3D Shape Retrieval Through Multilayer RBF Neural Network

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Outline

Problem and Overview

Training Data Creation

Deep RBF Neural Network Training

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Problem to solve

Currently most features designed from computer vision community are targeted at 2D images with extensive textures.

A significant number of 3D models contain little or no textures at all

3D models, mainly derived from the 3D point cloud, are too sparse to extract continuous textures

Corner features are generally not applicable for 3D objects retrieval

Most geometry features for 3D models, such as morphable models, are not robust to small curvature changes

Solution Overview

We learn a combination of radial basis functions, which can precisely interpret the curvatures

Each radial base function depicts a local region of the 3D object.

We apply the radial base function (RBF) neural network to learn the radial base functions.

We extract all the mean and variance values of the radial base functions to form a vector, which performs as the feature of the 3D model

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Training Data Creation

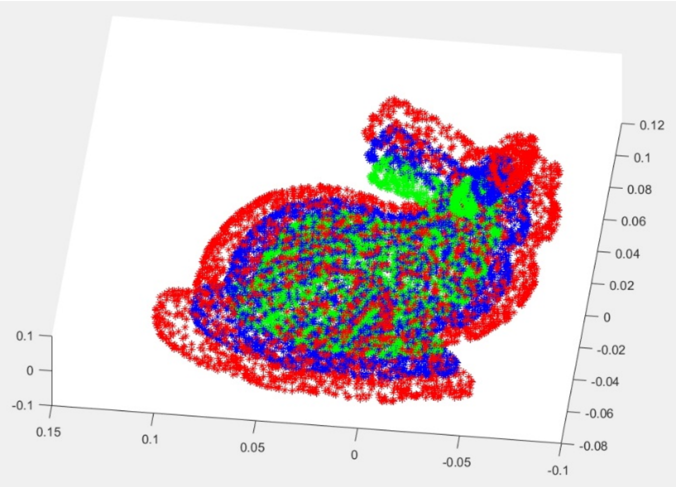
Since our target is 3D models, the boundary points of training models compose the positive samples, which we want to accurately represent.

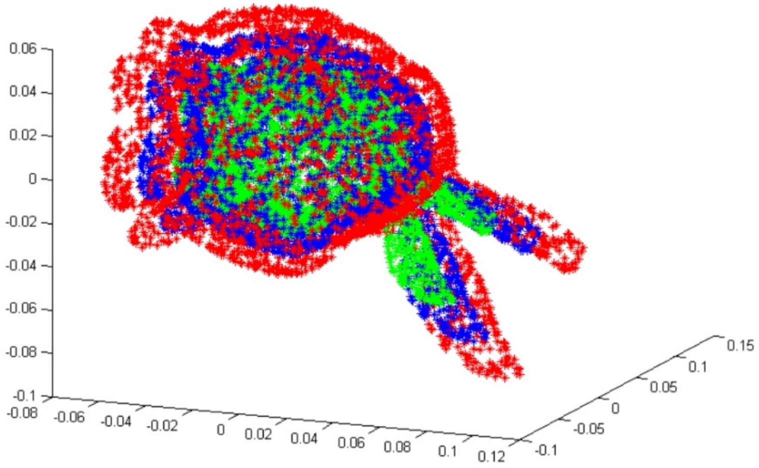
We artificially create negative data by expanding and shrinking the point cloud.

The expanding rate is controlled between 1.1 and 1.2 times the original 3D point position.

The shrinking points are generated by multiplying the original points by a value randomly chosen between 0.8 and 0.9.

Training Data Creation





Our training data sample. Positive data: blue points in the middle boundary. Negative data: red points on the most outside boundary and green points on the most inside boundary.

