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Radargram-to-point-cloud reconstruction for augmented building inspection workflows

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Abstract : *The structural integrity of civil infrastructure necessitates rigorous, regular, and highly accurate inspection methodologies to prevent catastrophic failures and ensure public safety. Among the various non-destructive testing modalities, ground penetrating radar has emerged as a premier technology for subsurface investigation. However, the interpretation of standard two-dimensional radargrams is notoriously complex, requiring highly trained personnel and often resulting in cognitive overload during on-site inspections. This paper presents a comprehensive framework for radargram-to-point-cloud reconstruction specifically designed to enhance augmented building inspection workflows. By transforming raw electromagnetic echo data into rich three-dimensional point clouds, the proposed system bridges the semantic gap between abstract radar signals and physical building structures. The methodology encompasses advanced signal preprocessing, automated hyperbola detection, spatial mapping through coordinate transformation, and point cloud refinement. Furthermore, the integration of these reconstructed point clouds into augmented reality environments facilitates intuitive, real-time visualization of embedded structural elements such as reinforcement bars, conduits, and hidden defects. Extensive experimental evaluations conducted on reinforced concrete testbeds demonstrate the efficacy, spatial accuracy, and computational efficiency of the proposed pipeline. The results indicate significant improvements in defect localization and user interpretation speeds, establishing a robust foundation for next-generation interactive structural health monitoring systems.*

Keywords : *Ground Penetrating Radar, Point Cloud Reconstruction, Building Inspection, Augmented Reality, Non-Destructive Testing*

1 .INTRODUCTION

1.1 Background and Motivation

The rapid expansion of urban environments globally has led to an unprecedented increase in the construction of complex civil infrastructure. Concurrently, a significant proportion of existing buildings and infrastructural assets are approaching or have already exceeded their designed service lives. The degradation of these structures, driven by environmental weathering, mechanical loading, chemical corrosion, and unforeseen anthropogenic impacts, poses a severe risk to both economic stability and human safety. Consequently, structural health monitoring and building inspection have become critical components of modern civil engineering practice. Traditional inspection methodologies have historically relied upon destructive testing or rudimentary visual assessments. YOLO9000 extends unified detection, offering a

visual baseline when environmental objects must be localized before downstream geometric or connectivity reasoning [1]. Destructive testing, while providing direct empirical evidence of material properties, is inherently limited due to the localized damage it inflicts upon the structure under examination. Visual inspections, on the other hand, are strictly confined to assessing surface-level phenomena such as external cracking, spalling, or discoloration, leaving critical internal anomalies completely undetected until they manifest as macroscopic structural failures. Wang and colleagues examine advancing spatiotemporal reasoning in surgical videos through a Chain-of-Thought benchmark [2]. In response to these limitations, the field of non-destructive testing has evolved significantly over the past several decades. Various techniques, including ultrasonic pulse velocity, impact-echo, infrared thermography, and ground penetrating radar, have been widely adopted to evaluate the internal integrity of structural components without causing any physical harm. Among these methodologies, ground penetrating radar stands out due to its exceptional capability to rapidly and continuously scan large areas while penetrating deep into dielectric materials such as concrete, masonry, and soil. The fundamental operating principle of ground penetrating radar involves the emission of high-frequency electromagnetic pulses into the structural medium via a transmitting antenna. As these electromagnetic waves propagate through the material, they encounter boundaries between media exhibiting different dielectric constants. These interfaces cause a portion of the electromagnetic energy to be reflected back to the surface, where it is captured by a receiving antenna. By analyzing the time delay, amplitude, and phase of these reflected signals, inspectors can infer the depth, location, and characteristics of subsurface targets such as steel reinforcement bars, post-tensioning ducts, utility pipes, and internal voids.

Despite its robust technological capabilities, the widespread adoption of ground penetrating radar in routine building inspection workflows is significantly hindered by the complexity of data interpretation. The raw output of a ground penetrating radar scan is typically presented as a two-dimensional image known as a B-scan or radargram. In these radargrams, point-like subsurface targets, such as the cross-sections of reinforcement bars, appear as hyperbolic signatures rather than explicit geometrical representations. This phenomenon occurs due to the conical radiation pattern of the radar antenna; the antenna begins to detect the target before it is directly positioned over it and continues to detect it after it has passed. Consequently, interpreting radargrams requires extensive specialized training, domain expertise, and significant mental effort to map these abstract hyperbolic patterns onto the physical, three-dimensional geometry of the building structure. This cognitive burden frequently leads to subjective interpretations, human error, and prolonged inspection times, thereby reducing the overall efficiency and reliability of the inspection process. Zhang and colleagues examine inferring 3d hands from both text prompts and body dynamics [3].

