

TECHNISCHE UNIVERSITÄT KAISERSLAUTERN

MASTER THESIS

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# Improved Normal Inference from Calibrated Illuminated RGBD Images

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August 10, 2022



## Declaration of Authorship

I, Jingyuan SHA, declare that this thesis titled, “Improved Normal Inference from Calibrated Illuminated RGBD Images” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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TECHNISCHE UNIVERSITÄT KAISERSLAUTERN

## *Abstract*

Augmented Vision  
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Master of Science

### **Improved Normal Inference from Calibrated Illuminated RGBD Images**

by Jingyuan SHA

In this work, a learning based approach for surface normal estimation based on illuminated calibrated RGB-D images is proposed.

This approach extends the geometry based approach by techniques of photometric stereo, which uses calibrated illuminated images for normal estimation. The two types of data gives a superior performance on normal inference task. One of the key points of our approach is, the proposed method require only one light source for each scene capture instead of multiple light sources, which can be very easy to configure in the practice.

Our model is trained on a gated convolution neural network (Trip-Net). The gated convolution design is intended to handle the missing pixels in the depth map, which is a common defect of the depth sensor. We also created a dataset of 55 point clouds called *Synthetic-50-5* for training. We trained our model on this synthetic dataset and then applied it to a real dataset. Finally, a qualitative and quantitative evaluation is performed.



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## Chapter 1

# Introduction

In 3D computer vision tasks, the *point cloud* (i.e., an unstructured set of 3D points representing the surfaces in the scene) is a common input file to describe the object surface. Based on the geometry information in the point cloud, we can calculate the corresponding surface normal, which is an important feature in computer vision. The surface normal can be used for surface reconstruction, shading generation and other visual effects. The common method for determining the surface normal from the point cloud is the optimization approach, which considers the neighboring points in the same plane and calculates the surface normal.

However, for single input data with only one shot, such as the data acquired by a depth camera, the point cloud is converted from a depth map and the given calibration information. In the case of active depth sensors, the depth map is usually only semi-dense due to optical noise and reflections in dark and shiny areas of the object surface, missing many pixels and holes. This limits the neighborhood-based approach because the missing data results in a smaller number of neighbors for each point. However, recent advances in the field of image inpainting have motivated researchers to use deep neural networks to recover the missing regions in the input data and achieve good performance. For example, [35] uses a gated convolution network to recover user-defined removed regions in the images. [16] uses a normalized convolution network to extend the semi-dense depth map to a fully dense depth map. In both cases, incomplete input data is used and converted to a fully dense output. Therefore, a Deep Learning based approach can be a way to deal with semi-dense depth maps for surface normal estimation tasks.

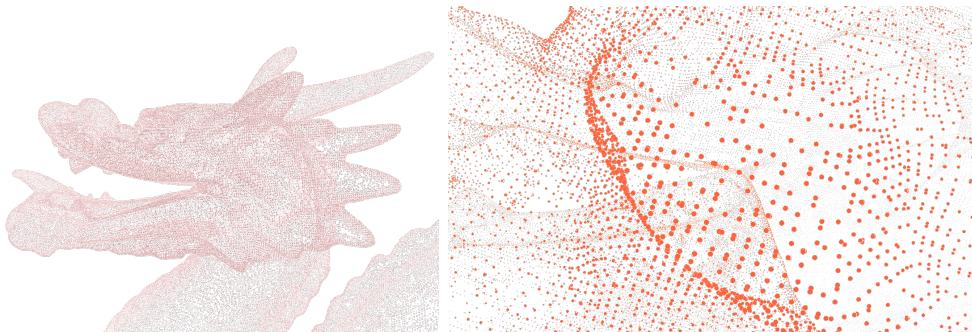


Figure 1.1: Left: A portion of the point cloud of the *dragon* object. Right: Zoom in of the point cloud.

Photometric stereo is another approach in computer vision that can be used for estimating surface normals, where the normals are derived from appearance variations under different illuminations. The corresponding methods are usually solved using the least squares problem, which is based on the point-wise image formation

model [11] and on the assumption of the Lambert surface. However, the Lambert surface generally cannot account for global illumination effects, which is an unavoidable problem due to light interactions.

Both of the above directions have been widely explored using deep learning approaches. However, the approach that considers both geometry and illuminated information for normal estimation remains insufficient. We present a Deep Learning based approach that considers both geometric and photometric information for normal inference. For practical reasons, we consider a semi-dense depth map with only one additional illuminated image based on the calibrated camera as input data to find a compromise between the two methods.

One of our challenges is to apply the semi-dense input data to the neural network in an image-aware manner. *U-Net* is a good network for computer vision tasks with up-sampling requirements. We modified it with a gated activation unit called *gated convolution layer (gconv)* to handle semi-dense input data. Another challenge is to merge the different feature maps of the input data to cooperatively improve the surface normal inference task. We propose a *multi-fusion* scheme for integrating separate feature maps. We will show that this *multi-fusion* design can be leveraged by combining different input data types and improving the performance of surface normal inference. To train our network, we create a synthetic RGB-D image dataset by using a light source and ambient light illumination to simulate application scenarios. To simulate depth maps in the real world, we added uniformly distributed drop-out noise to the input data, with the noise density controlled by a parameter.

We trained our models on our proposed synthetic dataset *synthetic-50-5* and evaluated them on 6 different metrics. The results show that our approach based on calibrated illuminated RGB-D images further improves the normal accuracy. We also applied our model to a real dataset and compared it with the optimization-based approach.

The structure of the paper is as follows: In Chapter 2, we briefly discuss related work on the normal inference task. Chapter 3 briefly introduces a traditional optimization-based approach and photometric stereo, and then proposes two learning-based approaches for surface normal estimation. Chapter 4 presents the dataset created for the training work and its preprocessing. Chapter 5 analyzes the experiments and provides both qualitative and quantitative evaluations of the models. Chapter 6 is the summary of the entire thesis.

## Chapter 2

# Related Work

Surface normal inference is a widely researched topic and can be solved in several ways. Traditionally, it can be derived from a point cloud. There are many optimization-based approaches to computing surface normals pixel-by-pixel using neighborhood information. [15] gives a comparison between some of these approaches. [10] proposed a method of using local neighbors with an interest parameter  $p$  and derives the surface normal from the eigenvectors of the corresponding covariance matrix. These approaches work well for dense input data based on a well-chosen window size. However, in many practical datasets such as NYU Depth Dataset V2 [28] and KITTI-Depth[32], the point clouds are often converted from depth maps. But the depth maps are usually very noisy and contains many missing pixels and holes in dark, shiny, or transparent areas. This poses more of a challenge for neighborhood-based approaches, as neighborhood information is not available in many of these areas.

To solve this problem, some approaches focus on improving the depth map by estimating missing regions. [34] proposed an approach that considers the depth distributions of neighboring regions to fill the holes in the depth map. [4] uses a deep learning-based approach for painting semi-dense depth maps, which mainly uses the normalized convolution proposed by [16]. This approach considers a 0-1 mask to distinguish valid and invalid data points. [6] improved this approach by proposing an input confidence estimation network to replace the binary mask with an estimated confidence mask. [12] also uses a normalized convolution for inpainting the depth map and also uses an RGB image as a guidance.

On the other hand, some of the approaches use RGB-D images to estimate the surface normal or use RGB images to estimate the fully dense depth map. [3] proposed a two-level network for predicting the depth map based on RGB images, where the global and local features of the object are considered separately. [17] also predicts the depth map from the image, using a residual network for feature extraction and developing an up-sampling part with the un-polling layers. [18] proposed a method that adaptively generates depth map prediction information based on RGB images. [7] uses RGB-D images to estimate surface normals. It proposes a method for learning discriminative and geometrically informative primitives from RGB-D images, which is then used to recover the surface normals of a scene from a single image. [25] uses ResNet [8] to derive a coarse surface normal from an RGB image, and refines it using a depth map based on the [7] method. [36] derives surface normals based on an RGB-D image using the *U-Net* architecture.

However, these approaches mainly rely on RGB images as input for estimating the normal or the full depth map. The applied scenarios are mainly indoor scenes such as bedrooms or offices, where the focus is not on the fine details of the object surface, but only on the main directions of each area, such as the directions of the floor, walls, or seats, etc as shown in Figure 2.1

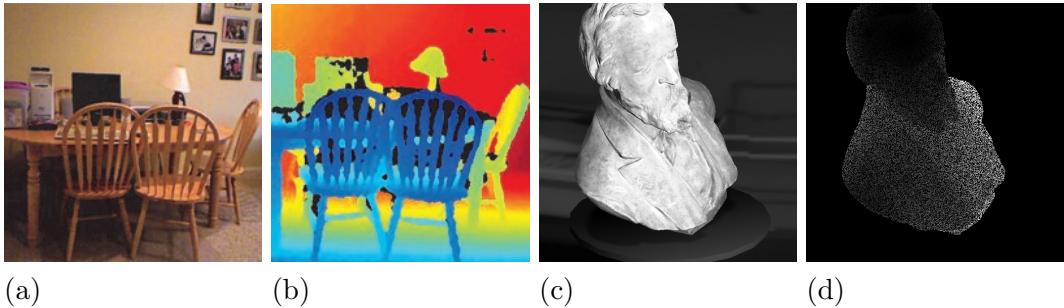


Figure 2.1: (a)-(b): Output from the RGB camera (a) and depth camera (b) of a scene in *NYU Depth Dataset V2* [28]. (c)-(d): Output from the gray-scale camera (c) and depth camera (d) of a scene in our proposed dataset *synthetic-50-5*.

Photometric stereo is another approach that derives the surface normal from the BRDF-based surface model. The surface normal is related to the observed intensity, the direction of incident light, the direction of outgoing light, and the light intensity. Several light conditions are required to obtain an optimal solution. [13] uses a CNN-based approach to learn the relationship between photometric stereo input and the surface normal under hundreds of lighting conditions, which is also robust to the effects of global illuminations. [37] is based on an illumination interpolation network to use only a sparse set of lights for photometric stereo tasks.

Our approach uses an RGB-D image but known light direction and calibrated information for surface normal inference, which considers multiple input data types into account for the estimation.

## Chapter 3

# Approaches

The normal inference task involves estimating the surface normal of a 3D object, assuming that the surface of the object is mathematically unknown. This means that we cannot simply use the cross product of two non-parallel surface vectors to find the normal. Instead, the surface is sensed by digital sensors under certain types of data, which can be divided into two groups. The first group is geometry data, where a point cloud is used to capture the geometry information of the surface in 3D space. The approach that uses point clouds for normal estimation is called geometry-based approach. Another type of data is images that record the reflectance and shading of the surface under the following lighting conditions. The surface normal is calculated based on specific light models such as BRDF. The other approach, which uses the relationship between reflectance and shading to calculate the surface normal, is called photometric stereo.

In this chapter, the geometric and photometric stereo based approaches are presented separately. Then, a method for estimating the surface normal using both types of data based on deep learning approaches is introduced.

### 3.1 Notations

In the following chapters of this thesis the following standard notations are used. The bold capital letters stand for matrices, while the bold lowercase letters stand for vectors. The Greek capital letters stand for planes. The subscript  $i = \{1, 2, \dots\}$  stands for the index of observations, the superscript for the dimension of the matrices or vectors, e.g.  $\mathbf{n}^{3 \times 1}$  for a vector of dimension 3 *times* 1. We use  $W$  for the width,  $H$  for the height and  $C$  for the number of channels.

### 3.2 Geometry-based Normal Estimation

Geometry-based normal estimation uses the point cloud of the object surface as input. The task can be formulated as follows.

Given a structured point cloud  $\mathbf{V}^{W \times H \times 3}$ , in which the 3D point positions are stored with respect to the image grid. We want to compute the corresponding normal map  $\mathbf{N}^{W \times H \times 3}$ . The normal map is simply a matrix representation of the normals of all points in the point cloud. A normal  $\mathbf{n}^{3 \times 1}$  at the point  $\mathbf{p}^{3 \times 1} \in \mathbf{V}$  is a unit vector whose direction is outward from the surface and perpendicular to the tangent plane of the surface at point  $\mathbf{p}$ .

The idea behind the neighborhood-based method is to fit a plane  $\tilde{\Pi}$  containing the  $k$  neighbors  $\mathbf{p}_1, \dots, \mathbf{p}_k \in \mathbb{R}^{3 \times 1}$  of the point  $\mathbf{p}$ , then compute the normal  $\tilde{\mathbf{n}}$  of the plane  $\tilde{\Pi}$ . The  $\tilde{\mathbf{n}}$  is considered as an approximation to the normal  $\mathbf{n}$  of the tangent plane  $\Pi$ .

The point and its neighbors are assumed to lie in the same plane  $\Pi$ , which is exactly the tangent plane of the surface at the point  $\mathbf{p}$ . This is usually not true for most of the surface, since the surface is usually not flat, but has some degree of curvature. But if  $k$  is of a suitable scale and the point cloud is dense enough, we can approximately consider all  $k$  neighboring points in a small area on the same tangent plane. Then we have an approximation  $\mathbf{n} \approx \tilde{\mathbf{n}}$ , where  $\tilde{\mathbf{n}}$  denotes the estimated normal. Similarly, the estimated tangent plane  $\tilde{\Pi} \approx \Pi$ .

Based on the above assumption, the task of normal inference is trivial, since the surface is then mathematically describable. We can generate the approximate tangent plane at each point with its neighbors, then the normal  $\tilde{\mathbf{n}}$  of the tangent plane can be derived from the following equations.

$$\tilde{\mathbf{n}} \cdot \mathbf{v}_{ij} = 0$$

where

$$\mathbf{v}_{ij} = \mathbf{p}_i - \mathbf{p}_j, \text{ for } i, j \in \{1, 2, \dots, k\}, i \neq j$$

To find a normal, we need at least 3 neighbors that are not on the same line to solve the above equation. Calculate the normal for each point on the point cloud, then we can get the corresponding normal maps.

If we consider more than 3 neighbors, the points are usually not on the same plane. In this case, the system of equations is overdetermined. We can use the optimization approach to find a plane that has the least distance to all points in 3D space. By  $\mathbf{A} \in \mathbb{R}^{k \times 3}$  we denote the vector matrix vertically stacked by the  $k$  vectors we found on the approximated tangent surface. Then the system of equations is transformed into an optimization problem

$$\begin{aligned} \min \quad & \| \mathbf{A}\mathbf{n} \|_2^2 \\ \text{s.t.} \quad & \| \mathbf{n} \|_2^2 = 1 \end{aligned} \tag{3.1}$$

where the additional condition is added to avoid trivial solutions, and the normal is supposed to be a unit vector.

The above problem can be solved by singular value decomposition (SVD), where.

$$\mathbf{A} = U\Sigma V^T$$

The last column of  $V$  is the solution of the system of equations and consequently the surface normal.

The optimization based approach using SVD is more robust compared to selecting only 3 points for normal computation, since the plane generated by 3 neighbors is not guaranteed to be a good approximation to the actual tangent plane. However, the size of the neighbors  $k$  is a key parameter of this approach. For the smooth surface, a relatively larger  $k$  can help the system of equations find a plane that is closer to the tangent plane. For the sharp surface,  $k$  must be small enough to ensure that the points it contains are still approximately in the same plane, otherwise the more points it contains will just be the outliers for the equation solution.

Finally, after solving the above equation, we should convert all normals to the viewpoint  $\mathbf{s}$  for uniformity. Thus, the direction of a normal should be inverted if

$$\mathbf{n} \cdot (\mathbf{p} - \mathbf{s}) > 0 \tag{3.2}$$

Since the above approach is essentially solved by SVD, this method will be referred to as *SVD* in the remainder of the paper for simplicity.

### 3.3 Photometric Stereo based Normal Estimation

Photometric stereo was originally introduced by [33] and is a completely different approach from the geometry information based approach such as *SVD*. It estimates the surface normal of the object by observing the object in the same position under different illuminated conditions. It is based on the fact that the light reflected from a surface depends on the surface normal and the light direction.

Before presenting this approach, let us discuss what we can actually obtain from the images. An image  $\mathbf{I}$  can be decomposed into two parts: the reflectance  $\mathbf{R}$  and the shading  $\mathbf{S}$ ,

$$\mathbf{I} = \mathbf{R} \odot \mathbf{S}$$

where  $\odot$  denotes the element-wise product. This decomposition of the image is based on the intrinsic image model proposed by [1]. It interprets the observed image into a reflection image and a shading image. Figure 3.1 shows a visualization of the decomposition.

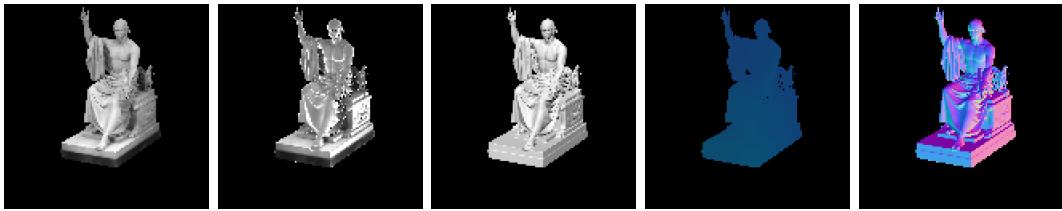


Figure 3.1: Intrinsic image analysis of the Washington object. From left to right: original image, reflection image, shading image, light image, normal image.