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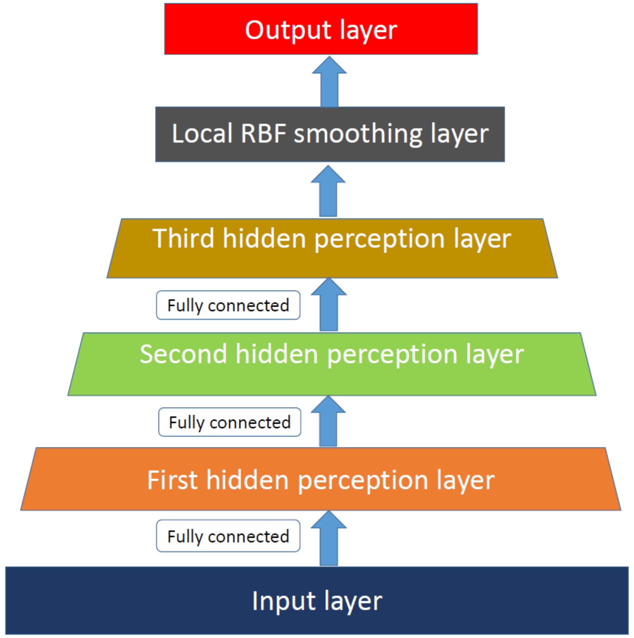
Deep RBF Neural Network Training

With multiple neural network layers, the original non-linear separation issue can be resolved by mapping between the hidden layers.



Our deep neural network training framework, which is composed of an input layer, 3 hidden perception layers, and an output layer

Deep Multiple Layer Perception

Inputs are the 3D points (x, y, z) coordinates

The middle layers are sigmoid functions to map linear input to non-linear.

The output layer is composed by Radial Base Functions. The inputs for output layer are clustered by K-means to initiate the centers of the basis function.

Learning Feature for 3D Object Retrieval

When the learning process converges, the combination of the radial base functions can accurately represent 3D shapes

We extract all the mean and variance values of the RBF functions to form a vector as the feature of the 3D point cloud.

Based on the memory requirement, the output dimensionality can be modified

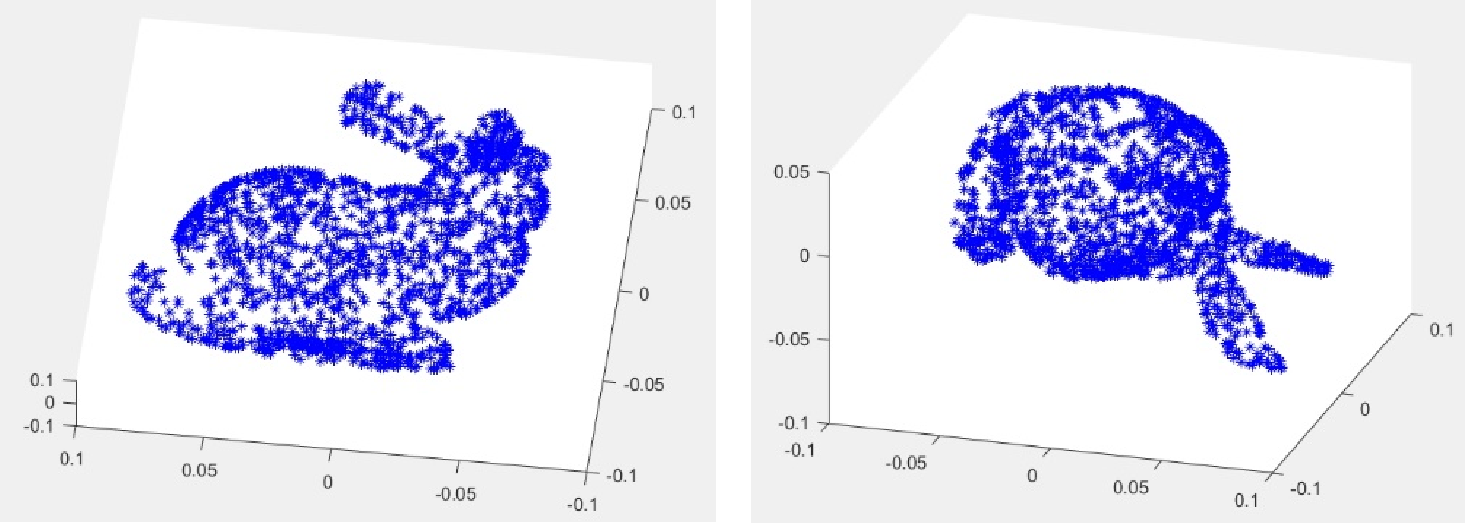
Representing 3D Shape

To recover the shape of the objects, we just fit all the points in the 3D space to the trained neural network.

