Decoding the Past: A Genetic Algorithm-based Method for Extracting Decorative Patterns in Heritage Digital Twins

Siyuan Meng[1], Guangji Xu[2], Wenjin Zhang[3], Fan Xue[4*]

Abstract: In the smart construction era, Heritage Digital Twin (HDT) is increasingly created as the digital replica of physical heritage buildings and relics. Extraction of the unique patterns and decorative elements on the HDTs is not only of academic interest to heritage conservation but also of business interest to fashion and design, such as the recent Hanfu fever. However, the patterns' complex curvature surfaces and subtle protrusions make it challenging to extract and analyze them accurately and efficiently. This paper presents a Genetic Algorithm-based semi-automatic method for extracting decorative pattern texture from HDTs. This method has three steps: (i) extraction of cross-section contour as Non-uniform rational B-spline (NURBS) curves; (ii) Fitting of arcs and curvature projection based on Genetic Algorithm (GA); and (iii) clustering and extraction of patterns of interest. We tested the method on 3D data of a heritage building and a heritage bronze drum preliminarily. The high accuracy of the results, i.e., F_1-value > 90% in all tasks, validated our automated extraction method for detailed patterns and decorations. The proposed GA-based method can enrich the literature of HDT in smart heritage and smart construction, whereas the extracted heritage's patterns and decorations have the potential for cultural and business applications.

Keywords: Heritage Digital Twin; Heritage decorative patterns; 3D point cloud; Genetic Algorithm; Smart Construction.

[1] Siyuan Meng
Department of Real Estate and Construction, The University of Hong Kong, Hong Kong SAR, China
[2] Guangji Xu
Anthropology Museum of Guangxi, Nanning, China
[3] Wenjin Zhang
Guangzhou Okay Information Technology Ltd., Guangzhou, China
[4*] Fan Xue
Corresponding author, Department of Real Estate and Construction, The University of Hong Kong, Hong Kong SAR, China
E-mail: xuef@hku.hk

1 Introduction

1.1 Background

Smart construction implies the incorporation of automation and information technologies in the construction sector to tackle engineering challenges, such as cost, quality, safety, and sustainability[1, 2]. Benefiting from the rapid development of information technology, Digital Twin (DT), a network physical integration, has played a greater role in smart construction[3] since it enables interoperability, automation, and intelligent systems for whole-life-cycle buildings management. From the perspective of real-time geometric information (one of the DT objectives), 3D point clouds serve as a suitable data source because they can accurately depict the shape and texture of detected object surfaces. With expert handling, these point clouds can be transformed into digital documents such as Building Information Models (BIMs) and DT models[4].

The Heritage Digital Twin (HDT) is a digital representation of the intricate knowledge structure pertaining to heritage assets[5], in which both generating a high-fidelity virtual model of physical objects and efficiently processing the gathered data and diagnosing the digital twin to facilitate decision-making are challenging[6]. One of the objectives of HDT is to create 3D models with semantically rich coverage[7].

More specifically, in heritage conservation, the preservation of texture, material, and decorative elements is essential for experts to evaluate the detailed status[8]. Besides, the decorative pattern found in cultural heritage possesses significant commercial value due to its extensive applicability in design and fashion industries, such as Hanfu. The feature of decorative pattern texture is slightly raised at the edges of the pattern. Current literature mainly focuses on presenting image level of texture information. For instance, [9] utilize a photogrammetry method to acquire masonry patterns as the texture for BIM objects, and [10] create a detailed restoration map for HBIM through photogrammetry. Furthermore, detail texture should not only be limited to image presentation but also provide the appearance with further information[11], such as performance assessment, texture detection, extraction, and classification. Hence, from the perspective of integrating texture semantic information, there is a need to extract pattern texture characterized by slight protrusions from point cloud data.

1.2 Texture-related extraction method

Ornamental pattern texture exhibits subtle elevations along the boundaries; thus, the extraction of pattern texture is often modeled as discontinuous characteristics extraction from input 3D point cloud. Such discontinuous characteristics extraction methods have been developed for two decades, e.g., in the field of rock surface[12]. Features that are often used for classification are angles, normal vectors, curvatures, planar parameters (e.g., Random sample consensus, RANSAC), and density (e.g., density-based spatial clustering of applications with noise, DBSCAN). Current rocks discontinuities analysis contains two major groups of methods, i.e., K-means and region growing, while there existed other algorithms as well.

