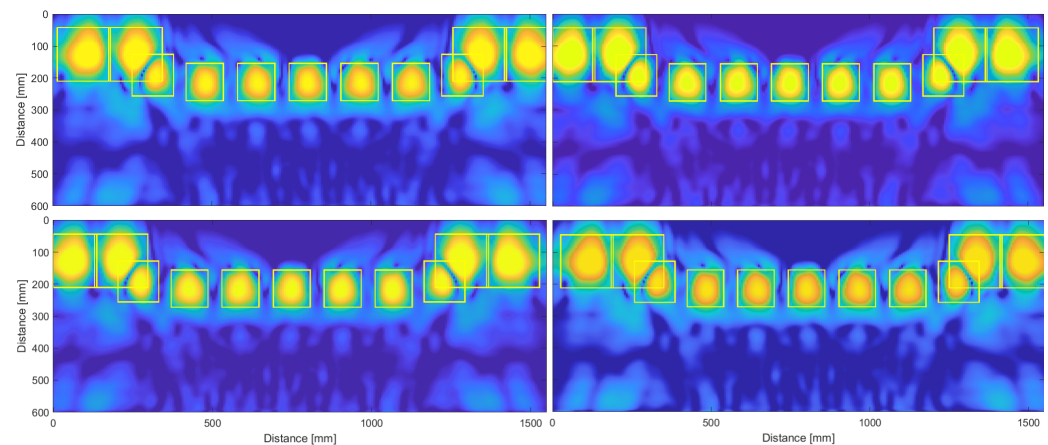


Figure 27. Augmented data process to increase the number of samples.

6.3. Model Architecture and Training

For rebar detection, the YOLOv4-tiny object detection architecture was employed due to its balance between accuracy and computational efficiency, making it suitable for near-real-time applications. YOLOv4-tiny is a simplified version of the original YOLOv4, featuring a reduced number of layers and parameters while retaining the core strengths of the YOLO family: unified detection and fast inference.

As discussed in the previous subsection, the input size of the network was set to 416 by 416 pixels, aligned with the resized B-scan images. Anchor boxes were generated using k-means clustering on training data. The network was configured for a single object class (rebar) with two detection heads, following the YOLO [86] design principles.

Training was performed using the Adam optimizer [87] with a learning rate of 0.001, a mini-batch size of 4, and a maximum of 80 epochs. The gradient decay factor and the squared gradient decay factor were set at 0.9 and 0.999, respectively, and L2 regularization was set to 0.0005 to mitigate overfitting. The loss function used was the standard YOLO multi-part loss, combining localization, objectness, and classification components. The hyperparameters used during the training are summarized in Table 3.

The learning process was monitored using a training progress graph, shown in Figure 28, which illustrates the convergence behavior of training and validation losses. As depicted, both losses steadily decreased and stabilized without significant divergence, indicating the absence of overfitting.

Table 3. Training hyperparameters.

Hyperparameter	Value
Optimizer	Adam
Initial Learning Rate	0.001
Gradient Decay Factor	0.9
Squared Gradient Decay Factor	0.999
Mini-Batch Size	4
L2 Regularization	0.0005
Max Epochs	80
Input Size	$416 \times 416 \times 3$
Anchor Boxes	6 clusters (auto-generated)
Average Inference Time per Image	0.2491 s
Frames Per Second (FPS)	4.01
Average Precision (AP)	0.72

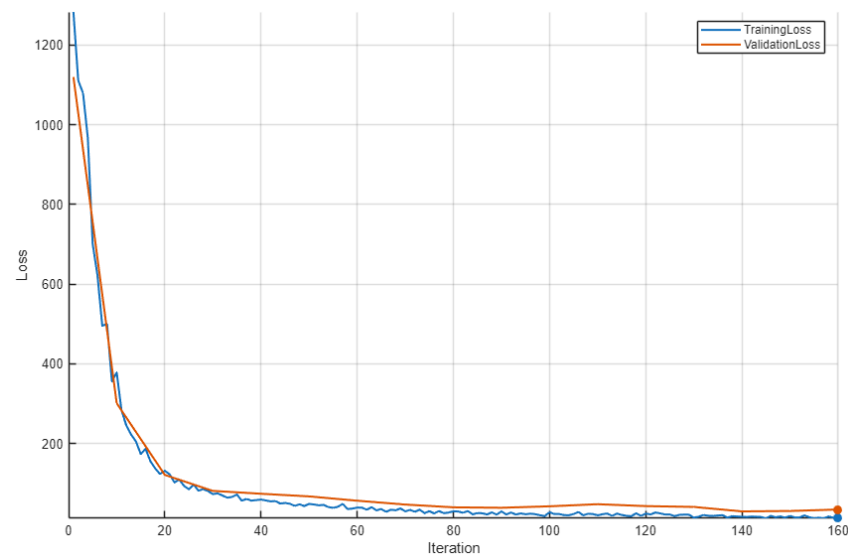


Figure 28. Training and validation loss curves over epochs.