The points obtaining the distance smaller than a threshold is considered on the boundary of the 3D objects

With a larger number of RBF perceptrons, more detailed curvatures can be depicted.

Representing 3D Shape



The reconstructed point cloud of the bunny 3D model based on the trained deep RBF neural network.

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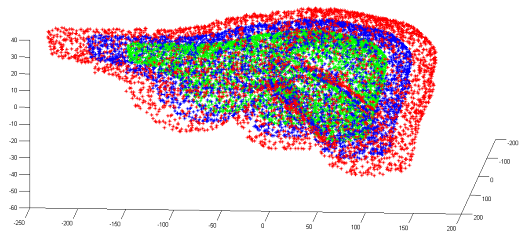
Experiment Setting

We conduct the experiments on the public liver dataset [1], which provides the 3D liver model reconstructed from the CT machine.

There are totally 5 different livers. For each liver, we randomly select 1 percent of the points to make a small change in its original position by multiplying a value in the range of [0.96, 1.04].

For each liver, we repeat this process 100 times, for which 100 samples are created for each liver.

The training liver data is still created through expanding and shrinking the boundary data



[1] Tobias Heimann et al., “Comparison and evaluation of methods for liver segmentation from ct datasets,” TMI, vol. 28, no. 8, pp. 1251–1265, 2009.

