Adaptive PCA-Scale Optimization for Edge Extraction from 3D Scanned Cultural Heritage Point Clouds

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Abstract

In recent years, as the digitization of cultural heritage has become increasingly important, 3D scanning has emerged as a key method for capturing accurate geometric structure. However, visually analyzing complex structures—such as intricate relief carvings and architectural details—remains challenging due to occlusion and measurement noise. This study proposes an adaptive neighborhood scale selection method for local PCA, designed for robust edge extraction from large-scale 3D scanned point clouds. The core contribution is an automatic scale selection framework that determines the optimal analysis scale by minimizing the variance of Eigentropy, enabling the most consistent representation of local geometric structures. To enhance the visibility of such structures, we further introduce a dual 3D edge extraction technique based on opacity gradation within a Stochastic Point-Based Rendering (SPBR) framework, allowing simultaneous visualization of both acute sharp edges and rounded soft edges while mitigating occlusion. The effectiveness of the proposed method is demonstrated through case studies on the reliefs of Borobudur Temple and the Red Brick Storehouse. Experimental results show that the adaptive approach significantly improves the visibility of overlapping structures compared to conventional fixed-scale methods. In addition, the use of octree-based spatial indexing ensures computational efficiency, making the method practical for field-based heritage conservation and structural analysis on consumer-grade hardware.

1. Introduction

In recent years, the digital archiving of cultural heritage has gained significant importance, with three-dimensional (3D) scanning emerging as a primary technique for capturing precise digital representations (El-Hakim et al., 2005, Remondino and Rizzi, 2010). These resulting point clouds offer high geometric fidelity. Furthermore, the increasing frequency of natural disasters and the gradual erosion caused by environmental factors have made the rapid and non-destructive documentation of cultural heritage a global priority. Detailed 3D records not only serve as a digital backup for restoration but also provide a primary source for longitudinal structural health monitoring. However, the ability to visually analyze complex structures—such as intricate relief carvings and architectural details—remains a critical challenge, necessitating advanced edge-highlighting visualization techniques. Traditional methods for edge extraction often rely on fixed-scale principal component analysis (PCA), which frequently fails to balance the extraction of fine details with the suppression of measurement noise; specifically, large scales tend to over-smooth sharp edges, whereas small scales are overly sensitive to surface irregularities (Kawakami et al., 2020). As a result, many cultural heritage objects cannot be analyzed using conventional edge extraction methods because they fail to distinguish between fine structures and edges, causing them to be extracted as a single edge that cannot be used for structural analysis. To overcome these limitations, this study proposes an adaptive PCA-scale optimization method specifically designed to extract and enhance both sharp and rounded *soft* edge regions from large-scale 3D scanned data. By dynamically adjusting the analysis scale based on local geometric characteristics, the proposed approach ensures robust performance across diverse materials and objects, providing a feasible and computationally efficient solution for field-based conservation and structural analysis. The remainder of this paper details the methodology, experimental validation on various cultural heritage objects, and the practical implications of this adaptive visualization framework.

2. Automatic Optimization of Local PCA Scale and Opacity Control for Edge Extraction

2.1 Stochastic Point-Based Rendering and Edge Extraction

The complex geometric shapes of cultural heritage sites, such as 3D structures and multi-layered wall reliefs, often cause severe occlusion issues and the emergence of artifacts in traditional opaque rendering. To address this, we employ Stochastic Point-Based Rendering (SPBR) (Tanaka et al., 2016, Uchida et al., 2020, Tanaka, 2023) as a core transparent visualization method. SPBR is a fast and high-precision rendering method that achieves accurate depth representation without performing conventional depth sorting. The algorithm of SPBR is shown in Fig. 1. This method allows control of opacity by manipulating point density. Opacity is determined by the following Eq. (1). The important point of this method is that it enables visualization of internal information. However, 3D scanned point cloud data containing internal information suffers from reduced visibility in transparent visualization due to overlapping points.