The equation can be further decomposed based on different surface models. If we assume that the object surfaces are Lambertian surfaces, i.e. surfaces that reflect light in all directions, as shown in Figure ??, then the reflectance is equal to the albedo  $\rho$ , the shading image can be decomposed as the product of the radiance of the incident light  $L_0$  and the cosine of the angle of incidence, which is the dot product of the surface normal  $\mathbf{N}$  and the light source direction  $\mathbf{L}$ .

$$\mathbf{I} = \rho \odot (L_0 \mathbf{L} \cdot \mathbf{N})$$

Note that each surface normal in the matrix  $\mathbf{N}$  and each light direction in the matrix  $\mathbf{L}$  is a unit vector, so they have only two degrees of freedom.

The equation can be rearranged as follows

$$\mathbf{I} = (L_0 \rho \odot \mathbf{N}) \cdot (\mathbf{L})$$

Let  $\mathbf{G} = L_0 \rho \odot \mathbf{N}$ , the equation simplifies to

$$\mathbf{I} = \mathbf{G} \cdot \mathbf{L}$$

If we use a set of  $k$  images for the same scene, taken based on different light projections. Then, for each pixel  $(x, y)$  in a scene, we can set up a system of equations

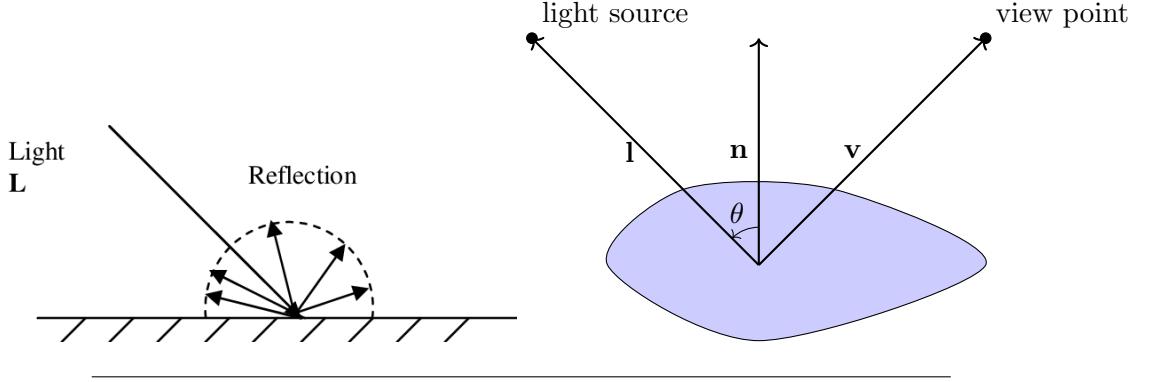


Figure 3.2: Left: the reflection of light on a Lambertian surface. (Image source [20]). Right: the surface normal, the light direction of the source and the viewing direction, where  $\theta$  denotes the angle between the light direction and the normal.

$$\begin{pmatrix} \mathbf{l}_1^T \\ \mathbf{l}_2^T \\ \dots \\ \mathbf{l}_k^T \end{pmatrix} \mathbf{G}(x, y) = \begin{pmatrix} \mathbf{I}_1(x, y) \\ \mathbf{I}_2(x, y) \\ \dots \\ \mathbf{I}_k(x, y) \end{pmatrix}$$

For simplicity,  $\mathbf{l}_i^T$  for  $1 \leq i \leq k$  denotes the direction of light at position  $(x, y)$  in  $k$ -th image . The equation can be solved using the least squares method. Then, the albedo can be determined with the light intensity, since the normal is a unit vector,

$$\|\mathbf{G}(x, y)\|_2 = \|L_0 \rho(x, y) \mathbf{N}(x, y)\|_2 = L_0 \rho(x, y)$$

Then the normal can be determined as follows

$$\mathbf{N}(x, y) = \frac{\mathbf{G}(x, y)}{L_0 \rho(x, y)}$$

We compute the surface normal for each point to obtain the surface normal map.

This approach is also called Shape from Shading (*SFS*) [11]. Both normal maps and the corresponding albedo are obtained from a series of images under different lighting conditions. Since the direction of light is used in the calculation, the cameras and the position of the light source must be calibrated beforehand.

In the shape from shading approach, at least three light positions are considered for normal estimation on a pixel. It is also common to use more than three light sources to cover most points of the surface as much as possible.

We assume that in each neighborhood there is a coherent behavior for the albedo that can be modeled by the filters in the neural network, and in the following section we propose an learning based approach for normal inference from geometry information, but using only one illuminated scene.

### 3.4 Gated Convolution Neural Network for Surface Normal Estimation

Recently, Deep Learning based methods have achieved great success in image processing[26], [30]. These network architectures use a stack of RGB/grayscale images as input and are used for classification problems. Typically, the images are convolved with convolutional layers and sampled with pooling layers. The output values of the networks consist of a single value representing the index of the corresponding class, or a set of values representing the position of the bounding boxes[26]. However, in many other image processing tasks, such as inference of normal maps, the output is required to have the same form as the input, while each pixel in the output image requires a prediction. Therefore, the output consists not only of one or several labels, but of a matrix similar in size to the input. In this case, the traditional network architecture with full connections in the last layers is no longer suitable for label prediction.

[27] has proposed an architecture called *U-Net* for biomedical image segmentation. The architecture is shown in Figure 3.3. This net has a very regular architecture for data processing, while the down/up sampling part has a similar design. For the feature extraction part, called down-sampling, the architecture follows the traditional CNN architecture. For the up-sampling part, the network uses an architecture similar to the down-sampling operations, which uses the same convolutional operations but replaces the max-pool layers with up-conv layers. An important design is the skip connection in the up-sampling part. The feature maps extracted in the down-sampling part are concatenated with the feature maps in the up-sampling part. This helps the network to find the locations in the original image and use them to predict a sharp output.

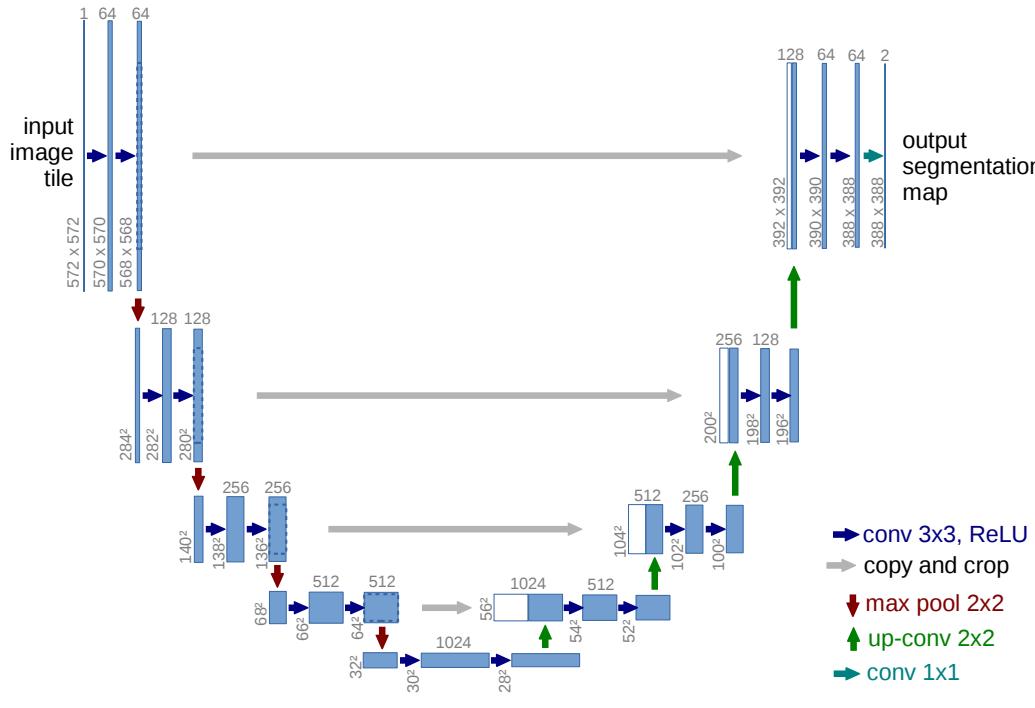


Figure 3.3: The structure of UNet. [27]

The *U-Net* relies on standard convolutional layers to construct the network. This is useful for image processing tasks with fully dense input data, since there are no

missing pixels. However, for some other input data, such as depth maps acquired by light scanners, it is not always fully dense data, but data with many missing pixels and holes. In this case, we can still apply the standard convolutional layers to extract the feature maps from the semi-dense depth map, but then the valid pixels and the invalid pixels (the missing pixels) will be mixed up during training, resulting in blur and color discrepancy as mentioned by [19]. Therefore, it is useful to find a way to distinguish the valid and invalid pixels during training.

[5] use a binary mask to denote valid pixels, and also use normalized convolution as a surrogate for the default convolutional layer in the training model. The normalized convolution is represented as follows

$$O(x, y) = \begin{cases} \frac{\sum_i^k \sum_j^k W(i, j) \odot I(x - i, y - j) \odot M(x - i, y - j)}{\sum_i^k \sum_j^k W(i, j) \odot M(x - i, y - j)}, & \text{if } \sum_i^k \sum_j^k M(i, j) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

where  $k$  is the kernel size,  $(x, y)$  is the position in the input,  $(i, j)$  is the displacement in the kernel, and  $M$  is the corresponding mask. A binary mask uses 1 to indicate valid pixels, and 0 otherwise.  $\odot$  denotes element-wise multiplication.

### 3.4.1 Gated Convolution

[23] proposed a gated activation unit to model more complex interactions compared to standard CNN layers. This was mainly inspired by the multiplicative units that exist in the Long Short-Term Memory (*LSTM*) proposed by [9] and the Rated Recurrent Unit (*GRU*) proposed by [2]. [35] has deployed the same gated unit and uses it as a gated convolution layer for training tasks with incomplete input data, such as image inpainting tasks. In this gated convolution layer, the mask used to distinguish between valid and invalid pixels is not specified in advance, but learned during training. The advantage is that the erroneous measurements that are not masked in the depth data can be learned during training to further improve performance.

The structure is shown in Figure 3.4. Instead of using a mask as input to indicate valid pixels, a standard convolutional layer is used to learn this mask directly from the data, and a sigmoid function is used as an activation function to indicate the confidence of pixel validation. Meanwhile, another standard convolutional layer is set aside to learn the feature maps with a ReLU/LeakyReLU activation function. Therefore, both the mask and the input features are learned during training. Then, an element-wise multiplication is performed with the feature map and the mask as the final feature map of this gated convolution layer.

Formally, the gated convolution is described as follows: the layer with the input  $(N, C_{in}, H, W)$  and the output  $(N, C_{out}, H_{out}, W_{out})$ :

$$o(N_i, C_{o_j}) = \sigma\left(\sum_{k=0}^{C_{in}-1} w_g(C_{o_j}, k) * i(N_i, k) + b_g(C_{o_j})\right) * \phi\left(\sum_{k=0}^{C_{in}-1} w_f(C_{o_j}, k) * i(N_i, k) + b_f(C_{o_j})\right) \quad (3.4)$$

where  $\phi$  is the LeakyReLU function,  $\sigma$  is the sigmoid function, so the output values are in the range  $[0, 1]$ .  $*$  is the valid 2D cross-correlation operator,  $N$  is the batch size,  $C$  denotes the number of channels,  $H$  is the height of the input planes in pixels, and  $W$  is the width in pixels,  $w(C_{o_j}, k)$  denotes the weight of the  $j$ -th output channel corresponding to the  $k$ -th input channel,  $i(N_i, k)$  denotes the input of the  $i$ -th stack

corresponding to the  $k$ -th input channel,  $b(C_{o_j})$  denotes the bias of the  $j$ -th output channel.

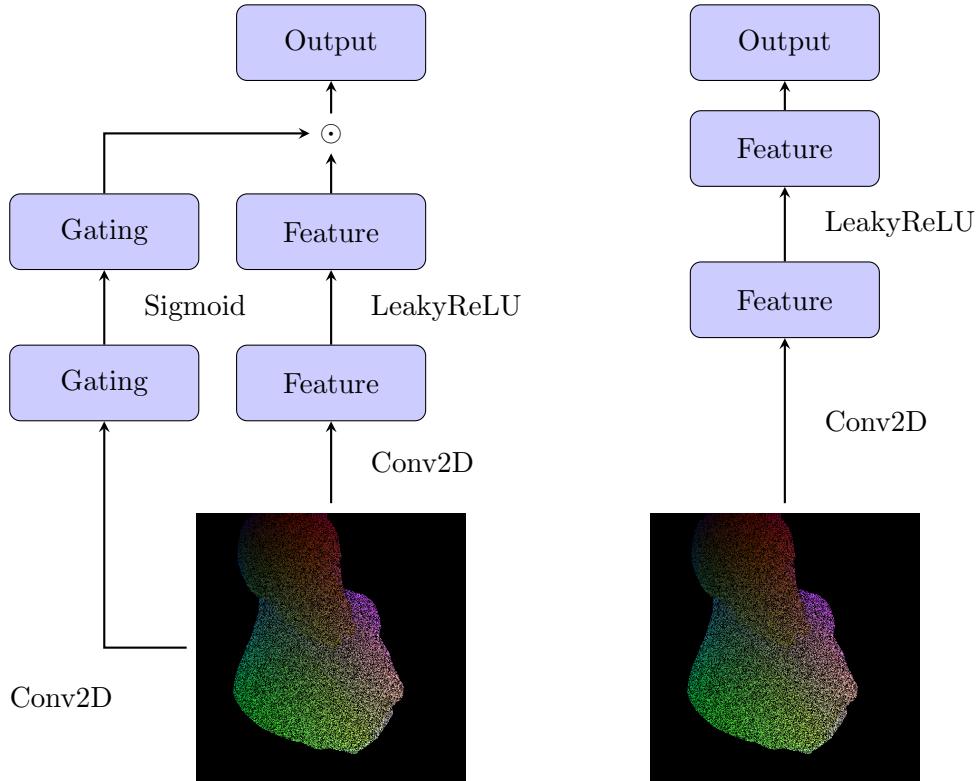


Figure 3.4: Left: Gated Convolution Layer, where  $\odot$  denotes element-wise multiplication. Right: standard convolution layer.

### 3.4.2 GCNN Architecture

Based on the above implementation, we proposed a network based on the *U-Net* proposed by [27], replacing the standard convolutional layers with gated convolutional layers used for semi-dense normal inference tasks, called gated convolution neural network (*GCNN*), as shown in Figure 3.5.

To describe the network in a uniform way, the parameters of the network are represented by letters. The network consists of a downsampling part and an upsampling part. In the downsampling part, the input has the form  $\mathbf{X}_{in} \in \mathbb{R}^{H \times W \times C_{in}}$ , while the output is of the form  $\mathbf{X}_{out} \in \mathbb{R}^{H \times W \times C_{out}}$ . The input matrix goes through 3 down-samples. A down-sampling block consists of two gated convolution layers with stride (1,1) and an additional gated convolution layer with stride (2,2) to reduce the resolution of the feature map. Thus, there are a total of 3 gated convolution layers in each downsampling operation. The total of three downsamplings extract the geometry features  $\mathbf{X}_f$  from the input matrix  $\mathbf{X}_{in}$  (represented as regression function  $f$ )

$$f : \mathbf{X}_{in} \rightarrow \mathbf{X}_f$$

After feature extraction, the network upsamples the feature map three times to obtain the output matrix  $\mathbf{X}_{out}$ . Each upsampling consists of an interpolation operation that uses nearest neighbor interpolation for upsampling the feature map, and a concatenation layer that concatenates the interpolated result and the corresponding

high-resolution feature map  $\mathbf{X}_{df_1}, \mathbf{X}_{df_2}, \mathbf{X}_{df_3}$  from the downsampling part. This is also called a skip connection. In the last step, a gated convolution layer is used to reduce the channel size to fit the next upsampling block. After upsampling three times, the resolution goes back to the original size. After that, two standard convolutional layers without activation function are added to predict the surface normals. The entire upsampling branch can be represented as a regression function  $n$ ,

$$n : \mathbf{X}_f, \mathbf{X}_{df_1}, \mathbf{X}_{df_2}, \mathbf{X}_{df_3} \rightarrow \mathbf{X}_{out}$$

All convolutional layers of the network use the same kernel size  $3 \times 3$ .

One of the main features of the network is that the output has the same size as the input. This is achieved by (1,1) padding and the same number of channels in the convolution layers. Thus, the surface normal can be estimated 1:1. Another important point of the network is its robustness to noise using gated convolutional layers. The network can take a semi-dense matrix as input and then predict the fully dense matrix as output. The last feature is the multipurpose use of scenarios. No specific input type is given in the description. The network is also fully convolutional and therefore can accept different input resolutions.

## 3.5 Illuminated Calibrated RGB-D Image based Normal Inference

The GCNN architecture is designed for one type of input, since it has only one pipe to process the data. In our work, the input refers to a structured point cloud. Therefore, it is suitable for a geometry-based approach that uses the point cloud as input and estimates the corresponding surface normal. However, as mentioned in the introduction, the goal of this work is to discuss the improvement of normal inference based on an illuminated calibrated RGB-D image, i.e., we want to see if we can improve the performance of normal estimation not only based on geometry information such as the point cloud or the depth map, but also with illumination information such as the image and the light map. Therefore, we need to find an architecture that takes into account all these types of data.