6.4. Post-Processing and Refinement

Following initial detection, a post-processing stage was applied to refine the model output and improve the reliability of the detected bar positions. The post-processing pipeline consisted primarily of confidence thresholding and non-maximum suppression (NMS).

During inference, the model predicts the bounding boxes with associated confidence scores. A confidence threshold of 0.3 was empirically selected to filter out low-confidence detections, retaining only those with a reasonable likelihood of corresponding to the rebar signatures. Nonmaximum suppression with an Intersection over Union (IoU) threshold of 0.5 was subsequently applied to eliminate redundant bounding boxes that overlap significantly, ensuring that a single detection represents each rebar.

To further improve detection precision, domain-specific knowledge was considered. In particular, the vertical position of rebars within the B-scan image was leveraged. Since rebars typically appear within a specific depth range relative to the concrete surface, detections falling outside a predefined vertical window could be excluded to reduce false positives. However, in this study, such depth filtering was not applied to maintain generality and avoid overfitting to the simulated dataset.

6.5. Evaluation Metrics

The performance of the rebar detection model was evaluated using standard object detection metrics, with a focus on precision, recall, and average precision (AP). Precision is defined as the ratio of correctly predicted bounding boxes (true positives) to the total number of predicted bounding boxes (true positives and false positives). Recall is the ratio of correctly predicted bounding boxes to the total number of ground-truth bounding boxes, reflecting the model's ability to detect all relevant objects. To balance the trade-off between precision and recall, the average precision (AP) metric was used. AP represents the area under the precision-recall (PR) curve and provides a single scalar value that summarizes the detection performance across all confidence thresholds. The PR curve for the trained model is shown in Figure 29, with an AP of 0.72 achieved on the unseen test set.

The model's evaluation was performed using a hold-out test set. No enhancement or preprocessing was applied to the test images during the review, ensuring a fair assessment of the model's generalizability. For a prediction to be considered correct, the Intersection over Union (IoU) between the predicted and ground-truth bounding boxes had to exceed 0.5. Detections below this threshold were counted as false positives or false negatives, respectively. Precision and recall were calculated at varying confidence thresholds to construct the PR curve.

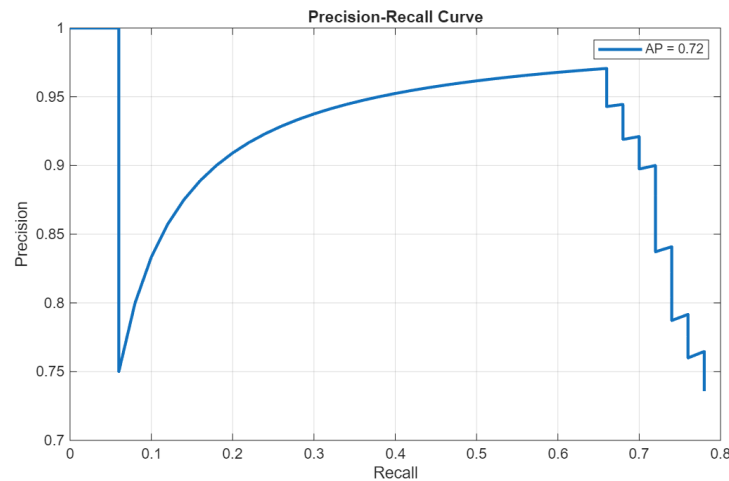


Figure 29. Precision–recall (PR) curve of the trained model. The average precision (AP) is 0.72.

6.6. Results and Discussion

The performance of the proposed YOLOv4-tiny model was evaluated on both training and test data using standard object detection metrics. The example detections in the training images are shown in Figure 30, where the model successfully localized multiple bars with high confidence, demonstrating effective learning and generalization during training.

For test data, Figure 31 presents representative detection results. The model accurately localized and identified the rebars in various B-scan scenes, with bounding boxes that were closely aligned with the ground truth annotations. Most detections achieved confidence scores exceeding 0.85, reflecting the model's robustness in handling variations in signal intensity and rebar spacing. Minor variations in the size of the bounding boxes were observed, primarily attributed to overlapping reflections or attenuation at greater depths; however, these did not significantly affect the detection accuracy.