Therefore, this study takes advantage of the ability to control the opacity of SPBR to enhance and visualize edge regions (Kawakami et al., 2020). The edge enhancement method used in this study will be described in section 2.3.

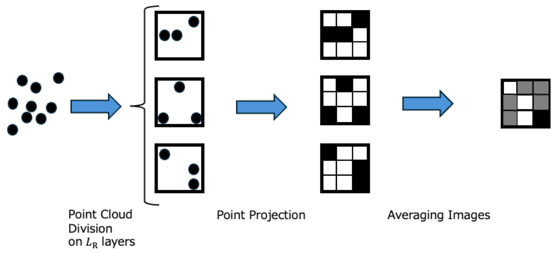

Figure 1. Algorithm of SPBR.

$$\alpha = 1 - (1 - \frac{s}{S})^{\frac{n}{L}} \quad (1)$$

where α = opacity
n = number of points
s = size of point
S = area size to count n
L = repeat level

2.2 PCA and Feature Value

To analyze the local geometric properties of cultural heritage objects, this study performs local PCA (Dittrich et al., 2017). Each 3D point in the captured cloud is defined as a coordinate vector $p_i = (x_i, y_i, z_i)^T$ within a 3D Cartesian coordinate system (Weinmann et al., 2013). For each point p_i in the point cloud, a neighboring point cloud is defined as a set of points within a sphere of radius r centered at p_i. The local geometric structure is captured by the 3D covariance matrix S, which is computed as shown in Eq.(2).

$$S = \begin{pmatrix} s_{xx} & s_{xy} & s_{xz} \\ s_{yx} & s_{yy} & s_{yz} \\ s_{zx} & s_{zy} & s_{zz} \end{pmatrix} \quad (2)$$

where s_{xx}, s_{yy}, s_{zz} = variance
$s_{xy}, s_{xz}, s_{yx}, s_{yz}, s_{zx}, s_{zy}$ = covariance

We calculate the eigenvalues $\lambda_1, \lambda_2, \lambda_3$ of the matrix S defined by Eq.(2), and order them such that $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$. These eigenvalues quantify the spread of the local point distribution along the corresponding principal directions. Specifically, λ_1 corresponds to the greatest variance, while λ_3 captures variation in the normal direction within a local region. The geometric relationship between these three orthogonal principal axes and the local point distribution is illustrated in Fig. 2.

To describe local 3D structures, eigenvalue-based measures such as linearity, planarity, and eigentropy are frequently employed to capture intrinsic geometric properties effectively (Weinmann et al., 2013). In this study, two different feature

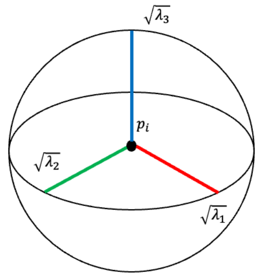

Figure 2. Geometric representation of local PCA: the three orthogonal eigenvectors (v_1, v_2, v_3) define the principal axes of the point distribution, with their corresponding eigenvalues $(\lambda_1, \lambda_2, \lambda_3)$ representing the variance along each axis.

values are utilized: "Change of Curvature (C_λ)" and "Eigentropy (E_λ)". The Change of Curvature is defined in Eq.(3).

$$C_\lambda = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3} \quad (3)$$

Change of Curvature serves as a descriptor for surface variation, where higher values indicate potential edge regions or corners. However, since Change of Curvature is a feature value that depends on the extent of local regions, the edge regions change depending on the scale used for PCA. Therefore, in this study, we introduce "Eigentropy" as a measure for optimizing the PCA scale. The definition of Eigentropy is given in Section 2.4.

