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Intelligent Geometric Quality Inspection for Multiple Prefabricated Components in Large-Scale Storage Yard Based on BIM-LiDAR-UAV/UGV

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Abstract: Quality inspection in outdoor prefabricated storage yards is highly challenging due to the large volume, diversity, and complex management demands of components. Currently, these inspections are conducted manually, which is insufficient to fully meet industry needs. This study proposes an innovative approach to enable intelligent inspection for multiple prefabricated components in large-scale prefabricated storage yards by integrating Building Information Modeling (BIM), LiDAR, Unmanned Aerial Vehicles (UAVs), and Unmanned Ground Vehicles (UGVs). First, an intelligent sensing environment and stepwise collaboration mechanism are established, where UAVs are used to reconstruct a 3D comprehensive environment of the prefabrication site, providing a map to plan the optimal scanning path for LiDAR-equipped UGVs. Next, a point cloud-driven integrated geometric quality inspection method is introduced, where UGVs autonomously collect, and process point cloud data to extract precise geometric features of large components within expansive spaces. To verify the effectiveness of the proposed method, an experiment at a large-prefabricated component factory that produces a variety of types of prefabricated components is conducted. By integrating point cloud processing results with BIM model design information, this research achieves high-precision, large-scale quality inspections of the non-structural performance of prefabricated components, significantly enhancing inspection efficiency and accuracy.

Keywords: Large-scale prefabricated storage yard, geometric quality inspection, prefabricated components, UAV/UGV integration, LiDAR.

1. INTRODUCTION

During the manufacturing process of prefabricated components, quality issues often arise, such as dimensional deviations and surface defects, which can significantly impact the quality of engineering projects and subsequent assembly. Currently, quality inspection in outdoor prefabricated storage yards faces challenges due to the large quantity, diversity, and management complexity of components. Traditional manual inspection methods are limited by time and labor costs (Tan et al., 2020), making them insufficient to meet the needs of large-scale storage yard inspections.

To improve the automation of geometric quality inspection for prefabricated components, many researchers have explored new algorithms and technologies, including computer vision(B. Wang et al., 2022), 3D laser scanning (M.-K. Kim et al., 2015; Qian Wang, Kim, Cheng, et al., 2016; Qian Wang, Kim, Sohn, et al., 2016; Li et al., 2020), and augmented reality(Chi et al., 2022). Also known as reality capture technology, 3D laser scanning offers unique advantages in efficiency and precision. Laser scanning can generate high-density, accurate point cloud data, capturing the geometry of components in fine detail, including subtle features and curved surfaces. Building Information Modeling (BIM) provides a digital model of the construction that includes geometric, spatial, and attribute information of components. Combining LiDAR-based 3D laser scanning with BIM in component inspection enables a more comprehensive, accurate, and real-time approach to detection and management (Tan et al., 2023). By comparing the acquired point cloud data with the design BIM model, geometric deviations in components can be effectively detected(Bosché & Guenet, 2014; Tan et al., 2024).

Although 3D laser scanning-based methods are fully automated, non-contact, and highly precise, current research primarily focuses on geometric quality inspection for single prefabricated components and typically requires manual intervention for point cloud data collection. This has clear limitations and does not meet the needs of diverse component detection in storage yards. With advancements in communication, machine intelligence control, and spatial positioning technologies, Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs) are increasingly used for environmental sensing and data collection in large-scale engineering contexts (Tan et al., 2021; Rachmawati & Kim, 2022). Therefore, combining UAVs with LiDAR-equipped UGVs could help address the current inefficiencies in point cloud data collection.

To address the above issues, this study aims to develop a framework for point cloud data collection and geometric quality inspection for multiple prefabricated components in large-scale prefabricated storage yards by integrating UAV, UGV, LiDAR, and BIM technologies. The innovations of this study include: (1) environmental sensing of the prefabricated storage yard and point cloud data collection method based on combining UAV and UGV. (2) A target component extraction method based on a density projection algorithm by utilizing the Z-axis projection distribution of the point cloud for stacked components to locate the position of timbers and extract target component. (3) A two-step classification and recognition process for identifying component types and providing reliable data for subsequent quality inspection. Initially, the PointNet++ detection method is used to classify the component, followed by a Scan-vs-BIM comparison to determine the specific component type. The proposed technical framework has significant potential to advance the intelligent management of large-scale prefabricated storage yards and automate quality inspection of prefabricated components.

The organization of this paper is as follows: Section 2 presents background information, covering (1) research on data collection combining UAV and UGV, and (2) point cloud-based geometric quality inspection for prefabricated components. Section 3 details the proposed methodology for environmental sensing, point cloud data collection and geometric quality inspection of multiple prefabricated components in large-scale storage yards based on BIM-LiDAR-UAV/UGV. Section 4 describes the experimental validation of the proposed technique. Finally, Section 5 concludes the study and discusses directions for future research.