[13, 14]obtained the mesh vertices features from the point cloud and used K-means to cluster gentle and discontinuous regions semi-automatically. This approach exhibits high computational requirements, and its efficacy depends on the acquired mesh quality (e.g., a point cloud with high morphological complexity will result in incorrect and distorted polygonal surfaces) and easy-to- neglect small features[12]. The region growing methods choose seed points randomly and expand the region by including neighboring points that satisfy predetermined criteria[15]. It has significant advantages in reducing computation time compared to the K-means method but still requires 90% of time to calculate millions of vertices features. Besides, supervised deep learning method such as Artificial Neural Networks (ANN) is considered in extracting rock discontinuities[16], which is less effective for heritage due to the uniqueness of each pattern's features (such as color, shape complexity, and curvature) across different cases.

It should be noted that rock discontinuity identification and texture extraction are different in at least two aspects. Firstly, the subtle features along the pattern edges can be easily overlooked when dealing with complex global features. Secondly, in contrast with patterns, rocks are typically characterized by planar surfaces and sharp edges, resulting in relatively straightforward feature extraction. Whereas patterns in heritage are sometimes attached to curved surfaces, making it difficult to extract features accurately using methods such as RANSAC and resulting in the wrong discontinuity analysis output. To conclude, current discontinuity extraction methods are insufficient for achieving the semantic interpretation of the given pattern texture in heritage point cloud data. Therefore, inspired by[17], we introduce the Genetic Algorithm (GA) to address the above issues through global arc fitting.

1.3 Research objectives

This paper aims to present an automated method to extract heritage texture and decorative elements from HDTs, such as 3D high-resolution point clouds or mesh models. Three objectives are arranged:

1. To detect cross-sectional contour nonuniform rational B-splines (NURBS) curves;
2. To apply GA to arc-fitting of NURBS curves; and
3. To extract features using the adapted K-means clustering method and DBSCAN method.

As a result, the input point cloud is segmented into two parts: the continuous and smooth base regions (including planes and curved surfaces) and the raised regions that are extracted and clustered into object instances.

The main theoretical novelty in the proposed method lies in the sectional-arc fitting formulation. The formulation transforms the traditional discontinuous pattern analysis into a novel optimization problem solvable by modern computational algorithms such as GA. The method proposed in this paper enables the detailed semantic interpretation for the semantic enrichment of HDTs. Additionally, the patterns and decorations extracted from heritage assets through this method hold promise for further industrial applications in culture and business.

2 Research methods

Figure 1 shows the three steps of the proposed method and the required parameters. The input to this method is the original point cloud. Firstly, generate sectional contour NURBS curves. In Step 2, transform NURBS curves into arcs through fitting. And in Step 3, partition the unfitted regions and cluster pattern objects. Finally, the output is clustered pattern objects at different locations.

