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Leveraging BIM for Enhanced Camera Allocation Planning at Construction Job Sites: A Voxel-Based Site Coverage and Overlapping Analysis

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Abstract: In the construction industry, the imperative for visual surveillance mechanisms is underscored by the need for safety monitoring, resources, and progress tracking, especially with the adoption of vision intelligence technology. Traditional camera installation plans often move toward coverage and cost objectives without considering substantial coverage overlap, inflating processing and storage requirements, and complicating subsequent analyses. To address these issues, this research proposes a voxel-based site coverage and overlapping analysis for camera allocation planning in parametric BIM environments, called the PBA approach. The first step is to collect information from the BIM model, which is the input for the parametric modeling step. After that, the PBA approach simulates the virtual devices and the construction layout by employing visual language programming and then generates a coverage area. Lastly, the performance simulation and evaluation of various placement scenarios against predefined criteria are conducted, including visual coverage and overlapping optimization for eliminating data redundancy purposes. The proposed approach is evaluated through its application to construction projects. The results from these various implementations indicate a marked decrease in data overlap and an overall enhancement in surveillance efficacy. This research contributes a novel, BIM-centric solution to visual information adoption in the construction industry, offering a scalable approach to optimize camera placement while mitigating overlapping areas.

Keywords: BIM; visual device; generative design; computer vision

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1. Introduction

Visual surveillance systems are becoming increasingly indispensable in the construction industry, primarily due to the need for comprehensive monitoring, including ensuring safety, tracking resources, and monitoring progress [1–3]. In particular, the advent of vision intelligence technology has significantly enhanced the capabilities of surveillance systems, offering real-time environmental monitoring through image and video capture. Surveillance cameras, as the most commonly deployed sensory devices in this domain [1], have the potential to improve many aspects of construction project management vastly. For instance, in recent years, the construction industry has successfully implemented camera systems for safety management [2,4,5], where cameras placed strategically around high-risk areas like scaffolding [6] and excavations [7] have reduced the incidence of workplace accidents. Tran et al. [8] presented an approach for detecting intrusion at construction job sites. According to Chian [9], the vision system can provide support to prevent falls from height accidents by detecting missing fences.

Additionally, vision-based monitoring systems are now pivotal in tracking the progress of construction activities [10], verifying the presence and use of resources [9], and ensuring that project milestones are met on schedule [1]. Cameras equipped with vision intelligence technology can analyze video feeds to recognize specific machinery, materials, and even personnel, offering a level of operational oversight that was previously unattainable. This capability allows project managers to make informed decisions based on real-time data, optimizing workflow and resource allocation for maximum efficiency [2,11,12].

Developing camera placement plans is essential to maximize the benefits of visual surveillance systems [13,14]. This involves determining the optimal locations for cameras to effectively cover critical areas of the construction site. A well-thought-out placement plan enhances the system's ability to monitor activities, identify potential hazards, and ensure comprehensive coverage without leaving blind spots [15–18]. Factors to consider in developing a placement plan include the type of cameras, for instance, drones, CCTV, fixed cameras, etc., the construction site layout, the nature of the construction activities, and the specific objectives of the surveillance system, such as safety monitoring, progress tracking, or resource verification [19]. For instance, a drone can offer an efficient solution in critical areas, providing dynamic coverage that complements fixed camera systems. The literature suggests that drones can be particularly effective in monitoring large or complex sites and areas that are difficult to reach with fixed cameras [20,21]. However, this research focuses on fixed camera planning, where the coverage patterns differ due to the static nature of fixed cameras compared to the dynamic operations of drones.

Traditionally, camera placement decisions have leaned heavily on the experiential judgment of site managers, a method fraught with challenges due to construction projects' changing conditions and layouts. This approach has often led to suboptimal monitoring, characterized by inadequate coverage, overlapping views, or blind spots in areas prone to hazards [13]. Traditional approaches to determining the placement of cameras on construction sites have often relied on the subjective judgment of site managers. This method, while practical, can lead to issues such as insufficient coverage, redundant views, or overlooked areas that are particularly vulnerable to hazards due to the dynamic nature and varying layouts of construction projects. In response to these challenges, various studies have explored different strategies to optimize camera positioning, including the use of the two-dimensional (2D) or three-dimensional (3D) mapping of surveillance areas, application of algorithms targeting single or multiple objectives, and adjustments for the type of construction project and whether the site layout is static or dynamic [15,22,23]. For example, research by Kim et al. [24] proposed a mixed simulation optimization for camera placement on construction sites. Tran et al. [19] considered the dynamic environment that leads to obstruction position changes following the schedule for optimization problems. Yang et al. [15] aimed to enhance camera positioning by considering multiple objectives, including coverage and cost.

Nonetheless, these solutions often focus on optimizing camera positions for particular site configurations or further installation cost problems. In the era of adopting vision intelligence technology, other issues, which are overlapping areas, remain a gap. Overlapping fields of view, despite offering the potential for enhanced accuracy by providing multiple perspectives on the same scene, introduce several challenges that can impede the efficiency and effectiveness of surveillance systems. Overlapping coverage between cameras leads to redundant data collection. This redundancy necessitates additional processing power and storage capacity to handle the duplicate information. Analyzing and processing video feeds in real-time requires substantial computational resources in computer vision systems. Redundancy from overlapping areas increases the workload on these systems, potentially slowing down processing times and affecting the system's overall efficiency. On the other hand, complications arise in accurately tracking the movement of objects or personnel across overlapping zones, and added system configuration complexity is required to handle overlapping inputs adequately. This calls for an approach that addresses traditional challenges and considers the overlapping coverage ratio to fully integrate vision intelligence technology during construction.

Building information modeling (BIM) facilitates more accurate and realistic site layout planning and enables the automatic adjustment of design and surveillance plans based on dynamic project parameters [19]. By employing a generative design process, planners can optimize the allocation of sensor devices, such as cameras, fire detection sensors, etc., to achieve optimal coverage, safety, and efficiency goals, considering the inherent dynamism and complexity of construction projects [13,14]. Therein, the planners can obtain geometric and non-geometric information about the construction site, enabling a more informed and dynamic approach to camera placement planning. These technologies facilitate the creation of detailed, three-dimensional representations of construction projects, incorporating crucial data about the physical and functional characteristics of the building or infrastructure. This comprehensive modeling capability allows for the simulation of various camera placement scenarios, optimizing coverage and identifying potential blind spots or areas of overlap before actual installation. Thus, a parametric BIM-based approach for allocating visual detection devices at construction sites represents a holistic and adaptive solution when considering coverage and overlapping problems when adapting computer vision systems at construction job sites.

The organization of this article is as follows: Following the introduction, Section 2 provides a review of the current landscape, including visual information gathering at construction sites, strategies for planning surveillance camera installations, the role of parametric BIM in this context, and the importance of using the PBA approach for allocating visual detection devices. Section 3 details the research method, explaining the process of data collection, parametric BIM-based modeling, and performance simulation and evaluation for camera device allocation. Section 4 describes creating and validating the PBA prototype. Section 5 discusses the results and implications of the research, including an analysis of the contributions and limitations of the approach. The last part summarizes the findings and examines their significance for future research.

2. Literature Review

2.1. Visual Information Collection at Construction Job Sites

Collecting visual information at construction job sites has significantly transformed, moving from reliance on direct human observation to adopting digital technologies. Traditionally, site managers and safety officers conducted regular walkthroughs to monitor project progress, identify safety hazards, and ensure adherence to safety regulations and specifications [25]. These methods, while foundational, were marred by limitations such as time consumption, vulnerability to human error, and inconsistent coverage, leading to a demand for more efficient and reliable monitoring solutions.