2.3 Dual 3D Edge Extraction

To visualize the extracted geometric features with high clarity, this study employs a "Dual 3D Edge Extraction" method (Yamada et al., 2024). This method assigns different opacities to each point based on the calculated feature value f (in this study, Change of Curvature C_λ). Unlike binary edge extraction, which applies a uniform opacity to all points above a threshold, our approach utilizes an opacity gradation function $\alpha(f)$ to distinguish between sharp edges and rounded *soft* edges. Soft edges correspond to regions with gradual geometric variation, typically characterized by intermediate curvature values. The opacity $\alpha(f)$ is defined by the following function.

$$\alpha(f) = \begin{cases} \frac{\alpha_{\text{max}} - \alpha_{\text{min}}}{(F_{\text{th}} - f_{\text{th}})^d}(f - f_{\text{th}})^d + \alpha_{\text{min}} & (f_{\text{th}} \leq f < F_{\text{th}}) \\ \alpha_{\text{max}} & (F_{\text{th}} \leq f \leq 1) \end{cases} \quad (4)$$

where $\alpha_{\text{max}}, \alpha_{\text{min}}$ = maximum, minimum opacity
$F_{\text{th}}, f_{\text{th}}$ = feature value threshold
d = speed of opacity gradation

In this function, the parameters f_{th} and F_{th} represent the lower and upper feature value thresholds, respectively. The lower threshold f_{th} serves to filter out measurement noise and fine surface irregularities, and points with features value below this threshold are rendered as transparent non-feature points. On the other hand, points with feature value larger than F_{th} are considered to have "sharp" edges and are assigned the maximum

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opacity $\alpha_{\max}$. In addition to the opacity gradation defined by $\alpha(f)$, color gradation is also introduced for soft edges, such that the color gradually transitions from the highlight color assigned to sharp edges to the background color. These combined opacity and color gradations are essential for resolving occlusion issues; by rendering soft edges with gradual changes in opacity and color, the method alleviates the filled appearance often observed in conventional methods, where overlapping enhanced points obscure internal structures (as seen in Figs. 4 and 8). This dual edge extraction makes it possible to visualize the continuity of complex 3D structures—such as the relationships between columns and beams in a building—without losing the context of the surrounding geometry.

2.4 Proposed Method

Multi-scale analysis enables the efficient and robust extraction of geometric features by adaptively adjusting the spatial characteristics to account for varying point densities and sensor-induced noise (Pauly et al., 2003, Demantké et al., 2011, Weinmann et al., 2013, He et al., 2017). In this study, we propose an edge extraction method for 3D scanned point clouds of cultural heritage objects, which determines the optimal scale for local PCA based on the clustering characteristics of feature values. The core of our proposal is the automatic identification of the optimal scale r_{opt} where geometric features are most consistently clustered. To achieve this, we introduce Eigentropy (E_λ) as a measure of structural disorder (Weinmann et al., 2014):

$$E_\lambda = -\sum_{i=1}^{3} \frac{\lambda_i}{\lambda_1+\lambda_2+\lambda_3} \ln \frac{\lambda_i}{\lambda_1+\lambda_2+\lambda_3}. \tag{5}$$

In our method, we choose Eigentropy as the feature value for determining the optimal scale, and Change of Curvature as the feature value for extracting edge regions. By performing local PCA at the adaptively selected scale, the proposed approach effectively detects both sharp and soft edge regions, enhancing the visibility of intricate structures often found in cultural heritage objects.

The optimization process is organized into the following five steps. Minimizing the variance of Eigentropy corresponds to identifying the scale at which geometric structures are most consistently represented across the point cloud.
Step 1: Define a set of M candidate scales $\{r_1, r_2, ..., r_M\}$ based on the bounding box of the target object.
Step 2: For each scale r_i, calculate the Eigentropy (E_λ) for every point in the point cloud with PCA.
Step 3: Calculate the variance V_i of the Eigentropy calculated for each point in the point cloud at each scale r_i.
Step 4: Compare the variance values across each scale, and select the scale with the minimum variance $\min(V_1, V_2, ..., V_M)$ as the optimal scale r_{opt}.
Step 5: Perform Dual 3D Edge Extraction (described in Section 2.3) using the Change of Curvature (C_λ) calculated at r_{opt}.

