LOCAL GEOMETRY-BASED FINGERPRINTING OF 3D MESHES*

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ABSTRACT: *This paper presents a robust fingerprinting method for polygonal 3D networks based on local geometric descriptors extracted from mesh surfaces. Instead of directly hashing Cartesian coordinates of vertices, the proposed approach represents the local geometry of the network using normalized dependencies between the faces of neighboring surfaces. These descriptors are designed to remain invariant under translation, arbitrary rotation, and uniform scaling. Subsequently, the descriptors are organized into a canonical representation and transformed into a compact cryptographic fingerprint.*

The method is evaluated under controlled geometric transformations, including different rotation angles, uniform scaling factors, and Gaussian coordinate noise, seeking a compromise between robustness and discriminative ability. The proposed method is targeted for applications in 3D model identification, authentication, copy detection, and integrity checking.

KEYWORDS: *3D geometric fingerprinting; 3D mesh; dihedral angle; geometric descriptor; mesh invariance; 3D model identification*

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1 Introduction.

Three-dimensional polygonal models are widely used in computer graphics, computer-aided design, digital manufacturing, virtual reality, and scientific visualization [1,2]. The increasing number of available 3D models creates a need for methods capable of identifying geometrically identical or highly similar objects [3]. Another research direction focuses on robust hashing of 3D mesh models for applications such as authentication, indexing, copy detection, and content protection [4].

Direct comparison of OBJ files is not sufficient for this purpose. The same geometric object can be represented using different vertex numbering, face ordering, coordinate origins, orientations, or uniform scales. Small numerical differences may also occur during model conversion and processing.

A geometric fingerprint should therefore describe the geometry of the object rather than its file representation. Ideally, the fingerprint should remain unchanged when an object is translated, rotated, or uniformly scaled. It should also be independent of the ordering of vertices and faces.

This work proposes a compact geometric fingerprint based on local surface geometry. The method uses dihedral angles between neighboring triangular faces and applies local statistical normalization to reduce sensitivity to coordinate perturbations. A canonical spatial representation is additionally used to obtain a stable and spatially distributed subset of geometric descriptors.

The main objective is to investigate whether this combination can provide a simple and computationally practical representation for identifying and comparing 3D objects.

2 Methodology and Proposed Approach

The proposed method consists of the following main steps: (1) loading the triangular mesh, (2) identifying manifold edges, (3) calculating dihedral angles, (4) calculating local statistical descriptors, (5) constructing a canonical coordinate system for spatial selection, (6) dividing the canonical space into a three-dimensional grid, (7) selecting a fixed number of spatially distributed edges, (8) quantizing and sorting the selected descriptors, and (9) calculating an exact SHA-256 fingerprint.

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The original mesh coordinates are retained for all geometric calculations. Canonical coordinates are used only to determine the spatial distribution of selected descriptors.

Dihedral-Angle Descriptor

Dihedral angles provide a natural geometric representation of triangular meshes and can be used to characterize mesh geometry [5].

For two adjacent triangular faces, the dihedral angle is determined from their unit normal vectors. If the normals are n_1 and n_2, the angle associated with edge e is calculated as

(1) $$\theta e=\arccos(\text{clip}(n1\cdot n2,-1,1))$$

where θe is the dihedral angle associated with edge *e*, and n1 and n2 are the unit normal vectors of the two adjacent faces.

For a triangular face with vertices a, b, and c, its unit normal vector is calculated as

(2) $$n = \frac{\|(\mathbf{b}-\mathbf{a})\times(\mathbf{c}-\mathbf{a})\|}{(\mathbf{b}-\mathbf{a})\times(\mathbf{c}-\mathbf{a})}$$

where n is the unit face normal, a, b and c are the three vertex position vectors of the face, × denotes the vector cross product, and ‖·‖ denotes the Euclidean vector norm.

Only manifold edges shared by exactly two triangular faces are considered. Boundary edges and non-manifold edges are excluded from the current descriptor construction.

Local Descriptor Normalization

The raw dihedral angle describes the local geometric configuration of an edge, but its absolute value may vary between different regions of the same object. To reduce this dependence on the local geometric context, each dihedral angle is normalized with respect to the angles in its neighborhood.