The emergence of cameras and video recording technology marked a turning point, facilitating a shift towards automated surveillance systems. These systems, equipped with networks of cameras, offer real-time, continuous monitoring capabilities across construction sites [26]. For instance, fixed cameras are strategically placed to constantly monitor specific areas, ensuring they are continuously observed without interruptions [27]. In contrast, UAVs offer dynamic and flexible monitoring capabilities, capturing high-resolution images and videos from various angles and altitudes [20]. Further integrating computer vision technologies into these surveillance systems has dramatically improved their efficiency, enabling the automated analysis of video feeds to detect anomalies, track resources, and monitor safety, as illustrated in Figure 1. For instance, computer vision algorithms can automatically identify safety violations, such as workers not wearing hard hats or harnesses in designated areas, by analyzing video streams from cameras around the site. Additionally, these systems can track the movement of heavy machinery to prevent collisions and ensure that equipment is being used safely and efficiently [28–31]. Another noteworthy application of computer vision in construction monitoring involves using time-lapse photography and AI analysis to track project progress against planned schedules [32]. By analyzing sequences of images, computer vision systems can identify delays or discrepancies in the construction process, allowing project managers to make informed decisions and adjustments. Hence, procuring visual data is a crucial initial step in integrating computer vision technology into construction sites. This phase holds great importance as it directly influences subsequent analyses that rely on image processing. Surveillance cameras have become indispensable in construction site applications due to the vital visual data they supply for monitoring health and safety [19]. To optimize the utilization of computer vision algorithms in the construction industry, it is critical to establish monitoring tasks and the precise locations of those tasks before initiating construction activities.

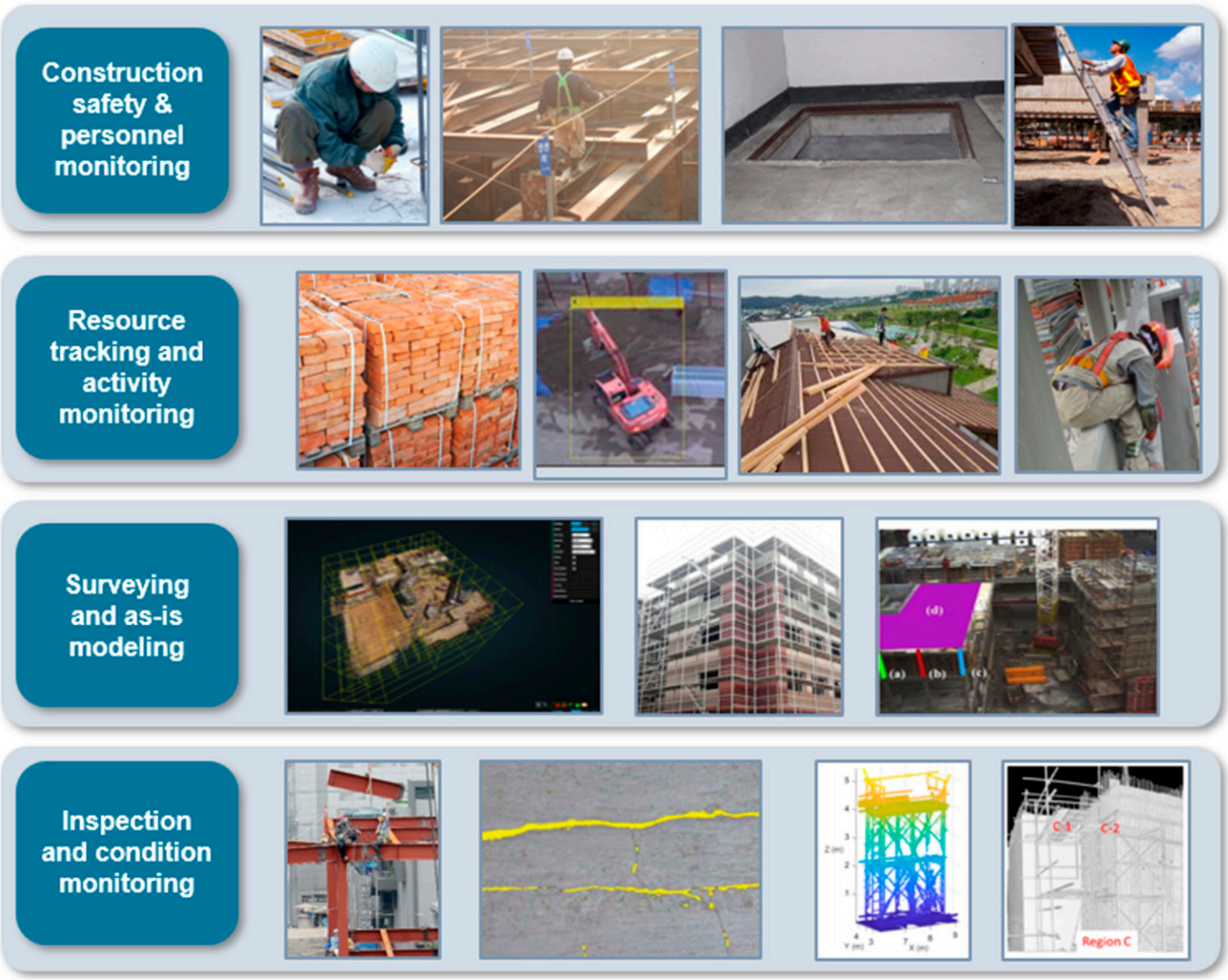

Figure 1. Visual information for construction.

2.2. *Surveillance Camera Installation Planning*

At construction job sites, the contractor develops plans that specify the location and spatial arrangement of prospective monitoring zones [18]. As a result, providing effective direction regarding the installation of cameras becomes essential in guaranteeing the seamless incorporation of computer vision technology in the construction sector [33].

Nevertheless, achieving a specified level of coverage for a given physical area while reducing the number of cameras in use poses a complex optimization dilemma. Camera placement in practical situations is commonly performed manually, necessitating the knowledge and observations of experts [34]. This approach can be laborious and expensive, as well as time-consuming. Scholars have made concerted efforts to tackle this obstacle by employing diverse methodologies, with the primary objective of resolving the Art Gallery Problem (AGP) [35]. Various objectives, camera types, project-specific attributes, workspace dimensions (two-dimensional or three-dimensional), algorithmic considerations, and obstruction types have been incorporated into these endeavors. As listed in Table 1, the hybrid simulation optimization approach proposed by Kim et al. [24] for positioning cameras on construction sites is presented. The researchers employed a methodology that included conducting expert interviews to identify crucial issues related to installing fixed cameras. They also devised a systematic camera positioning framework and visualized and quantified the camera network. Likewise, Jun et al. examined the optimization of camera coverage and cost in the context of bridge and city projects [17]. In the interim, Yang et al. addressed extensive undertakings utilizing 2D site layouts [36]. Zhang et al. optimized camera placement throughout three stages of a metro station project to attain complete coverage, disregarding explicit cost-effectiveness considerations [15].

Table 1. Related studies about visual device placement plans.

Reference	Objective		Type of Camera	Type of Case Study	Layout Dimension
Albahri (2017) [34]	Coverage	Cost	CCTV	Building (Inside)	3
Jun, S (2017) [22]	Coverage		CCTV	Bridge	3
Yang (2018) [36]	Coverage	Cost	CCTV	Temporal parking lots and storage areas	2
Zhang (2019) [15]	100% coverage		Fixed camera	Metro station	3
Kim, J (2019) [24]	Coverage	Cost	Fixed camera	Hybrid simulation–optimization	2
Chen, X (2021) [14]	Coverage		Pan-tilt-zoom cameras	Building (Inside)	2
Tran (2022) [19]	Coverage	Cost	Fixed camera	Building (Outside)	3
Chen (2023) [13]	Coverage	Cost	CCTV	Building (Inside)	3
Houng (2024) [37]	Coverage	Cost	Pan-tilt-zoom cameras	Building (Outside)	3
This study	Coverage	Overlapping	Fixed camera	Building (Inside)	3

Despite the notable contributions made, obstacles must be overcome to optimize camera placement for computer vision applications in the construction industry. An area for improvement pertains to the overemphasis on particular site configurations in prior investigations; site layouts are susceptible to modification for many reasons, including storage and safety concerns. Furthermore, the ability to relocate cameras in response to changing site layouts is frequently limited. While addressing schedule modifications and optimizing camera placement for three phases, Chen et al. restricted their calculations of the surveillance area to two dimensions [14]. Another challenge that requires attention in optimizing camera placement is reducing overlapping camera coverage. Overlapping coverage can lead to redundancy and duplicated events detected during monitoring.