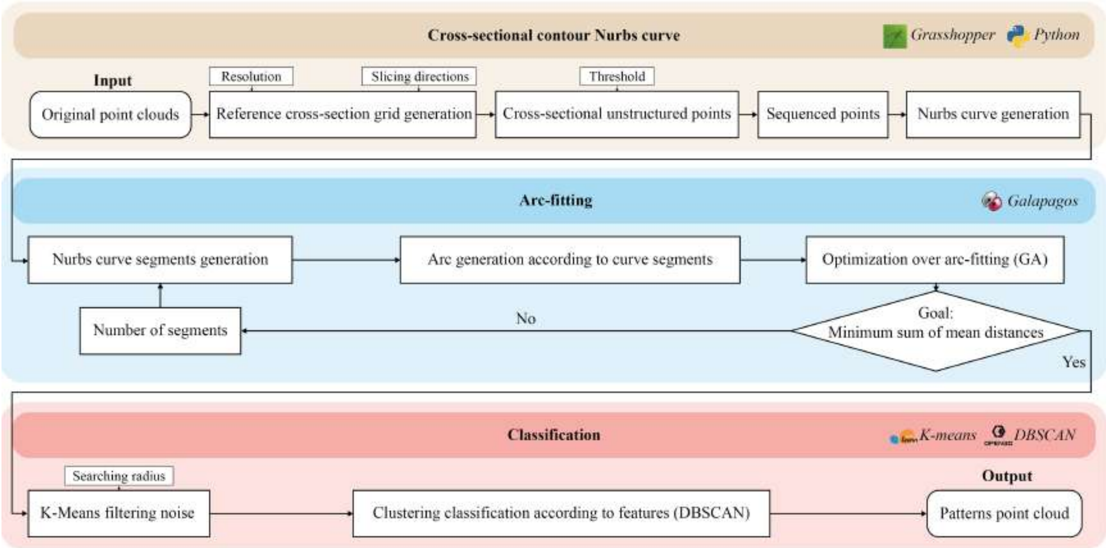

Fig. 1. General workflow of the proposed three-step method.

2.1 Cross-section contour NURBS curve extraction

The first step aims to obtain the cross-section contour curves of the input 3D data. First, a series of reference planes are determined in the point cloud regarding the combinations of the bounding box of the point cloud, resolution (grid size) (e.g., 1 mm), and slicing directions (e.g., x, y, or z). The input point cloud is then separated into a series of point cloud cross-sections according to a threshold distance value (e.g., 1 mm) between each point and the given plane. Next, the unstructured points are sequenced for generating NURBS curves through the *sort along curve* plugin in Grasshopper (ver. 1.0.0007, Rhino). The *Nurbs Curve* plugin then fits NURBS curves from the sequenced point lists. The outputs of this step are cross-sectional NURBS curves.

2.2 Arc fitting using Genetic Algorithm

The second step targets fitting arcs to the cross-sectional NURBS curves. The arc-fitting process is divided into two steps. Firstly, split the NURBS curve into curve segments according to the given value n, then generate arc segments based on the endpoints and midpoints of the curve segments. Secondly, use the *Galápagos* plugin in Grasshopper to complete arc-fitting optimization. The basic principle of *Galápagos* is GA, which is a method that utilizes natural selection to address both constrained and unconstrained optimization problems[18]. The constrained optimization objective is to minimize the sum of the mid-point distances between the arcs and the corresponding curve segments, as shown in Eq. 1. The output of this stage is the fitted arc lists of cross-sections.

$$\min \Sigma_{i=0}^{n} D_i^k \quad (1)$$

D is the distance between i-th curve segment and i-th arc of cross-section k. After optimization, obtained the arc lists of cross-sections.

2.3 Clustering and classification of extracted patterns

The objective of the third step is to separate unfitted arcs and cluster unstructured points into pattern objects. Combined with the given filter criteria (usually the mean or median number of *D*), we separate the imperfect fitting regions (i.e., the slightly raised areas) from the cross-section groups, the remaining regions are smooth planes or curved surfaces.

For clustering pattern objects, it is insufficient to obtain only the raised regions point clouds, as various patterns may exist in different locations within a region, and non-pattern sharp edges may become intertwined with the pattern point clouds, leading to mixed extraction results among different patterns and non-pattern results. Therefore, we utilize K-means, an unsupervised machine learning method, to semi-automatically perform secondary classification according to the specific K value = 3, with the clustering objective as the point surrounding points count. For the 3 clusters, we further segment the clusters based on density using DBSCAN to calculate the number of clusters that can be formed. The least number of DBSCAN clusters represents the noise point group, which is less dense than pattern clusters. To better partition the noise point groups, we maintain a consistent searching radius for K-means and eps for DBSCAN.

Next, we apply a second DBSCAN clustering to the filtered point clouds, setting the $e\ ps$ as the fourth neighboring point distanced mean value plus two standard deviations[19], and min points as 10. The final result of the third step is well-clustered pattern objects.

2.4 Validation and evaluation

We introduced quantitative validation to evaluate the performance of the algorithm. The validation compared the output with manually labeled ground truth at two levels, i.e., the point level and the object level. We adopted three evaluation metrics, precision (the proportion of points correctly detected by the proposed method), recall (the proportion of points identified as edges in the ground truth), and F_1-value (the harmonic mean of the precision and recall, to reflect the algorithm's accuracy) [20], as shown in Eqs. 2, 3, and 4.