2. Literature review

2.1 Data collection based on UAV/UGV

To achieve integrated inspection of large-scale prefabricated components, it is crucial to rapidly and efficiently conduct comprehensive 3D sensing of the inspection environment. Traditional methods for manually reconstructing BIM models of building scenes are fraught with challenges, such as high costs and lengthy timelines, rendering them inadequate for continuously collecting dynamic project information throughout the lifecycle. Photogrammetry using UAV can quickly extract point cloud data to reconstruct 3D models of scenes or stitch images to create high-resolution panoramic views(S. B. H. K. H. Kim, 2017)， However, the precision of this data often falls short of the requirements for geometric quality inspection of prefabricated components。 Moreover, UGV control systems, as a core component of construction robotics, have attracted considerable attention from researchers both domestically and internationally. Scholars have utilized 3D laser point clouds (NamanPatel et al., 2019; Fei Yan, 2020), computer vision(Park et al., 2019) , and the fusion of computer vision with 3D laser point clouds(LiuYisha et al., 2018; Pierzchała et al., 2018) to construct and localize sparse semantic maps, thereby providing route navigation for UGVs operating in complex environments. The integration of BIM technology with UGVs for autonomous path planning and obstacle avoidance facilitates intelligent inspection in challenging settings. Nevertheless, UGVs possess limited global sensing capabilities within their operational environments during inspections, which can diminish their overall efficiency. By considering the respective advantages of UAVs and UGVs, employing UAVs as a complementary tool for UGVs' environmental awareness can effectively address challenges related to trajectory planning (Hernandez et al., 2014; FernandoRopero et al., 2019) , localization and navigation (O.Sivaneri & N.Gross, 2017, 2018) , and data collection (Heß et al., 2012; Asadi et al., 2020) in complex environments. Drawing on precedents established by scholars who have utilized heterogeneous collaborative control systems, this research intends to explore a collaborative control approach between UAVs and UGVs. The goal is to achieve comprehensive 3D sensing of the prefabricated component inspection environment, thereby enabling rapid and intelligent data collection for inspections.

2.1 Point cloud-based geometric quality inspection for prefabricated components

A substantial amount of research has proposed methods for geometric quality inspection of prefabricated components based on 3D point clouds. Bosché (Bosché, 2010) proposed a method using 3D CAD models to identify steel structures from laser scanning data and used them for dimension compliance control. Wang et al. (Q. Wang et al., 2017) used color laser scanning data and BIM to estimate the positions of rebars. The team also developed a mirror-aided laser scanning system for the geometric quality inspection of concrete elements (M. K. Kim et al., 2019). However, most of these algorithms primarily focus on the quality inspection of individual prefabricated components and do not adequately address the identification and measurement of multiple component types in complex scenarios. Deep learning methods have gained widespread attention in the Architecture, Engineering, and Construction (AEC) industry. Li et al. (Li et al., 2022) introduced a comprehensive indoor acceptance system that encompasses indoor semantic segmentation, component surface segmentation, as well as flatness and verticality quality assessments. Perez-Perez et al.(Perez-Perez et al., 2021) also presented Scan2BIM-NET to semantically segment building point clouds into structural, architectural, and mechanical subcomponents. Shu et al.(Shu et al., 2023) developed an automated recognition and measurement assessment method for prefabricated concrete components based on a Prefabricated Concrete Component Recognition Network (PCCR-Net) and 3D point clouds, succeeding in segmenting the synthetic point clouds dataset into rebars and concrete. In practical inspections of component storage yards, prefabricated components exhibit a variety of types and inspection criteria. Therefore, further research is needed to achieve classification of various components and identification of different inspection targets.

3. METHOD

This study proposes an integrated data collection and assessment framework using UAV (Unmanned Aerial Vehicle), UGV (Unmanned Ground Vehicle), LiDAR, and BIM (Building information modeling) to automate and efficiently inspect the quality of large-prefabricated components in the yard. Figure 1 illustrates the proposed framework, which consists of three main parts: (1) UAV-based environmental sensing; (2) UGV-based point cloud data collection; and (3) geometric quality inspection.

