An Automatic Measurement Method for Architectural Heritage Based on Point Cloud Semantic Segmentation Algorithm: A Case Study of the Hollow Watchtowers of the Ming Great Wall

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Abstract

Dimensional data are critical for the assessment, conservation, and restoration of architectural heritage. Traditional manual measurement methods are time-consuming and labor-intensive, particularly for large, complex, and difficult-to-access structures such as the hollow watchtowers of the Ming Great Wall. This study proposes a new method that combines low-altitude UAV photogrammetry with point cloud semantic segmentation algorithms, using watchtowers along the Ming Great Wall as case studies. First, images were collected using low-altitude UAV, and point cloud data are generated via photogrammetry to capture information of the difficult-to-reach watchtowers located on mountain ridges. Second, a semantic segmentation algorithm was applied to classify different components of the watchtower, and dimensional data were automatically calculated by fitting geometric models. Finally, experimental results showed that this automated method significantly outperforms traditional techniques in both efficiency and accuracy. The overall accuracy of the point cloud semantic segmentation algorithm reaches 90.80, and the error in automatically calculating the length and width of the watchtowers is less than 10%. Through the dimensional analysis of 601 watchtowers, the study identifies dimensional differences among watchtowers under three military jurisdictions during the Ming Dynasty. In summary, this study develops an automatic dimensional analysis method for watchtowers of the Ming Great Wall, improving the efficiency of heritage surveys. The method also shows potential for extension to other large-scale architectural heritage, offering a valuable tool for rapid analysis and digital archiving.

1. Introduction

1.1 Background

1.1.1 The Importance of Architectural Heritage Conservation: Architectural heritage serves as a material embodiment of human civilization, bearing witness to history while also forming the foundation of cultural diversity and ancient technological development. It encapsulates the construction techniques, social structures, and aesthetic values of specific historical periods, acting as a medium for dialogue across time and space. Therefore, the protection and documentation of architectural heritage are essential for preserving its historical and cultural significance and safeguarding the collective memory of human culture. This, in turn, holds profound importance for the continued development of human society. However, amid rapid development and environmental changes, architectural heritage is increasingly subjected to severe damage from both human activities and natural forces, facing unprecedented threats and an urgent need for protection and restoration.

1.1.2 Dimensional Data for Heritage Assessment and Restoration: In the conservation and restoration of architectural heritage, the acquisition and analysis of dimensional data play a fundamental role. Accurate dimensional data form the basis for assessing the current condition of heritage structures, formulating conservation strategies, carrying out restoration work, and uncovering historical information. For example, structural stability assessments rely on precise measurements to calculate load-bearing capacity and overall stability (Giaccone et al., 2020); in historical research, dimensions influence the appearance, internal spatial form, functional use, and user experience of buildings (Calvano et al., 2022; Sewasew and Tesfamariam, 2023; Zhuo et al., 2024). Therefore, accurate dimensional information is a critical foundation for effective architectural heritage conservation.

However, traditional methods of acquiring architectural heritage data primarily rely on manual measurements. This approach has several limitations. First, manual measurement is time-consuming and labor-intensive. For large-scale heritage sites such as the Ming Great Wall, which contain numerous architectural elements and complex spatial features, the measurement process requires significant manpower and time. Manual methods involve detailed measurements of individual structural components and recording their dimensions one by one, resulting in low efficiency and potential human error. Second, manual measurement is particularly challenging for heritage sites that are difficult to access. For example, defensive military heritage is often located in steep, rugged terrain that is hard to climb (Lauro et al., 2023). These conditions make it difficult to comprehensively and accurately collect all necessary dimensional data through manual means. Finally, manual measurement can cause physical disturbance or even damage to the heritage structures themselves. The presence of personnel and the use of measurement equipment during the survey may affect the surfaces and structural integrity of the buildings, potentially exacerbating the deterioration of fragile areas.

Therefore, there is a need to establish a non-contact, rapid method for acquiring dimensional information from heritage sites.