In brief, to ensure the successful integration of surveillance cameras into construction sites for computer vision purposes, it is imperative to confront obstacles to optimizing camera coverage, considering overlapping ratio, cost-efficiency, and flexibility in response to changing site configurations. Although considerable progress has been achieved in this field through prior investigations, there are still prospects for additional advancements and novel approaches [14].

2.3. Parametric BIM-Based Modeling

Building information modeling (BIM) and parametric modeling have revolutionized the construction industry by facilitating the development of detailed, digital representations of physical and functional characteristics of spaces [16,38,39]. BIM's application extends across various phases of construction, including design, documentation, construction, and facility management, enabling stakeholders to visualize projects in a simulated environment before actual construction commences. This visualization aids in identifying potential issues, optimizing designs, and improving collaboration among architects, engineers, and contractors. Parametric modeling, a feature within BIM, allows for manipulating data-driven models, where changes to parameters dynamically update the entire model. This capability supports the development of virtual models that adapt to various design and construction requirements, enhancing efficiency and reducing the likelihood of errors during the construction phase.

The collaboration between BIM and parametric modeling creates the framework for using generative design in construction. Generative design is an iterative approach that uses algorithms to produce diverse design options depending on user-specified limitations and parameters. For example, in sustainable building design, generative design might investigate a variety of configurations to improve energy efficiency while considering sun orientation, material qualities, and thermal performance. This technique broadens the range of available options and simplifies decision-making by giving optimum solutions that match preset criteria. As a result, merging BIM, parametric modeling, and generative design offers a transformational shift in how construction projects are conceived, developed, and implemented, giving a more agile, efficient, and imaginative way to solving complex design issues.

2.4. Need for Parametric BIM-Based Approach for Developing Camera Device Allocation Reaching Coverage and Overlapping Target

The literature review indicates that the careful planning of camera placement is paramount. This aims to optimize field coverage while minimizing overlaps. By doing so, the construction industry can fully harness computer vision capabilities, ensuring accurate monitoring, enhanced safety, and improved operational efficiency on construction sites. The strategic placement of cameras is paramount for ensuring optimal coverage and the management of overlapping fields of view, which can complicate the analysis. These challenges highlight the critical need for careful planning and calibration in camera deployment to fully leverage computer vision's potential in enhancing construction site surveillance. Hence, adopting a parametric BIM-based approach for allocating camera devices within construction sites addresses critical needs for achieving comprehensive coverage while managing overlapping areas effectively. This methodology facilitates the strategic placement of surveillance cameras, ensuring optimal site monitoring with minimal redundancy. By leveraging BIM's dynamic and detailed modeling capabilities and parametric tools that allow for adjusting variables (such as camera angles, field of view, and placement height), stakeholders can simulate various placement scenarios and assess their impact on coverage and overlap in a virtual environment. By incorporating algorithms within the BIM environment, this approach can automate the generation of camera placement plans that meet predefined coverage objectives and minimize overlapping zones, thereby reducing data redundancy and processing demands on computer vision systems. This targeted and efficient planning is crucial for deploying advanced surveillance technologies that rely on high-quality data inputs to perform accurately.

3. Research Method

The PBA prototype introduces an approach for positioning camera devices on construction sites that optimizes coverage and minimizes overlap. The PBA approach operates through a tripartite module structure, as illustrated in Figure 2, for processing camera placement plans. Initially, the approach entails extracting relevant data from BIM models to inform device placement plans. After data collection, the parametric BIM-based modeling employs visual language programming to simulate the deployment of virtual detection devices within the construction environment, thereby generating an anticipated coverage area. They include the camera modeling, rotation angle, and position for placement simulations. Besides, the site layout is translated to a voxel model which is used to calculate the coverage and overlapping ratio. The last module is the performance simulation and evaluation, where various device placement scenarios are assessed against criteria such as maximized visual coverage and minimized overlapping. The subsequent sections of this document will offer a detailed analysis of the approach and proposed solutions and explore the theoretical basis and implementations.

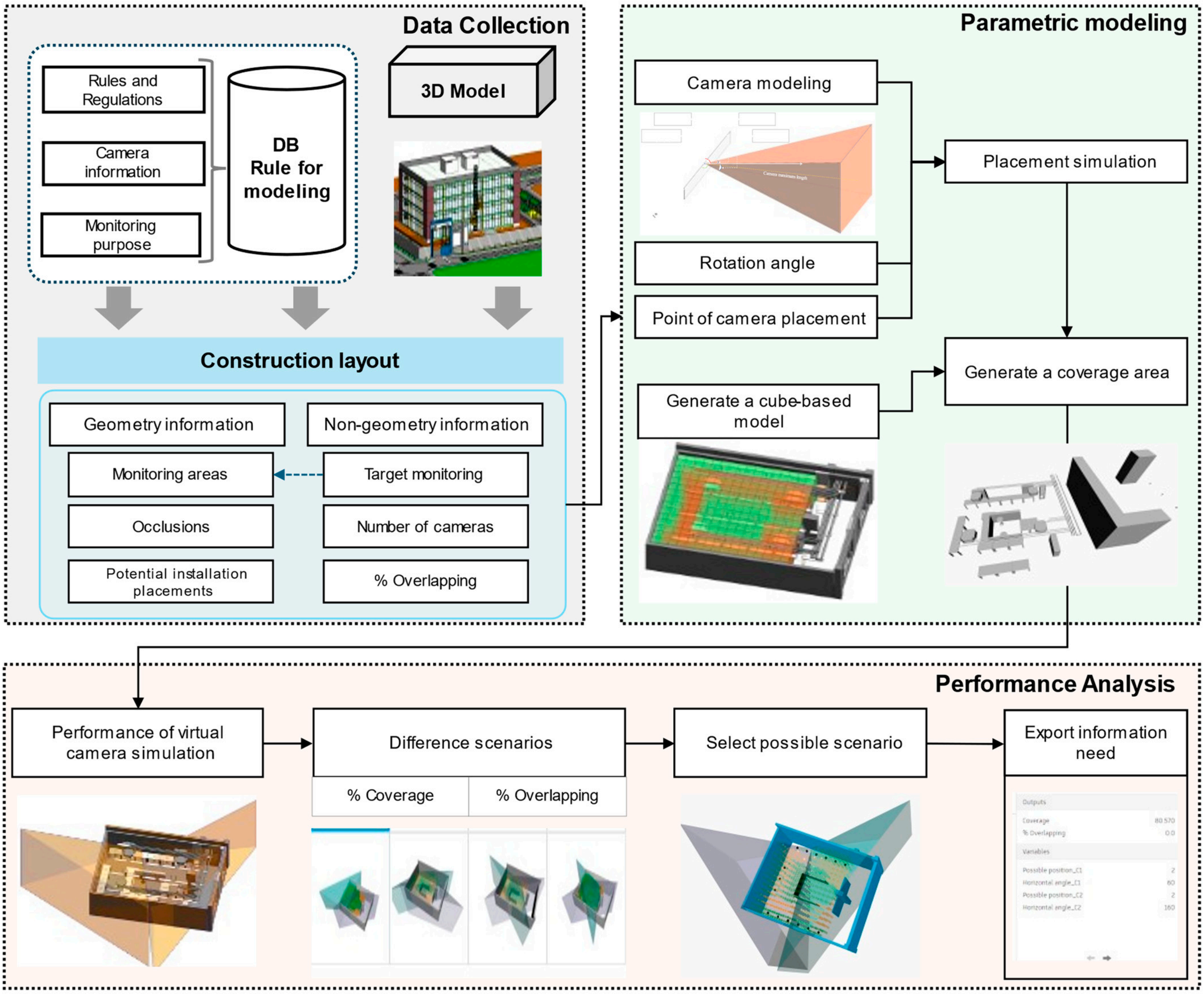

Figure 2. Parametric BIM-based approach for visual detection device allocation at construction job sites considering redundant data collection.