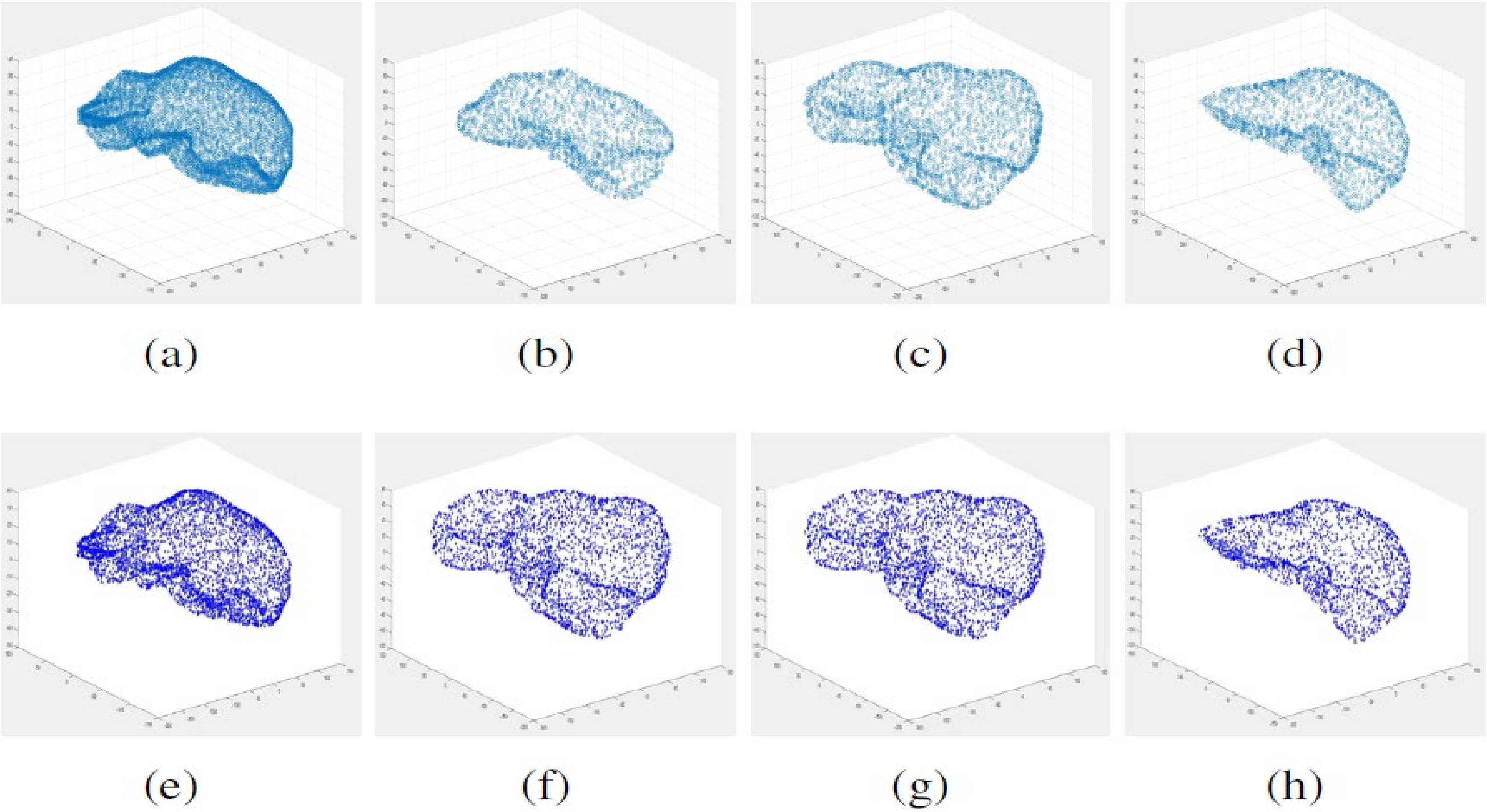
Experiment Setting

We mark the original boundary points as 1 and the expanded and shrunk points as -1, which are the labels for points.

For each liver, we apply 40 samples for training and 60 samples for testing

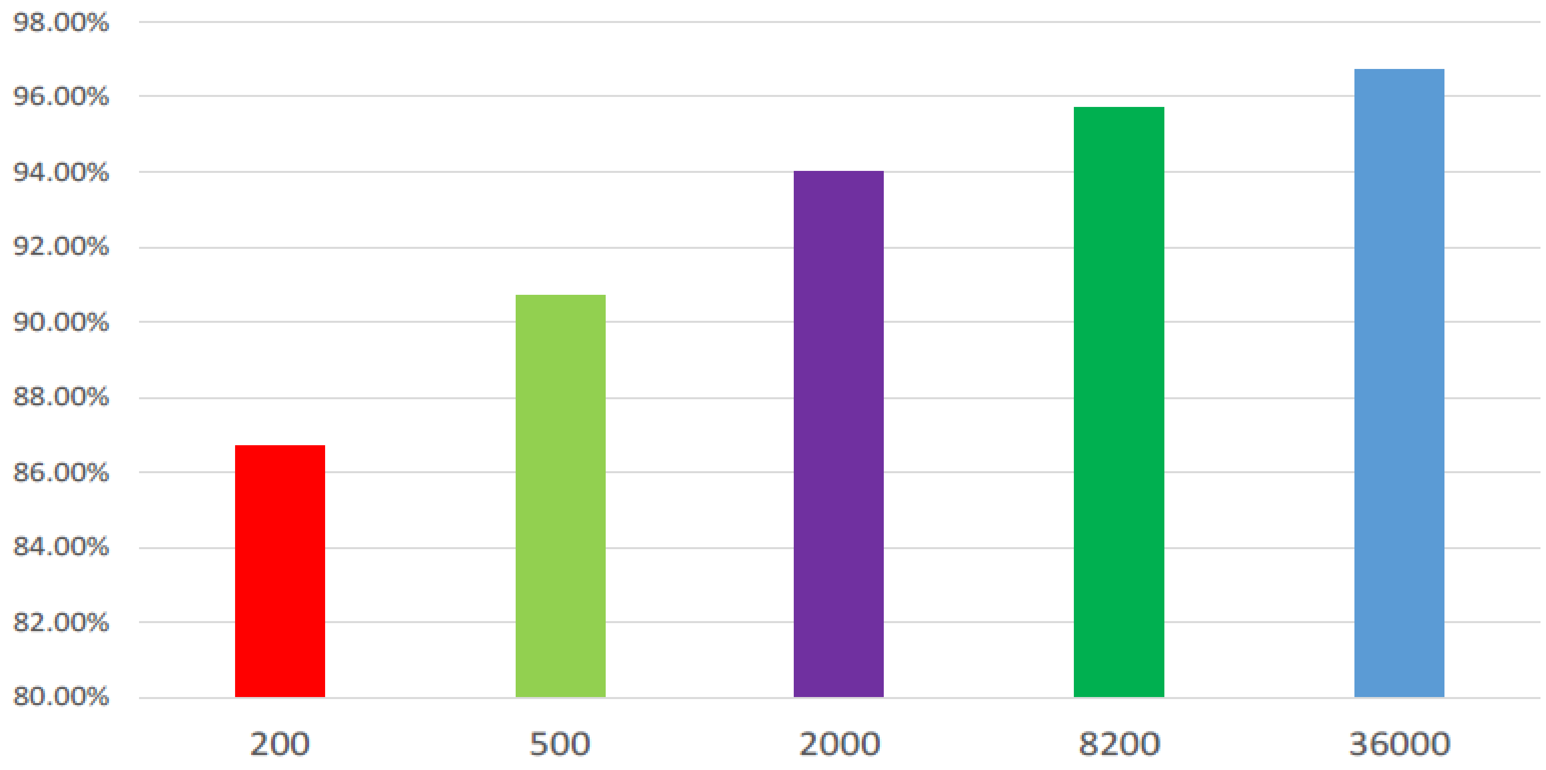
Here, we apply 500 output radial base functions