The above five steps enable the identification of the optimal scale at which the local geometric structure is most consistently represented across the point cloud. The proposed method identifies the optimal scale for local PCA by evaluating M candidate scales. For each candidate scale, the Eigentropy is computed for every point in the point cloud using octree-based neighborhood searches. After processing all N points at a specific scale, the variance of the Eigentropy values is calculated for the entire point cloud. This process is repeated for each of the M scales, resulting in a set of variance values $\{V_1, V_2, ..., V_M\}$. The scale that yields the minimum variance is selected as the optimal scale r_{opt}, as it represents the scale where the geometric features are most consistently clustered. Consequently, this methodology can perform calculations much faster than the brute-force search. This iterative multi-scale approach ensures that the edge extraction is tailored to the specific geometric complexity of the target cultural heritage object.

3. Case Studies

In this section, we describe the results of applying the methodologies of this study to specific historical cultural heritage sites. In this study, the scale for performing PCA on the spherical neighborhood radius was set such that the diagonal length of the point cloud's bounding box was 1.

3.1 The Reliefs of Borobudur Temple

In this section, we discuss the reliefs of Borobudur Temple, a UNESCO World Heritage Site located on the island of Java in Indonesia. Borobudur Temple is a large-scale Buddhist archaeological site, and research on its digitization has been progressing in recent years (Pan et al., 2021). Figure 3 shows the results of visualizing the point cloud data used in this section using the SPBR described in Section 2.1.

Figure 3. Original point cloud of the Borobudur reliefs visualized by SPBR without edge enhancement.

As shown in Fig. 3, while the texture of the wall surface, including the relief, is visualized, what is depicted in the relief becomes unclear in this visualization. Therefore, edge enhancement as described in Section 2.3 is used to improve visibility. Figure 4 shows the results of edge enhancement using a conventional method. This method assigns the same opacity to all points above a threshold value. As a result, while the edges are extracted and enhanced, the overlapping of these enhanced points reduces visibility.

In conventional edge-extracted visualization, edge regions can be identified relatively clearly. However, ambiguous regions

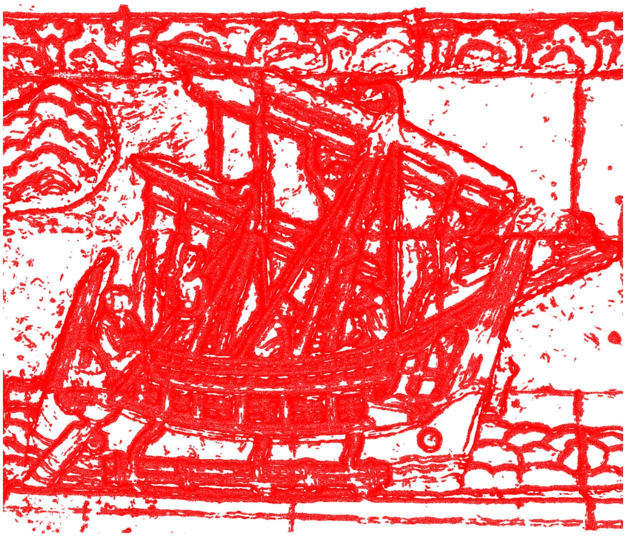

Figure 4. Edge extraction including soft-edge regions using the conventional method. The soft-edge regions appear filled and indistinguishable due to the lack of opacity gradation.

between clear edge and non-edge regions are not extracted or visualized sufficiently. These regions correspond to soft edges and are essential for analyzing subtle structural transitions. To effectively extract both sharp and soft edges, we use Eigentropy as the feature value and select the scale that minimizes the overall variance. Fig. 5 shows the variance at each scale when Eigentropy is used as the feature value.