1.2 Objectives and Contributions

To address the profound challenges associated with radargram interpretation and to modernize building inspection workflows, there is an urgent need to transition from abstract two-dimensional signal representations to intuitive three-dimensional spatial models. The overarching objective of this research is to develop, implement, and evaluate a fully integrated, automated pipeline for radargram-to-point-cloud reconstruction. By converting complex electromagnetic reflections into dense, geometrically accurate three-dimensional point clouds, this research aims to democratize subsurface data interpretation, making it accessible not only to radar

specialists but also to civil engineers, architects, and on-site construction personnel. Furthermore, this research is driven by the paradigm shift towards digitalization in the construction industry, encapsulated by concepts such as Building Information Modeling and digital twins. A critical component of this digitalization is the utilization of augmented reality technologies, which overlay digital information onto the user's physical field of view. The reconstructed point clouds generated by the proposed system are specifically optimized for ingestion into augmented reality environments. This capability allows inspectors wearing mixed reality headsets to literally look through concrete walls and floors, visualizing hidden reinforcement bars and structural anomalies precisely where they exist in the physical space. Another relevant line of investigation concerns geometry-enhanced attentive multi-view stereo for challenging matching scenarios [4]. The specific contributions of this comprehensive study are manifold. First, a robust algorithmic framework for the automated processing of raw radargrams is established, encompassing advanced filtering techniques and noise suppression strategies tailored for complex concrete environments. Second, a novel methodology for the precise extraction of hyperbola apices and their subsequent mathematical transformation into three-dimensional Cartesian coordinates is presented. Third, the research details the integration of spatial tracking systems with ground penetrating radar data acquisition to ensure that every reconstructed data point is accurately georeferenced within a global coordinate system. Finally, the paper demonstrates a complete augmented reality building inspection workflow, validating the proposed pipeline through extensive physical experiments on custom-fabricated reinforced concrete testbeds. The comprehensive performance evaluation provides quantitative metrics regarding spatial reconstruction accuracy, computational overhead, and the qualitative enhancement of user inspection experiences.

2. Literature Review

2.1 Ground Penetrating Radar in Civil Engineering

The application of ground penetrating radar in civil engineering has been the subject of extensive academic research and industrial development over the past three decades. Initially conceptualized for geological surveying and military applications such as landmine detection, the technology was rapidly adapted for infrastructural evaluation due to its high resolution and non-invasive nature. Early implementations in civil engineering primarily focused on the assessment of pavement thicknesses and the detection of large-scale geotechnical features beneath transportation infrastructure. As high-frequency antenna technologies advanced, enabling millimeter-level resolution at shallower depths, the scope of ground penetrating radar expanded significantly to encompass detailed structural assessments of concrete bridge decks, retaining walls, and commercial buildings. The literature also considers traversal-Free ParallelFiltering and adaptive shrinkingfor Large-Scale LoD 3D GaussianSplatting [5]. Z. Wang examines singing timbre popularity assessment based on multimodal large foundation model [6]. The interpretation of ground penetrating radar data has historically been a manual and highly subjective process. Researchers recognized early on that the dependence on human expertise represented a critical bottleneck in the scalability of the technology. Consequently, substantial efforts have been dedicated to automating the detection of subsurface features within radargrams. OverFeat integrates recognition, localization and detection, illustrating how shared visual features can support several inspection tasks [7]. Early automation attempts relied heavily on classical digital signal processing and computer vision techniques. Algorithms based on the Hough transform, template matching, and edge detection

were frequently employed to identify the characteristic hyperbolic signatures indicative of embedded rebars and pipes. While these classical methods achieved moderate success in controlled laboratory environments with homogeneous background materials, their performance often degraded significantly when applied to real-world data. Real-world concrete structures are inherently heterogeneous, containing varying moisture levels, aggregate distributions, and secondary reflections that introduce substantial clutter and noise into the radargram, thereby confounding traditional pattern recognition algorithms. Chen and colleagues examine accurate and convenient method of vehicle spatiotemporal distribution recognition based on computer vision [8]. In recent years, the advent of deep learning and convolutional neural networks has revolutionized the automated analysis of ground penetrating radar data. YOLO casts object detection as a unified prediction problem, making it a relevant reference for latency-sensitive visual inspection [9]. Researchers have trained complex neural architectures on vast datasets of annotated radargrams to automatically classify and localize subsurface targets with unprecedented accuracy. Architectures such as You Only Look Once and Region-based Convolutional Neural Networks have been adapted to draw bounding boxes around hyperbolic signatures in real-time. Furthermore, semantic segmentation networks have been utilized to classify every pixel within a radargram, distinguishing between background noise, target reflections, and structural interfaces. Despite these significant advancements in two-dimensional automated analysis, the fundamental limitation remains: the output is still inherently a two-dimensional image that must be mentally projected onto a three-dimensional physical space by the end user. The literature also considers real-driven image synthesis framework for adapting pre-trained scene text detectors [10].

