SphereDepth: Panorama Depth Estimation from Spherical Domain

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Abstract

The panorama image can simultaneously demonstrate complete information of the surrounding environment and has many advantages in virtual tourism, games, robotics, etc. However, the progress of panorama depth estimation cannot completely solve the problems of distortion and discontinuity caused by the commonly used projection methods. This paper proposes SphereDepth, a novel panorama depth estimation method that predicts the depth directly on the spherical mesh without projection preprocessing. The core idea is to establish the relationship between the panorama image and the spherical mesh and then use a deep neural network to extract features on the spherical domain to predict depth. To address the efficiency challenges brought by the high-resolution panorama data, we introduce two hyper-parameters for the proposed spherical mesh processing framework to balance the inference speed and accuracy. Validated on three public panorama datasets, SphereDepth achieves comparable results with the state-of-the-art methods of panorama depth estimation. Benefiting from the spherical domain setting, SphereDepth can generate a high-quality point cloud and significantly alleviate the issues of distortion and discontinuity.

1. Introduction

Depth estimation attempts to infer the distance between the objects and the camera in the captured scene, which is a classical but important vision problem for many upstream 3D applications, such as scene reconstruction, semantic understanding, robotics navigation, etc. Traditionally, researchers focus on the problem of monocular depth estimation [16], which learns the traditional 2D content captured by typical pinhole projection model-based cameras. To obtain the novel information (360° sensing) of a 3D scene, they integrate those single views based on multi-view consistency [42, 43] and structure-from-motion (SfM) [35, 36]. However, as the consumer-level 360° cameras are becoming more popular and rapidly developed in recent years, inferring the depth information from a panorama image naturally attracts the community. The panorama camera has a field-of-view (FoV) of 360° and can acquire a comprehensive view in just one shooting spot.

However, as the best way to display the panorama image is using the sphere (a non-Euclidean space), the existing studies of monocular depth estimation based on convolutional neural networks (CNNs) [12, 26, 46] cannot be directly applied to its depth task. Therefore, the most popular solution is using some projection methods to convert the
panorama image into a standard 2D image, such as equirectangular projection and cube map projection. Equirectangular projection provides a wide FoV mimicking a peripheral vision but introduces distortion [38, 37, 47], while cube map projection provides a smaller and non-distorted FoV mimicking the foveal vision but introduces discontinuity [6, 23, 24]. Overall speaking, those methods based on projection will inevitably suffer more or less from distortion and discontinuity and bring systematic errors to the upstream visual perception tasks.

To this end, this paper proposes a novel panorama depth estimation method called SphereDepth, that directly predicts the depth map in the spherical domain without any projection. SphereDepth uses a spherical mesh to approximate the sphere and treats each triangle in a spherical mesh as a pixel in an image. After assigning each triangle with an RGB value, we can use a customized mesh convolution kernel to extract the features for depth estimation. We then construct a mesh-based convolution to directly perform depth estimation on a spherical mesh. Fig. 1 compares the point cloud generated by SphereDepth with the existing state-of-the-art algorithm BiFuse [41] and SliceNet [30]. From the enlarged parts of the point cloud, we observe that SphereDepth provides accurate and smooth results while BiFuse and SliceNet exhibit discontinuity and distortion.

However, representing a high-resolution panorama image needs a spherical mesh with high resolution and more triangles. Unlike the perspective image organized in a 2D pixel matrix, the spherical mesh uses triangles to represent each pixel. The topological complexity of the spherical mesh exponentially grows with the number of triangles increasing, which degrades the computing efficiency and increases the memory footprint.

To address this challenge, we split the spherical resolution (SR) into two types of resolutions: the mesh resolution (MR), which indicates the number of triangles on a spherical mesh, and the triangle resolution (TR), which represents how many pixels each triangle has. On the one hand, a higher MR can represent a higher resolution panorama image with more details and naturally lead to larger resource consumption. On the other hand, compared to increasing MR, a high TR can enhance the local features of a mesh triangle with much less computational demand and memory demand. In practice, we can tune MR and TR in the spherical domain to balance the accuracy and processing speed of the deep network. Our contributions are summarized as follows.