3.1. Data Collection

The data collection module is the initial phase in preparing inputs for parametric modeling, facilitating the development of effective and efficient camera placement solutions tailored to the unique characteristics of each project. This module is designed to systematically gather and organize relevant information that will inform the subsequent stages of parametric design. Its primary function is to extract essential data from various sources, such as BIM models, monitoring purposes, related regulations, and requirements, ensuring that the parametric modeling process is grounded in accurate and comprehensive site layout details. The geometry information includes the precise mapping of monitoring areas, identification of potential occlusions, and delineation of feasible installation locations. Such geometric data are pivotal in understanding the spatial dynamics of the construction site, enabling the identification of optimal positions for device placement to ensure comprehensive coverage. Besides, the module delves into the technicalities of camera information to develop the virtual camera model. This includes camera range, resolution, field of view, and other critical specifications that directly impact the effectiveness of the surveillance setup. The module also prioritizes collecting non-geometric information, such as the specific objectives of the monitoring initiative, the desired number of cameras, and the acceptable percentage of overlapping coverage. This amalgamation of geometric and non-geometric data equips the parametric modeling process with a nuanced understanding of the project's requirements, facilitating the development of tailored, efficient, and regulation-compliant surveillance solutions.

3.2. Parametric BIM-Based Modeling

This module simulated virtual cameras and generated these coverage areas. The visual language programming facilitates the creation of a virtual model that replicates the construction site environment. The initial step involved translating the construction site layout from the BIM model into geometrical forms within optical programming engines to establish boundary conditions. These components encompassed walls, buildings, paths, and temporary facilities. The planner also defines potential camera positions represented as $S = \{s = (x,\ y,\ z)\}$, indicating the collection of possible camera locations. The surveillance camera field of view (FoV) was modeled onto a rectangular pyramid. The camera's possible placements were designated at the pyramid's apex, with its foundation based on the camera type's maximum length, horizontal angle, and vertical angle. The camera parameters include $\varphi = (\varphi_h, \varphi_v)$, where $\varphi_h,\ \varphi_v$ represent the horizontal and vertical view angles, respectively, predefined for each camera type. $\theta = (\theta_h, \theta_v)$ describes the camera's pose, including its horizontal and vertical installation angles. The camera type is denoted as t.

Figure 3 illustrates the process of voxelization applied to the surveillance area of a site layout, transforming the site layout into a voxel model, which is a grid of discrete, cube-shaped elements—voxels. In this study, each voxel represents a portion of the site's volume, and the voxel is presented by its centroid point $Q_{(i)} = \left(x_{Q,i}, y_{Q,i}, z_{Q,i}\right)\big\}$ for $i = 1, 2, \ldots N$, with N signifying the total count of cubes. After voxelization, these centroid points are extracted, as illustrated in Figure 4. The monitoring area includes "normal" and "high focus" areas. For instance, the area around scaffolding should be monitored with high focus to prevent falling object hazards, according to OSHA. Additionally, the site layout includes various obstructions, modeled as axis-aligned bounding boxes (AABB), that could hinder visibility. These centroid points which are contained in obstructions are removed. This analysis outputs a set of visible points V, comprising centroid points from which at least one camera can obtain an unobstructed view.

The methodology establishes an empty set $V = \{\}$ to collate the visible centroid points from any camera position within the set S. When the camera is positioned within the dataset S, the process constructs a set of lines from the camera to each centroid point $Q_{(i)}$. It then assesses whether each line intersects with any AABBs representing physical obstructions. A lack of intersection indicates that the centroid point Q(i) is visible from the camera position s, warranting its inclusion in set V, following these equations:

$$\mathrm{L}_{s,i} = \sqrt{\left(x_{Q,i} - x_s\right)^2 + \left(y_{Q,i} - y_s\right)^2 + \left(z_{Q,i} - z_s\right)^2} \tag{1}$$

$$V_i = \begin{cases} 1,\ if\ L_{s,i}\ does\ not\ intersect\ any\ AABB \\ 0,\ otherwise \end{cases} \tag{2}$$

where $L_{s,i}$ represents the line segment from camera s to voxel Q_i. The intersection check $(L_{s,i},\ AABB)$ returns true if the line segment intersects with any axis-aligned bounding box, thus obstructing the view from camera s to point Q_i.

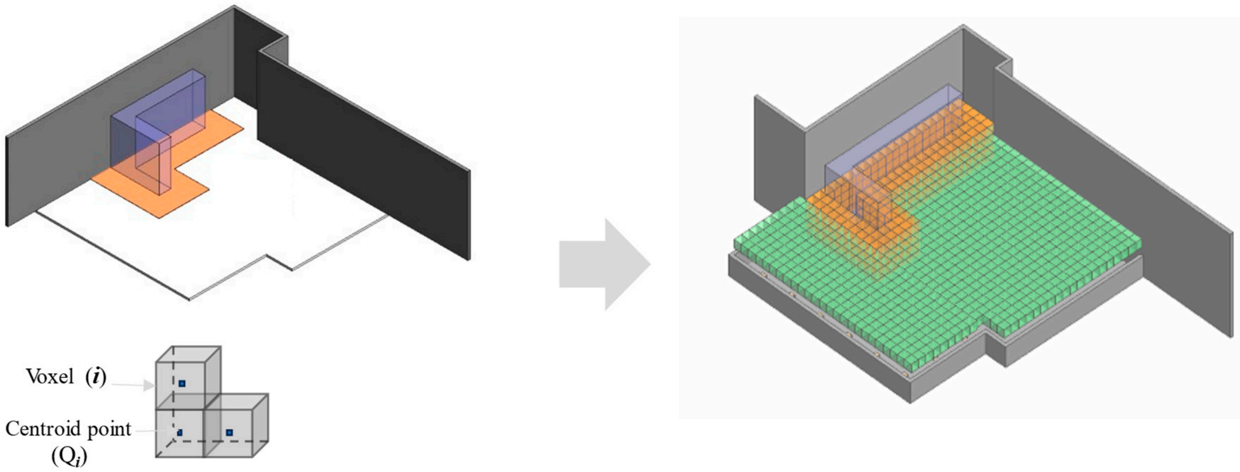

Figure 3. Voxelization of site layout.