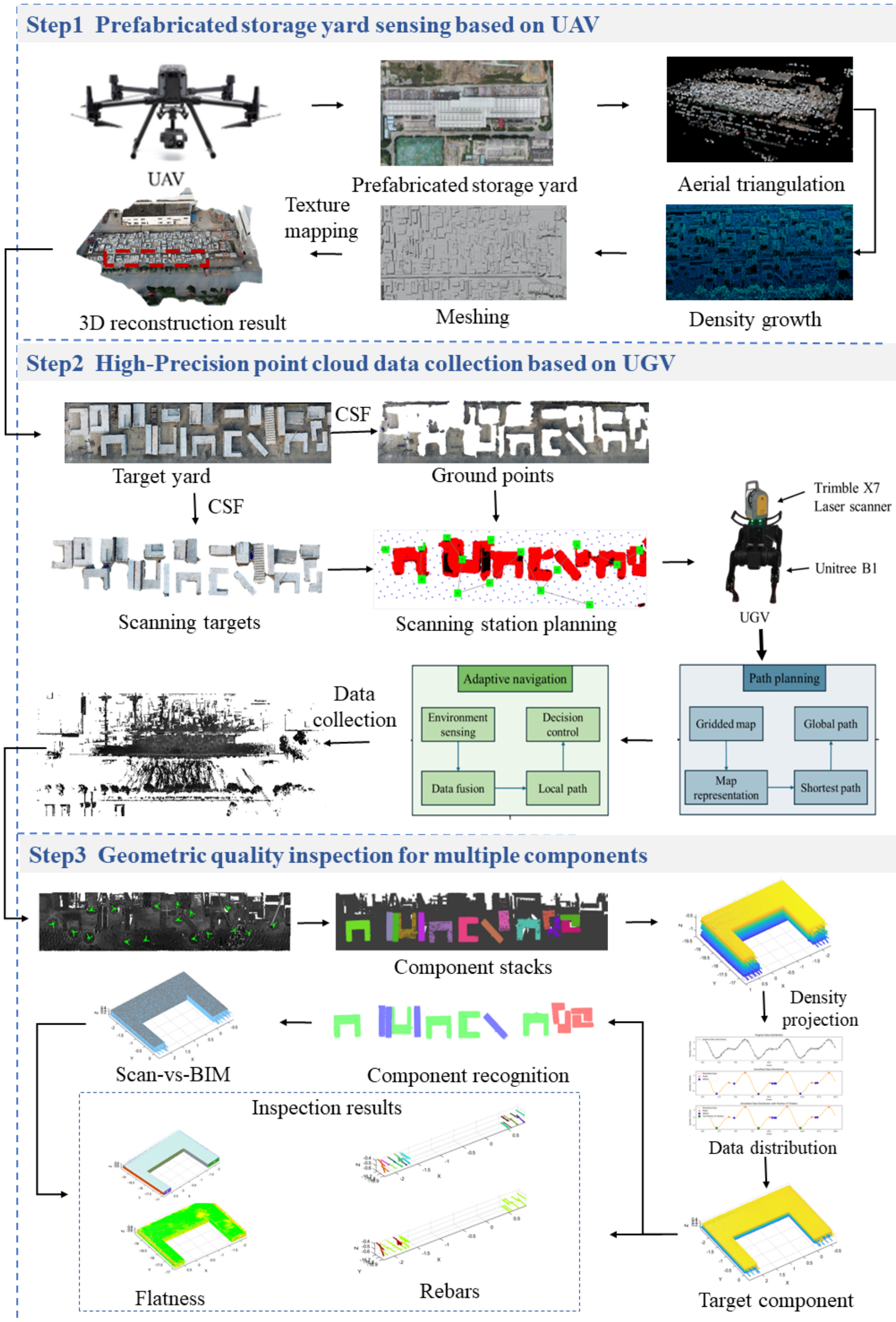


Figure 1. The framework of the proposed method.

3.1 Prefabricated storage yard sensing based on UAV

The UAV-based environmental sensing system consists of two primary components: image data acquisition and 3D reconstruction, as depicted in Figure 2. Initially, the UAV employs an HD camera to capture high-resolution images and utilizes advanced wireless technology to ensure real-time, seamless data transmission. Subsequently, this image data is processed to create a detailed and accurate 3D environmental model that effectively captures the intricacies and characteristics of the terrain. This system enhances the UGV's autonomous capabilities, enabling it to perform tasks like path planning and adaptive navigation with greater precision and efficiency.

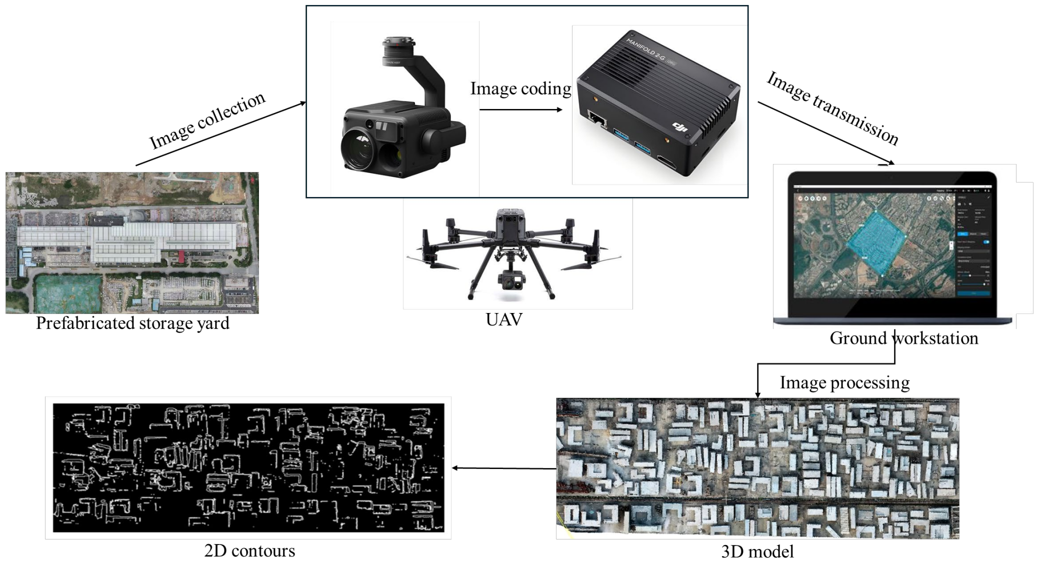


Figure 2. The process of 3D reconstruction of perceived environment.

(1) Image collection and transmission

Before image acquisition, operators only need to set the reconstruction range and image overlap rate, allowing the UAV to automatically plan its flight path and collection strategy based on these parameters. These UAVs are equipped with advanced navigation and positioning systems, enabling precise task execution and ensuring comprehensive coverage and high-quality image capture. With onboard high-definition cameras, UAVs can obtain high-resolution images in critical areas. The cameras feature high pixel counts and wide-angle lenses, adapting to various lighting conditions to capture clear and detailed visuals, providing solid data support for subsequent 3D reconstruction.