• SphereDepth is an end-to-end network to infer the panorama depth map in the spherical domain, which fundamentally solves the problem of distortion and discontinuity caused by projection methods;

• We sample the features from a panorama image in the spherical domain and propose customized operations to tackle spherical features for panorama depth estimation. We also propose two hyper-parameters for SphereDepth, MR and TR, to balance the efficiency and accuracy;

• Superior to those existing methods, SphereDepth achieves comparable accuracy in panorama depth estimation and generates a much higher quality point cloud. SphereDepth suggests a new direction to apply the sphere mesh convolution to the panorama image instead of traditional convolution networks.

2. Related

Perspective Depth Estimation Perspective Depth Estimation is a hot topic in computer vision. Eigen [12] proposed the first deep learning network that can estimate a depth map directly from an RGB image. Laina [26] uses ResNet [19] as the encoder and skip connections to merge high-level and low-level features. DORN [15] divides the space into discrete intervals and treats the depth estimation problem as a classification problem. DenseDepth [1] introduces more loss functions to obtain a smoother depth map. Recently, Midas [33] and BoostedDepth [29] have explored some strategies that can improve the quality of depth estimation, such as a mixture of different datasets and changing the image resolution. Meanwhile, Adabins [3] uses ViT[10] to guess the best discrete depth distribution, and DPT [32] directly proposes a transformer network that can perform dense prediction.

All the above methods require a label for each pixel, which is difficult to satisfy in natural scenes. So some researchers turn to self-supervised methods. SfMLearner [46] uses the photo-metrics as a guide to train the network and predict the depth and the relative pose at the same time. MonoDepth2 [17] uses a robust error detection method to filter out dynamic areas and invisible areas, which is against the static scene assumption in the self-supervised method. SfMLearner-SC [4] tries to solve the problem of scale drift in the self-supervised method by encouraging the consistency of depth maps. TrainFlow [45] realizes the unreliable of the pose net and uses an optical flow to calculate the relative pose to improve the robustness. CVD [28] uses colmap [36] to obtain the pose directly and apply a deep network to predict the depth by the photo consistency.

However, all methods mentioned above only work for perspective cameras and ignore distortion. Thus, they cannot be directly adapted to the 360° panorama images.

Panorama Depth Estimation Although the progress of perspective panorama depth estimation is enormous, the study of panorama depth estimation is still at a certain early
Figure 2. SphereDepth uses mesh convolution to estimate depth on triangles of the spherical mesh to avoid distortion and discontinuity, instead of directly using traditional 2D convolution, such as BiFuse [41] and SliceNet [30].

Table 1. The Resolution Look-Up Table

| Image Resolution (IR) | Spherical Resolution (SR) |
|-----------------------|---------------------------|
| 32×64                | 4                         |
| 64×128               | 5                         |
| 128×256              | 6                         |
| 256×512              | 7                         |
| 512×1024             | 8                         |

To eliminate the disadvantages of the above two projection methods, some recent studies attempted to process the panorama image in the spherical domain and apply a designed convolution in some 2D vision tasks, such as semantic segmentation in [22, 27, 44, 11], object detection/classification in [27, 7] and layout estimation [31]. However, it still lacks discussions on applying spherical convolution to inferring 3D information, such as depth, from a panorama image, because of the heavy computation burden. We propose a new panorama depth estimation using the spherical mesh and follow the setting of the SubdivNet [21], which is more efficient than MeshCNN [18] and MeshNet [13]. Our experiments show that our method can achieve a comparable result with state-of-the-art results.
3.1. Spherical Mesh

Instead of applying the equirectangular projection or cubemap projection to the panorama image, we use the spherical mesh to process the panorama image in the spherical domain. The spherical domain can help us avoid discontinuity and distortion caused by projections. A popular method to represent the panorama image in the spherical domain is based on the icosahedron spherical mesh (ISM) [11], which can generate a higher resolution of spherical mesh to approximate a sphere by loop-subdivision [21].