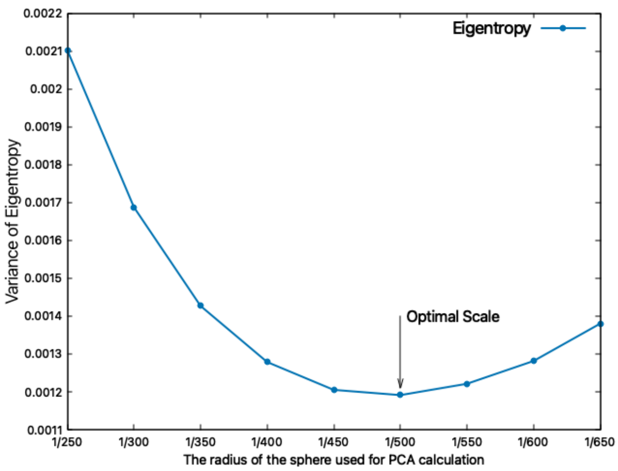

Figure 5. Variance of Eigentropy across different PCA scales for the Borobudur dataset. The minimum variance at $1/500$ indicates the optimal scale for structural coherence.

As shown in Fig. 5, the variance was minimal at a scale of $1/500$. Therefore, for this target object, this scale is the one at which PCA can be performed with the points most tightly clustered. Figure 6 shows the results of also performing edge extraction with Change of Curvature based on this result. The parameters used for this result are shown in Table 1.

As shown in Fig. 6, the adoption of soft edges enables the visualization of finer structures compared to Fig. 4. Especially, the human form near the base of the mast and the structure of the hull of a ship are more clearly visible.

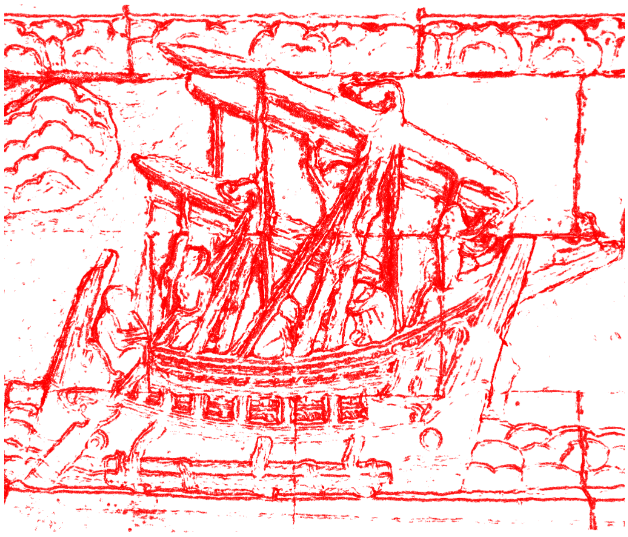

Figure 6. Enhanced visualization using the proposed adaptive PCA-scale optimization and dual edge extraction. Note the improved clarity of the human figures and ship structures.

Parameters	
r_{opt}	$1/500$
f_{th}	0.02
F_{th}	0.0358535
d	0.85
R_L	30

Table 1. Parameters for making Fig. 6.

3.2 Red Brick Storehouse

This section conducts experiments on objects possessing 3D structures. We focus on the red brick storehouse in Maizuru City, Kyoto Prefecture, designated as an Important Cultural Property of Japan. This architectural structure is significant in that it exemplifies the architectural styles of modern Japan. Figure 7 shows the target red brick storehouse visualized using SPBR. Since this target object has been measured in detail not only externally but also internally, combining SPBR with edge-enhanced visualization enables the visualization of the structure's detailed features.

Figure 8 shows the results of edge enhancement on this data using conventional methods. The internal structure, including columns and beams, is visualized with transparent visualization. However, similar to Fig. 4, the extracted points overlap, reducing visibility. While the existence of 3D features can be confirmed, the level of visibility is such that detailed structures cannot be identified.

The graph shown in Fig. 9 depicts the trend of the variance values of the Eigentropy assigned to each point at each scale of the point cloud data for the Red Brick Storehouse.

As shown in Fig. 9, the variance value of Eigentropy is minimized at $1/450$. Therefore, this scale is determined as the scale that enables the most consistent edge extraction.