### 3.5.1 Light Map, Gray-scale Image and Vertex Map

First, we present the required input types for our network.

**Vertex Map** The vertex map  $\mathbf{V}$  is converted from the depth map presented in chapter 4, while the depth map is acquired from a depth camera. It contains a set of surface point locations in 3D space. Each pixel in the vertex map corresponds to a point position. These vertices contain the geometry information of the object surface, which can be further used for training deep learning models. For each scene, the camera takes only one image, leaving only one vertex map. However, as mentioned earlier, the vertex map is only semi-dense. We use such a semi-dense vertex map as input for the surface normal estimation.

**Grayscale Image** The grayscale image  $\mathbf{I}$  is acquired in correspondence with the depth map using the same calibrated camera equipment, so the intrinsic matrix  $\mathbf{K}$  and the extrinsic camera matrix  $[\mathbf{R}|\mathbf{t}]$  are known. Unlike the vertex map, it is usually completely dense.

**Light Map** The light map  $\mathbf{L}$  can be derived from the vertex map  $\mathbf{V}$ . The position of the light source  $(s_x, s_y, s_z)$  is given by the input data. As shown in Figure 3.2, the direction of the incident light is a vector point from the light source to the surface point and can therefore be calculated as follows.

$$\mathbf{L}(x, y, z) = \frac{\mathbf{V}(x, y, z) - (s_x, s_y, s_z)}{\|\mathbf{V}(x, y, z) - (s_x, s_y, s_z)\|_2} \quad (3.5)$$

where both  $(s_x, s_y, s_z)$  and  $\mathbf{V}$  refer to the camera space. The light direction map  $\mathbf{L}$  is normalized since only the direction of the light is considered. Applying the above equation for all pixels in the point cloud, we obtain the corresponding light map, which is a matrix with the same size as the point clouds. However, it should be noted that the light map is calculated based on the vertex map, while the vertex map in the training pipeline is only semi-dense, so the light map is also semi-dense and has the same noise feature as the vertex map, as shown in Figure 3.6.

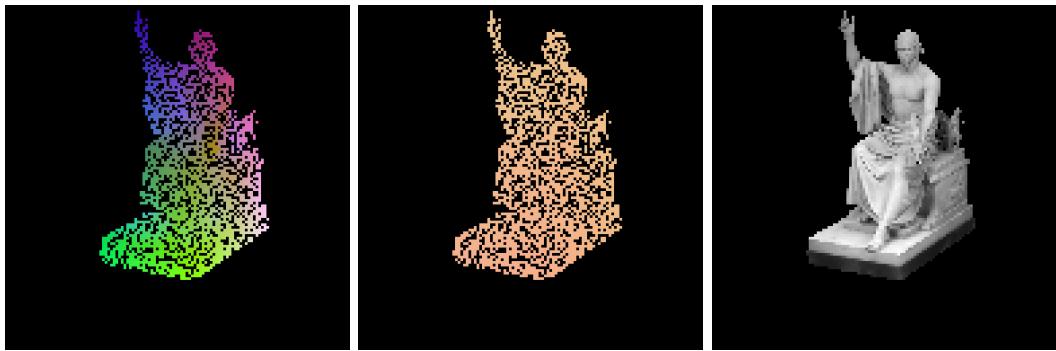


Figure 3.6: Three kinds of input data. From left to right, vertex map, light map, gray-scale image.

See chapter 4 for more details on how to set up the dataset.

### 3.5.2 Trip-Net Architecture

We proposed a network that considers the vertex map, the light map, and the grayscale image for surface normal inference, which is called the Triple-Pipe-Gated Network (*Trip-Net*). The *Trip-Net* uses the GCNN architecture three times to perform the normal inference task, so we call it *Triple-Pipe-Gated*. The architecture is shown in Figure 3.7.

The network consists of three pipes combined with one main pipe and two side pipes. Each pipe deals with a different task. The Main Pipe deals with the geometry information, which takes the vertex map as input and is used to predict the surface normal. The light map takes a Side Pipe as input, from which the light features are extracted and then passed to the Main Pipe as additional information for normal estimation. The image map takes another Side Pipe to extract the image features, and then forwards the features to the Main Pipe as well. The additional pipes provide the illumination information that helps the Main Pipe refine the inferred normals.

**Side-Pipe (Light)** The structure of the Light-Pipe is almost identical to the architecture of the GCNN. It takes the light map  $\mathbf{L} \in \mathbb{R}^{W \times H \times 3}$  as input and then passes through gated convolution layers three times to obtain the feature maps,  $\mathbf{X}_{L1D} \in \mathbb{R}^{W \times H \times C}$ , which has the same resolution as the input map. Then three

downsampling operations are followed afterwards. In each downsampling, 3 gated convolution layers are used to further extract the feature maps, where the first two gated convolution layers have stride (1,1) and the third gated convolution layer has stride (2,2). Then we get

$$\mathbf{X}_{L2D} \in \mathbb{R}^{\frac{W}{2} \times \frac{H}{2} \times C}, \mathbf{X}_{L3D} \in \mathbb{R}^{\frac{W}{4} \times \frac{H}{4} \times C}, \mathbf{X}_{L4D} \in \mathbb{R}^{\frac{W}{8} \times \frac{H}{8} \times C} \text{ (represented as a regression function } l_{down})$$

$$l_{down} : \mathbf{L} \rightarrow \mathbf{X}_{L1D}, \mathbf{X}_{L2D}, \mathbf{X}_{L3D}, \mathbf{X}_{L4D}$$

For the up-sampling operation, it takes 3 times up-sampling to generate higher resolution light feature maps  $\mathbf{X}_{L1U} \in \mathbb{R}^{W \times H \times C}$ ,  $\mathbf{X}_{L2U} \in \mathbb{R}^{\frac{W}{2} \times \frac{H}{2} \times C}$ ,  $\mathbf{X}_{L3U} \in \mathbb{R}^{\frac{W}{4} \times \frac{H}{4} \times C}$  respectively, whereas each up-sampling also considers the feature maps in the down-sampling part, (represented as a regression function  $l_{up1}, l_{up2}, l_{up3}$ )

$$\begin{aligned} l_{up3} &: \mathbf{X}_{L3D}, \mathbf{X}_{L4D} \rightarrow \mathbf{X}_{L3U} \\ l_{up2} &: \mathbf{X}_{L2D}, \mathbf{X}_{L3U} \rightarrow \mathbf{X}_{L2U} \\ l_{up1} &: \mathbf{X}_{L1D}, \mathbf{X}_{L2U} \rightarrow \mathbf{X}_{L1U} \end{aligned}$$

In our network, each up-sampling is done in three layers, an interpolation layer based on the nearest neighbor algorithm, a concatenation layer to concatenate the interpolated feature maps and the corresponding feature maps in the down-sampling part, and a gated convolution layer to reduce the channel size. The light pipe branch is completed in the last layer of the third up-sampling.

In this branch, four kinds of feature maps  $\mathbf{X}_{L4D}, \mathbf{X}_{L3U}, \mathbf{X}_{L2U}, \mathbf{X}_{L1U}$  are used as guided information for further operation.

**Side-Pipe (Image)** The task of the Image-Pipe in the network is to predict the image features. This pipe is a pipe cooperating with the Light-Pipe. The architect is the same as that of the Light-Pipe, but only the input is the image matrix  $\mathbf{I} \in \mathbb{R}^{W \times H \times 1}$ . The first set of the feature maps are  $\mathbf{X}_{I1D} \in \mathbb{R}^{W \times H \times C}$ , noting that it has the same channel as the light feature maps. Then, the down-sampling is performed three times to extract the image feature maps

$$\mathbf{X}_{I2D} \in \mathbb{R}^{\frac{W}{2} \times \frac{H}{2} \times C}, \mathbf{X}_{I3D} \in \mathbb{R}^{\frac{W}{4} \times \frac{H}{4} \times C}, \mathbf{X}_{I4D} \in \mathbb{R}^{\frac{W}{8} \times \frac{H}{8} \times C} \text{ (represented as a regression function } i_{down})$$

$$l_{down} : \mathbf{I} \rightarrow \mathbf{X}_{I1D}, \mathbf{X}_{I2D}, \mathbf{X}_{I3D}, \mathbf{X}_{I4D}$$

It requires three times upsampling to produce higher resolution image feature maps.  $\mathbf{X}_{I1U} \in \mathbb{R}^{W \times H \times C}$ ,  $\mathbf{X}_{I2U} \in \mathbb{R}^{\frac{W}{2} \times \frac{H}{2} \times C}$ ,  $\mathbf{X}_{I3U} \in \mathbb{R}^{\frac{W}{4} \times \frac{H}{4} \times C}$  respectively, whereas each up-sampling also considers the feature maps in the down-sampling part, (represented as a regression function  $i_{up1}, i_{up2}, i_{up3}$ )

$$\begin{aligned} i_{up3} &: \mathbf{X}_{I3D}, \mathbf{X}_{I4D} \rightarrow \mathbf{X}_{I3U} \\ i_{up2} &: \mathbf{X}_{I2D}, \mathbf{X}_{I3U} \rightarrow \mathbf{X}_{I2U} \\ i_{up1} &: \mathbf{X}_{I1D}, \mathbf{X}_{I2U} \rightarrow \mathbf{X}_{I1U} \end{aligned}$$

whereas the layers in the upsampling part have the same architecture as the Light Pipe. In the Image Pipe, four types of feature maps  $\mathbf{X}_{I4D}, \mathbf{X}_{I3U}, \mathbf{X}_{I2U}, \mathbf{X}_{I1U}$  are used as guided information for further operation.

**Main-Pipe (Vertex)** The task of the vertex pipe in the network is to predict the normal map directly, also taking into account the feature maps in the other channels.

The input is the vertex map  $\mathbf{V} \in \mathbb{R}^{W \times H \times 3}$  converted from the point cloud. The downsampling part is still the same as for the other two pipes. The feature maps in each downsampling part are of the form  $\mathbf{X}_{V1D} \in \mathbb{R}^{W \times H \times C}$ ,  $\mathbf{X}_{V2D} \in \mathbb{R}^{\frac{W}{2} \times \frac{H}{2} \times C}$ ,  $\mathbf{X}_{V3D} \in \mathbb{R}^{\frac{W}{4} \times \frac{H}{4} \times C}$ ,  $\mathbf{X}_{V4D} \in \mathbb{R}^{\frac{W}{8} \times \frac{H}{8} \times C}$ , respectively, (represented as a regression function  $i_{down}$ )

$$v_{down} : \mathbf{V} \rightarrow \mathbf{X}_{V1D}, \mathbf{X}_{V2D}, \mathbf{X}_{V3D}, \mathbf{X}_{V4D}$$

The up-sampling operation has a different situation than the other two pipes. It merges the output feature maps with the corresponding resolution from three pipes to get a merged feature map  $\mathbf{X}_{F3U} \in \mathbb{R}^{W \times H \times C}$ ,  $\mathbf{X}_{F2U} \in \mathbb{R}^{W \times H \times C}$ ,  $\mathbf{X}_{F1U} \in \mathbb{R}^{W \times H \times C}$ , in each up-sampling stage, (represented as regression functions  $f_{up1}, f_{up2}, f_{up3}, f_{up4}$ )

$$\begin{aligned} f_{up4} &: \mathbf{X}_{I4D}, \mathbf{X}_{L4D}, \mathbf{X}_{V4D} \rightarrow \mathbf{X}_{F4U} \\ f_{up3} &: \mathbf{X}_{I3U}, \mathbf{X}_{L3U}, \mathbf{X}_{F4U} \rightarrow \mathbf{X}_{F3U} \\ f_{up2} &: \mathbf{X}_{I2U}, \mathbf{X}_{L2U}, \mathbf{X}_{F3U} \rightarrow \mathbf{X}_{F2U} \\ f_{up1} &: \mathbf{X}_{I1U}, \mathbf{X}_{L1U}, \mathbf{X}_{F2U} \rightarrow \mathbf{X}_{F1U} \end{aligned}$$

Each upsampling consists of 5 layers: An interpolation layer to double the resolution using the nearest interpolation algorithm, a gated layer to reduce the channel size to 1/3 of itself for inter-pipes feature reduction, a concatenation layer to connect the output with the corresponding feature map in the downsampling part (skip connection), a gated layer to reduce the channel size to 1/2 of itself for skip-connection feature reduction, a concatenation layer to merge the corresponding upsampling feature map from the other two pipes with the feature map in the current pipe altogether. These 5 layers take into account both the information from the other pipes and the feature maps from the downsampling part.

At the end of the network, to fit the task of normal inference, two standard convolutional layers are added to convert the normal map  $\mathbf{X}_N \in \mathbb{R}^{\frac{W}{8} \times \frac{H}{8} \times 3}$  (represented as a regression function  $n$ )

$$n : \mathbf{X}_{F1U} \rightarrow \mathbf{X}_N$$

### 3.5.3 Loss Functions

We have investigated different loss functions for training our network. The most common loss functions are the L1 loss and the L2 loss for image simulation. In our experiments, we used a modified BerHu loss function to train our model, which yields a lower error in the evaluation compared to a pure L1 or L2 loss function.

**L1 Loss** L1 loss, also known as absolute error loss, which calculates the absolute difference between the prediction and the ground truth. It leads to the mean value of the absolute errors of the observations.

$$L_1(\tilde{y} - y) = |\tilde{y} - y|$$

**L2 Loss** The standard loss function for optimization in regression problems is the L2 loss, also known as squared error loss, which minimize the squared difference between a prediction and the actual value. It leads to the mean of the observations.

$$L_2(\tilde{y} - y) = \|\tilde{y} - y\|_2^2$$

**Reversed Huber Loss** Inspired by [17], we use the reversed Huber loss provided by [24] for our model training, which indeed achieves a better error than a simple L2 loss. It can be described mathematically as follows.

$$\mathcal{B}(y) = \begin{cases} |y| & |y| \leq c \\ \frac{y^2 + c^2}{2c} & |y| > c \end{cases} \quad (3.6)$$

where  $c = 0.2 \max(|\tilde{y} - y|)$ . The shape of the loss is shown in Figure 3.8. Reversed Huber loss, also called BerHu loss, is a combination of L1 and L2 loss, being L1 loss in the range  $[-c, c]$  and L2 loss outside this range. The loss is also differentiable at the junction of two first order intersection functions. As mentioned in [17], the parameter  $c = 0.2 \max(|\tilde{y} - y|)$  corresponds to the 20% of the maximum error per batch.

The choice of the combination losses is reasonable because they give more weight to the errors compared to the L2 loss, but also preserve the outlier suppression features in the L2 loss. The output type in our model is the surface normal, which has a range between  $[-1, 1]$ , so we need the L2 loss to penalize larger errors. On the other hand, the L2 loss suppresses small values near zero more than the values greater than 1 or smaller than -1, because it uses a quadratic curve. Therefore, flattening the region near zero is a good choice for equilibrium. In our experiments, the BerHu loss shows better performance for all the models we trained.

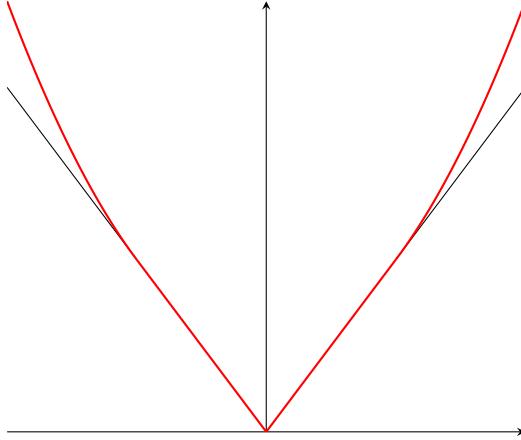


Figure 3.8: The shape of Berhu Loss (show in red line).