Table 1: Summary of Historical Approaches to Ground Penetrating Radar Data Interpretation

Interpretation Method	Primary Technique	Main Advantages	Key Limitations
Manual Analysis	Visual inspection by experts	High adaptability to unique edge cases	Subjective, time-consuming, requires extensive training
Classical Computer Vision	Hough transform, edge detection	Mathematically interpretable, low compute	Poor performance in noisy or heterogeneous environments
Deep Learning Object Detection	Convolutional neural networks	High accuracy, robust to certain noise types	Requires large annotated datasets, remains in two dimensions

2.2 Point Cloud Generation Techniques

The concept of representing spatial data as point clouds has gained immense traction across various domains, predominantly driven by the proliferation of Light Detection and Ranging sensors and photogrammetric techniques. A point cloud is fundamentally a set of data points situated within a three-dimensional coordinate system, typically defined by X, Y, and Z axes, where each point represents a specific location on the external surface of an object. While point clouds are ubiquitous for capturing the exterior topography of buildings and landscapes, generating point clouds that represent internal, hidden structural elements poses a unique set of interdisciplinary challenges. Qu and colleagues examine conditional denoising diffusion probabilistic model for point cloud upsampling [11]. The transition from ground penetrating radar

data to three-dimensional representations has been explored in specialized contexts. The conventional approach involves collecting multiple parallel two-dimensional B-scans over a predefined grid pattern. These parallel slices are then interpolated using algorithms such as inverse distance weighting or kriging to create a pseudo-three-dimensional volume of data, often referred to as a C-scan. While volumetric rendering provides a better spatial understanding than isolated B-scans, it is computationally expensive and typically produces a solid block of translucent data rather than discrete, actionable geometric primitives. The volumetric representation is often cluttered with background reflections, making it difficult to isolate specific structural components such as individual rebars for integration into Building Information Modeling platforms. Related work has addressed knowledge-Refined dual Context-Aware network for partially relevant video retrieval [12]. For a broader comparison, related research addresses identification markers for *salvia miltiorrhiza* and its close relatives based on cell wall component characteristics [13]. To overcome the limitations of volumetric rendering, recent literature has begun exploring the direct conversion of radargram features into discrete point clouds. This process generally involves the extraction of high-intensity reflection points or the apices of detected hyperbolas in the two-dimensional domain, followed by a coordinate transformation based on the trajectory of the radar antenna. Previous studies have demonstrated the feasibility of linking ground penetrating radar systems with optical tracking cameras or robotic total stations to accurately record the position and orientation of the antenna during data collection. By synchronizing the temporal radar data with spatial tracking data, researchers can map the extracted subsurface targets into a global Cartesian coordinate system. However, integrating these reconstructed subsurface point clouds into augmented reality environments for seamless building inspection workflows remains an open research challenge, requiring novel approaches to data compression, spatial alignment, and real-time visualization. Related work has addressed time- and Memory-Efficient method for axis alignment of very large point clouds using orthogonality in buildings [14].

3. System Architecture and Methodology

3.1 Radargram Preprocessing

The foundation of an accurate radargram-to-point-cloud reconstruction system lies in the rigorous preprocessing of the raw ground penetrating radar data. Raw radargrams are inherently contaminated with various forms of systemic and environmental noise that obscure the critical hyperbolic signatures required for accurate spatial mapping. Therefore, a comprehensive signal processing pipeline is essential to enhance the signal-to-noise ratio and isolate the true reflections originating from subsurface targets. The proposed methodology begins with time-zero correction. Due to the mechanical and electronic delays inherent in the radar equipment, the exact moment the electromagnetic pulse enters the physical material often varies. Time-zero correction shifts the entire radargram along the time axis to ensure that the surface reflection aligns perfectly with the zero-depth reference point, thereby ensuring accurate depth calculations during the later stages of the reconstruction process. The literature also considers indirect diffusion-guided neural radiance fields for generalizable view synthesis [15]. Following the time-zero correction, background removal is applied. Ground penetrating radar antennas frequently capture continuous, flat, horizontal bands across the radargram. These bands are primarily caused by the direct coupling of the electromagnetic wave between the transmitting and receiving antennas, as well as reflections from the uniform interface between the air and the concrete surface. Background removal is typically achieved by calculating the average

trace across the entire B-scan and subsequently subtracting this average trace from every individual trace in the dataset. This procedure effectively eliminates the static horizontal bands, significantly enhancing the contrast of the localized, hyperbolic reflections caused by discrete embedded objects. Related work has addressed this in the details [16].