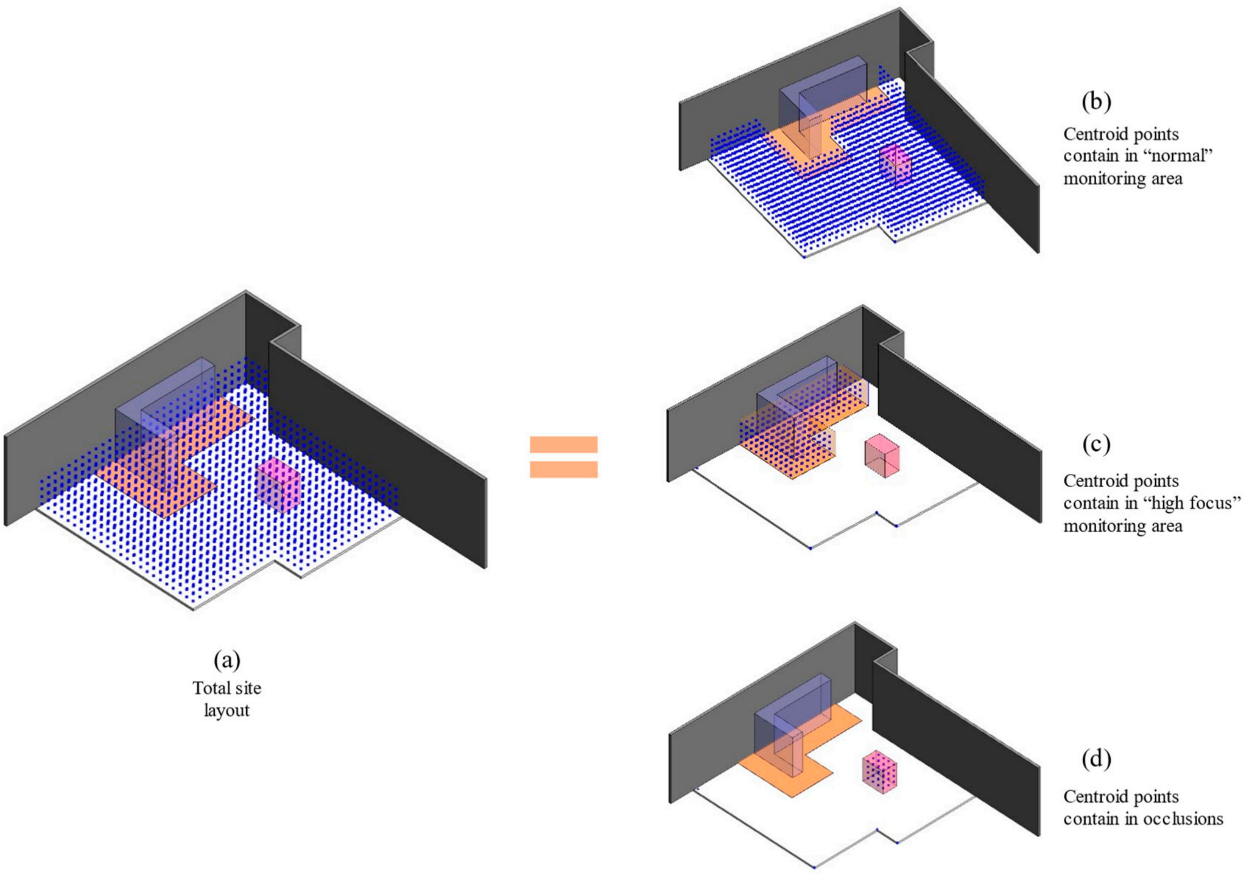

Figure 4. Centroid point extraction after voxelization.

Algorithm 1 presents a detailed algorithm for conducting a visibility analysis within a surveillance area, considering the various obstructions that might impede the view of the cameras.

Algorithm 1. Surveillance Area Visibility Analysis

```
Require: Cameras: A list of tuples (x_s, y_s, z_s) representing camera position
Require: Cubes: A list of points (x_Q, y_Q, z_Q), centroids of cubes in the surveillance area
Require: Obstruction: A list of Axis-Aligned Bounding Boxes (AABBs)
Ensure: VisiblePoints: Set of visible centroid points
  Initialize VisiblePoints as an empty set
  for each camera position in Cameras do
      for each centroid point in Cubes do
          Construct a line segment from the camera to the centroid point
          Set isVisible to true
          for each obstruction in Obstructions do
              if line segment intersects the obstruction then
                  Set isVisible to false
                  Break
              end if
          end if
          if isVisible is true then
              Add the centroid point to VisiblePoints
          end if
      end for
  end for
  return VisiblePoints
```

3.3. Analytics Module

The performance analysis module employs specific criteria and metrics, including the coverage ratio, field of view analysis, and overlap percentage, to ensure that the surveillance camera system covers the construction site to the greatest extent possible. Additionally, it is required to limit the duplication of hazard detection events during construction monitoring by minimizing the overlapping area. The strategy for optimal installation involves a systematic approach that includes (1) an initial site analysis to identify critical monitoring areas, (2) the simulation of various camera placement scenarios using optimization algorithms, and (3) the evaluation of these scenarios based on the defined metrics to identify the configuration that maximizes coverage while minimizing overlap. This method ensures a comprehensive surveillance system that is both effective and efficient.

The mathematical model of the performance analysis for minimizing the overlapping rate and maximizing the coverage of cameras for the site layout is formulated as a multi-objective optimization problem; therein, a set of objectives is scalarized into a single objective as follows:

$$\omega(\mu, \gamma) = \min\Big(-w_{coverage} f(\mu, \gamma) + w_{overlap} h(\gamma)\Big) \tag{3}$$

Subject to:
$\mu_{k,t,\theta,s} \in \{0, 1\}$, indicating whether camera k of type t with pose θ is placed at position s.
$\gamma_{k,t,\theta,s,i} \in \{0, 1\}$, denoting if camera k covers point i in its field of view.

$$h(\gamma) = \sum_i \max\Big(\sum_{k,t,\theta,s} \gamma_{k,t,\theta,s,i} - 1, 0\big) \tag{4}$$

where $\omega(\mu, \gamma)$ denotes the objective function encapsulating the optimization goals. Therein, the function $f(\mu, \gamma)$ represents the coverage performance ratio, aiming to cover as much of the surveillance area as possible, weighted by $w_{coverage}$. $f(\mu, \gamma)$ is a mathematical representation that aggregates the coverage provided by each camera, considering their types (t), poses (θ), and placements (s). It evaluates how well the surveillance area is covered based on the positioning and characteristics of the cameras. $h(\gamma)$ is the function for overlapping percent minimization, weighted by $w_{overlap}$. This function is summed over all overlapping centroid points in the surveillance area. $h(\gamma)$ calculates the extent of overlapping camera coverage across all points in the surveillance area and sums it up. By minimizing this value in the objective function, the optimization aims to reduce redundant camera coverage, thereby enhancing the efficiency of the surveillance system.

The interaction between maximizing $f(\mu, \gamma)$ and minimizing $h(\gamma)$ of $\omega(\mu, \gamma)$ lies at the heart of the optimization model for surveillance camera placement. Balancing these objectives ensures that the surveillance system achieves broad and effective coverage of the monitored area without squandering resources on excessive overlap. This balance is crucial for designing a surveillance system that aims to achieve specific performance objectives, such as achieving over 80% of the construction site coverage while ensuring an overlapping ratio of 0%. These objectives are crucial for comprehensive monitoring capabilities. Besides, previous research indicates that minimizing overlapping areas can significantly reduce computational resource usage. This ensures the system provides comprehensive monitoring capabilities while efficiently using technological and computational resources.

The data collected are then input into a visual language programming environment. Specifically, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is employed to simulate the deployment of virtual detection devices within the construction environment. The NSGA-II is utilized for its effectiveness in solving multi-objective optimization problems. This algorithm iteratively evaluates numerous configurations to identify the optimal camera placements that maximize visual coverage and minimize overlapping areas. The parametric modeling module is a tool for exploring different design scenarios, such as determining the best placement of cameras to ensure adequate coverage and overlap. Once different scenarios have been created, the performance analysis module is used to identify the most effective design strategy to meet specific goals.

An initial set of potential solutions is generated based on a defined population size and parameter range. This helps guide the parametric model in producing various design variations that can be further optimized. Each design variation is evaluated for its site coverage ratio and associated overlapping ratio. The effectiveness of each option is measured against set goals, achieved through an automated cyclical simulation and optimization process, allowing for continuous iterations until a specified stopping point is reached. This generative design process ultimately aims to uncover possible solutions, enabling planners to select the most balanced option among the objectives.

4. Prototype Development

4.1. Case Application

The authors undertook a comprehensive case study focusing on safety monitoring throughout a maintenance project, as depicted in Figure 5. The project spanned ten days, encapsulating various activities categorized into preparatory tasks, exterior and interior maintenance, electrical and HVAC (heating, ventilation, and air conditioning) work, and testing and completion. To facilitate the automatic monitoring of the project's progression, computer vision technology was employed, supported by the deployment of two webcams, the specifications of which are detailed in Table 2. Given the monitoring system's limitation in identifying duplicated events within overlapping areas, the PBA approach was applied to devise camera placement plans. This approach aimed to minimize the overlap ratio between the two cameras, thereby enhancing the efficacy and efficiency of the surveillance system in capturing distinct activities without redundancy.

Table 2. The webcams used for case implementation.