Figure 10 shows the results of optimizing the PCA scale and

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Figure 7. External view of the Red Brick Storehouse visualized by SPBR.

visualizing the data, including soft edges. Table 2 lists the parameters of the equations used.

Parameters	
r_{opt}	$1/450$
f_{th}	0.21
F_{th}	0.318638
d	0.75
R_L	100

Table 2. Parameters for making Fig. 10.

Figure 10 shows clearer visualization of the outlines of pillars and stairs compared to Fig. 8, particularly the window frames and flooring materials on the second floor.

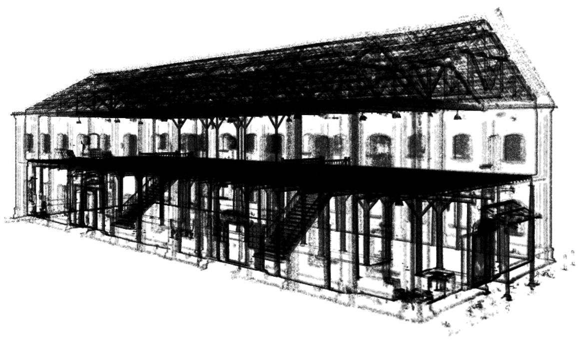
4. Discussion

4.1 Comparative Analysis with Conventional Methods

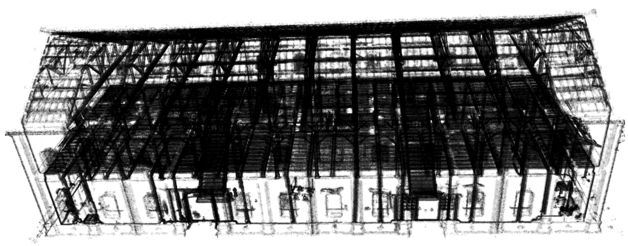
The limitations of edge enhancement using conventional fixed-scale PCA are particularly evident in objects with complex geometric shapes, such as cultural heritage sites. As demonstrated in the case studies, a globally fixed scale often results in a trade-off between detail preservation and noise suppression. In the Borobudur reliefs, the conventional binary edge extraction method caused high-opacity points to cluster together, reducing visibility. In contrast, the dual-edge extraction method used in this study employs an opacity gradient function $\alpha(f)$ to render soft edges as opacity graduations. This enables the visualization of data that is essential for understanding the overlapping fine structures, such as masts and figures, found in the ship's reliefs. By quantitatively optimizing the scale through minimization of Eigentropy variance, this method ensures the most consistent structural features are visualized, effectively enabling detailed visualization of cultural heritage.

4.2 Versatility Across Different Geometries

A significant challenge in cultural heritage archiving is the vast diversity of target objects, ranging from fine-grained surface carvings to large-scale structural elements. The result of our adaptive framework on two fundamentally different datasets — the wall reliefs of Borobudur Temple and the brick and timber architecture of the Red Brick Storehouse — demonstrates its high versatility. In the Borobudur Temple case, the optimal scale r_{opt} effectively captured the subtle depth of overlapping figures in the reliefs, whereas for the Red Brick Storehouse, a different scale was automatically identified to highlight structural components like internal beams and stairs. This result underscores the necessity of the proposed adaptive approach; a single, manually fixed scale would inevitably fail to represent the distinct geometric characteristics of both fine art and robust masonry. By providing a consistent level of visual clarity across diverse materials and scales, our method serves as a multi-purpose tool suitable for both archaeological interpretation and structural health monitoring in heritage science.



(a) Edge enhancement using conventional methods (visualization from the side).



(b) Edge enhancement using conventional methods (visualization from the top).

Figure 8. Edge enhancement visualization using binarization, as in conventional methods.