Subsequent to background removal, a bandpass filter is implemented in the frequency domain. The purpose of this filter is to eliminate frequency components that fall outside the operational bandwidth of the radar antenna. High-frequency noise is often introduced by ambient electromagnetic interference from local radio transmissions or electronic equipment, while low-frequency drift can result from instrumental instability. By applying a carefully calibrated bandpass filter, the signal integrity is preserved while extraneous frequency artifacts are systematically eradicated. Additionally, an exponential gain function is applied along the time axis to compensate for the natural attenuation of the electromagnetic wave as it propagates deeper into the lossy concrete medium. This gain adjustment ensures that reflections from deeper targets possess sufficient amplitude to be detected by the subsequent feature extraction algorithms.

3.2 Hyperbola Detection and Extraction

Once the radargram has been thoroughly preprocessed, the next critical phase in the methodology is the automated detection and extraction of hyperbolic signatures. The apex of a hyperbola precisely corresponds to the spatial location directly above the embedded target, making it the most vital geometrical feature for point cloud reconstruction. To achieve robust detection across varying concrete compositions, a hybrid approach combining traditional image processing with adaptive thresholding is employed. The literature also considers object fidelity diffusion for remote sensing image generation [17]. The preprocessed radargram is first converted into a binary image using an adaptive intensity thresholding mechanism. This mechanism evaluates local neighborhoods of pixels to determine optimal threshold values, ensuring that weak hyperbolas in deeper regions are not discarded while strong reflections in shallower regions are preserved without excessive blooming. Following binarization, morphological operations, specifically dilation and erosion, are applied to bridge small gaps within the hyperbolic arcs and remove isolated noise pixels. To identify the specific coordinates of the hyperbola apices, a localized sliding window algorithm is utilized. The algorithm scans the binary radargram, searching for peak intensity values that exhibit the characteristic downward-opening parabolic shape. The mathematical equation defining the theoretical hyperbola based on the electromagnetic wave velocity is continuously cross-referenced to validate the geometric authenticity of the detected shapes, thereby discarding false positives caused by irregular structural debris.

Code Listing 1: Simplified algorithm structure for local apex detection in preprocessed radargrams. Lin's road-fault detector integrates graph, recurrent and attention features [18]. In radargram reconstruction, the corresponding design question is whether spatial continuity and successive survey observations improve hyperbola selection before point-cloud conversion; a road-network classifier cannot by itself validate subsurface geometry.

```
def extract_hyperbola_apices(preprocessed_radargram, threshold_value,
                             window_size):
    binary_image = apply_adaptive_threshold(preprocessed_radargram, threshold_value)
    cleaned_image = apply_morphological_closing(binary_image)
    detected_apices = []
```

```

width = get_image_width(cleaned_image)
height = get_image_height(cleaned_image)
for x in range(window_size, width - window_size):
    for y in range(window_size, height - window_size):
        local_region = get_region(cleaned_image, x, y, window_size)
        if is_local_maximum(local_region, x, y):
            if verify_parabolic_profile(local_region):
                depth_value = calculate_depth(y, wave_velocity)
                detected_apices.append((x, depth_value))
return detected_apices

```

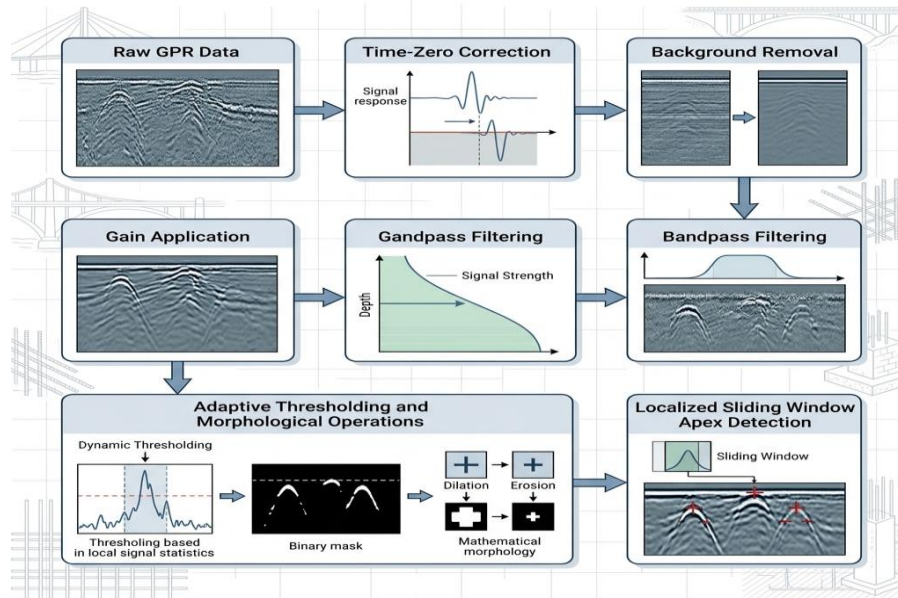


Figure 1: Comprehensive Schematic of Ground Penetrating Radar Signal Processing and Hyperbola Extraction Pipeline