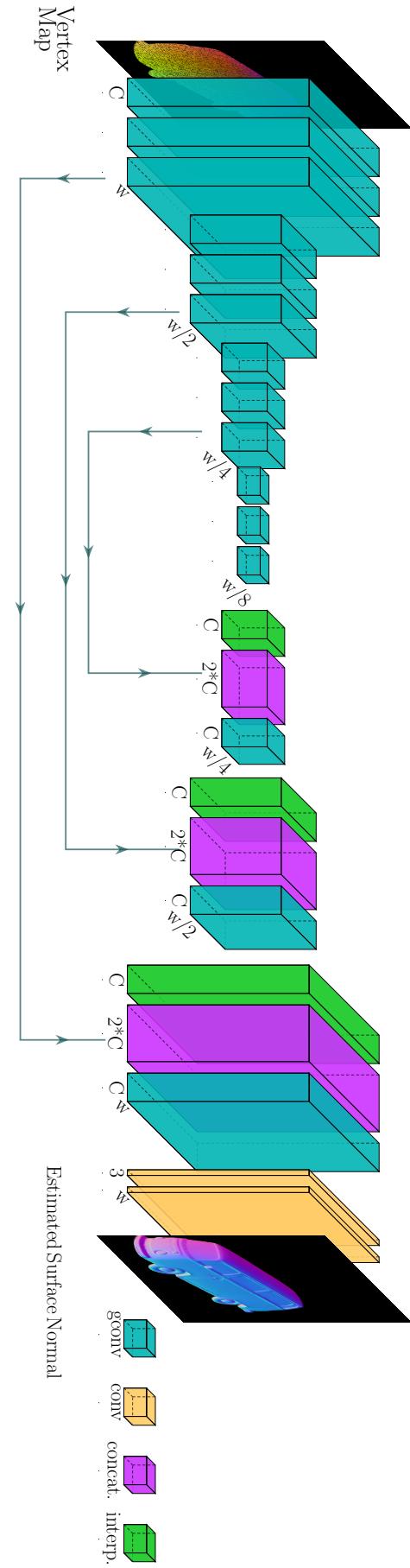
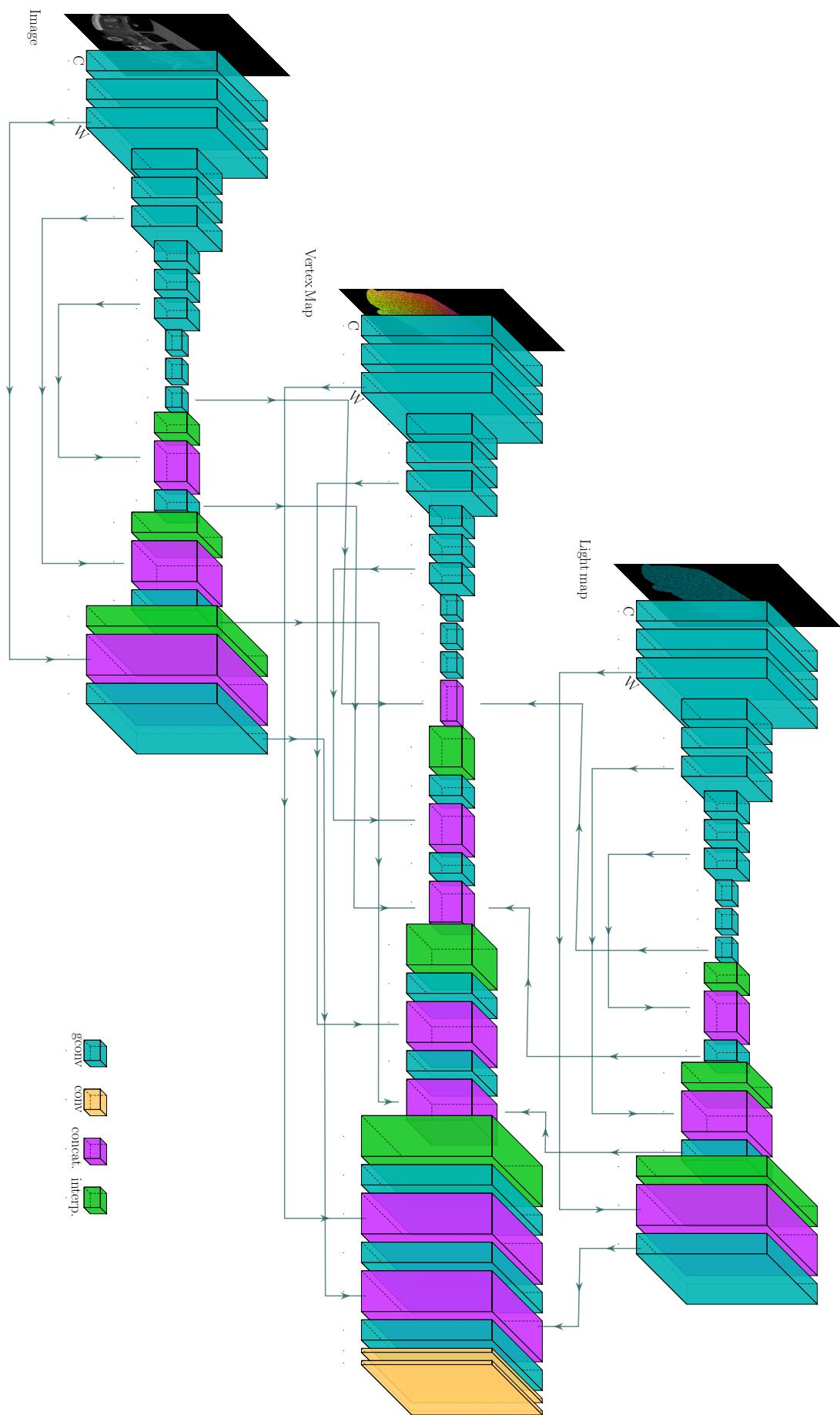


Figure 3.5: The architecture of Gated convolution neural network (*GCNN*) based on Gated convolution and *U-Net* Architecture.

Figure 3.7: The architecture of the *Trip-Net*.



## Chapter 4

# Dataset

In this work, we need two types of input data to train our models. First, we need to know the geometry of the object surface. This can be captured by a depth camera, which records the distance of the object surface from the optical center of the camera and can be converted into a point cloud. Second, we need information about the illumination of the object surface, which is used as photometric information for further improvements. This type of information requires an observed image of the object with the light directions projected onto the object surface.

To obtain this data, we can use a structured light scanner to scan the objects in the laboratory. However, the scanner usually cannot scan the dark, shiny, and transparent areas, resulting in many missing pixels and holes in the depth map. This incomplete surface information makes it difficult to train our model because the ground truth corresponding to the depth map is also incomplete. Second, training a deep learning-based model usually requires a large dataset, especially for a network without a backbone. Creating a single deep map dataset for this work would require too much work and resources. A suitable way to obtain huge depth map data with illumination information is to use a game engine that can simulate an arbitrary number of data.

We use the Unity game engine for data generation. Using a *C#* script, we can set up a similar configuration in the lab. We then create a dataset based on the collected objects. The dataset we created for this work is called *synthetic-50-5* because it contains 50 different object models for training and 5 object models for testing.

### 4.1 Data Resources

The object models we used were collected from the Internet. A number of point cloud datasets for image processing research have been published by [31], [22], [21], and [29]. Some of these point clouds were scanned from real objects using high-resolution scanners such as the Cyberware 3030 MS+ and calibrated with post-processing. These objects were scanned hundreds of times, fully capturing the original objects with up to millions of points[31]. Some of them are fully digitally synthesized. The dense point clouds make the normal inference task trivial, as the neighborhood-based method works adequately for this type of task. Some of the point clouds even contain pre-computed normal maps based on more advanced methods. They all provide the accurate ground truth for the supervised learning method.

The *synthetic-50-5* is a dataset we created in this work based on 50 point clouds as the training set and 5 point clouds as the test set. In creating the dataset, we tried to use as many object types as possible to cover a robust and wide range of training scenarios. There are several categories of models, such as figurines, animals, statues, toys, furniture, antiques, and car models, some of which have relatively smooth surfaces, such as model *arm*, *bus*, *rabbit*, *cat*, *zebra*, and some of which have very intricate details, such as model *Washington*, *Car-Engine*, *Armadillo*. We created

this dataset for normal inference tasks. Figure 4.1 shows illustrations of some objects. Appendix A contains a complete version of the models of the dataset.

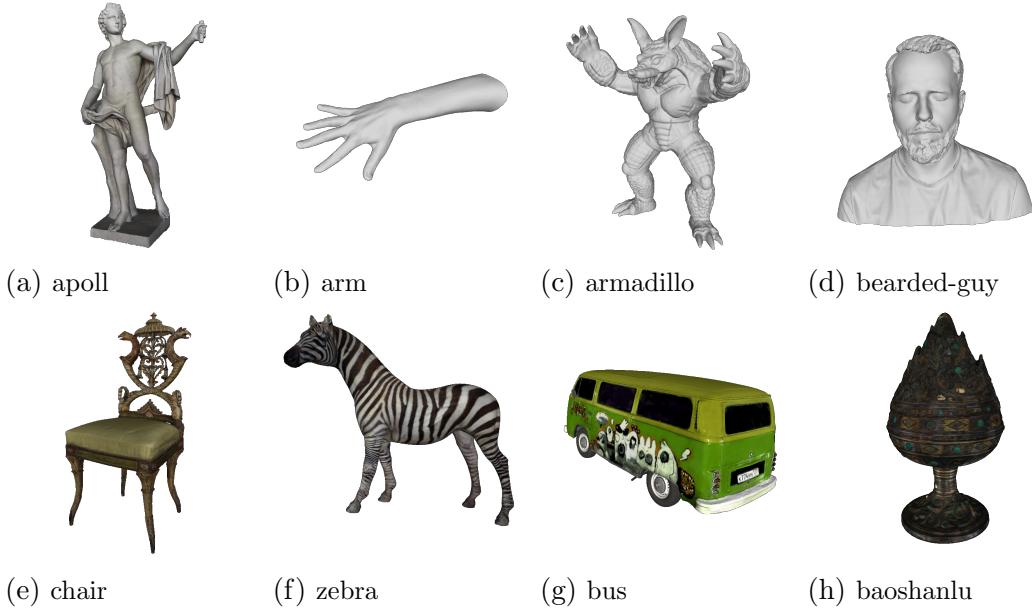


Figure 4.1: Some of the objects used for *Synthetic-50-5*

In addition, some objects also have colored textures, as shown in the second line of Figure 4.1. This is specifically prepared for the illuminated approach, since the image is used to evaluate the surface normals. By using textured models, our models get closer to the real dataset and have improved robustness that can be further applied to the real dataset.

## 4.2 Synthesizing Scenes using Unity

To simulate the data acquisition scenario as realistically as possible. We made the following settings. A flat cylinder, called *stage*, is placed in the center of the 3D space as a platform for placing objects. We fixed the *stage* in a predetermined position that will not be changed when images are captured. A directional light with RGB color FFF4D6 is placed 25 m away in the top view direction as an ambient light, which also has a fixed position. An RGB-D camera is placed about 10 m away from the stage in the top-view direction. The camera captures the depth map and the grayscale image, which are randomly arranged after each scene. The movement range of the camera is 0.1 m in both directions of the X, Y and Z axes and a randomly changed Euler angle of 1°. A point light is placed about 5 m away as the illumination light, which is also moved randomly after each scene. The range of motion is 0.3 m in both directions of the X, Y and Z axes and 1° randomly in the Euler angle.

During data acquisition, the object is randomly selected and placed on the stage. The object has a random rotation of up to 30° in the *roll* axis direction, a 30° rotation in the *pitch* axis direction, and a 180° degree rotation in the *yaw* axis direction. This gives the camera the ability to capture most directions of the objects. The layout in the Unity game engine is shown in Figure 4.2. We generate 3000 scenes with resolution 128 × 128 and 5000 scenes with resolution 512 × 512.

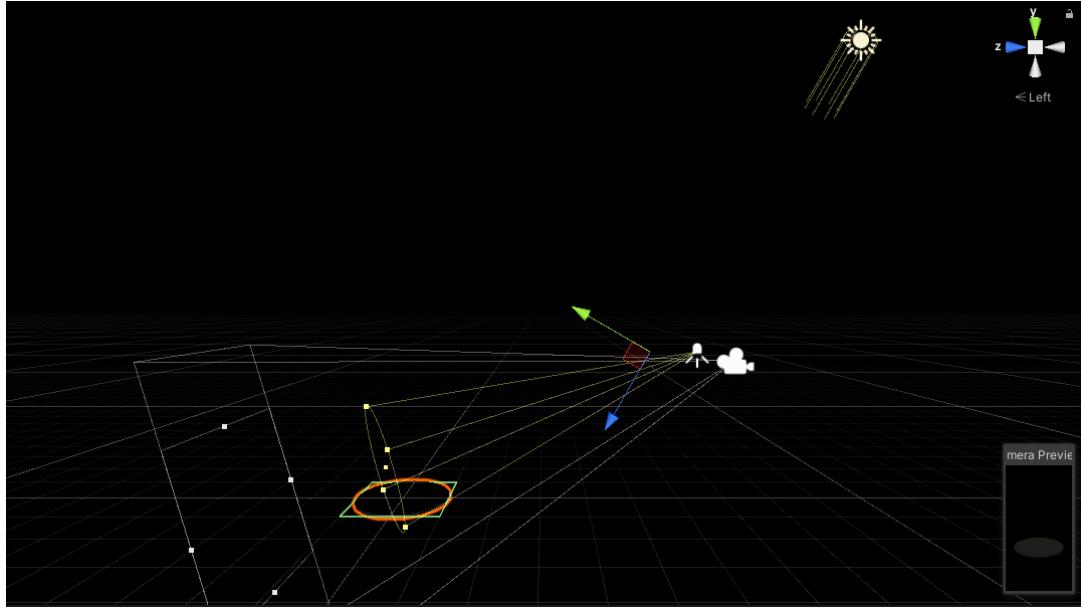


Figure 4.2: The layout of synthetic scene generation in Unity.

Data	Size
Depth map	Width×Height× 1
Depth range	MinDepth, MaxDepth
Grayscale Image	Width×Height× 1
Normal Map	Width×Height× 3
Light Position	3 × 1
Camera Intrinsic Matrix	3 × 3
Camera Extrinsic Matrix	3 × 4

TABLE 4.1: The information saved for each scene in *synthetic-50-5*.

The main advantage of generated scenes is the availability of complete information. We can capture the depth map in a lossless way. The corresponding normal map can also be safely considered as ground truth. And the scale of the dataset is easy to control. Table 4.1 gives more dataset information.

A critical detail we need to pay attention to is the exposure of the camera. Or we need to control the light emission on the object surface. As can be seen in Figure 4.3, too much exposure causes the surface texture to be difficult to see, resulting in clipping. In our experiments, we found that an appropriate light setting is essential for the illumination-based approach. Too much or too little lighting effects do not improve the illumination-based approach.

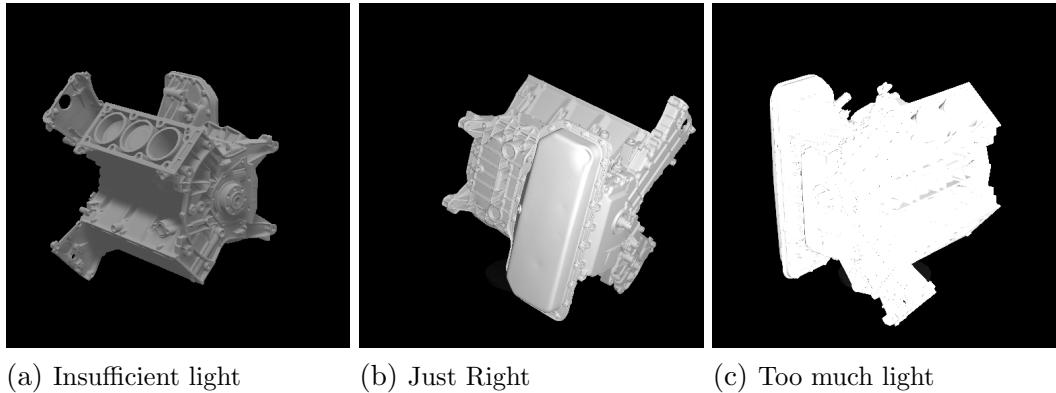


Figure 4.3: Different exposure to the objects.

### 4.3 Data Preprocessing

The raw data collected by Unity required further processing before it could be fed into the training models.

**Depth Map** A depth map is a 1-channel image that contains information about the distance from the object surface to the camera center. It is stored as a 16-bit grayscale image, meaning that each pixel is in the range 0 – 65535.

The raw depth maps in real data acquired by light scanners usually have missing pixels. To achieve a good match to the real data, a uniformly distributed noise was added to the synthetic data to randomly remove the valid pixels in the depth maps. The simulated noise is uniformly distributed over the entire map with a certain noise intensity. A parameter  $\mu$  is used to control the intensity of the noise. It specifies the  $\mu$  pixel drop in percent. For example, at  $\mu = 10$ , 10% of the pixels are randomly removed. For each scene, the noise operation is based on a random  $\mu$  in a range [0, 50]. In some scenes there are more missing pixels, in others less. The random noise intensity also allows the model to learn scenarios not only with noise, but also with low noise or even no noise. Figure 4.4 shows the noise effect at different  $\mu$ .

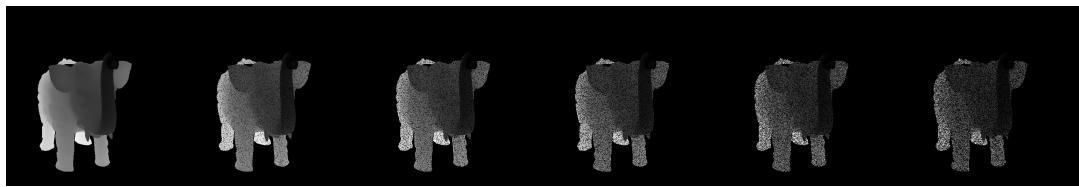


Figure 4.4: From left to right: Noise-intensity on  $\mu = 0, \mu = 10, \mu = 20, \mu = 30, \mu = 40, \mu = 50$ . Object Name: *elephant-zun-lid*.

The depth map is converted to a 3D vertex map after adding the noise. Consider a 3-dimensional Euclidean space. The  $X$  and  $Y$  axes are perpendicular to each other align with the direction of width and height of the depth map separately. The  $Z$  axis is point inward (i.e., from view point to the depth map). The depth provided in the depth map is the distance from camera center to the object surface. Thus, in order to find the corresponding 3D vertex map  $\mathbf{V}_C$  with respect to the camera coordinate

system, we only need to multiple the depth matrix **Depth** with the point direction matrix **Dir**.

$$\mathbf{V}_C = \mathbf{Depth} \odot \mathbf{Dir}$$

For the direction  $\mathbf{Dir}(x, y, z)$  of a point  $\mathbf{V}(x, y, z)$ , it's X and Y components can be mapped from the corresponding pixel position  $(u, v)$  on the depth map, whereas the Z component is the focal length  $fk$  in pixels. Then we have to further normalize it to an unit vector.

$$\mathbf{Dir}(x, y, z) = \frac{(u, v, fk)}{\|(u, v, fk)\|_2^2}$$

Conversion of a point from the camera coordinate system to the world coordinate system using the extrinsic matrix  $R$  and  $t$

$$\mathbf{V}_W = \mathbf{V}_C R + t$$

The sizes of the individual training objects are different. We normalized them to a unit scale so that they have a relatively similar distance from the camera. In Figure 4.5 we have plotted the variations in value in each axis before normalization. Table 4.2 gives a quantitative evaluation of the corresponding average values.