To enhance transmission efficiency and reliability, UAVs utilize mainstream video compression technologies such as H.264 and H.265, which effectively compress images to reduce storage and bandwidth requirements while preserving image quality. This optimization improves both data transmission speed and cost-effectiveness. By optimizing data streams through RTSP (Real-Time Streaming Protocol), UAVs achieve fast and stable transmission from the air to ground workstations: RTP ensures real-time packet transmission and minimizes latency, while RTSP provides flexible streaming control mechanisms, enhancing the manageability and reliability of data transfer. The combination of these protocols significantly boosts the data transmission efficiency and system robustness of UAVs, ensuring stable operation in complex environments.

(2) 3D reconstruction

During UAV data collection, changes in lighting and weather conditions significantly impact image quality. Factors like strong sunlight, shadows, clouds, and haze can reduce image clarity, cause color distortion, and increase noise, all of which affect 3D reconstruction quality. Additionally, limitations of imaging equipment and transmission interference can further degrade image quality. To address these issues, this study employs a range of image processing techniques to enhance image quality, as illustrated in Figure 3. (a). First, the BM3D algorithm is applied to remove random noise while preserving details, making images captured in low light or complex weather conditions clearer. Then, the CLAHE algorithm is used to enhance local contrast and emphasize texture details, improving the accuracy of feature extraction in 3D reconstruction. Furthermore, image data processing includes geometric correction and optical calibration to eliminate image distortion and ensure geographical accuracy. This study uses Ground Control Points (GCPs) and resampling techniques to correct geometric distortions and improves image clarity and realism through lens distortion, chromatic aberration, and radiometric calibration, allowing images to more accurately reflect scene details and colors.

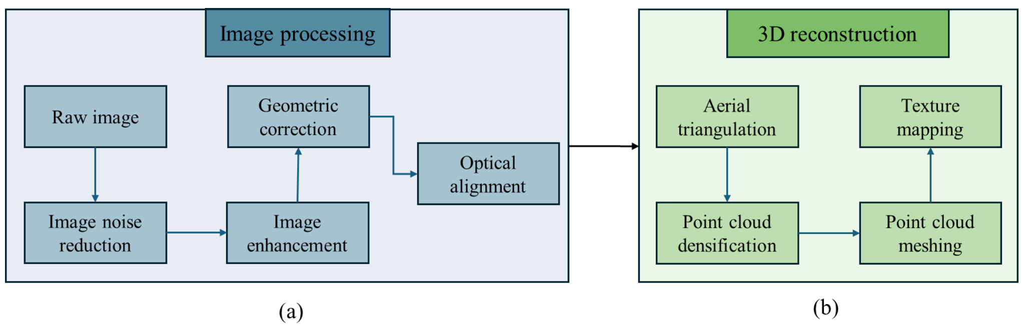


Figure 3. 3D reconstruction process.

3D reconstruction is the process of converting processed 2D image data into accurate 3D models, involving 4 key steps: aerial triangulation, point cloud densification, point cloud meshing, and texture mapping, as illustrated in Figure 3(b). The process begins with aerial triangulation, which utilizes overlapping images to match ground features, allowing for the deduction of geometric relationships that determine the geographic coordinates of objects. This method effectively combines GCPs with automatic feature extraction, employing adjustment algorithms to ensure precise positioning. Next, dense matching generates depth maps using techniques such as semi-global matching and multi-baseline stereo vision. These depth maps are then integrated to create a detailed 3D point cloud model. Following this, point cloud meshing transforms the discrete point cloud into a continuous surface through triangulation. Notably, TIN (Triangulated Irregular Networks) are more efficient than DEM (Digital Elevation Model) for modeling complex terrains, facilitating effective local updates. Finally, the process concludes with texture mapping, where image textures are overlaid onto the mesh surface to enhance realism. By aligning the images with the mesh, color information is accurately mapped, employing techniques like image-by-image mapping and multi-image blending to produce a textured model that showcases realistic colors and details.

3.2 High-Precision point cloud data collection based on UGV

After reconstructing the prefabricated component yard model, the UGV point cloud data collection is optimized for better efficiency and quality. First, optimal scanning station locations are determined to ensure comprehensive coverage and reduce data redundancy. Then, considering the construction site conditions and using these stations, precise path planning and navigation strategies are established for the UGV.

(1) Scanning station planning

Given the complex and obstructed environment of the prefabricated storage yard, a single scanning station is insufficient for capturing all target components effectively. Therefore, multiple scanning stations are necessary to obtain complete point cloud data. The process begins with the use of the CSF (Cloth Simulation Filter) ground filtering algorithm to distinguish between ground and non-ground points, where the ground points help identify suitable locations for scanning stations. Non-ground points are subsequently clustered using the Euclidean filtering algorithm to isolate the scanning targets. These targets are then transformed into voxel grids, and the voxel surfaces are analyzed to assess the visibility between the targets and potential scanning stations. For the scan planning, considerations include coverage, accuracy, detail, and overlap to ensure thorough coverage of all areas. A greedy algorithm is applied to solve the planning problem, iteratively choosing stations that offer the best coverage. With each selection, the additional coverage area is computed to minimize redundancy and optimize station placement and quantity. Lastly, the overlap between neighboring stations is evaluated to meet the requirements for global registration. Should the overlap be inadequate, the algorithm automatically adds new scanning stations to ensure effective global registration.