1.1.3 Historical Significance and Structural Characteristics of the Hollow Watchtowers of the Ming Great Wall: As a UNESCO World Cultural Heritage site, the Great Wall is the largest military defense structure in China—and indeed the world—preserving the construction wisdom of the Chinese people and embodying thousands of years of historical and cultural tradition. It stands as a symbol of the Chinese nation's spirit (Li et al., 2023). The hollow watchtower is a distinctive architectural feature of the Ming Great Wall. Its origin, evolution, and structural form have been key areas of research, and even today, in the planning and design of Great Wall tourism zones, hollow watchtowers remain essential subjects of analysis (Li et al., 2023). The watchtower was invented by Qi Jiguang[1], who provided a detailed account of its construction, methods, and functions in his military treatise Lian Bing Shi Ji (The Record of Military Training). Qi described its features as follows: "The middle level is hollow, with arrow windows on all four sides. The upper level is a tower with parapets surrounding it" (Jiguang, 2001). According to current surviving examples, their structural form generally aligns with Qi Jiguang’s original construction concept (see Figure 1A and 1B).

A. Watchtower Structures in Ancient Book By Qi Jiguang.

B. Existing Watchtower on the Ming Great Wall.

Figure 1. Watchtower structures in ancient books and existing watchtower on the Ming Great Wall.

However, due to prolonged natural erosion and human-induced damage, the overall preservation state of the Great Wall is generally poor. As of now, only 12.3% of its wall structures remain in relatively good condition (Ministry of Culture and Tourism" and "National Cultural Heritage Administration, 2019). Many watchtowers have suffered varying degrees of damage, making their documentation, conservation, and restoration particularly urgent. Conducting a systematic statistical study on the dimensional database of these watchtowers can not only provide scientific support for their preservation and restoration but also offer important data for understanding the historical evolution of the Great Wall, the architectural logic behind their design, and the structure of its military defense system. At present, statistical studies on hollow watchtowers along the Ming Great Wall are mostly limited to measurements of their spatial distribution along the wall. Research on their dimensional characteristics remains focused on individual sites or specific segments, with a lack of comprehensive statistical data covering large-scale or full-length analyses of hollow watchtower dimensions.

Watchtowers were often constructed in remote mountainous regions with steep terrain, making them difficult to access and unsuitable for large-scale conventional field surveys. Moreover, the number of watchtowers is vast. According to historical records (Zuoguo, 2003), during Qi Jiguang’s tenure, he oversaw the construction of 1,340 watchtowers. It is evidently impractical to complete dimensional measurements of all these towers in a short time through manual surveying alone. The design and construction of watchtowers integrated multiple functions, including military defense, residential living, and material storage. Their external components are diverse, and internal spaces are complex, featuring elements such as barrack rooms, parapets, arrow windows, and a variety of materials including bricks, dressed stone, and rough stone. This wide variety of materials and architectural elements imposes high demands on the accuracy of measurement and documentation efforts.

In summary, dimensional data serve as the foundation for the conservation and restoration of architectural heritage. However, how to efficiently and accurately acquire data on large, complex, and inaccessible heritage structures—such as watchtowers—has become one of the key bottlenecks restricting further progress in their preservation, documentation, research, and restoration. Therefore, this study takes the hollow watchtowers of the Ming Great Wall as a case to explore a new non-contact method capable of automatically estimating the dimensions of historical buildings. Using statistical data from 601 hollow watchtowers, the feasibility of this method is demonstrated. This research not only analyzes the underlying causes of the dimensional characteristics of hollow watchtowers but also provides a practical case of methodological innovation for dimensional statistics in the field of cultural heritage conservation.

1.2 Research Questions and Challenges

1.2.1 Limitations of Traditional Manual Measurement Methods: In the field of architectural heritage conservation, traditional methods of dimensional data collection primarily rely on surveyors conducting close-range measurements using tools such as measuring tapes, rangefinders, and leveling instruments to manually record the dimensions of architectural components. Although this approach offers certain advantages in terms of precision, it presents notable limitations when applied to large-scale, complex, or difficult-to-access heritage structures:

1. **Low Efficiency**: Manual measurement requires surveyors to operate on-site, recording the dimensions of architectural elements one by one. For large-scale heritage sites—such as the Ming Great Wall or the Tea Horse Road—with complex structures and extensive geographic spread, this approach is extremely time-consuming and labor-intensive. For instance, the Ming Great Wall spans a total length of 8,851.8 kilometers (Zhao et al., 2012), making it impractical to complete the measurements within a short timeframe. This inefficiency hampers the timely documentation of deteriorating heritage sites and delays the progress of conservation efforts.
2. **Human Error**: Although manual measurements use surveying instruments, they depend heavily on the operator’s skill, experience, and environmental conditions.