The normalization was performed as follows. First, the points are translated to the original point as much as possible, then the range value of an axis is chosen as the scaling factor, and the points are normalized to unit vectors. The equation is represented as follows

$$\begin{aligned} X_n &= \frac{X - \min(X)}{s} \\ Y_n &= \frac{Y - \min(Y)}{s} \\ Z_n &= \frac{Z - \min(Z)}{s} \\ s &= \max(X) - \min(X) \end{aligned}$$

where  $s$  is a scaling factor calculated as the range of the  $X$  axis, but theoretically it can also be the range of  $Y$  or  $Z$  axis.

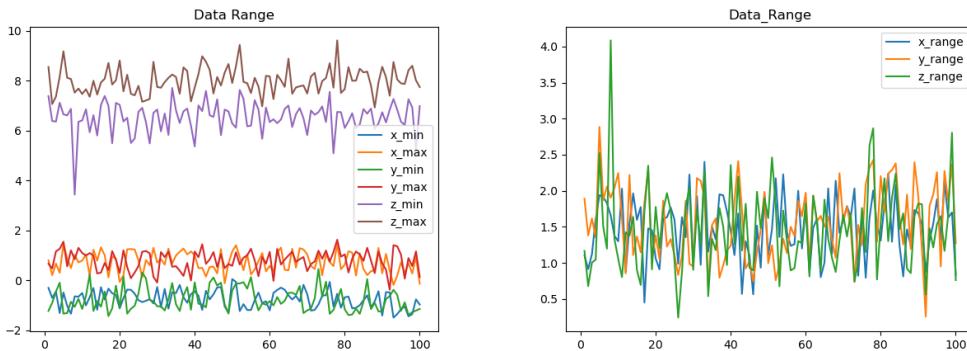


Figure 4.5: Left: Extreme value in 3 axis; Right: Vertex range in 3 axis

Axis	Scale	Min	Max
X	1.48	-0.75	0.73
Y	1.56	-0.76	0.80
Z	1.47	6.53	8.00

TABLE 4.2: The fluctuation of extreme values and their ranges in 100 random training items.

**Image** The grayscale image can be used for the photometric stereo method and also as readable information for humans. Since the image captured by the camera is in RGB format, we need to convert it to grayscale to fit our models. This is done using the following equation.

$$\text{gray} : \frac{R + 2G + B}{4}$$

**Normal Map** The normal map is the tangential surface normal stored in an 8-bit/channel RGB image. The surface normal  $(n_x, n_y, n_z)$  and the corresponding RGB color  $(R, G, B)$  can be converted using the following equation:

$$\begin{aligned} n_x &= \frac{R}{255} \cdot 2 - 1 \\ n_y &= \frac{G}{255} \cdot 2 - 1 \\ n_z &= 1 - \frac{B}{255} \cdot 2 \end{aligned}$$

## Chapter 5

# Experiments

### 5.1 Training Details

The models are trained on the dataset *synthetic-50-5* with 3000 scenes mentioned in chapter 4. Each scene has a depth map with dimension  $128 \times 128$  in height and width, an image with dimension  $128 \times 128$ . The depth map is converted from the 3D vertex map as introduced in chapter 4. The light map is computed from the vertex map and the known light position. We create a tensor in PyTorch containing the vertex map, image, and light direction for each scene and consider it as a training case. Thus, 3000 scenes correspond to 3000 training cases. For each scene, there is a corresponding ground truth normal map for loss calculation and evaluation. Figure 5.1 shows some of the training cases. Note that the position of the objects is not always placed naturally on the stage, but with a random rotation in the X, Y and Z axes.

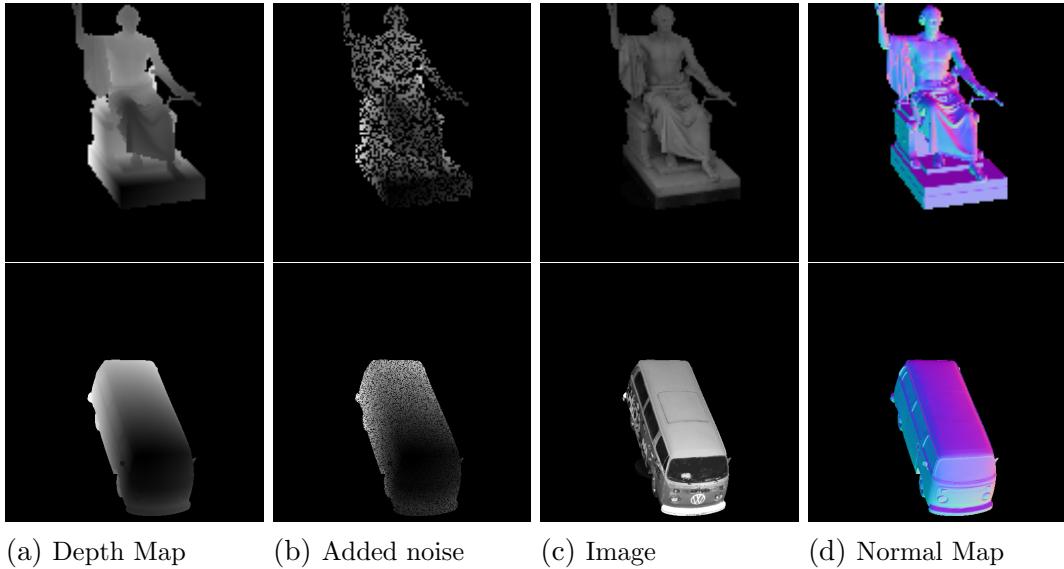


Figure 5.1: Some of the evaluation scenes during the training. The objects from top to bottom rows: *Washington, Bus*

Besides the 3000 training scenes, 100 additional scenes with 5 different object models are used as evaluation dataset during the training. They are evaluated in each epoch.

For the training parameters, we set the training pipeline with a batch size of 8, since we found that a higher batch size decreases the final performance. Adam Optimizer ([14]), learning rate starting at  $1 \times 10^{-3}$ , it will decrease at epoch 8 with

learning decay factor 0.5. The model is trained using PyTorch 1.10.0a0, CUDA 11.4.1, GPU with an NVIDIA GEFORCE RTXA 6000. It takes 14 hours to train the GCNN and 35 hours to train the Trip-Net. We stop training when the angular error of the normal map stops decreasing.

GCNN model is the base model of the whole thesis. The architecture is described in 3.4. We use a single GCNN to estimate the surface normal as a geometry based approach. It uses vertex map as input to estimate the corresponding tangent surface normal map. In order to verify the applicability of the skip connection and the gated convolution layers, we trained two extra models as a comparison. In the first model, we replace all of the gated layer to standard convolution layers in the network but keeps all of the other settings same, and give it a name *CNN*. It is used to compare the performance between gated convolution layer and standard convolution layer for our normal inference task. As mentioned in chapter 3, the gated layer is designed to deal with noised input. Since all of the vertex map in the dataset has been added noise, the GCNN is supposed to over-perform *CNN*. Another model called *NOC* is designed to verify the skip connection, which simply removes the skip connections in the network but keeps other settings same. It is designed to show to which content will skip connection help the model performance. We use Reversed Huber Loss as loss function during the training. We found it gives a better final error compared to L2 loss.

The *GCNN* is the base model of the whole work. The architecture is described in 3.4. We use a single *GCNN* to estimate surface normals as a geometry-based approach. It uses a vertex map as input. To verify the applicability of the skip-connection and gated-convolution layers, we trained two additional models for comparison. In the first model, we replace all gated layers with default convolutional layers in the network, but keep all other settings and give it the name *CNN*. It is used to compare the performance between the gated layer and the default convolutional layer for our normal inference task. As mentioned in 3, the gated layer is designed to process noisy input. Since the entire vertex map in the dataset was noisy, the *GCNN* should outperform *CNN*. Another model called *NOC* is used to check skip connections, which simply removes the skip connections in the network but leaves the other settings unchanged. Its purpose is to show to what extent the performance of the model is improved by skipping connections. We use Reversed Huber Loss as a loss function during training. We have found that it gives a better final error compared to L2 loss.

Model	#Total	V-P	L-P	I-P	Size /MB
CNN	17	32	-	-	25.5
NOC	32	32	-	-	30.6
GCNN	32	32	-	-	45.8

TABLE 5.1: GCNN model information. The V-P, L-P, and I-P columns indicate the number of convolutional layers in the vertex pipe, light pipe, and image pipe, respectively. Note that a gated convolution layer consists of 2 standard layers and is therefore counted as 2.

The trip-net model uses a triple GCNN architecture with 4 times fusions, which is more difficult to train. It takes the calibrated illuminated RGB-D images as input to estimate the surface normal map. When we train this model, we take the GCNN model as the baseline to observe the advantages of the illuminated information with the trip-net architecture. We also examined the optimal fusion times of the Trip-Net to determine a possible simplification of the model. A set of similar models

was trained with the same settings but different fusion times, denoted Trip-Net- $F_x$ , where  $x$  denotes the fusion times. We score the fusion times from 1 to 4. For the learning rate, we initially set  $1e - 3$ . This fits the GCNN model well, but leads to a loss explosion in the trip-net. Therefore, we set a learning rate schedule with an additional decay step at epoch 8. The decay factor is 0.5. The batch size is set to 8.

During the training we found that trip-Net with four times fusion converges obviously faster than fewer fusion times model. However, model F3 with 3 times fusion converge slower than F4 but in the end it achieves a similar evaluation loss with F4(see Qualitative evaluation). The F1 and F2 models are relatively less accurate than the other two models, but the sacrifice of accuracy gives a relatively lighter model. Since they have less fusion times, the corresponding upsampling layers in the image and light pipes can also be removed. The model can be trained in a faster way and the size is reduced as well. Table 5.2 gives a comparison of the size and training time among different models.

During training, we found that the trip-net with 4 fusions converges significantly faster than models with fewer fusion times. However, model F3 with three times fusion converges slower than F4, but ends up with a similar loss of score as F4 (see Qualitative Evaluation). Models F1 and F2 are relatively less accurate than the other two models, but the sacrifice of accuracy results in a relatively lighter model. Since they have fewer fusion times, the corresponding upsampling layers in the image and light pipes can also be removed. The model can be trained faster, and the size is also smaller. Table 5.2 contains a comparison of the size of different models.

Model	#Total	V-P	L-P	I-P	Size /MB
Trip-Net-F1F	88	40	24	24	106
Trip-Net-F2F	92	40	26	26	137
Trip-Net-F3F	96	40	28	28	167
Trip-Net	100	40	30	30	198

TABLE 5.2: Trip-Net Model information. Columns V-P, L-P and I-P represent the number of convolution layers in vertex pipe, light pipe and image pipe respectively. Note that one gated convolution layer is constructed with 2 standard layers, thus it is counted as 2.

## 5.2 Quantitative Evaluation on 6 Metrics

We evaluated our models on synthetic dataset with resolution  $128 \times 128$ . Based on metrics proposed by [7], 6 different metrics are used for evaluation. Note that the input vertex map is only semi-dense. One of the benefit of GCNN architecture is the robustness to the noisy input, thus in the evaluation, all the points including missing points in the input vertex map are taken into account. We use  $\tilde{\mathbf{N}}$  denotes the estimated normal map,  $\mathbf{N}$  denotes the ground-truth normal map,  $P$  denotes the set of valid points,  $ValidNum$  denotes the number of valid points.  $abs$  is a function to calculate the absolute value of the given value,  $median$  is a function calculate the median value of a given set.

**Average Angle Error Metric (AAE)** The metric calculates the average angle error for each point between the inferred normal and ground-truth normal map.

$$AAE = \frac{1}{ValidNum} \cdot \sum_{i \in P} abs \left( \arccos \frac{\mathbf{N}_i \cdot \tilde{\mathbf{N}}_i}{|\mathbf{N}_i||\tilde{\mathbf{N}}_i|} \cdot \frac{180}{\pi} \right)$$

**Median Angle Error Metric (MED)** The metric calculates the median angle error of all of the points in the normal map.

$$MED = \text{Median} \left( \left\{ i \in P \mid \text{abs} \left( \arccos \frac{\mathbf{N}_i \cdot \tilde{\mathbf{N}}_i}{|\mathbf{N}_i||\tilde{\mathbf{N}}_i|} \right) \right\} \right)$$

**5 Degree Error Metric** The metric calculates the percentage of the predicted normals that has error less than 5 degrees comparing to ground-truth. It first calculates the number of normals that have error less than  $5^\circ$

$$D_5 = \sum_{i \in P} \left( \text{abs} \left( \arccos \frac{\mathbf{N}_i \cdot \tilde{\mathbf{N}}_i}{|\mathbf{N}_i||\tilde{\mathbf{N}}_i|} \cdot \frac{180}{\pi} \right) < 5 \right)$$

Then it calculate the percentage of the normals that error less than  $5^\circ$ .

$$E_5 = \frac{D_5}{ValidNum} \times 100\%$$

**11.5 Degree Error Metric** The metric calculates the percentage of the predicted normals that has error less than 11.5 degrees comparing to ground-truth. It first calculates the number of normals that have error less than  $11.5^\circ$ .

$$D_{11.5} = \sum_{i \in P} \left( \text{abs} \left( \arccos \frac{\mathbf{N}_i \cdot \tilde{\mathbf{N}}_i}{|\mathbf{N}_i||\tilde{\mathbf{N}}_i|} \cdot \frac{180}{\pi} \right) < 11.5 \right)$$

Then it calculate the percentage of the normals that error less than  $11.5^\circ$ .

$$E_{11.5} = \frac{D_{11.5}}{ValidNum} \times 100\%$$

**22.5 Degree Error Metric** The metric calculates the percentage of the predicted normals that has error less than 22.5 degrees comparing to ground-truth. It first calculates the number of normals that have error less than  $22.5^\circ$ .

$$D_{22.5} = \sum_{i \in P} \left( \text{abs} \left( \arccos \frac{\mathbf{N}_i \cdot \tilde{\mathbf{N}}_i}{|\mathbf{N}_i||\tilde{\mathbf{N}}_i|} \cdot \frac{180}{\pi} \right) < 22.5 \right)$$

Then it calculate the percentage of the normals that error less than  $22.5^\circ$ .

$$E_{22.5} = \frac{D_{22.5}}{ValidNum} \times 100\%$$

**30 Degree Error Metric** The metric calculates the percentage of the predicted normals that has error less than 30 degrees comparing to ground-truth. It first calculates the number of normals that have error less than  $30^\circ$ .

$$D_{30} = \sum_{i \in P} \left( \text{abs} \left( \arccos \frac{\mathbf{N}_i \cdot \tilde{\mathbf{N}}_i}{|\mathbf{N}_i||\tilde{\mathbf{N}}_i|} \cdot \frac{180}{\pi} \right) < 30 \right)$$

Then it calculate the percentage of the normals that error less than  $30^\circ$ .

$$E_{30} = \frac{D_{30}}{ValidNum} \times 100\%$$

We evaluated our trained models on “synthetic-50-5”. 5 objects are considered in the test dataset. They are: *Baoshanlu*, *Bus*, *Dragon*, *Garfield*, and *Washington*. Each object has 20 scenes with total 100 scenes for 5 objects. The test objects do not exist in the training dataset. We evaluate all the presented models on the test dataset, in order to fit them in one table, the name of each models are simplified. *SVD* model use SVD optimization method, *NOC* model is the no skip connection version of *GCNN*, *CNN* is the CNN version of *GCNN*. *F1*, *F2*, *F3*, *F4* means the fusion times in the Trip-Net.

When evaluate the *GCNN* models, we can take *SVD* model as baseline, *NOC* and *CNN* are used to verify the performance of *GCNN* model. When evaluate the *F1-F4* models, we can take *GCNN* model as baseline.

From the table we can see that all the learning based approaches achieves a better result than SVD approach. In the 30 degrees error metric, GCNN based approach achieves 95 % accuracy whereas Trip-Net is even higher, some of the models like *dragon* achieves 98%. The best performance is around 90%, 75 %, 45 % in 22.5°, 11.5° and 5° degrees error metrics respectively. Another notable result is the close performance of F3 and F4 models, where they achieves a very comparable performance. We also found that during the training, F4 model converges faster than F3, but F3 in the end achieves a similar loss with model F4. However, based on the 30°, 22.5°, 11.5° metrics, we can still see that F4 model gives a more stable performance with less high error normals. This is reasonable since the last fusion in the original resolution provides more high resolution information to the models.