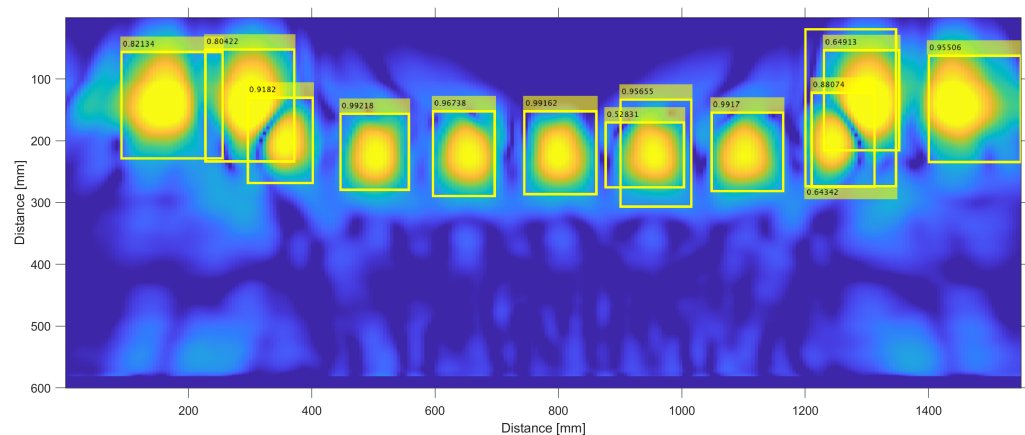


Figure 30. Cont.

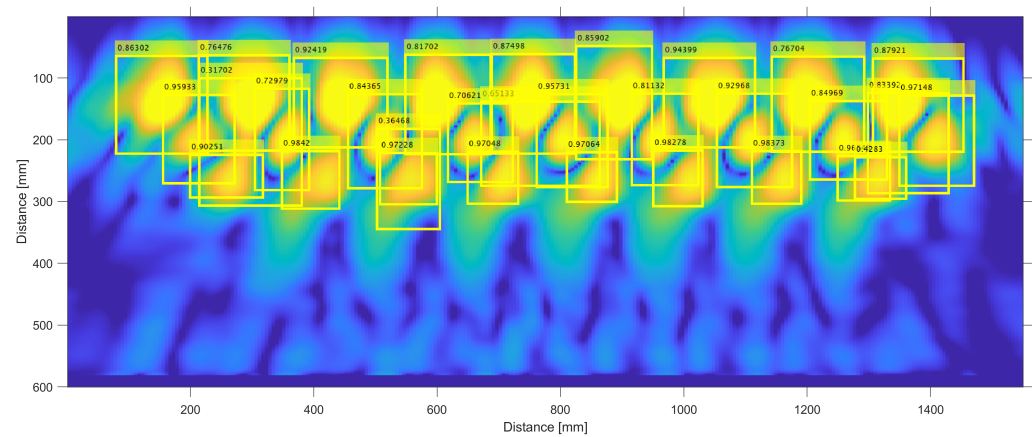


Figure 30. Examples of rebar detections on training images. Detected bounding boxes are shown in yellow.