For an edge e, the normalized descriptor is calculated as:

(3) $$z_e = \frac{(\theta_e - \mu_e)}{\sigma_e}$$

where θe is the dihedral angle of edge e, while μ_e and σ_e denote the mean and standard deviation of the dihedral angles in its local neighborhood.

The resulting value z_e describes how much the angle of the current edge differs from the typical angle in its local region. This makes the descriptor more suitable for comparing geometric structures occurring at different locations on the model.

The locally standardized dihedral angle is used as the primary geometric descriptor in the proposed fingerprint. The normalized descriptors are subsequently subjected to spatial selection, quantization, and sorting.

Canonical Coordinate System

The spatial distribution of selected descriptors is determined using a canonical coordinate system [2]. This coordinate system is not used to modify the geometry or calculate the dihedral angles.

For N mesh vertices with position vectors v_i, the centroid is

(4) $$c = \frac{1}{N}\sum_{i=1}^{N} v_i$$

where c is the mesh centroid, N is the number of vertices, and v_i is the position vector of vertex i.

The vertex coordinates are centered by subtracting the centroid. Principal component analysis is then applied to determine the main axes of the object. A deterministic sign convention is used to orient these axes, followed by a right-handedness correction. The resulting coordinates are normalized by a characteristic scale z-score = e^{-MAE}. The canonical coordinate system is used only for spatial selection. The original coordinates remain the basis for calculating the geometric descriptors.

Three-Dimensional Grid Selection

The locally standardized dihedral-angle descriptors are associated with the spatial locations of their corresponding mesh edges. To obtain a representative and spatially distributed subset of descriptors, the canonicalized mesh is divided into a regular three-dimensional grid.

The canonical coordinate system described in the previous section is used only for this spatial selection step. The geometry of the mesh is not modified, and the dihedral-angle descriptors remain those calculated from the original mesh.

For each manifold edge, the midpoint of its two endpoints is determined in the canonical coordinate system. The midpoint is then assigned to a cell of the three-dimensional grid according to its spatial position. This provides a simple way to divide the mesh into spatial regions independently of the original vertex and face numbering.

A fixed number of descriptors is selected from the available grid cells. In the experiments, 256 descriptors are retained. The selection is performed so that the resulting subset is distributed across the spatial extent of the object rather than being concentrated in a single region.

This spatial selection reduces the size of the fingerprint while preserving information from different parts of the model. It also makes the selection independent of the original OBJ indexing and provides a consistent basis for comparing different transformed versions of the same object.

The grid is therefore used as a spatial sampling mechanism rather than as a geometric descriptor itself. Its role is to determine which locally standardized dihedral-angle descriptors are retained for the subsequent quantization, sorting, and fingerprint construction steps.

Fingerprint Construction

After the spatial selection step, a fixed set of locally standardized dihedral-angle descriptors is obtained. In the proposed implementation, 256 descriptors are retained for each model. These values form the basis of the geometric fingerprint.

Before constructing the fingerprint, the selected descriptor values are quantized using a fixed quantization step of 0.5. Quantization reduces the influence of very small numerical differences that may arise from floating-point calculations or minor changes in the input data.

The quantized descriptor values are then sorted into a canonical sequence. Sorting removes the dependence on the original ordering of edges and vertices in the OBJ file. Consequently, equivalent geometric information produces the same ordered descriptor sequence even when the underlying mesh uses a different indexing order.

The resulting sequence is serialized into a consistent representation and processed using the SHA-256 cryptographic hash function. The resulting hash value constitutes the exact geometric fingerprint of the model.

The SHA-256 fingerprint is used for exact comparison. Two models with identical fingerprints have identical quantized descriptor sequences under the proposed procedure. For cases where small geometric differences are expected, the underlying descriptor sequences are compared directly using the similarity measure described in the following section.

More recent approaches have explored compact perceptual hashes for 3D assets [6].

Similarity Measure

Approximate similarity is calculated directly from the sorted descriptor vectors before hashing.

(5) $$\mathrm{MAE} = \frac{1}{\mathrm{K}} \sum_{I=1}^{K} |d_i^A - d_i^B|$$

where MAE is the mean absolute error, K is the number of selected descriptors, d_i^A and d_i^B are the corresponding sorted descriptors of objects A and B. The similarity is then calculated as exponential function of MAE. A similarity value close to one indicates very similar descriptor

vectors, while lower values indicate greater differences. No universal classification threshold is defined in this study.