Object	#	SVD	GCNN	NOC	CNN	F1	F2	F3	F4
Baoshanlu	20	35.66	11.09	13.58	15.55	11.22	10.36	<b>9.77</b>	9.80
Bus	20	31.93	<b>7.79</b>	8.95	11.93	7.49	7.85	<b>7.30</b>	7.62
Dragon	20	39.57	10.60	15.29	16.03	10.47	10.23	8.16	<b>7.79</b>
Garfield	20	39.69	10.20	12.50	14.46	9.94	10.36	9.71	<b>9.39</b>
Washington	20	42.83	13.43	17.59	18.71	13.32	13.40	12.62	<b>12.60</b>

TABLE 5.3: Average Angle Error of the evaluation dataset.

Object	#	SVD	GCNN	NOC	CNN	F1	F2	F3	F4
Baoshanlu	20	34.06	8.86	10.82	13.25	8.95	8.02	7.54	<b>7.50</b>
Bus	20	34.14	4.44	5.02	8.69	4.11	4.58	<b>3.65</b>	4.47
Dragon	20	36.43	7.62	11.10	13.26	7.60	7.12	5.87	<b>5.52</b>
Garfield	20	37.60	6.40	8.90	11.31	6.30	6.72	6.21	<b>6.04</b>
Washington	20	36.89	7.64	11.38	13.64	7.49	7.60	<b>7.03</b>	7.25

TABLE 5.4: Median Angle Error of the evaluation dataset.

Object	#	SVD	GCNN	NOC	CNN	F1	F2	F3	F4
Baoshanlu	20	0.01	0.25	0.18	0.11	0.24	0.31	<b>0.33</b>	0.32
Bus	20	0.00	0.56	0.50	0.23	0.59	0.54	<b>0.63</b>	0.55
Dragon	20	0.00	0.31	0.17	0.10	0.31	0.34	0.43	<b>0.46</b>
Garfield	20	0.00	0.41	0.27	0.14	0.42	0.39	0.42	<b>0.43</b>
Washington	20	0.00	0.38	0.26	0.10	0.36	0.36	<b>0.40</b>	0.37

TABLE 5.5: Percent of error less than 5 degree of the evaluation dataset.

Object	#	SVD	GCNN	NOC	CNN	F1	F2	F3	F4
Baoshanlu	20	0.03	0.62	0.52	0.41	0.62	0.66	<b>0.69</b>	<b>0.69</b>
Bus	20	0.05	0.81	0.78	0.65	0.83	0.82	<b>0.83</b>	<b>0.83</b>
Dragon	20	0.02	0.69	0.51	0.40	0.70	0.71	0.79	<b>0.81</b>
Garfield	20	0.03	0.72	0.62	0.51	0.73	0.71	0.74	<b>0.75</b>
Washington	20	0.02	0.62	0.50	0.40	0.63	0.62	0.64	<b>0.65</b>

TABLE 5.6: Percent of error less than 11.5 degree of the evaluation dataset.

Object	#	SVD	GCNN	NOC	CNN	F1	F2	F3	F4
Baoshanlu	20	0.18	0.90	0.84	0.79	0.90	0.91	<b>0.92</b>	<b>0.92</b>
Bus	20	0.26	0.93	0.91	0.89	0.93	0.93	0.93	<b>0.94</b>
Dragon	20	0.14	0.90	0.79	0.80	0.90	0.90	0.94	<b>0.95</b>
Garfield	20	0.13	0.89	0.86	0.84	0.90	0.89	<b>0.91</b>	<b>0.91</b>
Washington	20	0.14	0.81	0.72	0.72	0.81	0.81	<b>0.83</b>	<b>0.83</b>

TABLE 5.7: Percent of error less than 22.5 degree of the evaluation dataset.

Object	#	SVD	GCNN	NOC	CNN	F1	F2	F3	F4
Baoshanlu	20	0.37	0.96	0.93	0.90	0.96	0.96	<b>0.97</b>	<b>0.97</b>
Bus	20	0.43	0.96	0.94	0.93	0.96	<b>0.96</b>	<b>0.96</b>	<b>0.96</b>
Dragon	20	0.30	0.95	0.88	0.90	0.95	0.95	0.97	<b>0.98</b>
Garfield	20	0.27	0.94	0.92	0.91	0.94	0.94	0.94	<b>0.95</b>
Washington	20	0.28	0.88	0.81	0.82	0.88	0.88	<b>0.89</b>	<b>0.89</b>

TABLE 5.8: Percent of error less than 30 degree of the evaluation dataset.

### 5.3 Visual Evaluation on SVD

The SVD approach can predict the normal map in a good way when the given point cloud is dense. As shown in Figure 5.2. It can successfully predict the smooth surface of the dragon object, especially the flakes and the tails of the dragon.

However, it failed in the areas such as hindleg, horn and the mouth, which consists mainly by sharp edges. This is because the neighbors points in these area do not hold the assumption of coplanarity well, the normals of these neighbors can be very different. The SVD approach is depended on a well-chosen parameter  $k$ . Figure 5.3 shows the evaluation on different  $k$  values. When  $k = 1$ , the average error of the



Figure 5.2: Normal map of a dragon object predicted by neighbor based method.  $k=2$ , angle error=5. **Left:** ground-truth normal map **Middle:** predicted normal map, **Right:** Error map

whole image is the lowest one, most of the normals are close to the ground-truth but the outline edges, which are the areas that surface normal changed extremely sever. For the case  $k = 2$ , the sharp edges are more smooth and cause more error, like the eyes area of the dragon. Compare to the first case, the outline edge error goes better. Most of the edge errors are reduced when  $k = 2$ , since more neighbor points join the evaluation and it reduces the effect of outliers. However, for the area of horn outline, hindleg outline, the error goes worse. In this case, most of the neighbors of these points are outliers and thus failed this approach.  $k = 3$  and  $k = 4$  further increase the angle errors based on  $k = 2$ .

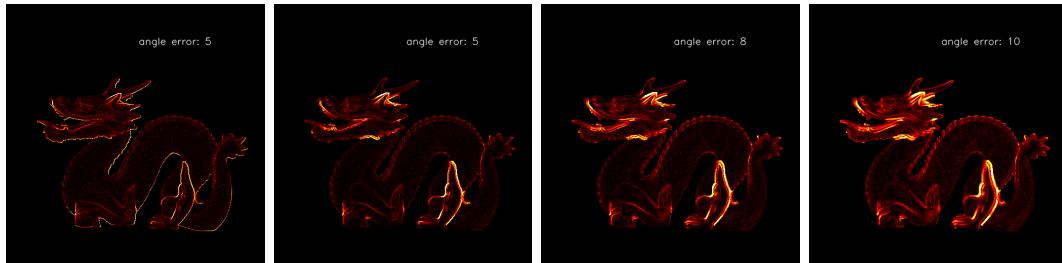


Figure 5.3: Error map of neighbor based method with different  $k$  values. From left to right,  $k = 1, 2, 3, 4$  separately.

The performance of neighbor based method is good enough for a well chosen  $k$ . However, for the case of noised point cloud as input, this approach will broken, since the noise will failed the neighbor assumption and also reduce the number of possible neighbors of each point for a fixed  $k$ .

## 5.4 Visual Evaluation on GCNN

A qualitative evaluation on object "dragon" is shown in Figure 5.5. As shown in the figure, GCNN model achieved a mean angle error in 9 degrees on this dragon object. The image has an overall good performance on the whole object. A closer evaluation is shown in Figure 5.6, the normal accuracy especially good on the smooth surface, like the body area. In the same case, NOC model as shown in Figure 5.7 has a overall worse normal than GCNN model in the smooth area. CNN model keeps the

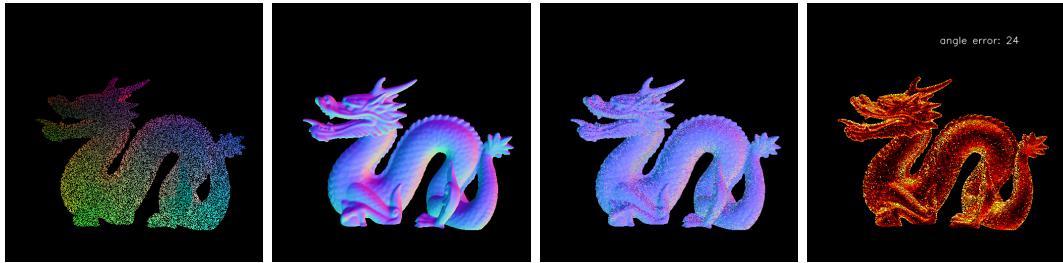


Figure 5.4: SVD visual evaluation on a noised dragon model ( $128 \times 128$ )

skip connection thus gives a sharper result than NOC model, however, the overall smooth part of the model is still worse than GCNN. Besides, the sharp area like the hindleg and the head area of dragon object, CNN model gives a much brighter error map (which means a higher angle error). Figure ?? shows more evaluation on GCNN model.

We can get a good result from GCNN model, but from model ‘‘Washington’’ we still can see it lacks the sharpness in the detail area like the face and clothes area.

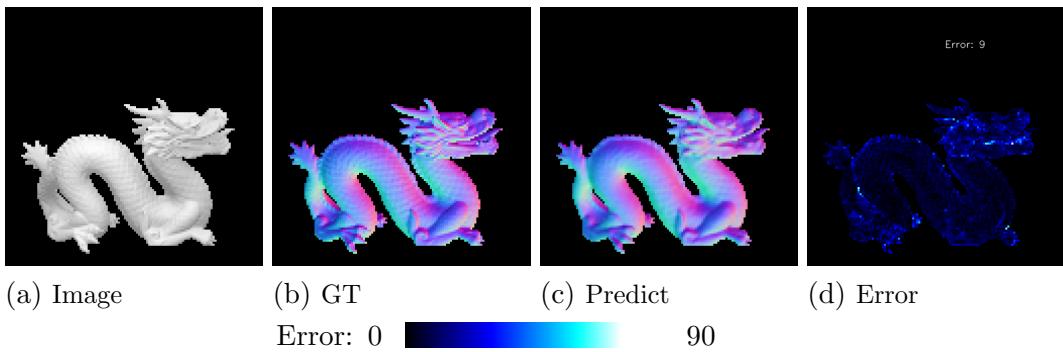


Figure 5.5: GCNN visual evaluation. Window size  $128 \times 128$

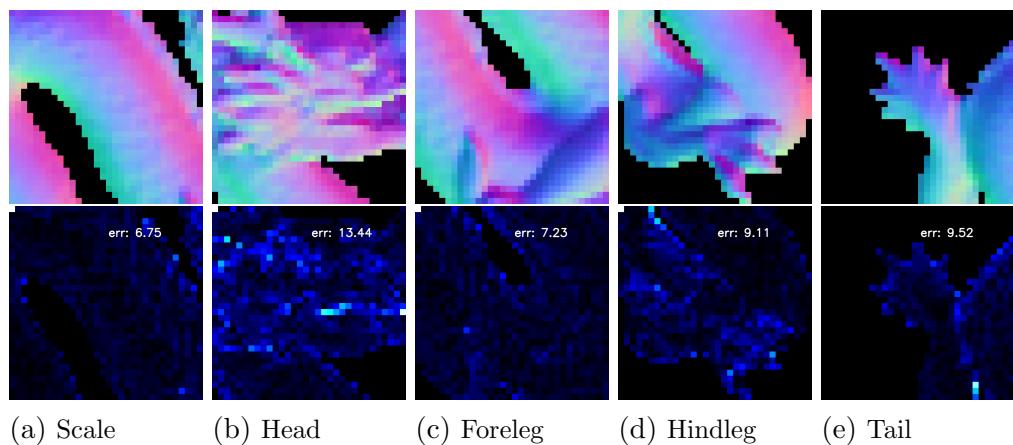


Figure 5.6: Zoom in of some regions of Dragon object (GCNN models). Window size  $32 \times 32$ .

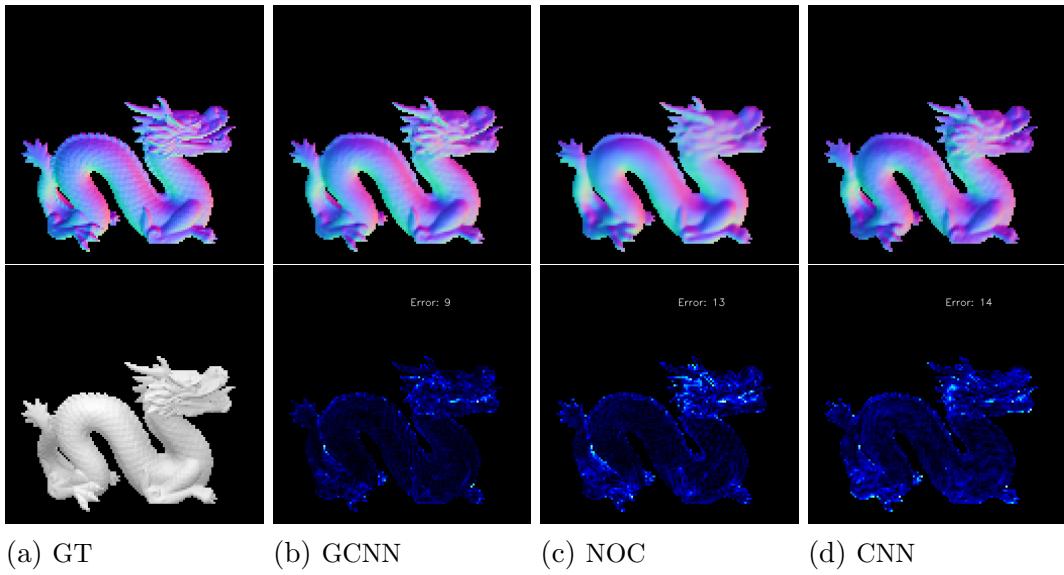


Figure 5.7: Comparison of GCNN based models.

## 5.5 Discussion on the Feature Maps in GCNN

As shown in figure 5.8, we also visualize the feature maps of the last gated convolution layer in the first up-sampling part for CNN and GCNN models, which corresponding the 128 feature maps with size  $32 \times 32$  in width and height. The input data is also same dragon object that we used for normal visualization. For each feature map, we map the minimum value to the left-most color in the color bar and the maximum value to the right-most color in the color bar. We want to discuss the the difference of the feature maps between CNN, NOC and GCNN models.

In order to see the result clearly, we use one color for the feature map visualization and use the brightness to distinguish the scale of the values, the white corresponds 1, the black corresponds 0, and the green-hue colors corresponds some values in between.

From the CNN feature maps, we can see that the high value areas are usually more than one in a single feature map. Many of them have more than two bright areas. For the GCNN feature maps, the brightness areas are usually concentrate only in one area or even one point. If we map the brightness areas to the original image, they correspond to the dense sharp edges areas, like mouse, horn, or tail of the dragon object, which is usually the hardest areas for normal estimation task. We suspect that these feature maps with few bright areas or only one bright area are the detail feature maps that for sharp edges inference. Based on this assumption, we can say that gated convolution layer describes the detail features in a more accurate way compare to standard convolution layer, since the brightness areas is smaller. Most of the GCNN feature maps usually has only one bright pixel with a few set of dim green pixels whereas CNN feature maps has more bright pixels with a lot of dim pixels all around the image. This accurate feature extraction provides our GCNN model a better performance on the detail area.

Second, for the GCNN model, we observed that some feature maps have very evenly bright areas distributed on the whole object. They are either overall dim or overall bright. Nevertheless, these feature maps are different from the detail feature maps with only few pixels with high values(brightness) but most of the other pixels with relatively low values. We suspect that these evenly value distributed features

maps are the global feature maps that provide an over-view of the objects for a coarse prediction. So that they can cooperate with detail feature maps and further used to sharpen the prediction. It also holds for NOC model, since it does not equip with skip connections, most of the feature maps are global feature maps, so that the corresponding normal maps predicted by NOC model are more coarse than the GCNN model. For the CNN model, there also exists global feature maps, however, they are mostly incomplete, either missing the tails or missing the paws. Actually, these missing areas can usually be found in the detail feature maps. This also explained why the CNN detail feature maps has several bright areas in their detail feature maps. The detail feature maps and global feature maps are mixed together. And this unclear feature map extractor leads to reduce the performance on normal estimation task.