(2) Path planning and navigation

In Section 3.2.2, the optimal scanning station for UGV data collection was determined and point cloud data can be collected according to the process shown in Figure 4. To ensure the UGV completes the task safely and cost-effectively, path planning is divided into three stages: map representation, path planning, and global path optimization. First, grid-based mapping is used to create an accurate environment map, dividing the 3D reconstructed area into grids marked as passable or impassable based on obstacles. Next, the A* algorithm is employed to find the shortest obstacle-free path from the UGV's starting point to the target scanning station, combining heuristic search with a cost function. Finally, a genetic algorithm is used to optimize the initial path, generating new path combinations through selection, crossover, and mutation, and evaluating the total cost to find the global optimum.

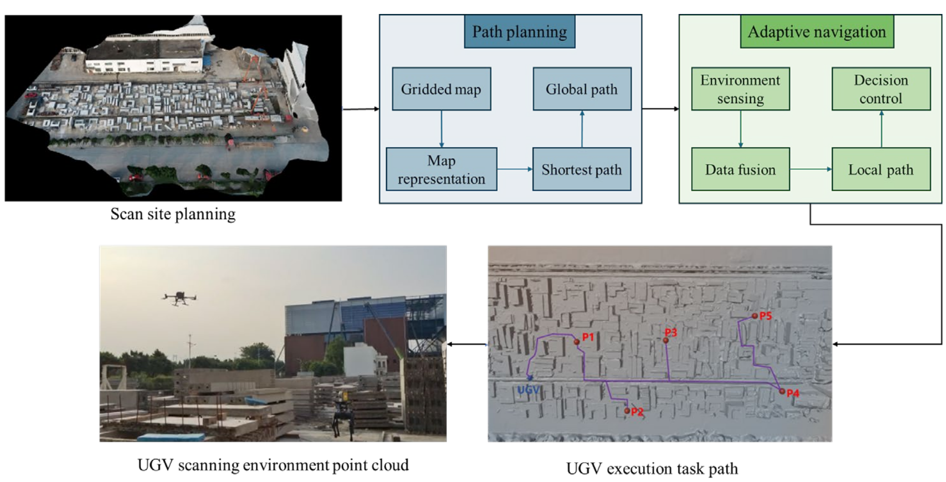


Figure 4. UGV data collection process.

However, the dynamic environment of the prefabrication plant requires adaptive navigation. This is achieved using SLAM (Simultaneous Localization and Mapping), which includes environmental sensing with LiDAR, cameras, and ultrasonic sensors to build real-time maps and identify obstacles; data fusion using Kalman and particle filtering to enhance accuracy; dynamic local path planning with the A* algorithm to ensure obstacle avoidance and efficient movement; and real-time decision-making and control to adjust the UGV's actions for safe navigation. Once the UGV reaches a designated scanning point, the LiDAR scanner captures high-precision 3D point cloud data of the surrounding environment.

3.3 Geometric quality inspection for multiple components

In the previous section, the high-precision point cloud data for the prefabricated component storage yard was obtained. This section introduces the processing of point cloud data and the methods for component recognition and inspection, including component stack extraction, target component extraction, component recognition, and quality inspection.

(1) Component stack extraction

On-site prefabricated components are typically organized by lifting sequence and types, with components of the same template and batch stacked together to save space and facilitate management. In Section 3.2.1, feasible areas and scanning targets (component stacks) were extracted. This step presents a sparse-dense component stack point clouds extraction method.

In this process, a global registration algorithm is first applied to achieve an initial alignment of the UAV and the dense UGV point clouds after voxel down-sampling. Following this, the Iterative Closest Point (ICP) algorithm is used to refine the alignment and improving the precision of the registration. Noting that the sparse UGV point cloud remains fixed during the registration process. Subsequently, the sparse point cloud collected by the UAV is clustered using a fast Euclidean clustering algorithm proposed by Cao et al.[3], generating bounding boxes for each component stack. These bounding boxes are then applied to the original high-precision point cloud data from the UGV. Since scan point clouds often contain mixed pixels, the DBSCAN algorithm is used to remove mixed pixels, resulting in isolated component stacks ready for inspection.

(2) Target component extraction

For small-prefabricated components with complex shapes, such as air-conditioning panels, balconies, and staircases, spacer blocks or beams are often added between stacked components for support. Since these prefabricated components are manufactured in a controlled factory environment following standardized processes, components of the same template and batch generally exhibit high consistency in dimensions and geometric features. As a result, a comprehensive inspection of a single component from the same template and batch can reasonably infer the quality and performance compliance of the other components.

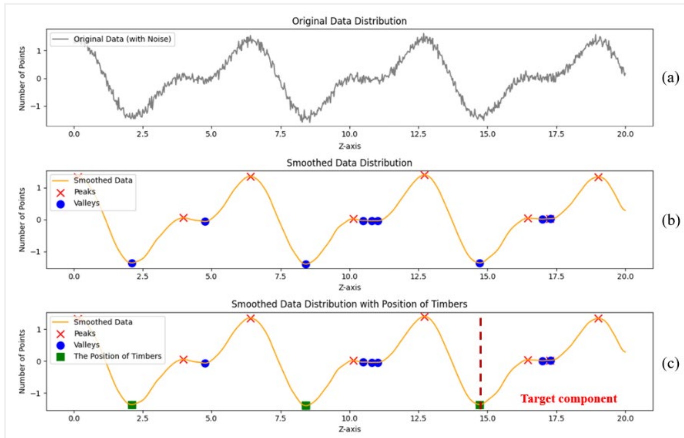


Figure 5. Target component extraction: (a)point cloud density projection on Z-axis; (b) Gaussian smoothing and valleys and peaks detection; (c) position of the timbers