As most panorama images are stored in the equirectangular projection, we have to represent them by the spherical mesh. Considering the fundamental element of the spherical mesh is the triangle, a straightforward method is to project the triangle’s center \( p = (x, y, z) \) to the image plane and sample color on the image plane based on the projected point \( i = (u, v) \). We can derive the geometric relationship between the 3D point \( p \) and 2D point \( i \) on an image with the image resolution (IR) \((W,H)\) by Eq. 1.

\[
\begin{align*}
  u &= (1 + \tan(\arctan(y/x)/\pi)) \times W/2 \\
  v &= (0.5 + \tan(\arctan(z, \sqrt{x^2+y^2})/\pi)) \times H
\end{align*}
\]  

(1)

When a triangle only displays one pixel, it is easy to realize that a higher IR needs a higher spherical resolution (SR) that determines the number of triangles by \(20 \times 4^{SR} \). Following Tangent [11], we can list out the IR-SR relationship in Table 1. For a given IR, we must use the corresponding SR to get the best results. However, we could not process spherical mesh with lots of triangles efficiently [21]. Therefore, instead of only displaying one pixel by a triangle, we split the SR into mesh resolution (MR) and triangle resolution (TR).

3.2. Mesh Convolution and Pooling/UnPooling

After representing a panorama image in the spherical domain by a spherical mesh, we design a customized mesh convolution kernel to extract the spherical features and follow pooling/unpooling from SubdivNet [21].

Unlike the 2d pixels, which can directly access neighboring pixels by coordinates, the triangles in the spherical mesh cannot find their adjacent triangles by coordinates. The only way to gather this kind of information is through the topological relationship of the mesh, called face adjacent face (FAF). Considering that the number of FAF of a triangle is not fixed, we simplify this by defining adjacent triangles as the subset of the FAF with edges in common to reduce the number of adjacent triangles to 3, as Fig. 4.

**Mesh Resolution**  Mesh resolution (MR) refers to the number of times the ISM is loop-subdivided and decides the number of triangles on a spherical mesh. The higher of MR, the closer is between the spherical mesh and the standard sphere. Tangent [11] uses the Surface Area Ratio to measure the difference and finds out that it is almost equal to 1 when \(MR > 3\). However, the computational complexity of the mesh convolution is linear to MR, and higher MR will bring a more complex topological relationship and make it difficult to process. Therefore, we have to find out a proper MR.

**Triangle Resolution**  Triangle resolution (TR) means the number of points sampled within a triangle. TR is also achieved by loop-subdivision, but we only keep triangles’ center and ignore topological relationships. The relation between the number of points and TR is \(4^{TR} \). During the training and inference procedure, we directly concatenate all the features coming from TR together in a fixed order and feed them to the network simultaneously. Fig. 3 shows three triangles with different triangle resolutions, which shows how to get a spherical mesh with higher resolution and how to generate more points in a triangle.
shows that there are only three triangles around $n_3$. We define a simple mesh convolution kernel in Eq. 2 with a fixed number of adjacent triangles, in which $f_{\text{out}}$ is the output features, $n_i (i = 0, 1, 2, 3)$ are the input features, and $w_i (i = 0, 1, 2, 3)$ are kernel parameters needed to be learned (Bias is used, but not visualized here).

$$f_{\text{out}} = w_0 n_0 + w_1 n_1 + w_2 n_2 + w_3 n_3$$  \hspace{1cm} (2)

The mesh pooling/unpooling kernel is also an indispensable module for building a network of encoder-decoder paradigms. Due to the unique nature of the spherical mesh, we can directly merge subdivided triangles into one triangle, and the reverse operation is unpooling. As Fig. 4 shows, four triangles $n_0, n_1, n_2, n_3$ merge into one triangle $m_3$ by pooling, and one triangle $m_3$ can be split into four triangle $n_0, n_1, n_2, n_3$ by unpooling. Furthermore, the pooling will change the spherical resolution of the feature map in the spherical domain, which means that the number of pooling layers cannot exceed MR. Throughout our paper, we use max-pooling.