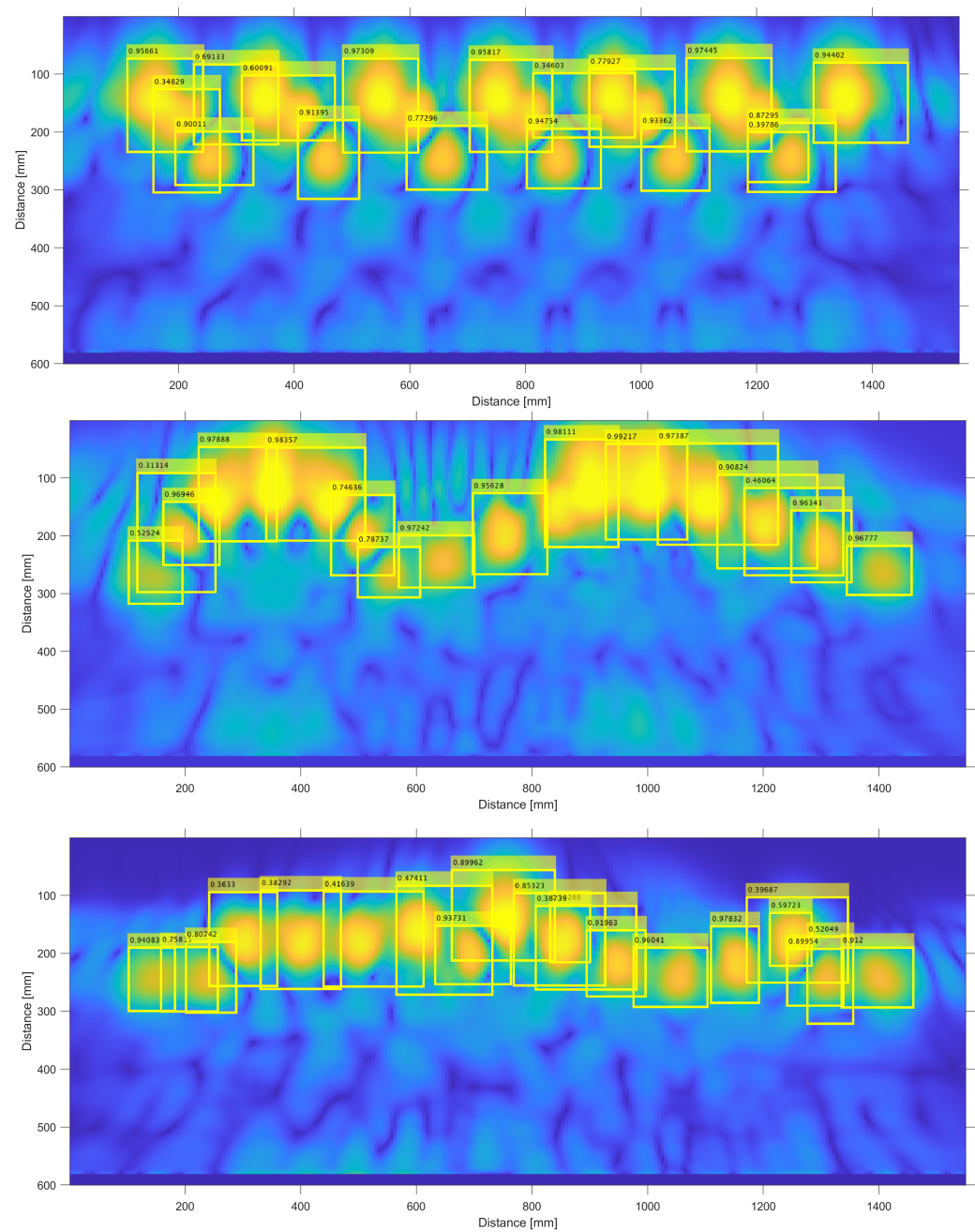


Figure 31. Detection results on test images. Yellow boxes represent detected rebars.

Quantitative evaluation yielded an average precision (AP) of 0.72, as illustrated above by the precision-recall curve (PR) in Figure 29. In addition to AP, the detection performance was assessed using precision, recall, and F1-score metrics. The model achieved a maximum F1-score of 0.8935, with a corresponding precision of 0.9706 and recall of 0.66. These results emphasize the model's balanced performance and its ability to maintain high detection confidence while capturing the majority of relevant rebar instances. In terms of computational performance, the model achieved an average inference time of 0.2491 s per image, corresponding to approximately 4.01 frames per second (FPS). This confirms the feasibility of the model for near-real-time detection applications, such as automated structural inspections. In general, the test results validate the ability of the trained YOLOv4-tiny model for accurate and reliable rebar detection in the synthetic B-scan images of the UAS-based radar, under the constraints of rebar placement at depths between 40 and 200 mm, with a minimum separation of 67 mm and the assumed parameters, such as conductivity, permittivity, antenna-to-surface distance, and diameter of the rebars.

7. Conclusions and Future Work

This study examines the feasibility of utilizing a radar sensor system solution as UAV payloads for civilian infrastructure inspection missions, specifically a low-size, low-weight, and low-cost UWB impulse radar sensor, which offers benefits such as improved spatial coverage, enhanced temporal mobility, and increased inspection accuracy. The developed simulation tools, incorporating realistic antennas and propagation models, have demonstrated good agreement with laboratory measurements. Novel image generation and correction have been described and verified. These generated images formed the basis for a machine learning (ML)-driven detection framework. Using a synthetic data set and a YOLOv4-tiny architecture, the ML model successfully detected multiple rebars with an average precision (AP) of 0.72 and near-real-time inference speeds. The results demonstrate the potential of combining advanced simulation techniques with deep learning to automate the detection of structural anomalies. Table 4 presents a comparative analysis between existing UAV-based GPR systems and the sensor architecture developed in this study. This table outlines key performance parameters, including operating frequency, antenna design, imaging depth, and AI-driven processing.