[1] Qi Jiguang was a renowned military general of the Ming Dynasty and is regarded by later generations as one of the most successful military reformers in ancient China. In his early career, he was responsible for coastal defense in the southeastern region, and later was reassigned to the north to guard key strategic areas such as Jizhen against invasions by Mongol tribes. He oversaw the construction of the Great Wall, reorganized defensive lines, and authored military treatises including *Ji Xiao Xin Shu* and *Lian Bing Shi Ji*, which summarized his experiences in fortification and combat. These works had a profound influence on later military thought.

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Errors may arise from instrument limitations or visual misreading during data collection, leading to measurement inaccuracies (Liu and Bin Mamat, 2024).

3. **Difficult Access to Certain Areas**: Many heritage sites, including the Great Wall, are located in remote or physically constrained environments, where surveyors cannot easily reach interior or elevated sections for measurement. For example, underwater archaeological sites or sunken ships cannot be measured manually and require technologies such as 3D laser scanning or sonar (Bräuer-Burchardt et al., 2023).
4. **Potential Damage to the Structure**: During manual measurements, the presence of personnel and use of equipment can cause disturbances or even damage to the heritage structure itself (Shimoi et al., 2018).

1.2.2 Current Research on Surveying Technologies and Point Cloud Processing Algorithms in the Field of Cultural Heritage: With continuous technological advancements, new digital surveying methods have opened up possibilities for acquiring dimensional data of architectural heritage. In recent years, emerging technologies such as 3D laser scanning, low-altitude UAV photogrammetry, and point cloud processing have been increasingly applied in the field of architectural heritage conservation, yielding promising results，UAVs can efficiently collect large-scale data in a short time, making them well-suited for surveying extensive heritage structures. However, the point cloud data obtained from UAV photogrammetry still require specialized software and algorithms to extract accurate heritage information.

Point cloud processing refers to a series of methods for analyzing and interpreting 3D point cloud data, which can assist in obtaining architectural heritage information (Du et al., 2015). Traditional point cloud segmentation algorithms are based on the geometric properties of the data or features derived from statistical histograms. Examples include edge detection-based algorithms (Xi et al., 2016), region-growing algorithms (Vo et al., 2015), and feature clustering-based algorithms. However, these methods typically require manual feature extraction, are computationally expensive, and are not well-suited for large-scale point cloud datasets.

1.2.3 Current Research on Point Cloud Semantic Segmentation Algorithms: With the emergence of large-scale 3D point cloud semantic segmentation datasets and the continual advancement of GPU computing power, deep learning has increasingly taken a dominant role in point cloud segmentation algorithms. However, due to the unordered and non-uniform distribution of point cloud data in space, traditional convolutional neural networks (CNNs) designed for 2D images cannot be directly applied. To address this, a variety of approaches have been developed, including voxelization-based methods, multi-view methods, and graph convolution-based algorithms.

Deep learning algorithms rely heavily on standardized datasets. At present, research in point cloud semantic segmentation is primarily based on datasets designed for autonomous driving in urban street scenes or for indoor environments used in smart home systems and SLAM technologies(Hua et al., 2016; Munoz et al., 2009). In the field of modern construction engineering, some scholars have utilized the uniformity in shape and dimensions of prefabricated components to extract their dimensional information automatically using point cloud geometric features (Li et al., 2020). However, in the domain of architectural heritage, there are currently no datasets specifically designed for segmenting structures like the Great Wall watchtowers. Therefore, this study proposes to manually annotate a custom dataset for the segmentation of watchtower point clouds. Based on the characteristics of this dataset, appropriate algorithms are selected and trained to develop a model capable of segmenting different components of hollow watchtowers.