4.3 Computational Efficiency

From a practical implementation perspective, the computational efficiency achieved through octree-based spatial partitioning is a critical factor for analyzing big data like cultural heritage. In-

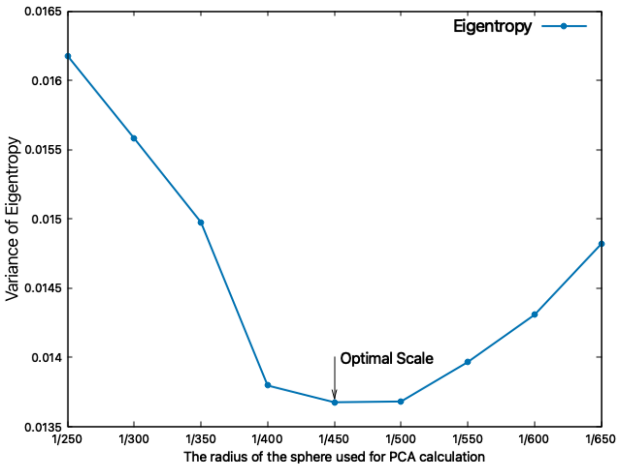
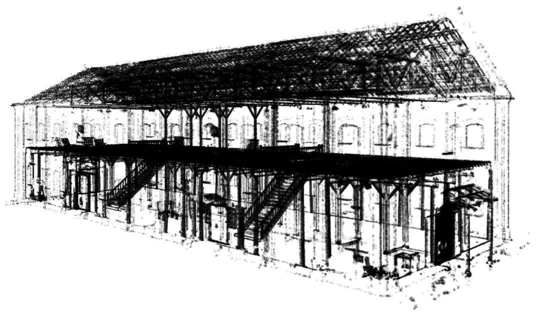
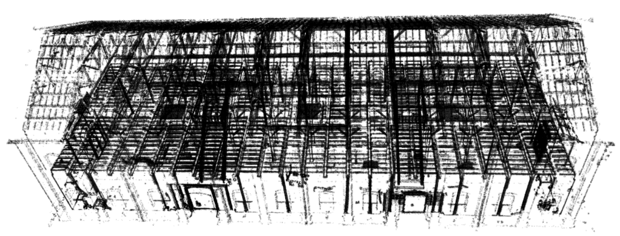


Figure 9. Eigentropy variance plot for the Red Brick Storehouse, showing an optimal PCA scale at $1/450$.



(a) Proposed adaptive PCA-scale optimization (visualization from the side).



(b) Proposed adaptive PCA-scale optimization (visualization from the top).

Figure 10. Edge-enhanced visualization with improved visibility achieved through the proposed adaptive PCA scaling method.

stead of an exhaustive brute-force search across the entire dataset for every candidate scale, our framework utilizes a hierarchical spatial index to prune unnecessary calculations during neighborhood searches. This method reduces unnecessary computations during the neighborhood search process. This process significantly reduces the search scope for each point, enabling the processing of large-scale cultural heritage datasets exceeding tens of millions of points within a reasonable timeframe, even on standard hardware. Such efficiency enables high-quality visualization and structural analysis, facilitating efficient and accurate, informed analysis in conservation and analysis.

5. Conclusion

In this study, we have presented an advanced edge extraction framework for 3D scanned point clouds, specifically designed for the high-fidelity digital archiving of cultural heritage. The core contribution is the integration of automatic PCA-scale optimization with a dual edge extraction technique. By utilizing Eigentropy as a quantitative measure, the proposed method identifies an optimal scale that maximizes structural coherence while mitigating sensor-induced noise . Experimental results on the Borobudur Temple and the Red Brick Storehouse demonstrate that our adaptive approach significantly improves the visibility of overlapping structures compared to conventional fixed-scale methods . The implementation using octree-based spatial indexing ensures that the method is computationally feasible for large-scale data. As future work, we anticipate that adaptively modifying the analysis region size according to the local point density and geometric curvature at each point will enable even more flexible edge enhancement. This approach enables effective edge enhancement that is not affected by the density variations or measurement noise within the 3D scanned point clouds, and is expected to facilitate more accurate analysis.

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