The overall workflow of the proposed 3D geometric fingerprinting method is illustrated in Figure 1.

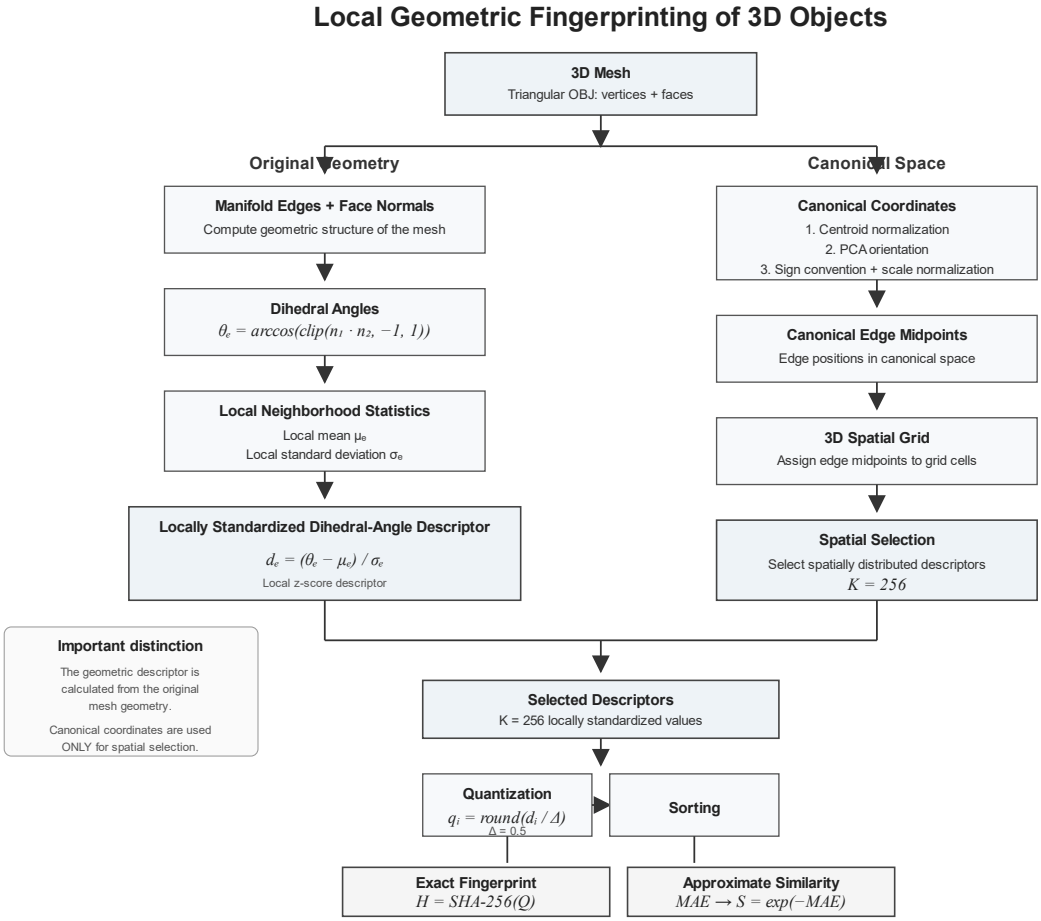


Figure 1. Overview of the proposed 3D geometric fingerprinting method

3 Experimental Results and Discussion

The proposed method was evaluated using triangular OBJ meshes. For each model, manifold edges and their dihedral angles were calculated, followed by local standardization and spatial selection in the canonical coordinate system. In tables bellow are presented average results for experiment with 3 Standford models: bunny.obj, armadillo.obj and dragon.obj.

The experiments used 256 selected descriptors, a spatial grid spacing factor of 0.005, 0.01 and 0.02. The locally standardized dihedral angle was used as the primary descriptor, while the absolute dihedral angle was used as a reference descriptor.

The evaluation considered three main aspects: invariance to geometric transformations, robustness to coordinate noise, and independence from mesh indexing. Pairwise comparisons between different models were also performed to examine the behavior of the resulting fingerprints.

Invariance and Robustness

Translation, rotation, and uniform scaling were applied to the test model. The fingerprint and descriptor comparisons remained unchanged for all tested transformations, including rotations up to 90° and scaling factors between 0.5 and 2.0.