Camera Type	Length (m)	Horizontal Angle (°)	Vertical Angle (°)
A	15	100	58
B	15	80	60

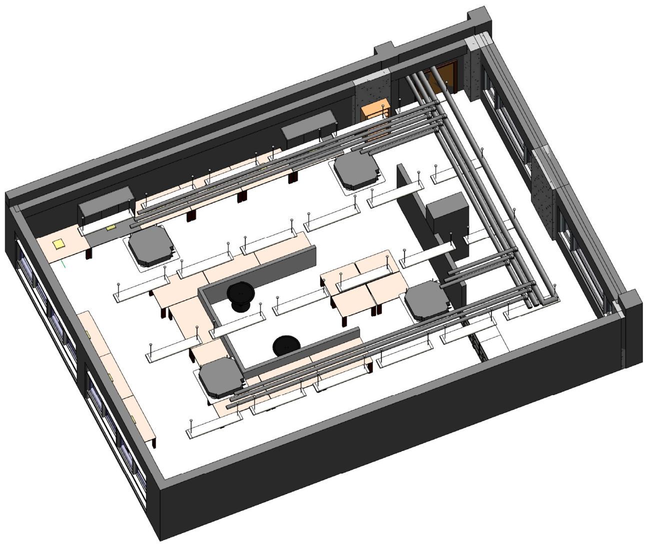

Figure 5. The project workspaces.

4.2. Implementation

In the implementation phase of the study, the research team leveraged the capabilities of the Autodesk platform, specifically integrating Dynamo with Autodesk Revit to advance prototype development in the realm of surveillance system optimization. This integration facilitated a seamless transition of parametric modeling techniques into the surveillance system's design process. This approach began with converting a BIM model from Revit to the Dynamo environment, a strategic move that enabled the comprehensive simulation of the construction site's layout. The simulation incorporated detailed depictions of potential impediments and projected fields of view for each surveillance camera, thus establishing a foundational layer for the meticulous planning of camera placements.

Figure 6 illustrates the Dynamo script employed to extracting site layout boundary and voxelization. The site layout includes obstruction, "high focus", and "normal" monitoring areas, as illustrated in Figure 7. Hence, the author extracts a list of centroid points from the surveillance area. A list of centroid points is imported to the central virtual environment to represent monitoring areas accurately, as illustrated in Figure 8. This approach allows for the precise positioning of cameras to ensure optimal coverage and minimize blind spots. The centroid points, derived from the voxelization of the site layout mentioned in Section 3.2, represent discrete locations within the construction site that need to be monitored. By utilizing these centroid points, the system can dynamically adjust camera positions based on the visibility of these points, ensuring that all critical areas are covered. Figure 9 illustrates a group Dynamo code of virtual camera development. This step is essential for dynamically modifying decision variables to the positioning and orientation of cameras within the intricate Revit–Dynamo framework. Further, the process was further refined by pinpointing exact locations for camera installation within the model, indicating the optimum spots for achieving comprehensive surveillance coverage. To ascertain that these spots were devoid of visual obstructions, the Dynamo script was enhanced with functionality to create bounding boxes around potential barriers, as illustrated in Figure 8. Subsequently, a generative design tool was used within this enriched modeling environment, systematically evaluating diverse placement alternatives against predetermined criteria to ascertain the most viable locations for installing surveillance cameras, as depicted in Figure 10. This systematic approach optimized surveillance coverage across the site while concurrently minimizing the incidence of redundancy that typically arises from overlapping fields of view between cameras.

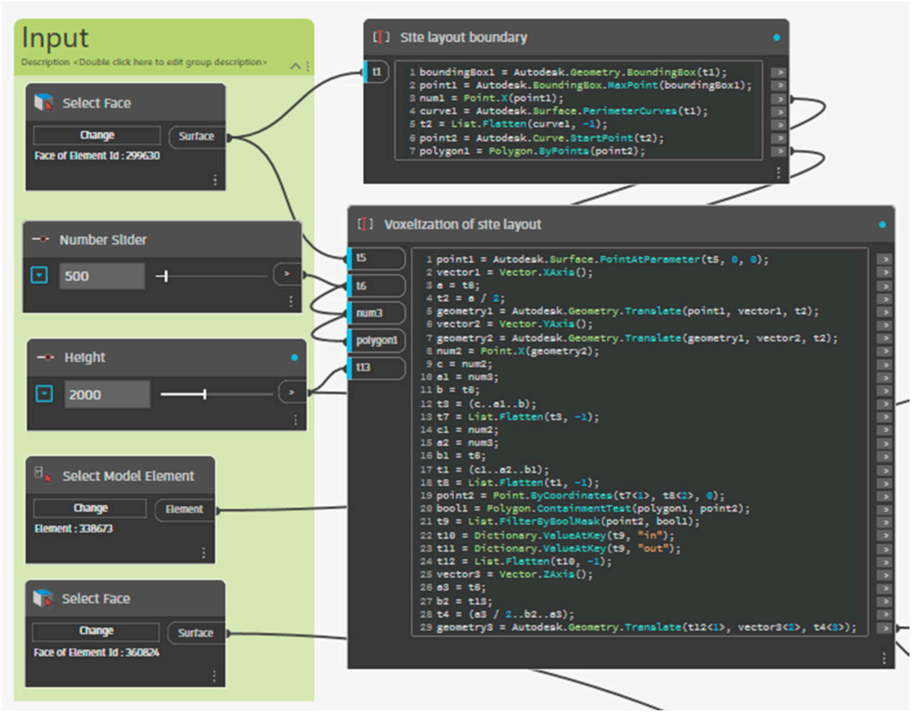

Figure 6. Extracting site layout boundary and voxelization using Dynamo.

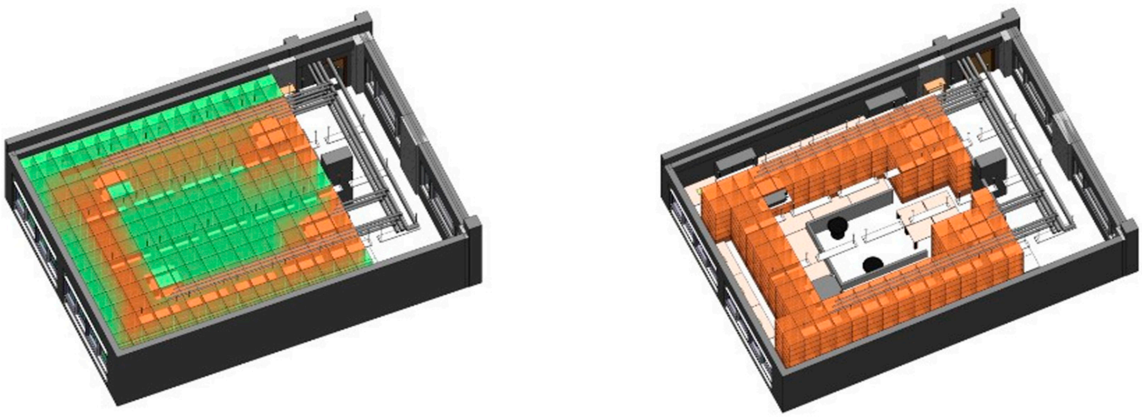

Figure 7. Voxelization of "high focus" and "normal" monitoring areas.

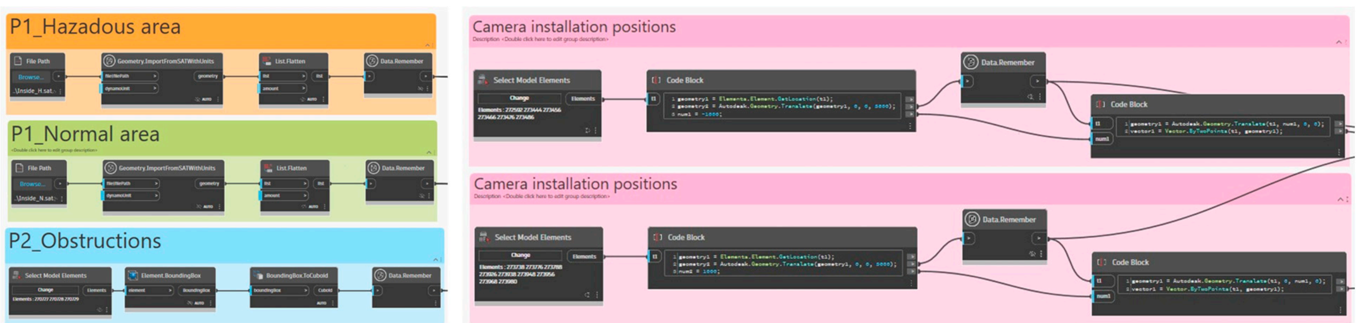

Figure 8. The group Dynamo code of importing list of centroid points, obstruction and camera installation positions.

