Analysis of 3D Artwork Styles Using Mesh Laplacian Eigen-features

メッシュラプラシアン特徴に基づく三次元芸術作品のスタイル分析

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Abstract

Understanding artistic style is essential for interpreting works of arts. Comparing stylistic difference of works by different artists can help us better understand how art style is expressed. While artistic style is often regarded as subjective, objective geometric descriptors can offer measurable view to analyze individual tendencies in three-dimension artworks. In this study, we explore how geometric and spectral properties vary across three-dimensional artworks by different creators. We collected clay sculptures created by professional artists and analyzed curvature, saliency and Laplacian operator. By calculating similarity matrices based on these features, we aim to identify the stylistic patterns and differences. Our results demonstrate that the geometric features can serve as quantitative indicators of sculptural style.

1. Introduction

In the field of two-dimensional art, such as paintings and prints, lots of research has already been conducted on style analysis. A large body of work has examined how brushstrokes, color palettes, or compositional patterns can serve as indicators of artistic style [1]. However, systematic studies of style in three-dimensional artworks are limited.

With the advancement of three-dimensional (3D) scanning technology, obtaining high-quality 3D data has become increasingly accessible due to the decreasing cost and improving accuracy of commonly used scanners. The technology progress has opened new opportunities for the study of artworks, particularly 3D objects like crafts and sculptures. While some researches have focused on surface reconstruction or geometric modeling, few attempts have been made to connect measurable geometric descriptors directly to artistic individuality of three-dimensional artworks. Our study addresses this gap by investigating curvature, saliency [2], and Laplacian eigenfeatures [3] to capture stylistic tendencies in clay sculptures created by different artists. Specifically, we focus on Laplacian eigenfeatures, which summarize global spectral properties of shape. By analyzing these features in clay sculptures created by different artists (Figure 1), we aim to explore whether geometric and spectral analysis can reveal consistent stylistic patterns that distinguish one author's work from another.

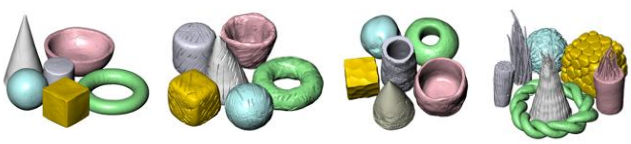

Figure 1. Clay artworks from various artists

2. Method

We designed the study to test whether geometric descriptors can reflect artistic styles in 3D forms. Four artists were asked to model six basic clay shapes: cone, cube, cup, cylinder, sphere and torus, using the same amount of clay material to keep the works comparable. We choose these limited shapes to control variables for comparative analysis. Each piece was digitized through x-ray CT scanning and reconstructed as a mesh, which serves as the basis for further analysis. To obtain a standardized representation of the surface geometry, we performed voxel thresholding using Otsu's method [4], followed by Marching Cubes [5] to extract its surface.

Our analysis proceeded on two levels consisting of local feature analysis and global feature analysis. To capture local surface features, we computed mean curvature at mesh vertices and applied a mesh saliency algorithm to highlight perceptually prominent regions. The results were displayed with surface color maps, and their distributions were summarized in histograms for quantitative comparison.

To characterize global shape structure, we performed Laplacian eigen-analysis on the meshes and extracted eigenvalues as spectral features. These descriptors provide a compact representation of overall form that complements the local measures. Geometrically, each eigenvector corresponds to a harmonic basis function defined on the surface: low-frequency modes smoothly across large area while high-frequency modes wave rapidly over local regions.

Given a triangular mesh with vertices $V = \{v_i\}_{i=1}^{N}$ and faces $F = \{f_j\}_{j=1}^{M}$, we construct the cotangent Laplacian matrix $L \in \mathbb{R}^{N\times N}$ as:

$$L_{ij} = \begin{cases} -\frac{1}{2}(\cot \alpha_{ij} + \cot \beta_{ij}) & \text{if } (i,j) \text{ are adjacent} \\ -\sum_{k\neq i} L_{ik} & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where i and j are neighboring vertex indices. The matrix L_{ij} encodes the geometric relation between vertex v_i and its neighboring vertex v_j. The two angles α_{ij} and β_{ij} are opposite to the edge ij in the neighboring triangles.

The resulting sparse symmetric matrix is solved for its first k eigenpairs $(\lambda_k, \boldsymbol{e}_k)$. The eigenvalue λ_k corresponds to the frequency of intrinsic surface vibration modes, while the eigenvector $\boldsymbol{e}_k$ represents a spatially varying shape base. In practice, we compute the first 100–1000 larger eigenvalues per model.

After computing the Laplacian spectrum, we extract compact descriptors from the eigenvectors to represent each model's geometric characteristics. Each eigenvector describes a vibration mode of the surface, and its overall distribution reflects how the shape's geometry varies at different scales. To obtain comparable numerical features, we summarize the amplitude of the frequency over all mesh vertices positions and then compare the histograms according to the amplitude.

By computing a similarity matrix based on the histograms, we can visualize and analyze how closely related the shapes created by different artists are in terms of their geometric styles.

3. Experiments and Results

3.1 Dataset

To evaluate the effectiveness of the proposed spectral analysis, we applied our method to a collection of 3D scanned clay sculptures created by different artists as summarized in Table 1. To scan the sculptures, we used X-ray CT scanning system as shown in Figure 2 with the setting in Table 2.