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The value *TP* denotes the number of correctly detected points, while *FP* represents the number of wrongly detected points. *FN* indicates the false rejections, i.e., points belonging to the ground truth but not detected by the edge extraction technique.

3 Case study and results

3.1 Case selection

This paper employed two cases, as shown in Fig 2, to preliminarily validate the efficacy of the method. The first case was the commemorative plaque texture of Guangtong Association Hall, of which the input was a high-resolution 3D point cloud. The other case was the No. 0158 bronze drum's deformed feathered human pattern, which was a high-resolution mesh model from the Anthropology Museum of Guangxi, Nanning, China. These two cases are representative of their respective scales and exhibit different pattern characteristics (i.e., one is discretely distributed and the other arranged centripetally). Therefore, they are suitable for exploring the feasibility of the algorithm in scenarios with different pattern distributions.

In Fig 2a, Guangtong Association Hall in Lechang, Guangdong, China consists of various building sections, including a porch, foyer, main hall, wing rooms, corridors, a theater building, and a courtyard. The hall's doors, windows, beams, and pillars are decorated with intricate and detailed patterns that hold significant symbolic meanings. We selected the hall's commemorative plaque as the experimental example since it contains the title of Guangtong Association Hall. The point cloud includes 142,953 points, with bounding box size x: 3955mm, y: 202mm, z: 918mm.

Bronze drums are significant archaeological artifacts found in southern China and Southeast Asia, with scattered discoveries from the Yangtze River of China to the Indonesian islands[21]. The decorative elements of bronze drums reflected the manufacturer's purpose, era, affiliated ethnic groups, and artistic expression of the drums[8], which are thought to be linked to the totemic worship traditions of various ethnic groups, such as the Karen, Zhuang, Wa, and others, which developed over time. We chose bronze drum No. 0158 for testing and performed point sampling (999,900 points, with bounding box size x: 619mm, y: 647mm, z: 25mm) of the face mesh. Fig 2b illustrates the selected example.

3.2 Experimental settings

The proposed method was tested using an AMD Ryzen 9 5900HS computer with Radeon Graphics 3.30 GHz and 32 GB RAM. The slicing direction of the experimental object was determined based on its geometric shape. For instance, for the commemorative plaque, the slicing direction and grid sizes were set as *XY*, *XZ* planes, and 500 planes in each direction; while for the drum, they were set as *XZ*, *YZ* planes, and 500 planes in each direction. We selected parallel lines on the corresponding section planes as reference curves to sort the section point cloud. In addition, the generated cross-sectional NURBS curves were curves with sharp changes in curvature instead of smooth curves. This was because the given surface of the point cloud produced slight undulations on the smooth surface due to the unavoidable quality problem of the collected data, which would not influence the texture extraction results since we introduced the arc-fitting procedure.

Following the establishment of the objective and automatic value range for *Galápagos* (0-100 curve segments number), 100 iterations were performed to obtain the final convergent solution arc-curve lists for all cross-sections. For the drum, the most appropriate segment number was 100, while for the commemorative plaque, it was 98. The progress of GA effectively separated the imperfect fitting surfaces, i.e., the slightly undulating point cloud regions. Thereafter, we filtered the noise points using K-means and DBSCAN; the search radius was set as 90mm for the commemorative plaque and 7mm for the drum.