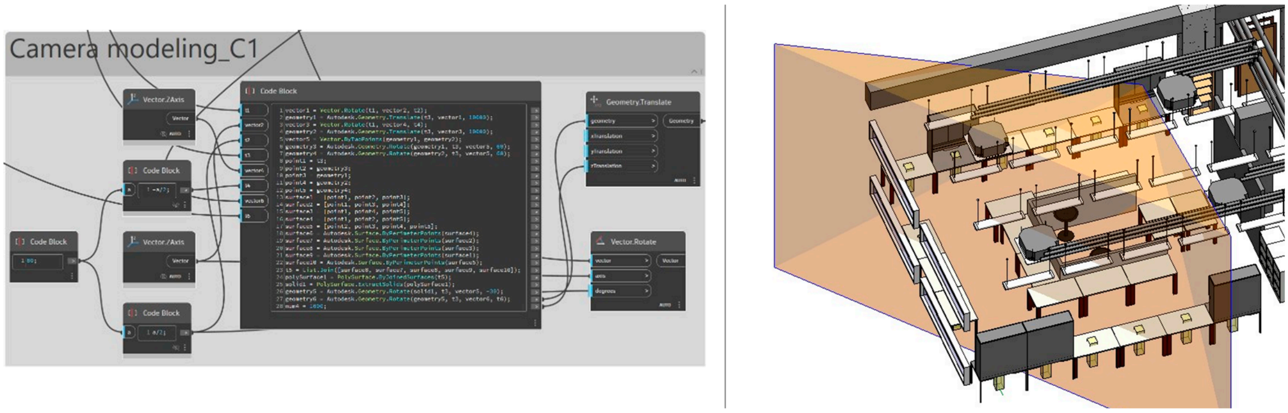

Figure 9. The group Dynamo code of virtual camera development.

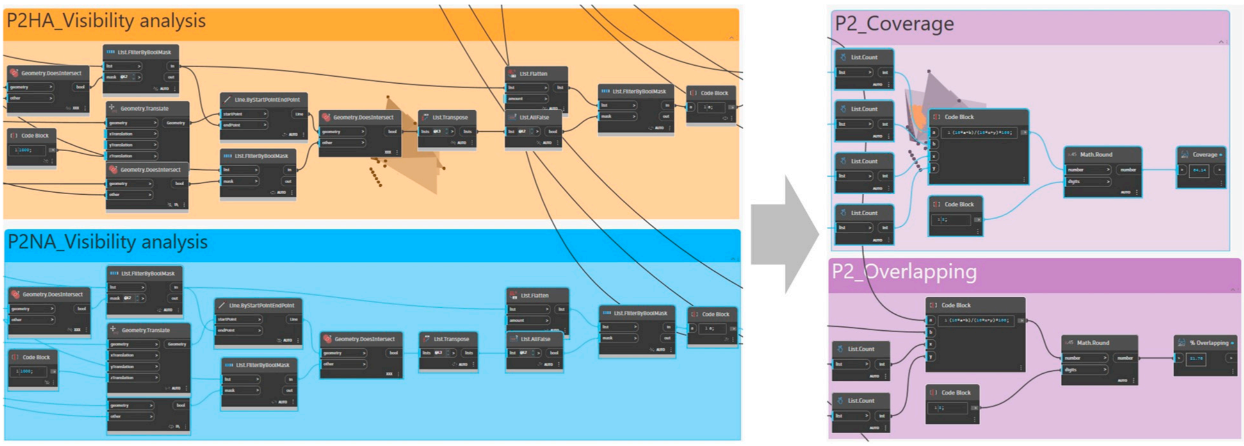

Figure 10. Dynamo code for visibility analysis and performance analysis.

5. Results and Discussion

The maintenance project has two critical activities within the interior maintenance phase: "Office Furniture Arrangement" and "Electrical and HVAC Maintenance". The workspace was strategically planned to accommodate these activities, as illustrated in Figure 5. Electrical and HVAC systems play a critical role in maintaining the functionality and safety of indoor environments, making their maintenance paramount. Hence, the surveillance monitoring system should focus on these areas, as the yellow cubic units in Figure 7 indicated.

The PBA approach was used to ensure the efficient organization of camera placement before implementing surveillance monitoring systems supported by two webcams. The author used the NSGA-II to find a possible plan for camera placement. The planner set constraint conditions with a coverage ratio higher than 80%. Another challenge is the overlapping coverage of cameras; this overlap could lead to redundancy in recording hazard events. Hence, two objective functions are defined, including maximizing coverage and minimizing overlapping ratio. After running a generative design, there were nine possible solutions for placing two webcams at the job sites, as illustrated in Figure 11. All solutions had a coverage ratio higher than 80%. Notably, these solutions indicated a proportional relationship between coverage and overlap ratios, underscoring a critical challenge in surveillance system design—achieving extensive coverage often leads to increased overlap between camera fields of view. Hence, the planer chose the solution with 0% overlapping, as illustrated in Figure 12.

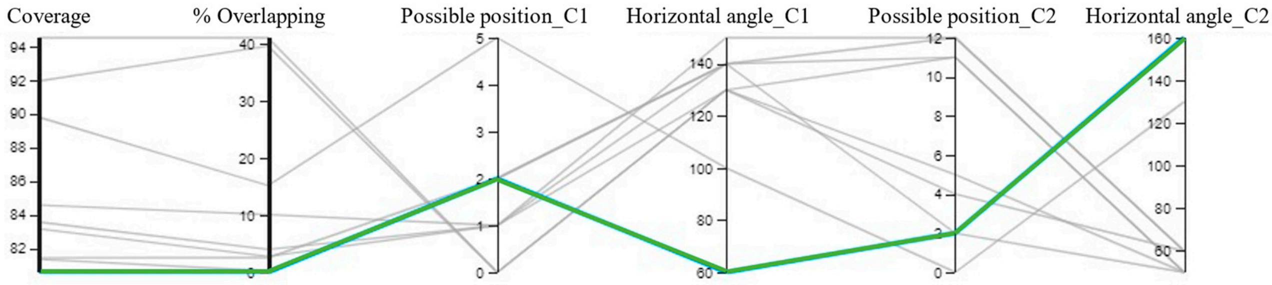

Figure 11. The installation solutions of generative design.

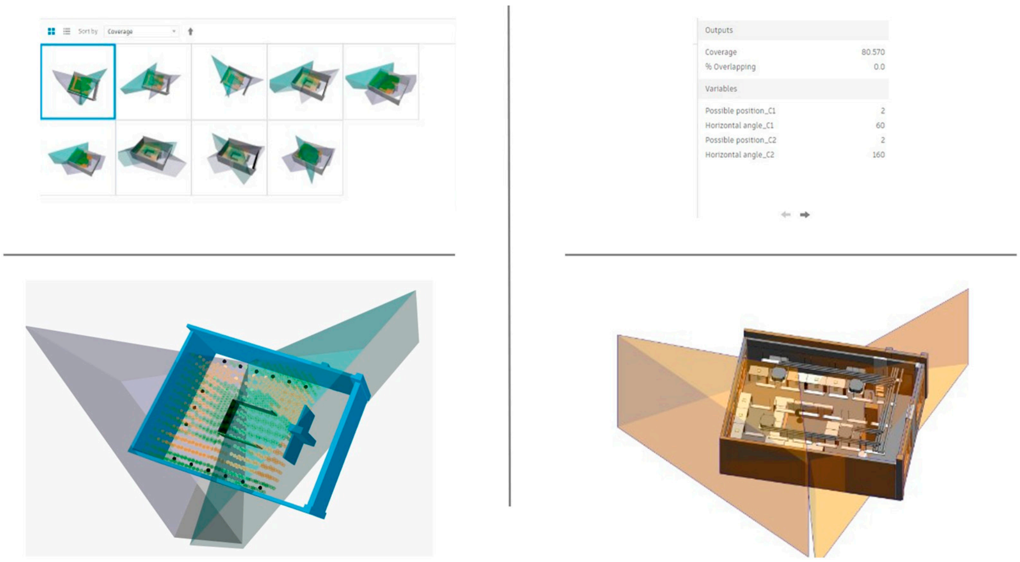

Figure 12. The installation solution with zero overlapping ratio.