3.3. Network and Loss Function

Network We construct our SphereDepth based on UNet Structure [34], as shown in Fig. 2. The encoder part consists of five pooling layers to increase the reception field and 2 or 3 mesh convolution blocks in each layer to extract robust features. In each mesh convolution block, we follow the design of ResNet [19] and stack three Conv Layers together with a residual connection. On the decoder side, we use five unpooling layers to increase the resolution of the feature map and concatenate them with feature maps from the encoder by skip-connection. Benefiting from the design of UNet [34], SphereDepth can generate depth maps with different spherical resolutions. The input and output of the SphereDepth are represented in the spherical domain. For an input with $MR = m$ and $TR = t$, the shape of input is $(1, 20 \times 4^m, c \times 4^t)$ and the shape of output is $(1, 20 \times 4^{m-s}, 4^t)$. $c$ is the channel number of the image, and $s$ is the output stage.

Log Loss Function We utilize the multi-resolution depth maps predicted by SphereDepth and construct a multi-scale loss as Eq. 3 shows, where $r$ is the spherical resolution of the depth map, $l_r$ is the weight set for each resolution, $R$ is the max spherical resolution, $V$ is the set of valid pixels, $N_r$ is the number of valid pixels in the $r$ resolution level, $gt$ is the ground truth, and $pr$ is the predicted depth map. During training, we define valid pixels by gt depth maps whose values are inside a preset depth range.

$$\text{loss} = \sum_{r}^{R} \sum_{p \in V} l_r \frac{|log(gt_r(p)) - log(pr_r(p))|}{N_r}$$  \hspace{1cm} (3)

4. Experiments

4.1. Datasets

We test our method on three popular panorama datasets, Stanford2D3D [2], Matterport3D [5] and 360D [47]. Details of each dataset are introduced below.

Stanford2D3D Stanford2D3D [2] is collected from the real world. It contains 1413 panoramas from three types of buildings, including six large-scale indoor areas. We resize the panorama images and depth maps into $512 \times 1024$ and follow the official splits for training and testing.

Matterport3D Matterport3D [5] is a real-world dataset, which has 10800 panorama images from 90 different rooms captured by Matterport’s Pro 3D Camera. We use the official split, including 61 rooms for training and 29 rooms for testing. We resize the panorama image to $512 \times 1024$.

360D 360D [47] is a large synthetic dataset rendered by OmniDepth [47] using Ray Tracing Method. 360D uses texture models from four different datasets (including Stanford2D3D and Matterport3D) and generates 35977 panorama images. From Omnidepth, 34679 of this dataset are used for training, and the rests are for testing. Unlike the real-world datasets, the resolution of 360D is $256 \times 512$.

4.2. Implementation

We implement SphereDepth by the Jittor [20] framework, which is a high-performance deep learning framework based on JIT (just in time) compiling and metadata. We set the batch size to 4 and use Adam [25] optimizer with a learning rate of 4e-4. Considering the small size of Stanford2D3D, we use the trained model from Matterport3D to fine-tune this dataset. We compare our method with FCRN [26], OmniDepth [47], BiFuse [41] and SliceNet [30]. Following BiFuse and SliceNet, we use MAE, MRE, RMSE, RMSE(log) and $\delta$ as evaluation metrics and set the max depth value to 10 meters for 360D and 16 meters for Stanford2D3D and Matterport3D. Details of those metrics are explained in the supplementary materials.

4.3. Ablation Study

In this section, we present the ablation study on the architecture settings of SphereDepth, including the loss function, convolution kernel, and spherical resolution. We use the largest 360D for all the ablation experiments to get robust
results. Our default setting is using UNet [34] as an encoder with a log loss function, and the SR is \( \{MR = 5, TR = 2\} \). We only modify part of the setting in each ablation experiment and keep the rest fixed.

**Loss function** To improve the performance of SphereDepth, we conduct experiments on three different loss functions, Log-loss, Absolute-loss, and Huber-loss [41]. Log-loss is calculated in the logarithmic domain and can pay more attention to the information in the closer area. Absolute loss directly calculates the difference, also known as L1 loss. Huber-loss combines L1 loss and L2 loss, which is more robust to outliers. Table 2 shows the results of different settings. The Log-loss function gets the best results, and the worst is the Huber-loss function. Based on these results, in the later experiments, we choose UNet as the encoder of SphereDepth and the Log-loss function.