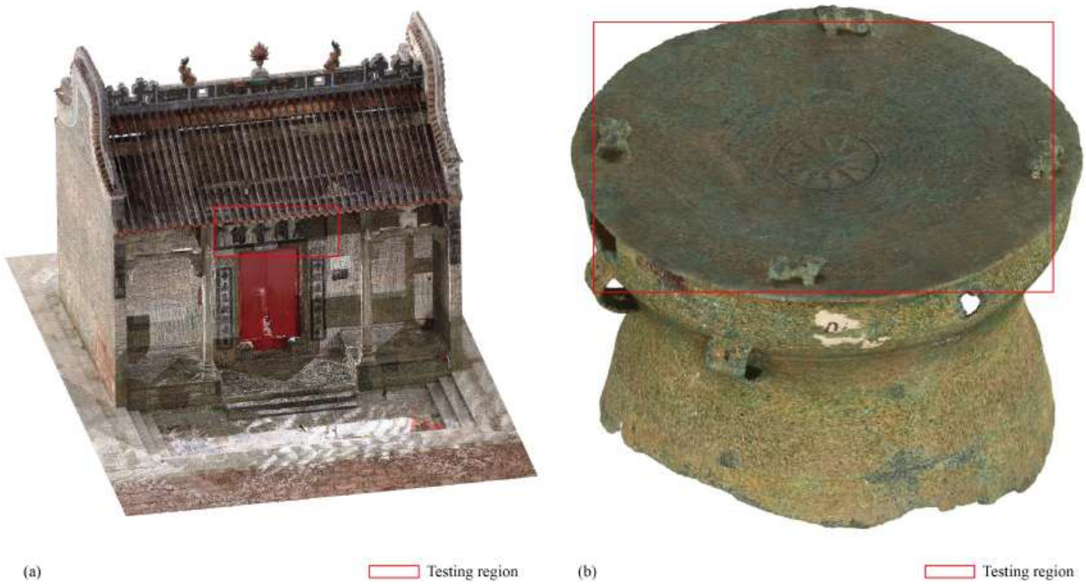

Fig. 2. The original point cloud and mesh model of two test cases. (a) The commemorative plaque of Guangtong Association Hall; (b) No. 0158 bronze drum's deformed feathered human pattern.

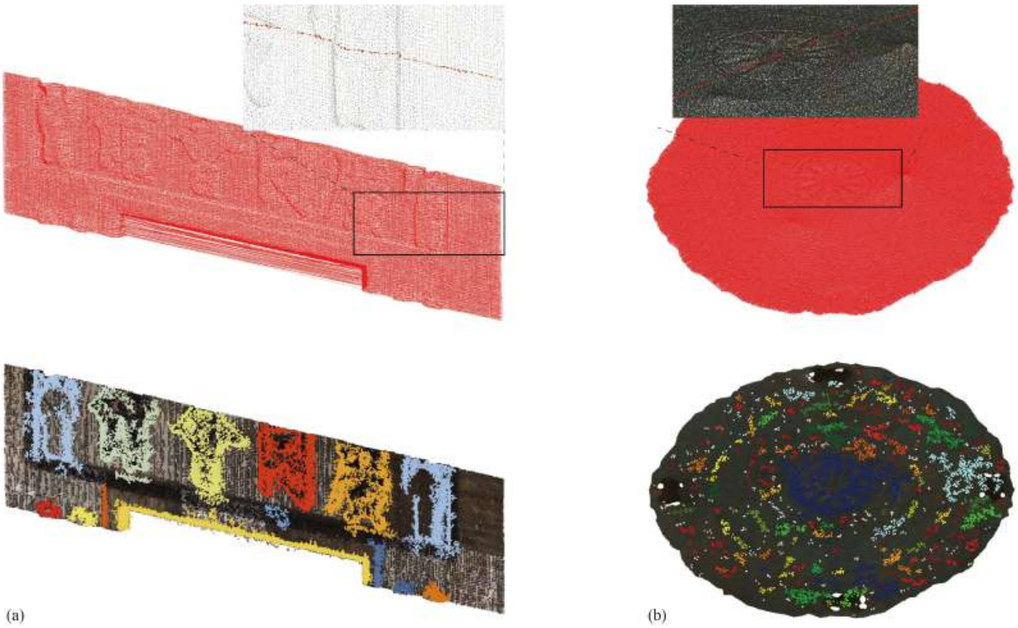

Fig. 3. The pattern extraction results of two experiment objects. (a) The commemorative plaque texture of Guangtong Association Hall; (b) No. 0158 bronze drum's face texture.

3.3 Results of extracted patterns

Fig 3 shows the pattern extraction results from the two cases. The upper sub-charts display the cross-sectional NURBS curves, with one example curve highlighted in each sub-chart. The bottom sub-charts demonstrate the clustered pattern objects of two example cases. One can distinguish the object-level clusters with colors in the bottom charts from the points and curves at lower levels during the processing.