2. Method

2.1 Framework of the method

The method established in this study is illustrated in the Figure 2. First, UAVs are used to capture images of the hollow watchtowers from multiple angles, and point cloud data are generated through photogrammetry. Next, a subset of the point cloud data is randomly selected for annotation to create a semantic segmentation dataset. A segmentation model capable of identifying different parts of the hollow watchtower is then trained using a semantic segmentation algorithm. Subsequently, a shape-fitting algorithm is applied to extract dimensional data based on the geometric features of each component in the point cloud. Finally, the trained model is used to segment all hollow watchtower point clouds and extract their dimensions, followed by a geospatial analysis to explore the distribution patterns and underlying causes of dimensional variation.

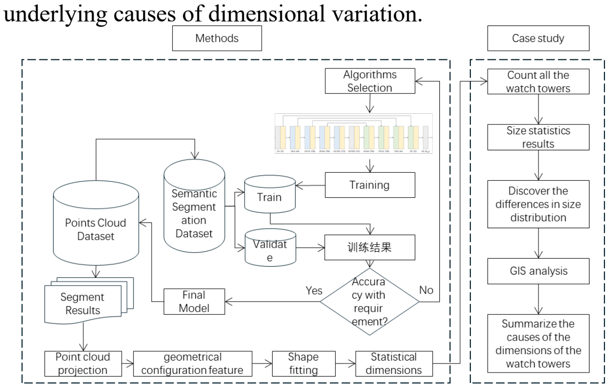


Figure 2. Method framework.

Based on the review of point cloud semantic segmentation algorithms in Section 1.2.3, it is evident that 3D semantic segmentation algorithms can be used to segment point clouds of specific architectural elements. By leveraging the geometric shape information contained in point cloud clusters, it is possible to extract the length, width, and height of specific features, thereby enabling automated dimensional statistics of architectural components based on 3D point cloud data. However, because semantic segmentation algorithms depend on the quality of the dataset and require algorithmic adjustments tailored to the structural characteristics of the point cloud data to improve accuracy, and because appropriate dimensional calculation methods must be selected based on the geometric forms of different components, this study must complete the following three tasks:

1. Train a segmentation model capable of identifying specific architectural elements based on a manually annotated dataset.
2. Implement automated dimensional extraction based on the segmented point cloud data.
3. Apply the proposed method to automatically segment all collected hollow watchtower point clouds, extract their dimensions, and use the GPS coordinates embedded in the point cloud data to analyze the spatial distribution patterns of various dimensional attributes.

2.2 Research Object and Study Area

This study takes the hollow watchtowers of the Ming Great Wall as the application target for the automated dimensional extraction method. To ensure the representativeness and generalizability of the findings, a total of 601 relatively well-preserved hollow watchtowers located in Beijing, Tianjin, Hebei, and Shanxi were selected from existing Ming Great Wall sites across China.

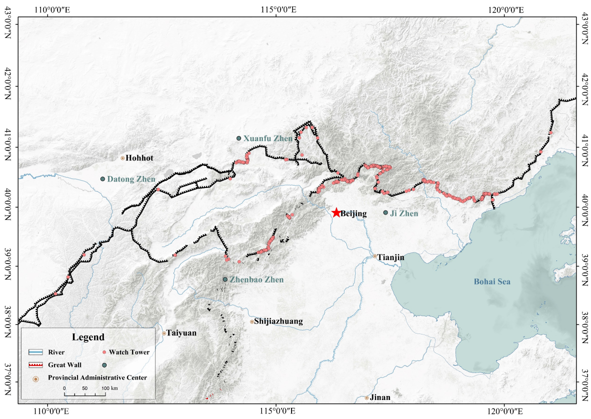


Figure 3. Study area.

The study spans four northern provinces (municipalities) of China and includes 601 hollow watchtowers, whose spatial distribution is shown in the accompanying Figure 3. These areas constitute key defensive lines of the Ming Great Wall, featuring a high density of watchtowers, relatively good preservation, and a wide range of dimensional characteristics—making them valuable for research. Additionally, most of these regions are mountainous, with many watchtowers built along steep ridgelines, where traditional measurement methods are difficult to implement, making them ideal for testing the efficiency of the automated dimensional extraction method proposed in this study.