3D Model Recovery



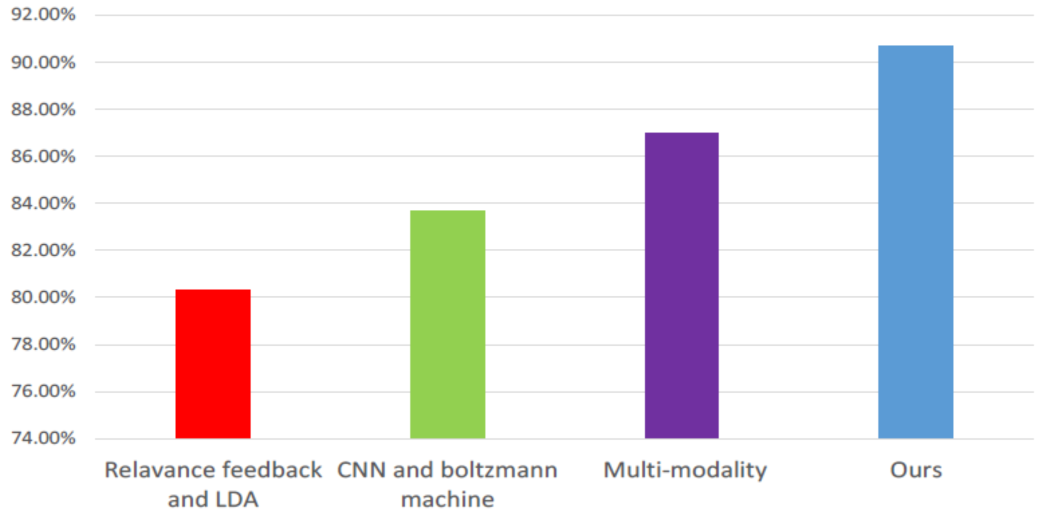
The original 3D models (a, b, c, d) and correspondingly the reconstructed 3D models (e, f, g, h).

Affect of RBF number



Retrieval accuracy based on different numbers of radial base functions.

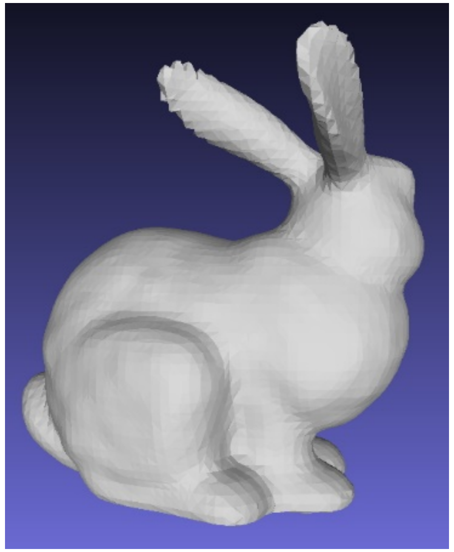
Comparison with Recent State-of-the-art Methods