Fig 3a presents the commemorative plaque texture of Guangtong Association Hall; the word pattern clustering was well obtained. Whereas drum circular patterns in Fig 3b were fragmented, except for the sunburst at the center. The clustering result of the drum was slightly inferior compared to the commemorative plaque. This is related to the production age, excavation from underground, and lack of maintenance, resulting in excessive noise (e.g., drum face broken and rusted) and the circular and centripetal distribution of the drum pattern.

Overall, the extraction of point-level patterns was satisfactory, and the clustering results of object- level patterns were good in the case of discrete patterns. However, noise and variations in pattern distribution probably impacted the accuracy of pattern cluster results.

3.4 Evaluation using error metrics

Table 3.4. The validation results at Point-level and Object-level

	Point-level accuracy			Object-level accuracy		
	Precision	Recall	F_1	Precision	Recall	F_1
Guangtong	93.05%	97.91%	95.42%	91.70%	98.90%	95.16%
0158 Drum	83.00%	99.79%	90.62%	82.26%	100.00%	90.27%

Table 3.4 lists the evaluation results of two cases in Fig 3. The mean precision at the point level for the experimental participants was 87.88%, while the recall was 98.85%, and F_1 was 92.99%. The instance level precision was 86.85%, with a recall = 99.45%, F_1 = 92.68%. According to the values of unbiased metric F_1, the proposed GA-based method was highly effective. In addition, the method was shown feasible and stable in extracting taller objects like words as well as insignificant patterns on the drum. Yet, the precision values of extracting insignificant patterns were considerably lower (for about 10%), according to Table 3.4.

4 Discussion and Conclusion

Heritage Digital Twins (HDT) as a method of documenting and preserving heritage under new technological developments, complements the digital information of smart construction. The detection of decorative patterns is a necessary complement to HDT, as these patterns serve as a link to confirm the conservation status of heritage objects and possess significant academic, artistic, and commercial value. Pattern texture extraction from point clouds can be regarded as discontinuity detection of point clouds. However, current point cloud discontinuity methods tend to ignore small undulating edges when encountering complex point cloud shapes and have difficulty extracting textures on curved building shapes. Therefore, the proposed method in this paper aims to extract cross-sectional contour lines of the point cloud at the given directions, uses GA to fit the NURBS curve into arcs, separates imperfectly fitted regions, and reclassifies them to find slightly undulating pattern edges in the point cloud. Two examples are given in this paper to quantitatively evaluate the feasibility of our method for finding pattern texture edges in point clouds based on accuracy and recall. Our contributions can be summarized in three aspects: (1) the proposed Genetic Algorithm-based contour edge extraction; (2) edge extraction applicable to small edges and corners, and (3) avoiding geometric feature calculation for point clouds. The results can provide object-level patterns semantic interpretation for fields such as HDT, BIM, HBIM, heritage protection, and Scan-to-BIM.

There are limitations in the method presented in this paper. First, the current method can only be applied to the raised patterns on a single plane. The reference curve obtained from the bounding box of the point cloud cannot be utilized for determining the point order of cross-sections in cases of complex geometric shapes (i.e., exhibit varied orientations and edges), resulting in confusing NURBS curves and inaccurate fitting results. A possible solution is using the Alpha shape, often used to generalize bounding polygons containing sets of points according to a given alpha value. Thus, it can adjust the point order of complex geometric point cloud cross-sections. Besides, the current method mainly considers the geometric features of the point cloud; for point clouds with color (R, G, and B) attributes, the color difference can also be exploited to improve the accuracy of pattern extraction. Finally, the computational tests exhibited a slow computational performance due to the single-threaded computing and inefficient data structure in Grasshopper (*Galápagos*) for handling 3D point cloud data. The GA itself consumes an ignorable portion of the computer resources. Therefore, Grasshopper is unsuitable for processing large-scale points, though it is sufficient for proof-of-concept of extracting patterns within a given local range in this paper.

For future research directions, we suggest improving the extraction method of the contour curve first. It is also interesting to incorporate other features, such as colors and normals, into GA's multiple objectives to formulate a multi-objective optimization, which might improve the performance of the algorithm. To enhance the computational efficiency of the proposed method, a program incorporating advanced point clouds data structures (e.g., *k*-d tree, voxel, and supervoxel), along with CPU concurrency and GPU computation, will be implemented in Python and C++ to replace the existing Grasshopper-based program.

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