In a component stack, the top component typically has the most comprehensive scan coverage, capturing both the top and four side surfaces, while other components only have their four side surfaces scanned. Therefore, it is recommended to select the top component in the stack as the representative of the component stack. To extract the representative component, a Z-axis-based point cloud density projection method is used. To minimize noise interference, Gaussian smoothing is first applied to the projected point cloud data. As shown in Figure 5. (a), the raw data with noise results in less distinct extremum points, while Figure 5. (b) shows the data curve after smoothing, where local extremum features become clearer. After smoothing, the distribution of point cloud data along the Z-axis is analyzed by calculating the first derivative to identify local maxima (peaks) and minima (valleys). Due to the lower number of scan points on spacer blocks between components, these blocks usually appear at the lowest valley in the Z-axis distribution. By identifying the lowest valley with a tolerance range, the location of the timber can be accurately determined, as illustrated in Figure 5. (c).

(3) Component recognition

Prefabricated components come in a wide variety, including floor slabs, beams, columns, walls, and stairs. These components vary significantly in shape, size, inspection criteria, and standards. Based on functional requirements, even components of the same type can differ in design and performance. For instance, floor slabs include both composite slabs and hollow-core slabs, with different specifications across projects. To identify these diverse components, this study developed a two-step classification approach: first, the PointNet++ classification network architecture determines the component category, followed by the Scan-vs-BIM method to identify specific types according to project requirements.

To support this classification, a point cloud dataset resembling ModelNet40 was constructed, covering slabs, beams, columns, walls, and stairs. This dataset combines point cloud data from onsite scans and simulated scans, with data augmentation applied through noise addition, random dropout, and scaling. After creating the dataset, training and testing were conducted. Ultimately, the PointNet++ classification network is used to classify point clouds of detected components and output the component category.

The component recognition method based on Scan-vs-BIM is applied by registering the point cloud under inspection to each BIM point cloud within the same category, with the overlap score used to evaluate the match. The component type corresponding to the BIM point cloud with the highest overlap score is assigned to the inspected point cloud. For any transformed scan point within the inspected point cloud, if a point from the BIM point cloud falls within the specified tolerance range, that point is considered overlapping. By Equation (1), the overlap rate (OR) is defined as the ratio of overlapping points to the total number of points, which is calculated on a scale from 0 to 1, where a score closer to 1 indicates a higher degree of overlap and better registration quality.

$$\mathrm{OR} = N_{match}/N_{total} \times 100\% \quad (1)$$

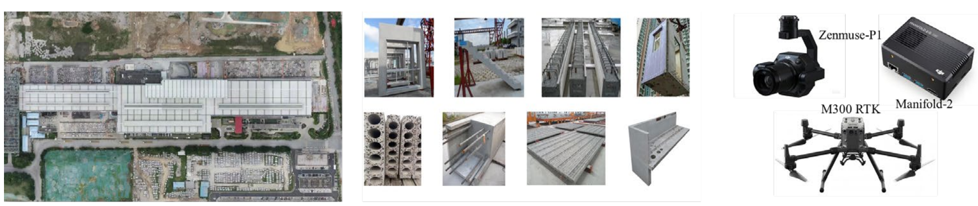
- N_{match} : the number of overlapping points
- N_{total} : the total number of points

(4) Geometric quality inspection

Through the previous step, the BIM model corresponding to the scanned component is identified, and the information of the component can be matched. The method based on support vector machine proposed by Wang et al. (Q. Wang et al., 2017) is used to segment concrete components and rebars. For concretes, horizontal and vertical points are extracted based on normal vectors. Subsequently, the RANSAC algorithm is employed to fit the planes of the nearest BIM model plane and the flatness is evaluated by the distance of each point to the corresponding BIM plane. For rebars, the center point of the bounding box of each rebar is calculated and compared with the center point of the adjacent BIM rebar to evaluate the position.

4. RESULTS

To validate the proposed method, a case study was conducted at a prefabricated component yard in Guangzhou, which produces a variety of prefabricated components, including beams, columns, slabs, and stairs, as shown in Figure 6. (a) - (b).



(a) Prefabricated component storage yard (b) Types of prefabricated components (c) UAV

Figure 6. Experimental scenario and devices.

As shown in Figure 6. (c), a UAV (DJI M300 RTK) equipped with multifunctional HD camera (Zenmuse-P1) and edge computing module (Manifold-2) was used to capture environmental data for the prefabricated storage yard. First, during the UAV's waypoint mission, the HD camera captures real-time images of the site. The footage is then compressed into H.265 format in real-time using a compiled computing module and transmitted to the ground workstation via wireless network using the RTSP protocol. Finally, the images are processed to complete the 3D reconstruction, as shown in Figure 7.