Table 1. Data collection

Artists	4 artists (A, B, C and D)
Shapes	6 shapes (cone, cube, cup, cylinder, sphere and torus)

Figure 2. Scanning environment

Table 2. Scanning setting

Machine	ZEISS METROTOM 1500 G1
X-ray tube voltage	160kV
Current	1mA
Voxel Size	132 um
Integration time	1 sec.
Projections	2050

The 3D models used in this study were first obtained as voxel data through scanning and then converted into polygonal meshes. To obtain a standardized representation of the surface geometry, we performed voxel thresholding using Otsu's method, followed by Marching Cubes to extract the surfaces. The scanned meshes were then cleaned to remove internal fragments and small isolated components.

3.2 Visualization

Laplace-Beltrami [6] operator is a fundamental differential operator defined on the surface of a manifold. Each eigenvector $\boldsymbol{e}_k \in \mathbb{R}^N$ of the discrete Laplace-Beltrami operator can be interpreted as a sampled version of a continuous eigenfunction defined over the mesh. The value $\boldsymbol{e}_k(v_i)$ represents the basis function of the k-th harmonic mode at vertex v_i. To visualize these manifold harmonic basis functions, we mapped the basis $\boldsymbol{e}_k$ to colors at the mesh vertices, as illustrated in Figure 3. Figure 3 shows the torus models from two different artists and their spatial patterns of Laplacian eigenvectors with three different values of k.

3.3 Comparison and Similarity Analysis

To analyze the structural characteristics and stylistic differences of 3D models, we computed the feature value based on the mesh Laplacian operator. For each eigenvector, we measured its overall magnitude S_k on the mesh surface by taking account the dot products with the mesh vertex positions.

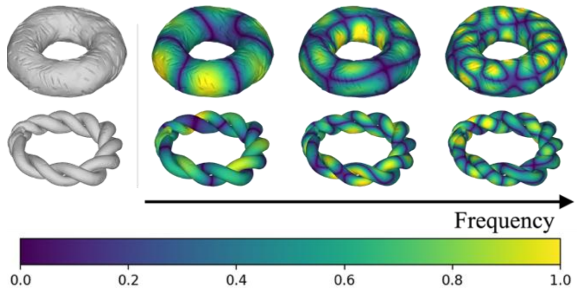

Figure 3. Visualization of spatial patterns of Laplacian on 3D surfaces

$$S_k = \sqrt{(\boldsymbol{e}_k \cdot \boldsymbol{v}_x)^2 + (\boldsymbol{e}_k \cdot \boldsymbol{v}_y)^2 + (\boldsymbol{e}_k \cdot \boldsymbol{v}_z)^2} \quad (2)$$

where $\boldsymbol{v}_x$, $\boldsymbol{v}_y$ and $\boldsymbol{v}_z$ are N-D vectors summarizing the mesh vertex positions. This value measures the strength of the k-th basis function over the entire mode, reflects how geometric frequency components are distributed over the shape surface. The resulting sequence $\{S_k\}$ serves as a compact spectral signature of each model.

To compare the works of different artists, these sequences are normalized and transformed into histogram representations. Figure 4 focuses on tours models from four artists. Each histogram shows the statistical distribution of the Laplacian energy values $\{S_k\}$ across a model. The horizontal axis represents the energy magnitude, and the vertical axis indicates the frequency.

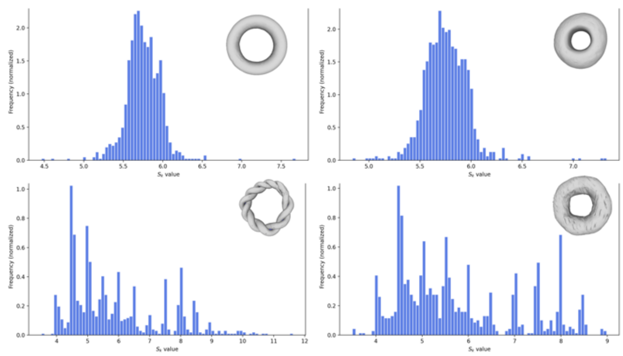

Figure 4. Eigenvalue distributions

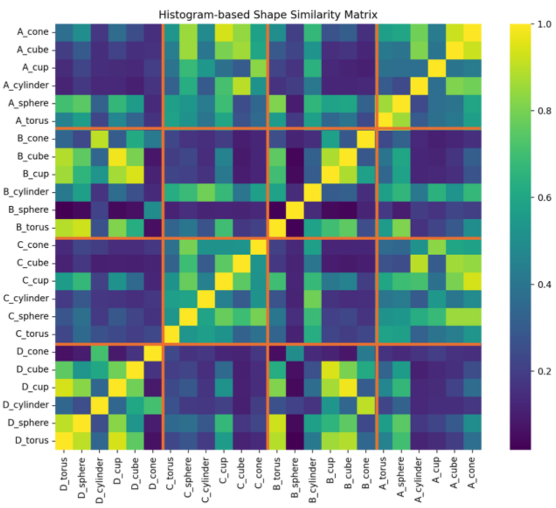

Figure 5. Comparison matrix

Figure 5 shows how similar different 3D artworks are in terms of their Laplacian spectra. Brighter colors indicate higher similarity while darker regions represent more distinct shapes. In the ideal case, the similarity matrix exhibits a block-diagonal structure, where the 6×6 shapes modeled by the same artist show higher mutual similarity.

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