**The Convolution Kernel** We conduct another ablation experiment on the convolution kernel. The convolution kernel of SubdivNet [21] focuses on the geometry information of the mesh and uses a rotation-invariant kernel to process the features. In contrast, the convolution kernel of SphereDepth follows the principle of 2D convolution kernel and applies weighted aggregation to the input features. Notice that the original paper of SubdivNet only discusses the case of image classification. We modify the code of SubdivNet to fit our depth estimation pipeline accordingly. Table 3 shows the kernel of SphereDepth outperforms the kernel of SubdivNet with a lower computational.

**MR and TR** Our last ablation experiment discusses the impact of different spherical resolution strategies on SphereDepth. For a chosen SR, there are different strategies to set the MR and TR resolutions that lead to different GPU memory requirements, computing efficiency, and depth map quality. The IR of 360D is 256×512 and their corresponding \( SR = 7 \) according to Table 1. We test three different SR strategies, including \( \{MR = 5, TR = 1\} \), \( \{MR = 5, TR = 2\} \), and \( \{MR = 6, TR = 1\} \). Table 4 shows the results of different strategies. The SR strategy \( \{MR = 5, TR = 1\} \), which is inconsistent with \( SR = 7 \), gets the worse results. The results of \( \{MR = 6, TR = 1\} \) are the best, but it requires more GPU memory and more time during training for an epoch. We should ensure \( IR = SR \) and fully consider the computational efficiency in setting a larger MR based on these results. We choose \( \{MR = 5, TR = 2\} \) for 360D, and \( \{MR = 6, TR = 2\} \) for 360D.
for Stanford2D3D and Matterport3D.

4.4. Quantitative Evaluation

Following the results of ablation studies, we use the UNet as the encoder with our convolution kernel and the Log-loss function. Table 5 shows the quantitative results of different methods on three datasets.

SphereDepth outperforms BiFuse [41] and achieves comparable results with SliceNet [30] and HohoNet [39]. On the Standford2D3D dataset, SphereDepth does not achieve the best results, as the size of the dataset is small, and our method cannot benefit from the pre-trained model of ImageNet [9]. On the Matterport3D, SphereDepth almost achieves the best results among those existing studies with only a slight drop in some metrics. On the 360D, the metrics of SphereDepth are generally close to SliceNet but perform better than BiFuse. One interesting phenomenon is that SphereDepth does better in the δ metric than others almost on all three datasets, which shows SphereDepth has better-reconstructed results in the structure.

4.5. Qualitative Evaluation

To further prove SphereDepth’s reliability, we visualize some depth maps predicted by different methods. However, BiFuse and SliceNet only open-sourced parts of trained models; hence we cannot visualize them on all the datasets. We also compared the point clouds, which is much more straightforward to show the advantages of SphereDepth, instead of only comparing the depth map.

Fig. 5 and Fig. 6 show the depth maps on 360D and Standford2D3D, respectively. SphereDepth achieves better results on the scene’s structure but lacks details such as boundaries compared with the depth map. The second row in Fig. 6 shows that SphereDepth can even generate correct depth in GT missing regions, but SliceNet fails to do that. Fig. 7 shows two point clouds generated by SliceNet and SphereDepth. SphereDepth can generate a smoother and cleaner point cloud compared with SliceNet, which produces lots of noises in the point cloud.