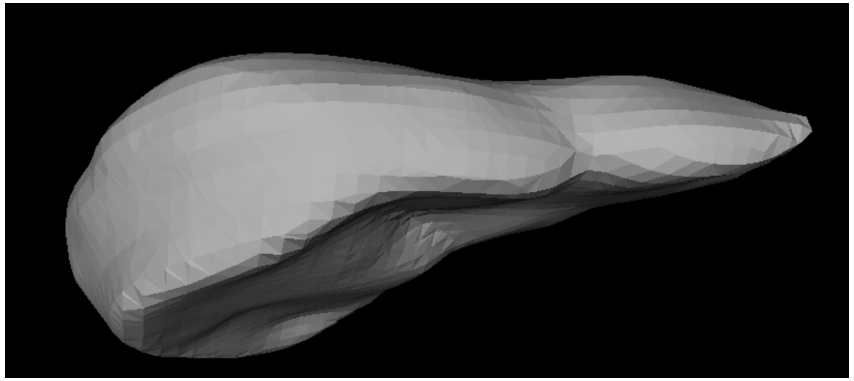


Retrieval accuracy comparison with other state-of-the-art methods (relevance feedback and LDA, CNN and Boltzmann machine, and multi-modality).

relevance feedback and LDA: Biao Leng, Jiabei Zeng, Ming Yao, and Zhang Xiong, “3d object retrieval with multitopic model combining relevance feedback and lda model,” IEEE Transactions on Image Processing (TIP), vol. 24, no. 1, pp. 94–105, 2015.
CNN and Bolzmann Machine: Zhizhong Han, Zhenbao Liu, Junwei Han, Chi-Man Vong, Shuhui Bu, and Xuelong Li, “Unsupervised 3d local feature learning by circle convolutional restricted boltzmann machine,” ,” IEEE Transactions on Image Processing (TIP), vol. 25, no. 11, pp. 5331– 5344, 2016.
Multi-modality: Shuhui Bu, Lei Wang, Pengcheng Han, Zhenbao Liu, and Ke Li, “3d shape recognition and retrieval based on multi-modality deep learning,” Neurocomputing, 2017.

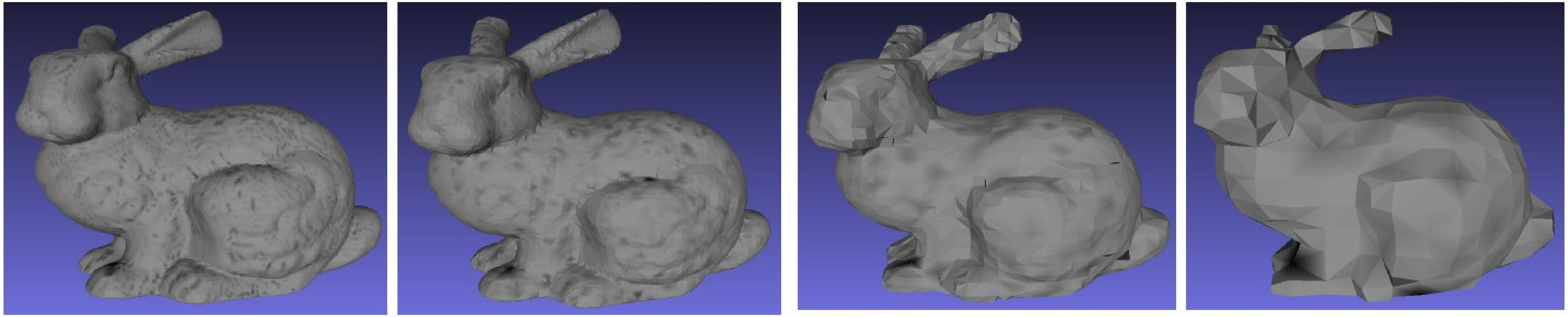
Poisson Reconstruction Model





Poisson reconstruction model based on RBF reconstructed model.

Reconstruction based on Different Number of RBF Functions



(a) (b) (c) (d)

Poisson reconstruction models based on different number of radial base functions: (a) 36000 RBF; (b) 8200 RBF; (c) 2000 RBF; (d) 500 RBF.

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We design a feature to represent the 3D models based on the parameters of radial base functions;

The combination of radial base functions are learned from the RBF neural network

The parameters of the RBF neural network is optimized through a multiple layer setting.

Thank you.

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