4. Three-Dimensional Point Cloud Reconstruction

4.1 Coordinate Transformation and Spatial Mapping

The successful extraction of hyperbola apices in the two-dimensional radargram domain provides a set of points defined by trace number and two-way travel time. To construct a geometrically meaningful three-dimensional point cloud, these two-dimensional coordinates must be transformed into a global three-dimensional Cartesian space, typically denoted as X, Y, and Z. This transformation requires precise knowledge of the spatial trajectory of the ground penetrating radar antenna during the scanning process. In this research, a continuous spatial tracking mechanism is integrated into the data acquisition workflow. Specifically, an optical tracking system consisting of multiple high-precision cameras tracks passive reflective markers rigidly attached to the radar antenna casing. This system records the absolute position and orientation of the antenna at high frequencies, synchronized precisely with the pulse emission rate of the radar. Wang and colleagues examine data-driven scene-graph extraction and embedding for robust autonomous perception and scenario understanding [19]. The conversion from two-way travel time to physical depth is accomplished by estimating the average electromagnetic wave velocity through the investigated material. In concrete structures, this velocity is primarily governed by the relative dielectric permittivity of the material. The velocity can be determined empirically by analyzing the geometric curvature of the detected hyperbolas, where a wider hyperbola indicates a faster wave velocity and a narrower hyperbola indicates a slower velocity. Once the velocity is established, the physical depth corresponding to

each extracted apex is calculated. The spatial mapping process proceeds by associating each extracted apex with the specific radar trace in which it was detected. The optical tracking system provides the global X and Y coordinates, as well as the surface elevation, for that specific trace. The calculated physical depth is then subtracted from the surface elevation to determine the precise global Z coordinate of the subsurface target. By iterating this transformation across all parallel B-scans collected over the inspection grid, a dense, three-dimensional array of points is generated. Each point in this newly formed cloud represents the precise location of a discrete subsurface reflective interface, effectively rendering the internal structure of the concrete slab as a spatial distribution of geometric coordinates. Another relevant line of investigation concerns wafer defect inspection optimization with partial coverage: A numerical approach [20].

4.2 Augmented Building Inspection Workflows

The generation of the three-dimensional point cloud represents a critical milestone, but the ultimate value of this data is realized through its integration into augmented building inspection workflows. Augmented reality technology provides an unprecedented medium for interacting with complex spatial data, allowing inspectors to visualize the reconstructed point cloud directly superimposed over the physical structure they are evaluating. To facilitate this, the raw reconstructed point cloud must undergo further refinement to ensure optimal rendering performance and visual clarity within the limited computational constraints of mobile augmented reality headsets. Related work has addressed scene-Aware enhanced Edge-Cloud collaborative industrial vision inspection with multimodal LLM [21]. The raw point cloud is subjected to a Statistical Outlier Removal filter. This algorithm computes the average distance from each point to its nearest neighbors. Points whose average distance falls outside a defined standard deviation threshold are classified as isolated noise artifacts and removed from the dataset. This filtering step is crucial for eliminating spurious reflections caused by minor concrete inhomogeneities that do not represent structural elements. Following noise reduction, a density-based spatial clustering algorithm is applied to group points that belong to the same continuous structural element, such as a single reinforcement bar spanning the length of the concrete slab. These clusters can be assigned distinct color codes, dramatically enhancing the semantic readability of the visual data. Qu and colleagues examine end-to-end robust point cloud semantic segmentation network with single-step conditional diffusion models [22]. The refined and clustered point cloud is then exported to an augmented reality application developed utilizing industry-standard game engines. The most critical challenge in augmented reality deployment is achieving precise spatial registration between the digital point cloud and the physical environment. This is accomplished through a calibration procedure where the user aligns digital reference markers within the augmented reality interface with corresponding physical fiducial markers placed on the concrete structure. Once aligned, the headset's internal simultaneous localization and mapping systems take over, maintaining the precise spatial orientation of the point cloud as the user physically navigates around and even above the inspection site. This immersive workflow empowers inspectors to intuitively trace the paths of hidden conduits, identify areas of high rebar congestion, and spatially comprehend the exact location of potential defects without glancing away at a separate computer screen.