In contrast to previous investigations about the surveillance camera system installation plan implemented at construction sites, this study is anticipated to provide significant additions to the existing body of knowledge within the architecture, engineering, and construction (AEC) sector: (1) The study's literature review noted a tangible advancement in the utilization of computer vision technology for project management and surveillance purposes; the overlapping and coverage ratio of surveillance systems affected the efficiency of monitoring. While existing studies, such as those by Tran et al. (2022) [19] and Chen et al. (2023) [13], addressed various aspects of the camera placement cost and coverage ratio, our literature review highlighted the necessity of minimizing the overlapping ratio to reduce data capture during vision intelligence monitoring. The voxel-based site coverage and overlapping analysis enable precise camera placement that adapts to ongoing changes in the site layout. (2) The novel PBA approach for optimizing camera placement underscores the method's effectiveness in addressing surveillance challenges in dynamic project environments. By prioritizing the reduction of overlap in the fields of view of cameras, the approach effectively mitigates the issue of redundant data capture, thereby enhancing the efficiency of data processing and storage. (3) The prototype development findings illuminate the intricate balance required in surveillance system optimization between achieving extensive coverage and minimizing redundancy in camera views. This distinction ensures that comprehensive monitoring coverage is maintained while data collection redundancy for vision monitoring is reduced. The decision to select a camera placement plan with 0% overlap, as depicted in Figure 12, highlights a strategic prioritization of minimizing redundancy without compromising the surveillance system's effectiveness. This solution is particularly relevant in monitoring critical activities, where clarity and coverage are paramount to identifying and addressing potential hazards. For instance, Figure 13 depicts monitoring non-hardhat events when workers enter job sites.

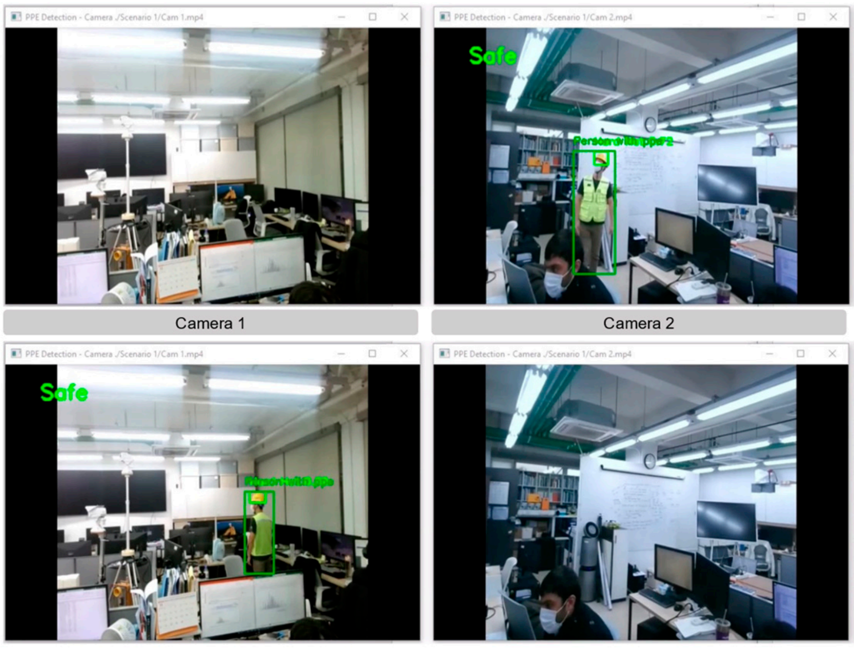

Figure 13. Automatic monitoring of non-hardhat events at job sites.

Nevertheless, this research has limitations: (1) Although one of the objective functions of the generative planning algorithms is to minimize the percentage of overlap between cameras, in practice, job sites may require more cameras, and the overlapping situation is inevitable. This study has not considered the potential hazards at overlapping areas where the hazard events can be recorded by multiple cameras. (2) Within the PBA approach, which incorporates the BIM model, a crucial assumption pertains to the level of detail concerning construction site layouts. The potential inability of the PBA approach to adequately capture and address the myriad of activities and changes that occur over shorter periods affects obstructions. (3) Other factors like variable lighting, obstructions, and the inherent complexity of construction environments can affect algorithm performance, which is still not considered when developing camera installation plans. Furthermore, the current optimization process did not consider environmental factors such as dirt and dust, which can significantly degrade the quality of captured images and videos. Future research should incorporate these environmental constraints to enhance the reliability and accuracy of the surveillance system in construction sites.

6. Conclusions

This research introduces a novel PBA approach to enhance the deployment and efficacy of surveillance systems within the construction industry, mainly focusing on optimizing camera placement to improve coverage and minimize overlap. This methodology is systematically unpacked through a tripartite modular framework, which includes (1) data extraction from BIM models, where the initial step involves gathering essential data from BIM models to inform the strategic placement of surveillance devices. This module is pivotal in understanding the spatial dynamics and critical areas of the construction site that necessitate vigilant monitoring. (2) The virtual deployment simulation utilizes visual language programming to simulate the placement of virtual detection devices within the construction layout. This simulation process is crucial for generating a visual representation of the anticipated coverage area, thereby facilitating the optimization of camera locations in a virtual environment before installation. This step significantly aids in preemptively addressing potential coverage gaps and overlapping zones. (3) The performance simulation and evaluation step is used to rigorously assess the simulated camera placement plans against defined criteria, notably the maximization of visual coverage and the reduction of overlapping views. This evaluative phase is instrumental in refining the surveillance setup to ensure the final implementation achieves comprehensive coverage with minimal redundancy. The case study identified nine possible solutions by setting a coverage ratio objective of over 80% and aimed to reduce overlapping areas, ultimately selecting an installation plan with zero overlaps to enhance monitoring efficiency. This decision underscores the critical balance between achieving extensive surveillance coverage and minimizing redundancy in data capture, particularly in monitoring essential areas of project safety and efficiency. Implementing this approach has been shown to significantly reduce data redundancy, thereby improving the capability of surveillance systems to provide clear and comprehensive coverage of essential maintenance activities within construction projects.

Future research directions should aim to expand the PBA approach by integrating advanced analytics for dynamic site monitoring, considering the temporal changes in construction site layouts and activities. Additionally, exploring the integration of AI and machine learning algorithms could offer predictive insights into optimal device placement strategies, adapting to the evolving needs of construction projects. Further investigation into the scalability of the PBA approach across different types and sizes of construction projects could also provide valuable insights into its applicability and effectiveness in diverse construction environments. This multi-project validation underscores the robustness of the approach and supports its generalizability across different construction environments, demonstrating its potential for broader applicability. Additionally, it also supports analyzing the reduction of computational resources. Finally, by addressing these limitations and exploring these potential research areas, future studies can continue to refine and improve the strategies for deploying visual surveillance technologies in the construction industry. For instance, integrating planning surveillance systems with fixed cameras and dynamic cameras such as drones, UAVs, UGVs, etc., ensures safety and efficiency in increasingly complex project environments.

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