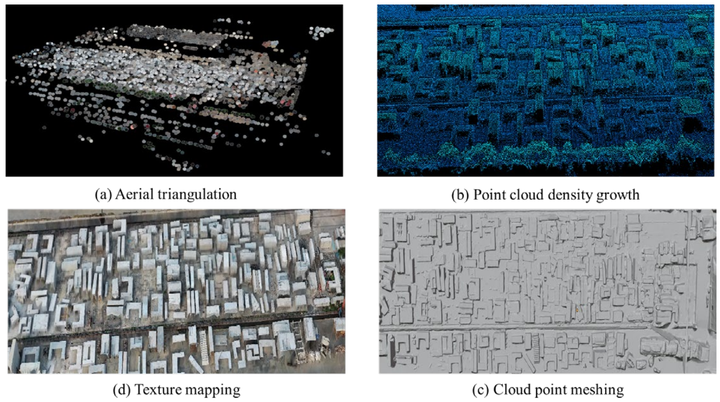


Figure 7. 3D reconstruction of the prefabricated storage yard.

Based on the 3D scene reconstructed by the UAV, feasible areas and the target component stacks are extracted to plan the scanning path for the UGV. Finally, the UGV was employed for high-precision point cloud data acquisition of the prefabricated yard equipped with a Trimble X7 laser scanner. In this case, a total of 19 stations were collected with 224,493,417 points.

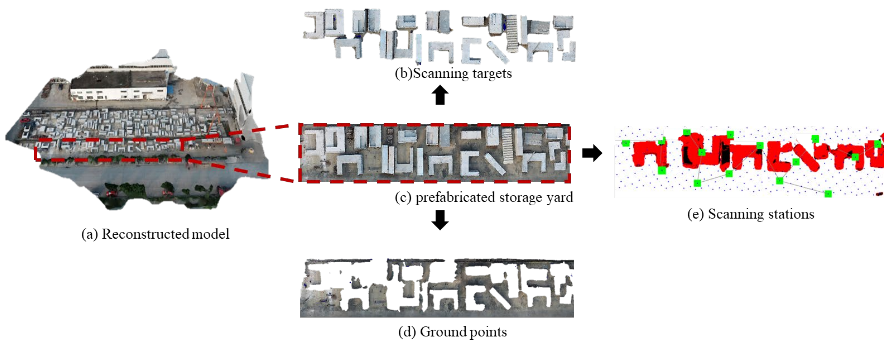


Figure 8. Prefabricated storage yard sensing and data collection.

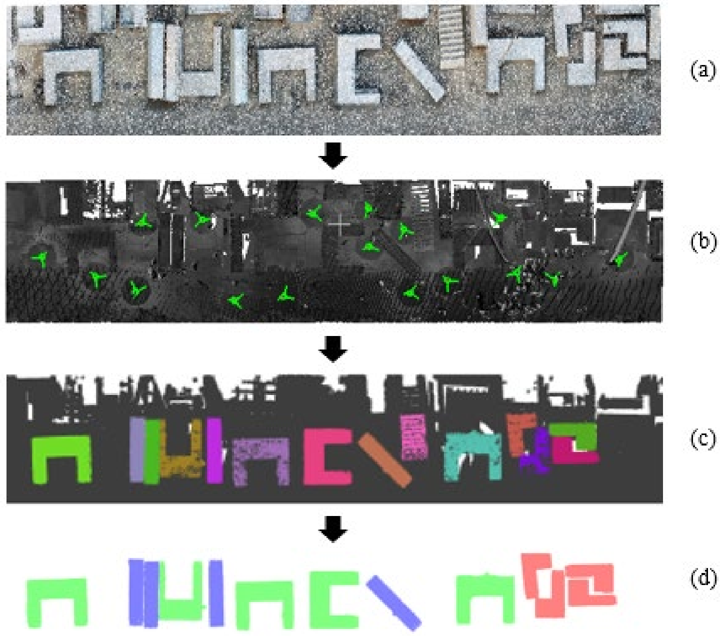


Figure 9. (a)sparse UAV point cloud; (b) dense UGV point cloud; (c) component stack extraction;(d) component recognition

After acquiring the high-precision point cloud data of the prefabricated component storage yard, individual component stacks were isolated using the proposed sparse-dense registration approach, bounding boxes, and DBSCAN for noise removal. Next, targeted components were extracted from the stacks based on point cloud density projection on Z-axis. As described in Figure 10. (b), the highest peak corresponds to the upper surface of the top component. Following this, the density curve sharply decreases and then levels off, representing the component's side edges. The lowest point in the density curve marks the spacer position between two components. Then, by extracting points with Z-axis values greater than the lowest valley, the target component point cloud is obtained (Figure 10. (c)).

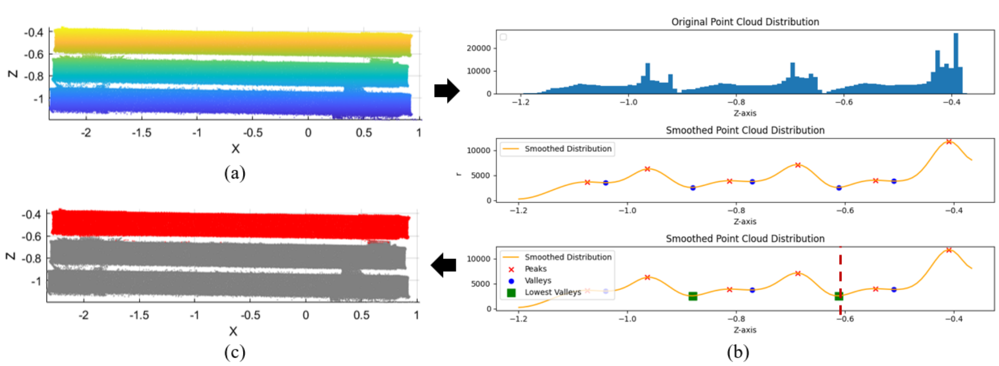


Figure 10. (a) a component stack; (b) the proposed method for target component extraction; (c) extraction of the target component

Following that, the target component point cloud was input into the PointNet++ network for classification to identify the component category, Figure 9. (d) shows the result of the recognition of each component stack. The classified point cloud is then matched individually with BIM component point clouds within the same category. The component with the highest overlap score is identified as the corresponding component (Figure 11. (b)).