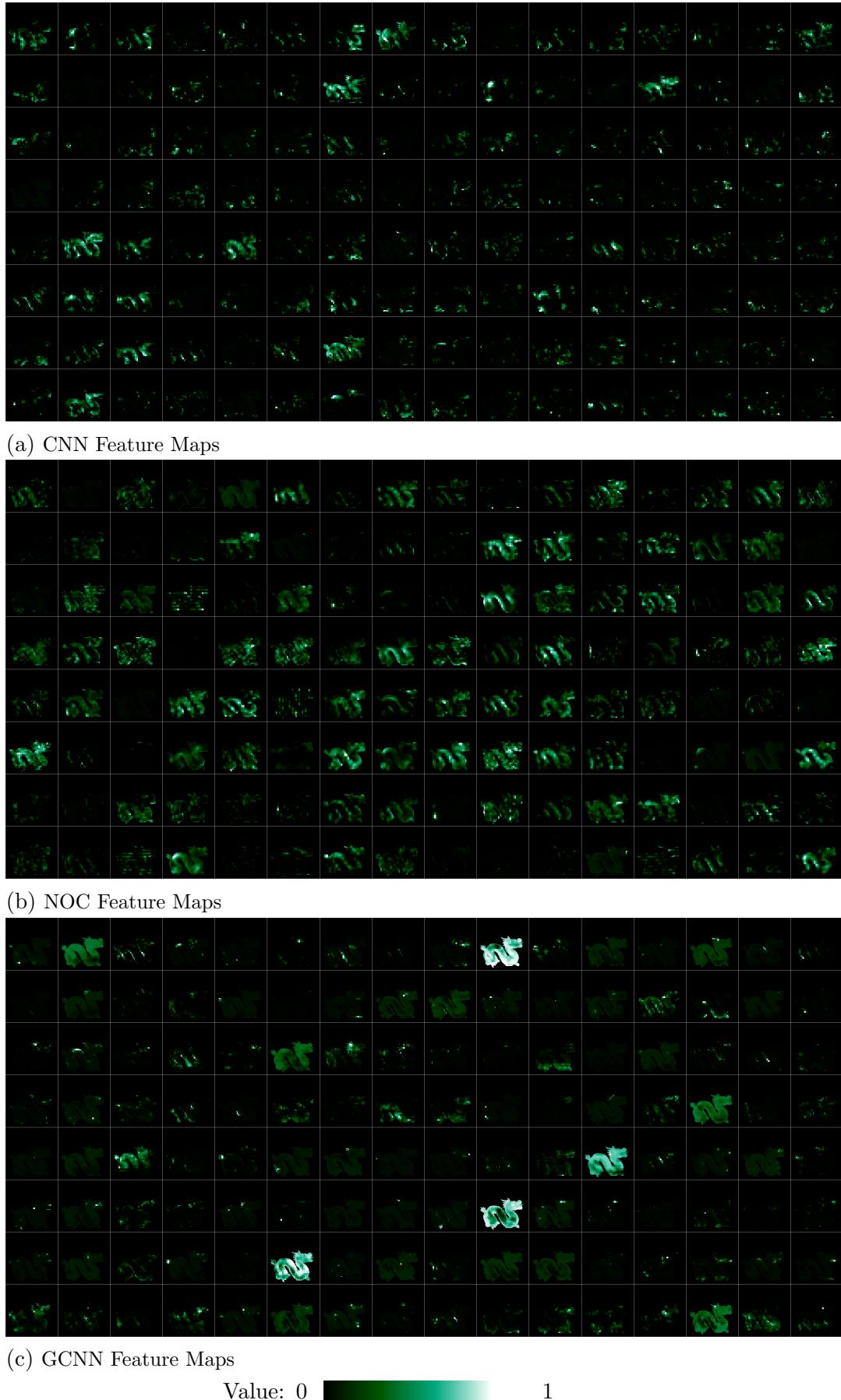


Figure 5.8: Feature maps of GCNN architecture based models at the first up-sampling gated convolution layer. All 128 feature maps are visualized for each model with normalization and filtered background.

## 5.6 Visual Evaluation on Trip-Net

For the approach using illuminated calibrated RGBD image, the task is undertaken by Trip-Net introduced in 3.5. The Trip-Net uses illuminated information align with the geometry information achieves a sharper and more accurate result compare to the GCNN model.

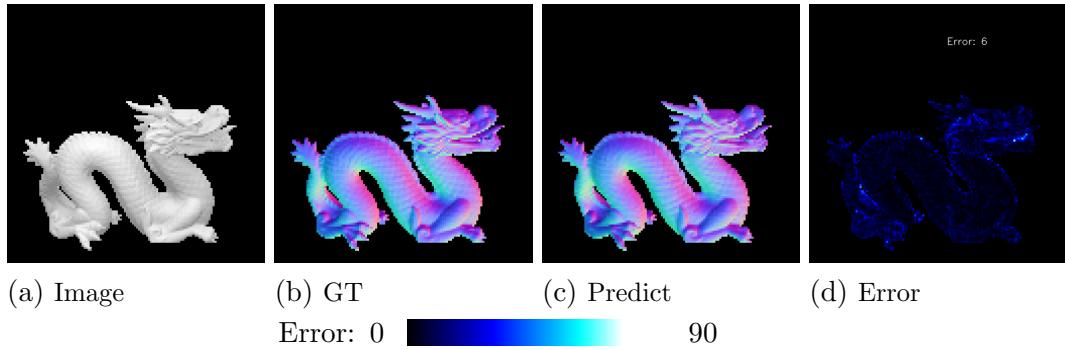


Figure 5.9: Trip-Net visual evaluation on resolution  $128 \times 128$

The qualitative evaluation is shown in figure 5.9. In order to show the effectiveness of added illuminated information, the training settings for all the models are exact the same. We also use the same input as we did in GCNN evaluation. The error of Trip-Net is  $6^\circ$  whereas the GCNN is  $9^\circ$ .

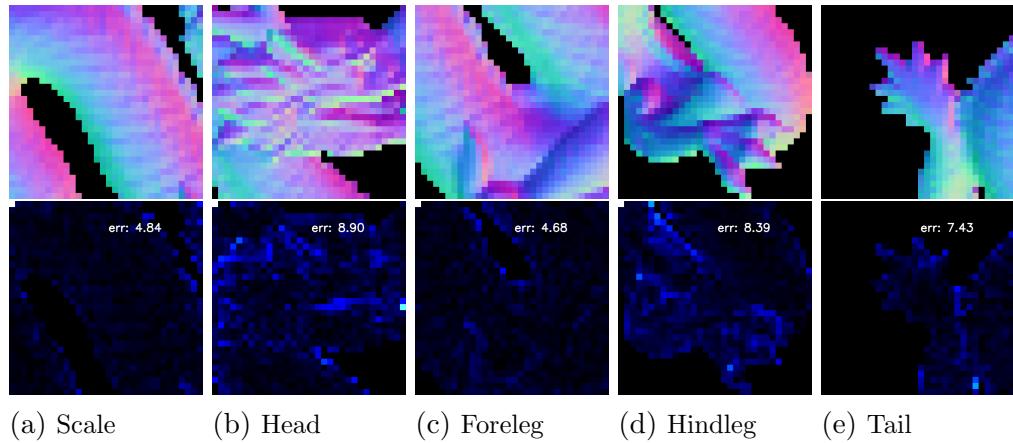


Figure 5.10: Zoom in of detail regions ( $32 \times 32$ ) of Dragon object (Trip-Net model).

As shown in the figure 5.10, the scale on the dragon body is much easier to detect and also close to the ground-truth. The head region gives a sharper edge prediction. All of the five sampled zoom-in regions in the Trip-Net has a better performance than GCNN.

Figure 5.11 compares different fusion times on Trip-Net model. We can see that model F1 with one fusion and F2 with two fusions did not achieve a better result compare to GCNN model, which means the illuminated information doesn't work if we only consider the lower resolution feature maps. F3 model with 3 times fusion and F4 model with 4 times fusion give a much better result and also beyond the

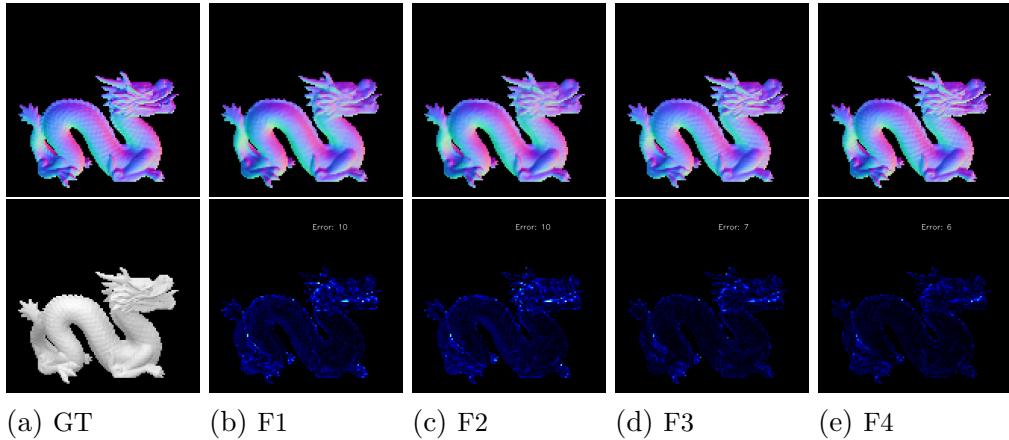


Figure 5.11: Comparison between different fusion times on Trip-Net Architecture ( $128 \times 128$ ).

GCNN model. These two times fusion include high resolution features in the last up-sampling and the final output-size features before the standard convolution layers. We can observe the dragon scale in the figures, they are much sharper in the last two images.

## 5.7 Trining on Higher Resolution

We also trained our models on a higher resolution dataset with  $512 \times 512$  in width and height for each scene. Higher resolution data gives more information about the surface feature using the same model compare to lower resolution. The benefit is, if we extract a fixed sized patch from the normal map, say  $32 \times 32$ , it might correspond a hindleg area of the dragon object in  $128 \times 128$  resolution but maybe only a toe in  $512 \times 512$  resolution. Therefore if we still use the same kernel size in the network for the same dataset, (like we did with  $3 \times 3$ ) the higher the resolution it has, the less area it will cover. Thus the surface in the same window size will more smooth and easy to be calculated the surface normal. This is a good thing. Because then we might only need to use these  $32 \times 32$  points to calculate a toe in  $512 \times 512$  resolution image. But in  $128 \times 128$  resolution image, the same area  $32 \times 32$  might corresponding to entire hindleg of the dragon object. In another word, we can also say that the higher resolution “smooth” the object surface within the same size area. Thus the higher resolution helps the model to calculate a more accurate normal maps.

Metrics	SVD	GCNN	Trip-Net
Mean	8.88	5.82	5.33
Median	3.66	3.98	3.67
$5^\circ$	0.63	0.63	0.66
$11.5^\circ$	0.79	0.89	0.91
$22.5^\circ$	0.89	0.97	0.97
$30^\circ$	0.92	0.98	0.99

TABLE 5.9: High resolution dataset evaluation of SVD, GCNN and Trip-Net models on 6 different metrics based on 100 test scenes.

Since our model is fully convolution network, the architecture keeps exactly same on the high resolution dataset. We use the same settings and the same models for training work on dataset with  $512 \times 512$  resolution. The training on high resolution network takes longer time but achieves a lower angle error.

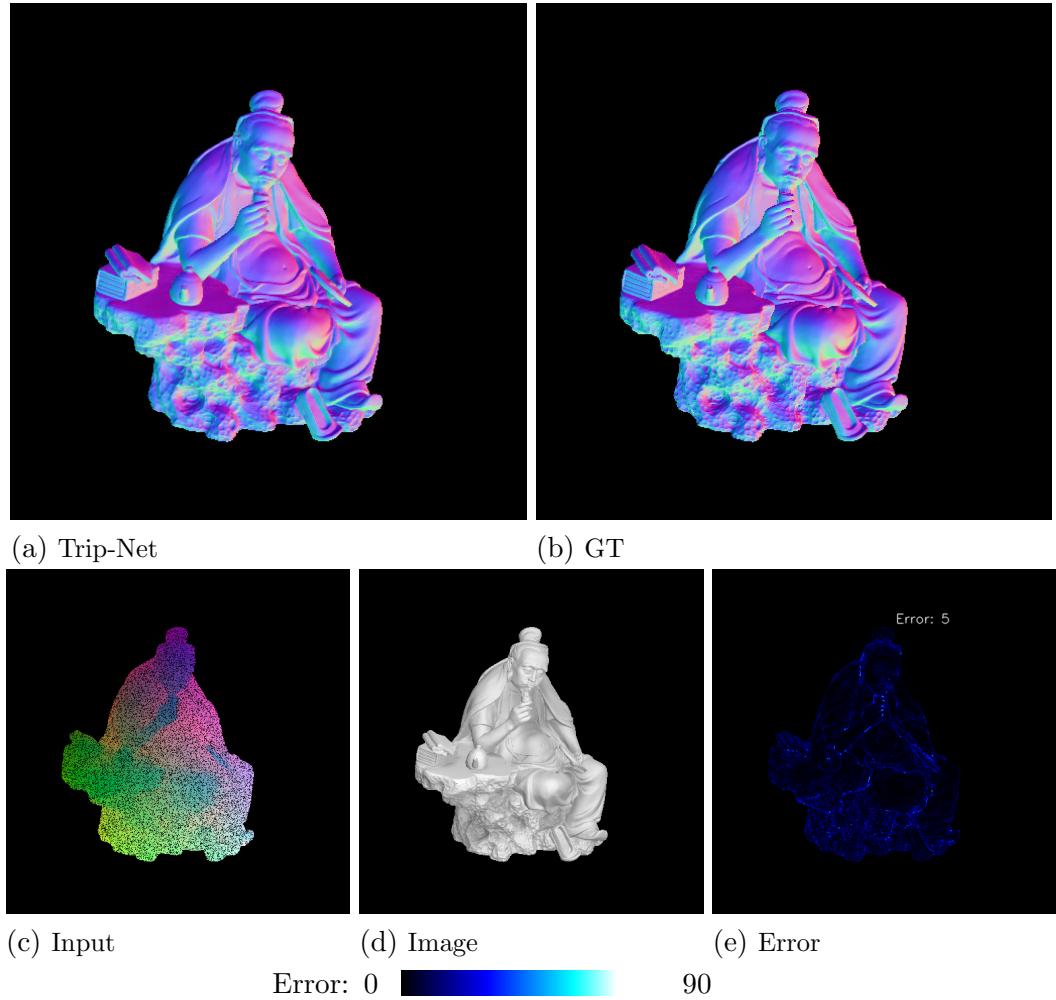


Figure 5.12: Trip-Net visual evaluation on high resolution dataset  
 $512 \times 512$ .

A quantitative evaluation is shown in table 5.9. It follows the same performance ranking compares to lower resolution, which is GCNN better than SVD approach and Trip-Net slightly better than GCNN. The accuracy is 99 % in the  $30^\circ$  metric. In mean error metric, the error is  $5^\circ$ . A qualitative evaluation is shown in figure 5.12. We use a figure object with both smooth area (the belly and arm) and highly detailed area with sharp surface (the uneven surface of stone table) for evaluation. Our models gives an  $5^\circ$  in mean degree metric.

A comparison with other models is shown in figure 5.13. Note that we use the same dragon object (but slightly moved the place since they have been captured in different time in high resolution dataset) for evaluation this time as a coherent comparison with low resolution dataset. The SVD based approach gives a good result ( $8.88^\circ$  in mean degree metric). Like we discussed, the surface are relatively more smooth if we keep the same window size for normal inference. In the high resolution scenes, although the percentage of missing pixels in a fixed windows are remain the same compare to

small resolution scenes, but the remain valid pixels in the same window size are on a relatively flat plane thus they are good enough for an accurate normal inference. However, as we expected, we can still see the high degree error in the sharp edges of the dragon object, like the horns and the hindleg areas as shown in 5.13.

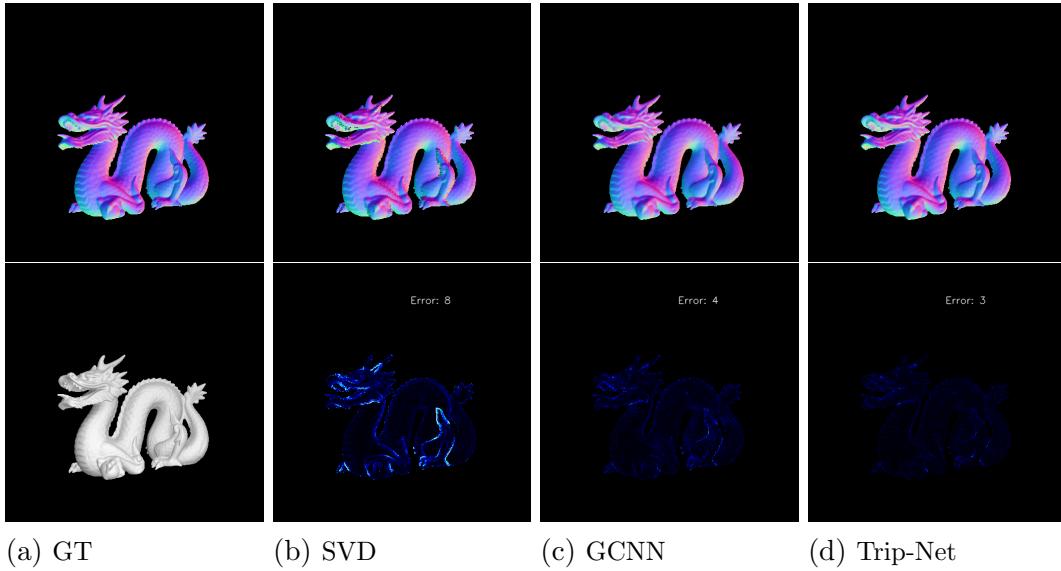


Figure 5.13: Comparison on high resolution dataset ( $512 \times 512$ ) .

## 5.8 Training on Real-Dataset

We also applied our model on a dataset that captured by a light scanner in our laboratory in order to see our model’s applicability to the real-dataset. For the geometry information based approach, we directly use the GCNN model that trained on synthetic dataset since it only require the depth map as input, the scenarios of two dataset are the same. For the illuminated calibrated RGB-D image based approach, the model has to be refined based on the real-dataset, since the light intensity and position, camera matrix are different. We refined the Trip-Net based on a pre-trained GCNN model with the same settings in previous experiments, and observe the results.