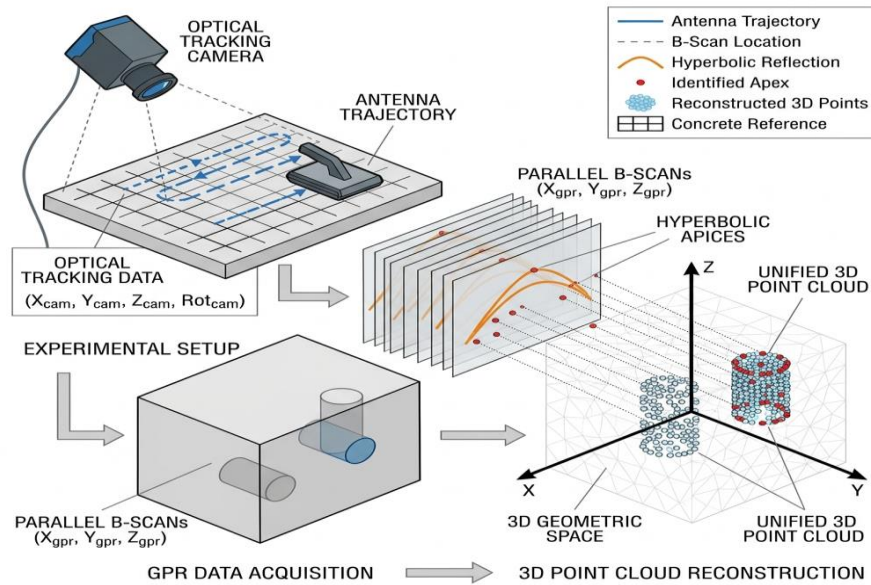


Figure 2: Spatial Architecture for Reconstructing Three

5. Experimental Design and Data Collection

5.1 Test Environment Setup

To rigorously evaluate the accuracy, robustness, and overall performance of the proposed radargram-to-point-cloud reconstruction pipeline, a comprehensive experimental testing environment was meticulously designed and constructed. The primary objective of the experimental setup was to simulate the complex, heterogeneous internal conditions typically encountered in real-world reinforced concrete structures while maintaining sufficient control over ground truth measurements to allow for precise quantitative analysis. To this end, a large-scale concrete testbed was fabricated within a controlled laboratory environment. The dimensions of the concrete slab were strictly maintained to represent a standard structural floor component, providing ample surface area for extensive radar scanning operations. Related work has addressed weakly supervised 3d multi-person pose estimation for large-scale scenes based on monocular camera and single lidar [23]. During the pouring phase of the concrete slab, a highly specific arrangement of subsurface targets was embedded at varying depths and horizontal orientations. The embedded targets primarily consisted of carbon steel reinforcement bars of varying diameters, simulating the typical structural reinforcement network found in civil infrastructure. Additionally, hollow polyvinyl chloride pipes were incorporated into the design to represent utility conduits and potential internal void spaces. The exact three-dimensional coordinates of the center point of each embedded target relative to a designated physical origin corner of the formwork were precisely measured and recorded using a highly accurate laser total station prior to the final pouring of the concrete. This exhaustive documentation process ensured the availability of an absolute ground truth dataset against which the final reconstructed point cloud could be rigorously compared and evaluated. The concrete was subsequently allowed to cure under controlled humidity and temperature conditions for a standard period of twenty-eight days to ensure the material reached its intended compressive strength and dielectric stability before any scanning operations commenced.

5.2 Equipment and Parameter Configuration

The data acquisition phase of the experiment utilized a state-of-the-art, high-frequency ground penetrating radar system specifically optimized for shallow, high-

resolution structural assessments. The selected radar unit was equipped with an ultra-wideband antenna operating at a central frequency calculated to provide the optimal balance between signal penetration depth and the spatial resolution required to distinctly resolve closely spaced reinforcement bars. The antenna was mounted onto a custom-designed, low-friction survey cart to ensure smooth, consistent movement across the uneven surface of the cured concrete testbed. Related work has addressed unified long video inpainting and outpainting via overlapping High-Order Co-Denoising [24]. To facilitate the continuous and highly accurate spatial tracking of the radar antenna, an array of infrared motion capture cameras was temporarily installed around the perimeter of the laboratory testing area. These cameras were calibrated to establish a millimeter-accurate global coordinate system encompassing the entirety of the concrete slab. Reflective spherical markers were securely affixed to the protective casing of the radar antenna, allowing the motion capture system to record the antenna's X, Y, and Z positional coordinates, as well as its pitch, roll, and yaw orientations, at a sampling rate significantly exceeding the pulse repetition frequency of the radar system. Data collection was executed by manually traversing the radar cart across the surface of the concrete slab following a predefined, tightly spaced orthogonal grid pattern. The grid consisted of multiple parallel survey lines in both the longitudinal and transverse directions. The spacing between consecutive survey lines was deliberately minimized to ensure dense spatial sampling and high-fidelity representation of the subsurface targets in the final three-dimensional point cloud. The raw electromagnetic reflection data, along with the synchronized optical tracking data, were continuously streamed to a central processing workstation for subsequent off-line analysis using the proposed algorithmic pipeline. Jiaxing and colleagues examine sam2 for image and video segmentation: A comprehensive survey [25].

