Deep Learning 3D Shape Surfaces using Geometry Images

Motivation
Learning 3D shape volume surface using geometry image representation

Why Geometry Images?
- Representation is 2D while encoding pertinent shape information, reducing memory and computational complexity.
- Can be flexibly encoded with intrinsic or extrinsic signatures suitable for non-rigid and rigid shape analysis using convolutional neural networks (CNNs).

Contributions
1. Established relevance of authalic spherical parametrization for creating geometry images used subsequently in CNN.
2. Robust authalic parametrization of arbitrary shapes using area restoring diffeomorphic flow and barycentric mapping.
3. Creation of geometry images (a) with appropriate shape feature for rigid/non-rigid shape analysis, (b) which are robust to cut and amenable to learn using CNNs.

Data Preprocessing
1. Voxelize shape to follow Euler characteristic: \( 2 - 2m = |V| - |E| + |F| \)
2. Convert to genus-0

Medial-axis filling

α-shape filling

Shape Analysis Pipeline

Non-Rigid Shape

Rigid Shape

The pixels in the geometry image corresponding to points on the original shape are encoded with principal curvatures for rigid shapes and HKS for non-rigid shapes. Then a standard CNN architecture can be modeled to learn the 3D shape.

Spherical Authalic Parametrization

Why Spherical Parametrization?
- Invariance to viewpoint.

Why Authalic Parametrization?
- Convenient parameterization for computing gradient flows.

How do we do parameterize?
1. Solve a reaction-diffusion equation to get area distortion field
2. Get area restoring vector field from area distortion scalar field
3. Progression of area restoring flow

Creating Geometry Images for CNN Learning

Encoding Geometry Images

Padding Geometry Images

Seamless padding informs CNN about warped geometry and implicitly makes learning robust to cut

Experiments

Cuts & Data Augmentation

Cuts serve to augment data and rotated spherical parametrizations create images which are projected from different viewing directions.

Shape Classification and Retrieval

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