Metrics	SVD	GCNN	Trip-Net
Mean	8.20	8.74	<b>8.09</b>
Median	<b>4.87</b>	5.70	5.00
$5^\circ$	<b>0.51</b>	0.44	0.50
$11.5^\circ$	0.79	0.79	<b>0.81</b>
$22.5^\circ$	0.93	0.93	<b>0.94</b>
$30^\circ$	0.96	0.96	0.96

TABLE 5.10: Evaluation of SVD, GCNN and Trip-Net models on 6 different metrics based on 100 test scenes in real dataset.

Since in the real-dataset, we don’t have a ground-truth for evaluation. But if we see directly from the visualization in figure 5.14, we can see that Trip-Net approach has good ability to “mend” the missing pixels in the scenes and also gives a sharp

result. The folds on the gowns are recognizable and even countable. Figure 5.15 compares the Trip-Net with other approaches.

But we also noted that the big holes in the base stage remains in the normal maps. These big holes corresponds to the shiny and dark texture area, which common exist in the depth map captured by the scanners. Since these big holes are related with only special feature areas and also has irregular shapes, we didn't simulate this type of noise in the synthetic dataset but only with a sparse binary mask. Thus our models failed to mend missing big holes in the estimated normal map. This can be a further work of this topic, that find a way to generate high similar depth map noise to get a more robust training dataset.

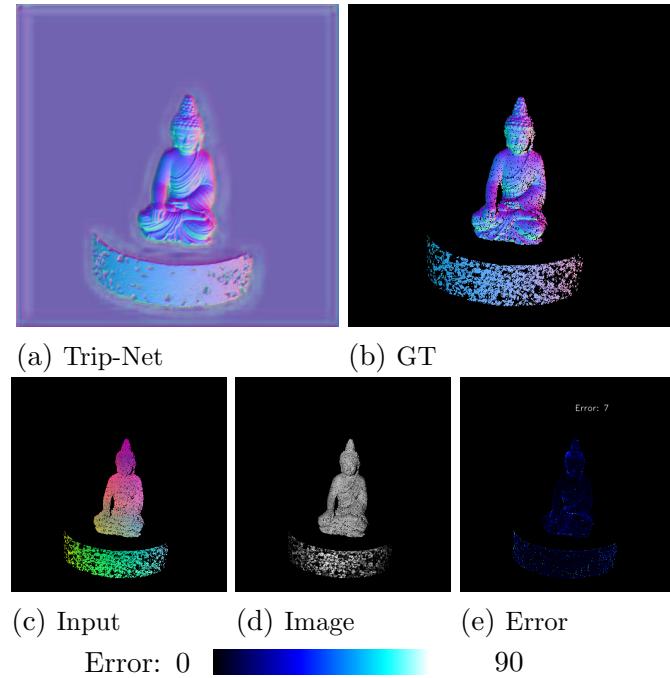


Figure 5.14: Real Dataset ( $512 \times 512$ ) evaluation (Trip-Net)

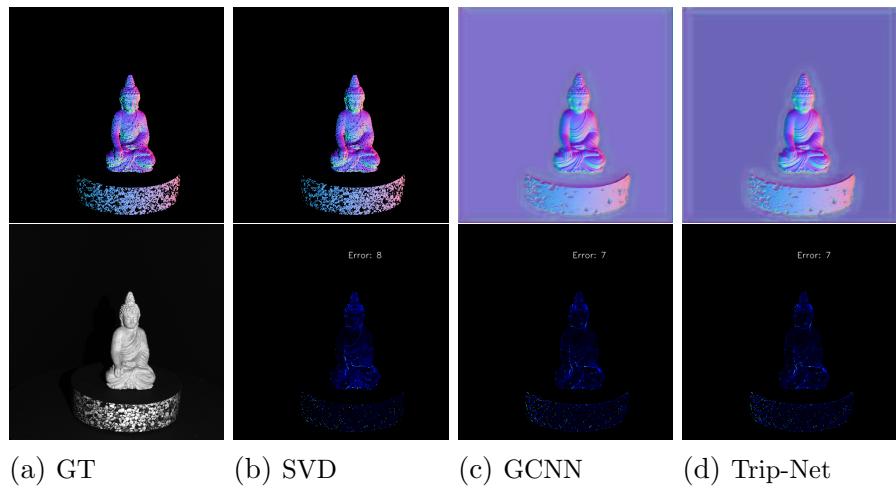


Figure 5.15: Real dataset ( $512 \times 512$ ) comparison.

## Chapter 6

# Conclusion

In our approaches, two networks have been proposed. The first network called GCNN is used for geometry information based approach, which is our baseline method. It is especially good for the semi-dense input data which is benefited with gated convolution layer design. Using this network we achieved a more accurate normal inference than using standard layers network based on the same architecture. We also show the effectiveness of skip connection in the U-Net. Besides, the fully convolution design enables it to use various resolution images as input.

The second network is called Trip-Net, which is based on the GCNN model. It is designed for illumination calibrated RGB-D image based approaches. This model utilises GCNN architecture three times in order to handle vertex map, light map and image map separately. We have also found that 3 to 4 times fusion times among 3 pipes in our models is the key point for the performance enhancement. Based on our experiments, it shows that the models trained on illuminated calibrated RGB-D images achieve a better performance than geometry information only based approach and gives more sharpness in the normal map.

We also explored the performance of our models on a real dataset and compare with traditional method like SVD based approach. Especially, our gated convolution layer based model can fill the missing pixels in the real input data and keep an accurate normal estimation, whereas the optimization based approach like SVD is failed to do so.

We collected 55 high density point clouds from internet and used them for our dataset generation. Specifically, we use a RGB-D camera, an ambient light and one directional light collect thousands of scenes. The scene generation is simulated by game engine Unity. Furthermore, we also simulated noise in our synthetic dataset by a uniform distributed drop off to fit our model and adopt it with semi-dense input data. However, for the large missing areas, we did not generate a similar noise in the training set, which leads to our model cannot fill the holes in the real data. Exploring a sensor-noise mimic algorithm to generate more reality closed data for training work can be a direction of further work.



## Appendix A

# Dataset

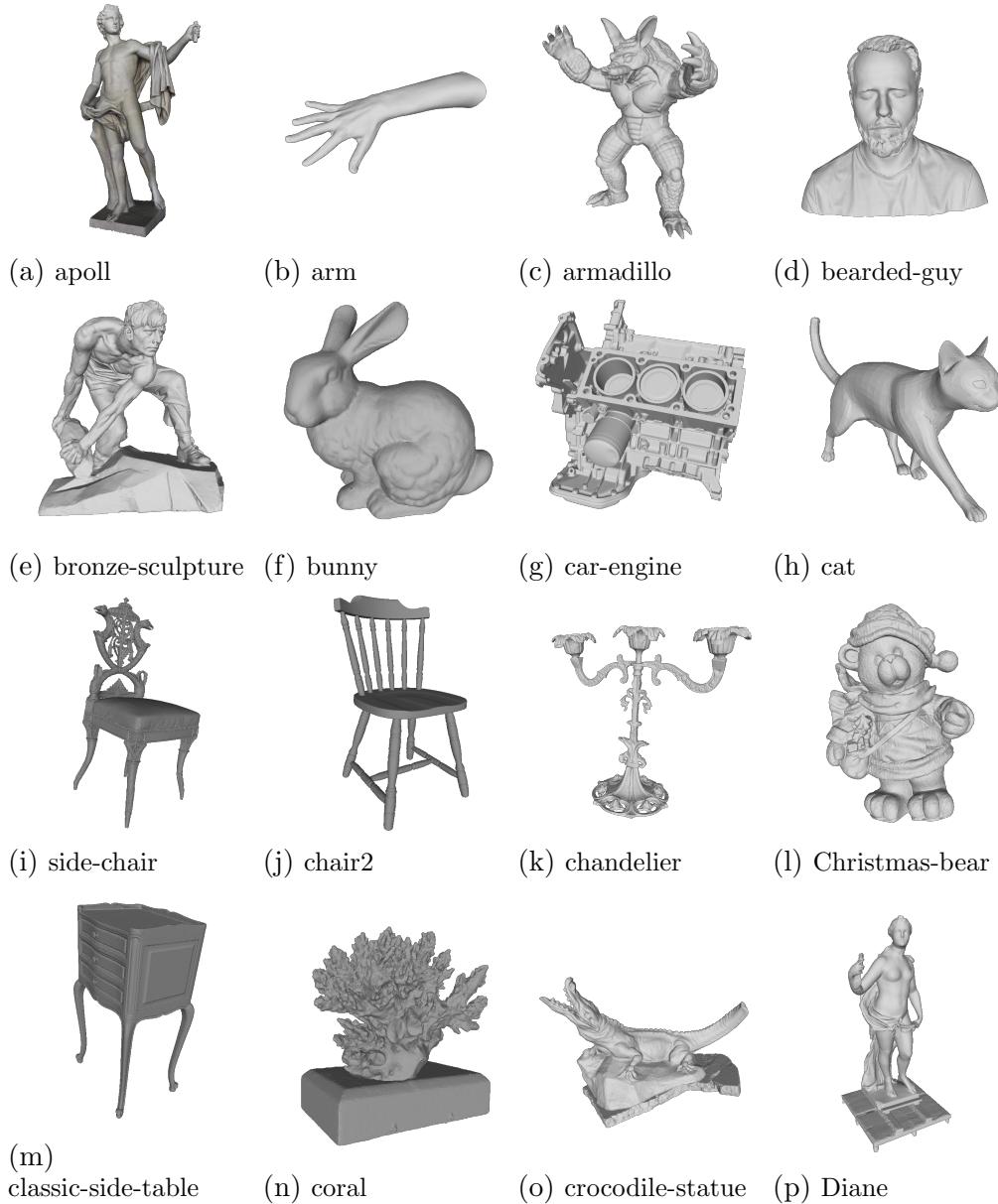


Figure A.1: Point clouds in dataset A

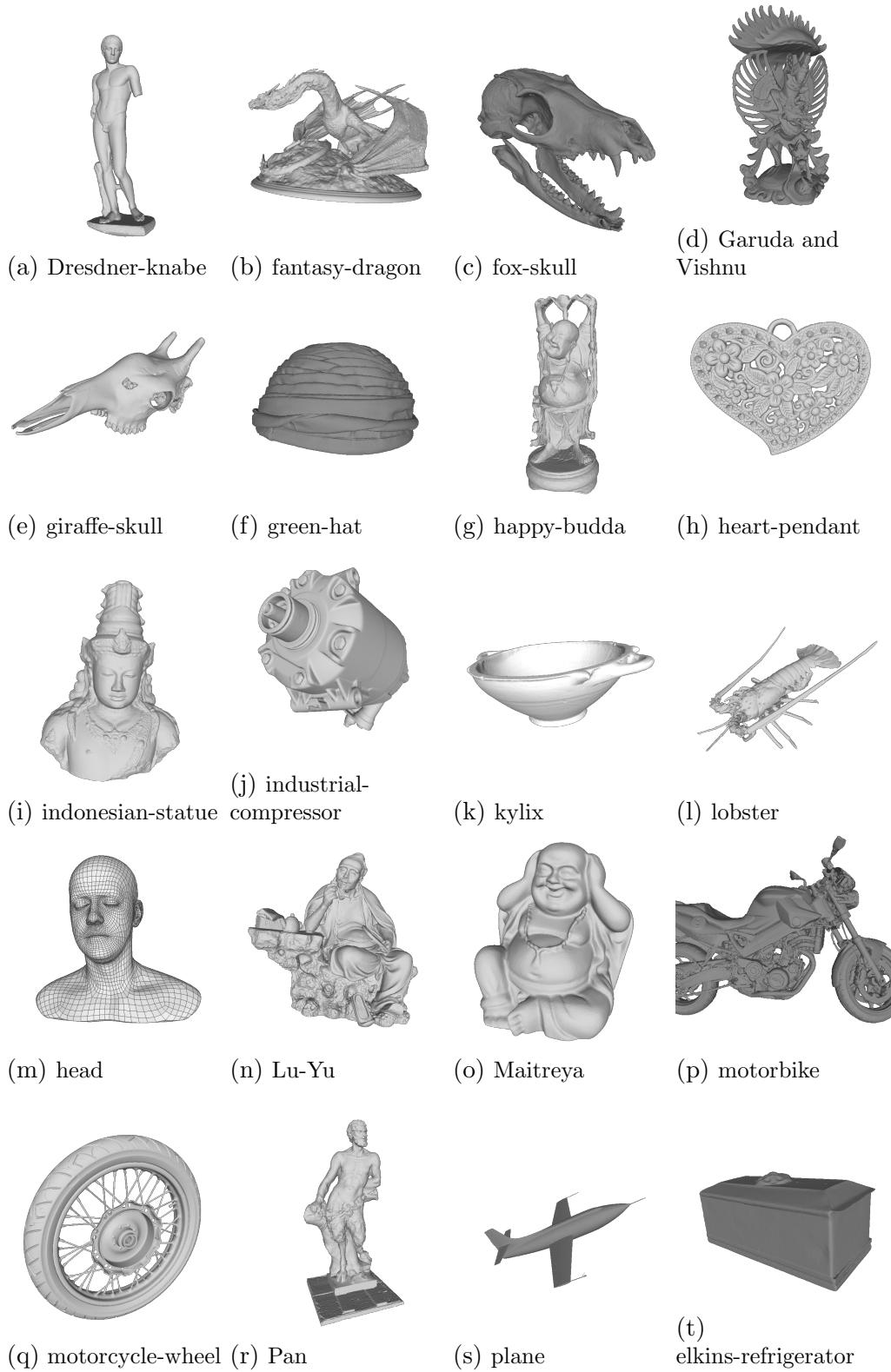


Figure A.2: Point clouds in dataset B

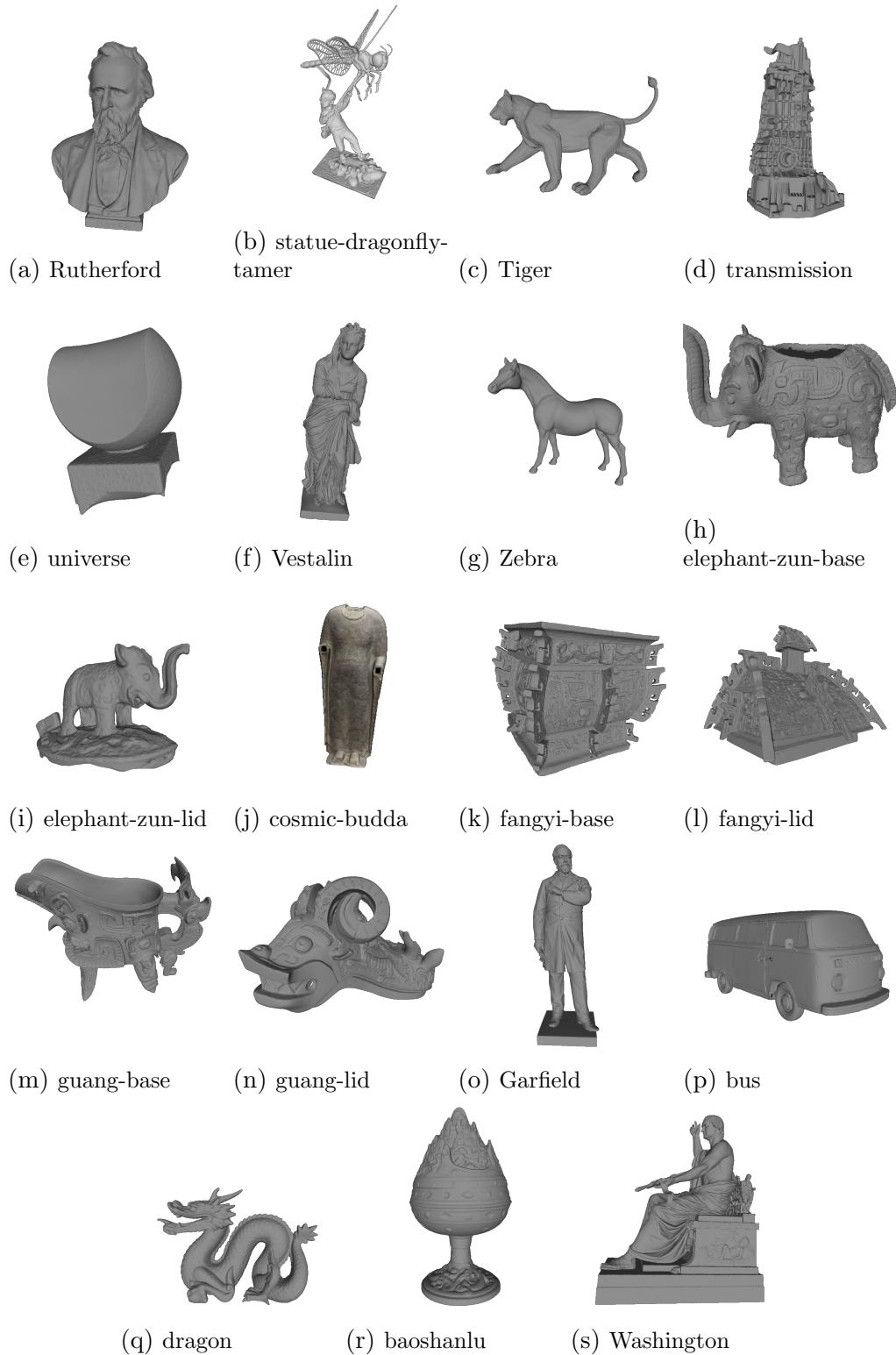


Figure A.3: Point clouds in dataset C



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