Exploring Generative 3D Shapes Using Autoencoder Networks

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Motivation

- We wanted to see if we could apply Machine Learning to some form of 3D procedural content generation

Umetani, 2017
Motivation

- Learning the 3D shape
  - Finding low dimensional manifold in space

Umetani, 2017
Preview of the Result: Our Latent Space
Parameterization problem

- Shape need to be represented by fixed dimensional vector/tensor

Umetani, 2017
Parameterization problem

- Triangle mesh are not suitable for Machine Learning
  - Topology and Number of points are inconsistent

Umetani, 2017
Related work: Voxel model

- limited resolution / expensive memory cost, noise…

FPNN, Li et al., 2017
3D Shape as Height Field

• Storing XYZ coordinates is redundant
• Height field from a cube in its normal

Umetani, 2017
Hierarchical Projection

• Repeat subdivision and projection to avoid distortion

Umetani, 2017
Our Approach:

• Triangle mesh with constant topology
• Deforming a template mesh into input shape
Our Approach:

- Sphere Normal

Spherical normal $\vec{d}$ are predefined for each vertex.
Subdivision & Projection

Parameter Vector

XYZ positions

Heights

Level 0 Level 1 Level 2 Level 3 Level 4 Level 5
Example of Our Result

Level 5 output

input
Autoencoder

- Input and output of network is as same as possible

{ 0.3, ... 0.1, ... 0.9 }

Configuration of our autoencoder network.

{ 0.3, ... 0.1, ... 0.9 }
Our Result

We obtained over 1,200 Car Shapes from ShapeNet [chang et al. 2015]
Future work

• Advanced generation framework
  • GAN / VAE

• Non-Convex Shapes
Poly Cube

wikipedia.org/wiki/Polycube

Umetani, 2018
References