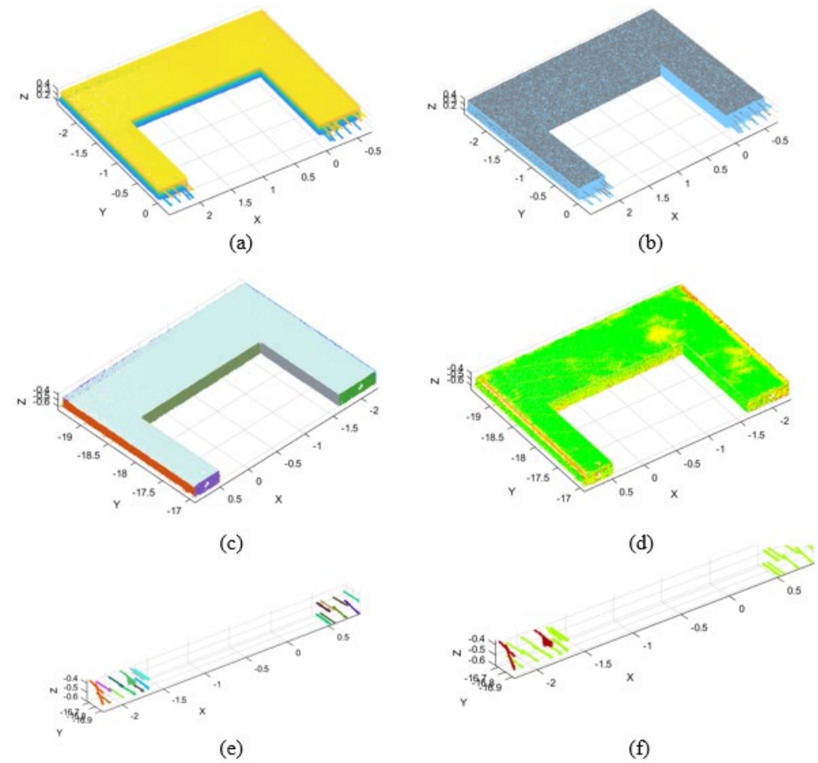


Figure 11. (a) target component; (b) target component with the corresponding BIM point cloud; (c) scanned concrete planes; (d) result for the flatness of the concrete planes; (e) scanned rebars; (f) result for the position of the rebars

After identifying the component type, the scanned point cloud was then segmented into concrete points and rebars, as shown in Figure 11. For concrete, the distance of each point to the nearest plane of the BIM point cloud is calculated to evaluate the flatness of accuracy. For rebars, the center point of the bounding boxes of each rebar is calculated and compared with the center point of the adjacent BIM rebar. Through computational validation, it was found that the proposed method can maintain an error within 5mm, with the inspection time for a single component being approximately 2 minutes, compared to 8 minutes for manual inspection. This represents a 75% increase in efficiency, which becomes even more significant as the number of components increases, which fully meets the geometric quality inspection requirements for large- prefabricated component factories, as shown in Table 1.

Table.1 Comparison of efficiency between manual and proposed method.

Method	Processing	Time	Total time for 14 components
Manual method	Flatness Rebars	5 mins 3 mins	14*8=112 mins
Proposed method	Environmental sensing Data collection Geometric quality inspection	40 mins 42 mins 28 mins	110 mins

5. CONCLUSIONS

To automate and efficiently inspect the quality of large-prefabricated components in the yard, this study proposes a data collection and assessment framework that integrates UAV, UGV, LiDAR, and BIM. First, the UAV performs 3D reconstruction of the storage yard. Based on this 3D model, feasible regions and scan targets are identified, and the A* and genetic algorithms are used to plan the UGV's scanning path. The UGV then uses SLAM with onboard sensors to perceive real-time environmental information, enabling adaptive navigation and the collection of high-precision point cloud data across the yard. Using this high-precision data, a density projection method extracts target components, and a PointNet++ classification network combined with a Scan-vs-BIM approach identifies and inspects the geometry of components. This innovative method demonstrates high efficiency and accuracy in data collection and component classification.

The proposed framework has been proposed and validated in large-scale prefabricated component yards, with the main contributions as follows: (1). A step-by-step collaborative mechanism for comprehensive intelligent environmental sensing based on UAV-UGV. (2). An intelligent matching and evaluation system for large-scale prefabricated components' 3D geometric features and inspection criteria based on point cloud processing has been developed.

However, several limitations remain: (1). The UGV’s scanning height is limited, requiring component stacks to be below this height for full surface scanning. Future work could focus on enhancing the UGV's scanning capabilities or optimizing stacking arrangements. (2). The study primarily addresses geometric dimensions and rebar inspection, but other quality criteria, such as surface appearance (e.g., cracks, honeycombing) and embedded parts, need further consideration. Future research should aim for a more comprehensive inspection approach.

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