Vertex and face ordering were also modified without changing the geometry of the model. The resulting fingerprints and descriptor sequences remained identical, demonstrating that the method does not depend on the original OBJ indexing.

Table 1. Independence from vertex and face ordering

Test	Result
Maximum coordinate difference after vertex reordering	0
Geometric edge overlap	1.0000
Absolute dihedral similarity	1.0000
Local z-score similarity	1.0000
Absolute descriptor hash identical	Yes
Local z-score descriptor hash identical	Yes

The results for translation, rotation, and uniform scaling are presented in Table 2.

Table 2. Invariance to translation, rotation, and uniform scaling

Transformation	Tested values	Geometric edge overlap	Absolute dihedral similarity	Local z-score similarity
Identity	—	1.0000	1.0000	1.0000
Rotation	5°, 20°, 45°, 90°	1.0000	1.0000	1.0000
Scaling	0.5, 0.75, 0.9, 1.1, 1.5, 2.0	1.0000	1.0000	1.0000
Translation	(0.1, −0.2, 0.3)	1.0000	1.0000	1.0000
Translation	(1.0, 2.0, −1.5)	1.0000	1.0000	1.0000
Translation	(−3.0, 1.5, 4.0)	1.0000	1.0000	1.0000

The robustness of the descriptors to Gaussian coordinate noise is evaluated for different grid resolutions, as shown in Table 3. Gaussian coordinate noise was used to evaluate robustness to small geometric perturbations. The locally standardized descriptor maintained substantially higher similarity than the absolute dihedral-angle descriptor as the noise level increased. This indicates that local normalization reduces the influence of small coordinate perturbations on the resulting descriptor values.

Table 3. Robustness to Gaussian coordinate noise for different grid resolutions

Grid factor	Normalized σ	Absolute σ	Edge overlap	Absolute dihedral similarity	Local z-score similarity
0.005	0.0001	0.00002494	0.5781	0.522862	0.957941
0.005	0.0005	0.00012469	0.1836	0.137198	0.905191
0.005	0.001	0.00024938	0.0977	0.088064	0.903425
0.005	0.005	0.00124688	0.0625	0.000000	0.941250
0.005	0.010	0.00249376	0.0117	0.000000	0.950487
0.010	0.0001	0.00002494	0.4297	0.539460	0.921243
0.010	0.0005	0.00012469	0.1289	0.303794	0.986421

Grid factor	Normalized σ	Absolute σ	Edge overlap	Absolute dihedral similarity	Local z-score similarity
0.010	0.001	0.00024938	0.0586	0.315896	0.860372
0.010	0.005	0.00124688	0.0234	0.000000	0.891157
0.010	0.010	0.00249376	0.0352	0.000000	0.899903
0.020	0.0001	0.00002494	0.1211	0.225320	0.875629
0.020	0.0005	0.00012469	0.0391	0.449856	0.952345
0.020	0.001	0.00024938	0.0352	0.377340	0.872216
0.020	0.005	0.00124688	0.0352	0.000000	0.891157
0.020	0.010	0.00249376	0.0195	0.000000	0.917652

Normalized σ is the noise standard deviation expressed relative to the model bounding-box diagonal, while Absolute σ is the corresponding standard deviation in model original coordinate units.

4 Conclusion

This paper presented a local geometric fingerprinting method for triangular 3D meshes based on dihedral angles, local statistical normalization, and canonical spatial selection.

The method calculates dihedral angles on manifold edges and represents them using local statistical descriptors. A canonical coordinate system is used only to distribute a fixed number of descriptors spatially using a three-dimensional grid. The selected descriptors are quantized, sorted, and converted into an SHA-256 fingerprint.

The experiments demonstrate exact agreement under the tested translation, rotation, uniform scaling, and vertex/face reordering operations. The locally standardized dihedral-angle descriptor also provides substantially greater robustness to Gaussian coordinate noise than the absolute dihedral-angle descriptor.

The method therefore provides a simple and compact approach to local geometric fingerprinting of triangular 3D objects.

Future evaluation should include a larger collection of 3D models, remeshing and retriangulation, highly symmetric objects, different mesh resolutions, and statistically validated similarity thresholds.

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