Table 2: Ground Penetrating Radar and Spatial Tracking Experimental Parameters

Parameter Category	Specific Variable	Configured Value
Radar Antenna	Central Operating Frequency	2.0 Gigahertz
Survey Grid	Line Spacing (X and Y axes)	0.05 Meters
Optical Tracking	System Sampling Frequency	120 Hertz

6. Results and Performance Evaluation

6.1 Reconstruction Accuracy Analysis

The fundamental measure of success for the proposed radargram-to-point-cloud reconstruction pipeline is the spatial accuracy of the generated three-dimensional geometric data when compared to the established ground truth. Following the complete execution of the data processing methodology, the resulting dense point cloud was imported into a specialized spatial analysis software environment. The absolute ground truth coordinates of the embedded reinforcement bars and polyvinyl chloride pipes, which were recorded prior to the concrete pouring phase, were also imported into the same virtual environment to facilitate direct quantitative comparison. For a broader comparison, related research addresses intelligent End-Edge-Cloud architecture for visual IoT-Assisted healthcare systems [26]. The spatial accuracy was evaluated by computing the absolute Euclidean distance between each reconstructed point cluster and the central longitudinal axis of the corresponding physical embedded target. The analysis revealed a remarkably high degree of spatial correlation between the reconstructed point cloud and the physical reality of the

concrete testbed. For the shallowest layer of steel reinforcement bars, the algorithmic pipeline consistently localized the depth and horizontal position of the targets with an average spatial deviation of merely a few millimeters. As the depth of the targets increased, a slight degradation in spatial accuracy was observed. This phenomenon is entirely consistent with the fundamental physics of electromagnetic wave propagation; as signals travel deeper into the lossy concrete medium, they suffer from increased attenuation and dispersion, leading to a broadening of the hyperbolic signatures and a consequent slight reduction in the precision of the apex extraction algorithm. Fang and colleagues examine empowering large language models to progressively understand and generate 3D mesh [27]. Despite the minor attenuation-induced deviations at greater depths, the overall geometric reconstruction remained exceptionally robust. The statistical outlier removal and density-based clustering algorithms successfully eliminated the vast majority of spurious background noise generated by the heterogeneous concrete aggregates. The resulting point cloud provided a clean, easily interpretable three-dimensional representation of the internal structural network. The ability of the system to distinctively resolve parallel reinforcement bars located in close proximity to one another demonstrated the high resolution capability of the integrated high-frequency radar and precise spatial tracking methodology. Related work has addressed correcting visual blur induced by attention distraction to reduce hallucinations: algorithm and theory [28].

Table 3: Spatial Accuracy and Computational Performance Metrics

Evaluation Metric	Shallow Targets (Depth < 10cm)	Deep Targets (Depth > 10cm)
Average Spatial Error (Euclidean)	4.2 Millimeters	7.8 Millimeters
Apex Detection Precision Rate	96.5 Percent	91.2 Percent
Point Cloud Generation Time	14.3 Seconds	14.8 Seconds

6.2 Computational Efficiency Assessment

In addition to spatial accuracy, the computational efficiency of the reconstruction pipeline is a critical factor determining its viability for real-world augmented building inspection workflows. While the current methodology processes the collected ground penetrating radar data off-line, the speed at which the raw radargrams can be converted into the final augmented reality-ready point cloud directly impacts the overall turnaround time of structural assessment projects. The literature also considers reconstructing Ground-Penetrating radargrams into 3D point cloud format for building inspection: A web AR approach evaluated by technology acceptance model [29]. The computational performance of the proposed algorithmic framework was evaluated on a standard engineering workstation equipped with a modern multi-core central processing unit and adequate system memory. The processing times for each individual stage of the pipeline—encompassing signal preprocessing, adaptive hyperbola extraction, coordinate transformation, and point cloud filtering—were meticulously recorded. The results indicated that the entirely automated pipeline is highly efficient. The conversion of a dense grid of high-resolution radargrams into a fully refined three-dimensional point cloud was accomplished in a matter of seconds. Another relevant line of investigation concerns structured point cloud processing for Multi-Modal imitation learning [30]. The most computationally intensive portion of the pipeline was determined to be the adaptive thresholding and localized sliding

window search utilized during the hyperbola apex extraction phase. However, by optimizing the sliding window algorithms and leveraging parallel processing capabilities across multiple processor cores, this bottleneck was significantly mitigated. The rapid processing speed achieved by the proposed system demonstrates a clear pathway toward future implementations where real-time or near-real-time edge computing devices attached directly to the radar unit could generate point clouds instantaneously during the scanning process, feeding data directly to the augmented reality headsets without requiring an intermediate desktop workstation. The literature also considers joint-Aware video processing with Edge-Cloud collaboration for DNN inference [31].