2.3 Data Acquisition and Preprocessing

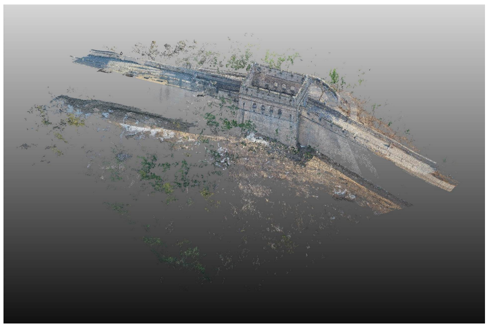
2.3.1 Implementation Process of Low-Altitude UAV Photogrammetry: As previously described, hollow watchtowers of the Ming Great Wall are primarily located along mountainous ridgelines, where the terrain is complex and difficult to access. Therefore, UAV technology is required to acquire point cloud data. In this study, low-altitude UAV photogrammetry is employed, with the UAV capturing images by circling around the watchtowers to ensure sufficient overlap between adjacent images. In addition, GPS information automatically embedded in the photographs during UAV flight enables the mapping of the geographic distribution of the hollow watchtower point clouds.

2.3.2 Point Cloud Denoising and Redundant Information Removal: To improve the accuracy of point cloud segmentation and the quality of architectural dimension extraction, it is necessary to remove scattered outlier points and irrelevant noise points outside the main structure.

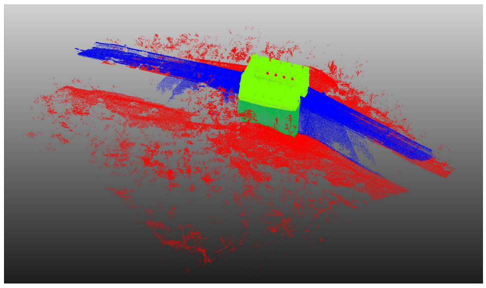
Various algorithms are available for point cloud denoising, including: Statistical Outlier Removal (SOR), Radius Outlier Removal, Voxel Grid Downsampling, Moving Least Squares (MLS), Gaussian Filtering, Edge-Preserving Filtering, Bilateral Filtering, and machine learning-based methods.Considering the efficiency of the experiment and the density characteristics of the point cloud models in this study, statistical filtering and clustering-based machine learning filtering were jointly adopted for denoising.

2.4 Point Cloud Semantic Segmentation Method

2.4.1 Annotation of the Segmentation Dataset: A total of 164 point cloud datasets containing watchtowers were selected as the training set. Using CloudCompare software, annotation was performed to classify the point clouds into four categories: brick-masonry upper structure, stone-masonry foundation, walls connected to the watchtower, and surrounding vegetation (Figure 4.).



A. Point cloud in RGB format



B. Point cloud in Labelled format

Figure 4. Example of annotated point cloud dataset.

2.4.2 Selection of Segmentation Algorithm and Parameter Settings: Analysis of mainstream point cloud datasets reveals that four datasets—S3DIS (Armeni et al., 2016), SemanticKITTI (Behley et al., 2019), SensatUrban (Hu et al., 2021), and STPLS3 (Chen et al., 2022)—are most similar to the Ming Great Wall watchtower point cloud dataset used in this study. A transfer learning approach was adopted, using these datasets as pre-training sources and for algorithm performance comparison.

Among these datasets, the algorithms with relatively high accuracy include Swin3D (Yang et al., 2025), Point Transformer (Zhao et al., 2021), PointNet++ SSG, and RepSurf. Swin3D has high GPU memory requirements; thus, considering computational efficiency and hardware cost, this study selects the latter three as the base algorithms for point cloud segmentation. Their performance on the S3DIS dataset is shown in Table 1.

Model Name	mIoU	mAcc	OA
Point Transformer	**70.37**	**77.02**	**90.80**
PointNet++ SSG	64.05	71.52	87.92
RepSurf	68.86	76.54	90.22

Table 1. Computational performance of the S3DIS dataset on three network models: Point Transformer, PointNet++ SSG, and RepSurf.

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Point Transformer (Zhao et al., 2021) constructs its network model based on a self-attention mechanism. By designing self-attention layers specifically for point cloud data and incorporating positional encoding into Transformer blocks, it enables the execution of semantic segmentation, part segmentation, and classification tasks. The main contribution of this work is the introduction of a self-attention layer tailored for point clouds. As the self-attention layer is inherently sequence-independent, it is well-suited for processing unordered point cloud data.