Future work will focus on expanding the data collections to incorporate more complex and realistic scenarios, including system noise, interference, various material properties, different rebars distributions, concrete surface roughness, heterogeneous materials, and more realistic crack simulations, to improve model generalization. In addition, UAV flight tests will be conducted in real-world environments to collect radar data from traditionally inaccessible locations. Domain adaptation techniques and transfer learning approaches will be explored to bridge the gap between synthetic and real-world data. Further enhancements to radar hardware and machine learning (ML) algorithms are also used to improve detection performance in challenging operational environments. In summary, the proposed system represents a promising step toward a new class of UAV-based airborne radar sensors for structural health monitoring, capable of performing high-resolution, noninvasive, and autonomous inspections in challenging operational environments.

Table 4. Detailed radar sensor parameters and comparisons with the state of the art.

Sensor Parameters	Existing UAV-Based GPR Systems	UWB Penetration Radar Sensor in This Study
Applications	Landmine detection [24,43,88–95], generic buried object detection [96], snow/soil properties [97–99], archaeological inspection [100].	Specifically designed for road and bridge inspection, with a focus on concrete and pavement
Operating Frequency	Mostly from VHF to S band, following traditional GPR bands.	Upper C band and X-Band (7.29 GHz in the study).
Size, Weight, and Power	The best from the literature is about 0.07 lbs (weight), about 4 by 2 inches (dimensions), and 4.2 W power consumption [24].	0.1 lbs (weight), 3 by 3 inches in dimension, and 0.12 W power consumption, suitable for small UAVs and longer flight time.
Antennas	Various: Vivaldi [88,94–96], horn [24,93], helix [89].	Custom-designed miniature planar Vivaldi antenna.
Scanning and UAV flight profile	Forward-looking. [101,102], side-looking [92], down-looking [94,103], and circular SAR [91,104].	Downward looking for surface penetration, supports all types of scan profiles.
RF Chipset and Architecture	Discrete and integrated RF electronics.	Single-chip system and on-chip radar transceiver.
Simulation and Modeling	Limited modeling comparison.	Novelty: FDTD-based, 3D domain simulation with realistic antenna and propagation models that match the current measurements and directly support imaging processing.
Calibration Method	Limited near-field or far-field measurement-based.	Novelty: Calibration is supported by software and ray-tracing simulations.
Transmit Waveforms	UWB impulse [105,106], CW (SFCW or FMCW) [107].	UWB impulse waveform.
System Bandwidth	Up to 16 GHz sweeping.	Between 1.5 and 2 GHz.
Image Resolution	Reported to be up to 5 cm in GPR images.	<10 cm in down range, <3 cm in cross-range.
Signal Processing Methods	Singular value decomposition filtering [94,108], time-gating [109,110], SAR processing [40,58,111], AI-based [112–115].	Novelty: Combination of cross-range SAR, down-range impulse profiling for 2D imaging, ray-tracing-based calibration, and ML-based detections.
Imaging Depth	5 cm to 2 m are used in most UAV-GPR applications depending on the frequency [116].	Designed to be 2 m deep underneath the surface for inspection.
Detection capability	99.5% on simulated datasets and 92.5% on field datasets in [115], 92.64% for B-scan feature detection in [114], and 97% average classification accuracy in [112].	Achieved 88–93% detection precision and recall for automated rebar identification using simulated GPR radar images with YOLO-based object detection.
AI-Application	Limited, deep learning usage in [113–115] for underground object detection.	YOLOv2 deep learning object detector trained on EM-simulated radar scenes with automated rebar labeling, augmented with domain-aware post-processing to improve physical detection reliability.

Table created mainly based on [12].

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

2D	Two Dimensions
3D	Three Dimensions
AP	Average Precision
BW	Bandwidth
CFL	Courant–Friedrichs–Lewy
DOT	Department of Transportation
EM	Electromagnetic
FDTD	Finite Difference Time Domain
FPS	Frames Per Second
GPR	Ground-Penetration Radar
IoU	Intersection over Union
IR	Infrared Radiation
LIDAR	Light Detection and Ranging
MC	Moisture Content
ML	Machine Learning
NI	Noninvasive
NII	Noninvasive Inspection
NMS	Non-Maximum Suppression
PLL	Phase-Locked Loop
PR	Precision-Recall
PSD	Power Spectral Density
RF	Radio Frequency
RFID	Radio Frequency Identification
R/D	Research and Development
SAR	Synthetic Aperture Radar
SoC	System-on-Chip
SWaP	Size, Weight, and Power
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicles
USDOT	US Department of Transportation
UWB	Ultra-WideBand
YOLO	You Only Look Once

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