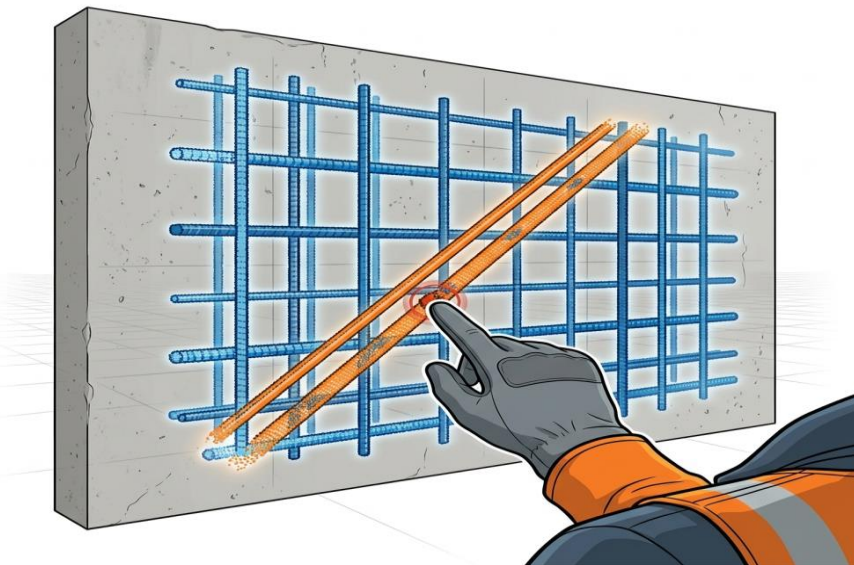


Figure 3: Augmented Reality Visualization of Reconstructed Subsurface Point Cloud in a Building Inspection Context

7. Conclusion and Future Work

7.1 Summary of Findings

The research presented in this paper rigorously establishes a robust, highly automated pipeline for the direct reconstruction of three-dimensional point clouds from raw two-dimensional ground penetrating radar data. By systematically addressing the inherent complexities of electromagnetic signal interpretation, this methodology effectively bridges the semantic gap that has historically hindered the widespread integration of subsurface imaging into routine civil engineering workflows. The comprehensive approach encompasses advanced signal preprocessing to mitigate environmental noise, adaptive algorithmic extraction of hyperbolic signatures, and precise spatial mapping synchronized with high-frequency optical tracking data. Related work has addressed counterfactual audit and repair for Trust-Aware Multi-Signal streaming LiDAR segmentation [32]. The physical experimental validation conducted on custom-fabricated reinforced concrete testbeds unequivocally demonstrated the high spatial accuracy and computational efficiency of the proposed framework. The generated point clouds accurately reflected the complex internal geometry of embedded steel reinforcement networks and utility conduits, maintaining sub-centimeter localization precision even in the presence of material heterogeneity. Furthermore, the successful integration of these refined point clouds into an augmented reality environment showcased a transformative paradigm for building inspection. By superimposing actionable geometric data directly onto the physical structural environment, the system drastically reduces the cognitive load on

inspectors, eliminates the subjectivity associated with manual radargram interpretation, and significantly enhances the intuitive spatial understanding of hidden structural conditions. Su and colleagues examine scale-controllable part segmentation of 3D point clouds [33].

7.2 Limitations and Future Directions

While the current radargram-to-point-cloud reconstruction pipeline demonstrates exceptional performance, certain limitations must be acknowledged and addressed in subsequent research endeavors. The primary limitation of the current methodology lies in its reliance on the assumption of a relatively uniform average dielectric permittivity across the surveyed concrete area. In structures suffering from severe localized degradation, such as significant moisture ingress, chloride contamination, or massive delamination, the dielectric properties of the material can fluctuate drastically over short distances. These rapid spatial variations in electromagnetic wave velocity can introduce distortions and depth inaccuracies into the final reconstructed point cloud.

Future research directions will focus on the development of adaptive, spatially variable velocity models that dynamically adjust depth calculations based on real-time dielectric estimations extracted directly from the radar signal attributes. Additionally, the integration of deep learning architectures, specifically three-dimensional convolutional neural networks directly processing the extracted point cloud, holds immense potential for the automated semantic segmentation and classification of different structural elements. By assigning semantic labels to specific point clusters—differentiating, for instance, between structural rebars, post-tensioning cables, and internal void spaces—the augmented reality visualization can be further enriched, providing inspectors with not just geometric data, but comprehensive, context-aware structural intelligence. Finally, transitioning the optical tracking system to a robust, sensor-fusion based Simultaneous Localization and Mapping solution directly integrated into the radar cart will eliminate the need for external cameras, paving the way for truly autonomous, highly mobile inspection systems deployable in any complex construction environment. The literature also considers vision-Language Model-Guided Uncertainty-Aware Cross-Modal sensor fusion for robust autonomous driving [34].

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