2.4.3 Model Training: The dataset comprising 164 point cloud models was split at a ratio of 7:3, resulting in a training set of 115 models and a validation set of 49 models for evaluating model performance. The training was conducted on a platform based on the PyTorch framework, with system specifications of CPU: 14 vCPUs Intel(R) Xeon(R) Gold 6330 and GPU: RTX 3090 (24GB). Training was halted upon model convergence. The trained model is subsequently used to perform semantic segmentation on the complete set of hollow watchtower point clouds.

2.5 Automatic Dimensional Statistics of Structural Components

This section calculates the shape dimensions of each segmented component of the hollow watchtower based on its geometric features.

Based on the spatial structural relationships of architectural point clouds and incorporating computer vision analysis techniques, this study proposes an algorithm for directly computing point cloud dimensions. The workflow consists of the following steps:

1. Base Surface Segmentation: Utilizing the characteristic that architectural walls are vertically oriented (parallel to the z-axis), the semantically segmented point cloud is projected along the z-axis onto the x–y plane, resulting in a 2D projected point cloud (Figure5).
2. Base Length and Width Estimation: For the projected 2D point cloud, the minimum bounding rotated rectangle is calculated. The length and width of this rectangle are considered approximate estimations of the base dimensions.
3. Facade Point Cloud Segmentation: Using the rotated rectangle from the previous step, the four edges of the rectangle are treated as projection planes. The point cloud is then projected perpendicularly to the z-axis onto these planes, generating four facade projections. As only height is needed from the facade, one of the four projection planes is selected for analysis.
4. Facade Height Estimation: For the selected facade projection, the minimum bounding rotated rectangle is computed (Figure 6), and its length and width are determined. Since these values do not contain directional information, the previously computed base dimensions are used as references. The value that does not match the base length or width is taken as the facade height, as it corresponds to the z-axis dimension.

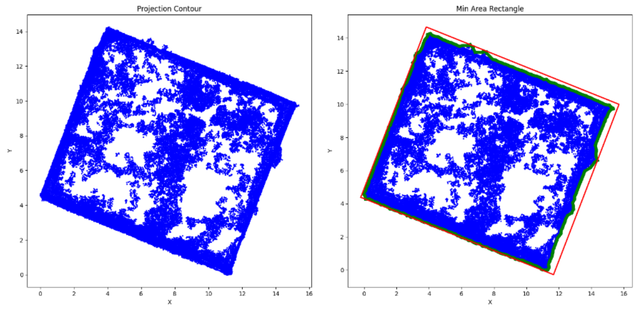


Figure 5. Minimum bounding rectangle computed from projected base edge after z-axis projection

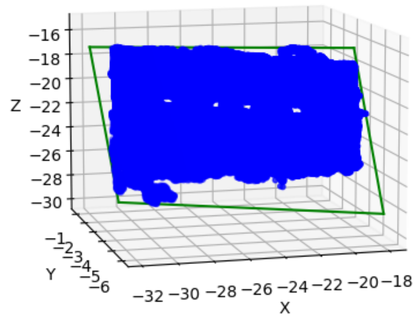


Figure 6. Minimum bounding rectangle of the façade extracted from segmented façade point cloud based on base bounding rectangle.

3. Results and Discussion

3.1 Accuracy Evaluation of Dimensional Statistics

To assess the accuracy of the proposed method in dimensional extraction, evaluations were conducted from two perspectives: the performance of the point cloud semantic segmentation algorithm and the accuracy of the dimensional statistics.

3.1.1 Evaluation of Semantic Segmentation Algorithm Performance: To comprehensively and objectively validate the performance of the trained hollow watchtower semantic segmentation model, this study evaluates the model using point cloud semantic segmentation metrics.

3D Semantic Segmentation Evaluation Metrics
Point cloud semantic segmentation models are commonly evaluated using the following metrics (definitions provided in Table 2): Accuracy, Mean Accuracy, Intersection over Union (IoU), Mean IoU, Overall Accuracy (OA), Precision, Mean Average Precision (mAP), and Floating Point Operations (FLOPs) to measure computational efficiency. Here, N denotes the total number of samples, C denotes the number of segmentation classes in the dataset, and TP, TN, FP, and FN correspond to True Positives, True Negatives, False Positives, and False Negatives, respectively—similar to standard metrics used in 2D image object detection.