Fig. 8 compares the depth maps generated by BiFuse, SliceNet and SphereDepth on Matterport3D. BiFuse and
Table 5. Evaluation on three datasets. 'S2D3D' is short for Standard2D3D. 'M3D' is short for Matterport3D.

| Dataset | Method     | MRE↓ | MAE↓ | RMSE↓ | RMSE(log)↓ | δ1 ↑ | δ2 ↑ | δ3 ↑ |
|---------|------------|------|------|-------|------------|------|------|------|
| S2D3D   | FCRN [26]  | 0.1837 | 0.3428 | 0.5774 | 0.1100 | 0.7230 | 0.9207 | 0.9731 |
|         | OmniDepth [47] | 0.1996 | 0.3743 | 0.6152 | 0.1212 | 0.6877 | 0.8981 | 0.9578 |
|         | BiFuse [41] | 0.1209 | 0.2343 | 0.4142 | 0.0787 | 0.8660 | 0.9580 | 0.9860 |
|         | SliceNet [30] | 0.0998 | 0.1737 | 0.3728 | 0.0765 | 0.9038 | 0.9623 | 0.9863 |
|         | HoHoNet [39] | 0.1014 | 0.2027 | 0.3834 | 0.0668 | 0.9054 | 0.9693 | 0.9886 |
|         | Ours       | 0.1185 | 0.2323 | 0.4512 | 0.0754 | 0.8666 | 0.9642 | 0.9863 |
| M3D     | FCRN [26]  | 0.2409 | 0.4008 | 0.6704 | 0.1244 | 0.7703 | 0.9174 | 0.9617 |
|         | OmniDepth [47] | 0.2901 | 0.4838 | 0.7643 | 0.1450 | 0.6830 | 0.8794 | 0.9429 |
|         | BiFuse [41] | 0.2048 | 0.3470 | 0.6259 | 0.1134 | 0.8452 | 0.9319 | 0.9632 |
|         | SliceNet [30] | 0.1764 | 0.3296 | 0.6133 | 0.1045 | 0.8716 | 0.9483 | 0.9716 |
|         | HoHoNet [39] | 0.1488 | 0.2862 | 0.5138 | 0.0871 | 0.8786 | 0.9519 | 0.9771 |
|         | Ours       | 0.1205 | 0.3311 | 0.5922 | 0.0806 | 0.9038 | 0.9519 | 0.9770 |
| 360D    | FCRN [26]  | 0.0699 | 0.1381 | 0.2833 | 0.0473 | 0.9532 | 0.9905 | 0.9966 |
|         | OmniDepth [47] | 0.0931 | 0.1706 | 0.3171 | 0.0725 | 0.9092 | 0.9702 | 0.9851 |
|         | BiFuse [41] | 0.0615 | 0.1143 | 0.2440 | 0.0428 | 0.9699 | 0.9927 | 0.9969 |
|         | SliceNet [30] | 0.0467 | 0.1134 | 0.1323 | 0.0212 | 0.9788 | 0.9952 | 0.9969 |
|         | Ours       | 0.0550 | 0.1145 | 0.2364 | 0.0369 | 0.9743 | 0.9944 | 0.9978 |

1 We recalculated all metrics using open source models. 2 HoHoNet does not provide results on 360D.

SliceNet cannot correctly estimate the depth of the ground and ceiling areas caused by lacking the corresponding GT in these regions. However, SphereDepth can still obtain relatively correct depths in these areas. The ground and ceiling areas are relatively small regions on the spherical domain instead of large areas in the panorama image in the equirectangular projection. Therefore, SphereDepth can automatically fill these missing regions with the predictions on the sphere space. Fig. 9 further reflects the superiority of SphereDepth, which can generate complete and noise-removed point clouds.

4.6. Limitations

We propose SphereDepth for panorama depth estimation and achieved comparable results with the state-of-the-art results. However, SphereDepth still has some limitations. On the one hand, it is difficult for SphereDepth to process ultra-high-resolution panorama images because the higher SR will significantly increase the computational complexity. On the other hand, the network structure of SphereDepth is not tailor-made for the panorama image, and we still need more studies to find out the best.

5. Conclusion

This paper proposes a new depth estimation network for the panorama image, called SphereDepth, which can avoid the issues of distortion and discontinuities caused by projection methods, such as equirectangular projection or cube map projection. SphereDepth uses a customized convolution kernel to directly extract features on the spherical domain and perform depth estimation. The experimental results on the three datasets show that SphereDepth can obtain high-quality point clouds, which also shows that the SphereDepth can be further applied to other tasks under panorama images.

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