Evaluation metrics	Equations
accuracy	$\text{accurarcy} = \dfrac{\text{TP} + \text{TN}}{TP + TN + FP + FN}$
mAcc	$\text{mAcc} = \dfrac{1}{C+1}\sum_{i=0}^{n} accuracy$
IoU	$\text{IoU} = \dfrac{TP}{TP + FP + FN}$

mIoU	$\mathrm{mIoU} = \frac{1}{C+1}\sum_{i=0}^{C} IoU$
OA	$\mathrm{OA} = \frac{1}{N}\sum_{C} TP_i$

Table 2. Common evaluation metrics for point cloud segmentation.

To evaluate the accuracy of the point cloud semantic segmentation model, this study adopts three commonly used metrics: mIoU, mAcc, and OA.

A comparison of the three semantic segmentation algorithms trained in Section 2.4.3 shows that PointTransformer achieves the best performance across all three metrics (Table 3), indicating the highest segmentation accuracy. Therefore, this study selects PointTransformer for the segmentation of hollow watchtower point clouds.

Model Name	mIoU	mAcc	OA
PointNet++ SSG	53.64	68.81	75.88
PointTransformer	**75.01**	**84.65**	**91.43**
RepSurf	55.26	69.72	78.27

Table 3. Performance comparison of semantic segmentation algorithms.

However, in the PointTransformer segmentation model, although the mIoU is higher than that of the other two models, its value is relatively lower compared to mAcc and OA, with mIoU reaching only 75.01. This discrepancy is likely due to the class imbalance in the point cloud segmentation model established in this study, as previously mentioned. The segmentation performance for categories with fewer point samples is relatively poor. In future work, incorporating point cloud class balancing algorithms may help improve the accuracy of the semantic segmentation model.

3.1.2 Accuracy of Dimensional Analysis: To evaluate the performance of the proposed point cloud dimensional analysis algorithm, seven segmented point clouds were selected, and the dimensional results obtained using the proposed method were compared with those from manual measurements. The average errors in the sampled point clouds were 0.09 meters (length), 0.07 meters (width), and 0.16 meters (height). The length and width errors were within 10%, approximately around 0.1 meters. These discrepancies may be attributed to misclassifications during point cloud segmentation or scattered outliers within the model.

The error in height measurements was relatively larger. Given that the Great Wall is often surrounded by dense vegetation, the number of points at the base of the watchtowers is limited and the edges are unclear. This hampers the effectiveness of both the semantic segmentation and boundary extraction algorithms in accurately identifying the base, leading to greater error in vertical dimension estimation. Based on the above analysis, the proposed method will primarily be used for statistical analysis of the length and width of watchtowers in the subsequent sections, while the height results will be referenced for supplementary analysis only.

3.2 Dimensional Distribution Characteristics of Hollow Watchtowers

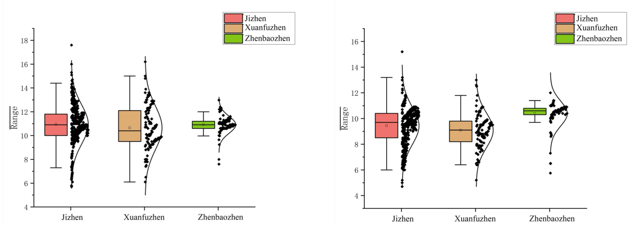
Using the automated dimensional extraction method described earlier, the dimensions of hollow watchtowers and their arrow windows have been successfully obtained. Based on these results, this section applies a component-based approach to compare architectural dimensions of the Ming Great Wall across different regions, aiming to identify patterns in the dimensional distribution.

The hollow watchtowers analyzed in this study are distributed across four military jurisdictions of the Ming Dynasty: Jizhen, Xuanfuzhen, Zhenbaozhen, and Datongzhen. Given the relatively small number of watchtowers in Datongzhen, this analysis focuses on the three regions with larger sample sizes: Jizhen, Xuanfuzhen, and Zhenbaozhen. During the Ming Dynasty, the construction of hollow watchtowers was organized within military jurisdictions and overseen by commanders of each regional section. As a result, differences in administrative jurisdiction may have led to variations in the dimensions of the watchtowers. Therefore, this study conducts a dimensional variation analysis of hollow watchtowers based on the territorial divisions of these three military regions.

Box plots were used to visualize the length and width distributions of watchtowers within the three military regions—Jizhen, Xuanfuzhen, and Zhenbaozhen. As shown in the results (Figure 7), both length and width generally follow a normal distribution.

In terms of length (Figure 7A):
Jizhen exhibits a wide data range, with a median of approximately 11 meters. The distribution is relatively dispersed, with numerous outliers. Xuanfuzhen also has a broad range, with a median around 10 meters. Its data are more concentrated and contain fewer outliers. Zhenbaozhen shows the narrowest range, with a median close to 9 meters. Its distribution is the most concentrated and includes few outliers.

In terms of width (Figure 7B):
Jizhen again shows a wide data range, with a median of about 9 meters, and a dispersed distribution with many outliers. Xuanfuzhen's range is also broad, with a median around 8 meters. The distribution is relatively concentrated with few outliers. Zhenbaozhen has the narrowest range, a median of approximately 7 meters, and the most concentrated distribution, with few outliers.



A. Length box plot B. Width box plot

Figure 7. Box plots of length and width of watchtowers in Jizhen, Xuanfuzhen, and Zhenbaozhen.

In summary, both length and width are generally larger in Jizhen, but exhibit greater variability. Xuanfuzhen follows with relatively consistent dimensions. Zhenbaozhen displays the smallest and most stable dimensions. The box plot results reveal clear distinctions among the three regions.

4. Conclusion

4.1 Research Findings

The method proposed in this study—“low-altitude UAV photogrammetry & semantic segmentation & automated dimensional extraction”—demonstrates significant advantages in efficiency, accuracy, and applicability. It enables the automated acquisition of dimensional data for various components of a large number of hollow watchtowers, with accuracy maintained within an acceptable margin of error. This method effectively supports large-scale dimensional analysis of cultural heritage and allows for rapid surveying of hollow watchtowers located on ridgelines that are difficult to access manually. The study not only provides a foundation for analyzing the structural origins and historical evolution of architectural heritage but also supplies essential baseline data for the development of digital archives and restoration strategies.

By applying the automated point cloud–based dimensional analysis method developed in this study, the dimensions of 601 relatively well-preserved hollow watchtowers along the Ming Great Wall were successfully estimated. Through in-depth analysis, significant differences in the dimensional distribution of these watchtowers were identified across three military jurisdictions of the Ming Dynasty—Jizhen, Xuanfuzhen, and Zhenbaozhen. Combined with geographic and spatial autocorrelation analysis, the study suggests that the generally shorter lengths (enemy-facing sides) of watchtowers along the northern outer edge may be a defensive adaptation to closer enemy proximity, aiming to reduce exposure and enhance protection. This conclusion fills a gap in previous research regarding the lack of large-scale statistical analysis of hollow watchtowers and offers a comprehensive perspective on the structural variations of the Ming Great Wall, supporting further studies on the architectural development of this historical defense system.

4.2 Future Research Directions

Although the automated dimensional analysis method established in this study has introduced a Transformer-based architecture at the point cloud segmentation stage to enhance the model's global structural understanding, the issue of class imbalance remains to be addressed to further improve segmentation accuracy. Future research may consider updating the training dataset or refining the segmentation algorithm architecture to enhance both the accuracy and generalization ability of heritage point cloud segmentation. This study successfully implemented large-scale automated dimensional analysis of hollow watchtowers and conducted an initial investigation into the factors influencing dimensional variation. In future work, multivariate linear regression models could be introduced to explore in greater depth the relationships between watchtower dimensions and factors such as geographic environment and historical context.

While this research primarily focuses on a specific type of architectural heritage—the hollow watchtowers of the Ming Great Wall—the proposed method demonstrates strong generalizability and transferability. It can be extended to other types of heritage conservation, such as modern industrial heritage with a high degree of standardization, infrastructure like bridges and railway facilities, or ancient urban defense systems including gates and walls with continuous spatial features. These applications could benefit from large-scale automated surveying and statistical analysis. Moving forward, we will continue to optimize and expand this method to advance heritage conservation toward a more intelligent and efficient future.

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